Application of an Agent Based Model to Study the Resource Exchanges within Eco-industrial Parks

Ganiyu Olabode Ajisegiri

Submitted in accordance with the requirements for the degree of Doctor of Philosophy

The University of Leeds

School of Chemical and Process Engineering

August, 2019

The first three years of this project received funding from the Federal Government of Nigeria, Tertiary Education Trust Fund (TETFund).

This project has received further funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No 680843

Declaration

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

The work which appears in the jointly authored publications (with Ganiyu Olabode Ajisegiri as the lead author) appears in chapters 3 and 4, the detail of the publication is as follow:

O. Ajisegiri G. and L. Muller F. (2018). “Effect of Price Dynamics in the Design of Eco-Industrial Parks: An Agent-based Modelling Approach”. Proceedings of 8th International Conference on Simulation and Modeling Methodologies, Technologies and Applications – Volume 1: SIMULTECH, ISBN 978-989-758-323-0, pages 83-90. DOI: 10.5220/0006836300830090, 29 – 31 July, 2018 Porto, Portugal.

In this case the work was directly attributable to the lead author with the co-author performing supervisory roles in the research.

Conferences and Publications

Conference:

O. Ajisegiri G. and L. Muller F. (2018). “Effect of Price Dynamics in the Design of Eco-Industrial Parks: An Agent-based Modelling Approach”.

Proceedings of 8th International Conference on Simulation and Modeling Methodologies, Technologies and Applications – Volume 1: SIMULTECH, ISBN 978-989-758-323-0, pages 83-90. DOI: 10.5220/0006836300830090, 29 – 31 July, 2018 Porto, Portugal.

G. O. Ajisegiri G. (2018). “Evolution of Eco-Industrial Park: An Agent-based Modelling Approach”.

ChemEngDayUK 20178, Molecules to Manufacturing, 27-28 March 2018, University of Leeds.

G. O. Ajisegiri G. (2017). Design and Simulation of Eco-Industrial Parks using Agent-based Modelling Approach”.

ChemEngDayUK 2017, Better Life, Better World, 27-28 March 2017, University of Birmingham.

Acknowledgements

Prophet Muhammed (SAW) in one of his sayings said “He who is ungrateful to his fellow human being will be ungrateful to his Lord”. I give glory to God.

I would like to show my profound, heartfelt and sincere gratitude to Professor Frans Muller, my caring and understanding supervisor, for his expert advice, encouragement and careful guidance through the successful completion of this work. The relationship has definitely blossomed and transcended that of student-supervisor. I cherish every moment of our encounter. Keep going on the tract, it is an endeavor of no regret. I would also like to sincerely thank my other supervisors, Professor Tim Cockerill and Dr Costas Velis for their commitment throughout my programme.

My sincere appreciation goes to the Federal Government of Nigeria, through Tertiary Education Trust Fund (TETFund), Nigeria for sponsoring my PhD programme for three years. I also wish to extend my regard to all the staff of my department (Industrial and Production Engineering, University of Ibadan, Nigeria) for their support. My appreciation also goes to the SHAREBOX, UNILEEDS team and Professor Andrew Heyes (My former supervisor) for sponsoring me through the fourth year of my study till I submitted the thesis. God bless you all.

On a personal note, I would like to thank my family, my parents, my in-law and brother in-law for all the prayers and sacrifices ventured since I started this journey. I would also like to thank my Uncle Alhaji L. B. Ajisegiri for his prayers and supplication all the time, you will long sir. Amin. I would also like to thank my beloved wife Adenike Ajisegiri and my Queens; Naadirah Morayo Ajisegiri and Nabeelah Morire Ajisegiri for being my inspiration, immeasurable support, patience and prayer through the long journey. I will be ungrateful if I forgot to show my appreciation to my mum Alhaja Ajisegiri Khadijat and my aunt Alhaja Fausat Shodiya for their caring and to all my brothers Mr. L.B. Ajisegiri, Mr Habeeb Ajisegiri, Engineer Kareem Ajisegiri, Alhaji Luqman Ajisegiri and my uncle Dr. A. A. Ajisegiri. Above all, my deepest gratitude goes to Almighty Allah (SWA), for seeing me through. I am very grateful.

Abstract

Industrial symbiosis (IS), emerges when diverse organizations interact to share resources with each other in order to increase their overall economic outcomes simultaneously reducing the overall environmental impact. However, it is difficult for companies to identify waste and potential resources. The European Union project SHAREBOX is developing an online platform that supports companies identifying each other resources and nucleate industrial symbiosis. When such opportunities are energy related, conversion technologies are typically required depending on nature of the energy resource and the mismatch between time of supply and user needs may necessitate energy storage. This research work focused on forecasting supply and demand time series as this data is important but typically difficult to obtain.

To model demand and supply time series, the Réseau agent-based model was developed. Here the agents; factories (internal agents), market buyers and market sellers (external agents) represent the players in the industrial ecosystems. The agents have dynamic behaviour (e.g. varying price) and heterogeneous characteristics (e.g. production method). Agents combine complex decision rationale with process models (here simplified as input-output model and maintaining the material and energy balance).

The decision strategies implemented in the model are; random seller selection and seller sells based on best price, random price changes and risk based price changes. The model was demonstrated on three different case studies with increasing complexity. Case study one demonstrated random decision strategies on single input single output industrial ecosystem. This validated the software concept. Case study two evaluates all combinations of decision strategies in and industrial ecosystem with factories that have multiple input multiple output. This showed that the risk based seller decision strategy developed in this work provides significantly more realistic demand and supply time series. This is independent on whether buyer choses the seller randomly or based on best price. For the third case study, Réseau was extended with multiple period contracts between factories within the ecosystem. We compared scenario with and without such contracts. This showed that the industrial ecosystem is more stable and the Symbiosis Relationship Index (the ratio between internal and external transaction) increased significantly when long duration contracts are available.

To summarise, I created Réseau a demand and supply simulation tool, to model the manufacturing processes and the decision rationale of players (agents) in the industrial ecosystem. The three case studies validate the software concept, demonstrate that the seller risk based decision criteria developed in this work generate the most realistic supply and demand time series and shows that contract based relationship between factories significantly increases the duration of industrial symbiosis. The output of Réseau is used in SHAREBOX to support identification of feasible industrial symbiosis projects.

Table of Contents

List of Tables

List of Figures

Abbreviations

IES	Industrial Ecosystem
IE	Industrial Ecology
IS	Industrial Symbiosis
ABM	Agent-based Modelling
CHP	Combined Heat and Power Plant
AD	Anaerobic Digestion Plant
BIO	Bio-refinery Plant
SRI	Symbiotic Relationship Index
LCA	Life Cycle Assessment
IOA	Input-Output Analysis
MFA	Material Flow Analysis
SD	System Dynamics
CAS	Complex Adaptive Systems
ODD	Overview, Design concept and Details
SISO	Single Input Single Output
MIMO	Multiple Input Multiple Output
BDS	Buyer Decision Strategy
SDS	Seller Decision Strategy
ST	Strategy Type

Chapter 1
Introduction

1.1 Background

The World Commission on Environment and Development defined sustainable development (SD) in 1987 as “development that meets the need of the present without compromising the ability of future generations to meet their own needs” (Brundtland 1987). Over the last two decades the concept of SD has become important to decision makers in the industry (Hammond 2007).

(Fiksel 2003) defines a systems approach to sustainable development, and suggest a ‘nested’ systems logical framework that is likely to help system designer. The definitions are; (1) A sustainable society is one that continues to satisfy the current needs of its population without compromising quality of life for future generations; (2) A sustainable enterprise continues to grow and adapt in order to meet the needs and expectations of its shareholders and stakeholders (This encompasses the overall socio-economic system); and (3) a sustainable product or service is one that continues, possibly with design modifications, to meet the needs of its producers, distributors and customers (This is a component of the overall enterprise system).

Research and practice in SD have focused on three specific types of outcomes (or performance indicators): economic, environmental & societal outcomes (Lovins, Lovins and Hawken 1999; Jovane *et al.* 2008). The three areas of sustainability are interconnected (Cato 2009). Economic prosperity can be secured by privileging the needs of a small group over the broader society’s needs, but this undermines social equity. Economic prosperity can also compromise environmental integrity by quickly consuming natural resources in order to generate higher short-term profits. However, it is possible to construct win-win-win practices that support all three area.

A range of indicators have been adopted to evaluate the impact of a processes and supply chains on sustainability. Economic indicators, e.g. Profit, ROI, are based on the cost of raw material, labour, capital. Environmental indicators are based on measurable mid points such as kgCO_2 emitted, kg natural resource consumed. The mid points are calculated using Life Cycle Assessment (LCA) and generally indicate the extent to which the earth's resources are reduced and the average Disability-Adjusted Life Years (DALY) are lost by the conducting the manufacturing process. Societal indicators cover quality of life, perceived risk, and community trust as well as employee satisfaction. Societal indicators are the least understood, often overlooked among the different ways of measuring sustainability and we will not focus on it in this work further.

For processing industries economic and environmental outcomes are closely linked:

$$resources + Capital \; => \; Product \; + \; waste + profit$$

To change the process, alternative resources with additional capital are required and will generate the same product, but different quantities of waste and profit. This offers opportunities for sustainable supply chain management for instance through the design of new symbiotic Industrial parks where the waste of one company becomes a resource for another. Here the term symbiotic is used in a positive sense, as in both companies benefit.

The concept of industrial symbiosis is what underpins SHAREBOX project funded by European Union Horizon 2020 (Grant agreement number, 680843) which centres on logical work flow that covers from the identification of new symbiotic synergies right through optimised connection among companies and organisations in established symbiotic relationships. SHAREBOX tend to develop and bring to market a secure platform for the flexible management of shared process resources with intelligent decision support tools. It will provide plant operations and production managers with the robust and reliable information that they need in real-time in order to effectively and confidently share resources (plant, energy, water, residues and recycled materials) with other companies in an optimum symbiotic ecosystem.

Ayres *et al.* (1996) and Korhonen (2001b) described Industrial Symbiosis as a "hands-on" concepts within the larger concept of Industrial Ecology in which the objective is to increase economic sustainability by exchange of waste material and energy between factories. The Kalundborg industrial park in Denmark, has become a model for illustrating industrial symbiosis, see (Lowe 1997; Frosch and Gallopoulos 1989; Chertow 2000; Jacobsen 2006) where materials, energy and by-product exchanges between factories evolved rather than through design.

In recent years, attention for industrial ecosystem development projects has grown enormously among national and regional governments and industries in many countries. The National Industrial Symbiosis Programme (NISP) in the UK is an example of numerous industrial ecosystems (Mirata 2004). The hypothesis is that a well-planned, functioning symbiotic industrial ecosystem has the potential to both benefit the economic and environmental indicators in and near its location (Allenby and Richards 1994; Heeres, Vermeulen and De Walle 2004; Jacobsen 2006; Fraccascia, Albino and Garavelli 2017). Previously discarded resource typically offers financial savings to both the utilising company and the waste provider. This reduces raw materials, energy or water use and avoids disposal to landfill. The benefit of IS are not limited to improvements in economic and environmental indicators as seen in (Karlsson and Wolf 2008; Wolf and Karlsson 2008); but also social benefits Geng *et al.* (2009) which include job creation, cleaner environment, and aesthetic improvements (e.g. reduction of waste piles).

The concept of Industrial Ecology (see Figure 1-1) describes in general the flow of materials, energy and money so as to determine the impact on economic and environmental indicators. It describe manufacturing systems at the factory level, inter-factory level, and at the regional or global level (Chertow 2000). Industrial symbiosis only occurs at the inter-factory level because it includes exchange options among several organizations. It integrate a cleaner production into the interactions of companies in a specific industrial region or park with its local and global level (Lowe and Evans 1995). Various researchers have viewed each of this concept differently, in terms of various models and terminologies, ranging from eco-industrial parks Côté and Cohen-Rosenthal (1998), industrial symbiosis, Chertow (2004) and industrial ecosystems (Cote and Hall 1995). It is to be noted that the all concepts of industrial ecology described above can be used interchangeably. Henceforth we adopt the use of Industrial ecosystems (IES) to describe the problem statement in this research work.

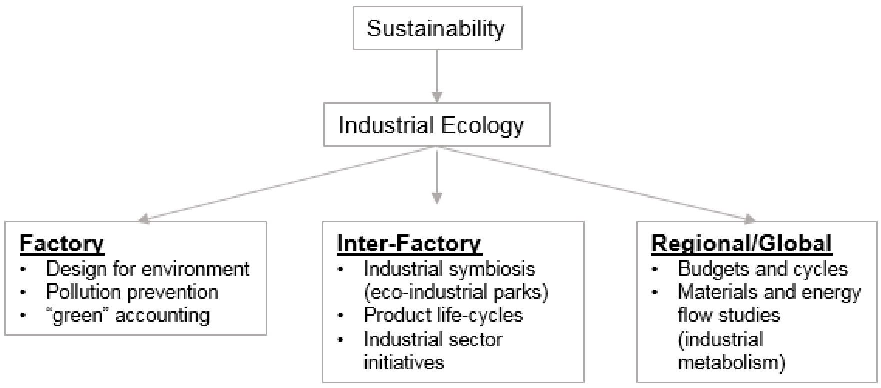


Figure 1-1: Industrial ecology operational levels (Chertow 2000). The three different manufacturing system are: (1) Factory (2) Inter-Factory and, (3) Regional/Global

Industrial ecologists have suggested the redesigning of industrial system using the natural ecosystem. Despite the fact that industries in the United Kingdom, UK have substantial improvements in its energy efficiency – 35% between 1990 – 2006 and has also set a high target for reduction of greenhouse gas emissions (GHG) of 34% by 2020 and 80% by 2050 (Cooper and Hammond 2018), industrial ecosystems is one of the ways of achieving this goal. Designing or redesigning an eco-industrial park is a complex undertaking, demanding integration across many fields of design and decision making.

Industrial ecosystems are complex system according to Cao, Feng and Wan (2009) that are viewed as self-organizing systems (Chertow and Ehrenfeld 2012; Yazan, Romano and Albino 2016) whose evolution is a function of complex interactions among multiple organizations, each with its own objectives, which may have conflicting interests. The complexity of industrial ecosystem development can best be managed by an evolutionary design process in which top-down control is avoided as shown in Lowe and Evans (1995) and a bottom-up method is used instead of using top down approach. The best form to analyse the evolution or dynamics of industrial ecosystem is through complex adaptive system (CAS) theory. The study of complex adaptive systems has fascinated natural and socio-economic from across a tremendous range of disciplines (Dijkema and Basson 2009).

Jacobsen (2006) analysed the impact of the material, water and energy exchanges in IS Kalundborg using economic and environmental data. However, his result could not reflect the dynamic nature of industrial symbiosis. In the same vein, Cao, Feng and Wan (2009) applied agent-based model (ABM) to the design of eco-industrial park to simulate only inventory and profit fluctuations. But there are other important behaviour and interaction mechanisms. Such as price, demand, supply and impact of storage system etc. One of the most important drivers over cooperation decision of companies is the economic return which fluctuates according to prices offered and costs to be dealt with by companies over time. Therefore, Dynamic modelling techniques such as agent-based modelling could be efficiently used to analyse the negotiation and decision-making phase in cooperative business-making based on industrial symbiosis principles (Yazan, Romano and Albino 2016)

Since the emergence of industrial ecology in the 1950s and its take-off during the 1990s, much progress, in theory, policy and practice has been achieved for designing a fruitful and sustainable eco-industrial parks. Almost all research into IS/IES system involves either proposing a frame work, Martin *et al.* (2009) or mathematical model, Gonela and Zhang (2014) to design of IS/IES. There are few works, see (Cao, Feng and Wan 2009; Batten 2009; Bichraoui, Guillaume and Halog 2013) that focus on the simulation of IS to understand its complexity. There is still progress to be made in the area of computational modelling of the actions and interactions of the autonomous agents that formed the ecosystem. Major problems to unravel the complexity of IS include but not limited to price, profit and supply-demand fluctuations. Also part of the problem that exist in the design of industrial ecosystems is the difficulties that companies face in identifying each others resources. When such opportunities are energy related, conversion technologies are typically required depending on nature of the energy resource. The results of this is that there will generally be periods of excess supply (supply greater than demand) and shortage (demand exceeds supply). Agent-based model (ABM) also known as bottom-up modelling according to Borshchev and Filippov (2004) has proved to be a promising tool to simulate the evolution of eco-industrial park (Cao, Feng and Wan 2009; Ghali, Frayret and Ahabchane 2017).

In order to bridge the gap in literature, this research work focus on the application of agent-based model to simulate industrial ecosystem to unravel the complexity of eco-industrial system and generate demand and supply time series. We analyse IS considering materials and energy flows and the related supply-demand match for each output products (finished goods, by-products, useful waste) becoming primary input for entirely new processes that are co-located or within the same vicinity. University of Leeds is part of the SHAREBOX project and one of our goals is to generate demand and supply time series to express the dynamic of Industrial ecosystem, using the new tool that will be developed in this work so as to support the design of energy based IS opportunities. The resulting demand and supply profiles from the developed agent-based tool will be used by a modified version of STRATHCLYDE'S MERIT (from University of Strathclyde) which act as a brute force analysis to work out waste heat recovery options that are finally automatically assessed and ranked according to user determined criteria of demand met, cost or emissions. This will allow SHAREBOX to identify feasible IS projects by ranking of the different short list of candidate schemes. More importantly, to estimate the impact of the different decision criteria between the demanding and supplying agents. Different case studies are conducted to illustrate the effectiveness of the proposed methodology to gain managerial insights on the industrial ecosystem.

1.2 Problem statement

This work addresses the issue of developing agent-based model to simulate industrial ecosystem in on order to forecast supply and demand time series as this data is important but typically difficult to obtain. Figure 1-2 show the structure of the problem.

