Analysis of the uptake of small and medium scale wind turbines under the Feed-in Tariff in Great Britain

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The candidate confirms that the work submitted is his/her own, except where work which has formed part of jointly-authored publications has been included. The contribution of the candidate and the other authors to this work has been explicitly indicated below. The candidate confirms that appropriate credit has been given within the thesis where reference has been made to the work of others.

Over the course of the research project described here in this thesis, a number of research papers have been published or submitted for publication;

D.J. Allen, A.S. Tomlin, C.S.E. Bale, A. Skea, S. Vosper, M.L. Gallani, (2017), "*A boundary layer scaling technique for estimating near-surface wind energy using numerical weather prediction and wind map data*", Applied Energy, In Press. https://doi.org/10.1016/j.apenergy.2017.09.029

This paper contains research detailed in Chapter 4. I developed the novel aspects of a higher spatial resolution map of surface roughness and the increased number of wind direction sectors used in the boundary layer scaling model and conducted the research which is presented in the paper. My co-authors at the Met Office provided data and guidance during the development and implementation of the model, while Professor Tomlin and Dr Bale provided extensive guidance and editorial supervision.

D.J. Allen, A.S. Tomlin, C.S.E. Bale, (2017), "*Influencing factors on the adoption patterns of wind turbines under the Feed-in Tariff in Great Britain*", In Preparation

This paper contains research detailed in Chapter 5. I developed the approach presented in the paper, collected, collated and conducted the research. Professor Tomlin and Dr Bale provided extensive guidance and editorial supervision.

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Abstract

As part of the UK's energy system transition to a low-carbon electricity supply, decentralised energy sources such as small and medium scale wind turbines have become increasingly relevant. Decentralised energy generation has a central role in a proposed societal pathway to deliver a low-carbon energy system transition. Given the vast onshore wind energy potential of Great Britain, small and medium scale wind turbines will be a key part in this transition. With the introduction of the Feed-in Tariff (FIT) in April 2010, small and medium scale wind turbine deployment was expected to increase towards the technical potential of the technology, estimated to be up to 400,000 turbines. However, only 6,000 wind turbines have been installed in Great Britain since April 2010, highlighting there is still significant potential for small and medium scale wind turbine deployment.

To fulfil this potential, an understanding of the influencing factors on previous wind turbine adoptions is required. A key part of this analysis is an investigation of the wind resource assessment methodology prescribed in the FIT policy. The Microgeneration Certification Scheme (MCS) is designed to offer a low-cost and quick scoping tool for prospective wind turbine installations. Analysis carried out in this work shows that long-term mean near surface wind speed predictions from the MCS method have a mean percentage error of 2.36 %. Over the same sample of 124 sites across Great Britain, a Boundary Layer Scaling (BLS) method, developed in this work, using UK wind map data offered wind speed predictions with a mean percentage error of 1.43 %. While these errors appear small, they equate, in the most extreme cases, to a difference of over £500 in annual FIT payments for a single wind turbine. While the MCS method is mandated in the FIT accreditation process, there is a risk that the potential financial returns of an installation can be severely miscalculated.

Using the more accurate wind speed predictions available from the BLS model, it is possible to understand the influence of available wind resource on wind turbine adoption patterns. Throughout this work, wind turbine adoptions in Great Britain from 1995 until 2015 at both local authority and statistical geography resolution were analysed. Using a regression model, it is shown that wind resource explains up to 34 % of the spatial variance in adoption patterns. A threshold wind speed of 4.5 ms^{-1}, above which wind turbine deployment is likely, was found in the current adoption patterns. These results highlight that while wind resource is an important factor, it is not the sole factor which influences wind turbine deployment in Great Britain.

Previous literature has identified a number of socio-economic factors that have influenced adopters of other microgeneration technologies. Using a regression model and additional variables, such as land availability and agricultural statistics, it is possible to understand the influence of these socio-economic factors on wind turbine adoption patterns. The Socio-Economic and Resource (SER) model developed in this work highlights that wind turbine adoptions are more likely to occur in rural areas where wind resource, availability of land and prevalence of agriculture are high. Wind adopters are more likely to be older, hold degree-level qualifications and live in a detached home. This regression model however, only accounts for up to 65 % of the spatial variance in adoption patterns. This is an improvement over using only the resource model, however, there are still additional factors which influence wind turbine adoption patterns.

The additional factors examined in this research were the influence from changes to the subsidy level of the FIT and the potential visibility of neighbouring turbines on adoption patterns. The visibility of neighbouring microgeneration installations has been cited as a factor which raises awareness in adopters, a factor particularly prevalent to wind turbines, which are highly visible to close neighbours. The influence of these factors was examined using a peer effects model in areas of high installations. The model shows that reductions in the FIT subsidy level have severely affected deployment. A peer effect from visible neighbouring turbines can be seen in these clusters of installations, however, it is secondary to the level of FIT subsidy available. In some clusters, evidence for a slow diffusion of wind turbines between peers was observed. Overall, the model indicates that the subsidy level available from the FIT was more influential than the visual peer effects. However, it is anticipated that this peer effect, will increase as deployment increases.

In conclusion, the research has found that adoptions of wind turbines in Great Britain are influenced by a number of factors, namely available wind resource, rurality of turbine location, income of individual adopters and the subsidy level available for energy generation. These findings indicate that the small and medium scale wind turbine market in Great Britain is approaching a critical stage in its adoption lifecycle. Additionally, the results were used to develop a number of potential deployment estimates to understand where future growth in the market may occur. To meet these potential deployment estimates, there needs to be higher levels of deployment in order to help reduce capital costs. To achieve this future deployment, the levels of subsidy available from the FIT need to be maintained, in addition to the introduction of a BLS methodology in the FIT policy to facilitate more accurate financial assessments. A reduction in capital costs and maintaining of FIT subsidies will increase the number of sites which are financially viable for wind turbine installation. Potential new sites must still have a sufficient long-term mean wind resource of 4.5 ms^{-1} or above to be economically viable, highlighting the need for the introduction of the more accurate BLS methodology. If these conditions occur, deployment of small and medium scale wind turbines can increase towards the technical potential and play a central role in the transition to a low-carbon electricity market in Great Britain.

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Nomenclature

Abbreviations

BLS	Boundary layer scaling
BP	Breusch-Pagan test for heteroskedasticity
Capex	Capital expenditure
CEH	Centre for Ecology and Hydrology
CFD	Computational fluid dynamics
CT	Connecticut
CV	Coefficient of variation
DECC	Department of Energy and Climate Change
DEFRA	Department for Environment, Food and Rural Affairs
DW	Durbin-Watson test for autocorrelation
DZ	Data zone
ESCOs	Energy service companies
EU	European Union
EW	England and Wales
FES	National Grid's Future Energy Scenarios
FIT	Feed-in Tariff
GHG	Greenhouse gas emissions
IBL	Internal boundary layer
ID	Identifier
IZ	Intermediate zone
KS	Census key statistics
KfW	German state-owned development bank
LA	Local authority
LCBP	Low Carbon Buildings Programme
LCM	Land Cover Map
LCOE	Levelised cost of electricity
LSOA	Lower Super Output Area
MAE	Mean absolute error
MCS	Microgeneration Certification Scheme

MIDAS	Met Office Integrated Data Archiving System
MoD	Ministry of Defence
MPE	Mean percentage error
MSOA	Middle Super Output Area
NCIC	National Climatic Information Centre
NFU	National Farmers Union
NOABL	Numerical Objective Analysis of Boundary Layer
NRS	National Records for Scotland
NS-SeC	National Statistics socio-economic classification
NUTS	Nomenclature of Territorial Units of Statistics
NWP	Numerical Weather Prediction
Ofgem	Office of Gas & Electricity Markets
OLS	Ordinary least squares
ONS	Office of National Statistics
PV	Photovoltaic
QS	Census quick statistics
REPD	Renewable Energy Planning Database
S	Scotland
SEC	Socio-economic classification
SER	Socio-economic and resource
SG	Statistical geography
SNS	Scottish Neighbourhood Statistics
SWM	Spatial weight matrix
TIC	Total installed capacity
UK	United Kingdom
UK4	4 km resolution Numerical Weather Prediction model for UK
UKV	1.5 km resolution Numerical Weather Prediction model for UK
UM	Unified Model
US	United States of America
VMM	Virtual Met Mast™
WTP	Willingness to pay

Units

°	Degrees of arc
%	Percentage
£	Pound sterling
GWh	Gigawatt hours
$kgCO_2eq/kWh$	Kilograms of carbon dioxide equivalent per kilowatt-hour
km	Kilometre
km^2	Square kilometre
kW	Kilowatt
kWh	Kilowatt-hour
M	Metre
m^2	Square metres
ms^{-1}	Metres per second
$MtCO_2$	Megatonne of carbon dioxide
MW	Megawatt
MWh	Megawatt-hour
p/kWh	Pence per kilowatt hour
TWh	Terawatt-hour

Wind Speed Modelling

A	Area
$\partial u/\partial z$	Vertical wind speed gradient
c	Weibull scale factor
C_f	Scaling factor
c_k	Empirical coefficient for vertical change in shape factor
C_p	Coefficient of performance
d	Displacement height
d_{eff}	Effective displacement height
d_i	Displacement height of roughness patch
d_{site}	Displacement height of site

du'_{max}	Maximum velocity change due to roughness patch
$du'(z_{0,t})$	Change in wind velocity due to roughness changes across the whole fetch
$\overline{du'(z_{0,t})}$	Mean velocity change due to roughness patch
E_w	Energy in wind
E_{year}	Annual energy production
$Elec_{year}$	Annual savings on grid electricity
$F(u)$	Cumulative density function
$f(u)$	Probability density function
$f(u_i)$	Probability of specific hub height wind speed
f_i	Surface fraction
FIT_{year}	Annual FIT payment
i	Site
k	Weibull shape factor
κ	Von Kármán constant
k_{obs}	Observed Weibull shape factor
k_{pred}	Predicted Weibull shape factor
k_s	Weibull shape factor at surface
l	Prandtl mixing length
L_d	Characteristic length scale
L_p	Variability scale
m	Mass
$\dot{m}$	Mass flow rate
MAE	Mean absolute error
MPE	Mean percentage error
N	Sample size
$Opex_{year}$	Annual operational expenditure
Pb	Payback period
P_d	Power density in wind
$P_{d,norm}$	Dimensionless power density
P_t	Power extracted by turbine

P_w	Theoretical power in wind
$P(u_i)$	Turbine wind power at specific hub height wind speed
T_c	Terrain classification of a site,
u	Wind speed
$\bar{u}$	Mean wind speed
u_*	Friction velocity
$u_{*,1}$	Friction velocity 1
$u_{*,2}$	Friction velocity 2
u'	Fluctuation in horizontal velocity component
u_{10}	Wind speed at 10 m
u_{bh}	Wind speed at blending height
u_{ch}	Wind speed at canopy height
u_{hh}	Wind speed at hub height
u_i	Mean wind speed in a region
$\bar{u}_{mcs}$	MCS wind speed
$\bar{u}_{NOABL}$	NOABL wind speed
$\bar{u}_{obs,i}$	Observed mean wind speed at site i
$\bar{u}_{pred,i}$	Predicted mean wind speed at site i
u_{ref}	Wind speed at reference height
$\bar{u}_z$	Mean wind speed at height, z
w'	Fluctuation in vertical velocity component
z	Height
z_0	Surface roughness length
$z_{0,1}$	Roughness length of surface 1
$z_{0,2}$	Roughness length of surface 2
$z_{0,3}$	Roughness length of surface 3
$z_{0,4}$	Roughness length of surface 4
$z_{0,i}$	Roughness length of patch i
$z_{0,t}$	Roughness of preceding roughness patch in upwind fetch
z_{0eff}	Effective roughness length
z_{0ref}	Roughness length of wind climatology

z_{0site}	Roughness length of site
z_{10}	Height of 10 m
z_{bh}	Blending height
z_{ch}	Canopy height
z_{hh}	Hub height
z_{lo}	Highest local obstacle
z_o	Surface roughness value
$z_{o,i}$	Individual roughness length patch
z_r	Reversal height of diurnal cycle
z_{ref}	Reference height
z_s	Surface height
Γ	Gamma function
λ_f	Frontal area of obstacle
ρ	Density
σ^2	Variance in wind resource
σ_d^2	Diurnal wind speed variance
σ_u^2	Long-term wind speed variance
σ_w^2	Synoptic wind speed variance
τ	Shear stress

SER Modelling

Age_i	Median age of residents in a region
$Area_i$	Geographical area of a region
$AveElec_i$	Percentage of homes in a region with electric central heating
$Detach_i$	Percentage of homes in a region which are detached
$Educa_i$	Percentage of residents in region with degree-level qualifications
$ElecCH_i$	Percentage of homes in a region with electric central heating
$GasCH_i$	Percentage of homes in a region with gas central heating
$HouseSales_i$	Mean number of annual house sales in a region
i	Region
$Income_i$	Median weekly income of residents in a region

$IndA_i$	Percentage of residents in a region employed in the agriculture industry
K	Vector width
LA Cap	Installed capacity at local authority level
LA Inst	Installation at local authority level
SG Cap	Installed capacity at statistical geography level
SG Inst	Installations at statistical geography level
N	Vector length
$Owned_i$	Percentage of homes in a region which are owned
R^2	Coefficient of determination
$\bar{u}_i$	Mean wind speed of region
u_i	Wind speed metric of region
WT_i	Wind turbine installations or installed capacity in a region
x	Independent variable
y	Dependent variable
$\hat{y}$	Predicted value of dependent variable
β_0	Intercept term
β_1	Estimated regression coefficient
β_n	Regression coefficient
ε	Residual term
ε_i	Residual value of a region

Peer Effects Modelling

$AR_{i,t}$	Wind turbine adoption rate in region
$b_{i,t-1}$	Installed base in neighbourhood
C	Social neighbourhood
CV	Coefficient of variation
FIT_{t-1}	Feed-in Tariff subsidy level
I_i	Local Moran's I
$I_{i,t-1}$	Previous wind turbine installations in region
$I_{i,t}$	Wind turbines installed in neighbourhood in time step
j	Neighbour

n	Number of neighbours
OD_i	Number of owner-occupied detached homes in a region
PA_i	Total number of potential adopters in region
$PA_{i,t}$	Number of potential adopters in region in time step
PC_i	Fraction of land area in the region not covered by an environmentally sensitive region
PS_i	Fraction of utility-scale wind turbines which gained planning permissions from the local council
R^2	Coefficient of determination
t	Time step
w_{ij}	Spatial weight matrix
WR_i	Fraction of land area in each region with sufficient mean wind speed
WT_i	Wind turbine installations or installed capacity in a region
$WT_{i,t-1}$	Previously installed neighbouring wind turbines in region
y	Dependent variable
$\hat{y}$	Predicted value of dependent variable
α_0	Intercept term of peer effects model
β_1	Endogenous peer effect
γ_1	Influence of FIT
ε	Residual term
ε_i	Residual value of a region
ε_j	Residual value of the neighbour
$\bar{\varepsilon}$	Mean residual value of neighbouring area
σ	Standard deviation of sample
μ	Mean value of sample

Potential Deployment Estimates

SER_{pred_redu}	Prediction of potential deployment at reduced tariff rate
SER_{pred_curr}	Prediction of potential deployment at current tariff rate

Chapter 1 – Project introduction

At the end of World War II, the countries of Western Europe were ravaged by war with their economies left decimated. With the introduction of the Marshall Plan in 1948, economic prosperity swept across Europe as industrial and agricultural production boomed. In the UK, electricity demand increased 150 % as economic growth increased in the post-war years [1]. To meet this energy demand, the UK government began to exploit their natural fossil fuel resources for electricity production. The coalfields of the UK provided around 90 % of the UK's primary energy resources in the 1940's [1]. In the early 1990s, the newly privatised electricity sector began to prioritise energy production from North Sea gas in the Dash for Gas. However, domestic coal and gas reserves have dwindled, causing the UK to import around 40 % of its primary energy in 2015 [2]. Coal and gas fired generation accounted for 52 % of all UK electricity supply in 2015 [2]. Coupled with decreasing fossil fuel electricity generating capacity [2], the ability of the UK's energy systems to provide sufficient electricity for future energy demands is reducing.

A long-term structural change of the UK's energy systems is therefore required to meet future energy demand. A key consideration of the UK's energy system transition is the "energy trilemma" and any future energy system must be designed to provide energy which satisfies the three principles of the trilemma [3]. This trilemma, seen in Figure 1, is composed of; security of the energy supply, sustainability of the energy and the production and affordability of the energy [3]. In the UK electricity market, these issues are prevalent due to the UK's increasing dependency on energy imports for ageing generation infrastructure [2]; the need to meet the legally binding greenhouse gas (GHG) emission reduction targets of the 2008 Climate Change Act [4]; the legally binding European Union (EU) Directive to provide 15 % of the UK's total energy supply from renewable sources by 2020 [5]; and the fact that in 2014 in England alone, 2.38 million households were in fuel poverty [6].

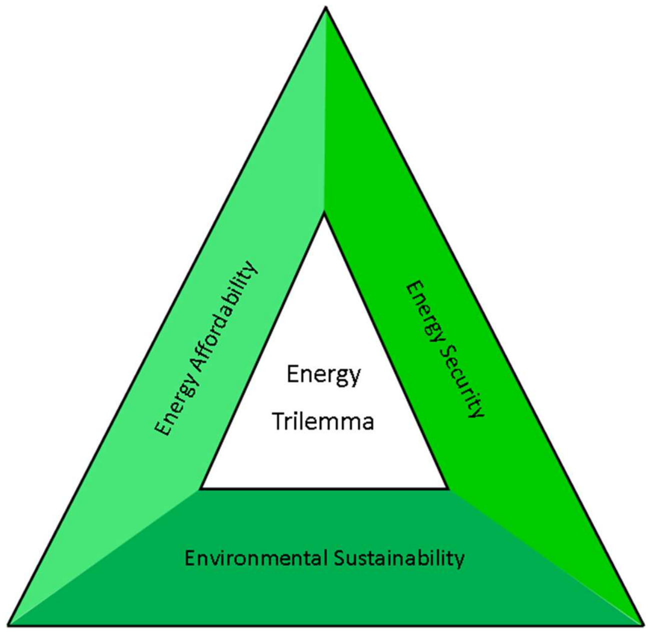

Figure 1 — The energy trilemma

The United Kingdom has one of the highest onshore wind resource potentials in Europe [7] and therefore utility-scale and small and medium scale wind power will be key components in the UK's energy system transition. Small and medium scale wind turbines can be installed to provide energy for a single home or a community of homes [8]. Small and medium scale wind turbines are traditionally defined as wind turbines with an installed capacity below 500 kW [9, 10]. This definition can be split further into: small scale wind turbines as turbines with an installed capacity below 50 kW [11] while medium scale turbines have an installed capacity above 50 kW but below 500 kW [10]. In this research, a sample of wind turbines installed under the Feed-in Tariff (FIT) was used [12]. In this sample, 98.4 % of the wind turbines were small or medium scale wind turbines [12]. Full details of the sample used throughout this research are given in Section 1.3.

1.1 Small and medium scale wind turbines as part of the energy system transition

Small and medium scale wind turbines generate electricity by extracting energy from wind flow. Kinetic energy in the wind flow is extracted by the blades of the turbine to produce electricity through a generator [13]. However, the wind resource available to a wind turbine is highly variable [14] and load factors of a wind turbine are therefore, site dependent. For small-scale turbines in Great Britain, the annual load factor of a wind turbine can range from 5 % to 44 %, depending on location [15]. It is therefore likely that a wind turbine adopter may also require electricity from the national grid to meet their electricity demands. A wind turbine installation would therefore increase the security of an adopter's energy supply but may not fully mitigate the risks.

Electricity generated on-site by a wind turbine is free, as an adopter has to pay no charges to utilise the electricity. However, the levelised cost of the electricity (LCOE) from a small scale wind turbine, which considers the capital and operating costs incurred to install the turbine is high [16]. For an onshore wind turbine rated under 50 kW in 2016, the LCOE is £227 per MWh, this drops to £128 per MWh for onshore turbines rated between 100 kW and 1500 kW during the same year [16]. Despite this, small-scale wind technologies have a lower hurdle rate, representative of the risk associated with not realising a financial return, than either offshore wind or nuclear technologies [16]. Therefore, if an adopter is able to secure sufficient capital for a wind turbine installation, a wind turbine would represent a relatively low risk investment, which can provide affordable electricity.

There are no direct GHG emissions from the production of electricity by a small-scale wind turbine [17]. However, GHG emissions and other environmental impacts occur during the lifetime of a wind turbine [17]. An assessment of a wind turbine's manufacture, installation and operation has shown that a 6 kW wind turbine operating in the UK over a 20 year lifecycle with an mean load factor of 19 %, produces 0.048 $kgCO_2eq/kWh$ over its lifetime [17]. In comparison, grid electricity produced 0.332 $kgCO_2eq/kWh$ in 2015, where the mix of electricity contained 24.6 % renewable energy and 21 % nuclear energy generation [2]. Without nuclear and renewable energy in this electricity mix, the carbon intensity of all UK fossil fuelled electricity generation in 2015 would have been 0.618 $kgCO_2eq/kWh$ [2]. Additionally, during its lifecycle, a wind turbine would have a lower impact on terrestrial life through lower air, water and soil pollution than grid electricity which is dominated by fossil fuelled thermal power [17]. Installation of a wind turbine for electricity generation can therefore be considered more environmentally sustainable than the current mix of grid electricity, where the majority of electricity is generated using fossil fuelled thermal power.

While small and medium scale wind turbines are able to meet the aims of the energy trilemma, the installation of small-scale wind turbines cannot be considered a panacea for the energy system transition. Small-scale wind turbines must be part of a wider strategy to achieve an energy system transition, but given the onshore wind resource of the UK [18], they could potentially play a key role in societal pathway's contribution to the energy system transition.

To achieve the energy system transition to a low carbon electricity market, three pathways, a state driven, a market driven and a society driven energy systems transition have been suggested [19]. These pathways are differentiated by the driving force behind the transition. However, in each pathway, all three factors play a role with varying degrees of influence [19]. The state-driven pathway relies on central government, through various bodies, to deliver energy policy which co-ordinates an energy system transition with the large-scale commercial electricity generators [19]. The market driven pathway envisages an energy system transition driven by competition in the electricity market, brought about by high-level policy frameworks which force large scale energy suppliers to develop low-carbon technologies [19]. The societal pathway involves greater engagement with communities and individuals to deliver an increasing number of community and individual-level energy systems coupled with increased levels of energy efficiency measures to reduce energy demand [19]. In this societal pathway, renewable energy adoption decisions are not evaluated solely on a cost-benefit basis but rather on the wider quality of life benefits [19]. These pathways are clearly defined, in terms of the different actors which are the driving force behind the deployment. Additionally, there may be other transition pathways, such as those illustrated in the National Grid's Future Energy Scenarios (FES) [20] which contribute to the transition of energy systems. All of these pathways are likely to contribute towards the overall transition of the UK's energy systems. The contribution of each pathways will depend on the actors of the scenarios and their levels of engagement in an energy systems transition.

For small and medium scale wind turbines to contribute sufficiently to the energy system transition, it is this societal pathway which will be most influential [19]. Through the societal pathway, small-scale generation or microgeneration technologies, such as small scale wind turbines, would become commonplace and acceptance of such technologies and their utility-scale counterparts would increase [19]. This would also lead to changes of the business models in the energy sector, moving away from the current scenario, where 95 % of all domestic electricity is supplied by the "Big Six" utility companies [3]. The electricity market envisioned under the societal pathway is led by energy service companies (ESCOs), who partner with local stakeholders to provide energy for individual communities [19]. This causes larger utility companies to adopt the ESCO business model [19]. An energy system transition via the societal pathway is typified at the local level by smaller-scale generation and greater individual involvement in the energy decisions that affect their communities.

However, to achieve an energy system transition through this societal pathway, small-scale renewable energy generation technologies need high rates of uptake at an early stage [19]. In this scenario, high levels of early deployment lead to rapid growth in the 2020’s, as such technologies move into the mainstream [19]. Therefore, for small and medium scale wind turbines to contribute to an energy system transition, high levels of deployment need to be achieved in the immediate future. The key risk which can prevent the high levels of deployment being achieved is the capital cost of the small-scale technologies [19], an issue which is particularly prevalent for small and medium scale wind turbines. Capital costs for a wind turbine rated under 15 kW are estimated to be between £2,000 to £6,000 per kW installed [21]. For a 5 kW wind turbine, the capital costs can range from £10,000 to £30,000, which is a significant cost for individuals to bear. To overcome these high capital costs and promote deployment, the societal pathway requires central government to incentivise small-scale electricity generation to attract individuals into the market [19]. In Great Britain, this incentivisation of small-scale electricity generation has already occurred with the introduction of the Feed-in Tariff policy [22].

1.2 Feed-in Tariff

Introduced in April 2010, the Feed-in Tariff (FIT) scheme was designed to drive uptake for small-scale low carbon technologies to deliver higher rates of deployment [23]. Introduction of the FIT was also designed to engage the general public in low carbon electricity generation, to enable broad participation by individuals and communities in a “big energy shift” towards a low carbon economy [23]. These stated aims are key components of any governmental policy to stimulate an energy system transition via the societal pathway [19]. The FIT policy is therefore considered a policy intervention by the UK government to facilitate an energy systems transition through the societal pathway.

The FIT policy incentivised on-site electricity generation by providing a payment for each kWh of electricity produced by an eligible microgeneration technology [24]. Solar photovoltaics (PV), wind turbines, hydropower technologies, anaerobic digestion and combined heat and power, with a total installed capacity (TIC) of up to 5 MW per site, are eligible for FIT payments [25]. The FIT is only available for technologies installed in England, Wales and Scotland [25] and therefore it was only within these countries of Great Britain that wind turbine deployment was analysed in this project.

The payments from the FIT policy are provided by, either mandatory or voluntary FIT licensees [12]. Mandatory FIT licensees are any licensed electricity suppliers with over a quarter of a million domestic electricity customers while, voluntary FIT licensees are any licensed electricity suppliers, with under a quarter of a million domestic electricity customers, who decide to participate [12]. In 2015, there were 9 companies and their subsidiaries who were mandatory licensees and 30 companies who were voluntary licensees [12]. Each individual who applied for the FIT entered into an agreement with one of the licensees, who agreed to provide quarterly remuneration based upon the readings of an electricity meter specifically installed to monitor the amount of electricity generated by the technology [12].

To qualify for FIT payments, each installation of an eligible technology must meet a set of accreditation criteria, which differs depending on the installed capacity of the installation. For solar and wind turbine installations under 50 kW, the Microgeneration Certification Scheme (MCS) is the accreditation route, while for installations of all technologies above 50 kW accreditation is gained through the ROO-FIT scheme [26]. To gain ROO-FIT accreditation, individuals who are considering or have installed a technology must apply through the FIT central register [26]. The pre-requisite documentation required for accreditation is, approval of planning permission from the local planning authority and a grid connection agreement with the transmission or distribution network operator [26]. Accreditation via the MCS route requires individuals to select an MCS-accredited technology and an MCS-accredited installer to complete the installation [26]. To gain accreditation via this route, the installation must also meet the MCS installer standards, which set out a number of assessments that must be undertaken prior to the construction phase of the installation [27]. For a wind turbine installation, these assessments cover noise levels and flicker from the turbine as well as providing an estimation of the annual energy generation from the proposed wind turbine [27].

An estimation of the annual energy generation of a proposed wind turbine must be conducted using the MCS wind resource assessment [27]. The

MCS methodology is described as a "*simple method using freely available wind speed data (NOABL) and simple tabulated correction factors for the local terrain, obstructions and turbine height*" [27]. The Numerical Objective Analysis of Boundary Layer (NOABL) wind speed database is a set of gridded long-term mean wind speeds for the whole of the UK [28] and is the only freely available wind map in the UK. The calculated MCS mean hub height wind speed is then utilised to derive the annual energy production of a proposed turbine, from the manufacturer's data [27]. The manufacturer's estimates of annual energy production are produced using international standards [29] and are derived from the independently tested power curve of each wind turbine. However, these power curves are typically derived from testing at sites with considerable wind resource and therefore, any annual energy production estimate derived from this data will be the maximum annual energy production of the wind turbine at a mean wind speed.

The correction factors used in the MCS wind resource assessment attempt to remedy inaccuracies in raw NOABL data [30, 31] using a simple, empirically based approach. These corrections are fixed and therefore do not account for any idiosyncrasies of surface roughness or local conditions at a prospective site. It is suggested here that this approach is insufficient to provide accurate mean wind speed predictions. If any annual energy production estimates produced using an alternative methodology are provided during the scoping stage of the small scale wind turbine project, the results of the MCS method must be given equal prominence and if the additional estimates are significantly greater than the MCS results, it must be prefaced with a warning to potential wind turbine adopters [27]. Assessment of the annual energy production, through estimation of the wind resource at a site, is vital during the initial stages of a wind turbine project [32, 33]. If a site is shown to have sufficient wind resource, it is likely that further financial resources will be invested to fully characterise the wind resource available to a proposed turbine.

The estimated MCS wind speed is likely to be viewed by potential adopters as the upper estimate of long-term mean wind speed of a site and if the MCS methodology under-predicts the wind speed, a potential adopter could possibly be dissuaded from installing a wind turbine in a location with sufficient wind resource. The risk is that the MCS methodology may produce inaccurate wind speed estimates and it is argued in this research that if other wind resource assessment techniques were available at the initial stages of a wind turbine project, it may be possible to provide more accurate wind speed estimates.

Once a wind turbine installation gains accreditation through either route, the adopters are eligible to receive payment for each kWh of on-site electricity generation [25]. These payments are guaranteed whether the electricity is consumed on-site or exported via a grid connection [25]. The FIT subsidy rate at the time the installation is commissioned is guaranteed for the lifetime of the installation, which for wind turbines is 20 years. The subsidy level per kWh is based upon the total installed capacity of each technology and when the installation was registered with Ofgem [25].

There have been a number of changes in the tariff levels since the introduction of the FIT in 2010, with current tariff levels, as of October 2016 being between 8.33 p/kWh for wind turbines under 1.5kW TIC, and 0.83 p/kWh for wind turbines with a TIC over 1.5 MW [34]. In addition to the payment for on-site electricity production, there is also a flat rate of 4.91 p/kWh for electricity exported to the wider electricity grid [34]. At the beginning of 2016, the tariff bandings for wind turbines were also altered, so that all turbines with MCS accreditation gained the same tariff. A full breakdown of the changes to tariff bandings and subsidy levels since the introduction of the FIT is provided in Table 1.

Table 1 — FIT Tariff levels for wind turbines since April 2010 [34]

Tariffs in pence/kWh	TIC subsidy level banding					
Date installation registered with Ofgem	**Less than 1.5 kW**	**1.5 kW to 15 kW**	**15 kW to 100 kW**	**100 kW to 500 kW**	**500 kW to 1.5 MW**	**Greater than 1.5 MW**
1 April 2010 to 31 March 2012	41.25	31.91	28.85	22.43	11.32	5.33
1 April 2012 to 30 November 2012	38.98	30.48	27.66	22.43	11.32	5.33
1 December 2012 to 31 March 2014	22.86	22.86	22.86	19.06	10.33	4.88
1 April 2014 to 30 September 2014	18.28	18.28	18.28	15.24	8.27	3.5
1 October 2014 to 31 March 2015	16.46	16.46	16.46	13.71	7.45	3.16
1 April 2015 to 30 September 2015	14.62	14.62	14.62	12.19	6.62	2.80
1 October 2015 to 15 January 2016	13.89	13.89	13.89	10.98	5.96	2.80
Date installation registered with Ofgem	**Less than or equal to 50 kW**		**50 kW to 100 kW**	**100kW to 1.5 MW**		**Greater than 1.5 MW**
16 January 2016 to 31 March 2016	8.74		8.74	5.60		0.88
1 April 2016 to 30 June 2016	8.46		7.61	4.89		0.85
1 July 2016 to 30 September 2016	8.39		6.85	4.40		0.85
1 October 2016 to 31 December 2016	8.33		6.08	3.92		0.83
NB. Between 15 January 2016 and 8 February 2016, a pause was placed on accreditation.						

Since December 2012, changes in the FIT subsidy level have been implemented using a default degression mechanism [35]. Default degression allowed the subsidy level to be reduced based upon the total capacity of all wind turbines installed in the preceding period [35]. Initially, the degression mechanism was planned to be implemented annually, however, the mechanism had a six-monthly review and the option to implement a degression of tariff rates at these intervals [35]. The rate of degression implemented is related to the difference between the actual installed capacity and the expected installed capacity of wind turbines deployed during the reference review period [35].

For wind turbines with a capacity under 100 kW, the expected annual deployment is 4.3 MW, while for all other capacities of wind turbine, expected annual deployment is 24.5 MW [35]. Should annual deployment exceed 300 % of these figures, annual degression of the tariff rate would be a 20 % reduction of the subsidy rate [35]. The level of degression reduces to a 10 % degression for 150-300 % of expected annual deployment, 5 % for 75-150 % of expected annual deployment and 2.5 % for less than 75 % of expected annually deployment [35]. Should deployment during a six month period exceed the expected annual deployment by over 200 %, a six-monthly degression of 10 % is applied [35]. A 5 % degression every six months is applied if deployment exceeds expected deployment by 100-200 %, while if deployment in the same period is below expected deployment, the degression reverts to the annual degression mechanism [26]. Since January 2016 a contingent degression mechanism has also been introduced [26]. A contingent degression of 10 % is applied quarterly if the deployment cap for a technology is reached. These deployment caps for each technology are consistent with the tariff bandings for wind turbines, seen in Table 1. All wind turbines installations which apply for accreditation after the deployment cap has been met will not receive accreditation until the next deployment cap period.

The rationale behind the introduction of the degression mechanism was as a cost saving mechanism for the FIT [35]. Introduction of the degression was designed to ensure that the FIT was not over-compensating adopters for technologies whose capital costs have decreased since the introduction of the FIT [35]. However, it was only PV systems in Great Britain that saw any major reduction in capital costs during the lifetime of the FIT [36]. In comparison, capital costs for wind turbines have remained similar between 2011 [37] and 2015 [21]. Such a policy mechanism could be detrimental to further wind deployment and may hamper the ability of the societal pathway to deliver an energy system transition. Investigation of the influence of the degression mechanism on wind turbine deployment was therefore a vital part of understanding if wind turbines can play a role in the societal pathway's required energy system transition in Great Britain. As such, the influence of changing levels of FIT subsidy on wind turbine adoption patterns were studied during this research with the outcomes presented in Chapter 6.

1.3 Wind turbine deployment under the FIT in Great Britain

Wind turbine deployment under the FIT in Great Britain on 31st December 2016 was 7,374 wind turbines, totalling 649 MW of installed capacity [12]. However, an industry wide report estimated that 27,819 wind turbines were installed between 2005 and 2014 [10]. This industry wide report considered all wind turbines under 500 kW in Great Britain and Northern Ireland and included off-grid installations [10]. Wind turbines in Northern Ireland, those without access to the national electricity grid and wind turbines which are not MCS accredited are ineligible for the FIT and this is likely to be one cause of the differing deployment estimates. While the industry wide figures were significantly higher than the FIT data, there was a lack of detailed information in the industry wide figures, upon which analysis could be performed and therefore, the FIT installation data was utilised throughout the remainder of this project. However, it is worth considering that wind turbines outside of the FIT sample have also been installed in the UK.

The FIT installation data used throughout this project was extracted from Ofgem's central register of quarterly reports of all wind turbine installations under the FIT [12]. Within the data sample extracted, there are wind turbine installations from January 1995 until December 2016, providing 22 years of installation data for analysis [12]. Wind turbines installed prior to 2010 were still eligible for the FIT, once they were accredited. The installation sample was split by year, as seen in Figure 2, by installation type, as seen in Figure 3, and by installed capacity, as seen in Figure 4, to understand further wind deployment under the FIT [12].

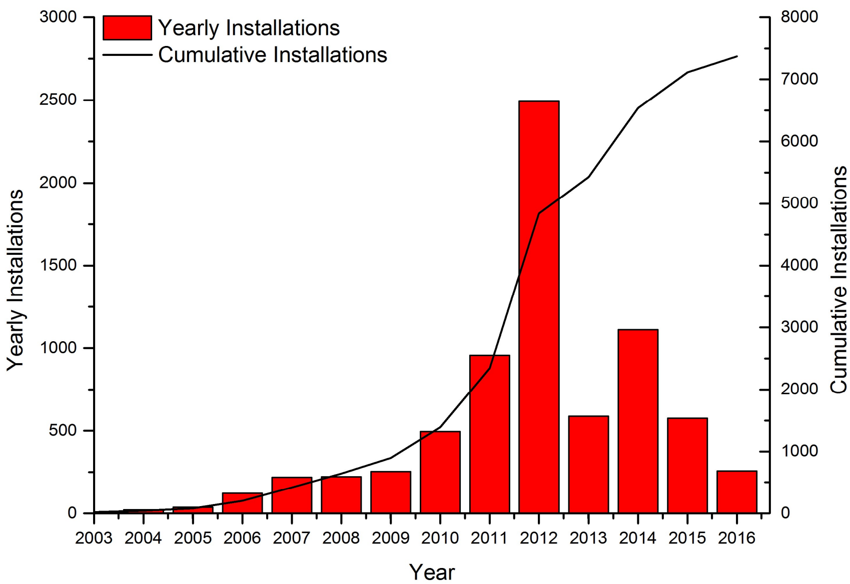

Figure 2 — Yearly wind turbine installations and cumulative wind turbine installations under the FIT since 2003 [12]

Figure 2 shows that wind turbine installations under the FIT peaked in 2012, with just under 2,500 wind turbines installed during 2012 [12]. Prior to 2012, annual wind turbine deployment had been increasing year on year, with almost a doubling of wind turbine installation numbers in 2010 and 2011. However, following 2012, annual deployment returned to a level similar to those seen in 2010 and 2011, of around 1,000 turbines or less per year [12]. This temporal installation data suggests that the introduction of the FIT policy in 2010 had a significant effect on wind turbine deployment, with 86.7 % of all wind turbines installed after April 2010 [12]. The largest peak of annual deployment in 2012 and the smaller peak in 2014, suggests that introduction of the degression mechanism in 2012 and the initial degression of the subsidy level in 2014 has affected wind deployment. The data presented in Figure 2 reinforces the need to examine the influence of the degression mechanism, suggested in Section 1.2.

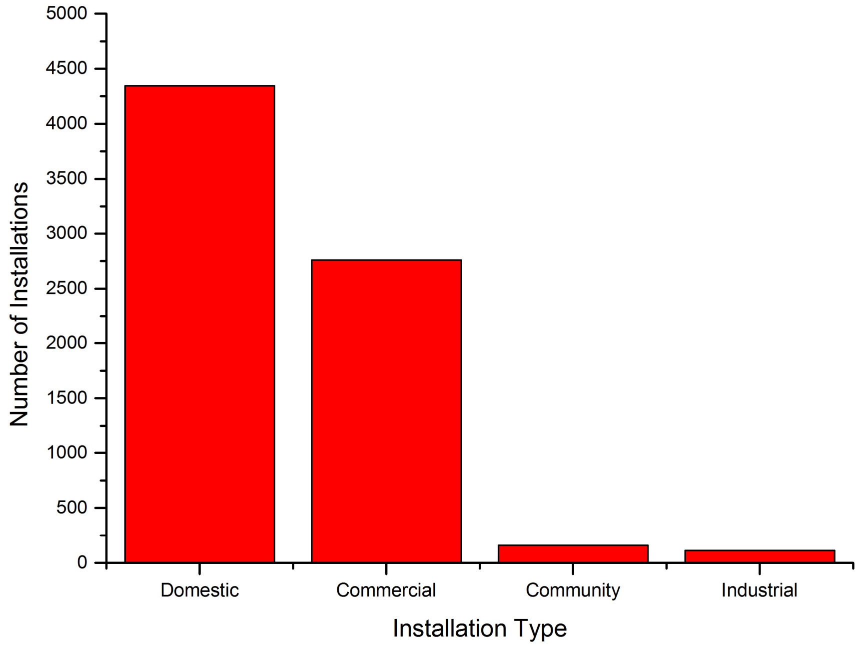

Figure 3 — Number of wind turbine installations for each installation type [12]

To understand the type of potential adopters in the FIT wind turbine market, the data in Figure 3 must be considered. The data demonstrates that wind turbines installed under the FIT were predominately installed to provide electricity for either domestic or commercial customers. 96.3 % of all wind turbines registered under the FIT were for domestic and commercial electricity generation, with the 58.9 % of all wind turbines installed for domestic energy generation. This highlights that the FIT wind turbine market has, so far, been dominated by individuals making the decision to adopt a wind turbine for their domestic properties. The data also supports the assertion that it is the societal pathway, where individuals are the dominant actors in the energy system transition, that is the most appropriate energy system transitions pathway for small and medium scale wind turbine installations.

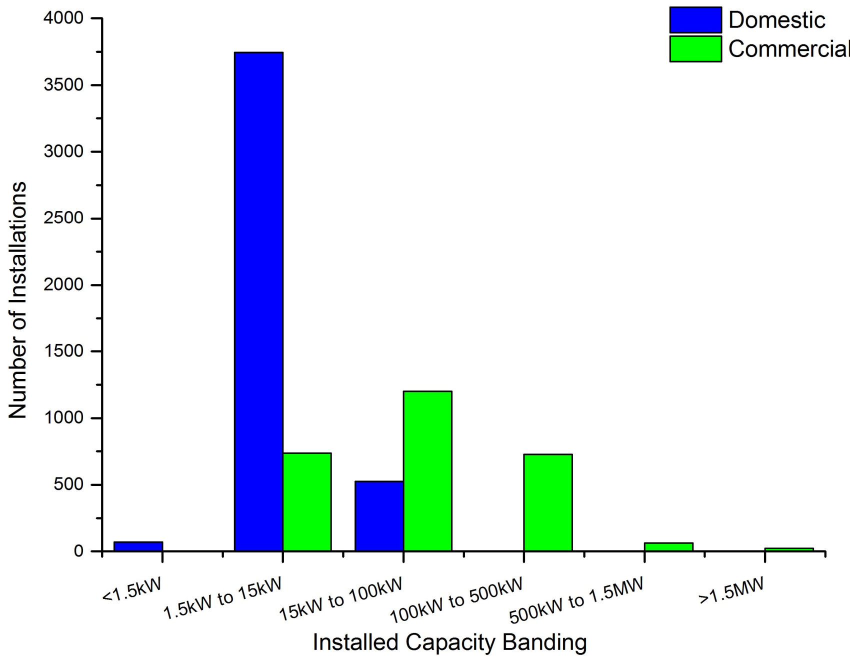

Figure 4 — Number of domestic and commercial wind turbine installations in each of the original FIT capacity bandings [12]

The number of installations of either domestic or commercial installations in each of the original FIT capacity bandings is shown in Figure 4. The data highlights that domestic and commercial wind turbines must be considered differently. While domestic wind turbines were predominately lower capacity turbines, commercial wind turbines typically had much higher installed capacities. These differing installed capacities are likely to be a result of the differing levels of capital, which domestic and commercial customers were able to provide. As a wind turbine is ineligible for the FIT payments if it receives any grant for the costs of the installation [26], domestic and commercial adopters would have had to provide sufficient capital to cover the costs of the installation. Additionally, the adoption process for these wind turbines differed, with domestic turbines likely to be adopted by individuals while commercial turbines are likely to have been subject to some degree of collective decision making process. These factors are important to understand when examining the characteristics of wind turbine adoptions using either installation or installed capacity data. As discussed, 58.9% of all turbines in the installation sample were domestic turbines. However, 85.4 % of the total installed capacity of the sample has been installed for commercial electricity generation [12]. Analysis of the installation data will therefore, focus on the domestic adopters while analysis of the installed capacity data will focus on commercial adopters. Each data set was utilised in this work to analyse the factors which have influenced each of these different types of wind turbine adopters.

Initial analysis of current wind turbine deployment under the FIT policy highlights that with the introduction of the FIT policy, wind turbine deployment has increased. However, current deployment must be considered in the context of the number of potential wind turbine installations possible in Great Britain to determine if the required levels of deployment for the societal pathway are currently being reached.

1.3.1 Potential small and medium scale wind turbine deployment in Great Britain

Assessments of the potential for small and medium scale wind turbine deployment across the UK or Great Britain have previously been published [9, 31, 38]. These assessments range from the unrestricted potential for deployment, irrespective of cost [9], to more conservative estimates which considered the influence of numerous factors on deployment potential [31]. By considering all of these assessments, it was possible to identify what can be considered the most appropriate estimate of potential small and medium scale wind turbine deployment in Great Britain.

A 2007 Carbon Trust report estimated that the unrestricted potential deployment of small scale wind energy in the UK could provide 41.3 TWh of electricity and abate 17.8 $MtCO_2$ annually [9]. 41.3 TWh of electricity would represent 13.6 % of total electricity demand in 2015 [2]. In this estimate, it was assumed that 90 % of electricity generation would be at rural sites with the remaining 10 % of electricity generation at urban sites [9]. This estimate also assumed 100 % market penetration of small-scale wind energy and an electricity price of 100 p/kWh, which would be offset by an installation of a wind turbine [9]. This unrestricted potential deployment is considered by the author to be unrealistic and to represent the maximum potential deployment of small scale wind turbines in the UK. Realistically, wind turbine deployment will never reach this estimated level, because the assumptions of market penetration and electricity price were improbable, a fact acknowledged in the report [9]. However, it has been included here to demonstrate that the unrestricted potential for small-scale wind energy is exceptionally high. The estimate, however, only discussed deployment in the context of potential electricity generation and provided no wind turbine installations numbers, with which the current FIT deployment could be contextualised.

Estimates of small and medium scale wind turbine deployment numbers were provided in two reports from 2009, prior to the introduction of the FIT policy [31, 38]. An Element Energy report was commissioned by the Department of Energy and Climate Change to provide quantitative analysis of the design of the FIT [38]. James et al. built on the estimates from the 2007 Carbon Trust report through the use of data collected from wind trials of small-scale wind turbines across Great Britain [31]. Each of these reports provided potential deployment estimates, however, these estimates differed significantly. The Element Energy report estimated that in Great Britain, a total of 3.4 million domestic wind turbines could be installed [38]. This figure was estimated based upon a mean wind speed from the NOABL wind speed database and the rurality of electoral wards [38]. In wards considered non-urban and that had a mean wind speed above 5.5 ms^{-1}, it was assumed that every home, which was not in an apartment complex, would install a wind turbine [38]. The estimate from the Element Energy report is considered by the author as over-optimistic for two reasons. The assumption that all the homes in an area would install a wind turbine seems impractical, as this assumed that all residents would be able to afford a wind turbine installation. Additionally, use of the NOABL wind speed database as the baseline dataset for sufficient wind resource is questionable. NOABL wind speeds have been shown to be inaccurate [31, 32] and therefore, this will have had an influence on the number of wind turbines which were considered viable. The Element Energy potential deployment estimate is therefore considered here to over-predict potential wind turbine deployment.

In comparison, James el al. predicted that a potential 407,950 domestic wind turbine installations were possible across Great Britain [31]. Based on the market economics of 2009, a minimum mean wind speed of 5 ms^{-1} from the MCS methodology and adequate availability of land or building profiles [31], this estimate is considered here as more realistic than the estimate from Element Energy. Despite this, there were still assumptions within the James et al. estimate that are questionable. It was assumed that for all sites where the wind speed and siting criteria were met, a wind turbine would be installed [31]. This assumption is considered here to be over-optimistic and relied on all residents in the suitable locations to have access to sufficient capital to install a wind turbine. Additionally, the wind speed criteria of a minimum mean wind speed of 5 ms^{-1} was based upon the wind speed predictions from the MCS methodology and its ability to provide accurate wind speed predictions has been questioned in Section 1.2. However, the estimate of 407,950 wind turbine installation across Great Britain [31] is considered by the author to be the most accurate prediction of the maximum potential of small and medium scale wind turbine deployment in Great Britain achieved to date.

Using this maximum potential wind turbine deployment, the current levels of wind turbine deployment under the FIT were reconsidered. There is a gap between potential and actual deployment of around 400,000 potential wind turbines. Therefore, there is significant growth potential in the small and medium scale wind turbine market of Great Britain. Should this potential be realised, small and medium scale wind turbines can potentially play a vital role in the societal pathway's contribution to an energy system transition in the UK electricity market. However, to achieve this, an understanding of why this potential growth has not yet been achieved is required and through analysis of the current uptake in the wind turbine FIT market, conducted during this project, this can be determined.

The potential deployment estimate of James et al. was based on the market economics of 2009 [31]. Given that capital costs of wind turbines between 2011 and 2015 have not changed dramatically, it was assumed that the capital costs of wind turbines in 2009 would have been similar. With the introduction of the FIT in 2010, it was assumed that the financial case of a wind turbines would become more attractive to potential adopters and therefore annual wind turbine deployment would increase dramatically. While annual wind turbine deployment did increase following introduction of the FIT [12], the increase is not considered by the author as dramatic. Introduction of a 31.91 p/kWh FIT subsidy rate for wind turbines rated between 1.5 kW and 15 kW [39] resulted in a two-fold increase in the financial returns available for on-site electricity generation in 2010. This suggests that the assumptions, presented by James et al. [31], that wind turbine deployment was solely influenced by the availability of wind resource and sufficient land are therefore flawed. The current deployment levels suggest that other factors, in addition to these assumed factors, have an influence on wind turbine adopters. To bridge the gap between potential deployment and actual deployment, an understanding of small and medium scale wind turbine deployment characteristics is crucial. By understanding the deployment characteristics of wind turbines, it has been possible to develop approaches through which the deployment of wind turbines could be appropriately analysed.

1.4 Spatial and temporal characteristics of wind turbine deployment

Both large-scale renewable energy [40] and microgeneration deployment [41] have been shown to have spatial and temporal adoption characteristics. These characteristics, relating to where and when such deployment occurred creates adoption patterns in renewable energy technology deployment data [41]. These patterns can be analysed to understand the underlying factors which have influenced them. Previous research has focused on the spatial and temporal adoption patterns of PV systems in Great Britain [41-43]. To fulfil the potential of small and medium scale wind turbines in Great Britain, the factors which drive the spatial and temporal adoption patterns of wind turbines must also be investigated. Through this investigation, it was possible to determine whether the presence of these factors were conducive to promote wind turbine deployment.

Spatial adoption patterns of small and medium scale wind turbines are likely to be driven by multiple factors. The availability of wind resource is likely to be an important factor, given the spatially variant nature of wind resource and the need for a wind turbine to be able to access sufficient wind resource to ensure technical and economic viability. Previous research has also suggested that spatial PV adoptions have been influenced by multiple demographic and environmental factors [42, 44]. It was envisioned that similar factors would have influenced spatial wind turbine adoption patterns. These demographic and environmental factors were available from decadal census data and formed the basis of the research into spatial adoption patterns undertaken during this project.

The use of decadal census data to examine the spatial adoption patterns precludes examination of the temporal adoption patterns during the same piece of research. Temporal adoption patterns of PV systems have been shown to vary over a time period of months [41]. This was expected to be similar in the temporal wind turbine adoption patterns and therefore, decadal data would be insufficient to examine these patterns. It has been suggested that temporal PV adoption patterns have been influenced by changes to the FIT [41] and therefore it was important to investigate if FIT changes also influenced temporal wind turbine adoption patterns.

The introduction of the FIT was the initial stimulus of the societal pathway transition to a low-carbon electricity market. The societal pathway relies on the engagement of individuals and communities to initially drive the energy system transition. Increased deployment of small and medium scale wind turbines offers a visual symbol of the changing face of electricity generation in Great Britain. Increased wind turbine deployment also highlights a greater level of engagement by individuals who have installed wind turbines and may influence their peers to install a wind turbine. Deployment of PV systems in neighbourhoods has been shown to lead to an increase in future PV deployment in the neighbourhood, due to a visual peer effect from the initial PV system [43, 45-47]. It was, therefore, important to examine whether wind turbine installations, which are significantly more visible than PV systems, exerted a similar influence on neighbouring peers.

Through analysis of wind turbine adoption patterns, it was possible to determine if the factors discussed, had a significant influence on the spatial and temporal adoption patterns of small and medium scale wind turbines in Great Britain. This research was undertaken due to a lack of literature which has previously examined the influence of any factors on adoption patterns. To conduct this research, a number of research questions must be addressed.

1.5 Research questions

To develop an understanding of the influential factors which stimulate wind turbine deployment, analysis of the current patterns of small and medium scale wind turbine deployment under the FIT was required. The analysis, presented in this thesis, is focused solely on wind turbines which were eligible for the Feed-in Tariff. The wind turbines analysed had an installed capacity under 5 MW and were installed across only England, Wales and Scotland. However, 98.4 % of all turbines in this sample had an installed capacity under 500 kW [12]. Furthermore, unless explicitly stated when referring to wind turbines throughout this thesis, the author will be referring to wind turbines which are eligible for the FIT or have previously been installed under the FIT.

Central to any small and medium scale wind turbine installation is the assessment of wind resource available and the resulting annual energy production and financial returns of the wind turbine. For small-scale wind turbines, whose project budgets are considerably smaller than larger scale wind turbines [16, 33], the initial scoping stage of the project is crucial. On-site anemometry is unviable for small scale wind turbines, due to the costly requirement for multiple years of data to be collected [33]. Therefore, a desk study is typically undertaken to assess wind resource, utilising a wind map and an empirical scaling methodology. At a minimum, this desk study should provide an accurate prediction of mean hub height wind speed and power density in the wind flow, from which the annual energy production of the wind turbine can be estimated [33]. Given the cubic relationship between wind speed and power available to a wind turbine [14], an accurate assessment of wind speed is vital. The MCS methodology detailed in the FIT installer standards is an empirical scaling methodology, which can be utilised at the initial stages of a small-scale wind turbine project to provide wind speed and annual energy production estimates. However, the approach of the MCS has been criticised in Section 1.2 as being insufficient to provide accurate mean wind speed predictions. This raised an important question, which was addressed in this project;

Are the wind resource assessment techniques available at the initial scoping stage of a wind turbine installation able to predict wind speed with sufficient accuracy?

With the need for an accurate wind speed prediction so important to small and medium scale wind turbine projects, it is suggested here that an alternative methodology could provide more accurate wind speed predictions than the MCS methodology. Previous studies have suggested a boundary layer scaling (BLS) technique as suitable for the prediction of the mean wind speed of a site [11, 33]. A BLS model applies a number of correction factors to a reference wind climatology, based on the surface characteristics of a site such as the presence of buildings or trees and surface morphology [11, 33]. The theoretical basis of the BLS model and the fundamentals of wind speed prediction in the boundary layer is presented in Chapter 2 while the comparison of the accuracy of wind speed predictions from the BLS and MCS methodology will be presented in Chapter 4.

While the importance of wind resource to ensure the economic viability of a wind turbine has been discussed extensively [9, 11, 13, 32, 33, 48-52], the influence of the availability of wind resource on wind turbine deployment is, as yet, unknown. The spatial variability of wind resource, which is heavily influenced by surface morphology and roughness [14], is likely to have contributed to the spatial adoption patterns of wind turbine deployment. Wind turbines are unlikely to have been installed in areas where the wind resource was insufficient to ensure economic viability, however, the exact nature of the relationship between wind resource availability and adoption numbers is currently unclear. To determine the nature of this relationship, a further research question was developed and addressed during this project;

What was the influence of wind resource availability on the spatial adoption patterns of small and medium scale wind turbines in Great Britain?

Using the wind resource assessment methodology which proved to be most accurate in the research of Chapter 4, the influence of wind speed availability on spatial adoption patterns in Great Britain is investigated in Chapter 5. The analysis of spatial adoption patterns was not limited to the influence of wind resource alone. The potential deployment estimates of James et al. also considered the availability of land as a factor which affected wind turbine deployment [31, 38]. However, the gap between potential and actual deployment suggests that the availability of sufficient wind resource and land were not the only factors which affected spatial adoption patterns.

Previous literature has discussed a variety of motivations and factors which has influenced microgeneration adoptions in the UK [42, 53-56]. The majority of this research has focused on PV adopters, given the much higher deployment of PV under the FIT [42, 54-56]. The factors which influence spatial patterns in wind turbine adoption in Great Britain are relatively unknown, due to a lack of literature, despite wind turbine deployment being second only to PV deployment under the FIT. In order to identify policy recommendations to promote wind turbine deployment, these factors must be investigated prompting the research question;

What factors have influenced the spatial adoption patterns of small and medium scale wind turbines in Great Britain?

The spatial adoption patterns of wind turbine deployment in Great Britain were analysed, with respect to a number of factors identified from previous literature. The factors selected are reviewed and discussed in Chapter 3, while the analysis of the influence that these factors had on spatial wind turbine adoption patterns will be presented and discussed in Chapter 5.

In addition to analysing the spatial adoption patterns of wind turbine deployment, the temporal wind turbine adoption patterns must be analysed. Introduction of the FIT in April 2010 to promote uptake appears to have had an influence on the level of wind turbine deployment. However, the subsidy level available from the FIT has changed since 2010 and the influence of these changes on temporal adoption patterns must be examined. In addition to the temporal changes to the FIT subsidy level, increased deployment of wind turbines in a neighbourhood may have had an influence on an individual's decision to adopt a wind turbine.

It was important to analyse the factors that influence temporal adoption patterns of wind turbine deployment in Great Britain, in order to identify policy recommendations that could promote further wind turbine deployment through the following research question;

> *What factors have influenced the temporal adoption characteristics of small and medium scale wind turbine market in Great Britain?*

Temporal factors, their influence on temporal adoption patterns and approaches to analysing these influences are discussed in Chapter 3. Analysis of the influence of visible neighbouring turbines and the changing subsidy levels of the FIT scheme on temporal adoption patterns of wind turbine deployment in Great Britain will be presented in Chapter 6.

1.6 Thesis outline

Chapter 2 will present a review of the physical phenomena which must be considered when predicting wind speeds in the boundary layer. The chapter aims to identify the most appropriate approach for this research's boundary layer scaling model, by reviewing previous literature to identify possible improvements to the approach which could be included within this research. In addition to this, the chapter will present the theoretical basis for estimation of the power density in the wind flow, a vital part of estimating the annual energy production of any wind turbine.

Chapter 3 will present a review of previous literature examining the factors which have influenced spatial and temporal adoption patterns of microgeneration technologies. Initially, the chapter will examine the motivation and barriers to adoption, which previous microgeneration adopters have experienced. Chapter 3 will then review studies which have considered the demographic and environmental factors that have influenced adoption, with a view to utilising similar factors during analysis of the spatial adoption patterns of wind turbines. In addition to a critical analysis of relevant factors, a review of techniques previously utilised to analyse spatial adoption patterns of PV systems will be presented. From this review, the appropriate approach to analysing the influence of the selected factors on spatial wind turbine adoption patterns will be identified. The chapter will introduce an examination of the factors that are likely to influence temporal wind turbines adoption patterns. Finally, Chapter 3 will present a review of previous studies, which examined the influence of neighbouring microgeneration technologies on potential adopters in their neighbourhood. Such a review allowed for the most appropriate model, with which to analyse the influence of the selected factors on temporal wind turbine adoption patterns, to be identified.

Chapter 4 will introduce the BLS and MCS methodologies and the various facets of each model, which have been constructed for this research. As part of this research, the reference wind climatologies which were used in each methodology will be discussed, as will the methodology for estimated power density in the wind flow. The results and analysis of each of the BLS and MCS methodologies will be presented with validation of these methodologies across 124 sites in Great Britain. Within this chapter, a definition of sufficient accuracy in an estimation of wind speed will be provided and used to evaluate the results of each wind resource assessment methodology. The aim of the chapter is to address the first research question and to determine if these methodologies could predict mean wind speed with sufficient accuracy. The accuracy of wind speed predictions from the BLS model using the differing reference wind climatologies and the results of the power density prediction techniques examined will also be presented.

The most accurate set of wind speed predictions identified in Chapter 4 will be utilised in Chapter 5 to identify the influence of wind resource on spatial wind turbine adoption patterns in Great Britain. In addition to this, the influence of demographic factors, consistent with previous literature will also be examined. Both of these data sets and additional environmental factors will then be then examined collectively to understand their influence on spatial wind turbine adoption patterns across Great Britain. As part of this chapter, the data collection and processing which was undertaken will be presented and discussed. In addition to the quantitative analysis of wind turbine adoption patterns, a qualitative analysis of the residuals of the regression models, examining the spatial wind turbine adoption patterns, focusing on the areas of low wind turbine deployment will also be presented.

Chapter 6 will describe a technique for the identification of a number of case study areas in Great Britain, where the temporal adoption patterns of wind turbines were examined. In these areas, the influence of the temporal changes to FIT subsidy levels and a visual peer effect from locally installed wind turbines on deployment levels were examined using a peer effects model. Development of the peer effects model for each cluster of installations will be presented, in addition to a characterisation of clusters and their residents.

Chapter 7 will recount the conclusions presented in Chapter 4, Chapter 5 & Chapter 6 and will also present the overall conclusions for this research. These overall conclusions were drawn from the conclusions of each chapter and focus on developing an understanding of the small and medium scale wind turbine market under the FIT in Great Britain. Potential wind turbine deployment estimates, based upon the findings of the research will also be presented within Chapter 7. A series of policy recommendations which are aimed at promoting future deployment of small and medium scale wind turbines will also be outlined. In addition, a reflection of the research presented in this thesis will be presented and a number of suggestions for future research topics will be offered.

Chapter 2 – Small and medium scale wind turbine resource assessment techniques

Prospective wind turbine adopters have identified the economic barriers, arising from the capital expenditure required to install a wind turbine and the ability of the turbine to payback this capital outlay as the most important when considering an installation [8, 53-55]. Financial returns which determine the payback period of a small or medium wind turbine can be realised from either the payments of the Feed-in Tariff (FIT), for on-site generation, exporting to the grid [26], and by offsetting the requirement for electricity to be bought from the grid. To determine the potential energy generation of a wind turbine, on which these financial returns are estimated, the energy and power available within the wind at a prospective site must be determined. In order to determine the potential energy, a wind resource assessment must be conducted. For small and medium scale wind turbines, this assessment must consider the energy available to a turbine from near-surface wind flow in the atmospheric boundary layer.

In this chapter, a description of the energy available in the wind and how this is characterised over differing timescales will be presented. The fundamentals of boundary layer wind flow will be presented, as will a review of the fundamentals for estimating wind resource in the boundary layer. As part of this review, a boundary layer scaling technique for wind resource assessment will be discussed.

2.1 Energy in the wind

Wind turbines are designed to capture the kinetic energy in the wind to produce electrical power. Kinetic energy in the wind, E_w, is a function of the wind speed, u, and mass of air, m;

$$E_w = \frac{1}{2} m u^2$$

Equation 1

Theoretical power in the wind, P_w, can be estimated, by substituting the mass flow rate of air, $\dot{m}$, passing the turbine blades, into the kinetic energy equation;

$$\dot{m} = \rho A u$$

Equation 2

$$P_w = \frac{1}{2}\dot{m}u^2 = \frac{1}{2}\rho A u^3$$

Equation 3

where, ρ, is the air density and, A, is the area of air passing the turbine blades, known as the swept area of the turbine. The relationship between available power in the wind and wind speed is shown to be cubic. Wind speed is, therefore, the dominant factor in determining the power in the wind available to a turbine. However, the power available in the wind and the power that can be extracted by a wind turbine differ.

Power output from a wind turbine is restricted by the Betz limit [57] and the mechanical and aerodynamic efficiencies of a turbine. The Betz law states that a wind turbine can extract a theoretical limit of 16/27 ≈ 59.3 % of the power available in the wind flow [57]. Mechanical and aerodynamic inefficiencies of the turbine reduce the amount of power extracted from the wind flow further. Inefficiencies of a particular turbine are expressed as a coefficient of performance, C_p, a ratio of power extracted by a turbine, P_t, and the theoretical power in the wind, P_w;

$$C_p = \frac{P_t}{P_w}$$

Equation 4

The physical and mechanical limitations of a wind turbine mean that the estimated power output of a wind turbine is only a fraction of total power available in the wind. A full understanding of the wind speed and its variability at a site is therefore, vital when estimated potential power output of a wind turbine.

Wind speed varies due to atmospheric conditions and synoptic variations in weather systems [14, 58]. Energy in the wind has been shown to peak at three timescales [59].

Figure **5** shows the three peaks of the synoptic, diurnal and turbulent peaks of energy in the wind. Each of the three peaks of energy are the result of different factors, which cause wind speed variability.

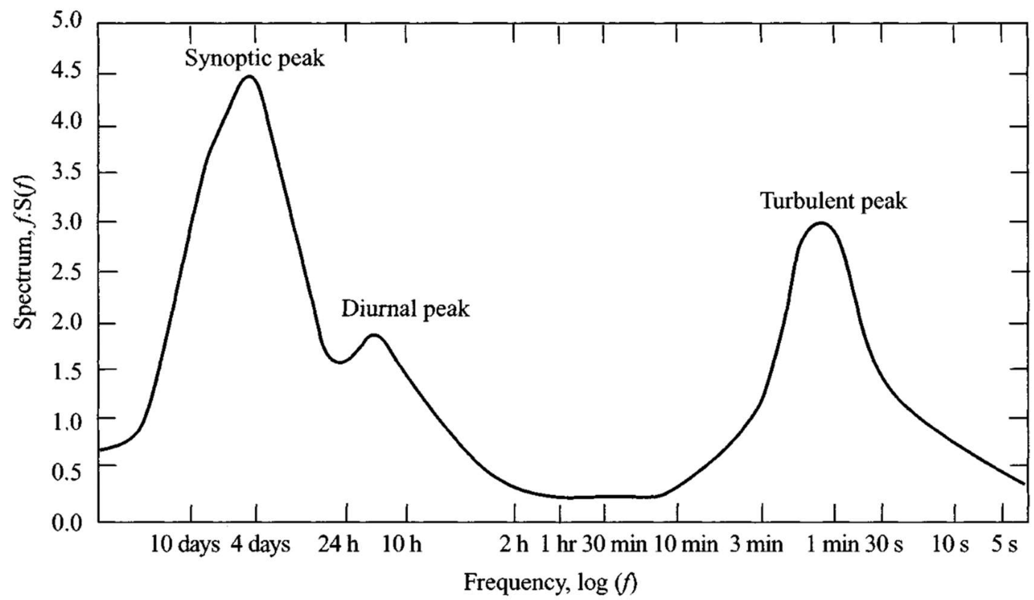

Figure 5 — Energy spectrum of wind speed displaying synoptic, diurnal and turbulent peaks in energy in wind at 100 m. Reproduced from [59]

Synoptic variability in the energy in the wind is the result of synoptic movements in weather systems in the atmosphere [14]. Driven by the geostrophic wind and the Coriolis effect, changes in the weather systems cause variations in the wind speed [14] over a timescale of days, as shown in Figure 5. Energy fluxes, in the form of heat in the atmosphere, cause diurnal variations in the energy in the wind [58]. As solar irradiance varies throughout the day, the magnitude of heat flux in the atmosphere alters, causing a variability in wind speed [14]. The diurnal variations in solar irradiance and surface heat fluxes result in the diurnal peak in energy in the wind [14]. Mechanical and convective turbulence from the surface causes the turbulent peak of energy in the wind [59]. Turbulence in the wind flow occurs over much shorter timescales, shown in Figure 5 with a peak in energy at a minute timescale [59]. However, turbulence in wind flow can occur on a timescale of a matter of seconds [58, 60].

These different timescales must all be considered when assessing the wind resource of a prospective turbine site. To accurately describe the fluctuations of wind velocity due to turbulence, wind speeds must be captured at a timescale at or above 1 Hz, to ensure that the smallest fluctuations in wind speed are captured [61]. In order to capture the synoptic or diurnal peak, such a short timescale would be ineffective. For the peaks at larger timescales, wind speed must be captured either daily for the synoptic or hourly for the diurnal peak. It is therefore impossible to capture all of the peaks in energy, using a single timescale for a model.

The synoptic peak of energy in a site's wind flow can however, be characterised by collection of long-term hourly wind speeds. It is therefore, suggested that within this research the use of hourly wind speeds would be most suitable, as it allows for two of the three peaks to be characterised whilst allowing a long term assessment required for wind resource predictions. Typically, hourly wind speeds are collected on-site as ten-minute mean wind speeds every hour. While such a timescale for data collection allows the description of the diurnal and synoptic peaks, it does exclude any description of the turbulent peak in the energy of wind flow. To include such a description of turbulence would require extensive numerical modelling [62, 63]. For an accurate computational fluid dynamics (CFD) model, the height and shape of buildings, trees and other surface obstacles, in addition to diurnal atmospheric conditions over each area considered is required [62]. For this research project, where the modelling domain was across Great Britain and over a timescale of years, the breadth and depth of data required to achieve this was unavailable and therefore turbulence could not be modelled in this project.

While the modelling of turbulence is impractical for this research, it cannot be excluded completely. The influence of turbulence on wind speed at a site can be time averaged using similarity theory [64]. Time averaging of turbulent velocity fluctuations from surface elements allows for the influence to be included but averages out the influence over a longer timescale. Similarity theory is described further in Section 2.2.1.

2.1.1 Describing the wind resource

Variability in the wind resource occurs when the wind speed at the selected timescale deviates from the mean wind speed. As discussed, the timescale in this project is at best hourly or derived from hourly data, in the case of long-term mean wind speeds from wind map data. Variability of a wind resource can be defined using the variance of the wind resource, σ^2, which is the square of the standard deviation of a sample of hourly wind speeds. The variance of a sample of wind sample therefore describes how wind speed deviates from the mean value for the majority of the sample. The wind speed variability can be described statistically by fitting a probability distribution to the hourly wind speeds of a site [65]. Traditionally, for wind engineering applications, the probability distribution utilised is the two parameter Weibull distribution [65-67]. The two parameters of the Weibull distribution are the shape parameter, k, and scale parameter, c, where, u, is a particular wind speed [67]. The probability density function, $f(u)$, of a two parameter Weibull distribution [67] is expressed as;

$$f(u) = \left(\frac{k}{c}\right)\left(\frac{u}{c}\right)^{k-1} exp^{-\left(\frac{u}{c}\right)^{k}}$$

Equation 5

with the cumulative density function, $F(u)$, expressed as [67];

$$F(u) = 1 - exp^{-\left(\frac{u}{c}\right)^{k}}$$

Equation 6

The Weibull parameters can be related to the mean wind speed, $\bar{u}_z$, at height, z, of the distribution using the gamma function, Γ;

$$\bar{u}_z = c\Gamma\left(1 + \frac{1}{k}\right)$$

Equation 7

The magnitude of the shape factor is directly related to the variance of hourly mean wind speeds at a site [68]. The relationship between the shape factor and the long-term variance of wind speed, σ_u^2, [69] can be expressed as;

$$\sigma_u^{\,2} = c^2\left(\Gamma\left(1 + \frac{2}{k}\right) - \Gamma^2\left(1 + \frac{1}{k}\right)\right)$$

Equation 8

The long-term variance in the wind speed, σ_u^2, is composed of two partial variances, the synoptic variance, σ_w^2, and the diurnal variance, σ_d^2 of a site [70];

$$\sigma_u^{\,2} \approx \sigma_w^{\,2} + \sigma_d^{\,2}$$

Equation 9

The influence of the synoptic or diurnal variability on wind speed differs with height, with the synoptic variance dominating at heights above 100 m [59] and diurnal variance, more influential closer to the surface [71]. The diurnal variance is therefore, the dominant factor when estimating power availability in near-surface wind flow which is collected by small and medium scale wind turbines, which will have hub heights under 100 m.

Lower values of the Weibull shape factor represent a wind profile with a distribution of wind speeds with higher variance. A shape factor of 2.5 indicates that the hourly wind speed deviates from the mean wind speed by a smaller margin than a value of shape factor of 1.5, where the variance in the sample is much greater, as seen in Figure 6 [13].

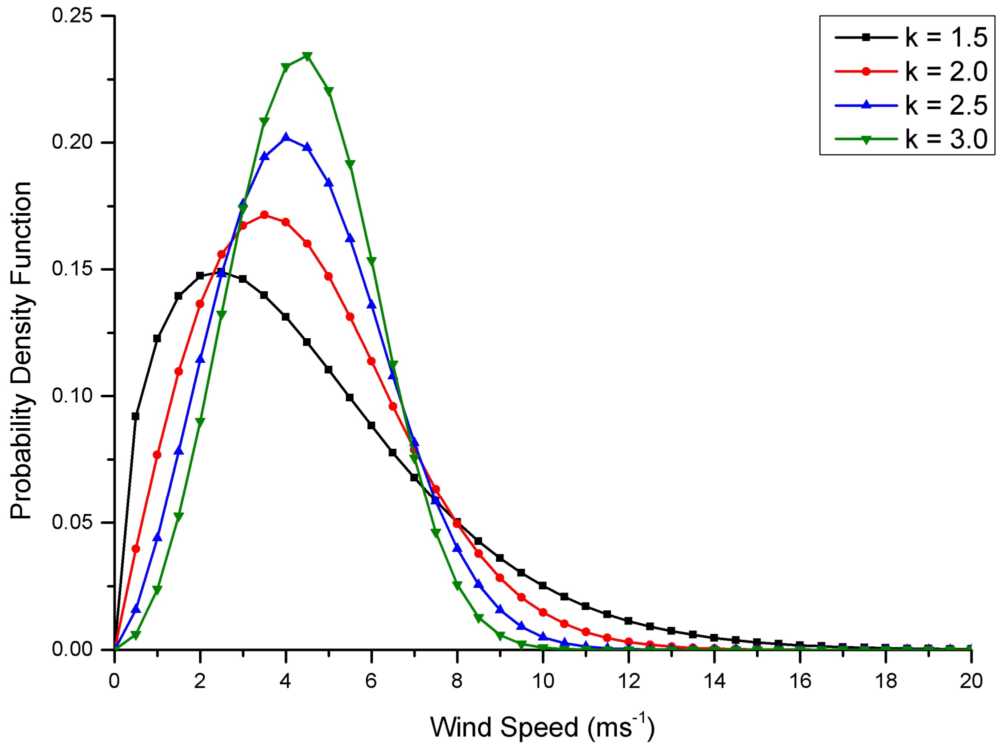

Figure 6 — Comparison of Weibull distribution shapes for differing values of shape factor with a constant scale factor of 5

To estimate the Weibull parameters, a Weibull distribution can be fitted to hourly wind speeds. Hourly wind speeds can be collected through on-site anemometry.

However, implementation of on-site anemometry is resource intensive, in terms of both time and money [72]. An on-site monitoring regime is required to be conducted for upwards of a year, typically 2 or 3 years, to ensure that all seasonal or annual variations in the wind are characterised [72]. These timescales result in a vast amount of data that must be collected, stored and analysed to produce a long-term on-site characterisation of the wind regime [72]. Such a monitoring regime could cost in excess of £15,000 for 2 years of monitoring at a height of 40 m [72]. The costs of on-site anemometry can be prohibitive for smaller wind turbine projects as the cost of such a measurement regime is unrealistic, relative to the planned level of investment [33].

For projects where on-site measurement is not practicable, observational data can be obtained from one of the monitoring sites across the UK operated by the Met Office. The Met Office Integrated Data Archive System (MIDAS) sites records the hourly wind speed on-site in conjunction with other atmospheric conditions [73]. This observational data from a local

MIDAS site can provide a description of wind speed variability at a prospective site. However, wind conditions are liable to vary even a short distance from the MIDAS site. Differences in the surface roughness conditions between the observational and prospective sites can result in differing amounts of turbulence in the wind causing different wind speeds. Use of the observational data from MIDAS sites is therefore, inappropriate to determine wind speed at prospective sites, where there are significant changes in topological or surface roughness conditions from the monitoring site.

For sites where no observational data is available or the local MIDAS data is considered unsuitable, alternative methods must be utilised to assess a site's available wind resource. Using empirical or statistical methods [11, 33, 74], modelling of a site's wind resource can be undertaken.

Modelling of the wind resource requires an understanding of the governing principles which influence wind flow. When estimating wind resource for small and medium scale wind turbines, whose hub heights are exclusively located within the atmospheric boundary layer, an understanding of wind flow in the boundary layer is therefore required.

2.2 Boundary layer wind flow

A boundary layer is formed within the atmosphere due to the underlying atmospheric subsystems that control the fluxes in energy, mass and momentum [75]. The atmospheric boundary layer is directly influenced by frictional drag, evaporation and transpiration of atmospheric moisture and heat transfer, both within the air and to and from the surface [58].

The height of the boundary layer can extend from tens of metres up to a couple of kilometres [75], depending on the atmospheric processes occurring at the time. The height of the boundary layer varies diurnally [14] and is dependent on the roughness and topography of the surface and heat flux to and from the surface [14, 58, 75]. During the daytime, sunlight heats the Earth's surface causing a transfer of heat into the cooler upper atmosphere [14]. The vertical mixing caused by heat flux from the warming surface causes the boundary layer to reach a kilometre in height [14]. During the night-time, this heat flux is reversed as the Earth's surface cools and buoyancy forces in the atmosphere suppress mixing and reduce boundary layer height significantly [14].

