

Control of Naturally Ventilated Buildings: a Model Predictive Control Approach

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“essentially, all models are wrong, but some are useful”

George Box

Abstract

During operation, buildings consume a large amount of energy, around 40% of global final energy use. A major challenge is to reduce the amount of energy used while still providing a comfortable environment for building occupants. The use of passive techniques, such as natural ventilation, is promoted in certain climates to provide low energy cooling and ventilation. However, controlling natural ventilation in an effective manner to maintain occupant comfort can be a difficult task, particularly during warm periods. One area which has been identified as having the potential for reducing energy consumption while maintaining occupant comfort is the use of more advanced control techniques.

A technique which has been much explored in recent years for application in mechanically ventilated buildings is Model Predictive Control (MPC). MPC is a control technique which uses a model of the system dynamics and by solving an optimisation problem is able to determine the optimal control inputs.

In this thesis the application of MPC to naturally-ventilated buildings is investigated. The essential component of an MPC strategy is the predictive model of the building's thermal dynamics. An empirical approach to modelling was taken using multilayer perceptron (MLP) neural network models. To use empirical data from a building to create a predictive model it is essential to ensure the quality of the data is appropriate. In order to assess the data available from buildings during normal operation four studies were carried out in different buildings. The data collected from these studies represent a range of natural ventilation scenarios and building types in different locations in the UK. To test the impact of identification procedures upon the resulting neural network models, an identification experiment was carried out using dynamic thermal simulation. Neural network models were trained using both the data from real buildings and the simulation data.

Results showed that neural network models trained using data from real buildings were capable of good predictions. However, the lack of input excitation during normal operation resulted in models which did not capture the effect of the window opening control. The identification experiment demonstrated that by exciting the control input the resulting neural network models captured the effect of the control, making them suitable for MPC.

The main focus of this thesis is the investigation of techniques to develop predictive models which can be utilised as part of an MPC strategy. However, to demonstrate the potential benefits of MPC a controller designed to maintain a suitable internal temperature is demonstrated. The controller utilised the neural network models developed using the data

from the system identification experiment and a non-linear optimiser. The MPC method showed the potential to reduce overheating and improve upon the typical control used in the majority of buildings.

Findings in this thesis demonstrate that empirical models capable of good predictions can be trained and could be successfully applied to the control of natural ventilation systems. Furthermore, the potential advantages of adopting an MPC approach to natural ventilation control are shown.

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Nomenclature

Symbols

A_{GL}	-	m^2	geometric leakage area
C_i	-	m^3	air mass flow coefficient
e	-		network errors
E_D	-		data-dependant error
E_W	-		regularisation term
g	-	m/s^2	acceleration due to gravity,
			gradient
H	-		Hessian matrix
I	-		identity matrix
J	-		Jacobian matrix
$J_{\delta u}$	-		manipulated variable move suppression
J_ϵ	-		constraint violation
J_y	-		output reference tracking
k	-		current control interval
k_C	-	$^\circ C$	change in temperature over 15 minutes due to cooling
k_r	-	s	room time constant
k_w	-	s	time constant for transfer from a room to outside
\dot{m}_i	-	kg/s	air mass flow rate at the i_{th} linkage
M	-		number of hidden units
MN_{trans}	-		number of manipulated variable transitions
n_y	-		number of plant output variables
N	-		prediction horizon,
			number of training data
p	-		probability of window being opened or closed,
			number of control intervals
ΔP	-	Pa	total pressure difference
ΔP_i	-	Pa	pressure difference across the i_{th} linkage
P_m	-	Pa	exit static pressure
P_n	-	Pa	entry static pressure

$q[n]$	-	$^{\circ}\text{C}$	change in temperature due to occupants and equipment
$r_j(k+i k)$	-		reference value for the j th plant output at the i th prediction horizon step
s_j^y	-		scale factor for the j th plant output
t_{ai}	-	$^{\circ}\text{C}$	zone temperature
T	-	$^{\circ}\text{C}$	temperature
δT	-	$^{\circ}\text{C}$	difference between indoor and outdoor temperature
T_{ai}	-	$^{\circ}\text{C}$	indoor air temperature
T_{ao}	-	$^{\circ}\text{C}$	outdoor air temperature
T_c	-		control horizon
T_{comf}	-	$^{\circ}\text{C}$	comfort temperature
T_e	-	$^{\circ}\text{C}$	daily mean outdoor temperature
T_p	-		prediction horizon
T_{rm}	-	$^{\circ}\text{C}$	weighted running mean outdoor temperature
$u(t)$	-		control signal, newline neural network input
v	-		unmeasured disturbance
v_e	-	m/s	outdoor air speed
V_m	-	m/s	exit airflow velocity
V_n	-	m/s	entry airflow velocity
\mathbf{w}	-		weight vector elements
w	-		measured disturbances
$w_{i,j}^y$	-		tuning weight for the j th plant output at the i th prediction horizon step
W_k	-		vector of current weights and biases
x	-		raw datum
x_i	-		input
$y_j(k+i k)$	-		predicted value of the j th plant output at the i th prediction horizon step
$y(t)$	-		output
$\hat{y}(t)$	-		predicted output
z	-		standard score
z_k	-		optimal control inputs
z_m	-	m	exit elevation
z_n	-	m	entry elevation
α_{rm}	-		constant
δ	-		standard deviation of the population
ϵ_k	-		slack variable at control interval k
λ	-		regularisation term
μ	-	Pa.s	air viscosity, mean of the population, scalar

ρ	-	kg/m ³	air density
ρ_ϵ	-		constraint violation penalty weight
$\rho\delta_u$	-		manipulated variable move suppression penalty weight

Abbreviations and Acronyms

AC	-	Air Conditioner
ACH	-	Air Change Rate
ANV	-	Advanced Natural Ventilation
ARIMA	-	Autoregressive Moving Average
ARMAX	-	Autoregressive Moving Average with Exogenous Inputs
ARX	-	Autoregressive with Exogenous Inputs
BCVTB	-	Building Controls Virtual Test Bed
BFGS	-	Broyden-Fletcher-Goldfarb-Shanno
BMS	-	Building Management System
BRITE	-	Berkeley Retrofitted and Inexpensive HVAC Testbed for Energy Efficiency
CHAID	-	Chi-square Automatic Interaction Detector
CTU	-	Czech Technical University
DCV	-	Demand-Controlled Ventilation
DMPC	-	Deterministic Model Predictive Control
EMPC	-	Economic Model Predictive Control
EMS	-	Energy Management System
GLM	-	Generalised Linear Model
GWN	-	Gaussian White Noise
HVAC	-	Heating, Ventilation and Air Conditioning
IAQ	-	Indoor Air Quality
IEQ	-	Indoor Environmental Quality
FCU	-	Fan Coil Unit
MAE	-	Mean Absolute Error
MAPE	-	Mean Absolute Percentage Error
MLP	-	Multi-Layer Perceptron
MOGA	-	Multi-Objective Genetic Algorithm
MPC	-	Model Predictive Control
MV	-	Manipulated Variable
NAR	-	Nonlinear Autoregressive
NARX	-	Nonlinear Autoregressive with External Input
NMPC	-	Nonlinear Model Predictive Control
NMPC-NO	-	Nonlinear Model Predictive Control with Nonlinear Optimisation

NMPC-	-	Nonlinear Model Predictive Control with Nonlinear Prediction and Linearisation
NPL	-	Non-Renewable Primary Energy
NRPE	-	Non-Renewable Primary Energy
PI	-	Proportional-Integral
PID	-	Proportional-Integral-Derivative
PMV	-	Predicted Mean Vote
PPD	-	Predicted Percentage of Dissatisfied
PRBS	-	Pseudo Random Binary Signal
PSO	-	Particle Swarm Optimisation
RBC	-	Rule-Based Control
RBF	-	Radial Basis Function
RC	-	Resistance-Capacitance
RSM	-	Response Surface Model
SMPC	-	Stochastic Model Predictive Control
SQP	-	Sequential Quadratic Programming
StdAE	-	Standard Deviation of Absolute Error
StdMAPE	-	Standard Deviation of Mean Absolute Percentage Error
SVM	-	Support Vector Machine
TDL	-	Tapped Delay Line
TER	-	Target Emissions Rate
TES	-	Thermal Energy Storage
VRF	-	Variable Refrigerant Flow

Chapter 1

Introduction

1.1 Background and Motivation

Energy costs, climate change, mounting political and social pressure are examples of some of the drivers for the increasing attempts to reduce energy consumption. Buildings account for around 40% of total final energy consumption in developed countries, (Pérez-Lombard et al. 2008), and in European countries around 76% of the energy consumed by buildings is used for comfort control, i.e. heating, ventilation and air conditioning (HVAC) (Laustsen 2008). Reducing the amount of energy required by HVAC systems can be approached in a number of ways, for example: increasing airtightness, better insulation, increasing appliance efficiency, passive ventilation techniques, improved control etc.

In addition to energy concerns, there has been a growing awareness of the impact of indoor environmental quality (IEQ) upon occupants wellbeing (ASHRAE 2013). IEQ refers to the quality of a building's environment in relation to the health and wellbeing of those who occupy the space (Centers for Disease Control and Prevention 2013). There is a number of factors which contribute to IEQ including: air quality, temperature, lighting, contaminants etc. Ventilation is important for air quality, temperature, contaminants, and therefore the design and control of ventilation is important.

To provide good quality indoor environments at a low energy cost good control is essential. The Low Carbon Innovation Coordination Group (2012) identified improvements in design, building process, management and operation, and materials and components as areas which could make a significant reduction in energy consumption. The use of predictive controls is particularly highlighted as being important for reducing energy use in buildings, and enabling them to function optimally.

This thesis therefore focused on the application of Model Predictive Control (MPC) to building operation. MPC is a control method which originated in the process industries (Camacho & Bordons 2013). MPC utilises a system model to optimise future outputs based upon possible inputs over a finite receding time horizon. At each time step, a minimisation of some objective function is carried out to determine the optimal control signals over a finite horizon. At each iteration, only the first step of the control strategy is

then implemented. The control horizon is then shifted one step forward and the process repeated ad infinitum (Camacho & Bordons 2013)).

Although there is a growing body of work in MPC for buildings, the selection of the most appropriate model is an open question. Further for the UK climate there is great opportunity to make use of natural ventilation to provide passive ventilation and cooling, when combined with high thermal mass. However, in order for this to function well (particular in providing cooling consistently during long periods of hot weather) automatic control is often provided alongside occupant controlled windows. Due to the long time constants of such buildings, and the need to ‘charge’ the thermal slabs, a purely responsive control system may not be able to provide adequate cooling. However, a predictive model may be able to take account of this providing higher levels of comfort. By improving the control, and performance of such systems we may be able to make natural ventilation become more attractive to clients and may reduce overall energy use by reducing the reliance on air conditioning.

There is therefore a need to investigate the appropriateness of MPC for natural ventilation. Current research in MPC tends to focus on HVAC systems, whereas natural ventilation often has the added combination of a centrally controlled set of windows alongside those operated by occupants. The occupant use of manual windows can add a significant disturbance which must be handled by the control. This indicates that an empirical approach to creating a predictive model using real building data may be more appropriate to account for this disturbance. Such methods have only been applied in limited scenarios, and never to natural ventilation previously.

1.2 Scope and Objectives of the Thesis

This research aims to investigate the potential application of MPC to natural ventilation systems. While the overall aim of the thesis is demonstrating and evaluating the MPC approach; the most important element in an MPC strategy is the system model. The choice of modelling strategy is critical. There are two main approaches to system modelling which can be taken when applying MPC to HVAC systems. One approach is the use of first-principles models. These models are based upon our knowledge of the physical processes taking place within the building. The alternative to the first-principles models is the use of ‘black-box’ data-driven models.

In this thesis the black-box data driven model approach is taken, using neural network models. The development of the neural network models and issues relating to modelling, such as data collection and system excitation, will form the majority of the research. Current literature on the application of empirical models for MPC is far from mature, with minimal investigation into the use of empirical models for HVAC systems. In particular, developing a method for modelling natural ventilation, where there is a combination of automatic window control and manual operation by occupants has not been studied.

This thesis, therefore, has the following aims:

1. Identify appropriate methods to develop an empirical model of building performance in naturally ventilated buildings.
2. Evaluate the data requirements to generate a model appropriate for control.
3. Determine an optimum model training methodology for developing empirical models.
4. Evaluate the potential of MPC (using the model developed in objectives 1-3) for improving the performance of naturally ventilated buildings.

1.3 Thesis Outline

This chapter has highlighted the importance of adequate control in buildings and the effect this can have upon both occupant comfort and energy usage. The remainder of the thesis is organised as follows:

Chapter 2 - Literature Review

This chapter provides background information on natural ventilation and ventilation control. Model predictive control is described and previous applications to HVAC systems are summarised. The key differences between empirical and physics based models are highlighted and the decision to utilise an empirical approach in this research is justified.

Chapter 3 - Data Collection and Pre-Processing

In this chapter the importance of data upon which to train models is discussed. The training data collected from buildings are described, as well as discussing the difficulties encountered when carrying out data collection in buildings during operation.

Chapter 4 - Neural Network Modelling

The data described in the previous chapter are used to train neural network models to predict internal temperature and CO₂ concentration. A range of network architectures are investigated and the impact of model structure upon prediction accuracy is discussed. The performances of the models are evaluated and potential deficiencies in the training data highlighted.

Chapter 5 - Simulation Model

To enable further training data to be generated and to test system identification strategies, a building simulation model was built. This chapter details the modelling and validation processes.

Chapter 6 - System Identification

Open-loop system identification is carried out using the building model described in Chapter 5. The results of the identification experiment are then used to train neural network models. The performance of the neural network models are analysed and compared with the models trained using data from real buildings.

Chapter 7 - Model Predictive Control

In this chapter the models developed in the previous chapter are utilised as part of an MPC ventilation control system. The potential to use MPC for the control of natural ventilation systems is demonstrated through the use of simulation. The neural network models are incorporated within a MPC controller which is used to control the window openings in a dynamic thermal simulation model. The ability of the controller to maintain a suitable indoor environment is analysed and compared with a more traditional rule based controller. The effect of varying control and prediction horizons are also investigated.

Chapter 8 - Summary and Conclusions

This chapter summarises the research and makes suggestions for future work.

Chapter 2

Ventilation: Theory and Control

This chapter provides background information on building ventilation. Methods of ventilating buildings are described, with a focus upon natural ventilation. As the purpose of ventilation is to provide an acceptable indoor environment for occupants, the impact of ventilation upon health and productivity is briefly outlined. The way in which occupants interact with buildings, in particular the ventilation control, is also described.

This chapter describes current best practice for the control of ventilations systems. In recent years there has been a growing interest in the application of MPC techniques to building control. A review of existing research applying MPC techniques to building systems is included. This is used to highlight the gaps in the current knowledge base which this thesis will address.

2.1 An Introduction to Ventilation

Ventilation is essential for maintaining a suitable environment within the space being ventilated, in terms of air quality (removal of pollutants) and thermal environment. There are two main ways in which spaces can be ventilated, natural ventilation and mechanical ventilation. Natural ventilation refers to air exchanges through windows and louvres which is driven by the wind and/or thermal buoyancy (often referred to as stack effect). Mechanical ventilation refers to the use of fans for supplying and/or extracting air. Mechanical systems may include conditioning the outside air before it enters the ventilated space. Mechanical ventilation can typically give a tighter control upon the internal environment compared to natural ventilation; however mechanically ventilated buildings typically consume more energy over the course of a year Bordass et al. (2001).

Dwellings have been naturally ventilated for thousands of years but during the twentieth century technologies started to be developed to introduce mechanical systems into buildings. The shift towards mechanical ventilation was caused by a number of factors. Towards the end of the nineteenth and the twentieth century a large number of urban environments where heavily polluted, initially due to the burning of coal and oil for energy and later due to the rise of the internal combustion engine (Heinberg 2009). High levels of outdoor air

pollution translated into equally poor internal conditions in naturally ventilated spaces. To overcome this new technology was developed to improve the air quality inside buildings. One of the first examples of a large mechanically ventilated non-domestic building is the Larkin Building in New York. Designed by American Architect Frank Lloyd Wright and built in 1906, the Larkin Building was designed as a sealed structure with mechanical ventilation to reduce the level of internal contaminants and reduce the noise levels from the nearby railway (Thomas 2013).

In addition to the problem of high levels of pollution, during the majority of the twentieth century energy was relatively cheap, this meant that the running costs of mechanical systems were not sufficiently high for building owners and designers to look for alternative methods of ventilation. Thomas (2013) argues that to an extent this is still the case today, with the main driver for more energy efficient policies being to reduce the environmental impact, rather than reduce the cost.

The aesthetics and symbolism of the modern style of glass box architecture also had an influence on the increasing use of mechanical ventilation systems. This type of architecture, was seen as a *“potent symbol of architectural modernity and social progress”* (Thomas 2013) which was aspired to by many clients and architects. In many ways the ventilation systems in these buildings can be viewed as highly effective. Through the use of mechanical ventilation, external noise and pollutants are reduced and comfortable temperatures can be maintained in even the hottest of conditions; however this is at a cost of large amounts of energy.

The financial cost in maintaining a comfortable environment using mechanical systems has increased in recent years due to the rising costs of energy (Popescu et al. 2012). Alongside this financial cost, there has also been an increase in awareness surrounding issues such as global warming, environmental impact and depletion of natural resources. This has led to political and public pressure upon companies and individuals to look for less energy intensive alternatives.

While reducing the energy consumption and environmental impact of buildings, the comfort of building occupants must also be considered. The indoor environmental quality (IEQ) can have a significant impact upon occupants satisfaction, productivity and health (see Sections 2.2 and 2.2.1). In building design and management the main goals are often in competition, i.e. minimising energy consumption and maximising occupant comfort.

2.2 Occupant Comfort

In modern society, people spend a significant percentage of their time inside buildings. Therefore, maintaining a suitable environment for occupants should be a high priority for building stakeholders. Indoor environmental quality (IEQ) can encompass a wide range of areas such as thermal comfort, indoor air quality (IAQ), acoustics, lighting, ergonomics, visual comfort etc. In reality, it is impossible to maintain an internal environment which will satisfy every occupant, as each individual may have a slightly different preference

upon their ideal conditions.

To account for the fact that people's perception of comfort can differ, Fanger et al. (1970) proposed indices which can be used to classify the thermal environment of a building. The Predicted Mean Vote (PMV) and Predicted Percentage of Dissatisfied (PPD) indices can both be used to quantify the number of occupants who will be satisfied by the thermal conditions. PPD and PMV are both widely used in both literature and standards (ASHRAE 2013, CIBSE 2013).

The comfort indices proposed by Fanger et al. (1970) have received both support and criticism (Candido & Dear 2012). The indices were originally proposed for use in tightly controlled spaces, using mechanical ventilation systems (van Hoof & Hensen 2007). Despite this, they have been widely used for a number of building types, including naturally ventilated. One of the most widely criticized aspects of the work by Fanger is the concept of a universal, 'neutral' temperature (Candido & Dear 2012).

With the general acceptance of adaptive comfort, which assumes that occupants' thermal expectations and preferences are influenced by the recent thermal history, the problems with PMV and PPD were mostly overcome. The notion of an adaptive rather than static comfort model has appeared in literature for around four decades (Auliciems 1981, Humphreys 1978, De Dear et al. 1998). According to Candido & Dear (2012), it was not until the realisation that the use of energy and carbon to air condition spaces was unsustainable, that adaptive comfort came to the fore. The key difference between the adaptive and static models, is that the adaptive approach takes into account thermal history, occupant expectations and attitudes, their perceived level of control over the environment and being able to make behavioural adaptation (such as changing clothing levels). By using an adaptive model for thermal comfort, natural ventilation strategies that previously would have been deemed unacceptable due to fluctuations in temperature, may in fact be found acceptable to occupants (CIBSE 2013).

Previous studies on improving the control of mechanical ventilation systems often aim to improve occupant satisfaction while minimising energy consumption (Aswani et al. 2012, Ferreira et al. 2012, Oldewurtel et al. 2012). As this thesis is focussed upon natural ventilation, the primary goal is to improve occupant comfort. By demonstrating that improved control can make natural ventilation a more viable alternative to mechanical systems, this could also indirectly reduce energy consumption.

2.2.1 Effect of Ventilation on Occupant Health and Productivity

In addition to occupant dissatisfaction, there is also a relationship between IEQ and occupant health and productivity. In terms of health, the belief used to be that the greatest source of indoor pollutants were the occupants themselves, due to the release of bioeffluents and tobacco smoke (Awbi 2003). However, the understanding of indoor pollutants has advanced in recent decades. In a modern building chemicals and contaminants can be released from a variety of sources, such as surface finishes, furniture, equipment etc. Biological pollutants are also found in buildings. Inadequate ventilation and humidity can

cause condensation to occur. This in turn can lead to the growth of bacteria and fungi. Bacteria such as *Legionella*, which thrive in warm and wet conditions, can be found in hot water systems, HVAC chillers and evaporative coolers (Edagawa et al. 2008, Nguyen et al. 2006). All of which can have an impact upon occupant health and well-being.

Illness and health symptoms related to buildings and the indoor environment are often referred to as sick building syndrome (SBS) symptoms. Symptoms of which may include: headaches, fatigue, respiratory difficulties, irritation of eyes, nose and skin (Fisk 2000*b*). In some buildings, complaints and symptoms can become severe and affect a large percentage of occupant. These buildings are often referred to as “sick buildings”. However, SBS symptoms are also experienced by a large number of people in buildings which have no history of widespread problems (Nelson et al. 1995, Brightman et al. 1997).

Some studies have found that the number of cases of SBS reported in naturally ventilated buildings is fewer than in mechanically ventilated buildings. Muhič & Butala (2004) measured parameters and carried out surveys in naturally and mechanically ventilated buildings over a six month period. They found that the presence of SBS is significantly higher in mechanically ventilated buildings. With the exception of eye inflammation and swollen eyelids, higher frequency of building-related symptoms were found in the mechanically ventilated buildings. Similarly, Vincent et al. (1997) compared questionnaire results from 1144 workers across three buildings. One building was naturally ventilated, one air conditioned and one cooled by fan coil units (FCUs). In both the air conditioned and FCU buildings the occupants showed a slightly higher risk of non-specific symptoms compared with those in the naturally ventilated building. However, natural ventilation cannot be recommended in some circumstances. For example, in highly polluted areas with high particulate matter, instances of SBS may decrease but other health problems can result if natural ventilation is used. Dutton et al. (2013) investigated the use of natural ventilation in California offices and found that despite an overall reduction in SBS symptoms, health cost would increase significantly due to pollutant exposure.

Experiencing SBS symptoms can lead to disruption through absences from work. This can have an associated financial cost for both the employer and employee. However, according to Fisk (2000*b*) the cost of small decreases in productivity due to SBS symptoms are likely to dominate the total financial cost to the employer.

The IEQ can affect the ability of occupants to perform physical and mental tasks, without directly causing health symptoms. A number of studies have found that thermal comfort of occupants can have a significant impact upon their productivity (Fisk 2000*a*, Wyon 1993, 1997, Wyon et al. 1979). IAQ has also been shown to affect occupant productivity (Heerwagen 2000, Wyon 2004, Clements-Croome 2006). Problems relating to inadequate ventilation and poor IAQ are particularly prevalent within schools. A wealth of literature is devoted to the potential to improve the learning performance of students through improvements in IAQ (Clements-Croome et al. 2008, Daisey et al. 2003, Ole Fanger 2006). In particular, high concentrations of CO₂ have been shown to have an impact upon pupil’s performance and health (Myhrvold et al. 1996).

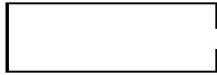
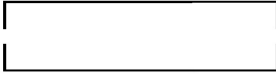
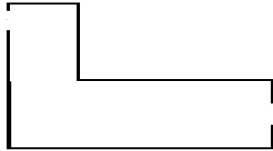
Type	Diagram	Main driver for flow	Comments
Single		buoyancy or wind	only shallow plans are possible
Cross		wind	deeper plans are possible
Stack		buoyancy	greatest potential for large spaces

Table 2.1: Basic forms of naturally ventilated spaces

Increasing ventilation rates has been shown in a number of studies to lower the number of cases of sick building syndrome and improve occupant productivity (Fisk et al. 2012, Sundell et al. 2011, Seppänen 2006). Similarly, maintaining adequate thermal comfort has also been shown to improve productivity (Fisk 2000*b*). By improving the controllability of natural ventilation systems, the MPC approach investigated in this thesis has the potential to achieve improvements in both IAQ and thermal comfort.

In addition to benefits in occupant satisfaction, health and productivity, there are potential financial gains to improving the control of natural ventilation systems. While prior research into the application of MPC to HVAC systems may have more easily quantifiable financial benefits, through energy saving, improving ventilation in naturally ventilated buildings could have financial rewards. Although more difficult to quantify, increased productivity and improved health is likely to equate to significant financial gains.

2.3 Natural Ventilation Design

Natural ventilation utilises the wind and temperature differences to drive air flow. The conventional approach to natural ventilation is to employ windows or vents which can be opened by the buildings occupants to provide airflow. Although there are lots of possible variations for positioning of windows and openings, naturally ventilated spaces can usually be categorized as one of following three distinct types: single sided, cross ventilated or stack ventilated (Table 2.1). This taxonomy is used to describe spaces within the case study buildings in Chapter 3.

In single sided ventilation openings are only present on one side of the space being ventilated. With a single opening, airflow is primarily driven by wind turbulence. Although it is possible for buoyancy to drive flow, if the opening is sufficiently large vertically (CIBSE 2005*a*). If multiple openings are provided in the façade at different heights, the ventilation rate can be increased due to buoyancy flow. The degree to which the flow rate increases will depend upon the vertical distance between the openings and the temperature differ-

ence between inside and out. Even with openings at multiple heights, the maximum room depth is small for spaces which utilise single sided natural ventilation. CIBSE (2005*a*) suggests rules of thumb of a maximum depth between 2 and 2.5 times the floor to ceiling height.

When ventilation openings are present on both sides of the space this is considered cross ventilation. Airflow in cross ventilated spaces is driven primarily by the wind. Although in some designs buoyancy flow can be incorporated. By utilising cross ventilation the depth of plan can be increased compared with single sided ventilation. However, as the air flows across the space, the temperature will increase and air quality is likely to become poorer.

Both single sided and cross ventilation necessitate building forms with shallow plans. Shallow plans also allow for better use of daylighting. Hence, most naturally ventilated buildings have traditionally had a narrow plan depth. To enable deeper plans stack ventilation can be utilised. In stack ventilation buoyancy is the predominate driver for flow. When taking this approach air is drawn through the room being ventilated and exhausted through some form of vertical space, such as a chimney or atrium space. Utilising chimneys to enhance ventilation through buoyancy and wind driven flow is not a recent development, with wind towers being used in some Middle Eastern architecture for hundreds of years Bahadori (1978). Other the past few decades the use of the stack effect to drive ventilation flow has increased in popularity, in the UK and around the world.

In the case of single sided and cross ventilation, it is possible to make use of manual occupant controlled windows. Although in a number of larger buildings some level of automation is likely. A common technique is to utilise low level manual openings with automated openings at a higher level. With stack ventilation systems some level of automation will nearly always be required. This is due to the inaccessible location of the exhaust openings and the fact that the ventilation flow is usually linked to a number of occupied spaces making it infeasible for a single occupant to regulate the ventilation.

Lomas (2007) utilises the term ‘advanced natural ventilation (ANV)’ to describe buildings which utilise the stack effect to drive airflow. This term is particularly applicable due to the more complex control required, using actuators to regulate the position of windows and vents. A taxonomy to describe ANV buildings was proposed by Lomas & Cook (2005) whereby buildings are categorised based upon where air enters and leaves the building. This taxonomy gives four possible building forms: edge-in, centre-out; edge-in, edge-out; centre-in, edge-out and centre-in, centre-out (see Figure 2.1).

One of the key reasons to utilise natural ventilation is to reduce energy consumption and thus reduce emission of greenhouse gases, in particular CO₂. In temperate climates, such as in the UK, natural ventilation should be able to provide a suitable internal environment in most cases (Lomas & Ji 2009); while using significantly less energy than mechanically ventilated or air-conditioned buildings. In the UK PROBE studies (Bordass et al. 2001), post occupancy evaluation was carried out on 16 buildings. The naturally ventilated buildings emitted less CO₂ than the full air-conditioned, mechanically ventilated or mixed-mode buildings. In addition to reduced energy consumption, there are some studies which

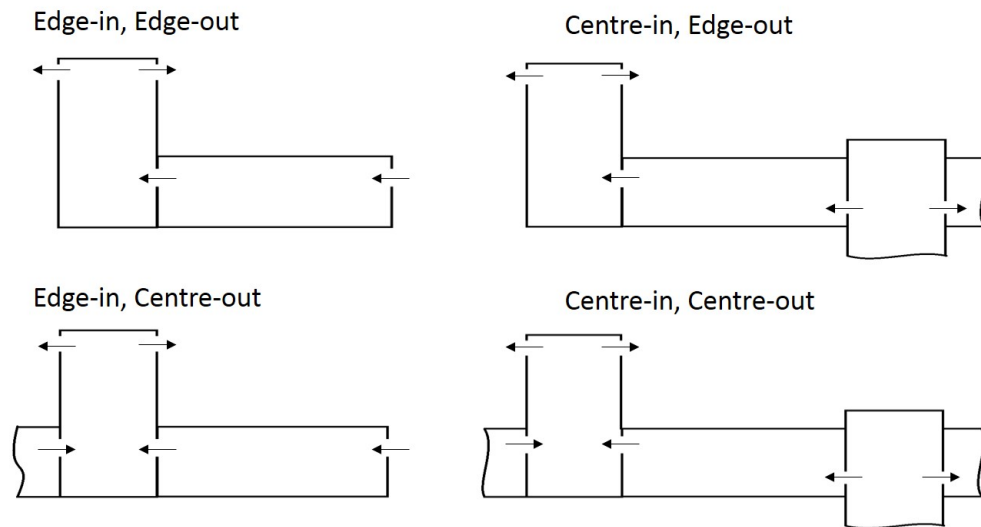


Figure 2.1: Taxonomy of advanced natural ventilated buildings proposed by Lomas (2007). Arrows are used to illustrate typical direction of bulk airflows.

suggest that natural ventilation can have health benefits for occupants (Muhić & Butala 2004, Vincent et al. 1997). This is discussed further in Section 2.2.1.

While there are advantages to natural ventilation, there are a number of potential shortcomings which can either make natural ventilation unsuitable or require design decisions to be taken to mitigate their impact. Such as, protection from the local environment, including noise attenuation, security and air quality due to pollution. ANV can mitigate these issues to a certain degree. For example, centre-in strategies have the potential to reduce urban noise attenuation and increase security (Lomas 2007).

Resilience to global warming is also a significant concern with regards to naturally ventilated buildings. Despite efforts to mitigate climate change, most sources suggest that some climate change up to 2040 and beyond is unavoidable (Luber & McGeehin 2008, Parry 2007, Ruosteenoja et al. 2003, Change 2007). Given a warmer climate, simple natural ventilation techniques may be unable to maintain acceptable indoor conditions in the majority of public buildings in the UK (CIBSE 2005*b*). One solution would be the wider use of mechanical ventilation or air-conditioning, however this could result in furthering the problem of climate change. Furthermore, disruptions to the electricity supply are potentially more likely in both the near and more distant future (Dorian et al. 2006, Ofgem 2013). Utilising a natural ventilation approach may help mitigate this, but also in a situation where supply dropouts occur more frequently, natural ventilation may be required to maintain airflow. A hybrid ventilation strategy, which makes use of a combination of natural and mechanical ventilation (discussed in Section 2.3.1), may also be a potential solution. Using a hybrid strategy would help to ensure occupant comfort during particularly hot conditions, while utilising the less energy intensive natural ventilation when possible. Additionally, in a scenario where disruption to energy supplies occurs more frequently, natural ventilation could ensure that some level of ventilation is possible at all times.

Rather than exacerbate the problem using energy intensive methods, ANV techniques may

prove more more resilient to climate change. Lomas & Ji (2009) demonstrated that an edge-in, edge-out ANV strategy could be capable of maintaining an acceptably low risk of overheating given predicted future weather conditions in hospital wards. While quite a specific scenario, the findings are likely to be applicable to a range of building types.

The unpredictability of natural ventilation can also cause difficulties both during the design and operation phases. According to Chenari et al. (2016), architects and engineers avoid the use of natural ventilation due to the uncertainties associated with its performance and the difficulties in implementing effective control. While this suggestion is arguably hyperbole, at least in the case of the UK, the issues raised are valid. The changeable nature of weather conditions make predictions of ventilation rates difficult, particularly for buildings which use wind as the predominate driver for airflow. This has implications both for the ventilation design and control (see Section 2.4).

2.3.1 Mixed-Mode or Hybrid Ventilation

Although this work is focussed on natural ventilation, the author acknowledges that there are situations where the use of mechanical systems is appropriate, while natural ventilation is not. This may be the case if the local environment has poor air quality or has high levels of noise pollution, making openable windows impractical. Rooms which have a deep plan or are fully enclosed may also require ventilation by mechanical means. In some cases close control of the conditions within the space or the necessity to ensure a clean environment may also make natural ventilation unsuitable. In some situations natural ventilation systems may not always be able to maintain an adequate thermal environment in the space being ventilated. This could be due to particularly hot summer conditions, high occupancy or large heat gains from equipment. To combat this a combination of natural and mechanical ventilation can be utilised. By utilising the natural ventilation for most of the cooling season and only switching to mechanical ventilation during peaks in temperature; summer overheating can be reduced while maintaining a lower energy cost than in a purely mechanically ventilated building.

Mixed-Mode or hybrid ventilation strategies combine natural ventilation and mechanical systems. Theoretically, this can reduce some of the disadvantages of each system, while retaining the advantages (Kleiven 2003).

Mixed-mode buildings are typically classified into one of three topologies: zoned, changeover and concurrent (Brager et al. 2007). In zoned control, the building is subdivided into zones based upon usage. Natural ventilation and mechanical ventilation can occur within the building at the same time, but only in different zones. This strategy is typically used when some spaces within the building have high thermal loads, such as server rooms, which require mechanical ventilation. In changeover control, both natural and mechanical ventilation are used within a zone but never at the same time. Finally, in concurrent operation, natural and mechanical ventilation can occur within the same same zone at the same time. It is not always possible to categorise a mixed-mode buildings, as a combination of control approaches may be used in different zones.

In this thesis natural ventilation has been chosen as the topic of study, in part due to its ability to maintain a suitable environment while using less energy than mechanical ventilation, at least in temperate climates such as the UK (Bordass et al. 2001). However, one of the most logical progressions is to investigate the control of mixed-mode ventilation.

2.4 Challenges of Natural Ventilation

In this section some of the key challenges associated with natural ventilation are discussed. A number of issues which are associated with the design of naturally ventilated buildings, such as predicting ventilation flow rate and occupancy patterns, can also impact upon the control.

2.4.1 Design

In Section 2.3 problems with predicting natural ventilation flow rates were mentioned. Natural ventilation is driven by pressure differences caused by temperature differences between the internal and external air and the wind. Most modern buildings are very airtight, having low rates of infiltration through cracks in the fabric. They also have high levels of insulation. Current building regulations for new buildings in the UK specify a maximum air permeability of $10 \text{ m}^3/(\text{h}\cdot\text{m}^2)$ at 50Pa and minimum U-values of $0.25 \text{ W/m}^2\cdot\text{K}$ for floors and roofs, and $0.35 \text{ W/m}^2\cdot\text{K}$ for walls (Regulations 2010). However, to achieve compliance with the Target Emissions Rate (TER) the required value will often be considerably lower. The combination of these factors is ideal for reducing heat loss during winter months. However, it also raises the danger of overheating during the summer months. Consequently one of the main concerns of building designers is ensuring that the air temperature does not increase above acceptable levels.

To ensure that adequate ventilation can be achieved, openings in the fabric (windows or vents) need to be sized sufficiently. However, this is not a simple task. As Linden et al. (1990) note:

“In practice, ventilation flows are turbulent, unsteady and three-dimensional, and it is not possible to make accurate theoretical calculations of these flows.”

To attempt to make the problem more manageable most ventilation design is carried out using the well-mixed assumption. Whereby, it is assumed that the conditions within a space are uniform. The well-mixed assumption makes calculation of bulk flows through openings in the external envelope and through any internal partitions easier. However, it does not address issues such as temperature stratification and containment distribution within spaces.

While wind is often important to building ventilation design it is hard to predict. Temperature differences between the internal and external air are easier to quantify and often used in design. However, care must still be taken to ensure that wind does not interfere with buoyancy driven flow. For example, ensuring openings are positioned taking into

account both dominant and prevailing wind conditions.

Problems within the design process are very similar to some which can be experienced when attempting to control a naturally ventilated building. For example, sensors which measure internal conditions such as temperature, humidity and CO₂ concentration may be limited to one sensor per zone. This is very similar to the problems encountered in designing a building using the well-mixed assumption. With only one sensor it can be hard to infer if conditions are suitable within the entire space. Furthermore, in spaces with significant stratification, such as atria, a single temperature reading may be meaningless.

2.4.2 Commissioning

Commissioning and handover of new buildings can often be the cause of a number of challenges. This is particularly the case with more innovative solutions such as the ANV techniques previously described.

Innovate UK carried out a study of 50 “*leading-edge*” non-domestic buildings, many of which were naturally ventilated (Palmer et al. 2016). In this study the buildings were monitored, an assessment of the building fabric and systems was carried out and the satisfaction of the occupants was investigated. One of the aims of this study was to attempt to determine if any overarching lessons could be learned about design practices. The commissioning of building systems was identified as a key area where shortcomings were evident across all of the projects. Some of the findings are summarised below:

- Innovative designs rarely function perfectly initially. Short commissioning periods are likely to result in poorly calibrated systems.
- Issues can occur if the systems control logic does not match what is happening in reality.
- Building users may not fully understand how the building works. Additionally, the staff who are ultimately responsible for operating the building may not be present during handover.
- Commissioning can often be rushed when clients are in a hurry to move in and occupy the building. This often results in the fine tuning of systems not being completed adequately.

The need for a long period of commissioning may be particularly true in naturally ventilated buildings, where a significant period may be required to calibrate the control for a variety of weather conditions.

Considering the points listed above, it is clear that there is a number of attributes which are desirable for a prospective control system to mitigate problems found during commissioning. An intuitive and easy to understand strategy is advantageous. Additionally, fine tuning of the control is likely to be essential. Methodologies which have the capability to be easily, or even automatically, updated would be beneficial.

The fact that issues were found where the control logic was adequately specified and did not match what was happening in the real building is interesting. All of the buildings studied were recently built and thus it is assumed that the engineers who designed the control strategy had access to detailed information regarding the building. Despite this, in some case it was found that what was expected to happen was not how the building functioned in reality. This point is critical to the justification of the modelling strategy used in this thesis. That even with detailed information related to a specific building, for any number of reasons, the building may not run as expected. Therefore, in order to gain a true model of what is happening an empirical approach is preferred to methods based upon our physics based knowledge of the processes occurring in the space.

2.4.3 Occupant Behaviour

Previously in this chapter, the impact of ventilation upon occupant health and productivity has been discussed. However, the behaviour of the buildings occupants can have a significant affect upon the internal environment (Iwashita & Akasaka 1997). Factors such as the number of occupants and their activity levels will have a direct impact upon the heat gains in the space. Furthermore, the way in which occupants interact with ventilation controls can have a significant impact upon the ventilation rate and subsequently the indoor environment conditions. In two separate studies, occupant behaviour was found to have a greater affect upon energy usage and the internal environment than changes to the building fabric (Ioannou & Itard 2015, Bek et al. 2011). As occupant behaviour can have such a large impact upon a number of areas, it has become a vast field of research. For this project an understanding of occupant behaviour is required as it is a significant factor which influenced the choice of the predictive model.

In its simplest form, a naturally ventilated building utilises occupant controlled manual windows. While the simplicity of this control action can make naturally ventilation appealing, the number of factors which influence occupant behaviour can make accurate prediction of when control actions will be taken very complex. A number of studies have found that window usage is strongly linked to the outdoor climate, in particular temperature (Roetzel et al. 2010, Zhang & Barrett 2012, Andersen et al. 2009) However, other factors such as IAQ and noise can play a role (Andersen et al. 2009). As the interaction between occupants and manual controls can have a significant impact upon the indoor environment, any strategy for controlling automated windows in a building which also contains manual windows, would have to take this into account.

Personal comfort sensation will impact upon an occupants decision to open or close windows. This can differ significantly between individuals. In addition, the ability to control their clothing and/or activity level may impact upon an occupants decision to open a window. In some circumstances, such as a home residence, occupants are free to adapt their clothing and activity at will. However, in some professional or educational settings occupants may not be able to moderate their clothing (Chenari et al. 2016). Similarly, occupants may have a different level of control upon their ventilation based upon the set-

ting. In a residential setting, or a single-occupant office, occupants are typically free to control their ventilation as they please. However, in multiple-occupant offices individuals may feel less able to adjust ventilation controls or windows (Haldi & Robinson 2008).

While the typical trend is that occupants will open windows if the internal environment becomes too hot or stuffy, studies have shown that some occupants simply do not interact with their ventilation. Leech et al. (2004) found that just under 10% of occupants did not use their ventilation at all.

The combination of the factors previously discussed make predictions of occupant behaviour and subsequently, building energy consumption and thermal conditions difficult. This has implications for developing a suitable control strategy. In the majority of naturally ventilated buildings which incorporate some form of automated window control, there are also manual windows controlled by building occupants. As such the control of the automated windows must be capable of dealing with the disturbance caused by the occupants' use of manual windows.

2.4.4 Changes to the Building Fabric or Occupancy

In the previous section the difficulties in predicting how occupants interact with buildings was discussed. Even if we assume that the building designers/operators had perfect knowledge of how the initial occupants will interact with the building and that commissioning had achieved close to optimal control, this is likely to change over time. Fluctuations in occupant densities and activity levels will have an impact upon the thermal conditions in a building and may require adaption of the control. Subtle changes in performance may occur due to building fabric and plant degradation (Rockett & Hathway 2016). While significant, almost instantaneous, changes can occur if the building fabric is modified, for example by changing the layout of internal partitions. Even changes to the surrounding buildings may impact upon the performance of a building. For example, if a building is erected or demolished nearby this could change the solar gains and/or wind pressures on the controlled building (Hathway et al. 2013).

Current practice for the control of building systems (described in Section 2.5.1) has little scope for automated tuning or adaption. Most systems are tuned heuristically by building managers based upon their own analysis of the buildings performance and feedback from occupants. Given that changes will happen throughout a buildings lifespan a control methodology which can update automatically is desirable. The model predictive control (Section 2.5.4) approach being investigated in this thesis, particularly the use of empirical models, has the potential to achieve this through re-identification of the plant model or re-estimation of the model parameters.

2.5 Ventilation Control Methods

In small commercial and residential buildings, HVAC control is most likely to be achieved through the use of manual opening windows with separate thermostatic control for heating and cooling (if available). As building size increases there is typically a higher level of automation. This may involve a range of sensors and actuators, controlled by either discrete controllers or more typical in larger buildings a central station. Building Management Systems (BMSs) have become the norm in modern buildings (Levermore 2013). In addition to HVAC control the BMS can control a number of building systems, such as the fire alarm, security, communications etc. In this section the current practise for HVAC control is discussed and the potential for more advanced methods highlighted.

2.5.1 Rule-Based Control

The current industry standard for controlling ventilation is Rule-Based Control (RBC). As the name suggests, RBC determines the control inputs based upon a number of rules. At a basic level the rules are of the form “IF condition, THEN action”. For example, the control of automated windows in a natural ventilation system could use a conditional statement of the following form:

$$IF \ t_{ai} < 22 \ THEN \ windows \ closed$$

Where t_{ai} is the zone temperature. This statement would ensure that the windows remain in the closed position. To open the windows a additional statement could be used, such as:

$$IF \ t_{ai} > 22 \ THEN \ windows \ closed$$

As ventilation is used to moderate the internal thermal environment and IAQ, indoor air temperatures and CO₂ are the most commonly used parameters. However, depending upon the number and type of sensors in the building there are a range of parameters which can be used as part of a RBC strategy. Such as: outdoor temperature, relative humidity, wind speed and direction. CO₂ set points are used not only because of the effects of CO₂ on occupant comfort and productivity, but also because CO₂ concentration is considered a good indicator for other occupant-related pollutants Awbi (2003).

The previous statements were very simple examples of control rules. In a real building there are a number of complexities which need to be managed. For example, to improve IAQ window opening control may be determined based upon multiple parameters, commonly CO₂ and temperature. The opening of the windows is also likely to be modulated, rather than a fully open/closed strategy. Further complications, such as integration with other

building systems, security concerns, avoiding rain ingress, night cooling etc. need to be considered. The number of factors which need to be considered and related systems which need to be managed can often result in a complex series of control rules. As such, the performance of RBC is critically dependent upon the choice of rules and parameters. Successful operation can rely upon the expertise of the designers and building operators.

In a paper investigating the application of MPC for the control of HVAC systems; Oldewurtel et al. (2012) compared RBC to a theoretical performance bound. The theoretical performance bound was defined as the optimal control, based upon perfect knowledge of the system dynamics as well as all future disturbances. In more than half of the cases simulated, the energy use of the HVAC system controlled using RBC was more than 40% higher than the theoretical performance bound. This demonstrated the potential scope for reducing energy consumption using more advanced control methods.

Achieving close to optimal performance with RBC is unlikely to be achieved in practice, due to the level of complexity required to express anything near optimal control using a rule set (Hathway et al. 2013). Clear inadequate control using RBC can often be found. For example, Levermore (2013) describes situations where heating and cooling have occurred simultaneously within the same building. This was also observed by Hathway et al. (2013) in a recently built, award-winning office building.

2.5.2 Demand-Controlled Ventilation

Demand-controlled ventilation (DCV) is a method whereby ventilation is provided based upon the occupancy level. While the control rules used in this method are typically rule-based, the underlying strategy merits independent classification and discussion. DCV has been shown to achieve energy savings in mechanically ventilated spaces which have variable occupancy patterns, such as restaurants, shopping facilities, offices etc. (Erickson et al. 2009, Diraco et al. 2015). Initial DCV strategies made use of occupancy schedules (Pavlovas 2004). However, the stochastic nature of how occupants interact with spaces as discussed in Section 2.4.3, can make generating meaningful schedules difficult. The modern approach to DCV is through the use of sensors (typically CO₂) however, the application of cameras (Erickson et al. 2009) and 3D depth sensors (Diraco et al. 2015) has also been demonstrated.

2.5.3 Proportional-Integral-Derivative Control

Proportional-Integral-Derivative (PID) control is used in a number of industrial control systems and is the most commonly used feedback controller (Åström & Hägglund 2006). By using a closed-loop feedback system, PID can be used to maintain a set point. When the process deviates from the set point corrective action is taken. The proportional control function determines the rate at which the system output reacts to a process variation. With proportional control there is typically a persistent error, or offset, with proportional control. Integral control determines the reaction based upon a sum of variations. In practice this

can correct offsets from the set point caused by the proportional control function. The derivative term determines the rate of change of the error.

PID control dates back to the 19th century and has been applied to a wide range of control problems such as: navigation systems, pneumatic PID control, power supply conditioning, industrial processes etc. (Bennett 1993).

PID control is used in a number of HVAC application to control air handling units (AHUs), water pumps and cooling-tower fans (Ahn & Mitchell 2001). The derivative term can be sensitive to measurement noise and potentially cause instability. Therefore, in a number of HVAC applications the derivative term is not used, resulting in Proportional-Integral (PI) control (Levermore 2013). PI or PID control often performs much better than ON/OFF plant control. By modulating plant output, for example a boiler within a building, problems such as overshoot can be reduced.

PID has been applied successfully to mechanical ventilation systems. However, some studies have shown that MPC has the potential to outperform it. For example, Vranken et al. (2005) compared PID with MPC for the control of the ventilation rate in a mechanical ventilation system using axial fans. They found that MPC gave better performance than PID over a wider range of ventilation rates.

In terms of natural ventilation, there are reasons to believe that PID control may be unsuitable. For example in the case of a mechanically ventilated space, if the set point temperature was overshoot this could be corrected by increasing the ventilation rate or comfort cooling. However, in a natural ventilated building it may not be possible to increase the ventilation rate due to the dependence upon weather conditions.

2.5.4 Model Predictive Control

Model Predictive Control (MPC) is an approach to control which originated in the late 1970s and is used extensively in oil and gas, chemical and refining industries (Camacho & Bordons 2013). MPC does not refer to a single control strategy, rather a family of strategies, for example: Dynamic Matrix Control (DMC), Generalised Predictive Control (GPC), Model Algorithmic Control (MAC), etc. The key components shared by the MPC strategies can be summarised as (Camacho & Bordons 2013):

1. Utilising a model to predict future plant outputs.
2. Minimising an objective function to calculate a control sequence.
3. Applying only the first control input at each time step, followed by displacing the horizon towards the future. Hence, MPC is considered to be a receding horizon strategy.

The general methodology utilised by MPC controllers is represented in Figures 2.2 and 2.3.

The first step is the calculation of future plant outputs, using a system model. Future outputs are predicted for a specified time, called the prediction horizon, N . The predicted outputs $\hat{y}(t+k|t)$ for $k = 1 \dots N$ ^[i] depend upon the past inputs and outputs up to the current time, t , and on the future control signals $u(t+k|t)$, for $k = 0 \dots N-1$.