The system have three different categories; factory, market seller and market buyers. Henceforth we will refer to these entities as factory agent, market buying agent and market selling agent. In this work, only relationship between factories are considered to symbiotic. The industrial ecosystem is made up of $S\ (i\ =\ 1,2,3, \dots S)$ number of agents. Note that each agent is unique and are not related. For example we have n number of market selling agent i.e. $MS_1, MS_2, MS_3, \dots MS_n$. The production chain in factory agent i is modelled using input-output approach. The market selling and buying agents are the infinite sources and sinks (i.e., unlimited capacity). As shown in the structure of the problem, the factory agent interact with each other (Internal) and as well with the market buying and selling agents (external). That is Materials/energy exchange occur within and outside the park. Our problem formulation is unique because a factory agent i can act as either a buying or selling agent. That is factory agent can purchase its input raw material internally or externally, used the raw material to produce based on demand for its finished good and then sell it finally to its pair internally or externally. The structure of the thesis addresses three phases of the developed agent-based model (Réseau) with increase complexity. The three phases are:

1. When the industrial ecosystem is made of single input-output material/energy exchange agents;

2. When the industrial ecosystem is made up of multiple input-output material/energy exchange agents and;

3. When the industrial ecosystem is made up of multiple input-output material/energy exchange agents that can have contract agreement with local demands (e.g., chemical factories) and/or local suppliers (e.g., wind turbine).

At the beginning, each of the factory agents source for its input materials (energy/materials) internally and externally. If the required input raw material is available in the internal market, the buying agent makes the offer and the seller agent accept the offer and the demand is fulfilled. However, if the input is not available within the internal environment of the ecosystem, a request is send to the market selling and the order is completed. Furthermore, if the input type quantity available from the selling agent is less than the input type demand by the buying agent, the remainder is source from the market selling agent, and if the demand is less than the availability from the plants, the selling agent sells it out to market buyers. The environment is assumed to be an infinite source and sink. It can provide any inputs requested within the park and can absorb any excess output from the park. Our model is to ensure that the flow of inputs (materials/energy) from the environment into the parks is minimised while outputs (energy) flow from the park to the environment is maximised with optimal synergy in the park.

The main problem is to model the industrial ecosystem using an agent based model, combine complex decision rationale with process models (here simplified as input-output model and maintaining the material and energy balance, simulate the agents' interaction in the park and understand how different behaviours affect the network evolution. This will allow forecasting of supply and demand time series as this data is important but typically difficult to obtain.

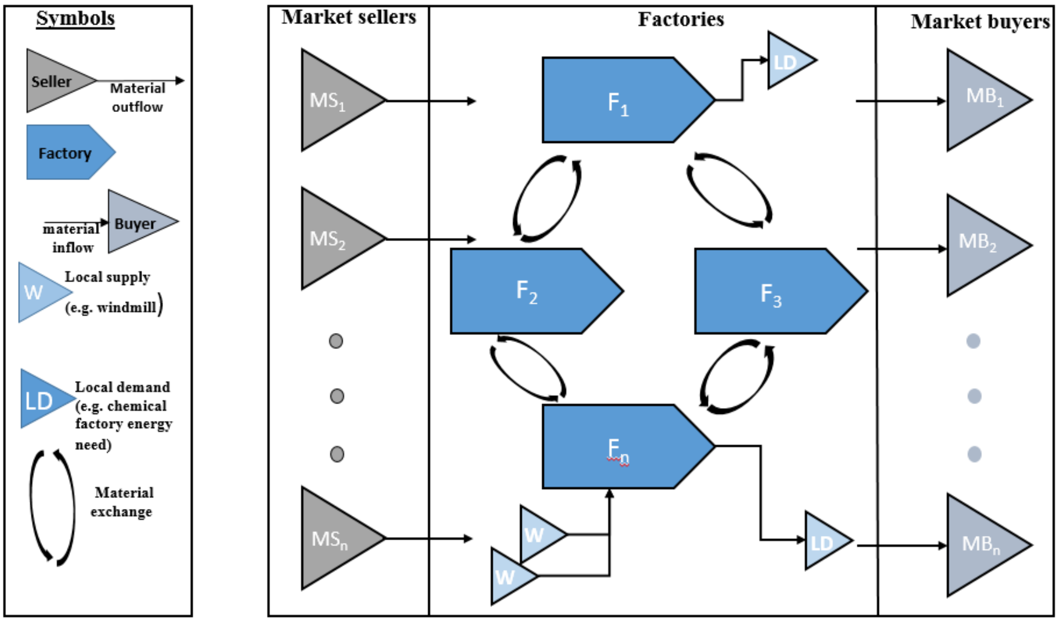


Figure 1-2: Schematic abstraction of industrial ecosystem showing all the internal (factories, local demand and suppliers) and external (market sellers and buyers) agents in the industrial ecosystem.

1.3 Research Motivation

This work is motivated firstly on the basis of working on a part of a bigger problem that encompasses different interest groups, industries and business worlds. The global project is titled "Secure Management Platform for Shared Process Resources (SHAREBOX) with grant agreement number, 680843. The SHAREBOX project major aim is to create a logical work flow that covers from the identification of new symbiotic synergies right through optimised connections among companies and organisations in established symbiotic relationships. This research work fit in one of the objectives of SHAREBOX which involve generating demand and supply time series to serve as pool of available data for different business players on the developed platform.

Secondly, the residuals from industrial process plants, often dismissed as wastes is attracting increasing attention as a methodology to increase the competitiveness of process operations (Kim, Ryu and Lee 2012) . Some wastes are reused within the facility where they are generated, others are reused directly by nearby industrial facilities. This work is also motivated on the basis that matching the input-output (waste water, emissions, and by-product) of industries in the ecosystem will enhance efficient resource utilization, economic opportunities for the companies, both in terms of cost savings as well as opportunities to offer greener products and services. Industrial symbiosis networks, an aspect of industrial ecology have proven successful not only in diverting waste from landfill, but also in contributing to the preservation of resources and moving waste up the value chain. They have also been an accelerator of innovation and creation of green jobs. Inadequate business-to-business information on what resources a product or process contains hinders efficient material flows and the creation of value in the circular economy. Therefore, there is the need to shift from the present open loop system of resource management to a closed loop system where output of one process can be an input in an entirely new process.

To close the loop, industrial ecosystem is view as a dynamic network of interconnected industrial process plants or industrial actors (Ghali, Frayret and Ahabchane 2017; Yazan, Romano and Albino 2016). Different studies have been carried out and used various advanced tools for analysing material and energy flows in the ecosystem. However, there are few research works that have used simulation approach to determine how industrial ecosystem evolve overtime and use the model to analyse the decision-making phase in cooperative business-making based on IS principles. Therefore, the approach in this work is to use agent-based modelling coupled with a quantitative approach based on input-output to simulate the interaction between the participating companies and the external market. This will enable us to predict and evaluate the impact of some key decision parameters that form parts of the day-to-day running of the participating companies in the ecosystem. The chosen simulation approach will also support the analysis of responses to change in the system behaviour and finally, implementing this simulation methodology for industrial ecosystem will require a shift in the current culture of researchers working at distributed sites with individual outcomes to a culture that includes the pooling of capabilities, sharing of information, materials, technology, and knowledge.

1.4 Research Objectives

The objective of this study is to apply agent-based modelling (ABM), a bottom-up approach method coupled with a quantitative approach based on input-output, to the design of industrial ecosystem in order to gain insight into their response to any changes in internal and external decision criteria e.g., price variation in the market. The main goal is to improve the economic performance of the industrial actors and the same time minimizing their environmental impact and attaining a win – win condition.

The primary aim is to provide answer to the question below:

“How do company decisions affect the flow of green and waste energy supply and demand in an industrial ecosystem”?

In order to achieve this overarching question, the following objectives have been set:

(i) To develop agent-based model integrated with input-output model for simulating industrial ecosystem.

(ii) To simulate industrial ecosystem and generate demand and supply time series.

(iii) To evaluate the effect of different buying and selling decision strategies on the behaviour of agents and the resulting supply and demand time series of agents in the industrial ecosystem.

1.5 Thesis Structure

The thesis is organised into seven chapters and a brief description of the chapters are given below.

In the Literature Review (Chapter 2), a review of the important literature regarding the industrial ecosystem modelling. An extensive survey starting from the discussion on industrial ecology as a novel approach to achieve sustainable development. Different industrial ecology in practice were also reviewed particularly the industrial symbiosis Kalundborg in Denmark. This section of the thesis concludes with a detailed critical review of complex adaptive system, agent-based modelling and their application in modelling industrial ecosystem as a self-organizing systems.

In Chapter 3, on Research Methodologies, a detailed description of the methods employed in the research is presented. It begins with the Overview, Design concepts and Details (ODD) protocol the new developed agent-based model (Réseau agent-based model). The different decision strategic by buyers and sellers in the industrial ecosystem are described. The implementation of the developed tools is described in detail and the procedure for the simulation of the model with an example.

Chapter 4 is the application of the Réseau agent-based model described in chapter 3 to model an energy based eco-industrial park. A case study was carried out on industrial ecosystem consisting of single input single output factories. A hypothetical system of this case study is then simulated. The effect of price variation on the network is evaluated.

Chapter 5 further expresses the usefulness of agent-based modelling to assess the potential benefits of industrial ecosystem. This chapter builds on Chapter 4 to model a more complex industrial ecosystem consisting of multiple input multiple output factories. By this, more comprehensive assessment of agents' behaviour in the industrial ecosystem can be carried out.

Chapter 6 presents the Réseau agent-based extended previous chapters to model industrial ecosystem consisting of multiple input multiple output factories that has entered into contractual agreement with a fixed price to enable demand is met. The results of the simulation is also discussed.

Chapter 7 gives summary of this research work and highlight the main outcomes in the conclusions section. The thesis concludes with suggestion for future work.

Chapter 2
Literature Review

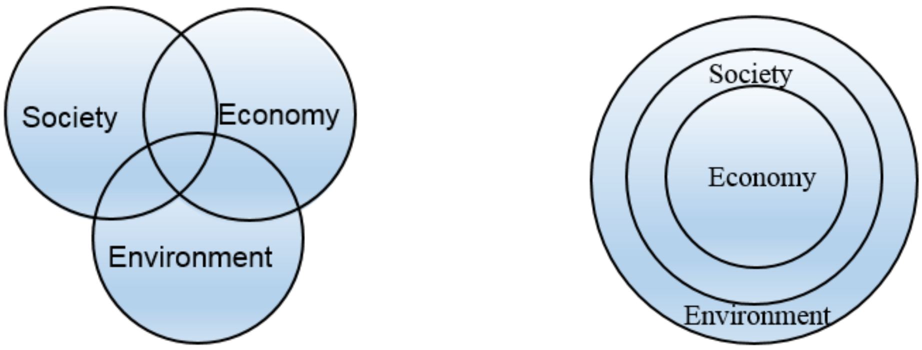
2.1 Introduction

The goal of this chapter is to provide a literature review of research works on sustainable development and sustainability, industrial symbiosis, and different industrial ecosystem modelling approaches. The next is to the provide theoretical links to complex adaptive systems as a promising area to model the evolution industrial ecosystem. The chapter is structured as follows: Section 2.2 gives a background on sustainable development and sustainability focusing on two of its key performance indicators: economic and environmental sustainability. Section 2.3 presents different research works on industrial ecology (IE) as a means to achieving sustainability. In addition, a review of the complexity of IE is presented in this section. In Section 2.4 and 2.5, we review works on industrial symbiosis concept and its application using different real life examples. Lastly, Section 2.6 discussed different industrial ecosystem modelling approaches, how it is viewed as a complex self-organizing. We focused on agent-based modelling as a promising tool to the simulation of industrial ecosystem, its benefit as well as its drawback.

2.2 Sustainable industrial development

Since early 1990, sustainable development (SD) is being applied continuously to enhancing global developmental growth, although the concept is viewed differently, with different interpretation and practice (Ashton 2009). Within the context of this work, sustainability entails maintaining a beneficial industrial ecosystem interaction with desirable environmental and in particular economic opportunities.

As mentioned in Chapter 1, the three indicators of sustainable development are interdependent. However, they are qualitatively different (Korhonen 2003). Despite the recent attention to separate the dimensions of sustainability, the need to address sustainability has historically focused on how the three performance indicators are interrelated. For example, Cato (2009) shown in his model (see Figure 2-1), that the conventional economic view believes there exist interaction between economy, environment and society but are not interdependent. The circles are drawn in equal size and therefore showing equal importance; although in reality the economy carries much more weight in decision making, with society bearing the cost and the environment paying the highest price of all. However, this is viewed differently by the green economics that the economy is, in the first instance, a subsystem of human society, which is itself, in the second instance, a subsystem of the totality of life on Earth (the biosphere). And no subsystem can expand beyond the capacity of the total system of which it is a part.



(a) The conventional economic view of the interaction between economy, society and environment

(b) The green economic paradigm; economy operates within social relationships and the whole society is embedded within the natural world

Figure 2-1: Relationship between indicators of sustainable development (Cato 2009).

The Economic indicator is more related to the cost of raw materials, labour costs, capital cost and so on. The environmental indicator includes the global impact of atmospheric emissions, the energy and material consumption couple with the local and regional impact of things like acid rain precursors, while societal indicators refer to the quality of life as well as employee satisfaction. The three indicators have been adopted as useful tools for decision making in conveying information on countries' performance in fields such as environment, economy, society, or technological development (Singh *et al.* 2009). To achieve the goals of sustainability, a good understanding of the complexity of industrial ecosystem interactions need consideration by decision makers. The role of industrial ecology has now been seen as a concept of ecological modernization that can reconcile the three dimensions of sustainability: social, economic and environmental (Veiga and Magrini 2009). Implementing sustainable development globally is still a challenge, however industrial ecology has been accepted widely as one of the tools used to develop sustainability (Robèrt *et al.* 2002). Korhonen (2004) work clearly shows that the concept of industrial ecology can be used extensively for all the five hierarchical and interdependent levels defined in (Robèrt *et al.* 2002).

2.3 Industrial Ecology (IE)

Industrial ecology is a concept that can be viewed the way the natural ecosystem operates. Industrial ecology is a framework for guiding the transformation of industrial system to a sustainable level. IE operates on this principle, by interacting with natural ecosystems and shifting away from the present open loop systems to a closed loop, in which resource and capital investments flow through the entire system to become waste, to a closed loop system where wastes, by-product from one process become inputs for new processes. The systematic moving from the linear throughput to closed loop material and energy flows are important themes in industrial ecology (Ehrenfeld 1995; Ehrenfeld and Gertler 1997). The concept of industrial ecology was made popular by an article written by Frosch and Gallopoulos (1989) and further developed later by the work of (Ayres *et al.* 1996). Even though the concept is still relatively new, it has been a well-researched area with numerous examples of application at inter-prise level.

There are different definitions of industrial ecology (Glavič and Lukman 2007). Some of these definitions are; Ayres *et al.* (1996), regard IE in their work has a concept involving several industrial processes in which the respective actors co-operate by using each other’s waste material and waste energy flows as resources. Another definition given by Boons and Berends (2001) indicate that IE is concerned with assessing and reducing the ecological effects of a group of factories, rather than with the ecological effects of individual factories. Tibbs (1992), work suggests that industrial ecology is based on seven different principles which are:

1. Creating closed loop industrial ecosystems
2. Dematerialization of industrial output
3. Improving the metabolic pathways of industrial processes and materials use
4. Creating new action-coordinating structures, communicative linkages, and information.

5. Aligning policy to conform with long-term industrial system evolution
6. Systematizing patterns of energy use and
7. Balance industrial input and output to natural ecosystem level

Korhonen and Snäkin (2003), described IE as Type I, Type II and Type III models (see Figure 2-2). In Type I ecology, the immature type, discussed in the work of Korhonen and Snäkin (2003) show that there is affluence of independency among species and flows of energy are linear. The Type II is a more efficient ecosystem than Type I, whereby organisms and species begin to develop material cycles, energy cascades, and the diversity of the system increases. In Type III, there is a complete cyclic flow of material, energy cascades and high level of interrelationship among species. Hardy and Graedel (2002) modelled IE in three different ways like Korhonen and Snäkin (2003); linear, quasi-cyclic , and cyclic resource flow IE models. The Type I or linear model considers linearity in resource exchanges and have greatest negative impact on the environment. The quasi-cyclic IE model or Type II reduces negative impact on the environment through cycled resource exchange in the industrial ecosystem. The cyclic IE model is a closed resource exchange where energy is solely the input to ensure sustainability of the ecosystem.

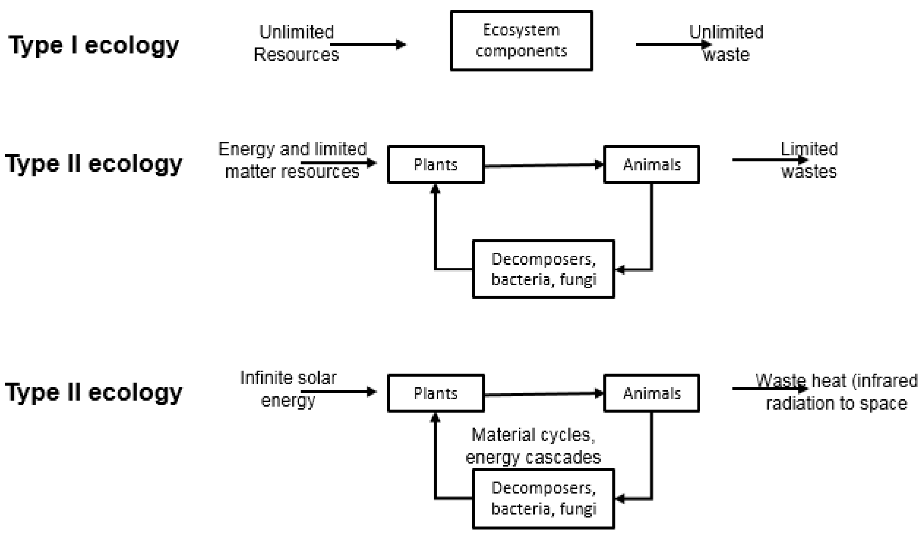


Figure 2-2: Development of the ecosystem as a metaphor for sustainability of economic and environmental systems. (Korhonen & Snäkin 2003).