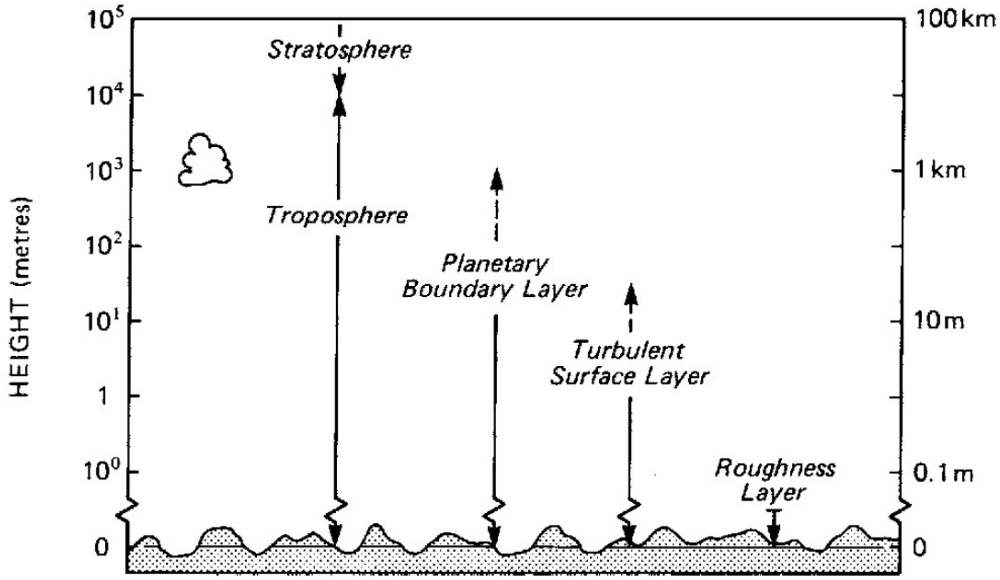

Figure 7 — Schematic diagram of the atmospheric boundary layer. Taken from [58]

Within the atmospheric boundary layer, there are multiple internal layers which are influenced by differing atmospheric phenomena that govern the wind flow in these layers [75]. Figure 7 provides a diagrammatic representation of the boundary layer structure [58].

The turbulent surface layer is characterised by fully developed turbulence [75], as a result of convection and roughness at the surface [58]. Momentum fluxes in the atmosphere caused by drag at the surface and convection from the surface, result in the movement of turbulent eddies vertically in the turbulent surface layer [58]. As these eddies move vertically in the atmosphere, they mix with existing fluid in the layer [58]. During the mixing of the eddies, shear stress between the layers with differing velocities is produced, contributing to the turbulent flow in the layer [75].

Below the turbulent surface layer is the roughness sub-layer [58] where flow is highly dependent on the roughness of the surface. The elements of roughness at the surface cause complex air flow [58]. The complexity of flow is dependent on the spatial distribution, size and shape of the roughness elements [14]. Wind flow velocity in these different sub-layers is influenced by the differing atmospheric fluxes in each layer [14]. The vertical wind profile of velocity can be described as a function of height and the magnitude of these fluxes [14].

The vertical velocity profile of wind flow is also dependent on the stability of the atmosphere [58]. Atmospheric stability is understood by considering the likely movement of a parcel of air within the atmosphere [14]. As the parcel of air moves vertically in the atmosphere, it’s volume increases as atmospheric pressure decreases [14]. The vertical movement of the air is adiabatic and as it rises, the temperature of the air parcel decreases [14]. When the temperature of the air and surrounding atmosphere are equal, equilibrium is reached and vertical movement ceases [14]. Vertical mixing in the atmosphere occurs when numerous parcels of air are displaced simultaneously due to the difference between the bulk temperature of the atmosphere and the temperature of the air parcels [14]. The degree of vertical mixing is therefore dependent on the variation of temperature with height in the atmosphere [14]. At the simplest level, atmospheric stability is categorised under three types of conditions;

Unstable conditions occur when buoyancy forces enhance vertical mixing in the atmosphere due to greater heat flux from the surface [58]. Vigorous mixing occurs as air parcels rise due to the temperature decreasing rapidly with height [14]. Vigorous mixing causes a greater degree of turbulence in the atmosphere [14].

Stable atmospheric conditions are prevalent when the buoyancy forces restrict vertical mixing. Vertical mixing is dampened by cooling of the surface. The vertical profile of temperature is shallow as temperature variations with height are minimal [14].

Neutral atmospheric conditions occur when heat flux from the surface is virtually zero. The vertical movement of the air parcel therefore reaches an equilibrium quickly, as the temperature differential between the air and atmosphere is minimal [58].

To allow for the modelling of wind resource in the boundary layer, a simplification of these processes, by assuming a neutral boundary layer where the thermal effects are insignificant, can be utilised. Typically, neutral conditions yield higher wind speeds, which are preferential for wind energy applications. However, at sites where non-neutrality must be considered, stability parameters can be introduced to account for their influence on wind speed [76]. In this research, stability was not considered during the prediction of mean hub height wind speed and this decision stemmed from two factors. The research was developed in part to analyse the accuracy of long-term mean wind speed predictions from the MCS and BLS methodologies. Each of these methodologies utilised decadal mean wind speeds. To derive a suitable and accurate stability parameter would require a large amount of historical observational data, from which to estimate atmospheric stability. Such levels of data were unavailable and therefore precluded the use of stability in this part of the research. Additionally, the diurnal nature of atmospheric stability should be considered only when the influence of atmospheric stability can be examined on hourly wind speeds and use of a long-term mean wind speed prevented this. The research also utilised hourly Numerical Weather Prediction (NWP) data as input data to the scaling methodologies. Stability was not considered in this case, as the raw NWP data contained an estimation of atmospheric stability from the NWP models from which it is derived. Therefore, an additional stability parameter would be liable to overestimate the influence of atmospheric stability on mean hub-height wind speed and was excluded from this research. A further and more in-depth description of the scaling methodologies and input datasets utilised within this research is provided in Chapter 4.

For small and medium scale wind turbines, where hub heights are traditionally below 100 m, it is the turbulent surface layer and roughness sub-layer which are the most vital to understand. It is within these layers that a small and medium scale wind turbine will operate and therefore, it is the flow within these layers which must be estimated in a wind resource assessment. To estimate the wind speed, the complex processes that influence wind flow in the differing sub-layers of the boundary layer must be expressed numerically [64].

2.2.1 Similarity theory

The atmospheric fluxes occurring within the turbulent surface layer cannot be effectively described using first principles [14], due to the presence of turbulence that causes rapid variations of the wind speed [64]. To estimate wind speed within the turbulent surface layer, Monin-Obukhov similarity theory can be used [14, 64]. Similarity theory is most appropriately applied for onshore sites, where the proposed turbine will have a hub height under 80 m [77]. Additionally, similarity theory is most appropriate in non-urban areas, where the complexity of the terrain and surface obstacles is low. Similarity theory is therefore ideal for this research, which is focused on wind resource assessment for onshore turbines in non-urban areas. Similarity theory provides a description of how atmospheric fluxes affect wind flow in the boundary layer [64]. A number of relationships, which average the effects of turbulence in the flow, have been developed to create a theory of similarity between dimensionless groups [14].

Similarity theory assumes neutral atmospheric stability and states that the mean wind speed has a logarithmic vertical profile in the atmosphere [64].

Mean wind speed is initially derived from the fluctuations of the velocity components, due to turbulence as a function of height, *z.*

Turbulent fluctuations in the horizontal, *u',* and vertical, *w',* velocity components are assumed to be proportional to the vertical wind speed gradient, *∂u/∂z,* when expressed in relation to the Prandtl mixing length, *l,* the averaged length-scale of turbulent eddies in the flow;

$$u' = w' = l\frac{\partial u}{\partial z}$$

Equation 10

The shear stress, *τ*, acting upon the air flow, due to vertical mixing can be expressed by averaging the, *u'*, and *w'*, fluctuations in the velocity components and incorporating the density of the air, *ρ*;

$$\tau = -\rho\overline{u'w'} = \rho l^2 \frac{\partial u}{\partial z}\left|\frac{\partial u}{\partial z}\right|$$

Equation 11

To express the shear stress in terms of velocity, a measure of the effect that shear stress has on mean wind speed is introduced [58], known as the friction velocity, u_*;

$$u_* = \sqrt{\frac{\tau}{\rho}}$$

Equation 12

The original formulation of the Prandtl mixing length related to wall bounded flows and stated that the mixing length was constrained by the presence of the walls. In the boundary layer context, the surface is considered to be equivalent to the wall and the mixing length is therefore proportional to height, *z* [75];

$$l = \kappa z$$

Equation 13

The proportionality constant, *κ*, is the Von Kármán constant which has been shown to range in value between 0.32 [78] and 0.43 [79]. However, the value of 0.40 is generally accepted for turbulent flow over smooth or rough surfaces [78].

The friction velocity and the Prandtl mixing length description of the velocity fluctuations can be combined into the wind shear equation;

$$\frac{u_*}{\kappa} = z\frac{\partial u}{\partial z}$$

Equation 14

The wind shear equation is then integrated between the surface and height, *z*, for the mean wind speed, $\bar{u}_z$;

$$\int_{0}^{u} \partial u = \frac{u_*}{\kappa} \int_{z_0}^{z} \frac{\partial z}{z}$$

Equation 15

$$\overline{u_Z} = \frac{u_*}{\kappa} \log\left(\frac{z}{z_0}\right)$$

Equation 16

where, z_0, is the roughness length of the surface.

The wind speed equation derived under similarity theory is a time-averaged approach. As discussed in Section 2.1, this approach averages the effect of turbulence occurring on shorter timescales. This approach allows the influence of mechanical turbulence to be included within wind speed modelling. The mean wind speed equation is only strictly valid for neutral conditions [64]. When the neutral assumption is invalid, a stability parameter can be included in the mean wind speed equation to characterise the turbulence in the wind flow, due to buoyancy [76]. However, as discussed in Section 2.2, atmospheric stability was assumed to be neutral during this research.

This derivation shows that mean wind speed is a function of both height and the roughness of the surface. Determining the roughness of the surface is therefore of vital importance when modelling the wind resource of a site.

2.2.2 Surface roughness

The surface creates turbulence in the wind flow through surface drag and forced convection [58]. The aerodynamics of the surface must be understood to determine the magnitude of the frictional effects on the momentum of wind flow.

The roughness of the surface is a function of the surface morphology and the frictional elements at the surface [11, 58]. Surface morphology and frictional elements, such as buildings or trees, create drag at the surface that affects the momentum of wind flow [11]. The magnitude of the frictional effects is dependent on the spatial size, distribution or density of the roughness elements at the surface [14]. Surface drag on wind flow is greatest in urban areas, where the density and size of frictional elements are highest due to the greater number of large buildings [80]. In forested areas, a comparatively high roughness length is used to account for the frictional effect of trees on wind flow [81]. In rural areas, the density and distribution of roughness elements is much lower, causing the surface roughness to be lower [81].

The frictional effect on wind flow momentum from the surface must be parameterised during wind speed modelling [14]. The parameterisation of surface roughness results in a set of aerodynamic parameters that describe the frictional effects of surface drag on wind flow [14]. The surface aerodynamic properties of surface roughness length, z_0, zero-plane displacement height, *d*, and canopy height, z_{ch}, were the aerodynamic properties, utilised in this research, to describe the frictional effects of the surface [11].

Surface roughness length, z_0, is a parameterisation of the drag force exerted by surface frictional elements on wind flow [14]. Zero-plane displacement height, *d,* is the effective height of the displaced surface, due to the presence of multiple roughness elements [14]. Canopy height, z_{ch}, is the geometric mean height of roughness elements, such as buildings or trees [82]. Zero-plane displacement height and canopy height only become influential where the number of roughness elements at the surface is higher, such as suburban, urban [80] or densely forested areas [14]. In more rural areas, zero-plane displacement height is set to zero as the density of roughness elements is low [33]. To account for the zero-plane displacement phenomena, the mean wind speed equation can be adjusted to include the zero-plane displacement height, *d*;

$$\overline{u_z} = \frac{u_*}{\kappa}\log\left(\frac{z-d}{z_0}\right)$$

Equation 17

Experimental derivation of the surface roughness is possible on individual sites, where data on the vertical wind profile is available [14]. The nature of this project, and the desire to offer wind resource assessments on sites where no experimental data is available, dictates that parameterisation of the surface roughness was necessary. Parameterisation of the surface roughness can be undertaken through analysis of the vegetative land cover of a site and a body of experimental literature [81, 83, 84]. Using a land cover map, the vegetative land cover can be parameterised to surface roughness values [33]. A land cover map for the UK exists [85] from which surface roughness can be parameterised. Typical values of surface roughness length stated in literature, range from $0.1\text{x}10^{-5}$ m for still open water [14] to 2 m for large cities with heterogeneous building heights and layouts [81].

As with the surface roughness length, the zero-plane displacement height can be determined experimentally, either through field tests, wind tunnel experiments or use of morphometric methods [82]. Experimental methods involve measurements of the vertical wind profile, from which the zero-plane displacement height can be calculated [82]. Morphometric methods calculate the zero-plane displacement height from the plan and frontal area of buildings [80, 82]. However, both experimental and morphometric methods require field data to calculate the displacement height. In the absence of experimental data, approximations from previous work [86] for both the displacement height and the canopy height can be utilised. While the approximation of displacement height differs between vegetative land covers [87, 88], an approximation for all land surfaces, relating the parameters of surface roughness, displacement height and canopy height has previously been suggested [86];

$$z_{ch} = 10z_0 \text{ , } d = \frac{2}{3}z_{ch} \;\; \therefore d = \frac{20}{3}z_0$$

Equation 18

The approximations of displacement and canopy height are both based upon the value of surface roughness. This highlights the importance of the surface roughness parameterisation when estimating mean wind speed. This places a heavy burden on the parameterisation process to yield suitable and realistic surface roughness values.

Parameterisation of the surface roughness is required as the land cover of Great Britain is not homogenous. If the land cover was homogenised, a single value of surface roughness would be applicable when estimating wind speed. The presence of differing surface roughness patches leads to the consideration of how wind flow is influenced as it flows over these differing patches.

2.2.3 Internal boundary layer formation

As wind flows from one patch of surface roughness to another, the wind flow must adjust to the new surface roughness characteristics [89]. Adjustment of the wind flow over the new patch of roughness occurs as differing roughness patches have differing aerodynamic and likely thermodynamic properties. These differing properties of the surface influence the magnitude of mechanical and convective turbulence induced in the wind flow. An internal boundary layer (IBL) forms at the interface of the different patches of surface roughness [89] as shown in Figure 8. Close to the ground, in neutral conditions, an equilibrium layer forms where the wind flow is completely adjusted to the new surface roughness [89]. Above this layer and within the bulk of the IBL, a blending layer exists, where the vertical velocity gradient is gradually adjusting from the logarithmic form of the initial roughness to the logarithmic form of the downstream roughness [89].

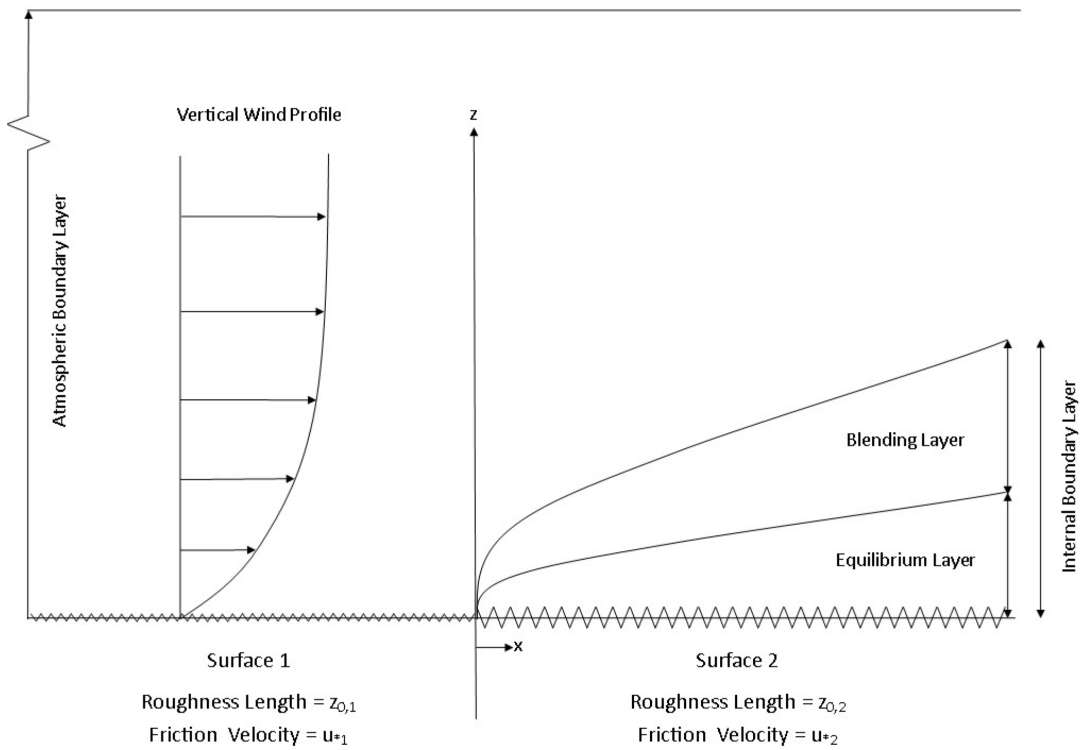

Figure 8 — Representation of the internal boundary layer growth at the transition of different surface roughness patches. Reproduced from [90]

The size, growth rate and distance over which the adjustment of the wind profile occurs is related to the ratio between the roughness patches [89]. The vertical wind profile will adjust quickly between two patches of similar roughness compared to the time required to adjust to the change between two dissimilar roughness patches. The calculation of IBL depth can vary in complexity based upon surface characteristics, stability effects and atmospheric fluxes [89-91]. While the growth of an internal boundary layer will influence the wind speed, the transition over only two surface roughness patches is considered as an isolated case. Transition of the wind flow over multiple varied roughness patches is a more realistic scenario. Calculation of the effect that multiple patches of differing surface roughness on wind speed is therefore of greater importance when a realistic estimate of wind speed is desired.

Differing patches of surface roughness in close proximity will each influence wind flow differently and at each interface of surface roughness patch, an internal boundary layer will form, as seen in Figure 9 [92]. Each of the IBLs will influence the wind speed differently [92].

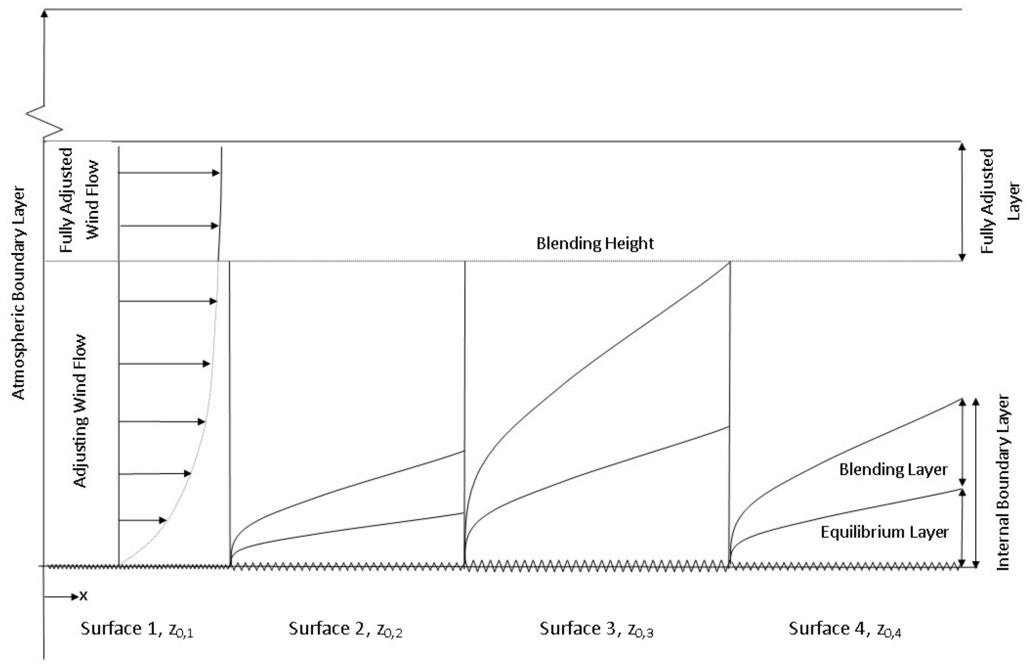

Figure 9 — Representation of the multiple internal boundary layer growth and the concept of blending height. Reproduced from [93]

A method of describing and quantifying the differing effects from each IBL on wind speed is required, while maintaining consistency with similarity theory [94]. Similarity theory was originally developed for homogenous surfaces [64, 94]. In order for similarity theory to be applicable over heterogeneous surfaces, further aerodynamic parameters must be developed [92, 94, 95]. Similarity theory is applicable above the blending height, z_{bh}, of a heterogeneous surface [95]. Blending height is the height in the atmospheric boundary layer, where the influence of each IBL and the frictional effect of each surface roughness patch is homogenised [95]. At this height, the surface can be considered homogenous and therefore the assumptions of similarity theory are valid. At the blending height, the roughness of the surface will also be homogeneous [92]. To estimate wind speed at the blending height, a description of the roughness of this 'homogenised' surface is required. This roughness, known as effective roughness, z_{0eff}, is equivalent to the surface stress resulting from each patch of the heterogeneous surface roughness [92].

The parameters of blending height, z_{bh}, and effective roughness, z_{0eff}, are known as the regional aerodynamic parameters. Methods of calculating regional aerodynamics can range from simple approximations [92] to complex computational fluid dynamic simulations of the surface and resulting IBL [94]. The basis of all methods of regional aerodynamic calculation is however, the surface roughness values [92-95]. This, once again, highlights the importance of the surface roughness parameterisation.

Calculation of the blending height must capture how the different surface roughness patches cause fluctuations in the wind speed [92, 94]. By determining how each surface roughness influences wind flow individually, the growth of the internal boundary layers from each patch can be tracked [94]. Tracking of the boundary layer must be examined over a sufficient distance of the fetch, to ensure that appropriate variation in surface roughness is captured [94]. The required size of the fetch has been shown to be a tenth of the suggested boundary layer height [96].

2.2.4 Blending height

A method for calculating blending height which tracks the growth of internal boundary layers, using a variability scale has been developed by Bou-Zeid et al. using CFD simulations [94]. This method was further extended to account for the complex and varied changes in surface roughness [97]. Use of a variability scale allows the fluctuations in wind velocity, due to differing surface roughness to be quantified in the blending height calculation [97].

Tracking the growth of the internal boundary layer assesses the turbulent velocity fluctuations, due to changes in upwind surface roughness, $z_{0,i}$, as a function across the whole upwind fetch [97];

$$du'(z_{0,t}) = \left(u'(z_{o,i} + z_{0,t}) - u'(z_{0,i})\right)^2$$

Equation 19

where the likely turbulent velocity fluctuations, u', induced by a change in surface roughness are compared to the likely turbulent velocity fluctuations from the preceding patches of surface roughness, $z_{0,t}$, in the fetch.

The inverse ratio of the maximum likely turbulent velocity fluctuations, *max du'*, and mean likely turbulent velocity fluctuations, $\overline{du'(z_{0,t})}$, in the fetch is integrated over the characteristic length scale, L_d, of the fetch to estimate the variability scale, L_p, of the fetch;

$$L_p = \int_0^{L_d} \left[1 - \frac{\overline{du'(z_{0,t})}}{\max du'}\right] dz_{0,t}$$

Equation 20

The term, L_d, is suggested as the length of the longest path of the upwind fetch examined. The variability scale, L_p, can then be utilised to solve for the blending height, z_{bh}, iteratively;

$$\left(\frac{z_{bh}}{1.7\kappa L_p + z_{bh}}\right)^2 = \sum_{i=1}^{N}\left(\frac{f_i}{(\ln\frac{z_{bh}}{z_{0,i}})^2}\right)$$

Equation 21

where, $z_{0,i,}$ is the roughness length of each patch, f_i, is the fraction of the fetch which the roughness length covers and N, is the number of patches in the fetch.

Effective roughness must be calculated once the blending height has been estimated. Effective roughness will vary with height as the frictional effect of the surface diminishes with distance. Effective roughness, as previously described, is the spatially averaged roughness of the surface of the whole fetch expressed as a single value. Use of the whole fetch requires a blending method to calculate effective roughness [11]. An example of the fetch used within this research is provided in Chapter 4.

The blending method for effective roughness initially blends the differing friction velocity from two different but equally sized patches of surface roughness [11];

$$u_*^2 = \frac{1}{2}(u_{*1}^2 + u_{*2}^2)$$

Equation 22

At the blending height, the vertical wind profile is fully adjusted with the homogenised roughness of the surface. The friction velocity can then be expressed in terms of the roughness length of each patch, $z_{0,1}$ and $z_{0,2}$;

$$\left(\log\left(\frac{z_{bh}}{z_{0eff}}\right)\right)^{-2} = \frac{1}{2}\left(\left(\log\left(\frac{z_{bh}}{z_{0,1}}\right)\right)^{-2} + \left(\log\left(\frac{z_{bh}}{z_{0,2}}\right)\right)^{-2}\right)$$

Equation 23

This formulation of effective roughness, z_{0eff}, over two roughness patches can be extended to include the whole fetch over which the blending height is calculated;

$$\left(\log\left(\frac{z_{bh}}{z_{0eff}}\right)\right)^{-2} = \sum_i f_i\left(\left(\log\left(\frac{z_{bh}}{z_{0,i}}\right)\right)^{-2}\right)$$

Equation 24

where f_i is the fractional size of each patch of roughness in the fetch.

This blending method allows the effective roughness to be calculated based upon the blending height and underlying roughness at surface. The blending method can be extended using an effective displacement height, d_{eff}, to include the zero-plane displacement height, in areas which warrant it. Effective displacement height is applied in fetches where the density of the roughness elements causes the zero-plane height of mean wind speed to be above the surface. Such fetches are likely to be predominately over urban, suburban or forested areas. No rigorous analytical method is available for the calculation of effective displacement height [11]. An approximation from the effective roughness value, identical to the displacement height approximation from surface roughness values provided in Section 2.2.2, is therefore suggested for this research. These factors of surface and regional aerodynamics must be considered when estimating wind speed in the boundary layer.

2.3 Wind resource assessment in the boundary layer

Description of wind flow in the boundary layer must be central to a wind resource assessment at a prospective wind turbine site. Wind resource estimation is a vital part of a prospective turbine's feasibility study [32], particularly at the initial stages of the project. For small and medium turbine projects, where project budgets can be limited, the cost of a wind resource estimation must be as low as possible. To conduct a quick, cheap but effective assessment of wind resource, a desk study is undertaken [52]. At a minimum, this desk study should provide an accurate prediction of mean hub height wind speed and power density in the wind flow, for which annual energy production of the wind turbine can be estimated [33].

To achieve a prediction of mean hub height wind speed, an initial assessment of wind resource will utilise a wind map to provide the reference wind climatology [33, 52]. Within the UK, two observational based wind maps, which provide a long-term mean wind speed are available, the Numerical Objective Analysis of Boundary Layer (NOABL) [98] and National Climatic Information Centre (NCIC) [99]. However, these wind maps can only provide a long-term mean wind speed for each 1 km^2 grid square. From the mean wind speeds of the wind maps, power density cannot be estimated and the use of a fixed Weibull shape factor to represent wind speed distribution and from which power density can be estimated has been suggested [11]. However, both power density and hub height wind speed can be estimated from the hourly time-series of wind speeds available from Numerical Weather Prediction (NWP) data. NWP wind speed data was provided for this research by the Met Office, from their UK4 and UKV NWP models [100]. These NWP models estimate hourly wind speed at resolutions of either 4 km or 1.5 km for UK4 and UKV respectively [100]. These reference wind climatologies are discussed in greater detail in Chapter 4.

2.3.1 Boundary layer scaling methodologies

For small and medium turbine projects, NOABL data, which is freely available, has been utilised in the reference wind climatology [32]. However, multiple studies have questioned the accuracy of NOABL [11, 31, 101, 102]. To address the inaccuracies in NOABL wind speed data, a correction methodology was introduced [33, 101]. The original methodology has been superseded by a correction methodology, as part of the Feed-in Tariff accreditation process [27].

As discussed in Chapter 1, the correction methodology introduced as part of the Feed-in Tariff accreditation process is known as the Microgeneration Certification Scheme (MCS) wind resource assessment [27, 31]. The MCS methodology is a component of the installer's standards, which must be completed for accreditation to be awarded and payments received for energy generation by a wind turbine installation [27]. The methodology is described as "*a simple method using freely available wind speed data (NOABL) and simple tabulated correction factors for the local terrain, obstructions and turbine height, and hence has a relatively high degree of uncertainty*" [27]. Implementation of the MCS methodology has been shown to improve the accuracy of wind speed predictions when compared to unscaled NOABL [31]. Installers are advised to provide other wind speed estimates for the site, however, they are informed to treat the results of each methodology equally [27]. Despite this caveat, it is entirely possible that the MCS methodology could be viewed as a suitable estimation of a site's wind speed given the equal weighting. There are severe flaws within the MCS methodology, which excludes any description of surface roughness or internal boundary layer formation in the upwind fetch. These flaws suggest that the MCS methodology is unsuitable for providing accurate wind resource estimates. An alternative approach to the correction of reference wind climatologies, such as NOABL is required.

Boundary layer scaling (BLS) models offer an alternative methodology to estimating wind speed in the boundary layer. BLS models for estimating wind speeds for small and medium scale wind turbines have previously been published [11, 33, 49]. Originally developed by Best et al. for the Met Office [11], the approach involves scaling a reference wind climatology from the surface level at 10 m, up to a reference height, before scaling down to the blending height and then to the hub height [11, 33]. Two studies have utilised 8 classifications of surface roughness on a 1 km resolution as part of a BLS model [11, 33]. As previously stated, the importance of surface roughness in boundary layer wind speed estimation questions whether 8 classifications offer sufficient breadth to a BLS model. Additionally, a UK land cover map is available on a finer spatial resolution than 1 km [85]. It is argued here that surface roughness could be parameterised in this research on a finer resolution than 1 km into a greater number of surface roughness classifications. In both studies, blending height is assumed to be the larger of 10 m or twice the canopy height [11], which results in blending heights of between 10 m and 40 m [11]. For areas of highly variable surface roughness, blending height has been shown to be significantly higher than 40 m [94]. The use of these blending height approximations is therefore considered unsuitable and an alternative approach to blending height calculation is required in this research.

Weekes and Tomlin increased the size of the upwind fetch to 2 km [33] from the 500 m fetch in the original Met Office study [11]. The increase in the size of the fetch is based upon a study which indicates that the fetch size must exceed by a factor of ten, the reference height [96], which is set at 200 m in the Weekes study [33]. In the original Met Office study, regional aerodynamics are calculated for the whole fetch, independent of wind direction [33]. However, the fetch is split over the four cardinal directions in Weekes [33] for the calculation of the regional aerodynamics. Another study has also extended the directional dependent calculation of regional aerodynamics further into 8 wind direction sectors of 45° [49].

Both studies have utilised NCIC data as the reference wind climatology [11, 33] and Weekes and Tomlin complimented this with use of NOABL data as an additional reference wind climatology [33]. In the Met Office study, no validation of the wind speed estimates is presented [11]. However, Weekes does provide validation for both wind speed and power density predictions over 38 sites [33].

Only NCIC data was utilised in the modified BLS model of Weekes and Tomlin, as during the initial comparison, BLS NCIC wind speeds was shown to have lower errors than BLS NOABL wind speeds [33]. BLS NCIC achieved wind speed predictions with a mean absolute error of 0.70 ms^{-1} and mean percentage error of 19.1 % compared to wind speed predictions with errors of 0.84 ms^{-1} and 22.7 % achieved with BLS NOABL [33]. In the modified approach, the wind speed predictions were improved achieving errors of 0.52 ms^{-1} and 16.2 %, when using a larger fetch and the directionally dependent regional aerodynamic calculations [33]. The adoption of the modified approach highlights its ability to offer more accurate wind speed predictions with a larger fetch and directionally dependent regional aerodynamics. However, the errors achieved suggest that further improvements could be introduced to the BLS model in this research to further improve wind speed accuracy.

Within the study, Weekes and Tomlin examined the sensitivity of fetch size, concluding that a fetch of 4 km, effectively assessing 2 km upwind from the site was the most appropriate fetch size [33]. Based upon this analysis, it is concluded that a fetch of 4 km is the most appropriate for this research. Further improvements available to this research have been identified with the inclusion of the parameterisation of more surface roughness classifications and the introduction of a calculation of the blending height.

A land cover map, from which surface roughness can be parameterised, is available on a 25 m resolution [85]. Theoretically, surface roughness can therefore be parameterised at 25 m. However, this would be exceptionally computationally intensive. The resolution of parameterised surface roughness is therefore limited by computational resources. The availability of a land cover map at such a fine resolution suggests that the resolution of surface roughness that can be achieved in this project is finer than 1 km. In addition to a finer resolution of surface roughness, the use of 8 surface roughness classification can be extended. The use of 13 surface roughness classifications has previously been presented [103] and extension of the breadth of surface roughness classification in this research could offer significant improvements in the accuracy of BLS wind speed predictions.

An extension of the breadth of surface roughness classifications is predicated on the selected land cover map being able to offer sufficient distinction between land uses. Surface roughness is highest in urban and suburban areas [11, 81, 82, 84]. Ideally, a land cover map would offer clear distinctions between the differing densities of urban land use to allow for the surface roughness of each to be parameterised [82]. However, the land cover available for Great Britain offers only two urban categories for urban and suburban areas [85]. This will limit the extension of surface roughness parameterisation and thus predicted BLS wind speeds in these areas. However, BLS modelling can be applied successfully to urban areas with appropriate parameterisation of the urban fabric using a morphometric model [63]. While this research will predict wind speed in the urban centres of Great Britain, no validation will be presented as urban areas are not the focus of this research. The breadth of land uses available in more rural regions is more applicable for small and medium scale wind turbines, where future deployment in the market is more likely [104]. The extension of the surface roughness breadth is therefore a suitable improvement available to the BLS model in this work.

The introduction of a finer resolution of surface roughness parameterisation leads to questions on whether the estimation of blending height can be improved in the proposed BLS model. Increased resolution of surface roughness will lead to a parameterisation of the surface with a higher degree of variability. High variability of surface roughness causes multiple IBLs to form [93] and therefore an approximation of blending height [11] is considered insufficient to characterise the regional aerodynamics of a site. The calculation of blending height, presented in Section 2.2.3, offers an analytical approach to estimating blending height. Introduction of this analytical method for blending height estimation can be extended to a greater number of wind direction sectors. Weekes and Tomlin utilised four wind direction sectors [33], while a study at an urban site utilised eight wind direction sectors [49]. Use of a greater number of wind direction sectors in study of the urban site suggests that in areas with greater surface roughness variability, additional wind direction sectors may also offer better characterisation of regional aerodynamics. A BLS model with a finer resolution of surface roughness would benefit from additional wind directions and it is suggested that twelve, rather than eight, wind directions are implemented. Implementation of twelve wind directions of 30° with the finer resolution of surface roughness allows any surface roughness variability, which influences regional aerodynamics, to be characterised to a greater degree. This approach aims to better describe upwind conditions and therefore contribute to more accurate wind speed predictions from this proposed BLS model in this research. The proposed BLS model and the specifics of the improvements detailed in this section are discussed further in Chapter 4.

2.3.2 Power density scaling methodologies

In addition to improvements to the BLS model, the accuracy of power density predictions must be considered. Power density is an important facet of a desk based wind resource assessment at initial project stages. From the power density, the annual energy production of a proposed wind turbine can be estimated.

As discussed previously, the variability in the wind speed is described statistically using the Weibull distribution. The Weibull shape factor has been shown to be the appropriate factor to describe diurnal variability of near-surface wind speeds and therefore, the power density available in the wind flow [33]. Power density available in the wind is a dimensionless metric [33] which allows prospective adopters to understand likely turbine power output, irrespective of turbine size or efficiency. Power density of the wind flow, P_d, can be estimated from the shape factor, k, and the mean wind speed, $\bar{u}_z$, of the site [33, 105];

$$P_d = \frac{1}{2}\left(\frac{16}{27}\right)\rho\left(\frac{\bar{u}_Z}{\Gamma(1+1/k)}\right)^3 \Gamma(1+3/k)$$

Equation 25

Weekes was unable to offer accurate power prediction using a fixed shape factor of 1.8 [33]. A fixed shape factor of 1.8 was originally suggested by Best et al. [11]. This factor was derived from the wind speed distribution at sites across Europe [106]. Using a fixed shape factor and the modified approach, power predictions with a 63 % mean percentage error were achieved by Weekes [33]. An approach to power density predictions with such a high degree of error are unsuitable as part of a wind resource estimation.

Power density in the wind flow is a function of the variability in the wind speed [70]. As discussed, long-term variability in wind speed is composed of synoptic and diurnal variability in the wind speed [70]. The influence of the synoptic or diurnal variability on wind speed differs with height, with synoptic variability dominant at heights above 100 m [59] and diurnal variability more influential closer to the surface [71]. The hub heights of small and medium scale wind turbines are likely to be below 100 m. Therefore, the diurnal variability of wind speed is the factor which must be characterised when estimating power availability for small and medium scale turbines.

Diurnal variability in wind speed has been shown to be height-dependent, with the variability reaching a minimum at the mean reversal height of the diurnal cycle [70]. The reversal height is the mean height at which the diurnal wind cycle of each site changes phase, from its night time minimum near the surface, to the night time maximum higher in the boundary layer. Figure 10 illustrates the reversal height phenomena with Weibull shape factors, recorded at various heights from two onshore sites in the US, published in a study by Wieringa [70].

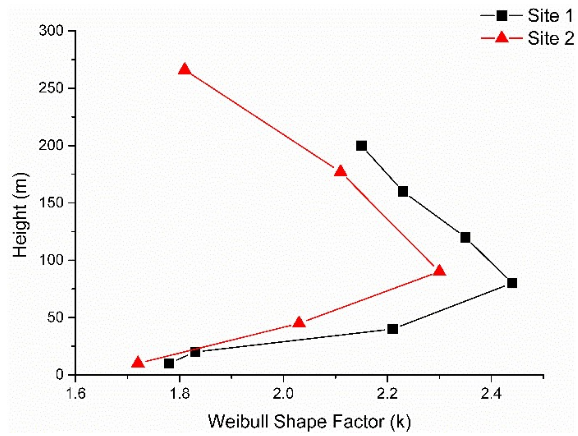

Figure 10 — Weibull shape factors at various heights of two US sites. Reproduced here using data taken from [70]

This reversal height over land is estimated to be an mean height of 80 m [70]. However, field trials observed reversal heights of 40 m up to 177 m at onshore sites in both the US and the Netherlands [70].

The relationship between diurnal variability and Weibull shape factor has been shown to be inverse [70]. The value of the shape factor is therefore height dependent [70]. The shape factor will reach a maximum over land at the reversal height where diurnal variability is at a minimum [70].

The height dependence of the shape factor must therefore, be accounted for in the estimation of power density. Shape factor, k_s, at the surface, z_s, can be scaled vertically to account for the reversal height, z_r, of the diurnal cycle of a site to estimate shape factor, k, at a selected hub height, z [70];

$$k = k_s + c_k(z - z_s)e^{\left(\frac{z-z_s}{z_r-z_s}\right)}$$

Equation 26

where, c_k, is an empirical coefficient, calculated as the gradient of a linear regression fit of observed vertical shape factors of a site on a log scale against height [70]. In the literature, c_k, is estimated to be between 0.022 and 0.023 dependent on site location [70]. These values of c_k, are taken from an inland and coastal site respectively [70]. Selection of the most appropriate value will be considered during implementation of the shape factor scaling in this research. The vertical scaling of shape factor can therefore be considered when assessing power density.

2.3.3 Proposed research

This review of current BLS model literature is motivated by a desire to understand if the current wind resource assessment techniques in the small and medium scale wind turbines market are suitable. Deployment of such turbines has been aided by the introduction of the Feed-in Tariff, as deployment has increased seven-fold since its introduction in April 2010 [12]. The stimulus to deployment provided by the Feed-in Tariff, increases the prominence of the MCS wind resource estimation methodology. The severe flaws identified in the MCS methodology raise questions over its suitability to support future wind turbine deployment.

To assess the suitability of the MCS methodology, an analysis to compare the methodology with the proposed BLS model, described here, will be undertaken. No quantified comparison of the MCS has been undertaken before, with only a graphical comparison with raw NOABL data presented previously [31]. To assess the suitability of each methodology to support the future deployment of wind turbines, a definition of “sufficient accuracy” of the wind speed predictions from each methodology is required. Predictions of wind speed are liable to contain a degree of error, due to any assumptions implemented during the prediction process. While these assumptions may lead to error, they are a vital part of the prediction process to ensure expedient wind speed predictions are produced. The magnitude of the intrinsic error in a wind speed prediction, which is considered acceptable and will not detrimentally impact the wind resource estimation to a prospective consumer, must be determined. Validation of the wind speed predictions against observed wind speeds will identify the relative error in each prediction. These errors can be translated into estimated annual energy production, estimated annual payments under the Feed-in Tariff and estimated payback periods to understand how the errors in the wind speed prediction impact these metrics. Analysis of the differences in these metrics, with those produced using observational wind speeds, will allow a judgement on the definition of sufficient accuracy in a wind speed prediction to be conducted in this research.

The proposed BLS model in this project extends advancements made to an original BLS approach [11] made by Weekes [33]. The introduction of an analytical approach to regional aerodynamics calculations, over a greater number of wind direction sectors using an increased breadth of spatial resolution of the surface roughness values are proposed here as improvements to the BLS approach, which can be investigated in this research. These improvements to the BLS model, coupled with the use of NWP data as a reference wind climatology, are aimed at improving the accuracy of wind speed predictions. Use of scaled NWP data and introduction of a vertical scaling approach to Weibull shape factor are designed to improve the accuracy of power density predictions, compared to the use of a fixed Weibull shape factor alone.

With these improvements to the BLS and power density prediction approach, it will be possible to determine if the accuracy of the wind speed and power density predictions is improved. The value of the improvements to the BLS model can be analysed against the results of Weekes [33]. More importantly, the ability of the proposed BLS model to offer more accurate wind speed and power density predictions than the MCS will be analysed. The proposed improvements to the BLS model and the comparison between the wind resource assessment methodologies are presented in Chapter 4.

Chapter 3 – Factors that influence wind turbine adoption patterns in Great Britain

While the wind resource available to a small and medium scale wind turbine is likely to influence wind turbine adoptions, it is suggested here that other factors also play a role in an individual's decision to adopt. In order to fulfil the potential of small and medium scale wind turbines in Great Britain and contribute to the energy system transition, the factors that influence wind turbine deployment must be determined. In determining the factors that influence wind turbine adoptions, it was possible to identify a number of policy strategies that could be implemented to promote future deployment. By examining the factors that influence both spatial and temporal wind turbine adoption patterns, it will be possible to answer the second, third and fourth research questions posed in Chapter 1. This chapter will establish the background for the analysis of the spatial and temporal factors which influence a decision to adopt a wind turbine in Great Britain. By reviewing the literature on the factors that have influenced previous adopters of other microgeneration technologies, it will be possible to identify the appropriate factors and analysis techniques required for this research.

Determination of the influencing factors or motivations on an individual's decision to adopt could be achieved through extensive survey work [53-55]. To conduct a survey on adopters of wind turbine receiving the FIT, personal information of each would need to be collected. Adopters agree a contract with a licensed electricity supplier who remunerates the adopters for energy generation under the FIT policy [25]. UK data protection laws prevent the licensed electricity suppliers from releasing any personal information about these adopters. Survey work was therefore not pursued as a methodology to determine the influencing factors on a decision to adopt a small and medium scale wind turbine in this research. Alternatively, an analytical approach examining the motivations and barriers to microgeneration uptake, identified in previous studies, was undertaken.

The aim of this literature review is to identify the factors which have influenced adoption decisions of microgeneration technologies. Literature details the motivation and barriers to microgeneration technology adoption for those, who are at each differing stages of the installation process [54, 55]. Ideally, this literature would focus solely on factors which influence a decision to adopt a small and medium scale wind turbine. However, due to the comparatively small size of the microgeneration market, many studies have considered the influencing factors on the uptake of microgeneration technologies collectively [53-55, 107-109]. These influencing factors on the uptake of microgeneration will be considered, but with specific focus on the factors which are relevant to the uptake of small and medium scale wind turbines in Great Britain.

3.1 Motivations and barriers to uptake

The motivations and barriers experienced by microgeneration adopters can be considered as either financial or non-financial [53-55]. Non-financial factors that influence a decision to adopt can be further considered as either informational or environmental concerns of the adopters [54, 55]. Informational concerns are centred on a potential adopter’s ability to acquire impartial information, regarding the likely performance of a microgeneration technology, while the self-sufficiency concerns are borne out of potential adopter’s desire to protect against rising fuel prices [54, 55].

Financial barriers to the adoption of microgeneration technologies are considered the most important by potential adopters and those who have previously installed a microgeneration technology [53-55]. Both those considering adoptions and those that have previously adopted have identified the capital costs of an installation as most important [54, 55]. In a 2011 survey undertaken to review the performance of the FIT, 93 % of respondents considering a microgeneration installation have contemplated delaying the installation until the capital costs of installation reduce [55].

Financial barriers are extremely prevalent in the wind turbine market, where capital costs range from between £2,000 and £6,000 per kW installed [21]. When presented with similar cost estimates for a wind turbine installation, 60 % of respondents suggested they were higher than expected [55]. Prospective wind turbine consumers have identified a willingness-to-pay (WTP) of between £1,288 [110] and £1,685 per kW installed [108]. These WTP estimates are significantly different from the current capital costs of a small and medium scale wind turbine. The difference between the current price per kW of a wind turbine and the WTP figure demonstrates that individuals who have previously installed a wind turbine are likely to have a higher WTP than suggested by either Scarpa [110] or Claudy [108]. This highlights that the WTP of each individual is subjective [108] and current wind turbine adopters were likely to have a higher WTP because they were able to access sufficient capital to afford the current capital costs of an installation.

If a prospective adopter does have sufficient access to capital to afford the upfront costs of an installation, a proposed turbine must offer an attractive payback period. The payback period of each turbine is governed by the financial returns available from a wind turbine. A study of Irish residents identified 11 years as an acceptable payback period for small wind turbines [108]. In comparison, individuals in Great Britain have suggested a shorter payback period is desired for all types of microgeneration technologies [55]. The acceptable payback periods differed between an mean of 9.4 years for individuals who had previously installed, and 5.5 years for individuals considering an installation [55]. However, a suitable payback period and WTP have been shown to be determined by adopters, using not only a cost-benefit evaluation [108]. These values differ depending on each individual's subjective assessments of a technology's benefits and the individual's personal views [108].

The ability to gain financial returns through lower energy bills and financial incentives for energy generation is one of the key benefits for adopters [54]. This motivator and the ability to protect against rising energy costs have been identified as the key reasons that individuals consider and then adopt a microgeneration technology [54, 55]. These benefits are realised through the electricity generation of a wind turbine, for which payments from the FIT are available, and which offsets the requirement to buy electricity from the grid [53]. The power output of a wind turbine is a function of a number of factors, key amongst them being the wind resource available to the wind turbine. To ensure that the benefits are sufficient and the payback period for each adopter are attractive, there must be sufficient wind resource available on-site. While an individual's subjective judgement on the attractiveness of the payback period will vary, some areas will not have sufficient wind resource to offer any payback on the capital outlay of a turbine. The financial barriers to adoption are among the most important to individuals either considering, adopting or rejecting microgeneration technologies [54, 55, 108].

Non-financial motivations are predominately borne out of a desire to be more sustainable and self-sufficient. An individual's desire to become self-sufficient is cited by 46 % of adopters as a motivation in their decision to adopt [55]. A desire for self-sufficiency ties into environmental concerns also cited by both adopters and those considering an installation [54, 55]. Adopters have also expressed a desire to exhibit their environmental commitment to others as a motivator in their decision to adopt [54]. In comparison, individuals considering or having rejected a microgeneration technology, cite this factor as less important than other factors, such as increasing their home value or protecting from power outages [54]. This suggests that the individuals who have adopted, value the social aspects of adoption differently than those who are still considering an adoption, thus reinforcing the subjective nature of an individual's adoption decision.

The informational barrier to adoption stems from individuals being unable to find a source of trustworthy or reliable information about a proposed installation [54]. Adopters, and those considering an adoption, value this barrier much more than those who have previously rejected adoption [54]. This highlights that the informational barrier is likely to be influential later in the adoption process, after an individual attempts to research the viability of a prospective installation. Information regarding the performance of a prospective wind turbine are available from a number of sources, including installers and manufacturers [55]. However, adopters have identified consumer organisations, local or central government as the most trusted sources of information when investigating the potential installation of a microgeneration technology [55]. It is unlikely that these impartial sources of information will be able to offer specific performance information for an individual's proposed wind turbine, and prospective consumers must therefore rely on performance estimates from turbine manufacturers and installers. Consumers viewed this data as much less impartial [55] as such estimates are likely to promote the specific manufacturer's or installer's wind turbine as most suitable.

The major theme that can be identified within the literature is the subjective nature of the motivation and barriers to adoption. Each individual will value the respective motivation and barriers differently [108]. Their perception of each of the motivations, barriers and the microgeneration technology itself, will influence their decision to adopt. An individual's perception and adoption decisions have been shown to correlate with the demographics of the individual [53, 111]. In this project, where surveying was not undertaken, analysis of adopter demographics is a suitable method of understanding the influencing factors on small and medium scale wind turbine adoptions in Great Britain.

3.1.1 Socio-demographic relationship to microgeneration adoption

Studies have analysed the demographics of both adopters and those considering an installation of microgeneration technologies [53, 55, 56, 111-116]. However, none of these studies have specifically focused on wind turbine adopters in Great Britain. It is envisaged that wind turbine adopters may exhibit similar demographics to adopters of other microgeneration technologies. However, the need for wind turbines to be in areas with sufficient wind resource, which are likely to be more rural areas, could result in the demographics of the wind turbine adopters, differing from those of adopters of other microgeneration technologies, which can be viable in suburban or urban areas. By examining the demographics of wind turbine adopters in Great Britain, it will be possible to understand if wind turbine adopters have a common set of demographics. Previous literature has shown that adopters of other microgeneration technologies have similar demographics [56, 112, 113, 115-117]. These studies have mainly focused on six demographic factors; age; income; education; household size; home ownership and the social class of adopters [53].

3.1.1.1 Age

Awareness of microgeneration technologies generally increases with age, and peaks between the ages of 50 and 60, before awareness begins to drop [109]. This inverted u-shaped correlation between awareness and resident age has been shown specifically for micro-wind turbines [109]. However, the study only examined awareness of wind turbines, rather than actual adoption. Adoption of micro-wind turbines has been shown to decline sharply after individuals reach the age of 65 years old [112]. However, this study only examined adoption in relation to whether the head of household was aged over or under 65 years old [112]. Therefore, no conclusion on the influence of adopter age could be drawn from the results, merely that it was more likely for adopters to be aged below 65 [112]. Analysis of the age of solar photovoltaic (PV) adopters shows that the vast majority of adopters are aged over 45 [56]. The results of previous studies suggest that microgeneration adopters tend to be older residents who are below retirement age. The relationship between adopter age and wind turbine adoption is not clearly defined in the literature.

3.1.1.2 Income

The role of income in the adoption of microgeneration technology in the UK has been examined in PV uptake [56]. Around 40 % of survey respondents, who had installed PV systems, had an annual household income of greater than £50,000 [56]. While this is a statistically significant difference from the national average [56], the study highlighted that respondents still experienced the financial barrier of upfront cost [56]. The assertion that microgeneration technology adopters have higher levels of income has been backed up in other studies, albeit qualitatively [108, 118]. Income of adopters is likely to be a much more significant factor for small and medium scale wind turbine adoption, as the upfront costs of wind turbines are higher than those for PV systems [36].

3.1.1.3 Education

Microgeneration technologies, particularly PV systems, have been shown to be adopted by individuals with higher levels of education. 77 % of PV adopters in the UK had a degree-level qualification compared to 30 % nationally [56]. Another study, examining the adoption of wood stoves, found that the relationship between adoption and education was actually inversely proportional [119]. A comparable study found residents with higher educational qualifications tended to live in urban areas, which is likely to be the cause of inverse relationship with the adoption of wood stoves [120], which are less suitable for higher density urban housing. While the literature finds a correlation between education and adoption of PV [56, 118, 121, 122], other factors can influence this correlation. Wind turbines are more effective in rural areas due to higher wind resource, whereas those who have gained a degree level qualification are more likely to leave rural areas for better employment opportunities in cities [123]. However, the exact nature of the relationship between education and wind turbine adoption is unclear from the literature.

3.1.1.4 House type

As the size of a household increases, the likelihood of a microgeneration adoption also increases [53]. Although there appears to be no relationship between awareness of microgeneration and household size [109], it seems logical that residents with larger homes would install microgeneration technologies. In addition, to having a larger home to heat and power [53], residents who live in larger homes are likely to have higher income [53]. This is supported by a study that shows that residents who live in detached homes have a higher WTP for wind turbines, than residents of other housing types [108]. Conversely, household size may also suggest that residents have a larger family to support. In relation to PV adoptions, household size has been shown to have a negative effect on adoption [42] which is suggested by Balta-Ozkan et al. to be because larger families have lower disposal income for an installation. This was contradicted in another survey, which found that the presence of children under 16 in a household exhibits no influence on microgeneration adoption [53]. In terms of wind turbine adoption, it is envisaged that house type could be key as detached homes are more likely to have sufficient land available to accommodate a wind turbine installation. However, this assertion is untested and was investigated during this research.

3.1.1.5 Homeownership

Homeownership is a key demographic factor in microgeneration adoption [53, 109, 118], with 97 % of PV adopters surveyed being homeowners [56]. Various studies confirm this [43, 45, 56, 108]. Homeownership is required as the homeowners have the power to decide whether to adopt [53]. Homeownership is crucial to the “landlord-tenant” dilemma [43, 109, 124], which occurs when a residence is rented, neither the landlord or the tenant has an incentive to pursue adoption. While the tenant may benefit from adoption, it will be the landlord that must provide the capital for an installation. Adoption is therefore unlikely when the decision maker does not own the property. Homeownership is therefore an important factor which influences many microgeneration adoptions, and this is envisaged to be the case for wind turbine adoptions.

3.1.1.6 Social class

Awareness of microgeneration technologies are shown to be highest amongst upper middle class residents, likely to be employed as professionals or in higher managerial positions [109]. The awareness of small scale wind energy is also high in farmers [109]. Adopters of microgeneration technologies under the FIT are likely to be in the higher social classes of A or B [55]. These social classes cover individuals considered as professionals and those in managerial positions. However, an issue arises when examining social class in relation to wind turbine adoption patterns. Social class is interlinked with education and income [125] as individuals with higher educational achievement and income are likely to be in a higher social class. Use of social class is therefore useful in an analysis, however, is likely to be a secondary indicator to the influence of education and income on adoption.

3.1.1.7 Influence of wind resource on wind turbine adoptions

In addition to the demographic variables examined in previous studies, other factors which influence wind turbine adoptions in Great Britain must be considered here. Of the factors, which will be discussed in this chapter, the wind resource available to a proposed wind turbine is considered here as key.

The capital costs of a wind turbine are considerably higher than other microgeneration technologies [21, 36] and therefore the payback period of wind turbines can be considerable. To achieve a suitable payback period, sufficient financial returns from the power output of a turbine are required. The power output of the wind turbine is directly related to the available wind resource. The availability of wind resource is therefore suggestion here as a highly influential factor in wind turbine adoptions in Great Britain. This assertion is supported when examining the technical potential estimates of wind turbines in Great Britain, discussed in Chapter 1. These technical potential estimates were based upon sites having sufficient wind resource to ensure the technical and financial viability of a wind turbine on these sites [31].

The availability of solar resource was shown to have a positive influence on PV adoptions in England and Wales [42]. However, long-term solar irradiance across Great Britain has lower spatial variation which is consistent with latitude [126]. The power output of a PV system can therefore be predicted more efficiently. In comparison, wind resource can vary greatly over small distances and the wind resource available to a wind turbine can vary rapidly [14]. This places a great emphasis on sufficient wind resource being available at a site to ensure that a suitable payback period is achieved. The availability of wind resource is likely to be influential on wind turbine adoptions.

Previous literature which offered technical potential estimates for wind turbine deployment, defined sufficient wind speed as a long-term mean wind speed above either 5 ms^{-1} [31] or 5.5 ms^{-1} [38]. However, these estimates were created using Microgeneration Certification Scheme scaled NOABL wind speeds [31] or unscaled NOABL wind speeds [38] respectively. Unscaled NOABL data can be highly inaccurate in certain locations with a tendency to over-predict long-term mean wind speed [30, 32] and doubts have been cast here on the suitable of the MCS methodology as an accurate wind resource estimation technique, as was detailed in Chapter 2. It was therefore prudent to investigate within this research if the definitions of sufficient wind speed detailed in previous literature are correct.

3.1.1.8 Additional socio-economic and environmental factors considered for analysis

In addition to the demographic variables from previous studies and the influence of wind resource, additional demographics must be considered for their inclusion in this research. These additional factors, which are considered, will be examined and justification for their inclusion in this research will be discussed here.

The issue of losing money should an adopter move home has been cited by previous adopters as a barrier to adoption [54]. It is hypothesised here that adopters are therefore unlikely to move home following an installation. The number of house sales in a region will be considered for inclusion. With such data, it will not be possible to understand if individual adopters within a region have moved home since their installation. This data can only offer an indication if a high proportion of homes in a region are sold annually. This factor is therefore suggested for inclusion in the analysis as a proxy for residents not moving home.

Wind turbines produce electricity and therefore the energy produced by a wind turbine will offset the domestic electricity demand of an adopter's residence. It is suggested here that residents with higher domestic household electricity consumption will be more motivated to install a wind turbine, if their location is suitable. This ties into the findings of previous literature that microgeneration adopters have ranked highly a desire to achieve lower energy bills and protect against raising energy costs as a motivation to adoption [54]. A study of the influencing factors on PV adopters in Great Britain also found adopters were more likely to have higher domestic electricity demand [42]. Household electricity consumption is therefore theorised as an influencing factor on wind turbine adoptions in the UK.

Regions with a comparatively low prevalence of homes with gas-fired central heating are likely to be more rural areas. Some rural areas are unable to access the national gas grid and therefore homes in these regions will have to be heated using another fuel. It is therefore reasonable to assume that the higher the number of homes in a region, which do not have gas fired central heating systems, the more rural the area can be considered. In rural areas, it is likely there will be higher wind resource and greater land area available. These factors have previously been suggested as influencing factors on wind turbine deployment through their use as the basis for technical potential estimates [31, 38].

The awareness of wind turbines has been shown to be highest in farmers [109]. In addition to the awareness amongst farmers, another study has suggested that farms are the ideal locations for wind turbines [31]. It would be remiss to conduct analysis of wind turbine adoption patterns and exclude data regarding the influence of the presence of agricultural industry in an area.

Areas which are considered rural are likely to have a higher wind resource, due to the lower density and distribution of roughness elements at the surface [81]. Therefore, the inclusion of environmental variables which characterise the rurality of the area are necessary in this research.

The socio-economic and environmental factors discussed in this section are theorised as influencing factors or serve as proxies for influencing factors on the adoption patterns of wind turbine installations in Great Britain. While analysis of the demographics of adopters will not be able to offer the specific motivations of each individual's decision to adopt, it will be able to demonstrate if certain socio-economic factors are likely to influence the adoption patterns of small and medium scale wind turbines. Although the importance of these motivations or barriers is specific to each individual, a prevalence of a certain demographics can highlight that adopters who have similar demographics are more likely install. Through analysis of the relationship between these demographic factors and wind turbine adoptions patterns, it will be possible to understand the influence of each factor on adoption patterns. In order to determine this influence, the analysis techniques utilised in previous studies examining microgeneration adoptions are reviewed to identify the most appropriate technique for the analysis of wind turbine adoption patterns in this research.

3.1.2 Socio-economic and demographic analysis techniques

Literature on analysis of the demographics of wind turbine adopters is minimal, at best. However, analysis of British PV adopters by Balta-Ozkan et al. and American PV adopters by Kwan assessed the influence of a number of socio-economic and environmental factors on PV adoption patterns [42, 44]. The study by Balta-Ozkan analysed PV adoptions on a regional scale in

England and Wales [42], while Kwan analysed PV adoptions in US postal codes [44]. Both studies implemented regression models to determine the influencing factors on spatial adoption patterns of PV systems [42, 44]. Balta-Ozkan et al. utilised multiple spatial regression models [42] while, Kwan implemented a negative binomial regression [44]. Kwan developed a number of categories of socio-economic indicators as the independent variables of the regression model, each represented by binary values [44]. PV adoptions were also represented by binary values. Use of a binomial regression model negates the value of information regarding terms of multiple adoptions in a single area, by reducing this to a binary value. Additionally, the use of categorical socio-economic indicators only offers the ability to identify the existence of an influence rather than examine the relative influence of the socio-economic indicators. For this reason, a binomial regression model of any form would be unsuitable for this research.

Balta-Ozkan et al. utilised multiple spatial regression models in order to capture the spatial dependency in PV adoption patterns [42]. Analysis of the spatial dependency in PV adoptions is implemented to understand the peer effects for neighbouring regions [42]. However, this is not the focus of this particular piece of analysis. The influence of neighbouring installations on wind turbine adoption patterns is discussed in Section 3.2 and examined in Chapter 6. This analysis aimed to determine the influencing factors on wind turbine adoption patterns, exclusive of the influence of neighbouring wind turbine installations. The decision to exclude the influence of neighbouring installation from this part of the research stems from the lack of available literature. The model presented by Balta-Ozkan et al. is considered a complex model and supported by a body of complementary literature. An extensive body of literature does not exist for the influence of demographics on wind turbine adoptions and therefore the complexity of the model developed for this research must be minimal. It is yet to be established if any of the factors discussed here have any influence on wind turbine adoption patterns in Great Britain. Therefore, use of a model within minimal complexity is required to establish if the factors suggested had any influence on wind turbine adoption patterns. Once the influence of these factors has been established, then it would be suitable to consider more complex models with which to examine the influence of neighbouring wind turbines on subsequent wind turbine adoptions.

To determine the influence of demographic factors on adoption patterns, an alternative method must be identified. Balta-Ozkan et al. initially utilised a linear regression model before the ordinary least squares (OLS) regression coefficient estimator becomes inefficient in the more complex spatial regression model [42]. This approach is also implemented in a study examining of the demographics of PV adopters in the San Francisco Bay area [45]. Both studies utilised a multi-variate regression approach to understand the influence of each demographic factor on respective PV adoption patterns. Use of a varied set of demographic variables, discussed in Section 3.1.1 in this research, requires the understanding of the influence of each individual factor on wind turbine adoption patterns. A linear regression approach is therefore considered the most appropriate method for the analysis of spatial adoption patterns of wind turbine in Great Britain in this research.

Using this linear regression approach, a number of scenarios can be investigated to understand the differing influences on wind turbine adoptions. This research has been developed to examine the spatial wind turbine adoption patterns. Initially, only the influence of wind resource on wind turbine deployment can be examined. The importance of financial barriers and motivations for microgeneration adopters [54] results in the available wind resource onsite being a key factor when determining a wind turbine's viability. However, the influence of available wind resource on wind turbine adoption patterns is currently unclear. This investigation is therefore a vital part of this research's analysis of wind turbine adoption patterns. In addition to the influence of wind resource, a definition of sufficient mean wind speed required to ensure viability of a wind turbine installation will be examined. The current definitions of sufficient mean wind speed provided in the technical potential estimates were developed, from what is considered by the author, an inappropriate wind speed estimation methodology. It is therefore necessary to examine whether the definition of sufficient mean wind speed can be refined, using a wind speed estimation technique with greater accuracy, available from research presented in Chapter 4

Current literature on the factors which have influenced microgeneration adoptions identified six factors of resident age, income, education, house type, homeownership and social class [42, 56, 108, 110-118]. It was therefore important to analyse the influence of these factors on wind turbine adoption patterns. The results of this analysis were then compared to the results of previous studies on microgeneration adoption in Great Britain [42, 53, 56]. Through this comparison of results, it was possible to understand if

British wind turbine adopters have similar demographics to adopters of other microgeneration in Great Britain.

In addition to these demographic factors, it was theorised here that other demographic and environmental factors will also have an influence on wind turbine adoption patterns. To analyse the influence of the demographic factors, in addition to the factors of house sales, domestic electricity consumption, types of central heating, prevalence of agricultural in a region, availability of land area and mean wind resource, an additional linear regression model was developed. A full description of the three regression models developed to identify the influence of these factors on spatial wind turbine adoption patterns and the results of each model is provided in Chapter 5.

3.2 Influences on the temporal adoption patterns

The uptake of microgeneration technologies have temporal adoption characteristics, in addition to spatial characteristics [41]. Analysis of the demographics of wind turbine adopters helps to understand the spatial characterisations of adoption. To ensure that the temporal characteristics are also understood, a further scheme of research is required to examine temporal influences on wind adoptions in Great Britain.

The ability to receive government incentives such as the Feed-in Tariff (FIT) is an important motivator for microgeneration adopters [53, 55]. Financial returns available from FIT payments increase the financial viability of wind turbines, increasing the number of locations in which a wind turbine would be cost effective. The FIT is therefore hypothesised here to be an influencing factor on uptake of wind turbines in Great Britain. However, changes have been made to the levels of financial subsidy available to wind turbines since the introduction of the FIT April 2010 [34]. Subsidy levels have been reduced from 31.91 p/kWh in April 2010 to 8.33 p/kWh in October 2016 for wind turbines, with a capacity greater than 1.5 kW but not exceeding 15 kW [34]. These temporal changes in subsidy levels will reduce the financial viability of prospective turbines and are likely to influence temporal wind turbine adoption patterns.

In addition to the FIT subsidy level changes, the influence of visible neighbouring turbines can also be examined. Around 20 % of microgeneration adopters have cited viewing a neighbouring installation as a motivation for their decision to adopt [55]. The visibility of wind turbines is considerably higher than other microgeneration technologies, as a wind turbine can potentially be seen by neighbours a number of kilometres away [127]. The influence of visible neighbouring turbines has a temporal nature. As new turbines are installed in a neighbourhood, the influence on a neighbour's decision to adopt a wind turbine may increase. Examination of the subsidy level changes to the FIT and the visibility of neighbouring wind turbines is required to understand the factors which influence temporal wind turbine adoption patterns in Great Britain.

3.2.1 Feed-in Tariff

The introduction of the FIT in April 2010 was intended to drive uptake of a range of small-scale low carbon electricity technologies by offering guaranteed financial returns to adopters [23]. Assessment of FIT policy design in other European countries highlighted that the introduction of such a policy can drive deployment of PV systems but has little to no effect on onshore wind deployment [128]. However, this study only considered deployment before 2008, prior to the introduction of the FIT in Great Britain [128]. Two studies have highlighted that the FIT has created demand for PV systems in Great Britain [41, 129]. Both studies highlighted that changes to the FIT levels has induced peaks in monthly installation numbers [41, 129]. Literature on the effect of the FIT on wind turbine installations in Great Britain is lacking and therefore the effect of subsidy changes on wind turbine installation numbers was examined in this research.

Reductions in the FIT subsidy level in April 2012, December 2012 and April 2014 were all proceeded by a peak of wind turbine installations in the month prior to the change. The presence of these peaks highlights that the FIT and particularly the level of subsidy available, play a role in a consumer's decision to adopt. Adopters who are able to install a wind turbine prior to a reduction in the tariff level are guaranteed the higher tariff for the lifetime of the FIT, which is currently 20 years [26]. The desire to access higher levels of subsidy is likely to be an underlying cause for these peaks in monthly installations. These peaks are similar to those seen in PV installations [41, 129]. However, Snape [41] associated the peaks of PV installations with announcements of a change in FIT subsidy, rather than change in the subsidy level. Announcements of changes in the subsidy level available typically occurs 3 to 6 months prior to the change coming into effect [35]. The difference between the timing of peaks in installations of PV and wind turbine is due to the different timeframes required to complete an installation of each technology. PV systems can be installed considerably more quickly than wind turbines and therefore when a change in FIT is announced, the peak of installations in PV will occur before the peak of wind turbine installations. The peak in PV installation data therefore appears to be associated with the announcement, rather than the change in subsidy level.

Since December 2012, changes in the FIT subsidy level have been due to an degression mechanism [35]. Degression allows for the subsidy level to be reduce based upon the total installed capacity of wind turbines in the preceding period [35]. The degression mechanism was introduced for non-PV technologies to ensure consistence with the degression mechanism introduced for PV FIT subsidy levels [35]. This was despite significantly higher levels of PV deployment [12] and the reticence of non-PV technologies stakeholders, expressed during the consultation phase of the tariff review [35].

Since its introduction, the degression mechanism for wind turbines has been implemented once annually and three times at the six-month period. As a result, deployment appears to have slowed in the small and medium scale wind turbine market as tariff levels have dropped by 60 % since December 2012 [34]. In comparison, the rate of monthly installations increased after the introduction of the FIT in April 2010 but prior to subsidy level cut in December 2012. The changing rate of monthly wind turbines installations suggests that introduction of the degression mechanism and subsequent changes in the subsidy level have influenced the deployment rates of wind turbines. This analysis must be extended to understand to what extent these subsidy level changes have temporally influenced wind turbine adoptions patterns.

3.2.2 Visibility of wind turbines

The influence of visible microgeneration technologies raises awareness of these technologies in the neighbours of the adopters [55]. 19 % of microgeneration adopters and 27 % of those considering an installation have identified seeing a neighbouring installation as a factor which has prompted their interest in pursuing an installation [55]. A previous study has suggested that the visual influence of PV installations has an effect on the subsequent PV adoptions of their neighbours [43]. The visibility of wind turbines is higher than other microgeneration technologies, such as PV systems, due to the high hub and blade tip heights of a wind turbine. It is therefore logical to question whether neighbouring wind turbine installations have had a similar influence on the adoption patterns of their neighbours. To understand this influence, the radius over which this visible influence from a turbine may act must be determined.

The visibility radius of a wind turbine is dependent of the height and size of the turbine, the topography of the turbine site, the position of the neighbour who is viewing the turbine [130] and the atmospheric conditions, such as haze or sky colour, when the turbine is viewed [127]. However, studies have shown that a wind turbine with a hub height of around 50 m is visible within 10 km of the installation [127, 130, 131]. Lower capacity wind turbines, such as those examined in this research, are likely to have a hub height below 50 m and therefore the visibility radius of these turbines will be lower. However, it is likely that wind turbine installations will exert an influence on prospective adopters further than 10 km away. The influence of a visible turbine on immediate neighbours is limited to those with direct line of sight from their residences. However, if the turbine siting is located near transport routes, it is possible that an installation will be visible to a greater number of individuals, including those outside of the immediate neighbour. The viewing of an installation during a prospective adopter’s journey could prompt interest in their own wind turbine installation. The distance over which a wind turbine can be viewed by neighbours is specific to each installation and each neighbour. To investigate the influence of a turbine’s visibility on a neighbour’s decision to adopt, it should be considered over a number of distances.

A wind turbine’s visibility also influences neighbours in a temporal nature. The installation of a wind turbine is not completed overnight and therefore an installation will be viewed throughout its construction phase. However, the time at which the influence begins to act during the construction phase will differ between neighbours. Neighbours with prior knowledge of wind turbines are likely to recognise that a wind turbine is being constructed earlier than those without prior knowledge [127]. To ensure that the influence of a visible turbine begins to act at the same time for all neighbours, the visibility of a turbine is considered to be influential only once the turbine is fully operational. This choice is in line with literature, where the influence of PV systems is only considered to act on neighbours, once an installation has been completed [45].

The influence that a neighbour experiences will also increase temporally as the number of turbines within their neighbourhood increases. The degree to which each new turbine influences individuals is dependent on the siting and physical characteristics of each turbine, however, the overall influence will increase as new turbines are installed. An increasing number of turbines is likely to exert a greater influence on a neighbour, with multiple turbines more easily distinguishable than a single turbine [130].

In addition to the changing visual influence of wind turbines as new installations become operational, there is a temporal aspect stemming from the individuals who view the turbines. The level of influence of visual microgeneration installations increases between those who have adopted and those considering a microgeneration technology [55]. The difference between the proportion of current adopters and potential adopters who were influenced by a visible microgeneration installation [55] suggests that individuals at different stages of the adoption process are affected by this visual influence differently. The data indicates that those who adopt later are more likely to be influenced by the visibility of a wind turbine than those who adopt earlier. The results suggest that the characteristics of adopters and the degree to which different factors influence their decision to adopt will change as uptake increases. These different individual adopter characteristics must be understood when considering the temporal adoption patterns of wind turbines in Great Britain.

3.2.3 Temporal adoption characteristics

A description of adopters at different stages of an innovative technology's market growth is offered in Rogers' Diffusion of Innovations model [132]. This model has previously been utilised as the theoretical basis of an analysis of PV adoption in the UK [42]. In addition, microgeneration technologies have previously been considered as an innovative technology, in terms of adoption rates [108, 118]. It is therefore likely that characteristics of wind turbine adopters in Great Britain will fit with the adopter characteristics in Rogers' Diffusion of Innovations model.

Rogers' model offers a framework to understand why, and at what rate, an innovation such as a new technology spreads [132]. Rogers' model states that diffusion of the innovation occurs within a social system as members of the system communicate regarding the innovation [132]. Once a member learns of an innovation, there is theorised to be a multi-stage adoption process of which knowledge of the innovation is the initial stage [132]. Awareness of micro-wind turbines is high amongst British residents, with 69 % of respondents having a basic knowledge of the technology [55]. The majority of residents in Great Britain have therefore reached at least the knowledge stage of diffusion. The knowledge stage is followed by the persuasion stage, where the individual seeks further information regarding an innovation [132]. Once an individual has gathered sufficient information, a decision to adopt occurs [132]. This decision to adopt is categorised based upon whether the decision is made by an individual, collectively by all members of the social group or by an individual in a position of power [132]. For small scale wind turbines, it is typically individuals who make this decision, with some community wind installations occurring following a collective decision making process involving multiple individuals. The decision to adopt is either positive or negative, with individuals who make a positive decision becoming known as adopters [132].

Rogers' model characterises individuals based upon when their adoption occurs, in terms of overall market share, as shown in Figure 11 [132].

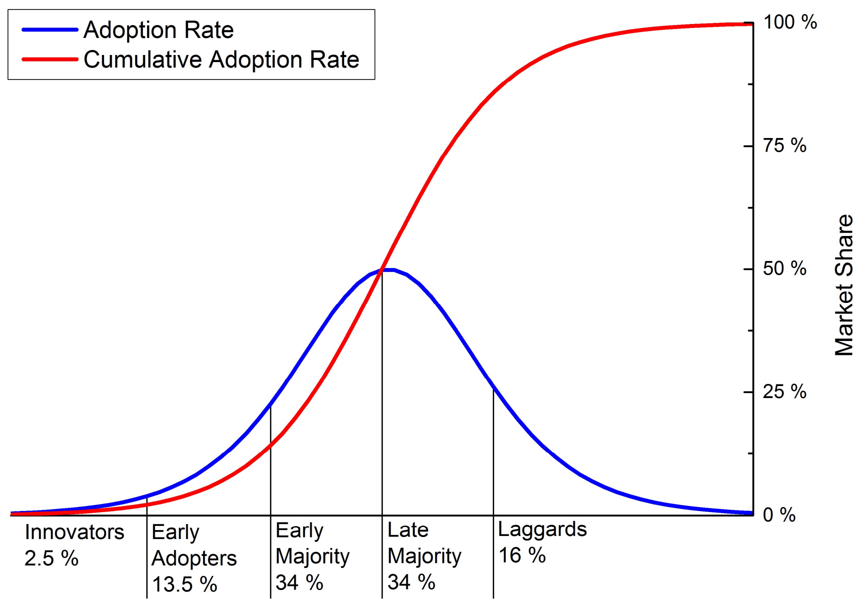

Figure 11 — Rogers' Diffusion of Innovation model. Reproduced from [132]

This characterisation categorises adopters into one of five adopter categories. The five categories, summarised in Table 2 describe the characteristics and values of each adopter category [132].