To determine the optimal future control signals to maintain the process on a trajectory as close as possible to the desired reference trajectory, an objective function (often referred to as the cost function) is minimised. In Linear Model Predictive Control (LMPC), the objective function is often a quadratic function which evaluates the difference between the predicted output and the predicted reference trajectory (Camacho & Bordons 2013). The optimisation process can take into account any constraints placed upon the system and will often include a function to evaluate the control effort.

In the final step, the first control input, $u(t|t)$, is sent to the plant. The control signals calculated for future time instants are discarded, and the prior steps are then repeated for the next time instant. The new control input for the following timestep, $u(t+1|t+1)$, may well be different from that which was calculated at the previous instant, $u(t+1, t)$. This is because the actual plant output is now known. In this way feedback is introduced using the receding horizon method.

Camacho & Bordons (2013), give a number of advantages for MPC over other methods of control, for example:

- The concepts involved in MPC are intuitive, making it attractive for applications where staff may have only a basic knowledge of control.
- It can be applied to a range of control problems, including systems with simple or more complex dynamics.
- Multivariable cases present no problems.
- The feedforward nature of MPC control can compensate for disturbances.
- Constraints can be included.

For example, for application to a ventilation system, the system model may predict future internal thermal conditions. An optimum control sequence would be calculated to minimise a cost function, such as thermal comfort or energy, subject to any constraints (e.g. zone temperature limits, range of actuators etc.). The first control action is then taken, for example changing the position of a window actuator. Then the process is repeated. By using the receding horizon strategy, feedback is introduced into the system.

LMPC is considered to be a mature field, with a great deal of research and numerous industrial applications (Qin & Badgwell 1997). Where possible the use of linear models is desirable as the optimisation step can be carried out using direct methods, such as quadratic programming. In such an optimisation, the computational effort is typically

^[i]The notation is that used by Camacho & Bordons (2013), in this case it indicates the value of the predicted output at the instant $t+k$ calculated at instant t .

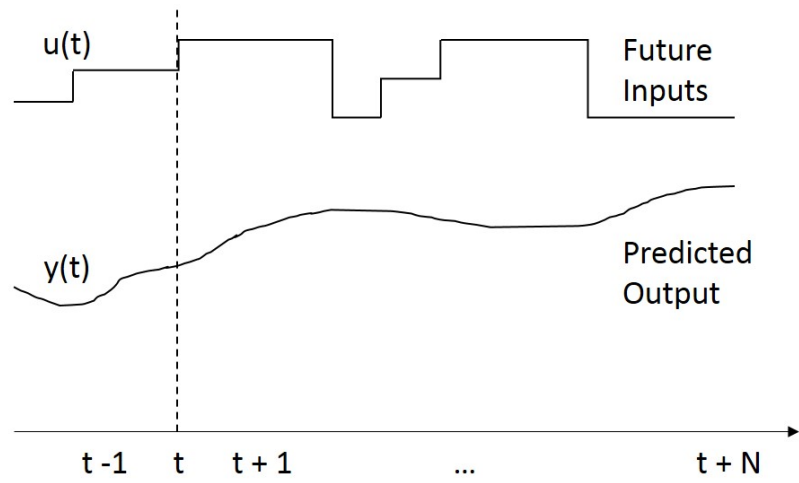


Figure 2.2: MPC strategy (adapted from Camacho & Bordons (2013)).

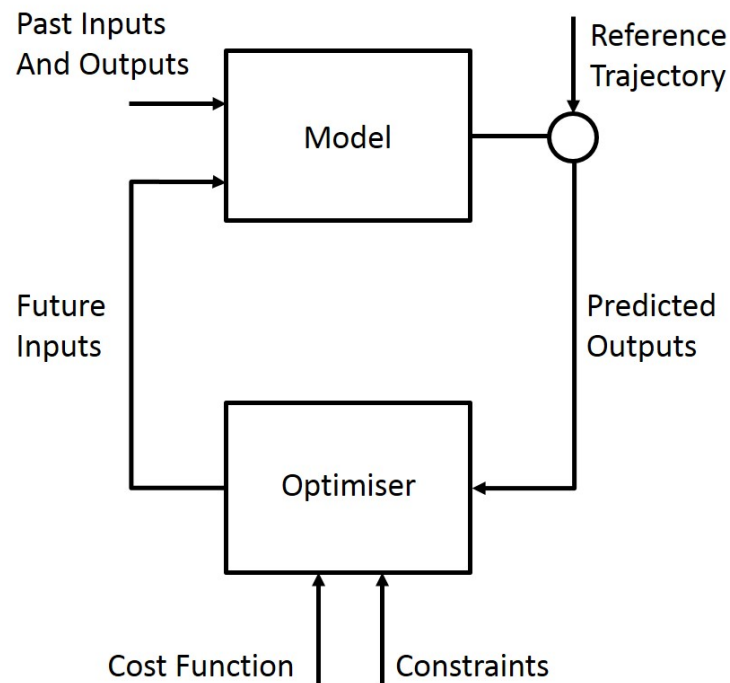


Figure 2.3: Basic MPC structure (adapted from Camacho & Bordons (2013)).

small (Allgöwer et al. 2004). However, in some applications linear models may be unsuitable to adequately describe non-linear processes (Allgöwer et al. 2004). To overcome this, a non-linear system model can be utilised, giving Non-linear Model Predictive Control (NMPC).

NMPC utilises the same steps as LMPC previously described. However, the use of a non-linear model introduces a number of challenges. Camacho & Bordons (2007), argue that NMPC has challenges in a number of aspects, such as: identification, stability and implementation. However, the key problem associated with NMPC is usually the optimisation. The use of a non-linear model complicates the optimisation process, increasing the computational effort and potentially obtaining a result which is not the global minimum. As buildings are recognised as displaying non-linear characteristics (Afram & Janabi-Sharifi 2014, Huang 2011), the issues associated with NMPC need to be considered. Issues relating to NMPC and potential solutions are discussed further in Chapter 7.

Compared with RBC and PID, MPC has seen little use in buildings. According to Oldewurtel et al. (2012), this is primarily due to the difficulties/costs in developing models of individual buildings to utilise in the MPC controller. In the past energy costs were also less significant. Hence, the need to develop improved control for building systems was less critical. Developments in building modelling and simulation techniques over recent decades have resulted in such tools becoming standard tools in both industry and academia. Similarly, an increasing use of sensing equipment and automation in buildings has also given rise to the potential to develop statistical models. In turn, this has potentially made developing models of the building systems dynamics more feasible than it was in the past.

Further discussion of MPC theory, on topics such as prediction and control horizon, cost function, optimisation techniques etc. is given in Chapter 7. Prior applications to buildings are summarised in the following section.

2.6 Prior Applications of Model Predictive Control to Buildings

Over the past decade, interest in MPC for the control of buildings systems has risen dramatically. Previous studies have involved a range of building systems, such as: chillers (Mendoza-Serrano & Chmielewski 2012), AHUs (West et al. 2014), oil filled head emitters (Rogers et al. 2013) etc. In this section prior applications of MPC to building systems is discussed in detail, with a focus upon system modelling. As of yet natural ventilation has received very little attention.

Typically, a good model for MPC needs to be descriptive enough to capture the important dynamics of the system. It also needs to be simple enough to enable the optimisation problem to be solved. In natural ventilation control, it is undesirable to carry out multiple control actions over a short period of time. This is because of the distraction caused by the window actuators and also the wear on the actuator itself. One of the implications of

this is that there is a significant amount of time in which the optimisation problem can be solved. However, it is still desirable to create a model which is as simple as possible.

In prior applications of MPC to building systems, there have been two main approaches taken to system modelling. The first approach is to use a physics based model to capture the thermal behaviour. Physics based models are based upon the fundamental knowledge of the dynamics of the system. Physics based models can range in complexity. Previous studies have used linear analytical equations Mendoza-Serrano & Chmielewski (2012), thermal Resistance-Capacitance (RC) networks (Oldewurtel et al. 2012) and multizone thermal simulation tools (May-Ostendorp et al. 2011). The second approach is to utilise data-driven, empirical models. This could be any of a range of statistical models, neural networks (Kusiak & Xu 2012, Chen et al. 2011, Tang 2010, Neto & Fiorelli 2008, Ferreira et al. 2012), support vector machines (SVMs) (Kusiak et al. 2011, Lixing et al. 2010), fuzzy logic (Homod et al. 2012, Soyguder & Alli 2009) first and second-order time delay models (Xu et al. 2010) etc.

In the following sections, prior applications of MPC to building systems are discussed. As the system model is such a critical component in MPC, the discussion of existing key studies is ordered based upon the modelling strategy. In addition to discussing studies which have investigated MPC, work which has looked at alternative control methodologies incorporating a model of the building system have also been included. While the particular control strategies being investigated differ from the approach taken in this thesis; the techniques used to develop the models could often be directly applicable.

2.6.1 Physics Based Models

White-box or physics based models are based upon the knowledge of the processes occurring in either a particular component, room, or building. Physics based models have been developed for fans (Wemhoff & Frank 2010), AHUs (Tashtoush et al. 2005), individual zones (Oldewurtel et al. 2012) and multizone buildings (May-Ostendorp et al. 2011, Mendoza-Serrano & Chmielewski 2012). Table 2.2 summarises some of the key studies which have utilised physics based models for control.

Dynamic first-order models have been used to represent thermal processes in buildings (Oldewurtel et al. 2012, Mendoza-Serrano & Chmielewski 2012, May-Ostendorp et al. 2013). These models are analogous to electrical RC network, using thermal capacitance and thermal resistance to calculate thermal conditions or energy usage.

More extensive dynamic thermal simulation tools such as EnergyPlus (May-Ostendorp et al. 2011) and TRNSYS (Henze et al. 2005) have also been used as predictive models for MPC of HVAC systems. These simulation tools are commonly used for forecasting building energy consumption and thermal conditions. However, they are not ideally suited to control. This is in part due to the amount of computation required and also the difficulties involving with integrating the software within a control scheme. The key difficulty is linking the control software with simulation tools. Tools such as MLE+ and BCVTB (Bernal et al. 2012, Wetter 2008) make communication between the two disparate systems

simpler, yet to the authors knowledge this has not been commercially implemented for the control of a real building. Some studies have utilised the more comprehensive simulation tools to facilitate the development of simplified models to use for control. For example, Candanedo & Athienitis (2011) used data obtained from an EnergyPlus simulation to develop a state-space model of both radiant floor heating and a solar heat pump. In previous studies researchers have used simpler models for the development of the controller; while utilising the more comprehensive models to evaluate the performance of the controller (Ma et al. 2012).

In one of the seminal papers on the application of MPC to building systems, Oldewurtel et al. (2012) made use of physics based models as part of a stochastic model predictive control strategy (SMPC), to control a range of HVAC systems. SMPC takes into account uncertainty in the model inputs, for example in this case weather predictions. It also allows constraints to be enforced based upon a predefined probability. This would allow constraints upon internal environmental conditions to be defined in a similar manner to that used by building standards (CIBSE 2013). In most commercial applications and in the previous studies discussed here deterministic model predictive control (DMPC) is used. Unlike SMPC, DMPC does not take into account the uncertainty in model inputs, it assumes that all inputs are correct.

Oldewurtel et al. (2012) made use of a thermal RC network to model the thermodynamics of the buildings. Five different variations of HVAC system were investigated, with varying building types and weather conditions.

One of the interesting elements of the paper by Oldewurtel et al. (2012) is the method used to evaluate the performance of the MPC control strategy. In the majority of papers, the performance of the proposed control strategy is compared with more commonly used techniques, such as RBC. However, Oldewurtel et al. (2012) make use of a theoretical benchmark which they term the performance bound. The authors define the performance bound as the optimal control which can be achieved with perfect knowledge of both the dynamics of the system and of all future disturbances which can act upon the system. To calculate the performance bound, Oldewurtel et al. (2012) used a DMPC algorithm with perfect weather (i.e. observed weather) predictions. In computing the performance bound a prediction horizon of seven days and a control horizon of three days was used. Hence, the performance bound can be thought of as the performance limit of DMPC.

Oldewurtel et al. (2012) found that both DMPC and SMPC outperformed RBC both in terms of Non-Renewable Primary Energy (NRPE) usage and thermal comfort statistics. SMPC was found to outperform DMPC, however the performance is dependent upon the quality of the weather forecast.

May-Ostendorp et al. (2011) utilised an EnergyPlus model as the predictive model in an MPC system to control windows in a mixed-mode building. While the building being investigated was mixed-mode, the MPC controller only controlled the automated windows. This makes the paper of particular relevance to this thesis. The goal of the MPC controller was to minimise the energy usage whilst preserving thermal comfort. In summer the re-

sulting control is essentially a night ventilation strategy. With the automated windows being opened during cooler nighttime periods. This passive technique, whereby the thermal mass of the building is cooled, reduced the daytime cooling loads. The optimiser used in the MPC controller reached this solution with no expert knowledge and with minimal constraints. The initial cost function was simply a minimisation of the cooling energy with a penalty for the number of transitions between window states to prevent excessive switching. Despite this the solution mimics a heuristic approach, which is used in many naturally ventilated and mixed-mode buildings.

The simple cost function used by May-Ostendorp et al. (2011) did result in a significant reduction in energy used for cooling against a reference control scheme, the details of which are unclear. However, the night cooling also resulted in overcooling the space, sometimes below the heating setpoint. To overcome this heating energy was included in the cost function. With the new cost function the savings in the cooling energy were decreased. However, overall energy usage and thermal comfort were improved.

A number of practitioners who make use of physics based models often justify dismissing the data driven alternatives due to problems with insufficient input excitation (Afram & Janabi-Sharifi 2014). This is certainly a valid concern. However, it must be stressed that by their nature the physics based models will always be a model of what is believed to be happening within a building or system. The performance gap between energy simulations and real building performance is a well documented problem (De Wilde 2014, Demanuele et al. 2010, Attia et al. 2013). Some of the uncertainties which contribute to this gap are present predominantly at the design stage. For example, changes in the building design and specifications or uncertainty regarding how the building will be used by the eventual occupants. However, even when building a model to describe a building which is already built and occupied, there is still a great deal of uncertainty. For example, without extensive testing it is difficult to know how airtight a building is or the level of insulation. While reasonably accurate information should be available for recently built or prospective buildings, this is unlikely to be the case for older buildings. To have a significant impact on UK Carbon Dioxide emissions, the ability to be applied in a retrofit scenario should be essential for a potential controller.

Beyond issues relating to the fabric, the stochastic nature in which occupants make use of a building can be hard to quantify, even in the case of a currently occupied building. Attempting to more accurately simulate occupancy patterns in buildings is a current active area of research (Gunay et al. 2013, Rijal et al. 2008, Page et al. 2008). However, this is the cutting edge of building simulation and the techniques used are not established within the building services community.

Studies which compare physics based models to empirical options are of particular interest. Neto & Fiorelli (2008) compared the ability of EnergyPlus and neural network models to forecast building energy consumption. Despite energy forecasting being the primary function of tools such as EnergyPlus, both types of models had a similar error range. The authors concluded that either method would be suitable for energy forecasting. Ruano et al. (2006) compared the performance of EnergyPlus and neural networks to predict

zone air temperature. Radial Basis Function (RBF) neural networks were trained using multi-objective genetic algorithms. The neural networks outperformed the EnergyPlus simulation. A sliding window adaptive methodology was also demonstrated. This adjusted the neural network model's parameters to allow adaption to recent conditions.

Study	Problem Description			Predictive Model	Main Aim	Findings and Comments
	Building	System	Element Controlled			
May-Ostendorp et al. (2011)	Simplified office building in Boulder, Colorado (simulated in EnergyPlus)	Mixed-mode building	Window position	Physics based model using EnergyPlus	Demonstrate an MPC approach to window control in a mixed-mode building. Additionally present a rule extraction method using generalised linear models (GLMs) for control.	Results for specific location showed a potential energy saving of above 40%. The GLM approach achieved between 70-90% of the optimiser energy savings, but at a fraction of the computational expense.
Mendoza-Serrano & Chmielewski (2012)	Theoretical building of 100 rooms, each subdivided into 4 zones	HVAC with thermal energy storage (TES) and chiller	Heat flow to the chiller and TES	White-box physics-based linear model	Apply economic model predictive control (EMPC) in conjunction with TES to time-shift power consumption away from periods of high demand to periods of low energy cost.	Energy costs were reduced through the use of EMPC. The use of short control horizons gave similar operational costs with large computational savings compared with the longer horizons.
Neto & Fiorelli (2008) *	Administration Building, University of São Paulo	HVAC with window-type and split air conditioners	N/A	EnergyPlus and neural network	Comparison between neural network model and physics based model (EnergyPlus) for forecasting building energy consumption.	Results showed that both methods are suitable for energy forecasting and had a similar error range.
Oldewurtel et al. (2012)	Four different European buildings	Five variants, primarily mechanically ventilated	Multiple possibilities depending on HVAC scenario	Thermal Resistance-Capacitance (RC) network	The development and analysis of a stochastic model predictive control (SMPC) strategy for building climate control that takes into account the uncertainty due to weather predictions	SMPC was shown to outperform RBC, in terms of Non-Renewable Primary Energy (NRPE) usage, thermal comfort statistics and in terms of advantageous room temperature dynamics.
Ruano et al. (2006) *	Secondary school building located in the south of Portugal	Air conditioned	Air conditioner ON/OFF state	EnergyPlus and RBF neural network	Design models for prediction of inside air temperature prediction.	The neural network models were shown to achieve better results than the EnergyPlus simulations. Simple control technique was demonstrated for the purpose of validating the models. Predictive control was stated as the preferred usage for the models developed.

Table 2.2: Summary of key studies on application of MPC to building control systems using physics based models. * Relevant studies which investigated different control methodologies or were limited to system identification.

2.6.2 Empirical Models

The key difference between the white-box, physics based models and the black-box, empirical models is that no physical understanding of the system dynamics is required. Hence, no heat transfer equations, no information on the building geometry, occupancy or thermal performance. Empirical models rely solely upon data gathered from the building. This is utilised as training data, upon which statistical models can be trained. There is a range of models which can be used to model plant in buildings. Some of the key methods, and examples of their application to building systems are described below. Additionally, Table 2.3 summarises some of the key studies which have utilised empirical models for control.

Autoregressive Models

There are a range of autoregressive models which could be applied to modelling the dynamics of a building system. For example: autoregressive models with exogenous inputs (ARX), non-linear autoregressive models with exogenous inputs (NARX), autoregressive moving average with exogenous inputs (ARMAX) etc.

Ferkl & Široký (2010) compared ARMAX models with subspace models for predicting ceiling temperature and zone temperature in a space heated by a radiant ceiling. Both methods were found to give good predictions, with the subspace models achieving a lower standard deviation on the verification data. However, the authors note that the ARMAX models require a priori information relating to model structure. While the subspace methods are a true black-box approach, where prior knowledge cannot be easily incorporated. The subspace methods also require a larger set of input/output data. This work was built upon in Cigler & Prvara (2010), when the subspace models were applied as part of an MPC strategy in a real building (discussed in the subsequent section on subspace methods).

Box-Jenkins Models

Box-Jenkins models are used in time-series modelling which utilise an autoregressive moving average (ARIMA) model (Box et al. 2015).

Mustafaraj et al. (2010) developed multiple time-series models including: ARX, ARMAX, and BJ. Models were trained to predict zone temperature and humidity in a mechanically ventilated space with prediction horizons of 30min and 2h. Overall they found that the BJ models gave better performance than the other alternatives, although this was marginal.

The authors concluded that the models developed could be utilised as part of a HVAC control strategy. While this may be the case, such short prediction horizons may not prove suitable for MPC. Particularly in the case of buildings with a high thermal mass. Likewise the ability of the linear time-series models to provide accurate predictions could simply be due to the short prediction horizon. Indoor air temperature typically changes slowly in buildings (Afram & Janabi-Sharifi 2014), thus over a short period a linear approximation may be suitable. The real test of linear models would be over a longer prediction horizon.

Subspace Methods

Subspace identification is used for the identification of linear dynamic time-invariant models. ‘Subspace’ refers to the fact that the models can be obtained from spaces within certain matrices, calculated from input-output data (Van Overschee & De Moor 2012).

Cigler & Prvara (2010) utilised subspace methods to model a ceiling radiant heating system in a university building in Prague; these models were then used as part of a MPC strategy in the building. Models were initially identified through normal operation and then re-identified after carrying out an identification experiment. The prediction performance of the models was improved through carrying out this experiment. The authors attribute this to the lack of input excitation during normal operation and stress the need for an identification experiment when utilising empirical models. The identification experiment was carried out during December 2009 and January 2010. Limited details are provided and it is unknown if the building was occupied at the time of carrying out the identification experiment.

What sets the work of Cigler & Prvara (2010) apart from the majority of other studies is that the MPC controller was tested in a real building block and that a “*nearly identical*” block was used to compare the performance. In one block the MPC controller was used and in the other a weather-compensated controller. Testing of the controllers was carried out over three months of real operation. The MPC controller outperformed the weather-compensated controller, with energy costs almost 30% lower. The authors attribute this to the ability of the MPC controller to account for the thermal capacitance of the building and determine an optimum input which is “*not so aggressive in comparison to conventional control strategy*”.

As the subspace models are linear this allows for a LMPC approach, hence the optimisation process is relatively simple. However, the linear nature of the models may prove unsuitable for processes which display greater levels of non-linearity.

Artificial Neural Networks

The artificial neural network is a statistical model capable of capturing non-linear relationships. Neural networks are inspired by the central nervous system. They consist of layers of nodes. The nodes are connected by weights and output signals which are a function of the sum of the inputs to the node modified by a transfer, or activation, function. It is the use of non-linear transfer functions which enable the network to approximate highly non-linear functions. During model training the individual weights are adjusted, such that the relationship between the input and output is accurately represented by the network.

Neural networks have a number of advantages which make them suitable for this application. They are capable of capturing non-linear relationships, can handle noisy or incomplete data and once trained have efficient simulation times (Priddy & Keller 2005). Feedforward neural networks are considered to be universal approximators Hornik et al. (1989) (this characteristic is discussed further in Chapter 4). They are also capable of

handling binary and continuous input and predicted variable forms, which are found in building systems. Neural networks have been shown to perform similar or better than EnergyPlus models for control (Neto & Fiorelli 2008, Ruano et al. 2006).

The primary disadvantage with neural network models is that they do not perform extrapolation tasks well. While they are good at approximation and interpolation; for regions outside of where the networks are trained, the prediction performance tends to be poor (Priddy & Keller 2005). Another disadvantage associated with neural networks is the number of parameters which can be varied and the lack of any proven methodology to determine them. Such as the number of hidden nodes and layers.

Ferreira et al. (2012) utilised radial basis function (RBF) neural networks as the predictive model in an MPC control scheme, for the control a HVAC system. Experiments were carried out in different rooms within the University of the Algarve, both in summer and in winter. The HVAC system used in this work comprised of three independent variable refrigerant flow (VRF) systems, each having an outdoor air cooled inverter compressor unit connected to indoor ducted units.

Ferreira et al. (2012) determined the structure of the RBF neural network models, i.e. the number of neurons, was identified using a Multi-Objective Genetic Algorithm (MOGA) (Ferreira & Ruano 2011, Ferreira et al. 2003). The use of the genetic algorithm eliminates the problem of determining the optimum number of neurons within the neural network. Individual autoregressive models were trained to predict outdoor conditions: temperature, humidity and global solar radiation. The model predictions for the outdoor weather conditions are then used as inputs for models which predict the internal temperature and humidity.

In order to train models to predict internal temperature and humidity identification experiments were carried out. The temperature setpoint for the HVAC system is controlled randomly using Pseudo Random Binary Signals (PRBS). The collected data is then used to train neural network models. This was carried out for both summer and winter conditions.

The MPC strategy used by Ferreira et al. (2012) aimed to maintain thermal comfort while minimising energy consumption. This was done by including the PMV index, in addition to the minimisation of energy within the cost function. They found that the MPC strategy was able to achieve energy savings of approximately 50% while maintaining thermal comfort.

Summary of Empirical Models

Model selection is one of the most important elements in MPC. There are wide range of techniques available for empirical modelling, which have been discussed above. It is hard to assess which method will perform the best, as most studies only present one technique. In a paper which used empirical models to optimise setpoints for a HVAC system, Kusiak et al. (2011) compared five different algorithms for training models: Exhaustive General Chi-square Automatic Interaction Detector (CHAID) (Biggs et al. 1991), Boosting

Tree (Friedman 2002), Random Forest (Breiman 2001), Support Vector Machines (SVM) (Friedman et al. 2001) and Multi-Layer Perceptron (MLP) Neural Networks (Bishop 1995). Models were trained to predict energy consumption, room temperature and humidity. Of the five different model types MLP neural networks showed the best performance across four evaluation criteria.

While the study by Kusiak et al. (2011) is very interesting, in that it develops and compares different model types, there is one serious flaw with the methodology. When dividing the training data random sampling was used with 85% used for model training and 15% used as a testing set. Withholding data in order to test the models on unseen data is common practice. However, with time-series problems random sampling is inappropriate.

One of the key advantages with empirical modelling is that models can be developed from collected data, without the need for a detailed understanding of the system dynamics. However, the total reliance upon data can also be considered a weakness. In some buildings collecting data may be difficult due to lack of appropriate sensing equipment or BMSs which are poorly suited to storing large quantities of data. There is also the question of how to implement a data-driven control approach during the initial occupancy period in a new building.

Prívará et al. (2011) propose an approach to deal with the lack of data in a newly built building. They utilised an implicit model of the building upon which identification experiments can be carried out to develop black-box models. EnergyPlus was used as the building model. Using the Building Controls Virtual Test Bed (BCVTB), Prívará et al. (2011) were able to link the EnergyPlus model to Matlab. This co-simulation setup was necessary to allow for flexible simulation input. Having initially trained black-box model using an excitation experiment carried out using EnergyPlus, the MPC controller could be deployed in the real building. The black-box models could then be refined as data is gathered during the operation of the real building.

The quality of data is also an important factor in black-box modelling. A number of modelling techniques do not extrapolate well. Therefore the training data need to cover a range of conditions under which the building is likely to operate.

Study	Problem Description			Predictive Model	Main Aim	Findings and Comments
	Building	System	Element Controlled			
Cigler & Prvara (2010)	Czech Technical University (occupied real building)	Ceiling radiant heating and cooling system	Water temperature	Subspace identification	Test a MPC controller which takes into account weather forecasts and thermal model of a building to control inside temperature.	The predictive controller was compared with a weather compensated controller in an almost identical building. Energy costs were approximately 30% lower for the MPC controller. Study is important due to use of real building for model identification and testing.
Ferreira et al. (2012)	Four rooms within the University of Algarve, Portugal	HVAC with three Variable Refrigerant Flow (VRF) systems, independent internal units in each room	AC set point temperature	Radial basis function (RBF) neural networks	To achieve thermal comfort and energy savings in both summer and winter seasons.	RBF neural network models were able to predict temperature and humidity to an acceptable level of accuracy. The MPC approach achieved energy savings greater than 50%.
Kusiak et al. (2011) *	Energy Resource Station, Iowa (controlled lab environment)	HVAC with two independent air handling units (AHUs)	Supply air temperature and static pressure set point	MLP, SVM, Exhaustive CHAID, Boosting tree and Random forest	Reduce energy consumption through setpoint optimisation while maintaining IAQ	Of the five algorithms, MLP neural networks performed best. Optimisation of set points resulted in energy saving of 21.4%. Method for dividing training data unsuitable due to random division of training and test data.
Neto & Fiorelli (2008) *	Administration Building, University of São Paulo	HVAC with window-type and split air conditioners individually controlled by the users	N/A	EnergyPlus and neural network	Comparison between neural network model and physics based model (EnergyPlus) for forecasting building energy consumption.	Results showed that both methods are suitable for energy forecasting and had a similar error range.
Ruano et al. (2006) *	Secondary school building located in the south of Portugal	Air conditioned	Air conditioner ON/OFF state	EnergyPlus and RBF neural network	Design models for prediction of inside air temperature prediction.	The neural network models were shown to achieve better results than the EnergyPlus simulations. Simple control technique was demonstrated for the purpose of validating the models. Predictive control was stated as the preferred usage for the models developed.

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Study	Problem Description				Predictive Model	Main Aim	Findings and Comments
	Building	System	Element	Con- trolled			
Prvara et al. (2011) *	20000m ² office building (modelled in EnergyPlus)	of- Two AHUs, each with independent temperature control	N/A		Subspace identification using N4SID function in Matlab and Combined deterministic-stochastic algorithm	Demonstrate a detailed modelling by a building design software with a black-box subspace identification suitable for MPC.	The model developed showed good prediction ability for internal temperature. Step responses from a subset of inputs demonstrate that the model is valid from a physical point of view.
Shen et al. (2013) *	Dairy building at the Danish Cattle Research Centre	Naturally ventilated	Window opening size		CFD simulations used to develop response surface model (RSM)	Develop control method to ensure desirable opening sizes for the control of the ventilation air exchange rate in dairy buildings.	Over ventilation was identified as a problem. A model based control could be used to regulate window opening sizes.

Table 2.3: Summary of key studies on application of MPC to building control systems using empirical models. * Relevant studies which investigated different control methodologies or were limited to system identification.

2.6.3 Grey-Box Models

There is a middle ground between the two approaches discussed previously. Namely, the use of grey-box models. With this approach an initial model structure is formulated based upon the physical behaviour of the system being studied. Statistical methods are then used to determine model parameters. Table 2.4 summarises some of the key studies which have utilised grey-box models for control.

In one of the few papers on the control of natural ventilation using MPC, Mahdavi & Proglhof (2008) used grey-box models to model air change rate and indoor air speed. They then demonstrated a simplistic model based control strategy. To create a simple predictive model, they hypothesized that the air change rate (ACH) was affected by the window opening position (this was expressed in terms of geometric leakage area (A_{GL}), outdoor air speed (v_e) and the temperature difference between indoor and outdoor air temperature (Δt). This gave the following function:

$$ACH = f_1(A_{GL}v_e\sqrt{|\Delta T|}) \quad (2.1)$$

where f_1 is a parameter which can be adapted based upon experimental data. Mahdavi & Proglhof (2008) found that this simple model was able to effectively reproduce measured results for air exchange rate. Similar results were found for a grey-box model of the indoor air speed. However, the prediction performance was only assessed over a short period, and would unlikely perform poorer over the longer term due to seasonal variations.

Using the grey-box models of air change rate and indoor air speed, Mahdavi & Proglhof (2008) demonstrated some form of model based control strategy. The details of the controller are not clear as the focus seems to have been upon developing the models. However, the choice of parameters to model and subsequently employ as part of a control scheme are interesting. Air exchange rate and indoor air speed are not parameters which are typically measured by a BMS. Hence, in this study a series of in situ measurements were taken. Application of this methodology in a number of large buildings is likely to be hugely time consuming and uneconomical.

Aswani et al. (2012) utilised a grey-box model to model the temperature dynamics of a single mechanically ventilated space. In this study the room being modelled was a computer laboratory on the Berkeley campus, ventilated by a single-stage heat pump air conditioner. The authors built a mathematical model, which was then refined using statistical methods to determine the heating load due to occupants and equipment. This model was then used as part of a MPC strategy, which demonstrated potential to achieve a reduction in energy consumption compared to two-position control.

The model used in this study was a discrete time model with a time step of 15 minutes. The room temperature was given by:

$$T[n+1] = k_r T[n] - k_c T[n] + k_w w[n] + q[n] \quad (2.2)$$

where $T[n]$ is the temperature of the room in degrees Celsius, $k_r > 0$ is the time constant of the room, $k_c > 0$ is the change in temperature over 15 minutes in degrees Celsius caused by cooling, $k_w > 0$ is the time constant for heat transfer from the room to the outside, $w[n]$ is the outside temperature in degrees Celsius, and $q[n]$ is the change in temperature due to the occupants and any equipment.

The model structure was proposed based upon basic knowledge of the physical processes occurring within the space. The model parameters were then identified using root-n-consistent semiparametric regression (Robinson 1988).

Aswani et al. (2012) describe the effect of occupancy as “*highly non-linear*”, yet this is being captured by a linear model. The desire to utilise a linear model is understandable, as this allows for a linear solver in the MPC optimiser. However, it is hard to envision how such a model could be capable of capturing complex occupancy patterns or in the case of a naturally ventilated building, the impact of changing weather upon the thermal conditions in the room. In this study the space being studied was cooled using a single-stage heat pump air conditioner. Single-stage heat pumps use motors which operate at one fixed speed. This is likely one of the reasons that such a simple model structure is capable of capturing the effect of the AC to cool the space. Given a more complex mechanical system such a simple linear model may prove ineffective. Similarly in a natural ventilation scenario, the impact of a control action such as opening a window is much more changeable and potentially harder to capture using a simple model. As it will vary depending upon a number of different factors (zone temperature, outdoor temperature, wind speed and direction etc.).

Postulating an initial model structure may be a relatively simple task when modelling a single zone or component of a HVAC system. However, the task will become more complex in a multizone building; particularly if different ventilation strategies are utilised in individual zones. Furthermore, whilst the approach of refining a physics based model using statistical means seems promising, as yet it has only been demonstrated using relatively simple initial models.

Study	Problem Description			Predictive Model	Main Aim	Findings and Comments
	Building	System	Element Controlled			
Mahdavi & Proglhof (2008)	Typical office in the University of Technology, Vienna (occupied real building)	Natural ventilation, single-sided with casement windows	Window position	Empirical and numerical multi-zone air flow model	Demonstrating the potential of empirically based and numeric air flow models as part of a hybrid natural ventilation control scheme.	The paper illustrated the principle of empirically derived equations as well as in situ calibrated numerical simulation as the predictive engines in an MPC approach to natural ventilation. Prediction performance of the models was modest. Air change rate was measured, this information is not typically gathered by BMSs.
Rogers et al. (2013)	Controlled zone using a dedicated test cell	Oil filled heat emitter	Heat emitter input power	State space model with parameters determined using branching algorithm	Test MPC approach to control of fluid filled heat emitters.	Demonstrated that MPC can be implemented in a dwelling with minimal prior modelling and still achieve set point tracking compared to conventional methods resulting in energy savings of up to 22%.
West et al. (2014)	Two office buildings on the east coast of Australia	Building 1 had an under-floor air distribution system driven by 15 AHUs. Building 2, 17 AHUs.	Zone temperature set points where available, or supply air temperature if not	Grey box, mathematical model of the temperature dynamics refined using statistical methods	Present a supervisory control and optimisation system for commercial HVAC, aimed at minimising energy consumption and occupant thermal discomfort.	Significant energy reductions were observed in both real world trials (19% and 32%). PPD calculations showed a slight increase in occupant comfort. Suggest that optimisation may have been balanced towards energy savings.

Table 2.4: Summary of key studies on application of MPC to building control systems using grey-box models.

2.6.4 Summary of Previous Modelling Studies and Focus of this Thesis

The review of existing studies carried out in this chapter was used to evaluate the state of research in this area and to identify potential gaps/opportunities. Despite significant levels of research into the application of MPC to mechanically ventilated systems, natural ventilation has thus far received little attention.

A number of studies suggest that MPC can have significant benefits over the existing control methods used in buildings (primarily RBC). For example, the findings of Cigler & Prvara (2010), who found that energy costs were approximately 30% lower for the MPC controller. Ferreira et al. (2012), found that a MPC approach achieved energy savings greater than 50%. Rockett & Hathway (2016), highlight the need to view such predictions critically. Comparisons based upon real buildings may be questionable, due to different weather conditions and potential changes in occupancy patterns. Rockett & Hathway (2016), suggest that *“the ideal testbed should comprise two identical, adjacent buildings with identically-behaving occupants and subject to the same weather and solar gains”*. The authors do concede that the opportunity to conduct such an experiment is rare. Additionally, they suggest that some of the projections for energy savings may be due to the comparison between a finely tuned MPC controller and baseline systems which have not received the same level of attention.

It is clear that the different modelling techniques each have potential advantages and drawbacks. In this thesis, black-box modelling using neural networks will be utilised to investigate the control of natural ventilation systems. One of the primary justifications for this is that physics based models are typically time consuming to develop, as they must take into account the specifics of each individual building. Black-box techniques have the potential to be much easier to apply to different buildings. Once a suitable model training process has been developed; it should be possible to apply this to data from different buildings. It is also likely that increasing amounts of sensor data will become available in modern buildings. This should only further increase the applicability of black-box modelling techniques. Neural networks in particular, have been shown to be suitable in a number of studies (Ferreira et al. 2012, Kusiak et al. 2011, Neto & Fiorelli 2008, Ruano et al. 2006), and often outperformed alternative methods (Kusiak et al. 2011, Ruano et al. 2006).

Lack of input excitation is often cited as one of the main shortcomings associated with black-box models. In this thesis data from real buildings during normal operation will be first used to train models to investigate if this is indeed the case.

Chapter 3

Data Collection and Pre-Processing

This chapter describes the training data collected during this project. When using an empirical modelling approach the quality of data are critical. In order to assess the data available four studies were carried out in different buildings. The predominant focus of this chapter is a description of the data collected and the pre-processing required to enable network training to be carried out. This chapter also highlights some of the difficulties which can be encountered when collecting data from buildings which are in use and the implications which this could have upon utilising data-driven models.

3.1 Data Collection and Potential Difficulties

The essential component in the empirical approach being attempted in this project is sufficient good quality building data from which identification procedures can be investigated. Obtaining data from real buildings has been difficult. Before describing the four studies used in this thesis, it is worthwhile to discuss the difficulties which were encountered when trying to gather input data.

One of the main challenges encountered while trying to obtain building data was convincing building managers, designers and other stakeholders to hand over information which could be considered sensitive as it highlights how well or not their buildings are functioning. This was a hindrance to this research, however it is unlikely to be an issue if the buildings stakeholders were actively seeking to deploy a new control system within their building.

The second major obstacle encountered was the functionality of most building management systems. While most BMSs have the built in capability to record data such as internal and external conditions, actuator positions etc. they are rarely designed to store large amounts of data over long periods. By default a BMS will typically store fine resolution data for a short period. This data may be overwritten on a weekly basis. Some systems do have the capacity to record variables over a long period but this not the case in all

systems (Palmer et al. 2016). However even if the system has the capacity to store data, in practise it was found that recorded data are vulnerable to the system being reset or altered.

3.2 Dataset A: School

It has been previously noted that building managers and designers are often not comfortable sharing information about their buildings which could highlight poor design or operation. The first dataset used in this project is from a school in the North of England. The data were collected by the company responsible for managing and fine-tuning the BMS. Unfortunately, in this case some of the stakeholders were uncomfortable with building data being used. While permission was given for the building data to be used, there were certain conditions attached. The primary stipulation was a degree of anonymity. Therefore the building is described but the author is precluded from naming it specifically. It was also not possible to arrange a visit to the building and make any first hand observations. While these constraints were unfortunate, the volume and quality of data available made its study worthwhile.

The inclusion of data from a school within this project was also seen as beneficial. The quality of the internal environment and its effect upon the occupants ability to learn is a active area at the moment, both within the research community and legislation. There are a number of studies which find a relationship between the ventilation rate and pupils performance (Bakó-Biró et al. 2012, Daisey et al. 2003, Shaughnessy et al. 2006). Also natural ventilation has been used a lot in schools built as part of the *'Building Schools for the Future'* programme (Santamouris et al. 2007). Schools are likely to be an ideal target for the application of the control methodology proposed in this project.

3.2.1 Description of Spaces

The school was built within the past five years as part of the Building Schools for the Future programme. It is an all-through school, i.e. provides teaching for students aged 3-16. The building is of lightweight construction, with a layout based around a central atrium with four wings radiating outwards.

The school is predominately naturally ventilated, with manual occupant controlled windows at low level and automated windows linked to the BMS at high level. For this study, eight classroom spaces were selected. They were chosen in an effort to select a range of spaces with different orientations and ventilation scenarios (summarised in Table 3.1).

Nothing is known about how the occupants use the space beyond the room description provided on the building plans. In this case obtaining detailed information about the occupancy patterns was not possible due to constraints regarding access to the building. Even without these constraints, compiling detailed information related to occupancy patterns for a building of this size would be very time consuming, as such it is not likely to

Zone	Floor	Usage	Orientation	Ventilation Scenario
1	Ground	Humanities classroom	North	Windows on three sides
2	Ground	Humanities classroom	North-west	Single-sided
3	Ground	Humanities classroom	East	Single-sided
4	Ground	Humanities classroom	East	Single-sided
5	First	Junior classroom	South	Single-sided
6	First	Junior classroom	North-west	Windows on north and west
7	First	English classroom	South-west	Windows on north and west
8	First	English classroom	North-west	Windows on south and west

Table 3.1: Description of spaces in dataset A.

be a method used in a commercial application of MPC. Information of this kind would be necessary to develop accurate physics based models of the space using dynamic thermal simulation. The lack of available occupancy information when applying MPC to buildings is a key justification to utilise a black-box modelling approach.

3.2.2 Recorded Variables

Environmental conditions and window state data were collected over a period of eighteen months using sensors linked to the BMS. The frequency of recorded observations varied over the period. The frequency varied as some observations are stored based upon a control action being taken, in addition to the regular recording of one observation every five minutes. The environmental variables recorded were temperature, carbon dioxide concentration and relative humidity. In each zone there is only one value for each variable, i.e. classrooms have not been subdivided into smaller zones. As mentioned in the preceding section, windows were a mixture of occupant controlled manual windows and automated windows. The opening state of the automated windows was recorded by the BMS based upon the window actuator position, given as an opening percentage between 0 and 100% at intervals every 10%. The condition of the space heating was also recorded, this was stored as a boolean (on/off) value.

No information was available for the manual windows. This was because the manual windows are not equipped with sensors. If access to the building had been possible, data for the window opening state of the manual windows could have been gathered using data loggers. This would have given a boolean (open/closed) variable for the manual windows. However, one of the main motivations of this project is to develop a control strategy which can easily be applied to a range of buildings. As of yet the author has not encountered a building where the opening position of manual windows are logged by the BMS. Ideally, models should be capable of capturing the effect of the automated windows, while treating manual windows as an unmeasured disturbance. If this is possible it would allow for models to be developed for existing building stock without having to install further monitoring equipment or additional sensors.



Figure 3.1: Above: Google earth image showing location of the SE Controls building. Below: Google streetview showing the building.

3.2.3 Weather Data

The school had an on-site weather station linked to the BMS. This recorded the outdoor temperature, wind speed and wind direction. There was also a sensor which gave a boolean value if it was raining (this is linked to the BMS and is used to close some of the automated windows in the case of rain).

3.3 Dataset B: Office Building

The second dataset was collected in the SE Controls office building in Lichfield, in the West Midlands, UK. As can be seen in Figure 3.1, the office building is in an industrial estate in a rural setting. Some shelter is provided by surrounding buildings and planting but the building remains quite exposed to the wind.

3.3.1 Description of Spaces

The building is mixed use, with naturally ventilated office space and an unconditioned warehouse area. It is of lightweight brick and block construction combined with a cor-

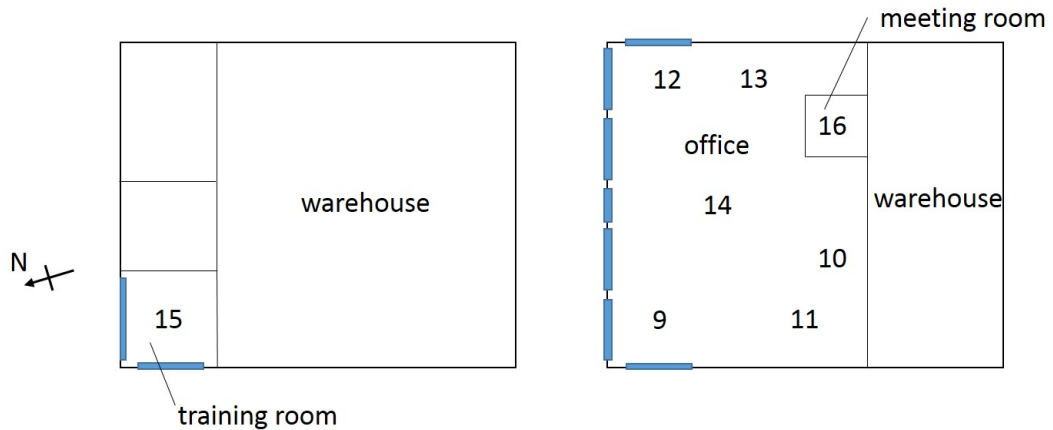


Figure 3.2: Sketch layout of SE Controls building. Ground floor on the left and first floor on the right. The numbers correspond with the space descriptions given in table 3.2.

Zone	Usage	Orientation	Ventilation Scenario
9	Multiple occupant office	North-west	Windows on three sides & ceiling vents
10	Multiple occupant office	South	Windows on three sides & ceiling vents
11	Multiple occupant office	West	Windows on three sides & ceiling vents
12	Multiple occupant office	North-east	Windows on three sides & ceiling vents
13	Multiple occupant office	North-east	Windows on three sides & ceiling vents
14	Multiple occupant office	North	Windows on three sides & ceiling vents
15	Training room	North-east	Single-sided
16	Meeting room	South	Ceiling vents

Table 3.2: Description of spaces in dataset B.

rugated metal façade. The divide between the offices at the front of the building and warehouse space to the rear can be seen in Figure 3.2. The warehouse space is identifiable by the lack of windows and increased use of metal cladding. Three rooms within the building are studied: a meeting room, a large multiple occupant office and a room used for meetings/training (detailed in Table 3.2).

Natural ventilation is provided through manual occupant controlled windows, automated windows and automated ceiling vents. The ceiling vents were installed to reduce overheating in the offices spaces and vent air into the unconditioned warehouse space. The offices have heat gains from ICT and lighting associated with a typical modern office. The large multiple occupant office is subdivided into zones each with its own sensing equipment. This differs from the school data previously discussed, where similarly sized rooms had only one sensor.

3.3.2 Recorded Variables

As with the previous school dataset, environmental and window state variables were recorded using the BMS over a period of eighteen months. The same variables were

recorded i.e.: temperature, carbon dioxide concentration, relative humidity, automated window position and heating state. Again, no information was available for the position of the manual occupant operated windows.

3.3.3 Weather Data

The office building also had a roof mounted weather station linked to the BMS. This recorded outdoor temperature, wind speed, wind direction and if it was raining.

3.4 Dataset C: University Single Occupant Offices

The final dataset utilised in this project was collected as part of an investigation into occupant window use behaviour by Bruce-Konuah (2015). As part of this work, a study was carried out in which a number of single occupancy offices were monitored for one month during the summer and one month during the winter. In this study, indoor environmental conditions and window and door opening states were recorded using data logging equipment. In this study all of the windows were manually controlled by the occupants.

Model fitting was carried out using this dataset in addition to the data collected specifically for this project for one key reason. In the data collected in both the school and offices described in the preceding sections, there was a mix of occupant controlled and automated windows. However, information was only available for the automated windows. This necessitated treating the occupant controlled windows as an unmeasured disturbance, which is likely to be the way in which an MPC approach would use the building data. The data provided by Bruce-Konuah (2015) only considers spaces with occupant controlled windows, but the opening state was recorded. This will allow for a comparison between models developed using data where all openings are captured and the models developed where any manual occupant controlled windows are treated as an unmeasured disturbance.

Five offices were monitored in both summer and winter by Bruce-Konuah (2015). The data from these five spaces were utilised in this study.

3.4.1 Description of Spaces

The offices were located in two of the University of Sheffield's buildings, The Arts Tower and Jessop West (see Figure 3.3). Both of the buildings are large, predominantly naturally ventilated buildings with a mix of office and teaching spaces. The offices monitored were single occupant rooms used by academic staff. The office spaces in both of the buildings feature single-sided natural ventilation controlled by the occupants using manual windows. In this study, three of the offices monitored within the Jessop West building and two within The Arts Tower are considered. Orientation and window types for the offices are given in Table 3.3.

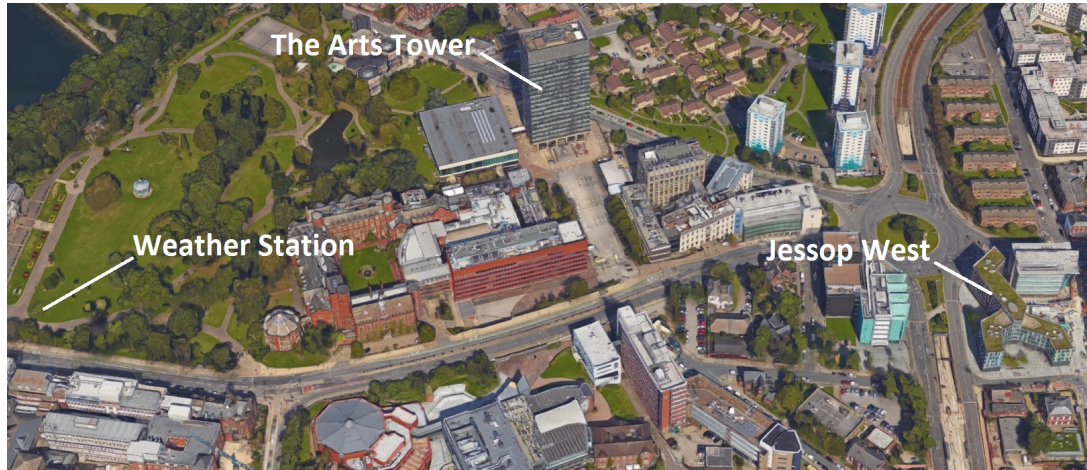


Figure 3.3: Google earth image showing location of the two buildings and the weather station.

The Arts Tower

The Arts Tower is a high-rise building that, at a height of 78m, is significantly taller than the surrounding buildings. Built in 1965, the building is of medium weight construction, utilising concrete cores and columns to support the concrete floor slabs. The facade of the building has been recently refurbished and is now double glazed. Occupants can control the ventilation through opening manual sash windows, with the opening being at a high level.