One common thing from the above definitions is that industrial ecology can be seen as one of the means of achieving sustainability and it is closely related to industrial ecosystem. In ecology, an ecosystem consists of various interconnected complex environs and sub-systems. Therefore, the industrial ecosystem represents a group of factories that utilize each other's materials and by-products such that waste materials are reduced to an absolute minimum. The connectivity among species in the natural ecosystem as described by these three metaphor can be compared to the throughput in the industrial system. A facility or a lone plant can be viewed as Type I where material flows in as an input, processes in the plant and leaves as an output with little or no relationship with other facilities in the entire system. A shift from Type I to Type II can also been seen in the industrial settings, where resources are scarce relative to the amount needed thereby calling for interactions among respective parties. Nowadays industrial setting is still linear and a pragmatic swift to Type III is a welcome idea that can transform and provide economic opportunities to each of the respective collaborators. The food web as an example, biomass transfers the chemically bound energy in a cascade chain to different levels for the use of organisms and energy generated from the ground and the organisms end up as heat in the physical surroundings and it is radiated back to space (Korhonen 2000). Achieving economic growth and greener environment simultaneously requires an entirely new approach in achieving a sustainable environment. Therefore, IE principles which include but not limited to protocooperation, commensalism and mutualism, Glavič and Lukman (2007) have the tendency of reducing the flows of energy and materials into and out of an economy, Ehrenfeld and Gertler (1997), thereby shifting the environment to a more sustainable level.

Protocoperation means interrelated entities received conditional benefits, but can survive separately; commensalism is a situation where only one species receives benefits and the other is not impaired while mutualism entails both species receive benefit. These three principles of IE are understood as symbiosis, because systems either not impaired or receive benefits due to the interactions (Glavič and Lukman 2007). The key aim of industrial symbiosis are closing the loops, collaboration, and the exchange of resources possibilities offered at the inter-factory level (Chertow, 2003). The concept of industrial symbiosis and some examples of its practical application are reviewed in the next section.

2.4 Industrial Symbiosis (IS) and Industrial Ecosystem

The theory of industrial ecology considers industrial symbiosis as one of the most effective ecosystems in which interrelationships result in cooperative actions alongside competition, together with biophysical and social dimensions improving the characteristics of a local industrial ecosystem (Tao *et al.* 2019). Industrial symbiosis is synonymous to industrial ecosystem (IES). Industrial symbiosis (IS) is closely related to industrial ecology and involves the creation of linkages between firms to raise the efficiency that is measured at the scale of the system as a whole material and energy flows through the entire cluster of processes. Chertow (2004) succinctly shows that industrial ecology is primarily concerned with the flow of materials and energy through systems at different scales whereas industrial symbiosis focus on the flow through networks of businesses and other organisations in local and regional economies as a means of approaching ecologically sustainable industrial development. The work of Gibbs (2008) reveals that industrial symbiosis is one aspect of industrial ecology with new opportunities to combine environmental improvement, economic development and local regeneration through the construction of industrial ecosystem. In the same vein, the work of Martin *et al.* (2009) shows that industrial symbiosis is a branch of industrial ecology which focus is mainly on the physical exchanges of materials, energy and by-products on the inter-firm level, where the company is not viewed as an “island” but involved interactively with numerous companies. Thus, the two terms cannot in any way be used interchangeably.

IS represents mutual efforts to increase sustainability and aims to achieve this through the three indicators or sustainable development. For example, companies benefit economically by access to cheaper sourcing, disposal costs reduction, and/or increasing profit from selling the by-product Environmentally, the benefits ranges from reduction in natural resources consumption and waste disposal to atmospheric emission from the conversion process of the raw materials (Herczeg, Akkerman and Hauschild 2018). Finally, social benefit of IS include cooperation of the business management, the local community, and the government body to contribute to regional economic development (Baas and Boons 2004)

IE principles are based on natural ecosystem when designing and redesigning industrial systems for more efficient interactions within and outside the ecosystem (Ayres *et al.* 1996; Lombardi and Laybourn 2006). IS applies the principles of IE to create a collaborative approach to industrial synergy. Planning approach for designing or redesigning of industrial ecosystem is based on two different models Chertow (2007); the planned industrial ecosystem and the self-organizing symbiosis model. In the planned IES model considerable efforts is made to synergize different company for the benefit of sharing of resources. The participating companies may be co-located or be within a define distance from each other.

Another view in the development of industrial ecosystem is shown (Korhonen 2001b). His work based the development of industrial ecosystem on four principles; roundput, diversity, locality and gradual change. The summary of these principles are in Table 2-1.

Table 2-1: Ecosystem principles in industrial ecosystems (Source: Korhonen, 2001b)

Ecosystem	**Industrial system**
Roundput Recycling of matter Cascading of energy	Roundput Recycling of matter Cascading of energy
Diversity Biodiversity Diversity in species, organisms Diversity in interdependency and co-operation Diversity in information	Diversity Diversity in actors, in interdependency and co-operation Diversity in industrial input, output
Locality Utilising local resources Respecting the local natural Limiting factors Local interdependency, co-operation	Locality Utilising local resources, wastes Respecting the local natural Limiting factors Co-operation between local actors
Gradual change Evolution using solar energy Evolution through reproduction Cyclical time, seasonal time Slow time rates in the development of system diversity	Gradual change Using waste material and energy, renewable resources Gradual development of the system diversity

In order to achieve a practical application of roundput in industrial ecosystem settings, there must be a major “system driver” (Korhonen and Snakin 2001). The idea of having a system driver, refer to “an anchor tenant” (Korhonen and Snakin 2001; Korhonen 2002; Korhonen 2001a) is to drive and manage the synergy that exits between the respective actors. An anchor tenant could be a “physical” or “institutional” anchor tenant (Korhonen 2000; Burström and Korhonen 2001) responsible for regional environmental management toward the features of roundput or the vision of an industrial ecosystem. In (Korhonen 2001a), a combined heat and power generation (CHP) plant serves as an anchor tenant as it provides heating for the facilities as well as an opportunity to produce electricity for the eco-park, to further reduce the operational cost. Our intention in this work is to use this approach in developing the industrial ecosystem in this research work.

However, the self-organizing symbiosis emerges as a result of initiative by private actors motivated to exchange resources for the enhancement of their production processes. Some predominantly commercial and industrial activities that include materials exchange component to qualify the activity as industrial symbiosis exists in the literature; examples include cases from the United Kingdom, United States, Finland, Sweden, Denmark (Chertow 2000; Mirata and Emtairah 2005; Jacobsen 2006) and considerable progress has been made also in China (Albino, Fraccascia and Giannoccaro 2016; Fraccascia, Albino and Garavelli 2017). In the following section, brief review of each of these industrial symbiosis in practice are discussed.

2.5 Industrial symbiosis in practice

From literature, there exit quite a lot of industrial symbiosis in practice. A review done by Gibbs, Deutz and Proctor (2005) show that, Europe has more operational ecosystems than the USA by 44.4%. In comparison, USA has higher proportion of planned (25.7%) and attempted (45.7%) industrial ecosystem. The summary of their work also indicates that the UK contributes 18.75% of the operational ecosystems in Europe out of which two of them focused majorly on waste recycling. However, in 2014, the report by Federal office for the Environment (FOEN) shows that out of the 168 industrial ecosystem in the world only five are situated in the UK. Four out of these five

IES are majorly industrial park with core interest in waste management while the remaining one is the combination of industrial process and residential areas.

2.5.1 Landskrona Industrial Symbiosis Programme (LISP)

This is the first example of official Industrial Symbiosis programme in the industrial town of Landskrona in South-West Sweden initiated in 2003. The programme was financed and promoted by the NUTEK (Swedish Business Development Agency) and was facilitated by researchers from the International Institute for Industrial Environmental Economics (IIIEE) and Lund university (Mirata and Emtairah 2005). The companies involved in the synergy are more than twenty industries from different sectors, chemicals, waste management, metal processing and recycling, printing and printed packaging that collaborate to share resources, information and personnel in order to maximize resources, e.g. district heating, environmental affairs and business development. Some of the operational and potential connections that are, or can be, associated with activities in Landskrona are depicted in Figure 2-3. Landskrona IS project has benefited the town in different ways. In particular, there had been significant improvement on environmental sustainability and business structure of the city has also changed positively (Mirata and Emtairah 2005).

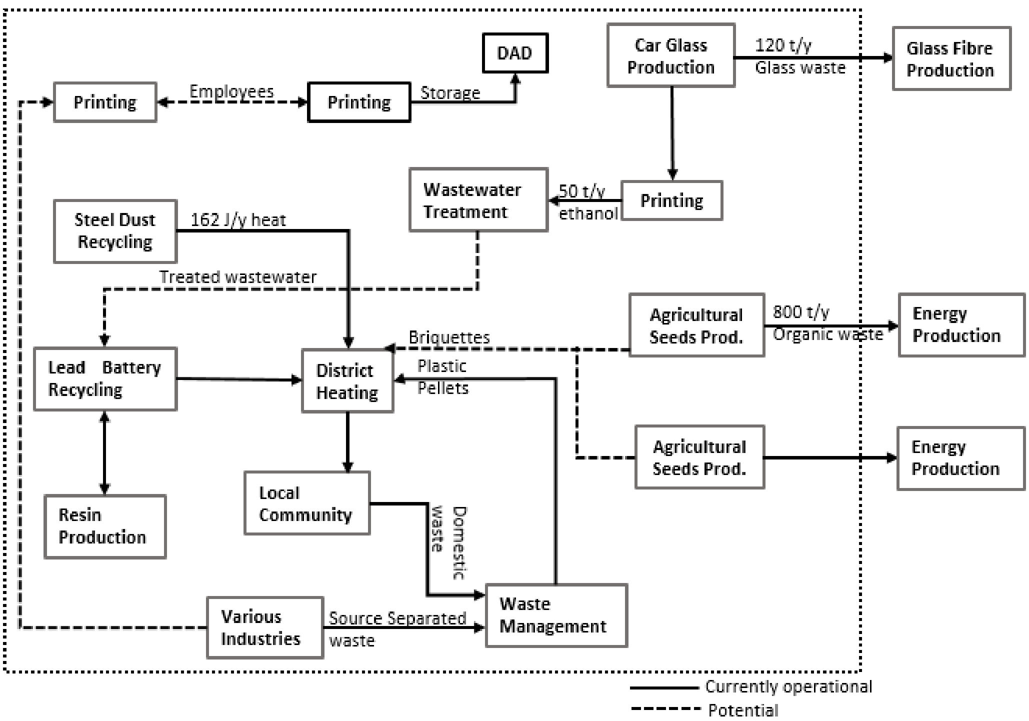


Figure 2-3: Existing and potential connections associated with activities in and around Landskrona (Mirata and Emtairah 2005)

2.5.2 Kalundborg Park in Denmark

Even though waste exchange between industrial processes has long existed, the first known and the most reference industrial ecosystem in the literature is the Kalundborg industrial park in Denmark (Jacobsen 2006). The schematic diagram of Kalundborg industrial park is as shown in Figure 2-4. This ecosystem promote the use of by-product of one enterprise to be used as an input by another enterprise, for example, steam and other raw materials such as sulphur, fly ash and sludge are exchange between plants (Jacobsen 2006). The Participating firms individually and as a whole benefit economically from reduce costs for waste disposal, improved efficiencies of resource use and improved environmental performance. Another example as indicated in the diagram shows that gas captured from the oil refinery which had previously been flared off is now sent to the electrical power station which expects to save the equivalent of 30,000 tonnes of coal a year. Over the years more and more businesses were linked into the Kalundborg industrial park from the inception till date.

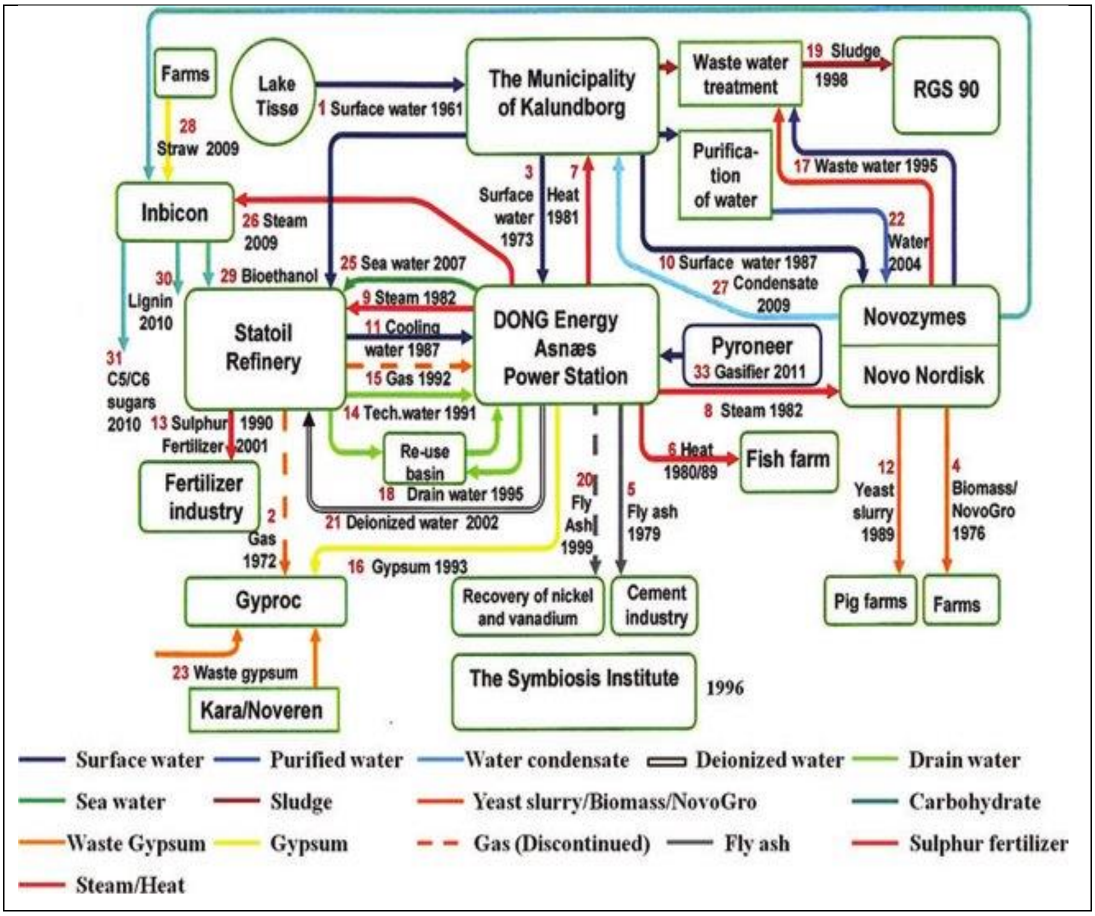


Figure 2-4: The Kalundborg Industrial symbiosis. Factories and exchanges of materials and energy. Exchanges are numbered from 1 to 33 and the years

shown indicate when an exchange began. Discontinued links are shown as dotted lines. Modified from http://www.symbiosis.dk/en/system by John R. Ehrenfeld.

Generally, the flows of this park can be distinguished in two categories:

- The flow of energy between plants (Steam, Fuel, Gas, Heat), and
- Material flow (Fly ash, gypsum, sulphur, sludge, fertilizer, water)

Some of the economic and environmental performance over the period of 1990 – 2002 are highlighted below:

- DONG Energy Asnaes power station replaced groundwater with surface water and saved approximately 7.6 million Danish Kroner (DKK) or more than 35 million DDK for the selected period.
- Statoil refinery gained a direct saving of approximately 1.8 million DKK in 2002 by trading cooling water with the energy company
- Another 4.5 million DDK was made in the period as a result of replacing surface water with wastewater.
- Between 1997–2002, an emission reduction of 154,000 tons of CO_2 and 389 tons of NO_x has been achieved by the delivery of steam and heat from the power plant compared with the production of the same number of GJ/yr from a hypothetical stand-alone facility fuelled with natural gas.
- Some of the steam/heat production fuelled by coal are removed in 2002 due to the interaction with other companies e.g. Statoil refinery thereby reducing emission into the atmosphere.

2.5.3 Styria, Austria

This is one the self-evolved industrial parks like the Kalundborg Park, Denmark. The park was discovered in the Province of Styria, Austria, by Erich Schwarz at Karl-Franzens-Universität Graz (Schwarz and Steininger 1997). It is a complex network of exchanges of recyclable materials like papers, gypsum, iron scrap, used oil, tires and a wide range of other by-products. A considerable number of participating industries like agriculture, food processing, plastics, fabrics, paper, energy, metal processing, woodworking, building materials, and a variety of waste processors and dealers. Over the time, this park has contributed in economic and social development of Austria by improving the economic advantage of the participating industries; savings on raw materials, emissions are reduced and landfill lifetimes are extended.

2.5.4 National industrial symbiosis programme (NISP)

NISP has been operating in the UK since 2003, and is the world's first National Industrial Symbiosis Programme (Mirata 2004). NISP is a UK government support programme to facilitate links between industries from various sectors to create sustainable commercial opportunities and to improve resource efficiency. NISP is a business-led programme with over 15,000 participating industry members who form part of a unique network. Through the network, NISP identifies mutually profitable transactions between companies so that underused or undervalued resources (including energy, waste, water and logistics) are brought into productive use. Between year 2003 and 2015, the UK symbiosis programme has contributed immensely to the economic growth of the participating industries as well as regenerate, reuse and recycling of most of waste generated. Some of the NISP achievement over this period is highlighted below:

- Divert 47 million tonnes of industrial waste from landfill
- Generate £1 billion in new sales
- Reduce carbon emissions by 42 million tonnes
- Cut costs by £1 billion by reducing disposal, storage, transport & purchasing costs
- Reuse 1.8 million tonnes of hazardous waste
- Create and safeguard over 10,000 jobs
- Save 60 million tonnes of virgin material
- Save 73 million tonnes of industrial water

2.5.5 Humber region industrial symbiosis programme (HISP)

This is the first IS programme in the Humber region and one of the largest harbour complexes in the UK. The efforts to catalyse the development of IS networks started in 2000 when the “Business Council for Sustainable Development – United Kingdom” (BCSD-UK2), which by that time was BCSD-North Sea Region assumed the role of facilitating an IS network development among the economic activities located in the Humber Estuary (Mirata and Pearce 2006; Velenturf 2017). Immingham CHP is one of the largest combined heat and power (cogeneration) plants in Europe. The 1,220 MWe facility provides steam and electricity to Phillips 66’s Humber Refinery, steam to the neighbouring Lindsey refinery and merchant power into the UK market. With more recent regional investment in wind power and the bioethanol plant at Saltend that add to the existing CCGT and CHP power plants, the Humber has been positioned as the ‘Energy Estuary.