Table 2 — Summary of adopter category characterisation and values [132]

Adopter Category	Characterisation and Values
Innovators	Innovators are willing to take on a higher level of risk associated with a new innovation and have the financial means to offset any failures. Innovators have the technical knowledge required to understand the technical complexities of a new innovation. In a social context, innovators are likely to be less connected within their local social system, making their opinions less influential to others in the same social system.
Early Adopters	Considered as the opinion makers and role-models in the local social system. They are more connected within the local social system making their opinion more influential. Adoptions by early adopters helps to decrease the uncertainty surrounding the viability of a new innovation for future adopters.
Early Majority	Early majority adopters have a much longer lead time between knowledge of the innovation and adoption. A longer deliberation period is common as they are more likely to spend a longer time gaining information about an innovation. The longer lead time also occurs as the early majority wish to understand the earlier adopters' experience following their adoption.
Late Majority	Adoption for late majority members is usually out of economic necessity and because of increasing peer pressures. The majority of the social system must have adopted to motivate the late majority to adopt. Late majority requires much of the uncertainty surrounding an innovation to have dissipated prior to their adoption.
Laggards	Laggards are the last in the social system to adopt and require the uncertainty of an innovation to dissipate fully before adoption. Laggards hold much more traditional views on innovations and are suspicious of new innovations. Economic constraints of the laggards makes them extremely cautious in their decision to adopt.

Of the five categories of adopters described in Table 2, it is the first three categories which are considered here to be prevalent in the small and medium scale wind turbine market. Based upon current deployment levels, it is suggested here that the current adopters in the market are more likely to exhibit the characteristics of innovators, early adopters and possibly, early majority in some cases.

Innovators are typically more adventurous in terms of adoption of a new innovation [132]. This leads them to accept the higher risk associated with a new innovation as the innovation has not matured significantly [132]. An innovator's acceptance of this higher risk leads them to have a short time period between the knowledge and decision stages of the adoption process

[132]. Early adopters are also willing to accept a high level of risk and their adoption helps to decrease the uncertainty surrounding an innovation for future adopters [132]. As with innovators, the time between the knowledge and decision for early adopters is considered short, although this time does exceed that of an innovator. In comparison, early majority adopters consider adoption of an innovation for much longer before a decision to adopt, empirically shown to be almost twice as long as innovators or early adopters [132]. This longer time period stems from early majority adopters wishing to gather a greater volume of information and allows them to assess the advantages and disadvantages of an innovation [132]. This longer lead time also allows early majority adopters to assess the perceived risks of adoptions from early adopters and allows the innovation to mature further and reduce the uncertainty of an adoption [132]. During this consideration period, early majority adopters are likely to garner knowledge about the adoption experience from early adopters [132]. This makes early adopters key to the continuing diffusion of an innovation.

Early adopters are seen as opinion makers in the social system and serve as role models for later adopters [132]. Their role in the social system is due to an early adopter's level of communication with other members of the social system [132]. Early adopters have a greater deal of communication with other members of the social system, compared to innovators who tend to have a greater number of social connections with members outside of the local social system [132]. The number of connections in the social system dictates the level of influence that these adopters have.

Communication of an innovation is categorised into two major channels; mass communication and interpersonal communication [132]. Mass communication transmits to a wider audience, whereas interpersonal communication is a personal exchange of information between individuals [132]. For the small and medium scale wind turbine market in Great Britain, deployment is low and therefore mass communication is likely to be important for current adopters. Traditionally, mass communication is considered as stemming from mass media formats such as radio and television [132]. However, mass communication in the wind turbine market is suggested here as not being limited to traditional mass media formats. The visibility of a wind turbine can be considered a form of mass communication as the turbine can be seen by neighbours a number of kilometres away. The visible wind turbine communicates to multiple individuals the viability of an installation in a particular region. It is therefore argued here that this is a form of mass communication, which can influence potential adopters through observational learning [43, 133]. As potential adopters view a wind turbine in their neighbourhood, they are able to observe and begin to learn about the operation of a wind turbine [133]. This observational learning extends the potential adopter's knowledge and increases their awareness. The increase in a potential adopter's knowledge and awareness can cause them to advance to the next adoption stage and eventually to a positive adoption decision. The visibility of a wind turbine installation is therefore considered an important method of communicating the diffusion of the wind turbines in Great Britain.

The communication of the positive aspects of installing a wind turbine will be better received by prospective consumers with similar characteristics to the adopter imparting the information [132]. The degree of similarity or homophily between neighbours increases the effectiveness of the communication flow [132]. Homophily occurs when individuals share similar beliefs, education and socioeconomic status [132]. Geographical proximity also creates homophily, due to increased contact with neighbours [134]. If homophily exists between neighbours, a neighbour's decision to adopt could influence others in the neighbourhood to adopt through the visibility of the neighbouring wind turbine. However, the homophilous nature of peers in a social system can also be a barrier to diffusion of the innovation out of this system to other individuals [132]. Heterophilic individuals are too different, in terms of beliefs and socio-economic status, for the communication to be valued by either, thereby halting the diffusion of the innovation. Therefore, in order to investigate the influence of the neighbouring wind turbine on a decision to adopt, areas where homophily between peers is present must be considered.

The areas that are likely to be utilised to investigate the influence of visible neighbouring wind turbines are likely to be areas with a high numbers of wind turbine installations. It is within these areas with high levels of deployment that the influence of a peer's wind turbine installation can be best examined. If an area has only a few installations, any peer effect may be indistinguishable or negligible. Areas of high installation offer a greater number of adoptions which can be utilised to investigate the influence of peer effects on subsequent adoptions.

3.2.4 Peer effects

To analyse the peer effects which influence a neighbour's decision to adopt a wind turbine, the types and sources of peer effects must be discussed.

Peer effects can be categorised into one of three different peer effects [135, 136];

- endogenous effects;
- exogenous effects; and
- correlated effects.

Each of these effects influences an individual’s behaviour. However, the source of the effect differs between the different peer effects. Endogenous effects are characterised by an individual’s behaviour mirroring those of others in the same group and motivated by the behaviour of the social group [135]. Exogenous effects are the effects on an individual’s behaviour that result from an externality of the social group [135]. Correlated effects are a result of individuals in the social group having similar characteristics or environmental views, which drives their similar behaviour [135].

The visual influence of a wind turbine is therefore considered an endogenous peer effect. This conclusion is supported by past literature where previous microgeneration installations have been considered to have an endogenous effect on the adoption decisions of peers [43, 45]. Use of a peer effects model is therefore suitable to examine the influence of visible neighbouring turbines on subsequent decisions to adopt wind turbines.

Development of the peer effects model in this research was based upon research into the influence of peer effects in the uptake of PV systems [43, 45-47, 137]. Literature regarding the peer effects on uptake of wind turbine in Great Britain is lacking, hence the reliance on peer effects literature for another microgeneration technology. The novelty of this work therefore lies in the previously unexamined influence of peer effects on temporal wind turbine adoptions in Great Britain.

3.2.4.1 Peer effects literature

Previous literature has examined the influence from visible PV systems on a neighbourhood’s PV adoption patterns [43, 47]. The peer effects literature is primarily for PV adoptions either in the United States of America (US) [45, 46] or Germany [47, 137], with only Richter examining PV system adoptions under the Feed-in Tariff in the England and Wales [43]. Rode and Weber [47] and Richter [43] suggest that the peer effect from a visible PV system can lead to observational learning [43] by subsequent adopting peers. Rode and Weber argue that observational learning between peers is possible without direct social interaction of the peers [47]. This assertion is consistent with the definition of wind turbine visibility as a form of mass communication under Rogers' Diffusion of Innovation model [132].

All of the literature identifies that a peer effect between previously installed neighbouring PV systems and adoptions can be observed [43, 45-47, 137]. Richter found that this effect is small but significant in the UK [43], while Bollinger and Gillingham and Graziano et al. found a stronger effect on PV adoption in US states [45, 46]. Graziano et al. and Rode and Weber both demonstrated that a peer effect has no effect after certain distances, estimated to be 4 km in the US [46] or 1 km in Germany [47]. The visual peer effect from a wind turbine is likely to be influential over a greater distance, as the visibility characteristics of a wind turbine differ greatly from PV system.

Further research by Palm, examined how the peer effects differed when PV adopters had had direct contact with previous adopters, known as an active peer effect or had seen PV installations, known as a passive peer effect [138]. Palm suggests that the active peer effect is of greater importance than the passive visual peer effect in PV adoptions in the Swedish neighbourhoods examined [138], contrasting with other literature which places equal importance on either peer effect [45, 46]. While Palm's results show the greater importance of an active peer effect, the results of the study show that a passive peer effect still exerts an influence on neighbours [138]. Palm extended his research further to examine how an individual's perception of PV technologies differed depending the type of peer effect which each adopter experiences [138]. For adopters who were influenced by the passive peer effect, 41 % of the respondents agreed that the passive peer effect indicated the PV could be considered a "low-risk" investment [138]. 54 % of the respondents also stated that the passive peer effect demonstrated that PV systems were technically and economically feasible in the neighbourhood, while 38 % suggested a passive peer effect caused them to adopt sooner [138]. The ability of passive peer effects to alter an individual's perception on the feasibility of the technology is an important finding for wind turbine adoptions. As discussed, the technical and thus economic feasibility of a wind turbine is dependent on the wind resource of a neighbourhood. The fact that a passive peer effect can demonstrate such feasibility suggests that it will be influential in the wind turbine market. As wind turbines are installed, each turbine further demonstrates that a wind turbine installation is both technically and economically feasible in the neighbourhood, increasing the likelihood that a potential adopter will pursue an installation.

The previous studies also show that a peer effect can be observed in PV markets which are subsidised [43, 47, 137], which is particularly relevant for this work. It is theorised in this research that the ability to receive a financial subsidy from the FIT is an influencing factor on the temporal adoption patterns of wind turbines. The fact that a peer effect has been seen in similarly subsidised microgeneration markets demonstrates that choice of the peer effects model in this work is suitable.

Despite the presence of subsidies for energy generation from PV systems in both Great Britain [25] and Germany [139], none of the peer effects models examining adoption in either country included the specific subsidy levels available for generation [43, 137]. The FITs in Great Britain and Germany are similar, offering payments per kWh of generation and including a degree of degression of the subsidy level [139, 140]. In each of these peer effects studies, the influence of subsidy degression was included through the use of fixed effects in the model to represent the influence of a tariff [43, 47]. This approach is considered as insufficient for this work. While fixed effects in a peer effects model will model the influence of temporal changes to a subsidy level across all potential adopters, where information regarding the actual subsidy changes are available, inclusion of the fixed effects appears unnecessary. Data regarding the FIT subsidy degression for wind turbine is available for this project. Therefore, the FIT subsidy degression warrants inclusion in the peer effects model developed in this work to understand its relative temporal influence on small and medium scale wind turbine adoptions.

An alternative policy which promotes deployment has been included in the study of PV uptake in Connecticut (CT) by Graziano et al. [46]. Solarize CT promotes PV adoptions by partnering with installers and targeting residents of a single town or county [141]. Over a fixed time period, residents are able to sign up for an installation and with each resident registered, the unit price of the an installation for all residents decreases [141]. The presence of the Solarize CT policy was shown to be significant influencing factor on PV adoption rates in Connecticut [46]. This result shows that the influence of a policy in a peer effects model can be examined and therefore inclusion of the FIT in this research is justified.

In the peer effects models, where the data restrictions required analysis to be conducted on postal codes, the concept of potential adopters was introduced [43]. The concept was introduced to account for the fact that not all households in a postal code may be suitable for a microgeneration installation [43]. Richter defined potential PV adopters as all owner-occupied homes in a postcode district [43]. Selection of only owner-occupied homes in a district is a result of the “landlord-tenant” dilemma [43, 109, 124], discussed in Section 3.1.1.5. While all owner-occupied homes are suitable for PV installation, it is likely that additional factors such as available wind resource will need to be considered when estimating the number of potential wind turbine adopters in a region. The potential adopter metric estimated in this project must therefore include additional conditions to offer a realistic number of potential homes in each region at which a wind turbine may be adopted.

The definition of potential adopters highlights that a peer effects model essentially examines the decision maker of the household. With the potential adopter metric, it is assumed that a decision to adopt is led by a single individual. This may be unrealistic for partners who live together, with the decision to adopt likely to be a joint decision. However, the assumption is that these partners will be similar and therefore their judgement of the benefits of a microgeneration technology will also be similar. This model of a single decision maker in a household is in line with the previous literature [45], which assumed that a household and it’s residents will decide together whether to install a microgeneration technology.

The timing of the decision to adopt a microgeneration technology is one well examined in the peer effects literature on the diffusion of solar photovoltaics [43, 45-47]. This issue is covered thoroughly due to the “reflection” problem of examining endogenous peer effects [136, 142]. The reflection problem arises as individuals may be influenced to make a decision while simultaneously influencing others in the peer group [136]. This problem makes it difficult to discern the influence on an individual’s decision to adopt from their simultaneous influence on others [136]. However, in the adoption of microgeneration technologies, there is a solution to address this problem. A decision to adopt a microgeneration is not instantaneous and there is a time lag between the initial decision to adopt and completion of the installation. Previous models examining peer effects and PV adoptions therefore included a time lag of the “installed base” to negate the reflection problem [43, 45, 46]. This time lag exists for small and medium scale wind turbines, which must pass through assessment and evaluation stages before an installation can be completed. This creates a time lag between an adopter deciding to adopt and completing the wind turbine installation, when the peer effect will begin to act. Previous literature selected time lags between a single day [45] and quarter-years [43, 46]. The lead time for a wind turbine is likely to range between a single month and up to a year, depending on the specific requirements of each proposed turbine and the site.

To implement the necessary time lag, an "installed base" of previously installed wind turbines must be defined. In previous literature, where an installed base was utilised, it was defined as the number of previous installations in the neighbourhood [43, 45]. The installed base, $b_{i,t-1}$, is the number of installations, $I_{i,t-1}$, in previous time steps, $t-1$, across all neighbours, j, in the social neighbourhood, C;

$$b_{i,t-1} = \sum_{t=0}^{t-1} \sum_{j}^{C} I_{i,t-1}$$

Equation 27

The inclusion of an installed base allows the influence of all previously installed wind turbines to be examined, rather than just wind turbines installed in the previous time step. This is vital in the wind turbine peer effects model, where the diffusion is expected to be slow. Stemming from the high capital costs of a wind turbine, which means a decision to adopt requires significant consideration by prospective installations. Unlike some literature which finds a diminishing peer effect on PV adoptions in time [46], it is likely that the influence of visible wind turbines will persist over much longer time period. Therefore, inclusion of the installed base in this research is vital, as this influence may only be effective after a longer time period. Without an installed base, the specific turbines which influenced a subsequent decision to adopt in the neighbourhood may be excluded from the peer effects model.

The majority of peer effects literature on microgeneration adoption include some characterisation of the socio-economic and demographic data of adopters [43, 45, 46]. Bollinger and Gillingham included a characterisation of the demographics of adopters to understand the social spill over effects that adopter demographics may have on peer effects [45]. The results of the study find that larger households, with more residents and longer commutes, have a higher peer effect on others [45]. In this work, there has been an inclusion of the socio-economic influences prior to initialisation of the peer effects model. Clusters of high levels of wind turbine deployment can be identified, from the results of the research on the spatial wind adoption patterns, and used as case studies for the peer effects models to account for the influence of demographic factors on wind turbine adoptions.

Clustering of installations is discussed in some literature in the context of adopter “self-selection” [43, 46]. Self-selection occurs when residents with similar social status and beliefs form social groups [135, 142]. Self-selection has been suggested as a reason for spatial clustering of installations, as individuals who have a similar propensity to adopt a microgeneration technology will reside close to each other [43]. Additionally, self-selection of a peer’s social group can lead to correlated behaviour, which when examined may appear to be due to an endogenous peer effect [43, 45, 142]. A degree of homophily between residents, which could indicate that self-selection may occur, is required for diffusion of the innovation to occur [132]. Imitation and observational learning, which have been suggested to occur from the visual presence of microgeneration technology [43, 46, 47] are social mechanisms that require homophily of residents for diffusion to occur.

The final of the classic endogenous identification problems, along with the reflection and self-selection problem, is the correlated unobservables problem [43, 45-47, 137, 142]. Correlated unobservables, in the adoption of microgeneration, may stem from the influence of local marketing campaigns [43]. These unobservables will influence the adoption rate as residents who are likely to adopt will be aware that installers are available to install a technology. This influence can lead to spurious identification of an endogenous effect between peers [142]. While this may be an issue within this research, as there is no data regarding local marketing campaigns available, the use of clusters of installations may mitigate this slightly. The formation of the clusters themselves will be driven by an influence or a number of influences. It is entirely possible that a local marketing campaign by an installer may have caused such cluster formation. While the correlated unobservables are not limited to local marketing campaigns, any other influential factors, which have not been examined, are also likely to stimulate cluster formation. While the use of the clusters in this research will mitigate the influence of these unobservables, they must be considered when analysing the results of the peer effects model.

The technical specification of any peer effects model is crucial to ensure that the endogenous peer effect is estimated correctly. The models described in previous literature are limited to three different types; pooled ordinary least squares (OLS) models [43, 45], first-difference models [43, 45] and fixed or random effects models [46, 47, 137]. Each type of model was selected based upon the specification and breadth of data available in each project [46, 47, 137]. Fixed or random effects in a peer effects model are included to account for the three identification problems discussed [43, 46, 47, 142]. Inclusion of these effects is designed to control for their influences. Fixed effects are included where an influence is consistent across all residents while random effects are included when the influence is likely to vary between residents. Inclusion of the fixed or random effects in a peer effects model may be suitable for this research, due to the influence of correlated unobservables. However, previous literature has discussed the use of random effects in a peer effects model with a time lagged installed base variable [45]. Use of the time lagged installed base can contain factors modelled in the random effects, leading to an inconsistent estimation of the endogenous effect [45]. Inclusion of the fixed and random effects in this research is considered to account for the identification problems of self-selection.

First difference models examine peer effects by assessing the influence on adoption rate of changes between the model variables in sequential time steps [43, 45]. Utilised to mitigate the requirement for the inclusion of fixed effects [43], first difference models are the preferred models in some literature [43, 45]. By assessing the change in adoption rates as a function of the change in other independent variables, a first difference model essentially examines the influence from adoptions in the preceding time steps alone. Examination of the influence that adoptions in the preceding time step have on adoptions in the current time step implies that diffusion of the innovation is rapid and can occur within the time lag specified in each model. This limits a first difference model's effectiveness in assessing the peer effects of wind turbine adoptions. As discussed, wind turbine diffusion is likely to be a slower process than PV diffusion. The influence of a visible wind turbine will be act over a much longer timescale than PV systems, due to the higher capital costs, which potential adopters are likely to consider for a longer time prior to adoption. Use of a first difference model would ignore this slow diffusion process by only examining installations in the preceding time steps, rather than all previous installations. A first difference model is therefore not considered suitable for this research.

A pooled OLS model has been included in previous literature to examine peer effects [43, 45]. By pooling the data, the peer effect can be estimated for all turbines in the neighbourhood, rather than for individual turbines [45].

While estimating the peer effect of individual turbines would allow for comparison with the results from previous literature, this is difficult when examining the influence of visible wind turbines. The visibility of a wind turbine is dependent on a number of factors, which are not consistent for all residents or wind turbines in any cluster. The peer effect of each visible turbine will therefore be subjective for each resident. Use of a pooled OLS model discounts this subjective visibility of each turbine and considers only the peer effect of all the visible turbines in the neighbourhood. With the inclusion of the degression of the FIT, the pooled OLS model is therefore considered as the most appropriate model for the peer effects model developed in this work.

The review of literature presented here addresses the factors that are likely to influence both the spatial and temporal wind turbine adoption patterns in Great Britain, and the techniques which can be utilised to analyse these influences. The level of the influence of each factor was investigated through two pieces of research. Analysis of the influence of the factors of resident age, income, education, house type, homeownership and social class house sales, domestic electricity consumption, types of central heating, prevalence of agricultural in a region, availability of land area and mean wind resource on spatial wind turbine adoption patterns using multiple regression models will be presented, discussed and analysed in Chapter 5. The influence of changing levels of FIT subsidy and the presence of neighbouring wind turbines on temporal wind turbine adoption patterns in case study areas using a peer effects model, which will be presented, discussed and analysed in Chapter 6.

Chapter 4 – Boundary layer scaling model for wind resource assessment

Wind resource assessments are vital in determining the potential financial returns of a wind turbine. A wind resource assessment must be accurate to ensure that the estimated power output and financial returns represent reality as closely as possible. For small and medium scale wind turbines, the wind resource assessment methodologies at the initial stages of the project are vital. Due to the smaller project budgets of smaller wind turbine installations, the viability of a site must be determined as quickly and cheaply as possible. Previous studies have highlighted flaws in the current methodologies available at this stage of a small and medium scale wind turbine project in Great Britain [32, 33]. Appropriate wind resource assessment tools are crucial to support future deployment of small and medium scale wind turbines and the wider move towards a low-carbon economy in Great Britain.

As discussed in Chapter 2, a boundary layer scaling (BLS) approach to wind speed prediction is proposed in this project. The BLS model has been developed in this research to supersede the MCS methodology, which is currently required for wind turbines to gain accreditation under the FIT scheme in Great Britain. The accuracy of the MCS methodology is questioned in this work and it is perceived that more accurate wind speed estimations are available from the BLS model. To test this perception, wind speed predictions from each methodology must be produced. Using these wind speed predictions, it is possible to analyse their accuracy to determine which of the methodologies is considered the most suitable to support future wind turbine deployment.

The proposed BLS model in this research also introduces a number of potential improvements to a previous BLS model by Weekes [33]. The introduction of an analytical approach to regional aerodynamics calculations, over a greater number of wind direction sectors using an increased breadth and spatial resolution of the surface roughness values are the proposed improvements in this work's BLS approach. These improvements to the BLS model are aimed at improving the accuracy of wind speed predictions. An analytical approach which quantifies the error within the wind speed predictions from the BLS model will be able to determine the value of these improvements and identify future advances that could increase the accuracy of wind speed predictions from future BLS models.

In addition to wind speed predictions, power density predictions from hourly BLS NWP data will be compared to power density predictions achieved using a fixed Weibull shape factor. A fixed shape factor is commonly used for power density predictions when using wind map data [11, 33, 122]. However, the hourly time-series of NWP data allows for the Weibull shape factor to be calculated. These power density predictions, in addition to those gained when scaling BLS NWP data for the diurnal cycle's reversal height were analysed for their accuracy to determine the most suitable approach to power density predictions.

The research presented in this chapter was developed to understand if the accuracy of wind speed and power density predictions from small and medium scale wind turbines in Great Britain can be improved. For such turbines, where project budgets are limited, the ability to accurately estimate the wind resource of a site is key. Through the improvements that are presented in this chapter, it is hoped that future deployment can be supported to achieve the technical potential of small and medium scale wind turbines in Great Britain.

4.1 Methodology

4.1.1 Boundary layer scaling methodology

The boundary layer scaling approach that was utilised in this research is based on a BLS model originally developed by the Met Office [11]. The boundary layer scaling methodology has three scaling steps, as shown in Figure 12;

1. Wind speed from a raw reference wind climatology was scaled to a reference height of 200 m. Scaling to the reference height allowing any frictional effects contained in the raw climatology to be removed.
2. Wind speed at the reference height was scaled to the blending height of each wind direction sector of the fetch. The blending height and effective roughness length were calculated for each of the twelve wind direction sectors of a site.
3. Wind speed at the blending height of each wind direction sector was scaled to the desired hub height of the wind turbine. Based on the individual surface roughness for each site, this scaling accounted for the aerodynamics of the site, such as multiple roughness elements,

which necessitated the introduction of the displacement height in the wind speed calculation. At this final scaling step of the model, the long-term mean hub height wind speed was estimated through a frequency weighting of the hub height wind speeds in each wind direction sector.

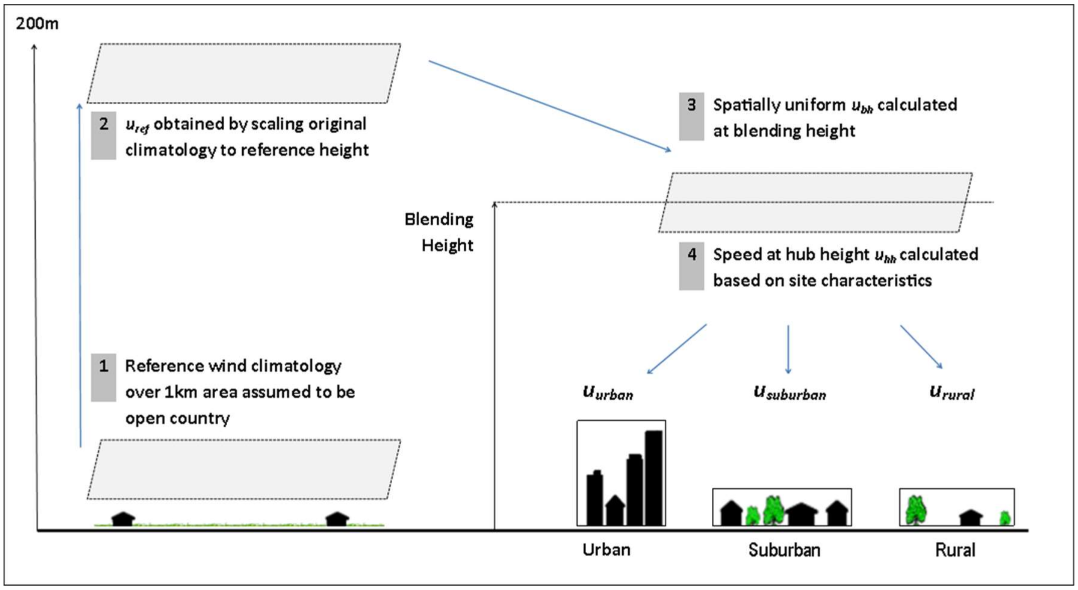

Figure 12 — A graphical representation of the boundary layer scaling technique used in this project. Reproduced from [33]

Wind speed at this reference height, u_{ref}, must be independent of any local or regional roughness effects [33]. Fixed reference heights have been suggested by some authors [11, 33], while a formulation of the reference height, based on internal boundary layer (IBL) height has also been suggested [49]. The reference height has been suggested as the top of the boundary layer. However, this would require a consideration of the Coriolis effect on wind speed, and would depart from similarity theory, upon which the BLS model is based [11]. A suitable reference height for this research was therefore selected as the top of the turbulent surface layer, which was estimated at a height of 200 m here, for a rural to urban transition of roughness patches where the blending height will be at its highest [11].

The reference wind climatology, u_{10}, at a height of 10 m, z_{10}, was scaled to the reference height, z_{ref}, of 200 m using a fixed roughness length, z_{0ref}, of 0.14 m, for all reference wind climatologies used within this work, to calculate wind speed at the reference height, u_{ref} of each site;

$$u_{ref} = u_{10} \frac{\log(z_{ref}/z_{0ref})}{\log(z_{10}/z_{0ref})}$$

Equation 28

From the reference height, the wind speed must be scaled to the blending height. Inclusion of the blending height in the BLS model assumes that the vertical wind profile has completely adjusted to the underlying surface roughness changes. By scaling wind speed to the blending height, a description of how multiple surface roughness changes across the whole fetch influences the wind speed at a site has been included in the BLS model. The wind speed at the blending height, u_{bh}, must therefore be calculated. Wind speed at the reference height was scaled to the blending height, z_{bh}, using the regional displacement height, d_{eff}, and the effective roughness of the upwind fetch, z_{0eff};

$$u_{bh} = u_{ref} \frac{\log((z_{bh} - d_{eff})/z_{0ef}\ )}{\log((z_{ref} - d_{eff})/z_{0eff})}$$

Equation 29

In sites, where the displacement height was not applicable, the regional displacement height was set to zero. It is unlikely that the hub heights of small and medium scale wind turbines will be above the blending height. The wind speed at the blending height must therefore be downscaled to the appropriate hub height. This presents a problem as it is reasonable to assume that the hub height will be within the blending layer of the IBL and the logarithmic vertical profile of wind flow is still adjusting to a new surface roughness in the fetch. It was therefore assumed that for each site, the neutral logarithmic vertical wind profile was in equilibrium with the surface roughness of each specific site. Wind speed at the blending height, u_{bh}, can therefore be scaled to the desired hub height, z_{hh}, using the aerodynamics of each site, the displacement height, d_{site} and surface roughness length of the site, z_{0site}. For sites, where no displacement height was required, such as those with a low spatial distribution of roughness elements, displacement height was set as zero. Wind speed at the hub height, u_{hh}, set at 10 m in this work for validation purposes, was calculated as;

$$u_{hh} = u_{bh} \frac{\log((z_{hh} - d_{site})/z_{0si}\ \ )}{\log((z_{bh} - d_{site})/z_{0sit}\ )}$$

Equation 30

If the desired hub height was below the canopy height, z_{ch}, of the site, the vertical profile of mean wind speed changed from a logarithmic profile to an exponential profile [11]. The wind speed at the hub height below the canopy height was calculated as;

$$u_{hh} = u_{ch}\exp\left(-9.6\lambda_f \frac{(z_{ch} - z_{hh})}{z_{ch}}\right)$$

Equation 31

where, λ_f, is the frontal surface area of an obstacle to wind flow, set as 0.3 in this project to represent high density urban areas [11] and, u_{ch}, is the wind speed at the canopy height. Use of the exponential vertical wind profile was very limited in this project, as it only applies for densely urban areas where the canopy height is likely to be above the hub height at 10 m.

As seen in each of the boundary layer scaling equations, the surface and regional aerodynamics of each site are crucial. As discussed in Chapter 2, the aerodynamics, regional or site specific, originate from the surface roughness value, z_0. The surface roughness values were utilised in the explicit calculations of regional aerodynamics and the approximations of the displacement height. The values of surface roughness were therefore considered thoroughly in this work's BLS model.

4.1.1.1 Surface Roughness and Aerodynamic Parameterisation

In this work, 13 surface roughness classifications were developed for use in the BLS model. Implementation of 13 surface roughness values is, as discussed in Chapter 2, an improvement over previous BLS models. Previous BLS models have only utilised 8 surface roughness classifications [11, 33] which were developed for the original Met Office model [11]. Given the considerable influence of the surface roughness value in the BLS model, use of a greater number of surface roughness classifications is an essential novelty in this work.

Surface roughness, z_0, was parameterised in this work based upon likely obstacles on the surface, the vegetation of the surface and the topology and morphology of the surface. All of these factors were considered when parameterising the appropriate surface roughness values. In order to parameterise the surface roughness for the whole of Great Britain, a land cover map which described the land use across Great Britain was utilised. Using the definitions of land use within the land cover map, it was possible to estimate the features of the surface, such as vegetative land cover or size of buildings or trees. The surface roughness value could then be parameterised for each of the land use categories in the land cover map.

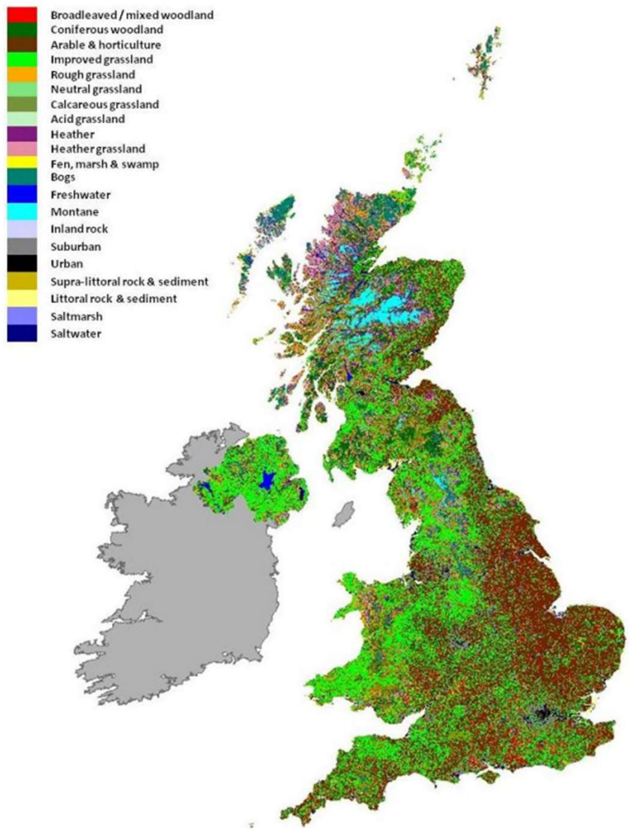

Figure 13 — The 25 m raster Land Cover Map 2007 in the UK. Reproduced from [85]. Note: Northern Ireland was excluded from the research as the Feed-in Tariff is not available in this territory

The Land Cover Map (LCM) 2007 [85] from the Centre for Ecology and Hydrology (CEH), seen in Figure 13, was utilised in this work. LCM 2007 provided land use in 23 separate categories at a 25 m raster across Great Britain [85]. Of the 23 land use categories in the LCM, only 2 categories describe suburban or urban areas. Roughness in suburban and urban areas can differ greatly depending on building density and building heights [82]. Ideally, the LCM would offer much greater detail regarding the differing urban land covers to allow for a detailed parameterisation of surface roughness in these areas. However, this detail was not available in the LCM. As discussed in Chapter 2, a BLS model can be implemented in urban areas through extensive calculations of the aerodynamics of the urban fabric [61, 63]. The breadth of land uses available in more rural regions, which is the focus of this work, was more applicable for small and medium scale wind turbines, where future deployment in the market is considered more likely [104].

An extensive literature review of published surface roughness values was undertaken [11, 81, 84, 143, 144] and the 13 surface roughness classifications were developed during this research. Each classification was developed based upon the land cover described in each category of the LCM and the corresponding surface roughness values in the literature. For each surface roughness classification, multiple surface roughness values were described in the literature, typically from experimental field tests. To select the most appropriate surface roughness value for this work, the majority of the surface roughness classifications were given the mean value of the ranges from the literature. In cases where the mean value was skewed, the most commonly reported value in the literature was utilised.

Each of the 23 land use categories in the LCM were associated with one surface roughness value, as seen in Table 3. Raw LCM data on a 25 m raster was parameterised to a surface roughness value at 25 m and then blended to a 100 m resolution, by averaging of all of the 25 m surface roughness values in the 100 m grid square. This resulted in each hectare or 10,000 m^2 of Great Britain being associated with a surface roughness value. This choice of resolution was dictated by the available computational resources but was a finer resolution of surface roughness than previous studies, which used a 1 km grid square of surface roughness [11, 33]. The finer spatial resolution of surface roughness in this research offered a better characterisation of the frictional effects of the surface. Wind turbines with lower hub heights will capture near-surface winds for energy generation and therefore better characterisation of surface roughness at a finer spatial resolution was designed to improve the accuracy of near-surface wind speed prediction.

Table 3 — The 13 surface roughness classifications and their roughness lengths used for each of the 23 categories in this project

LCM 2007 Category	Surface Roughness Classification	Roughness Length (m)	Reference
Saltwater Freshwater	Water	0.0002	[143]
Supra-littoral Rock	Sand	0.029	[144]
Improved Grassland Calcareous Grassland Neutral Grassland	Grassland	0.04	[84]
Rough Grassland	Rough Grassland	0.05	[84]
Bog Fens, Marsh & Swamps Saltmarsh	Wetland	0.09	[143]
Arable	Arable	0.105	[81]
Heather Grassland Heather	Heather	0.12	[84]
Rock & Sediment Littoral Rock	Coastal & Rock	0.28	[143]
Montane Habitats Inland Rock	Mountains	0.40	[84]
Suburban	Suburban	0.55	[82]
Mixed Woodland	Mixed Woodland	0.76	[11]
Coniferous Woodland	Other Woodland	1.05	[84]
Urban	Urban	1.1	[84]

From the surface roughness values, the displacement height, *d*, was approximated for each grid square of surface roughness. The approximation of displacement height from surface roughness values, z_0, is based on the empirical relationship between canopy height, z_{ch}, and displacement height, *d*, suggested by Garratt [145] and discussed in Grimmond and Oke [82], with respect to morphometric data from 7 different cities;

$$z_{ch} = 10z_0 \ ; \ d = \frac{2}{3}z_{ch}$$

$$\therefore d = \frac{20}{3}z_0$$

Equation 32

Approximation of displacement height was implemented since calculation of displacement height requires the frontal and plan area of all frictional elements in the domain [33, 146]. As discussed earlier in the section, such data for the whole of Great Britain was unavailable, necessitating the use of approximations in this research. In rural areas, the density of roughness elements is such that the displacement height will be effectively zero. The displacement height approximation was therefore only implemented for the final five surface roughness classifications of Table 3. However, the impact of using an approximation of displacement height is likely to be greater in suburban areas, where the influence of height variability in surface roughness elements has been shown to exhibit a larger influence on surface drag [80].

While surface roughness values parameterise the frictional effects of the surface, the roughness values were also utilised in the calculation of the regional aerodynamics, the blending height and effective roughness length of the fetch.

4.1.1.2 Blending Height and Effective Roughness of Fetch

Formation of an internal boundary layer (IBL) as wind flow passes over different patches of roughness necessitates the need to calculate the blending height in the BLS model. At this height, the differing frictional effects of each surface roughness patch are homogenised. Previous studies have utilised a fixed blending height in a BLS model [11, 33]. With the introduction of a finer surface roughness parametrisation in this research, a greater variability of surface roughness is likely to be observed. Greater variability of surface roughness cause more IBLs to form and therefore a fixed blending height is considered insufficient for this work's BLS model.

Blending height was calculated by tracking the growth of the IBLs as the wind flows over differing roughness patches in the fetch. The influence of each change in roughness patch on the depth of each IBL must be captured in the blending height calculation.

To track the growth of the IBLs in the fetch, the fluctuations in wind velocity, u', due to changes in surface roughness were captured. The change in wind velocity due to roughness changes across the whole fetch, $du'(z_{0,t})$, were identified by examining the influence of a single patch of roughness, $z_{0,i}$, on velocity fluctuations, in the context of all the fluctuations due to roughness in the preceding fetch, $z_{0,t}$;

$$du'(z_{0,t}) = \left(u'(z_{0,i} + z_{0,t}) - u'(z_{0,i})\right)^2$$

Equation 33

The variability in wind flow velocity due to roughness changes in the fetch was parameterised into a single variability scale, L_p for each wind direction in the fetch. The maximum likely velocity change, du'_{max}, and mean likely velocity change, $\overline{du'(z_{0,t})}$, in the fetch represent the velocity fluctuations which result in the highest and mean height of the IBLs in the fetch. These characteristic velocity fluctuations in the fetch were integrated over the characteristic length scale of the fetch, L_d, to calculate the variability scale, L_p;

$$L_p = \int_0^{L_d} \left[1 - \frac{\overline{du'(z_{0,t})}}{du'_{max}}\right] dz_{0,t}$$

Equation 34

In this work, the characteristic length scale, L_d, was set at 2,828 m. This distance equates to the length of central path in each wind direction sector and was calculated from the size of the upwind fetch of 2 km in either direction.

The blending height, z_{bh}, of each wind direction sector was solved iteratively, using the variability scale, L_p;

$$\left(\frac{z_{bh}}{1.7\kappa L_p + Z_{bh}}\right)^2 = \sum_{i=1}^{N} \left(\frac{f_i}{(\ln \frac{z_{bh}}{z_{0,i}})^2}\right)$$

Equation 35

where, $z_{0,i}$, was each individual roughness patch and, f_i, was its fraction of surface coverage in the fetch across all patches in the fetch, N. Effective roughness is the spatially averaged roughness of the surface of the fetch of the wind direction sector. Effective roughness across the fetch varies with height as the frictional effect of the surface diminishes with height. Using a blending method, the effective roughness, z_{0eff}, was calculated as a function of the blending height, z_{bh}, in each wind direction sector;

$$\left(\frac{(Z_{bh} - d_{eff})}{z_{0eff}}\right)^{-2} = \sum f_i \left(\frac{(Z_{bh} - d_i)}{z_{0,i}}\right)^{-2}$$

Equation 36

using each patch of roughness length, $z_{0,i}$, and displacement height of the patch, d_i. Regional displacement height of the wind direction sector, d_{eff}¸ and displacement height, d_i, of each roughness patch were approximated from the surface roughness value of each patch, using the approximation described in Section 4.1.1.1. Initially, d_{eff}, was approximated from the highest roughness length in each wind direction sector before an approximation from effective roughness was possible.

Regional aerodynamics were included in the BLS model to account for the effect of surface roughness in the upwind fetch of the site. To ensure that sufficient upwind variability was captured, the size of the fetch must be appropriately defined. A previous study has examined the sensitivity of fetch size on wind speed prediction accuracy from a BLS model [33]. The study found that an upwind fetch of 2 km offered the lowest error in wind speed [33]. It is noted however, that the surface roughness was spatially coarser and the number of wind direction sectors was lower in this previous study [33] than in this work. With a coarser surface roughness and lower number of wind direction sectors, it would be expected that a larger fetch may be required to capture sufficient variability at the surface. Selection of a 2 km upwind fetch is therefore considered to be sufficient in this work's BLS model.

A 2 km upwind fetch resulted in a 4 km by 4 km fetch surrounding each site. This 16 km^2 grid square around a site was then split into 12 wind direction sectors of 30° each. Use of 12 wind direction sectors is a novelty for this work's BLS model, as previous BLS models have used only 4 wind direction sectors of 90° [33] or 8 wind direction sectors of 45° [49]. To capture the variability of the surface roughness in each wind direction sector, the surface roughness of each fetch was collected. Use of surface roughness values at 0.01 km^2 resulted in each wind direction sector containing around 130 different patches of surface roughness. To calculate the regional aerodynamics of a site with sufficient accuracy but in a timely manner, all of these 130 different patches could not be included. Use of a central path through each wind direction sector was therefore implemented. Selection of the longest route from the edge of the fetch to the site being assessed allowed sufficient surface roughness variability to be captured for the regional aerodynamics calculation. Use of the central path concept did exclude roughness patches in the fetch which could influence the calculation of the regional aerodynamics. However, the influence of regional aerodynamics have been shown to be the least sensitive in a BLS model [147]. A sensitivity analysis conducted during the development of the model showed that the difference between the mean absolute error of wind speed predictions using either the central path or all roughness patches in a wind direction to calculate regional aerodynamics was less than 0.004 ms^{-1}. Use of the central path was therefore considered suitable for this research.

Figure 14 presents a diagrammatic representation of the central path through the three wind direction sectors of the site. The central path is highlighted in red indicating the patches of surface roughness which are included in the regional aerodynamic calculations.

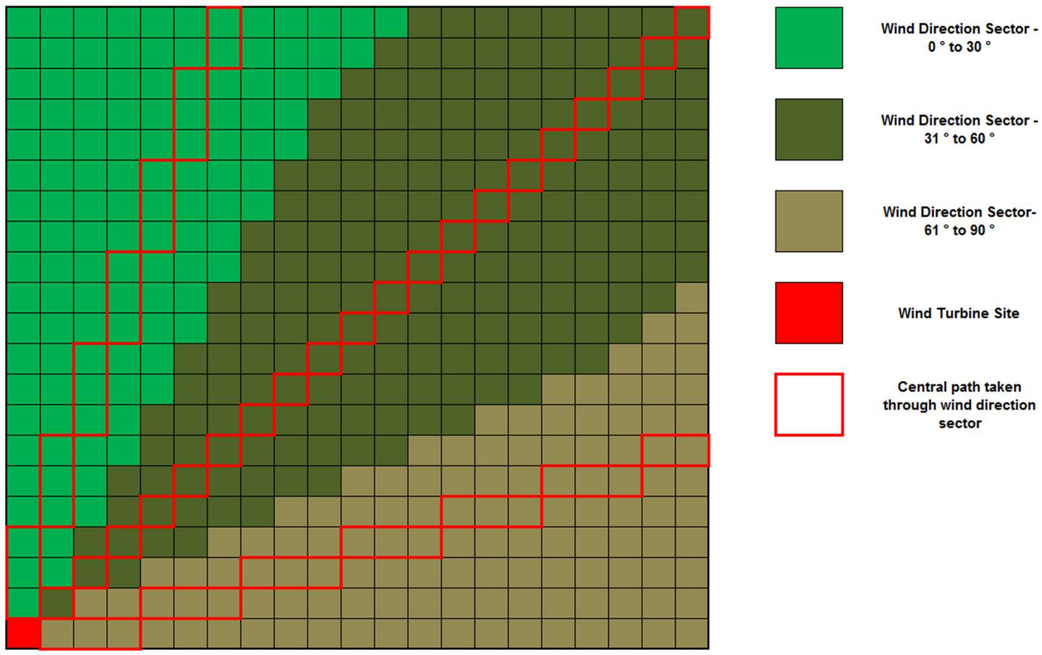

Figure 14 — Diagrammatic representation of central path of surface roughness taken from three wind direction sectors of the between 0° and 90° for regional aerodynamic calculations

The regional aerodynamics of each of the 12 wind directions were calculated and utilised in the BLS equations described in Section 4.1.1. For each site, the wind speed at the hub height was calculated in each wind direction sector. Using observational wind direction data from a nearby monitoring site, the relative frequency of each wind direction sector at the wind turbine site was estimated. The hub height wind speed in each wind direction sector was then weighted by the relative frequency of the wind direction sector. The mean wind speed at the desired hub height of a site was then calculated as a summation of the weighted wind speeds from each of the twelve wind direction sectors.

The BLS method described here allowed for the mean wind speed of a prospective wind turbine site to be calculated. As discussed in the initial stages of this chapter, the BLS model was developed in this work to compare the accuracy of wind speed predictions available, with those from the MCS methodology.

4.1.2 Microgeneration Certification Scheme model

The Microgeneration Certification Scheme (MCS) method is included as part of the wind turbine installer standards of the MCS accreditation process [27].

For a wind turbine to gain the accreditation required to receive Feed-in Tariff (FIT) payments, the MCS methodology must be conducted.

The mean wind speed is determined in the MCS methodology by scaling raw Numerical Objective Analysis of Boundary Layer (NOABL) wind speed data [27]. Mean wind speeds from the MCS, $\bar{u}_{MCS}$, are calculated by correcting raw NOABL data at 10 m, $\bar{u}_{NOABL}$, using a scaling factor, C_f,

$$\bar{u}_{MCS} = C_f \bar{u}_{NOABL}$$

Equation 37

The scaling factor, C_f, is a function of the ratio between the hub height of the turbine, z_{hh}, and the height of the highest local obstacle, z_{lo}, and the terrain classification of a site, T_c. A local obstacle is defined as any solid item, such as a wall, or semi-permeable item, such as a tree, which is wider than 0.5 m, with a height greater than a quarter of the hub height of the proposed turbine [27]. A representation of the area surrounding a turbine considered when assessing the height of local obstacles is given in Figure 15.

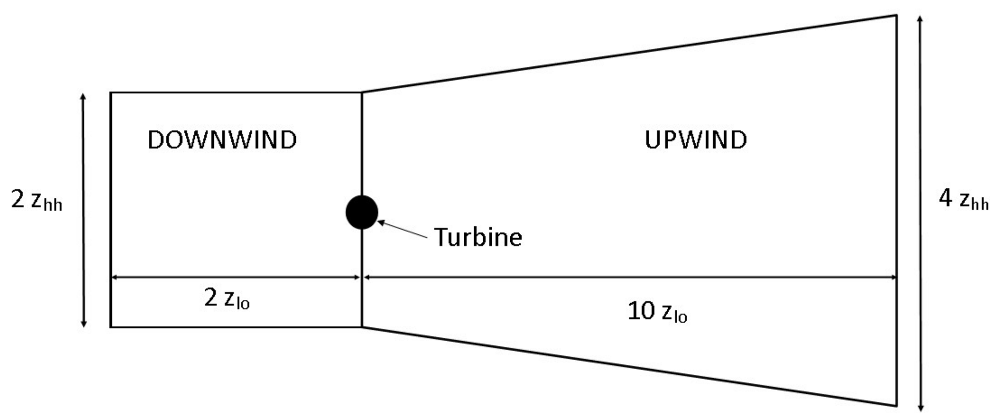

Figure 15 — Representation of the area surrounding a turbine site when considering the size of local obstacles in the MCS methodology. Modified from [27]

To conduct the MCS methodology, a site survey to identify the characteristics of the site and the surrounding area is required. In this work, site surveying was not possible due to the large domain covered in the mapping approach and therefore assumptions had to be made regarding the local obstacle height and the terrain classification of a site.

In lieu of observational data regarding local obstacle heights at each site, an approximation was developed in this work to estimate the height of the local obstacles from surface roughness values. Following the approach of Grimmond and Oke, the height of the highest local obstacle was approximated as $10z_0$, equivalent to the canopy height of a site [82].

The terrain of a site is classified in the MCS methodology into one of five categories which covers different terrain types from flat grassland up to dense urban areas. The classes are structured so that the higher the classification, the rougher the surface is liable to be. When considering 1 km upwind and 500 m downwind of a turbine, the terrain is classified as the highest terrain classification identified within this monitoring zone [27].

Terrain classification of each site was estimated in this work from the surface roughness values of the BLS model. The surface roughness values were banded into five categories corresponding to the terrain classes presented in the MCS method [27], as seen in Table 4.

Table 4 — Surface roughness value ranges used to determine the MCS terrain classification

Range of surface roughness values, z_0, (m)	**MCS terrain classification and description [27]**
< 0.041.	Category 1 – Flat grassland, parkland or bare soil without hedges and only a few isolated obstructions.
>= 0.041 and < 0.104.	Category 2 – Gently undulating countryside, fields with crops, fences or low boundary hedges and few trees.
>= 0.104 and < 0.54.	Category 3 – Farmland with boundary hedges, occasional small farm structures, houses and trees etc.
>= 0.54 and < 1.1.	Category 4 – Woodland or low rise urban/suburban areas (e.g. domestic housing) with a plan area density of up to about 20 %.
> 1.1.	Category 5 – Dense urban areas and city centres (e.g. buildings of four-stories or higher) with a plan area density greater than about 20 %.

Once the terrain classification and local obstacle height of each site was determined, the correct scaling factor could be identified. These scaling factors ranged from 0.05 for a wind turbine in densely urban areas with a local obstacle at a similar height as the hub height, to 1.32 for a wind turbine with a hub height of 100 m in flat grassland with no local obstacles [27].

The value of the scaling factors highlight that at most sites, the MCS methodology reduces the wind speed of the raw NOABL. Around 66 % of the scaling factors apply a reduction to the raw NOABL data. Given that raw NOABL has been shown to over predict [31, 32], this skew in the scaling factors of the MCS is unsurprising. This approach taken in the MCS appears to be designed to correct inaccurate NOABL data rather than offering a full consideration of the aerodynamics of the site and their influence of wind speed.

In comparison, the BLS model analysed fetch conditions over a greater distance and applied multiple corrections to produce a mean wind speed prediction. While simplicity is preferred when presenting a standardised correction methodology as it must be quick and easy to conduct, the complexity of a site's wind conditions is neglected through use of a single correction factor in the MCS methodology.

While caveats are given in the installer standards regarding the degree of uncertainty in the MCS methodology, it is also noted that presentation of any alternative wind resource assessment methodology must not be given greater significance than the results of the MCS methodology [27]. Additionally, installers are instructed to offer a warning if the alternative methodology predicts a mean wind speed greater than the MCS methodology [27]. It is foreseeable that the MCS methodology could be treated by installers and prospective consumers as an accurate representation of a site's mean wind speed. This could lead to a site's viability being incorrectly estimated and lead to wind turbines either not being installed on viable sites or installed on unviable sites. The estimated MCS wind speed could also be viewed by potential adopters as the upper estimate of long-term mean wind speed of a site and if the MCS methodology under-predicts the wind speed, a potential adopter could possibly be dissuaded from installing a wind turbine in a location with sufficient wind resource. The suitability of the MCS methodology to support future deployment of wind turbines in Great Britain is therefore questioned in this research. To determine the suitability of the MCS, the accuracy of its wind speed predictions across a sample of sites in Great Britain is presented in Section 4.2.

4.1.3 Reference wind climatology

To predict mean hub height wind speed from either the MCS or BLS model, a reference wind climatology was required. A reference wind climatology provides a raw wind speed, which can be scaled with either methodology. In total, four reference wind climatologies were utilised in this work; two wind map climatologies and two Numerical Weather Prediction (NWP) climatologies.

The wind maps of the Numerical Objective Analysis of Boundary Layer (NOABL) and National Climatic Information Centre (NCIC) were utilised in this work. In addition to these observational based wind speed databases, Numerical Weather Prediction (NWP) wind speed data from the UK Met Office's UK4 and UKV models have been utilised as reference wind climatologies. NOABL data was used in the BLS and MCS models, while NCIC data was only used in the BLS model. Only the NOABL wind speed data was utilised in the MCS methodology as this is specified in the FIT installer standards and the MCS methodology was designed to correct only NOABL data [27].

4.1.3.1 NOABL wind resource map

The Numerical Objective Analysis of Boundary Layer (NOABL) wind speed map provided a decadal mean estimation of wind speed for each 1 km grid square of the UK. NOABL was created using a wind flow model [98] with initialisation data taken from between 1975 and 1984 at 56 observational sites across the UK [98]. The NOABL wind flow model interpolated the observed wind field in three dimensions on a finite difference grid [98]. The wind field was then adjusted to account for the effects of terrain and corrected using surface roughness values at each grid point [98].

Using local surface roughness values derived from the topology within 5 km of each site, the observed wind speed from each station was scaled using a power log law, from 10 m to the top of the boundary layer, set at 60 m [98]. The meso-scale wind speed at the top of the boundary layer was scaled down using the fixed power log law exponent of 0.14 [98]. The power log law exponent was considered “most appropriate for smooth level terrain such as flat grassland” [98]. The use of fixed power law exponents within NOABL was designed to “obtain wind speeds appropriate to a terrain with uniform surface roughness” [98].

For areas where the use of the power log law was insufficient to predict the wind speed accurately, a correction for orography was applied to the estimated wind speed [28]. A Laplacian transformation of topological data indicated the areas where the topology varied greatly and therefore the scaled wind speed required an orography correction [28].

Validation of the NOABL wind speed data found that there was a mean difference of 0.1 ms^{-1} between the measured and predicted wind speeds [98]. However, this was performed at only two sites [98] and other studies have shown that the wind speeds in NOABL have a greater degree of inaccuracy, particularly in urban areas, where over prediction could be as high as 40 % [30, 101]. The use of a single exponent value for vertical interpolation that represents flat grassland [98] also raises questions about the accuracy of the predicted NOABL wind speeds. Wind speeds would be expected to be much higher in areas of flat grassland, and this could be the underlying reason for the inaccuracy in areas with higher surface roughness [30, 101]. Additionally, the surface roughness of Great Britain is not uniform and therefore the use of a single exponent value is inappropriate. NOABL has been utilised for previous boundary layer scaling studies [11, 33, 49, 101] and it is therefore suitable as a reference wind climatology in this work. However, the deficiencies in the raw NOABL data must be considered when scaling for wind speed predictions.

4.1.3.2 NCIC Wind Resource Map

The NCIC wind resource map provided a long-term mean wind speed for each 1 km grid square of the UK. NCIC was created by the Met Office [99] using observational data from 220 meteorological stations between 1971 to 2000 to create a gridded dataset of climatic parameters, including wind speed [99]. To create the wind map, a regression analysis and an inverse distance weighting interpolation of observational data was implemented [99].

The regression analysis variables utilised for the wind speed observations were: easting and northings to capture spatial variation; elevation to capture altitude effects; mean altitude within a 5 km radius of an observational station to capture the effects of terrain shape and; the percentage of open water within a 5 km radius of a grid point [99]. Following the regression analysis, the observational wind speed data was either normalised to make them dimensionless or converted to regression residuals prior to interpolation [99]. These techniques are implemented to remove any geographic effects, such as topological influences in the observational wind speed data [99].

An inverse distance weighting method was applied to the regression residuals to create a gridded set of wind speeds [99]. Interpolation was undertaken on station data within a given radius from the interpolation point. The selected observational data was weighted based upon distance from the interpolation point [99]. The interpolated values were added to the regression residuals or normalised observational data to estimate the mean wind speed in each grid square [99].

The NCIC has significant advantages over the NOABL data, namely the use of a greater number of meteorological stations and a longer span of observational data. Both NOABL and NCIC offer long-term mean wind speed estimates at heights of 10 m, 25 m or 45 m [99]. These heights are considered typical turbine hub heights, however, installers require the ability to estimate long-term mean wind speed at the specific hub height of the wind turbine. This is why the BLS model has, in part, been included to offer this functionality to potential adopters.

To utilise the wind map data as a reference wind climatology in the BLS model, wind speed at the reference height was required. As discussed, wind speed at the reference height must be independent of local or regional effects [33]. To utilise wind map data from any height as a reference wind climatology, it was scaled to the reference height. Using a reference roughness length, z_{0ref}, of 0.14 m for both the NOABL and NCIC data [11], the wind map data was scaled to the reference height in the BLS model.

The reference of roughness length of 0.14 m was suggested in the original Met Office report for ‘open countryside’, which was taken the Met Office’s Unified Model [11]. This reference roughness was also used within the creation of the NOABL data to represent flat grassland [98]. Use of this assumed reference roughness length was to remove any frictional effects within the reference wind climatology. Therefore, use with the NOABL data was more appropriate as this roughness length was applied across the modelling domain [98]. However, the roughness length within the NCIC data was less clear, as these wind speeds were estimated using a statistical approach [99]. Selection of the reference roughness length must be guided by the roughness lengths utilised during data creation, and for the NCIC data the exact values of these were undetermined. Use of a variable reference roughness length derived from the land cover map was considered. However, without the ability to determine the appropriateness of these values, it could introduce additional frictional effects to the climatology data rather than remove them. The reference roughness length of 0.14 m was therefore utilised for the NCIC data in this work, following communication with the Met Office.

To determine power density, when utilising wind map data, required the use of a fixed shape factor. These wind maps only provide a single mean wind speed, to which a Weibull distribution cannot be fitted. A fixed Weibull shape factor of 1.8 [11] has previously been suggested when estimating power density with wind map data. This fixed shape factor was suggested by the Met Office [11] and derived from the observed shape factors of wind speed distributions from a number of sites across Europe [106]. Use of the fixed shape factor for power density prediction has been shown to have significant errors [33]. However, use of the fixed shape factor is the only suitable method for power density predictions with long-term mean wind map data.

To estimate power density accurately requires an hourly time-series of wind speed data to which a Weibull distribution can be fitted.

4.1.3.3 Numerical Weather Prediction data

Numerical Weather Prediction (NWP) data was available from two of the Met Office's operational forecast models, the UK4 and UKV models [100] as a reference wind climatology. Operational forecast models are part of the Met Office Unified Model (UM) which produces both global and limited area NWP data [100] by unifying forecasting and climate models [148]. Limited area operational NWP models simulate large-scale atmospheric processes and sub-grid scale processes including convection, radiation and cloud microphysics [149, 150]. Within the UKV model, there is no convection parameterisation as the grid length is considered small enough to capture the effects [150], while the UK4 model operated with a mass flux based convection scheme [149, 150]. NWP models assimilate high-resolution data from radars or satellite [150] every 3 hours [149] to initialise their model runs.

UK4 and UKV are meso-scale operational models that cover the UK, with a horizontal resolution of 4.4 km and 1.5 km respectively [100]. UK4 and UKV models are run at 6 hour intervals daily to produce an hourly forecast spanning 48 hours from each run [100]. Each model has 70 vertical levels, with a finer vertical resolution in the boundary layer, providing 7 heights below 200 m [100]. Both NWP datasets were available for this research at the 8 lowest heights of the models; 10 m, 20 m, 35 m, 50 m, 100 m, 150 m, 200 m and 500 m. NWP data at 500 m has not been included as the reference height of the BLS model was set at 200 m.

Hourly time-series of wind speeds from the NWP models were available for this research. UK4 data was available from 2002 to 2012 while the UKV data was only available from 2010 to 2014, as the UKV model only became fully operational in 2011 [100]. NWP data was only utilised in the BLS model as a reference wind climatology. At each site assessed, each hourly wind speed of raw NWP was scaled to the hub height using the BLS approach, described in Section 4.1.1, to create a BLS NWP time-series. It was from these scaled time-series that a long-term mean wind speed of the site was calculated. To allow for a consistent comparison with the scaled wind map data, only a long-term mean wind speed was estimated from the BLS NWP data.

Unlike the BLS wind map data, a Weibull distribution could be fitted to the hourly time-series of BLS NWP data. Using the maximum likelihood method

[67], the Weibull distribution was fitted to each time-series of BLS NWP at the selected hub height and the Weibull parameters of shape, *k*, and scale, *c*, were estimated. Using the Weibull shape factor, the power density in the wind flow of each site could be estimated.

4.1.4 Scaling of Weibull shape factor for power density prediction

Power density in the wind flow is a function of the variability in the wind speed [70]. Power density of the wind flow, P_d, can be estimated using a gamma function, *Γ,* transformation of the shape factor, *k,* and the mean wind speed, $\bar{u}_z$, of the site [33, 105];

$$P_d = \frac{1}{2}\left(\frac{16}{27}\right)\rho\left(\frac{\bar{u}_Z}{\Gamma(1+1/k)}\right)^3 \Gamma(1+3/k)$$

Equation 38

The Weibull shape factor describes the long-term variability in the wind speed at a site [70]. The long-term variability in wind speed is composed of the synoptic and diurnal variability of the wind speed [70]. The diurnal variability of wind speed has been shown to be the dominant factor that influences near-surface power density and must be characterised when estimating power density available to small and medium scale wind turbines [70].

Diurnal variability in wind speed has been shown to be height-dependent, with the variability reaching a minimum at the mean reversal height of the diurnal cycle [70]. The relationship between diurnal variability and Weibull shape factor has been shown to be inverse [70] and therefore the value of the shape factor is considered height dependent [70]. The shape factor reaches a maximum over land at the reversal height of the diurnal cycle, where diurnal variability is at a minimum [70].

This reversal height over land is estimated in literature to be at an mean height of 80 m [70]. Without experimental field data available in this research, it was not possible to calculate the reversal height of each site. Literature identified the reversal height to range between 60 m and 80 m for onshore sites [70]. In this work, the reversal heights of 60 m, 70 m and 80 m were tested at each site.

The height dependence of the shape factor must be accounted for in the estimation of power density from BLS NWP data. Shape factor, k_s, at the surface, z_s, was scaled vertically to account for the reversal height, z_r, of the diurnal cycle of a site to estimate shape factor, k, at a selected hub height, z [70];

$$k = k_s + c_k(z - z_s)e^{\left(-\frac{z-z_s}{z_r-z_s}\right)}$$

Equation 39

where, c_k, is an empirical coefficient, estimated as the gradient of a linear regression fit of observed vertical shape factors of sites on a log scale against height [70]. In this work, the value of c_k, was estimated to be 0.022, based upon the values described in the literature [70].

BLS NWP data from all original forecasting heights available has been scaled around the reversal height to understand if the accuracy of the power density predictions could be improved with this technique.

4.1.5 Validation data

To determine the accuracy of wind speed and power density predictions, validation using observational data was required. The Met Office's Integrated Data Archive System (MIDAS) Land and Marine Surface Stations is a network of weather monitoring stations across the UK which collect multiple weather variables [73]. Of the weather variables collected, wind speed in knots and wind direction in degrees at 10 m above the ground was collected [73]. As the observational validation data was available at 10 m, this dictated the choice of 10 m as the hub height for each of the scaling methodologies examined in this research. The observational wind speed measurements are either hourly wind speeds, or 10-minute mean wind speeds, which are sampled every hour to represent hourly wind speeds [73]. The hourly wind speed observations from each MIDAS site were utilised to calculate a long-term mean wind speed for each site from which the wind speed predictions from either the MCS or BLS model were validated. A Weibull distribution was also fitted to the hourly wind speed observations to derive the shape factor, which was then used to validate the power density predictions.

From a larger sample of stations across Great Britain, 124 sites were selected to provide validation data for this research, seen in Figure 16. The 124 sites were selected using two criteria: sites that were operational between 2002 and 2012; and sites that achieved an hourly data coverage of 90 % or above during this decade.

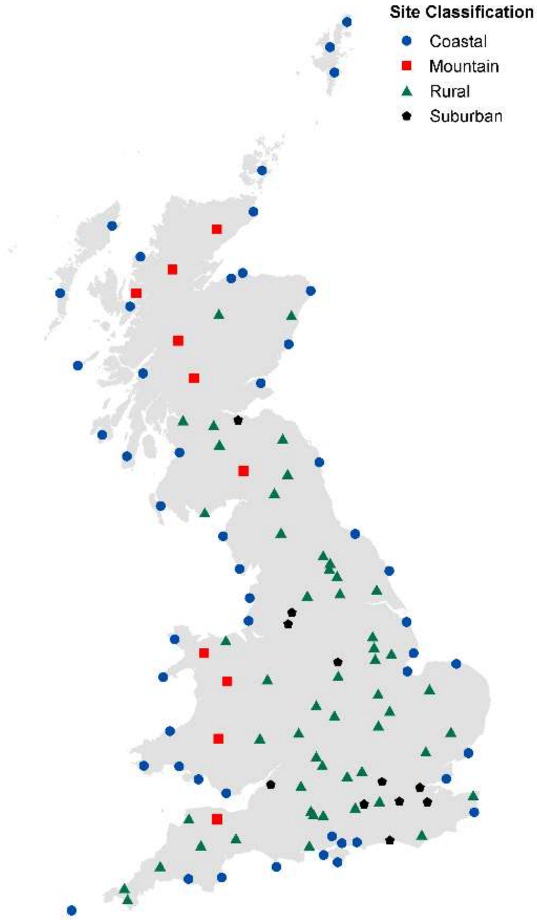

Figure 16 — Location of the 124 MIDAS sites used for validation in this work. The site classification of each MIDAS site is also detailed

A decadal mean wind speed at each observation site was required as the NOABL provided only a decadal mean wind speed, the shortest time period of observational data used in either wind map. The data coverage requirement of above 90 % hourly coverage during this decade was to ensure that sufficient variability of the wind speed at each site was captured. Such high levels of hourly data coverage allowed the capture of synoptic and diurnal variability in the observational wind speed.

Each of the 124 sites were classified visually from Ordnance Survey maps to determine their surrounding terrain and likely roughness elements [33]. This visual classification accounted for the presence of coastlines in the vicinity of the site, the likely types of buildings and vegetative land cover surrounding the site and the presence of any topological features, which could influence wind speed. This process allowed classification of the sites into one of four categories; coastal; mountain; rural and suburban, as indicated in Table 5 and seen in Figure 16.

Table 5 — Number of sites in each site classification sample

Site classification	Number of sites in sample
Coastal	50
Mountain	10
Rural	53
Suburban	11

Site classifications allowed the effects of the physical characteristics of the different terrain on the accuracy of wind speed predictions to be investigated [33]. Analysis in these differing terrains allowed any deficiencies in each methodology to be identified.

To determine the accuracy of wind speed predictions, error metrics that allowed for a consistent comparison of the errors in each wind speed prediction were required. Two metrics; mean absolute error (*MAE*) and mean percentage error (*MPE*) were selected to assess the accuracy of the wind speed predictions produced during this research [33].

Mean absolute error is defined as;

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|\bar{u}_{obs,i} - \bar{u}_{pred,i}\right|$$

Equation 40

where, $\bar{u}_{pred,i}$, is the predicted long-term mean wind speed at site, *i*, and, $\bar{u}_{obs,i}$, is the observed long-term mean wind speed at site, *i,* and, *N*, is the sample size.

Mean percentage error is defined as;

$$MPE = \frac{100\ \%}{N}\sum_{i=1}^{N}\frac{\left(\bar{u}_{obs,i} - \bar{u}_{pred,i}\right)}{\bar{u}_{obs,i}}$$

Equation 41

The mean absolute error and mean percentage error validation metrics were selected to offer a different assessment of the error within a wind speed prediction. Through examination of the absolute error in a wind speed prediction, the mean abolute error metric offered a comparison of the relative intrinsic error of each methodology. Mean percentage error, however, was able to indicate whether a methodology over or under predicted the wind speed. The metric was in a form that ensured when the prediction of wind speed was below the observed value, the resulting mean percentage error was negative.

By selecting validation sites with a high degree of hourly data coverage, the hourly observation data of each site could be fitted with a Weibull distribution to understand the distribution of wind speeds at the site. The observed Weibull distribution parameters from each site were used to validate power density predictions, calculated from the Weibull shape factor of a distribution fitted to the BLS NWP data. To assess the accuracy of power density predictions, a further metric for validation was required.

Predicted power densities at a site were validated by the observed power density of the site [33], using a dimensionless power density metric, $P_{d,norm}$;

$$P_{d,norm} = \left[\frac{\Gamma(1 + 1/k_{pred})}{\Gamma(1 + 1/k_{obs})}\right]^3 \frac{\Gamma(1 + 3/k_{obs})}{\Gamma(1 + 3/k_{pred})}$$

Equation 42

where, k_{pred}, is the predicted shape factor, k_{obs}, is the observed shape factor and Γ is the gamma function.

The size of the validation sample used for each reference climatology varied due to changes in modelling approaches of the reference climatologies. All of the 124 validation sites were available for the NOABL and UK4 data. 123 validation sites were available for the NCIC data, with one of the sites in the Shetland Islands unavailable. 121 validation sites were available for UKV validation with all of the sites in the Shetland Islands outside the modelling domain of UKV model. While the sample size differed slightly between the reference wind climatologies, the use of mean error metrics across each sample allowed for a consistent comparison between the different wind speed predictions from each reference wind climatology.

4.1.6 Comparison with past work

The introduction of an analytical approach to regional aerodynamics calculations, over a greater number of wind direction sectors using an increased breadth and spatial resolution of the surface roughness values, were proposed as improvements to the BLS approach. Details of the improvements in these areas were discussed in greater detail in Sections 4.1.1.1 and 4.1.1.2.

To understand if these improvements improved the accuracy of either the wind speed or power density predictions, the results of this work were compared with the results of a previous BLS model [33]. In the previous study by Weekes, the validation sample was only 38 sites across Great Britain. While this validation sample is smaller than the sample selected for this research, the study utilised the same validation metrics [33] which allowed for a comparison between the results of the studies.

The inclusion of these novel approaches was designed to advance the capability of the BLS model to provide more accurate wind speed predictions than previously possible. The differences between this work's and the previous study's BLS model are summarised in Table 6. The value of these improvements to the BLS will be assessed in Section 4.2.5.

Table 6 — Summary of improvements to the BLS model suggest in this work

Model facet	Weekes approach [33]	This work's approach
Spatial resolution of surface roughness	1 km^2	0.01 km^2
Breadth of surface roughness classifications	8 roughness classifications	13 roughness classifications
Number of wind direction sector	4 sectors of 90°	12 sectors of 30°
Regional aerodynamic estimation	Either fixed or estimated from canopy height of each wind direction sector	Analytical solution applied across the whole fetch for each of the twelve wind direction sectors

4.1.7 Sufficient accuracy

To determine the suitability of each approach to wind speed prediction described in this chapter, a definition of sufficient accuracy in wind speed predictions was required. Predictions of wind speed are liable to contain a degree of error, due to the assumptions implemented during the prediction process. While these assumptions may lead to error, they are a vital part of the prediction process to ensure expedient wind speed predictions are produced. The magnitude of the intrinsic error in a wind speed prediction which is considered acceptable, and will not detrimentally impact the wind resource estimation to a prospective consumer, must therefore be determined. In this work, validation of the wind speed predictions against the observed wind speed can identify the relative error in each prediction. These errors were then translated into estimated annual energy production, annual payments under the FIT and payback periods to understand how each of these estimations differed as the relative error in the wind speed prediction altered. These financial metrics were compared against the financial metrics calculated using the wind speed predictions with zero error. Analysis of the differences between these metrics allowed a judgement on the definition of sufficient accuracy in a wind speed prediction to be offered.

To estimate sufficient accuracy in wind speed predictions, the wind speed predictions must be converted to the estimated energy and power outputs of a wind turbine. As discussed in Chapter 2, the energy and power output of a wind turbine is dependent on the specifics of each wind turbine. To define sufficient accuracy in the wind speed predictions, the power curve of a specific wind turbine must be selected. The most common capacity of a wind turbine installed under the FIT is a 5 kW wind turbine, with 20 % of all turbines installed by December 2016 having a capacity of 5 kW [12]. The power curve of a 5 kW wind turbine was therefore selected. A smaller capacity turbine will produce less power than a larger capacity turbine at the same hub height wind speed. Therefore, meeting the financial viability thresholds will be more difficult for a smaller wind turbine, due to this lower power output. The financial metrics produced using a 5 kW wind turbine were therefore considered as a worst case scenario and would require the highest wind speed possible to ensure financial viability. This fact, coupled with the high levels of 5 kW wind turbine installations, motivated the selection of a comparatively low capacity wind turbine.

All wind turbines with an installed capacity of 50 kW or less wishing to receive the FIT payments must be an MCS accredited wind turbine [26]. Each MCS accredited wind turbine must be field tested by an independent assessor to determine its power curve and reference annual energy production. The turbine selected for this work was the Evance R9000 5 kW wind turbine [151]. The wind turbine was accredited by the Building Research Establishment, following field tests from November 2009 to June 2010 at two sites in Hoswick, Shetland and Pendeen, Cornwall [151]. The calculated power curve of the Evance R9000 is shown in Figure 17.

Using the wind turbine's power curve, the annual energy production of the turbine was calculated and from this, the annual FIT payments and likely payback periods were estimated. However, as also discussed previously, the variability of site's wind speed expressed as the Weibull parameters was also required. While the scale factor can be obtained from the mean wind speed [11], the shape factor must be estimated. A shape factor of 1.8 has previously been suggested for predicting power density using wind map data [11] and this shape factor was utilised in this work.

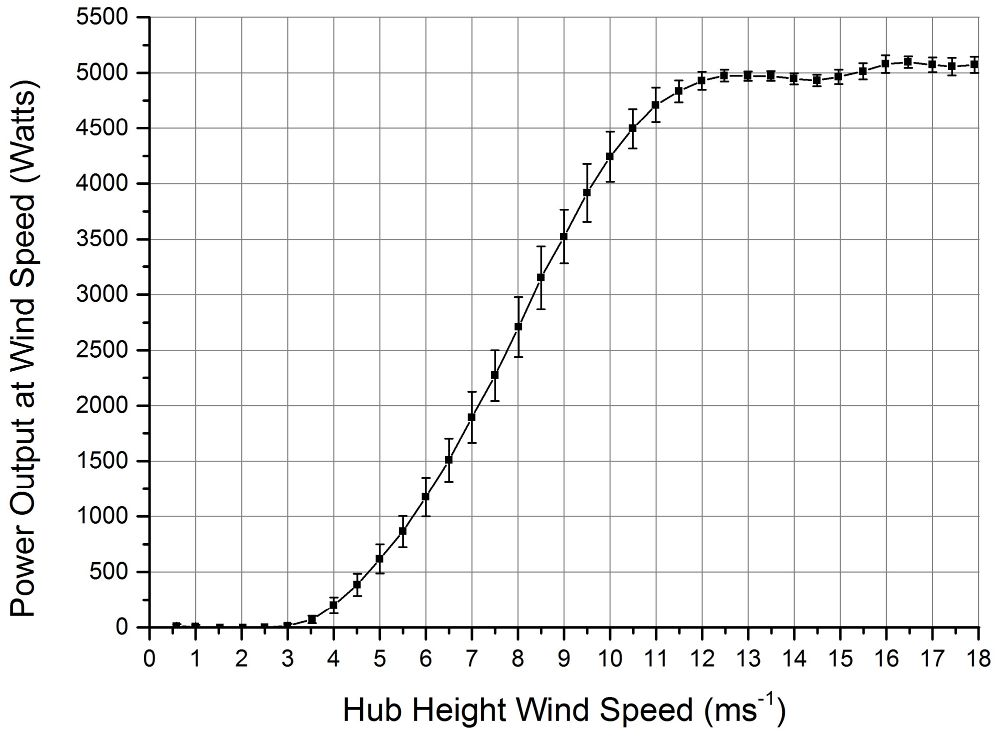

Figure 17 — Calculated power curve of Evance R9000 5 kW wind turbine. Errors bars represent standard uncertainty in power output measurements from manufacturers data [151]

Of the three metrics for defining sufficient accuracy, the calculation of annual energy production was considered the most important. The other two metrics are derived directly from the annual energy production estimate but use a more comprehendible quantification of the implications of wind speed error, hence their inclusion in this research. The annual energy production of a wind turbine in kWh, E_{year}, was estimated as;

$$E_{year} = (365.25 \times 24) \sum_{u} P(u_i)\, f(u_i)$$

Equation 43

where $P(u_i)$, is the power output at a specific hub height wind speed, u_i, and $f(u_i)$, is the probability of wind speed, u_i, derived from the Weibull distribution fitted to hourly wind speeds. Annual energy production estimate was then converted to annual estimated FIT payments and payback period of the wind turbine.

The FIT tariff used in the FIT payment estimate for a 5 kW turbine in October 2015 was 13.89 p/kWh [34]. At the time the analysis was conducted, this was the lowest tariff rate, however, this has since changed. However, to ensure consistency with the selected electricity price and the cost estimates only available from 2015, the tariff level from October 2015 was retained.

These FIT payments are only available for 20 years [26]. The FIT payment formed part of the payback period calculation. Financial returns of a wind turbine are composed of two parts, the FIT payments and the financial savings realised from not purchasing electricity from the grid. Average electricity price for Great Britain in 2015 was 15.95 p/kWh and the calculation assumed an mean annual domestic electricity consumption of 3,800 kWh [152]. This electricity price was calculated from 11 years of data available from Department of Energy and Climate Change (DECC) for the mean price of standard electricity consumption [152]. The assumption was made in this work that the FIT subsidy level and price of domestic electricity would remain constant and that no electricity was exported to the grid. The annual energy production of the wind turbine was therefore utilised to calculate the financial savings an adopter could achieve by installing a wind turbine. Addition of the FIT payments and the savings from offsetting electricity resulted in the gross profit available from a wind turbine. However, wind turbines incur operational and maintenance costs during their lifespan, which were included in this calculation.