Jessop West

The Jessop West building is one of the more recent additions to The University of Sheffield's building stock, being completed in 2008. It is of a more heavyweight construction compared to The Arts Tower. The majority of the concrete columns, soffits and other structural elements have been left exposed to assist with regulating the internal temperature. Occupants are encouraged to make use of night cooling to make best use of the thermal mass.

The building is in close proximity to a busy road on both the west and north sides. This necessitated specific façade treatments to prevent noise and pollution ingress into the building. To achieve this a double skin facade was installed along the north-west and west façades, while a single skin was deemed suitable for the east and south elevations. The double skin façade is a shaft box design (Poirazis 2004), with air inlets at each floor level and exhaust ducts adjacent to each window. In the façade, the exhaust ducts extend over several floors. This maximises the stack pressure and improves the ventilation rate compared to wind pressure alone.

All of the offices monitored by Bruce-Konuah (2015) featured single-sided natural ventilation, using manual occupant controlled windows. The window types for each space are shown in Table 3.3.

Office	Building	Orientation	Facade	Window Type
1	Jessop West	North-west	Double skin	Side hung
2	Jessop West	North-west	Double skin	Side hung
3	Jessop West	North-east	Single skin	Tilt and turn
4	Arts Tower	South	Single skin	Vertical slider
5	Arts Tower	South	Single skin	Vertical slider

Table 3.3: Description of spaces in dataset C.

3.4.2 Recorded Variables

The data gathered by Bruce-Konuah (2015) was collected using data loggers to continuously record indoor environmental variables and the opening state of both windows and doors. The environmental variables recorded were temperature, carbon dioxide concentration and relative humidity. Two different brands of instruments were used to measure and record the indoor air temperature and CO₂ concentration. One was the HOBO U-12-012 combined with the Telaire 7001 CO₂ sensor (Tempcon, UK) and the other was the Wöhler CDL 210 meter (PCE Instruments, UK). The opening of windows and doors was monitored using magnetic reed switches and HOBO U9-001 state loggers (Tempcon, UK). This gives a binary state (open/closed) condition for both the windows and doors. This differs from the previous two datasets where the opening position of the automated windows was given as a percentage opening, based upon the window actuator position. The binary nature of the window position data may prove more difficult for the neural network model to capture the effect of window opening. However, neural networks have previously been shown to be capable of dealing with continuous systems with boolean inputs (Holderbaum 2007).

3.4.3 Weather Data

With the previous two datasets weather data was available from a weather station situated on the roof of the buildings. In this case weather data was obtained from a local weather station located in a park close to the buildings. The relative position of the two buildings and the weather station can be seen in Figure 3.3. The weather station is approximately 280m from The Arts Tower and 500m from Jessop West.

The weather station is under the jurisdiction of Sheffield Museum’s Natural Science department and archived data are made publicly available upon request. The data gives average hourly values for outdoor temperature, humidity, rainfall, wind speed, wind direction and daily solar hours.

3.5 Dataset D: University of York Spaces

As part of this project a twelve month data collection study was carried out at The University of York's recently built Heslington East Campus. This comprised of monitoring three naturally ventilated spaces using a combination of data loggers and the BMS.

3.5.1 Description of Spaces

For this study a single-sided, a cross ventilated and a stack ventilated space were monitored in separate buildings. All three of the buildings are part of the recently built Heslington East Campus, which is outside of the city centre in an exposed semi-rural location.

The Ron Cooke Hub

The Ron Cooke Hub is a 7000sq ft building which includes a range of socialising spaces, an exhibition space, cafe and office spaces over three floors. There is a large full height naturally ventilated atrium space, which was monitored as part of this study. The atrium is stack ventilated using automated windows which open in banks depending upon the required ventilation rate determined by the BMS.

Law and Management Building

The Law and Management Building is primarily departmental and research office space but also includes lecture and seminar spaces. In this study a single occupant office was monitored. The office was ventilated on one side using automated windows at high level and manual windows at low level.

Department of Theatre, Film and Television

This building incorporates a range of teaching spaces, including two television studios and a range of office spaces. The space monitored was a cross ventilated multiple-occupant office (approx 10 occupants). Ventilation was provided by automated vents on one side of the space with automated and manual windows on the opposite façade. The space had a significant amount of ICT equipment, including servers and personal computers with most occupants using multiple monitors.

3.5.2 Recorded Variables

The BMS was used to monitor the positions of automated windows. In the case of the two offices this was an opening percentage between 0 and 100% with increments of 10%. In the atrium the windows were grouped into banks which could be either opened or closed, with the BMS recording a boolean value for opening condition. The temperature was

also recorded by the BMS. In addition, data loggers (HOBO U-12-012) were used to log temperatures. The use of additional data loggers were used in the large atrium space to capture the stratification of temperatures over different heights. In the offices data loggers were used to record CO₂ concentration using the HOBO U-12-012 combined with the Telaire 7001 CO₂ sensor. The opening of windows and doors was monitored using magnetic reed switches and HOBO U9-001 state loggers (Tempcon, UK).

3.5.3 Weather Data

A BMS linked weather station on the roof of the Law and Management Building recorded wind speed, wind direction and temperature. A further weather station was placed on the same roof which had the capability to measure solar radiation and humidity.

3.5.4 Problems Encountered

Unfortunately whenever data was downloaded it was found that the data from the BMS was incomplete. This was caused by the system being reset or changed. It was hard to prevent any of the several users of the BMS from making changes which interrupted the study. This may have been due to the buildings being recently built and a large number of changes being made to update both the BMS software and fine tune the control settings. Problems were also encountered when using data loggers to record internal environment conditions and window positions. When returning to download data from the loggers it was often found that loggers had been moved or had become detached. The loggers used to record window state were particularly prone to becoming dislodged. The action of repeatedly opening and closing the window would lead to the state sensor detaching from the window. As permanent fixings could not be used, due to the damage they would cause to the window frames, this was a hard problem to overcome.

While not yielding much in the way of useful training data to work with, the study at Heslington East did highlight the difficulty which can be faced collecting data in buildings during operation. Extracting data from a BMS, particularly during the initial occupation phase where the system is still being altered frequently, requires significant monitoring to ensure no data are lost. Were this data collection activity to be repeated, further use would be made of data-loggers which are independent of the BMS. These are not without their drawbacks, particularly the window state sensors. However, regular downloading of data and checks to ensure that loggers are still correctly installed should prevent any major losses of data.

3.6 Input Data Pre-Processing

This section describes the pre-processing steps required before model training can be undertaken. Pre-processing was carried out to remove any clearly erroneous data, for

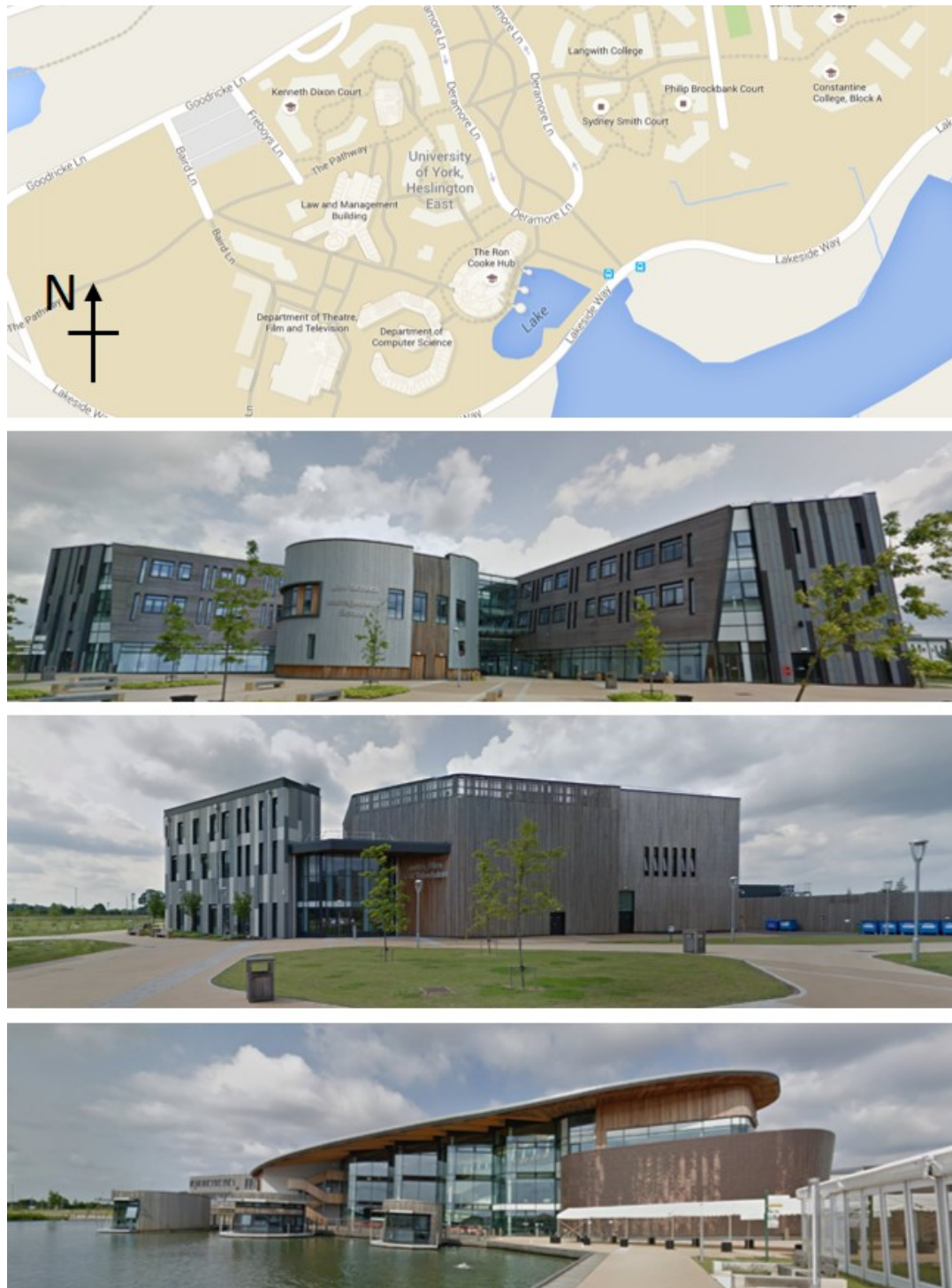


Figure 3.4: Buildings studied at Heslington East. From top to bottom: Google map showing layout of campus, Law and Management Building, Department of Theatre, Film and Television and The Ron Cooke Hub.

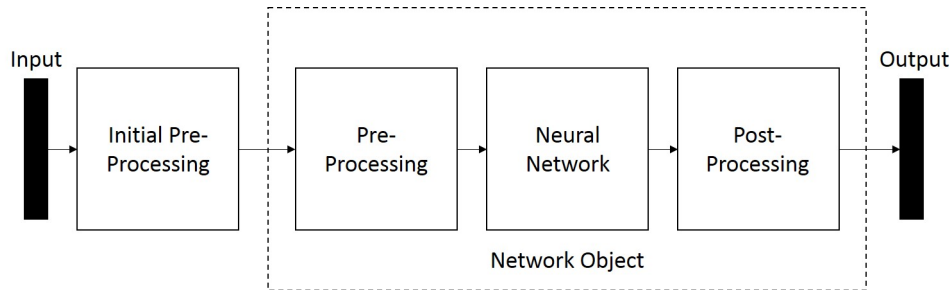


Figure 3.5: Workflow for data pre-processing.

example wind speeds of 1500m/s, and to improve the training of the neural network models.

The pre-processing of the data is carried out in two distinct phases as shown in Figure 3.5. The first stage involves identifying and dealing with any missing values and outliers. This is essentially ‘cleaning’ the data and removing any erroneous readings. The second phase of pre-processing is carried out to make the neural network training more efficient. This is usually carried out during the network training as any scaling of data needs to be reversed to generate network output at the correct scale.

3.6.1 Initial Processing of Missing Data

The data which were collected for all three datasets were sampled at ten minute intervals. There is a number of reasons for choosing this time-step:

- The thermal time constant of buildings is typically measured in hours. Given that the change in internal conditions typically occurs quite slowly a finer resolution was deemed unnecessary.
- The objective of the project is to test a control strategy. In buildings with automated windows a common complaint is frequent actuation of windows (actuators, particularly chain driven can be noisy). Regular activation is typically caused by the system hunting for a particular set point. To prevent occupants becoming irritated by regular adjustments in the window position, 10 minutes was deemed to be a reasonable minimum period between adjustments.

After sampling the data there were some missing values. In some situations if data was found to be missing the most appropriate action may be to remove both the input vector containing missing entries and the associated target vector (Ljung 1999). However, given the time series nature of the data and the low rate of change of internal conditions, generating new values to replace missing data was determined to be the most appropriate action. This was done by linear interpolation.

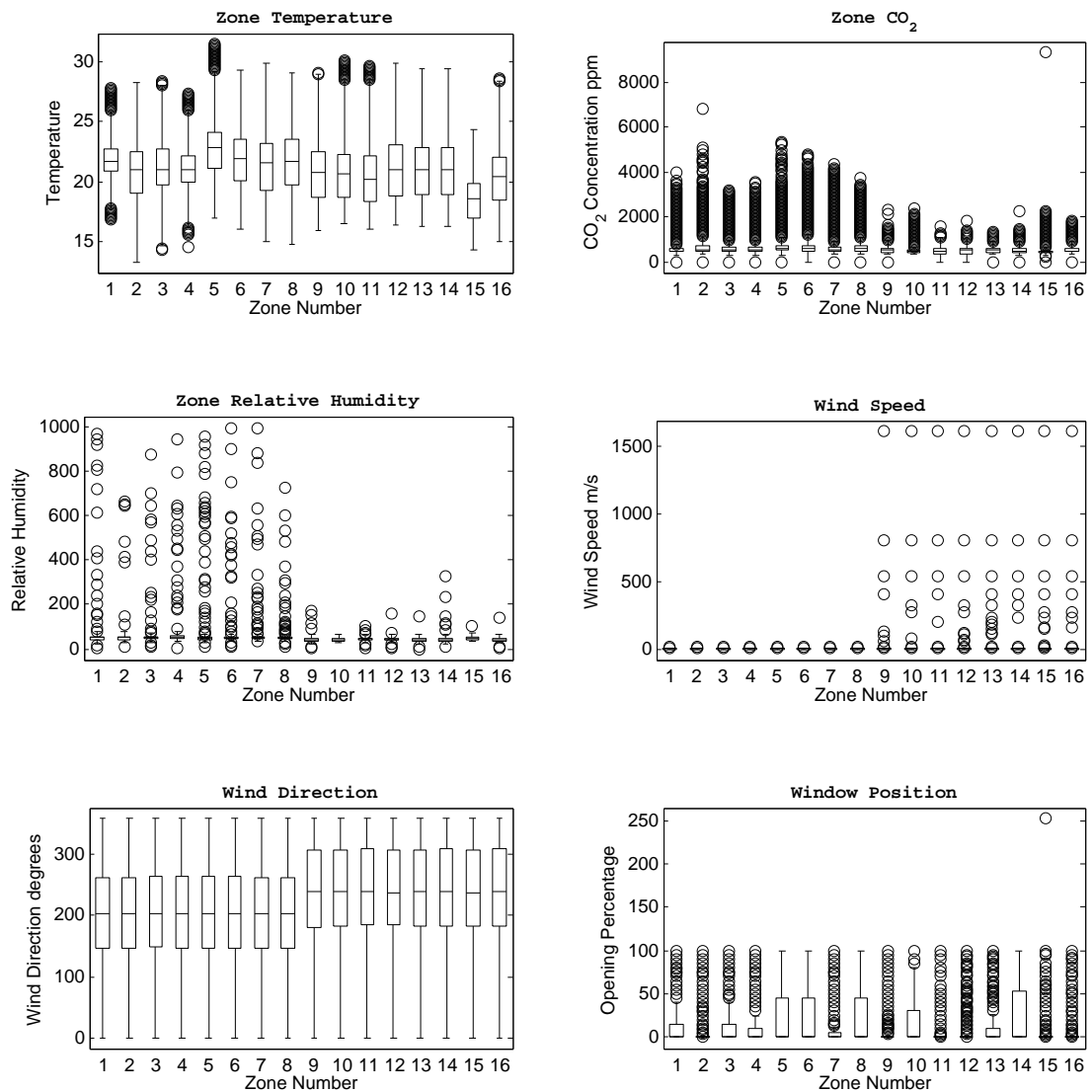


Figure 3.6: Box plots of the input variables for all 16 zones, outliers set at anything outside of three standard deviations from the mean.

3.6.2 Further Processing: Outlier Removal

Having sampled the original data and dealt with missing values, the next step was to remove outliers. In practice the equipment used to acquire the data is not perfect and erroneous values are likely to be present in datasets of this type and size. These outliers can have a significant negative effect upon model predictions and need to be removed (Ljung 1999). In order to check for outliers, the data were plotted. Box plots were found to be most suitable as an initial check as they enable large amounts of data to be visualised at once. If these plots showed likely outliers then further investigation was carried out by plotting individual variables.

When dealing with such large datasets one of the challenges can be how to identify outliers and remove them in a manner which is effective. Successful identification of bad data is

important but it must also be efficient in terms of time. In some instances it was a simple task to identify obvious outliers. For example, in the plot of window position shown in Figure 3.6 there is a single value in Zone 15 which shows an opening percentage of around 250%. This is one obvious bad value out of approximately 400,000 observations. It is completely possible that there are other erroneous data within the window position dataset however it is impossible to identify them as all of the values are within the expected range and there is no set pattern to how the windows open. Likewise the relative humidity and wind speed plots in Figure 3.6 show obvious outliers, with values of 1000% and 1500m/s respectively. These values are impossible as relative humidity can never be above 100% and wind speeds of 1500m/s are over ten times the maximum wind speed ever recorded (WMO 2010), these values are clearly erroneous and should be removed.

In order to speed up outlier removal, the standard score for each variable was plotted. Some methods recommend treating values beyond a certain number of standard deviations from the mean as outliers (Lehmann 2013). In this work each variable was investigated individually to see if the number of deviations from the mean could be used to define outliers. The standard score z of a raw datum x (raw datum being an original datum that has not been transformed) is:

$$z = \frac{x - \mu}{\delta} \quad (3.1)$$

where:

μ is the mean of the population;

δ is the standard deviation of the population.

Having plotted the standard score a judgement was made about how many deviations away from the mean should a datum be considered an outlier. For example, Figure 3.7 shows the standard score plot for relative humidity in zone 1 before outlier removal. Based upon this plot it was decided that any value that lies beyond three deviations should be considered an outlier and removed. In Figure 3.8 the same variable is shown before and after outlier removal. It can be seen that the impossible results have been removed. This does not ensure that any false readings or incorrect data no longer exists, but it has resulted in all values being within the expected range.

By analysing each variable in turn, a judgement was made about what would constitute an outlier. Although this is subjective, the use of judgement and prior knowledge about the type of data was found to be more effective than applying an arbitrary rule to all of the variables. For example, an often used heuristic for outlier detection is the 3-sigma rule (Lehmann 2013). If this method had been employed to all of the variables, observations which may not have been outliers would have been removed. In the box plots shown in Figure 3.6 observations outside of three standard deviations from the mean are shown as circles. Looking at the window position there is no reason to believe that all of these values are outliers, the only clear erroneous datum being the opening percentage of 250%.

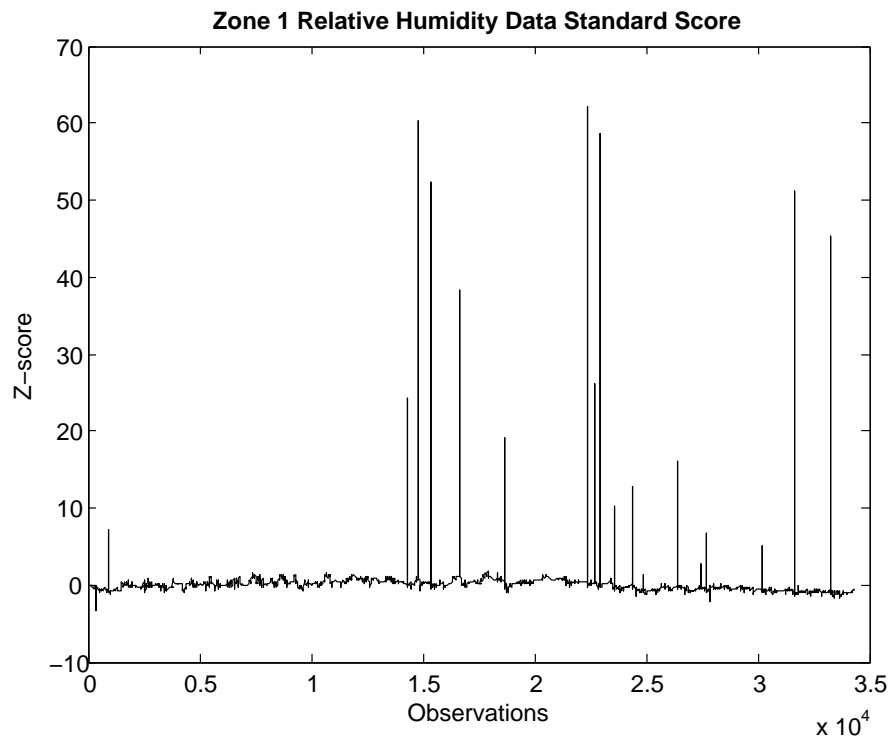


Figure 3.7: Standard score plots were used to identify outliers.

By inspecting data for each variable in turn, a decision was made to determine if any variables could be considered outliers and if so, the number of deviations from the mean beyond which data should be removed. In this manner a simple rule for each variable was created. This could allow automatic processing of data from larger datasets or multiple buildings with similar sensing equipment.

3.7 Normalisation

Neural network training can be made more efficient by carrying out one of a number of preprocessing steps. The most common is normalising the inputs. Normalisation is carried out to speed up network training and prevent saturation of the network transfer functions. Most multilayer neural networks use sigmoid transfer function in the hidden layers. If the network input is large then the weight attached to the node needs to be very small to prevent saturation. The rate of change of the weight is proportional to the size of the weight. Therefore, scaling the inputs speeds learning because it balances out the rate at which the weights connected to the node learn (LeCun et al. 2012).

The variables being considered in this project are at significantly different scales. For example carbon dioxide concentrations of up to 8000ppm were observed, while indoor temperatures rarely reached 30 °C. Normalisation was carried out as part of the network training process, with both inputs and targets scaled into the range of -1 to 1.

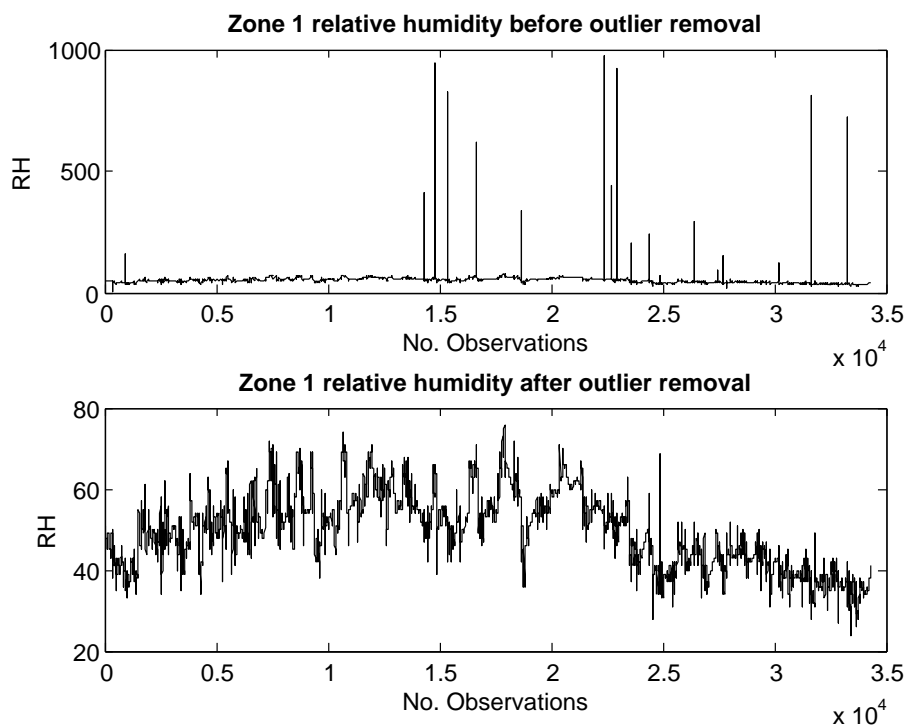


Figure 3.8: Example of an input variable before and after outlier removal. All values now lie within the expected range.

3.8 Summary

This chapter has described the three datasets obtained, as well as the methods used to prepare the data for model fitting. In order to use empirical data from a building to create a predictive model it is essential to ensure the quality of the data is appropriate. For this reason data was collected from a range of buildings. Finally, pre-processing of the data has been discussed covering requirements for the neural network models, and the practical implementation of the resulting predictive model into a building control system. In the next chapter, neural network training techniques are discussed and applied to this data.

Chapter 4

Neural Network Modelling

4.1 Introduction

This chapter details the model fitting process used to train the neural network models. Models are developed to predict both internal temperature and CO₂ concentration. Different model structures are defined and elements related to model architecture are discussed. By investigating different model architectures, not only can better models be developed, but the relationship between structure and model performance can also be determined. This is an important aspect to assess. The empirical approach taken in this work, of using neural networks was chosen for a number of reasons. One of which was that the black box approach has the potential to be easily applied to different datasets and is less susceptible to modeller's bias compared with other methods such as dynamic thermal simulation. Therefore, the degree to which decisions relating to model architecture and other modelling decisions affect model prediction performance is important to understand.

In this chapter neural network models and the methods used to train them are described. The prediction performance of the developed neural network models is assessed over different prediction horizons. A sensitivity analysis was also carried out to determine the impact of the various inputs upon model output.

4.2 Multi-Layer-Perceptron Neural Networks

A multi-layer perception (MLP) neural network is made up of a system of interconnected nodes, or neurons. The nodes are arranged in a network structure as illustrated in Figure 4.1. The nodes are connected by weights, and output signals are a function of the sum of the inputs to the node modified by a transfer, or activation, function. It is the use of nonlinear transfer functions which enable the network to approximate highly nonlinear functions. The transfer function does not have to be nonlinear. Linear transfer functions can be utilised if the neural network is being used to approximate a linear function. In this study the transfer function used is the logistic function (also referred to as the sigmoid function), given by:

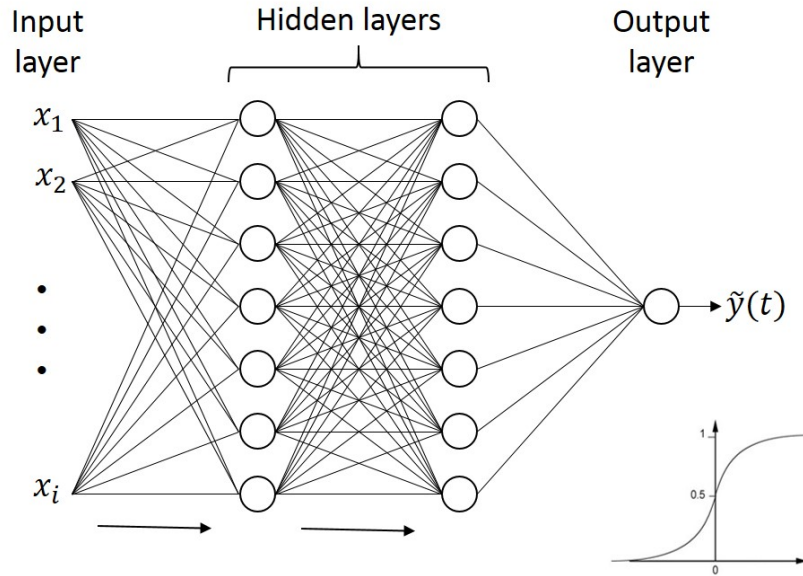


Figure 4.1: A multilayer perceptron neural network with multiple inputs, two hidden layers and a single output. The arrows represent the direction of information flow through the network and the circles represent nodes. Inset is the logistic function.

$$y = \frac{1}{1 + e^{-x}} \quad (4.1)$$

The output from a node is scaled by the connected weight and fed forward to become one of the inputs for the nodes in the next layer. The direction of information flow is in only one direction, from the input nodes to the output nodes. Hence, an MLP neural network is considered to be a feed-forward network. This is in contrast to recurrent neural networks where connections between neurons can form a cycle (Rojas & Feldman 2013).

A range of network architectures is possible. However, most networks consist of a number of different layers. The first layer is the input layer and the final is the output. Between the two layers there can be intermediate layers, known as hidden layers. If the problem is linear then no hidden layers will be required (McCullagh & Nelder 1989). Even when tackling problems which are mildly nonlinear hidden layers may not be needed as a linear model may generalise better than a nonlinear model (Sarle 2001). The optimum number of hidden layers required for nonlinear problems is dependent on the system being modelled. This is discussed further in Section 4.5.1. It is worth noting that in a feed-forward model a neuron can only be connected with neurons in the previous layer and the following layer. In more complex network models, such as the self-organized map architecture (Kohonen 1990), more sophisticated arrangements are possible.

4.3 Model Training

Model training is the process of adjusting the individual weights such that the relationship between the input and output is accurately represented by the network. The objective

of the training process is to find the combination of weights which results in the smallest error between model output and known target values.

MLP network training is carried out by presenting the network with training data. The MLP training process is a supervised learning task. The training data consist of both an input object and the desired output. The difference between the desired output and the output from the network is used as an error signal. The magnitude of the error signal determines by how much the weights in the network are adjusted in order to reduce the overall error.

There is a number of different algorithms which can be used to train a MLP network. One of the most well established is the backpropagation algorithm. Backpropagation is a gradient descent technique which has been shown to be effective at training large neural networks (Rumelhart et al. 1985). In backpropagation the weights are initially set using small random values. This is essentially selecting a random point on the error surface. The local gradient of the error surface is then calculated and the weights are adjusted in the direction of the steepest local gradient. The backpropagation algorithm can be summarised by the following steps:

1. randomly initialise network weights
2. propagate the first input vector (from training data) through the network and obtain an output from the network
3. calculate an error signal by comparing the output from the network with the desired actual output (from training data)
4. propagate the error back through the network
5. update network weights

Steps 2 to 5 are repeated until the error is suitably small or stops improving. When training networks it is important that the network will perform well on unseen data. This may necessitate stopping network training before the network error is fully minimised. This is discussed in greater detail in Section 4.3.1 and Section 4.3.2.

4.3.1 Dividing Training Data

Typically, when training neural network models the training data is divided into three subsets. The first subset is the training set, this is the data upon which the network is trained. The second subset is the validation set. The neural networks prediction performance for the validation set is monitored during network training. As the network training progresses the prediction error for both the training and validation sets decreases. However, if the model begins to overfit to the training data, then the error on the validation set will tend to increase. By monitoring the performance on the validation set overfitting can be avoided and generalisation improved (this is discussed in more detail in the following

section). The final subset is the testing set. The testing set is withheld during model training. It is this unseen data which is used to evaluate the prediction performance of the models.

The method used to divide the data can have a significant effect upon the networks performance. In this study the data was divided into three contiguous blocks (the first block is for training, validation the second and testing the third). Given the time-series nature of the problem, this is an appropriate method.

In some previous studies such as Kusiak et al. (2011), data has been divided into training and testing sets randomly. While random sampling can be suitable for classification problems, it is not recommended for time series data. In the study by Kusiak et al. (2011) models were developed for a mechanically ventilated space using a number of modelling techniques including neural networks. The data consisted of 576 observations at 1 hour intervals, 15% of the data was randomly selected and used as an unseen testing set. Using random sampling for withholding testing data should not be used for time-series problems. By doing so, it would be possible to overfit the models to the training data and still get good performance on the testing dataset. This would indicate that the models have good generalisation. However, if they were tested further using unseen data that was continuous the prediction performance is likely to be poor.

In this thesis, the data described in Chapter 3 is split up into the three sets with 70% used for training (255 days), 10% for validation (36 days) and 20% for testing (73 days). This gives a reasonable balance between training the network over a range of conditions, while still providing a significant amount of unseen test data.

4.3.2 Generalisation and Early Stopping

When training and selecting black-box models it is the model's ability to perform well on unseen data which is important to assess. This is referred to as the generalisation. In a neural network the number of input and output nodes is determined by the problem being tackled and the dimensionality of the dataset. In this thesis, the number of inputs varied between datasets depending on the recorded variables, such as outdoor temperature, wind speed etc. and the number of lagged inputs. In all of the models there was only one output node for either internal temperature or CO₂ concentration. The number of hidden units (M) is a free parameter which can be varied to improve the prediction performance of the model. Increasing the number of free parameters will result in models which agree better with the training data. However, the use of too many parameters can result in models which agree well with seen data but perform poorly with unseen data. In this case the model would be considered to be over-fitted.

As M controls the number of parameters (weights and biases) in the network, one would expect that there will be an optimum value of M which gives the best generalisation performance (Bishop 2006). This optimum will be the point at which there is the ideal balance between over-fitting and under-fitting to the training data.

Unfortunately, the generalisation error is not a simple function of M . If local minima are present the way in which neural networks are trained, with a random initialisation of weights and biases, can result in different prediction performances for the same value of M . One method to overcome this is to simply train multiple networks for each value of M . The performance of the network on unseen test data can then be analysed and the best performing network selected. This is however a time consuming approach to take. In practice there are other techniques which can be used to prevent over-fitting.

One approach is to select a large value for M and then to add a regularisation term to the training error function. This gives a total error function which is minimised during training in the form:

$$E_D(\mathbf{w}) + \lambda E_W(\mathbf{w}) \quad (4.2)$$

where \mathbf{w} is the weight vector elements, λ is the regularisation coefficient which determines the importance of the regularisation term $E_W(\mathbf{w})$ and the data-dependant error $E_D(\mathbf{w})$. There are a range of possible regularisation terms, one of the simplest and most frequently used is the sum-of-squares of the weight vector elements (Bishop 2006) given by:

$$\lambda E_W(\mathbf{w}) = \frac{1}{2} \mathbf{w}^T \mathbf{w} \quad (4.3)$$

One alternative approach to regularisation is early stopping. When training a network there is an iterative reduction in the error over the training dataset. If the error is monitored for a validation dataset (as described in the previous section), the error will initially decrease and then start to increase as the model over-fits to the training data. When using early stopping, network training is halted at the point where the error on the validation data is the smallest. This results in networks which have good generalisation performance.

In this project early stopping was used. This has been shown to be a suitable technique to avoid overfitting during network training (Giles 2001). The primary reason for using early stopping is that the degree to which it effects model performance is less dependent upon user decisions compared with regularisation. Using regularisation is more likely to introduce modeller's bias. Not only are there multiple options for regularisation functions but the user also needs to specify a value for the performance ratio parameter. If this parameter is too large, over-fitting may occur. Too small and the model will under-fit the data. Techniques to automate the process of finding the optimum regularisation parameter do exist, such as Bayesian regularisation (MacKay 1992). However, this adds a further level of complexity. Where possible the process of generating models is kept as simple as possible to allow for easy application to different buildings and datasets.

4.3.3 Training Algorithm

The general method for model training has been described in Section 4.3 and one of the most common techniques, backpropagation described. However, there are a number of

algorithms which can be used to train neural networks. The first algorithm used was the classical backpropagation (Rumelhart et al. 1985). This approach can yield good results, however it is known to have two drawbacks:

- convergence to local minima
- slow learning speed

The problem of local minima is normally dealt with in neural network training by training a number of networks from a range of random starting points. Alternatively, there are more complex methods for global optimisation in neural networks such as the use of genetic algorithms. In Yao (1999) a method for combining evolutionary algorithms with neural networks was demonstrated. Evolutionary computing can be used both to adjust the weights and to find near-optimal network architecture automatically (Yao 1999). While this approach does have advantages it adds an additional level of complexity to model training. In this project, the traditional heuristic approach of training multiple networks was taken.

Improving the slow learning speed of the classical backpropagation approach has been the focus of a number of studies and several algorithms have been developed to accelerate it (Castillo et al. 2006). Second order methods, where second derivatives are used have been shown to increase convergence speed in a range of applications (LeCun et al. 1991, Battiti 1992, Buntine & Weigend 1994). In this project several second order methods were tested to train networks using some of the data described in Chapter 3. The algorithms used were: Levenberg-Marquardt (Marquardt 1963), Bayesian Regularisation Backpropagation, Broyden-Fletcher-Goldfarb-Shanno Quasi-Newton (Battiti & Masulli 1990) and Scaled Conjugate Gradient (Beale 1972). These algorithms were chosen as they represent some of the most relevant examples of second order algorithms (Castillo et al. 2006).

Two zones from Dataset A and two from Dataset B were used to train models to predict internal temperature. The neural network model was a nonlinear autoregressive model with external inputs (see Section 4.4). The networks had one hidden layer containing twenty nodes. Using each algorithm ten models were trained for each zone, using different randomly initialised weights. The training was halted if either of the following criteria were met:

- The maximum number of epochs (iterations) were reached. This was set at 1000 epochs.
- The validation performance increased for more than 20 consecutive epochs.

Having trained the models, the best performing model for each training algorithm was selected. These were then compared, taking into account error on training data, error on test data, number of iterations and execution time. The results for each of the zones are shown in Table 4.1. The Levenberg-Marquardt algorithm gave the lowest error on test data. It

Algorithm	Zone	Initial Training Error	Final Training Error	Iterations	Execution Time (seconds)	Error on Test Data
Levenberg-Marquardt	A2	21.922	0.0192	20	16.94	0.0197
	A4	25.736	0.0201	27	23.94	0.0278
	B10	17.894	0.0197	19	16.02	0.0192
	B11	23.229	0.0187	27	24.14	0.0199
Bayesian Regularisation Backpropagation	A2	14.015	0.0174	117	103.29	0.0217
	A4	52.949	0.0293	206	199.72	0.0301
	B10	20.358	0.0305	97	95.01	0.0318
	B11	32.843	0.0285	115	109.77	0.0291
Broyden-Fletcher-Goldfarb-Shanno (BFGS) Quasi-Newton	A2	32.109	1.235	1000	978.50	1.339
	A4	46.732	1.122	1000	998.02	1.654
	B10	28.909	1.370	1000	982.87	1.098
	B11	30.188	1.215	1000	994.51	1.552
Scaled Conjugate Gradient	A2	20.239	0.0343	388	264.33	0.0388
	A4	23.638	0.0402	201	128.93	0.0411
	B10	38.008	0.0459	257	176.03	0.0481
	B11	44.115	0.0388	319	265.58	0.0404

Table 4.1: Statistics for NARX models used to predict temperatures in Dataset A (Zone 2, 4) and B (Zone 10, 11). Performance of different training algorithms is compared using the average squared error on both training and test data, number of iterations and execution time.

was also the quickest to converge. The fast convergence of the Levenberg-Marquardt algorithm is shown in Figure 4.2. Bayesian Regularisation gave very similar prediction performance to the Levenberg-Marquardt. This seems logical as Bayesian Regularisation is implemented within the framework of the Levenberg-Marquardt algorithm (Foresee & Hagan 1997). However, the execution time and number of iterations for Bayesian Regularisation was significantly higher than for Levenberg-Marquardt. BFGS Quasi-Newton performed poorly. Training was stopped after reaching 1000 iterations. While allowing for more iterations would likely result in better network performance, one of the desirable criteria for the model training algorithm is fast execution. The Scaled Conjugate Gradient method also required significantly more iterations than the Levenberg-Marquardt and performance prediction was slightly poorer. Based upon these findings, Levenberg-Marquardt was chosen as the training algorithm for all future modelling.

Levenberg-Marquardt is a combination of the steepest descent and the Gauss-Newton methods. If the current solution is far from a local minimum, the algorithm uses the steepest descent method. This is a slow technique but will guarantee convergence. When the solution is close to a local minimum the algorithm uses Gauss-Newton and converges faster (Marquardt 1963, Hagan & Menhaj 1994).

The Levenberg-Marquardt algorithm was designed to approach second-order training speed without computing the Hessian matrix (Beale et al. 2016). When using a sum of squares form for the performance function, the Hessian matrix can be approximated using:

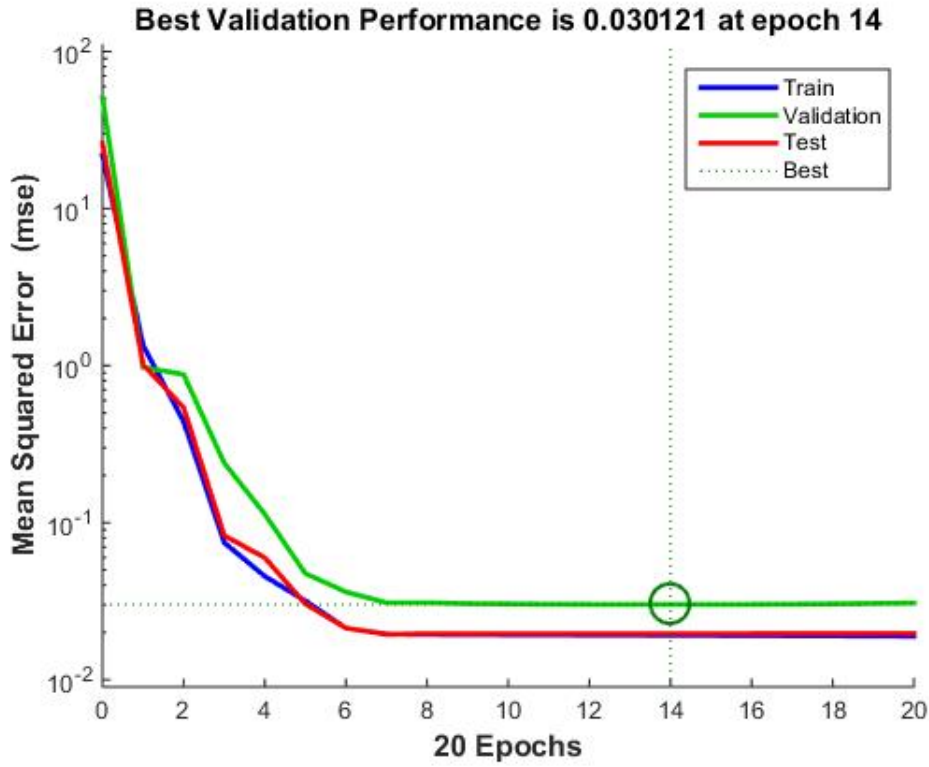


Figure 4.2: Training performance for NARX model trained with Levenberg-Marquardt algorithm for zone 2 in Dataset A.

$$H = J^T J \quad (4.4)$$

the gradient can then be computed as:

$$g = J^T e \quad (4.5)$$

where J is the Jacobian matrix containing the first derivatives of the network errors with respect to the weights and biases and e is a vector of network errors. The Jacobian matrix is computed through the use of standard backpropagation. This is less computationally intensive than calculating the Hessian matrix (Beale et al. 2016). Due to the use of the Jacobian matrix the performance function must be either the mean squared error or sum of squared errors. In this project mean squared error (MSE) was used, which is calculated as follows:

$$MSE = \frac{1}{N} \sum_{i=1}^n (\tilde{y}_i - y_i)^2 \quad (4.6)$$

where \tilde{y}_i is the model output, y_i is the actual output and N is the number of training data.

Using the previously stated approximation for the Hessian matrix, the Levenberg-Marquardt algorithm uses the following update, where W_k is a vector of current weights and biases:

$$W_{k+1} = W_k - [J^T J + \mu I]^{-1} J^T e \quad (4.7)$$

where I is the identity matrix and μ is a scalar. If μ is zero, this becomes Newton's method, using the approximation for the Hessian matrix. Conversely, if μ is large, the update becomes gradient descent using a small step size. As Newton's method is faster and indeed more accurate when close to a minimum, it is desirable to switch to Newton's method as quickly as possible. To achieve this μ is decreased after each successful step and is only increased if a tentative step would increase the performance function (Beale et al. 2016).

4.4 Model Structure

When dealing with time series problems there are three main model structures which can be utilised (shown in Figure 4.3). The first is the purely autoregressive model where the output is predicted based upon past values of itself. This structure can be expressed as:

$$\tilde{y}(t) = f(y_{(t-1)}, \dots, y_{(t-d)}) \quad (4.8)$$

An autoregressive model is not suitable for this project as the impact of the control input upon the model output needs to be captured. Additionally there are other available data which can be treated as exogenous inputs. By incorporating further inputs into the autoregressive model a nonlinear autoregressive with external input (NARX) model can be developed. Given by:

$$\tilde{y}(t) = f(u_{(t-1)}, \dots, u_{(t-d)}, y_{(t-1)}, \dots, y_{(t-d)}) \quad (4.9)$$

The final structure which can be used when dealing with time series problems is the input-output structure. This is where the output is predicted by the model using only past values of other inputs:

$$\tilde{y}(t) = f(u_{(t-1)}, \dots, u_{(t-d)}) \quad (4.10)$$

When dealing with time series problems, this input-output structure is typically only used if past values of the model output $y(t)$ will not be available when the model is deployed. This is because the NARX structure is likely to provide more accurate results. However, in a number of studies related to building systems an input-output structure has been used instead of a NARX (Ferreira et al. 2012). While it is likely that prediction accuracy will be poorer compared with NARX models, there are conceivable advantages to the input-output structure. Predominately, it is a case of simplifying the modelling process.

By using an input-output structure the model is essentially able to predict any number of steps into the future. In some cases, particularly over long prediction horizons, input-output structures can perform better than NARX models. However, in the case of a NARX network the error will often gradually increase as the prediction is increased. Therefore the predictions closest to the current timestep, which are most important for MPC, are likely to be better predictions than would be possible with an input-output structure.

With a NARX model, the training is typically optimised based upon one-step-ahead prediction performance, although models can be trained based upon optimum performance over any prediction horizon (this is discussed further in the subsequent section). This adds an additional problem when training models for the purpose of control. Namely, what prediction horizon should models be trained for? The optimal prediction horizon for the control system cannot be found without accurate system models and yet it is desirable to optimise the model training based upon the required prediction horizon.

To investigate this problem, in this project, a number of models were trained for each zone. Including both an input-output structured model and a number of NARX models for each zone. Multiple NARX models were trained with training optimised for a range of prediction horizons, while the input-output model was used to allow for predictions over long prediction horizons.

4.4.1 NARX Model Training

In a NARX network the target can be considered to be an estimate of the true output of the system being modelled. During training of the network, the true output is available. This allows a series-parallel or open-loop architecture to be used (as shown on the left in Figure 4.4) (Narendra & Parthasarathy 1991). There are two key advantages to a series-parallel architecture. Firstly, the input to the network is more accurate and hence the resulting network tends to have a greater performance. Secondly, the network has a purely feedforward architecture allowing static backpropagation to be used in training (Beale et al. 2016). This means that training is less computationally intensive.

However, by training the network using a series-parallel form, training has been optimised for one-step-ahead prediction. While this is a good starting point, multi-step-ahead prediction is required for MPC. One possible approach is to train the network using a series-parallel architecture and then close the loop to create a parallel architecture. However as the training has been carried-out using actual values of the network output and then tested with predicted values, performance is not optimal. However, it is undesirable to train the network in a closed-loop form from the outset due to the time and computational effort required.

To investigate the effect of training models in both series-parallel and parallel architectures, a short study was carried out. Using data from Dataset A and B, NARX models were trained to predict internal temperature for zones 1 to 16. For each zone two models were trained, one using a closed-loop structure and one an open-loop structure. The neural networks used all available inputs (described in Section 3.2 and Section 3.3), and had one

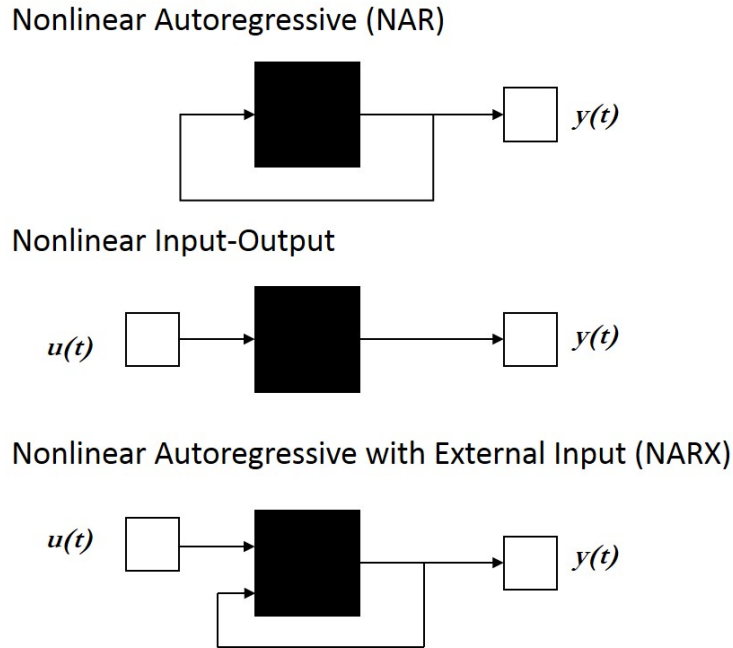


Figure 4.3: Typical model structures for dealing with time series problems. In this project both the nonlinear input-output and the NARX structure were utilised. A purely autoregressive structure is inappropriate as the influence of the control input upon model output is required in this project.

hidden layer containing 20 nodes. Once training was completed the loop on the open-loop models was closed. Both structures were then tested based upon their ability to predict outputs ten steps into the future (100mins).