2.6 Industrial Ecosystem Modelling Approaches

The challenge to create a sustainable industrial ecosystem will definitely be influenced by the combination of all the three sustainable development indicators. Also, an industrial ecosystem needs to have a contractual mechanism that will promote the dynamic of IS as a complex system. To achieve these goals, a framework for balancing the influence of these indicators requires a systematic methodology. A wide range of industrial ecology tools (Van Berkel, Willems and Lafleur 1997; van Berkel and Lafleur 1997) and approaches have been studied and had contributed to the development of major industrial parks in the world. In addition, these tools have been used extensively to gain insight about environmental problems. Examples of industrial ecology tools include material input-output analysis, life cycle analysis, environmental risk, etc. Despite a comprehensive study about the development of industrial ecosystem using different approaches, there are still gaps especially in the use of agent-based model. This section presents a literature review of the modelling methods applied to the design/redesign of IES. This will enable us underscores the gaps that exist in this research area.

Based on the literature, we have used different search methods e.g. Google Scholar, ISI Web of Science database and search for works relating to the application of some of the different modelling methods in developing industrial ecosystems. I searched for the words related to industrial symbiosis, industrial park, eco-industrial park, industrial ecosystem as part of the journal title. 30 published articles in international peer-review were identified over 10 year period. These published articles are the basis of the reviewed done in the subsections that follow. Figure 2-5 shows the number of published articles during the last 10 years with the above keywords and the modelling method used. Some of these article publications are summarized in Table 2-2 under the different modelling approach used for designing/redesigning of IS/IES.

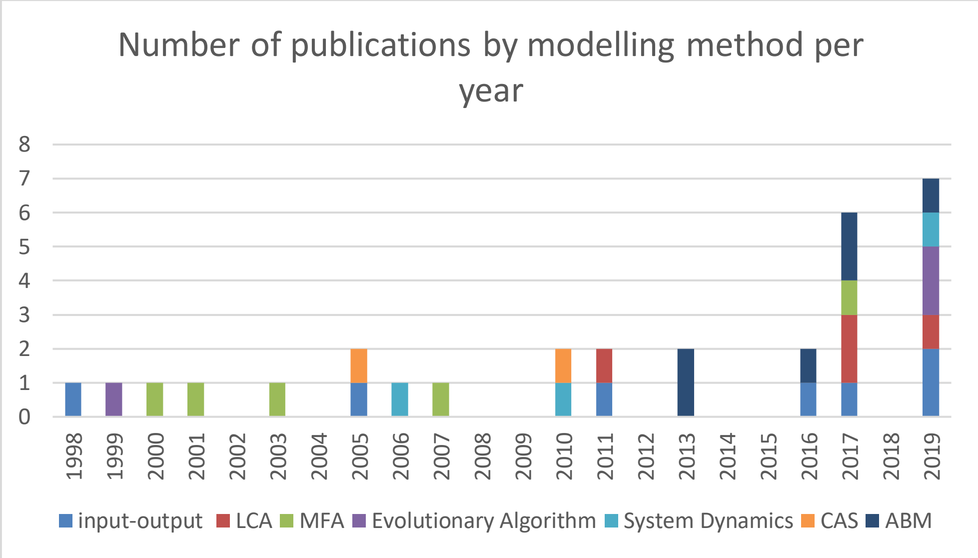


Figure 2-5: Number of articles referenced in the last 10 years under different modelling method/approach.

Table 2-2: Published articles referenced in the last 10 years showing different methods of modelling industrial ecosystem

Modelling methods	Publications and Year
Input-Output model	Lin and Polenske (1998); Suh and Kagawa (2005); Aviso *et al.* (2011);(Yazan, Romano and Albino 2016) ; Fraccascia, Albino and Garavelli (2017); Yazan, Romano and Albino (2016); Fraccascia (2019); Yazan and Fraccascia (2019)
Life Cycle Assessment (LCA)	Liu *et al.* (2011); Zhang *et al.* (2017);Daddi, Nucci and Iraldo (2017); Boix *et al.* (2017); Dong *et al.* (2017); Aissani *et al.* (2019)
Material Flow Analysis	Korhonen (2000); Korhonen and Snakin (2001); Albino, Dietzenbacher and Kühtz (2003); Sun *et al.* (2017); Sendra, Gabarrell and Vicent (2007)
Evolutionary Algorithm	Zitzler and Thiele (1999); Wang and Ma (2019); Saha and Mukherjee (2019); Simeoni *et al.* (2019)
System Dynamics	Lorenz and Jost (2006); Sopha *et al.* (2010); (Rao *et al.* 2019)
Complex Adaptive Systems	Zhou (2005); Cao, Feng and Wan (2009)
Agent Based Model	(Bichraoui, Guillaume and Halog 2013); (Romero and Ruiz 2013);(Albino, Fraccascia and Giannoccaro 2016); Ghali, Frayret and Ahabchane (2017); (Zheng and Jia 2017);(Yazan and Fraccascia 2019)

2.6.1 Input-Output Analysis

Input-output analysis (IOA) is a method of calculating income and employment multipliers which takes account of differences in technology between industries and of the linkages between industries. The data required is the input-output accounts for the region often referred to as the transactions matrix. Apart from this, IOA can be used in understanding the total environmental impact of a product by considering both the physical flows of money, resources or products into a single coefficient matrix (Suh and Kagawa 2005). This approach came to light from the work of (Leontief 1970; Leontief and Ford 1972) and has been come widely used in analysing the environmental impact of a product. In another view, IOA is essentially a production phenomenon, based on a particular type of production function. Its key relationships are technological, involving quantities of inputs and outputs in productive processes. In the real sense IOA does not present a theoretically complete picture of either the supply or the demand side of the economy, Christ (1955), in that it does not envision optimizing behaviour on the part of economic organisms faced with alternative courses of action. Optimizing on the supply side is precluded by the characteristic and controversial assumption that the quantities of inputs used are directly proportional to the quantity of output, which implies that there is only one "recipe" by which to produce a given product.

Input-output analysis of inter-industry exchange has proved to be useful in LCA. Input-output has a long history in economics. Less known, is that input-output influenced linear programming (LP) in its early development. In fact, Input-output models can be regarded as special cases of linear programming problems. Firms routinely use linear programming and other optimisation techniques in planning their activities, for example in logistics of supply chains, production scheduling, and resource allocation in general.

Input-output modelling is an appropriate tool for designing and/or redesigning of industrial ecosystem. Chertow (2000) stressed input-output matching as an important tool to promote IS concept. There are many works that have used input-output model to design IS, such as (Suh and Kagawa 2005; Aviso *et al.* 2011). Yazan, Romano and Albino (2016), work considered the condition for achieving a perfect IS using enterprise input-output approach and provide guidelines for the future of industrial areas operating on the basis of IS. Analysis of IS on the basis of materials and energy flows and the related supply-demand match for each waste becoming primary input can be useful to set strategies for companies and policies for local governments on how to move towards perfect IS condition. Similarly, Tan *et al.* (2019), model industrial complexes comprises clusters of industrial factories by formulating the problem using input-output models and solve in LINGO optimization tool. Their solution provide an outcome supporting the use of input-output models as one of the ways to promote IS/IES.

2.6.2 Life cycle Assessment

Life cycle assessment is a systemic approach used in assessing and evaluating environmental and potential impacts attributed with all stages of product, process, or service life from cradle to grave. LCA is a useful tool that was invented about 5 decades ago Klöpffer (1997) for the assessment of the entire life-cycle of the product, process or activity encompassing extraction and processing of raw materials, manufacturing, transportation and distribution, use/reuse, recycling and final disposal (Curran 1994). The main objective of LCA is that all environmental effects on a product or services has to be evaluated back to the input resources and down to waste removal (Klöpffer 1997). Life Cycle Assessment evaluates the environmental impacts generated by a production process or service. The International Organization for Standardization (2006) revealed that LCA is a commonly used tool in evaluating the emissions impact contributed by all the inputs and output related to a product in a particular function throughout its life cycle “from cradle to grave”.

There are four distinct phases in LCA study as pointed out in Reap *et al.* (2008), this include: Goal and Scope Definition, Life Cycle Inventory Analysis (LCI), Life Cycle Impact Assessment (LCIA), and Interpretation. The four phases of LCA can be illustrated as shown in Figure 2-6 below.

1. Goal and Scope Definition: in this phase, the set of product(s) to be assessed are defined, a functional basis for comparison is chosen and the required level of detail is defined.

2. Life Cycle Inventory Analysis (LCIA): The inventory of all inputs and outputs including emissions, the energy and raw materials used, and emissions to the atmosphere, water and land, are quantified for each process, then combined in the process flow chart and related to the functional basis

3. Impact Assessment: The effects of the resource used and emissions generated per resource are grouped and quantified into a limited number of impact categories which may then be weighted for importance decision making as regards to environmental sustainability.

4. Interpretation: The results are reported in the most possible informative way with the need and opportunities to reduce the impact of the product(s) on the environment are systematically evaluated.

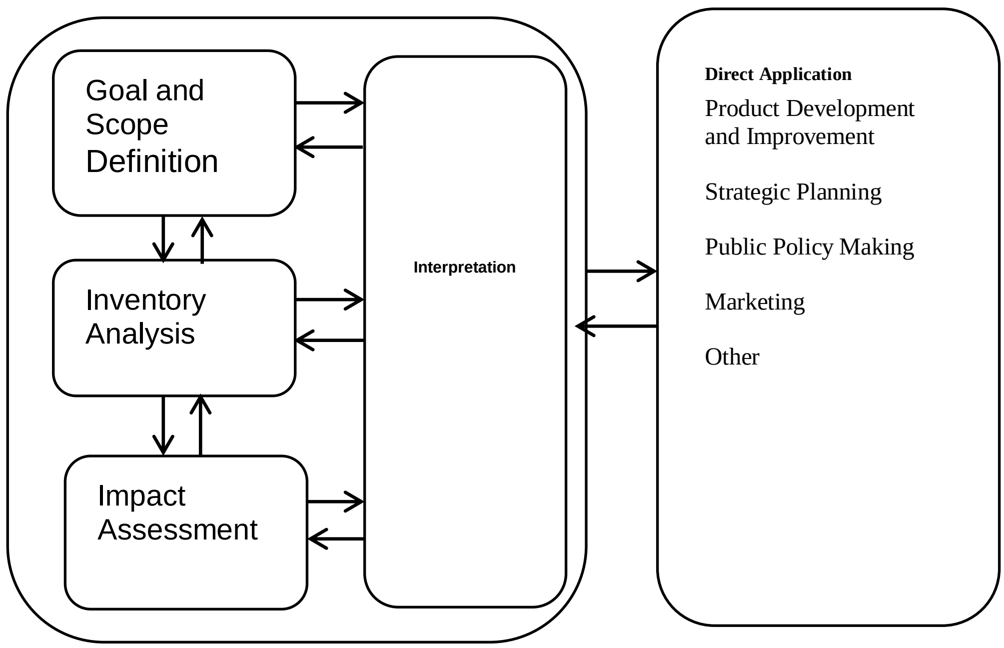


Figure 2-6: Phases and application of LCA (International Organization for Standardization 2006)

In addition to the aforementioned points, detailing in carrying out LCA procedure is very important in order to avoid problem-shifting. For example, from one phase of the life-cycle to another, from one region to another, or from one environmental problem to another (Finnveden *et al.* 2009). Even though LCA has four major phases, the critical and most tedious aspect of LCA is the Life Cycle Inventory (LCI). The objective of the inventory is to create a model of the product or activity identified during the goal and scope definition. According to Jiménez-González, Kim and Overcash (2000) the collection of data is the most time-consuming part in an LCA and involves a great deal of work to obtain faithful, transparent, and representative information about the many processes in a production system.

2.6.3 Material Flow Analysis

This is a quantitative procedure for determining the flow of materials and energy through the economy (Sendra, Gabarrell and Vicent 2007; Brunner and Rechberger). It uses Input-Output methodologies, including both material and economic information (Hendriks *et al.* 2000). MFA is an important tool to assess the physical consequences of human activities and needs in the field of industrial ecology. Material flow analysis is based on two fundamental and well-established scientific principles, system approach and mass balance. While these principles are applied wide across science and technology, it is the way they are applied to the socioeconomic metabolism that makes MFA a special method. The working outline of Kommission (2001) MFA is based on a model in which the system being analyzed is linked to its surrounding environment directly by the flow of materials and energy. MFA is carried out based on the assumption that a mass balance exists for a material into and out of the economics systems. The model can be further expanded to account for this flow of materials and energy on the basis of the first law of thermodynamics on the conservation of matter. In other words, everything that goes into a defined system must be accounted for in output or accumulation. MFA has the capacity to characterize the flow patterns of a material of interest on any scale, so long as there is a fixed boundary that is defined by the user. In order to carry out MFA as applicable to product, process or the system as a whole, there are must be some steps to be followed (Brunner and Rechberger) which are listed below:

- Definition of the problems, goals and the scope of the study
- The selection of relevant information that will be used for evaluation
- Space and time definition of the system
- Identifying all the flow path
- Calculation of the mass flows, stocks and concentrations
- Quantifying the total material flows and stocks
- Analysing and presentation of results

2.6.4 Evolutionary algorithms

According to the fossils-like history of Industrial Symbiosis of Kalundborg in Denmark, the development of the industrial group has been described as an evolutionary process in which a number of independent by-product exchanges have gradually evolved into a complex web of symbiotic interactions among collocated companies and the local municipality (Ehrenfeld and Gertler 1997). Huo and Chai (2008) set up a simulation to understand evolution of industrial ecology patterns and provide new implications on design, improvement, and prediction of structural evolutions. They investigate patterns and apply evolutionary principles as well as nonlinear partial differential equations with boundary conditions and thus computationally implement interacting organisms. Felicio *et al.* (2016) introduced industrial symbiosis indicators that detect the variation of symbiosis over time and that provide a dynamic perspective of the eco-industrial parks. Evolutionary algorithms often occur in order to solve multi-objective optimization problems (Zitzler and Thiele 1999). Evolutionary algorithms solve many nonlinear programs. However, other than

Huo and Chai (2008), most of the nonlinear programmes have an underlying mathematical model to be solved.

2.6.5 System Dynamics

System dynamics (SD) was first developed in the 1950s by Jay W, Forrester Sterman (2000) as an approach for understanding the dynamic behaviour of complex systems over time using stocks, flows, internal feedback loops. It deals with internal feedback loops and time delays that affect the behaviour of an entire system and related system, and has evolved into a widespread approach for modelling nonlinear, dynamic systems (Sopha *et al.* 2010). SD is deductive or top-down in approach. This method has a holistic perspective and assumes that the complex behaviour arises from the causal structure and the endogenous properties of the system (Lorenz and Jost 2006). The causal structure of the system considers feedback loops, time delays, flow diagrams and stock accumulation. SD can be applied to dynamic systems Sterman (2000), with any time and spatial scale. Sopha *et al.* (2010) proposed a framework that provides practical road map for the modelling process that connects relevant concepts and techniques in industrial symbiosis as a complex system. One of the demerits of system dynamics is that it does not provide numerical information for material flows or explicit information about location decisions. However, it helps to investigate relationships and impacts.

2.6.6 Complex Adaptive Systems

A complex adaptive system (CAS) is a system in which a good understanding of the individual parts do not necessarily mean a perfect understanding of the whole system's behaviour (Holland 1992; Gell-Mann 1994; Lansing 2003). It is a system where the interactions and relationships of different components simultaneously affect and are shaped by the system. The study of complex adaptive systems has fascinated natural and socio-economic from across a tremendous range of disciplines. It is easy to find books that discuss, with varying degrees of specificity, ecosystems, the biosphere, economies, organisms, or brains as complex adaptive systems. It is much harder to find a formal definition, as if investigators fear that by defining a CAS, they will somehow limit a concept that is meant to apply to everything (Levin 1998). In general, complex adaptive system is based on "complex behaviour that emerges as a result of interactions among system components (or agents) and the environment", and consequently, complex adaptive system modifies its behaviour to adapt to changes in its environment (Rammel, Stagl and Wilfing 2007; Cao, Feng and Wan 2009).

According to Holland (1992) CAS has no single governing equation, or rule, that controls the system. Instead, it has many distributed, interacting parts, with little or nothing in the way of a central control. Each of the parts is governed by its own rules. Each of these rules may participate in influencing an outcome, and each may influence the actions of other parts.

Cao, Feng and Wan (2009), stated that the core idea of complex adaptive system theory is: adaptability makes complexity. Through interacting with and learning from its environment, a complex adaptive system adapts to its environment. Although the mechanism for interactions among system components is simple, the complex behaviour will emerge from the system level. For example, the behaviour of an ant colony is typically complex and confusing. But if we can make the simple behaviour of every ant clear in computer simulation, and then generate many ant models in the simulation, at the same time, let these artificial ants interact with each other, we will find many complex behaviours emerges from the ant colony. Zhou (2005) considered an eco-industrial system to be a complex adaptive system because the evolution and the development of the system are the results of self-decision making, interaction, symbiosis and coupling of a large number of factories.

In the study of complex adaptive systems, computation has been applied to gain insight into mechanisms that govern the behaviour of various ecosystems, ranging from ant colonies to premodern human societies. One computational paradigm used for the study of complex adaptive systems is simulation based on interactions between multiple agents. While insights from CAS provide increased understanding of complex systems and a helpful framework for modelling, some kind of methods are needed in order to transform such an approach into tangible and understandable results, particularly from a management perspective The rationale behind such a method is that our research has brought out that managers need to be able to test and evaluate different “what-if” scenarios, simulate policy changes or changes in behaviour in order for them to understand and evaluate new ways of thinking and approaches to IS issues. In this regard, one modelling and simulation approach influenced by the complexity paradigm is ABM, derived partly from object-oriented programming and distributed artificial intelligence (Jennings, Sycara and Wooldridge 1998), and partly from insights from the science of (Kauffman 1995; Axelrod 1997). ABM provides a modelling and simulation approach which can be beneficial for a complex adaptive system approach and is useful in creating tangible, understandable results for managers.

ABM represents a new paradigm in modelling and simulation of dynamic systems distributed in time and space Jennings, Sycara and Wooldridge (1998) and ABM “allows the use of CAS approaches that can address the behaviour of each of the participants within complex systems” (Cao, Feng and Wan 2009). Agent-based modelling is related to, but distinct from, the concept of multi-agent systems or multi-agent simulation in that the goal of ABM is to search for explanatory insight into the collective behaviour of agents obeying simple rules, typically in natural systems, rather than in designing agents or solving specific practical or engineering problems. ABM technique is fairly new and since its emergence, no general consensus on the definition of agents. Jennings, Sycara and Wooldridge (1998) defined an agent as a self-contained, problem-solving entity.