The capital and operation costs of a wind turbine are specific to each wind turbine. However, no specific costs for the Evance 5 kW turbine could be collected. Capital costs have been estimated for small scale onshore wind in Great Britain [21]. The median estimate of the capital cost of a wind turbine rated between 1.5 kW and 15 kW is £3,991 per kW installed, while the operation costs for the same capacity turbines are estimated to be £66 per kW per year [21]. For the selected 5 kW turbine in this work, the estimated capital costs of the wind turbine were £19,955, while the operational costs were £300 per year. Using these costs, it was possible to estimate the payback period, P_b, of a 5 kW turbine;

$$P_b = \frac{Capex}{\left(\left(FIT_{year} + Elec_{year}\right) - Opex_{year}\right)}$$

Equation 44

where, *Capex*, is the capital expenditure, FIT_{year}, is the annual FIT payment, $Elec_{year}$, is the savings on grid electricity per year and $Opex_{year}$ is the annual operational costs of the wind turbine.

While these metrics provide information about the potential returns of a 5 kW wind turbine, the analysis was designed to assess the influence of wind speed error on the results of these metrics. The analysis was therefore run over a number of scenarios to determine what can be considered sufficient accuracy in a wind speed prediction.

The analysis was run for seven mean wind speeds of 4.0 ms^{-1}, 4.5 ms^{-1}, 5.0 ms^{-1}, 5.5 ms^{-1}, 6.0 ms^{-1}, 6.5 ms^{-1}, 7.0 ms^{-1}, and the scale factor of the Weibull distribution at each of these mean wind speeds was calculated. At these five mean wind speeds, a baseline estimate of each metric was calculated and against this baseline estimate, the influence of wind speed prediction error was analysed. A range of mean absolute errors from a 0.1 ms^{-1} error up to a 3 ms^{-1} error in long-term mean wind speed were utilised. Through analysis of the annual energy production, annual FIT payments and payback period, what can be considered sufficient accuracy within a wind speed prediction was determined. With a definition of sufficient accuracy, a framework in which to analyse the suitability of the wind speed predictions from the BLS and MCS methodology was developed.

4.2 Results and analysis

The results and analysis in this chapter will focus on five major topics which have been discussed throughout the chapter;

1. Definition of sufficient accuracy in wind speed prediction.
2. Analysis of the accuracy of wind speed predictions at 10 m from the MCS methodology and the BLS model using both the NOABL and NCIC wind map data as the reference wind climatology.
3. Analysis of NWP data as a reference wind climatology for the BLS model.
4. Analysis of the accuracy of power density predictions available from; a fixed shape factor of 1.8, BLS NWP data and vertically scaled BLS NWP data.
5. Analysis of the impact of improvements of the BLS model in this work, when compared to a previous BLS study by Weekes [33].

4.2.1 Definition of sufficient accuracy

To determine the influence of wind speed error on the estimates of annual energy production, annual FIT payments and payback period, the baseline estimates with a zero error were calculated. Table 7 presents the baseline estimates of each metric for a 5 kW wind turbine at seven different mean wind speeds.

Table 7 — The baseline estimates of annual energy production, annual FIT payment and payback period for a 5 kW wind turbine at seven different mean wind speeds

Mean wind speed (ms^{-1})	**4.0**	**4.5**	**5.0**	**5.5**	**6.0**	**6.5**	**7.0**
Annual energy production (kWh/year)	5,374	7,384	9,499	11,624	13,684	15,614	17,370
Annual FIT payment (£/year)	786	1,080	1,389	1,699	2,001	2,283	2,539
Payback period (years)	15.2	10.4	7.8	6.2	5.2	4.5	4.0

Figure 18 and Figure 19 show the difference in annual energy production and annual FIT payment estimates, due to error in the wind speed prediction at the seven mean wind speeds. Figure 20 shows the change in estimated payback period of the wind turbine due to error in the wind speed prediction.

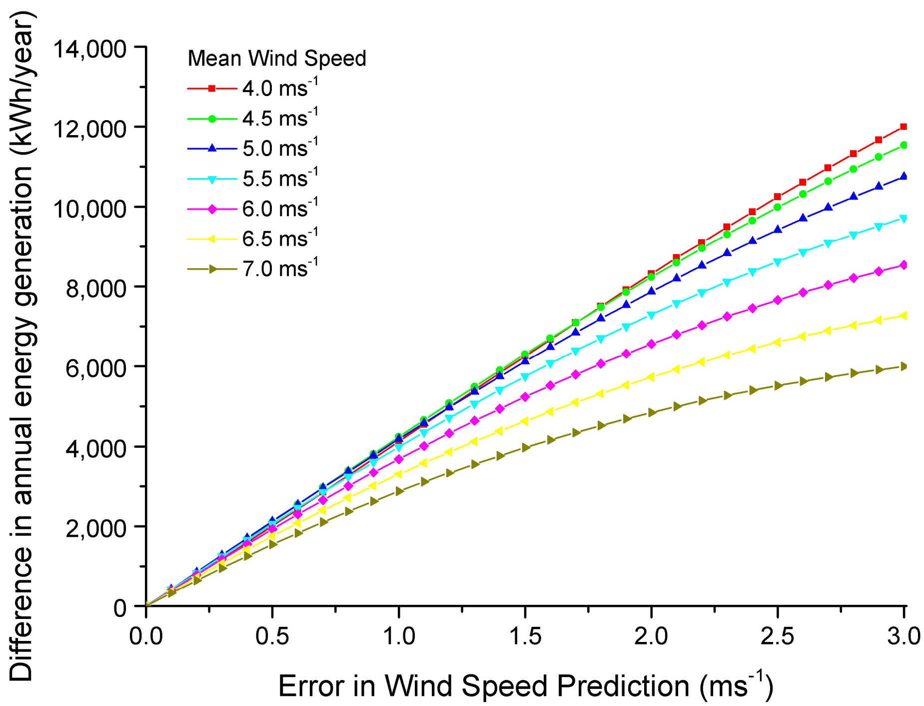

Figure 18 — Absolute difference in annual energy production estimates of a 5 kW wind turbine due to wind speed prediction error

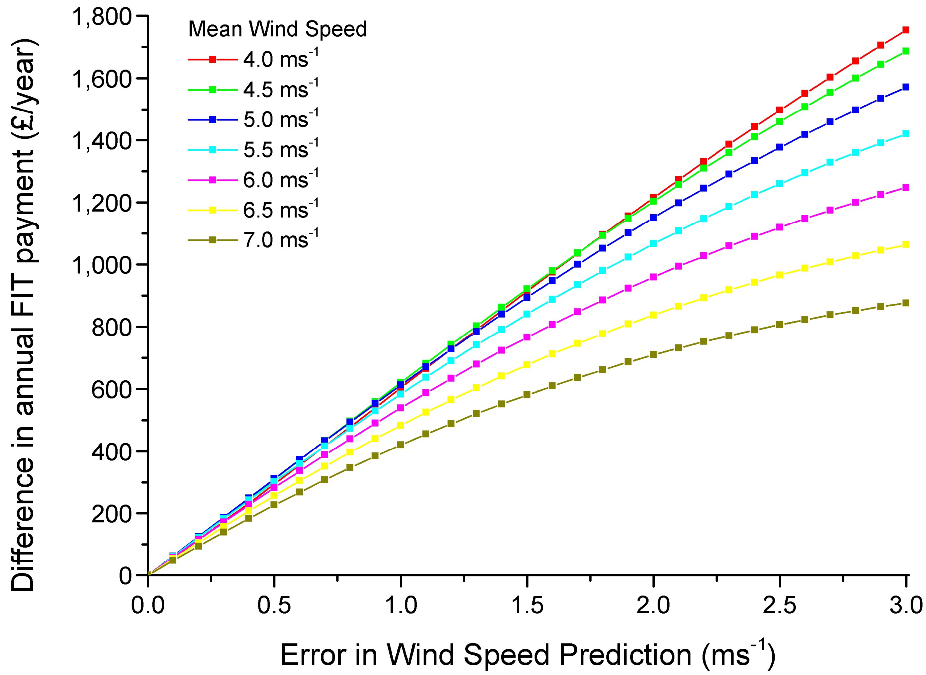

Figure 19 — Absolute difference in annual FIT payments estimates of a 5 kW wind turbine due to wind speed prediction error

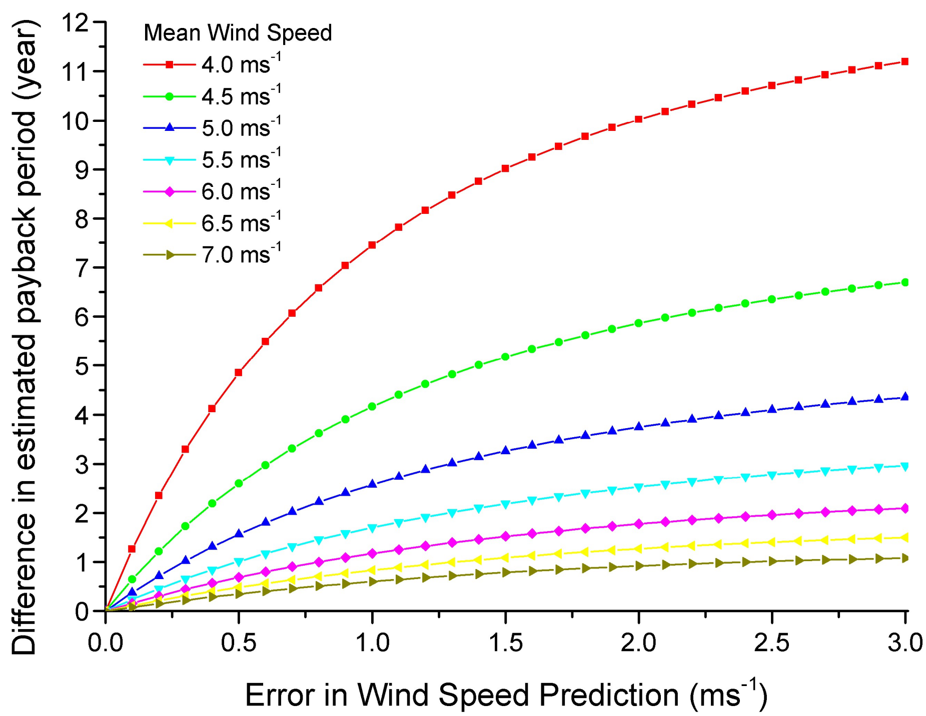

Figure 20 – Absolute difference in payback period estimates of a 5 kW wind turbine due to wind speed prediction error

Initially, the results highlight that wind speed prediction error is most influential at lower wind speeds. Given this conclusion, the difference in each metric at an mean wind speed of 4 ms^{-1} will be considered the worst case scenario in this analysis. Selection of a worst case scenario allowed the error in wind speed to be examined when it was at its most influential on FIT payment and payback period estimates and sufficient accuracy in wind speed prediction could be best defined.

Analysis of the estimates at 4 ms^{-1} concluded that a wind speed prediction methodology which was able to achieve a mean absolute error of 0.5 ms^{-1} or less can be considered sufficiently accurate. With this absolute error at a mean wind speed of 4 ms^{-1}, the annual energy production and annual FIT payments were 37 % larger than the baseline estimate, which equated to an over prediction of 2,010 kWh/year and £293 per year respectively. The payback period at this error in wind speed prediction was 5 years less than the baseline payback period. Selection of 0.5 ms^{-1} as the maximum absolute error was motivated by the increasing errors in each financial metric resulting from higher absolute error in wind speed prediction. With a 0.6 ms^{-1} error in wind speed prediction, the annual energy production and FIT payment estimates had a 45 % percentage error. Therefore, with a wind speed prediction which was not sufficiently accurate, the financial returns of a wind turbine installation could be estimated incorrectly by almost a half. This is considered unacceptable and could lead to wind turbine installations being carried out in locations where the wind resource is unsuitable. While the errors in the financial returns with a mean absolute error of 0.5 ms^{-1} were around a third, this degree of absolute error was the maximum perceived as permissible.

The definition of sufficient accuracy suggested here was taken from the worst case scenario and at higher mean wind speeds, a 0.5 ms^{-1} error resulted in smaller differences in the annual energy production. At an mean wind speed of 5.0 ms^{-1} or above, an absolute error of 0.5 ms^{-1} equated to an error of 22 % or less in the annual energy production estimate, while this fell further, to a 14 % error at a mean wind speed of 6.0 ms^{-1}. This definition of sufficient accuracy is therefore considered suitable and was utilised in the analysis of the BLS and MCS methodologies.

4.2.2 Comparison of MCS and BLS models

The BLS and MCS methodologies have been analysed for their suitability to provide sufficiently accurate wind speed predictions for prospective small and medium scale wind turbine adopters. Wind speed predictions from five different models were compared as part of the analysis; unscaled or raw NOABL data, unscaled or raw NCIC data, BLS model using NOABL, BLS model using NCIC and MCS scaled NOABL.

Wind speed predictions for each of the five models were estimated at a hub height of 10 m to ensure that validation by the observational data could be undertaken. This analysis was developed to determine if BLS model could provide a more accurate prediction of long-term mean near-surface wind speeds than those available from the MCS methodology. Use of the differing wind maps as reference wind climatologies in the BLS allowed for the identification of the most appropriate reference wind climatology for accurate wind speed predictions. Comparison with the raw wind map data at 10 m allowed for any improvement in wind speed prediction accuracy offered by the BLS model to be identified. The results of this analysis are presented in Figure 21 and Table 8.

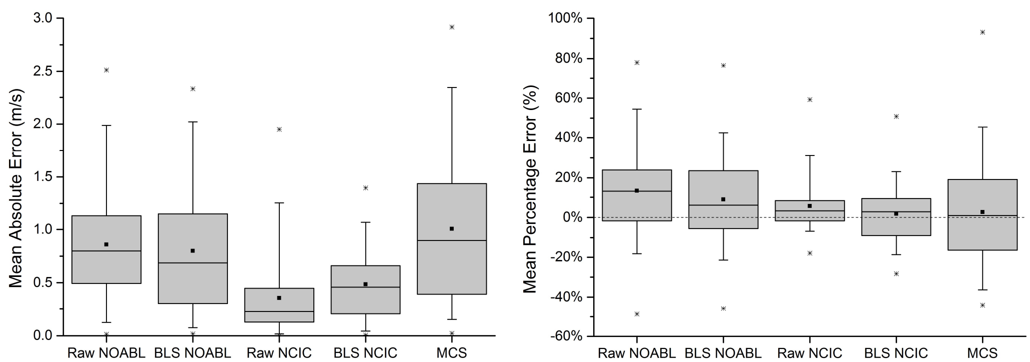

Figure 21 — Error in wind speed prediction of each prediction methodology and raw wind map data, validated by observational wind speeds. Left: Mean absolute error. Right: Mean percentage error. Large boxes are the interquartile range showing the 25th, 50th and 75th percentile values, small squares are the mean error, whiskers are the 5th and 95th percentile values and crosses are the 1st and 99th percentile values of each sample

Table 8 — Summary of mean error in each prediction methodology and raw wind map data from MAE and MPE metrics

Error Metric (mean error)	Raw NOABL	BLS NOABL	Raw NCIC	BLS NCIC	MCS
MAE (ms^{-1})	0.86	0.80	0.35	0.49	1.01
MPE (%)	13.36	8.71	5.50	1.43	2.36

The most accurate wind speed predictions were achieved from the BLS model when using the NCIC wind map data as the reference climatology. BLS NCIC wind speeds had a lower mean percentage and mean absolute error than the MCS wind speed. The results presented in Figure 21 and Table 8 therefore show that that the BLS model offered more accurate wind speed predictions than the MCS methodology. The MAE interquartile range of the BLS NCIC was lower than the MCS, 0.44 ms^{-1} in the BLS NCIC compared to 1.02 ms^{-1} in the MCS sample. This trend was continued in the 5th/95th and 1st/99th percentile ranges, where the BLS NCIC wind speeds had a smaller range of absolute error across both percentile ranges than the MCS wind speeds. The same conclusion was drawn for the MPE results. The interquartile range of the BLS NCIC was 18.1 % while for the MCS, it was 34.4 %. The percentile ranges of the percentage error results showed that the MCS range was almost double that of the BLS NCIC. Crucially, 60 % of the sites had a BLS NCIC wind speed which was below the 0.5 ms^{-1} threshold of sufficient accuracy compared to only 35 % of site's predicted MCS wind speeds. These results highlight that BLS NCIC can be considered a more suitable methodology for prospective wind adopters than the MCS methodology at a prediction height of 10 m. The errors in the BLS NCIC wind speed were significantly lower than the MCS wind speeds and therefore can offer a more accurate prediction of long-term mean wind speed.

This improvement in wind speed predictions over the MCS methodology was also seen in the BLS NOABL wind speeds. The MAE of the BLS NOABL sample was below that of the MCS sample, while its interquartile and both percentile ranges were all smaller than the MCS. While the improvement in wind speed accuracy of the MCS was not as significant for the BLS NOABL as it was for the BLS NCIC, it was an important improvement to achieve. This improvement is considered important for two reasons. Firstly, it highlights that NOABL data can be scaled more effectively using a BLS approach rather than the MCS approach. Secondly, there are commercial considerations regarding use of the NCIC wind map data. It is owned fully by the Met Office and therefore it's use as part of a future wind resource assessment technique may be limited by these commercial considerations. However, the results here indicate that use of NOABL data as the reference wind climatology to the BLS model could offer more accurate wind speed predictions than the MCS methodology, offsetting the concern around use of the NCIC wind map data.

The difference between the accuracy of the wind speeds of the BLS using NOABL and NCIC identified which is the most appropriate reference wind climatology for the BLS model. The error in the BLS NCIC wind speed was also lower than those of the BLS NOABL wind speed. The mean error from both error metrics of the BLS NCIC wind speeds was below that of the BLS NOABL wind speeds. In all of the percentile ranges of either the MAE or MPE results, the BLS NCIC had a much smaller range than the BLS

NOABL. These results show that to offer the most accurate wind speed predictions, the BLS model should utilise NCIC data as the reference wind climatology.

Raw NCIC wind speeds were more accurate across both metrics than its raw NOABL counterparts. The MAE and MPE of the raw NCIC was half that the raw NOABL. The accuracy of the raw NCIC was so significantly greater than the raw NOABL that the 1st/99th percentile of the absolute and percentage error of raw NCIC as less than the 5th/95th percentile range of the same metrics for the raw NOABL. This result is in line with previous literature which found that raw NOABL data is highly inaccurate [31, 32].

The accuracy of raw NCIC was such that the wind speeds had a lower MAE than that of the BLS NCIC wind speeds. BLS NCIC wind speed did, however, have a lower MPE across the sample. In both the absolute and percentage error, raw NCIC had a smaller interquartile and this trend remained consistent in the percentile ranges of the percentage error metric. However, in the absolute error metric, the 5th/95th and 1st/99th percentile of the BLS NCIC were smaller than the raw NCIC. These smaller percentile ranges for the BLS NCIC showed that the BLS model was able to improve the accuracy of the outlier wind speeds in the raw NCIC. This improvement of the outliers in the raw NCIC was likely to be due to the inclusion of a more accurate surface roughness parameterisation in the BLS model.

While the percentile ranges were reduced, the lower MAE in the raw NCIC must be understood to determine if application of the BLS model to the NCIC wind map data was suitable. Lower absolute error in raw NCIC wind speeds stems from the methodology which created the NCIC wind map. 220 MIDAS stations provided observational data for the interpolation and regression used to create the NCIC data [99]. It is therefore highly likely the 124 MIDAS sites, used for validation in this research, were part of the original 220 sites used to create the NCIC data. Raw NCIC data at these MIDAS sites therefore required little or no interpolation during creation of the NCIC, which resulted in the raw NCIC data being very close to the observational wind speeds. It is therefore exceptionally difficult for the BLS model to improve on the accuracy of raw NCIC at the validation sites selected in this work. An additional sample of validation sites, outside those 220 stations in the original NCIC sample, would be required to fully validate the performance of the BLS NCIC against the raw NCIC. However, it is likely that such sites would be commercial wind turbine sites and this additional validation data was not available for this research.

The BLS model does have certain advantages over raw climatology data. The BLS model can offer wind speed predictions at variable hub heights whereas raw data is only available at selected heights above ground level [99]. The BLS model can be adjusted for any hub height a prospective adopter wishes to analyse, a likely part of any due diligence on a prospective site. The BLS model presented can also provide wind speed predictions on a much finer spatial resolution than the raw climatology data. BLS wind speeds can be provided for each 0.01 km^2 of Great Britain whereas the raw wind map data is only available on a 1 km^2 grid square. For near-surface winds where the influence of surface roughness is high and thus the spatial variability in wind speed liable to be higher, this finer spatial resolution of wind speeds offers prospective adopters a crucial advantage in assessing a wind turbine's viability. These advantages in the BLS model offer considerable value over the use of raw climatology data alone, when assessing the technical and financial viability of a prospective wind turbine site.

The value added by the BLS model to wind speed predictions was further analysed by examining the results split into the site classifications of the validation sites. This analysis allowed the merits of the BLS model in each of the four site classifications to be understood. Figure 22 shows both error metrics of the differing wind speed predictions split across the site classifications. In the coastal, rural and suburban sites, the results mirror those observed when examining the error in wind speed predictions across the whole sample.

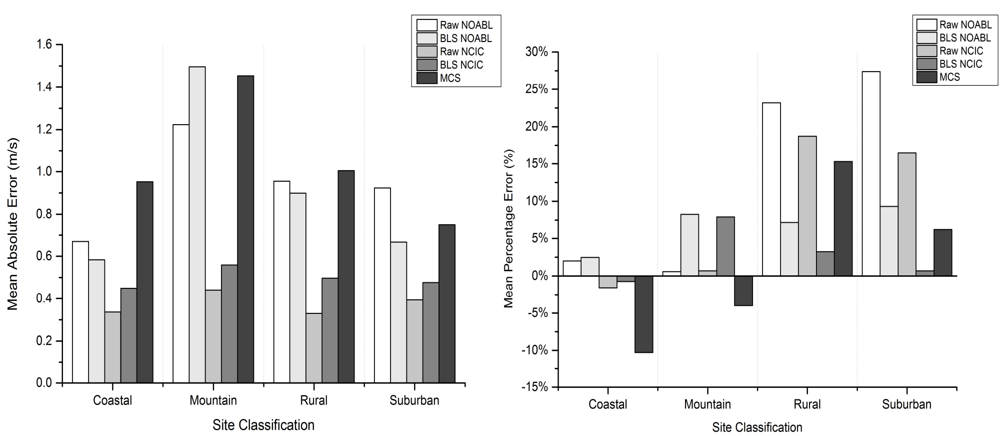

Figure 22 — Error in wind speed prediction of each methodology and raw wind map in each of the four site classifications. Left: Mean absolute error. Right: Mean percentage error

However, at the mountain sites, the MPE results deviated from this trend. The MPE of the BLS model with either reference wind climatology exhibited an over-prediction in wind speed, whereas the raw wind maps under-predicted the wind speed at the same sites. The over-prediction in BLS wind speeds was likely to be due the lack of orographic correction in the BLS model. No description of orographic wind speed change was included in the BLS model and the scaling of wind speeds at these mountain sites was based on the surface roughness values alone. At the mountain sites in the sample, the surface roughness alone appeared to be insufficient to accurately scale the wind speeds, resulting in the over-prediction in wind speed from the BLS model.

The performance of the MCS methodology was typified by the results in Figure 22. In the majority of site classifications, MCS wind speeds had the highest MAE of all of the scaled wind climatologies. At the coastal sites, MCS had a MAE of 0.97 ms^{-1}, compared to 0.46 ms^{-1} for BLS NCIC and 0.59 ms^{-1} for BLS NOABL wind speeds. This was replicated in the MPE results at coastal sites, where MCS wind speeds had an MPE of -10.51 % while BLS wind speeds had MPEs of -0.74 % and -1.67 % using NCIC and NOABL respectively. For 73 % of coastal sites, the MCS under-predicted the wind speed. A similar trend was observed in the MAE results for rural and suburban areas, with MCS wind speeds exhibiting the greatest absolute error of the scaled wind climatologies. Only at the suburban sites did the MCS methodology achieve a significant improvement in MPE over the BLS NOABL, a 6.19 % error compared to 16.51 %. However, in this sample of sites, BLS NCIC wind speeds achieved an MPE of 0.70 %. These results further highlight the differences between the BLS and MCS methodologies and the greater accuracy of estimated wind speeds available using the BLS methodology. The results in each site classification also highlighted that the scaling of wind speeds in the MCS methodology is insensitive to terrain type. In comparison to the BLS model, where the scaled wind speed may be over-predicted compared to the raw wind map data, MCS consistently reduced the wind speed in all areas. The MCS methodology reduced wind speeds in all areas, irrespective of surface roughness at the site, whereas the wind speed predictions of the BLS model could be over-predicted at sites where the raw wind map data under-predicted the wind speed. While the MCS approach is suitable in areas where the raw NOABL was inaccurate, it is not considered suitable for all areas.

The estimated MCS wind speed is likely to be viewed by potential adopters as the upper estimate of long-term mean wind speed of a site as, if an additional energy production estimate is significantly greater than the MCS results, it must be prefaced with a warning to potential wind turbine adopters [27]. Therefore, at sites where the MCS under-predicts the wind speed, there is a risk that a potential adopter could reject a wind turbine installation in a location with sufficient wind resource. 48.8 % of sites examined here had MCS wind speeds which were less than the observed long-term mean wind speeds. Therefore, the technical feasibility of potentially half of the sites in this sample could be misrepresented using the MCS methodology. This highlights that the MCS methodology is unsuitable as the wind resource assessment required as part of the FIT accreditation process.

The results of this section highlight two important conclusions; the deficiencies of the MCS methodology and the greater suitability of the BLS model, which can improve wind speed prediction accuracy when using NCIC rather than NOABL as a reference wind climatology.

The limitations of the MCS, in that it offered the most inaccurate scaled wind speed prediction, highlights its inappropriateness as a wind resource assessment for small and medium scale wind turbines. By comparison, the BLS model offered a more appropriate scaling of the wind map data, based upon a site's surface roughness. This improvement in the scaling of the raw wind map data and subsequent improved accuracy of wind speed predictions emphasised that the BLS is a more robust methodology than the MCS methodology. Replacement of the MCS methodology with the BLS methodology within the FIT accreditation process would ensure that prospective installers were able assess the viability of a site using a long-term mean wind speeds, which have been shown to be significantly more accurate. The assessment of a site's viability would therefore have a lower degree of risk and sites could be assessed effectively with the BLS model, ensuring that project budgets are not misspent.

The BLS model can offer the most accurate wind speed prediction to prospective installers and adopters when scaling the NCIC data, rather than the NOABL wind map data. While the BLS NOABL wind speeds were more accurate than the MCS, the wind speeds of BLS NCIC were significantly more accurate than the MCS. However, due to commercial constraints, use of the NCIC as a reference wind climatology may not be possible. In such a case, use of NOABL in the BLS model would offer more accurate wind speeds than the MCS. The role of the reference wind climatology was investigated further to understand if hourly NWP data was a suitable reference wind climatology for the BLS model.

4.2.3 Numerical Weather Prediction data as reference wind climatology

Hourly NWP wind speed data from both the Met Office's UK4 and UKV models were analysed, to determine their suitability as a reference wind climatology to the BLS model. NWP wind speed data offered an hourly time series of wind speed predictions for a site, rather than a long-term mean wind speed such as those available from wind map data. NWP data was available at 7 heights ranging from 10 m to 200 m for each of the 124 validation sites from the UK4 model and for 121 validation sites from the UKV model. The BLS model scaled each hourly wind speed of NWP data from the forecasting height to a hub height of 10 m, from which a long-term mean wind speed was calculated, to allow for validation by the long-term mean observational wind speeds.

Initially, BLS NWP wind speeds scaled from a forecasting height of 10 m were compared to the wind speeds from raw NWP at 10 m, presented in Figure 23 and Figure 24. For both NWP data sets, the raw NWP forecast at 10 m out-performed the BLS NWP forecast at 10 m in both error metrics. The MAE of raw UK4 at 10 m was 1.43 ms^{-1} compared to 1.58 ms^{-1} for the BLS NWP forecast from the same height. The difference between MAE of raw UKV and BLS NWP was similar, with a MAE of 1.04 ms^{-1} in the raw data compared to 1.29 ms^{-1} for the BLS NWP. These results highlight a key difference between the UK4 and UKV in that, UKV data provided more accurate wind speeds. This is because UKV was modelled on a finer spatial resolution allowing for a better characterisation of wind speeds at 10 m.

A possible underlying cause of raw NWP data offering more accurate wind speed predictions than the BLS NWP is the parameterisation of atmospheric stability in the NWP models. While the BLS model assumed a simple logarithmic vertical wind profile due to neutral atmospheric stability, both the UK4 and UKV modelled the atmospheric stability effects from the surface heat exchange and turbulence. The modelling of atmospheric stability effects on wind speed, resulted in a more realistic vertical wind profile in the NWP data. The more realistic vertical wind profile outweighed the effect of more realistic surface roughness from the BLS model and resulted in raw NWP outperforming the BLS NWP data at 10 m.

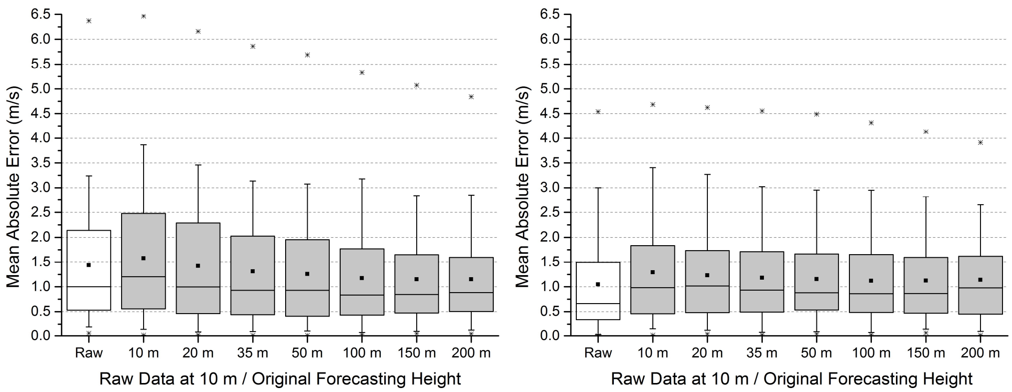

Figure 23 — Mean absolute error of BLS NWP from all forecasting height and raw NWP at 10 m, validated by observational wind speeds. Left: UK4 data. Right: UKV data. Large boxes are the interquartile range showing the 25th, 50th and 75th percentile values, small squares are the mean error, whiskers are the 5th and 95th percentile values and crosses are the 1st and 99th percentile values of each sample

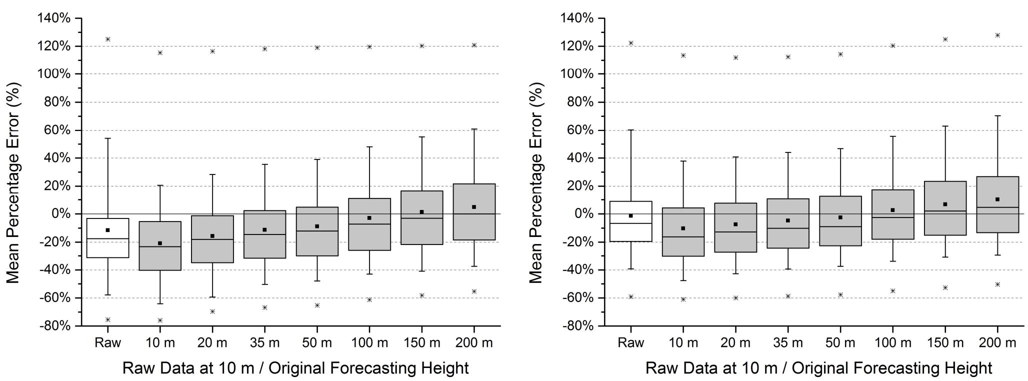

Figure 24 — Mean percentage error of BLS NWP from all forecasting height and raw NWP at 10 m, validated by observational wind speeds. Left: UK4 data. Right: UKV data. Large boxes are the interquartile range showing the 25th, 50th and 75th percentile values, small squares are the mean error, whiskers are the 5th and 95th percentile values and crosses are the 1st and 99th percentile values of each sample

BLS NWP data from all forecasting heights was scaled to 10 m, shown in Figure 23 and Figure 24, and then analysed to determine which height of NWP data offered the most accurate wind speeds when scaled using the BLS model. For the BLS UK4, it was possible to predict wind speed with a MAE of 0.81 ms^{-1} when scaling UK4 data forecast at 150 m. The MPE of wind speeds from the same height of BLS UK4 were also the lowest available in the sample at −1.02 %. These errors in the wind speed were an improvement on those in the raw UK4 data at 10 m. Using UK4 data forecast at 150 m, the percentile ranges were also smaller in the absolute error metric than for the raw UK4 at 10 m, while the percentile ranges of the percentage error were similar. In the BLS UKV, the lowest MPE in wind speed at 0.69 % was achieved scaling UKV forecast at 100 m. This MPE was an improvement over the percentage error in the raw UKV at 10 m. However, the MAE of BLS UKV was never lower than the MAE of the raw UKV at 10 m. The results showed that to achieve the most accurate wind speed prediction from BLS NWP data, the NWP data utilised as reference wind climatology must be forecast higher in the atmosphere. For UK4 data, data forecast at 150 m must be utilised while data forecast at 100 m must be utilised from UKV data as the reference wind climatology to the BLS model. NWP data forecast at these heights contain a description of the large-scale flow in the atmosphere. These large-scale flows characterise the synoptic variability in the wind speed. Coupling this description of large-scale atmospheric wind flow with the description of surface roughness from the BLS resulted in the comparatively accurate wind speed predictions. However, use of either NWP data as the reference wind climatology to the BLS model was not able to produce wind speed predictions with sufficient accuracy. In no sample of BLS NWP data did the percentage of sites with a sufficiently accurate wind speed prediction exceed 40 %. The highest percentage of sites which achieved this threshold was 47 % of sites in the raw UKV sample at 10 m. These results show that ultimately the BLS model was unable to scale the NWP data effectively and the wind speed predictions of BLS NWP were not more accurate than those achieved when scaling wind map data. Challenges still remain in improving the prediction of near-surface winds using high resolution NWP data as a reference wind climatology to the BLS model. However, the results from this work are not without merit for future developments of the BLS model. This research has identified that the NWP forecast higher in the atmosphere was most suitable for wind speed predictions from the BLS model. The availability of validation data sets, not used within forecast data assimilations of the NWP models, would perhaps provide a more stringent test of the different methodologies. Unfortunately, as previously discussed, such validation data is likely to be taken from commercial wind turbine sites, which were unavailable for this research due to their commercial nature. Future improvements can be made to how the BLS model incorporates the vertical wind profile within the NWP data during the wind speed prediction process. With multiple heights of NWP data available, the vertical wind profile could be estimated prior to implementation of the BLS model. Using this estimated vertical wind profile, the BLS model can be adjusted to account for this, either in through the parametrisation of a stability parameter for the BLS model or inclusion of the estimated vertical wind profile, in place of the logarithmic vertical wind profile in the BLS model. Implementation of such improvements would require a significant amount of research to identify the most appropriate technique. The focus of this research, however, was to understand if NWP data could be implemented as the reference wind climatology to the current BLS model. The results clearly show that this is not the case and with the current BLS model, wind map data is still the most appropriate choice of reference wind climatology.

Despite the challenges of accurately estimating near-surface long-term mean wind speed from the BLS model, hourly NWP data offered the ability to predict power density which is unavailable when using wind map data as the reference wind climatology.

4.2.4 Power density predictions

Weibull distributions were fitted to each BLS NWP dataset scaled to a hub height of 10 m and the shape factor of each distribution utilised to predict power density. The dimensionless power density predictions from the fitted shape factors were then compared to the dimensionless power density achieved using a fixed shape factor of 1.8, the shape factor suggested when estimating power density using wind map data [11]. A power density prediction which is equal to the observed power density would have a dimensionless power density of 1.

As shown in Figure 25, the fixed shape factor of 1.8 provided the dimensionless power density closest to the observed power density, achieving a mean dimensionless power density of 0.97. In comparison, all of the BLS NWP data over-predicted power density, resulting in mean power densities ranging from 1.07 for BLS UK4 from 20 m to 1.15 for BLS UKV at 200 m. In both BLS NWP datasets, the mean dimensionless power density increased as the forecasting height of the NWP data increased.

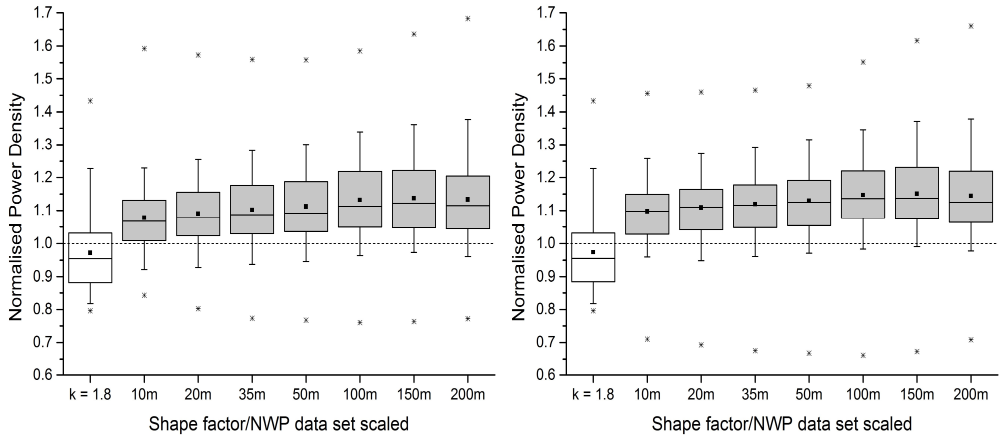

Figure 25 — Dimensionless power density from BLS NWP from all forecasting height and fixed shape factor of 1.8. Left: UK4 data. Right: UKV data. Large boxes are the interquartile range showing the 25th, 50th and 75th percentile values, small boxes are the mean error, whiskers are the 5th and 95th percentile values and crosses are the 1st and 99th percentile values of each sample

The over-prediction of power density contradicted the under-prediction of wind speeds, seen in the MPE of both BLS NWP datasets. The over-prediction in power density from BLS NWP data was caused by the lack of extreme wind speeds in the raw NWP data. This resulted in the Weibull distribution that was fitted to the BLS NWP data being narrower, with a higher shape factor, than the Weibull distribution which described the observational wind speeds, causing the over-prediction in power density.

As discussed in Section 4.1.4, the Weibull shape factor can be scaled vertically to account for the reversal height of the diurnal cycle, where shape factor is at a maximum, at a site [70]. This vertical scaling of the shape factors was undertaken with reversal heights of 60 m, 70 m and 80 m selected in this work for comparison.

Figure 26 shows the dimensionless power density achieved using a vertical scaling of shape factors fitted to BLS UK4 and BLS UKV from 20 m, using each reversal height. NWP data at 20 m was selected as it had the smallest error in the initial analysis of dimensionless power density from the BLS NWP data. The lower dimensionless power density error was due to a more accurate description of diurnal variation of near-surface wind speeds in the NWP data at 20 m.

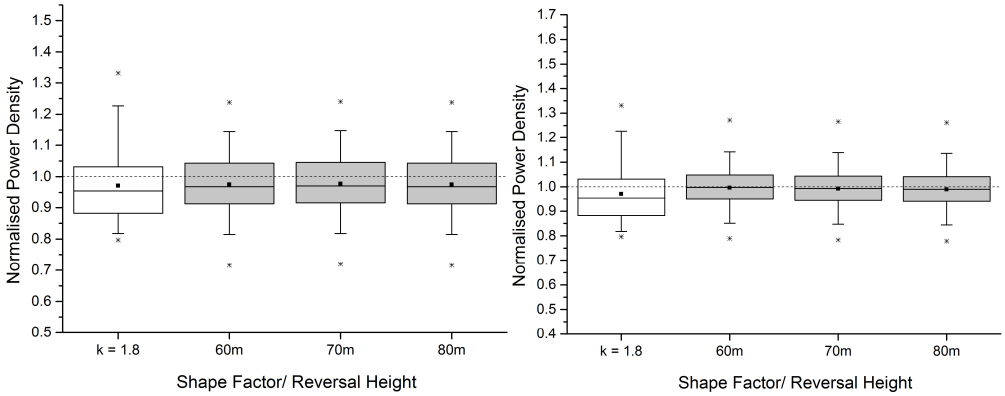

Figure 26 — Dimensionless power density from BLS NWP from 20 m scaled from reversal heights of 60 m, 70 m and 80 m and fixed shape factor of 1.8 without a vertical scaling. Left: UK4 data. Right: UKV data. Large boxes are the interquartile range showing the 25th, 50th and 75th percentile values, small boxes are the mean error, whiskers are the 5th and 95th percentile values and crosses are the 1st and 99th percentile values of each sample

Vertical scaling of shape factors fitted to BLS NWP data offered significant improvements in power density predictions over BLS NWP without a vertical scaling. Vertical scaling of the shape factor from BLS NWP data at 20 m resulted in a dimensionless power density of 0.98 for BLS UK4 and of 0.99 for BLS UKV. The differences in dimensionless power density between the reversal height were marginal, with the scaling for reversal height of 60 m offering the most accurate power densities. Introduction of the reversal heights also marginally decreased the percentile ranges of the power densities.

The dimensionless power densities achieved with the vertical scaling were an improvement over the BLS NWP data alone. Introduction of the vertical scaling is therefore a suitable technique when predicting power density from BLS NWP data. However, it must be noted that where BLS NWP is not available, use of a fixed shape factor of 1.8 has been shown here to be a suitable alternative for estimating power density. The power density predictions using a fixed shape, shown in Figure 26, achieved a mean dimensionless power density of 0.97. This approach can therefore be considered suitable for estimating power density when only wind map is data available at a proposed site.

However, scaling of NWP data forecast at a height of 100 m or 150 m provided the most accurate wind speed predictions. This highlights that different facets in the raw NWP data affect the accuracy of wind speed and power density predictions separately. For the most accurate mean wind speed predictions from the BLS model, a description of large-scale atmospheric flow available in NWP data, forecast between 100 m or 150 m is most suitable for the BLS model. However, the description of diurnal variation of wind speeds available in NWP data forecast at 20 m can be scaled most effectively to provide the most accurate power density predictions. These different descriptions of wind flow variations available in the different forecasting heights of raw NWP data account for the selection of different heights of NWP data for wind speed or power density predictions.

4.2.5 Value of BLS improvements

Within this work, a number of improvements were implemented in the BLS model. These improvements to the BLS model were designed to improve the accuracy of wind speed predictions. To quantify the value of these improvements, the accuracy of the wind speed predictions must be compared to a previous study by Weekes [33]. As discussed in Section 4.1.6, there have been four improvements suggested for this work's BLS model: a finer spatial resolution of the surface roughness, a greater number of surface roughness classifications, a greater number of wind direction sectors at each site and the calculation of regional aerodynamics in each of these wind direction sectors. The previous study examined the wind speed predictions of a BLS model using only NCIC data as the reference wind climatology [33]. The accuracy of these wind speed predictions was validated over 38 sites, which were split between coastal, rural, suburban and urban sites [33]. Of the 38 sites in the previous study, 26 sites were included in the validation sample of this work. It is therefore not to possible to examine the value of the improvements over the same sample of sites and the comparison was conducted using the wind speed predictions across the whole sample of each study. Additionally, as the site classifications in the previous study included urban rather than mountain sites, it will not be possible to assess the improvements in these sites. However, at the coastal, rural and suburban sites, this comparison was possible.

The previous study assessed wind speed accuracy with the mean absolute and mean percentage error metrics [33], The previous study predicted BLS NCIC wind speeds with a MAE of 0.52 ms^{-1} and a MPE of 16.2 % [33]. By comparison in this work, BLS NCIC wind speeds were predicted with a MAE of 0.48 ms^{-1} and a MPE of 1.48 %. The results of this comparison show that over the sample of each study, this work's BLS model was able to predict wind speed with a lower mean error. The lower error in this work's BLS NCIC wind speeds show that the improvements to the BLS model were able to increase the accuracy of wind speed predictions.

The added value of the improvements was further analysed across the site classifications from each study. In the coastal, rural and suburban sites, this work's BLS model achieved wind speed predictions with lower mean absolute and mean percentage error than the previous study [33]. In the previous study, the MAE of wind speeds at coastal, rural and suburban sites were 1.03 ms^{-1}, 0.57 ms^{-1} and 0.65 ms^{-1} respectively [33]. At the same site classifications in this work's BLS model, the MAE of wind speeds were 0.46 ms^{-1}, 0.50 ms^{-1} and 0.48 ms^{-1} for the coastal, rural and suburban sites respectively. This reduction in wind speed prediction error was more significant in the MPE metric. Coastal sites in the previous study had a MPE of 18.9 % whereas this reduced to −0.74 % at the coastal sites examined in this work's BLS model. This significant reduction in MPE was also seen at the rural and suburban sites. The MPE of the wind speed prediction reduced from 10.9 % to 3.25 % in rural sites and from 18.0 % to 0.70 % at suburban sites between the studies.

While this research has focused on wind speed prediction at sites in Great Britain, the results of the BLS model can be compared to other studies which estimated wind speed in other locations. It will then be possible to understand how the BLS model and the improvements presented here compared to other near-surface wind prediction methodologies, applied in locations outside of Great Britain. Where wind map data is unavailable, reanalysis data can be downscaled to predict near-surface wind speeds [153, 154]. Reanalysis data is created using climate models and typically provide hourly wind speed prediction on a horizontal resolution of around 30 km [155]. Comparison of wind speed accuracy with previous studies can be problematic, as each study examined sites in differing topology, utilised predict wind speed at different heights and validated using differing metrics [153, 154]. Additionally, reanalysis data can be extracted as hourly wind speed estimations and therefore many studies examined the accuracy of downscaling these hourly wind speeds [153, 154]. Despite these differences, a comparison of the accuracy of wind speed predictions with those produced from the BLS model can be offered. A study of wind speed prediction at sites on the US Great Plains, using the Climate Forecast System Reanalysis data, showed that without a bias correction, wind speed reanalysis data below 80 m exhibited a mean bias of −0.5 ms^{-1} [153]. With a bias correction, the mean bias improved to a level equivalent to that seen in the results of the BLS model [153]. In a study which examined sites in complex terrain in Portugal and used multiple reanalysis data sets, hourly wind speeds predictions at 60 m across all of the sites, exhibited mean bias between

0.3 ms^{-1} and 0.5 ms^{-1} [154]. However, the mean bias in the wind speed predictions was around 1.0 ms^{-1} for sites, with an mean wind speed below 4 ms^{-1} and around 0.5 ms^{-1} for locations with a mean wind speed between 4 ms^{-1} and 8 ms^{-1} [154]. The results from this study demonstrate that, at sites in complex terrain, reanalysis data can achieve more accurate wind speed predictions than the BLS model [154]. Mean bias in wind speed prediction is analogous to the mean absolute error metric used in this study and therefore the results show that are similar to those achieved by the improved BLS model in this work. This demonstrates that the improvements included in this research's BLS model have added significant value and are relevant to other locations, as they demonstrate the ability of the scaling techniques to improve upon reference climatology data, provided that sufficiently detailed land use data is available for a particular region. The methodology may be particularly useful for regions where very high resolution (~1 km) reference wind data cannot be obtained, but where a more detailed land use data set can be developed for use within the BLS method

These results reinforce the conclusion that the improvements to this work's BLS model are able to improve wind speed prediction accuracy. The increased resolution of surface roughness and the calculation of directionally dependent regional aerodynamics in this work's BLS model improved the wind speed prediction accuracy. These results indicate that future developments of the BLS model should include these improvements.

4.3 Conclusions

A boundary layer scaling model using NOABL, NCIC and NWP data as reference wind climatologies was investigated to determine the accuracy of wind speed and power density predictions at a hub height of 10 m. This analysis was undertaken to understand if the BLS model could offer wind speed predictions with greater accuracy than MCS methodology. Additionally, a vertical scaling technique of the Weibull shape factor to improve the accuracy of power density predictions, when compared to a fixed shape factor of 1.8 was also investigated. A comparison with a previous BLS model [33] was also undertaken to analyse if the advancements in the calculation of regional aerodynamic parameters and increased resolution of surface roughness included in this work has improved the accuracy of wind speed predictions from the BLS model.

The most accurate wind speed predictions from the BLS model were achieved with NCIC data as the reference wind climatology. BLS NCIC wind speeds had significantly lower errors than the MCS wind speeds over the validation sample. BLS NOABL wind speeds were also shown to have lower errors than the MCS wind speeds, across the validation sample. The BLS NCIC wind speeds were shown to be sufficiently accurate at 60 % of the validation sites, in comparison to around 33 % of sites with a sufficiently accurate MCS wind speed. These results show that the BLS NCIC model can be considered a more suitable wind resource assessment technique than the MCS. This conclusion has policy implications for the FIT scheme. The MCS methodology is the prescribed minimum resource assessment for wind turbines under 50 kW to gain the requisite accreditation to qualify for FIT payments. Implementation of a BLS model with NCIC wind map data as the prescribed wind resource assessment under the FIT could offer a more accurate long-term mean wind speed predictions to prospective wind energy developers. The caveat with this suggestion is the commercial constraints of the raw NCIC wind map. It may not be possible to implement a BLS NCIC model if commercial constraints around the use of the NCIC are not resolved. Implementation of the BLS NOABL could therefore be considered. The BLS NOABL provided more accurate wind speeds than the MCS and offered wind speeds with sufficient accuracy at 40 % of the sites. However, the accuracy of BLS NOABL wind speed was less than that of the BLS NCIC wind speeds. Implementation of the BLS NCIC would offer prospective wind turbine installers in Great Britain a more accurate wind resource assessment from which a site's viability can be determined quickly.

Analysis of the wind speed predictions available when using NWP data as the reference wind climatology to BLS model was undertaken. Utilising NWP data as a reference wind climatology, the BLS model was unable to improve the accuracy of long-term mean near-surface wind speed estimates when compared to raw NWP data alone. The high resolution NWP data offered a realistic vertical wind profile by modelling the stability effects from the surface heat exchange and turbulence, as opposed to the assumption of neutral atmospheric stability in the BLS model. This realistic vertical wind profile in the raw NWP data was likely to be the underlying cause of the more accurate long-term mean near-surface wind speed prediction.

However, the raw NCIC and NWP data for wind speed predictions at 10 m were more accurate than the BLS NCIC, as a result of the validation sites for this work being included in the original observational dataset used in the creation of raw NCIC data and the assimilation data used to initialise the NWP model. Validation using a sample of sites outside of the original observational sites sample used in the development of NCIC data, in addition, to data from existing wind turbine sites at hub heights other than 10 m, would provide a more rigorous validation of the wind speeds produced from the BLS model. This additional validation sample would allow it to be determined if the results observed during this research were due to limitations of the BLS model or limitations of the observational data available. However, such data is difficult to obtain due to its commercial sensitivity. Nevertheless, the BLS model can provide a vertical profile of mean wind speeds, which is unavailable from the raw NCIC data alone. A vertical wind profile of a site is necessary when selecting the appropriate hub height of a prospective wind turbine.

Future improvements can be achieved by adjusting how the BLS model operates with the vertical wind profile within the NWP data. The vertical wind profile could be estimated from the multiple heights of NWP data prior to implementation of the BLS model. The BLS model can be adjusted to account for the change in vertical profile, through the use of a stability parameter or inclusion of the estimated vertical wind profile in place of the logarithmic vertical wind profile. Implementation of these improvements could be included in future work. The results of the BLS NWP in this research clearly show that with the current BLS model, the NCIC wind map data is still the most appropriate choice of reference wind climatology.

While wind speed predictions using BLS NWP were insufficiently accurate, power density predictions achieved using a vertical scaling of shape factors fitted to BLS NWP data were encouraging. Mean power density predictions, using this approach, improved upon those achieved using a fixed Weibull shape factor of 1.8, the only possible method when using long-term mean wind map data. Vertically scaled BLS NWP data achieved mean power densities of 0.99 while the fixed factor of 1.8 achieved a mean dimensionless power density of 0.97. The high resolution time-series data available from NWP data therefore has clear advantages over the use of a fixed shape factor for power density predictions. However, at sites where the NWP data is unavailable, use of a fixed shape factor is a suitable alternative to predict power density.

Improvements in the BLS model, in the form of advancements of the regional aerodynamic calculations with an increased spatial resolution of surface roughness have been shown to offer improvements in wind speed prediction accuracy. When compared to a previous BLS model, without these facets, the wind speed predictions of this work’s BLS model were shown to improve accuracy across the sample of sites examined. These results vindicate the inclusion of these improvements, which should be included in all future developments of the BLS model.

As part of the research, a wind map for Great Britain was created using the BLS NCIC model. This wind map at a hub height of 10 m, presented in Figure 27, could be published to replace current wind maps. However, publishing of this wind map or any other at different heights would require consent from the owners of the datasets used as inputs to the BLS model. In addition to this wind map at 10 m, other wind maps at higher heights have also been created and could potentially be published. However, it is suggested here that publication of the wind maps would not be the most effective method of disseminating the results of this research. Dissemination of the BLS model will be discussed further in Chapter 7.

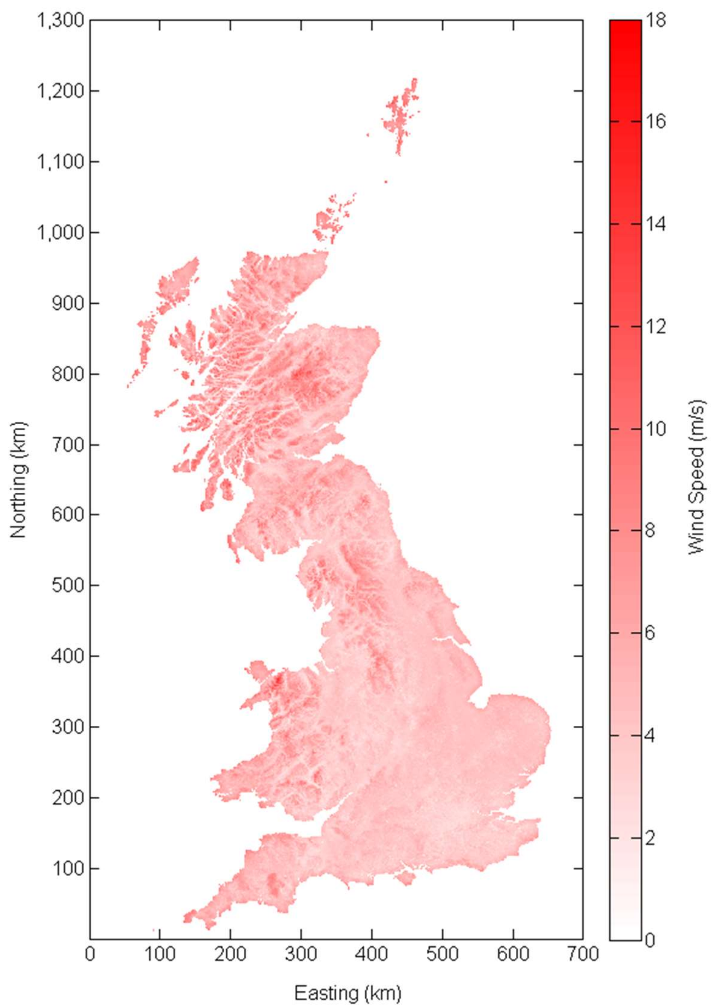

Figure 27 — BLS NCIC wind map at 10 m of Great Britain

The results presented in this chapter show that the BLS model is a more suitable wind resource assessment methodology than the MCS methodology. BLS NCIC wind speed predictions were significantly more accurate than the MCS wind speeds. It is therefore suggested that this configuration of the BLS model should replace the MCS in the FIT accreditation scheme. The more accurate wind speeds available from the BLS NCIC will also be taken forward into further research in this project. Using the BLS NCIC wind speeds, it will be possible to determine the influence of available wind resource on wind turbine deployment in Great Britain. This research on the influence of wind resource on wind turbine deployment will be presented in Chapter 5.

Chapter 5 – Socio-economic and resource analysis of spatial wind turbine adoption patterns

Accurate wind resource assessments can aid the future deployment of small and medium scale wind turbines by ensuring that wind turbines are sited in suitable locations. For small and medium scale wind turbines in Great Britain to reach the levels of deployment required for the societal or thousand flowers pathway suggested by Foxon, to deliver an energy systems transition, deployment needs to increase towards the upper estimate of potential wind turbine deployment [19]. The upper estimate of potential deployment, 407,950 installations across both domestic and non-domestic sites in Great Britain, estimated by James et al., was based upon three factors: sufficient wind resource, adequate land area, and suitable building profiles for a turbine installation [31]. Current deployment of small and medium scale wind turbines in Great Britain, as of December 2016, was 7,374 installations [12]. Given the gap between actual and potential deployment, it is argued here that the factors assumed in James et al. alone are not sufficient to explain trends in wind turbine adoption patterns.

To test this assertion, current wind turbine adoption patterns must be analysed. Wind turbines installed under the FIT are predominately below 15 kW capacity, with 64.0 % of total installations under this capacity [12]. Additionally 58.9 % of all installations are for domestic energy generation [12]. The uptake of small and medium scale wind turbines in the FIT market has therefore been dominated by individuals making adoption decisions. Analysis of the wind turbine adoption patterns conducted in this work focused predominantly on the factors that have influenced domestic adopters to install a wind turbine. As discussed in Chapter 1, wind turbine adoption patterns have both spatial and temporal characteristics. This chapter will present a scheme of research which was developed to analyse the factors which influence the spatial wind turbine adoption patterns of Great Britain.

As discussed in Chapter 3, a number of demographic and environmental factors have been suggested in this work as likely to exert an influence on an individual's decision to install a small and medium scale wind turbine. This chapter will present a regression analysis developed to determine the influence of these suggested factors, examining specifically the influence of wind resource alone before incorporating the additional factors suggested in

Chapter 3. The structure of the variables in the regression analysis will be discussed and the formation of multiple regression models using subsets of the available variables will be presented. Results and analysis of these regression models will be presented allowing the influence of the examined factors on small and medium scale wind turbine adoptions in Great Britain to be determined.

5.1 Methodology

To determine the influence of factors suggested in Chapter 3, an analysis framework must be established. Previous studies have applied regression analysis techniques to determine the influence of some demographic variables on the spatial deployment patterns of other microgeneration technologies [42, 44]. While spatial dependency between the residents has been exhibited in the deployment patterns of PV systems [42, 45], this has not been established for wind turbine adoption patterns in Great Britain. As literature regarding the influencing factors on spatial wind turbine adoption patterns in Great Britain is minimal, it is argued here that initially an approach using a regression model, which does not consider spatial dependency, was the most appropriate to establish this.

Use of a non-spatial linear regression model allowed the influence of each suggested factor to be analysed to understand the factors that have influenced spatial wind turbine adoption patterns. A non-spatial linear regression model was defined as [156];

$$\mathbf{y} = \beta_0 + \beta_n \mathbf{x} + \boldsymbol{\varepsilon}$$

Equation 45

where **y** is a $N \times 1$ vector of the dependent variable observations, **x** is a $N \times K$ vector of explanatory or independent variables while β_0 is the intercept term of fitted regression line, β_n is the parameter vector or regression coefficient of each of the independent variables and **ε** is the residual term of the linear regression model [156]. The residual term of each observation, ε_i, in the model is calculated as the difference between the predicted value, $\hat{y}_i$, and the actual value of the observation, y_i;

$$\varepsilon_i = y_i - \hat{y}_i$$

Equation 46

The value of β_n is commonly estimated using an ordinary least squares (OLS) technique [156] and it was an OLS regression coefficient estimation that was utilised in the analysis presented in this chapter. To implement this regression model, the dependent and independent variables for the regression model must be collected and analysed. In this research, the dependent variable was deployment data for wind turbines installed under the FIT in Great Britain, while the independent variables were the factors which were suggested to influence the spatial adoption patterns of wind turbines.

5.1.1 Dependent variable

Deployment data for small and medium scale wind turbines under the FIT in Great Britain is available from Ofgem [12]. The quarterly reports provide information regarding individual wind turbines installed under the FIT including: the commissioning and application dates; the installed capacity of the wind turbine; whether the installation was for domestic, commercial or industrial energy generation; and location identifiers (IDs) for some wind turbines in the report [12]. The data selected for this work's analysis was published in January 2017 and included all installations accredited from 1st April 2010 to 31st December 2016 [12]. Wind turbines in the report were installed between 1995 and 2016 and provided 22 years' worth of installations [12]. Turbines installed prior to the FIT were still eligible for payments, once they were accredited under the FIT. A total of 6,814 wind turbine installations across Great Britain were identified as suitable for this analysis from the reports [12].

In this work, a spatially dependent regression model was not implemented, however, the observations of wind turbine installations utilised in this research were recorded with a spatial location, in the form of the location IDs included in the register. These location IDs provided the location of each wind turbine at a statistical geography spatial unit. Statistical geographies are defined geographical areas within national territories, in which census data are recorded. Statistical geographical boundaries are constructed using population data to ensure that each statistical geographical unit covers a similar number of residents, so that the collected census data for each geography unit can be comparable [157]. The statistical geography units are not of uniform shape or size, as the boundaries of each were recalculated after the collation of decadal population data from each census [157, 158]. Statistical geographies are hierarchal, which allows for aggregation of the smallest statistical geographies into larger statistical geographies. For England and Wales, statistical geographies from the 2011 census were developed and constructed by the Office of National Statistics [159]. The statistical geographies for Scotland from the same census are managed by National Records for Scotland [160].

Use of statistical geographies allowed the observations of wind turbine adoptions to be utilised as the dependent variable in the regression model. Each of the statistical geographies, in which a wind turbine adoption had occurred, served as individual observations of the dependent variable within the regression models. The selection of statistical geography in the project was therefore crucial. Given the comparatively low number of wind turbine installations, a statistical geography with a comparatively small geographical area was required.

5.1.1.1 Statistical geography

The wind turbine installations selected from the Ofgem register were recorded at either Lower Super Output Areas (LSOA) [157] for English and Welsh installations or Data zones (DZ) [158] for Scottish installations. These are the smallest geographical areas of the respective statistical geographies of England & Wales or Scotland. LSOAs and DZs were developed to cover a maximum of 3,000 and 1,000 residents respectively [157, 158]. The hierarchal nature of statistical geographies allowed aggregation from the smallest statistical geographies to either Middle Super Output Areas (MSOA) for England and Wales or Intermediate zones (IZ) for Scotland [157, 161]. These areas could be further aggregated to local authority (LA) boundaries [159, 160]. MSOAs and IZs cover a maximum of 15,000 and 6,000 residents respectively. To perform analysis of wind turbine adoption patterns in this research, an appropriate statistical geography had to be selected.

Selection of the appropriate statistical geography was guided by the number of areas with at least a single wind turbine adoption. Only 5.6 % of all LSOAs or DZs had at least one installation compared to 16.2 % of all MSOAs or IZs. The percentage of LSOAs and DZs with a wind turbine installation was considered too low for analysis and therefore wind turbine adoption patterns were analysed on MSOA and IZ resolution, known as the statistical geography (SG) resolution, in this project. The wind turbine installation data sample at the SG spatial resolution was for 6,814 wind turbines across 1,377 regions across Great Britain. The total sample was composed of 3,946 installations in 1,081 regions of England and Wales and 2,868 installations in 296 regions of Scotland.

Selection of the SGs of MSOA and IZ for the adoption patterns analysis raised issues regarding the compatibility of the different SGs for England

and Wales or Scotland. Each SG covered a different number of maximum residents, which could lead to discrepancies in the analysis as the demographic data of each region was derived from a differing sample size of residents. Removal of the Scottish data from the sample was considered. However, because 38.9 % of all installations selected for this analysis are situated in Scotland [12] and the considerable wind resource available in Scotland [106], this would have severely limited the conclusions that could be drawn from the results, limiting the effectiveness of the analysis.

The mismatch between the number of residents in the MSOAs and IZs motivated the decision to include analysis of wind turbine adoptions on the local authority (LA) resolution. LAs are administrative rather than SG, with 380 different LA areas across Great Britain. A previous study examined photovoltaic (PV) adoption data at a higher statistical geographies, selecting Nomenclature of Territorial Units of Statistics (NUTS) 3 [42]. NUTS3 regions are composed of either single LA regions with a large geographical area or groups of smaller LAs regions. Introduction of analysis at LA in this chapter was therefore considered suitable, given that a previous study analysed PV adoptions in areas with a larger geographical area [42].

The number of wind turbine installations and the total installed capacity in each SG and in each LA, is presented in Figure 28 and Figure 29 respectively. These four datasets yielded two different wind turbine adoption patterns at two different resolutions, which were utilised as the dependent variables in the regression models. The choice of both wind turbine installation numbers and installed capacity in each region was motivated by the different characteristics of wind turbine adoption patterns available in each dataset. Wind turbine installation data in this analysis was dominated by domestic wind turbine installations, while the installed capacity data was dominated by commercial wind turbine installations. Therefore, utilisation of both sets of wind turbine adoption pattern data allowed the influences on these different types of users in the wind turbine market to be examined. The percentage of each different wind turbine installation type in the two deployment data samples used in this work is detailed in Table 9.

Table 9 — Proportion of installation types in different samples utilised in this work

Installation type	Installation number sample	Installed capacity sample
Domestic	63.3 %	9.2 %
Commercial	33.1 %	83.8 %
Community	2.20 %	2.1 %
Industrial	1.35 %	4.9 %
Total in Sample	6,814 wind turbines	468,255 kW

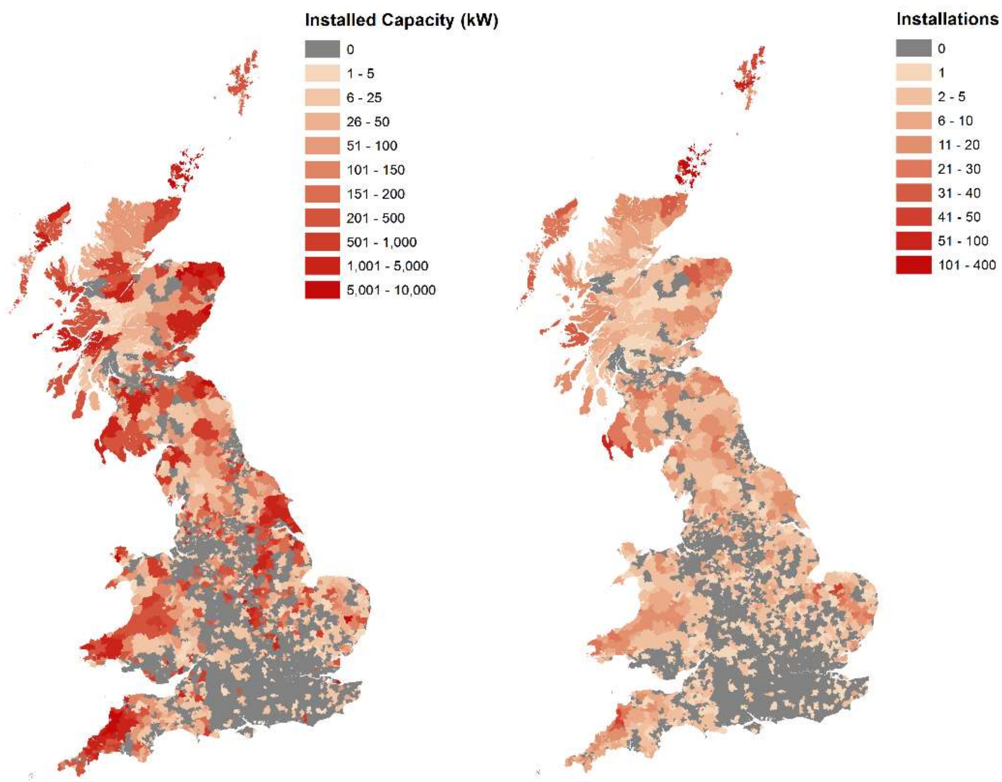

Figure 28 — Wind turbine installations at statistical geography level. Left: Installed capacity in each SG. Right: Installations in each SG

The spatial distribution of wind turbine installations highlights a key difference between wind turbine adoption data at LA or SG resolution. Figure 29 which presents the wind turbine adoptions at LA, demonstrates a wide coverage of wind turbine adoptions, with the majority of LAs containing at least one wind turbine installation. However, when this data was analysed at SG, the distribution of installations was sparser with many areas without a single wind turbine installation. While this was to be expected when examining on a finer spatial resolution, it highlighted that the distribution of wind turbine adoptions at LA level was composed of enclaves of installations in SGs in each LA.

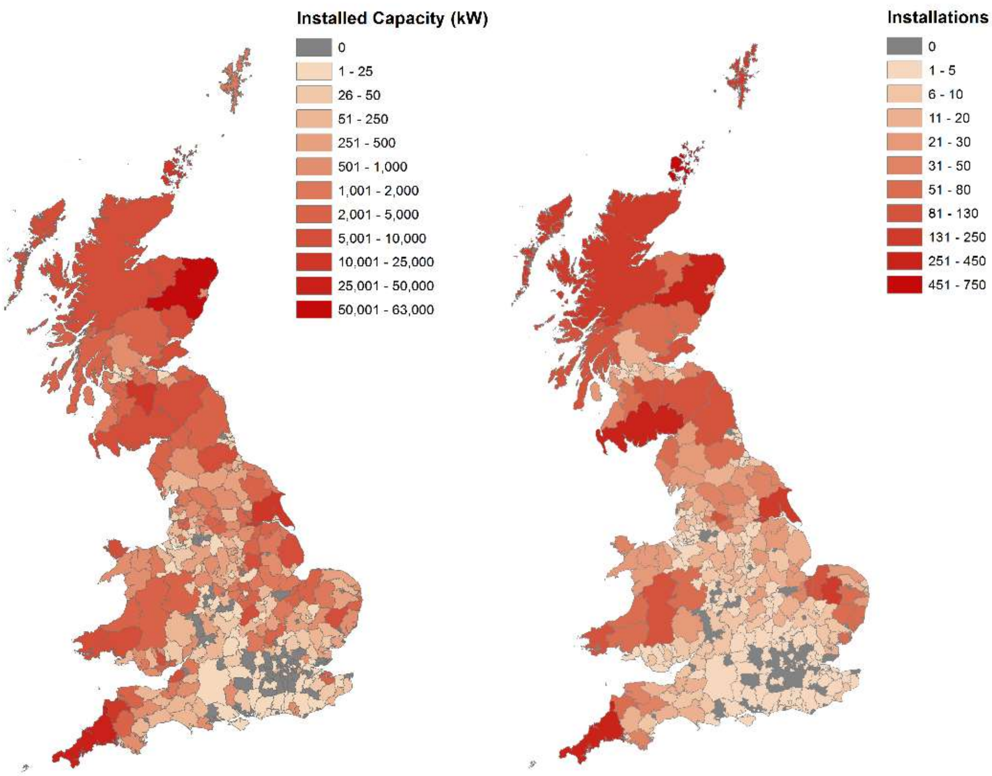

Figure 29 — Wind turbine installations at local authority level. Left: Installed capacity in each LA. Right: Installations in each LA

5.1.2 Independent variables

To analyse the influence of demographic factors on the wind turbine adoptions, the demographic data had to be collected and analysed prior to implementation of the regression models. Demographic data for Great Britain was available from the UK Census [161]. The SGs in this analysis were calculated from the 2011 census data. Therefore, the demographic data collected from the 2011 census was also utilised in this work. The census provided a wide variety of demographic statistics for residents of the UK. Due to the fact that the FIT was not available in Northern Ireland, only census data from England, Wales and Scotland was collected for this research [161]. For England and Wales, census data was available from the Office of National Statistics [161] while National Records for Scotland provided census data for Scotland [161].

Selection of the demographic variables for the analysis was guided by previous literature on the demographics of microgeneration adopters [42, 44, 56, 108, 110-120, 122]. Initially, the demographics of age, income, education, household size, homeownership and social class, which have been examined in previous studies were selected for each SG and LA [42, 56, 108, 110-118]. In addition to these variables, other census variables were also collected for analysis. Data on the martial status, number of dependent children, house sales, domestic electricity consumption, central heating types of home, industry classifications and geographical area of each SG and LA were extracted from the census for use in this work's analysis. As well as the census variables, data considering the farming statistics of each SG region was also collected from governmental sources [162-164]. Data regarding the long-term mean wind speed in each SG was calculated from the BLS model presented in Chapter 4. All of the data were collected from continuous datasets. The data sources and any data processing requirements of each data set collected is detailed in Table 10.

Table 10 — Data sources, data processing and notes of independent variables considered for inclusion in the analysis

Independent variable	Units	Country	Source	Census code	Spatial resolution	Data processing
Age*	Years	England and Wales	2011 Census - ONS	KS101EW	MSOA	-
		Scotland	2011 Census - NRS	KS101S	DZ	Aggregated to IZ
Income*	£/week	England and Wales	ONS – 2008	NA	MSOA	-
		Scotland	SNS - 2013	NA	IZ	-
Education*	% of residents	England and Wales	2011 Census - ONS	QS501EW	MSOA	-
		Scotland	2011 Census - NRS	QS501S	DZ	Aggregated to IZ
Home-ownership*	% of homes	England and Wales	2011 Census - ONS	QS405EW	MSOA	-
		Scotland	2011 Census - NRS	QS405S	DZ	Aggregated to IZ
House type*	% of homes	England and Wales	2011 Census - ONS	QS402EW	MSOA	-
		Scotland	2011 Census - NRS	QS402S	DZ	Aggregated to IZ
Social class	% of residents	England and Wales	2011 Census - ONS	QS607EW	MSOA	-
		Scotland	2011 Census - NRS	QS607S	DZ	Aggregated to IZ
Industry classifications*	% of residents	England and Wales	2011 Census - ONS	QS605EW	MSOA	-
		Scotland	2011 Census - NRS	QS605S	DZ	Aggregated to IZ
Farming statistics	Count/km^2	England	DEFRA	NA	LA	Estimated at MSOA
		Wales	Welsh Government	NA	“Small Area” statistics	Aggregated to MSOA
		Scotland	Scottish Government	NA	LA	Estimated at IZ
House sales*	Sales/year	England and Wales	ONS	NA	MSOA	
		Scotland	Registers of Scotland	NA	IZ	

Domestic energy consumption*	Mean kWh/year per SG region	England and Wales	DECC	NA	MSOA	-
		Scotland	DECC	NA	IZ	-
Type of central heating*	% of homes	England and Wales	2011 Census - ONS	QS415EW	MSOA	-
		Scotland	2011 Census - NRS	QS415S	DZ	Aggregated to IZ
Area*	km^2	England and Wales	2011 Census - ONS	NA	MSOA	-
		Scotland	2011 Census - NRS	NA	IZ	-
Wind speed*	ms^{-1}	Great Britain	BLS NCIC wind speed data[a]	NA	SG	-

*** - Variable was included in analysis**
ONS – Office of National Statistics
NRS – National Records of Scotland
SNS – Scottish Neighbourhood Statistics
DECC – Department of Energy and Climate Change
DEFRA – Department of Environment, Fisheries and Rural Affairs
KS – Census key statistics
QS – Census quick statistics
EW – England and Wales
S – Scotland
[a] - Created using the boundary layer scaling model presented in Chapter 4
NB. All data, except the wind speed data, was collected under the Open Government License

The specifics of each variable must be understood to ensure that the regression coefficient estimated for each variable could be interpreted accurately. Therefore, each of the variables in Table 10 will be discussed here and conclusions regarding their inclusion in the regression model will be presented.

The age variable utilised in this analysis was the median age of residents in each SG or LA [161]. Adopter income in this analysis was collected from estimates of the median weekly total household income in each SG, produced in 2008 in England and Wales and in 2013 in Scotland. These income estimates were normalised by the average median weekly household, calculated at £638 per week from all the SGs in Great Britain. This process effectively results in the income variable being dimensionless. The normalisation process was implemented to ensure that any skew from outlier income estimates in the sample was mitigated in the regression model. Both the age and income variables were selected for the regression model, based upon the findings of previous studies which examined their influence on the uptake of other microgeneration technologies [55, 56].

The education variable selected from the census was the percentage of residents in each SG with “Level 4” qualifications. Level 4 qualifications are defined as degree-level qualifications, Level 4 or 5 National Vocational Qualifications, higher level Business and Technology Education Council qualifications or any professional qualifications such as accountancy and nursing qualifications [161]. This was the highest level of qualification recorded in the 2011 census and was selected based on the findings of previous microgeneration adopter literature [56].