The averaged model performance across all sixteen zones is shown in Table 4.2 (performance measures used are described in Section 4.6.1). As anticipated, the models which were trained in a closed-loop form had better prediction performance compared with the models which had been trained as open-loop. However, the average training time was 21.6 seconds for the open-loop structure and 2632.7 seconds for the closed-loop. This is clearly a significant increase in training time for around a 10% improvement in prediction performance.

In order to achieve an accurate final model without a large computation requirement, the workflow shown in Figure 4.5 was utilised. By carrying-out the training initially using a series-parallel architecture and then using the resulting weights and biases as the starting point for the closed loop network, a 46% reduction in training time was observed (based upon a study using data from 5 zones and repeating training 10 times per zone).

4.5 Model Architecture

The process of designing a neural network involves making a number of decisions which may seem arbitrary, such as choosing the number of layers, hidden units, delayed inputs etc. In most situations these choices will be critical, however there is no defined strategy for making these decisions (LeCun et al. 2012). There is often no way to decide upon

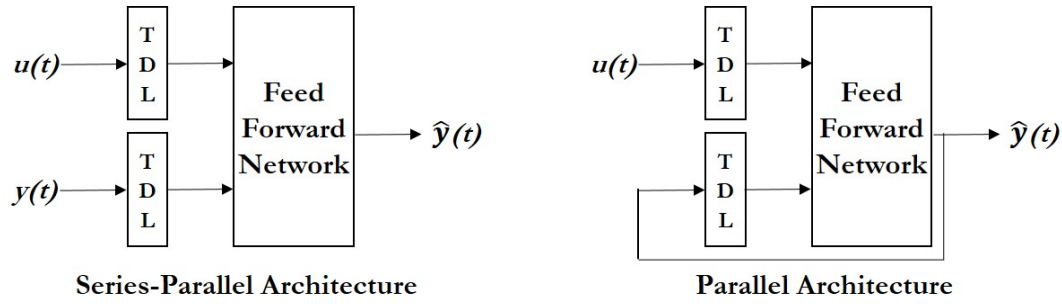


Figure 4.4: Feed forward network architectures for NARX networks. On the left is the series-parallel or open-loop configuration ideal for one-step-ahead prediction and on the right is the parallel or closed loop configuration. In a parallel architecture model predictions are fed back into the network through a tapped delay line (TDL) allowing for multi-step-ahead predictions. Adapted from Beale et al. (2016).

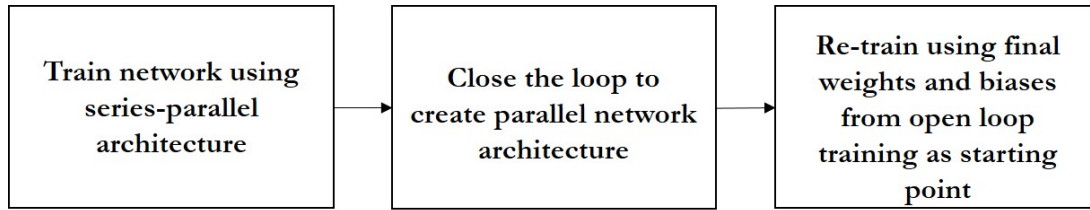


Figure 4.5: Optimal workflow for training closed loop NARX neural network models. Utilising this workflow resulted in significant time savings, compared with direct training of closed-loop models.

Training Methodology	Mean Absolute Error	Std Absolute Error	Mean Absolute Percentage Error (%)	Std Absolute Percentage Error (%)	Training Time (s)
Trained as an open-loop, loop closed after training	0.722	0.524	0.125	1.349	21.6
Directly trained as closed-loop	0.630	0.468	0.111	0.122	2632.7

Table 4.2: Averaged statistics for models trained to predict internal temperatures, using both training methodologies for zones 1-16. The performance metrics used are defined in Section 4.6.1.

the optimum network architecture without training several networks and assessing the prediction capability of each.

In the following sections, the process of training multiple networks and investigating the impact of network architecture upon prediction performance is clearly shown. It is important that this process is transparent. One of the main justifications for utilising an empirical approach to system modelling is that it has the potential to be quickly and easily applied to different datasets. If prediction performance is highly dependent upon model architecture and thus in future applications a significant amount of time needs to be spent optimising the models for different buildings, a significant advantage of empirical modelling is lost.

4.5.1 Hidden Layers

Hidden layers were introduced in Section 4.2. It was discussed that for linear problems hidden layers are not required. For nonlinear models one or more hidden layers must be used. However, for most problems one should be sufficient (Hornik et al. 1989). If an MLP contains one hidden layer with a large enough number of neurons, containing a nonlinear activation function, it should be possible to approximate any function (Bishop 1995, Hornik 1993, Hornik et al. 1989, Ripley 2007). Unfortunately, there is no theory for how many neurons or layers are required for a given function (see Section 4.5.2 and Section 4.3.2). Multiple hidden layers are required in certain specific applications for example when using threshold functions (Sontag 1992).

Based upon the existing literature, which suggests that the majority of applications only require one hidden layer, it was anticipated that for this project a single hidden layer would be sufficient to model the processes being studied. However, a brief investigation of networks with multiple layers was carried out. NARX networks were trained using the data from both Dataset A and Dataset B (described in Chapter 3). Models were trained to predict internal temperature, using external temperature, window position, wind speed and wind direction as inputs. Two model architectures were tested. One with a single hidden layer with 15 units and the one with two hidden layers with 15 units in each layer. Five random initialisations were used to train models for each architecture and zone, giving a total of 160 networks trained.

The one-step-ahead prediction performance for the resulting networks is shown in Figure 4.6. The best prediction performance for the networks with a single and two hidden layers is very similar. However, in some of the zones there is a larger range of prediction performance for the models with two hidden layers. This may be due to the problem of local minima. One of the pitfalls when using multiple hidden layers is that the models are more likely to experience the problem of local minima (Nakama 2011).

Based upon these results, one hidden layer was used for all future modelling as adding an additional layer was not observed to improve prediction performance and in some cases gave a much greater range of predictions.

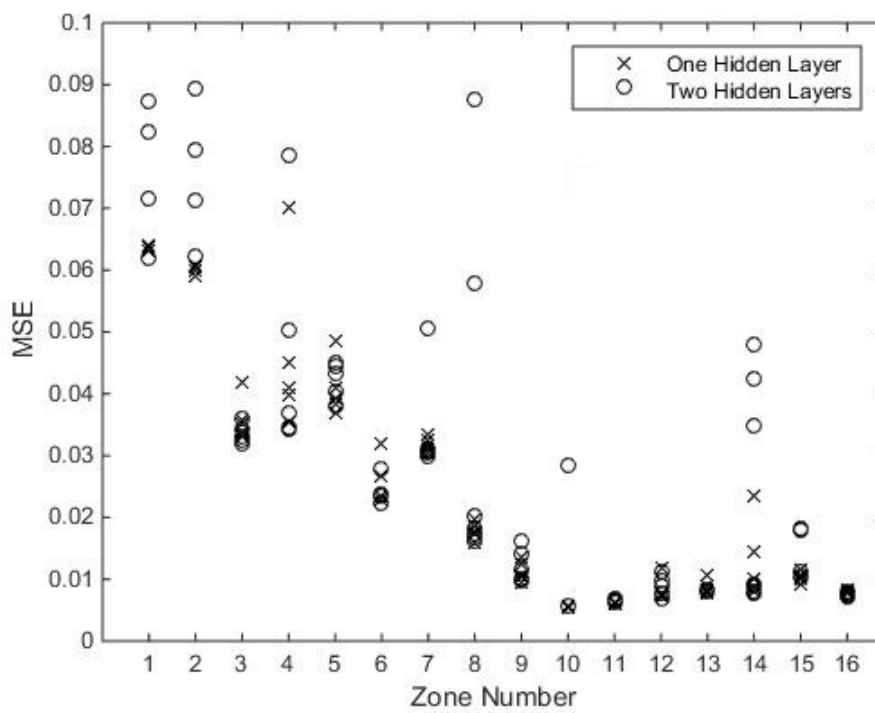


Figure 4.6: One-step-ahead prediction performance is shown for models trained with both one and two hidden layers for all zones in Datasets A and B. Five random initialisations were used for each model architecture. Mean squared error is shown for each zone for models with one hidden layer and two hidden layers.

4.5.2 Hidden Nodes

In Section 4.3.2, the impact of the number of hidden nodes (M) upon model prediction performance was discussed. In order to improve generalisation, early stopping is being used. Early stopping prevents overfitting the model to the training data by halting training when the performance on a validation dataset increases. This simplifies the process of training models. By using early stopping it is not necessary to train a large number of networks with a range of values for M and then select the model which gives the best generalisation. However, the use of early stopping does not completely remove the problem of determining the required number of hidden nodes. M must be sufficiently large to capture the relationship between model input and output. If it is greater than this, the use of early stopping should prevent overfitting. However, it is still necessary to ensure that the network does have enough hidden nodes to capture the underlying processes occurring.

In order to determine the minimum requirement for M NARX networks with one hidden layer were trained using the data from both Dataset A and Dataset B (described in Chapter 3). Models were trained to predict internal temperature, using external temperature, window position, wind speed and wind direction as inputs. The number of hidden nodes was varied between 1 and 150.

Figure 4.7 shows the results for zone 1. The error initially drops rapidly as the number of nodes is increased from 1 to 5. After this point the training, validation and testing errors remain very similar. The corresponding training time and best epoch are shown in Figure 4.8. The best epoch, i.e. the epoch at which the minimum validation error was achieved, remained relatively constant, while the training time steadily increased with the number of nodes. The results for all sixteen zones followed a similar pattern, with no significant change in prediction performance after approximately 5 to 10 hidden nodes.

4.5.3 Time Delays

In a NARX neural network predictions are made based upon previous observations of the output and other inputs. As with the previous parameters discussed in this chapter, there is no way to determine how many lags will give the optimum prediction performance. It is simply a case of training multiple networks and assessing their performance.

To determine if the number of input lags affected model output a number of networks were trained with exogenous input lags from 1 to 144 for all exogenous inputs. With the ten minute sampling, this equates to 10mins to 24hours. NARX networks with one hidden layer were trained using the data from both Dataset A and Dataset B (described in Chapter 3). The hidden layer contained 100 hidden nodes. This is quite a large number of hidden nodes. However, as increasing the number of lags increases the number of inputs to the network, a large number of hidden nodes may be required. Models were trained to predict internal temperature, using external temperature, window position, wind speed and wind direction as inputs.

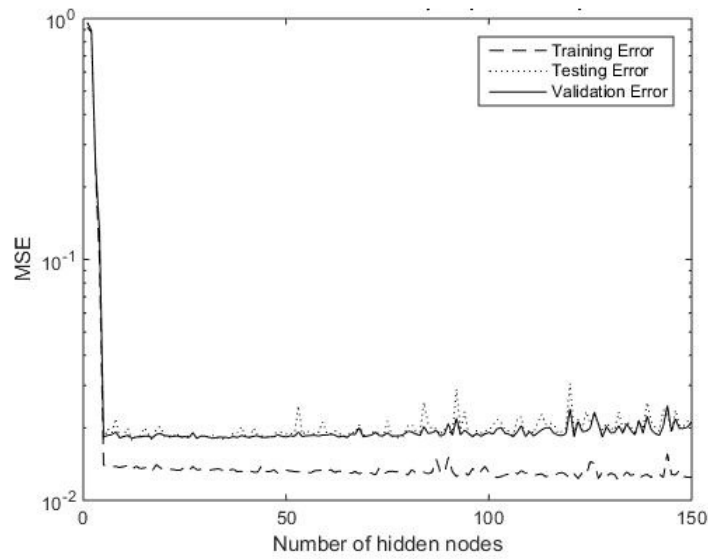


Figure 4.7: One-step-ahead temperature prediction performance for neural networks trained with a range of values for M , upon data from zone 1. It was observed that increasing values for M caused a rapid improvement in prediction performance. However, after M was greater than 5 additional nodes made no further improvement.

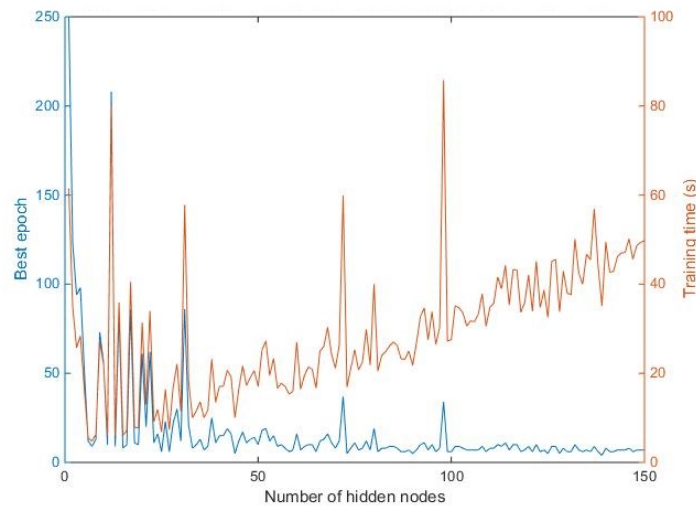


Figure 4.8: Training time and the epoch which gave the best generalisation performance corresponding to the prediction performance in the previous figure.

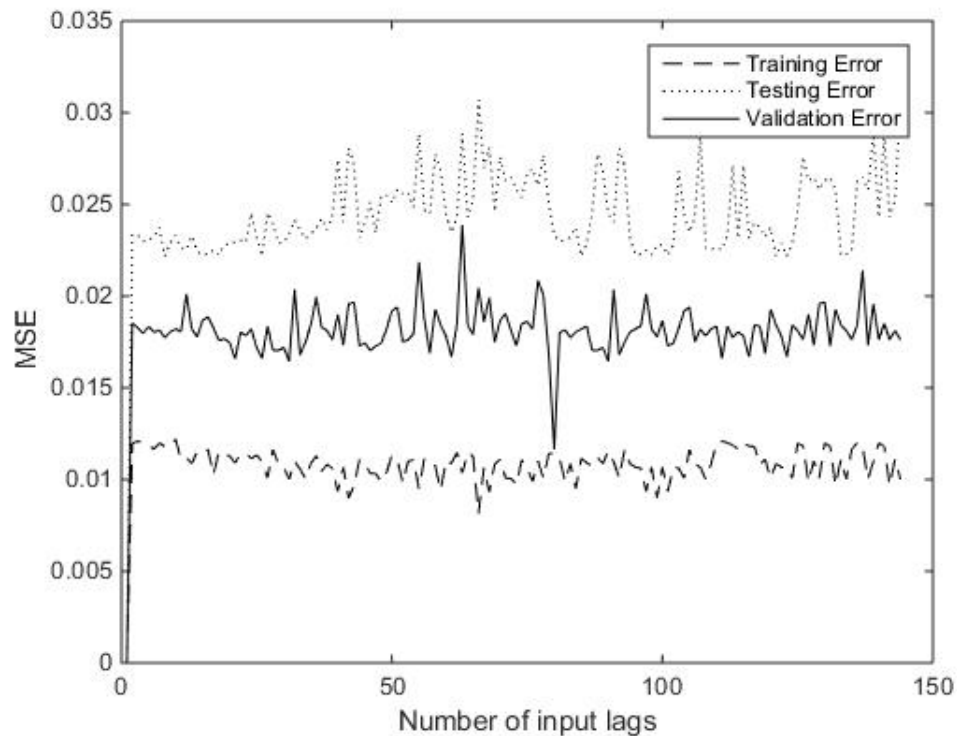


Figure 4.9: One-step-ahead temperature prediction performance for neural networks trained with a range of input lags upon data from zone 1.

Having trained the models the prediction performance was then analysed. In both one-step-ahead and multiple-step-ahead prediction increasing the number of input lags from 10mins had no impact upon prediction performance. For example, Figure 4.9 shows the one-step-ahead prediction performance for zone 1. A range of prediction horizons were tested, up to 24 hours. However, none showed an increase in performance from further input lags over any prediction horizon.

An investigation was also carried out to determine if increasing the number of lagged autoregressive inputs (zone temperature and CO_2 concentration) impacted upon prediction performance. Based upon knowledge of the system dynamics and analysis of the observed data, it was expected that including a lagged input for the same time during the previous day would improve prediction performance. In Table 4.3 it can be seen that for one-step-ahead prediction, including a lagged input for the same time the previous day had resulted in a small improvement in prediction performance compared with a model which included only the autoregressive inputs for the previous 2 timesteps (10 and 20mins). However, over a longer horizon the improvement was much more significant. Temperature prediction was improved more than CO_2 concentration by incorporating an autoregressive for the same time on the previous day. Further autoregressive lags were also tested at 6, 12 and 24h. Table 4.3 shows that this did result in some improvement but this was relatively small.

No. Steps-ahead	Change in temp test error (%)		Change in CO ₂ test error (%)	
	lag at 24h	lags at 6, 12 and 24h	lag at 24h	lags at 6, 12 and 24h
1	0.27	0.36	0.19	0.21
10	3.84	4.21	3.26	3.27
20	7.62	7.93	5.91	5.93

Table 4.3: Average improvement in prediction performance on unseen test data for zones 1-16 when including an autoregressive lagged input for the same time on the previous day and additional lags at 6 and 12hours.

4.6 Network Prediction Performance

In this section the prediction performance of the neural network models developed is presented. Results are shown for both internal temperature prediction and CO₂ concentration. The results shown are the output of neural network models developed after the process of investigating the impact of modelling decisions such as the choice of training algorithm, number of hidden nodes etc. had been carried out (Sections 4.3, 4.4 and 4.5). Therefore the results presented in this section are the best results obtained after attempting to optimise each component in the modelling process.

There are a number of similarities between the data in Dataset A and Dataset B, such as the observation period and available inputs (detailed in Chapter 3). Therefore, the results for models trained using data from both datasets is presented together. The data in Dataset C was collected over a much shorter time period, only one month (see Section 3.4). Given the comparatively small amount of data, the results are presented separately. Although, observed over a much smaller time period Dataset C has the advantage that all window openings were recorded. While in Datasets A and B manual window positions were not logged, necessitating that they be treated as unmeasured disturbances. It is for this reason that the inclusion of Dataset C was deemed worthwhile.

4.6.1 Performance Measures

To analyse the model performance, the model outputs were compared with the observed values for the unseen test data set. Alongside visual comparisons, the following four metrics were used to measure the prediction accuracy of the model: the mean absolute error (MAE), the standard deviation of absolute error (StdAE), the mean absolute percentage error (MAPE) and the standard deviation of the absolute percentage error (StdAPE):

$$AE = |\tilde{y} - y| \quad (4.11)$$

$$MAE = \frac{\sum_{i=1}^n AE_i}{N} \quad (4.12)$$

Number of steps-ahead	MAE	StdAE	MAPE (%)	StdAPE (%)
1	0.640	1.314	3.10	6.35
10	1.498	2.072	7.21	9.92
20	2.261	2.207	11.04	10.76

Table 4.4: Average internal temperature prediction performance on unseen test data for zones 1-16.

$$APE = \left| \frac{\tilde{y} - y}{y} \right| \quad (4.13)$$

$$MAPE = \frac{\sum_{i=1}^n APE_i}{N} \quad (4.14)$$

$$StdAE = \sqrt{\frac{\sum_{i=1}^n (AE_i - MAE)^2}{N - 1}} \quad (4.15)$$

$$StdAPE = \sqrt{\frac{\sum_{i=1}^n (APE_i - MAPE)^2}{N - 1}} \quad (4.16)$$

where y is the actual output, \tilde{y} is the predicted output and N is the number of predictions.

4.6.2 Datasets A and B: Temperature Prediction

The models developed were found to give good predictions on the unseen test data. The first models generated were for one-step-ahead prediction. As can be seen in Figure 4.10 the one-step-ahead model almost perfectly tracks the target temperatures and performs well in all of the evaluation criteria shown in Table 6.1. The multi-step-ahead models were also found to perform well. When predicting at ten and twenty-steps-ahead ($n=10$, i.e. 100mins in the future and $n=20$, i.e. 200 mins in the future) the error increased but the predictions still tracked the observed data reasonably well (see Figure 4.10).

The predictions strayed further from the targets during unoccupied periods. This can be seen in the last 48hours in Figure 4.10 which is a weekend.

4.6.3 Datasets A and B: CO₂ Prediction

The models used to predict CO₂ concentration exhibited very similar prediction performance to the temperature models. One-step-ahead models almost perfectly tracked the targets, with the error gradually increasing with the prediction horizon. Unlike the models to predict temperature, the error did not significantly increase during unoccupied periods. However, the error during unoccupied periods would likely be reduced if separate models

Number of steps-ahead	MAE	StdAE	MAPE (%)	StdAPE (%)
1	10.239	13.02	1.32	2.01
10	48.923	58.34	8.81	7.78
20	102.004	98.47	18.90	16.81

Table 4.5: Average CO₂ concentration prediction performance on unseen test data for zones 1-16.

were trained for occupied and unoccupied periods.

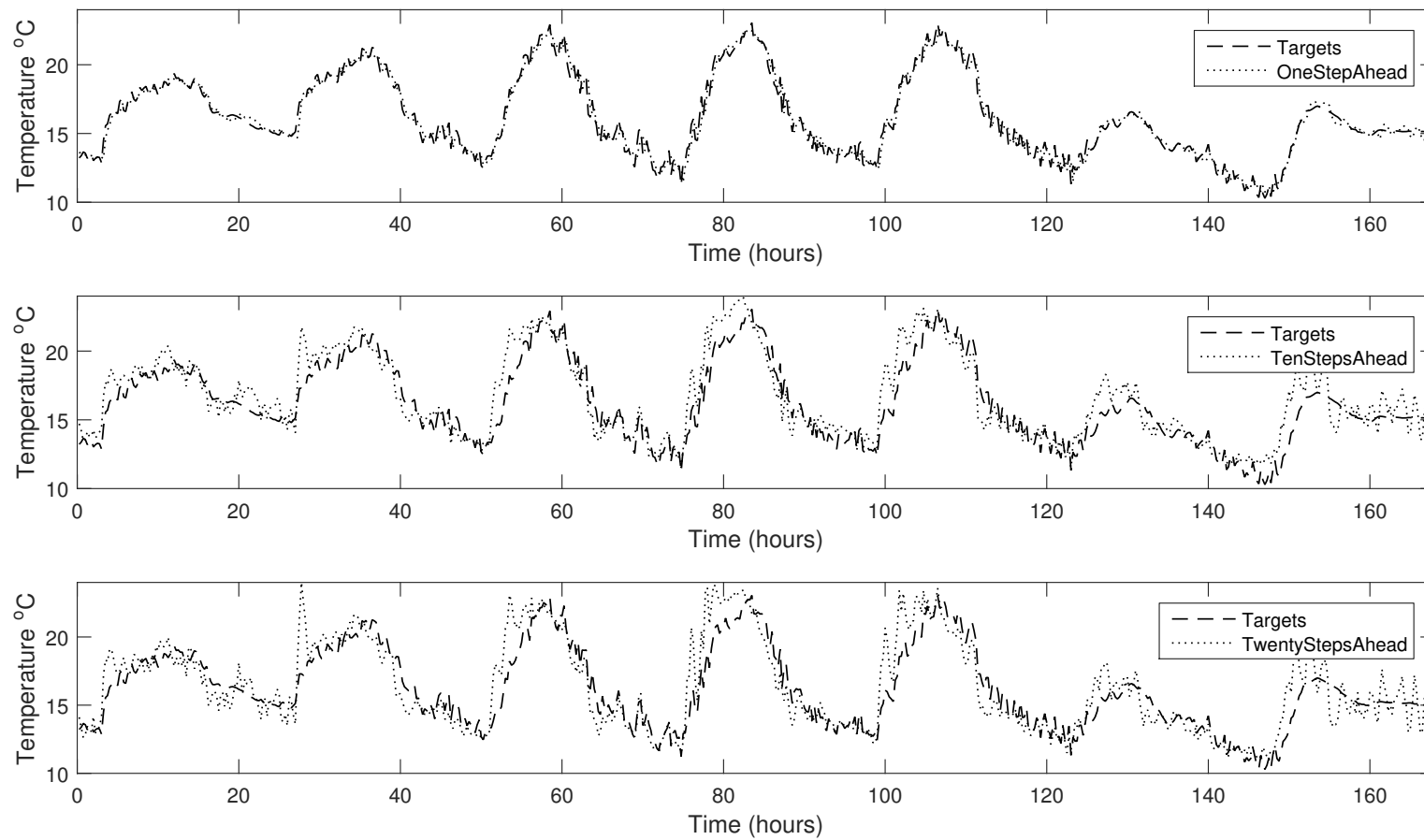


Figure 4.10: Plots showing predictions for one-step-ahead, $n=10$ and $n=20$ against observed internal temperatures. This represents one week of the unseen test data set for zone 5.

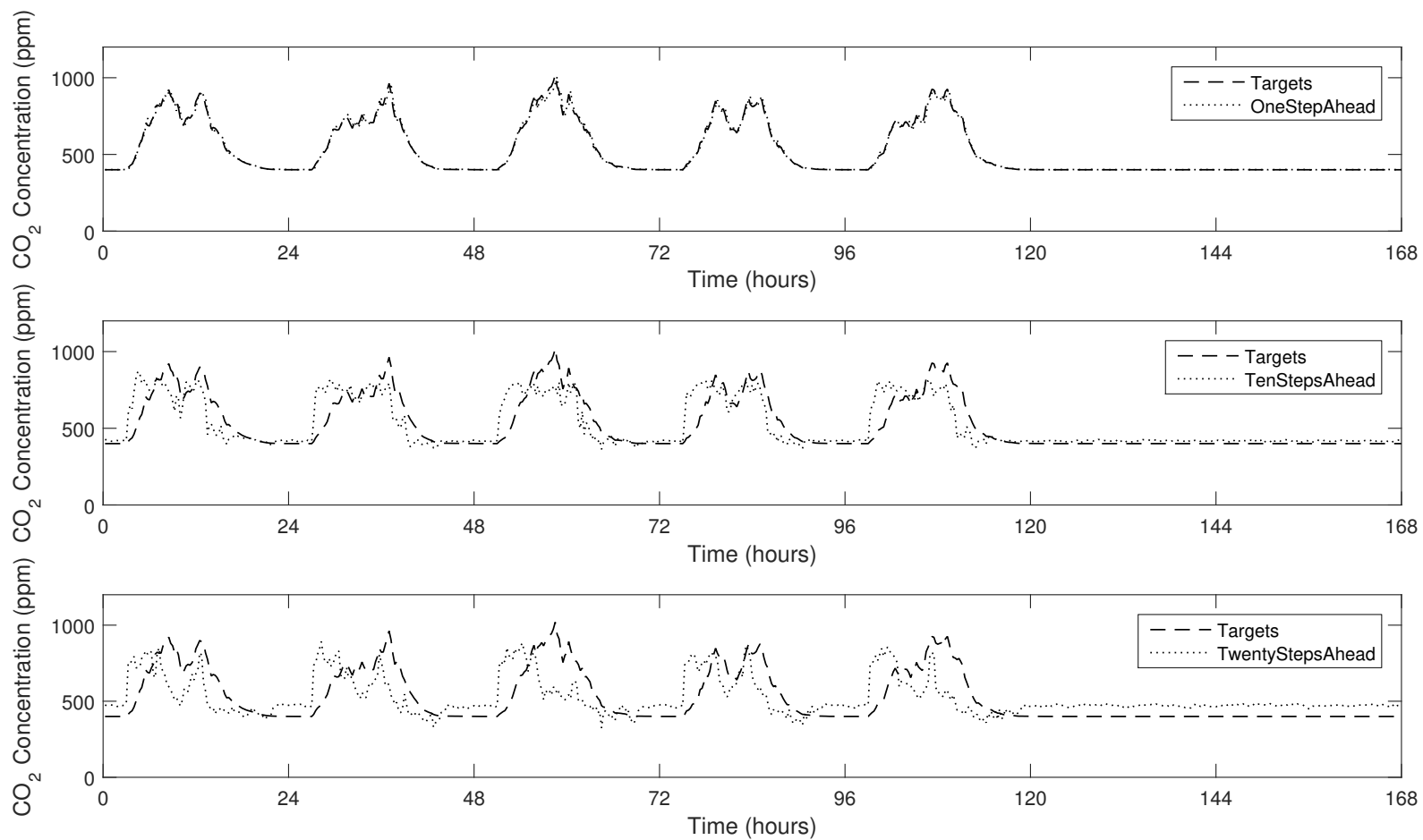


Figure 4.11: Plots showing predictions for one-step-ahead, $n=10$ and $n=20$ against observed CO₂ concentration. This represents one week of the unseen test data set for zone 5.

4.6.4 Datasets A and B: Sensitivity Analysis

After investigating the models' performance on the unseen test data further inputs were fed into the models. The aim of this process was to determine to what degree each individual input affected model output. Figure 4.12 shows an example of this process. The top plot shows the change in model output when the internal temperatures from the following week were fed into the model for one-step-ahead predictions. The output clearly changes. However, the bottom two plots show that when a different weather file or input signal is fed into the model there is no significant change in output.

Figure 4.12 also shows that the neural network models developed did not capture the effect of the window opening position, as there is negligible change when maintaining 100% window opening area. Following this further models were trained to investigate the impact of input selection upon model output. Models had initially been trained using all of the inputs available for each dataset. To investigate if additional inputs resulted in more informative output a range of models were trained, ranging from a purely autoregressive model, to models which contained the window opening state and weather conditions. The results are shown in Figure 4.13. This shows that additional inputs, such as external temperature, window opening, wind speed, wind direction and humidity do not improve the model performance over a purely autoregressive model.

4.6.5 Dataset C

In the previous sections, the performance of neural network models trained using datasets A and B were analysed. While giving a reasonable prediction for temperature and CO₂ concentration, they were unsuitable for control as the effect of the window opening was not captured. In these data, the window opening variable represented the position of automated windows in spaces which had a combination of manual and automated windows. No data were available for manual windows and as such they were treated as an unmeasured disturbance when training the neural network models.

One of the aims of this thesis is to demonstrate an MPC control strategy. The techniques for achieving a suitable controller have taken into account limitations in current buildings. One such limitation is the lack of sensing equipment on manual windows. The author is yet to encounter a BMS which logs the position of manual windows. Therefore to achieve a controller which could be widely adopted without installing additional sensing equipment, manual window data was not included in model training.

One possible explanation for the inability of the neural networks to capture the effect of the automated windows is that the unmeasured disturbance caused by the manual windows is significant. The spaces which were monitored in Dataset C were ventilated using only manual windows, with the opening state gathered using magnetic reed switches and state loggers. This gave a binary state (open/closed) condition for the windows. By training neural networks using these data it was possible to evaluate performance with knowledge of all window opening states for a space.

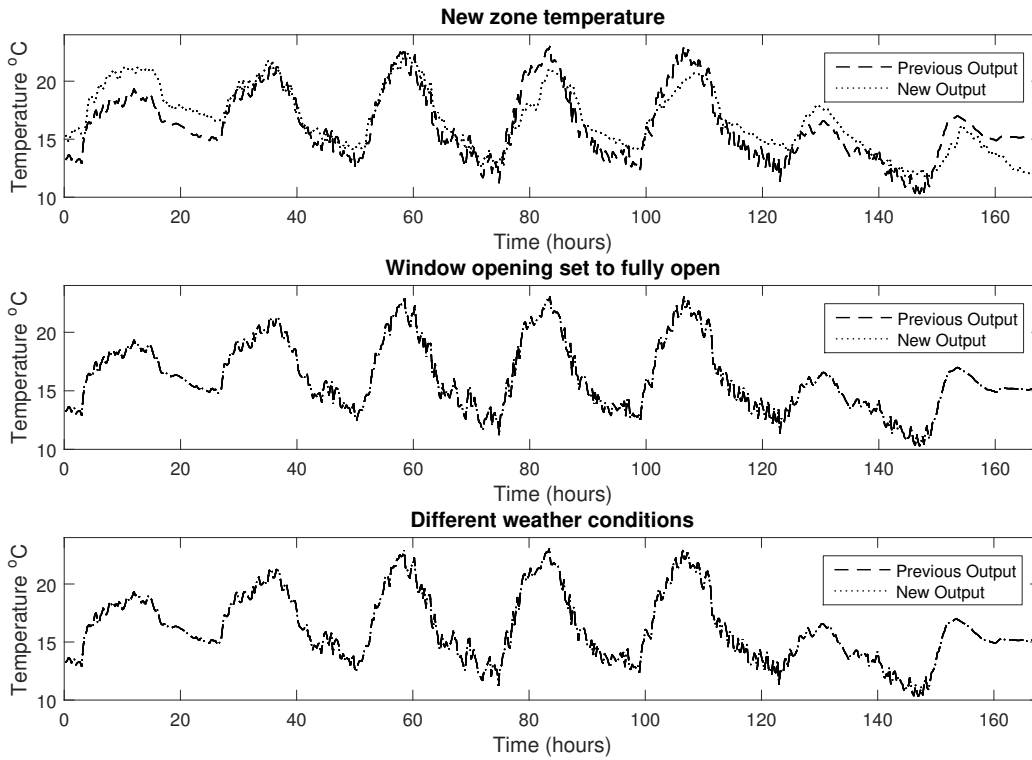


Figure 4.12: Models were tested with different inputs.

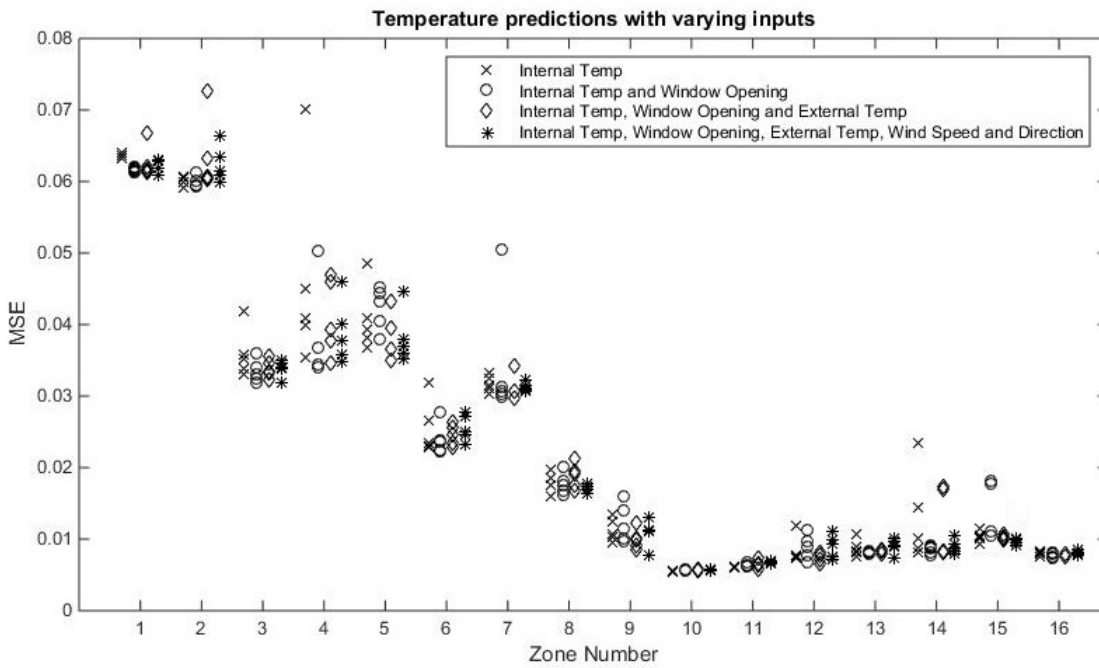


Figure 4.13: The impact of additional inputs is shown to have no advantage over a purely autoregressive model in terms of prediction performance.

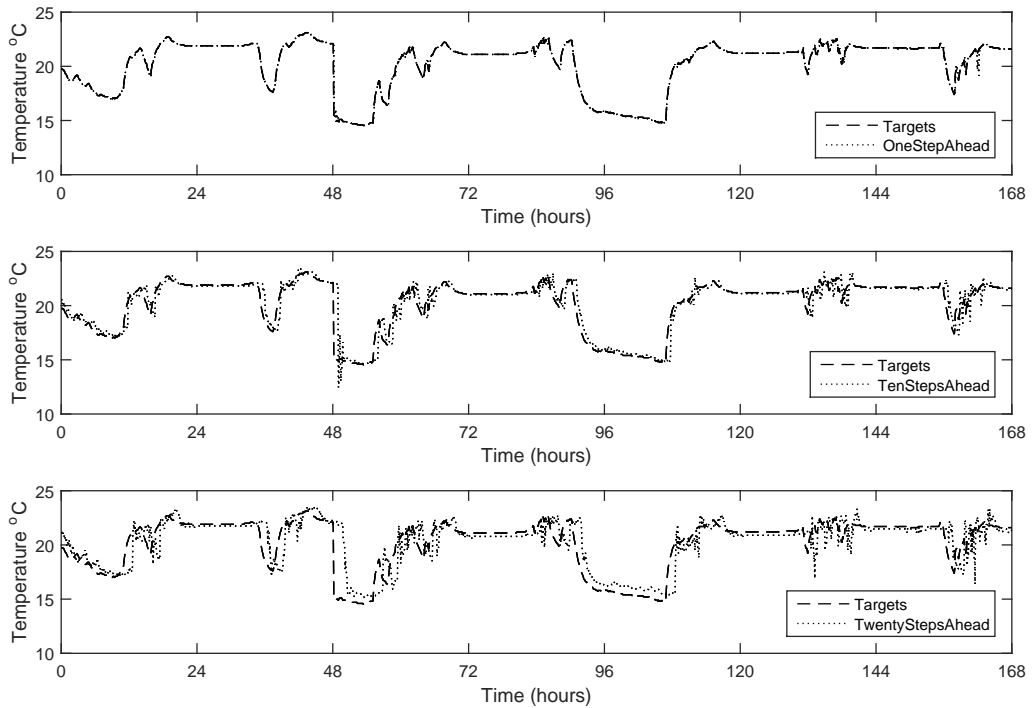


Figure 4.14: Plots showing predictions for one-step-ahead, $n=10$ and $n=20$ against observed internal temperatures. This represents one week of the unseen test data for office 3.

The neural networks were trained using the same techniques as those for Datasets A and B. As the collection period was much shorter only one week of unseen test data was possible. Figures 4.14 and 4.15 show the temperature and CO_2 prediction performance for Office 3. Performance on unseen test data was encouraging; however, the main reason for training models using this dataset was to determine if the effect of window opening could be captured.

In Figure 4.16 the model output for the same office is shown with different inputs for zone temperature and window opening. For the new zone temperature model input, observed data from another office (office 2) was used. Window opening inputs for both the fully open and fully closed condition were also tested. It can be seen that the new input for zone temperature had a significant impact upon model output; however, the window opening input did not change the model output. Hence, the model is not capturing the effect of the window opening. The same results were observed for all five of the office in Dataset C for both summer and winter months.

4.7 Discussion

The models developed were able to predict internal temperature and CO_2 concentration over a reasonable prediction horizon. The results from NARX networks are presented for up to 200mins into the future. This should be sufficient for a receding horizon control strategy. However, a thorough study is required to determine the optimum prediction

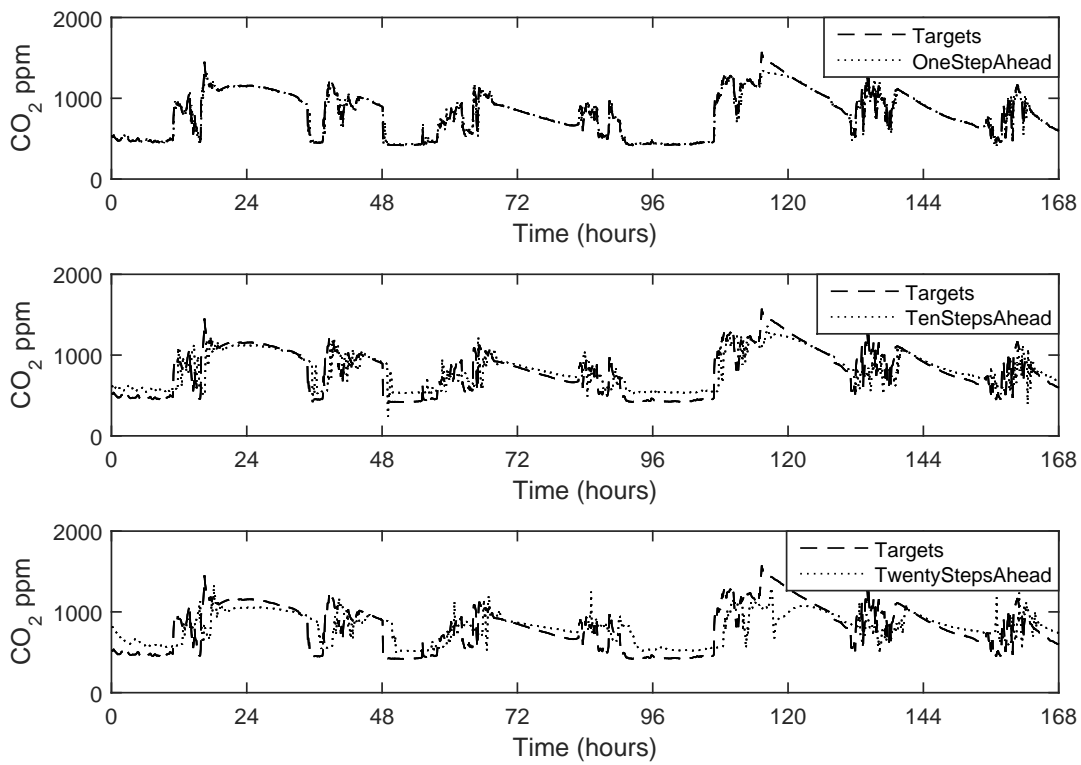


Figure 4.15: Plots showing predictions for one-step-ahead, $n=10$ and $n=20$ against observed CO_2 concentration. This represents one week of the unseen test data for office 3.

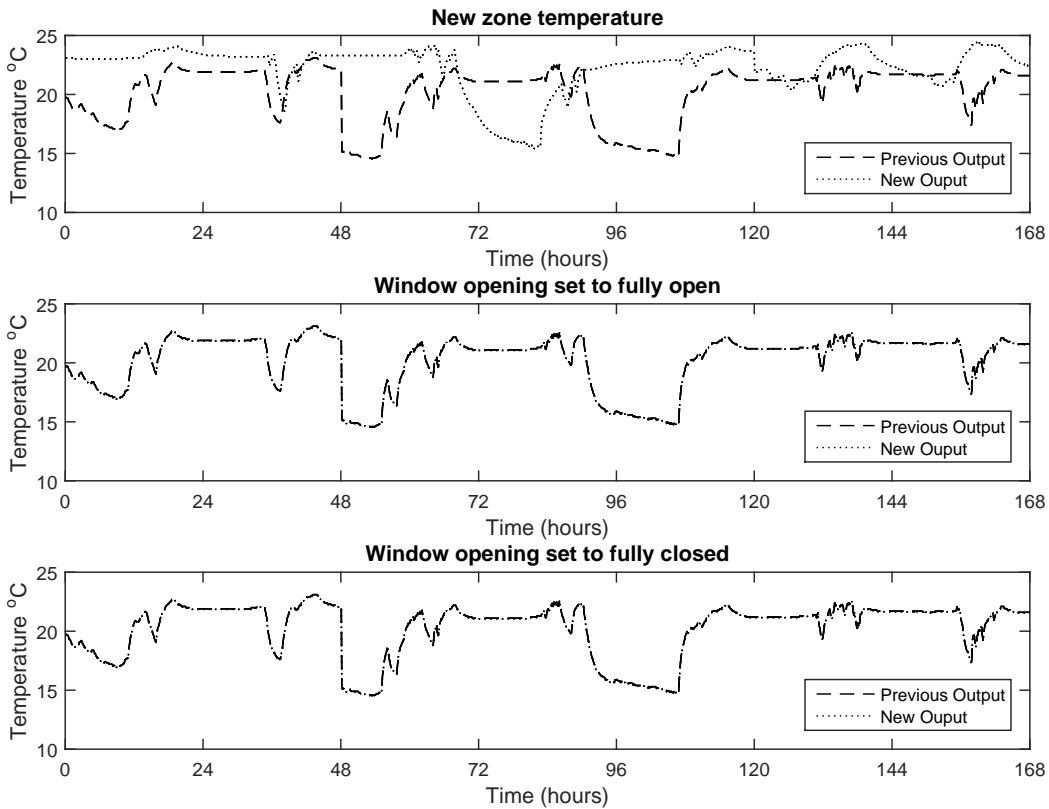


Figure 4.16: Testing trained neural network model for office 3 with different inputs.

horizon, which will likely vary between buildings. Unfortunately this cannot be determined until the MPC controller is tested.

Prediction performance was not heavily influenced by modelling decisions. One of the main user decisions when training neural networks is the number of hidden nodes. In Section 4.5.2 it was shown that increasing the number of hidden nodes beyond ten had a minimal impact on performance. Likewise, the increasing the number of exogenous lagged inputs beyond one timestep (10mins) did not improve prediction performance. Autoregressive lagged inputs at 6, 12 and 24h were shown to improve prediction performance, the improvement was more significant for longer prediction horizons. Tests upon different data may be required to make a conclusive statement however, this suggest that modellers' bias is unlikely to be a major concern.

Upon closer inspection of the model outputs, it was observed that model performance for predicting temperature was poorer during unoccupied periods. This can be seen in Figure 4.10. It was found that at the end of the week and during the nights, the predictions stray further from the target temperatures. This can be seen particularly during the weekends. In Figure 4.10, between 120 and 168 hours the school was unoccupied.

This seems to indicate that occupancy can have a high impact upon the models. Potentially this could be overcome by creating two models for each zone, one for occupied periods and one for unoccupied. This is likely to improve accuracy; however, the degree to which this would impact upon the control performance may not justify the extra complexity.

However, while the models gave reasonable predictions it was shown in Section 4.6.4 that the models did not capture the effect of the window opening. This would make them unsuitable for the MPC approach to ventilation control proposed in this thesis.

There are a number of possible reasons for why the models failed to capture the effect of the window opening. The first possibility is that the model structure used was not suitable to provide a good enough description of the system being studied. At a macro scale, neural network models may not be suitable to model the processes occurring. Given that neural networks can be considered to be universal approximators (Hornik et al. 1989), this should not be the case.

One aspect of the modelling process which could explain the neural networks inability to capture the influence of window opening is the use of early stopping. It was hypothesised that by using early stopping the training may have been halted before the models had captured all of the systems dynamics. To test this further models were developed without stopping the training early. A range of architectures were used, with between 10 and 200 hidden nodes. However, upon testing the models the control input still had no impact upon model output.

Another possibility is that the data upon which the model was trained was not informative enough to enable a suitable model to be developed. The lack of information concerning manual windows in Datasets A and B necessitated treating this as an unknown disturbance. This could have explained the inability to capture the effect of the window opening. However, in Dataset C all window openings were recorded and the models exhibited the

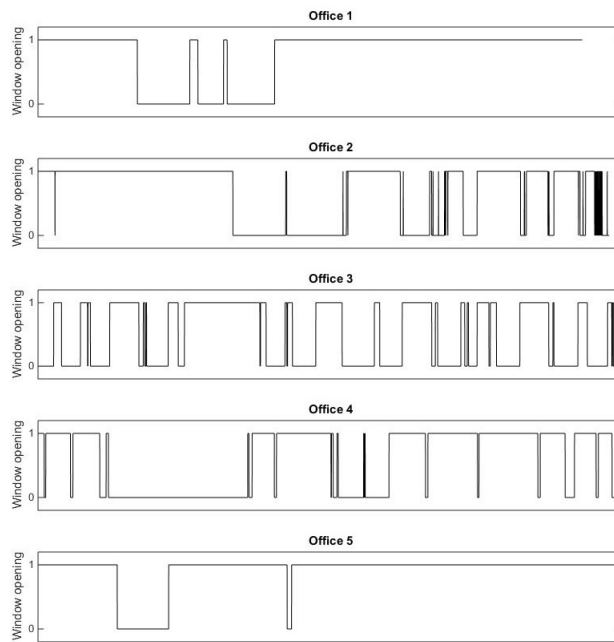


Figure 4.17: Plots showing the window opening inputs for all five office spaces in Dataset C during the summer month.

same behaviour.

By examining the input signals from Datasets A and B, it was found that the median position for all of the automated windows in the zones monitored is closed. In addition, the average time the windows were open was less than 6% during the observed period. While the windows being open for such a small percentage of time may have had an impact upon the indoor air quality it appears to have had an insufficient effect upon temperature to be captured by the models. In Dataset C windows were open for a significant amount of the observed period in the summer month. In Figure 4.17 it can be seen that, although the windows are open, there is little modulation. Some occupants opened windows upon entering and kept them open all day or in the case of office 1 and 5, kept them open for most of the observation period. Alongside the analysis of the neural network models developed, this suggests that if an empirical approach to modelling the thermodynamics of a naturally ventilated building is being taken, then collecting building data during normal operation is insufficient. In order for the models to capture the effect of inputs, an identification experiment may have to be carried out.

The inability of the models to capture the effect of the control input is most likely due to lack of sufficient input excitation, this is one of the common drawbacks when using data driven models (Shook et al., 2002), (Lauri et al., 2010). Buildings are typically operated within a tight range and the input is not persistently excited (Privara et al., 2011), (Cigler and Privara, 2010). This can lead to models which, while providing reasonable prediction capability, fail to capture underlying dynamics in essential physical relationships.