2.6.7 Agent-based Modelling

There are many approaches of simulating a complex system and one of the applicable methods is through agent-based modelling (ABM). ABM is extensively used within complexity theory and springs from object-oriented programming and distributed artificial intelligence. ABM is not comprehensive solution to explain all aspects of the complexity theory and complex systems, instead it should be seen as a useful tool to gain insight (Nilsson 2005).

ABM is a way to address these challenges as it offers a proactive problem solving tool. The focus of ABM is on agents and their relationships with other agents or entities. In comparison to other, more traditional programming methods, the agents in an agent-based model determine independently the best way to solve a problem in order to achieve an overall objective.

2.6.7.1 Agents and their Qualities

An intelligent agent is a software program that has the ability to operate autonomously to solve user-defined problems. According to Nilsson an agent, in a logistics context, might represent a machine, the order handling process, inventory handling and further production planning and scheduling. The definition of an intelligent agent suggests the following properties to be inherent:

- Autonomous – functions without the need for user intervention
- Proactive – operates independently to work towards a goal
- Reactive – responds to changes in the environment and changes in the course of action
- Social – interacts with other agents in order to exchange information as required

Cheeseman* *et al.* (2005) states that, in order to make the agents applicable to highly dynamic environments, further properties can be added. These properties concern reasoning and planning capabilities and are: beliefs, which is how an agent views the world, what it believes to be true; desires, which are the goals that an agent is trying to achieve; and intentions, what an agent plans to do, based on its beliefs, to achieve its desires. These properties enable the agents to view their environment in real time and adapt their approach to reach their goals which they are trying to achieve. This implies that, without any user intervention, unexpected fluctuations and in surroundings can be taken into account immediately and acted upon in real time.

2.6.7.2 Why ABM for Modelling Industrial Ecosystem?

Depending on the focus of any research, the suitability of the method used is of utmost importance. Figure 2-5 did show that researchers had moved towards a more quantitative approach to modelling IES than qualitative analysis. IS/IES is a complex system. In the last 5 years, majority of the research works focused on the use of input-output models and agent-based models separately to promote IS. However, this is not sufficient to reveal the complexity of the concept. Yazan, Romano and Albino (2016), designed industrial symbiosis using input-output approach. Even though their work introduces the concept of perfect symbiosis to enhance the future production area, it lacks in promoting the drivers (e.g., price, demand and supply) that enhance cooperation decision of the participating factories. The work of Albino, Fraccascia and Giannoccaro (2016) explores the benefit of contractual mechanisms and framed IS networks as a complex adaptive systems using agent-based model. Their work shows that ABM could be used for promoting the complexity of IS. Another factor considered in using ABM for this research work is because of the huge amount of data collected, therefore a computerised simulation model was an appropriate tool to use. ABM, as a simulation method, has shown in several cases that it is capable of handling complex systems such as logistics and manufacturing processes. Since input-output model and ABM are promising tools, we explore the possibility of combining these two methods together for modelling the ecosystem. Majorly, the input-output model is embedded in the production chain of the factories in the IS/IES while ABM is used for the entire IS components.

2.6.7.3 Drawbacks and Benefit of ABM

Nilsson and Darley (2006), work indicates simulation as a method that gives the researcher possibility to develop a model of a real or proposed system so that the behaviour of the system may be studied under specific conditions. Also, simulation enables the researcher to explore different “what if” scenarios which is a part of this study.

Another advantage is that by combining simulation with case study research the weaknesses of each method can be harmonised and at the same time increase their strengths. When starting with a case study the aim is to gain an in depth understanding of the phenomenon and context. The simulation method then can help to obtain further insights of behaviour and performance of the studied system.

Nilsson and Darley (2006) identified some of advantages of ABM as it facilitates:

- An iterative research process, which in turn enables: a way to identify and measure relevant characteristics; further insights; and a way to strengthen the theorising process.
- Triangulation of methods
- Systematic data collection
- An expanded time horizon of the study by using historical data or scenarios

The benefits of ABM in comparison to other modelling techniques can be viewed in three different ways according to (Bonabeau 2002):

- ABM captures emergent phenomena;
- ABM provides a natural description of a system; and
- ABM is flexible.

Although agent-based models are increasingly finding acceptance, such computer simulations are not without their critics. Computer simulation like ABM as arguably been described as 'fact-free science' (Maynard Smith 1995). In order to overcome such objections, build and gain the maximum use of a model the researchers have to possess knowledge within computer programming plus that a model often take some time to build. It also demands a great deal of knowledge about the system as well as the characteristics of the system under study. In that case the case study approach makes a contribution by providing the researcher with qualitative data to create an in-depth understanding of the case. ABMs has difficulty in their understanding without studying the program used to run the simulation.

Since a simulation aims to capture real-life behaviours one must see to the verification and validation of the simulation model. Model verification refers to the assurance that the computer programming of the conceptual model is correct. Model validation refers to the computerised models' accuracy consistent with the proposed application of the model. However, that the ability of ABM has to deal with emergent phenomena is what drives the other benefits.

2.6.7.4 Validation of agent-based models

One of the main valuable aspects of a simulation model is its validity. Primarily, validity means the model is demonstrated to be able to predict correctly for the problem at hand (Balci 1994). Put in another way, validation is a process of determining whether the programming implementation of conceptual model is correct. A good simulation that is able to produce reliable simulation output can be used to predict the behaviour of a real system. Simulation validation is often considered using Zeigler's hierarchy of model validity Zeigler, Kim and Praehofer (2000), that is, replicative, predictive, and structural. There are different variations on this calcification (Carley 1996; Richiardi *et al.* 2006; Chassin *et al.* 2015), but for the purposes of agent-based model validation, Klügl (2008) characterised validity along two dimensions using only two levels; *(1) Face validation and (2) Empirical validation.*

1. **Face validation:** This can be seen as the result of face validation. Face validity shows that the simulation processes and the output conforms with human judgment within the frame of theoretic basis and implicit knowledge of experts. This assessment of the simulation model is completed in three steps.
    - *Animations* are observed by human experts using graphical display in order to assess whether the macroscopic behaviours of the simulation replicate those of the real-world system.
    - *Output Assessment* human experts assessed the outputs of the simulation in order to determine the plausibility of the absolute values, relations between different values and also the dynamics and trends of the different output values of simulation runs.
    - *Immersive Assessment* a human expert evaluate directly whether the behaviour any particular agent is appropriate from the agent's perspective.

2. **Empirical validation:** This validation is done using statistical measures and tests to compare key figures produced by model with numbers gathered from the reference system. This is also performed in three steps.
    - *Sensitivity Analysis* show the effects of different parameters on the simulation output. This is a validation technique of how the uncertainty in the output of a model can be apportioned to different sources of uncertainty in its inputs.
    - *Calibration* in this method of validation, parameters to be used are repeatedly set to determine the appropriate values to use. The purpose of calibration process is to improve the consistency of outputs with the experimental data.
    - *Statistical Validation* in comparison to human assessment, this validation method is quantitative in nature. This is done by using different data sets to ensure that the model is not just highly tuned to a particular scenario.

2.7 Conclusions

While Industrial Symbiosis may not, be a perfect system (e.g. Kalundborg), it can be an ecosystem in which interrelationships result in cooperative actions alongside competition, as well as biophysical and social dimensions improve the characteristics of a local industrial ecosystem.

The prospects of agent-based models for modelling industrial ecosystem, particularly for simulation of the interaction and sharing of resources (waste and by-products) among agents (factories, market sellers and buyers) are quite promising but they have a major limitations. Maynard Smith (1995) has famously described these approaches as ‘fact-free science’. To overcome such objections and enable us to use this technique as a tool for exploring primate behavioural ecology, the models produced must be tested by using them to predict behaviours in a given population and comparing the predictions with field observations.

Existing agent-based models have focused on interactions between the agents and their environment, or pairwise interactions (e.g. dominance interactions) between individuals and emergent properties arising from such interactions. While there is literature on agent-based models of IES (Batten 2009; Bichraoui, Guillaume and Halog 2013; Romero and Ruiz 2014; Zheng and Jia 2017; Yazan and Fraccascia 2019) in some domains, including the use of ABM to express the evolution of IES, cooperative resource exchange Cao, Feng and Wan (2009) and mechanisms to foster the emergence of stable industrial symbiosis networks (Albino, Fraccascia and Giannoccaro 2016). To the best of our knowledge, none of the up-to-date literature has tackled the problem of simulating industrial ecosystem to forecast supply and demand time series using agent-based modelling integrated with input-output model.

The approach in this work is to use a complex adaptive system; sometime refers to as agent-based modelling to simulate certain aspect of IS (e.g., by-product or waste exchange between the industrial actors) to forecast supply and demand, evaluate the impact of some key decision parameters that form parts of the day-to-day running of the key actors in the industrial ecosystem.

Chapter 3
Methodology

3.1 Introduction

This chapter presents the model developed in this work to address the gaps identified in the previous Chapters. The developed model is named Réseau. The model is an integrated agent-based model and input-output approach and was developed using Python. Python is a general purpose programming language. In the following section, we outline the model development and describe our model of industrial ecosystem, using data from literature and wind data based on a UK city with the underlying assumptions. The Réseau agent-based model description follows the ODD (Overview, Design concepts and Details) protocol (Grimm *et al.* 2006; Grimm *et al.* 2010). We discussed in detail the decision strategies and a key performance index (symbiotic relationship index) to measure the level of synergy in the ecosystem. A hypothetical industrial ecosystem example was used to demonstrate how the model can be implemented.

3.2 Réseau ODD (Overview, Design concepts and Details)

There are two main and interrelated problems with descriptions of agent-based model; there is no standard method for describing them and are often described verbally without a clear indication of the equations, rules, and schedules that are used in the model. Grimm *et al.* (2006) developed a standard protocol for describing individual-based model (including agent-based models, multi-agent simulation, or multi-agent systems).

The basic idea of the protocol is always to structure the information about an agent-based model in the same sequence Table 3-1 This sequence consists of seven elements that can be grouped in three blocks: Overview, Design concepts, and Details. The overview consists of three elements (purpose, State variables and scales, process overview and scheduling), which provide an overview of the overall purpose and structure of the model. We adapted the ODD protocol to our model and described some of its elements as applicable to this work. The adapted form of the protocol is as shown in Table 3-1 and detail description is discussed in the following three sections below.

Table 3-1: Overview of the adapted ODD (Grimm *et al.* 2006; Grimm *et al.* 2010) protocol for describing Réseau agent-based model.

	Elements of the ODD protocol	**Element of the Réseau ODD (adapted)**
Overview	1. Purpose	1. Purpose
	2. Entities, state variables, and scales	2. Entities, state variables, scales
	3. Process overview and scheduling	3. Process overview and scheduling
Design concept	4. Design concepts • Basic principles • Emergence • Adaptation • Objectives • Learning • Prediction • Sensing • Interaction • Stochasticity • Collectives • Observation	4. Design concepts • Basic principles • Emergence • Adaptation • Objectives • Learning • Prediction • Sensing • Interaction • Stochasticity • Observation
Details	5. Initialization	5. Initialization
	6. Input Data	6. Input Data
	7. Submodels	7. Submodels

3.3 Overview of Réseau agent-based model

3.3.1 Purpose

Réseau is constructed for modelling industrial ecosystem. The configuration was done using Python, an object oriented programming (OOP) language. For collaboration purpose, the programming codes and other files can be found https://github.com/ganiyuajisegiri/reseauWindmultipleContract. The main (Réseau.py) is presented in Appendix A.4. The model is used to simulate the response of companies to price, demand and supply fluctuations and to expresses the dynamic nature of industrial ecosystem. The purpose of Réseau in detail is highlighted below:

- To model industrial ecosystem
- To model material exchange between sellers and buyers
- To model the decision companies make with respect to selling and buying
- To model the production processes in conjunction with decision processes
- To see if such model can predict emergence in industrial ecosystem

3.3.2 Entities, state variables, and scales

Réseau model consists of two core entities; system and agents (see Figure 3-1). The system overseas interaction between agents, maintain transaction history and provides data to agents. There are two agents in Réseau; buyer and seller agents. The buyer agents consist of the market buyer, factory (company) and local demand, while seller agents consist of market seller, factory (company) and local seller (e.g. wind turbine). The factory acts as buyer to get raw material, convert to product and then act as seller to sell product(s) manufactured in this or previous periods. The details of all the agents in the ecosystem with their attributes and objectives are presented in Appendix A.1.

The state variables refer to variables that changes with time in the model. The state variables in the model for the system is the period, number of period in hours, days, week etc. The agents variables are the stock (raw materials and products), the demand (buyers), product price (seller) and bank account (Bank balance).

Finally, the scale refers to the length of time-steps and whether the model is grid-based. The scale in the model can be daily, weekly, monthly or yearly and it is grid-based model with each of the agents have respective location in the ecosystem. The location is 2-dimensional; x and y coordinates. For example $agent\ i$ with 2 and 3 as its x and y coordinate is represented in the ecosystem as $a_i\ (2{,}3)$.

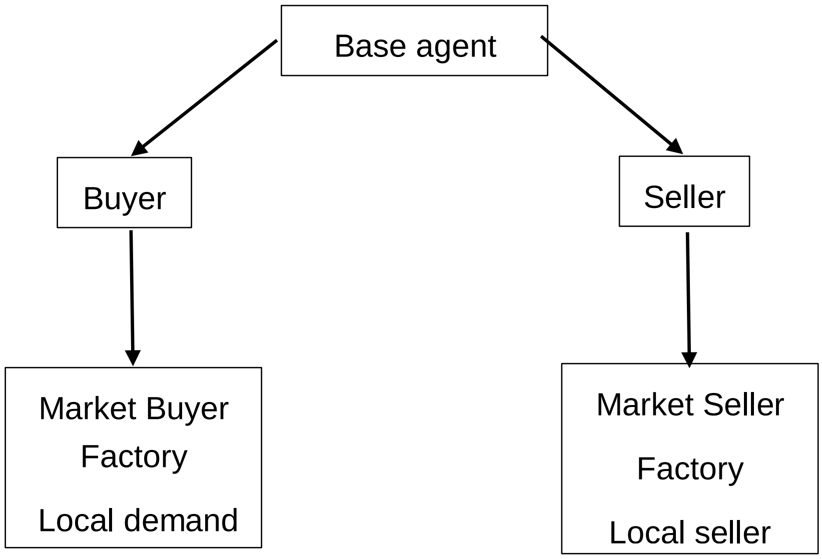


Figure 3-1: The different agents in Réseau agent-based model as inherited from the Base Agent Class.

3.3.3 Process overview and scheduling

Figure 3-2 shows Réseau agent-based transaction model logic flow for the industrial ecosystem while the full blown model logic is shown in Appendix 4. The model is assumed to run with a monthly time steps, however, the simulation run steps can be day, week, month, year. The high level of how the mode runs is describe below. At the start of the simulation:

- System entity, period, p is set to 0 and number of period N_p is set as well
- The list of buyer (market buyer, factory, local demand) and seller (market seller, factory, wind turbine) are populated from input file
- The history class is initialise
- The transaction class is initialise
- Transaction process begin by looping until period P is greater than N_p
    - All factory agents manufacture, converting available raw material, RM to product, P.
    - All buyers (factory, local demand and market buyers) estimate the quantity, Q of r RM types required and search for sellers
    - All sellers (factory, local seller and market sellers) evaluate the demand D, quantity q available for sale, and the price for the product in that period
    - Systems loops through all the buyers in random order

        - Buyer agent interact with seller agent to generate transaction until demand is fulfilled or material exhausted
        - Transaction is generated in the exchange of materials at an agreed price in the current period. The value V of the transaction is:

$$Q \times P$$

        - Each of the transaction is recorded and added to a list
    - The system then update the history based on the transaction recorded. The history contain e.g., the average price, average quantity.
    - Each agents record its transaction also and populate.
- All the transactions, history and each agent transaction are recorded in external file for analysis
- The program end.

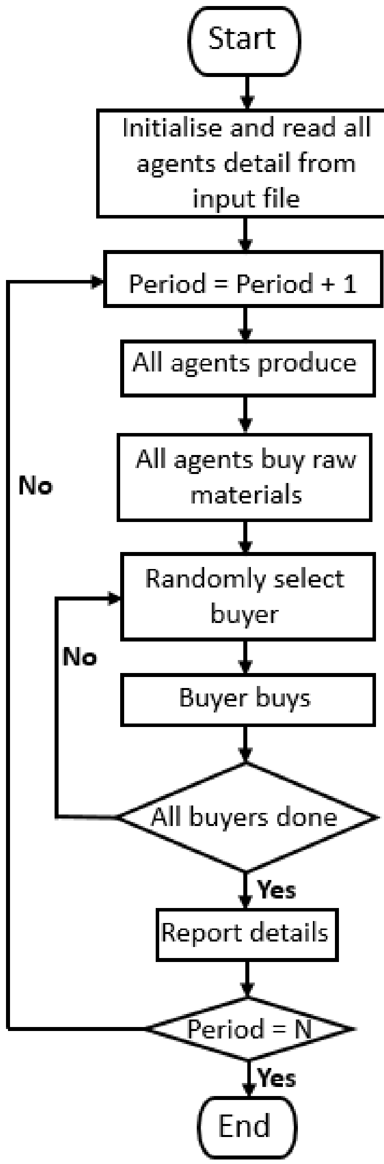


Figure 3-2 Réseau-EIP Transaction Model Logic Flow

3.4 Design Concepts of Réseau agent-based model

3.4.1 Basic principles

The concept of industrial symbiosis in industrial ecosystem is one of the basic principles used in Réseau. The other are the decision strategies implemented the Symbiotic Relationship Index developed and implemented as well as their respective mathematical formulations.

3.4.2 Emergence

The numerical results of the Symbiotic Relationship Index with price, demand and supply fluctuation represent the emerging of Réseau agent-based model.

3.4.3 Adaptation

This refer to the changes in the behaviour of entities in the model. All agents in the model do adapt to changes for every time-step. This is due to either the transactions taking place in the ecosystem. Sellers changes its price based on the history and the buyers respond accordingly to choose which seller to buy from based on the decision strategy selected for the simulation run.