Homeownership was included in the regression models from a census variable which described the percentage of residents in a SG who either owned their homes outright or owned their homes under a mortgage agreement [161]. The percentage of residents in each of these two categories was combined to describe the number of homes which are owner-occupied in each SG. Previous literature has stated that adopters are more likely to live in detached homes [53]. A census variable which describe the percentage of properties which are classified as detached homes in each SG was also collected from the census data.

Multiple social class variables were considered for inclusion in the analysis, as it has been examined in a previous study [55], with a range of socio-economic classifications (SEC) available from the census. The SEC variables are derived from a resident’s occupation, specifically their relative level of seniority with a business [165]. However, as discussed, social class of a resident is related to the resident's income and educational level. A high degree of correlation was found to exist between the social class variables and the income and educational variables, which have been specifically examined in previous literature [55, 56]. Such a high level of correlation between variables in a regression model has a severe limiting effect on the results of the model [166] and, therefore, the social class variables were not included in this work.

Previous literature has highlighted the suitability of farms as locations for wind turbines [31, 167] and therefore a variable describing the prevalence of agriculture in a region was required within the regression model. Using an industry classification variable available in the census, it was possible to examine whether wind turbine adoptions were prevalent in regions with high levels of agriculture. The industry classifications in the 2011 census provided 21 differing classifications of resident occupation [168]. A classification for the percentage of residents who are employed in the agricultural, forestry or fisheries industry was available from the census. Regions in which a high percentage of residents who were classified in this industry classification are likely to have a relatively high level of agricultural industry and therefore only this industrial classification which describes the percentage of residents in a region who are employed in the agricultural, forestry or fisheries industry was included in the regression model.

In addition to the industry classification, farming statistics on the area farmed and the number of farms in each LA were available for England & Wales and Scotland [162, 163]. To ensure that these statistics were available for this analysis, each variable had to be estimated for the SGs in England and Scotland. The farming statistics in Wales were available at "small-area" geographies [164] and could be aggregated up to the SGs in Wales. Using a weighting derived from the area of the SGs in each LA, the farming statistics were split into the relevant SGs. However, there are severe limitations to this estimation approach. The exact proportion of farmed land and the number of farms in a SG could not be determined or validated. With the inclusion of the industry classification in the regression model, it was deemed unnecessary to include the estimation of farmed land and number of farms in the regression models.

The risk of losing money invested in a microgeneration technology has been cited as a barrier to adoption by potential adopters [54]. Therefore, variables that characterise the number of house sales in each region were considered for inclusion. The total number of annual house sales in each SG were available over a 20-year period. For England and Wales, data was available for each SG between 1996 and 2016 [169], while in Scotland this data was for house sales in each SG between 1993 and 2013 [170]. From this data, an mean number of annual house sales in each region of Great Britain was calculated. The mean number of annual house sales was then made dimensionless by the total number of homes in an SG. This process was required as the total number of homes in each SG was not consistent and therefore, the absolute number of house sales would not be comparable across regions. The mean percentage of annual house sales in a SG was then utilised in the regression models. There were limitations to using house sale data as a proxy for residents remaining in their homes following a wind turbine installation. As a mean percentage of house sales was utilised, it was not possible to identify if the homes which were sold in the region were the homes which had a wind turbine installation. Additionally, a decision to move home can be motivated by family reasons, employment opportunities or a desire to live in a different area, which could outweigh the desire not to lose money on a wind turbine investment. However, without data regarding the length of time a resident has lived in a home, the proxy of house sale data was suggested as the most suitable method of examining if residents who are less likely to move home will adopt a wind turbine.

Mean annual domestic electricity consumption was available for each SG. The mean annual domestic electricity consumption data was taken from sub-national consumption statistics produced by the Department of Energy and Climate Change in 2011 [171]. The mean annual electricity consumption in each region was estimated in kWh. These figures were calculated from the total supply of electricity to each region and the total number of electricity meters in each region. The inclusion of mean domestic electricity demand was motivated by a previous study which showed that individuals with a higher electricity demand were more likely to install a PV system [42]. Inclusion of the mean domestic electricity demand in this model was to test if this was true for wind turbine adopters.

The percentage of homes in a region with a specific type of central heating system was selected for this analysis. The number of homes with either gas-fired or electric powered central heating were collected from the census. The selection of these central heating variables were selected as a proxy for a region's rurality. Regions with a lower number of homes that utilise gas-fired central heating are likely to be more rural, as less homes in the region are unable to access the gas grid. The selection of the electric central heating variable was motivated by a desire to understand if wind turbines were installed to provide domestic electricity for space heating requirements or household electricity demand.

The availability of land has been suggested as a factor that influences wind turbine adopters and to analyse this influence, the geographical area of each SG was included. The statistical geographies were created based upon the population density and therefore, in a larger geographical area, it is likely that each residence will have a greater area of land available for a wind turbine installation. The geographical area of each SG were calculated from the boundary data of each region [159, 160]. Using geographical information software, the area of each region in square kilometres (km^2) was calculated for inclusion in the regression model.

All the census data discussed here was extracted as a percentage of residents or homes within a SG. Use of percentages in the census variables allowed for direct comparison of regions where the number of residents or homes was not consistent.

5.1.2.1 Influence of wind speed on wind turbine adoptions

Previous literature has discussed the importance of accuracy in a wind resource estimation for small scale wind turbines in Great Britain [32]. However, literature on the influence of available wind resource on small and medium scale wind turbine deployment in Great Britain is lacking. To determine the influence of wind resource on wind turbine adoptions in Great Britain, a separate regression model was developed. This regression model will be presented in Section 5.2.1.

Wind speed predictions from the boundary layer scaling (BLS) model presented in Chapter 4 were utilised as the wind resource metric in this analysis. 68.5 % of all wind turbines installed under the Feed-in Tariff have an installed capacity below 15 kW [12]. The 5 kW wind turbine, detailed in Chapter 4, has a hub height of around 15 m [151] and therefore this height was selected as representative of the likely hub height of wind turbines adopted in Great Britain. Wind speeds at 15 m from the BLS NCIC model were predicted for each hectare of all regions of Britain.

Wind turbine installations at SG level have no specific location in the region. Consequently, the long-term mean wind speed for the exact location of the wind turbine cannot be determined. To mitigate this, the long-term mean wind speed for each SG was suggested here as measure of the wind resource available for all wind turbines in the region. Selection of the mean wind speed of a region alone would not include a description of a site with a higher wind resource that may be located in the SG and would be a more suitable location for wind turbine installation. Wind turbine adoption patterns were therefore analysed against the wind speed metrics of the mean, maximum, median or modal wind speed at 15 m in each region. These wind resource metrics were initially analysed to understand which was the most appropriate wind speed metric to be taken forward into the further regression model.

In addition to the influence of available wind resource on deployment, the minimum wind speed required for deployment was also analysed. Previous literature, which offered the technical potential estimates of wind turbine deployment, defined sufficient wind speed for an installation as either a long-term mean wind speed above 5 ms^{-1} [31] or above 5.5 ms^{-1} [38]. However, these estimates were created using either MCS corrected NOABL [31] or unscaled NOABL [38] respectively. As shown in Chapter 4, the BLS NCIC data was the most accurate scaling methodology for wind speed prediction. It was therefore sensible to assess if the estimation of minimum wind speed required for deployment was still consistent when using BLS NCIC data.

To estimate the minimum wind speed that is likely to be required for wind turbine deployment, a multifaceted approach was developed. Initially, through analysis of the mean wind speed in regions where wind turbines have previously been adopted, it was possible to identify the lowest mean wind speed in a SG, which has been considered technically viable by current wind turbine adopters. However, as discussed previously, use of the mean wind speed metric across a region would not provide a description of any locations in a region, where the mean wind speed was higher and therefore a turbine would be better located. Therefore, additional analysis must be included to counter this issue.

This additional analysis aimed to determine the minimum wind speed required to ensure that a 5 kW wind turbine achieved a certain payback period. An acceptable payback period of a wind turbine is a subjective judgement from each adopter [108] and therefore a range of payback periods were analysed. The lifetime of the FIT is 20 years [26] and therefore 20 years was selected as the maximum payback period. Payback periods of 10 and 5 years were also selected, based upon the mean payback periods viewed as acceptable by current microgeneration adopters and those considering an adoption in Great Britain [55]. The minimum wind speed required for deployment was calculated in line with the methodology of the financial metrics set out in Chapter 4. The payback period was calculated based upon the financial returns from FIT payments for generation and savings made by offsetting the requirement to buy electricity from the grid. A FIT payment of 13.89 p/kWh [34] and an average electricity price of 15.95 p/kWh [152] were utilised in this analysis. This electricity price was calculated from 11 years of data available from DECC for the average price of standard electricity consumption [152]. This data was adjusted for inflation, from 2010 prices, and assumed an annual standard electricity consumption of 3,800 kWh [152]. At the time the analysis was conducted, this was the lowest FIT tariff rate, however, this has since changed. To ensure consistency with the cost estimates, which were only available from 2015, the electricity price and tariff level from October 2015 were retained for this analysis.

Using these variables, it was possible to calculate the minimum mean wind speed required to meet the three payback periods discussed. Using the results of both schemes of analysis, the minimum mean wind speed required for wind turbine deployment was suggested. Using the wind speeds available from BLS NCIC, this minimum wind speed estimate was envisaged to be more accurate than those derived from either MCS corrected NOABL [31] or unscaled NOABL [38] wind speed.

5.1.3 Analysis of independent variables

A total of 12 demographic and environmental variables were taken forward from the initial data set, described in Section 5.1.2, for further analysis prior to implementation of the regression models. The 12 variables and the abbreviations that were used within this chapter are detailed in

Table 11.

Table 11 — Independent variables included in regression models

Variable name	Abbreviation in this work	Variable name	Abbreviation in this work
Median age of residents in region	Age	Percentage of homes in a region with gas-fired central heating	GasCH
Dimensionless median weekly household income in region	Income	Percentage of homes in a region with electric powered central heating	ElecCH
Percentage of residents in region with degree-level or equivalent qualifications	Educa	Mean annual domestic electricity consumption in a region	AveElec
Percentage of homes in a region which are owned	Owned	Geographical area of each region	Area
Percentage of homes in a region which are detached homes	Detach	Long-term mean wind speed at 15 m in each region	$\bar{u}$
Percentage of residents who are employed in either the agricultural, forestry or fisheries industry	IndA	Dimensionless mean number of house sales in a region	HouseSales

Initially, the variables were assessed to understand if a normalisation was required. For the variables extracted from the census, all those except Age, AveElec, Area and $\bar{u}$, were provided in the form of percentages for each region, which were comparable across all regions and therefore no further normalisation to make these variables dimensionless was required. For the variables of median age and mean electricity consumption, no normalisation was applied. The mean value of each of these variables, 44 years for median age and 3,800 kWh for mean electricity consumption, was utilised as a reference point for relative influence of each variable in the regression models. For example, if the median age was shown to have a negative regression coefficient, it would be concluded that wind turbine adopters were generally below this mean age. For the wind speed variable, a normalisation process was possible, however, given that it was investigated separately from the other demographic variables, the wind speed values extracted from the BLS model remained unchanged. For the geographical area of a region, no normalisation was possible, as this data was heavily skewed. A normalisation of these variables could have increased the skew of the variables and adversely influenced their results from the regression models.

The presence of skewed variables, such as the area variable, suggested that the possibility of transforming the independent variable should be analysed. The transformation of each variable was tested to identify the most appropriate transformation required for each variable in the regression model. In total, ten transformations were considered for each of the demographic and environmental variables and are presented in Table 12.

Table 12 — Ten transformations of each independent variable considered

Transformation Number	Transformation Formula	Transformation Number	Transformation Formula
1	x	6	$\sqrt{x}$
2	$log_{10} x$	7	x^2
3	$1/x^2$	8	x^3
4	$1/\sqrt{x}$	9	$a_1x + a_2x^2$
5	$1/x$	10	$a_1x + a_2x^2 + a_3x^3$

The relationship between each dependent variable and each transformed variable was assessed and the transformation of each variable which yielded the highest coefficient of determination was deemed the appropriate transformation of each independent variable. The differing combinations of transformations for each dependent variable were analysed to develop a unified set of transformations of the independent variables to be used in all the regression models. In total, only three of the ten transformations were utilised, with the transformation of each variable presented in Table 13

Table 13 — Transformation applied to each independent variable

Variable	Transformation Applied	Variable	Transformation Applied
Age	x	GasCH	x
Income	x	ElecCH	x
Educa	x^3	AveElec	x
Owned	x	Area	$log_{10} x$
Detach	x	ū	x
IndA	$\sqrt{x}$	House Sales	x

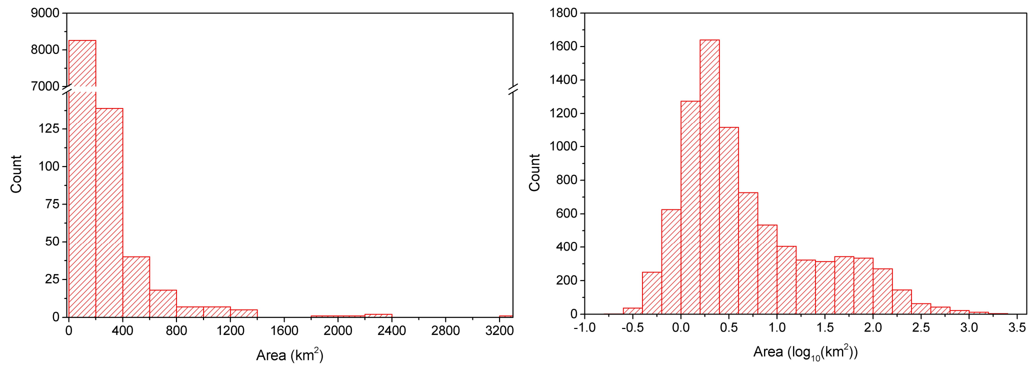

Figure 30 — Comparison of left: raw area variable and right: transformed area variable

The influence of the transformation and the rationale for their inclusion is illustrated best by Figure 30. The untransformed area variable, shown on the left of Figure 30, is heavily skewed with a long-tail distribution. Caused by a large number of SG regions in the sample with small geographical areas, the skew in the untransformed data could adversely affect the estimated regression coefficient. The transformed area variable, after undergoing a logarithmic transformation can be seen on the right of Figure 30. This data is more evenly distributed and therefore was less likely to skew the estimation of the regression coefficient.

Only the education, industry classification and area variables were transformed. While the transformations were assessed using the R^2 value, the quantitative outcome of the transformation was to normalise the distribution of these variables. As shown in Figure 30 for the area variable, the transformation of the education and industry variable prior to the regression normalised their distribution. This was particularly important for the industry variable where the range of the untransformed variable was small with the maximum value of 22%. Similar to the area variable, the majority of the regions have low levels of agricultural industry leading to a skewed distribution. The transformation of the educational, industry and area variables prior to the regression model effectively normalised their distribution which meant that estimation of the regression coefficient was adversely influenced.

Minimal use of transformed variables allowed the regression model to assess the linear relationship between wind turbine adoptions and each independent variable. As no inverse transformations of the variables were required, the direction of the relationship between each transformed variable and the dependent variable was the same as the untransformed set of each variable. The transformations influenced the value of the regression coefficients of the models, but as discussed were required to ensure that heavily skewed variables did not adversely affect the results of the regression model. This allowed for consistent analysis of the transformed and untransformed variables in the regression models to determine their influence on wind turbine adoptions in Great Britain.

The regression models in this chapter were undertaken in R, version 3.2.3 [172]. Within R, the “lmtest” [173] and “sandwich” [174] packages were utilised to provide the statistical packages to conduct the regression analysis and diagnostic tools to verify the models. Additionally, some data processing was conducted using MATLAB R2013b [175] under an academic license. Any maps presented in this chapter were created in MATLAB and visualised in ArcMap 10.2.2 [176].

5.2 Regression models and results

In total, three regression models were created to analyse the influence of: wind resource; the five demographic factors of age, income, education, homeownership and house type previously suggested in literature; and the other suggested demographic and environmental factors discussed throughout this chapter. The four dependent variables of: wind turbine installations at LA level (LA Inst); installed capacity of wind turbines at LA level (LA Cap); wind turbine installations at SG level (SG Inst) and installed capacity of wind turbines at SG level (SG Cap) were used in each of the three models described.

5.2.1 Wind resource regression model

Using the BLS NCIC wind speeds predicted at a hub height of 15 m, the influence of wind resource on wind turbine adoptions was analysed. The general form of the wind resource regression model was as follows;

$$\log_{10}(WT_i) = \beta_0 + \beta_1 u_i + \varepsilon_i$$

Equation 47

where $\log_{10}(WT_i)$ was a $N \times 1$ vector of logarithmic transformations of wind turbine installations or installed capacity in region, i, u_i was a $N \times 1$ vector of wind speed metrics of each region while β_1 was the regression coefficient of each wind speed metric, ε_i was the residual term in each region and β_0 is the intercept term of the model.

As discussed, four wind speed metrics, the maximum, mean, median and modal wind speed in each region, were initially examined. Multiple wind speed metrics were initially analysed as the mean wind speed of a region may not accurately describe sites with a higher mean wind resource in the region which would be more suitable for a wind turbine installation. To determine which of these metrics was considered the most appropriate and therefore to be investigated further, the coefficient of determination (R^2) of each model using each wind speed metric was calculated, and the results are presented in Table 14.

Table 14 — Coefficient of determination for each wind resource regression model with different wind speed metrics as the independent variables

	Wind speed metric				
Dependent variable	**Maximum (R^2)**	**Mean (R^2)**	**Median (R^2)**	**Mode (R^2)**	**Sample Size**
LA Cap	0.081	0.220	0.210	0.139	285
LA Inst	0.125	0.345	0.326	0.243	285
SG Cap	0.061	0.095	0.093	0.056	1377
SG Inst	0.173	0.202	0.187	0.136	1377

As seen in Table 14, the highest R^2 value was observed in the wind resource regression models which used the mean wind speed of a region at 15 m as the independent variable. The mean wind speed of each region was therefore used as the wind speed metric in the subsequent regression models of this work.

The wind resource regression models utilising mean wind speed as the independent variable were analysed further to determine the influence of wind resource on wind turbine adoptions. The regression coefficients, β_1, estimated to describe the influence of the mean wind speed of a region on the dependent variable, are presented in Table 15.

Table 15 — Wind regression models for each dependent variable

	Intercept, β_0	**Regression coefficient, β_1**	**R^2**
LA Cap	-0.500	0.589***	0.220
LA Inst	-1.298***	0.453***	0.345
SG Cap	0.376***	0.271***	0.095
SG Inst	-0.606***	0.202***	0.202

*** — Significant at 99 %
** — Significant at 95 %
* — Significant at 90 %

The scatter plots of mean wind speed at 15 m against each dependent variable and the apparent fit from each regression model are presented in Figure 31 and Figure 32.

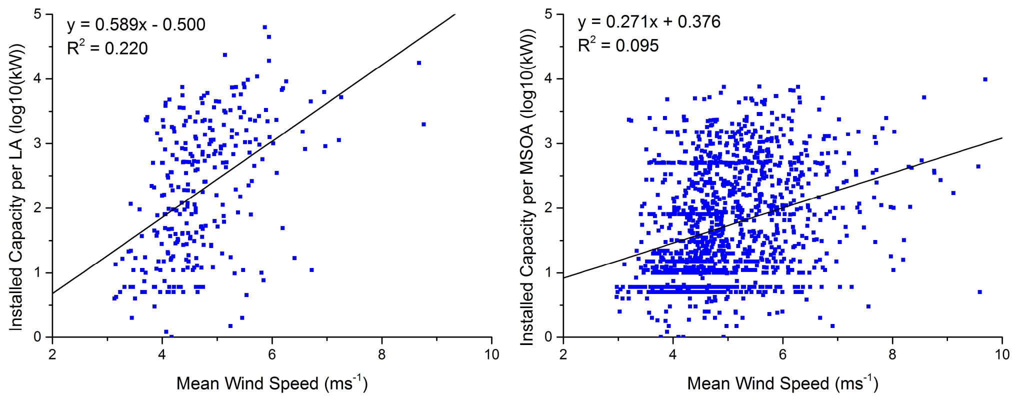

Figure 31 — Scatter plots of wind resource regression models with installed capacity as the dependent variable. Left: LA level. Right: SG level

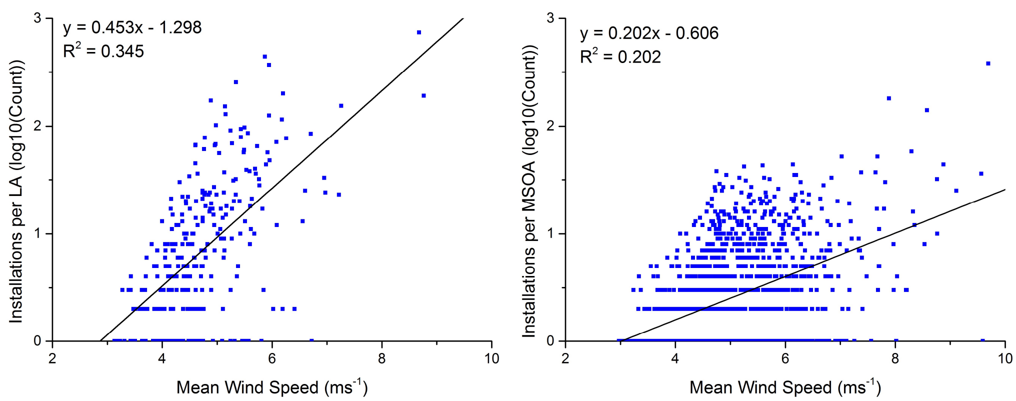

Figure 32 — Scatter plots of wind resource regression models with installations as the dependent variable. Left: LA level. Right: SG level

The trend in all of the apparent fits, shown by the straight lines on each plot, from the regression models was that the availability of wind resource has a positive influence on wind turbine adoptions. Regions with a higher mean wind speed were more likely to have a higher number of wind turbine installations and higher installed capacity. The regression coefficient of the mean wind speed in each model was significant as seen in Table 15. Mean wind speed and more broadly, wind resource is therefore concluded to be a significant influencing factor on wind turbine adoptions in Great Britain. This conclusion supports the findings in literature on PV adoptions which highlighted that the availability of solar resource was a significant influencing factor [42]. Additionally, this conclusion is supported by previous literature, which highlighted that the financial returns of a microgeneration installation were considered most important by adopters [54, 55]. The level of wind resource available to a wind turbine directly influences the financial returns through the financial incentives available from the FIT. Therefore, it is concluded that wind resource is an influencing factor on wind turbine adoptions.

The influence of wind resource appeared to differ between the dependent variables of the regression model. The coefficients of determination, R^2, were higher for the regression models using installations as the dependent variable. The difference between R^2 values of the installed capacity and installation models highlighted that wind resource, as an independent variable, could explain a greater degree of the variance in the adoption patterns of installation compared to the adoption patterns of installed capacity. The underlying reason for this is the different installation types and thus different types of wind turbine adopters, which were dominant in the installed capacity or installation data samples. Domestic wind turbine installations dominate in the installation data and therefore the results of the model suggest that wind resource was a more influential factor in domestic rather than commercial wind turbine projects. Commercial wind turbine projects are likely to have a higher installed capacity to provide sufficient electricity for a commercial site which has higher electricity demand than domestic homes. It is likely that the electrical demand of the individual sites and the ability to raise sufficient capital for a turbine will have had an influence on the capacity of wind turbine installed. However, a higher capacity turbine is also likely to have a higher hub height than 15 m to access higher wind speeds. Therefore, in these non-domestic wind turbine projects, it is likely that the mean wind speed at 15 m used in this research did not describe the wind speed captured by the higher capacity turbine and resulted in the lower influence observed in the results.

Conversely, while the R^2 values were lower, the regression coefficients estimated in the installed capacity models were higher than the comparable regression coefficients estimated in the installation models. The difference between the regression coefficients demonstrates that in regions with higher mean wind resource, the regression models predicted that higher capacity wind turbines would be installed. Adopters of higher capacity wind turbines were likely to desire higher wind resource, to ensure that the financial returns of a turbine were maximised and installed in regions with a higher mean wind resource, hence the results of the model.

Each of the regression models also showed that wind resource was likely to be one of multiple factors that influenced a wind turbine adoption. The highest R^2 of all of the models is only 0.345 for installations at LA level. Wind resource was therefore only able to explain, at most, 35 % of the variance in the wind adoption patterns of Great Britain. This suggests that there were other factors that influenced British wind turbine adopters. This conclusion highlights the rationale of developing other regression models in this work, which examined the influence of additional factors on wind turbine adoption patterns in Great Britain.

5.2.1.1 Minimum deployment wind speed

As wind resource was an influential factor on wind turbine adoptions, it was vital to understand the predicted minimum wind speed required for wind turbine deployment. Previous estimates have suggested a long-term mean wind speed of either 5 ms^{-1} [31] or 5.5 ms^{-1} [38] is required for wind turbine deployment. However, these estimates were produced using either MCS NOABL or raw NOABL data, which were both shown in Chapter 4 to be inaccurate for wind speed prediction. With estimated wind speeds available from the BLS NCIC, which had a greater degree of accuracy than either MCS NOABL or raw NOABL, it was possible to determine the long-term mean wind speed which was considered to be the viability threshold for deployment.

Initially, the mean wind speed of regions with at least a single wind turbine installation were examined. Through this analysis, it was possible to determine the minimum mean wind speed that current adopters have considered sufficient for a wind turbine to be viable. Figure 33 shows the histogram of mean wind speeds of LAs and SGs with at least a single wind turbine installation.

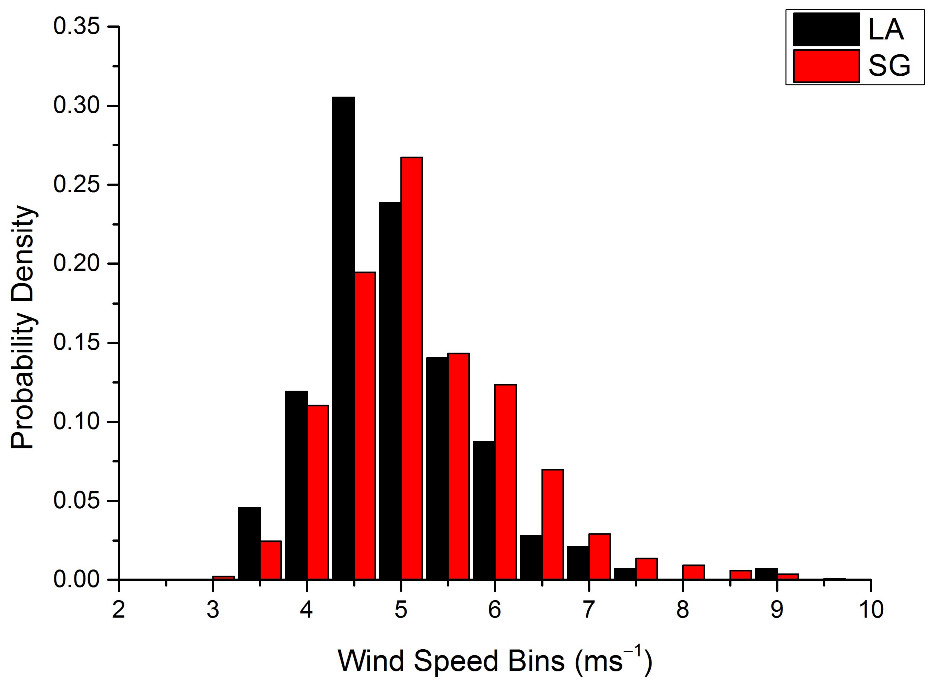

Figure 33 — Histogram of mean wind speeds of either LAs or SGs with at least a single wind turbine installation

Figure 33 showed that the lowest mean wind speed of any region with a wind turbine installation was just above 3 ms^{-1}. However, only 0.04 % of all turbines were installed in a region with such a low mean wind speed. It was concluded that the mean wind speed of the region was not likely to be representative of the mean wind speed at the site of this wind turbine. Similarly, this was considered the case for the wind turbines installed in regions with a mean wind speed below 4 ms^{-1}. Only 1.5 % of all turbines were installed in a region with a mean wind speed below 4 ms^{-1}. It was therefore concluded that the minimum mean wind speed required for deployment was between 4 ms^{-1} and 4.5 ms^{-1}. Only a small percentage of wind turbines, 6.4 % at LA level and 8.3 % at SG level, were sited in regions with a mean wind speed below 4 ms^{-1}. In regions with a mean wind speed between 4.5 ms^{-1} and 5 ms^{-1}, wind turbine deployment increased dramatically. 30 % of all turbines at LA level and 26 % of all turbines at SG level were sited in regions with a mean wind speed between 4.5 ms^{-1} and 5 ms^{-1}. While these results indicated a minimum wind speed for deployment, they must be treated with caution. As seen in regions with a mean wind speed below 4 ms^{-1}, the mean wind speed may not be representative of the actual mean wind speed of the turbine site. The calculation of the minimum mean wind speed required to achieve certain payback periods was therefore conducted.

Analysis of the minimum wind speed required to achieve payback periods of 20, 10 and 5 years was conducted. As discussed in Section 5.1.2.1, the payback period was calculated for a 5 kW turbine using a Weibull shape factor of 1.8, an average electricity price of 15.95 p/kWh [152] and a FIT payment of 13.89 p/kWh [34]. The results of this analysis are presented in Table 16.

Table 16 — Minimum mean wind speed required to meet payback period thresholds for 5 kW wind turbine

Payback period threshold (Years)	Mean wind speed (ms^{-1})	Actual payback time at mean wind speed
20	3.8	18 years, 5 months
10	4.6	9 years, 9 months
5	6.2	4 years, 10 months

The results of Table 16 supported the conclusions drawn from Figure 33, that the minimum wind speed of between 4 ms^{-1} and 4.5 ms^{-1} was required for deployment. To achieve a payback of under 20 years, a mean wind speed of at least 3.8 ms^{-1} was required. However, this payback period at 3.8 ms^{-1} of 18 years represented the minimum wind speed required for the wind turbine to payback within the lifetime of the FIT. Realistically, the payback period desired by potential adopters would be lower and therefore a higher mean wind speed would be required. Individuals considering a wind turbine installation have cited 11 years as a minimum desired payback period [108]. To achieve such a payback period, a mean wind speed of 4.5 ms^{-1} was required. It is therefore concluded that the minimum mean wind speed required for further wind turbine deployment in Great Britain is 4.5 ms^{-1}. At a mean wind speed of 4.5 ms^{-1}, a 5 kW wind turbine is predicted to pay back the capital expenditure required to install in 10 years and 4 months. However, it is noted that the minimum wind speed was determined using the FIT tariff from October 2015. With lower tariff rates, a higher minimum wind speed would likely be required for deployment.

The minimum wind speed of 4.5 ms^{-1} required for deployment, presented here, was lower than previous estimates. This was a result of the use of more accurate wind speeds estimates from the BLS NCIC model used in this analysis. The new minimum wind speed calculated in this analysis has an impact on the number of regions across Great Britain which have a sufficient mean wind speed. At 5 ms^{-1}, 22.5 % of all SGs have a sufficient mean wind speed, whereas 51.2 % of all SGs have a mean wind speed of 4.5 ms^{-1} or above. This conclusion therefore, has a consequence on future potential deployment estimates, as it has been shown here that there are more SGs in which a wind turbine could be installed. However, the impact of these findings on actual deployment may be less than predicted. While this analysis demonstrated that payback of a 5 kW turbine can be achieved in around 10 years in regions with a mean wind speed above 4.5 ms^{-1}, whether this is considered an acceptable payback period is subjective to each individual adopter.

5.2.2 Demographic regression model

The variables included in the demographic model were; the median age of residents, Age_i, dimensionless median weekly income of residents, $Income_i$, percentage of residents with degree-level or equivalent qualifications, $Educa_i$, percentage of homes that are owner-occupied, $Owned_i$ and the percentages of homes which are detached, $Detach_i$. The general form of the demographic regression model was as follows;

$$\log_{10}(WT_i) = \beta_0 + \beta_1 Age_i + \beta_2 Income_i + \beta_3 {Educa_i}^3 + \beta_4 Owned_i + \beta_5 Detach_i + \varepsilon_i$$

Equation 48

where $\log_{10}(WT_i)$ was a $N \times 1$ vector of logarithmic transformations of wind turbine installations or installed capacity in region, i, $\beta_{1 \ldots n}$ was the regression coefficient of each of the demographic variable included, ε_i was the residual term in each region and β_0 was the intercept term of the model. The education term underwent a cubic transformation, based upon the initial analysis of the independent variables presented in Section 5.1.3.

The estimated regression coefficients of each demographic variable in each regression model are detailed in Table 17.

Table 17 — Regression coefficients of each variable in the four demographic regression model, installed capacity at LA resolution, LA Cap, number of installations at LA resolution, LA Inst, installed capacity at SG resolution, SG Cap and number of installations at SG resolution, SG Inst

Variable	LA Cap	LA Inst	SG Cap	SG Inst
Age, β_1	0.005 (0.214)	0.037** (2.362)	-0.010* (-1.656)	0.012*** (4.169)
Income, β_2	-3.118*** (-6.709)	-1.795*** (-6.474)	-1.282*** (-10.392)	-0.644*** (-9.804)
Education, β_3	14.223*** (2.792)	11.75*** (3.928)	1.208 (1.161)	2.415*** (4.594)
Owned, β_4	2.177 (1.646)	-0.622 (-0.744)	0.662** (2.097)	-0.244 (-1.521)
Detached homes, β_5	1.833*** (2.933)	1.692** (4.121)	1.247*** (6.282)	0.901*** (8.351)
Constant, β_0	2.256***	0.228	1.992***	-0.064
R^2	0.258	0.314	0.110	0.189

t-test value for each coefficient is included in the parentheses
*** — Significant at 99 %
** — Significant at 95 %
* — Significant at 90 %

The regression coefficients estimated in each model, presented in Table 17, highlighted the relative influence of each variable on wind turbine adoptions. The demographic model suggests that the number of wind turbine installations was higher in regions where the median age of residents was higher. The age of the wind turbine adopters was likely to be higher than 44 years of age, the mean age for the sample analysed in the demographic model. It was noted that the age variable was only shown to be significant in the demographic models which utilised installations as the dependent variable. This links into the difference between installed capacity and installation data, discussed in Section 5.2.1. Turbines with a higher installed capacity are likely to be installed for non-domestic requirements. When examining the installation data, which is dominated by domestic adopters, the age of adopters becomes a significant factor which influenced wind adoptions. This finding is in line with previous literature, which showed that adopters of PV systems were likely to be aged over 45 [56]. The influence of adopter age was likely to be due to older adopters having capital to invest, following an accumulation through their working life [53]. Additionally, adopters aged around 45 may be approaching their peak career income [177], and be planning and saving for retirement. Adoption of a wind turbine may represent a method of protecting against rising fuel bills after retirement [178].

While wind turbine adopters could be reaching peak career earnings, the model results indicated that they may have a lower than mean weekly income. This is in sharp contrast to other literature, which suggested that PV adopters have higher than mean income [56]. However, the cause of this result regarding the influence of income was likely to be borne out of where wind turbines were installed. Wind turbines are likely to be more effective in rural areas, where the mean weekly incomes of residents were lower than national average. The mean weekly income in rural areas of the sample was around £515 per week, below the mean across the whole sample of £638 per week. This factor was likely to be the underlying cause of the negative regression coefficients for income observed in the demographic model. This result does not necessarily indicate that individual adopters of wind turbines in these regions have lower than average incomes, rather that they were likely to live in regions where the mean income of all residents was lower than the national average.

Additionally, the outcome of the demographic model indicates that it may have been the capital which an adopter has accumulated, rather than weekly income, having a greater influence on a decision to adopt. Previous literature has suggested that an adopter’s accumulated capital rather than annual household income was more influential for PV adoptions across Great Britain [42]. It is therefore suggested here that while an adopter’s weekly income may have played a role in an individual decision to adopt a wind turbine in Great Britain, it was likely that an adopter had sufficient capital saved and this may have had a greater influence on a decision to adopt than the weekly income of the adopter alone.

Wind turbine adoptions, both in terms of installed capacity and installation numbers was shown to increase in regions where high levels of adopters had a degree-level or equivalent education. This finding is in line with previous literature which suggested a positive correlation between adopter education and PV adoption [56, 118, 121, 122]. The link between adopter education and wind turbine adoption is also in agreement with Rogers’ description of the educational levels of earlier adopters of new innovations [132]. Earlier adopters of a new innovation are likely to have higher levels of education attainment, as they are more likely to be able to understand the technical complexities of a new innovation and therefore are more likely to adopt [132]. This conclusion was supported by the results of the demographic models, which showed that a resident’s level of education had a positive influence on wind turbine adoption patterns.

The regression coefficients for the homeownership variable were shown to not be significant, except for the model examining installed capacity of wind turbines at SG level. In this model, homeownership was shown to be a positive influence on the installed capacity of turbines in a region. This result is somewhat contradictory given that the installed capacity data was dominated by commercial installations, whereas the homeownership variable included only the ownership of domestic homes. It is therefore concluded that the result of this demographic model was coincidental with regions with high capacity turbines for commercial use were also likely to have been regions with high levels of domestic homeownership.

While homeownership has not been shown to be significant in the majority of the demographic models, it is still likely to have been an influence on individual decisions to adopt a wind turbine. The highest levels of homeownership are usually observed in suburban areas. Suburban areas are not as suitable for wind turbine adoptions, due to the likely lower wind resource than more rural areas [179], where homeownership could be lower. Lower homeownership in rural areas could be linked to increasing numbers of second or holiday homes, which have increased rural house prices and resulted in lower levels of owner-occupiers of the homes in these areas [180]. It is therefore envisaged that wind turbine adopters may live in regions where the levels of homeownership were comparatively low, however, they are likely own their home which allowed them to install a wind turbine. This would be consistent with the issues of the landlord-tenant dilemma [53] and other literature which had suggested that homeownership is an important factor in microgeneration adoptions [43, 45, 56, 108].

While homeownership may not have been shown to be influential, the percentage of detached homes of a region was shown to be a significant factor which influenced wind turbine adoption patterns in Great Britain. The demographic model showed that wind turbines were installed in areas where the number of detached homes was high. This conclusion is consistent with previous literature which suggested that higher levels of detached homes in a region had a positive effect on PV adoptions [42]. The influence of an adopter’s house type is particularly important for wind turbines, which are at their most effective in regions where the housing density is low and wind speed is likely to be higher. This is likely to be the underlying cause of the significant relationship, shown in the demographic models. The influence of detached homes shown in the model was likely to be centred around the greater availability of land for a wind turbine installation at a detached house.

Overall, the demographic models showed that current adopters of wind turbines in Great Britain were likely to be older, live in a region with a lower than mean income, hold a degree-level or equivalent qualification and live in detached home. It was possible that the adopter may own their home, however, the results of the demographic model did not conclusively prove this. These findings are significant as no previous research has identified any demographic profile of wind turbine adopters in Great Britain.

The scatter plots of predicted against actual installed capacity or installations from each demographic regression model are presented in Figure 34 and Figure 35.

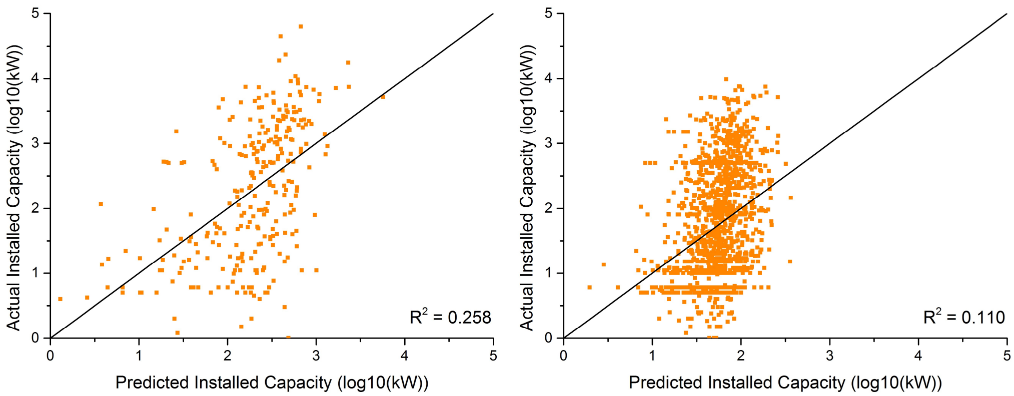

Figure 34 — Scatter of log predicted vs actual installed capacity from the demographic model, where the line represents one to one relationship. Left: LA level. Right: SG level

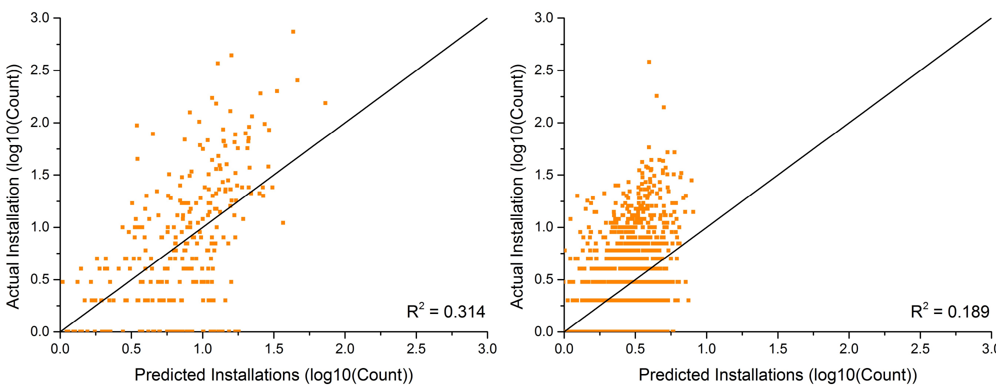

Figure 35 — Scatter of log predicted vs actual installations from the demographic model, where the line represents one to one relationship. Left: LA level. Right: SG level

Overall, the scatter plots in Figure 34 and Figure 35 showed the factors included in the demographic model offered a relatively good description of the variance in wind turbine adoption patterns. Explanation of the variance was considered better in the demographic models at LA than in the SG model, where the scatter was closer to the line representing an $y = x$

relationship in each plot. However, an interesting phenomenon was observed in these scatter plots. For each demographic model, there appeared to be an upper limit of the predicted value of the dependent variable. It was more apparent in the SG models, where the predicted logarithmic installed capacity did not exceed 2.5 while predicted logarithmic installations did not exceed 1. This phenomenon suggests that the variables of the demographic model were only able to explain a proportion of the variance in current wind turbine adoption patterns. This was further supported by the R^2 values of each demographic model, which were at a similar level to those of the wind resource regression model. The R^2 values suggested that while the factors of the demographic variables could explain some of the variance in wind turbine adoption patterns, additional factors may be able to improve the R^2 values further.

Additionally, the fact that the predicted dependent variables from the demographic model did not exceed certain levels suggests that the demographic variable were only able to explain the underlying cause of individual decisions to adopt. In areas where there was higher wind turbine deployment, the factors included in the demographic model were insufficient to explain this variance. It was therefore, logical to extend the demographic model to include other factors suggested as being influential, including the mean wind speed of each region.

5.2.3 SER regression model

The demographic regression model was extended to include the variables of percentage of residents employed in the agriculture industry, $IndA_i$, percentage of homes with gas central heating, $GasCH_i$, percentage of homes with electric central heating, $ElecCH_i$, mean annual domestic electricity consumption, $AveElec_i$, the mean number of house sales annually in a region, $HouseSales_i$, the geographical area, $Area_i$, and mean wind resource of each region, $\bar{u}_i$. Inclusion of these variables in the demographic model allowed the influence of these additional factors on wind turbine adoption patterns to be analysed. These variables were included to determine whether they could better explain the variance in wind turbine adoption patterns. With the inclusion of these variables, the new regression model, known as the Socio-Economic and Resource (SER) regression model was developed. The general form of the SER regression model was as follows;

$$\log_{10}(WT_i) = \beta_0 + \beta_1 Income_i + \beta_2 Educa_i{}^3 + \beta_3 Detach_i + \beta_4 \sqrt{IndA_i} + \beta_5 GasCH_i + \beta_6 ElecCH_i + \beta_7 AveElec_i + \beta_8 HouseSales_i + \beta_9 \, log_{10}(Area_i) + \beta_{10} \bar{u}_i + \varepsilon_i$$

Equation 49

where $\log_{10}(WT_i)$ was a $N \times 1$ vector of logarithmic transformations of wind turbine installations or installed capacity in region, i, $\beta_{1...n}$ was the regression coefficient of each of the variables included in the SER model, ε_i was the residual term in each region and β_0 was the intercept term. The variables of age and homeownership were removed from the SER model. Homeownership was removed as it was shown to not be significant in the demographic model and therefore inclusion in the SER model would be superfluous. The age variable was removed due to collinearity with the industrial classification variable. These variables were found to have a Pearson correlation coefficient of 0.56 in the LA data and 0.46 in the SG data. Removal of the age variable allowed the influence of agricultural industry in a region to be examined in the SER model using the industry classification variable. Age was the only factor removed during the modelling, although other pairs of variables had higher correlation factors. The paired variables with higher correlation coefficients were those variables which were expected to be have a degree of correlation, such as agricultural industry and levels of gas central heating which had a -0.84 correlation coefficient. To determine the variables that must be removed, the variance inflation factor was calculated. This approach was iterative to develop a set of variables where the collinearity between the variables was minimised. It was through this approach that the age variable was ultimately removed from the SER model. The regression coefficients of the SER model are presented in Table 18.

Table 18 — Regression coefficients of each SER regression model, installed capacity at LA resolution, LA Cap, number of installations at LA resolution, LA Inst, installed capacity at SG resolution, SG Cap and number of installations at SG resolution, SG Inst

Variable	LA Cap	LA Inst	SG Cap	SG Inst
Income, β_1	-1.433*** (-2.595)	-0.841*** (-3.452)	-0.558*** (-4.109)	-0.080 (-1.328)
Education, β_2	1.879 (0.351)	2.730 (1.205)	-2.986*** (-2.679)	-0.151 (-0.359)
Detached homes, β_3	-0.172 (-0.298)	-0.264 (-1.01)	0.057 (0.313)	-0.026 (-0.356)
Agricultural industry, β_4	2.270 (1.141)	1.093 (1.061)	1.951*** (3.888)	1.903*** (7.532)
Gas central heating, β_5	-0.712 (-0.667)	-1.027* (-1.915)	0.165 (0.89)	-0.198** (-2.211)
Electric central heating, β_6	-4.035 (-1.618)	-1.106 (-0.984)	-0.722 (-1.636)	-0.232 (-1.027)
Mean electricity consumption, β_7	-2.01E-4 (-0.729)	-1.11E-4 (-0.851)	1.15E-4** (2.121)	7.29E-6 (0.307)
Mean house sales, β_8	7.768 (1.065)	3.743 (1.249)	3.832** (2.528)	1.140* (1.88)
Area of region, β_9	0.861*** (4.574)	0.670*** (8.372)	0.193*** (2.986)	0.055* (1.877)
Mean wind speed, β_{10}	0.118 (1.24)	0.058 (1.225)	0.109*** (3.71)	0.094*** (6.166)
Constant, β_0	2.041	0.787	0.414	-0.333*
R^2	0.411	0.624	0.187	0.430
Breusch-Pagan (BP) statistic	21.2**	15.2	20.3**	118.7***
Durbin-Watson (DW) statistic	1.87*	1.71***	1.54***	1.42***

t-test value for each coefficient is included in the parentheses
*** — Significant at 99 %
** — Significant at 95 %
* — Significant at 90 %

The initial comment which must be made regarding the SER model is the results of the Breusch-Pagan (BP) test of heteroskedasticity [181] and the Durbin-Watson (DW) test for autocorrelation [182]. These tests are commonly used diagnostic tests for a regression model. The BP test examines whether the residuals of the model are randomly distributed and not dependent on the values of the independent variables of the model [181]. An example of heteroskedasticity is shown in Figure 36 and shows a sample of the residuals plotted against the fitted values from the SG Inst SER model. As discussed, the residuals should be randomly distributed around the dashed line, which represents a residual value of zero. However, this is not seen in Figure 36 where the residuals appear clustered for lower fitted values and thus exhibiting the heteroskedasticity of the model.

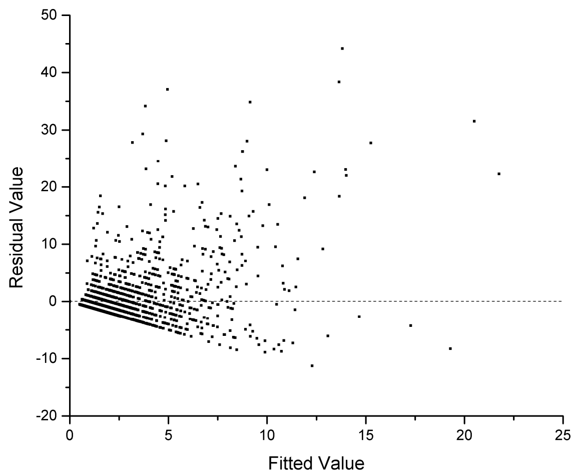

Figure 36 — A graphical example of heteroskedasticity in regression residuals

The value of BP test is calculated by performing an auxiliary regression using the residual values as the dependent variable and the fitted values as the independent variable [181]. The coefficient of determination of this auxiliary regression and the sample size is used to calculate the BP test value, with its significance calculated using the chi-squared distribution [173]. Table 18 shows that the SG Inst SER model has the highest BP test value and therefore exhibited the highest level of heteroskedasticity in this model's residuals.

The DW test examines whether the residuals of the regions in the model exhibited correlation with each other [182]. An example of autocorrelation is shown in Figure 37 and shows a sample of the residuals plotted against the identification number of each SG from the SG Inst SER model. Where no autocorrelation would be observed, the residuals would exhibit a more random distribution.

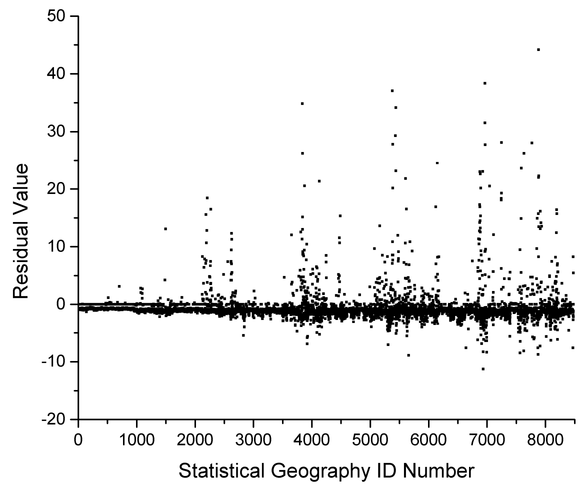

Figure 37 — A graphical example of autocorrelation in regression residuals

The residuals observed in Figure 37 show that residuals in certain areas of Great Britain are similar. While the SG identification numbers are not always sequential for neighbouring SGs, the identification numbers are typically sequential from some areas of Great Britain. Therefore, the peaks seen in Figure 37 demonstrate that residuals of SGs in some areas of Great Britain are similar and autocorrelation can be observed in the regression residuals.

The value of the DW test always a lies between 0 and 4 with a test value of 2 indicating no autocorrelation in the residuals [183]. A DW test value below 2 indicates that positive autocorrelation has been observed, where the residuals of neighbouring regions have the same sign while test values above 2 indicate negative autocorrelation [183]. The DW test values in Table 18 indicate that positive autocorrelation was observed in the model residuals, with the values closer to 0 being shown to be more significant.

The presence of autocorrelation or heteroskedasticity in the residuals could lead to biased and inconsistent estimation of the regression coefficient [184]. In previous literature, these issues have been mitigated through use of a spatially dependent model [42, 156]. However, where a spatially dependent model has been used, a number of previous studies were available that indicated that a spatially dependent model was the most suitable model. Literature which examined the spatial dependency in wind turbine adoption patterns in Great Britain was not available, which motivated the choice of a linear regression model to examine the influence of the selected variables in the SER models. Where heteroskedasticity and autocorrelation were identified in the residuals of this research's SER regression model, a heteroskedastic and autocorrelation consistent covariance matrix was used to correct the estimated regression coefficients. This is the case for the majority of the SER models, however for the SER model at LA Cap, only heteroskedasticity was observed and therefore only a heteroskedasticity consistent covariance matrix was used to correct these regression coefficients.

In the SER model, the influence of the income variable was shown to be negative. As with the demographic model, this regression coefficient was the result of wind turbines being installed in rural areas and the influence of a resident's accumulated capital on a decision to adopt. The education and house type variables were not shown be significant in any of SER models, except for the SER model for installed capacity at SG level. The insignificance in the majority of the models suggested that these factors were less influential in the SER model and the presence of additional variables in the SER models were better able to explain areas of higher wind turbine deployment. It is suggested here that the variables of education and house type still had a positive influence on individual wind turbine adoption decisions, but in terms of areas of higher deployment, there were other factors which had a greater influence. This explains the significantly negative education variable in the SER model for installed capacity at SG level. Regions with a high installed capacity are likely to have multiple high capacity turbines and these regions are likely to be extremely rural to ensure that each turbine has sufficient wind resource. In these areas, the number of residents with degree-level qualifications is likely to be minimal [123], causing the negative regression coefficient observed in the SER model.

The first of the additional variables included in the SER model was the industry classification, which detailed the percentage of residents who were employed in the agricultural, forestry or fishery industry. The results of the SER model showed that at SG resolution, the presence of agriculture had a positive influence on the installed capacity and number of wind turbines in a region. Around 10 % of all farms in Britain have a wind turbine [167], as farmers try to diversify their income streams and provide a source of electricity for their operations. Agricultural land is ideal for wind turbine installations, as farms are likely to have sufficient land and wind resource. Additionally, wind turbines do not require vast land area for the installations allowing the field in which it is installed to still be utilised for grazing or crop cultivation, highlighting their suitability to provide energy for agricultural operations. It is these underlying factors that are likely to have caused the significant positive regression coefficient observed in the SER model results.

The importance of rurality for a wind turbine adoption was shown in the SER model through the negative relationship between the number of wind turbine installations and the percentage of homes with gas central heating in a region. Such a relationship highlighted that in regions where the percentage of homes with gas central heating was lower, the level of wind turbine deployment was likely to be higher. Areas with fewer homes with gas central heating are more likely to be rural areas, as less homes in these regions are able to access the gas grid. The majority of SG regions with a geographical area of 50 km^2 or greater, had less than the national average of 78 % of homes connected to the gas grid. The inclusion of the variable concerning electric central heating was motivated by a desire to understand if wind turbines are installed to provide electricity for space heating. The SER model however, showed that the percentage of homes with electric central heating in a region was insignificant suggesting that the primary use of the electricity generated by a wind turbine was not for electrical space heating requirements.

Mean annual domestic electricity use was shown to have a significant influence for installed capacity at SG level. However, the installed capacity data was dominated by commercial turbines while the electricity variable described domestic electricity consumption only. This result was likely to be caused by installations of high capacity turbines in regions with larger homes and therefore higher domestic electricity consumption. Domestic electricity consumption was shown to be insignificant for installations at SG, the SER model most likely to identify the influence of the factor on domestic adopters. Previous microgeneration adopters have suggested that saving energy and protecting against higher fuel costs was a motivating factor for adoption [54]. It is therefore likely that a desire to offset electricity use through installation of a wind turbine was a factor in individual decisions to adopt to wind turbine, however, on the wider sample examined here, the influence of domestic electricity consumption could not be determined.

Previous literature has suggested that microgeneration adopters have viewed losing money, if they move house, as a barrier to adoption [54]. However, the results of the SER model suggest that wind turbine deployment was higher in areas where the percentage of mean annual house sales was higher. This result, observed at SG level in the SER models, could have been caused by multiple reasons, although it is doubted here that the number of house sales in a region had a major influence on an individual's decision to adopt a wind turbine. The underlying cause could be that the house sale variable described other homes in a region without a wind turbine that were being bought and sold, while the adopters in the region did not sell their homes. This highlights the uncertainty of using the house sale variable as a proxy to understand if adopters were more likely to stay in their homes after they installed a wind turbine. To determine this influence on an adopter's decision to install a wind turbine, survey work to investigate individual motivating factors would be required. However, as discussed, this was outside of the scope of this project.

The final variables in the SER model of geographical area and mean wind speed of the region reinforced the conclusion that the rurality of a region was an influential factor on wind turbine adoptions patterns. Both factors were shown to be significant, with the geographical area of the region being significant in all the SER models while mean wind speed was significant in the SER models at SG level.

Lower population density in a region resulted in the region having a larger geographical area. Lower population density is likely to result in lower housing density, suggesting that each property has a larger estate or more rural land is available on which a wind turbine could be installed. With the exception of woodland, rural land cover has a lower surface roughness than urban land covers. This lower surface roughness in rural areas has a lesser effect on wind flow momentum, resulting in a higher mean wind speed in the region. The increased deployment of wind turbines in these areas was because of adopters wishing to exploit the higher wind resource and having sufficient land on which a wind turbine could be installed. These results for the wind speed variable at SG level in the SER model support the findings of the wind resource regression model, presented in Section 5.2.1. However, at LA level, the wind speed variable was shown to be insignificant in the SER models.

In the SER models at LA resolution, only the income and area variables were shown to be significant. The reasoning behind this lies in the relative geographical sizes and number of residents covered by either the LA or SG geographies. LA geographies covered a mean of 160,000 residents with Birmingham City Council, the largest LA region, covering over a million residents. In comparison, a SG covered a mean of 7,200 residents. The demographic variables at LA level were averaged over a much greater sample of residents. Therefore, in an LA, it was likely that a greater number of residents had demographics that were vastly different from the mean demographic value of the LA. In comparison at SG level, the sample of residents was smaller and therefore the distribution of demographics across the residents of a single region was likely to be narrower. This was likely to be the underlying cause of the lack of significance of most variables in the LA model. While this was a limitation of the model, the significance of income and area variables at LA showed that the rurality of the region was the most influential factor on wind turbine adoptions

Evidenced by the significance of the variables for income, agricultural industry, gas central heating, geographical area and wind resource in the SER model at SG, these results support the conclusion that wind turbines were more likely to be installed in rural areas. The major conclusion of the SER model is therefore the influence of rurality on wind turbine adoptions in Great Britain. While this is an intuitive conclusion, no previous literature has proved this and therefore these findings are considered novel.

While the regression coefficients of the SER model explained the influence of each variable on wind turbine adoptions, the development of the SER model was also motivated to understand if the inclusion of additional variables in the SER model could explain more of the variance in wind turbine adoptions patterns. To analyse this, the apparent fits from the SER models were examined. The scatter plots of predicted against actual installed capacity or installations from each SER regression model are presented in Figure 38 and Figure 39.

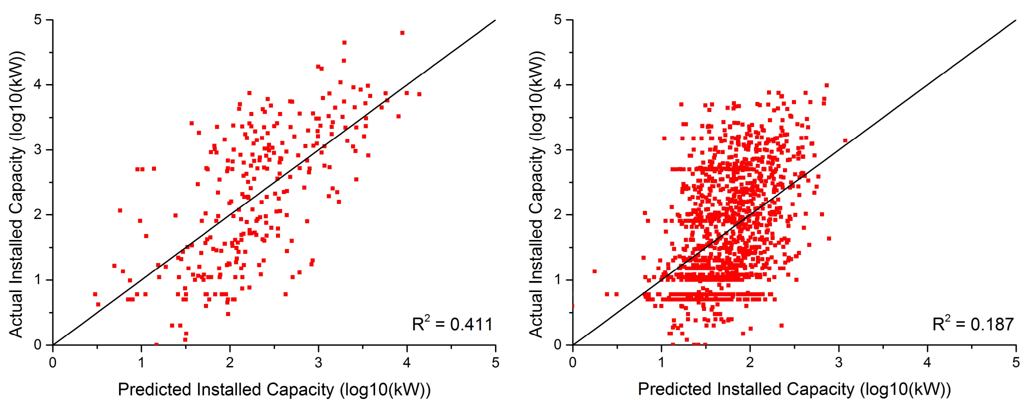

Figure 38 — Scatter of log predicted vs actual installed capacity from SER model, where the line represents one to one relationship. Left: LA level. Right: SG level

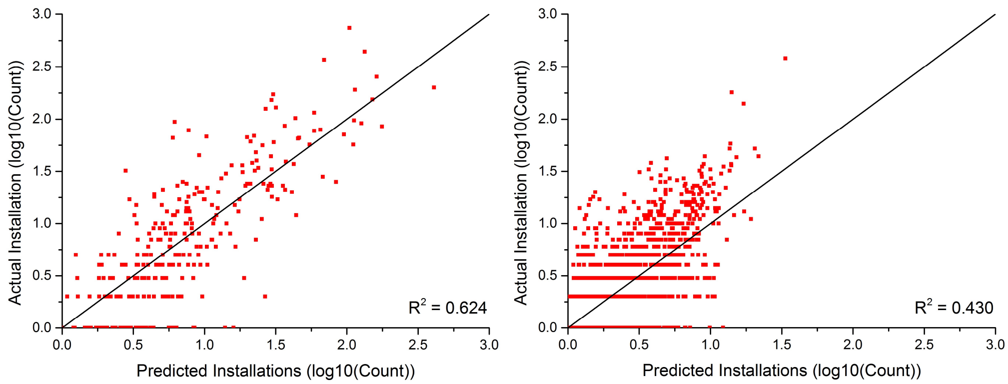

Figure 39 — Scatter of log predicted vs actual installations from SER model, where the line represents one to one relationship. Left: LA level. Right: SG level

The most immediate conclusion that can be drawn from the apparent fits of the SER model was the increase of the R^2 values from those achieved in either the demographic or wind resource regression models, peaking at 0.624 in the SER model for installations at LA level. An improvement in the R^2 values demonstrated that a larger proportion of the variance in wind turbine adoption patterns was explained by the additional variables included in the SER model. Therefore, inclusion of the additional variables in the SER model presented was justified.

The scatter plots of the SER model's predicted values differ from those of the demographic model. Where the demographic models appeared to be limited in accurately predicting the number of turbines in regions of high deployment, this limitation appears to be overcome, in part, in the SER model. In the SER models at LA, this was particularly apparent as the scatter of these models appeared linear to a greater degree than the corresponding scatter plots of the demographic models results. This highlights that the inclusion of variables, which described the rurality of a region, in the SER model improved the accuracy of the predicted value of both the installed capacity and wind turbine installations at LA. The difference between these models at LA was caused by the different adopters examined in either the installed capacity or installation data. Regions with higher installed capacity were likely to have a higher number of non-domestic wind turbine projects. In these projects, it was likely that the adoption decision was made by multiple individuals and therefore, the motivating factors of such an adoption may not be captured in the variables of the SER model, hence the lower R^2 values.

Factors not included in the SER model were also likely to contribute to the scatters at SG. For the SER model examining installed capacity at SG level, the scatter was similar to that of the demographic model, albeit with a wider range of predicted values. This wider range of predicted values was due to inclusion of the rural factors in the SER model. However, there still appeared to be factors that limited the accuracy of the predicted installed capacity from the SER model. This was likely to stem from the different factors that were influential for commercial projects, rather than domestic projects. For the SER models examining installations, the scatter was improved from the demographic model. The R^2 values of these SER models were almost double the R^2 value of the corresponding demographic model, further proving that inclusion of the additional variables to describe the influence on domestic adopters was justified. However, there was still a large degree of variance which was unexplained in the SER model. While some of the unexplained variance in wind turbine adoption patterns may be the result of the subjective judgement of adopters, it is envisaged that variance due to the subjective judgement of adopters would not account for such a high degree of unexplained variance.

Previous literature has identified that a spatial dependency [42] between regions has influenced PV adoptions in Great Britain and this observed spatial dependency could be the result of a peer effect influencing PV adopters [42]. Visible neighbouring PV systems can influence others in the neighbourhood to adopt a PV system [43]. It is suggested here that these peer effects may be influential on wind turbine adopters in Great Britain, as wind turbines are considerably more visible than PV systems. To determine if the peer effects may be present in the wind turbine market, the residuals of the SER model were examined to identify if any spatial dependency could be observed.

Using the DW test for autocorrelation, it was proved that a spatial dependency could be observed in the residuals of the SER models, indicating that there was a spatial element which influenced adoption patterns and was not considered in the SER model [42]. It is suggested here that this spatial dependency was, in part, as a result of peer effects between adopters in neighbourhoods. Therefore, a peer effects model was developed in this research to examine this influence in a number of case study areas and this model is presented in Chapter 6.

5.2.4 Model residuals

A qualitative analysis assessed the residuals of the SER model to identify in which areas of Great Britain, the SER models were able to accurately estimate wind turbine deployment. The residual term of each region, ε_i, in the model, as discussed in Section 5.1, was calculated as the difference between the predicted value of wind turbine deployment, $\hat{y}_i$, from the SER model and the actual value of wind turbine deployment, y_i;

$$\varepsilon_i = y_i - \hat{y}_i$$

Equation 50

The residuals of each SER model are presented in Figure 40 and Figure 41. In these figures, negative residuals were coloured in blue with the darker blue indicating that a region had a lower negative residual. A negative residual value demonstrates that the SER model predicted that greater wind turbine deployment was possible than has actually occurred. The regions coloured in red have positive residuals with a darker red showing a higher positive residual value. A positive residual value was the result of the level of wind turbine deployment being above the prediction from the SER model. Additionally, some regions were coloured grey, which showed that the residual value was closer to zero. In Figure 38, regions coloured grey had a residual value between -9 kW and 10 kW while in Figure 39, regions coloured grey had a residual value between -0.9 and 1 installation.

The majority of regions in the SER models at either LA or SG had similar residuals, in terms of the sign of the residual. However, in some areas, particularly the Scottish Highlands, Scottish Borders and Mid Wales, the residuals of the SER model at SG level differed from the residuals in the SER models at LA. Each SER model estimated different regression coefficients for each independent variable and it was these differing regression coefficients which resulted in the differing predicted values and residuals at either SG or LA level. Despite these differences in the predicted values from each SER model, there were some areas where the residuals were similar in all the SER models. These areas, typically, had negative residuals, coloured blue in Figure 40 and Figure 41, demonstrating that there may have been factors which impeded wind turbine deployment in these areas.

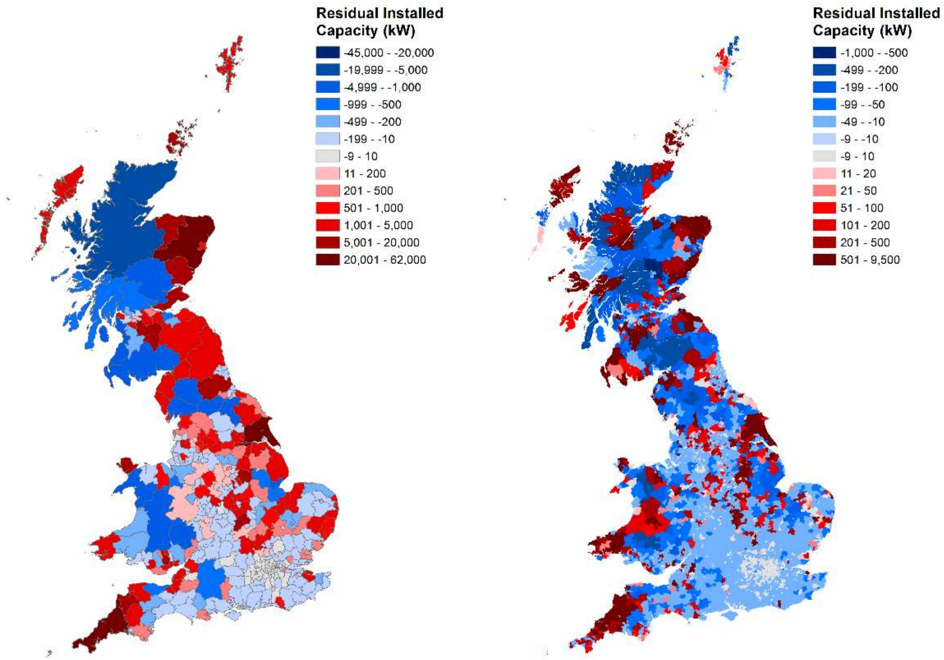

Figure 40 — Residuals of the SER models examining installed capacity. Left: LA level. Right: SG level

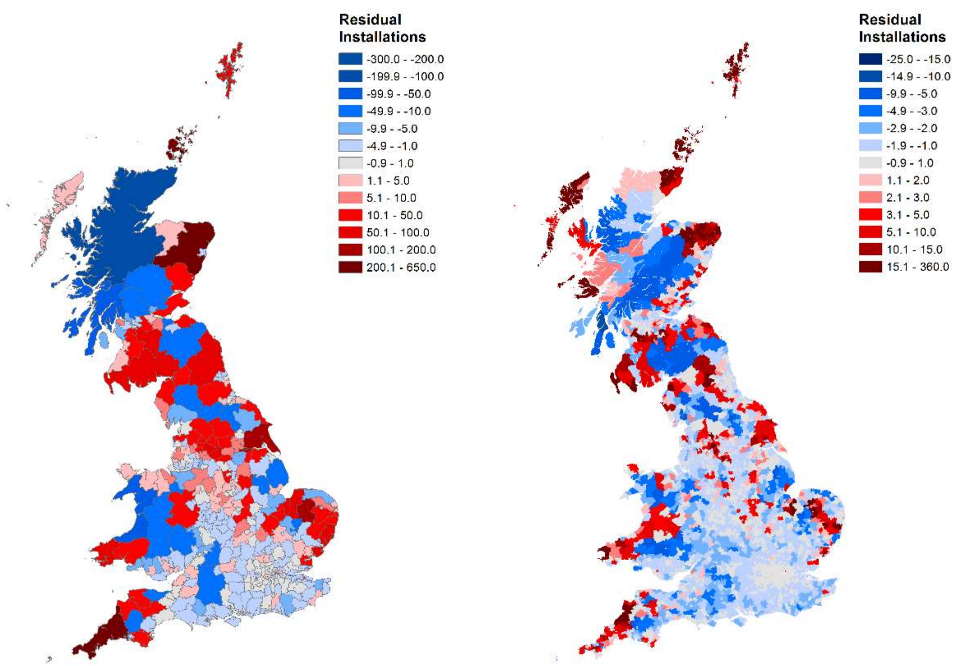

Figure 41 — Residuals of the SER models examining installations. Left: LA level. Right: SG level

One of the factors that may have impeded wind turbine deployment in Great Britain was the presence of National Parks and other regions where the development of wind turbine projects was restricted. Wind turbine installations are not prohibited within these environmentally protected areas, however, development of any kind must conserve the landscape and scenic beauty of the area [185]. There are wind turbine installations within these environmentally protected areas, as planning permission within the National Parks is controlled by each National Park Authority [185]. The location of the National Parks in Great Britain can be seen in Figure 42 which are shown in conjunction with both the residuals from the SER model for installations at SG and the number of wind turbine installations at SG level. Despite these installations in environmentally protected areas, the SER model over-predicted the number of installations within these regions, which resulted in the negative residuals. These areas were predicted to have higher levels of deployment, as they were rural areas with higher wind resource. The presence of these environmentally protected areas has therefore impeded the theoretical wind deployment, as number of wind turbine projects predicted in the SER model were unlikely to gain the requisite planning permission. While it is not suggested here that planning restrictions in these areas should be relaxed, it is merely a qualitative explanation of the SER residuals.

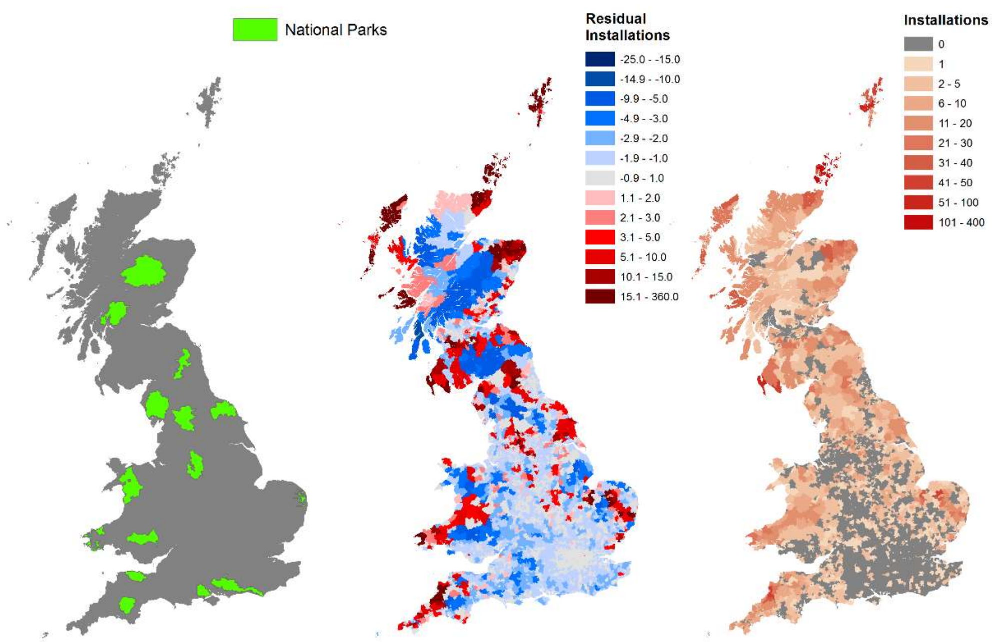

Figure 42 — Left: location of National Parks in Great Britain, middle: residuals of SER model for installations at SG and right: wind turbine installations at SG

Some areas of low deployment could also be the result of restrictions in the planning process for small scale wind turbines. Planning permission for wind turbines is not required if they meet a set of criteria, which would classify the wind turbine as a permitted development [186]. However, the set of criteria are exceptionally restrictive stating that a permitted wind turbine must not have a swept area above 3.8 m^2 and the tip height of the turbine must not exceed 15 m [186]. For a wind turbine to have a swept area of less than 3.8 m^2, the turbine blades must not exceed a metre in length. In comparison, the 5 kW wind turbine, presented in Chapter 5, has a swept area of 24 m^2 [151]. It is therefore likely that the majority of wind turbines installed in Great Britain would require planning permission. The planning process can be burdensome for small wind turbine projects as adopters could be requested to produce costly studies, more typical of larger scale turbines [167]. Such requests increase the costs of the project and, coupled with any delays in the planning decisions, risk missing key project dates, which can result in small wind turbine projects running over budget and potentially being scrapped [167]. While it was not possible to determine where such planning issues have previously impeded deployment, it was possible that some areas of Great Britain have lower wind turbine deployment as a result.

In addition to planning constraints, wind turbine deployment could be impeded by the proximity of aviation infrastructure, such as airports or Ministry of Defence (MoD) sites. Any site that is classified as 'safeguarded land' cannot be used for a wind turbine installation [187]. While the definition of safeguarded land is broad, it is typically considered as land surrounding an airport and its associated radar equipment [187]. For the MoD sites, it is likely that any land surrounding an MoD site would be restricted, however, this information was not publicly available. Low levels of deployment in regions, which have been identified by the SER model as suitable for greater deployment, could be the result of safeguarding land restrictions.

Lower deployment in areas could simply be because of individual's subjective views on wind turbines. Deployment of microgeneration technologies requires active engagement by those considering adoption [118]. 75 % of survey respondents when asked who was responsible to stimulate the uptake of microgeneration suggested central government compared to only 8 % suggesting this uptake was the responsibility of individuals [188]. While the FIT has been introduced by central government to stimulate uptake, this is an incentive based scheme which requires individual engagement to achieve greater deployment. It is likely that wind turbine deployment in some regions was lower than expected due to lack of engagement or desire by residents to install a wind turbine.

Greater penetration of the PV market due to the FIT may have limited wind turbine deployment. The number of PV systems installed in Great Britain was over 750,000 by December 2016 [12] and were installed in the majority of regions in Great Britain [41]. It is likely that in regions which would be suitable for a wind turbine installation, deployment may have been impeded by the deployment of PV systems in the region. It is unlikely that a domestic adopter would have sufficient capital for both a wind turbine and a PV installation and therefore if their neighbours had installed a PV system, they may be more inclined to opt for a PV rather than wind turbine installation [43]. Therefore, it is suggested here that the growth of the PV market under the FIT may have impeded wind turbine deployment in some regions.

Even in regions where there are individuals with sufficient desire and capital to consider adopting a wind turbine, there is the possibility of local opposition which may lead to a planning application being rejected. Residents opposed to local wind turbine developments are more likely to engage in the planning process [189] and these opponents are likely to cite various issues surrounding the turbine construction and operation to oppose the development [190]. It is therefore likely that if neighbours have a negative view of wind turbines, they will raise these objections during the planning process, resulting in a wind turbine deployment being delayed during the planning process. which could lead to the projects being scrapped.

Within the SER model residuals, there were also areas of positive residuals and, particularly from the SER model at SG, these areas of positive residuals appeared to be geographically clustered. These “clusters” of higher than expected installations and installed capacity seemed to occur in numerous areas around Great Britain. This clustering appears to be prevalent in Cornwall, East Anglia, North East Scotland and Southwest Wales. The underlying cause of these higher than predicted installations could be the result of multiple factors. It is possible the presence of a local marketing campaigns promoting wind turbine deployment, local councils who were particularly favourable towards wind turbine installations or these areas having numerous residents who were interested and motivated to install a wind turbine. Additionally, these regions of high levels of deployment could be the result of the peer effects from wind turbines installed in a neighbourhood. The influence of the peer effects in wind turbine deployment and clustering of installations will be examined in Chapter 6.