Although the models developed in this chapter are unsuitable for the purpose of MPC, there are other potential uses for accurate data driven models such as those developed in

this project. Previous studies have used empirical models for fault diagnosis (Lee et al., 2004), (Katipamula and Brambley, 2005) and to investigate potential overheating (Iddon et al., 2015). There could also be potential to incorporate a future temperature prediction within a traditional rule based control strategy.

4.8 Summary

In this chapter, the modelling process used to train neural network models has been described in detail. Models were developed that could make reasonable predictions for both internal temperature and CO₂ concentration. However, the effect of the control input, window opening, was not captured by the models. This is most likely due to lack of input excitation. In order to investigate how input excitation may be carried out in buildings the following chapter details the development of a dynamic simulation model which will be utilised to test a range operating conditions.

Chapter 5

Simulation Model

In the previous chapter neural network models were fitted to data obtained from real buildings. The resulting models were able to accurately predict the internal temperatures and CO₂ concentrations. However, the models did not capture the effect of the window opening percentage. This would make them unsuitable for an MPC approach to ventilation control.

In order to determine if the inability to capture the effect of the window opening percentage was caused by insufficient excitation a simulation model was developed. This model was based upon the school building described in Chapter 3. This allowed for testing of the relationship between control inputs and the resulting capabilities of the neural network models. In this chapter, justification is given for the choice of simulation tool and details of the building simulation model developed are given.

5.1 Building Performance Simulation Method Selection

5.1.1 Requirements

There are a range of tools/methods available to simulate ventilation performance. The ideal simulation tool will be able to do the following:

- The ability to simulate natural ventilation flows throughout a whole building as well as for individual spaces, taking into account the affect of varying the window opening.
- It must be possible to include different weather into the simulation.
- As well as outputting ventilation data such as flow rates and cooling due to ventilation; it would be preferable if the simulation can simultaneously calculate energy usage and thermal effects due to occupancy, building thermal mass, solar gains etc.
- Simulation time should be such that long periods (such as a year) can be simulated within a reasonable time given the computational resources available. The maximum

simulation time should be no more than a few days but ideally shorter to allow for a number of simulations to be carried out for different climates, occupancies, buildings etc.

- The stochastic nature of how occupants use buildings is something which is to be incorporated into the research, although it is unlikely that this will be a standard feature of many modelling methods ideally it should be possible to include this.

5.1.2 Summary of Potential Modelling Methods

There are a number of approaches for predicting ventilation performance, in this section a brief discussion of some of the most common is given.

5.1.3 Analytical Models

Analytical models are developed using the fundamental equations of fluid dynamics and heat transfer; depending upon the application some or all of the mass, energy, momentum and chemical species conservation equations are utilised. Developing usable analytical models typically requires simplifications in geometry or boundary conditions, this can mean that the equations developed can be quite different depending on the situation; although the methods used to obtain them are similar.

Analytical models have been used in a number of different ventilation studies, such as time dependant flows in displacement ventilation (Faure & Roux 2012); analysis of the effectiveness of wind catchers (Dehghan et al. 2013) and calculation of stack and wind driven ventilation in an office (Lepage & Irwin 1990).

In all of the previous studies the analytical models were validated using experimental modelling and generally the analytical models did show good correlation with the results from experiments. When considering a ventilation scenario, or building form which differs from those used to develop existing models some form of validation would be essential.

This type of modelling has been used extensively to study ventilation for a long time and is still used due to its simplicity and lack of requirement for extensive computational power. However, in complex ventilation scenarios, such as those frequently found in large naturally ventilated buildings, this type of modelling may be unreliable and the results inaccurate (Chen 2009). Although some researchers present analytical models in complex ventilation scenarios, such as Lomas (2007), the use of analytical models is more appropriate for use in initial design.

Analytical models are clearly a useful tool in ventilation modelling and can be used to generate time series data as in Faure & Roux (2012), who generated time series data for displacement ventilation. However, the complexities involved in deriving and using analytical equations are likely to make them unsuitable for this project.

5.1.4 Empirical Models

Empirical models are developed from the mass, energy and chemical species equations (Chen 2009). Empirical models are similar in their derivation to analytical models. However, empirical models use coefficients which are based on experimental measurements or computer simulation in order to make them applicable to specific scenarios (Chen 2009). This use of approximations makes the empirical models more generalisable to a range of scenarios than the analytical models which generally include case specific criteria in their derivation.

Empirical models are a widely used tool by engineers, where they are typically employed as a first estimate before carrying out more detailed calculations or simulations. They are commonly found in design guides (CIBSE 2015). Using coefficients such as those found in design guides allows empirical models to be applied to different scenarios easily although there is a sacrifice in the accuracy and usefulness of the results. However the presence of these equations within design guides is an indicator of the high degree of confidence in their reliability.

Empirical models have been used for ventilation studies for a long time, however they still appear in current research. For example, Wang & Chen (2012) developed an empirical model to predict the mean ventilation rate and fluctuating ventilation rate due to wind driven single sided ventilation and Haw et al. (2012) used empirical methods alongside CFD to investigate the performance of a wind-driven natural ventilation tower in hot climates.

5.1.5 Experimental Models

Experimental modelling of ventilation performance can be sub-divided into two categories: full-scale models and small-scale models.

Full-scale experimental models

Full-scale models have been used fairly extensively to study ventilation in buildings and in other scenarios such as ventilation and pollutant transport in aircraft cabins (Zhang et al. 2009). When applied to building ventilation full-scale models are typically carried out on-site in real buildings although less frequently full-scale mock-ups are purpose built in a laboratory setting.

Building a full-scale model of a building, or space within a building, in a laboratory environment is beyond the scope of this project, due to time and financial restraints. It is also far less flexible than many of the other approaches. For example, it is much more difficult to change the fabric or form of the space. Furthermore simulations would occur in real time. As this model is required for a preliminary investigation of identification procedures it is desirable to test multiple techniques over long periods. This could not be achieved in either a real building or laboratory mock up.

Small-scale experimental models

Small-scale models use a reduced scale of the room or building to predict the ventilation performance. Thermo-fluid conditions can be measured to give a realistic ventilation prediction if the flow is similar to reality. To ensure that the flows are similar to those in reality a number of dimensionless parameters must be kept the same. For isothermal flows dynamic similarity is maintained by matching the Reynolds number. However, for indoor air where buoyancy forces are also important the Prandtl number must also be kept the same.

By reducing the scale the cost is significantly reduced compared with the full-scale models. Small-scale models such as water baths and wind-tunnel experiments have been used extensively in the study of ventilation although their use is decreasing due to the advances being made in computer modelling techniques (Chen 2009, Linden et al. 1990). Small-scale experimental models have been used to study a number of ventilation problems; for example Chenvidyakarn & Woods (2007) investigated the stratification of temperature in transient natural ventilation of a warm room and the effect of pre-cooling using an acrylic tank filled with water.

The small-scale models overcome the issue of cost presented by full-scale modelling however they do struggle with complex geometry and could be unsuitable for studying complex building forms. Following a similar trend as with the full-scale models they are more commonly used now as a validation for analytical, empirical and numerical models (Chen 2009).

5.1.6 Multizone Models

Multizone models are most commonly used to investigate ventilation properties throughout an entire building and can be used in buildings which are naturally ventilated or which use mechanical systems. According to Chen (2009) *"the multizone models seem to be the only tool to obtain meaningful results for predicting ventilation performance in an entire building"*.

Buildings are subdivided into zones, typically rooms and results are calculated by solving the mass, energy and chemical species equations and by making the assumption that the properties of air within a zone are uniform. The effect of momentum can be removed as the multizone models assume still well mixed air within a zone. In some situations, such as in large spaces or where buoyancy is the main driver of the flow these assumptions can cause significant errors (Wang & Chen 2008). However, multizone models are still a commonly used tool, both in building design and research, predominately due to their ability to very quickly calculate ventilation performance values for entire buildings over long time periods. Additionally a number of multizone models are capable of modelling a range of other values related to buildings such as heating and cooling loads, lighting, water use etc. making them a very convenient tool for engineers and researchers.

Multizone models have been widely used to study a number of aspects of ventilation flows

such as airflow, pressure and contaminant distribution (Maatouk 2007), predicting particle distribution and airflows between zones due to difference in temperature (Sohn et al. 2007) and in a similar topic to this project, to validate advanced ventilation control methods generated using genetic algorithms (Congradac & Kulic 2009).

The multizone models appear to meet all of the criteria for this project, they can calculate results for long run periods in a short period of time, include energy and thermal calculations, calculate natural and mechanical ventilation, easily change weather data etc. The only concern with the multizone models is their ability to generate accurate data in certain situations, particularly when buoyancy is the main driver for flow (Wang & Chen 2008). In some situations commonly found in naturally ventilated buildings their use may not be suitable.

5.1.7 Zonal Models

The main assumption of the multizone models is that the air is well mixed, i.e. has the same properties at all points within a room. This assumption is not valid in a number of scenarios where the properties of the air (primarily temperature) varies significantly within a space. This is typically a problem in large spaces, high spaces such as atria and in buildings which use displacement ventilation. To overcome this problem zonal models can be used.

Zonal models split a space into a number of zones, this can be done in both two-dimensional and three-dimensional analysis, within these zones the well-mixed assumption is used.

Zonal models do overcome the major problem which could be encountered with multizone models however at present the models available are not capable of carrying out some of the additional project requirements such as simultaneous thermal and energy calculations. As such zonal models could still be utilised in this project but an additional tool would be required to calculate some of the required data.

5.1.8 Computational Fluid Dynamics (CFD)

Computational Fluid Dynamics (CFD) modelling numerically solves the fundamental partial differential equations for conservation of mass, momentum, turbulence and contaminant concentration. The simulations can provide a high level of detail for properties such as temperature, velocity, pressure and contaminant concentration throughout the modelled domain. The computational power and time taken to run these simulations can be very high. Additionally the results are highly dependant upon the user input to a much greater degree than say multizone models. As such obtaining reliable results requires an experienced user and/or further validation. Despite some of the issues with CFD models they are by far the most commonly used tool in ventilation performance prediction within the research community. In his survey of studies published in 2007, Chen (2009) found that CFD modelling accounted for 70% of the studies published within that year.

CFD modelling is particularly suited to studying natural ventilation for a number of

reasons, for example the changeable nature of the wind (in both direction and speed) can be hard to model by other methods particularly for buildings with complex geometries and as such CFD is often used to generate pressure coefficients for use in other models (Chen 2009). CFD can accurately model stratified environments, which is a shortcoming of the multizone, analytical and empirical models (although this can still cause difficulties with unsteady flows). This is demonstrated by Lau & Chen (2007), who used CFD to investigate the impact of number of diffusers, diffuser location, air exchange rate, occupant location, furniture arrangement, partition location, and arrangement of exhausts on indoor air quality in spaces with displacement ventilation.

The advantages in CFD modelling do come with a serious penalty in terms of time taken to run simulations. Transient simulations for entire buildings are not presently possible without extremely high computational resources.

5.1.9 Custom Methods, Coupled Models

All of the techniques described above have advantages, disadvantages and scenarios in which they are the most applicable. In some situations combining two different techniques can provide distinct advantages, most often in terms of accuracy and speed of simulation. A common coupling is that of CFD and multizone models. There are a number of scenarios where this is appropriate with the general advantages being the combination of the accuracy of CFD simulation and the reduced computing time of multizone modelling.

Wang & Chen (2007) used a coupled CFD and multizone model to predict internal airflows and contaminant distribution in buildings where momentum and buoyancy effects were strong, this is often the case when buildings have large internal spaces such as atria. Another common coupling is the combination of CFD and a multizone energy simulation to provide accurate simulation of ventilation and energy usage in naturally ventilated buildings (Wang & Wong 2008, 2007, Zhai & Chen 2005).

The examples given above used a custom coupling, i.e. combined two disparate software packages. This can be a complex and time consuming task to enable the two models to communicate between one another, however according to Chen (2009) it is a price which *“researchers seemed rather willing to pay”*. However the level of complexity involved in using coupled models for some applications is decreasing due to the number of packages which are introducing additional models which can be combined within the same software; for example ventilation and contaminant dispersal package CONTAM and a number of building energy calculation packages such as DesignBuilder (based on the DOE EnergyPlus simulation tool) and IES (Integrated Environmental Solutions Limited 2012) have now included CFD models which can be coupled with the existing multizone models.

5.1.10 Discussion of Suitability

The key requirement for the model to be used in this project is the ability to give a realistic prediction of the ventilation performance given a range of control inputs, over a

reasonably long simulation period. Generating such a large amount of data would not be easily accomplished using analytical or empirical models and as such they are unsuitable as the main tool for generating data. Experimental modelling or the use of a real building has the potential to generate the required information, however the costs involved make this option infeasible. Having demonstrated an identification procedure using simulation, the next logical step would be testing the methodology in a real building. However, the initial testing in a real building would be premature.

Of the remaining three disparate types of models investigated, multizone, zonal and CFD, all three have the potential to work for the purposes of this study. However, given that the aim of the modelling in this project is to generate data for year long time periods, CFD would not be the most suitable tool.

The multizone and zonal models have similar times for simulation, with multizone models able to obtain results for entire buildings over yearly run periods in a matter of minutes and zonal models not taking much longer (when run on a fairly standard modern desktop computer). As their computational and time requirements are very similar their other capabilities were closely examined to determine which method would be the most suitable. The main advantage of zonal models is their ability to more accurately simulate buoyancy driven ventilation flows. The multizone models on the other hand have the advantage that most have the built in capability to calculate a number of other criteria, of most interest to this project the thermal performance of the building and energy use. Having this ability within one tool would eliminate the need for a potentially complex coupling of software packages which would be necessary if using any of the zonal models currently available.

5.1.11 Conclusions

A thorough investigation of the types of modelling tools available has been carried out and based upon the project requirements, multizone modelling has been selected for use as the primary modelling tool to carry out the system identification experiment. In the following section, the specific tool chosen will be discussed.

5.2 EnergyPlus

The multizone simulation tool used in this project was EnergyPlus (EnergyPlus 2012*a*). EnergyPlus is an energy analysis and thermal load simulation program, based upon the BLAST (Building Loads Analysis and System Thermodynamics) and DOE-2 programs which were developed in the 1970s and 1980s as energy analysis tools for designers to size HVAC equipment, improve energy performance etc. (EnergyPlus 2012*b*). By using a user defined description of a building's geometry and construction, along with a description of any services and mechanical systems, EnergyPlus can calculate energy consumptions for heating and cooling, internal temperatures, ventilation flow rates and a number of other values.

There are a number of different multi-zone building ventilation modelling tools available. The capabilities of a number of tool were investigated before EnergyPlus was selected as being the most suitable. The following explains the main reasons for this selection and also highlights some of the shortcomings of EnergyPlus.

Advantages of EnergyPlus:

- As EnergyPlus's primary function is to serve as a whole building energy analysis tool, it carries out thermal and energy calculations alongside the ventilation calculations. Energy usage and the affect of thermal loads are often important elements in building ventilation studies, although this functionality is not included in all tools. For example CONTAM (Walton & Dols 2013), which is a popular multizone ventilation prediction tool, does not include this functionality but requires coupling with a thermal calculation engine such as TRNSYS (TRNSYS 2013).
- The EnergyPlus software is opensource. This is advantageous for a number of reasons, firstly it means that the software and all of its corresponding documentation is free but more importantly it is possible to develop the software and change functionality if this is required. As well as the ability to make changes to the software, the opensource nature of EnergyPlus also makes linking it to other tools a much easier process. This could be beneficial to this project, as it would allow EnergyPlus to be linked to other tools which have the ability to simulate more advanced control methods (Wetter 2011).
- The input files (.idf) are in ASCII text which can be created and read by the user (although this can be a time intensive process). The advantage of using a standard text format for input files is that it allows for third-party interfaces which can be tailored to specific applications using EnergyPlus as the simulation engine. This has resulted in a number of front-ends for which can be used to speed up the creation of EnergyPlus input files or to carry out specific calculations without having to deal with the complexities of creating .idf input files.

Disadvantages:

- Energyplus lacks a graphical user interface (GUI). Although this does not affect the results generated directly, it does make it easier for user errors to occur as well as increasing the time required to generate input files. This disadvantage has been largely mitigated by using DesignBuilder (DesignBuilder 2011) to create the building geometry and other aspects of the input file, before making finer adjustments using EnergyPlus's IDF Editor. DesignBuilder is a building simulation tool which runs on the EnergyPlus calculation engine. It's graphical interface makes creating building geometry, setting up simulations and obtaining results a much quicker and easier task than using EnergyPlus. However, DesignBuilder is much less flexible, both in terms of setting up more complex simulations and exporting all of the results which may be of interest. For this reason DesignBuilder will be used to save time

by generating a basic input file with the building geometry, which is then exported and fine-tuned within EnergyPlus.

- As is the case with all multizone models; situations where there is a non-uniform air temperature distribution cannot be accurately modelled. This can occur in large spaces such as atria and in displacement ventilation scenarios. To overcome this some multizone programs such as CONTAM have recently incorporated computational fluid dynamics (CFD) into the software (Walton & Dols 2013). This allows the user to specify zones in the model to be calculated using CFD methods, using the adjacent well-mixed zones as boundary conditions. The results are more accurate than those from a standalone multizone model without the computational time or resources increasing too drastically (as would be the case if CFD was used for all zone in a building). However, it is possible to link EnergyPlus to a separate CFD software (couplings of EnergyPlus and different CFD softwares has previously been achieved, for example Zhai et al. (2002)).

In this study no atria or high spaces with flow dominated by buoyancy are being modelling. Therefore one of the key disadvantages of EnergyPlus is negated. EnergyPlus has also been utilised in a number of studies investigating MPC of building systems. Being used as either the predictive model or as the plant model upon which control schemes are tested (Neto & Fiorelli 2008, Ruano et al. 2006).

5.2.1 EnergyPlus Modelling Overview

The EnergyPlus software can essentially be considered as a collection of a large number of individual modules. These modules are called upon, depending on the type of calculation being carried out, and collectively calculate energy consumption and other information. This is achieved by simulating the building including any plant systems when they are exposed to environmental and operating conditions. The core of the simulation is a model of the building based upon the fundamental heat balance principles (EnergyPlus 2012*a*).

As naturally ventilated buildings are the topic of this investigation, most of the calculations will be carried out by two of the three main blocks within the Integrated Solution Manager. Specifically the Surface Heat Balance Manager and the Air Heat Balance Manager. The Building Systems Simulation Manager will still be used in the calculation, to simulate any heating systems and other equipment such as lighting, but its primary function of simulating mechanical plant and air-conditioning will not be utilised. The critical module for natural ventilation calculations is the AirflowNetwork model. The thermal response of the building is also an important factor in this investigation. This is calculated using the Conductive Transfer Function (CTF) calculation module. This is briefly described in Appendix A.4. A detailed explanation of all the individual elements within the program is given in the extensive EnergyPlus documentation (EnergyPlus 2012*a*).

EnergyPlus calculates results using an integrated simulation. This means that all three major element, building, systems, and plant, are solved simultaneously. This is in contrast

to other programs such as BLAST or DOE-2, where the building zones, air handling systems, and other plant equipment are simulated sequentially with no feedback from one another (EnergyPlus 2012a). The starting point for the sequential simulation is the calculation of the zone conditions, using a zone heat balance, this then updates the zone conditions and determines any heating or cooling loads at all time steps. This information is then passed on to the air handling simulation, which determines the systems response; but this response does not affect zone conditions.

When utilising EnergyPlus for building energy simulation there are two ways of dealing with air exchange rates for natural ventilation, scheduled values can be used or values can be calculated at each time step. Scheduled ventilation rates can be specified by the user based upon typical values or from manual calculation however while this may be acceptable for some applications, such as during an initial design stage, calculated values are required in this study. The ventilation flow rates are calculated using the EnergyPlus Airflow Network.

The Airflow Network carries out calculations at each timestep. The flow rates are driven by pressure differences, due to temperature and wind. To begin the calculation the node pressures are determined using a linear approximation which relates airflow to pressure drop:

$$\dot{m}_i = C_i \rho (\Delta P_i / \mu) \quad (5.1)$$

where

\dot{m}_i = Air mass flow rate at the i_{th} linkage (kg/s)

C_i = Air mass flow coefficient (m^3)

ΔP_i = Pressure difference across the i_{th} linkage (Pa)

μ = Air viscosity (Pa·s)

A linkage model connects two nodes, an inlet and an outlet, these two nodes are linked by a linkage component. This could be a window, an air vent, a crack etc. It is the linkage component which gives the relationship between airflow and pressure. Bernouli's equation is used to calculate the pressure difference:

$$\Delta P = \left(P_n + \frac{\rho V_n^2}{2} \right) - \left(P_m + \frac{\rho V_m^2}{2} \right) + \rho g (z_n - z_m) \quad (5.2)$$

where

ΔP = Total pressure difference between nodes n and m (Pa)

P_n, P_m = Entry and exit static pressures (Pa)

V_n, V_m = Entry and exit airflow velocities (m/s)

ρ = Air density (kg/m^3)

g = Acceleration due to gravity (m/s^2)

z_n, z_m = Entry and exit elevations (m)

In a typical simulation there will be several nodes representing internal zones and the external conditions. These nodes can be connected by a range of linkage models to create a network. A more detailed description of the simulation procedure utilised by the AirflowNetwork can be found in Appendix A.

5.3 Model Creation

To create the dynamic thermal model of the building, EnergyPlus was used as the primary simulation program, with DesignBuilder used as a front end. This section provides detail on the modelling procedure used to develop a model which accurately represents the real building.

5.3.1 Model Geometry and Building Fabric

The model used in this study, was based upon one wing of the school previously discussed in Section 3.2. For the purposes of the identification experiment, only one zone within the space was considered (see Figure 5.1). By modelling only one wing of the building the results from the target zone are likely to be very similar to what they would have been had the entirety of the building been modelled but with a significant reduction in computational time and effort.

The zone being studied is a south facing junior school classroom on the first floor. Windows are a mixture of occupant controlled manual at low level and automated at high level, with external solar shading (Figure 5.2). The model geometry was generated in DesignBuilder and then exported to EnergyPlus for further development. The building model comprises two floors each of approximately 900m^2 , the studied zone is 25.5m^2 .

The simulation was carried out for a full year with a timestep of 10mins. This was the same timestep used for sampling data from the real building to train neural network models. This timestep is also the default recommended by the EnergyPlus documentation as longer intervals can cause errors (EnergyPlus 2012a).

The school was of a medium weight construction with a steel frame and concrete floor slabs. Some parts of the building were metal clad, however the wing being modelled had brick exterior walls. The exact specifications of the building are unknown. A reasonable determination was made through discussion with individuals responsible for managing the building services, analysis of plans and photographs, and knowledge of schools built during a similar period. Fine tuning of material choice, material thickness, airtightness etc. was carried out by analysing simulation output and comparison with data from the actual



Figure 5.1: Floor plan of the school building, the red area represents the wing modelled with the zone studied bordered in yellow.

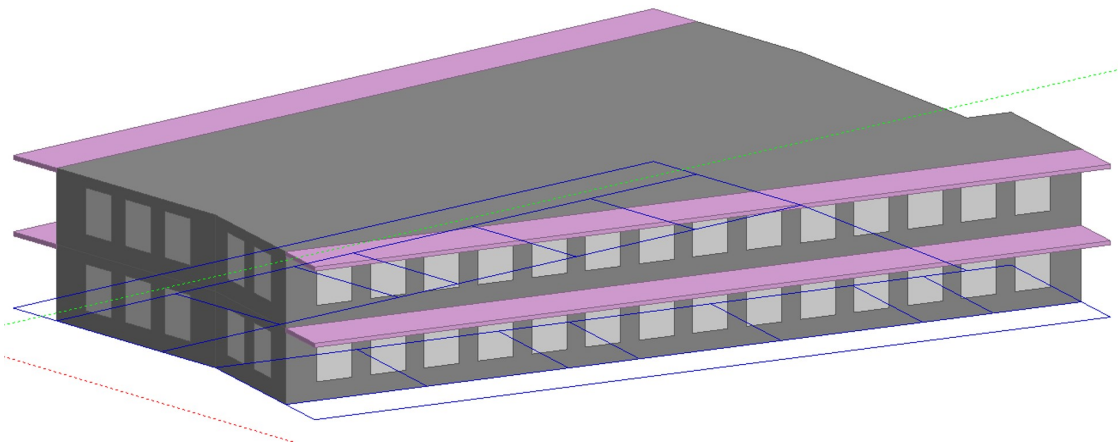


Figure 5.2: Whole building model view in DesignBuilder program. Surfaces coloured in pink represent standard component blocks which are used as shading surfaces.

Element	Constuction	Details	U-value W/m ² K
External Walls	Best practice wall	No. layers: 4 Outermost layer: Brickwork (0.105m) Layer 2: XPS Extruded Polystyrene (0.119m) Layer 3: Medium weight concrete block (0.1m) Innermost layer: Gypsum Plastering (0.013m)	0.250
Ground Floor	Part L2 2010 Notional ground floor, medium weight	No. layers: 4 Outermost layer: Urea Formaldehyde foam (0.1545m) Layer 2: Cast concrete (0.1m) Layer 3: Floor Screed (0.1m) Innermost layer: Flooring (0.03m)	0.220
Internal Floor	Concrete slab	No. layers: 4 Outermost layer: Flooring screed (0.05m) Layer 2: Cast concrete (0.15m) Layer 3: Services void (0.4m) Innermost layer: Ceiling tile (0.015m)	1.191
Internal Partitions	Lightweight plasterboard	No. layers: 3 Outermost layer: Gypsum Plasterboard (0.025m) Layer 2: Air gap (0.1m) Innermost layer: Gypsum Plasterboard (0.025m)	1.923
Roof	Flat roof concrete deck	No. layers: 5 Outermost layer: Gravel (0.013m) Layer 2: Asphalt (0.019m) Layer 3: EPS (0.05m) Layer 4: Concrete (0.15m) Innermost layer: Plaster (0.013m)	0.640
Glazing	Part L2 Notional Glazing	Double glazed, clear glass with 13mm gap	1.978

Table 5.1: Details of construction used for main building elements.

building. The final specification for the construction materials is given in Table 5.1 and airtightness in Table 5.2.

5.3.2 Heating and Internal Heat Gains

The heating in the simulation model was specified as hot water radiator heating provided by a natural gas boiler. In the real building binary data were available to indicate if the heating was on or off. By examining these data it was possible to determine the control logic. During winter months heating was typically only used to preheat the space on the morning before the classroom was occupied and in some cases remained on for a short period while the space was occupied. In all but the coldest months, this was typically only required for the Monday or Tuesday mornings.

Element	Flow Coefficient kg/s.m @ 1Pa	Flow Exponent
Windows	0.000060	0.70
Internal Doors	0.020000	0.70
External Doors	0.000600	0.70
Internal Walls	0.002000	0.75
External Walls	0.000040	0.70
Internal Floors	0.000300	0.70
Ground Floor	0.000300	1.00
Roof	0.000030	0.70

Table 5.2: Airtightness values used for cracks. Values for individual elements assume a good level of construction and airtightness.

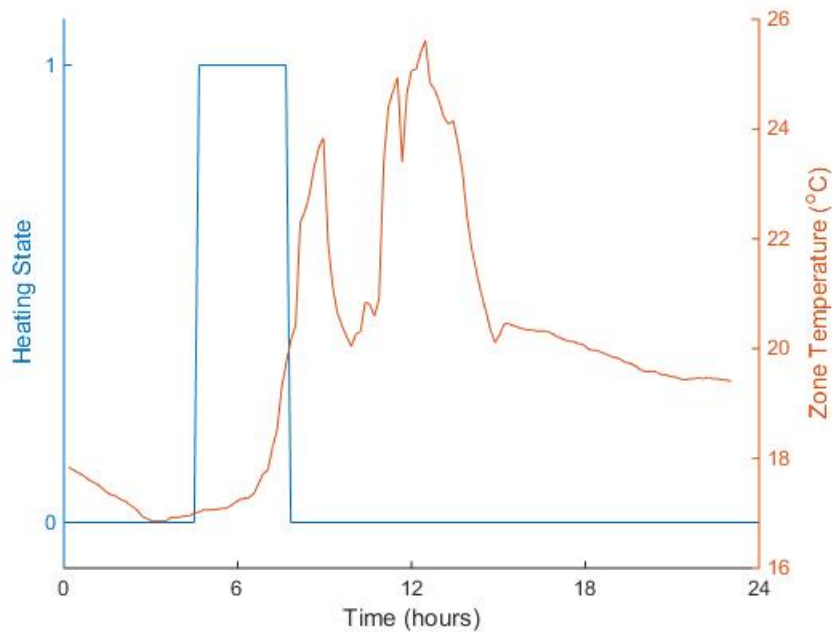


Figure 5.3: Zone heating and temperature for 24 hours in February.

Figure 5.3 shows the zone temperature and heating state for Monday 10th February 2014. Despite the zone temperature dropping cooler during the night, the heating turns on at 5am when the zone temperature is 17 °C and turns off when the temperature reaches 18.5 °C. This suggests that the heating is only allowed to be on from 5am and that 18.5 °C is the heating setpoint. This was confirmed by analysis of data over the winter period for several zones.

Based upon this analysis the heating setpoint temperature in the simulation model was defined as 18.5 °C. This setpoint is valid for occupied days between 5am and 6pm. A heating set back of 5 °C was also specified. This is to provide a low level of heating during unoccupied periods to prevent problems such as condensation, frost damage etc.

Internal Gains

Internal gains from occupants, lighting and computers and other equipment were included in the simulation model. Occupants represent a significant heat gain within the space. Based upon an assumed activity level including standing, walking and light office work a metabolic rate of 130 W/person was assumed (CIBSE 2015). To account for the majority of the occupants being children this was multiplied by a factor of 0.75. To calculate the total heat gains from occupants the EnergyPlus simulation uses the occupancy schedule (discussed in Section 5.3.3 to determine the number of occupants and then multiplies by the metabolic rate.

No specific information was available regarding lighting type or energy usage in the real building. In the simulation model, lighting was specified as surface mounted ceiling lights with no task lighting. The lighting energy was based upon a typical energy usage of 12 W/m² (CIBSE 2015). Again, for computers and other equipment no specific information was known. Therefore, the benchmark allowance given in CIBSE (2015), for education teaching spaces of 10 W/m² was used. Both lighting and equipment loads were assumed to be constant throughout occupied periods.

5.3.3 Occupancy Levels

Occupancy schedules are an important element in thermal simulation as occupants are one of the major sources of heat gains within the space. Determining a reasonably accurate schedule for when a zone is occupied can also inform schedules for other internal heat gains such as lighting and other internal zone equipment such as computers.

When obtaining the building data, only limited, and often anecdotal, information was available relating to occupancy patterns and how the spaces were being used. Therefore, in order to attempt to fully understand how the space is being used the building data was examined. The data logged by the BMS system gives an insight into the occupancy patterns. A number of studies have investigated using environmental variables for occupancy detection in offices and other spaces (Lam et al. 2009, Liao & Barooah 2010, Mumma 2004). These studies have shown that CO₂ concentration can provide the best information for occupancy levels. Some studies such as Ansanay-Alex (2013), propose relatively simple formulae to determine occupant numbers based upon sensor readings of CO₂ concentration, volume of the space and ventilation rate. However, in this case the ventilation rate is unknown. Therefore a more qualitative approach was taken to determine occupancy patterns.

Determining occupancy patterns in relation to school holidays and unoccupied days is a relatively simple task. Constant low CO₂ concentration was the most obvious sign of inactivity within a space. In some cases, temperature could also be used to suggest that the space was unoccupied, however it is much harder to separate internal gains caused by occupants from solar radiation. For example, in Figure 5.4 the final two days shown represent the weekend. During these two days the internal temperature remains relatively

constant in contrast to the rise of temperatures observed during the preceding weekdays. However, at different times of the year, particularly during the summer months, (this data is from a south facing zone) there was an increase in internal temperature throughout the day on weekends which followed a similar pattern to the increase in temperatures observed during occupied periods.

The internal conditions also allow for an approximation to be made about occupancy at a much finer scale. CO₂ concentration, in particular, can be quite informative. As can be seen in Figure 5.4 there are sudden drops in CO₂ concentration at similar times during week days, typically around 11am and 1pm. This information allowed for an approximation of times when the classroom is unoccupied. CO₂ concentration was found to be much more informative than internal temperature as the rate of change is more extreme. Even when windows were open during occupied periods the CO₂ concentration was observed to continue to increase. Hence, the sudden purges which occur are most likely explained by an exodus of occupants. By examining the building data in this manner, occupancy schedules, such as the one shown in Figure 5.5, could be created for individual zones that give a reasonable representation of their usage. The schedule occupancy values are multiplied by the maximum occupancy density to give the number of occupants at a given time.

5.3.4 Weather

When using building simulation tools such as EnergyPlus for design, typical weather data for the given location would normally be used. However, in this case the simulation model needs calibrating to an existing building. For this purpose actual meteorological data is required. To achieve this a custom EnergyPlus Weather Format file (EPW) was created, using a design typical weather file as a template. The design file was converted from EPW to CSV to allow for easy editing in spreadsheet format. The design weather data were then replaced with observed weather data. The file was then converted back into EPW format to allow for use in the simulation.

The weather station on the building itself recorded the temperature, wind speed, wind direction and relative humidity. For these variables it was possible to simply extract values at the required timestep and copy them into the weather file. However, not all of the required variables were recorded by the weather station. Solar radiation can have a significant impact upon internal conditions. Unfortunately it was not collected by the weather station on the building. In this situation there was a number of options:

1. Retain solar radiation values from the design weather file.
2. Calculate approximate values for solar radiation. For example, using the equations proposed by Hargreaves & Samani (1982), whereby solar radiation can be estimated based upon temperature difference.
3. Obtain solar radiation data from a nearby weather station.

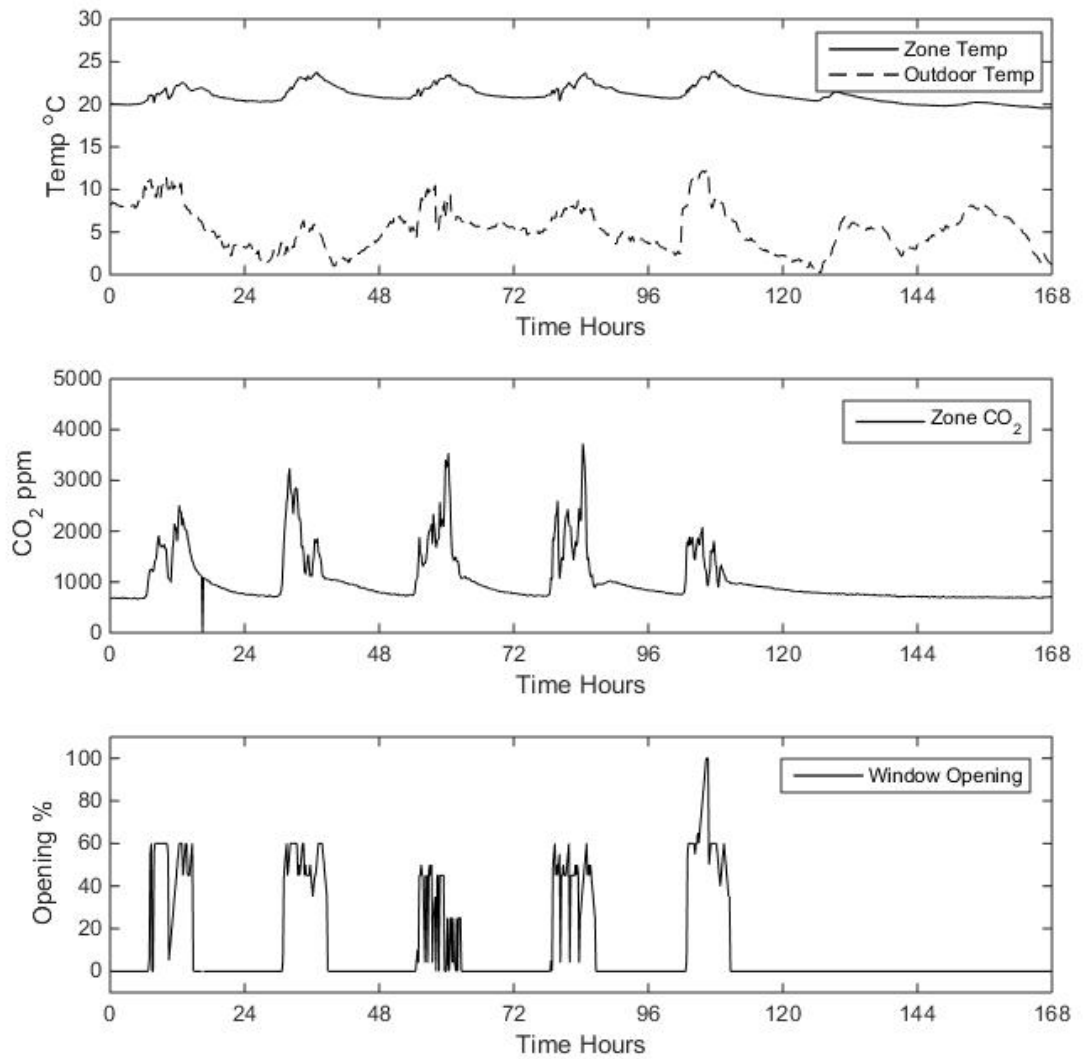


Figure 5.4: Internal zone conditions were used to determine occupancy patterns.

```

For: Weekdays,
Until: 08:00, 0,
Until: 08:30, 0.1,
Until: 09:00, 0.2,
Until: 11:00, 1,
Until: 11:20, 0.1
Until: 13:00, 1,
Until: 14:00, 0.1,
Until: 16:00, 1,
Until: 18:00, 0.1,
Until: 24:00, 0,
For: Weekends,
Until: 24:00, 0,
For: Holidays,
Until: 24:00, 0,

```

Figure 5.5: Example occupancy schedule for classroom for weekday, holidays and weekends. Occupancy density was based upon 30 pupils and one adult teacher. The zone occupancy at any given timestep is calculated by multiplying the value in the schedule by the maximum occupancy density.

Combining observed meteorological data with the synthetic data in the design weather file would likely lead to unrealistic results and as such was discounted. The use of empirical equations to calculate solar radiation has been shown to yield reasonable results (Hargreaves & Samani 1982), in the absence of data available from another weather station this method would be utilised. However, the ideal situation would be recorded data from a nearby weather station. In this case the closest weather station with the capability to record irradiation data was located just under 20 miles from the school building. Access to the data from this weather station was through the Meteonorm software (Meteotest 2016). With this package it is possible to use interpolation to attempt to improve accuracy of the data for a specific location but with the weather station being located relatively close to the school building this was not deemed necessary.

The ideal situation would be if the building weather station had the capability to record all of the required variables. However, the solution of incorporating data from another weather station was found to be acceptable. By doing so a custom weather file was created combining data from the weather station on the building itself and the nearby station.

5.3.5 Control of Windows

The windows in the school building are a combination of manual occupant controlled windows at low level and automated windows at high level. In the real building, the control of the automated windows is determined by setpoints for both internal temperature and CO₂ concentration.

In a typical EnergyPlus simulation of a naturally ventilated space, openable windows (both manual and automated) are opened if: $T_{ZONE} > T_{OUT}$ **and** $T_{ZONE} > T_{SET}$ **and** the Venting Availability Schedule allows venting. The Venting Availability Schedule is

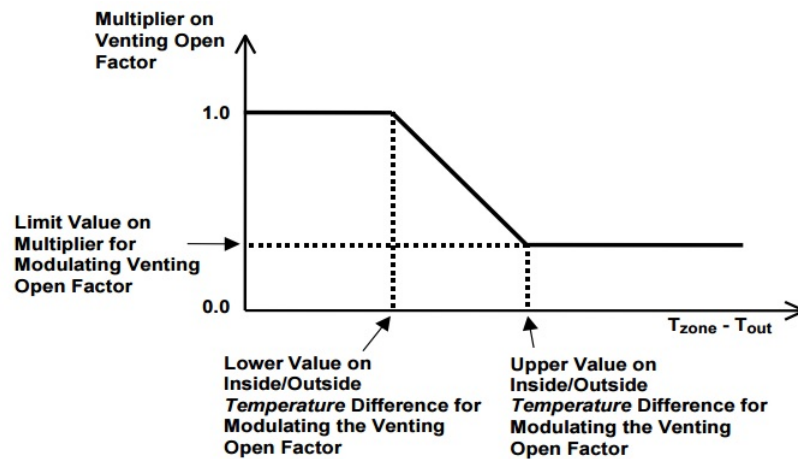


Figure 5.6: In a typical EnergyPlus simulation the modulation of window opening is determined according to inside-outside temperature difference (EnergyPlus 2012a).

used to define times during which windows can and cannot be opened. For example, this could be used to prevent windows from opening during unoccupied periods if there were security concerns. Should the aforementioned criteria be met then the windows will open. The percentage opening (or Venting Opening Factor) is then determined based upon temperature differences between the internal environment and the outdoor ambient temperature, as shown in Figure 5.6. Ventilation can be controlled using enthalpy in place of temperature however the methodology is the same (EnergyPlus 2012a). Alternatively, window opening can be controlled taking into account adaptive comfort instead of a fixed setpoint. Using either ASHRAE55 or CEN15251, the window will open if the zone temperature is greater than the comfort temperature (central line) calculated using either of the mentioned standards and if the Venting Availability Schedule allows venting. Again, the percentage opening of the window will be determined based upon the differences between the internal environment and the outdoor ambient temperature.

For most simulation applications the standard methods for controlling window opening are adequate. However, in this project a greater level of control is required, which more accurately represents the control in the actual building. To achieve this window actuator elements were defined, which could then be controlled using EnergyPlus’s Energy Management System (EMS). The EMS feature allows the user to develop custom control and modelling routines for EnergyPlus models. The EMS provides high level control which can override the default simulation controls (EnergyPlus 2012a). Through the use of the EMS a greater level of flexibility for window control is achieved.

5.3.6 Automated Windows

When initially creating and validating the EnergyPlus model, the use of window actuators and EMS code enabled the windows to be controlled in a similar manner to the real building using setpoints for both internal temperature and CO_2 concentration to determine the window opening percentage. This gave a more realistic output compared to standard sim-

ulation methods, whereby the opening percentage is modulated based upon temperature difference. This output could then be used as a control data set, to determine if simulation data is intrinsically easier to model using neural networks (see Section 6.3.1).

After validating the model, the EMS code used to control window openings in a realistic manner is removed. The actuator components can then be controlled using external software applications. This allowed the window opening percentage to be controlled in the excitation experiment described in Chapter 6.

5.3.7 Manual Windows

Occupant controlled windows are treated as an unmeasured disturbance during the neural network modelling. This is to replicate the scenario with the real building data, whereby information relating to occupant controlled windows was unavailable.

In typical use of EnergyPlus for design applications all windows would be opened proportionally based upon the temperature difference between the inside of the building and the outdoor temperature (described in Section 5.3.5). However, this does not represent the case in a real building, whereby occupant window opening is more stochastic. In an attempt to incorporate a more realistic model of occupant use of windows, the ‘‘Humphreys Algorithm’’ was implemented using EnergyPlus EMS code. This algorithm was developed based upon field studies in a free running office environment by Rijal et al. (2008). It has previously been utilised to simulate occupant window usage in a study on MPC of mixed-mode buildings by May-Ostendorp et al. (2011).

The window opening algorithm makes use of adaptive comfort standards (CIBSE 2013). The first step is to calculate the weighted running mean outdoor temperature for the current day, T_{rm} . This is done using the following equation (CIBSE 2013):

$$T_{rm} = (1 - \alpha_{rm})[T_{e(d-1)} + \alpha_{rm}T_{e(d-2)} + \alpha_{rm}^2T_{e(d-3)} + \dots] \quad (5.3)$$

Where α_{rm} is a constant which defines the rate at which the running mean responds to outdoor temperature (recommended value of 0.8), $T_{e(d-1)}$ is the daily mean outdoor temperature in °C for the previous day and $T_{e(d-2)}$ is for the day before that, etc.

Using T_{rm} , the comfort temperature, T_{comf} , can be calculated:

$$\text{for } T_{rm} > 10 : \quad T_{comf} = 0.33T_{rm} + 18.8 \quad (5.4)$$

$$\text{for } T_{rm} \leq 10 : \quad T_{comf} = 0.09T_{rm} + 26.6 \quad (5.5)$$

To define if occupants are either too hot or too cold a zone of ± 2 K either side of the comfort temperature is used (Rijal et al. 2007). If the internal temperature, T_{ai} , is within this range the occupants are assumed to be comfortable, below it and occupants are ‘‘cold’’

while above they are “hot”. If occupants are either too hot or too cold, equation 5.6 is used to determine the probability that they will either open or close the window.

$$\log\left(\frac{p}{1-p}\right) = 0.171T_{ai} + 0.166T_{ao} - 6.4 \quad (5.6)$$

Where p is the probability that the window will be either opened (when occupants are too hot) or closed (when occupants are too cold), T_{ai} is the indoor air temperature ($^{\circ}\text{C}$) and T_{ao} is the outdoor air temperature ($^{\circ}\text{C}$). EMS sensor objects were used to obtain both T_{ai} and T_{ao} at each timestep.

Having calculated the probability that a window will be either opened or closed, a random number between 0 and 1 was generated using the EMS “@RandomUniform” function. This function returns a uniformly distributed pseudo random number between the specified bounds. If p_w was greater than the random number, then the window state was changed (i.e. opened if occupants were too hot, or closed if occupants were too cold).

Initial simulations considered that all manual windows would open and close together. However, this is likely an oversimplification. Therefore, the process was then repeated for each individual window. This method was also used by Dutton et al. (2012), who demonstrated that it gave a reasonable representation of window usage in an office environment.

It is not clear if the algorithm for window opening behaviour developed by Rijal et al. (2008) is strictly applicable to different building types other than those used for its initial derivation. Ideally models for occupant window opening behaviour would be determined for each type of space. Dutton et al. (2012) suggest that models should be derived for different types of office space, such as large open plan, private offices etc. In this study the algorithm by Rijal et al. (2008) is being used in a classroom. The behaviour of occupants in a classroom may be significantly different than occupants in the offices which were observed to derive the algorithm. The algorithm is also limited to predicting window opening behaviour based upon the occupants thermal comfort, i.e. occupants only take action if they are either too hot or too cold. This does not take into account behaviour which has been observed in some studies, such as occupants who open windows upon entering a space over a wide range of temperatures and occupants who never open windows (Dutton et al. 2012). Despite the potential shortcomings the inclusion of a stochastic model for window opening behaviour was deemed essential to improve the realism of the building simulation model. Primarily because this provides a more significant disturbance for the neural network models to deal with.

5.3.8 Model Validation

Developing a dynamic thermal model which provides a realistic representation of a real building can be a difficult task. This was the overriding justification for the use of an empirical, neural network approach to MPC presented in this thesis. In the previous sections the steps taken to develop the EnergyPlus model have been described. Throughout the model development an iterative process of comparing EnergyPlus output to observed data

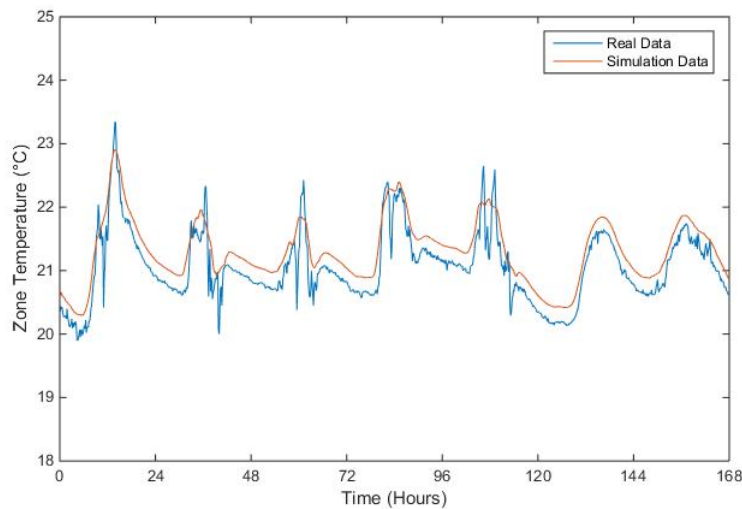


Figure 5.7: Comparison of measured internal temperatures from the real school building with EnergyPlus simulation data.

and adjusting the simulation model was carried out. The aim being, to develop a model which gave a reasonable prediction for internal conditions for the single zone of interest.

The final model gave reasonable performance and reacted in a similar manner to the real building. Comparing the zone temperature output from the EnergyPlus model to observed data gave a mean absolute percentage error of 2.79%. As the average temperature observed in the real building was around 21 °C, this equates to around an average error of approximately 0.5 °C. Figure 5.7 shows a typical occupied week. It can be seen that the simulation data reasonably tracks the observed data.

5.4 Summary

In this chapter a building simulation model was developed to enable testing of input excitation methods. A variety of simulation methods was investigated, before selecting a multizone method using EnergyPlus. The process of creating the simulation model has been described. This was a lengthy process, involving the inclusion of non-standard simulation techniques such as EMS control of windows, an occupant window opening model and a custom weather file. The final model was capable of accurately representing the target zone in the real building.

Chapter 6

System Identification

In Chapter 4 neural network models were fitted to data obtained from real buildings. The resulting models were able to accurately predict the internal temperatures and CO₂ concentrations. However, the models did not capture the effect of the window opening percentage. This would make them unsuitable for an MPC approach to ventilation control. In this chapter an excitation experiment is carried out, using the building simulation model developed in Chapter 5, to determine if lack of sufficient excitation is responsible for the previously developed models failure to capture the effect of the window opening.