3.4.4 Objectives

All agents in this model do not only seek to collectively maximize their ”purpose”, but instead make decision to buy, sell, produce goods and determine price as an autonomous agents. At each decision period, agents make decision in accordance with the sensed data and set of random techniques.

3.4.5 Learning

Each agent in the model learn from history by using the learning procedure to make decision at every time steps. An example is the history of the prices of goods in the market. All agents always check the previous price and based on Weibull distribution function make a decision either to change (increase or reduce) or maintain the price for the next time step.

3.4.6 Prediction

The history class is available per period for agents in the model to use for prediction and make adequate decision in the next period.

3.4.7 Sensing

All agents in the model know their own parameters, e.g. buyer agent knows their raw materials, quantity demand, unique identity etc.

3.4.8 Interaction

The system interact with the buyers until transaction is completed while buyer agents interact with seller agents in the ecosystem. The primary interaction is the exchange of resources for money. In the buying and selling modules, a buyer established synergy with seller(s) through the transaction sub-model.

based on the quantity, Q available and price. The buyer buys from seller(s) based on the buying decision strategy chosen (see section 3.6.1).

3.4.9 Stochasticity

Stochasticity plays a more detail role in the Réseau agent-based model. At the beginning, each agents load their parameters from an input file and based on some level of random distributions which adds an element of stochasticity into all subsequent runs.

3.4.10 Observation

For model testing, various scenarios were observed. For model analysis, transaction details of all agents in the model were populated, e.g. price, demand and supply fluctuations, bank balance etc. The simulation run time for different time-steps were also observed to know how fast is the model.

3.5 Details of Réseau agent-based model

3.5.1 Initialization

At the start of the simulation run all the agents are created from input file with their initial state variables values. The states variable changes during the simulation time-steps but the initial condition for all the parameters remain unchanged for all runs of the same scenario. The data were chosen from UK data purchased from Met Office, United Kingdom, between year 2001 to 2010; Met Office (2010) and some from the literature (see Chapter 4, 5 and 6). As mentioned earlier, the simulation environment is split into System, buyer and seller. The variables with their parameters for each agents are organized from external file (MS Excel) and the agents pre-load their data. Based on this, users can therefore run different scenario by varying input parameters and observing their impact on their output.

3.5.2 Input data

A sample of the input data is shown in Appendix A.2 for the single input single output. The input data is excel based. To solve a multiple input multiple output industrial ecosystem problem, the user has to create input data for the agent types in the model. Apart from the initialization data no other data is required to run the model. Note that the intial conditions are set as the initializationa values from the input file for all the parameters and are the same for all runs of the same scenario. The input file is user friendly and users can easily change the parameter to suit the problem in question.

3.5.3 Submodels

3.5.3.1 Manufacturing process model

The manufacturing process model included in the production stage of agent is an input-output ratio formulation. Therefore, input – output model is adopted and this is what formed one of the core innovation of this research work. There is no known eco-industrial park model based on input-output approach in the literature. The basic input-output approach for a production is shown below.

Let us assume we n industries denoted by $S_1, S_2, S_3, \dots, S_n$ the exchange of products can be described by open Leontief Model (Leontief 1970) where demand must be satisfied not only within but outside also. Each industry produces x_1 units of a single homogeneous good. In order for S_i industry to produce 1 unit, a_{ij} units must be purchased from industry S_j. Since industry S_i need to satisfy outside demand, let the demand be b_i. Then we have the followings:

Let:

p_i = the production level of industry S_i

a_{ij} = the number of units produced by industry S_i that is required to produce one unit by industry S_j

$a_{ij}\ p_j$ = the number of units produced by S_i and consumed by industry S_j

For $i = 1, 2, 3, \dots, n$

Then we can write:

$$\begin{aligned} p_1 &= a_{11}p_1 + a_{12}p_2 + a_{13}p_3 + \cdots + a_{1n-1}p_{n-1} + a_{1n}p_n + b_1 \\ p_2 &= a_2p_1 + a_{22}p_2 + a_{23}p_3 + \cdots + a_{2n-1}p_{n-1} + a_{2n}p_n + b_2 \\ p_3 &= a_{31}p_1 + a_{32}p_2 + a_{33}p_3 + \cdots + a_{3n-1}p_{n-1} + a_{3n}p_n + b_3 \\ &\vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \end{aligned} \tag{1}$$

$$p_n = a_{n1}p_1 + a_{n2}p_2 + a_{n3}p_3 + \cdots + a_{nn-1}p_{n-1} + a_{nn}p_n + b_n$$

Equation (1) can be written in matrix form as below:

$$P = \begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & & \vdots \\ a_{n1} & \cdots & a_n \end{pmatrix}, B = \begin{pmatrix} b_1 \\ \vdots \\ b_n \end{pmatrix}, A = \begin{pmatrix} a_1 \\ \vdots \\ a_n \end{pmatrix} \qquad (2)$$

Where $\boldsymbol{P}$ is the production level vector, $\boldsymbol{A}$ is called the input – output matrix and $\boldsymbol{B}$ is the external demand vector.

This can be written in matrix form as

$$\boldsymbol{P} = \boldsymbol{AP} + \boldsymbol{B} \qquad (3)$$

One way to solve equation (3) is to find the inverse and the solution become

$$\boldsymbol{P} = (\boldsymbol{I} - \boldsymbol{A})^{-1}\boldsymbol{B} \qquad (4)$$

To illustrate the use of input – output model for the production process, consider a two-industries producing steel and lumber. The current consumption is given in Table 3-2. Assume the new external demand for steel output is 100 units and 100 units for industry Lumber. We need to determine the new production levels.

Table 3-2: Two industries consumption

	Consumption		
	Steel (R)	Lumber (S)	External
Industry Steel production (R)	50	50	20
Industry Lumber production (S)	60	40	100

Solution: The total production is 120 units for R and 200 units for S. we obtain

$$P = \begin{pmatrix}120\\200\end{pmatrix},\ B = \begin{pmatrix}20\\100\end{pmatrix},\ A= \begin{pmatrix}\frac{50}{120} & \frac{50}{200}\\ \frac{60}{120} & \frac{40}{200}\end{pmatrix}$$

We solve the problem using equation (3) and (4)

$$\boldsymbol{P}' = (\boldsymbol{I} - \boldsymbol{A})^{-1}\boldsymbol{B}' = \frac{1}{41}\begin{pmatrix}96 & 30\\60 & 70\end{pmatrix}\begin{pmatrix}100\\100\end{pmatrix} = \begin{pmatrix}307.3\\317.0\end{pmatrix} \tag{5}$$

The new production levels are 307.3 and 317.0 for Steel and Lumber industries respectively.

3.5.3.2 Transaction

The Transaction class is where the buyer and seller exchange material(s) by forming synergy. The buyer searches for any seller that has the required material in the market and append this seller in a sellers' list. The list of the seller is sorted according to the decision strategy (see Section 3.6) used by the buyer for that simulation run. After sorting the buyer buys according to the quantity of material required and each of the seller, buyer details are updated in the Transaction class. The list of transaction is also update in the System and also reported in the external output for later analysis.

3.5.3.3 System history

This is the class that contain all the transaction that take place in the ecosystems. The system recorded per time-step the each agent transaction details and also report same using a util system (a reporting tool) in an external file (MS Excel). The history contain the average price, quantity and value. This enable either the selling or buying agents to make informed decision at the next time-step. For example, the seller check the history to know whether to change its price or not.

3.5.3.4 Contract

The contract class enable contract transaction to be done between buyer and seller that have entered into any contractual agreement. At the beginning of the simulation, each buyer source for seller but only the buyers that have contractual agreement enter the contract class domain. The contract agreement is also initialised from the beginning. In the contract class, the length of the contract (i.e., the start and end time of contract), buyer and seller are all known.

3.5.3.5 Parameter Loading

Each agent load its parameters from the input file (see Appendix A.2). The parameters are agent specific with unique identifier associated with each agent. For example, a Factory agent unique identifier is written as fac1 (i.e. Factor 1) , and market seller agent as ms1 (i.e., market seller 1).

3.5.3.6 Requirement Prediction:

This method is used by all the agents to predict their needed requirement at every time step. The method is modelled based on Gaussian distribution with mean and standard deviation. The market agent demand is equivalent to the requirement predicted while factory agent have two variables to be determined at the beginning of each time step. These are the sales quantity and price. These two variables are modelled using Gaussian distribution also. The market selling agents on the other hand only predict the selling price of all its goods.

3.6 Decision strategies in Réseau agent-based model

The traditional approach to buyer's selection has been to select suppliers solely on the basis of price (Pal *et al.* 2013) among other selection criteria (e.g. quality, delivery, rejection, capacities, rating and flexibility). Although, with the time passing on, price is not only a sufficient measure or criterion for supplier selection. In this research we focus on price evolution in the industrial ecosystem and describe the "Strategic characteristics" refers to the strategies the agent will use to reach the objective of selling or buying. We developed five and two decision strategies for the buyer and seller agents respectively. The strategies are discussed in the two sub-sections below.

3.6.1 Buyers' perspectives

In this section, we describe the five buyer decision strategies (*BDS*) a potential buyer to make decision in the industrial ecosystem. The decision making process by a potential buyer follow different steps before fulfilling its desired interest in the industrial ecosystem. The first stage of the process involve the potential buyers to work out exactly its requirement (demand recognition). This is followed by searching (information search) for the available good(s) in the industrial ecosystem from the different sellers. For each of the prospective seller, the buyer append each seller to a list. Next, the buyer evaluate (alternative evaluation) all the seller in the list using any of the search techniques. In this work , we developed five different evaluation searching techniques as follows: 1) Random, 2) cheapest price, 3) distance/cost, 4) trust and, 5) experience. All these five searching methods are introduced in the result chapters, i.e., chapter 4, 5 and 6. The last stage in the decision making process by the buyer is purchase. The potential buyer then buys from each of the seller by using any of the alternatives evaluation methods listed above. Each of these alternative evaluation search techniques are discussed below:

- **Random (BDS1):** In this search technique, a potential buyer choose its buyer randomly over the entire simulation period. For simplicity sake, we model this search method for the buyer to choose sellers from the seller's list as a normal (Gauss or Laplace-Gauss or Gaussian) distribution. In this search method, we assumed that the distributions of the variables are unknown.

- **Best Price (BDS2)**: The potential buyer behaviour in this case is to look out for the cheapest (best) price in the list of all the available sellers for a particular product/material. The best price is literarily the lowest price that a buyer is willing to pay for a good. When the buyer search the list of sellers in the industrial ecosystem, it make contract with the best seller and purchase the amount of quantity needed. If the best seller cannot fulfil its demand, it make contract with the next best seller until its demand is met. This procedure is followed till all the buyers demand are met.

- **Distance (cost) (BDS3):** The industrial ecosystem has two dimension (X, Y). This is discussed in section 3.3.2. As soon as each agent (buyers or seller) is created, its location in the space is also added by an (x, y) tuple and place in the grid. Each agent has distinct (x, y) coordinate and no two agents can occupy the same location in the space. A potential buyer (buyer agent) calculate its distance from each of the respective sellers with the available goods and rank the distance in the ascending order. The buyer then make contract with the seller with lowest distance and make a purchase. If the seller cannot fulfil all its demand, it make contract with seller with the next lowest distance from its own location until its demand is met. This procedure is followed till all the buyers demand are met.

- **Trust (BDS4):** It has also become apparent that although there may be potential benefits from industrial ecosystem policy initiatives, their development is not problem-free. Gibbs (2003) stated that there may be motivational barriers wherein firms, public sector agencies and other relevant local actors must be willing to co-operate and commit themselves to the process. Trust is a key factor here and companies may be unwilling to provide information about production processes and (by-) products for competitive reasons. Also Albino, Fraccascia and Giannoccaro (2016), mentioned that social embeddedness and trust are important properties of a self-organized industrial network. In this work, we model the level of trust between buyers and sellers as a probability which follows the normal distribution. We adapted Albino, Fraccascia and Giannoccaro (2016) and define TRUST (T) as the probability of maintaining the relationship, while (1-TRUST) is probability of seeking a new partner. Therefore, the higher the probability that the firms maintain mutual beneficial relationship, the higher the level of trust in the relationship. So at every period, a potential buyer rank the trust it has in each of the potential sellers in descending order and choose the one with the highest first in that order.

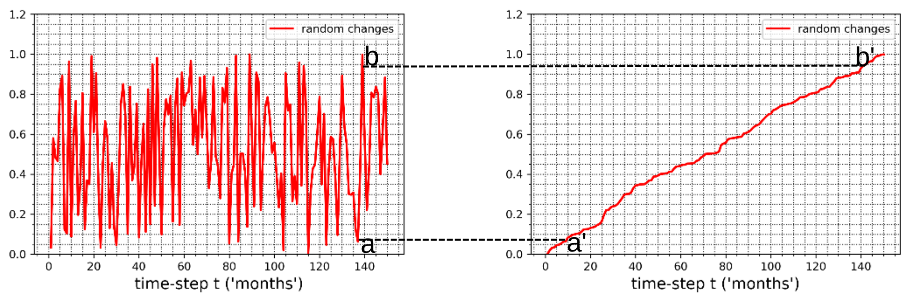
- **Experience (BDS5):** The experience is almost the same as the concept trust. In this case a potential buyer search based on the experience of each of the sellers. We also model the experience as a probability and it (EXPERIENCE, E) is define as the probability of maintaining high degree of experience. The higher the probability that the firms maintain mutual beneficial relationship, the higher the level of experience in the relationship.

3.6.2 Sellers’ perspectives

In this section, we describe seller decision strategy (*SDS*) to make decision in the industrial ecosystem

- **Randomized price setting (SDS1):** Under the randomized pricing strategy, the seller can randomize the price over the simulation period. For simplicity, we model the price as a Gaussian distribution with mean and standard deviation as indicated in , The first approach to price model was given by Bachelier in 1900 discussed in Sullivan and Weithers (1991) when he modelled price dynamics as an ordinary random walk where prices can go up and down due to a variety of many independent in this price setting, the simplest quantity to check is the average mean square fluctuation between (trade) time t and $t + l$. Here, the price P_n is defined as the mid-point just before the nth trade. One period may represents one unit of time, such as one hour, one day or one week etc. Randomized price setting follows the equation (6) as below, where P_t is the price at any time-step, $\overline{p}$ is the mean price and σ_p is the standard deviation. The graphical representation of this price setting is as shown in Figure 3-3(a) where the price changes between 0 and 1. Figure 3-3 (b) show how the changes per time step can be sudden due to the random nature of this method. This can be seen as the value changes suddenly from 0.12 (point a) to 0.90 (point b). Price can change suddenly like that in real life. However, the random price changes still follow the normal distribution as indicated in Figure 3-3 (b)

$$P_t = \overline{p} \pm \sigma_p \quad (6)$$



(a) Randomized walk (b) Cumulative distribution

Figure 3-3: Random price setting description

- **Risk-based price setting (SDS2):** This price changing method by sellers is one of the novelity of this work. Unlike the random price setting, the proposed price is a new one applicable to the behaviour analysis of how each seller respond to the activities in the market before changing its price. Price changes often make the buying decision indefinitely more complex. Buyers no longer have clear reference prices, so they don't know when to check out. Samper and Schwartz (2013) shows that when decisions become complex, many people delay making decisions or back out of them altogether. Factors such as relocation and financial distress motivate the supplier to facilitate sale by posting a lower list price, communicating the motivations to the marketplace, or offering sales incentives to agents (Springer 1996). In this price setting, the sellers always put into consideration the cost – benefit of changing the price at every time step. The risk-based price setting method is as follow and the logic is shown in Figure 3-4. At the beginning of the simulation, the price P_t follows the randomized price P_0. However this changes onward, by finding the difference (delta P, ∆P) between P_t and the average price history P_{his} in the market. The small changes in successive period is represented as:

$$\Delta \mathrm{P} = (P_{his} - P_t)/P_{his} \tag{7}$$

The seller then looks for the likelihood of changing its price in the next period by finding the cumulative density of this value (the probability of taken action). In this work, Weibull distribution is used to find the cumulative density of ∆P with a known values of scale (λ) and shape (k). The scale and shape values are between (0, ∞). After finding the probability of ∆P (ΔP_{prob}), the seller tosses a coin to obtain probability of success ($Coin_{prob}$). Comparison between the probabilities of ∆P and coin is then made and decision is made either to change the price or not. If the probability of success ($Coin_{prob}$) is more than the (ΔP_{prob}), the seller maintain its price, otherwise it changes. This is shown in the graph with four different values of λ and k. For the graph labelled (a), it will always take action (change price) when delta P equals ΔP_2 and will never take any action when delta P equal ΔP_1. The new price follows the equation as below:

$$P_t = P_{t-1} + (\Delta \mathrm{P} /5*\text{random}) \tag{8}$$

- The decision to either change the price or not by the seller shows the risk level of each of the seller. The graphical representation of this price setting is as shown in Figure 3-5. The price changes is not sudden unlike the setting in SDS1. The seller either take action or not when there is a small difference in previous price and current price.

```
Initialize the price of the seller to the randomized
price

Obtain the average price history in the market

Determine the price change (delta P) between the last
and present

Determine the cumulative distribution of delta P

Toss a coin a determine the probability of success

Make decision to change price:

If Probability of coin is < probability of delta P

      Retain price

Else

 Change price
```

Figure 3-4: Pseudocode for risk-based price setting

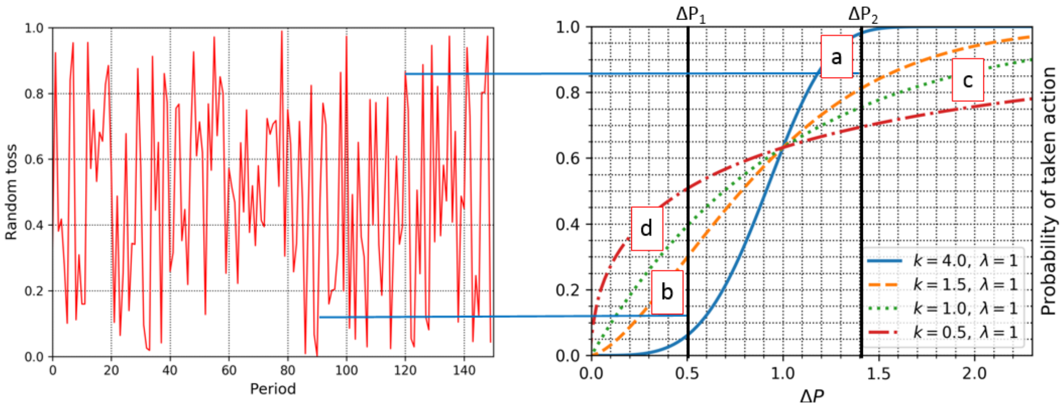


Figure 3-5: Risk-based price setting showing four different cumulative distribution function (CDF) for the Weibul distribution with different scale (λ) and shape (k) parameters.