5.3 Conclusions

A series of regression models were developed to determine the influence of several factors on wind turbine adoptions in Great Britain. These models were developed as no previous literature had examined the influencing factors on spatial wind turbine adoption patterns in Great Britain. Additionally, by understanding the factors that have influenced wind turbine adoption patterns, it will be possible to identify a number of policy strategies which could be introduced to promote future deployment.

Initially, a regression model examining the influence of mean wind speed of a region at a hub height of 15 m was developed. Mean wind speed of a region was shown to have a significant positive influence on wind turbine adoptions. The influence of available wind resource showed that adopters of wind turbines have, in part, decided to adopt based upon the prospect of financial returns being available from a wind turbine. These financial returns increase as the electrical output of the wind turbine, due to higher wind resource, increases. The results of this regression model suggested that the financial motivation to adopt a wind turbine was significant and thus turbines were installed in areas where they were financially and technical viable. Using the coefficient of determination values from each model, it was shown that the mean wind speed of a region could explain, at most, around 35 % of the variance in wind turbine adoption patterns. This result showed that while wind resource was significant, there was still a substantial degree of variance in the adoption patterns left unexplained.

In addition, an examination of the minimum mean wind speed required for deployment was also undertaken. Using a multi-faceted approach which examined the mean wind speed in regions with wind turbine installations and the estimated payback period of an example turbine, a mean wind speed of 4.5 ms^{-1} was identified as the minimum wind speed required for deployment. 90 % of all SGs with at least a single wind turbine installation had an mean wind speed of 4.5 ms^{-1} or above. Additionally, at 4.5 ms^{-1} and using current market prices for electricity and FIT subsidy level, a 5 kW wind turbine would pay back in 10 years and 4 months, marginally inside the 11 years, previously cited by wind turbine adopters as a suitable payback period [108].

The development of the additional regression models in this research was motivated by a desire to explain a greater degree of the variance in wind turbine adoption patterns. Previous literature has identified that an individual’s age, income, level of education, house type and homeownership has influenced whether they adopt a microgeneration technology [42, 56, 108, 110-118]. While these factors have been examined for other microgeneration technologies, these factors have not been examined for wind turbine adoptions in Great Britain. The results of this model showed that wind turbine adopters in Great Britain are likely to be older, have a degree-level qualifications and live in a detached home. It was also shown that adopters are likely to live in a region which has a lower than mean weekly income, which suggests that the regions in which wind turbine were installed are likely to be rural areas. In rural areas, mean income is typically lower than the national average, which was the underlying cause of the significant negative regression coefficient observed in the demographic model. However, the positive residuals seen in some of the rural regions could be the result of weathy land owners, who own the farms, having sufficient capital to afford a wind turbine installation. While these land owners have sufficient capital, their workers, who live in the local area, earn below the national avearge weekly wage which caused the lower avvearge weekly income in these SGs. The coefficient of determination values of the demographic models were similar in magnitude to those from the wind regression models. This showed that the demographic factors can explain a similar degree of variance in wind turbine adoption patterns as the mean wind speed. However, there was still a large degree of variance which was unexplained.

A final regression model, known as the SER model, was developed to incorporate some of the demographic factors, the mean wind speed and other suggested variables and examine their influence on wind turbine adoptions in Great Britain. The results of the model suggest wind turbine adoptions were installed in rural areas, where there was a greater availability of land and wind resource. This was evidenced by the significance of larger geographical area, higher mean wind speed, higher levels of agricultural industry, lower income and lower levels of gas central heating in a region in the SER model. While the factors of education and house type weren't significant in the SER model, this was due to the presence of additional variables in the SER models, which were better able to explain areas of higher deployment. The education and house type of an adopter were likely to therefore have a positive influence on individual wind turbine adoption decisions, but in terms of areas of higher deployment, the other factors in the SER model offered a better explanation of the variance in the adoption patterns. The highest coefficient of determination from any of the SER models was 0.624, almost twice that of the preceding two regression models. These results showed that inclusion of the additional variables could better explain the variance in wind turbine adoptions of Great Britain. However, there was still variance in the wind turbine adoption patterns which was unexplained. It was theorised here that factors outside of those examined in the SER model could explain this additional variance. Based upon the presence of autocorrelation in the residuals of each SER model, it was suggested that the peer effects of previously installed neighbouring wind turbines may have had an influence on wind turbine adoption patterns.

The overall conclusion of the analysis presented in this chapter is that wind turbine adoptions were more likely to occur in rural areas, where the availability of land and wind resource was greater. Wind turbine adopters in Great Britain were likely to be older, have a degree-level qualification, live in a detached home, work in the agricultural industry or live in an area where the level of agricultural industry was high. Adopters were also likely to live in a region where the mean income was below the national average. While these conclusions are seemingly intuitive, the results and conclusions here have not previously been presented in literature, highlighting the novelty and significance of this work.

This research was developed to understand how to promote future wind turbine deployment to meet the levels of deployment required for the societal pathway to deliver the transition to a low-carbon electricity market. By understanding the factors which influenced previous wind turbine adopters, it may be possible to identify how to promote deployment through a number of policy strategies. The results of the SER models also indicate that there are regions in Great Britain where there is potential for further deployment. The regions of the Highlands surrounding Inverness, the Scottish Borders north of Newcastle, southern Cumbria, the regions surrounding Lincoln, the regions around Northampton and Cambridge and the south coast of England appear to be the locations with the greatest potential for future deployment as current wind turbine deployment in these regions is currently lower than predicted by the SER models. However, the adoption of microgeneration technologies has been shown to have both spatial and temporal characteristics [41]. To develop policy strategies that will effectively promote deployment in these regions, both characteristics must be understood. While the model presented in this chapter examined the spatial characteristics of wind turbine adoption, the factors that influence the temporal adoption patterns must also be analysed. The spatial dependency observed in the residuals of the SER model suggests that the peer effect of wind turbines installed in a neighbourhood may influence an individual's decision to adopt. An examination of the factors that influence the temporal wind turbine patterns is presented in Chapter 6.

Chapter 6 – Peer effects modelling of temporal wind turbine adoption patterns

While the Socio-Economic and Resource (SER) model of Chapter 5 examined the influence of a number of factors on spatial wind turbine adoption patterns in Great Britain, the influence of the Feed-in Tariff (FIT) was not included in that research. The influence of the FIT on wind turbine adoptions in Great Britain has not previously been analysed either in this project or in other studies. A previous study has suggested that the introduction of a FIT policy caused greater wind turbine deployment in both Germany and Spain [191]. It is therefore likely that the availability of incentives for energy generation will have been a motivating factor for wind turbine adopters. This assertion was also supported by the findings of previous literature which showed that adopters ranked financial incentives highly, as a motivating factor for their adoption of a microgeneration technology [54, 55]. However, changes to the subsidy level available under the FIT have occurred since 2012 [34] and it is the influence of these changes on temporal adoption patterns which was of particular interest in this research.

The temporal nature of changes to the FIT subsidy level could not be included in the SER model and therefore must be examined in an alternative model. The presence of autocorrelation in the residuals of the SER model demonstrated that a spatial dependency existed between the regions of Great Britain and the adopters within these regions. This observed spatial dependency may be indicative of the influence which visible wind turbines, previously installed in a neighbourhood, had on a prospective adopter's decision to adopt a wind turbine. The visibility of microgeneration technologies has been cited by previous microgeneration adopters as a factor that raised their interest in installing a microgeneration technology [55]. Additionally, the visibility of PV systems has been shown to have a positive peer effect on neighbours, influencing them to adopt a PV system [43, 45-47]. Any peer effect from neighbouring turbines in a cluster would be considered an endogenous peer effect [43, 45]. The spatial dependency exhibited in the SER model results and the greater visibility of wind turbines demonstrate that it was important to investigate in this research if such a peer effect was present in the British wind turbine market.

To examine the temporal influence of both the changes to the FIT subsidy level and wind turbines installed in a neighbourhood on an adoption decision, a peer effects model has been developed. The peer effects model was applied to a number of case study areas of Great Britain, which were shown to have a greater number of wind turbine installations than predicted by the SER model. In these areas where the number of wind turbine installations was high, it is theorised here that the influence of endogenous peer effects from neighbouring turbines and influence of the FIT subsidy changes was most likely to be observed.

These areas of high levels of wind turbine deployment were identified by determining the difference between the actual wind turbine deployment and the predicted level of wind turbine deployment estimated using the SER model. The difference between these two variables is known as the residual value of a region and was positive when actual deployment was greater than predicted by the SER model. Using the residuals of the SER model on the statistical geography (SG) resolution, it was possible to identify a number of case study areas or clusters for analysis.

This chapter will present the statistical method used to identify clusters of regions across Great Britain where the peer effects model was applied. The peer effects model will be presented in Section 6.2. The peer effects observed in this model were then analysed to determine if the factors had a significant influence on temporal wind turbine adoption patterns in these clusters.

6.1 Methodology and results

The peer effects model developed during this work was the culmination of multiple pre-processing steps, as seen in Figure 43. Each of these pre-processing steps took data from previous research, both the SER residuals from Chapter 5 and the wind speed estimation data from Chapter 4. Additionally, data was also taken from a number of publicly available datasets. Each pre-processing step provided an input to the peer effects model. In the development of the peer effects model, there were three major strands of work; cluster identification, seen in the first pre-processing box of Figure 43; cluster characterisation and calculation of the number of potential adopters in a region, described in the second pre-processing box of Figure 43 and finally, development of the peer effects model, including pre-processing of the model variables, seen in the final two pre-processing boxes and the modelling box of Figure 43. In this chapter, the cluster identification methodology and its results will be presented in Section 6.1.1, cluster characterisation methodology and results will be presented in Section 6.1.3, and the peer effects model development and results will be presented in Sections 6.1.4 and 6.2 and discussed in Section 6.3.

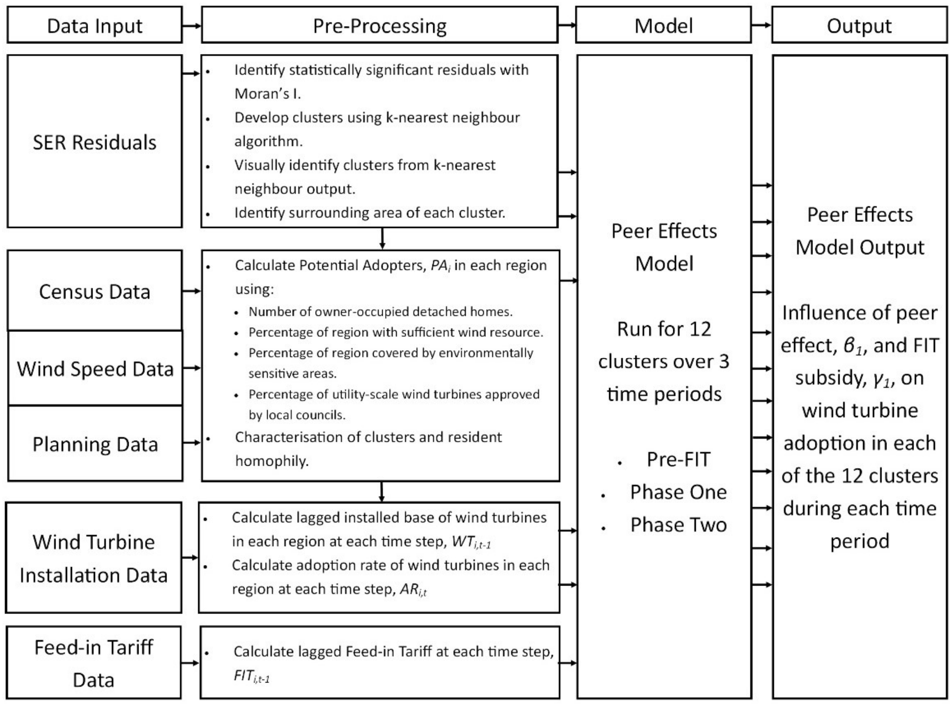

Figure 43 — Process flowchart for peer effects modelling

The peer effects model developed and presented in this chapter was undertaken in R, version 3.2.3 [172]. Within R, the “lmtest” [173] and “plm” [192] packages were utilised to provide the statistical packages and functions required to conduct the peer effects model. The identification of the clusters was conducted in R using the “spdep” package [193] and the k-nearest neighbour analysis was conducted in SPSS v 21.0 [194]. Additionally, some data processing was conducted using MATLAB R2013b [175] under an academic license. Any maps presented in this chapter were created in MATLAB and visualised in ArcMap 10.2.2 [176].

6.1.1 Clusters of installations

To identify any clusters of installations in the spatial adoption patterns, analysis of the installation data was undertaken. However, analysis of the raw installation numbers could identify clusters of installations which arose as a result of the prevalence of favourable socio-economic or environmental factors. To mitigate this, the residuals of the Socio-Economic and Resource (SER) model, presented in Chapter 5, were utilised.

Each region, at both SG resolutions, examined in the SER model had a residual value. Regions in which the SER model did not explain the high number of installed wind turbines and therefore had a positive residual value, indicated that additional factors may have influenced wind turbine deployment in these areas. It was within a selected number of these regions that the influence of the peer effects was examined.

The residuals from the SER model which examined wind turbine installation numbers on the SG level were selected to identify clusters. Given the likely visibility radius of a wind turbine of up to 12.5 km, considered in this project, the use of local authority (LA) areas in the peer effects model was considered insufficient. For the LAs with a large geographical area, this maximum visibility radius may not extend past their boundaries and therefore the analysis would not examine any spatial dependency between regions and the adopters of the regions. However, examination of the spatial dependency could be achieved by analysing the influence of the visual peer effects of neighbouring wind turbines on subsequent adoptions in clusters of multiple geographically smaller SG regions. As discussed, 63 % of wind turbine installations were for domestic use, compared to only 9 % of the total installed capacity installed for domestic use. Therefore, the ability to analyse the influence of each factor on domestic adopters motivated the choice of the SER residuals in this research, which are presented in Figure 44.

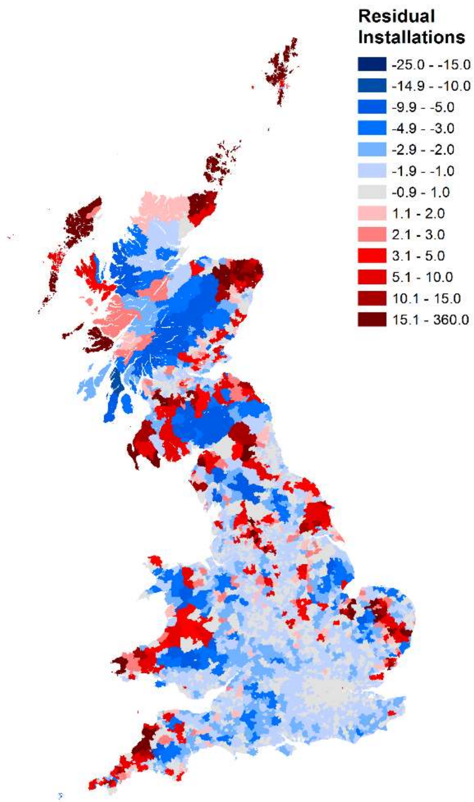

Figure 44 — Residuals of the SER model for installations at SG

6.1.1.1 Cluster identification methodology

To identify clusters of SG regions, suitable for analysis in the peer effects model, the residual value of each region must be analysed to determine if it was statistically significant or merely a misspecification within the SER model. Using the Local Moran's I metric [195], it was possible to analyse the significance of the residuals in each region and to identify clusters of statistically significant areas of wind turbine installations. This technique was also used to identify clusters in PV adoption patterns within Great Britain by Snape [41]. Local Moran's I, I_i, was used to determine the significance of a region's residual value by examining the value of the residual of the region, ε_i, in comparison with the mean residual value of the neighbouring regions, $\bar{\varepsilon}$;

$$I_l = \frac{(\varepsilon_i - \bar{\varepsilon})}{\sum_{j=1}^{n}\left(\varepsilon_j - \bar{\varepsilon}\right)^2/(n-1)} \sum_{j=1}^{n} w_{ij}\left(\varepsilon_j - \bar{\varepsilon}\right)$$

Equation 51

where, ε_j, was the residual value of the neighbouring region, *n*, was the number of neighbours and, w_{ij}, was the spatial weight matrix (SWM), the influence of each neighbouring region, *j*, on the selected region, *i*. Choice of the size of the SWM was crucial in identifying the clusters. Given that the aim of this clustering analysis was to identify areas in which to examine the influence of the visibility of a neighbouring turbine, it was judicious to adopt the distances of the likely visibility radii of a wind turbine for the SWM.

It has been shown that a wind turbine with a hub height of 45 m can be identified by observers up to 10 km away from the turbine, depending on the atmospheric conditions [127]. To account for the likely hub heights of turbines examined within this research, four different visibility radii were utilised. Initially, radii of 5 km and 7.5 km were selected. These distances account for the likely lower hub heights of smaller capacity turbines, which may not be visible 10 km away. The radii of 10 km and 12.5 km were also included. These distances would account for larger capacity turbines with hub heights around 50 m, turbines which were sited in visibly advantageous locations such as at the crest of a hill, and for those turbines which were viewed regularly during journeys by neighbours who resided outside of the visibility radii. The influence on neighbours who viewed a turbine during a journey may extend over greater distances than the suggested visibility radii. However, it is argued here that the influence of such a wind turbine will be less for neighbours who reside outside the visibility radii. Due to the likely variation in wind conditions between the turbine site and these neighbour's locations, the viewed wind turbine is less likely to demonstrate technical feasibility at the neighbour's property. Four SWMs with the maximum distance of 5 km, 7.5 km, 10 km and 12.5 km were therefore implemented in this work to account for the subjective visibility of a wind turbine.

The SWMs were created during this research using a hierarchical combination of spatial contiguity methods. Initially, using the centre of each region, all SG regions within each selected distance were identified as neighbours to the selected region. If the selected region was geographically large, this distance method was insufficient as the centre of neighbouring regions would be farther than the maximum distance of the SWM. In these cases, all neighbours, *j*, which shared any border with the selected region, *i*, known as queen's contiguity [196] and seen in Figure 45, were selected. Once all appropriate neighbours had been identified, the influence of each neighbour was weighted as a function of the total number of neighbours identified in the SWM.

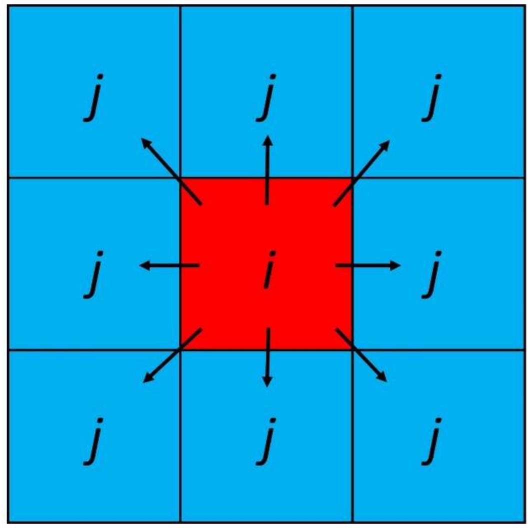

Figure 45 — Graphical representation of neighbour selection using queen's contiguity

Implementation of queen's contiguity allowed all regions of Great Britain to be examined using the Local Moran's I metric. While use of queen's contiguity violated the visibility assumptions by including regions which were further than the largest visibility radius, it allowed more remote regions to be included in the SWMs. These regions must be included in the analysis as they are more likely to be suitable for wind turbine installations, based upon the findings of the SER model. Queen's contiguity was used to selected neighbours in around 10 % of regions at 5 km distance and 1 % of regions at 12.5 km distance.

The Local Moran's I technique allowed differing types of outlier regions to be identified, based on the residual value of the region and the local mean residual value of its neighbours [41, 195]. There were four types of outlier regions which were identified, with outlier regions being classified as either "High-High", "High-Low", "Low-High" and "Low-Low" [195]. As seen in Figure 46, these classifications were derived from the value of a region's residual and the local residual values of its neighbours. Therefore, a region classified as High-High had a residual value which was significantly higher than the local mean derived from its neighbours, which was also considered high. The local mean residual value of neighbouring regions was considered high when it was significantly higher than an expected value for the whole sample.

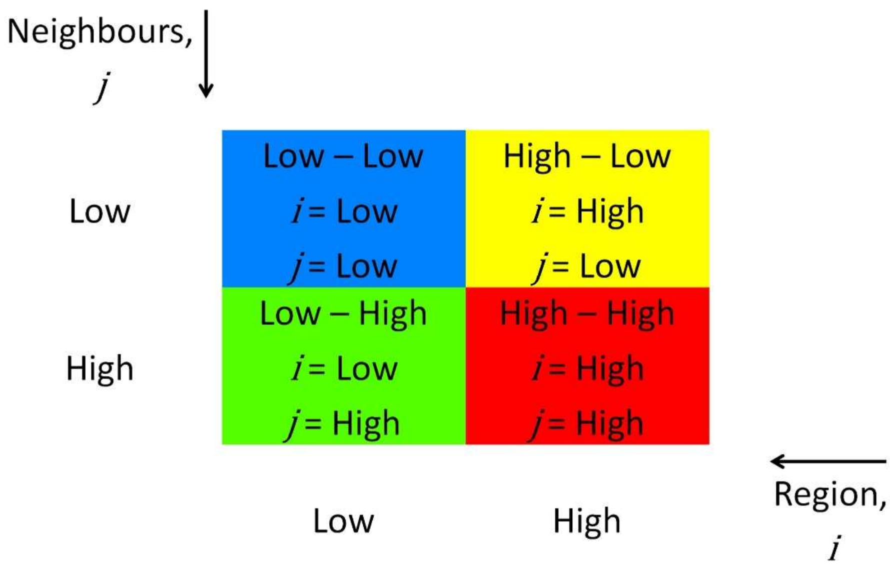

Figure 46 — Representation of classifications of outlier regions under Local Moran's I technique

The regions which were classified as either "High-High" or "High-Low" were the most suitable outlier types for this analysis. In these regions, the residual value was statistically significant and higher than the local mean of its neighbours. It is theorised here that in these regions, the influence of the endogenous peer effect and the FIT degression could be best examined due to the greater number of wind turbine adoption decisions which could be analysed.

While the Local Moran's I identified statistically significant areas, it did not identify geographical clusters of statistically significant areas. A region could be identified as statistically significant under the Local Moran's I test due to a lack of installations in neighbouring regions. This region would be unsuitable for the peer effects model, due to the lack of installations in neighbouring regions from which a visual peer effect may be observed. A further method was therefore required to identify the geographical clustering of suitable outlier regions. Identification of geographical clusters of significant areas was conducted using a cluster analysis technique. The k-nearest neighbour method allowed the nearest neighbour of a region to be identified and classified into clusters [197]. A similar technique has been applied to identify annual demand profiles from UK electricity demand data [198] and is a commonly used method to identify clusters in a wide range of topics, including crime [199] and disease data [200].

By minimising the difference in a selected variable, the k-nearest method identified the regions which were most similar in this selected variable. In this research's cluster analysis, the geographical co-ordinate of the centre point of each region was the selected variable and therefore the method identified regions whose Euclidean distances from each other was smallest and therefore were geographically clustered. In this work, the clusters were formed of multiple regions. The method initially identified the two outlier regions closest to each other and calculated the theoretical centre point of these regions. Other geographically close regions were then included in this cluster and a new centre point calculated as each region was added to the cluster. The process ended when all of the outlier regions were assigned into a cluster. This process was run for different numbers of total clusters, ranging from 5 clusters, up to 16 clusters. Multiple clusters solutions were required to ensure that smaller clusters were not included in larger clusters, even if they were geographically isolated from the larger clusters.

Each cluster solution was then analysed visually to determine its suitability. The visual classification was also required to exclude significant regions which were isolated and unsuitable for analysis but were grouped to nearby clusters using the cluster analysis technique.

For each cluster identified, a surrounding area to the cluster was also selected. In the surrounding areas of the clusters, deployment was typically lower than the cluster areas but were selected to determine if a peer effect from the cluster areas could be observed in these surrounding areas. Selection of the surrounding areas was conducted using queen's contiguity only and all the regions which shared a border with any of the cluster areas were selected.

6.1.2 Clusters

The Local Moran's I technique was implemented using four distances of 5 km, 7.5 km, 10 km and 12.5 km to identify any statistical significant regions at each of these distances. The number of outlier regions identified at each distance is presented in Table 19.

Table 19 — Number of outlier regions identified using the Local Moran's I at the distances of 5 km, 7.5 km, 10 km and 12.5 km

	Distance			
Region Outlier Type	**5 km**	**7.5 km**	**10 km**	**12.5 km**
High-High	104	97	91	109
Low-Low	8	7	5	4
High-Low	3	7	7	4
Low-High	10	12	12	9
Not Significant	8,355	8,357	8,365	8,354

The results in Table 19 show that only around 1.5 % of all the regions of Great Britain were considered significant outliers at any of the distances utilised in the research. The majority of these outlier types were classified as High-High, suggesting the majority of the outlier regions had high levels of wind turbine deployment, which was under predicted by the SER model. The locations of the outlier regions identified at each distance are presented in Figure 47 and show that some regions were consistently identified as statistically significant at all of the distances considered.

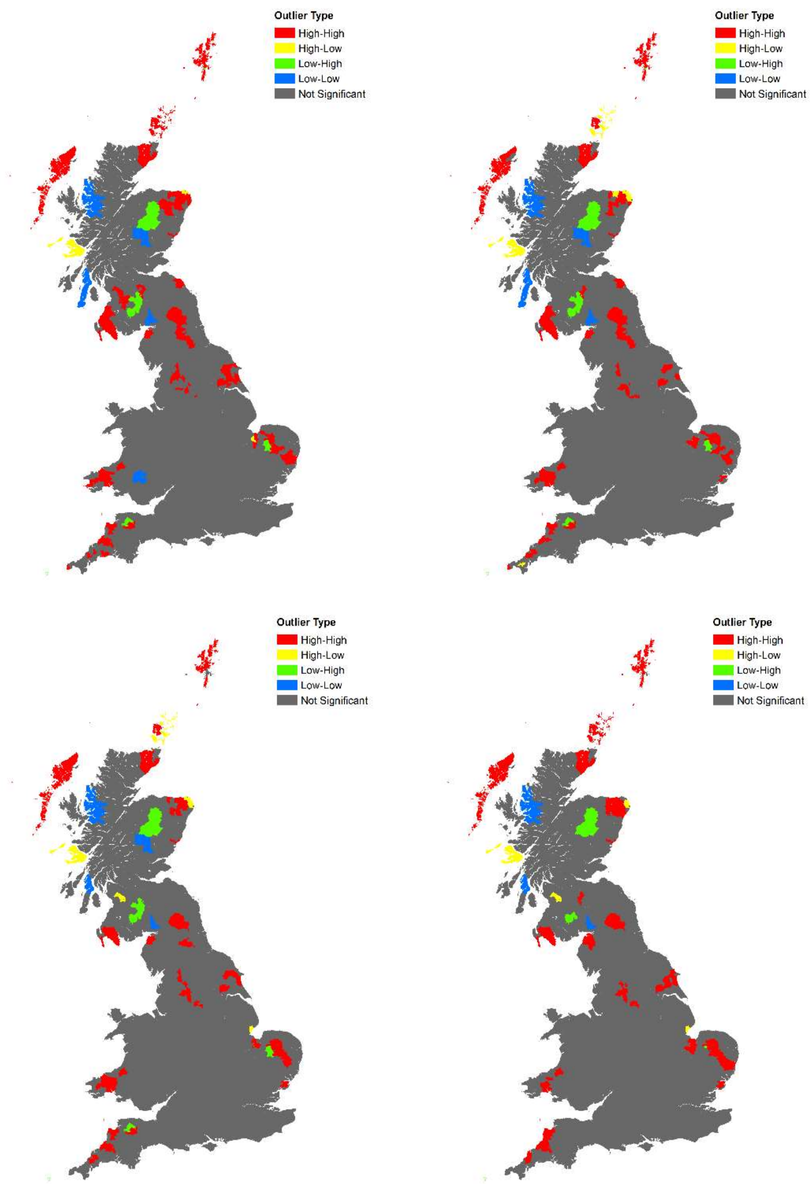

Figure 47 — Location of outlier regions identified under Local Moran's I test at, top left: 5 km, top right: 7.5 km, bottom left: 10 km, bottom right: 12.5 km

To identify the clusters, these outlier regions at all distances were combined so that any region identified as significant at any distance was considered during the cluster identification. All of the outlier regions from all distances are presented in Figure 48 with the residuals from the SER model for installations at the SG resolution, from which they were identified.

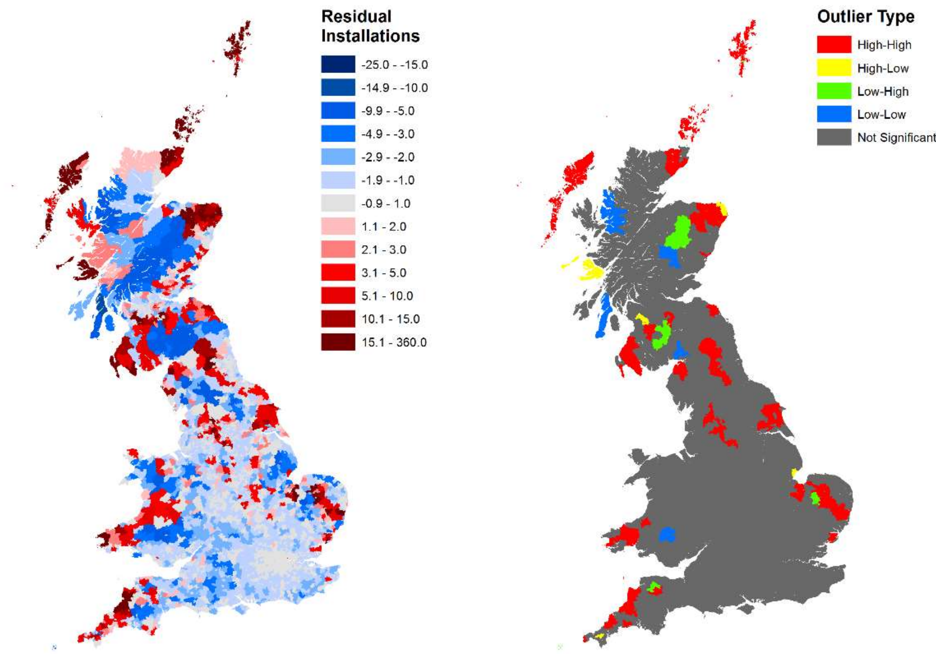

Figure 48 — Left: SER residuals for installations at SG. Right: Outlier regions at all distances identified under the Local Moran's I test

Comparison of all of the outlier regions with the residuals from which they were derived, highlighted that the majority of High-High or High-Low outliers were regions with high residual values, estimated to have at least 15 more wind turbines than predicted by the SER model.

In total, 12 clusters were identified in this analysis. The locations of the 12 clusters are presented in Figure 49. For each of the clusters, a surrounding area was also selected to assess if any diffusion of the wind turbine innovation from the cluster areas could be observed in the surrounding areas. The surrounding area of each cluster is presented in Figure 50.

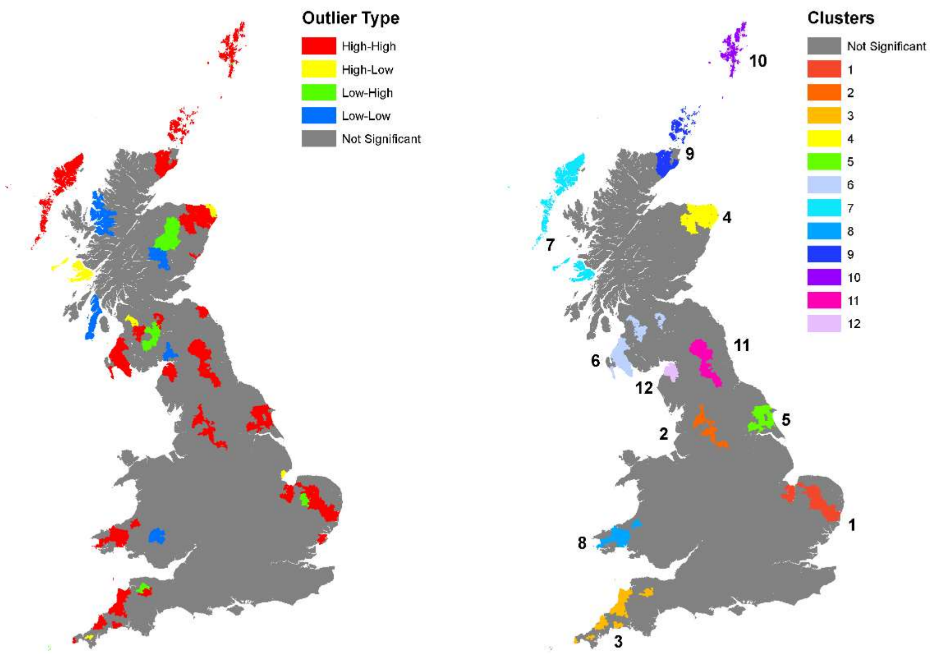

Figure 49 — Outlier regions at all distances identified under the Local Moran's I and the 12 clusters derived from the High-High and High-Low outlier types

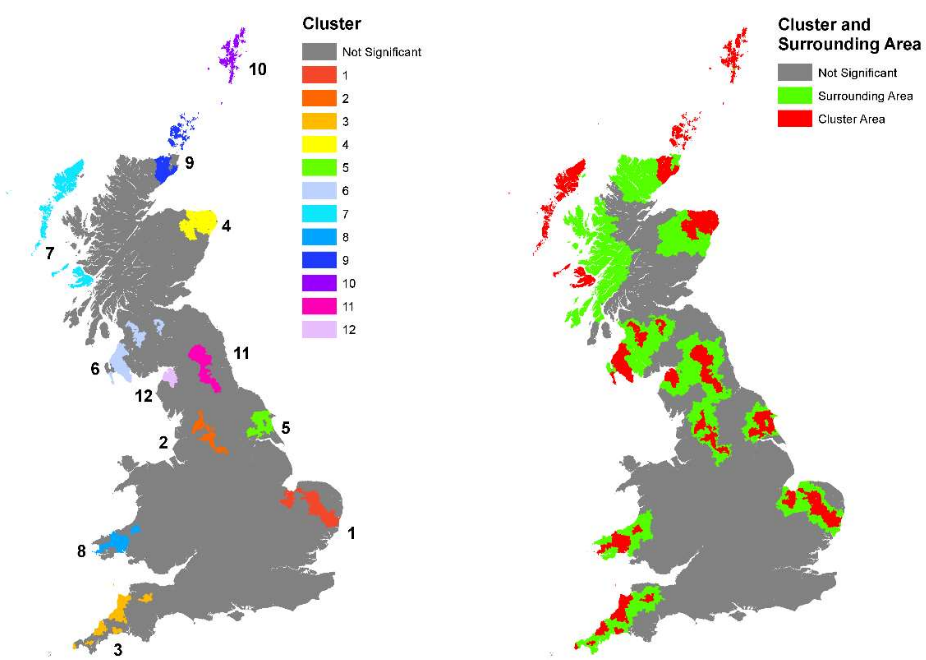

Figure 50 — The 12 clusters and the surrounding areas of each cluster

The number of regions in each cluster and its surrounding area is detailed in Table 20.

Table 20 — Number of regions in each cluster

Cluster number	Cluster name	Number of regions in cluster area	Number of regions in surrounding area	Total number of regions in cluster and surrounding area
1	East Anglia	30	56	86
2	Pennines	24	93	117
3	Cornwall	17	71	88
4	Aberdeen	17	88	105
5	East Yorkshire	10	42	52
6	Scottish Borders	8	104	112
7	Hebrides	7	18	25
8	South Wales	7	26	33
9	Orkney Islands	6	9	15
10	Shetland Islands	6	1	7
11	Northumberland	4	38	42
12	Cumbria	3	16	19

The location of the clusters identified were typically coastal or mountainous areas. Additionally, the majority of the clusters were away from major conurbations. The locations of the clusters can therefore be considered as rural and are likely to have a high wind resource, two factors which influenced spatial adoption patterns. These clusters must be characterised further to determine the number of potential adopters within each cluster.

6.1.3 Potential adopters and cluster characteristics

Once the clusters and surrounding area had been identified, the number of potential adopters in each region selected must be estimated. As discussed in Chapter 3, potential adopters are defined as individuals in a region who have the possibility to install a wind turbine. This metric was introduced to account for factors that would prevent a wind turbine installation, and is based on an approach previously published by Richter [43]. When utilised in relation to PV adoptions, the number of potential adopters was calculated as the number of owner-occupied homes in a region [43]. For wind turbine adoptions, it was likely that additional factors would limit wind deployment. The demographic model of Chapter 5 identified that house-type, specifically the prevalence of detached homes in a region was a significant factor which affected deployment. Therefore, the number of owner-occupied detached homes in a region formed the basis of the potential adopter metric for this research. This data was extracted from cross-sectional data of the 2011 census, which provided the number of homes in each region which were both detached and owner-occupied [161].

The influence of wind resource must also be considered in the calculation of the potential adopter metric. The results of Chapter 5 have shown that wind turbine deployment in Great Britain requires a minimum mean wind speed of 4.5 ms^{-1}. Inclusion of this wind resource metric as part of the potential adopter calculation was therefore required to account for this factor. BLS NCIC wind speed estimates from the research in Chapter 4, were produced for each 0.01 km^2 of the cluster regions. From these wind speed estimates across each region in the clusters, the percentage of land area in each cluster which had an mean wind speed of 4.5 ms^{-1} or above was calculated. Using this percentage, the potential adopter metric was scaled to account for the influence of wind resource on wind turbine deployment.

Finally, an estimation of the likelihood of planning permission being granted to a wind turbine was also included in the potential adopter metric. As discussed in Chapter 5, it is likely that the majority of wind turbines were subject to planning permission. The planning metric included in this research was composed of two parts; the percentage land area of a region covered by a restricted planning area and the planning statistics of the local council. The percentage land coverage of environmentally restricted planning area, such as National Parks and Areas of Outstanding Natural Beauty, was calculated by overlaying the location of these environmentally restricted planning areas for each region. While planning restrictions apply in these areas, it was possible to gain planning consent for a wind turbine installation from the relevant body, hence the inclusion of planning statistics from the relevant local authorities.

The local authority planning metric was calculated as the number of large scale onshore wind energy projects which have been approved, as a percentage of all onshore wind energy projects seeking approval, by the relevant local council. This data was selected to approximate the apparent support for large scale wind energy projects in the local council. The planning data was extracted from the Renewable Energy Planning Database (REPD) published by the UK Government for all renewable energy planning applications up to January 2017 [201]. While the number of planning rejections for utility scale wind turbines by a local authority may be influenced by factors others than council support, inclusion of the planning metric was important to calculate a more accurate potential adopter metric.

These factors were then combined to approximate the likely planning constraints of a region and this planning constraint metric was then utilised to calculate the number of potential adopters in each region, PA_i;

$$PA_i = OD_i \times WR_i \times (PC_i \times PS_i)$$

Equation 52

where OD_i was the number of owner-occupied detached homes in a region, WR_i was the fraction of land area in each region with sufficient mean wind speed, PC_i was the fraction of land area in the region not covered by an environmentally sensitive region and PS_i was the fraction of utility-scale wind turbines which gained planning permissions from the local council.

The introduction of the potential adopter metric was a vital part of the peer effects methodology. Without a potential adopter metric, it may not be possible to identify any peer effects as the model may examine areas with only a small number of potential adopters and therefore it would be unlikely to observe any peer effect. With the inclusion of the potential adopter metric, the peer effects model was able to efficiently estimate the temporal influence of neighbouring visible wind turbines and degression of the FIT subsidy rate on adoption rates in the clusters.

6.1.3.1 Cluster characteristics

The total number of potential adopters was calculated for both the cluster and their surrounding areas. However, given that each cluster was composed of differing numbers of regions, an mean number of potential adopters was calculated from the total number of potential adopters in a cluster and the number of regions in the cluster. This mean number of potential adopters in a single region of a cluster or surrounding area and the proportion of all residents considered as potential adopters is presented in Table 21.

Table 21 — Mean number of potential adopters and proportion of all residents classed as potential adopters in each cluster

Cluster name	Mean number of potential adopters in cluster area	Percentage of all residents in cluster area classified as potential adopters (%)	Mean number of potential adopters in surrounding area	Percentage of all residents in surrounding area classified as potential adopters (%)
East Anglia	1,345	39.9	954	29.3
Pennines	558	16.0	251	7.7
Cornwall	1,237	40.3	867	27.4
Aberdeen	850	48.2	299	15.3
East Yorkshire	1,185	35.5	687	19.5
Scottish Borders	575	30.6	321	18.1
Hebrides	569	39.7	484	28.8
South Wales	1,546	43.7	1,084	33.3
Orkney Islands	700	41.4	434	23.1
Shetland Islands	578	40.5	609	43.8
Northumberland	664	16.8	319	10.7
Cumbria	486	13.0	436	12.6

The mean number of potential adopters was typically higher in the cluster areas than the surrounding areas. This could suggest that the clusters may have formed due to the greater number of suitable properties within each cluster region. The higher mean number of potential adopters in the clusters was due predominantly to the higher wind resource available in the cluster regions. The lower number of mean potential adopters in the surrounding areas also suggested that diffusion to these surrounding areas may have been slow as there were fewer potential adopters which could be influenced by the visual peer effects from wind turbine installations in the clusters.

In total, 3,063 wind turbines were installed in the 12 clusters, up to December 2016. This accounted for 45 % of the total number of installations examined in the SER model, highlighting that the clusters selected in this research were the regions with the highest levels of wind turbine deployment. In addition to the installations in the cluster areas, there were 1,270 wind turbines installed in the surrounding areas of all clusters. Therefore, a total of 4,333 wind turbine installations across the clusters and surrounding areas were examined in the peer effects model, equal to 63.6 % of the total installations examined in the SER model.

Overall, 68.5 % of the wind turbines in the clusters and surrounding area had an installed capacity between 1.5 kW and 15 kW, while 67.5 % of these were installed for domestic electricity generation. Therefore, the examination of the peer effects in the clusters was primarily focused on the temporal adoption patterns of small-scale domestic wind turbines. The number of installations in each cluster and the surrounding area is presented in Table 22.

Table 22 — Number of wind turbine installations in each cluster

Cluster number	Cluster name	Number of installations in cluster	Number of installations in surrounding area	Total number of installations
1	East Anglia	459	95	554
2	Pennines	256	118	374
3	Cornwall	280	215	495
4	Aberdeen	338	126	464
5	East Yorkshire	125	68	193
6	Scottish Borders	224	240	464
7	Hebrides	184	91	275
8	South Wales	107	132	239
9	Orkney Islands	784	51	835
10	Shetland Islands	188	3	191
11	Northumberland	70	93	163
12	Cumbria	48	38	86
Total		3,063	1,270	4,333

The number of installations in the cluster areas was typically higher than the those in the surrounding areas, significantly greater in the East Anglia, Orkney and Shetland Islands clusters. However, in the Scottish Borders, South Wales and Northumberland clusters, the number of installations was greater in the surrounding areas, rather than the cluster areas. This suggests that diffusion of wind turbines was not a uniform process and differed in each cluster. Selection of these differing clusters therefore allowed the influence of the factors on these differing wind turbine diffusion rates to be examined.

As part of the potential adopter calculation, the mean wind speed from the BLS NCIC model, at 15 m in each 0.01 km^2 or hectare of a region was calculated. The total percentage land area of each cluster with an mean wind speed of 4.5 ms^{-1} or above was calculated from this data and is shown in Table 23.

Table 23 — Percentage area of each cluster with the minimum wind speed of 4.5 ms^{-1} or above

Cluster name	Percentage of area with minimum wind speed in cluster area (%)	Percentage of area with minimum wind speed in surrounding area (%)	Percentage of areas with minimum wind speed in all areas (%)
East Anglia	85.9	77.2	80.2
Pennines	75.8	50.1	55.4
Cornwall	96.2	86.5	88.3
Aberdeen	91.4	76.8	79.2
East Yorkshire	85.0	74.8	76.8
Scottish Borders	89.8	74.8	75.9
Hebrides	99.0	78.4	84.2
South Wales	95.1	92.9	93.4
Orkney Islands	98.1	94.5	95.9
Shetland Islands	100	100	100
Northumberland	71.1	41.6	44.4
Cumbria	46.6	66.7	63.6

With the exception of the Cumbria cluster, the majority of each cluster had sufficient mean wind speed for deployment. This was similar in the surrounding areas of the clusters, except for the area surrounding the Northumberland cluster. The mean wind speed in the clusters was higher than the average across the whole of Great Britain, where 64.2 % of all areas that had an mean wind speed above 4.5 ms^{-1}. This suggests that within the clusters, the availability of wind resource is generally high, which could have contributed to the high levels of deployment. The factor of wind resource was included in the SER model and hence in the residuals which were used to identify these clusters, the mean wind speeds in some of the clusters were higher than 4.5 ms^{-1}. In the majority of the clusters, at least 50 % of each cluster's land area had an mean wind speed above 5.5 ms^{-1}. The location of the clusters could also be the underlying cause of the higher than mean wind resource. All of the clusters were either in coastal or mountainous areas, where the wind resource was likely to be higher. These higher wind speeds may have contributed to cluster growth, as it was easily demonstrable from previously installed wind turbines that a potential adopter's proposed wind turbine would be technically viable.

While the wind resource may have been a contributory factor to cluster growth, the diffusion of the wind turbine innovation requires a degree of homophily between the residents [132]. It was therefore important to assess the resident homophily in each cluster, prior to implementation of the peer effects models, to understand if a diffusion of wind turbines was likely to be observed in the clusters.

The demographic variables of age, income and education, which were shown to be significant in the SER model, were selected to assess the homophily of residents in each cluster. Through examination of the value of each demographic variable in each region of a cluster, it was possible to understand the variability of these demographics factors across the residents in a cluster. Homophily between cluster residents would be seen as a lower variability in the demographic factors across residents of the cluster regions. Using the coefficient of variation (CV) metric, which is the ratio of the standard deviation, σ, and mean value, μ, of each sample [202], the relative variability of each demographic variable in a cluster can be expressed;

$$CV = \frac{\sigma}{\mu}$$

Equation 53

Lower values of CV indicate a narrower distribution and therefore a lower variability of the sample. The CV for each demographic variable in each cluster is presented in Table 24. In addition, a CV for each demographic variable across Great Britain is included to offer a comparison.

Table 24 — Coefficient of variation in each demographic variable in each cluster and for all of Great Britain

Cluster Name	Income	Age	Education
East Anglia	0.14	0.11	0.17
Pennines	0.14	0.11	0.32
Cornwall	0.08	0.09	0.24
Aberdeen	0.16	0.13	0.52
East Yorkshire	0.18	0.13	0.35
Scottish Borders	0.18	0.09	0.34
Hebrides	0.09	0.07	0.21
South Wales	0.06	0.08	0.19
Orkney Islands	0.15	0.08	0.23
Shetland Islands	0.06	0.06	0.16
Northumberland	0.21	0.10	0.25
Cumbria	0.13	0.07	0.24
Great Britain	0.29	0.15	0.46

Table 24 shows that the variability of the resident income, age and education variables in the regions of each cluster were low, in comparison to the variability across Great Britain. The results show that the residents within the clusters were likely to be similar in age, income and educational level. The residents in the clusters were therefore considered to be homophilic and that diffusion of the wind turbine innovation could theoretically occur between the residents of the cluster.

When examining the demographics of the residents in the surrounding areas, the CV data showed that the demographics had a higher degree of variability, particularly for educational level. This factor may have inhibited the rate of wind turbine diffusion from the cluster area to the surrounding areas as the residents may not be as similar. To determine if these assertions are correct, the results of peer effects model in each cluster must be analysed.

6.1.4 Peer effects methodology

The peer effects model was developed in this research to analyse the influence of visible wind turbines and changing levels of subsidy from the FIT on the temporal adoption patterns within the clusters. As discussed previously, the influence of the FIT on wind turbine adoptions in Great Britain has not previously been analysed, either in this project or in other studies. It is therefore likely that the availability of incentives for energy generation will have been a motivating factor for wind turbine adopters. However, changes to the subsidy level available under the FIT have occurred since 2012 [34] and it is the influence of these changes on temporal adoption patterns was of interest in this research.

The temporal nature of both changes to the FIT subsidy level and the number of neighbouring wind turbine installations lent themselves to being analysed in a temporal peer effects model. As discussed in Chapter 3, a pooled OLS model was identified as the most appropriate method for this research's peer effects model. The visibility of each turbine is dependent on the location of each viewer and therefore is different for every resident of the clusters. The influence of each visible turbine could not be modelled uniformly across all potential adopters in a cluster. Additionally, there was likely to be multiple wind turbines visible to each resident, each with a varying degree of visibility. The influence of the peer effect from neighbouring wind turbines consequently differed for each resident in a cluster. Use of a pooled OLS model discounted any subjective visibility of each turbine and considered only the influence of the peer effect of all the visible turbines in the cluster on a potential adopter [50, 52]. Additionally, a pooled OLS model could be used to examine the influence of all previously installed wind turbines on the wind turbine adoption rate of the whole cluster.

By incorporating the potentially influential factors of previously installed wind turbines in the cluster, $WT_{i,t-1}$, and the Feed-in Tariff subsidy level from the previous time step, FIT_{t-1}, the influence of each on the wind turbine adoption rate of the cluster, $AR_{i,t}$, at time, t, in region, i, could be examined;

$$AR_{i,t} = \alpha_0 + \beta_1 WT_{i,t-1} + \gamma_1 FIT_{t-1}$$

Equation 54

where, α_0, was the intercept term of model and the coefficient, β_1, was the endogenous peer effect while the coefficient, γ_1, was the influence of the FIT subsidy level. In the peer effects model of this research, the time step was set at 3 months.

The adoption rate in a neighbourhood, $AR_{i,t}$, was calculated as the number of installations in each time step, $I_{i,t}$, divided by the number of potential adopters, $PA_{i,t}$, in the neighbourhood at each time step;

$$AR_{i,t} = \frac{I_{i,t}}{PA_{i,t}}$$

Equation 55

While the adoption rate defined the number of installations per potential adopter in a region in the current time step, the number of wind turbine installations, $I_{i,t-1}$, in all previous time steps, $t-1$, across all neighbours, j, in the social neighbourhood, C, was defined as the installed base, $WT_{i,t-1}$;

$$WT_{i,t-1} = \sum_{t=0}^{t-1} \sum_{j}^{C} I_{i,t-1}$$

Equation 56

The inclusion of an installed base allowed the influence of all previously installed turbines, rather than just turbines installed in the previous time step to be examined. This was vital in the peer effects model, where the diffusion of wind turbines amongst the peers in a neighbourhood was expected to be slow and it was likely that the influence of visible wind turbines persisted over long time periods. Without an installed base metric, the wind turbine or turbines which influenced a subsequent decision to adopt in the neighbourhood may be excluded from the peer effects model.

In addition to the installed base of previously installed wind turbines in the cluster, the FIT variable of the peer effects models, $FIT_{i,t-1}$, must be considered. 63.3 % of all turbines examined in the peer effects model had an installed capacity above 1.5 kW and less than or equal to 15 kW and therefore the subsidy level for wind turbines matching these capacities was chosen [34]. The subsidy level for this banding ranged from 31.91 p/kWh in April 2010 to 8.33 p/kWh in December 2016, as seen Figure 51 and Table 25 [34].

Table 25 — Subsidy levels for wind turbines utilised in peer effects model

Time period	Subsidy level (p/kWh)	Time period	Subsidy level (p/kWh)
April 2010 to March 2012	31.91	April 2015 to September 2015	14.62
April 2012 to November 2012	30.48	Oct 2015 to March 2016	13.89
December 2012 to March 2014	22.86	April 2016 to June 2016	8.46
April 2014 to September 2014	18.28	July 2016 to September 2016	8.39
October 2014 to March 2015	16.46	October 2016 to December 2016	8.33

A decision to adopt a small or medium wind turbine is not instantaneous, and there will be a time lag between the initial decision to adopt and completion of the installation, when the visual peer effect would begin to influence neighbours. Therefore, the installed base variable was time lagged. Lagging of the installed base variable also addressed the reflection problem, seen in some previous peer effects models where peers are influenced and influence others within the same time step [136]. A time lag of 3 months was selected for the peer effects model in this work. Such a time lag represented a short lead time for a wind turbine installation, but was selected to ensure that a sufficient number of time steps were available.

In addition to the time lag for the installed base, a time lag of the FIT subsidy level was also introduced. This time lag of the FIT was selected due to the presence of peaks in the monthly wind turbine installation data, seen in Figure 51. These peaks were the result of an impending tariff change, which were typically announced 3 months before the subsidy level is implemented [35]. It was therefore reasonable to assume that potential adopters in the clusters were aware of an imminent change in the FIT subsidy, 3 months before the change occurred. Lagging of the tariff variable in the peer effects model allowed this phenomenon to be modelled.

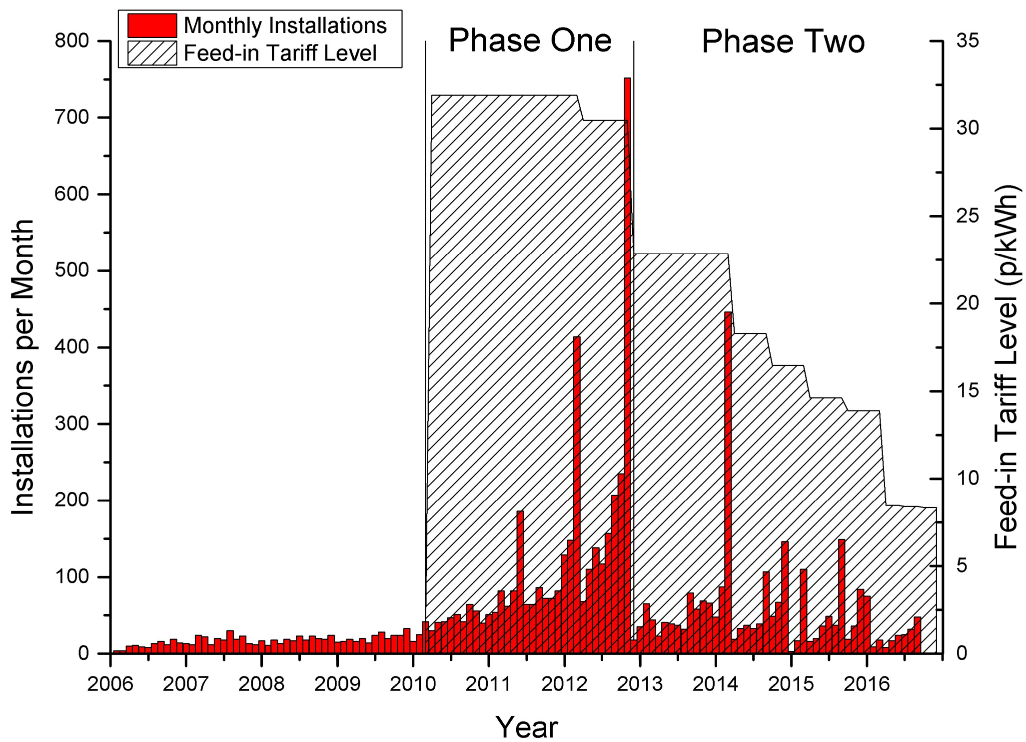

Figure 51 — Monthly wind turbine installations across Great Britain receiving FIT payments compared to changes in the FIT subsidy levels available between 2006 and 2016 [12]

Figure 51 shows the number of monthly wind turbine installations across Great Britain since 2006, in comparison with changes in the level of FIT subsidy available for wind turbines rated above 1.5 kW and less than or equal to 15 kW. The number of monthly installations appears linked to the tariff rate available and peaks of installations occur prior to a change in the tariff level. This suggests that the changes to the tariff have influenced wind turbine deployment, hence why it has been investigated in this peer effects model.

The wind turbine installation data which was utilised in the peer effects model was the same installation data from Ofgem [34] used in the models of Chapter 5. This dataset provided wind turbine installations from January 1995 to December 2016. With a time step of 3 months, there were 88 time steps available to be investigated in the model. The peer effects model was split into three time periods, prior to April 2010, between April 2010 to November 2012 and from December 2012 onwards. Each of these periods represented three distinct periods of the lifetime of the FIT policy, “Pre-FIT”, “Phase One of FIT” and “Phase Two of FIT”. The split across these time periods was based upon the data shown in Figure 51 and shows the influence of the tariff level during these three periods on wind turbine deployment.

Prior to April 2010, the only funding available for microgeneration technologies was from the Low Carbon Buildings Programme (LCBP) [203]. The LCBP provided grants for microgeneration installations including £4.6 million for 940 wind turbine installations [203]. During this period in the sample of data used here, 1,008 wind turbines were installed, which were later able to gain accreditation under the FIT.

From April 2010 and November 2012, the initial phase of the FIT, known as Phase One of the FIT policy, occurred [22]. During this time, the tariff level was between 31.91 p/kWh and 30.48 p/kWh [34] and the number of wind turbine installations totalled 3,815 in 32 months [12].

In December 2012, Phase Two of the FIT began and FIT subsidy levels reduced through the degression mechanism in the policy. As seen in Table 25, subsidy levels fell from 22.86 p/kWh in December 2012 to 8.33 p/kWh in December 2016 [34]. The number of installations during these 49 months was 2,532 [12].

The peer effects model was run over 88 3-month periods over 22 years of data for each cluster. Each year was subdivided into 3 month periods starting in January, April, July and October of each year. As discussed, the peer effects model for each cluster was split between January 1995 and January 2010 for the Pre-FIT period, April 2010 and July 2012 for the Phase One period and October 2012 onwards for the Phase Two period. In total, there were 60 quarters in the Pre-FIT period, 10 quarters in the Phase One period and 16 periods in the Phase Two period.

6.2 Peer effects model results

The peer effects model was run for the cluster areas, and also for the cluster and surrounding areas, to determine if a diffusion of wind turbine deployment was observed in the surrounding areas. The results of the peer effects model for each cluster were not intended for a quantitative comparison with those of other clusters. Each cluster was presumed to be different in terms of potential adopters and adoption rates and while some clusters may exhibit similar peer effects, the rationale was to examine the influence of peer effects in different locations across Great Britain.

The coefficients estimated in the peer effects model were not comparable given the different units of wind turbine installations and the Feed-in Tariff.

However, these values must be comparable during the analysis and therefore, the t-test value for the significance of each variable in the peer effects model was also reported. These t-test values allowed for the comparative significance of each variable to be assessed.

Across all of the clusters, no consistent description of when or how each factor influenced a decision to adopt could be observed. The differing geographical sizes and number of installations in each cluster resulted in the factors influencing adopters differently in each cluster. Therefore, a single conclusion on the influence of the endogenous peer effect or the FIT subsidy levels on temporal wind turbine adoption patterns could not be formulated. However, there were some key temporal adoption characteristics observed in a number of clusters. In some of the clusters, different adoption characteristics were observed during the different time periods modelled. This section will present these key results using the results of some clusters to illustrate the adoption characteristics. The results of the peer effects model in each cluster will be presented in the Appendix of this thesis. A further discussion of the likely underlying causes of these results will be presented in Section 6.3.

The first key result which was observed in all of the clusters modelled was that the number of installations increased dramatically after the introduction of the FIT in April 2010. In all of the clusters, at least 82 % of all total wind turbines were installed after April 2010, with 97 % and 95 % of all turbines in the East Yorkshire and East Anglia clusters installed after April 2010, with the evidence for this in the East Anglia cluster shown in Table 26. With the introduction of the FIT, an increased number of wind turbines will have been considered as an attractive investment by potential adopters. Despite the increased number of installations during Phase One, the significance of the FIT was not seen more prominently during this phase in the peer effects model. A lack of temporal change in the FIT during Phase One and the splitting of the peer effects model between the time periods caused this lack of significance for the FIT during Phase One. This idiosyncrasy of the peer effects model which caused this result will be discussed further in Section 6.3.

The increase in the number of installations during Phase One caused an increase in the significance of the endogenous peer effect from neighbouring wind turbines in 8 of the 12 clusters. The significance of the endogenous peer effect in these 8 clusters either peaked during Phase One or increased in Phase Two. These two characteristics were likely the result of either factors in the peer effects model, having a greater influence on temporal adoption rates in the relevant clusters.

6.2.1 Peak of endogenous peer effect in Phase One

The results of the East Anglia cluster, seen in Table 26, typified the temporal adoption characteristic which saw a peak in the endogenous peer effect during Phase One.

Table 26 — Peer effects model for the East Anglia cluster

	Cluster Areas Only			Cluster and Surrounding Areas		
Variable	**Pre-FIT**	**Phase One**	**Phase Two**	**Pre-FIT**	**Phase One**	**Phase Two**
Peer effect from wind turbines, β_1	1.79E−05 (1.535)	1.24E−04*** (5.042)	6.40E−06** (2.31)	1.58E−03 (1.066)	1.32E−03 (1.4)	1.81E−05 (0.615)
Feed-in Tariff, γ_1		−3.19E−05 (−1.085)	8.08E−06*** (3.911)		1.52E−03 (0.572)	2.16E−05* (1.702)
Intercept, α_0	3.52E−06***	1.05E−03	−1.35E−04***	9.45E−05	−4.76E−02	−3.06E−04
R^2	0.004	0.229	0.089	0.002	0.002	0.002
N	1800	330	510	5160	946	1462

t-test value of each coefficient is included in the parentheses
*** — Significant at 99 %
** — Significant at 95 %
* — Significant at 90 %

The results of Table 26 are indicative of a key temporal adoption characteristic, where the financial subsidy available from the FIT had the greatest influence over the wind turbine adoption rates. As discussed, the endogenous peer effect observed during Phase One was the result of a greater number of installations caused by the introduction of the FIT. During this phase, the endogenous peer effect peaks in significance before it dropped during Phase Two. In Phase Two, the degression of the FIT had greater significance than the endogenous peer effect. The increased significance of the FIT during this phase demonstrates that the reducing subsidy level is likely to have caused a drop in the adoption rates of the cluster. This is evidenced by the positive coefficient estimated during Phase Two, which demonstrated that as the FIT reduced so did the adoption rate of the cluster. This was also likely the cause of the reduction in the endogenous peer effect in Phase Two. It is therefore suggested that in clusters, such as East Anglia, the temporal adoption characteristics were influenced to a greater degree by the FIT.

While the East Anglia cluster has been used as an example in this chapter, this characteristic was also observed in the Pennine, East Yorkshire, Northumberland and Cumbria clusters. In these clusters, the percentage areas of the cluster which had an mean wind speed of 4.5 ms^{-1} or above were low in comparison to other clusters. In the Cumbria cluster, only 47 %

of the hectares in the cluster had a sufficient wind speed, the lowest percentage of all the clusters which exhibited this temporal adoption characteristic. It is suggested that the comparatively lower wind speeds in these clusters have contributed to the influence of the FIT on the adoption patterns. With a lower mean wind speed, the financial incentives available for a proposed wind turbine are likely to have to be high, to ensure that revenue from the turbine pays back the investment in a suitable time period. As the subsidy level of the FIT decreased, potential adopters within these clusters are likely to have concluded that a wind turbine would represent an investment with too much risk and decided not to pursue an installation, hence the drop in the adoption rates.

This temporal adoption characteristic was the most common characteristic observed in the results of the peer effects model presented in this chapter. Its presence in five of the twelve clusters, the highest proportion of the clusters which exhibited similar adoption characteristics, shows that the influence of the FIT on temporal adoption patterns was considerable.

6.2.2 Peak in endogenous peer effect in Phase Two

In contrast, the results of the Cornwall and Scottish Borders clusters and to a lesser extent, the Aberdeen cluster displayed a different temporal adoption characteristic. In these clusters, the endogenous peer effect increased during Phase Two. The results of the Cornwall clusters are shown in Table 27.

Table 27 — Peer effects model for the Cornwall cluster

	Cluster Areas Only			**Cluster and Surrounding Areas**		
Variable	**Pre-FIT**	**Phase One**	**Phase Two**	**Pre-FIT**	**Phase One**	**Phase Two**
Peer effect from wind turbines, β_1	1.64E−05** (2.354)	7.48E−05*** (6.347)	1.80E−05*** (18.379)	9.59E−05*** (6.196)	2.50E−04* (1.854)	2.36E−05*** (5.348)
Feed-in Tariff, γ_1		−5.56E−05 (−1.031)	1.15E−05*** (2.916)		−1.28E−04* (−1.732)	9.48E−06*** (5.139)
Intercept, α_0	9.81E−06***	1.80E−03	−2.00E−04***	1.84E−05***	4.09E−03*	−1.60E−04***
R^2	0.005	0.194	0.171	0.007	0.053	0.073
N	1020	187	289	5280	968	1496

t-test value of each coefficient is included in the parentheses
*** — Significant at 99 %
** — Significant at 95 %
* — Significant at 90 %

The increase in the significance of the endogenous peer effect observed during Phase Two was the major difference in these clusters, to those previously discussed. The significance of the endogenous peer effect from neighbouring wind turbines during Phase Two was likely to be as a result of a slow diffusion of the wind turbine innovation between the cluster residents.

During Phase Two, the greater significance of the endogenous peer effect suggested that, despite the FIT subsidy reducing, the diffusion of wind turbines between peers was occurring. This led to a greater number of wind turbines being installed during Phase Two in the Cornwall cluster.

The slow diffusion time, which was observed in these clusters, was likely to be the result of early majority adopters, who have a longer lead time between knowledge and adoption than earlier adopters, installing wind turbines in these clusters during the final time period. Coupled with comparatively high mean wind speed, 74 % of the Cornwall cluster had an mean wind speed above 5.5 ms^{-1}, these early majority adopters have decided that the risk associated with a wind turbine installation had been sufficiently diminished in this final time period. Through observational learning, early majority adopters may have been able to view operational wind turbines within the clusters to gather knowledge and observed the viability of wind turbines. This function of peer effect was observed in the diffusion of residential PV systems in Sweden [138]. The ability to observe operational wind turbines within these clusters is likely to have convinced later adopters, that despite the reducing subsidy rate available from the FIT, a wind turbine was still a viable investment.

Another feature that was common to these clusters was the significance of the endogenous peer effect in the Pre-FIT period. There were a number of wind turbines installed in these clusters prior to the introduction of the FIT. Linked to the longer time between knowledge and adoption for early majority adopters, these early wind turbines may have influenced later adopters by demonstrating the technical feasibility of a wind turbine in the cluster over a long time period. In the clusters described here, the significance of the endogenous peer effect during the Pre-FIT period was lower than in other periods.

6.2.3 Peak in endogenous peer effect in Pre-Fit Period

In some clusters, the endogenous peer effect was most significant during the Pre-FIT period. This phenomenon was seen in the Shetland and Orkney Islands clusters. The peer effects model results for the Shetland Islands are shown in Table 28.

Table 28 — Peer effects model for the Shetland Islands cluster

	Cluster Areas Only			Cluster and Surrounding Areas		
Variable	**Pre-FIT**	**Phase One**	**Phase Two**	**Pre-FIT**	**Phase One**	**Phase Two**
Peer effect from wind turbines, β_1	1.24E−04*** (7.676)	5.23E−05 (1.567)	2.23E−05 (1.249)	1.25E−04*** (7.75)	6.08E−05** (2.055)	2.22E−05 (1.381)
Feed-in Tariff, γ_1		−6.65E−04** (−2.106)	3.39E−05* (1.927)		−7.07E−04** (−2.559)	3.57E−05** (2.282)
Intercept, α_0	4.19E−05	2.17E−02**	−2.88E−04	3.54E−05	2.30E−02**	−3.28E−04
R^2	0.144	0.108	0.040	0.148	0.138	0.047
N	360	66	102	420	77	119

t-test value of each coefficient is included in the parentheses
*** — Significant at 99 %
** — Significant at 95 %
* — Significant at 90 %

In the Shetland Islands cluster, a different pattern of influencing factors on adopters was observed, in comparison to other clusters. In the cluster areas, an endogenous peer effect was seen in the Pre-FIT period, however, where the endogenous peer effect was not significant during Phase One and Phase Two, it was the FIT which became influential. It appears that the introduction of the FIT has reduced the significance of the visual peer effects from neighbouring wind turbines in these clusters.

During Phase One, the FIT was shown to be significant but was estimated to have a negative coefficient. This is indicative of the peak in installations during the final quarter of 2012, seen in Figure 51. This peak was caused by adopters wishing to secure a higher tariff rate before the impeding 25 % reduction in tariff rate. This peak in installations caused a rise in the adoption rate during the final time step of Phase One. The peak occurred when the tariff was 30.48 p/kWh, which was the lower of the two tariffs rates examined during Phase One of the peer effects model. The peer effects model therefore assumed that in Phase One, the relationship between adoption rate and FIT level was negative given the rise in adoption rate at a lower tariff rate.

The endogenous peer effect observed in the Pre-FIT period is likely to be the result of early adopters within these clusters installing wind turbines. Coupled with the considerable wind resource on these Scottish Islands, 87 % of the Orkney and 100 % of the Shetland Islands have an mean wind speed above 5.5 ms^{-1}, these adopters have decided prior to April 2010 that a wind turbine was a viable investment, possibly motivated by the ability to gain a grant to cover the capital costs from the LCBP [203]. These adoptions by early adopters, considered to be opinion leaders in Rogers' diffusion model, appear to have exerted a significant peer effect on others during this

Pre-FIT period. However, in the time periods that followed, the results of the peer effects model suggest that the level of financial subsidy available from the FIT dictated the adoption rates in these clusters, as evidenced by the peak in installations, observed as a significant negative coefficient estimated for the FIT during Phase One.

In these later time periods, it is likely that adopters were more likely to exhibit the characteristics of the early majority adopters. Less willing to assume a larger degree of financial risk, these adopters may have been influenced more by the changing subsidy rates to install wind turbines, rather than by the peer effects of the early turbines. In order to secure a higher tariff level, adopters in these clusters have installed prior to change in the tariff levels, leading the adoption rates to vary in line with the subsidy rate, as evidenced by the significance of the FIT during Phase One and Two shown in Table 28. This characteristic of temporal adoption, which was seen more prominently in other clusters, highlights that different adoption characteristics can be observed during different time periods of the same cluster.

6.2.4 Function of the endogenous peer effect

The final adoption characteristic was most evident in the results of the South Wales and Hebrides clusters. In these clusters, the significance of the endogenous peer effect was greater in the surrounding area than the cluster area. The results for the South Wales cluster are shown in Table 29.

Table 29 — Peer effects model for the South Wales cluster

	Cluster Areas Only			Cluster and Surrounding Areas		
Variable	**Pre-FIT**	**Phase One**	**Phase Two**	**Pre-FIT**	**Phase One**	**Phase Two**
Peer effect from wind turbines, β_1	1.16E−05* (1.785)	2.43E−05 (1.149)	8.96E−06 (1.107)	2.53E−05*** (3.284)	7.10E−05*** (4.662)	2.06E−05*** (5.745)
Feed-in Tariff, γ_1		−8.18E−06 (−0.143)	−4.66E−08 (−0.017)		−2.23E−05 (−0.417)	9.36E−06*** (4.348)
Intercept, α_0	6.46E−06*	2.96E−04	1.79E−05	8.59E−06***	7.76E−04	−1.35E−04***
R^2	0.008	0.018	0.010	0.008	0.060	0.050
N	420	77	119	1980	363	561

t-test value of each coefficient is included in the parentheses
*** — Significant at 99 %
** — Significant at 95 %
* — Significant at 90 %

The significance of the endogenous peer effect observed in the surrounding area but not in the cluster areas was due to the greater number of installations in the surrounding area than in the cluster areas during all the time periods. This result illustrated that the influence of any endogenous peer effect was apparently a function of the total number of turbines across all regions, rather than a higher number of turbines in a small number of regions. This result suggests, due to the differing visibility of each turbine for a resident, that if a resident viewed more turbines in the area surrounding their home, it was more influential on a decision to adopt than a greater number of turbines in their immediate neighbourhood.

This result is in contrast to some previous literature on peer effects in PV adoptions which suggested that the influence of the peer effect increased when neighbours where closer to PV systems [46, 47]. The results of the South Wales cluster showed that for wind turbines, the peer effect was influenced by more visible turbines rather than proximity.

In the surrounding area, the endogenous peer effect was observed in the majority of the clusters. However, it was typically less significant than the endogenous peer effect observed in the adjoining cluster area. These results suggest that while the endogenous peer effect did influence some potential adopters outside of the clusters, the lack of homophily between residents of the cluster and surrounding area is likely to have limited the diffusion outside of the cluster. The surrounding areas for the majority of the clusters were geographically large and therefore the turbines within the clusters may not have been visible to all residents, reducing the significance of the influence.

These temporal adoption characteristics observed in the results of the peer effects model of the clusters, are considered here as the most important to be discussed, to understand the likely causes of these adoption characteristics. While some brief explanations have been offered in this section, Section 6.3 will discuss the adoption characteristics and the likely causes for these further.

6.3 Discussion

The temporal adoption characteristics that will be discussed are: the influence of the Feed-in Tariff; the influence of the visual peer effect and how this occurs between adopters; and the adopter characteristics of wind turbine adopters in these clusters. In addition, the formation of the clusters will also be addressed.

6.3.1 Influence of the Feed-in Tariff

In all of the clusters, the number of installations increased during the Phase One period from the preceding period. Across all of the clusters, there was a 500 % increase in the number of wind turbine installations from the Pre-FIT period. The underlying cause for this increase in installations in all clusters was likely to be the introduction of the Feed-in Tariff. Introduction of the FIT subsidy improved the financial case for wind turbines, as the FIT provided payments for energy generation and reduced the payback period of a wind turbine. A reduced payback period of a wind turbine promoted the rapid uptake seen in Phase One. However, the results of the peer effects model for the FIT do not appear to support this, as changes to the FIT were not shown to be significant during Phase One.

Despite higher levels of deployment during Phase One, the lack of significance of the FIT was a result of how the peer effects model operates. The peer effects model was reliant on a temporal change in the variables to identify any influence on the dependent variable. The subsidy level only changed once during Phase One and did not capture any change in the adoption rates caused by the introduction of the FIT, due to the split of the model between time periods. The peer effects model was therefore considered less suitable to examine the influence of the FIT during Period One, given this lack of temporal change in the subsidy level. Despite the lack of significance observed in the peer effects models, the influence of the introduction of the FIT can be seen Figure 52, where the number of installations in the clusters increases dramatically after 2010.

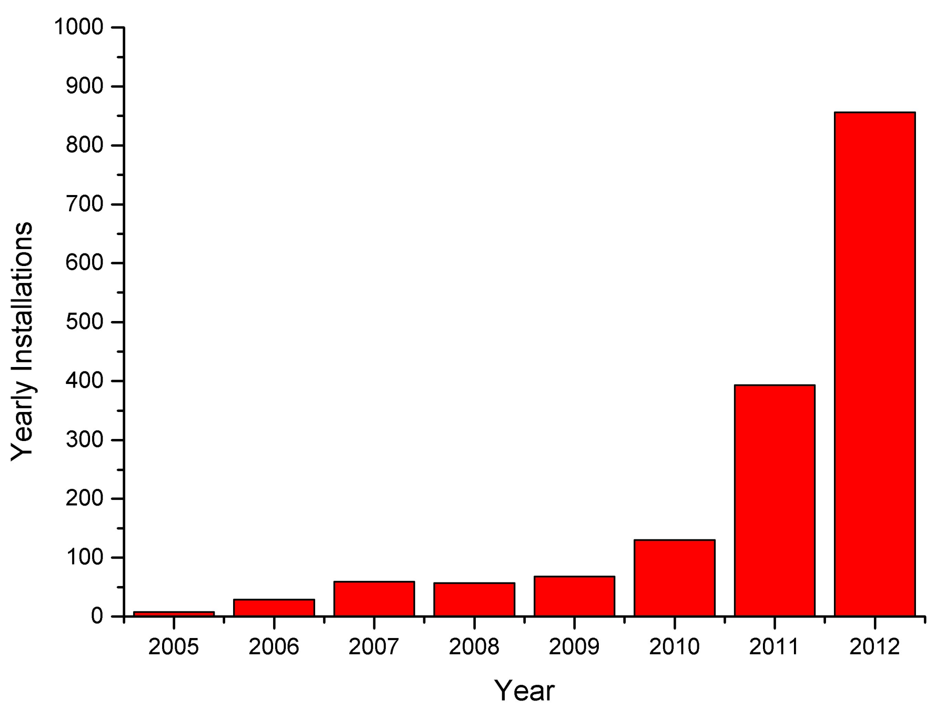

Figure 52 — Yearly installations in all clusters from 2004 to 2012

Given the apparent influence of the FIT and its lack of significance during Phase One, the question of the suitability of using a peer effects model to examine the influence of the FIT is a valid one.