6.1 Introduction

In Section 4.7 the inability of the neural network models to capture the effect of the window opening percentage was discussed. There were a number of possible reasons that could explain the models deficiency. These are summarised below:

- The procedure used to train the model was not appropriate.
- The model structure was not suitable to provide a good enough description of the system being modelled.
- The data set upon which the model was trained was not informative enough to enable a suitable model to be developed.

Through analysis of the input data it was determined that the final point is the most likely cause of the model's deficiency. In this chapter an identification experiment is carried out to confirm this.

Ljung (1999) describes system identification as dealing with: *“the problem of building mathematical models of dynamic systems based upon observed data from the system”*. This can incorporate a number of different activities. Figure 6.1 summarises the identification procedures. This can be an iterative process, informed by prior knowledge and

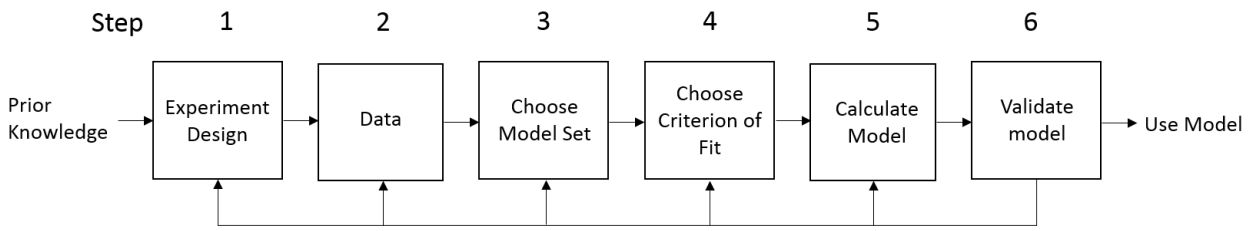


Figure 6.1: The system identification loop. System identification is often an iterative process and can involve repeating a number of steps should developed models prove unsuitable (adapted from (Ljung 1999)).

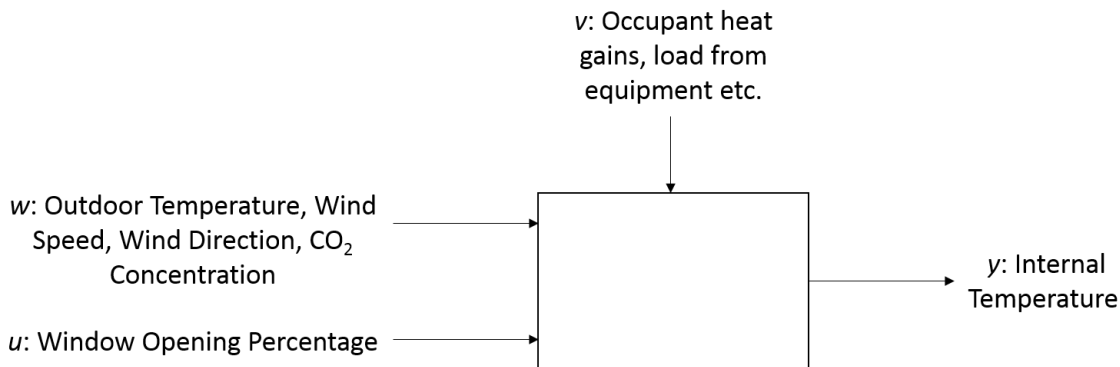


Figure 6.2: A representation of the system being investigated with output y , inputs u , measured disturbances w , and unmeasured disturbances v . Models were generated for both internal temperature as the desired output and CO_2 concentration.

the results of previous modelling results. In the first half of this thesis, the system identification carried out was focussed upon stages 2-6, collection of data and system modelling. Experiment design was not a factor as data was collected from buildings during their normal operation and it was not possible to have any influence upon how they were being controlled.

In this chapter, the focus is primarily upon step 1 of the system identification procedure, experiment design. Figures 6.2 describe the system being studied in this project. The goal is to develop models which can accurately predict the desired outputs (Internal Temperature and CO_2 Concentration) based upon observations of the measured disturbances, previous outputs and the control input (Window Opening Percentage). In order to generate informative data it is necessary to persistently excite the input signal, i.e. the window opening percentage.

When formulating this identification experiment there were three possible approaches which could have been taken. The experiment could have been carried out i) on a real occupied building in a similar manner to Cigler & Prvara (2010), ii) using an experimental setup, or iii) using dynamic thermal simulation (Prívvara et al. 2011). For this investigation, dynamic thermal simulation was chosen as being the most appropriate method. By using simulation in place of a real building or experimental setup results can be obtained quickly for a long simulation period. This allows for the experiment to be carried out using a range of weather conditions, in addition to allowing full control of the building form

and occupancy patterns. A detailed breakdown of the techniques used to develop the dynamic thermal model has been given in the previous chapter. Upon generating data, the procedure used to train and validate the neural network models was carried out using the same method as presented in Chapter 4, the only alteration is the input data.

6.2 Methodology

In this chapter an open-loop identification experiment is carried out using the EnergyPlus model developed in Chapter 5. The window opening control is excited in order to generate data from which neural network models can be trained. These models are then tested to determine if the effect of the window opening control has been captured.

6.2.1 Linking MATLAB and EnergyPlus

In the previous chapter, the modelling strategy carried out using DesignBuilder and EnergyPlus was outlined. In order to efficiently carry out an identification experiment it was necessary to link EnergyPlus with the MATLAB environment. By linking the two software packages the Matlab environment and toolboxes such as the Optimization Toolbox, System Identification Toolbox and Model Predictive Control Toolbox can be utilised. Directly linking MATLAB and EnergyPlus is possible, however it would require a considerable amount of time and effort for even the most experienced user (Bernal et al. 2012).

MLE+ was used as a front end to link the two software packages. MLE+ can be used as a graphical front-end for exchange of input and output variables between EnergyPlus and MATLAB/Simulink (Bernal et al. 2012). In this experiment, input variables are generated in MATLAB and communicated with EnergyPlus at each 10 minute timestep for a full year of simulation. Using co-simulation in this manner could be considered to be unnecessarily complex. However, setting up the identification experiment in this manner allowed for the same models to be used to test control strategies (see Chapter 7).

6.2.2 Open vs Closed-Loop Methods

In this project, an open-loop system identification experiment is carried out. Open-loop system identification, refers to identification carried out without output feedback. As a first step, open-loop system identification is often the logical choice as it is more likely to sufficiently excite the system and result in models which capture the underlying dynamics (Ljung 1999). Open-loop identification has been demonstrated in buildings by Aswani et al. (2012), Ferreira et al. (2012). However, in some cases it is not possible to carry out an open-loop identification. Factors such as unstable plant, operational constraints or safety reasons may necessitate the use of a closed-loop methodology. In the specific case of buildings, open-loop identification may cause conditions which occupants may find uncomfortable and/or result in increasing energy costs.

By using dynamic thermal simulation the potential problems with open-loop identification are avoided. The use of simulation allows for the building to be pushed beyond the constraints of occupant comfort which would exist in a real building and as such allows for the identification to be carried out without output feedback. Given the large range of temperatures which resulted from the open-loop identification using simulation, in an occupied building, feedback control and a closed-loop identification may be necessary.

One approach which could be applicable to buildings, is to operate the building under sub-optimal control using a basic model, and then carry out a closed-loop identification to produce an updated model. The sub-optimal control could be using a buildings existing control logic or MPC with an approximate system model. While operating under this control an excitation signal could be used to excite the system modes. However, closed-loop control can be difficult as the feedback control will treat the excitation signal as a disturbance and attempt to correct the system response (Rockett & Hathway 2016). Usually, closed-loop identification is carried out using a noise signal which is uncorrelated to the disturbance to minimally disturb the process (Genceli & Nikolaou 1996, Rathouský & Havlena 2013).

6.2.3 Input Signal Selection

In order to obtain data which are sufficiently informative the input signal for an open loop experiment should be persistently exciting of a certain order; i.e. it should contain adequately many distinct frequencies (Ljung 1999). This is a somewhat general requirement and leaves a large amount of freedom on input signal choice. Typical input signals used in system identification are summarised below:

Gaussian White Noise (GWN) is a series of normally distributed uncorrelated random variables with zero mean. GWN is often used as excitation in identification experiments (Nowak 2002). If a system is subjected to a GWN stimulus over a sufficiently long enough time, there is a finite probability that any given stimulus waveform will be approximately represented by some sample of the GWN signal. Essentially, the system is being tested with every possible stimulus, or at least a large variety depending on the period over which the experiment is being carried out (Marmarelis 2012). However, the amplitude of GWN is theoretically unbounded making it unsuitable in a number of applications.

Filtered Gaussian White Noise is GWN which has been passed through a linear filter. Choice of filter allows for virtually any signal spectrum (Ljung 1999). To overcome the problem presented by GWN being unbounded, the signal has to be clipped at a certain amplitude.

Random Binary Signal is a process which assumes only two values. According to Ljung (1999) the most common way to generate a random binary signal is to generate GWN, filter through an a linear filter and then take the sign of the filtered signal.

When choosing the input signal for this experiment random binary signal was immediately discounted as in this case the response of the system across the entire range of possible

opening positions is required, not just the fully open or closed conditions. In EnergyPlus the percentage of window opening is determined by the window opening factor, which is a value between 0 and 1, where 0 is fully closed and 1 is fully open. A typical controller may allow for window positions at 10% steps between full closed and fully open. To achieve a suitable input signal that has a random distribution of values, with values at intervals of 0.1, filtered Gaussian white noise was initially generated. By then translating this signal a normal distribution of random variables with a mean of approximately 0.5 was achieved. An example of the normally distributed input signal is shown in Figures 6.3 and 6.4.

In a number of applications, a normal distribution is often the most suitable with components which typically operate close to the middle of their range. However, based upon prior knowledge of natural ventilation systems and how they are used in practice, it could be argued that there is no particular inclination towards the window operating close to the middle of their range. For this reason a uniformly distributed random signal was generated (Figures 6.3 and 6.4). Data will be generated using both the normal and uniform distributions and the results compared. Uniformly distributed random signals have been shown to be successful in open-loop identification of the cooling capacity of an AC system (Aswani et al. 2012). The normally distributed signal was primarily tested to determine the degree to which input signal choice impacts upon the success of the identification procedure. Other signal types such as multilevel pseudo-random binary signals can also be used for identifying non-linear systems, as demonstrated by Ferreira et al. (2012).

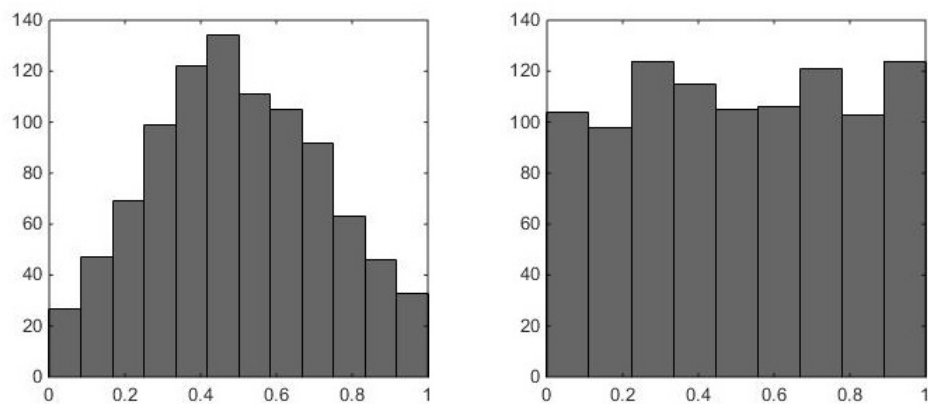


Figure 6.3: Histograms showing the chosen input signals, left normally distributed noise and right (approximately) uniformly distributed noise.

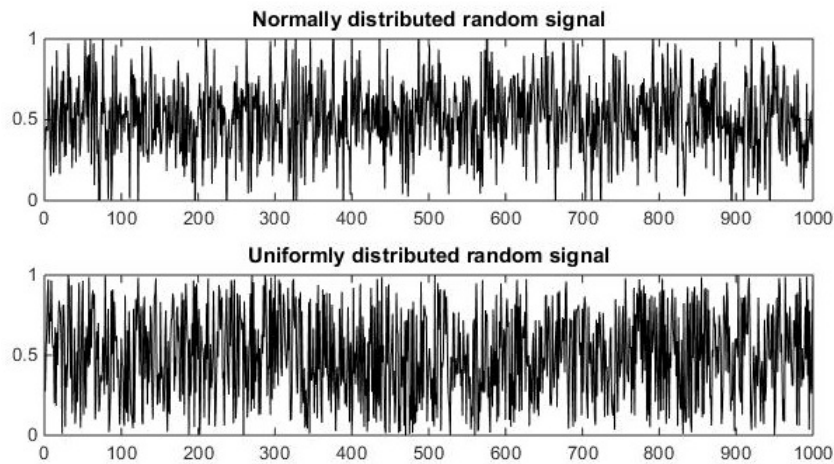


Figure 6.4: Line plots showing the chosen input signals, top normally distributed noise and below uniformly distributed noise.

6.3 Identification Results

The EnergyPlus model was simulated for a full year using the excitation signals to control the automated windows. The data from these simulations were then used to train neural network models.

The models developed using the data generated through simulation as part of the system identification experiment had a similar performance to the models created using real building data in Chapter 4. The same performance criteria (see Section 4.6.1) were used to evaluate the models, the results are summarized in Tables 6.1 - 6.4. As would be expected prediction performance decreased over longer prediction horizons for both temperature and CO₂. However, both the predictions of temperature and CO₂ concentration gave reasonable predictions.

A typical week of predictions for both temperature and CO₂ concentration are shown in Figures 6.5 and 6.6. Larger errors were observed in model predictions for temperature during unoccupied periods. This is similar behaviour to that observed in models generated using the real building data in Chapter 4. In Figure 6.6, it can be observed that over the weekend (last 48 hours on the plot) even the one-step-ahead predictions for temperature deviate more significantly than during the week.

Number of steps ahead	Mean Absolute Error	Standard Absolute Error	Mean Absolute Percentage Error	Standard Deviation of Absolute Percentage Error
1	0.388	0.327	3.33	4.04
10	1.260	0.936	11.11	12.18
20	2.050	1.615	17.03	16.50

Table 6.1: Temperature prediction performance of the neural network models generated using uniformly distributed input signal for one-step-ahead prediction, $n=10$ and $n=20$.

Number of steps ahead	Mean Absolute Error	Standard Absolute Error	Mean Absolute Percentage Error	Standard Deviation of Absolute Percentage Error
1	0.650	0.134	3.639	6.86
10	1.398	0.945	7.028	9.11
20	2.078	1.237	11.135	11.03

Table 6.2: Temperature prediction performance of the neural network models generated using normally distributed input signal for one-step-ahead prediction, $n=10$ and $n=20$.

Number of steps ahead	Mean Absolute Error	Standard Absolute Error	Mean Absolute Percentage Error	Standard Deviation of Absolute Percentage Error
1	8.387	12.930	1.26	1.68
10	45.829	56.565	7.82	7.91
20	93.506	84.300	16.81	11.12

Table 6.3: CO₂ prediction performance of the neural network models generated using uniformly distributed input signal for one-step-ahead prediction, $n=10$ and $n=20$.

Number of steps ahead	Mean Absolute Error	Standard Absolute Error	Mean Absolute Percentage Error	Standard Deviation of Absolute Percentage Error
1	9.009	13.180	1.41	1.95
10	49.905	59.082	8.15	8.33
20	89.488	83.725	16.62	11.02

Table 6.4: CO₂ prediction performance of the neural network models generated using normally distributed input signal for one-step-ahead prediction, $n=10$ and $n=20$.

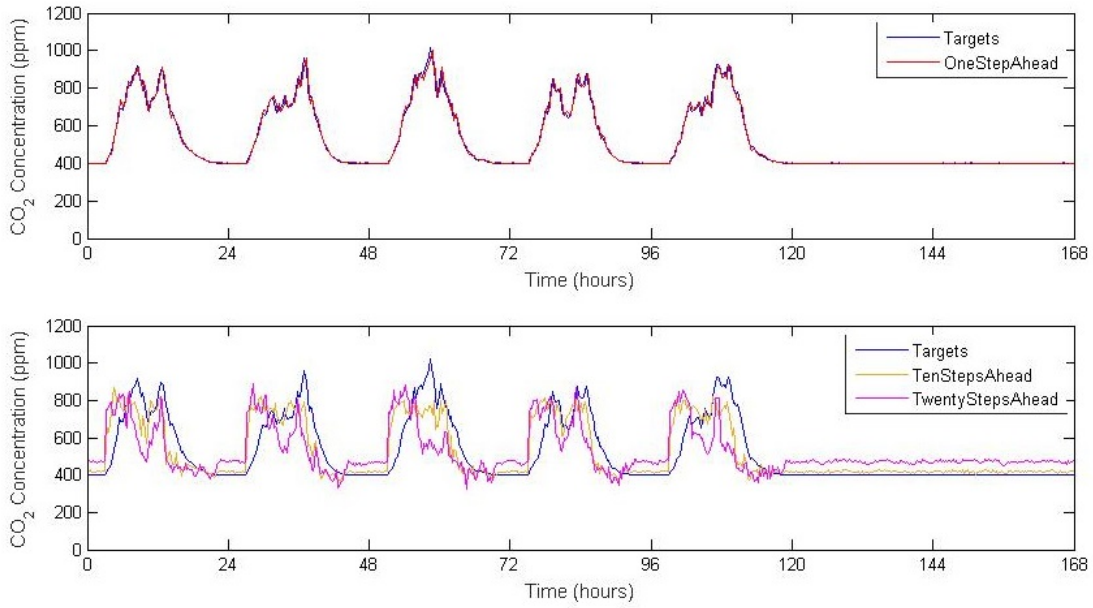


Figure 6.5: CO₂ prediction performance for one step ahead neural network model (top) and for $n=10$ and $n=20$ (bottom), trained using data obtained using excitation of the input signal.

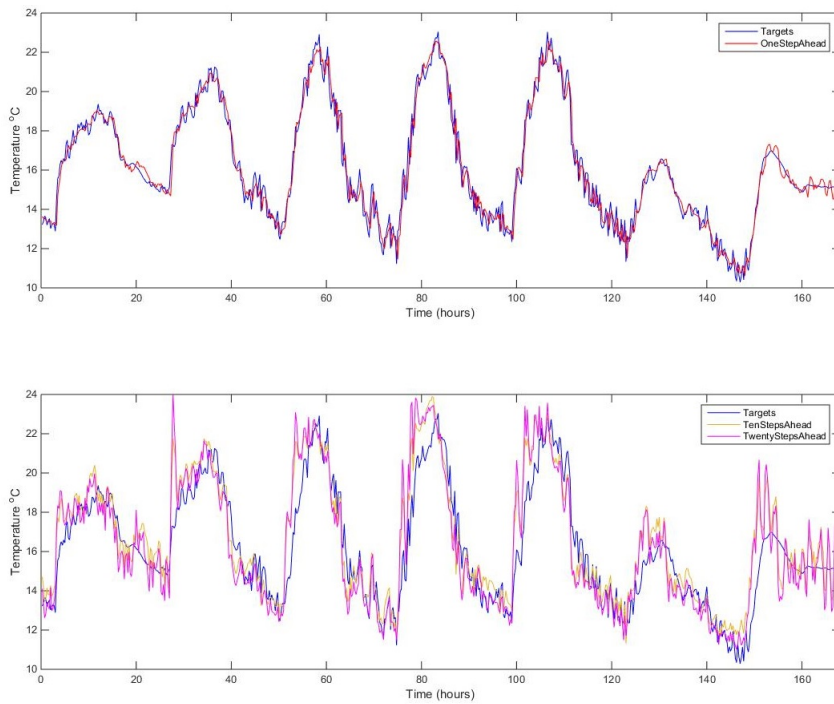


Figure 6.6: Temperature prediction performance for one step ahead neural network model (top) and for $n=10$ and $n=20$ (bottom), trained using data obtained using excitation of the input signal.

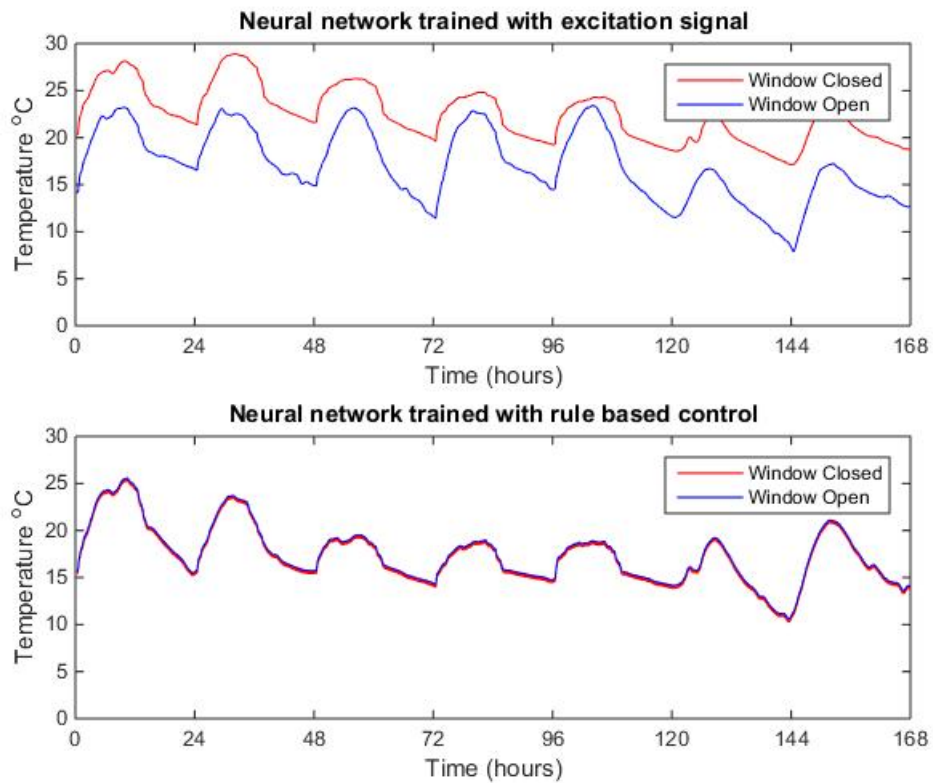


Figure 6.7: Neural Network model outputs for windows fully open and windows fully closed for a week in May. The upper graph shows neural network output for a model trained using data generated with input excitation. The lower graph shows neural network output for a model trained using data generated with control similar to that in the real building.

6.3.1 Sensitivity Analysis

As with the models generated using real building data, a sensitivity analysis was carried out. In this case, the window opening percentage was indeed having an influence on the model output. Figure 6.7 shows the output of the model for two extreme scenarios: windows fully open and windows fully closed for models trained using data generated using excitation. In both of these cases, the model outputs seem reasonable; with higher zone temperatures predicted when the windows are left closed and cooler predictions when the windows are left fully open.

Experimental Control

As the identification procedure presented has been shown to be successful, one may ask: “is this due to the identification procedure followed, i.e. the persistent excitation of the system? Or is it because dynamic thermal simulation is a simplified representation of reality which cannot fully represent the stochastic way in which occupants and other factors influence internal conditions in a real building?”.

In an attempt to separate these two factors, simulations were also carried out using an

input signal similar to the one used in the real building. This input signal was determined using the EMS code which was used to validate the EnergyPlus model in the previous chapter. By examining the data gathered from the real building an approximation of the control rules used to control window actuation were reverse engineered. This then allowed for simulations to be carried out and neural network models trained using the resulting data. These models can then be compared to the models developed by persistently exciting the system.

When testing the models generated using the control dataset (generated using simulation and a window control strategy similar to that in the real building during operation) a sensitivity analysis was also carried out. When subjected to different input signals for the window opening position, the neural network model output was unaffected (as can be seen in Figure 6.7. This shows that the use of simulation data is not responsible for the successful training of models which capture the underlying thermal dynamics of the system. Moreover, it is the persistent excitation of the system which has succeeded in generating useful models.

6.4 Discussion

The identification procedure presented in this chapter was successful. The resulting neural network models both gave accurate predictions over a reasonable horizon and captured the effects of window opening. However, the identification procedure used is relatively simple and would need refinement before being applied in a real building.

6.4.1 Open-Loop Identification

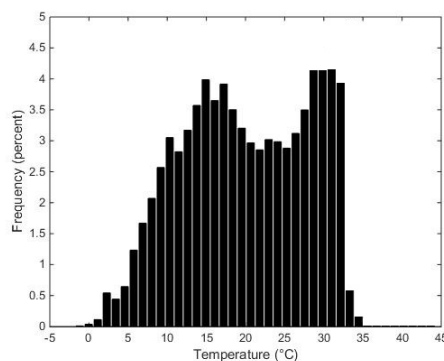


Figure 6.8: Histogram plot of the zone internal temperatures resulting from open-loop system identification.

In this experiment an open-loop identification was carried out. This proved successful in that it enabled models to be developed which gave accurate predictions and captured the underlying dynamics occurring within the naturally ventilated space. However, the range of temperatures which resulted from the system identification experiment would be unacceptable in a real building. Figure 6.8 shows the distribution of internal temperatures

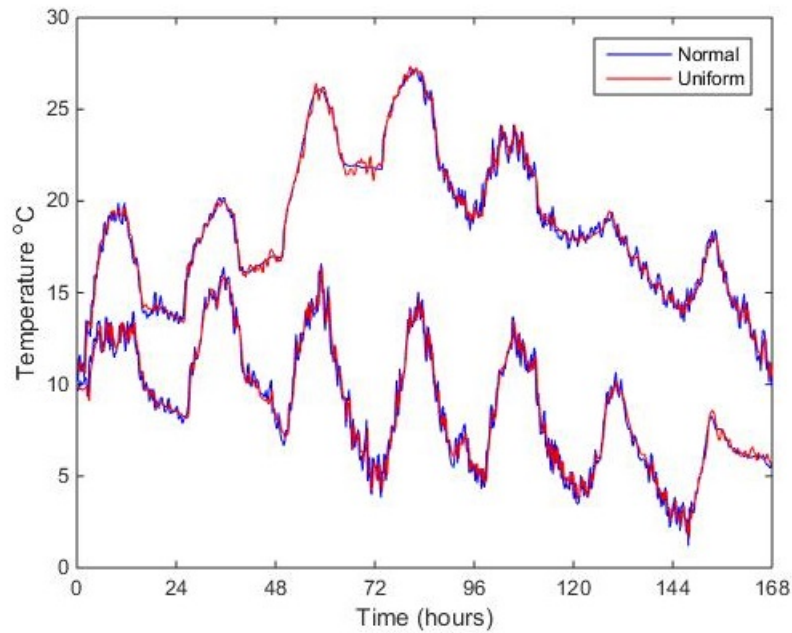


Figure 6.9: Sensitivity analysis, comparing models generated using normally and uniformly distributed random input signals. The uppermost two lines show neural network model output for windows closed and the lower two show output for windows open during a week in February.

for the full year of simulation. It can be observed that the resulting internal temperatures would clearly fall beyond the acceptable limits for occupant comfort. If a system identification experiment was to be carried out in a real occupied building a closed-loop methodology incorporating some level of feedback control would be needed. Further investigation and development of system identification procedures for naturally spaces is needed in this area to assess if closed-loop identification would be as informative as open-loop.

While the procedure demonstrated in this chapter may not be directly applicable in an occupied building, there are circumstances where it could be utilised. For example, an initial model of the dynamics of the building could be developed using simulation data and then a closed-loop identification carried out in the real building. Alternatively, an open-loop identification could be carried out during commissioning when the building is not yet occupied. This approach could potentially reduce the length of time required for further identification within the building itself, minimising disruption during operation.

6.4.2 Effect of Input Signal

Two input signals were used to excite the window actuators, a normally distributed random input signal and a uniformly distributed random signal. Neural network models were then developed to predict both internal temperature and CO_2 concentration for data generated using each signal. Tables 6.1 - 6.4 summarise the prediction performance of the resulting neural network models. In terms of prediction performance on the unseen test data there was a negligible difference between the two data sets trained using different input signals.

When carrying out a sensitivity analysis to determine if the developed neural network

models captured the thermal dynamics of the system and the effect of the window openings, the models were again compared. Figure 6.9 shows that the choice of input signal in the identification experiment has not affected the neural network model output. Both models output similar results for the windows fully closed and fully open scenarios.

6.5 Summary

The identification procedure demonstrated using EnergyPlus shows that with proper input excitation, empirical neural network models can be created to model the thermal dynamics occurring within a naturally ventilated space. These models were able to give an accurate prediction of internal temperature over a reasonable prediction horizon and captured the effect of the control input successfully. However, the internal temperatures which resulted from the open-loop identification experiment would have proved unsuitable in a real occupied building. Further development of closed-loop identification techniques would be required before implementation in a real building during use.

Chapter 7

Demonstrating Model Predictive Control

The majority of this thesis has dealt with developing predictive models to be utilised in a MPC strategy. In this chapter a MPC strategy for the control of a natural ventilation system, incorporating the previously developed models, will be tested. The impact of controller parameters, and in particular how they relate to the thermal mass of the building fabric, will also be investigated.

7.1 Introduction

Alongside air quality concerns, summer overheating is one of the common issues in naturally ventilated buildings. In this chapter an MPC controller is tested. The controller is designed to maintain a suitable zone temperature through a whole year of simulation, however, the prevention of overheating in the summer was a primary aim.

In this study, the neural network predictive models were developed using MATLAB, using the identification and training procedures described in Chapters 2 and 6. MATLAB, in particular the Model Predictive Control and Optimisation Toolboxes, was then utilised to design a nonlinear model predictive control (NMPC) controller. The *nmpc.m* algorithm (Grüne & Pannek 2011), was adapted for use by the controller. The neural network model is used to predict future temperatures within one zone of a larger building. An optimisation process, based upon a specified cost function, is then carried out to determine the optimal control actions. To carry out the optimisation, sequential quadratic programming (SQP) was used. Hence, the technique demonstrated is that of nonlinear model predictive control with nonlinear optimisation (NMPC-NO).

To enable the testing of the controller, building simulation in EnergyPlus was used. The school model, developed in Chapter 5, was used in place of a real building (to represent the plant, in control speak). The choice of simulation was in part a practical consideration due to access to a suitable building/experimental setup in which to carry out experi-

ments. However, simulation also has a number of advantages, making it ideally suited to a preliminary testing of a controller:

- Multiple years of simulations can be carried out in a short time. This allowed investigation of the impact of varying model parameters over multiple seasons.
- The building fabric can be easily changed.
- Weather conditions can be specified and adapted if needed.
- Relatively complex occupancy behaviour can be included through the use of Humphreys algorithm (discussed in Section 5.3.7)
- Before carrying out initial tests it was unknown if the MPC controller may result in unacceptable conditions, such as those which occurred during the identification experiment (Chapter 6).

The simulation was carried out for a typical non-heating season (1st May to the 30th September) (CIBSE 2013). During this period the automated windows in the EnergyPlus simulation model are controlled by the MPC controller in Matlab.

7.2 Simulation Setup

To enable the testing of the NMPC controller designed in MATLAB it was necessary to link EnergyPlus and MATLAB/Simulink. This allowed for cosimulation of the building model and the MATLAB controller. This was achieved using the MLE+ tool (Bernal et al. 2012).

Figure 7.1, shows a system diagram of the simulation setup in Simulink. The *E+ Cosimulation* block, part of the MLE+ Simulink library (Bernal et al. 2012), facilitates the co-simulation of EnergyPlus in Simulink.

There is one input and three output ports on the *E+ Cosimulation* block:

- The *real* input is the input into EnergyPlus. In this application, the input is the window opening percentage, expressed as a value between 0 and 1.
- The *flag* output is used as a monitor of the status of EnergyPlus. If the status of EnergyPlus is normal the output is 0, if the EnergyPlus simulation has stopped the output is 1 and if an error has occurred within EnergyPlus *flag* will be negative. The stop criteria within Simulink is any non-zero value.
- The *time* output is the simulation time of EnergyPlus in seconds.
- The *real output* is a vector output from EnergyPlus. In this case, the zone temperature.

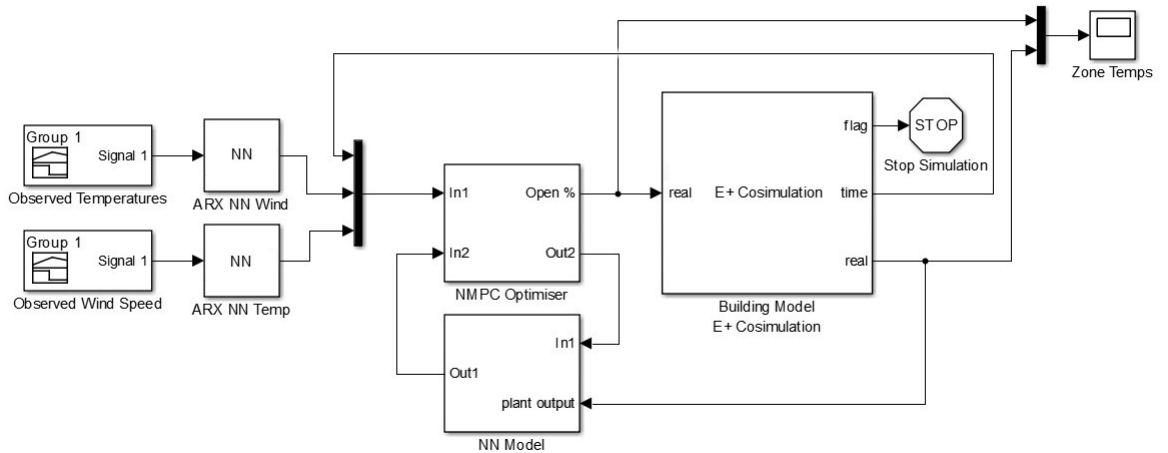


Figure 7.1: Simulink diagram of cosimulation setup.

Within the *E+ Cosimulation* block the parameters are used to define the EnergyPlus IDF file and the weather file. When the Simulink simulation start, the block will start the EnergyPlus simulation of the specified file, enabling the exchange of inputs and outputs. At each timestep (10mins), the control input for the automated windows is determined by the MPC controller (represented in Figure 7.1 by the NMPC Optimiser and NN Model blocks). This information is then sent to the EnergyPlus simulation. The plant output (i.e. zone temperature) is then fed back into the controller and the process is repeated.

7.2.1 EnergyPlus Model

The EnergyPlus model developed in Chapter 5, is again used in place of a real building. As with the identification experiment only a single zone is considered. Occupancy and occupant control of manual windows is identical to the procedures described in Section 5.3.5.

To determine if the thermal mass of the building has an impact upon the optimum parameters and performance of the MPC controller, two further models were created. Both were based upon the initial model of the school. In the original model the floor slab was 150mm concrete, this was reduced to 75mm to create a model with less thermal mass and increased to 300mm to create a much more heavyweight model. The three thermal mass scenarios are used to represent typical construction methods, ranging from a lightweight steel frame to a more heavyweight concrete structure.

7.3 Predictive Model

NARX neural network models trained using the identification procedure described in Chapter 6 were used as the predictive models in the MPC controller. The impact of

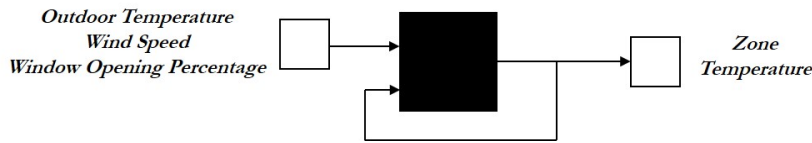


Figure 7.2: Neural network model inputs and output.

thermal mass is being investigated by adapting the simulation model. This necessitated training separate neural network models for each building, to capture the dynamics. Exogenous inputs used were outdoor temperature, wind speed and window opening percentage (as shown in Figure 7.2). Wind speed and outdoor temperature were included because they had a more significant impact upon model output than other potential exogenous inputs, such as humidity and wind direction.

7.3.1 Weather Inputs

In Chapters 4 and 6, neural network models were trained using observed weather data, from a local weather station on each of the buildings. This gives an upper performance bound for the prediction capability of the models, which when deployed will likely decrease depending on how weather predictions are incorporated into the control system. Four options were considered for including weather into the controller:

1. Incorporate some form of external weather forecast provided by a weather service into the controller.
2. Use persistence predictions, i.e. recycle weather data from the previous day/days. This is often used as a benchmark for assessing the quality of predictions in meteorology and could in be utilised in a predictive control strategy (Oldewurtel et al. 2012).
3. Only use already observed weather as inputs for the predictive model.
4. Train separate models. Ferreira et al. (2012) trained autoregressive RBF neural network models to predict the weather which could then be used as inputs for the indoor room temperature and humidity models.

The use of weather forecasts provided by an external service was not deemed desirable. In application in a real building this would add a potential weak link in the control system whereby any network problems could disrupt the controller. This risk could be mitigated to some degree by the use of a back-up control system, which could be used in the case of disruption to the MPC controller. This approach has been demonstrated by Sturzenegger et al. (2013), whereby, if the MPC controller malfunctioned the control switched to a back-up, in the form of a known BMS.

Additionally, while it is envisioned that a control strategy such as the one demonstrated in this work would be applied as part of a centralised BMS, it could also be used within

a stand-alone controller to control an individual zone. Requiring that a stand-alone controller must be networked would negate some of the flexibility provided by such a solution.

In this study, the approach taken by Ferreira et al. (2012) was used. Whereby, autoregressive models were trained to predict weather conditions to use as inputs for the building predictive model using data from a weather station on the building. This process was carried out for both external temperature and wind speed. For MPC to be successful when applied to real buildings, it is expected that a weather station either on, or very local, to the controlled building will be required. This enables observed local weather data to be utilised as model inputs and the training of models to predict future weather conditions.

Weather Models

Nonlinear autoregressive (NAR) neural network models for both external temperature and wind speed, were trained using observed weather data (described in Section 3.2). The training method was very similar to that used to train the predictive models for internal temperature and CO₂ in Chapters 4 and 6, however the only model inputs were the time delayed autoregressive inputs. As with the previously developed models, a number of different network architectures were trained and tested.

The prediction performance for one-step-ahead and twenty-steps-ahead is shown in Figure 7.3. The temperature model gave very reasonable predictions, capturing the general trend. The performance of the wind model was poorer. However, this was to expected given how wind speed fluctuates. The model output was much closer to the mean windspeed than truly capturing the changeable nature of the wind over significant prediction horizons, such as 24 hours.

7.4 Predictive Controller

One option for demonstrating MPC in building simulation is using the MATLAB Model Predictive Control Toolbox, in particular the default blocks within Simulink. However, this was not possible due to constraints on optimiser choice and available cost functions, such as the lack of non-linear optimisation and no penalty in the cost function for number of control actuations. Instead, a combination of code from the MATLAB MPC Toolbox and the *nmpc.m* code (Grüne & Pannek 2011) was used. The *nmpc.m* code from Grüne & Pannek (2011) was invaluable as it provided an example of the application of a nonlinear solver (MATLAB function *fmincon*) in the optimisation process (discussed in Section 7.4.4).

In this section, the key aspects of the controller, such as the cost function and optimisation technique used, are discussed. Additionally, the implementation of the control algorithm is described.

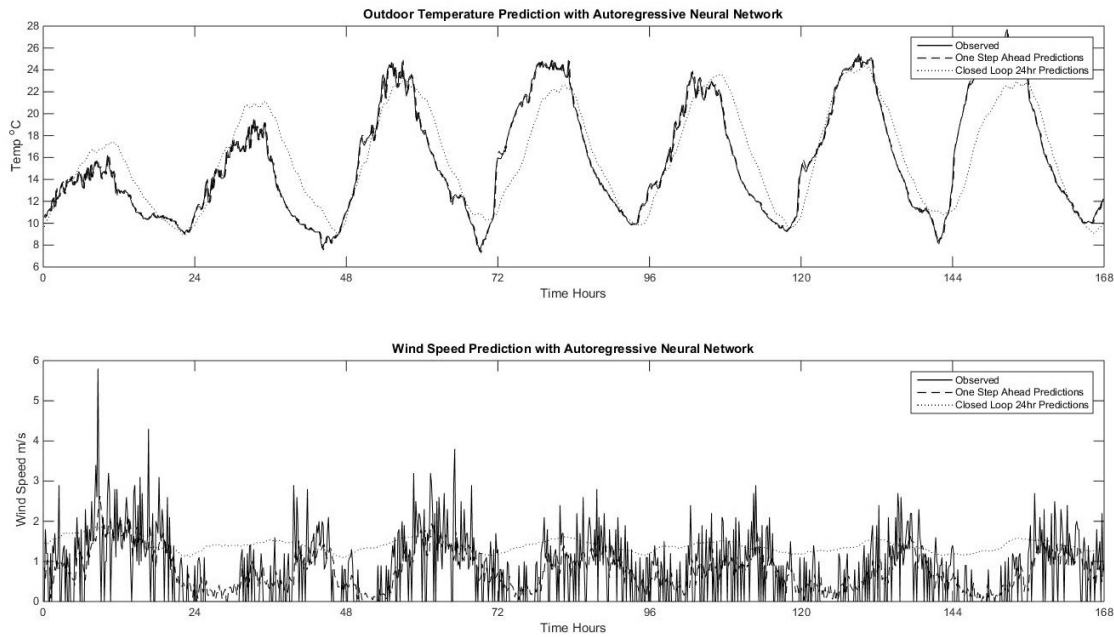


Figure 7.3: NAR models to predict temperature and wind speed.

7.4.1 Prediction and Control Horizon

The prediction horizon, T_p , is the distance into the future over which the controller evaluates model predictions. The control horizon, T_c , is the time over which the controller determines optimum control actions. T_p can be equal to T_c , however it is much more common that T_p is larger than T_c . This is necessary in applications where there are delays in the plant, to avoid situations whereby control actions have no impact upon plant output before the end of the prediction horizon.

In most applications increasing the prediction horizon does not have as significant an impact upon computational effort, compared with increasing the control horizon. This is particularly true in NMPC. Increasing the length of the control horizon means that there are more control variables to be solved at each time step. When using a nonlinear optimisation process this can be a significant issue.

Best practice when designing/implementing a MPC controller is to determine the prediction horizon during the initial stages of controller design. It can then be held constant while other variables, such as cost function weights and constraints, are tuned. However, to do this requires specific knowledge of the system being controlled. Ideally the prediction horizon should be long enough that the controller can anticipate constraint violations with enough time to take action. In the case of a naturally ventilated building, the optimum prediction horizon is likely to depend upon the thermal time constant of the building.

In their review of MPC applications to HVAC systems, Afram & Janabi-Sharifi (2014) suggest that for HVAC applications, the prediction horizon is typically between 5 and 48 hours, the control horizon between 4 and 5 hours, and the time step between 1 and

3 hours. Afram & Janabi-Sharifi (2014), justify these values based upon the work by Rehrl & Horn (2011), Široký et al. (2011) and Candanedo & Athienitis (2011). Based upon knowledge of naturally ventilated buildings and their control, the aforementioned estimates for the prediction and control horizon seem entirely reasonable. However, the timestep of between 1 and 3 hours is potentially high. Afram & Janabi-Sharifi (2014), suggest that for many applications a timestep of 1 hour is reasonable because temperature change is a slow process. This is certainly true in a number of cases. Yet in buildings such as the school described in Section 3.2, the changeable, at times high occupant density caused relatively quick increases in internal temperature. A controller with a long timestep could be unable to react to such occurrences. Furthermore, while this study is purely looking at controlling the ventilation based upon temperature, CO₂ concentrations can increase much more rapidly. In future studies where CO₂ is incorporated into the MPC controller a shorter timestep is likely to be required. For these reasons a timestep of 10 minutes is used.

In this study, both the prediction and control horizons will be varied to assess the impact upon controller efficiency. As discussed in Section 7.2.1, three scenarios are being considered for the building fabric. The first being the middleweight construction of the validated school model. This model was then adapted to create models with both a more lightweight and a more heavyweight fabric. The intention being to investigate the impact of the thermal mass of the building upon controller design and performance; particularly in regard to the prediction horizon.

7.4.2 Cost Function

The cost function, or objective function, is used to obtain the optimal control law. While the cost function can be any of a number of forms, the general aim is that the future system output should follow a determined reference signal for the considered horizon (Camacho & Bordons 2013).

In previous studies on the application of MPC to ventilation systems a range of cost functions have been used. For example, Ferreira et al. (2012) used a very simple cost function, which essentially represented the energy consumption by calculating the difference between the outdoor temperature and setpoint for switching on the HVAC. Such cost functions have a clear goal, which has obvious physical meaning, e.g. minimising energy consumption or minimising periods of unacceptable IEQ. However, such formulations leave little flexibility to fine tune controller performance. For example, penalising the amount of control effort.

In this study the aim was to investigate the ability of MPC to maintain comfortable internal temperatures and minimise overheating. To achieve this a cost function designed for output reference tracking was used.

In the MATLAB Model Predictive Control Toolbox there are two cost functions which can be utilised as a measure of controller performance to be minimised. In this work the cost function used is an adapted version of the MATLAB “Standard Cost Function”:

$$J(z_k) = J_y(z_k) + J_{\Delta u}(z_k) + J_\epsilon(z_k) \quad (7.1)$$

where:

z_k is the optimal control inputs

$J_y(z_k)$ is the output reference tracking

$J_{\Delta u}(z_k)$ is the manipulated variable move suppression (control effort)

$J_\epsilon(z_k)$ is the constraint violation

The individual components of the cost function are described in the subsequent sections.

Output Reference Tracking

In this application of MPC, the main aim of the controller is to keep the internal temperature at or near a chosen setpoint. During occupied hours, 22 °C was chosen as the temperature. This fixed setpoint was used for the full year of simulation. Various simulations were carried out and impact of varying prediction and control horizons, parameter weights etc. was investigated. Future investigation could utilise a varying setpoint based upon the adaptive comfort standards (CIBSE 2013).

The output reference tracking term is given by:

$$J_y(z_k) = \sum_{j=1}^{n_y} \sum_{i=1}^p \left\{ \frac{w_{i,j}^y}{s_j^y} [r_j(k+i|k) - y_j(k+i|k)] \right\}^2 \quad (7.2)$$

where:

k is the current control interval

p is the prediction horizon (i.e. the number of intervals)

n_y is the number of plant output variables

z_k is the optimal control inputs

$r_j(k+i|k)$ is the reference value for the j th plant output at the i th prediction horizon step (in engineering units)

$y_j(k+i|k)$ is the predicted value of the j th plant output at the i th prediction horizon step (in engineering units)

s_j^y is the scale factor for the j th plant output (in engineering units)

$w_{i,j}^y$ is the tuning weight for the j th plant output at the i th prediction horizon step (dimensionless)

The tuning weight $w_{i,j}^y$ is a time-varying weight. This allows the importance of maintaining the setpoint temperature to be varied at different times. In this case, it was used to disregard the setpoint temperature during unoccupied hours.

Manipulated Variable Move Suppression

In the standard cost function used by the MPC controller in MATLAB the manipulated variable (MV) move suppression term is used to limit the size of the MV adjustments (moves). This is because in a number of applications it is preferable to have small adjustments. In terms of the control of automated windows in a naturally ventilated building this is unlikely to be required. Furthermore, the inclusion of a penalty for large movements could even result in a controller which is slow to react.

While the size of the MV adjustment is not an issue in the control of natural ventilation the number of transitions between window states could be. Not only can frequent actuations of automated windows prove irritating for building occupants (due to the noise of the actuators) but also the service life of actuators must be considered.

The move suppression term is given by:

$$J_{\Delta u}(z_k) = \rho_{\Delta u} MV_{trans} \quad (7.3)$$

where:

z_k is the optimal control inputs

$\rho_{\Delta u}$ is the manipulated variable move suppression penalty weight (dimensionless)

MV_{trans} is the number of manipulated variable transitions

Constraint Violation

In MPC constraints can be placed upon both input and output values (discussed further in Section 7.4.3). When applying a MPC controller to a real system, some degree of constraint violation may be unavoidable. Softening constraints allows the optimiser to determine a solution in situations where constraint violation cannot be prevented. The cost function quantifies the worst case constraint violation using the variable ϵ_k . The performance measure is given by:

$$J_{\epsilon}(z_k) = \rho_{\epsilon} \epsilon_k^2 \quad (7.4)$$

where:

z_k is the optimal control inputs

ϵ_k is the slack variable at control interval k (dimensionless)

ρ_ϵ is the constraint violation penalty weight (dimensionless)

7.4.3 Constraints

One of the reasons for the success of MPC is the ability to handle constraints. Constraints can be placed upon both inputs and plant output.

As was mentioned in the previous section, it is not always possible to satisfy all of the constraints. In some cases it will be mathematically impossible for the optimiser to solve the control decision without violating constraints. If this was the case and the constraints were hard, i.e. they had to be satisfied by the optimiser, the solution is infeasible and the controller is likely to return an error. Most MPC controllers deal with this by not changing the manipulated variables, so their state remains the same as in the previous timestep. However, if this infeasibility continues it will result in a loss of control. Therefore, the constraints are relaxed, or softened (Maciejowski 2002, Rawlings & Mayne 2009).

Constraints were placed upon the plant output variable, i.e. zone temperature. During occupied hours the output is constrained to between 18 and 26 °C. Due to the nature of natural ventilation it is necessary that this constraint is soft, as at times it may not be possible to maintain a zone temperature within these limits (particularly with regards to the upper limit). Softening this constraint also allows the controller to sacrifice some constraint violation for an overall better performance. During unoccupied hours this constraint was further softened. This allows the controller more freedom and the potential to pre-cool the space.