3.6.3 Symbiosis Indicators for Eco-Industrial Park

One of the main approaches to support sustainable development is the use of performance indicators (Ramos and Caeiro 2010). Through this instrument, business professionals, representatives of regulatory protection agencies, brokers and governments can diagnose, manage, and make decisions favouring the reduction of environmental impacts. The success of industrial ecosystem depends on all these different bodies (e.g. broker) performance in providing the adequate information necessary (Felicio *et al.* 2016). To better understand industrial ecosystems, Hardy and Graedel (2002) applied food-web theory to the linear relationship that exit between an eco-industrial park. Tiejun (2010) developed two different indicators to evaluate an eco-industrial park using natural ecological theory. The first indicator is the eco-connectance of an industrial ecosystem that defines the degree of the connectivity among enterprises or factories in an industrial ecosystem; the second indicator defines the degree of by-product and waste recycling in an industrial ecosystem. Park and Behera (2014) proposed eco-efficiency indicator as an integral parameter for simultaneously quantifying the economic and environmental performance of industrial symbiosis (IS) networks. Felicio *et al.* (2016) analysed the different indicators and proposed a new indicator called Industrial Symbiosis Indicator (ISI) to provide support for measurement of symbiosis by brokers and managers, considering a dynamic perspective of the evolution of symbiosis in a specific industrial ecosystem. However, he did not mention the work (Park and Behera 2014). One of the limitations of these indicator is the inability to consider possible symbiotic relationship with external systems. In order to understand the mechanism of the strong relationship that exist between the agents in the industrial ecosystem, I proposed a metric called Symbiotic Relationship Index (SRI) developed to quantitatively measure the benefit of the symbiotic relationship between agents in the industrial ecosystem. The SRI is defined in equation (9) and it is a periodic function.

$$SRI = \frac{total\ no\ of\ internal\ transaction\ only\ per\ period}{total\ no\ of\ all\ interaction\ per\ period} \tag{9}$$

SRI is a factor between 0 and 1. Since SRI is the measure of how strong or weak is the symbiotic relationship of in the ecosystem, the closer the index 1, the stronger the relationship that exist among agents inside the park and vice-versa. For example, an SRI of 0.85 indicate a strong symbiotic relationship while an SRI of say 0.35 means a weak symbiotic relationship of agents within the internal environment of the industrial ecosystem. A perfect symbiosis will have an SRI of 1 while SRI of 0 indicate a non-symbiosis industrial ecosystem.

3.7 Implementation of Réseau agent-based model

3.7.1 Model Structure

The design structure of Réseau agent-based model is based on modularity. The model is divided into main categories: modelling and analysis. The modelling components consist of: system model class to store model-level parameters and serve as a container for the rest of the components; agent classes which describe the system agents; the transaction class that controls the interaction between the seller and buyer agents in the industrial ecosystem, history class keeps the update of the transaction that occur in the ecosystem for reference and usage at any point in time over the simulation period, and lastly, components describing the space objects representing the agents' environment. The second part is the analysis components, serving as a data recording utility. The analysis component is the data collectors where the data from each model run are recorded. The recording module is named utils. It houses many modules like; Tlist class, Reporting Class, Tpath Class and FLMSort Class. The third component of any agent-based model is the visualization components. This is not included in our model and the visualization is done through the analysis of the recoded data.

In the remainder of this chapter, we will show how Réseau and its core features can be implemented. To illustrate and demonstrate the core features of our model, we will describe and build a simple agent-based model, drawn from a made up hypothetical industrial ecosystem using the two categories mentioned above.

Figure 3-6 shows the potential structure of the proposed hypothetical industrial ecosystem that is used to describe how to use our model in this chapter. The Industrial ecosystem consist of the market buyers, factories and market sellers. The Industrial ecosystem include two different factory types (Combined heat and power and Anaerobic digestion plants) with their possible connection. Each of the factories can also make possible connection between the different external markets if the price of the external markets agent over shadow the factory agents. Three of the factories are combined heat and power plant (CHP) differentiated by their unique identifier, fact 4, fact 5, fact

6. The CHP's use biogas as main input raw material apart from other input which are not included in this simulation to fulfil the single input-output scenario to produce electricity. The other three factories are, anaerobic digestion (AD), represented as fact 1, fact 2 and fact 3. The AD plants use electricity as one of its input to generate biogas. The main input material for the AD system is the waste from cattle and food and bio-solid wastes but is not being consider in this work. Apart from the factories, the industrial ecosystem also contains market buyer agents (MB1, MB2 and MB3) that willing to buy from the source agents at a considerable price and also market seller agents (MS1, MS2 and MS3). The market agent either buys or sells directly from/to the factory agents. From the In the ecosystem, we have twelve different agents that interact to form synergy based on supply *(HAVE)* and demand *(WANT)*.

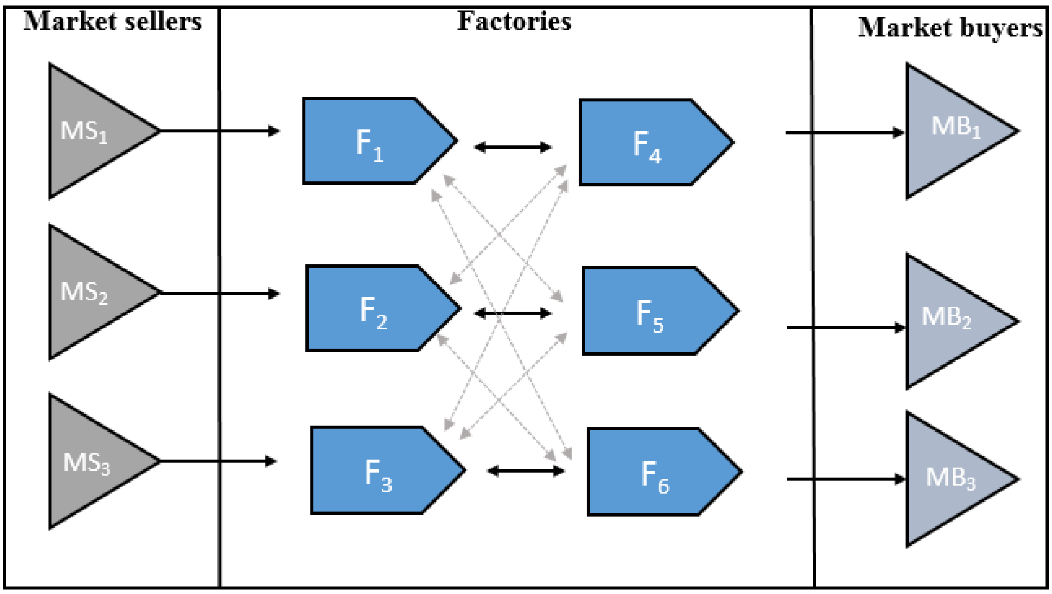


Figure 3-6: Example of hypothetical industrial ecosystem

The three CHP plants separately have demand capacity for biogas (methane) ranging from 80,000 – 500,000 cubic meter per month while the AD plants utilizes food and bio-solid wastes in the range of 0.3 - 0.6 million tons and required energy within 60 – 99 megawatt.

The core of the model is composed of *n* number of firm agents, all of whom begin with number of inputs raw materials that are converted to finished products, by-products and waste material through a conversion process. In our model, the conversion method used is input-output model (see Section 3.5.3.1) At every step of the model, an agent predict its requirement, produce and sell its outputs to some other agent. The model parameters are many and only few are shown. The numerical data on the main product demand are shown in Appendix A.2.

To begin building the example of the industrial ecosystem model described above, we first create four classes. Three out of these classes inherited from the base agent class and are the different system model agents while the remaining one is the system model object. To run the simulation, the user will create an MS Excel file as shown in Appendix A2 and name the reseau_input.xls file. If this is done correctly, no other thing is required than to run the model (System.py) by setting up the number of time-step or period the model should run. If no error

detected, the simulation run and terminate at the end of the set period. An output file is created automatically with name EIP Output vxxx.xls. The xxx indicate the number of times the model has been run. e.g. EIP Output v003.xls. Before discussing and showing sample(s) of the simulation run, we will discuss the scheduler and space as embedded in the model.

3.7.2 Scheduler

The scheduler is an important agent-based model design consideration. The scheduling was briefly mentioned in the ODD description of Réseau agent-based model.

Scheduling refers to how we model time. Unlike system dynamics models, times in agent-based models is almost never continuous. Thus, scheduling the agents' activation is important, and the activation regime can have substantial effect on the behaviour of our simulation (Comer 2014). Many agent-based model frameworks do not make this easy to change. For example, NetLogo defaults to a random activation system, while MASON's scheduler is uniform by default. In Réseau agent-based model the schedule adopted is the same as the default schedule in MASON. However, modeller can decide to use the Netlogo defaults agents activation by incorporating the random schedule in the model. This is possible by using the random function in Python.

Most models make a distinction between each step, with one “tick” representing a unit of time such as a minute, day, week, month or year. A step of the model generally involves the activation of one or more agents, and frequently of all of the agents. There are numerous possible scheduling regimes used in agent-based modelling, including:

1. Synchronous or simultaneous activation, where all agents act simultaneously. In practice, this is generally implemented by recording each agent’s decision one at a time, but not altering the state of the model until all agents have decided.
2. Uniform activation, where all agents are activated in the same order each step of the model.
3. Random activation, where each agent is activated each step of the model, but the order in which they are activated is randomized for each step.
4. Random interval activation, where the interval between each activation is drawn from a random distribution (most often Poisson). In this regime, there is no set model step; instead, the model maintains an internal ’clock’ and schedule which determines which agent will be activated at which time on the internal clock.
5. More exotic activation regimes may be used as well, such as agents needing to spend resources to activate more frequently.

As mentioned above, when the agents are initiated uniformly, each agent follow the same steps of schedule. The schedule in the model is as follow:

1. The `ProductionStep` method ensures the given agent in the park produces the required output based on demand requirement
2. The `PredicRequirements` method is the method that return the raw material and product output demand.
3. The `BuyRM` method is where the detail transaction take place. The interaction that occur between the agent that sells, when and at what price. Buyers that has entered into contractual agreement also complete the contract transaction.

3.7.3 Space

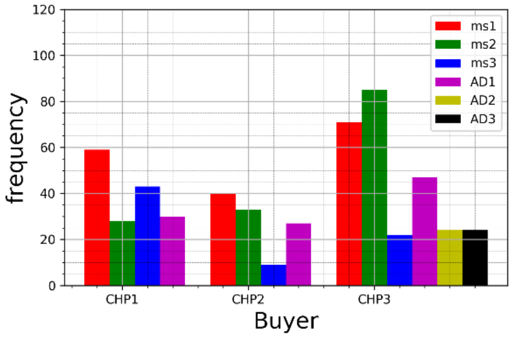
Most agents in any agent-based model platform are spatially distributed. In general, agents may have fixed positions or move around, and interact with their immediate neighbours or with agents and other objects nearby. The agents in Réseau are placed in fixed positions. The majority of agent-based models use two-dimensional spaces, which is how in Réseau current space modules are implemented. In NetLogo, agent motion was implemented using a built-in method that moves an agent to a location specified by X and Y coordinates; this is refer to as continuous space.

To add space to our example model, as soon as each agent is created, it location in the space is also added by an (x, y) tuple and place in the grid. Each agent has distinct (x, y) coordinate and no two agents can occupy the same location in the space.

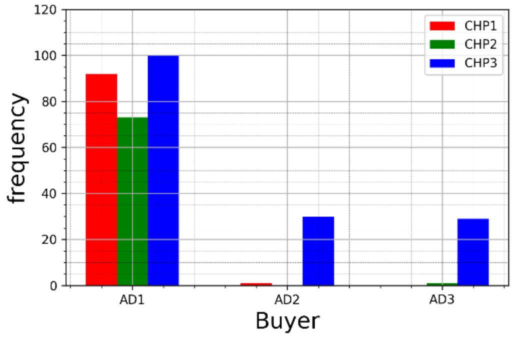
3.7.4 Data Collection

Having run the model and an output is generated, the next is to analyse the output data. An agent-based model toolkit is not complete without data collection library and may not be useful to the modeller to analyse the behaviour and output the model produced. Data collection in ABM can be done strictly in two ways (Robinson *et al.* 2007; Masad and Kazil 2015; Utomo, Onggo and Eldridge 2016); visualization and quantitative data collection. In our case, we used only quantitative data collection while the visualization method of data collection will be additional feature of the model in the future.

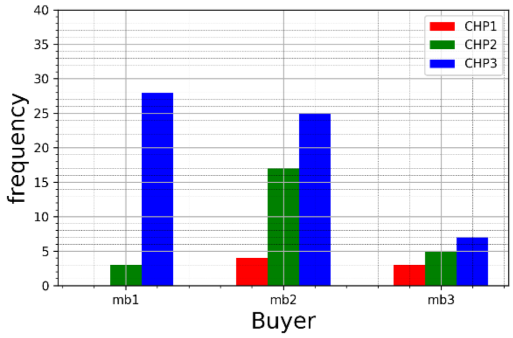
We built in a data collection library in Réseau namely *util* with some classes like Reporting, Tlist, Tpath classes etc. The Report module enable all the agents parameters to be recorded in an external file (xls or xlsx format) according to the object name. With a distinct object name, the reporting tool create a new sheet and append all the attributes of that object column by column. The Tpath class create a new output folder for every runs initiated in the system main. This is where all the output files are created from. Some of the outputs generated from this example is shown in Figure 3-7 for demonstration of how our model works. The figure can be explain as follow that there is synergy that occur within the ecosystem and the agents freely interact with each other to exchange resources. In particular, factories agents transacts more within each other when the resource exchange is by-products while finished products are sold to the external environment. This is one of the analyses that can be done from the out of Réseau simulation.



(a) No of times buyers (Combined heat and power plants) buys from the sellers



No of times buyers (Anaerobic digestion plants) buys from the sellers



(c) No of times buyers (market buyers) buys from the sellers

Figure 3-7: Frequency of transaction in the example of hypothetical industrial ecosystem showing the number of times each buyer transacts with a seller

3.8 Timeline of Réseau agent-based model

A significant modification was done to the agent based model of the co-industrial park developed in this research work. The modification is done in two different parts. Firstly, the initial Réseau is basically to simulate an eco-industrial park with agents that convert only a single raw material input to a single output. Having solve a single input-output model of industrial ecosystem, we proceeded by making most of the attributes (e.g. input material, capacity, product output etc.) as a list components. The second modification that needed to be done is the inclusion of a contracting methodology in the periodic market transaction. This is another important factor in the developed agent based model for simulating eco-industrial park. It has been stated in Stern (2012) that suppliers require long-term buyers to mitigate investment risks, and likewise consumers require secure supply (Edwards 2010). However, most models treat contracts only as the initial constraints for minimum flow amounts between corresponding regions. The assumption of this modelling design is that a full spot market would become dominant in the future. An example of a spot market can be liken to a wind power supplying a combined heat and power plant to mitigate the fluctuation in electricity supply.

3.8.1.1 The role of contract design in eco-industrial park

The industrial firms engaged in symbiotic relationship receive economic benefit by exchanging resources, however to establish an effective symbiotic relationship and solve the misalignment incentive problem arising in the symbiotic relationship is that of introducing contract (Albino, Fraccascia and Giannoccaro 2016). The contracting system applicable in this work is specific to the supply contract developed in supply chain management literature to rule the material flow relationships in supply chains so as to achieve system-wide efficiency (Govindan, Popiuc and Diabat 2013). Contracting system as related to supply chain are discussed (Tang 2006; Narasimhan and Talluri 2009; Govindan, Popiuc and Diabat 2013; Albino, Fraccascia and Giannoccaro 2016; Duan and Ventura 2019) in detail based on different classification such as pricing, minimum purchase commitment, sources of risk, quantity discount etc. The significance of contracts for eco-industrial park has is still in the early, with only few that has discussed the issue. An example of such are those discussed (Chertow 2004; Lombardi and Laybourn 2006), in which the firm using wastes agrees to pay fixed price to the supplying firm or, on the contrary, the firm supplying wastes pays the receiving firm. The contract mechanism logic flow incorporated as part of the timeline of the model is as shown in Figure 3-8. This will be explained furuther in Chapter 6.

To the best of our knowledge, no known studies have focused on analysing the effect of contractual agreement on the behaviour of agents in an eco-industrial park towards the formation of a stable symbiotic relationship with fixed price. In order to assess the effect of contract between the firms in the eco-industrial park, the developed model is modified and we created another class called Contract Class.

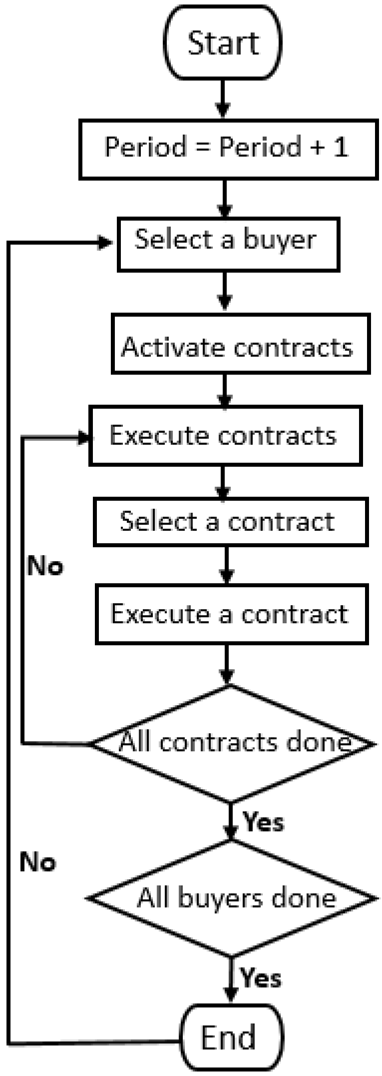


Figure 3-8 Contract mechanism logic flow

3.9 Conclusion

Industrial ecologists have faced some difficulties in modelling the complexity of ecological systems. One of the way to unravel the complexity of such systems, made up of autonomous entities is to use agent-based modelling (Zhou 2005). However, agent-based model has difficulty in proper description of how it was developed re often described verbally without a clear indication of the equations, rules, and schedules that are used in the model.