The influence of the changing subsidy level on temporal wind turbine adoption rates was seen in seven clusters during the Phase Two period. The increase in the significance of the FIT observed during Phase Two also typically caused a reduction in the significance of the endogenous peer effect during this period. As the FIT subsidy level reduced so did the number of wind turbine adoptions per quarter. This suggests that reducing subsidy levels affected the financial viability of some wind turbines, causing potential adopters to either delay or scrap their proposed wind turbine installations. This result justified the use of the peer effects model to examine the influence of the FIT.

This result also suggested that introduction of the degression mechanism has slowed wind turbine deployment in the clusters. It is also likely that this phenomenon, will have occurred in the temporal adoption patterns outside of the clusters. This assertion was supported by the cumulative installation curve, shown in Figure 53, where the rate of wind turbine deployment across the whole of Great Britain slowed following the first degression step to 22.86 p/kWh in December 2012. In the following months, the rate of deployment slowed further as the subsidy level available from the FIT underwent further degression steps. Coupled with the results of the peer effects model which showed the significant influence of subsidy level on adoption rates after December 2012, the reasoning behind the introduction of the degression mechanism in the FIT policy must be examined.

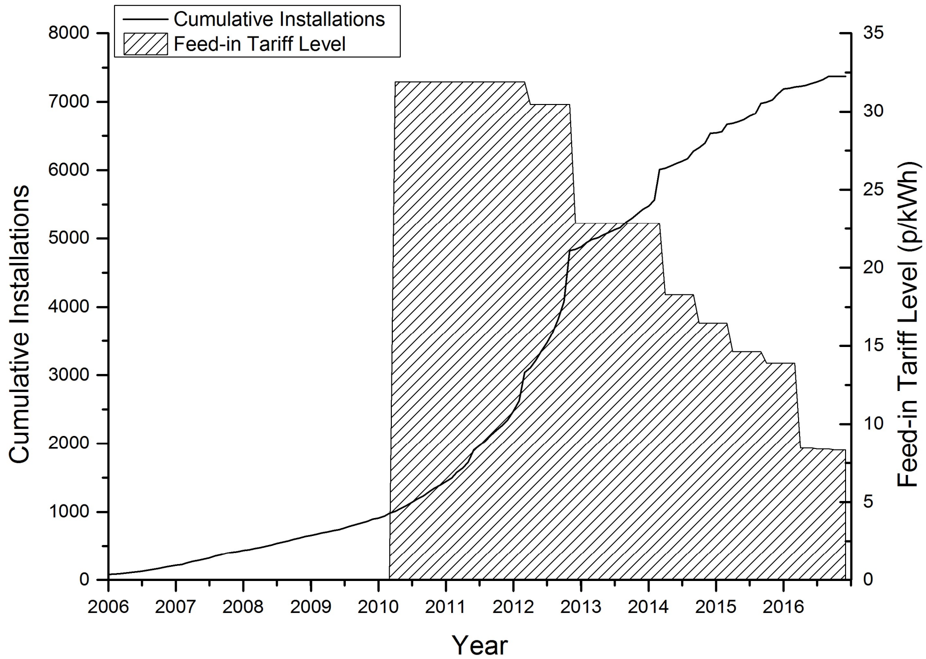

Figure 53 — Cumulative installations of wind turbines across Great Britain receiving FIT payments and changes in the FIT subsidy levels available [12]

The degression mechanism was first introduced in 2012 in conjunction with a tariff change, while the first degression of the FIT subsidy level for wind turbines occurred in April 2014 [35]. Introduction of the degression mechanism for wind turbines was in line with those introduced for PV systems. The degression mechanism was introduced to "*ensure that tariffs... reflect latest evidence on technology costs…reducing overcompensation of investors. The review also aims to drive cost reductions*" [204]. The rationale behind the degression mechanism was to ensure that as the capital costs of a technology reduced, the level of subsidy available was comparative to ensure that the market remained competitive [204].

A reduction in capital costs has occurred in the PV market, from around £3,500 per kW in 2011 [37, 205] to around £1,500 per kW in 2015 [21]. A cost reduction on this scale has not been seen in the wind turbine market of Great Britain. Median capital costs of a wind turbine have stayed consistent at around £4,000 per kW between 2011 [37] and 2015 [21]. A report commissioned by the Department of Energy and Climate Change (DECC), as part of the consultation process prior to introduction of the degression mechanism, even suggested that wind turbine capital costs had increased since 2010 [206]. Despite this, the degression mechanism was introduced to decrease the level of FIT subsidy available for wind turbines.

The impact of the degression mechanism on the wind turbine and PV markets of Great Britain has been different. Figure 54 shows the number of cumulative installations of PV systems across Great Britain compared to the subsidy level available from the FIT.

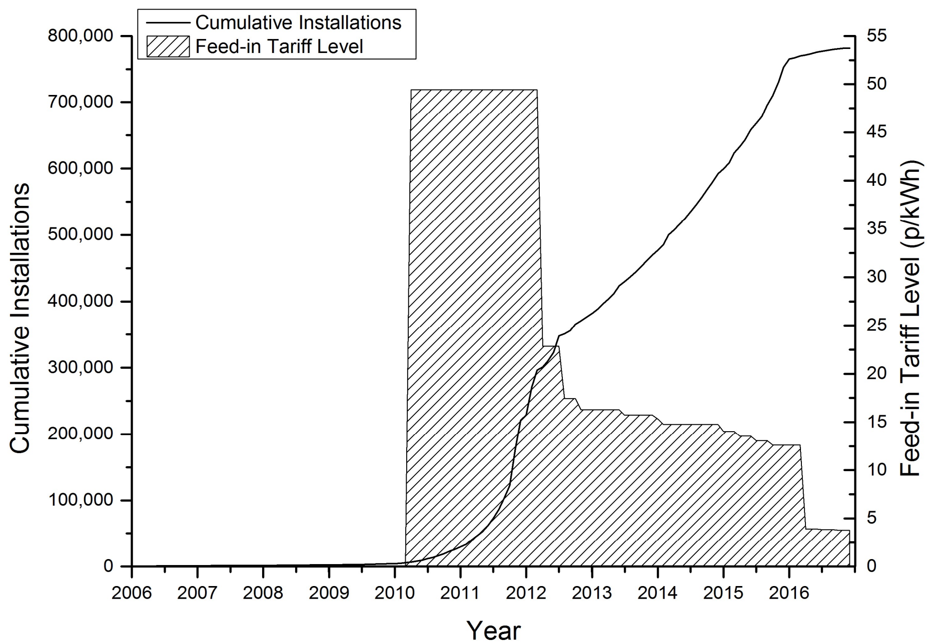

Figure 54 — Cumulative installations of photovoltaic systems across Great Britain receiving FIT payments and changes in the FIT subsidy levels available [12]

Comparison of the cumulative installation curves of wind turbines and PV systems following the reductions in subsidy level is striking. The rate of deployment of PV systems remained consistent following the tariff degressions, whereas the rate of wind turbine deployment reduced following tariff degressions. The reductions in the capital costs of a PV system meant that, even with a reduced subsidy level, an installation would have offered a suitable payback period for potential adopters. The number of PV systems installed and the initial level of FIT subsidy available has also contributed to a reduction in the capital costs of PV systems. This, however, has not been the case for wind turbines, where deployment has been around a tenth of PV systems and the reduction of the subsidy level has slowed deployment.

However, the rationale for introduction of the degression mechanism was predicated on the capital costs of a wind turbine reducing as they had for PV systems. This reduction in capital costs did not occur within the wind turbine market. Thus, the supply chain of the wind turbine market were unable to gain any cost advantages in their manufacturing and distribution processes that would have reduced capital costs. The capital costs of wind turbines have remained similar and rather than limiting overcompensation to adopters as intended, the degression mechanism has limited future wind turbine deployment in Great Britain. This demonstrates that the wind turbine market still requires subsidies from the FIT to promote future uptake.

It is argued here that introduction of the degression mechanism for wind turbines has damaged the market and has prevented any potential reductions in capital cost. The rationale for its introduction in 2012 appears arbitrary, without forethought of the long-term effects on the market and was driven by a desire to reduce FIT policy administration costs, rather than support deployment. It has had a severe effect on wind turbine adoption rates in the clusters and across Great Britain and therefore it is suggested by the author that to promote future wind turbine deployment, the degression mechanism for wind turbines must be removed from the FIT policy. Should the degression mechanism remain a central part of the FIT remuneration policy, it risks jeopardising the ability of the small and medium scale wind turbine market to provide the levels of deployment required for the societal pathway to deliver a transition to a low-carbon energy system in Great Britain.

6.3.2 Influence of visual peer effects

While the influence of the FIT was most significant during Phase Two in the majority of the clusters, the influence of the visual peer effect was observed throughout all three time periods. This highlighted that although the influence of the FIT appeared to be dominant in some clusters, especially in Phase Two, an increased number of visible wind turbines in a cluster did have an influence on the subsequent wind turbine adoption rates of the clusters.

One of the features apparent from the results of the peer effects model was that the endogenous peer effect was a function of the total number of visible wind turbines in a cluster rather than proximity to high levels of wind turbine deployment. This was most evident in the results of the South Wales cluster where a high level of deployment in a lower number of regions resulted in a low endogenous peer effect compared to an increased number of turbines across a greater number of regions. This result is counter to some results of the influence of endogenous peer effects on PV systems adopters, which have suggested that the magnitude of such a peer effect was a function of neighbour proximity [46, 47]. However, the difference between the results of peer effects in the PV and wind turbine market is likely to be the result of the differing visibility characteristics of each technology. Wind turbines are visible over a greater distance than PV systems and are visibly operational as the turbines blades turn, whereas PV systems have no moving parts.

Each visible wind turbine in a cluster and surrounding area was likely to offer a greater opportunity for observational learning, and allowing a potential adopter to observe more wind turbines in operation across a greater number of locations increased the chance of adoption. Given the operational characteristics of a wind turbine, this result suggested potential adopters were influenced more by the ability to observe a wind turbine [138]. During the knowledge phase of the adoption process, each potential adopter was able to view operational wind turbines within their neighbourhood to understand if such an installation would be suitable for them [132]. This process allowed potential adopters to evaluate the merits of a wind turbine, including the available wind resource in their neighbourhood, without the need for financial investment to gain this information. By observing multiple turbines, adopters could base their decision upon a sample of turbines, rather than a single wind turbine, thus increasing their confidence that such an investment was worthwhile. Observational learning is therefore theorised here to be the likely underlying mechanism that caused the visual endogenous peer effect observed in the result of this research's peer effects model. This theory was suggested by Richter as the underlying mechanism of the peer effects observed in the PV market of the UK [43].

The endogenous peer effect was observed in all three phases, however, the underlying causes are likely to have been different in each phase. Where the endogenous peer effect was significant during the Pre-FIT phase, this peer effect is likely to be motivated by adopter characteristics. This phase was the earliest examined in this research and therefore the adopters during this period were most likely to be considered as early adopters. While early adopters usually install later than innovators, they have more influence in the local social system. The endogenous peer effect observed within the Pre-FIT period is likely to be the result of early adopters, who are seen as opinion leaders in the local social system, influencing others to install a wind turbine.

Where the endogenous peer effect was seen during Phase One, it is likely to be the result of an increased number of installations. With the increased number of wind turbines, the opportunities for observational learning will have increased for potential adopters. Coupled with the ability to earn revenues for energy generation, the prevalence of visible operational wind turbines is likely to have resulted in the endogenous peer effect, seen in the peer effects model results. Due to the limitations of the peer effects model, it was not possible to determine from the results whether the FIT or endogenous peer effect was most significant during this period. However, it is likely that the endogenous peer effect seen during Phase One was as a result of the influence of the FIT which increased the number of wind turbines being installed. Therefore, it is assumed here that the endogenous peer effect would have been lower during the Phase One period if the FIT had not been available. This conclusion highlights that the FIT was the most significant influence on temporal adoption patterns in the majority of clusters examined.

In three of the clusters, the significance of the endogenous peer effect appears to have outweighed the influence of the FIT during Phase Two. In the majority of clusters, the endogenous peer effect decreased in Phase Two, however, in these three clusters, the significance of the endogenous peer effect increased in Phase Two. In two of the Scottish clusters, which this characteristic was observed, an increase in the number of installations compared to the previous time periods was observed. The financial incentives available from the FIT reduced during Phase Two and therefore it was likely that the greater number of installations during this period was due to the slow diffusion process of the wind turbine between adopters in these clusters.

Wind turbines installed earlier in the cluster have influenced decisions to adopt during Phase Two. The turbines installed during either the Pre-FIT or Phase One periods influenced peers in the neighbourhood over a long period of time. This slow diffusion process was likely to be the result of adopters during Phase Two being considered part of the early majority [132]. This type of adopter requires a longer lead time between knowledge of the innovation and adoption [132]. During this long lead time, such adopters gather as much information as possible regarding the innovation and wait for the risk associated with the innovation to reduce before they adopt [132]. This was seen in the peer effects model as a slow diffusion time, which was likely to cause the higher adoption rates during Phase Two in some clusters. Early majority adopters within the clusters could observe the neighbouring wind turbines for a longer time to understand if a wind turbine was a suitable investment for them. In these clusters, the wind resource was considered high and therefore neighbouring wind turbines were likely to be operational for long periods of time. This demonstrated to these later adopters that the financial returns of their potential turbine were likely to be favourable, mitigating some of the potential financial risk of a wind turbine investment which increased with the reducing FIT subsidy. Once a potential adopter was satisfied that a wind turbine would represent a worthwhile investment in their neighbourhood, they would be more likely to install a wind turbine. The slow diffusion time led to the increased significance of the endogenous peer effect observed during Phase Two in these clusters.

The fact that the influence of the visual peer effect has been observed during this research has implications for future wind turbine deployment strategies. Any strategies to promote future deployment of wind turbines could be designed to promote uptake using the endogenous peer effect. A future policy could aim to promote wind turbine deployment by initially increasing adoption in a neighbourhood, with the stated aim of using the endogenous peer effect from these initial turbines to promote further deployment [207]. The initial deployment within a neighbourhood would have to be significant, to ensure that enough opportunities for observational learning would be available for potential adopters. The effectiveness of such a policy would be limited by the visibility radius of the turbines. Therefore, any such policy would have to be introduced in areas where the potential for future wind turbine deployment is high.

6.3.3 Adopter characteristics

The results of the peer effects model suggest that currently, in the clusters examined, the majority of potential adopters are likely to exhibit the traits of the early majority. The results of the peer effects model offer an indication of the position along the innovation curve of wind turbines in these clusters.

As discussed, early majority adopters take a longer time between gaining knowledge and adoption of an innovation to understand how such an innovation will benefit their lives, hence the slow diffusion time observed. Additionally, these adopters are more sensitive to financial constraints than earlier adopters, which accounts for the influence of the FIT observed in the results. Based on these observations, it is concluded here that current wind turbine adoptions account around for a quarter of eventual wind turbine deployment in these clusters [132].

Therefore, results of the peer effects model suggest that, in the clusters examined, the wind turbine innovation is approaching or has reached the “chasm” in its adoption lifecycle [208]. This chasm, initially theorised by Moore, occurs when adopters in different adopter categories have different expectations of an innovation. While earlier adopters may adopt a wind turbine to display their environmental credentials, later adopters are more concerned with the financial benefits available from an installation. To "cross the chasm" and move into the mainstream, the risk surrounding an innovation must reduce to ensure that later adopters are confident of receiving a return on their investment [132]. Should this occur, the diffusion of the innovation can become self-sustaining and allow the innovation to be adopted by the majority of potential adopters [208].

For wind turbines to cross the chasm, in these clusters, deployment needs to increase. However, to increase deployment requires political support. As the financial case for a wind turbine becomes weaker with each degression of the FIT, it is currently likely that deployment rates will stall and fail to fulfil the technical potential. With either higher tariff rates or a reduction of capital costs of wind turbines, it may be possible for wind turbines to cross the chasm. Within these clusters, it may be likely that increased levels of face-to-face verbal communication between peers could promote deployment as previous adopters share their experiences of wind turbine adoption. However, it is an improved financial case for wind turbines that is more likely to have a greater impact on later adopters in the clusters.

It is only within the clusters modelled during this research, that any definitive conclusions on the characteristics of the adopters can be formed. It is clear from the results that diffusion of wind turbines in these clusters was not uniform. It is therefore assumed that in areas not examined within this research, adopter characteristics will be different. It is likely that potential adopters in other areas will exhibit the traits of earlier adopters. The clusters were areas of high levels of wind turbine deployment and therefore any area outside the cluster may have greater potential for wind turbine deployment. It is assumed that the adoption lifecycle is most advanced in these clusters and in other areas outside the clusters, this adoption lifecycle has not advanced as far and therefore the adopters in these areas are more likely to be early adopters. However, further work would be needed to test this hypothesis.

6.3.4 Cluster formation

It is reasonable to investigate why these clusters initially formed. By examining the clusters and their residents, it may be possible to identify reasons for their formation. Formation of these clusters may have been motivated by the influences examined during the peer effects model. In all clusters prior to 2010, less than 20 % of the total wind turbine installations had occurred. Therefore, it could have been the introduction of the FIT which has caused the high levels of deployment observed in the clusters. However, there must have been contributing factors that caused these clusters to form, otherwise it would be expected that similar levels of wind turbine deployment would have seen across all of Great Britain.

The cause of cluster formation has also been addressed in some peer effects literature, when discussing correlated unobservables in a peer effects model [43, 45-47, 137, 142]. In the context of a peer effects model examining microgeneration uptake, the correlated unobservable discussed most prominently was the influence of a local marketing campaign by a company who installed microgeneration technologies [43]. A local marketing campaign would increase residents' awareness of wind turbines. Such a marketing campaign would only be profitable for the company if they targeted an area with sufficient wind speed to ensure a wind turbine installation was financially viable. Investigation of the mean wind speeds in the clusters suggested that the majority of them would be considered suitable for such marketing campaign. By a company offering discounts for installations or implementing a scheme similar to Solarize CT, where the unit price of the microgeneration technology decreases with each installation [141], the number of wind turbine installations in a cluster would be likely to increase quickly. No evidence of any marketing campaigns in these clusters could be found and without surveying the individual adopters, it is difficult to determine if such a campaign occurred and caused cluster formation.

Clustering of installations was also discussed in some literature in the context of adopter “self-selection” [43, 46]. Self-selection occurs when residents with similar social status and beliefs form social groups [135, 142]. Other authors have identified this self-selection as a reason for spatial clustering of installations as individuals who have a similar propensity to adopt a microgeneration technology, reside close to each other [43]. The clusters identified in this analysis could be the result of homophily of residents in the clusters. Identification of the clusters, through use of the SER residuals already contained information regarding the relative socio-economic factors of each cluster. The demographics of the residents in the clusters, shown in Section 6.1.3.1, were also similar. This indicates that homophily between cluster residents was high and could have caused these clusters to form. Self-selection by the adopters, who decide to purchase properties close to others who were likely to install wind turbines could have caused the clusters to form. There is no method to test the self-selection hypothesis without surveying the adopters to understand their motivations for purchasing their homes and installing a wind turbine.

It is highly likely that adopters in the clusters will have been required to gain planning permission for their wind turbine from the local council. In the clusters, it was possible that the councils which granted the planning permission were favourable towards wind turbine installations. Given the high levels of wind resource in each clusters, wind turbine installations may be viewed by local councils as a way of meeting any local renewable energy targets which they have might set. While any local renewable energy targets may be set at council level, national planning policy states that "*local planning authorities should…contribute to energy generation from renewable or local carbon sources*" [185]. Research conducted by the University of Edinburgh and shared with the author, found that in the majority of the clusters, the relevant local authorities have a strategic plan to promote renewable and low carbon energy sources and either investment or ambitions to invest in low carbon energy projects [209]. This would suggest that the local councils, which administer the regions of the clusters were likely to be more favourable towards a planning application for a small wind turbine, leading to increased deployment in these clusters. While this was not consistent in all of the clusters, it may be a contributing factor in the formation of some of the clusters selected.

The results of the SER model have shown that agricultural industries are likely to be prevalent in the clusters. The National Farmers Union (NFU), as part of a wider steering group, have advocated that farmers should diversify their incomes through the installation of renewable energy technologies on their land [210]. This promotion of renewable energy by the NFU was likely to raise awareness in farmers and it is possible that any farmer who decided to adopt would consult the NFU for advice on which wind turbine to install and which company to install the turbine. 25 % of all adopters have indicated that they found their installer through a source other than the internet or friends and family [55]. It was possible that these alternative sources could include a trade body such as the NFU. Promotion of renewable energy by the farmers' union may therefore have contributed to formation of the clusters, where the level of agricultural industry was high.

While all of these factors may have contributed to formation of a cluster in certain instances, it is more likely that a combination of these factors will have caused cluster formation. As seen in the results of the peer effects model, each cluster was unique and therefore the combination of the contributing factors required for cluster formation is likely to have been unique.

6.4 Conclusions

The peer effects model was developed to examine the temporal adoption patterns of wind turbines in several clusters. Investigating the influence of the visible neighbouring wind turbines or changes to the subsidy rate available from the FIT, the peer effects model results showed that numerous temporal adoption characteristics influenced by either factor could be observed in the clusters. The model also provided results which offered a depiction of how the adopters of wind turbines have changed over time in these clusters.

The influence of neighbouring visible turbines was observed in the majority of the clusters, particularly during the time period after the introduction of the FIT. It is concluded here that the endogenous peer effect from these turbines did influence potential adopters. However, the increase in the number of wind turbine installations, seen in this period, can be attributed to the introduction of the FIT rather than the endogenous peer effect. The endogenous peer effect was likely to be an influencing factor in an adopter's decision to install when it was observed during the period prior to April 2010. In a minority of clusters, the endogenous peer effect was at its most significant during the final time period modelled. In these cases, it was the slow diffusion time of the wind turbine innovation between peers in the social system which caused this result.

However, it was the FIT which was the most significant influence on adopters during this final time period in many of the clusters examined. As the subsidy rate available from the FIT decreased during this period, the adoption rates within these clusters also decreased. This suggests that adopters were influenced to a greater degree by the subsidy level changes rather than the increased number of visible wind turbines. Coupled with the increase in installations, due its introduction in April 2010, it has been concluded that currently the FIT is the dominant influence on temporal wind turbine adoption patterns in these clusters. The significance of the FIT observed in this peer effects model has implications for future deployment which is likely to be hampered by future degressions.

The influence of the FIT indicated that potential adopters of wind turbines within these clusters are likely to exhibit the characteristics of early majority adopters. A long time between knowledge and adoption and an increasingly focus on the financial benefits of a wind turbine are the common attributes of an early majority adopter, a characteristic seen in the temporal adoption patterns of the clusters. The increasing significance of the FIT during the later time periods suggests that potential adopters were increasingly influenced by the financial benefits, and with reducing subsidy levels, decided against installing a wind turbine. Additionally, in the clusters where the endogenous peer effect was most significant during Phase Two, this is indicative of the longer lead time which early majority adopters typically exhibit. In the clusters where this was observed, it is likely that these early majority adopters have decided that a wind turbine was a suitable investment, despite the lower tariff rates.

The research presented in this chapter, when considered in conjunction with the results of previous chapters, offers a clear representation of the position of the wind turbine market under the FIT in Great Britain. The significance of rural factors, observed in the results of Chapter 5, and the findings of this chapter suggest that currently the wind turbine market is relatively immature. The significance of the FIT suggests that current adopters are focused on the financial benefits of wind turbines and therefore installations only occur in locations where the wind resource and availability of land is sufficient to offer a return on an investment. These factors, coupled with the comparatively high capital costs of wind turbines, suggest that the market has significant potential for future growth.

An understanding of the potential for growth in the wind turbine market will allow a number of policy suggestions to promote deployment to be provided. By determining where and how future growth in the market may occur, it will be possible to recommend policies to precipitate this deployment. Any policy recommendations must also consider the results presented in this chapter and understand how to use the influences examined here to promote deployment. Estimates of potential wind turbine deployment in Great Britain and a number of policy suggestions to achieve this are provided in Chapter 7.

Chapter 7 – Project conclusions and policy implications

To achieve the energy systems transition required to meet the renewable energy generation targets agreed to by the UK government [5], deployment of decentralised energy such as small and medium scale wind turbines could be important. Through high levels of wind turbine deployment, the societal pathway could contribute to the delivery of this energy systems transition. However, the high levels of deployment required are not currently being achieved as wind turbine deployment has only reached 7,374 by December 2016 [12], despite a potential for up to 400,000 wind turbines across Great Britain [31]. To achieve higher deployment, current wind turbine adoption patterns of Great Britain and the factors which have influenced these patterns were examined. From the results of this research, a number of policy recommendations to promote future deployment are suggested and will be outlined in Section 7.3.

A project of research was developed to assess a variety of factors which have influenced wind turbine adoption patterns. In total, three schemes of research were developed and presented in Chapter 4, Chapter 5 and Chapter 6 of this thesis. Chapter 4 presented a boundary layer scaling (BLS) methodology for wind speed predictions and offered a comparison of the accuracy of the BLS model using different reference wind map climatologies with the Microgeneration Certification Scheme (MCS) methodology. In addition to this comparison, Numerical Weather Prediction (NWP) data was utilised for wind speed and power density predictions from the BLS model. Chapter 5 examined the influence of various factors on spatial wind turbine adoptions patterns of Great Britain. Along with mean wind speed from the BLS model, various demographic and environmental factors were examined to understand their influence on spatial wind turbine adoption patterns. Chapter 6 examined the influence of previously installed neighbouring wind turbines and the changing levels of subsidy available from the FIT on the temporal wind turbine adoption patterns in a number of case study areas across Great Britain.

While the conclusions of the work offer the fullest picture of the small and medium turbine market under the Feed-in Tariff in Great Britain, the research is not without its limitations. The BLS model research of Chapter 4 was validated against a series of observational sites and therefore the accuracy of the wind speed predictions away from these sites is untested, While the sample size of 124 sites is considered sufficient to allow conclusions of the accuracy of these predictions to be drawn, the sample did not include any sites in urban areas. Therefore, the accuracy of the BLS wind speeds in this work are untested. Additionally, the ability to disseminate the results of the research may be limited as the input data used to create these results were provided under academic license for this project.

The limitations of the research presented in Chapter 5 and Chapter 6 stemmed from the use of statistical models to determine the influencing factors on wind turbine deployment. By using statistical models, the factors identified during this research are those which influenced the majority of adopters. Therefore, there could have been some individual adopters which were influenced by factors that were either considered uninfluential during this research or were not included in the study. These limitations ultimately stem from the subjective nature of adoption for each individual and the different factors which influence each individual adopter.

Bringing together these different pieces of research, it was possible to identify a number of factors which have influenced wind turbine adoptions in Great Britain. These schemes of research were developed to answer the research questions posed in Chapter 1 and the answer to each of these questions, formulated using the results of the research will be presented in Section 7.1. From the results of each chapter, an overall conclusion of the project was formed and a number of potential deployment estimates along with a number of policy suggestions for promoting wind turbine deployment were developed. This overall conclusion, the potential deployment estimates and the policy suggestions are presented in Section 7.2.

7.1 Research questions

The research questions of this project were;

1. *Are the wind resource assessment techniques available at the initial scoping stage of a wind turbine installation able to predict wind speed with sufficient accuracy?*
2. *What is the influence of wind speed availability on spatial adoption patterns of small and medium scale wind turbines in Great Britain?*
3. *What factors influence the spatial adoption patterns of small and medium scale wind turbines in Great Britain?*

4. *What factors influence the temporal adoption characteristics of small and medium scale wind turbine market in Great Britain?*

To answer the first research question, the results of the BLS model was considered. These results demonstrated that the MCS methodology, the currently mandated wind resource assessment technique at initial scoping stage for wind turbines receiving the FIT is, in the majority, unable to predict wind speed with sufficient accuracy, estimated in this research to be a maximum absolute error of 0.5 ms^{-1}. The MCS methodology was only able to predict wind speed with sufficient accuracy at 33 % of the validation sites examined. This improved to 60 % of sites when using BLS NCIC to predict long-term mean wind speed at 10 m. These findings suggest that the answer to the first research question is negative, as the MCS is a wind resource assessment technique at the initial scoping stages of a project. Replacement of the MCS methodology with the BLS model within the FIT accreditation process would provide a wind resource assessment technique which offers wind speed predictions with sufficient accuracy at a greater number of sites.

Using the improved wind speed prediction technique of the BLS NCIC at a hub height of 15 m, the second research question could be answered. The influence of wind resource availability on the spatial variability of wind turbine adoption patterns was shown to be at most 32 %. A further investigation of the factors which also influenced spatial adoption patterns and addressed the third research question, found that wind turbine adoptions were more likely to be installed in rural areas, where there was a greater availability of land and wind resource. Wind turbine adopters were likely to be older, have a degree-level qualification and live in a detached home. The research also highlighted that adopters are likely to live in regions with lower than mean household income, reinforcing the conclusion regarding the suitability of rural areas for wind turbine installations. Inclusion of these additional factors increased the explanation of variance in the spatial adoption patterns, peaking at 62 % in the SER model developed during this research. These findings answer the second and third research questions, demonstrating that wind resource availability and the factors of adopter age, educational attainment, house type, location and rurality of an adopter's home had a significant influence on spatial wind turbine adoption patterns.

The final research question was answered using the research presented in Chapter 6. The presence of neighbouring wind turbines and the subsidy level available from the FIT were shown to have had an influence on the temporal adoption patterns of wind turbines in a number of case study areas.

The introduction of the FIT in April 2010 increased deployment dramatically, leading to greater numbers of wind turbines, exerting an influence on neighbouring potential adopters. In some cases, the reduction of the FIT subsidy level in December 2012 resulted in a decrease in deployment. However, in other clusters, the slow diffusion of wind turbines had still influenced a sufficient number of potential adopters to cause a rise in wind turbine deployment numbers after December 2012. The results of this research address the final research question and demonstrate that the endogenous peer effect of neighbouring wind turbine installations and degression of the FIT subsidy levels have influenced the temporal wind turbine adoption patterns of Great Britain.

The results and conclusions of the research have therefore addressed each of the research questions. The research undertaken utilised a number of novel approaches to answer these research questions. The research which examined the influencing factors on wind turbine adoption patterns, both spatial and temporal were novel research, which had not been published previously. The improvements to the BLS model presented in this research, offered novel advancements to this wind resource assessment technique for small and medium scale wind turbines. The combination of these novel approaches has offered the most comprehensive examination of the factors that influenced the wind turbine market under the FIT in Great Britain currently available.

7.2 Overall conclusions and implications

The results of the research suggest that the wind turbine market in Great Britain is approaching the “chasm” within its adoption lifecycle [208]. This chasm has been suggested by Moore [208] and is caused by the different expectations of an innovation held by early adopters and the early majority. An innovation must mature sufficiently during the early adopter phase to ensure that the innovation meets the expectation of the early majority [208]. Should this happen, deployment of the innovation could become self-sustaining and less reliant on subsidies to promote deployment [208]. Moore suggests that this chasm is most commonly seen in “disruptive” innovations which create new markets and move away from established markets [208]. It is argued here that wind turbines can be considered a disruptive innovation as they represent a move away from a centralised energy generation market, which is currently seen in the UK electricity market. Therefore, this chasm will exist in the wind turbine market of Great Britain and considering how to cross the chasm is vital to increase deployment.

Overall, current uptake of wind turbines has fallen due to the reduction in FIT subsidy levels, with only 12 % of all wind turbine installations occurring after 2014 [12]. The findings of the SER model, that wind turbine adoptions have occurred in mostly rural area, suggest that the wind turbine market is still in its infancy having only reached the early adopter phase of its lifecycle. In these rural areas, wind turbines are more likely to be financially viable, due to large areas of open space and higher wind resource, which will allow a wind turbine to offer better financial returns. Due to the high capital costs of a wind turbine, potential adopters require the potential financial returns to be as attractive as possible. While this is a subjective judgement by each potential adopter [108], the SER and peer effects research suggests that currently, residents of rural areas are inclined to judge that the financial returns are attractive enough to install. This finding suggests that small and medium scale wind turbines have not crossed the chasm in their adoption lifecycle.

The results of the SER model suggest that wind turbine adopters are typically older adopters. This finding suggests that only adopters who have been able to save sufficient capital over their lifetime were able to afford a wind turbine installation. This is further supported by the fact that an adopter's weekly income was shown to not be a positive influence on adoption. Therefore, it is concluded that the accumulated capital of adopters had a more significant influence on wind turbine adoptions. These results suggest that the high capital costs of wind turbine are currently a significant barrier to adoption and this barrier will need to be overcome for wind turbines to cross the chasm in their adoption lifecycle.

There is evidence from the peer effects model, that in some clusters early majority adopters have begun to install wind turbines, demonstrating that the chasm can be bridged. The slow diffusion process observed during the final phase of some of the peer effects model runs, where deployment increased despite subsidy level cuts, indicated that some early majority adopters were installing wind turbines. These early majority adopters, within the clusters, have been able to observe neighbouring turbines in operation and understand that within their neighbourhoods such a wind turbine could be an attractive investment. It was only within these clusters of high levels of deployment, where the early majority adopters have been observed. It was therefore concluded that the wind turbine market is still in its infancy and current adopters are likely to be early adopters in most areas of Great Britain.

7.2.1 Potential deployment scenarios

As this research has investigated the factors which influence wind turbine adoption patterns, it is possible to offer estimates of the potential for future wind turbine deployment in Great Britain. Initially, an estimate of the unrestricted potential for deployment was made for comparison with those previously published in literature. The potential for deployment at current market rates of tariff level was then estimated and it was also possible to analyse how the levels of potential deployment may change if the FIT subsidy rates altered.

The scenarios were developed as a prediction of the unrestricted and potential future deployment. Each incorporated the results of the research to predict where future wind turbine deployment may occur. The development of these scenarios is also coupled with a number of policy suggestions, presented in Section 7.3, which identify strategies to potentially facilitate the deployment presented in these scenarios. The methodology and rationale for each scenario will also be provided and where possible, will be discussed in the context of other potential deployment estimates. All of these deployment scenarios were produced on the statistical geography (SG) resolution for number of wind turbine installations. Therefore, these scenarios are considered as an estimation of the potential deployment in the small-scale domestic market.

7.2.1.1 Unrestricted potential scenario

Initially, the unrestricted potential for wind turbine deployment was assessed. Based solely on the availability of sufficient wind resource and the number of adopters who own a detached home in a region, this scenario demonstrates the maximum number of wind turbines which could be installed in Great Britain. However, this scenario does not account for any financial, demographic or social factors which have been identified as influencing factors within this work. Additionally, this scenario does not account for current deployment. The scenario, presented in Figure 55, can therefore be considered as the maximum level of wind turbine deployment possible, but as a scenario that is unlikely to occur.

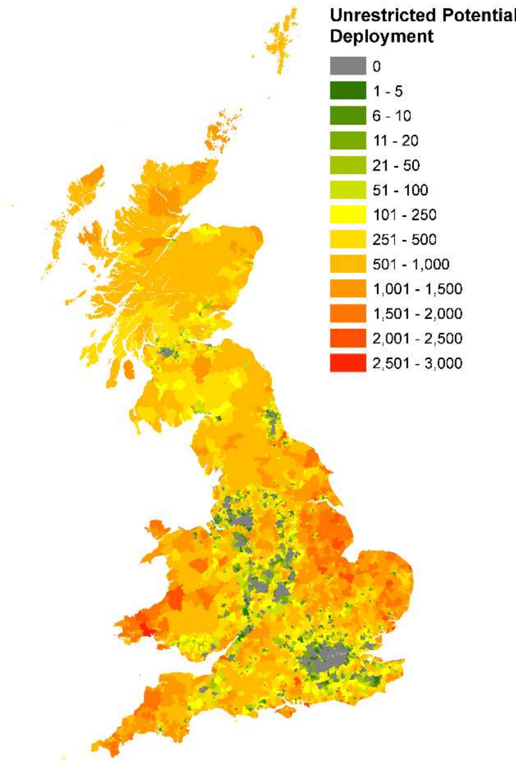

Figure 55 — Unrestricted potential wind turbine deployment scenario, as number of wind turbine installation in each SG region

The scenario, presented in Figure 55, estimated that across Great Britain, a total of 2 million wind turbines could potentially be installed. This scenario was developed using the number of detached homes which are owned in each region and the percentage land area of each region with an mean wind speed of 4.5 ms^{-1} or above at 15 m above ground level. The number of owned and detached homes in each region was scaled by the percentage area of the region with sufficient wind speed. For example, for a region with 100 detached homes and 30 % of the region with sufficient wind speed, an unrestricted potential of 30 wind turbines was estimated.

With the exception of the major cities of Great Britain, all of the regions are estimated to have the potential for at least a single wind turbine installation. Unrestricted potential deployment is typically lowest in the suburban areas and peaks in the rural areas, where the wind resource is high. The distribution of potential deployment across regions in this scenario is presented in Figure 56.

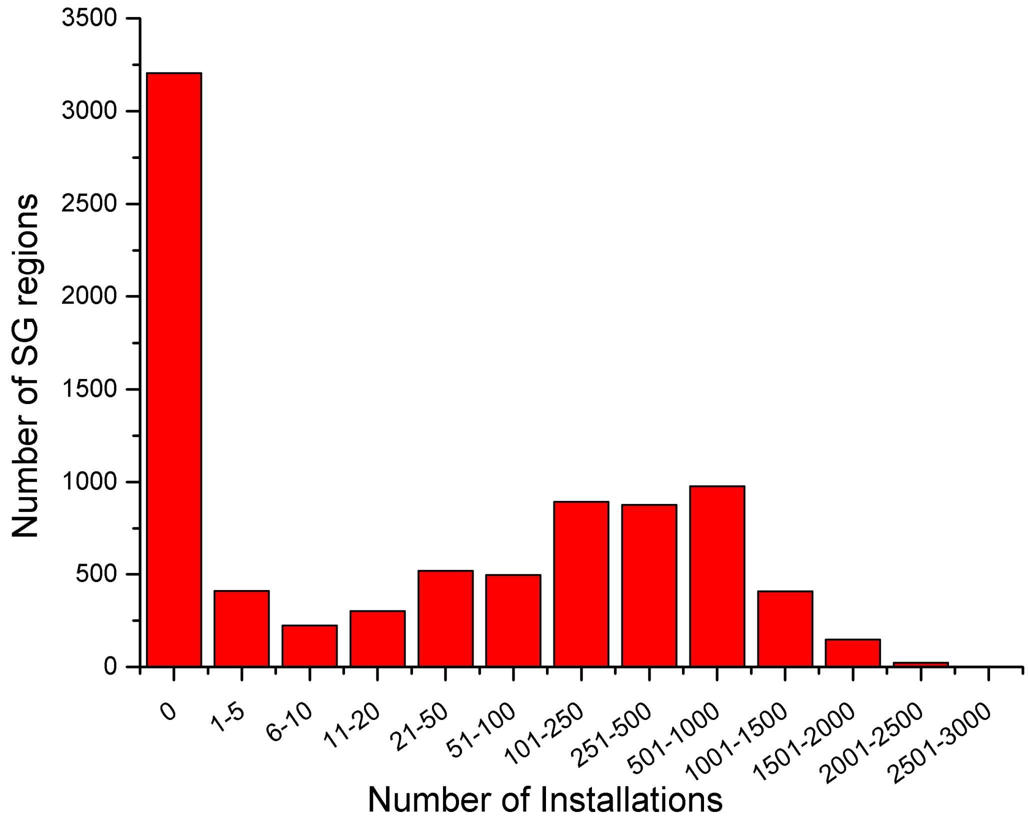

Figure 56 — Distribution of unrestricted potential deployment between regions in this scenario

The majority of regions, 37 % in this scenario, were estimated to have zero wind turbines. These regions are those located in major cities and therefore the wind resource is estimated to be not sufficient at 15 m. However, previous work has estimated that the potential for wind turbines in major cities could be greater [179]. By examining the wind resource available for building-mounted turbines, which will have hub heights higher than 15 m, Millward-Hopkins et al. estimated that up to 9,500 wind turbines were possible in Leeds alone [179]. This potential in urban areas was not considered in any scenario produced during this research, however previous research does demonstrate that the potential for growth in the market in urban areas does exist.

Around 30 % of regions were estimated to have the potential for between 100 and 1,000 wind turbine installations. This shows that there is significant unrestricted potential for growth in the wind turbine market. However, as discussed, this scenario did not account for any demographic and social influences and therefore resulted in a high estimate of potential deployment. It is considered here unlikely that wind turbine deployment in Great Britain will ever meet the levels described in this scenario. This unrestricted deployment scenario was compared with the Element Energy estimate, discussed in Section 1.3.1 which predicted that 3.4 million wind turbines could be deployed, compared to just over 2 million predicted here [38]. The difference between these two estimates is likely to relate to the inclusion of the potential adopter metric in this scenario. The Element Energy estimate assumed that a wind speed of 5.5 ms^{-1}, from the NOABL data was required [38], while this research's estimate assumed a wind speed of 4.5 ms^{-1} from the BLS NCIC. While these minimum wind speeds differ, sites examined in this research which were predicted to have a mean wind speed close to 5.5 ms^{-1} using the NOABL data were predicted to have a wind speed around 4.5 ms^{-1} using the BLS NCIC model developed in this research. It is therefore concluded that the differing potential deployment scenarios stem from the inclusion of the potential adopter metric in the unrestricted potential deployment presented here. The Element Energy prediction assumed that the rurality of an electoral ward resulted in a wind turbine being installed at all homes in the wards [38]. However, the potential adopter metric used here considered only the house types of residents of an SG region, in addition to the wind resource, and it is the inclusion of this factor, which resulted in a lower unrestricted potential deployment estimate presented here.

This scenario was presented here to highlight the levels of potential deployment which could be achieved in a perfect market. However, it is considered unlikely that wind turbine deployment will ever reached these levels and therefore more realistic estimates of potential deployment were produced.

7.2.1.2 Current market rates scenario

The current market rates scenario was developed from the results of the SER and peer effects model and was composed of three parts: prediction of deployment from the SER model results; prediction of the influence of peer effects in clusters areas; and prediction of the influence of peer effects outside of cluster areas. The current market rates scenario was developed using the Feed-in Tariff subsidy rate of 13.89 p/kWh, which has been used throughout this project. This scenario also used the minimum mean wind speed of 4.5 ms^{-1} at 15 m required for deployment.

Initially, the different between the actual and predicted wind turbine deployment, known as the residuals, of the SER model for installations at the statistical geography (SG) level were selected. In regions where the residuals were negative, it was assumed that the number of installations estimated by the SER model would be achieved. Where the residual value was a non-integer, it was assumed that any residual value less than −0.65 would equate to a single installation. Therefore, for a region with a residual value of −2.30, it was estimated that there would be the potential for 2 wind turbines, while for a region with a residual value of −0.8, the estimate would be a single wind turbine.

From these deployment estimates from the SER model residuals, the influence of the endogenous peer effect on potential deployment was estimated. For regions not included as a cluster area in the peer effects model, an adoption rate of 0.5 % was estimated. This adoption rate was the national average, calculated as the total number of wind turbine installations over the total number of potential adopters in Great Britain. For regions which were part of a cluster, the adoption rate was set at 2.7 %, the mean adoption rate across all the clusters.

The number of potential adopters, using the approach presented in Chapter 6, was recalculated for each region to account for the potential deployment estimated by the SER model. The new estimate of potential adopters was then multiplied by either the national adoption rate for regions outside of the clusters or the mean adoption rate in the clusters, for regions in a cluster, to estimate the potential deployment due to the visual peer effect.

Addition of the estimates of potential deployment from the SER model and the peer effects model then created the overall potential deployment estimate at current market rates, presented in Figure 57.

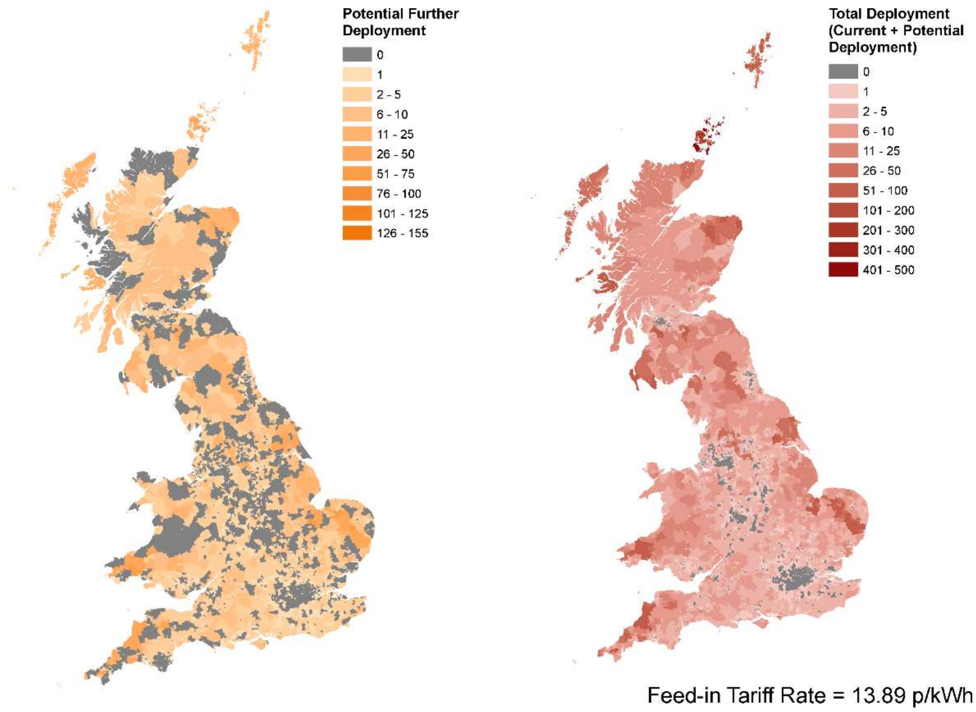

Figure 57 — Potential deployment estimate at current market rates. Left: Potential new deployment. Right: Total potential deployment, which includes currently installed wind turbines

This potential further deployment scenario predicted that at current market rates, an additional 13,882 wind turbines could be installed. In this scenario, it was estimated that 8,455 wind turbines would be installed across 3,866 regions, which have not previously had a wind turbine installed within them. The remaining 5,427 wind turbines would be installed in regions where a turbine has been installed. In total, it was estimated that 20,696 wind turbines, including those currently operating, could potentially be installed across Great Britain. In this scenario, the majority of the potential deployment would occur in regions where no wind turbines have previously been installed.

This potential deployment scenario estimates significantly fewer wind turbine installations are possible than the technical potential estimate of James et al [31]. While James et al. estimated a technical potential for around 400,000 wind turbines [31], this potential deployment scenario estimates that only 20,000 wind turbines may be possible. This is only 5 % of the estimated technical potential by James et al. [31] and around 1 % of the unrestricted potential presented in Section 7.2.1.1. The markedly lower estimate of potential deployment presented here shows that there are still significant barriers to adoption in the wind turbine market. The significance of age in the SER model suggests that only older adopters, with significant capital saved, are able to install a wind turbine. It is therefore concluded here that the financial barrier of the upfront costs of a wind turbine is currently the most significant barrier to adoption. Policy suggestions on how to overcome this barrier and to attract a greater number of adopters, particularly younger adopters, to the wind turbine market will be provided in Section 7.3.

7.2.1.3 Reduction of tariff rate scenario

The reduction of the tariff rate scenario was developed using the same three concepts as the previous scenario. However, in this scenario, it was assumed that the tariff rate would fall to 8.33 p/kWh. This tariff rate was the rate for wind turbines with a capacity below 50 kW in December 2016 [34]. This is considered a reduction in the tariff rate as a higher tariff rate of 13.89 p/kWh has been utilised during all the financial estimates presented in this thesis.

The reduction of the tariff rate influenced each of the three predictions which composed this potential deployment scenario. With a reduction of the tariff rate, the minimum wind speed required for deployment increased to 5.1 ms^{-1}. This affected the prediction from the SER model, which was adjusted to account for this different minimum wind speed. In each region, the percentage of land area with this minimum wind speed was calculated and was divided by the percentage land area with a minimum wind speed of 4.5 ms^{-1}. The prediction from the SER model at current market rates, SER_{pred_curr}, was then multiplied by this ratio to estimate the potential deployment from the first component, SER_{pred_redu};

$$SER_{pred\_redu} = \frac{\%\ land\ area\ of\ region\ with\ \bar{u} = 5.1\ ms^{-1}}{\%\ land\ area\ of\ region\ with\ \bar{u} = 4.5\ ms^{-1}} \times SER_{pred\_curr}$$

Equation 57

The reduction in tariff rate was also assumed to influence the adoption rates, due to peer effect. The ratio between the tariff rates of 8.33 p/kWh and 13.89 p/kWh adjusted the adoption rates outside the clusters to 0.30 %, down from 0.50 % utilised in the current market rates scenario. This ratio also reduced the assumed adoption rates in the clusters from 2.70 % to 1.62 %. These adoption rates were then utilised to predict the potential deployment, due to the peer effects and combined with the adjusted SER prediction. This produced the potential deployment scenario with a reduced tariff rate of 8.33 p/kWh, which is presented in Figure 58.

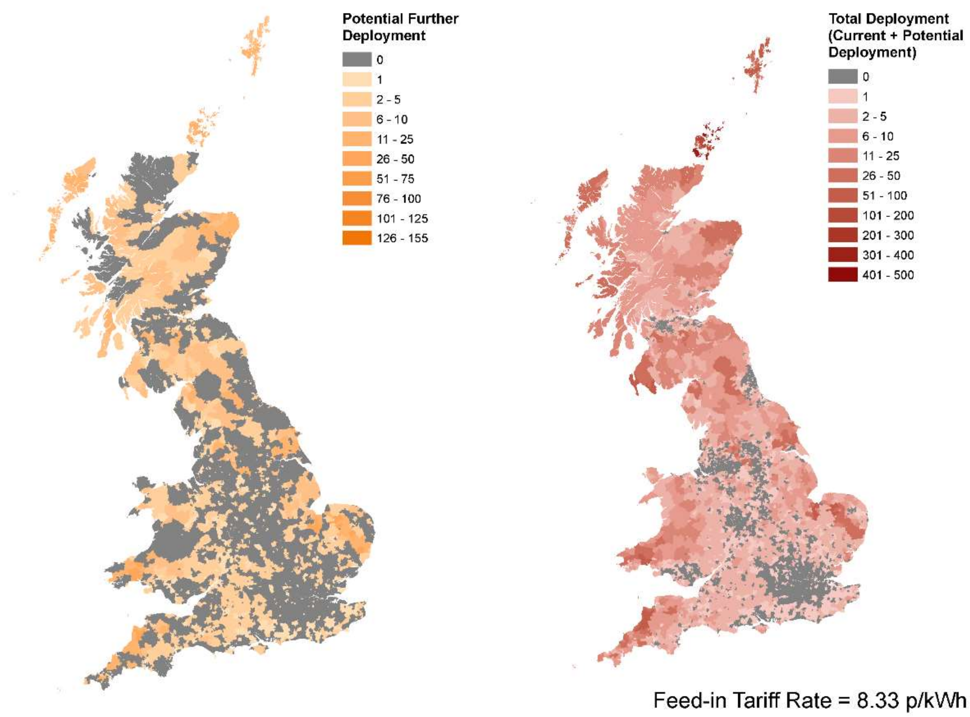

Figure 58 — Potential deployment estimate with a reduction of tariff rates. Left: Potential new deployment. Right: Total potential deployment, which includes currently installed wind turbines

In this scenario, the potential for an additional 4,727 wind turbines was estimated. This potential deployment was composed of 2,000 turbines across 1,023 regions, currently without a wind turbine installation and 2,727 turbines in 313 regions where deployment has previously occurred. In total, it was predicted that 11,541 turbines, including those currently operational, would eventually be installed across Great Britain. This scenario differs greatly from the current market rates scenario, as it estimated that potential deployment will be only a third of that at current market rates. Additionally, this scenario predicts that the majority of potential deployment will occur in regions, which currently have a wind turbine installed within them whereas, at current market rates, the majority of potential deployment was predicted to be in regions where there is no current wind turbine deployment. This scenario predicted the lowest level of potential deployment and highlights the potential consequences of further reducing FIT tariff rates on future deployment of wind turbines.

7.2.1.4 Increase of tariff rate scenario

Two scenarios which considered the influence of an increase of the FIT tariff rate are presented here. The first scenario assumed an increase of the tariff rate to 18.28 p/kWh, the tariff rate from April 2014 until September 2014, while the second scenario assumed a tariff rate of 31.91 p/kWh, the initial tariff rate in April 2010 for turbines with a capacity less than 15 kW but greater or equal to 1.5 kW [34].

Two scenarios for an increase in the tariff rate were included in this analysis to illustrate how different increases may influence potential deployment. Additionally, these two tariffs represent what is considered here as a realistic increase, 18.28 p/kWh and the maximum potential increase of the tariff level, 31.91 p/kWh. It is assumed here that under the current political conditions, the tariff may only be increased to a level similar to 18.28 p/kWh, if it were to be increased at all. However, if the deployment of microgeneration were to be prioritised by central government, it is possible that the tariff rate could increase towards 31.91 p/kWh, hence the development of the potential deployment scenario using this tariff rate.

These assumed tariff rates influenced each of the components of the potential deployment estimates in a similar way to that discussed in Section 7.2.1.3. The changes to the minimum wind speed and the adoption rates used within each scenario are detailed in Table 30.

Table 30 — Changes to minimum wind speed and adoption rates assumed with increased tariff rates

	Current market rates – 13.89 p/kWh	**Increased tariff rate – 18.28 p/kWh**	**Increased tariff rate – 31.91 p/kWh**
Minimum wind speed at tariff rate (ms^{-1})	4.5	4.4	3.9
Adoption rate outside of cluster area (%)	0.50	0.66	1.15
Adoption rate inside of cluster area (%)	2.70	3.55	6.20

The minimum wind speeds and adoption rates at each increased tariff rate adjusted the predicted potential deployment estimates from both the original SER and peer effects prediction. The potential deployment scenario for a tariff rate of 18.28 p/kWh is presented in Figure 59, while the potential deployment scenario for a tariff rate of 31.91 p/kWh is presented in Figure 60.

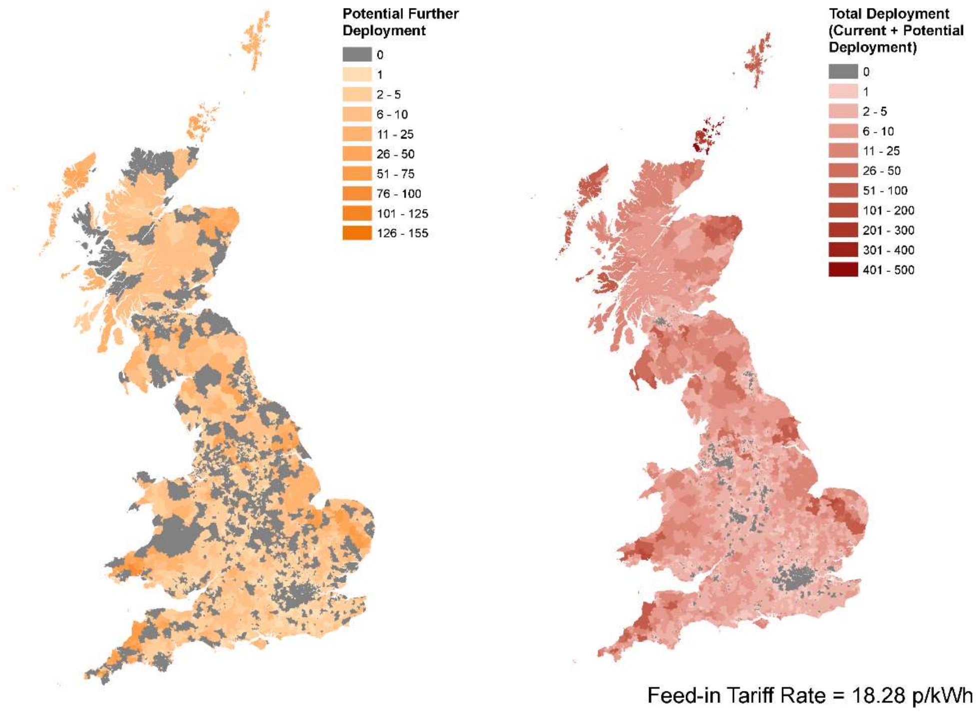

Figure 59 — Potential deployment estimate at 18.28 p/kWh. Left: Potential new deployment. Right: Total potential deployment, which includes currently installed wind turbines

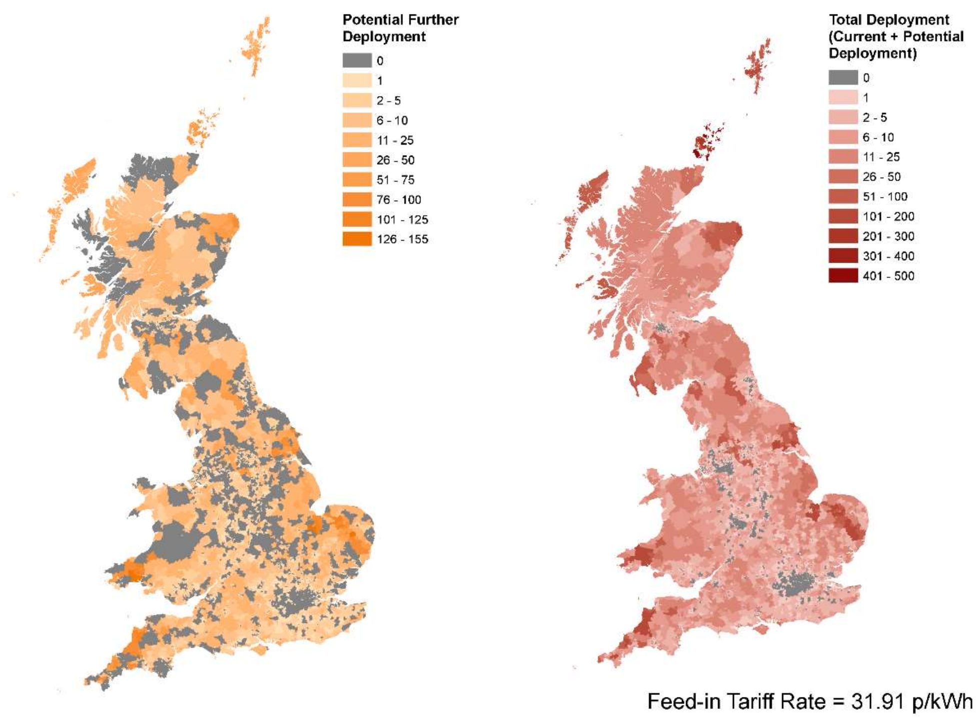

Figure 60 — Potential deployment estimate at 31.91 p/kWh. Left: Potential new deployment. Right: Total potential deployment, which includes currently installed wind turbines

The potential deployment scenario for a tariff rate of 18.28 p/kWh estimated that an additional 16,964 wind turbines could be installed, while in the scenario using 31.91 p/kWh, this increased to 26,708 wind turbines. In both scenarios, the majority of this potential deployment was estimated to occur in regions with no wind turbines currently installed. In the scenario at 18.28 p/kWh, there are 9,987 turbines in these regions compared to 6,977 in regions which currently have a wind turbine installed within them. This increased to 14,907 turbines in regions with no current deployment and 11,801 turbines in regions with wind turbines currently deployed, in the 31.91 p/kWh potential deployment scenario. These scenarios are significantly below the technical potential, with the scenario using a tariff level of 31.91 p/kWh only estimating around 8 % of the technical potential estimated by James et al [31]. At this tariff rate, estimated potential deployment was only 1.6 % of the unrestricted potential presented in Section 7.2.1.1. This supports the idea that there are still significant barriers to adoption in the market which must be overcome to fulfil the technical potential of small and medium scale wind turbines in Great Britain.

Table 31 — Potential deployment estimates developed or considered in this research

Scenario	Potential deployment estimate (Wind turbine installation numbers)	Notes
Unrestricted potential	~2 million	Based upon minimum wind speed and suitable house type in region
Current market rate	20,696	Tariff rate = 8.33 p/kWh
Reduction of tariff rate	11,541	Tariff rate = 13.89 p/kWh
Increase in tariff rate	27,030	Tariff rate = 18.28 p/kWh
Increase in tariff rate	33,522	Tariff rate = 31.91 p/kWh
Element Energy estimate [38]	~3.4 million	Based on minimum wind speed and rurality of electoral wards
James et al. estimate [31]	~400,000	Based upon minimum wind speed and availability of land

The major feature of the potential deployment scenarios presented here is that potential for growth in the wind market is estimated to be in regions where no deployment has previously occurred. In all of the scenarios, with the exception of the scenario using 8.33 p/kWh, up to 60 % of potential deployment was estimated to occur in regions with no previous wind turbine deployment. This demonstrates that the future growth in the market is possible across Great Britain and potentially wind turbines could be installed in almost half of the SGs of Great Britain. This is supported by the total potential deployment from the current market rates scenario, shown in Figure 61, which shows that wind turbine deployment could be widespread, with only the densely populated cities estimated here to have no potential deployment.

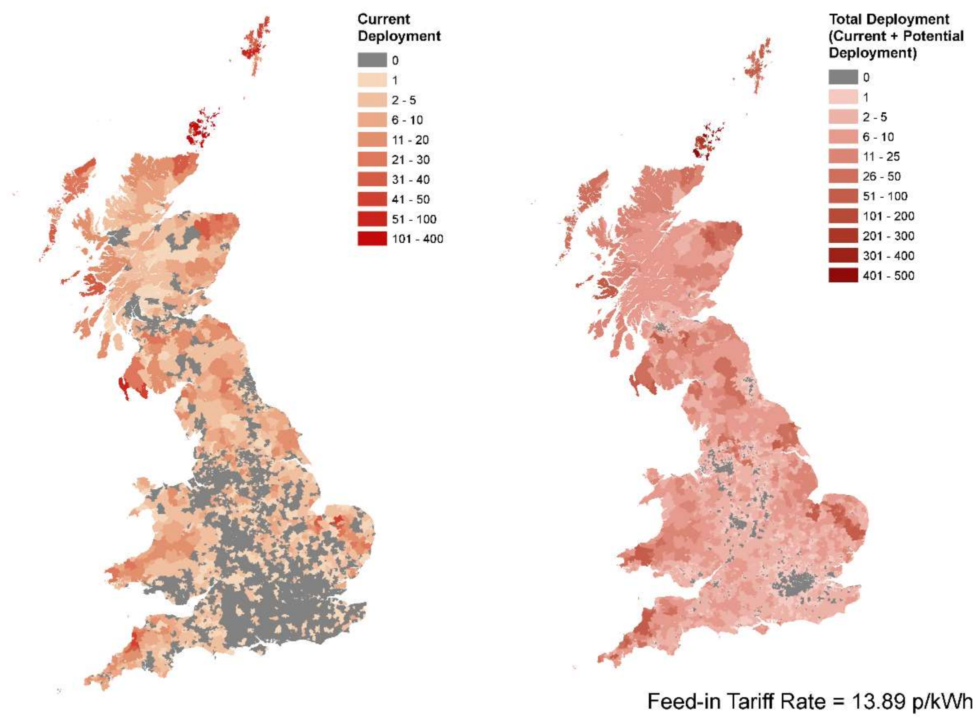

Figure 61 — Current wind turbine deployment and total potential deployment at current market rates. Left: Current deployment. Right: Total potential deployment

Figure 61 shows that at current market rates, it has been estimated that all the regions of Central England have the potential for at least one wind turbine. However, the areas which have the highest estimated potential for deployment appear to be East Anglia, Cornwall and South Wales, regions which were selected as clusters in Chapter 6. The majority of the clusters examined in the peer effects model were estimated to potentially have greater than mean wind turbine deployment. In these clusters, this potential deployment has been estimated to be increased by the peer effect. Of the areas not including in the peer effects research, it is the areas of the Highlands surrounding Inverness, the Scottish Borders north of Newcastle, and the region surrounding Lincoln which were estimated to have the greatest potential for future deployment.

While these potential deployment scenarios considered how changes to the tariff rate may influence future uptake of small and medium scale wind turbines, the cost estimate of wind turbines remained consistent in each scenario. Therefore, these potential deployment estimates can be considered as estimates which demonstrate how the wind turbine market may grow until it crosses the chasm in its adoption lifecycle, as discussed in Chapter 6. It is assumed that if wind turbines cross this chasm, the capital costs of wind turbines will reduce significantly. This reduction in capital costs will have an effect on the payback period of the turbines and thus the minimum wind speed required for deployment. Should a reduction in costs occur, it is suggested here that actual deployment may be higher than the scenarios presented here.

While these scenarios assumed an increase of the tariff rate would stimulate deployment, such a policy change would be unlikely in the current political climate. However, a decrease in the capital costs or an increased electricity price could improve the financial case of a wind turbine and may cause a similar effect on future deployment. To achieve the potential deployment scenarios presented here, the financial case of a wind turbine must be improved and a range of options could potentially result in the improvement of the financial case. This again highlights that the financial barriers of adoption are likely to be significant and while the non-financial barriers have been shown to influence adoptions, the policy suggestions to promote future wind turbine deployment presented here will focus on improving the financial case of a wind turbine.

7.3 Policy suggestions

To increase wind turbine deployment and cross the chasm to a position where the market can flourish as part of the UK's sustainable energy system transition, capital costs of wind turbines must reduce. Capital costs of wind turbines have stayed consistent at around £4,000 per kW between 2011 [37] and 2015 [21]. Despite the increased deployment of wind turbines, a reduction of capital cost has not been realised. This suggests that manufacturers and installers have been unable to utilise any cost advantages to reduce the unit cost of a wind turbine. To achieve cost advantages, such as economies of scale and advancement along the technology learning curve, deployment must increase. Therefore, a circularity evolves where to increase deployment, capital costs must reduce and to reduce capital costs, deployment must increase. A policy or series of policies must therefore be introduced to allow for deployment at the current price point.

Such a policy could introduce a financial subsidy or aid, for either potential adopters to promote deployment or manufacturers to reduce capital costs. Given that the FIT policy currently exists which aids potential adopters, it appears more likely that any additional policy that will be introduced would also be aimed at aiding potential adopters. FIT policies have been suggested as the most effective way to promote rapid deployment of renewable energy technologies [211]. Therefore, the policy recommendations of this project will solely focus on helping potential adopters, either through reform of the FIT policy or other policies which focus on providing finance options to potential adopters.

7.3.1 Changes to the current FIT policy

Initially, alterations to the remuneration mechanism of the FIT policy are recommended here. While the policies that are suggested here may not be the least cost route, they are designed to achieve societal benefits while aiding in the transition to a low carbon electricity system. Currently, the subsidy level available to wind turbine adopters is based only on the commissioning date and installed capacity of the wind turbine. The spatial adoption patterns of wind turbine demonstrate that adoption across Great Britain has not been uniform. Some areas have higher deployments than others, despite the residents of these areas having similar demographics and experiencing similar environmental characteristics. To promote uptake in areas where there the results of this research suggest that there is the potential for higher wind turbine deployment, the introduction of regional Feed-in Tariffs could be considered. By offering preferential subsidy levels in some areas, it would increase the number of locations in which wind turbines will be financial viable. Additionally, it is suggested that the form of the FIT is altered in these regions. By also offering preferential tariff rates during the initial phases of the scheme, known as a front-end loaded tariff model [211], wind turbine deployment in the selected regions could increase rapidly. The proposed policy change is envisaged to guarantee a higher initial tariff for adopters in a region to attract potential adopters to the market, as was seen in the FIT of Germany [212]. After a set time period, the tariff rate would revert to a lower rate for the remaining lifespan of the wind turbine.

Such a change to the remuneration policy would promote uptake in areas which could begin to exert an endogenous peer effect on neighbours. However, the issue of selecting the appropriate regions and subsidy level would require careful consideration. The results of the SER highlight some areas which would be ideal for such a regional FIT, however, to which level the subsidy is set would require further investigation. The SER results, and particularly the residuals of the SER model, highlight areas or regions where current deployment is below what is estimated in the SER model. This suggests that these regions are prime for deployment as the demographics of the residents share some similarities to the regions where deployment has been higher. The results of the SER model suggest that the regions of the Highlands surrounding Inverness, the Scottish Borders north of Newcastle and the region surrounding Lincoln are most likely to be the regions in which this policy should be initially considered. In these areas, wind turbine deployment was lower than predicted by the SER model and the potential deployment estimates suggested that there is significant growth which can be achieved in the wind turbine market of these areas. Such a change can be considered as a temporary measure in selected areas to kick start deployment before the FIT reverts to the national level, once deployment has increased sufficiently and the endogenous peer effect may become more influential. This regional FIT is suggested to have societal benefits as well as economic benefits for those adopters able to access the increased regional FIT. It is envisaged that the regional FIT would promote a boom in deployment as adopters install wind turbines to access the higher tariff rates available. This increase in deployment would offer a clear and visible symbol to neighbours that wind turbines are technically and economically viable within their neighbourhood. Through the endogenous peer effect, observed in the clusters examined in this research, it is hoped that this could promote further deployment in the neighbouring regions. The societal benefit of the policy and the endogenous peer effect which could potentially occur due to increased deployment is a key benefit which must be considered during the design of the policy.

An alternative approach to changing the subsidy level available to adopters would be to introduce a progressive tariff model, linking the tariff level to the electricity generated by each installation. This approach can be considered as a longer-term solution to promote wind turbine deployment nationwide and would be considered as a replacement to the degression mechanism, currently implemented in the FIT policy. The subsidy level for each kWh generated will be guaranteed for a set amount of electricity generation. For example, a 5 kW wind turbine could earn a subsidy level of 20 p/kWh for the first 1,000 kWh produced on-site per year, followed by 10 p/kWh for the next 3,000 kWh and 5 p/kWh for the next 5,000 kWh and 2 p/kWh for all generation above 9,000 kWh. While these generation and tariff figures serve as an example, they illustrate how the progressive tariffing scheme proposed here could remunerate adopters.

In contrast to the current degression mechanism, which reduces tariff levels for all entrants based upon the prior deployed capacity, this policy change aims to attract potential adopters and alter their subsidy level based upon on their generation output alone. The current degression mechanism is causing potential adopters to either postpone or scrap their proposed wind turbine installation, as the financial support is not sufficient to ensure an acceptable payback period. The proposed changes to the tariff would provide greater financial support. This style of remuneration model is designed to be beneficial for lower generation producers, likely to be domestic or smaller-scale commercial users. The progressive tariff system described, offers greater payments for lower annual energy generation than the current tariff levels, while reducing the overall level of payments for higher annual electricity generation production, when compared to current tariff levels, as seen in Table 32.

Table 32 — Estimated annual payments under the FIT using either the current rate or the proposed progressive tariff rate

Annual energy generation (kWh)	FIT payments at 8.33 p/kWh	FIT payments under progressive tariff
1,500	£12,495	£25,000
3,800	£31,654	£48,000
5,000	£41,650	£55,000
7,500	£62,475	£67,500
10,000	£83,300	£77,000
15,000	£124,950	£87,000
20,000	£166,600	£97,000

The rationale behind this proposed model is to promote uptake for domestic adopters and increase deployment towards the estimates presented in Section 7.2.1.4. The proposed policy change for a scaled tariff linked to generation is also more likely to promote deployment in areas of lower wind resource. In areas, where the wind resource is higher, a remuneration policy which offers higher tariff rates for greater generation may be more suitable. Such a policy would improve the financial case for larger turbines and possibly increase the carbon reduction achieved through the deployment of higher capacity wind turbines.

However, by guaranteeing a higher rate of tariff for the initial tranches of generation, adopters who are less likely to generate higher levels of electricity will be able to receive a higher payment for each kilowatt-hour produced. Lower generation would be expected in areas of lower wind resource and therefore such a remuneration model would increase the financial viability of wind turbines in such areas. Therefore, this model would ideally increase the number of regions in which a wind turbine is financially viable and attract a greater number of adopters to the market. Such a model would also increase the security of financial returns for adopters [211]. The results of Chapter 6 showed that changes to the FIT, which were only announced shortly before they occurred, had an adverse effect on wind turbine adoption rates. Therefore, the suggested change to the FIT would be required to be a long-term policy and any changes to the tariff rate would require a longer time between announcement and enactment than is currently used in the FIT. This would allow potential adopters sufficient time to evaluate the suitability of an installation and the potential effect of a tariff rate change on the viability of their prospective installation. Additionally, fixed price FIT models, which this proposed model and the current form of the FIT are, increases the participation of more risk-averse investors [211]. By guaranteeing a level of financial return, these investors are able to predict inward cash flow more securely from a fixed price model, increasing their likelihood to invest [211]. Such investors are likely to be in the early majority and by implementing such a change to the remuneration model of the FIT, can aid in crossing the chasm of the wind turbine adoption lifecycle and potentially attract sufficient numbers of adopters to achieve the levels of deployment required for the societal pathway to deliver the low-carbon energy systems transition.

While the progressive tariff model proposed here may be a policy which cannot be considered as a least cost route to achieving an energy systems transitions, it does have other benefits for adopters. By installing a wind turbine, adopters are able to protect themselves somewhat against the dilemmas of the energy trilemma. A wind turbine installation can, to some extent, protect adopters from rising energy prices by offsetting the need to buy electricity from the grid. By offsetting the need to buy grid electricity, adopters are also able to protect themselves from the risks of energy security and provide sustainable energy to cover their electrical demand. As the policy allows potential adopters to predict inward cash flow more accurately, these benefits could prove crucial as potential adopters assess the suitability of such an investment on more than a cost-benefit analysis.

These potential benefits, particularly becoming more self-sufficient and protecting against rising energy costs have been shown to be important motivating factors to those who have or are considering microgeneration technologies [54].

7.3.2 Further financial support for potential adopters

While these changes to the remuneration policy of the FIT are likely to increase deployment, they do not address an important issue identified in the potential deployment scenario. Neither policy suggestion would be able to overcome the financial barrier of initial investment costs and would only attract potential adopters with sufficient capital to afford the capital costs of wind turbines. As seen in the results of the SER model, these adopters are likely to be older residents who have been able to accumulate sufficient capital over their working life. However, the potential for growth with this type of adopter alone is limited, as demonstrated by the potential deployment scenario estimates which were significantly below the technical potential estimate. Therefore, alternative policy suggestions, which address this financial barrier of the high capital costs must be considered to attract younger adopters to the market.

A survey of British residents found that 57 % of those actively investigating a microgeneration installation were aged below 45, with two-thirds of this group aged under 35 [55]. However, only 32 % of microgeneration adopters were aged under 45, compared to 49 % of adopters who were aged over 55 [55]. This demonstrates that younger residents are more likely to be engaged in the transition to a low-carbon electricity market, but face significant barriers to adoption. 91 % of respondents in the same survey suggested that the upfront capital costs of a microgeneration technology was off-putting with 56 % of these respondents suggesting they would be not be able to install without financial aid to cover the capital costs [55]. These findings are in agreement with the conclusion draw from the results of the SER model and that to attract young adopters to the wind turbine market, financial aid must be available to fund the capital costs of an installation. Attracting younger adopters is crucial for the wind turbine market and more broadly, the transition to the low-carbon electricity market. The results of this survey of British residents [55] suggests that providing financial aid could attract younger adopters and therefore increase the deployment of wind turbines, towards the level required for the societal pathway to deliver an energy system transition. Two possible finance options will therefore be discussed here as a way to attract young adopters to the wind turbine market.

The initial policy suggestion to provide financial aid focuses on the provision of capital to allow individuals using a scheme, similar to one operated in Germany, where low-interest loans are provided to finance the installation of a renewable energy technology [213, 214]. These loans are provided by the German-state owned development bank, KfW, and are guaranteed at a fixed rate, typically 1.31 %, for up to 20 years [213]. The conditions of the loan can also include a repayment-free start-up period [213]. In Germany, these loans are available to private individuals in conjunction with a Feed-in Tariff for electricity generation [213, 214]. Such a policy could be introduced in Great Britain to promote wind turbine deployment. The Green Investment Bank, established in 2012, could provide finance to fund individual wind turbine installations [215]. The KfW raise their capital on the financial markets, using government bonds and a similar scheme could be used to allow the Green Investment Bank to raise sufficient capital to support significant future wind turbine deployment. Currently the Green Investment Bank is unable to raise funds and relies on private investment [215]. However, the Green Investment Bank typically invests in larger scale green projects [215] and therefore would require further reformation to provide finance to private individuals. By providing low-interest loans to individuals, the Green Investment Bank could promote wind turbine deployment. These loans would allow a potential adopter to fund either all or the majority of the capital costs required for a wind turbine to be installed. With the revenues generated through either FIT payments or savings from offsetting electricity purchased from the grid, the loan could be repaid over the lifetime of the turbine. Such a finance scheme would allow younger adopters who own a suitable site for a turbine, likely to be their own home but are unable to provide sufficient capital to overcome the financial barrier and install a wind turbine. It is envisaged here, given the high levels of younger potential adopters who are actively investigated installing a microgeneration technology, that such a scheme could increase wind turbine deployment significantly and possibly lead to wind turbine deployment above the prediction provided in Section 7.2.1. However, provision of these loans requires that individuals own their homes and have adequate availability of land area and wind resource at their property to ensure the revenue from the turbine was sufficient to make the repayments. With a low-interest rate on potential loans, it is assumed that the minimum wind speed required for deployment may be marginally below that predicted during this research.