The constraint upon the zone temperature during occupied hours is not strictly required. The output variable reference tracking term in the cost function (Section 7.4.2) would perform a similar role. By aiming to keep the output close to a setpoint it will implicitly aim to maintain a temperature within the wider limits imposed by the output variable constraints. However, the use of output variable constraints in addition to a reference tracking term in the cost function was found to give greater flexibility and tuneability. This is achieved by adjusting the tuning weight within the output reference tracking term, the softness of the output variable constraints and the constraint violation penalty weight. This allows for refining the balance between keeping the zone temperature close to the optimum and allowing greater movement within and beyond the output constraints.

To soften the constraints, a relaxation factor was used. Following the methodology used by the MATLAB MPC Toolbox the parameter could be varied between 0 and 20, with 0 meaning no violation allowed (i.e. a hard constraint) and 20 meaning large violation allowed. Tuning of constraints was done manually based upon controller performance.

Hard constraints were placed upon the manipulated variable (opening percentage) as this must clearly remain in the 0-100% range. Hard constraints could also be used to ensure that windows did not open at specific times. This would be applicable if there were security concerns and windows needed to be closed or have a limited opening during unoccupied hours. In this study, no such constraints were utilised. The predominate reason for this

was to allow the controller the maximum amount of freedom and the potential to utilise night cooling. Furthermore, the particular zone being controlled is on the first floor of the building, as such the opening of automated windows during unoccupied hours is likely to be allowed.

In this study, the building simulation did not include heating as the focus was primarily overheating in summer. To prevent the space from dropping too low during unoccupied periods a "very hard" soft constraint was used to prevent the zone temperature going below 10 °C. The constraint of 10 °C was used as a typical value for the purpose of plant and fabric protection during unoccupied periods. No hard constraints were placed upon plant output. The reason for using a "very hard" soft constraint in place of a hard constraint, is to prevent problems caused by unexpected constraint violations. It is possible that prediction errors or disturbances could cause a hard constraint to be violated (this is much more likely in a real building than in a simulation). This can lead to the controller becoming unable to find a feasible solution.

7.4.4 Optimiser

The optimisation process is used to find the sequence of control inputs which minimises the cost function. Nonlinear optimisation is a vast field of study and there is a number of possible methods which can be used for the optimisation process in NMPC. For example: Sequential Quadratic Programming (SQP) (Dhoodhat 2014, Diehl et al. 2009, Li & Li 2015, Martinsen et al. 2004), Genetic Algorithms (Al-Duwaish & Naeem 2001, Potočnik & Grabec 2002), Particle Swarm Optimisation (PSO) (Dhoodhat 2014, Mercieca & Fabri 2011, 2012, Sandou & Olaru 2009) etc.

For this study, SQP was chosen as the optimisation method. According to Boggs & Tolle (1995), "*Sequential Quadratic Programming (SQP) has arguably become the most successful method for solving nonlinearly constrained optimization problems*". SQP has been shown to be efficient in both small and largescale problems, and can handle linear and nonlinear constraints (Nocedal & Wright 2006). Furthermore SQP has previously been used successfully in MPC applications where neural networks were used as the predictive model (Akyurek et al. 2009, Ławryńczuk 2007, Li & Li 2015).

SQP solves constrained nonlinear problems by forming a quadratic approximation of the cost function. This results in a Quadratic Programming (QP) subproblem, the result of which is then used to define the next iteration. A full description of SQP can be found in Nocedal & Wright (2006) and Grüne & Pannek (2011).

The specific optimisation algorithm used in this study is the MATLAB function *fmincon* (MathWorks 2016), which is included in the Optimization Toolbox. The *fmincon* function includes a gradient based implementation of SQP. As such, it is susceptible to problems with local minima.

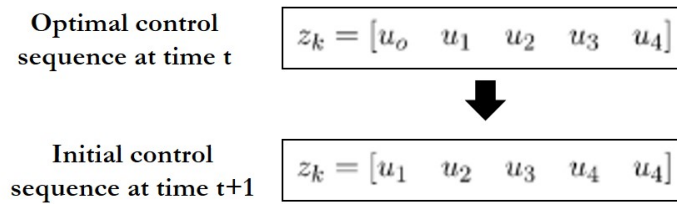


Figure 7.4: Example of the shift method for initialisation of subsequent timesteps. Control actions from the optimal solution at time t are shifted one step forward. To maintain a vector of the correct size the final value is duplicated and appended to the vector.

7.5 Implementation of MPC Controller

This section provides a brief description of the three main stages in the MPC control algorithm. Further information, specifically relating to the *nmpc.m* algorithm upon which this work is based, can be found in Nocedal & Wright (2006).

7.5.1 Initialisation

The algorithm's first step is to initialise all of the variables required to solve the optimal control problem. This includes the control and prediction horizons, initial input states, control input values and any constraints.

The initial value for the control input is specified by the user. For subsequent iterations the *nmpc.n* algorithm uses a technique called the “*shift method*” to determine starting values for the control vector (Diehl et al. 2009, Nocedal & Wright 2006). Using this technique, the optimal sequence of control actions, determined by the optimiser, is stored and used as the starting point for the following timestep. As the first control action will have already been applied to the plant, the control actions are shifted forward by one timestep. To maintain a vector of the correct size, the final control action is duplicated and appended to the vector (see Figure 7.4).

The shifted solution is unlikely to be the optimal for the new timestep. Unless the prediction model is very accurate and there are no disturbances. However, particularly in problems with systems which are slow to react and controllers which utilise long prediction horizons, it can be expected to be a good initial guess for the new solution (Diehl et al. 2009). By using techniques such as shift initialisation the computational time taken by the optimisation process can be reduced, as such is often incorporated into MPC controllers (Biegler & Rawlings 1991, Li & Biegler 1990, Mayne et al. 2000).

7.5.2 Optimisation

The second stage in the *nmpc.m* algorithm is solving the optimal control problem. This stage is responsible for the majority of the computational effort when executing the algorithm. The optimal control problem is solved by transforming it into a static nonlinear

Thermal Mass	Prediction Horizon (hours)	Time above 25 °C (hours)		Max Temp (°C)	
		MPC	RBC	MPC	RBC
Low	1	1361	1310	30.6	31.3
	48	529		29.2	
Medium	1	882	905	29.7	30.7
	48	245		27.8	
High	1	143	151	27.4	27.6
	48	21		25.8	

Table 7.1: Overheating for different thermal mass scenarios using 1 and 48 hour prediction horizons compared to RBC simulation results.

optimisation problem, which is then solved using the *fmincon* SQP optimisation function (see Section 7.4.4).

The SQP method is iterative, at each iteration it solves a quadratic programming problem to determine the optimal control strategy to minimise the cost function. Before implementing the control action, the sequence of optimal control inputs is stored so that it can be used to initialise the optimisation problem at the subsequent timestep.

7.5.3 Applying Control Input

Having solved the optimisation problem, the first control input in the optimal control sequence is applied to the plant (in this case the window opening percentage is sent to the EnergyPlus model of the building). The output from the plant is then fed back to the controller which updates the state values and moves forward an iteration. The process is then repeated until the maximum number of iterations are reached. At which point the algorithm terminates.

7.6 Results

The performance of the controller was analysed over what is typically considered the non-heating season (1st May to the 30th September). In all three scenarios (i.e. the middleweight model representative of the actual building, and the adapted lightweight and heavyweight models) increasing the prediction horizon improved performance by reducing overheating. Although, in the case of the lightweight building the MPC controller did not achieve results which would have been acceptable based upon the criteria outline in TM52 (CIBSE 2013). TM52 outlines three criteria to quantify overheating: duration of overheating, severity of overheating and an upper limit upon temperature. This can be seen in Figure 7.9, where a significant number of observations in the lightweight scenario are above the maximum acceptable temperature (T_{max}). Table 7.1 summarises the level of overheating for the three scenarios. It can be seen that for all three thermal mass cases a longer prediction horizon reduced both the number of hours above 25°C and the maximum

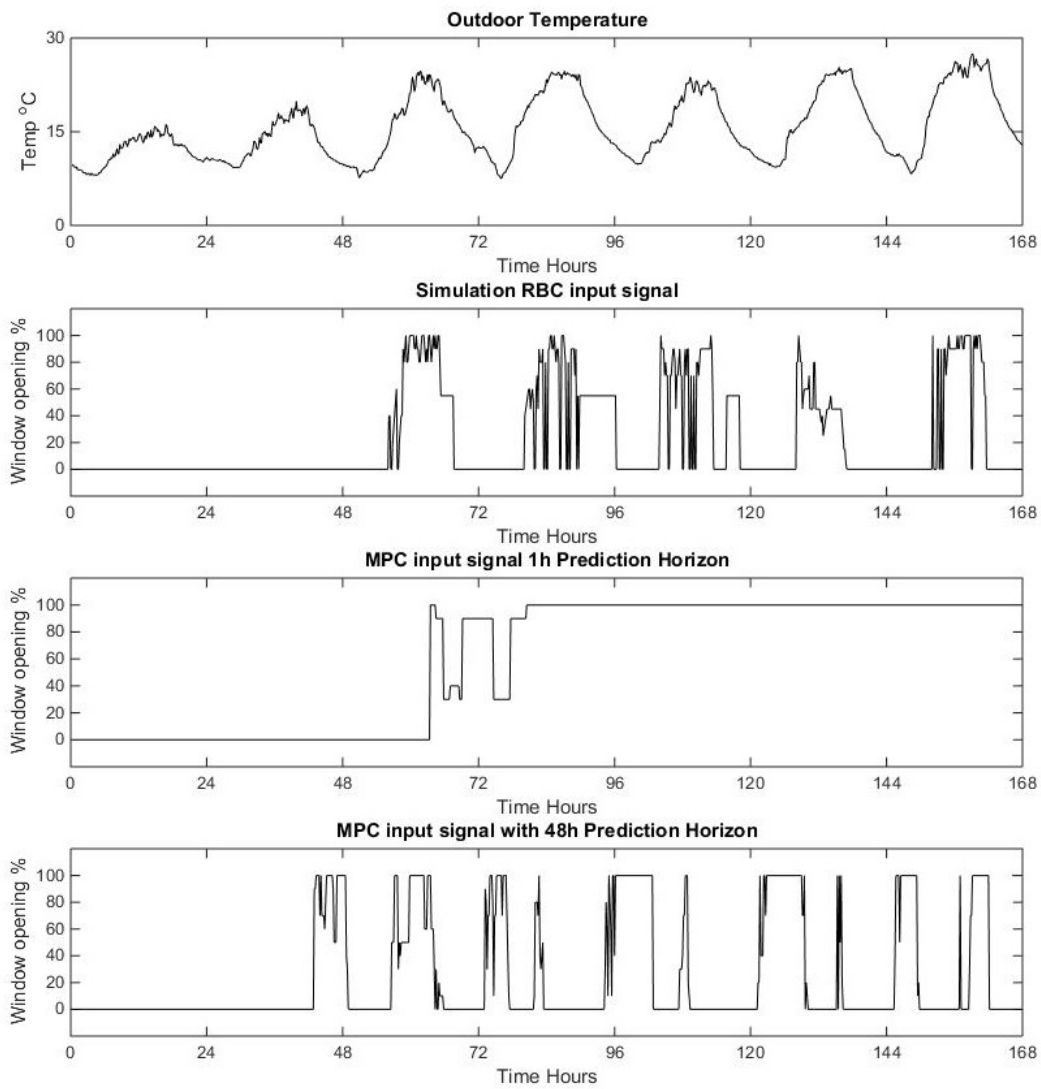


Figure 7.5: Comparison of control inputs calculated by MPC controller for different prediction horizons for the low thermal mass scenario.

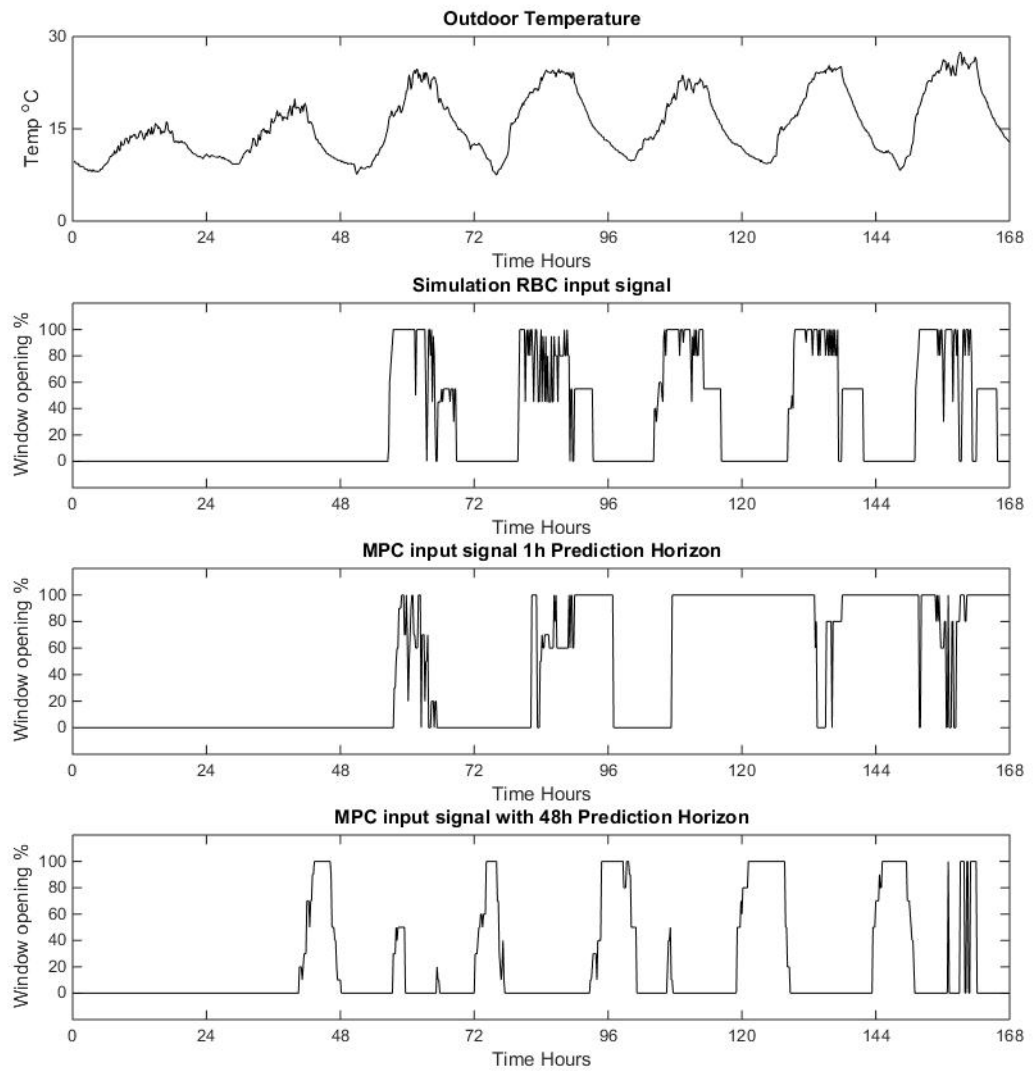


Figure 7.6: Comparison of control inputs calculated by MPC controller for different prediction horizons for the medium thermal mass scenario.

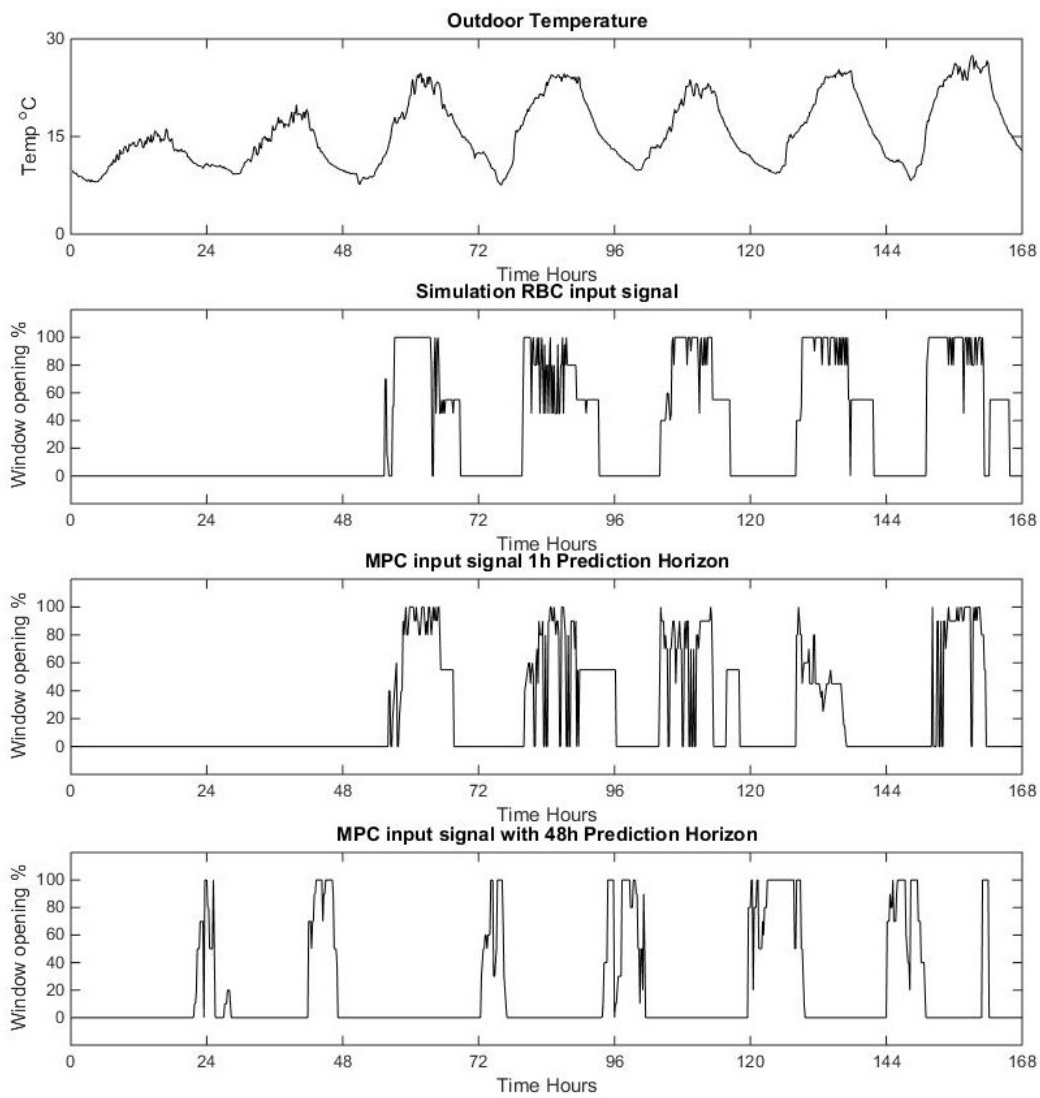


Figure 7.7: Comparison of control inputs calculated by MPC controller for different prediction horizons for the high thermal mass scenario.

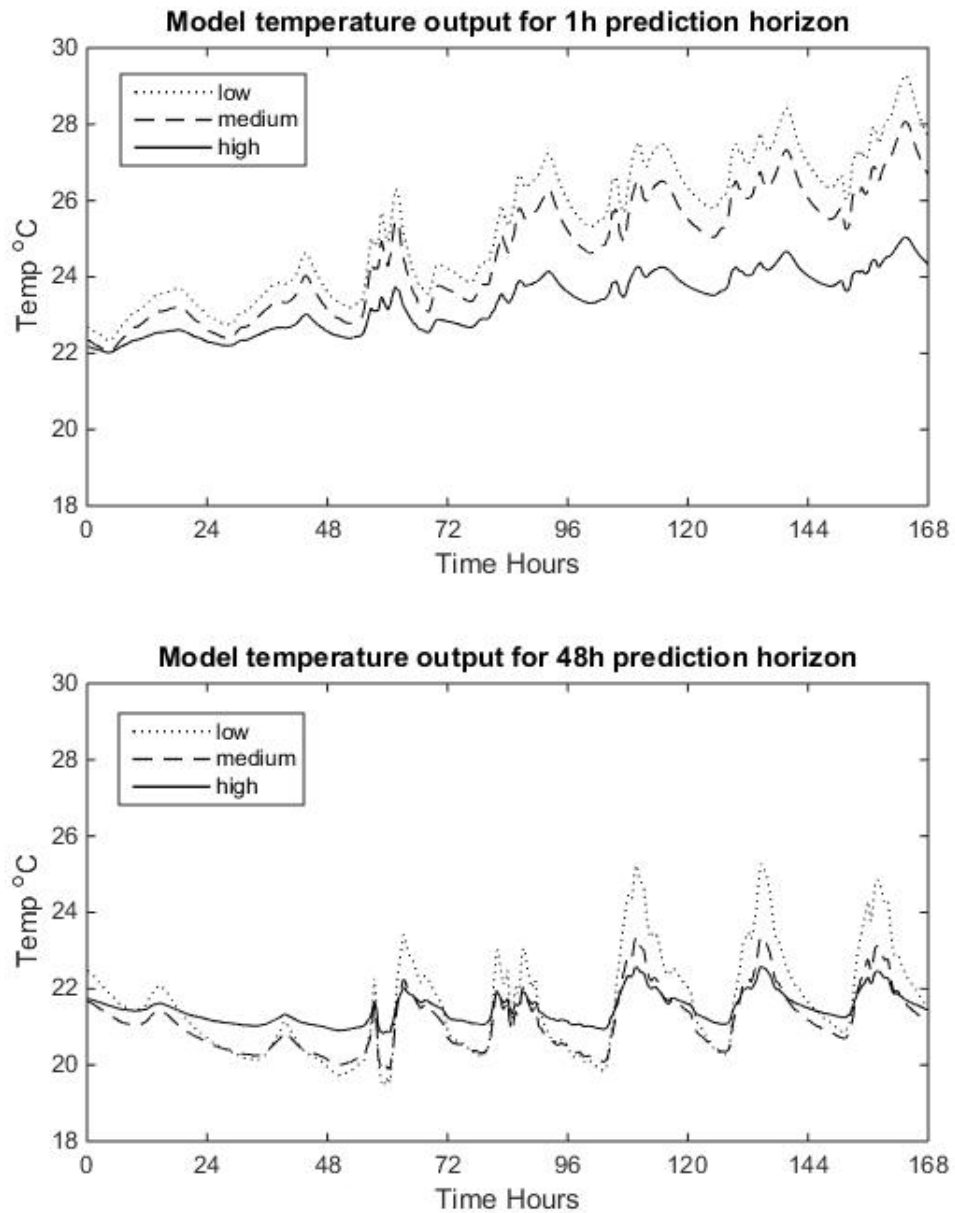


Figure 7.8: Zone temperatures for a week in June for all three thermal mass scenarios, for both a 1 and 48h prediction horizon (these results correspond to the control signals shown in Figures 7.5 to 7.7).

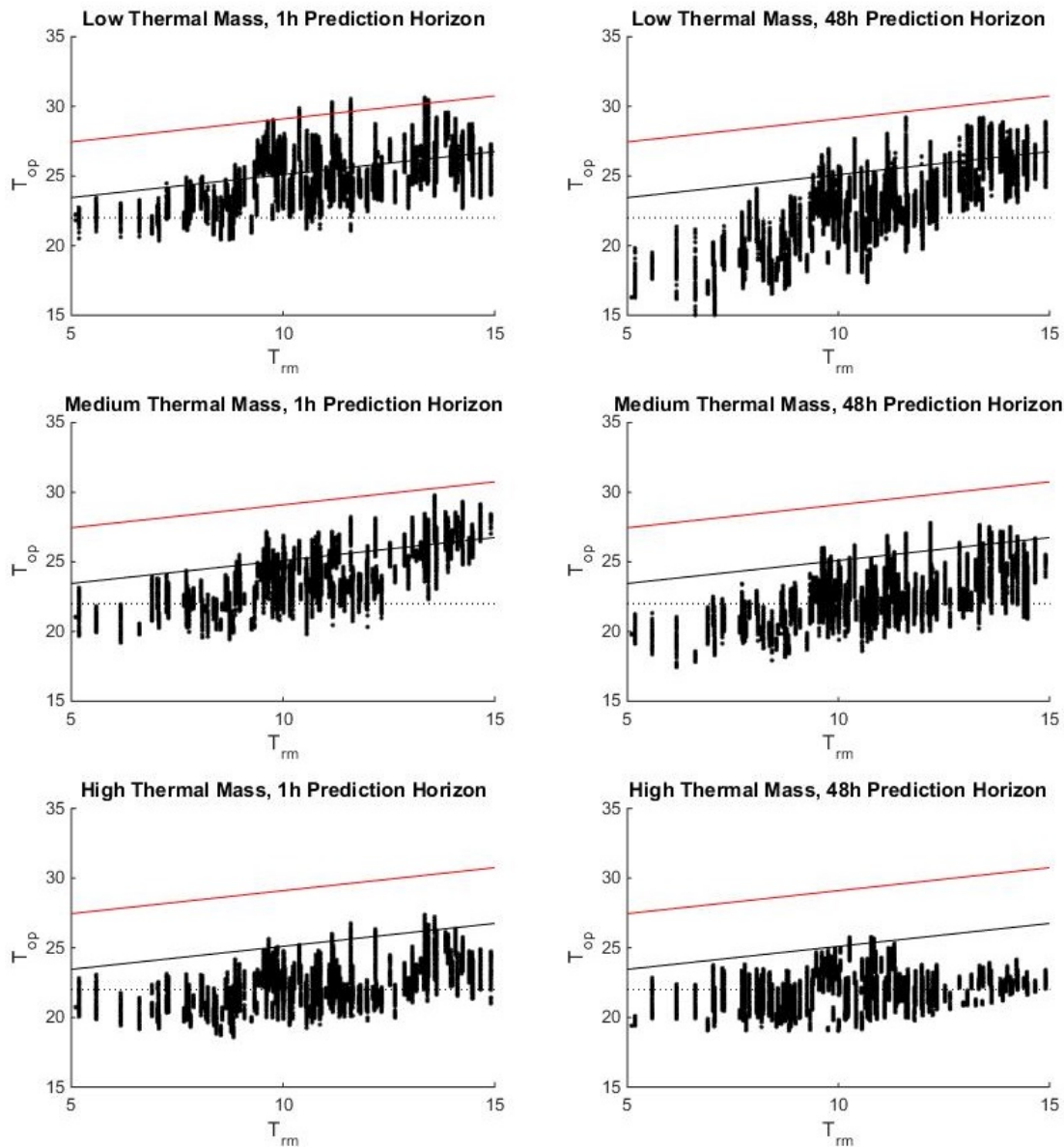


Figure 7.9: Plots showing the operative temperature in the zone (T_{op}) against the weighted running mean of outdoor temperatures (T_{rm}). The setpoint (22 °C) used by the controller is shown by the dotted line, the black line represents the maximum acceptable temperature (T_{max}) and the red line shows the absolute maximum upper limit temperature (T_{upp}). Using this style of plot made visualisation of the entire cooling period much easier, than the use of multiple-series plots.

temperature.

As part of this study the prediction horizon was varied, between 1 and 72 hours. One of the findings was that for short prediction horizons (1-2 hours), the MPC controller behaved in a similar manner to how RBC may have been expected to. Windows opened when the zone temperature exceeds, or in some cases is close to exceeding the setpoint temperature. The overheating results of the MPC controller were also compared to the RBC which was used to develop and validate the model in Chapter 5. In terms of overheating, MPC with short prediction horizons was found to give similar results to the RBC.

As the prediction horizon is increased the controller pre-empted increases in temperature. In the case of the medium and heavy weight the longer prediction horizons resulted in what was effectively a night ventilation strategy (Figures 7.6 and 7.7). Where the controller opened the windows during cool periods on a night to pre-cool the space for the following day. In the lightweight scenario night ventilation was also used however, significant ventilation took place during the day as temperatures increased in the space (Figure 7.5).

Figure 7.6 shows example control signals for a typical week in June for the middleweight model, representative of the real building. With a 1h prediction horizon, the windows first open on Monday afternoon as the temperature increased within the zone. When the temperature in the zone decreased in the evening the windows closed. This process was repeated on the following day. By the Wednesday the control signal kept the windows open for the majority of the time, only closing if the outdoor temperature was particularly high. This resulted in a gradual increase in temperature throughout the week, eventually peaking at 26 °C (see Figure 7.8). In contrast, when using a longer prediction horizon, the temperature was kept much closer to the 22 °C setpoint with a much less significant increase in zone temperature throughout the week.

7.7 Discussion

In this section the performance of the MPC controller is discussed. The review of controller performance is framed around three key areas: maintaining a suitable zone temperature, tuning of weights and constraints, and computational effort.

7.7.1 Zone Temperature

Advantages of MPC

In the previous section, the results showed that the MPC controller outperformed RBC which was based upon the control used in the real building. This was achieved by implementing a night vent strategy. This is a technique which mimics a heuristic approach used in some naturally ventilated and mixed mode buildings. As night ventilation is a widely acknowledged technique, an obvious question is *“what is the advantage of an MPC*

approach if it manifests as a known heuristic method?"

The main advantage of an MPC approach is that such a strategy can be implemented with no expert knowledge of the decision space. Based upon optimisation of a relatively simple cost function, the controller determines if a control action is required to maintain suitable conditions in the space. As this is repeated for each timestep, in this case 10 minutes, feedback is incorporated into the controller. As such, the controller will carry out night ventilation only if it is required. To achieve similar performance using RBC would be very difficult and would likely involve a significant amount of time and cost to fine tune the rule set.

Impact of Prediction Horizon and Thermal Mass

In the case of the medium weight model, the optimum prediction horizon was found to be around 24 hours. Increasing the prediction horizon further gave only marginal improvement in performance. For the more heavyweight model this increase to around 42 hours. For both of these models increasing the prediction horizon further gave no clear benefits. In the case of the lightweight model it was possible to achieve improvement in internal conditions by increasing the prediction horizon. However, it was not possible to achieve conditions which would be acceptable in a real building. In Figure 7.9 it can be seen that with the lightweight model overheating was reduced by using a longer prediction horizon. However, in some cases the temperature was significantly below the setpoint temperature. This could be caused by poor tuning of model parameters but even with significant tuning the behaviour could not be corrected.

Based upon this study, the results tentatively suggest that longer prediction horizons may yield better performance in buildings which have higher thermal mass.

Interestingly in the case of the model with high thermal mass, the maximum internal temperatures occurred during periods when the running mean of the outdoor temperature was relatively low (around 10 °C). While during periods of high average temperature the internal conditions were close to the setpoint. The main reason for this behaviour is that during periods of regular warm weather the controller is more likely to carry out night cooling in anticipation of hot conditions the following day. Hence, if there is a day much warmer than the previous sufficient night cooling may not have been carried out. This potentially highlights the need to incorporate more accurate weather predictions into the controller.

7.7.2 Tuning Weights and Constraints

One of the motivations for utilising MPC was that the control sequence is determined based upon the optimisation of a single function. Thus, avoiding the complex set of rules which are predominantly used by BMSs; the parameters of which are typically reviewed and adjusted in a heuristic manner during operation (Rockett & Hathway 2016). This task is often carried out over a significant period after the building has been handed over.

While carrying out this study it became clear that fine tuning MPC model parameters can be a similar task to the tuning of setpoints and rules used in traditional BMSs. In terms of temperature performance, initial guesses for prediction horizon, control horizon, weights upon the cost function parameters and constraint weights, outperformed rule based control. However, the control displayed some undesirable characteristics, such as hunting and in some cases over cooling. Further refinement of model parameters was needed to improve the temperature performance and improve the characteristics of the controller. This was done in a heuristic manner, observing performance and tweaking parameters.

If MPC is to be applied to real buildings the need to carry out fine tuning of model parameters could cause problems. While MPC is widely used in a number of industries, it is not a method which most building managers are likely to be familiar with. Adoption of an MPC approach to building control, would therefore necessitate the need for additional training for the people responsible for managing buildings or the use of external specialists.

One potential solution is to make use of some method to automate the tuning of model parameters. By utilising an autotuning method, the building management team may not need as extensive knowledge of MPC to fine tune the control system. A number of methods have been demonstrated to achieve this. Typically, an optimisation is carried out for the tuning parameters alongside optimisation of the cost function. Hence, two optimisation procedures are carried out at each timestep (Garriga & Soroush 2010). There is a clear downside, that computational effort will be increased (discussed further in Section 7.7.3.

There is a number of methods which have been used to automatically tune the model parameters in MPC. Alongside describing techniques for manually tuning MPC parameters, Garriga & Soroush (2010) summarised a number of studies used for automated tuning.

Han et al. (2006) demonstrated a automatic tuning strategy for Dynamic Matrix Control (DMC) using Particle Swarm Optimisation (PSO). DMC was one of the first MPC algorithms and has seen extensive use in the chemical process industry (Qin & Badgwell 1997). Suzuki et al. (2007) also used PSO to automatically tune MPC. While Qin & Badgwell (1997) optimised all of the parameters, Suzuki et al. (2007) left determining the control and prediction horizon to the user; while PSO optimised the weights and magnitudes of the inputs, outputs and rate of change of inputs. This reduces the computational effort as fewer parameters are determined by the optimisation process. Genetic algorithms (GA) have also been used to autotune MPC parameters. Van der Lee et al. (2008), used genetic algorithms and fuzzy decision making to automatically tune parameters for unconstrained DMC.

7.7.3 Computational Effort

In this study it was found that increasing the prediction horizon while keeping the control horizon fixed did not have a large impact upon the simulation time. However, increasing the control horizon did. For prediction horizons of 1 and 2 hours the control horizon was equal to the prediction horizon. For longer prediction horizons it was too computationally intensive to increase the control horizon beyond 2 hours. Given the receding horizon

strategy in MPC, further increases may have yielded little improvement in performance.

For application in a real building the time taken to compute the next control input, must clearly be shorted than the time-step. In this study the optimisation was carried out for only one room within a larger building, with a time-step of 10mins. With 5 months of calculations taking around 6 hours (with a 2h control horizon), on a desktop with a 4 core (8 thread), 3.6GHz processor and 16Gb of RAM. This suggests that in a real building the optimisation for a single room could be easily completed within the required time. However, the control of multiple zones could become challenging. The computational effort would depend upon the MPC architecture used, i.e. if the problem was treated as a single optimisation problem or if it was implemented as a series of smaller optimisation problems. However, with a large building it is likely that the method demonstrated in this thesis would require significant computational expense.

The NMPC approach with nonlinear optimisation (NMPC-NO) taken in this thesis has two main drawbacks. It is computationally intensive and the SQP optimisation is gradient based, hence may only find local minima. The problem of local minima could potentially be reduced by using a global strategy. However, this would further increase the computational burden and still give no guarantee of finding the global solution (Mahfouf & Linkens 1998).

One commonly used method to reduce the computational burden is to use NMPC with nonlinear prediction and linearisation (NMPC-NPL). In NMPC-NPL, the neural network model is linearised at each sampling instance. This allows for a LMPC algorithm to be used in place of the NMPC algorithm, as the optimisation has been simplified to a QP problem. The performance of NMPC-NPL is typically suboptimal compared with NMPC-NO (Ławryńczuk 2007), but in a range of practical applications the accuracy has been found to be acceptable (Babuska et al. 1999, Henson 1998, Kavsek-Biasizzo et al. 1997, Morari & Lee 1999).

While the use of linearisation is the most common method, there have been a number of alternatives proposed to obtain similar performance to NMPC-NO without the computational effort. One potential method is to use NMPC-NO to optimise the first control move, while the remaining moves are obtained using linear methods (Zheng 1997).

One of the more unusual methods to reduce the computational effort is to replace the MPC algorithm with a neural network (Kesson & Toivonen 2006, Cavagnari et al. 1999, Parisini et al. 1998). While an interesting approach, the training of the neural network model is difficult and may have limited applicability (Ławryńczuk 2007).

To summarise, there are a number of techniques which could be investigated to further reduce the computational effort. Not only is this important to enable application of MPC controllers to large multizone buildings, but it could also enable MPC to be utilised on stand-alone controllers in individual zones. These typically have a limited amount of processing power, potentially making NMPC-NO unsuitable.

7.7.4 Application to Multizone Buildings

In the previous section the need to consider computational effort was discussed in future applications to multizone buildings. In addition to an increased computational effort there are other difficulties which may be encountered when applying an MPC approach to multiple zones.

One problem which requires further consideration is the potential for connected zones to have conflicting control requirements. For example, one zone may require heating while another requires cooling, via opening the windows. This could occur in a situation with a zone on the south facing faade experiencing high solar gains while a north facing zone could be relatively cold. If these two zones are connected, as may be the case in a cross-ventilated or stack ventilated building, this could result in a conflict. Whereby, to maintain a suitable temperature one zone may require the windows to be opened while the other requires them to be closed.

To resolve a situation such as this would require a centralised optimisation of the building as a whole. To achieve the overall highest level of comfort in the building may necessitate some spaces straying further from their setpoint. Weighting of cost function parameters and constraint hardness will influence the degree to which conditions are allowed to change in each space. This could allow for some spaces to have a higher weighting than others if they have more stringent requirements. For example, in the case of a commercial office building the priority will be the offices themselves where occupants spend the majority of their time, while ancillary spaces such as kitchens and corridors are more transient. In this scenario the relative weighting for setpoint tracking for the offices could be greater than any ancillary spaces. This would allow for a greater deviation in spaces where occupant comfort is not as critical.

In the previous example, one zone had priority over the other in terms of maintaining internal conditions. In a situation where two interconnecting zones had conflicting demands and equal weighting the MPC controller would be required to evaluate which action has the smallest overall deviation from the desired conditions. To implement this in such a way as to avoid high levels of occupant dissatisfaction would require well defined constraints.

Occupant feedback could also be included within the controller. For example, if occupants could report being too hot or cold this could be used to increase the associated weighting to setpoint deviation in that particular zone. This could be used to prevent a situation whereby one zone is allowed to stray further from its setpoint to enable another zone to stay closer to setpoint conditions when it is either unoccupied or occupants are not dissatisfied with the conditions.

7.8 Summary

The MPC strategy in this chapter demonstrated potential to reduce overheating in naturally ventilated buildings. When appropriately long prediction horizons were utilised the

MPC controller essentially became a night ventilation strategy. This strategy used the thermal mass of the building to minimise overheating during the day by pre-cooling during the night. The controller determined this control strategy through the optimisation of a cost function which included no expert knowledge of the system.

In terms of implementing the MPC strategy, the majority of the time was spent identifying the predictive model. This is often cited as the most labour intensive element. However, a significant amount of time was also required for fine tuning the MPC controller. As such, in a real building sufficient time would have to be allocated for commissioning or methods of automated tuning developed.

There is great potential for further research and development. Particularly with regards to tuning of MPC parameters and reducing the computational effort required. The simulation setup demonstrated in this chapter was found to be well suited to testing the capabilities of the controller. A similar setup is envisioned to further test controllers before application to a real building.

Chapter 8

Summary and Conclusions

8.1 Summary

This thesis has addressed a clear gap in the current research. While MPC has been applied to a number of building systems in research literature there is limited evidence for how to develop the most appropriate model for MPC in HVAC and none associated with natural ventilation, where perturbation due to occupant window use can be substantial.

MPC is a control strategy which makes use of a model of the system dynamics to predict future plant output. By optimising an objective function, optimal control inputs can be determined to keep the plant upon the desired trajectory. The first control input is used and then the process is repeated for the subsequent timestep. It is this receding strategy which introduces feedback into the control. MPC was investigated as it has potential to improve upon the current rule-based control used in the vast majority of non-domestic buildings, which given the complexity of the decision space is unlikely to achieve near optimal control.

The key element in MPC is the predictive model. In prior applications to HVAC two main approaches to modelling were identified. Firstly, use of physics based models, including simple linear models and dynamic thermal simulation. The second approach is the use of black-box empirical models, such as neural networks, SVMs, etc. In this thesis an empirical approach using neural networks was taken. Methods for developing models, in particular the importance of suitable data, has been a major component of the thesis.

In order to demonstrate the potential benefits of MPC, a controller was demonstrated using cosimulation. The controller was designed to maintain a suitable temperature and prevent overheating in a naturally ventilated space during summer months.

The findings of this thesis are summarised in the following section. They are discussed in relation to the objectives of the thesis as defined in Chapter 1, where appropriate recommendations are made.

8.2 Conclusions and Recommendations

8.2.1 Objective 1

Identify appropriate methods to develop an empirical model of building performance in naturally ventilated buildings.

Naturally ventilated spaces present a number of challenges, in particular disturbances caused by occupants interacting with manual windows. In Chapter 2 a review of the current literature identified a number of empirical methods which could be applicable to modelling the dynamics of a naturally ventilated space. Neural networks were established as a potentially suitable modelling method. Using data from a range of different building types (described in Chapter 3) and simulation data (Chapter 6), neural network models were trained and their prediction capabilities tested. Based upon this work the following conclusions can be drawn:

1. Neural networks are capable of modelling the dynamics of zone temperature and CO₂ concentration in naturally ventilated spaces, using only variables typically collected by BMSs in modern buildings.
2. No a priori knowledge relating to building fabric or occupancy is required to develop models capable of reasonable predictions.

8.2.2 Objective 2

Evaluate the data requirements to generate a model appropriate for control.

Appropriate training data are critical to the success of an empirical approach to modelling. Modern BMSs offer an excellent opportunity to gather data. With increasingly ‘smart’ buildings the potential to develop more informative models should only improve. However, if MPC using empirical models is to be widely adopted a minor shift in BMS design and implementation is required. The inability of some BMSs’ to store fine resolution data for long periods is a problem. This could be easily remedied with software updates and increasing storage capacity (potentially utilising the cloud). Furthermore, the value of this data is significant and as such systems should be put in place to create backups and prevent accidental loss.

In this thesis data from three studies of real buildings were used to train neural network models to predict zone temperatures and CO₂ concentrations. These data encompassed a range of ventilation scenarios and building types located in different parts of the UK. Additionally, an excitation experiment was carried out using dynamic thermal simulation (Chapter 5 and 6). The resulting data were used to train further neural network models and the impact of persistent excitation of the window opening upon model predictions was evaluated. The performance of the resulting neural network models enable the following conclusions to be drawn:

1. While capable of reasonable prediction of temperature and CO₂ concentrations, models developed using data collected from buildings during normal operation are unlikely to capture the effect of the control (window opening).
2. In order to obtain suitable data for the training of empirical models for the control of natural ventilation systems, persistent excitation of the control input is required.
3. Open-loop excitation procedures were shown to be capable of generating suitable training data. However, the resulting extreme internal conditions suggest that closed-loop methods may be more suitable.

Recommendations

Data collected during normal operation are likely to be unsuitable for training suitable models. To obtain suitable training data input excitation must be carried out. Open-loop excitation will result in informative data, however the resulting internal conditions may cause disruption and occupant discomfort. Therefore a closed-loop identification is recommended, although further work is required to develop this. In closed-loop identification inputs are excited while the system remains under some form of feedback control. In the case of an existing building, feedback control could be maintained using the existing control logic. Alternatively, open-loop excitation could be carried out for new builds during commissioning, or in situations where the disruption will be minimal (buildings with seasonal occupancy such as schools/universities). The model obtained from the open-loop excitation could then be incorporated into the controller and re-identified using closed-loop methods during occupied periods.

Ideally training data should be acquired over as long a period as possible to ensure the data covers a sufficient range of conditions. However, as periodic re-identification is recommended to ensure that the model adapts to any changes in occupancy or fabric, a shorter period is acceptable to develop an initial model. Even a period of 1-2 weeks should be sufficient in most cases to develop an approximate model which could be used for control and subsequently re-identified using closed-loop methods.

8.2.3 Objective 3

Determine an optimum model training methodology for developing empirical models.

One of the key advantages of using neural networks is that the user does not need to include a priori information relating to the system being studied into the model. However, the user does need to specify the neural network model architecture and choose a suitable training algorithm. Previous studies on the application of neural network models to HVAC give minimal details on the procedures used to obtain a suitable model architecture. In this thesis a range of training algorithms and model architectures were tested.

It was concluded that model architecture can have a significant impact upon model performance. However, having established a suitable methodology similar prediction performance could be achieved on a range of data. Key components of the methodology are given below in the form of recommendations.

Recommendations

A NARX neural network structure is recommended as the autoregressive component can have a significant impact on prediction performance. Training in open-loop initially and then closing the loop is recommended for optimal performance without excessive computational effort in model training.

Based upon the training data used in this thesis, one hidden layer with 20 nodes is sufficient. Multiple lags are not required for exogenous inputs. However, some lagged autoregressive inputs (e.g. at 6, 12 and 24 hours) can improve prediction performance.

The Levenberg-Marquardt algorithm provides a good degree of accuracy with low computational effort. Multiple random initialisations should be carried out to mitigate the issue of local minima.

Early stopping should be used to prevent model overfitting. Increase in validation performance over 20 epochs is a suitable criteria to halt training.

8.2.4 Objective 4

Evaluate the potential of MPC (using the model developed in objectives 1-3) for improving the performance of naturally ventilated buildings.

In Chapter 7 an NMPC-NO controller was demonstrated using cosimulation. The controller utilised neural network models to predict the internal temperature in a single zone and a cost function designed for output reference tracking. The optimisation was carried out using SQP. The ability of the controller to maintain suitable temperatures and reduce overheating was investigated for three thermal mass scenarios. The conclusions based upon this study are as follows:

1. The NMPC-NO controller implemented was capable of reducing overheating and maintaining more comfortable temperatures in a naturally ventilated space. Overheating was reduced compared to RBC similar to that used in the actual building for the low, medium and high thermal mass scenarios, with hours over 25 °C reduced by 39%, 28% and 15% respectively.
2. The MPC controller was found to make use of night cooling when appropriate. The key advantage of this control method is its ability to determine when such a strategy is appropriate. Similar performance would be incredibly difficult to achieve using RBC due to the complexity of the rule set.

3. The thermal mass of the building being controlled impacts upon the optimum prediction horizon. In more heavyweight buildings a longer prediction horizon is required to achieve optimal performance.

Recommendations

To obtain good performance from the MPC controller a suitably long prediction horizon is required. A minimum of 24 hours is recommended. In the case of a building with high thermal mass increasing this to 48 hours will likely improve performance. Increases in the control horizon can have a significant impact upon computational effort. A period of around 2 hours (based upon a 10 minute timestep) should give good performance.

8.3 Evaluation and Future Work

This thesis has developed and demonstrated the methods of using an neural network modelling approach for MPC of natural ventilation systems. However there are several areas where further work is required before this can be rolled out for use as a commercial product. The focus upon empirical modelling, in particular the detailed investigation of the importance of appropriate data and identification has furthered the understanding of application of empirical methods to building systems.

In Chapter 3 the datasets which were used in this thesis were described. The issues encountered when carrying out data collection in large buildings during normal operation highlight a significant drawback with both the empirical approach to modelling and current BMSs. Most BMSs are not designed to safely store fine resolution data over long periods. The study at York showed that even if the BMS has the capability to store data it can be vulnerable to deletion. In future studies, greater engagement with all individuals involved in working with the system should be attempted to try to avoid such losses of data. Furthermore, if control strategies which are reliant upon data are to become the norm, BMSs themselves should be developed to ensure data loss is not a common problem. This could be as simple as a regular automatic back-up of data.

The methodology used to train neural network models in this thesis did not take into account the need for adaption as a building form or usage is likely to change over time. Models could be re-identified using the same procedure. However, more elegant adaptive solutions are possible. For example, the use of a closed-loop re-identification which could be carried out to adapt model parameters.

The system identification experiment conducted in Chapter 6 used an open-loop methodology. This was carried out using a thermal model of a building. The identification was successful, i.e. the neural network models trained using the data from the simulation under excitation were able to capture the effect of the control input (automated window opening). However, the simulation indicated that temperatures within the space would have been unacceptable in an occupied building. Open-loop identification was used as it

typically guarantees that the system is excited across its full range. If identification was to be carried out while a building was occupied some nominal control would be required to maintain acceptable conditions. In the case of a new build this could be achieved by carrying out open-loop identification as demonstrated in this thesis during a short commissioning period before the building was occupied. The resulting model could then be used to control the building while closed-loop identification was carried out during occupation to refine the model.

The MPC control demonstrated in Chapter 7 was only used to control a single zone within a larger simulation model. One of the key reasons for only using one space was that when building the simulation model in Chapter 5, the aim was to obtain performance as close to reality as possible. This was achieved by close study of the data from the real building, creation of detailed occupancy schedules, application of stochastic models for occupant behaviour, fine tuning of construction parameters etc. To achieve this level of detail across multiple zones in the building would have been impractical. Hence, the decision was made to develop a model which gave a realistic prediction for a single zone rather than a mediocre performance across multiple zones.

A logical progression is to investigate how the controller would need to be adapted for the control of multiple zones. For example, if the optimisation would be carried out using a centralised approach, within a single computation or if multiple smaller optimisations would be required. The scaling of the controller demonstrated may also necessitate study of alternative options for the optimisation procedure, as the computational effort may be significant.

The controller only controlled the window actuators based upon maintaining a suitable temperature within the space. This could result in excessively high levels of CO₂ and other contaminants. To counter this future studies could include CO₂ in the cost function or as an additional constraint on the optimisation. Further systems could also be incorporated such as heating.

The conclusions which are drawn in this thesis should be used as evidence that an MPC approach to control has significant potential to improve the control of natural ventilation systems. The methodology demonstrated could be adapted for further research topics and eventual applications in real buildings.

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Appendices

Appendix A

EnergyPlus Airflow Network

To calculate airflow rates EnergyPlus utilises The AirflowNetwork Model. This is a multi-zone airflow network model, which consists of a number of nodes which are linked by airflow components, such as openings, vents, cracks etc.