However, individuals would require sufficient land and the right to authorise an installation on this land. Therefore, it is possible that while this policy may attract a greater number of adopters, there will still be potential adopters who will be unable to install a wind turbine.

An alternative approach would be to facilitate the financing of community energy projects by local residents. A scheme that allowed residents to invest in community wind energy projects would promote wind deployment and engage those residents in the energy system transition by allowing them to make energy decisions that affect their communities [19]. Community energy schemes could also access low-interest loans, such as those suggested previously for individuals, to fund the installation. Schemes in Denmark and Germany have seen successful community energy schemes that are either community-led or partnered with local businesses, universities or commercial developers [216]. To finance these schemes, loans were available in Germany from KfW [217, 218], while in Denmark, the schemes were part-owned between the commercial and community partners with the revenues from the scheme shared [216]. These schemes involve either a single large-scale renewable energy installation or multiple smaller-scale installation to provide energy for the whole community [216]. The schemes in Denmark and Germany were typified by local stakeholder engagement to overcome local opposition and demonstrated the long history of energy co-operatives in these countries [216]. By contrast, community energy schemes in Great Britain have struggled and have been affected by changes to the Feed-in Tariff and local opposition [216]. Therefore, future community energy schemes in Great Britain need to address these problems. Community Energy England and the Energy Saving Trust are able to promote community energy by providing advice on how to form an energy co-operative, attract local residents to invest and facilitating contacts in the local council and potential partners [219]. Therefore, the framework to facilitate greater community engagement and partnering of local councils and businesses is currently available for community energy projects. However, it is the inability to raise funds which has hindered some community energy projects [220]. In Germany, KfW provides low-interest loans for community projects [218, 221] and it is suggested that the proposed changes to the Green Investment Bank, previously discussed, could be extended to provide finance for community projects. These loans could be used to fully finance the schemes or be used in conjunction with resident and partner investment [220, 222]. These proposed changes are envisaged to be a central part of the societal pathway to energy system transition in Great Britain. They could result in a greater number of Energy Saving Companies (ESCOs) who would operate the community energy schemes and would see a greater number of residents becoming involved in energy decisions which affect their communities [3]. These are the central pillars of the proposed energy system transition under the societal pathway [19].

Both the financing options discussed here are predicated on changes being made to how the Green Investment Bank operates and greater support from central government. Through the provision of government bonds to the Green Investment Bank and the creation of a community energy advisory body, it will possible for wind turbine deployment to increase past the potential deployment scenarios towards the technical potential. As discussed, the Green Investment Bank must be reformed to provide financing to private individuals and small communities, as it currently only provides funds for large-scale green projects [220]. A scheme, known as the Green Deal, provided funding to British individuals to retrofit their homes with energy-efficiency measures [223]. However, the Green Deal is no longer being funded by central government and is close to failure [223]. The failings of the Green Deal policy were centred on how it was marketed to consumers and the financing of the loans to cover the retrofitting [223]. The loans were offered with uncompetitive interest rates, between 2 % and 4 % and typically higher than available from high street banks at the time, and the qualification criteria for these loans required the savings made from the energy-efficiency measures to cover the repayments [223]. Therefore, for many residents, the financing options available under the Green Deal were unattractive [223]. Additionally, the Green Deal was marketed with a focus on the financial benefits of retrofitting [223]. However, consumers do not install these measures solely for financial returns, but rather value the broader benefits of greater comfort and wellbeing [224]. Therefore, any policy which offers loans to finance future wind turbine deployment should be designed to avoid the failings of the Green Deal. By offering low-interest loans, which are available for a wide range of projects and the structuring of the repayments to consider the individual circumstances of each project, it is likely that any new policy would be more successful. Additionally, promotion of the policy should adopt a holistic approach and emphasise the wider benefits available from wind turbine deployment rather than focus solely on the financial returns available. By providing the means to overcome the barriers which currently exist, it will be possible to attract a greater number of a younger adopters to the wind energy market.

These changes to how future installations are funded and how the remuneration from the FIT operates would require alterations to the FIT contracts, which adopters and electricity suppliers who provide the payments enter into. However, if such changes were to be introduced, it would represent an opportunity for further reformation of the FIT administration process.

7.3.3 Additional policy suggestions

The MCS methodology has a prominent position in the FIT accreditation procedure and all wind turbine installers are required to conduct a wind resource assessment using the methodology to receive FIT payments [26]. Despite it being referred to as a wind resource methodology with a "*relatively high degree of uncertainty*" [27], any additional wind resource estimates provided to potential adopters "*must not be given greater prominence than the standard estimate and must have an associated warning that they should be treated with caution if they are significantly greater than the result given by the standard method*" [27]. It is therefore entirely likely that the wind resource estimate provided by the MCS methodology may be treated as a methodology with sufficient accuracy, which this research has shown is not the case. This has been shown to be incorrect in the BLS research of Chapter 6 and therefore it is suggested that the MCS methodology should be replaced in the FIT accreditation process for wind turbines. Ideally, the BLS NCIC would replace the MCS methodology in the FIT policy, as this was shown to be the most accurate wind resource assessment technique. However, due to commercial constraints surrounding the NCIC data utilised in the BLS model, this may not be practicable. Alternatively, the BLS NOABL could be implemented instead of the MCS methodology, as this was also shown to be more accurate than the MCS. However, the wind speed predictions of BLS NOABL have been shown to be less accurate than the BLS NCIC and therefore its introduction would not be as effective. Replacing the MCS methodology is a vital part of the FIT policy reform required to support future wind deployment in Great Britain.

While replacing the MCS methodology with the BLS model would offer more accurate long-term mean wind speed, this needs to be easily accessible to potential adopters and installers. For practitioners to implement the BLS model, it requires that they have access to either the NCIC or NOABL wind map and the surface roughness map created during this research. There are constraints on the commercial usage of both the NCIC and surface roughness map, which would need to be addressed. This procedure also requires these practitioners to possess the requisite skills to properly implement the BLS model. In order for practitioners to implement the BLS model, in it's current form, it would require the development of a standard operating procedure which could be followed to produce the mean BLS wind speed at a prospective site. Throughout this research, the BLS model was developed in the MATLAB programming environment and therefore currently, practitioners would need a license for this software to implement the BLS model. The price for a commercial MATLAB license is £1,800, a price point which is likely to be prohibitive for smaller wind turbine installer firms and individual potential adopters. Therefore, the BLS model in the form created during this research is considered here as unsuitable for the majority of potential small and medium wind turbine projects.

To ensure that the results of this research are available to the adopters who will directly benefits, the output of the BLS model needs to be available within an alternative format. Creation of a web-based tool would allow the results of the BLS model to be easily disseminated. It is envisaged that practitioners would be able enter their location, likely to be in postcode form and their proposed hub heights to extract the long-term mean wind speed from the BLS model. The proposed tool would perform the necessary calculations behind the graphical user interface and would present only the mean wind speed and likely power density to the user. For such a tool to be successful, it is suggested here that simplicity for the users is crucial. It is therefore suggested that the tool be freely available and require minimal data entry from the user.

However, for this tool to use the BLS NCIC data, which was the most accurate scaled wind speed data examined during this research, assent for the owners of the NCIC wind map data and the land use data would be required. Previous discussion with the Centre for Ecology and Hydrology (CEH) have indicated that the surface roughness data created from their land cover map could be made available for research purposes. This is also true of the NCIC wind map data, which it's owners the Met Office allow access for research purposes. The proposed tool is likely to be used for commercial use and therefore further discussions would be required with the dataset owners to ensure that a web-based BLS model could be published.

While the current FIT policy has served the PV market in Great Britain well, as evidenced by almost 800,000 installations, it has not functioned as effectively for the wind turbine market. The current system only provides the details of approved installers and technologies to consumers. It is therefore these wind turbine installers who will undertake the wind resource and financial assessments for prospective consumers. While solar resource is relatively consistent with latitude, wind resource has been shown to vary spatially over short distances. A prospective consumer therefore must place their trust in the installer to provide an accurate wind resource estimation, which is vital in determining financial viability. Less than 10 % of all individuals considering a microgeneration installation in Great Britain have stated that they considered an installer as a trusted source of information [55]. It is therefore proposed that an independent body should be formed to provide impartial advice on the suitability of a proposed site, including an independent estimation of wind resource. Impartial advice from an independent body provides potential adopters a reference point, from which to evaluate the estimates offered by installers, who have a vested interest in a potential adopter purchasing their services. Additionally, this independent body could provide an alternative source of freely available wind speed data. While the NOABL data is currently freely available, the results of this research showed it to be of insufficient accuracy. Any future independent body could provide long-term mean wind speeds from the BLS model to potential adopters, from which they will be able to evaluate the estimates of potential energy and financial returns provided by a wind turbine installer using a more accurate estimate of long-term mean wind speed.

While reformation of the FIT policy will be able to promote future deployments, additional reforms can be implemented to aid wind turbine deployment. Introduction of clear pathways for wind turbine planning applications would aid deployment [167]. By establishing the criteria on which a wind turbine will be considered during the planning process allows potential adopters to understand the likelihood of their applications being accepted. While each planning application for a wind turbine is site specific, it will be possible to develop a set of planning criteria, either nationwide or by each local council on which a wind turbine would be assessed. This would allow installers and their customers to evaluate an application prior to submission and would also streamline the process for planning officers. Additionally, a timetable for wind turbines and more generally, decentralised energy planning applications could be developed to ensure that potential adopters can meet key project dates without any delays from the planning process. These changes to the planning process for wind turbines would ensure that project budgets are not wasted, due to either delays in the planning process or rejection of the applications [167].

These proposed reforms could promote deployment in the wind turbine market under the FIT in Great Britain. The reforms would provide significant drivers in the market which could lead to a reduction in the capital costs of wind turbines in Great Britain. This reduction in capital costs is likely to lead to further deployment, as more locations become financially viable for a wind turbine. Such a development in the market would represent the crossing of the chasm in the adoption lifecycle of wind turbines, as it is likely that uptake may become more self-sustaining and less reliant on subsidies, following a reduction in the capital costs of small and medium scale wind turbines. Future deployment is vital in the wind turbine market in Great Britain and would allow the market to fulfil its technical potential. Increased deployment of wind turbines is also crucial to ensure that the societal pathway is able to deliver the required energy system transition across Great Britain.

7.4 Future work

During the course of the research and based upon the findings, a number of opportunities for future work have been identified. These opportunities focus on: improving the performance and accessibility of the BLS model and; use of surveying to determine individual adopter's motivations for a wind turbine installation in Great Britain.

Advancements to the BLS model that are proposed here focus on a wider validation sample of observational sites, developing improvements to offer more accurate wind speed predictions for mountain sites and to accommodate the use of NWP data. Additionally, the development of a web-based tool using the BLS model to allow developers and installers to access the results of this research.

The performance of the raw NCIC data and the NWP data, which offered more accurate wind speed predictions than available from the BLS model, stems from the assimilation dataset used to create either the NCIC or NWP data. The observational sites used in the validation sample of this research was likely to be part of the assimilation dataset of both the raw NCIC and NWP data. As the observational data was used to create or initiate the wind speeds in these datasets, it is likely that the prediction from each model will be highly representative of the actual wind speed. This is why the wind speed predictions from the BLS model were shown to be less accurate than those from either the raw NCIC and NWP data. Therefore, future work should develop an additional validation sample of observational data. The additional validation sample should not include any MIDAS sites, which are likely to be part of the assimilation data for NWP data and possibly used in the creation of the NCIC data. It is likely that observational wind speed data would be taken from existing wind turbines sites. It was not possible to gather such data during this project and therefore it is likely that development of an additional validation sample could be a long-term project which requires the cooperation of the adopters to allow for long-term monitoring of the wind speed at their sites. Additionally, an enhanced validation sample could include observational wind speeds at heights other than 10 m, which was the only height at which wind speed was validated in this research. This enhanced validation sample would allow the performance of the BLS model to be compared with the raw NCIC and NWP data to be fully validated. This work would determine whether the results of the research presented in Chapter 4 was the result of limitations of the BLS model or limitations of the validation sample available.

Development of the BLS model for mountain sites should include an orography correction methodology, which estimates wind speed change due to topological change. The results of the BLS research highlighted that at sites where the topological change was complex, the accuracy of wind speed available from the BLS using either NCIC or NOABL was considered low. This was due to the lack of an orographic correction within the BLS model. Introduction of an orographic correction through analysis of terrain data would allow the BLS model to correct a reference wind climatology in mountain sites more effectively. An orographic correction for the BLS model would be based on a methodology developed for correcting NWP wind speed forecasts for sub grid orography [100, 225]. Based upon topological data, this correction methodology would apply a roughness and height adjustment to a raw wind speed prediction, which for the BLS model would be the reference wind climatologies of NCIC or NOABL wind maps. These corrections account for the changes in wind speed which occur as wind flows over a hill [226]. This orography correction methodology would allow the BLS model to account for topological change in areas, where the BLS model over-predicted the wind speed. The overall value of this improvement to the BLS is considered to be low, certainly in Great Britain. In these mountain sites of Great Britain, it may be more suitable to utilise the raw reference wind climatology data as the estimation of long-term mean wind speed from these datasets exhibited greater accuracy than the scaled methodologies in this research. It is also highly likely that more advanced wind resource estimation techniques may be suitable for highly complex terrain. The value of adding an orographic correction to the BLS model is likely to be higher if the BLS model was applied to other countries. Additionally, implementation of an orographic correction must be tested thoroughly to ensure that any parameterisation of orography within an input climatology is not overestimated. Each of the input climatologies utilised in this work contained an orographic correction [98-100] and therefore an additional orographic correction in the BLS model, if not appropriately developed, could adversely affect the accuracy of wind speed predictions.

Improvements could also be made to the BLS model when utilising NWP data as the reference wind climatology. The results of the research have highlighted that the BLS model was not currently suitable for scaling NWP data, evidenced by the wind speed predictions having lower accuracy than the raw NWP data. The lack of accuracy in the BLS NWP wind speed stems from the incompatibility of the assumption of a logarithmic vertical wind profile under neutral stability in the BLS model equations and the realistic vertical wind profile offered in the raw NWP data. To address this factor, changes must be implemented in the BLS model to maximise the value of using NWP data as its reference wind climatology. The hourly time-series of wind speed in the NWP data can offer significant value for wind resource assessments of small and medium scale wind turbines, if scaled correctly. To achieve this, the BLS model should be modified to include a correction to account for the stability effects contained in the raw NWP data. By analysing the vertical wind profile in the raw NWP at multiple heights, it will be possible to understand how the modelled vertical wind profile differs from the assumed logarithmic vertical profile in the BLS model. A correction factor can then be applied during the estimation of the BLS NWP wind speed to account for this difference. The correction factor would have to be developed for each hourly wind speed as atmospheric stability differs with diurnal changes of atmospheric conditions. The need to develop a correction factor for each hour would be an intensive process, and one that must be carefully considered and validated. However, this change would allow the BLS model to maximise the potential of NWP data as a reference wind climatology. It would also allow the BLS model to enhance the value of the wind resource assessment by offering a description of seasonal and annual variations in a proposed site's wind regime.

In addition to these improvements to the BLS model, consideration of how this research can be disseminated into the market is required. Currently, the only freely available wind speed database for the UK is the NOABL database. Development of a web browser based tool, from which potential adopters and installers could extract the BLS wind speed for their proposed site will allow for the results of this project to be applied to real-world situations. Ideally, this tool would utilise the BLS NCIC wind speeds as these were shown to be the most accurate of the scaling methodologies examined. However, there may be commercial constraints on use of the raw NCIC and Land Cover Maps, which may limit the use of BLS NCIC data in any proposed tool. If these commercial constraints do affect the implementation of BLS NCIC, BLS NOABL could be considered as an alternative source of wind speeds for the proposed tool. Such a tool would allow potential adopters to extract a long-term mean wind speed at any hub height for their site, which has been shown to be more accurate than raw NOABL. A development of this tool would also allow potential adopters to use the BLS wind speed as a reference point against which they can assess any further wind resource estimates. Such a tool is currently being created and trialled at the University of Leeds.

Opportunities for future work with regards to the research conducted for the SER and peer effects model is centred on the use of survey work to analyse an individual wind turbine adopter's motivations for installing. Survey work was not conducted during this project, as the adopters could not be identified due to privacy laws. Therefore, any future work which focused on surveying wind turbine adopters must overcome this barrier. Through greater partnership and collaboration with the electricity suppliers and regulatory bodies, it may be possible to gain access to these wind turbine adopters. If this were possible, these adopters can be surveyed to identify their individual motivations for installing a wind turbine.

Any survey work that would be considered could be conducted as either a cross-sectional survey or a longitudinal survey of wind turbine adopters in Great Britain. A cross-sectional survey would allow for a single snapshot of an adopter's motivations and views on their wind turbine installation, while a longitudinal survey would allow for an adopter's perception of a wind turbine to be analysed over the wind turbine's lifecycle. Each of these survey types have their merits and implementation of both would allow differing factors to be analysed. Cross-sectional survey work would allow the motivations to an individual's decision to adopt to be identified. This would allow any future work to understand if these motivations are different between early and later adopters. A cross-sectional survey is likely to yield results which would focus on factors similar to those examined in the SER and peer effects research of this project. It is envisaged that a cross-sectional survey could offer a definitive explanation of the underlying causes of the results presented in this project. The results of a cross-sectional survey would also allow for a spatio-temporal modelling of the uptake of wind turbine installations under the Feed-in Tariff in Great Britain. In comparison, a longitudinal survey of wind turbine adopters would allow for an individual adopter’s views and perception of their wind turbine installation over its lifespan be analysed. This research would analyse the operation of the Feed-in Tariff and any other financial incentives, including those proposed in Section 7.3, and how these have influenced wind turbine adopters. These research surveys, which can supplement the results presented in this thesis, will allow for an understanding of the individual motivations and perceptions of adopters in the wind turbine market of Great Britain. The results of such surveys could potentially be used to propose policy reforms which could promote future wind turbine deployment.

7.5 Wider context for the research

While this project has examined the small and medium scale wind turbine market in Great Britain, the results must be considered in the wider context of the electricity market of UK. The electricity market and particularly the generating sources of electricity in the market are slowly beginning to change. Despite renewable energy, both large and small scale, recently contributing it’s highest proportion of the UK’s electricity mix, 25 % in 2016 [227], it is still a market dominated by fossil fuel generation. As both domestic and international reserves of fossil fuels, begin to become scarce, the need for an energy systems transition in the UK becomes greater, year on year. The role of the small and medium scale wind turbine market in this transition can be crucial, more for its influence on the population through the societal pathway rather the overall contribution to the electricity mix.

As individuals and communities seek to ensure that the energy for their homes and businesses is economically and environmentally sustainable, the role of decentralised energy such as wind turbines becomes increasingly important. These technologies allow individuals to govern how their electricity is produced and protects them from increasing energy prices. Increased deployment of wind turbines demonstrates to other potential adopters that a change is possible, through the highly visible construction of a wind turbine. High levels of decentralised energy deployment could lead to the energy systems transition that is required in this country. While small and medium scale wind turbines are not the panacea, they are an important part of the solution across Great Britain.

List of References

1. International Business Publications, *UK Energy Policy, Laws and Regulations Handbook Volume 1 Strategic Information and Basic Laws*. 2015: LULU Press.

2. Department of Business Energy & Industrial Strategy. *Digest of United Kingdom Energy Statistics 2016*. 2016; Available from: https://www.gov.uk/government/statistics/digest-of-united-kingdom-energy-statistics-dukes-2016-main-chapters-and-annexes.

3. Johnson, V.C. and Hall, S., *Community energy and equity: The distributional implications of a transition to a decentralised electricity system.* People, Place and Policy, 2014. **8**(3).

4. HM Government, *Climate Change Act 2008*, 2008.

5. EU, *Directive of the European Parliament and of the Council of 23 April 2009 on the promotion of the use of energy from renewable sources*, in *2009/28/EC*2009, European Commission. p. 16-62.

6. Department of Business Energy & Industrial Strategy. *Annual Fuel Poverty: Statistics Report 2016, England*. 2016; Available from: https://www.gov.uk/government/statistics/annual-fuel-poverty-statistics-report-2016.

7. European Topic Centre for Air and Climate Change. *Europe's onshore and offshore wind energy potential : An assessment of environmental and economic constraints*. 2009; Available from: https://www.energy.eu/publications/a07.pdf.

8. Allen, S.R., Hammond, G.P., and McManus, M.C., *Prospects for and barriers to domestic micro-generation: A United Kingdom perspective.* Applied Energy, 2008. **85**(6): p. 528-544.

9. Carbon Trust and Arup. *Small-scale wind energy: Policy insights and practical guidance*. 2008; Available from: https://www.carbontrust.com/media/77248/ctc738_small-scale_wind_energy.pdf.

10. RenewableUK. *Small Wind Systems - UK Market Report*. 2015; Available from: http://c.ymcdn.com/sites/www.renewableuk.com/resource/resmgr/Docs/small_medium_wind_uk_market_.pdf.

11. Best, M., Brown, A., Middleton, D., Rooney, G., Clark, P., Gallani, M., Hollis, D., Thomson, D., and Watson, C. *Small-scale Wind Energy - Technical Report*. 2008.

12. Ofgem. *Feed-in Tariff Installation Report 31 December 2016*. 2016; Available from: https://www.ofgem.gov.uk/environmental-programmes/fit/contacts-guidance-and-resources.

13. Burton, T., Jenkins, N., Sharpe, D., and Bossanyi, E., *Wind energy handbook*. 2011: John Wiley & Sons.

14. Stull, R.B., *An introduction to boundary layer meteorology*. Vol. 13. 1988: Springer.

15. Department of Energy and Climate Change. *Quarterly and Annual Load Factors for Feed-in Tariff technologies*. 2015; Available from: https://www.gov.uk/government/publications/quarterly-and-annual-load-factors.

16. Department of Business Energy & Industrial Strategy. *Electricity Generation Costs*. 2016; Available from: https://www.gov.uk/government/publications/beis-electricity-generation-costs-november-2016.

17. Greening, B. and Azapagic, A., *Environmental impacts of micro-wind turbines and their potential to contribute to UK climate change targets.* Energy, 2013. **59**: p. 454-466.

18. Johansson, T.B., Patwardhan, A.P., Nakićenović, N., and Gomez-Echeverri, L., *Global energy assessment: toward a sustainable future*. 2012: Cambridge University Press.

19. Foxon, T.J., *Transition pathways for a UK low carbon electricity future.* Energy Policy, 2013. **52**: p. 10-24.

20. National Grid PLC. *Future Energy Scenarios*. 2017; Available from: http://fes.nationalgrid.com/media/1253/final-fes-2017-updated-interactive-pdf-44-amended.pdf.

21. Parsons Brinckerhoff. *Small-Scale Generation Cost Update*. 2015; Available from: https://tinyurl.com/y8w6h2ht.

22. Department of Energy and Climate Change. *Feed-in Tariff: Government's Response to the Summer 2009 Consultation* 2010; Available from: https://tinyurl.com/y9stmtsu.

23. Department of Energy and Climate Change. *Impact Assessment of Feed-in Tariffs for Small-Scale, Low Carbon, Electricity Generation*. 2010; Available from: http://webarchive.nationalarchives.gov.uk/20121217165258/http://www.decc.gov.uk/assets/decc/consultations/renewable%20electricity%20financial%20incentives/2710-final-ia-feed-in-tariffs-small-scale.pdf.

24. Department of Energy and Climate Change. *The UK Renewable Energy Strategy*. 2009; Available from: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/228866/7686.pdf.

25. Ofgem. *Feed-in Tariff Annual Report 2015-16*. 2016; Available from: https://www.ofgem.gov.uk/environmental-programmes/fit/contacts-guidance-and-resources.

26. Ofgem. *Feed-in Tariff: Guidance for Renewable Installations*. 2016; Available from: https://www.ofgem.gov.uk/environmental-programmes/fit/contacts-guidance-and-resources.

27. Microgeneration Certification Scheme. *Microgeneration Installation Standard : MIS 3003*. 2013; Available from: http://www.microgenerationcertification.org/images/MIS_3003_Issue_3.4_Micro_Wind.pdf.

28. Burch, S., *Computer Modelling of the UK Wind Energy Resource: Phase I Optimisation of the Methodology*. 1992: Great Britain, Department of Trade and Industry.

29. International Electrotechnical Commission Standard, *61400-12, International Electrotechnical Commission (IEC)(2002)*, in *Wind Turbine Generator Systems Part* 2002.

30. Encraft. *Warwick Wind Trials Project*. 2009; Available from: http://www.microwindturbine.be/Rapportering_files/Warwick+Wind+Trials+Final+Report+%281%29.pdf.

31. James, P., Bahaj, A., Anwar, A.A., and Myers, L. *Location, location, location: domestic small-scale wind field trial report*. 2009; Available from: https://eprints.soton.ac.uk/353113/.

32. Drew, D.R., Barlow, J.F., Cockerill, T.T., and Vahdati, M.M., *The importance of accurate wind resource assessment for evaluating the economic viability of small wind turbines.* Renewable Energy, 2015. **77**: p. 493-500.

33. Weekes, S. and Tomlin, A., *Evaluation of a semi-empirical model for predicting the wind energy resource relevant to small-scale wind turbines.* Renewable Energy, 2013. **50**: p. 280-288.

34. Ofgem. *Feed-in Tariff (FIT): Tariff Table 1 April 2016 Non-PV Only*. 2016; Available from: https://www.ofgem.gov.uk/publications-and-updates/feed-tariff-fit-tariff-table-1-april-2016-non-pv-only.

35. Department of Energy and Climate Change. *Government Response to Consulation on Comprehensive Review Phase 2B: Tariffs for non-PV technologies and scheme adminstration issues*. Feed-in Tariffs Scheme 2012; Available from: https://www.gov.uk/government/consultations/tariffs-for-non-pv-technologies-comprehensive-review-phase-2b.

36. Department of Energy and Climate Change. *Solar PV cost data*. 2016; Available from: https://www.gov.uk/government/statistics/solar-pv-cost-data-201516.

37. Arup. *Review of the generation costs and deployment potential of renewable electricity technologies in the UK* 2011; Available from: https://www.gov.uk/government/publications/review-of-the-generation-costs-and-deployment-potential-of-renewable-electricity-technologies-in-the-uk-study-report-by-arup.

38. Element Energy. *Design of Feed-in Tariffs for Sub-5MW Electricity in Great Britain: Quantitative analysis for DECC*. 2009; Available from: http://www.element-energy.co.uk/wordpress/wp-content/uploads/2012/05/Quantitative-Issues-in-FIT-DesignFINAL_2009.pdf.

39. Ofgem. *Feed-in Tariff Payment Rate Table for Non-Photovoltaic Eligible Installations for FIT Year 4 (1 April 2013 to 31 March 2014)*. 2013; Available from: https://www.ofgem.gov.uk/environmental-programmes/fit/fit-tariff-rates.

40. Zeyringer, M., Daly, H., Fais, B., Sharp, E., and Strachan, N. *Spatially and Temporally Explicit Energy System Modelling to Support the Transition to a Low Carbon Energy Infrastructure–Case Study for Wind Energy in the UK*. in *International Symposium for Next Generation Infrastructure*. 2015. London: UCL STEaPP.

41. Snape, J.R., *Spatial and Temporal Characteristics of PV Adoption in the UK and Their Implications for the Smart Grid.* Energies, 2016. **9**(3): p. 210.

42. Balta-Ozkan, N., Yildirim, J., and Connor, P.M., *Regional distribution of photovoltaic deployment in the UK and its determinants: A spatial econometric approach.* Energy Economics, 2015. **51**: p. 417-429.

43. Richter, L.-L. *Social Effects in the Diffusion of solar Photovoltaic Technology in the UK*. 2013; Available from: http://www.eprg.group.cam.ac.uk/wp-content/uploads/2013/12/1332-Final.pdf.

44. Kwan, C.L., *Influence of local environmental, social, economic and political variables on the spatial distribution of residential solar PV arrays across the United States.* Energy Policy, 2012. **47**: p. 332-344.

45. Bollinger, B. and Gillingham, K., *Peer effects in the diffusion of solar photovoltaic panels.* Marketing Science, 2012. **31**(6): p. 900-912.

46. Graziano, M. and Gillingham, K., *Spatial patterns of solar photovoltaic system adoption: the influence of neighbors and the built environment.* Journal of Economic Geography, 2015. **15**(4): p. 815-839.

47. Rode, J. and Weber, A., *Does localized imitation drive technology adoption? A case study on rooftop photovoltaic systems in Germany.* Journal of Environmental Economics and Management, 2016. **78**: p. 38-48.

48. Brower, M., *Wind resource assessment: a practical guide to developing a wind project*. 2012: John Wiley & Sons.

49. Heath, M.A., Walshe, J.D., and Watson, S.J., *Estimating the potential yield of small building-mounted wind turbines.* Wind Energy, 2007. **10**(3): p. 271-287.

50. Jung, S., Arda Vanli, O., and Kwon, S.-D., *Wind energy potential assessment considering the uncertainties due to limited data.* Applied Energy, 2013. **102**: p. 1492-1503.

51. Peacock, A.D., Jenkins, D., Ahadzi, M., Berry, A., and Turan, S., *Micro wind turbines in the UK domestic sector.* Energy and Buildings, 2008. **40**(7): p. 1324-1333.

52. Zhang, J., Draxl, C., Hopson, T., Monache, L.D., Vanvyve, E., and Hodge, B.-M., *Comparison of numerical weather prediction based deterministic and probabilistic wind resource assessment methods.* Applied Energy, 2015. **156**: p. 528-541.

53. Balcombe, P., Rigby, D., and Azapagic, A., *Motivations and barriers associated with adopting microgeneration energy technologies in the UK.* Renewable and Sustainable Energy Reviews, 2013. **22**: p. 655-666.

54. Balcombe, P., Rigby, D., and Azapagic, A., *Investigating the importance of motivations and barriers related to microgeneration uptake in the UK.* Applied Energy, 2014. **130**: p. 403-418.

55. Consumer Focus. *Keeping FiT: Consumers' attitudes and experiences of microgeneration*. 2011; Available from: https://tinyurl.com/y7qgl4t8.

56. Keirstead, J., *Behavioural responses to photovoltaic systems in the UK domestic sector.* Energy Policy, 2007. **35**(8): p. 4128-4141.

57. Betz, A., *Introduction to the theory of flow machines*. 1966: Pergamon.

58. Oke, T.R., *Boundary layer climates*. 1992: Routledge.

59. Van der Hoven, I., *Power spectrum of horizontal wind speed in the frequency range from 0.0007 to 900 cycles per hour.* Journal of Meteorology, 1957. **14**(2): p. 160-164.

60. Watson, S., *Quantifying the variability of wind energy.* Wiley Interdisciplinary Reviews: Energy and Environment, 2014. **3**(4): p. 330-342.

61. Emejeamara, F. and Tomlin, A., *A method for mapping the turbulence intensity and excess energy available to building mounted wind turbines over a UK City.* Wind Energy, 2016. **19**(8): p. 1423-1438.

62. Meroney, R.N., Leitl, B.M., Rafailidis, S., and Schatzmann, M., *Wind-tunnel and numerical modeling of flow and dispersion about several building shapes.* Journal of Wind Engineering and Industrial Aerodynamics, 1999. **81**(1): p. 333-345.

63. Millward-Hopkins, J.T., *Predicting the wind resource available to roof-mounted wind turbines in urban areas*. 2013: University of Leeds.

64. Monin, A. and Obukhov, A., *Basic laws of turbulent mixing in the surface layer of the atmosphere.* Contrib. Geophys. Inst. Acad. Sci. USSR, 1954. **151**: p. 163-187.

65. Carta, J.A., Ramírez, P., and Velázquez, S., *A review of wind speed probability distributions used in wind energy analysis: Case studies in the Canary Islands.* Renewable and Sustainable Energy Reviews, 2009. **13**(5): p. 933-955.

66. Lun, I.Y. and Lam, J.C., *A study of Weibull parameters using long-term wind observations.* Renewable Energy, 2000. **20**(2): p. 145-153.

67. Seguro, J. and Lambert, T., *Modern estimation of the parameters of the Weibull wind speed distribution for wind energy analysis.* Journal of Wind Engineering and Industrial Aerodynamics, 2000. **85**(1): p. 75-84.

68. Kelly, M., Troen, I., and Jørgensen, H.E., *Weibull-k Revisited:"Tall" Profiles and Height Variation of Wind Statistics.* Boundary-Layer Meteorology, 2014: p. 1-18.

69. Gryning, S.-E., Batchvarova, E., Floors, R., Peña, A., Brümmer, B., Hahmann, A.N., and Mikkelsen, T., *Long-term profiles of wind and Weibull distribution parameters up to 600 m in a rural coastal and an inland suburban area.* Boundary-Layer Meteorology, 2014. **150**(2): p. 167-184.

70. Wieringa, J., *Shapes of annual frequency distributions of wind speed observed on high meteorological masts*, in *Boundary Layer Studies and Applications*. 1989, Springer. p. 85-110.

71. Gomes, L. and Vickery, B., *On the prediction of extreme wind speeds from the parent distribution.* Journal of Wind Engineering and Industrial Aerodynamics, 1977. **2**(1): p. 21-36.

72. Bailey, B.H., McDonald, S.L., Bernadett, D., Markus, M., and Elsholz, K. *Wind resource assessment handbook: Fundamentals for conducting a successful monitoring program*. 1997; Available from: https://www.nrel.gov/docs/legosti/fy97/22223.pdf.

73. UK Meteorological Office, *Met Office Integrated Data Archive System (MIDAS) Land and Marine Surface Stations Data (1853-current)*, UK Meteorological Office, Editor 2012, NCAS British Atmospheric Data Centre.

74. Weekes, S., Tomlin, A., Vosper, S., Skea, A., Gallani, M., and Standen, J., *Long-term wind resource assessment for small and medium-scale turbines using operational forecast data and measure–correlate–predict.* Renewable Energy, 2015. **81**: p. 760-769.

75. Peixoto, J.P. and Oort, A.H., *Physics of climate*. 1992: American Institute of Physics.

76. Holtslag, A., *Estimates of diabatic wind speed profiles from near-surface weather observations.* Boundary-Layer Meteorology, 1984. **29**(3): p. 225-250.

77. Emeis, S., *Current issues in wind energy meteorology.* Meteorological Applications, 2014. **21**(4): p. 803-819.

78. Högström, U., *Review of some basic characteristics of the atmospheric surface layer.* Boundary-Layer Meteorology, 1996. **78**(3): p. 215-246.

79. Foken, T., *50 Years of the Monin–Obukhov Similarity Theory.* Boundary-Layer Meteorology, 2006. **119**(3): p. 431-447.

80. Millward-Hopkins, J., Tomlin, A., Ma, L., Ingham, D., and Pourkashanian, M., *Estimating aerodynamic parameters of urban-like surfaces with heterogeneous building heights.* Boundary-layer meteorology, 2011. **141**(3): p. 443-465.

81. Wieringa, J., *New revision of Davenport roughness classification.* Proc., 3EACWE, Eindhoven, The Netherlands, 2001: p. 285-292.

82. Grimmond, C. and Oke, T.R., *Aerodynamic properties of urban areas derived from analysis of surface form.* Journal of Applied Meteorology, 1999. **38**(9): p. 1262-1292.

83. Davenport, A.G., *Rationale for determining design wind velocities.* ASCE Journal of the Structural Division, 1960. **86**(5): p. 39-68.

84. Hansen, F., *Surface Roughness Lengths*. 1993: US Army Research Laboratory.

85. Morton, D., Rowland, C., Wood, C., Meek, L., Marston, C., Smith, G., Wadsworth, R., and Simpson, I. *Final Report for LCM2007-the new UK land cover map. Countryside Survey Technical Report No 11/07*. 2011; Available from: https://www.ceh.ac.uk/sites/default/files/LCM2007%20Final%20Report.pdf.

86. Garratt, J.R., *The atmospheric boundary layer*. 1994: Cambridge University Press.

87. Hanna, S.R. and Chang, J.C., *Boundary-layer parameterizations for applied dispersion modeling over urban areas.* Boundary-Layer Meteorology, 1992. **58**(3): p. 229-259.

88. Raupach, M., *Simplified expressions for vegetation roughness length and zero-plane displacement as functions of canopy height and area index.* Boundary-Layer Meteorology, 1994. **71**(1-2): p. 211-216.

89. Garratt, J.R., *The internal boundary layer — A review.* Boundary-Layer Meteorology, 1990. **50**(1): p. 171-203.

90. Rao, K., Wyngaard, J., and Coté, O., *The structure of the two-dimensional internal boundary layer over a sudden change of surface roughness.* Journal of the Atmospheric Sciences, 1974. **31**(3): p. 738-746.

91. Elliott, W.P., *The growth of the atmospheric internal boundary layer.* Eos, Transactions American Geophysical Union, 1958. **39**(6): p. 1048-1054.

92. Mason, P.J., *The formation of areally-averaged roughness lengths.* Quarterly Journal of the Royal Meteorological Society, 1988. **114**(480): p. 399-420.

93. Goode, K. and Belcher, S.E., *On the Parameterisation of the Effective Roughness Length for Momentum Transfer over Heterogeneous Terrain.* Boundary-Layer Meteorology, 1999. **93**(1): p. 133-154.

94. Bou-Zeid, E., Meneveau, C., and Parlange, M.B., *Large-eddy simulation of neutral atmospheric boundary layer flow over heterogeneous surfaces: Blending height and effective surface roughness.* Water Resources Research, 2004. **40**(2).

95. Wieringa, J., *An objective exposure correction method for average wind speeds measured at a sheltered location.* Quarterly Journal of the Royal Meteorological Society, 1976. **102**(431): p. 241-253.

96. Panofsky, H.A. and Townsend, A.A., *Change of terrain roughness and the wind profile.* Quarterly Journal of the Royal Meteorological Society, 1964. **90**(384): p. 147-155.

97. Bou-Zeid, E., Parlange, M.B., and Meneveau, C., *On the Parameterization of Surface Roughness at Regional Scales.* Journal of the atmospheric sciences, 2007. **64**(1).

98. Burch, S., *Computer Modelling of the UK Wind Energy Resource: Phase II Application of the Methodology*. 1992: Department of Trade and Industry.

99. Perry, M. and Hollis, D., *The development of a new set of long-term climate averages for the UK.* International Journal of Climatology, 2005. **25**(8): p. 1023-1039.

100. Standen, J., Wilson, C., Vosper, S., and Clark, P., *Prediction of local wind climatology from Met Office models: Virtual Met Mast techniques.* Wind Energy, 2017. **20**(3): p. 411-430.

101. Drew, D.R., Barlow, J.F., and Cockerill, T.T., *Estimating the potential yield of small wind turbines in urban areas: A case study for Greater London, UK.* Journal of Wind Engineering and Industrial Aerodynamics, 2013. **115**: p. 104-111.

102. James, P., Sissons, M., Bradford, J., Myers, L., Bahaj, A., Anwar, A., and Green, S., *Implications of the UK field trial of building mounted horizontal axis micro-wind turbines.* Energy Policy, 2010. **38**(10): p. 6130-6144.

103. Silva, J., Ribeiro, C., Guedes, R., and Ulrich, F. *Roughness length classification of Corine Land Cover classes*. in *Proceedings of the European Wind Energy Conference, Milan, Italy*. 2007.

104. Bahaj, A.S., Myers, L., and James, P.A.B., *Urban energy generation: Influence of micro-wind turbine output on electricity consumption in buildings.* Energy and Buildings, 2007. **39**(2): p. 154-165.

105. Ramírez, P. and Carta, J.A., *Influence of the data sampling interval in the estimation of the parameters of the Weibull wind speed probability density distribution: a case study.* Energy Conversion and Management, 2005. **46**(15): p. 2419-2438.

106. Troen, I. and Lundtang Petersen, E. *European wind atlas*. 1989; Available from: http://www.wasp.dk/dataandtools#wind-atlas__european-wind-atlas.

107. Bergman, N. and Eyre, N., *What role for microgeneration in a shift to a low carbon domestic energy sector in the UK?* Energy Efficiency, 2011. **4**(3): p. 335-353.

108. Claudy, M.C., Michelsen, C., and O'Driscoll, A., *The diffusion of microgeneration technologies–assessing the influence of perceived product characteristics on home owners' willingness to pay.* Energy Policy, 2011. **39**(3): p. 1459-1469.

109. Claudy, M.C., Michelsen, C., O'Driscoll, A., and Mullen, M.R., *Consumer awareness in the adoption of microgeneration technologies: an empirical investigation in the Republic of Ireland.* Renewable and Sustainable Energy Reviews, 2010. **14**(7): p. 2154-2160.

110. Scarpa, R. and Willis, K., *Willingness-to-pay for renewable energy: Primary and discretionary choice of British households' for micro-generation technologies.* Energy Economics, 2010. **32**(1): p. 129-136.

111. Devine-Wright, P. *Reconsidering public attitudes and public acceptance of renewable energy technologies: a critical review*. 2007; Available from: http://www.sed.manchester.ac.uk/research/beyond_nimbyism.

112. Willis, K., Scarpa, R., Gilroy, R., and Hamza, N., *Renewable energy adoption in an ageing population: heterogeneity in preferences for micro-generation technology adoption.* Energy Policy, 2011. **39**(10): p. 6021-6029.

113. Mahapatra, K. and Gustavsson, L., *An adopter-centric approach to analyze the diffusion patterns of innovative residential heating systems in Sweden.* Energy Policy, 2008. **36**(2): p. 577-590.

114. Leenheer, J., De Nooij, M., and Sheikh, O., *Own power: Motives of having electricity without the energy company.* Energy Policy, 2011. **39**(9): p. 5621-5629.

115. Devine-Wright, P., *Local aspects of UK renewable energy development: exploring public beliefs and policy implications.* Local Environment, 2005. **10**(1): p. 57-69.

116. Sopha, B.M., Klöckner, C.A., Skjevrak, G., and Hertwich, E.G., *Norwegian households' perception of wood pellet stove compared to air-to-air heat pump and electric heating.* Energy Policy, 2010. **38**(7): p. 3744-3754.

117. Spence, A., Poortinga, W., Pidgeon, N., and Lorenzoni, I., *Public perceptions of energy choices: The influence of beliefs about climate change and the environment.* Energy & Environment, 2010. **21**(5): p. 385-407.

118. Sauter, R. and Watson, J., *Strategies for the deployment of micro-generation: Implications for social acceptance.* Energy Policy, 2007. **35**(5): p. 2770-2779.

119. Scodari, P.F. and Hardie, I.W., *Heating costs and household wood stove acquisition: a discrete choice demand model.* Northeastern Journal of Agricultural and Resource Economics, 1985. **14**(1).

120. Kasanen, P. and Lakshmanan, T., *Residential heating choices of Finnish households.* Economic Geography, 1989. **65**(2): p. 130-145.

121. Davidson, C., Drury, E., Lopez, A., Elmore, R., and Margolis, R., *Modeling photovoltaic diffusion: an analysis of geospatial datasets.* Environmental Research Letters, 2014. **9**(7): p. 74009-74023.

122. Jager, W., *Stimulating the diffusion of photovoltaic systems: A behavioural perspective.* Energy Policy, 2006. **34**(14): p. 1935-1943.

123. Gibbs, R.M., *Going away to college and wider urban job opportunities take highly educated youth away from rural areas.* Rural Development Perspectives, 1995. **10**: p. 35-44.

124. Schleich, J. and Gruber, E., *Beyond case studies: Barriers to energy efficiency in commerce and the services sector.* Energy Economics, 2008. **30**(2): p. 449-464.

125. White, K.R., *The relation between socioeconomic status and academic achievement.* Psychological bulletin, 1982. **91**(3): p. 461.

126. Burnett, D., Barbour, E., and Harrison, G.P., *The UK solar energy resource and the impact of climate change.* Renewable Energy, 2014. **71**: p. 333-343.

127. Bishop, I.D., *Determination of thresholds of visual impact: the case of wind turbines.* Environment and Planning B: Planning and design, 2002. **29**(5): p. 707-718.

128. Jenner, S., Groba, F., and Indvik, J., *Assessing the strength and effectiveness of renewable electricity feed-in tariffs in European Union countries.* Energy Policy, 2013. **52**: p. 385-401.

129. Cherrington, R., Goodship, V., Longfield, A., and Kirwan, K., *The feed-in tariff in the UK: A case study focus on domestic photovoltaic systems.* Renewable Energy, 2013. **50**: p. 421-426.

130. Rodrigues, M., Montañés, C., and Fueyo, N., *A method for the assessment of the visual impact caused by the large-scale deployment of renewable-energy facilities.* Environmental Impact Assessment Review, 2010. **30**(4): p. 240-246.

131. Molina-Ruiz, J., Martínez-Sánchez, M.J., Pérez-Sirvent, C., Tudela-Serrano, M.L., and García Lorenzo, M.L., *Developing and applying a GIS-assisted approach to evaluate visual impact in wind farms.* Renewable Energy, 2011. **36**(3): p. 1125-1132.

132. Rogers, E.M., *Diffusion of innovations*. 5th ed. 2003: Simon and Schuster.

133. Bandura, A., *Social cognitive theory of mass communication.* Media psychology, 2001. **3**(3): p. 265-299.

134. McPherson, M., Smith-Lovin, L., and Cook, J.M., *Birds of a feather: Homophily in social networks.* Annual review of sociology, 2001: p. 415-444.

135. Soetevent, A.R., *Empirics of the Identification of Social Interactions; An Evaluation of the Approaches and Their Results*.* Journal of Economic Surveys, 2006. **20**(2): p. 193-228.

136. Manski, C.F., *Identification of endogenous social effects: The reflection problem.* The review of economic studies, 1993. **60**(3): p. 531-542.

137. Müller, S. and Rode, J., *The adoption of photovoltaic systems in Wiesbaden, Germany.* Economics of Innovation and New Technology, 2013. **22**(5): p. 519-535.

138. Palm, A., *Peer effects in residential solar photovoltaics adoption—A mixed methods study of Swedish users.* Energy Research & Social Science, 2017. **26**: p. 1-10.

139. Hoppmann, J., Huenteler, J., and Girod, B., *Compulsive policy-making—The evolution of the German feed-in tariff system for solar photovoltaic power.* Research Policy, 2014. **43**(8): p. 1422-1441.

140. Nolden, C. and Department of Energy and Climate Change. *Performance and Impact of Feed-in Tariff Scheme: Review of Evidence*. 2015; Available from: https://tinyurl.com/y88o83ry.

141. McCarthy, K. and Hansen, L. *Connecticut Clean Energy Finance and Investment Authority Initiatives*. 2013; Available from: https://www.cga.ct.gov/2013/rpt/2013-R-0175.htm.

142. Hartmann, W.R., Manchanda, P., Nair, H., Bothner, M., Dodds, P., Godes, D., Hosanagar, K., and Tucker, C., *Modeling social interactions: Identification, empirical methods and policy implications.* Marketing letters, 2008. **19**(3-4): p. 287-304.

143. FEMA. *Multi-Hazard Loss Estimation Methodology: Hurricane Model*. 2003; Available from: https://www.fema.gov/media-library-data/20130726-1820-25045-8522/hzmh2_1_hr_um.pdf.

144. Hsu, S.-A., *Measurement of shear stress and roughness length on a beach.* Journal of Geophysical Research, 1971. **76**(12): p. 2880-2885.

145. Garratt, J.R., *Transfer characteristics for a heterogeneous surface of large aerodynamic roughness.* Quarterly Journal of the Royal Meteorological Society, 1978. **104**(440): p. 491-502.

146. Beirlant, J. and Goegebeur, Y., *Regression with response distributions of Pareto-type.* Computational statistics & data analysis, 2003. **42**(4): p. 595-619.

147. Weekes, S.M. and Tomlin, A.S., *Low-cost wind resource assessment for small-scale turbine installations using site pre-screening and short-term wind measurements.* IET Renewable Power Generation, 2014. **8**(4): p. 349-358.

148. Brown, A., Milton, S., Cullen, M., Golding, B., Mitchell, J., and Shelly, A., *Unified modeling and prediction of weather and climate: A 25-year journey.* Bulletin of the American Meteorological Society, 2012. **93**(12): p. 1865-1877.

149. Lean, H., Bornemann, J., Tang, Y., Mittermaier, M., Roberts, N., and Trueman, M. *Experiences with a 1.5 km version of the Met Office Unified Model for short range forecasting*. in *Proc. 24th Conf. on Weather and Forecasting/20th Conf. on Numerical Weather Prediction*. 2011.

150. Lean, H.W., Clark, P.A., Dixon, M., Roberts, N.M., Fitch, A., Forbes, R., and Halliwell, C., *Characteristics of high-resolution versions of the Met Office Unified Model for forecasting convection over the United Kingdom.* Monthly Weather Review, 2008. **136**(9): p. 3408-3424.

151. EvanceWind. *Product Certification: Evance R9000 MCS Certification Summary*. 2012; Available from: https://tinyurl.com/y8nn2aaj.

152. Department of Energy and Climate Change. *Average annual domestic standard electricity bills for UK countries*. 2016; Available from: https://www.gov.uk/government/statistical-data-sets/annual-domestic-energy-price-statistics.

153. Rose, S. and Apt, J., *Quantifying sources of uncertainty in reanalysis derived wind speed.* Renewable Energy, 2016. **94**: p. 157-165.

154. Carvalho, D., Rocha, A., Santos, C.S., and Pereira, R., *Wind resource modelling in complex terrain using different mesoscale–microscale coupling techniques.* Applied Energy, 2013. **108**: p. 493-504.

155. de Jong, P., Dargaville, R., Silver, J., Utembe, S., Kiperstok, A., and Torres, E.A., *Forecasting high proportions of wind energy supplying the Brazilian Northeast electricity grid.* Applied Energy, 2017. **195**: p. 538-555.

156. Elhorst, J.P., *Applied Spatial Econometrics: Raising the Bar.* Spatial Economic Analysis, 2010. **5**(1): p. 9-28.

157. Office for National Statistics. *A Beginner's Guide to UK Geography*. 2016 v1.1 2016; Available from: https://www.ons.gov.uk/methodology/geography/ukgeographies.

158. Office of Chief Statistician. *Intermediate Geography Background Information*. 2005; Available from: http://www.gov.scot/Publications/2005/02/20732/53084.

159. Office for National Statistics *2011 Census: Digitised Boundary Data (England and Wales)*, Office for National Statistics Editor 2016, UK Data Service Census Support, .

160. National Records of Scotland *2011 Census: Digitised Boundary Data (Scotland)*, National Records of Scotland Editor 2016, UK Data Service Census Support, .

161. Office for National Statistics, National Records of Scotland, and Northern Ireland Statistics and Research Agency, *2011 Census aggregate data* Office for National Statistics, National Records of Scotland, and Northern Ireland Statistics and Research Agency, Editors. 2016, UK Data Service, .

162. Department of Environment Food & Rural Affairs. *Structure of the agricultural industry in England*. 2013; Available from: https://www.gov.uk/government/collections/structure-of-the-agricultural-industry.

163. Scottish Government. *Structure of the agricultural industry in Scotland*. 2015; Available from: http://www.gov.scot/Topics/Statistics/Browse/Agriculture-Fisheries/PubEconomicReport.

164. Welsh Government. *Agricultural Small Area Statistics*. 2014; Available from: http://gov.wales/statistics-and-research/agricultural-small-area-statistics/?lang=en.

165. Office for National Statistics. *The National Statistics Socio-economic Classification: Rebased on the SOC2010 User Manual* 2010 [cited 3; Available from: http://webarchive.nationalarchives.gov.uk/20160106042025/http://www.ons.gov.uk/ons/guide-method/classifications/current-standard-classifications/soc2010/soc2010-volume-3-ns-sec--rebased-on-soc2010--user-manual/index.html.

166. Mason, C.H. and Perreault, W.D., *Collinearity, Power, and Interpretation of Multiple Regression Analysis.* Journal of Marketing Research, 1991. **28**(3): p. 268-280.

167. RenewableUK. *Small and Medium Wind Strategy. The current and future potential of the sub-500 kW wind industry in the UK*. 2014; Available from: http://c.ymcdn.com/sites/www.renewableuk.com/resource/resmgr/Docs/small_medium_wind_strategy_r.pdf.

168. Office for National Statistics. *UK Standard Industrial Classification of Economic Activities 2007 (SIC 2007)*. 2009; Available from: https://www.ons.gov.uk/methodology/classificationsandstandards/ukstandardindustrialclassificationofeconomicactivities.

169. Office for National Statistics. *House Price Statistics for Small Areas Explained*. 2015; Available from: https://www.ons.gov.uk/peoplepopulationandcommunity/housing/bulletins/housepricestatisticsforsmallareas/yearendingdec1995toyearendingsept2015.

170. Registers of Scotland. *Property Market Report 1993 - 2013*. 2013; Available from: https://www.ros.gov.uk/__data/assets/pdf_file/0009/3978/RoS_10-Year_Report2003-2013.pdf.

171. Department of Business Energy & Industrial Strategy. *Sub-national Consumption Statistics: Methodology and guidance booklet*. 2016; Available from: https://www.gov.uk/government/collections/sub-national-electricity-consumption-data.

172. R Core Team, *R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. 2013*, 2014.

173. Hothorn, T., Zeileis, A., Farebrother, R.W., Cummins, C., Millo, G., Mitchell, D., and Zeileis, M.A., *Package 'lmtest'.* Testing linear regression models. https://cran. r-project. org/web/packages/lmtest/lmtest. pdf. , 2015.

174. Lumley, T. and Zeileis, A. *sandwich: Robust Covariance Matrix Estimators*. 2017; Available from: https://cran.r-project.org/web/packages/sandwich/sandwich.pdf.

175. MathWorks, *MATLAB 2013b.* Natick, MA. Available at http://uk.mathworks.com/products/matlab/, 2013.

176. Environmental Systems Research Institute, *ArcGIS. Version 10.2. 2*, 2014, Environmental Systems Research Institute Inc. Redlands, California, USA.

177. Mincer, J.A., *Schooling and earnings*, in *Schooling, experience, and earnings*. 1974, NBER. p. 41-63.

178. Faiers, A. and Neame, C., *Consumer attitudes towards domestic solar power systems.* Energy Policy, 2006. **34**(14): p. 1797-1806.

179. Millward-Hopkins, J., Tomlin, A., Ma, L., Ingham, D., and Pourkashanian, M., *Assessing the potential of urban wind energy in a major UK city using an analytical model.* Renewable energy, 2013. **60**: p. 701-710.

180. South Lakeland District Council, Lake District National Park Authority, Cumbria Rural Housing Trust, and Eden District Council. *Review of Second Home Data and Assessment of the Effects Second Homes are Having on Rural Communities*. 2015; Available from: http://www.lakedistrict.gov.uk/__data/assets/pdf_file/0005/410873/Review-of-second-home-data-and-assessment-of-effects-on-rural-communities.pdf.

181. Breusch, T.S. and Pagan, A.R., *A Simple Test for Heteroscedasticity and Random Coefficient Variation.* Econometrica, 1979. **47**(5): p. 1287-1294.

182. Durbin, J. and Watson, G.S., *Testing for Serial Correlation in Least Squares Regression. III.* Biometrika, 1971. **58**(1): p. 1-19.

183. Gujarati, D.N. and Porter, D.C., *Essentials of econometrics.* 1999.

184. Zeileis, A., *Econometric Computing with HC and HAC Covariance Matrix Estimators.* 2004, 2004. **11**(10): p. 17.

185. Department of Communities and Local Government. *National Planning Policy Framework*. 2012; Available from: https://www.gov.uk/government/publications/national-planning-policy-framework--2.

186. Department of Communities and Local Government. *Planning Permission: Permitted Developments for Wind Turbines*. [cited 2016 13th July]; Available from: https://www.planningportal.co.uk/info/200130/common_projects/57/wind_turbines.

187. Civil Aviation Authority. *Civil Aviation Authority Policy and Guidelines on Wind Turbines*. 2006; Available from: https://publicapps.caa.co.uk/docs/33/CAP764%20Issue6%20FINAL%20Feb.pdf.

188. London Renewables, *Attitudes to renewable energy in London: public and stakeholder opinion and the scope for progress*. 2003, London: Greater London Authority.

189. Bell, D., Gray, T., and Haggett, C., *The 'social gap'in wind farm siting decisions: explanations and policy responses.* Environmental politics, 2005. **14**(4): p. 460-477.

190. Devine-Wright, P., *Beyond NIMBYism: towards an integrated framework for understanding public perceptions of wind energy.* Wind energy, 2005. **8**(2): p. 125-139.

191. Toke, D., Breukers, S., and Wolsink, M., *Wind power deployment outcomes: How can we account for the differences?* Renewable and Sustainable Energy Reviews, 2008. **12**(4): p. 1129-1147.

192. Croissant, Y. and Millo, G., *Panel data econometrics in R: The plm package.* Journal of Statistical Software, 2008. **27**(2): p. 1-43.

193. Bivand, R., Bernat, A., Carvalho, M., Chun, Y., Dormann, C., Dray, S., Halbersma, R., Lewin-Koh, N., Ma, J., and Millo, G., *The spdep package.* Comprehensive R Archive Network, Version, 2005: p. 05-83.

194. IBM SpSS, *SPSS version 21.0.* IBM SPSS, Chicago, Illinois, USA, 2012.

195. Anselin, L., *Local indicators of spatial association—LISA.* Geographical analysis, 1995. **27**(2): p. 93-115.

196. Anselin, L., Sridharan, S., and Gholston, S., *Using Exploratory Spatial Data Analysis to Leverage Social Indicator Databases: The Discovery of Interesting Patterns.* Social Indicators Research, 2007. **82**(2): p. 287-309.

197. Keller, J.M., Gray, M.R., and Givens, J.A., *A fuzzy k-nearest neighbor algorithm.* IEEE transactions on systems, man, and cybernetics, 1985(4): p. 580-585.

198. Green, R., Staffell, I., and Vasilakos, N., *Divide and Conquer? k-Means Clustering of Demand Data Allows Rapid and Accurate Simulations of the British Electricity System.* IEEE Transactions on Engineering Management, 2014. **61**(2): p. 251-260.

199. Grubesic, T.H. and Mack, E.A., *Spatio-temporal interaction of urban crime.* Journal of Quantitative Criminology, 2008. **24**(3): p. 285-306.

200. Deekshatulu, B. and Chandra, P., *Classification of heart disease using k-nearest neighbor and genetic algorithm.* Procedia Technology, 2013. **10**: p. 85-94.

201. Department of Business Energy & Industrial Strategy, *Renewable Energy Planning Database*, Department of Energy and Climate Change, Editor 2017.

202. Brown, C.E., *Coefficient of variation*, in *Applied multivariate statistics in geohydrology and related sciences*. 1998, Springer. p. 155-157.

203. Gardiner, M., White, H., Munzinger, M., and Ray, W. *Low Carbon Building Programme 2006-2011: Final Report*. 2011.

204. Department of Energy and Climate Change. *Impact Assessment of Comprehensive Review Phase 2B - Consulation on Feed-in Tariffs for anaerobic digestion, wind, hydro and micro-CHP installations* 2011; Available from: https://www.gov.uk/government/consultations/tariffs-for-non-pv-technologies-comprehensive-review-phase-2b.

205. Cambridge Economic Policy Associates Ltd and Parsons Brinckerhoff. *Updates to the Feed-in Tariffs Model : Documentation of changes for Solar PV consulation*. 2011; Available from: https://www.gov.uk/government/consultations/tariffs-for-non-pv-technologies-comprehensive-review-phase-2b.

206. Parsons Brinckerhoff. *Update of non-PV data for Feed-in Tariff* 2012; Available from: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/42912/5900-update-of-nonpv-data-for-feed-in-tariff-.pdf.

207. Bale, C.S., McCullen, N.J., Foxon, T.J., Rucklidge, A.M., and Gale, W.F., *Harnessing social networks for promoting adoption of energy technologies in the domestic sector.* Energy Policy, 2013. **63**: p. 833-844.

208. Moore, G.A. and McKenna, R., *Crossing the Chasm: Marketing and Selling High-Tech Products to Mainstream Customers:* . 1999: HarperBusiness.

209. Hawkey, D., Tingey, M., and Webb, J., *Local Engagement in UK Energy Systems*, School of Social and Political Science and University of Edinburgh, Editors. 2015.

210. Farm Power. *Exploring the Size of the Prize*. 2014; Available from: https://www.forumforthefuture.org/sites/default/files/Farm%20Power_Size%20of%20the%20Prize%20report_Nov-2014.pdf.

211. Couture, T. and Gagnon, Y., *An analysis of feed-in tariff remuneration models: Implications for renewable energy investment.* Energy policy, 2010. **38**(2): p. 955-965.

212. Lesser, J.A. and Su, X., *Design of an economically efficient feed-in tariff structure for renewable energy development.* Energy Policy, 2008. **36**(3): p. 981-990.

213. Nicola, S.-L. *Renewable energy policy database and support . National Profile: Germany*. 2015; Available from: http://www.res-legal.eu/search-by-country/germany/tools-list/c/germany/s/res-e/t/promotion/sum/136/lpid/135/.

214. Hall, S., Foxon, T.J., and Bolton, R., *Financing the civic energy sector: How financial institutions affect ownership models in Germany and the United Kingdom.* Energy Research & Social Science, 2016. **12**: p. 5-15.

215. Blyth, W., McCarthy, R., and Gross, R., *Financing the UK power sector: Is the money available?* Energy Policy, 2015. **87**: p. 607-622.

216. Simcock, N., Willis, R., and Capener, P. *Cultures of Community Energy: International case studies*. 2016; Available from: https://www.britac.ac.uk/sites/default/files/Documents/CoCE_International%20Case%20Studies_online.pdf.

217. Yildiz, Ö., *Financing renewable energy infrastructures via financial citizen participation – The case of Germany.* Renewable Energy, 2014. **68**: p. 677-685.

218. IEA-RETD. *Cost and financing aspects of community renewable energy projects. Volume II: German Case Study*. 2016; Available from: http://ecologic.eu/sites/files/publication/2016/2119-cost-and-financing-community-renewables-volume-ii-german-report.pdf.

219. Community Energy England. *State of the Sector: A study of community energy in England Wales and Northern Ireland*. 2017; Available from: https://communityenergyengland.org/pages/state-of-the-sector-report.

220. Nolden, C., *Governing community energy—Feed-in tariffs and the development of community wind energy schemes in the United Kingdom and Germany.* Energy Policy, 2013. **63**(Supplement C): p. 543-552.

221. Simpson, A. *Community Energy Strategy: DECC Consultation* 2013; Available from: http://www.communityenvironment.org.uk/cms/wp-content/uploads/2013/08/Community-owned-energy-generation-Alan-Simpson.pdf.

222. Seyfang, G., Park, J.J., and Smith, A., *A thousand flowers blooming? An examination of community energy in the UK.* Energy Policy, 2013. **61**(Supplement C): p. 977-989.

223. Rosenow, J. and Eyre, N., *A post mortem of the Green Deal: Austerity, energy efficiency, and failure in British energy policy.* Energy Research & Social Science, 2016. **21**(Supplement C): p. 141-144.

224. Wilson, C., Crane, L., and Chryssochoidis, G., *Why do homeowners renovate energy efficiently? Contrasting perspectives and implications for policy.* Energy Research & Social Science, 2015. **7**(Supplement C): p. 12-22.

225. Howard, T. and Clark, P., *Correction and downscaling of NWP wind speed forecasts.* Meteorological Applications, 2007. **14**(2): p. 105-116.

226. Jackson, P. and Hunt, J., *Turbulent wind flow over a low hill.* Quarterly Journal of the Royal Meteorological Society, 1975. **101**(430): p. 929-955.

227. Department of Business Energy & Industrial Strategy. *Digest of United Kingdom Energy Statistics 2017*. 2017; Available from: https://www.gov.uk/government/statistics/digest-of-uk-energy-statistics-dukes-2017-main-report.

Appendix

This appendix provides the results of the peer effects model in each of the 12 clusters which were described in Chapter 6.

The results of the peer effects model for the East Anglia cluster is presented in Table 33.

Table 33 — Peer effects model for the East Anglia cluster

	Cluster Areas Only			Cluster and Surrounding Areas		
Variable	**Pre-FIT**	**Phase One**	**Phase Two**	**Pre-FIT**	**Phase One**	**Phase Two**
Peer effect from wind turbines, β_1	1.79E−05 (1.535)	1.24E−04*** (5.042)	6.40E−06** (2.31)	1.58E−03 (1.066)	1.32E−03 (1.4)	1.81E−05 (0.615)
Feed-in Tariff, γ_1		−3.19E−05 (−1.085)	8.08E−06*** (3.911)		1.52E−03 (0.572)	2.16E−05* (1.702)
Intercept, α_0	3.52E−06***	1.05E−03	−1.35E−04***	9.45E−05	−4.76E−02	−3.06E−04
R^2	0.004	0.229	0.089	0.002	0.002	0.002
N	1800	330	510	5160	946	1462

t-test value of each coefficient is included in the parentheses
*** — Significant at 99 %
** — Significant at 95 %
* — Significant at 90 %

The results of the peer effects model for the Pennine cluster is presented in Table 34.

Table 34 — Peer effects model for the Pennine cluster

	Cluster Areas Only			Cluster and Surrounding Areas		
Variable	**Pre-FIT**	**Phase One**	**Phase Two**	**Pre-FIT**	**Phase One**	**Phase Two**
Peer effect from wind turbines, β_1	1.20E−04 (1.607)	1.98E−04*** (3.616)	3.53E−05*** (2.832)	1.72E−03* (1.898)	1.47E−03** (2.405)	7.08E−04 (1.249)
Feed-in Tariff, γ_1		−4.69E−05 (−0.745)	7.87E−06** (2.341)		1.25E−04 (0.058)	7.07E−05 (1.216)
Intercept, α_0	1.20E−05**	1.49E−03	−1.33E−04**	1.80E−05	−2.91E−03	−1.57E−03
R^2	0.022	0.253	0.064	0.048	0.005	0.029
N	1440	264	408	7020	1287	1989

t-test value of each coefficient is included in the parentheses
*** — Significant at 99 %
** — Significant at 95 %
* — Significant at 90 %

The results of the peer effects model for the Cornwall cluster is presented in Table 35.

Table 35 — Peer effects model for the Cornwall cluster

	Cluster Areas Only			Cluster and Surrounding Areas		
Variable	**Pre-FIT**	**Phase One**	**Phase Two**	**Pre-FIT**	**Phase One**	**Phase Two**
Peer effect from wind turbines, β_1	1.64E−05** (2.354)	7.48E−05*** (6.347)	1.80E−05*** (18.379)	9.59E−05*** (6.196)	2.50E−04* (1.854)	2.36E−05*** (5.348)
Feed-in Tariff, γ_1		−5.56E−05 (−1.031)	1.15E−05*** (2.916)		−1.28E−04* (−1.732)	9.48E−06*** (5.139)
Intercept, α_0	9.81E−06***	1.80E−03	−2.00E−04***	1.84E−05***	4.09E−03*	−1.60E−04***
R^2	0.005	0.194	0.171	0.007	0.053	0.073
N	1020	187	289	5280	968	1496

t-test value of each coefficient is included in the parentheses
*** — Significant at 99 %
** — Significant at 95 %
* — Significant at 90 %

The results of the peer effects model for the Aberdeen cluster is presented in Table 36.

Table 36 — Peer effects model for the Aberdeen cluster

	Cluster Areas Only			Cluster and Surrounding Areas		
Variable	**Pre-FIT**	**Phase One**	**Phase Two**	**Pre-FIT**	**Phase One**	**Phase Two**
Peer effect from wind turbines, β_1	6.07E−05*** (2.677)	9.22E−05*** (5.491)	2.19E−05*** (5.612)	8.31E−05** (1.982)	2.34E−04 (1.601)	7.93E−05** (2.138)
Feed-in Tariff, γ_1		1.47E−04* (1.885)	1.16E−05*** (3.726)		−1.20E−03* (−1.864)	3.73E−05 (1.458)
Intercept, α_0	1.50E−05***	−4.55E−03*	−1.85E−04***	2.60E−05*	3.87E−02*	−5.42E−04
R^2	0.032	0.158	0.079	0.000	0.006	0.004
N	1020	187	289	6300	1155	1785

t-test value of each coefficient is included in the parentheses
*** — Significant at 99 %
** — Significant at 95 %
* — Significant at 90 %

The results of the peer effects model for the East Yorkshire cluster is presented in Table 37

Table 37 — Peer effects model for the East Yorkshire cluster

	Cluster Areas Only			Cluster and Surrounding Areas		
Variable	**Pre-FIT**	**Phase One**	**Phase Two**	**Pre-FIT**	**Phase One**	**Phase Two**
Wind Turbines, β_1	−3.79E−06 (−0.092)	1.01E−04*** (2.793)	2.64E−05*** (2.787)	5.98E−05*** (2.932)	5.01E−04* (1.783)	2.63E−04 (1.319)
Feed-in Tariff, γ_1		−1.64E−04 (−1.6)	6.97E−06 (1.397)		−2.61E−04 (−1.53)	3.97E−05 (1.173)
Intercept, α_0	3.79E−06	5.34E−03	−1.33E−04	3.66E−06*	8.52E−03	−8.46E−04
R^2	0.000	0.103	0.077	0.003	0.045	0.051
N	600	110	170	3120	572	884

t-test value of each coefficient is included in the parentheses
*** — Significant at 99 %
** — Significant at 95 %
* — Significant at 90 %

The results of the peer effects model for the Scottish Borders cluster is presented in Table 38.

Table 38 — Peer effects model for the Scottish Borders cluster

	Cluster Areas Only			Cluster and Surrounding Areas		
Variable	Pre-FIT	Phase One	**Phase Two**	**Pre-FIT**	**Phase One**	**Phase Two**
Peer effect from wind turbines, β_1	3.06E−04** (2.533)	3.38E−04*** (10.463)	4.56E−05*** (20.074)	2.43E−04*** (2.672)	3.83E−04*** (10.759)	5.87E−05*** (4.012)
Feed-in Tariff, γ_1		7.46E−05 (0.51)	2.85E−05 (1.328)		−1.69E−04* (−1.901)	9.22E−06*** (2.916)
Intercept, α_0	2.14E−05*	−2.33E−03	−5.55E−04	1.08E−05***	5.40E−03*	−1.67E−04***
R^2	0.099	0.637	0.156	0.040	0.279	0.082
N	480	88	136	6720	1232	1904

t-test value of each coefficient is included in the parentheses
*** — Significant at 99 %
** — Significant at 95 %
* — Significant at 90 %

The results of the peer effects model for the Hebrides cluster is presented in Table 39.

Table 39 — Peer effects model for the Hebrides cluster

	Cluster Areas Only			Cluster and Surrounding Areas		
Variable	**Pre-FIT**	**Phase One**	**Phase Two**	**Pre-FIT**	**Phase One**	**Phase Two**
Peer effect from wind turbines, β_1	8.87E−05** (2.161)	6.51E−05 (1.646)	3.19E−05*** (3.469)	8.40E−05*** (4.68)	1.33E−04*** (5.073)	2.92E−05*** (4.328)
Feed-in Tariff, γ_1		−1.27E−04 (−0.469)	3.07E−05*** (3.161)		−1.77E−04* (−1.765)	2.16E−05*** (3.971)
Intercept, α_0	1.98E−05*	4.56E−03	−5.05E−04***	2.50E−05**	5.80E−03*	−3.16E−04***
R^2	0.045	0.042	0.087	0.014	0.139	0.061
N	420	77	119	1500	275	425

t-test value of each coefficient is included in the parentheses
*** — Significant at 99 %
** — Significant at 95 %
* — Significant at 90 %

The results of the peer effects model for the South Wales cluster is presented in Table 40.

Table 40 — Peer effects model for the South Wales cluster

	Cluster Areas Only			Cluster and Surrounding Areas		
Variable	Pre-FIT	**Phase One**	**Phase Two**	**Pre-FIT**	**Phase One**	**Phase Two**
Peer effect from wind turbines, β_1	1.16E−05* (1.785)	2.43E−05 (1.149)	8.96E−06 (1.107)	2.53E−05*** (3.284)	7.10E−05*** (4.662)	2.06E−05*** (5.745)
Feed-in Tariff, γ_1		−8.18E−06 (−0.143)	−4.66E−08 (−0.017)		−2.23E−05 (−0.417)	9.36E−06*** (4.348)
Intercept, α_0	6.46E−06*	2.96E−04	1.79E−05	8.59E−06***	7.76E−04	−1.35E−04***
R^2	0.008	0.018	0.010	0.008	0.060	0.050
N	420	77	119	1980	363	561

t-test value of each coefficient is included in the parentheses
*** — Significant at 99 %
** — Significant at 95 %
* — Significant at 90 %

The results of the peer effects model for the Orkney Islands cluster is presented in Table 41.

Table 41 — Peer effects model for the Orkney Islands cluster

	Cluster Areas Only			Cluster and Surrounding Areas		
Variable	**Pre-FIT**	**Phase One**	**Phase Two**	**Pre-FIT**	**Phase One**	**Phase Two**
Peer effect from wind turbines, β_1	1.61E−04*** (13.284)	1.02E−04*** (11.21)	2.67E−05*** (4.735)	1.18E−04*** (3.507)	1.14E−04*** (7.447)	2.95E−05*** (3.682)
Feed-in Tariff, γ_1		5.38E−06 (0.051)	1.54E−05** (2.446)		−1.12E−04 (−0.862)	3.02E−05*** (2.99)
Intercept, α_0	1.51E−05**	−1.49E−04	−2.65E−04**	1.35E−05**	3.75E−03	−4.45E−04**
R^2	0.282	0.639	0.252	0.101	0.263	0.073
N	360	66	102	900	165	255

t-test value of each coefficient is included in the parentheses
*** — Significant at 99 %
** — Significant at 95 %
* — Significant at 90 %

The results of the peer effects model for the Shetland Islands cluster is presented in Table 42.

Table 42 — Peer effects model for the Shetland Islands cluster

	Cluster Areas Only			Cluster and Surrounding Areas		
Variable	Pre-FIT	**Phase One**	**Phase Two**	**Pre-FIT**	**Phase One**	**Phase Two**
Peer effect from wind turbines, β_1	1.24E−04*** (7.676)	5.23E−05 (1.567)	2.23E−05 (1.249)	1.25E−04*** (7.75)	6.08E−05** (2.055)	2.22E−05 (1.381)
Feed-in Tariff, γ_1		−6.65E−04** (−2.106)	3.39E−05* (1.927)		−7.07E−04** (−2.559)	3.57E−05** (2.282)
Intercept, α_0	4.19E−05	2.17E−02**	−2.88E−04	3.54E−05	2.30E−02**	−3.28E−04
R^2	0.144	0.108	0.040	0.148	0.138	0.047
N	360	66	102	420	77	119

t-test value of each coefficient is included in the parentheses
*** — Significant at 99 %
** — Significant at 95 %
* — Significant at 90 %

The results of the peer effects model for the Northumberland cluster is presented in Table 43.

Table 43 — Peer effects model for the Northumberland cluster

	Cluster Areas Only			Cluster and Surrounding Areas		
Variable	**Pre-FIT**	**Phase One**	**Phase Two**	**Pre-FIT**	**Phase One**	**Phase Two**
Peer effect from wind turbines, β_1	7.82E−05* (1.823)	1.22E−04** (2.072)	1.78E−05 (1.066)	9.95E−05 (0.624)	6.65E−05 (0.205)	1.81E−05 (0.408)
Feed-in Tariff, γ_1		1.27E−04 (0.498)	8.43E−06 (0.907)		3.44E−04 (0.244)	2.46E−06 (0.098)
Intercept, α_0	2.67E−05	−3.97E−03	−1.36E−04	9.41E−05	−1.00E−02	1.40E−04
R^2	0.014	0.089	0.026	0.000	0.000	0.000
N	240	44	68	2520	462	714

t-test value of each coefficient is included in the parentheses
*** — Significant at 99 %
** — Significant at 95 %
* — Significant at 90 %

The results of the peer effects model for the Cumbria cluster is presented in Table 44.

Table 44 — Peer effects model for the Cumbria cluster

	Cluster Areas Only			Cluster and Surrounding Areas		
Variable	**Pre-FIT**	**Phase One**	**Phase Two**	**Pre-FIT**	**Phase One**	**Phase Two**
Peer effect from wind turbines, β_1	4.33E−04 (1.314)	5.53E−04*** (5.197)	8.43E−05** (2.164)	4.10E−04*** (5.235)	4.62E−04*** (5.299)	8.45E−05*** (4.69)
Feed-in Tariff, γ_1		9.16E−05 (0.171)	4.59E−05 (1.211)		−3.23E−04 (−1.273)	2.18E−05** (2.009)
Intercept, α_0	4.67E−05	−3.12E−03	−7.12E−04	8.00E−06	1.05E−02	−3.09E−04
R^2	0.086	0.453	0.092	0.084	0.136	0.069
N	180	33	51	1140	209	323

t-test value of each coefficient is included in the parentheses
*** — Significant at 99 %
** — Significant at 95 %
* — Significant at 90 %