The airflow calculations for natural ventilation are carried out at the same time step as any HVAC systems, this makes it possible to simulate hybrid ventilation systems. At each time step there are three sets of calculations which are carried out by the AirflowNetwork model:

- Pressure and airflow calculations
- Node temperature and humidity calculations
- Sensible and latent load calculations

The initial pressure and airflow calculations determine the pressure at each node and the airflow through each linkage due to wind pressures and any forced airflows. The node temperatures and humidity ratios are then calculated using given zone air temperatures and humidity ratios. The zone sensible and latent loads are then calculated and included in the energy balance equation (EnergyPlus 2012a).

A.1 Pressure and airflow calculations

A.1.1 Initialisation

To initialise the calculation node air pressures are estimated using Newton's method. A linear approximation relating airflow to pressure drop is used to determine the initial pressures:

$$\dot{m}_i = C_i \rho (\Delta P_i / \mu) \tag{A.1}$$

where

\dot{m}_i = Air mass flow rate at the i_{th} linkage (kg/s)

C_i = Air mass flow coefficient (m^3)

ΔP_i = Pressure difference across the i_{th} linkage (Pa)

μ = Air viscosity (Pa·s)

A.1.2 Convergence criteria

Convergence of the solution is determined by conservation of mass flow rate at each linkage in the model. The AirflowNetwork uses two convergence criteria, relative and absolute airflow tolerance:

$$\text{Relative airflow tolerance} = \frac{|\sum \dot{m}_i|}{\sum |\dot{m}_i|} \quad (\text{A.2})$$

$$\text{Absolute airflow tolerance} = |\sum \dot{m}_i| \quad (\text{A.3})$$

Relative airflow tolerance is the ratio of the absolute value of the sum of all the network airflows to the sum of the network airflow magnitudes. The solution is considered to be converged when these two criteria approach zero, i.e. when conservation of mass is achieved.

A.1.3 Linkage models

A linkage model connects two nodes, an inlet and an outlet, these two nodes are linked by a linkage component. This could be a window, an air vent, a crack etc. It is the linkage component which gives the relationship between airflow and pressure (there is an extensive library of components within EnergyPlus which all have different characteristics for flow, some of which can be very complex). Bernouli's equation is used to calculate the pressure difference:

$$\Delta P = \left(P_n + \frac{\rho V_n^2}{2} \right) - \left(P_m + \frac{\rho V_m^2}{2} \right) + \rho g(z_n - z_m) \quad (\text{A.4})$$

where

ΔP = Total pressure difference between nodes n and m (Pa)

P_n, P_m = Entry and exit static pressures (Pa)

V_n, V_m = Entry and exit airflow velocities (m/s)

ρ = Air density (kg/m^3)

g = Acceleration due to gravity (m/s^2)

z_n, z_m = Entry and exit elevations (m)

By including the effect of wind pressure and simplifying this can be rewritten as:

$$\Delta P = P_n - P_m + P_S + P_W \quad (\text{A.5})$$

where

P_n, P_m = Total pressures at nodes n and m (Pa)

P_S = Pressure difference due to density and height differences (Pa)

P_W = Pressure difference due to the wind (Pa)

A.2 Node temperature and humidity calculations

A.2.1 Node temperature calculations

The following equation is used to calculate the temperature distribution across a flow element for a given airflow rate:

$$\dot{m}C_p \frac{dT}{dx} = UP(T_\infty - T) \quad (\text{A.6})$$

where

C_p = Specific heat of airflow (J/kg·K)

\dot{m} = Airflow rate (kg/s)

P = Perimeter of a duct element (m)

T = Temperature as a field variable (°C)

T_∞ = Temperature of air surrounding the duct element (°C)

U = Overall heat transfer coefficient (W/m²·K)

Node humidity ratio calculations

The humidity calculations follow a similar form to the node temperature calculations:

$$\dot{m} \frac{dW}{dx} = U_m P (W_\infty - W) \quad (\text{A.7})$$

where

\dot{m} = Airflow rate (kg/s)

P = Perimeter of a duct element (m)

W = Humidity ratio (kg/kg)

W_∞ = Humidity ratio of air surrounding the duct element (kg/kg)

U_m = Overall moisture transfer coefficient (kg/m²·s)

A.3 Sensible and latent load calculations

The sensible and latent load calculations included in the AirflowNetwork have three parts: multizone, duct conduction and leakage. When considering natural ventilation the applicable calculation is multizone which considers airflows from outside and those from adjacent zones. The sensible loads for the multizone calculation can be written as:

$$MCP_{airflow} = \dot{m}_{inf}C_p + \sum(\dot{m}_{mix}C_p) \quad (A.8)$$

$$MCPT_{airflow} = \dot{m}_{inf}C_pT_{amb} + \sum(\dot{m}_{mix}C_pT_{zone}) \quad (A.9)$$

where

$MCP_{airflow}$ = Sum of air mass flow rate multiplied by specific heat for infiltration and mixing (W/K)

$MCPT_{airflow}$ = Sum of air mass flow rate multiplied by specific heat and temperature for infiltration and mixing (W)

\dot{m}_{inf} = Incoming air mass flow rate from outdoors (kg/s)

\dot{m}_{mix} = Incoming air mass flow rate from adjacent zones (kg/s)

T_{amb} = Outdoor air dry-bulb temperature (°C)

T_{zone} = Adjacent zone air temperature (°C)

and the latent loads can be written as:

$$M_{airflow} = \dot{m}_{inf} + \sum \dot{m}_{mix} \quad (A.10)$$

$$MW_{airflow} = \dot{m}_{inf}W_{amb} + \sum \dot{m}_{mix}W_{zone} \quad (A.11)$$

where

$M_{airflow}$ = Sum of air mass flow rate for infiltration and mixing (kg/s)

$MW_{airflow}$ = Sum of air mass flow rate multiplied by humidity ratio for infiltration and mixing (kg/s)

\dot{m}_{inf} = Incoming air mass flow rate from outdoors (kg/s)

\dot{m}_{mix} = Incoming air mass flow rate from adjacent zones (kg/s)

W_{amb} = Outdoor air humidity ratio (kg/kg)

W_{zone} = Adjacent zone air humidity ratio (kg/kg)

The loads calculated in the AirflowNetwork are then integrated into the EnergyPlus heat balance equation.

A.4 Conductive Transfer Function (CTF) calculations

The zone temperatures are calculated using the Conductive Transfer Function Calculation Module. The zone temperature is dependant upon the heat gains in the space. These heat gains consist of specified internal heat gains, air exchange between zones, air exchange with the outside environment, and convective heat transfer from the surfaces in the zone (EnergyPlus 2012a). Of the aforementioned gains, the convective heat transfer from zone surfaces involves the most complex calculations. This is because it requires a detailed energy balance at the inside and outside surface of each element within the zone. The transient heat conduction within the material must also be solved in order to give the surface temperatures and heat fluxes. These values are required before the convection component, which contributes to the zone load, can be calculated. Although the calculations are complex and can, in some situations, significantly increase the simulation time, they form a vital part of the program. The thermal processes occurring within the space are of great interest to this project, as overheating and the effects of thermal mass in naturally ventilated buildings are of high importance.

The CTF calculations in EnergyPlus use the state space method. The state space method allows the outputs of thermal calculations (heat fluxes) to be given as a function of the environmental temperature only. This is in contrast to other methods, such as Laplace method, which additionally requires the nodal temperatures. The accuracy of the state space method for calculating CFTs has been validated. Ceylan & Meyers (1980) compared the state space method to other techniques for calculating heat fluxes on the surface of a solid slab. Their results showed that the state space method obtained results within 1% of the analytical methods.

Appendix B

Publications



Neural network modelling of naturally ventilated spaces

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ABSTRACT. During operation, buildings consume a large amount of energy, in developed countries around 40% of total final energy use. A major challenge is to reduce the amount of energy used while still providing a comfortable environment for building occupants. The use of passive techniques, such as natural ventilation, is promoted in certain climates to provide low energy cooling and ventilation. However, controlling natural ventilation in an effective manner to maintain occupant comfort can be a difficult task, particularly during warm periods. One area which has been identified as having the potential for reducing energy consumption while maintaining occupant comfort is the use of more advanced control techniques and a move towards “intelligent” buildings. A technique which has been much explored in recent years for application in mechanically ventilated buildings is Model Predictive Control (MPC). The essential component of an MPC strategy is the predictive model of the building's thermal dynamics. In this paper a data driven, neural network approach to system modelling is taken to model internal temperatures. Building data from a recently built naturally ventilated school and an office building are used to train multilayer perceptron neural network models and the resulting models performance are examined. The models developed were found to have good prediction capabilities over reasonable prediction horizons; however the effect of the control input was not captured.

KEYWORDS. MPC; Neural Networks; Ventilation.

INTRODUCTION

Energy costs, climate change, mounting political and social pressure are examples of some of the drivers for the increasing attempts to reduce energy consumption. Buildings account for around 40% of total final energy consumption in developed countries [1], and in European countries around 76% of the energy consumed by buildings is used for comfort control, i.e. heating, ventilation and air conditioning (HVAC) [2]. Reducing the amount of energy required by HVAC systems can be approached in a number of ways, for example increasing airtightness, better insulation, increasing appliance efficiency, passive ventilation techniques etc. In addition to energy concerns, there has been a growing awareness of the impact of indoor environmental quality (IEQ) upon occupants' wellbeing [3]. IEQ refers to the quality of a building's environment in relation to the health and wellbeing of those who occupy the space [4]. There is a number of factors which contribute to IEQ including air quality, temperature, lighting, contaminants etc. Natural ventilation is the process of supplying and removing air to an indoor space without the aid of mechanical systems. Natural Ventilation is driven by pressure differences caused by wind or temperature differences. As natural ventilation is

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affected by a number of factors such as external temperature, wind speed, wind direction, internal temperatures etc. It can be hard to predict the consequence of opening a window or vent. This makes control of naturally ventilated spaces more challenging than mechanically ventilated or air-conditioned spaces [5]. In this paper we propose a control method which has the potential to reduce energy consumption and optimise occupant comfort in naturally ventilated spaces. Model Predictive Control (MPC) is a control method which originated in process industries [6]. MPC utilises a system model to optimise future outputs based upon possible inputs over a finite receding horizon. At each time step a minimisation of some objective function is carried out in order to determine the optimal control signals over a finite horizon. At each iteration only the first step of the control strategy is then implemented. The control horizon is then shifted one step forward and the process is repeated [6].

PROBLEM DESCRIPTION

Modelling Strategy

In order for MPC to be successful, an accurate model of the system is required. The model should be as simple as possible and have good prediction characteristics over the control horizon [7, 8]. There are two main approaches to system modelling which can be taken when applying MPC to HVAC systems. One approach is the use of first-principles models, typically multizone-network models such as EnergyPlus, TRNSYS etc. These models are based upon our knowledge of the physical processes taking place within the building. The alternative to the first-principles models is the use of black-box data-driven models. These models are typically less computationally intensive to use and once a suitable workflow has been devised, relatively simple to create. Empirical models have the advantage of modelling the processes which are actually happening within a space without including the assumptions which are necessary with a first-principles model. For example, with a simulation tool, such as EnergyPlus, it is possible to include detailed occupancy and activity schedules but it will be hard to fully capture the stochastic manner in which occupants interact with the building and their effect upon the building's thermal environment. Additionally, as we move towards "smart buildings", there are an increasing amount of data available about how buildings are actually running, which have the potential to drive a data-driven approach.

In this paper, we take a data driven approach using multilayer perceptron (MLP) neural networks to predict zone temperatures in naturally ventilated spaces. Neural Networks have been used in previous studies for control of HVAC systems [9] and automated window blinds [10]. The Neural Network Toolbox within MATLAB was used to train and test the networks using the workflow shown in Fig. 1.

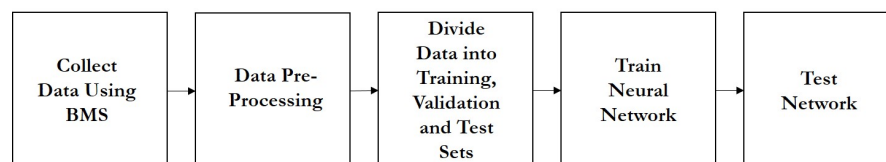


Figure 1: Workflow for Neural Network modelling strategy.

Building Descriptions

The essential component in the empirical approach taken in this paper are the building data with which a model can be trained. Obtaining suitable data was found to be challenging. There were two main problems experienced when attempting to obtain real building data for this project. Firstly, convincing building managers, owners and other stakeholders to give access to data which could highlight poor performance in their buildings. In cases where this initial hurdle was overcome there are practical difficulties related to gathering building data. While most building management systems (BMS) are capable of recording data they are not typically designed to store large amounts of data over prolonged periods. It was additionally quite common that there were gaps in the data and erroneous sensor readings. This had implications for the amount of pre-processing which was required before the models could be trained.

The building data used in this project comes from two sources: a recently-built school, and an office building in the north of England. Both are naturally ventilated and have a range of single-sided, cross and buoyancy ventilated spaces. The windows are a combination of occupant-controlled manual windows, and automated windows and vents. Data are available for the opening position of the automated windows in both buildings, however due to the lack of sensors on the



manual occupant-operated windows, there is no information available. For this reason the manual windows can be treated as a disturbance which will affect the models. A total of eight zones within each building were studied. Data was collected for a full year and sampled at 10 minute intervals.

SYSTEM IDENTIFICATION

The first stage in system identification is pre-processing. In this study there were two distinct phases in the pre-processing. First was the processing carried out to extract and clean the data recorded by the BMS. This included linearly interpolating to replace missing data points and removing any obvious outliers. Outlier removal was carried out by calculating the standard score for each variable and then removing all values which fell outside of an expected range. The second phase of pre-processing was carried out to improve network training. This included normalization to prevent saturation of the sigmoid transfer units in the network and to adjust the magnitudes of the various inputs. Typically, it is beneficial for network performance if inputs to have a similar magnitude unless there is intentional weighting being applied.

Following the initial data cleaning and pre-processing, the data were divided into three subsets using three contiguous blocks of the original data set. The first set is used for model training, the second for validation (this set is used to prevent over-fitting) and the final set is withheld from model training and used as an unseen test set.

For the control of natural ventilation we want to model internal zone temperatures based upon the previous zone temperatures and the effect of other inputs shown in Tab. 1. These are all inputs that were collected using the building management system. This is essentially a non-linear autoregressive with exogenous external inputs (NARX) model. The defining equation for a NARX model is given by:

$$y(t) = f(y(t-1), y(t-2), \dots, y(t-n_y), u(t-1), u(t-2), \dots, u(t-n_u)) \tag{1}$$

where the target (y) is a function of previous values of itself and of other inputs (u). In a NARX network the target can be considered to be an estimation of the true output of the system being modelled. During training of the network, the true output is available. This allows a series-parallel or “open-loop” architecture to be used (as shown on the left in Fig. 2). There are two key advantages to a series-parallel architecture. Firstly, the input to the network is more accurate and hence the resulting network tends to have a greater performance. Secondly, the network has a purely feedforward architecture allowing static backpropagation to be used in training [11]. This means that training is less computationally intensive.

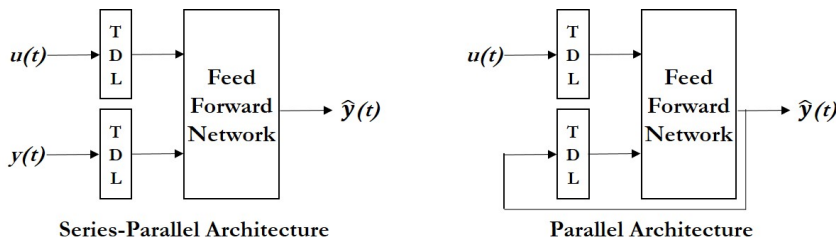


Figure 2: Feed forward network architectures for NARX networks. On the left is the series-parallel or open-loop configuration ideal for one-step-ahead prediction and on the right is the parallel or closed loop configuration. In a parallel architecture model predictions are fed back into the network through a tapped delay line (TDL) allowing for multi-step-ahead predictions. Adapted from Beale et al. [11].

However by training the network using a series-parallel form, training has been optimized for one-step-ahead prediction. While this is a good starting point, multi-step-ahead prediction is required for MPC. One possible approach is to train the network using a series-parallel architecture and then close the loop to create a parallel architecture. However as the training has been carried-out using actual values of the network output and then tested with predicted values, performance is not optimal. However, it is undesirable to train the network in a closed-loop form from the outset due to the time and computational effort required. In order to achieve an accurate final model without a large computation requirement, the workflow shown in Fig. 3 was utilised. By carrying-out the training initially using a series-parallel architecture and then

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using the resulting weights and biases as the starting point for the closed loop network, a 46% reduction in training time was observed (based upon a study using data from 5 zones and repeating training 10 times per zone).

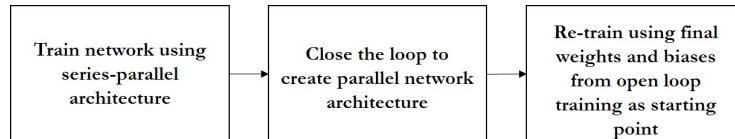


Figure 3: Optimal workflow for training neural network models.

The structure of neural network models is in some respects determined by the system being modelled (number of input and output nodes), however it is up to the user to determine the optimum number of hidden layers and hidden nodes contained within them. Although there is some guidance in the literature, this can often be contradictory [12, 13, 14]. Therefore, determining the optimum structure for a particular problem and set of data is largely a process of trial and error. In addition to training networks with a range of architectures a number of combinations of inputs and input delays were also tested.

Variable	Type	Notes
Zone Temperature	Output	
Outdoor Temperature	Input	
Wind Speed	Input	
Wind Direction	Input	
Window Opening Percentage	Input	Only available for automatic windows
Heating Status	Input	Boolean value showing heating on/off state

Table 1: Variables used for system identification.

RESULTS

The models developed in this paper were found to perform well upon the unseen test data. The first models generated were for one-step-ahead prediction. As can be seen in Fig. 4 the one-step-ahead models almost perfectly track the target temperatures, typical mean squared errors (MSE) were in the range of 0.1-0.2. This performance is good, however the prediction horizon of 10mins is very short. When the models were trained in a parallel architecture the multi-step-ahead prediction capabilities were also found to be good; as can be seen in Fig. 4. When predicting the zone temperature at twenty-steps-ahead ($n=20$, i.e. 200mins in the future) the typical MSE was approximately 0.5. MSE was used as an initial metric by which to judge model performance as it was the performance function minimised during network training [11]. Other measures of model performance such as the standard deviation and mean absolute percentage error were also calculated and used for model selection [15]. However, for analyzing results a visual comparison of model outputs and targets was found to give the best insight into how the model performed. It can be seen in Fig. 4 that the model outputs closely track the target temperatures for the unseen test data. Upon closer inspection it was observed that model performance was poorer during unoccupied periods. Fig. 4 shows test data for a week in one of the zones within the school. It can be seen that at the end of the week and during the nights the predictions stray further from the target temperatures. This seems to indicate that occupancy can have a high impact upon the models. Potentially this could be overcome by creating two models for each zone; one for occupied periods and one for unoccupied. This is likely to improve accuracy, however the degree to which this would impact upon the control performance may not justify the extra complexity.

While the initial results appeared very promising, upon closer inspection there were clear inadequacies with the models developed. During training of the models a number of different combinations of the inputs shown in Tab. 1 were used. The addition of further information to the model did not improve performance over a purely autoregressive model based



upon previous values of zone temperature. This suggests that previous values for zone temperature are a good enough predictor without additional weather data. While being able to discard weather inputs could have potential benefits in reducing model complexity, it is essential that the influence of control inputs (window opening positions) are captured by the model. It was confirmed by carrying out a sensitivity analysis that the window position had no impact upon the output temperature. This would prevent the models from being suitable for an MPC application.

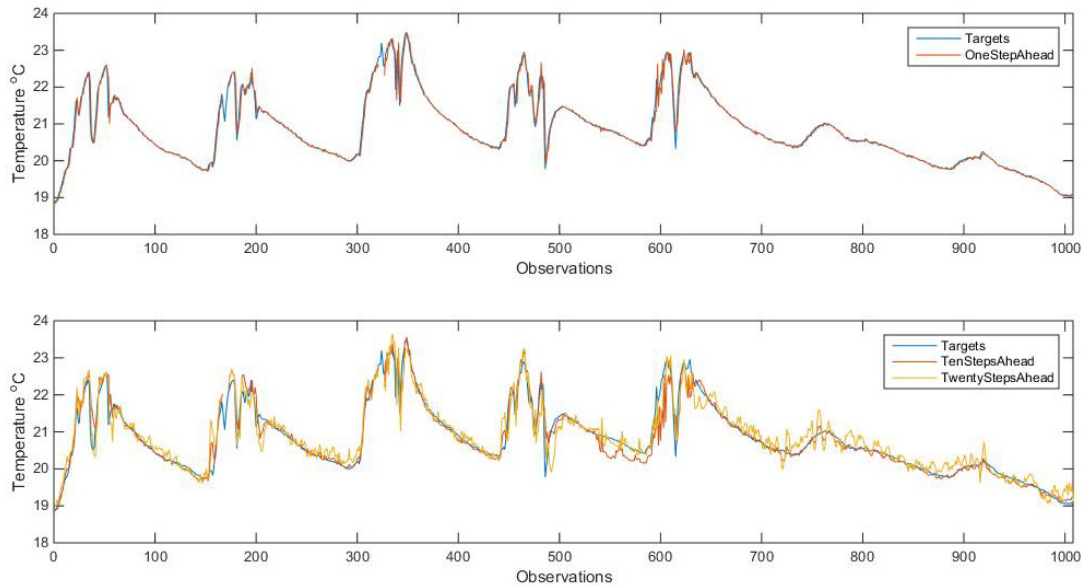


Figure 4: Comparison of model output temperatures and observed temperature for unseen test data. The top graph shows the one-step-ahead performance and the bottom shows $n=10$ and $n=20$ (10 minute time step).

DISCUSSION

The models developed were able to predict internal temperature over a reasonable prediction horizon. However the effect of the window opening percentage was not captured by the models. This would make them unsuitable for the MPC approach to ventilation control proposed in this paper. The inability of the models to capture the effect of the control input is most likely due to lack of sufficient input excitation and is one of the common drawbacks when using data driven models [7, 8]. Buildings are typically operated within a tight range and the input is not persistently excited [16, 17]. This can lead to models which while providing reasonable prediction capability, are lacking in essential physical relationships. The inability of the models generated to capture the effect of the control input is most likely due to this issue. This could potentially be overcome by carrying out an identification experiment where more complex signals are used to excite the system over a greater range.

Carrying out an identification experiment on a real building during occupation has the potential to cause disruption. In some cases it would be possible to carry out identification experiments during periods of low occupancy such as those experienced in schools and other academic institutions [17] or in the case of new buildings it could take place during commissioning.

CONCLUSIONS

Although the models developed are unsuitable for the purpose of MPC, there are other potential uses for accurate data driven models such as those developed in this project. Previous studies have used empirical models for fault diagnosis [18, 19] and to investigate potential overheating [20]. There could also be potential to incorporate a

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future temperature prediction within a traditional rule based control strategy.

Further Work

In order to determine if the inability of the developed models to capture the effect of window opening is caused by lack of input excitation, an identification experiment is proposed. Due to the high costs involved this will not be performed in a real building or experimental mock up but through the use of computer generated data using a multizone building simulation tool such as EnergyPlus. This experiment is not proposed to increase the accuracy of the model predictions but to generate a model which better represents the physical processes occurring and is suitable for the MPC application.

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MODEL IDENTIFICATION FOR THE CONTROL OF NATURALLY VENTILATED BUILDINGS

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ABSTRACT

In this paper, predictive models are developed to enable the application of model predictive control (MPC) to naturally ventilated buildings. The essential component of an MPC strategy is the predictive model of the building's thermal dynamics, which is the focus of this study. An empirical approach is taken using multilayer perceptron (MLP) neural network models. The models presented were generated using data gathered from real buildings during operation and building simulation data generated using EnergyPlus. The resulting models were able to accurately predict internal conditions such as zone temperature. The problem of insufficient input excitation is highlighted and an identification procedure to overcome it is presented.

INTRODUCTION

Energy costs, climate change, mounting political and social pressure are examples of some of the drivers for the increasing attempts to reduce energy consumption. Buildings account for around 40% of total final energy consumption in developed countries, (Perez-Lombard et al., 2008), and in European countries around 76% of the energy consumed by buildings is used for comfort control, i.e. heating, ventilation and air conditioning (HVAC) (International Energy Agency, 2008). Reducing the amount of energy required by HVAC systems can be approached in a number of ways, for example, increasing airtightness, better insulation, increasing appliance efficiency, passive ventilation techniques, etc. In addition to energy concerns, there has been a growing awareness of the impact of indoor environmental quality (IEQ) upon occupants' wellbeing (ASHRAE, 2013). IEQ refers to the quality of a building's environment in relation to the health and wellbeing of those who occupy the space (CDC, 2013). There is a number of factors which contribute to IEQ including: air quality, temperature, lighting, contaminants etc.

Natural ventilation is the process of supplying and removing air to/from an indoor space without the aid of mechanical systems. Natural Ventilation is driven by pressure differences caused by wind, or temperature gradients (Awbi, 2003). As natural ventilation is affected by a number of factors, (such as

external temperature, wind speed, wind direction and internal temperatures), it can be hard to predict the consequence of opening a window or vent, making control of naturally ventilated spaces more challenging than mechanically ventilated or air-conditioned spaces (Thomas, 2006). In this paper, we consider a control method which has the potential to reduce energy consumption and optimise occupant comfort in naturally ventilated spaces. Model Predictive Control (MPC) is a control method which originated in the process industries (Camacho and Bordons, 2007). MPC utilises a system model to optimise future outputs based upon possible inputs over a finite receding time horizon. At each time step, a minimisation of some objective function is carried out to determine the optimal control signals over a finite horizon. At each iteration, only the first step of the control strategy is then implemented. The control horizon is then shifted one step forward and the process repeated ad infinitum (Camacho and Bordons, 2007).

MODELLING

Modelling Strategy

Previous studies have investigated the potential to apply MPC techniques to HVAC systems. Existing work has focussed predominantly on applying MPC to mechanically ventilated buildings with a limited number of studies on mixed-mode spaces. In the current paper, the application of MPC to naturally ventilated spaces is investigated. Application of MPC to naturally ventilated spaces is likely to be more difficult compared with a mechanically ventilated scenario. With mechanical ventilation there is always some measure of how much cooling is being delivered in a space (e.g. fan power). However, with natural ventilation the cooling is provided by opening windows. In this scenario, the effect of the control action is highly changeable due to the number of variables that influence flow rate, such as temperature differences and wind speed. While the basic modelling procedure demonstrated in this paper is similar to previous studies on mechanical systems, a more complex identification procedure is carried out in order to incorporate the effect of opening windows.

In order for MPC to be successful, an accurate model of the system is required. The model should be as

simple as possible and have good prediction characteristics over the control horizon (Shook et al., 2002), (Lauri et al., 2010). There are two main approaches to system modelling which can be taken when applying MPC to HVAC systems. One approach is the use of first-principles models. These models are based upon our knowledge of the physical processes taking place within the building. In early applications, the first-principles models used were relatively simple linear models. Initial studies applied first-principles models to individual components in HVAC systems and then to simplified single-zone buildings and HVAC systems (Wang and Jin, 2000), (Yuan and Perez, 2006).

Recently there has been an increasing use of building energy modelling tools, typically multizone-network models such as EnergyPlus, TRNSYS etc. (Zhao et al., 2013), (May-Ostendorp et al., 2011). As with simple linear models, these models are based upon our knowledge of the physical processes taking place within the building. However, the use of building energy modelling tools allows for more complex building geometry and system modelling.

The alternative to the first-principles models is the use of ‘black-box’ data-driven models. These models are typically less computationally intensive to use, and once a suitable workflow has been devised, relatively simple to create. Empirical models have the advantage of modelling the processes which are actually happening within a space without including the assumptions which are necessary with a first-principles model. For example, with a simulation tool, such as EnergyPlus, it is possible to include detailed occupancy and activity schedules but it will be hard to fully capture the stochastic manner in which occupants interact with the building and their effect upon the building’s thermal environment. Empirical models can allow the relationship between variables to be mapped without calculating further, hard to predict variables. For example, in naturally ventilated buildings, it can be difficult to determine air flow rates; by using an empirical approach this becomes unnecessary as the effect of the weather conditions and window controls on indoor temperature can be modelled without the need for further information. Additionally, as we move towards “smart buildings”, there are increasing amounts of data available about how buildings are actually running, which have the potential to enable a data-driven approach.

A black-box approach to system modelling has a number of advantages over first-principles models. However, there is one significant disadvantage of the black-box approach. Often the inputs are insufficiently excited, and thus data collected from buildings during normal operation can fail to capture some important physical properties, resulting in a model inappropriate for MPC (Cigler and Privara, 2010). The need to carry out a specific identification experiment, whereby the inputs are excited, is often

given as a reason to discount black-box modelling of HVAC systems (Cigler and Privara, 2010).

In this study, the initial models were generated using data collected from buildings during normal operation. Upon analysing the resulting models, lack of input excitation was found to be a problem. Although the resulting models were able to accurately predict future temperatures, the models did not capture the effect of the control input (window actuators). To investigate how this may be overcome, an identification experiment was carried out using EnergyPlus.

Neural Network Modelling

In this paper, we take a data-driven approach using multilayer perceptron (MLP) neural networks to predict zone temperatures in naturally ventilated spaces. Neural Networks have been used in previous studies for control of HVAC systems (Kusiak and Xu, 2012) and automated window blinds (Chen et al., 2009). According to Haykin (1998), neural networks are perhaps the most well-known class of nonlinear models. A multilayer neural network model is shown in Figure 1. An MLP neural network consists of multiple layers of nodes, where each layer is fully connected to the next. With the exception of the input nodes, each node has an associated non-linear processing function, in this case a sigmoid function (“S” shaped mathematical function (Bishop, 2006)), and a weight and bias parameter. As the neurons are nonlinear functions, the output of the network is a nonlinear function of the parameters (Nowak, 2002).

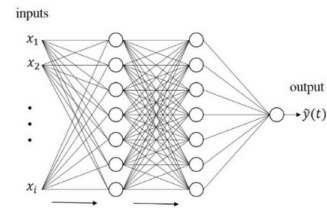


Figure 1 Multilayer Neural Network Model. The arrows denote the direction of information flow through the network during forward propagation (Bishop, 2006).

In this paper, we are using neural networks to model zone temperatures. As the current zone temperature will be related to previous temperatures, we can consider previous values as inputs. Hence, the model structure is essentially a non-linear autoregressive with exogenous external inputs (NARX) model. The defining equation for a NARX model is given by:

$$\tilde{y}(t) = f(y(t-1), y(t-2), \dots, y(t-n), x(t-1), x(t-2), \dots, x(t-n)) \quad (1)$$

After comparing five different data-mining approaches, Kusiak et al. (2011) found that MLP neural networks gave the best prediction performance when predicting energy consumption in a mechanically ventilated space. In this study, the Neural Network Toolbox within MATLAB was used to train and test the networks.

The structure of neural network models is in some respects determined by the system being modelled (number of input and output nodes), however it is up to the user to determine the optimum number of hidden layers and hidden nodes contained within them. Although there is some guidance in the literature, this can often be contradictory (Blum, 1992), (Swingler, 1996), (Boger and Guterman, 1997). Therefore, determining the optimum structure for a particular problem and set of data is largely a process of trial and error. In this study, in addition to training networks with a range of architectures, a number of combinations of inputs and input delays were also tested.

Real Building Data

The building data used in this project comes from two sources: a recently-built school, and an office building in the north of England. Both are naturally ventilated and have a range of single-sided, cross-ventilated and buoyancy-ventilated spaces. The windows are a combination of occupant-controlled manual windows, and automated windows and vents.

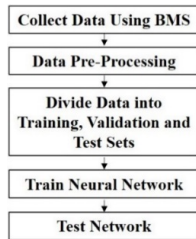


Figure 2 Workflow when using real building data.

The workflow process is shown in Figure 2; the initial step was to collect the building data using the building management system (BMS). Data are available for the opening position of the automated windows in both buildings, however due to the lack of sensors on the manual occupant-operated windows; there is no information available on these. For this reason, the manual windows were treated as a disturbance. A total of eight zones within each building were studied. Data were collected for a number of variables (shown in Table 1) in 16 zones, for a full year of operation and sampled at ten-minute intervals.

In this study, there were two distinct phases in the pre-processing. First, was the processing carried out to extract and clean the data recorded by the BMS. This included linearly interpolating to replace missing data points and removing any obvious outliers. Outlier removal was carried out by calculating the standard score for each variable and then removing all values that fell outside of an expected range. The standard score of a variable is given by:

$$z = \frac{x - \mu}{\sigma} \tag{2}$$

Upon calculating the standard score, the results were used to determine the number of standard deviations away from the mean for which an observation could

Table 1 Variables recorded by BMS for use in system identification.

VARIABLE	TYPE	NOTES
Zone Temperature	Target	
Zone CO ₂	Input	
Zone Humidity	Input	
Outdoor Temperature	Input	
Wind Speed	Input	
Wind Direction	Input	
Window Opening Percentage	Input	Only available for automated windows
Heating Status	Input	Boolean value showing heating on/off state. Due to well insulated construction and level of occupancy, heating was rarely on during occupied hours (<1% of the time)

be considered an outlier (Howell, 1998). This was carried out on a case-by-case basis for each variable (typically three standard deviations from the mean was used to define outliers).

The quality of the data differed between variables. The model target (zone temperature) showed no obvious outliers in any of the 16 zones. However, input variables such as zone humidity, zone CO₂ and wind speed had a relatively high number of erroneous observations. For example, in Figure 3 we can see the standard score plot for relative humidity in one of the zones within the school. There are clearly erroneous observations in these data as a standard score of around sixty equates to a relative humidity of almost 1000%. However, by removing observations which were outside 3 standard deviations of the mean, most of the sudden jumps, which were likely caused by errors in the measurement or recording equipment, were removed.

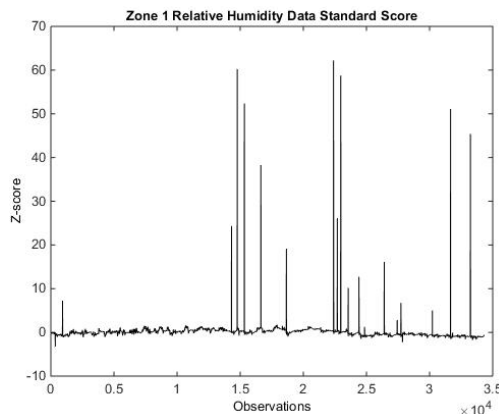


Figure 3 Standard Score plot for one of the classrooms within the school.

The second phase of pre-processing was carried out to improve network training. This included normalization to prevent saturation of the sigmoid transfer units in the network and to adjust the magnitudes of the various inputs. Typically, it is beneficial for network performance if inputs have a similar magnitude, unless there is intentional weighting being applied.

Following the initial data cleaning and pre-processing, the data were divided into three subsets using three contiguous blocks of the original data set. The first set was used for model training, the second for validation (this set was used to prevent over-fitting) and the final set was used as an unseen test set.

System Identification using Building Simulation

As previously mentioned, lack of input excitation can be a problem when using data collected from a building during occupation. Typically, buildings operate within a tight range of pre-specified temperatures and the standard input signals used to control actuators are insufficient to develop models with a suitable prediction capability. To overcome this, an identification experiment can be carried out, whereby the system is persistently excited. In this study, it was not possible to carry out an identification experiment on a real building. Therefore, building simulation was used to test the identification procedure using the workflow shown in Figure 4.

Simulation was used for the identification experiment as it allows you to test the building to extremes. Had a real building been used in this initial identification experiment there would have been significant disruption and unsuitable internal conditions for the building occupants. In this project, an open-loop system identification procedure is demonstrated. This resulted in a much greater range of internal temperatures than would be tolerated by building occupants. As a first step, open-loop system identification is the logical choice as it is more likely to sufficiently excite the system and result in models

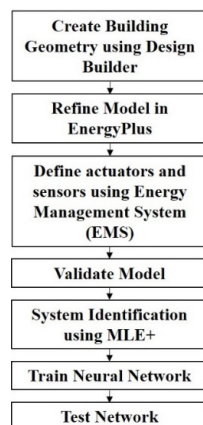


Figure 4 Workflow for system identification using simulation data.

that capture the underlying dynamics. Given the large range of temperatures which resulted from the open-loop identification using simulation; in an occupied building, feedback control and a closed-loop identification may be necessary.

The model used in this study, was based upon one wing of the school building previously discussed (see Figure 5). For the purposes of the identification experiment, only one zone within the space was considered. EnergyPlus was used as the primary simulation program, with DesigBuilder used to generate the initial model geometry. To enable more complex control strategies to be tested, the Energy Management System functionality within EnergyPlus was then used to define temperature sensors and actuators for controlling the automated windows.

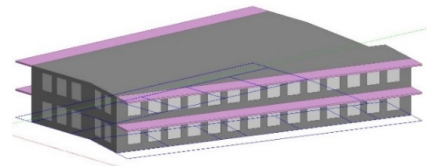


Figure 5 Building model view in the DesignBuilder program, one wing containing 25 zones was modelled (footprint approximately 900m²).

To implement the identification experiment, MLE+ was used. MLE+ is an open-source Matlab/Simulink toolbox for co-simulation with EnergyPlus (Bernal et al., 2012). By utilising MLE+, we can take advantage of the features available within the Matlab System Identification Toolbox.

In order to identify the parameters of a system model, the input signal used in the identification must be sufficiently rich. In this study, Gaussian white noise (GWN) was used as excitation to the system. GWN is often used as excitation in identification experiments (Nowak, 2002). If a system is subjected to a GWN stimulus over a sufficiently long enough time, there is a finite probability that any given stimulus waveform will be approximately represented by some sample of the GWN signal. Essentially, the system is being tested with every possible stimulus, or at least a large variety depending on the period over which the experiment is being carried out (Marmarelis and Marmarelis, 1978).

Using MLE+, the simulation was carried out with the window actuators being persistently excited. The resulting zone conditions along with the input signals were used to generate neural network models using the procedure previously described.

RESULTS

Real Building Data

To analyse the model performance, the model outputs were compared with the observed values for the unseen test data set. Alongside visual comparisons

(see Figure 6), the following four metrics were used to measure the prediction accuracy of the model: the mean absolute error (*MAE*), the standard deviation of absolute error (*StdAE*), the mean absolute percentage error (*MAPE*) and the standard deviation of the absolute percentage error (*StdAPE*):

$$AE = |\hat{y} - y| \quad (3)$$

$$MAE = \frac{\sum_{i=1}^n AE_i}{N} \quad (4)$$

$$APE = \left| \frac{\hat{y} - y}{y} \right| \quad (5)$$

$$MAPE = \frac{\sum_{i=1}^n APE_i}{N} \quad (6)$$

$$StdAE = \sqrt{\frac{\sum_{i=1}^n (AE_i - MAE)^2}{N - 1}} \quad (7)$$

$$StdAPE = \sqrt{\frac{\sum_{i=1}^n (APE_i - MAPE)^2}{N - 1}} \quad (8)$$

The models developed in this paper were found to perform well with the unseen test data. The first models generated were for one-step-ahead prediction. As can be seen in Figure 7 the one-step-ahead model almost perfectly tracks the target temperatures and performs well in all of the evaluation criteria shown in Table 2. The multi-step-ahead models were also found to perform well. When predicting at ten and twenty-steps-ahead ($n=10$, i.e. 100mins in the future and $n=20$, i.e. 200 mins in the future) the error increased but the predictions still tracked the observed data reasonably well (see Figure 8).

Table 2 Temperature prediction performance of the neural network models generated using real building data for one-step-ahead prediction, $n=10$ and $n=20$.

n	MAE	STD_AE	MAPE (%)	STD_APE (%)
1	0.195	0.164	0.0334	0.040
10	0.630	0.468	0.111	0.122
20	1.027	0.808	0.170	0.165

Upon closer inspection, it was observed that model performance was poorer during unoccupied periods. It was found that at the end of the week and during the nights, the predictions stray further from the target temperatures. This seems to indicate that occupancy can have a high impact upon the models. Potentially this could be overcome by creating two models for each zone, one for occupied periods and one for unoccupied. This is likely to improve accuracy; however, the degree to which this would impact upon the control performance may not justify the extra complexity.

While the initial results appeared very promising, there were clear inadequacies with the models developed. During training, a number of different

combinations of the inputs shown in Table 1 were used. The addition of further information to the model did not improve performance over a purely autoregressive model based upon previous values of zone temperature alone. This suggests that previous values for zone temperature are a good enough predictor without additional data. While being able to discard weather inputs could have potential benefits in reducing model complexity, it is essential that the influence of control inputs (window opening positions) are captured by the model. It was confirmed by carrying out a sensitivity analysis that the window position had no impact upon the output temperature for both the single and multi-step-ahead models. This would prevent the models from being suitable for an MPC application.

System Identification: Building Simulation Data

The models developed using the data generated using EnergyPlus show a similar performance to those generated using the real data. When comparing the different performance criteria, it can be seen in Table 3 that the MAE for the models generated using the simulation data is slightly larger than that for the models generated using real building data, while the MAPE is actually smaller for the models generated using simulation data. This is because the input signal, used to regulate the window openings in the system identification experiment, is causing the building to operate over a larger range of temperatures. Hence, the percentage error is actually smaller while the mean is larger. The greater range of temperatures caused by the system identification experiment can be seen in Figures 9 and 10.

Table 3 Temperature prediction performance of the neural network models generated using simulation data for one-step-ahead prediction, $n=10$ and $n=20$.

n	MAE	STD_AE	MAPE (%)	STD_APE (%)
1	0.064	0.131	0.31	0.63
10	0.150	0.207	0.72	0.99
20	0.261	0.221	1.1	1.07

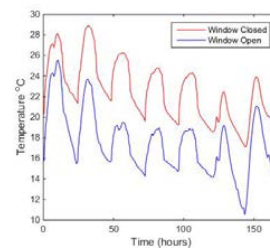


Figure 6 Model outputs for windows fully open and windows fully closed for a week in the May.

As with the models generated using real building data, a sensitivity analysis was carried out. In this case, the window opening percentage was indeed having an influence on the model output. Figure 6 shows the

output of the model for two scenarios: windows fully open and windows fully closed. In both of these cases, the model outputs seem reasonable; with higher zone temperatures predicted when the windows are left closed and cooler predictions when the windows are left fully open.

DISCUSSION

The models developed using the real building data were able to predict internal temperature over a reasonable prediction horizon. In this study, results are presented for up to 200mins into the future. This should be sufficient for a receding horizon control strategy. However, a thorough study of is required to determine the optimum prediction horizon, which will likely vary between buildings.

The effect of occupancy seems to have been modelled well by the neural network models. However, the real building models did not capture the effect of the window opening. This would make them unsuitable for the MPC approach to ventilation control. The inability of the models to capture the effect of the control input is most likely due to lack of sufficient input excitation and is one of the common drawbacks when using data driven models (Shook et al., 2002), (Lauri et al., 2010). Buildings are typically operated within a tight range and the input is not persistently excited (Privara et al., 2011), (Cigler and Privara, 2010). This can lead to models which, while providing reasonable prediction capability, fail to capture underlying dynamics in essential physical relationships.

Although the models developed using real building data are unsuitable for the purpose of MPC, there are other potential uses for accurate data driven models such as those developed in this project. Previous studies have used empirical models for fault diagnosis (Lee et al., 2004), (Katipamula and Brambley, 2005) and to investigate potential overheating (Iddon et al., 2015). There could also be potential to incorporate a future temperature prediction within a traditional rule based control strategy.

By examining the input signals from the real building data set, it was found that the median position for all of the automated windows in the zones monitored is 'closed'. In addition, the average time the windows were open was less than 6% during the observed period. While the windows being open for such a small percentage of time may have had an impact upon the indoor air quality it appears to have had an insufficient effect upon temperature to be captured by the models. Alongside the analysis of the neural network models developed, this suggests that if an empirical approach to modelling the thermodynamics of a naturally ventilated building is being taken, then collecting building data during normal operation is insufficient. In order for the models to capture the effect of inputs, an identification experiment such as the one demonstrated in this study must be carried out.

The identification procedure presented in this paper was successful. The resulting neural network models both gave accurate predictions over a reasonable horizon and captured the effects of window opening. However, the identification procedure used is relatively simple and would need refinement before being applied in a real building. The range of temperatures which resulted from the system identification experiment would be unacceptable in a real building. Further work is required with more refined proposals for the identification procedure. In particular, closed-loop system identification procedures may be more suitable for application in a real building. However, the degree to which the system is excited during a closed-loop experiment may result in models which are less informative.

CONCLUSIONS

The models developed using real building data gave a reasonable prediction for internal temperature. However, they did not capture the effect of window opening and as such, were unsuitable for MPC.

The identification procedure demonstrated using EnergyPlus shows that, with proper input excitation empirical neural network models can be created to model the thermal dynamics occurring within a naturally ventilated space. These models were able to give an accurate prediction of internal temperature over a reasonable prediction horizon and captured the effect of the control input successfully.

While the need to carry out an identification experiment is a disadvantage of empirical modelling, there are a number of advantages over using a simple first-principles or building simulation model: (1) once familiar with the techniques involved, creating the models is significantly less time intensive than building a dynamic thermal model; (2) empirical models do not require assumptions to be made about the building fabric or occupancy and are more likely to model the actuality within the building; (3) once developed, the models can output predictions much quicker than multi-zone building simulation programs as they require less computational effort.

Further Work

Having shown that empirical modelling techniques can be used for naturally ventilated spaces, there are two logical progressions. Firstly, further refinement and investigation of the identification procedure for application in a real building. Secondly, demonstrating a MPC approach in a naturally ventilated space.

NOMENCLATURE

μ	=	Mean of the population
σ	=	Standard deviation of the population
AE	=	Absolute Error
APE	=	Absolute Percentage Error
MAE	=	Mean Absolute Error

<i>MAPE</i>	=	Mean Absolute Percentage Error
<i>N</i>	=	Number of observations
<i>stdAE</i>	=	Standard Deviation of Absolute Error
<i>stdAPE</i>	=	Standard Deviation of Absolute Percentage Error
<i>x</i>	=	Input variable
<i>y</i>	=	Measured target output
\hat{y}	=	Predicted output from the model
<i>z</i>	=	Standard Score

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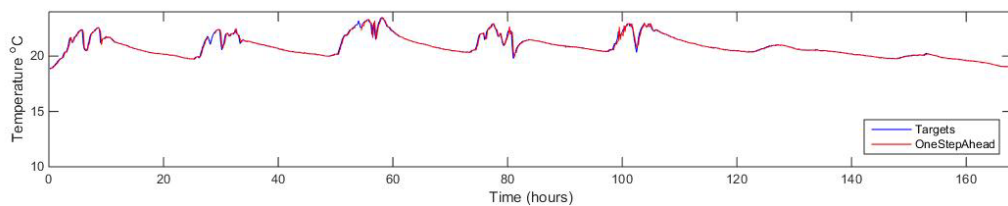


Figure 7 Comparison of one-step-ahead model output and observed temperatures for models developed with real building data.

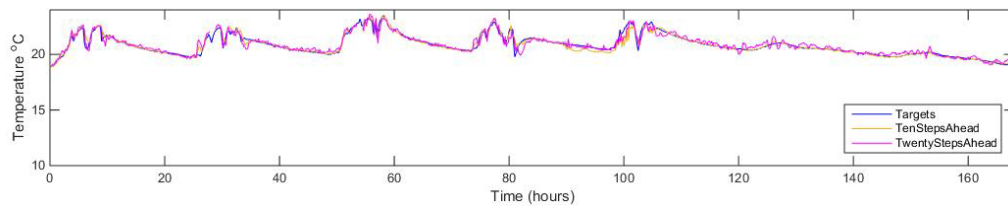


Figure 8 Comparison of model output for $n=10$ and $n=20$, and observed temperatures for models developed with real building data.

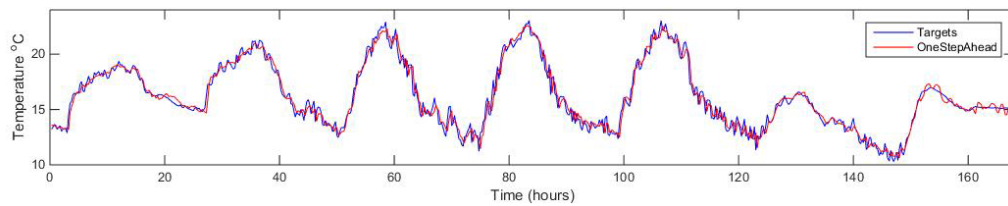


Figure 9 Comparison of one-step-ahead model output and observed temperatures for models developed using data from system identification simulation.

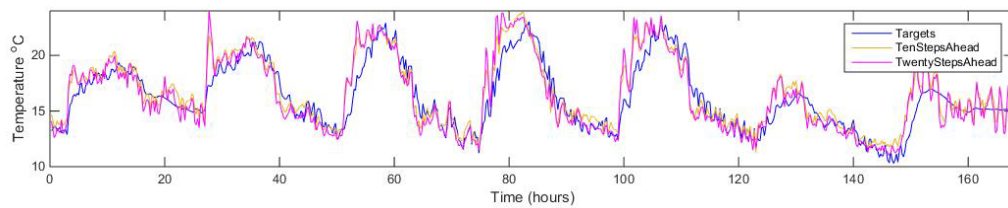


Figure 10 Comparison of model output for $n=10$ and $n=20$, and observed temperatures for models developed using data from system identification simulation.