We adapted ODD protocol Grimm *et al.* (2006) to construct Réseau and described the three basic steps in the protocol as applicable to this research work. We presented the input-output model as the core of what is different in the approach of other researchers in modelling the factory agent production process in the eco-industrial parks system. The input-output model has been used extensively (Albino, Dietzenbacher and Kühtz 2003; Mattila, Pakarinen and Sokka 2010) and proven to provide a measure of resources consumption and of the environmental impact of the district production processes (Albino, Dietzenbacher and Kühtz 2003). We developed different decision strategies and implemented four in Réseau. Two (random and best price decision) from buyers' perspective and two (random and risk based price setting) from the sellers' perspective. We also developed a metric called Symbiosis Relationship Index (SRI) to measure the degree of symbiosis in an industrial ecosystem. The decision strategies and key performance measure developed were presented and we show how Réseau can be implemented by any user using a single input single output. Many factory production chain are multiple input multiple output, but a description of the single input single output model is necessary to understand the concept. It is our believe that if the single input-output model of eco-industrial park simulation works then a model of the industrial ecosystem with multiple input-output will definitely work. Lastly we presented the timeline for t Réseau so as to accommodate a more robust industrial ecosystem problem.

In subsequent chapters, Réseau will be further developed and applied to three different case studies of an industrial ecosystem with different complexity. Case study one will be used to demonstrate random decision strategies on single input single output industrial ecosystem. This will serve as validation of the software concept. Case study two will evaluates all combinations of decision strategies in and industrial ecosystem with factories that have multiple input multiple output. This will be used to evaluate the different decision strategies developed and implemented in this work and showcase the ones that provide significantly more realistic demand and supply time series. The third case study, will extend Réseau with multiple period contracts between factories within the ecosystem. We will compare scenario with and without such contracts. This is to investigate if short or long contract promotes industrial symbiosis. The results output from each of these case studies will be analysed to showcase the robustness of our proposed methodology.

Chapter 4
Agent-Based Model of Single Input Single Output (SISO) Industrial Ecosystem

4.1 Introduction

In this chapter, we present an application of the developed Réseau agent model to simulate a simple case study. In this case study, we only consider industrial ecosystem consisting of single input single output factories. This is to establish a base line for our model before using the model to solve a more complex industrial ecosystem (IES) with multiple input multiple output factories. It is our believe that if the single input single output (SISO) model of industrial ecosystem simulation works then a model of the industrial ecosystem agents with multiple input multiple output will definitely work.

To build our simulation of the industrial ecosystem described in Figure 4-1, we used data referring to real case study concerning an energy based ecosystem discussed in (Gonela and Zhang 2014). Although the United kingdom (UK) is presently well behind some other European countries in terms of the number of anaerobic digestion plant installations, this is changing fast due to the subsidies (Whiting and Azapagic 2014). We present an hypothetic configuration consisting of how combined heat and power and anaerobic digestions plants can benefit from industrial synergy. The reason for using an hypothetic IES for this case study is because in real life, hardly can we find a a system with single input single output. In the IES, we have the internal and external environment. The internal environment of the IES consists of 6 factories; 3 Anaerobic Digestion (AD1, AD2, and AD3) operations on food, manure or bio-solids and 3 combined heat and power (CHP1, CHP2, and CHP3) plants that convert methane into heat and electricity. The heat is delivered to local demand (not modelled) and electricity is either sold internally to the AD's or to the external environment (market buyers). Market sellers (MS1, MS2 and MS3) provide methane and electricity while market buyers (MB1, MB2, and MB3) purchases electricity and methane. The market sellers can sell directly to the market buyer and vice versa.

Each companies and the market sellers in the ecosystem observed a stochastic final buyer demand over time, distributed according to Gaussian distribution with a given mean and standard deviation as described in section

3.3.3 of the methodology. Numerical data on product demand, raw material requirements and other necessary data are shown in Table 4-1 - Table 4-4. Note that the intial conditions are set as the initializationa values from the input file for all the parameters and are the same for all runs of the same scenario. The Réseau agent-based model is used to simulate the interaction between firms, infinite source and sink in the IES so as to understand the dynamic behaviour of all the candidates in the park particularly the process plants. The simulation results of this case study are presented and discussed in the next section. This section that follows presents the detail configurations of each of the agents (factories, market buyers and sellers) in the IES for this case study.

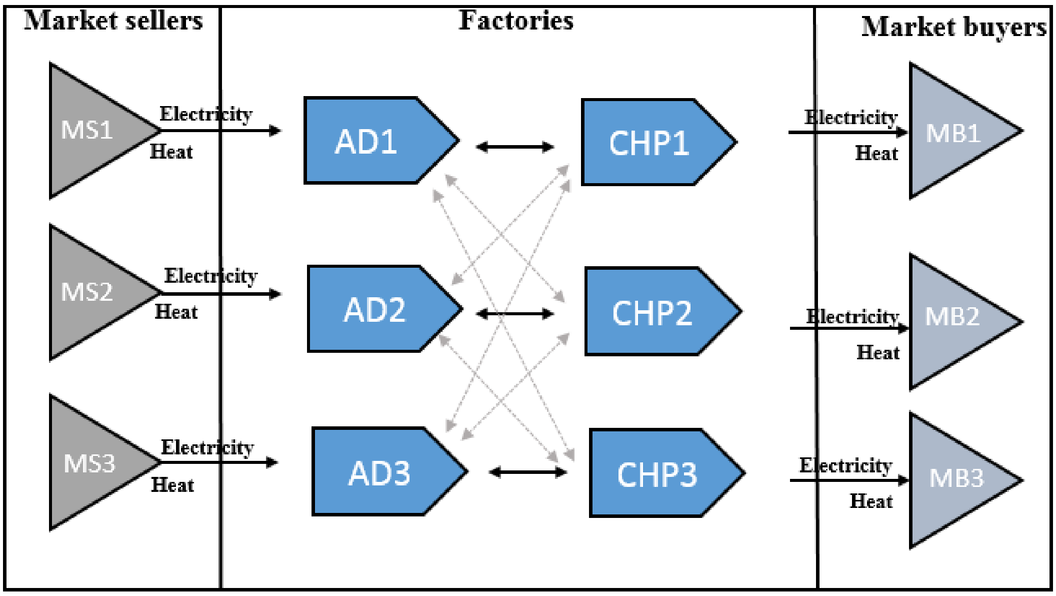


Figure 4-1: Case study of single input single output *(SISO)* industrial ecosystem

4.2 AD factory one (AD1)

This anaerobic digestion plant uses all its input waste generated onsite, that is fed into an on-site hopper and mixer. An average of 14 tonnes per day of waste is fed into the digester. Based on the average 14 tonnes of waste per day, the biogas yield is 145 Nm^3/t feedstock or 2028 Nm^3/day. The assumption is that the biogas from digester is composed of 60% methane, 40% carbon dioxide and traces of other gases (Lansing, Botero and Martin 2008). This gives a methane yield of 87 Nm^3/t feedstock. The AD1 factory also required some process steam to heat up and maintain the desired level of the digester.

Figure 4-2 illustrates input and outputs required for this plant. Table 4-1 displays the numerical data of material/energy flows for this AD plant.

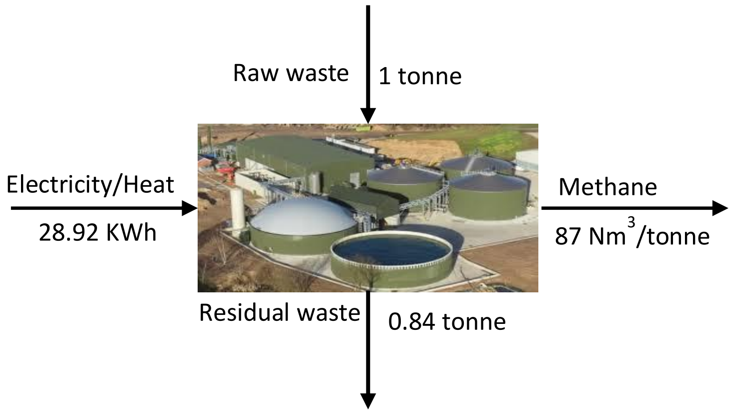


Figure 4-2: AD factory one (AD1) configuration

The following assumptions are made for AD1:

1. All input waste (cheese whey, waste maize silage and fodder beet) are generated onsite.
2. The process steam and/or electricity can be purchased either from external market (market seller agents) or combined heat and power factories in the ecosystem.
3. Biogas can be sold to either the combined heat and power factories or directly to the external market (market buyer agents).
4. Biofuel residual generated is not useful and are discarded.

4.2.1 AD factory two (AD2)

This anaerobic digestion plant is a co-digestion plant Berglund and Börjesson (2006) that used municipal organic waste. Co-digestion is preferably used for improving yields of anaerobic digestion of solid organic wastes due to its numeral benefits (Poschl, Ward and Owende 2010). An average of 14 tonnes per day of waste is fed into the AD2 digester. Based on the average 14 tonnes of waste per day, the biogas yield is 3,200 Nm^3/day. The assumption is that 60% of methane as mention in AD1 above. The factory agent also requires some heat to maintain the desired level of the digester and pre-treatment method. Figure 4-3 illustrates input and outputs required for this plant. Table

4-1 displays the numerical data of material/energy flows for this AD plant. The assumptions made for factory AD1 is the same for AD2.

Figure 4-3: AD factory two (AD2) configuration

4.2.2 AD factor three (AD3)

This anaerobic digestion plant is a co-digestion plant Berglund and Börjesson (2006) that used slaughterhouse waste. The assumption is that an average of 14 tonnes per day of waste is fed into the digester. Based on the average 14 tonnes of waste per day, the biogas yield is 2,800 m^3/day. The assumption is that 60% of methane is in biogas and the remaining is 40 % carbon dioxide. The AD factory also required some heat to maintain the desired level of the digester and pre-treatment method. Figure 4-4 illustrates input and outputs required for this plant. Table 4-1 displays the numerical data of material/energy flows for this AD plant. The assumptions made for factory AD1 is the same for AD3.

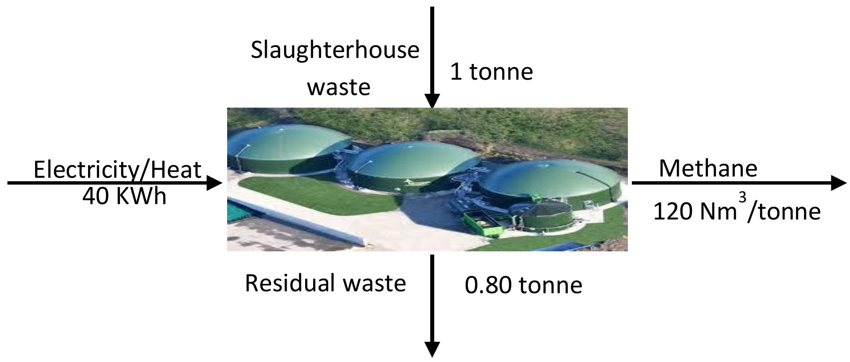


Figure 4-4: AD Plant Three configuration

Table 4-1: Numerical data for combined heat and power plants

Plant Type	Main product generated/day		Raw material requirement/day		Waste	
AD1	Biogas	2028 m^3/day	Farm manure	14 t/day	Residual waste	12.88 t/day
			Heat	405 kWh		
AD1	Biogas	3200 m^3/day	Municipal organic waste	14 t/day	Residual waste	9.8 t/day
			Heat	640 kWh		
AD1	Biogas	2800 m^3/day	Slaughterhouse waste	14 t/day	Residual waste	11.62 t/day
			Heat	560 kWh		

Table 4-2: Configuration of the Anaerobic plants in the industrial ecosystem

Plant Type	Capacity	Output product		Input product	
		Product	Potential input to plant	Product	Potential output from plant
AD1	14 tonne/day of farm manure	Biogas	CHP1, CHP2, CHP3, MB1, MB2, MB3	Electricity / Process Steam	CHP
AD2	14 tonne/day of municipal organic waste	Biogas	CHP1, CHP2, CHP3, MB1, MB2, MB3	Electricity / Process Steam	CHP
AD3	14 tonne/day of slaughterhouse waste	Biogas	CHP1, CHP2, CHP3, MB1, MB2, MB3	Electricity / Process Steam	CHP

a m^3 == a unit of biogas in m^3 , b kWh == b unit of biogas in kWh. Therefore, (a x 1.02264 x 39.2)/ 3.6 = 0.089 m^3 which implies that 1 m^3 is approximately 10 kWh. This information is obtained from www.eia.gov and www.gov.uk

4.3 Combined Heat and Power (CHP) factories

In the industrial ecosystem, we also have three different combined heat and power plant. These are CHP 1, CHP 2 and CHP 3. Each of the CHP plant use biogas as input fuel to fire the plant to generate electricity and heat. The difference between these three plant is in their capacity and the electricity/heat ratio being generated. The electricity capacity of CHP1, CHP2 and CHP3 are 170 kW_{ele}, 180 kW_{ele} and 200 kW_{ele} respectively, while the heat capacities are 200 kW_{th}, 220kW_{th}, and 240 kW_{th} respectively. For 1 m^3 of biogas, each plant can generates 1.46 kWh_{ele} and 2 kWh_{th}. The total efficiency of the CHP plant is fixed for 85%. The electricity/heat efficiency for all the three plants are CHP 1 : 0.49/0.33, 0.40/0.35 and 0.52/0.33. Figure 4-5 represent the representation of any of the CHP plant.

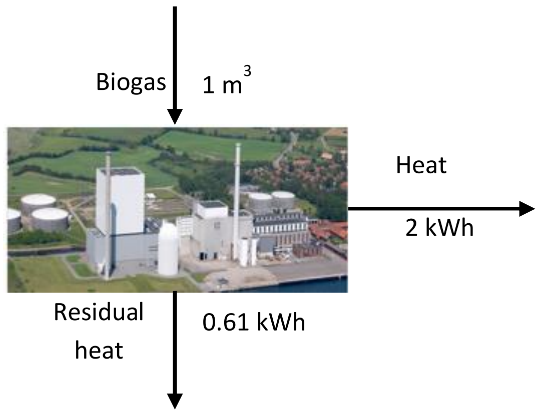


Figure 4-5: CHP Plant configuration

The following assumptions are made for CHP factories:

1. Biogas can be purchased either from external market (market seller agents) or anaerobic digestion factories in the ecosystem.
2. Process steam can be sold to either the anaerobic digestion factories or directly to the external market (market buyer agents).
3. The residual heat generated is not useful and are discarded.

4.4 Market Sellers and Market Buyers

The markets sellers formed the first part of the external environment in the IES. In our case, we have three different market sellers; market seller 1 (MS 1), market seller 2 (MS2) and market seller 3 (MS3). The market sellers are distinct by their identification name e.g. MS1 and are part of the sellers agent in the entire IES. Each market seller agents has unlimited capacity to supply any of the buyer agents.

The market buyers formed the second part of the external environment in the IES. As in the case of market sellers, there are three different market buyers also; market buyer 1 (MB 1), market buyer 2 (MB 2) and market buyer 3 (MB 3). The market buyers are distinct by their identification name e.g. MB 1 and are part of the buyer agents in the entire IES. Each market buyer agent has unlimited capacity to absorb any quantity from the seller agents.

4.5 Simulation scenarios

To investigate the behaviour of agents in the industrial ecosystem towards variation in demand and price fluctuation, we consider in this chapter two different decision strategies. As illustrated in Table 4-5, we have two different decision strategies; Strategy Type I (STI) and Strategy Type II (STII). STI is a combination of BDS1 – SDS1 while Type STII is BDS1 – SDS2 decision strategies. STI is a decision strategy in which buyer randomly select seller(s) from a list of n – number of seller while each sellers adjust its selling price per period randomly as described in section 3.6. The demand of each agent at each time period t was drawn at random. Each factory agent in all the stages and the market seller observed a stochastic demand over time, distributed according to Gaussian distribution with a given m mean and s standard deviation, from a normal distribution of m mean and s standard deviation. Thus, s controlled the environmental uncertainty: the higher the standard deviation, the higher the uncertainty. Table 4-1 - Table 4-4 summaries the values of all parameters used to define the simulation scenarios.

Table 4-3: Numerical data for combined heat and power plants

Plant Type	Main product generated		Raw material requirement		Waste	
CHP1	Electricity	2.497 MWh	Biogas	1710 m^3/day	Heat	3.42 MWh
CHP2	Electricity	3.650 MWh	Biogas	2500 m^3/day	Heat	5.0 MWh
CHP3	Electricity	3.066 MWh	Biogas	2100 m^3/day	Heat	4.2 MWh

Table 4-4: Configuration of the Combined heat and power plants in the IES

Plant Type	Capacity	Output product		Input product	
		Product	**Potential input to plant**	**Product**	**Potential output from plant**
CHP1	200 KW	Heat	AD1, AD2, AD3	Biogas	AD
CHP2	220 KW	Heat	AD1, AD2, AD3	Biogas	AD
CHP3	240 KW	Heat	AD1, AD2, AD3	Biogas	AD

Table 4-5: Buyer/Seller decision strategies types

		Seller	
		SDSI	SDSII
Buyer	BDSI	**ST I**	**ST II**

a m^3 == a unit of biogas in m^3 , b kWh == b unit of biogas in kWh. Therefore, (a x 1.02264 x 39.2)/ 3.6 = 0.089 m^3 which implies that 1 m^3 is approximately 10 kWh. This information is obtained from www.eia.gov and www.gov.uk

4.6 Simulation Results and Discussion

4.6.1.1 Biogas/Process steam usage

The results of a single simulation run are shown in Figure 4-6 and Figure 4-7. Figure 4-6 shows the biogas consumption (volume) of the three combined heat and power plant in the IES while Figure 4-7 shows the process steam usage over the simulation period for each of the anaerobic digestion plants. Note that one simulation cycle stands for a time period of one month.

It can be seen in Figure 4-6, when the simulation starts, the biogas usage for the three CHP plants is relatively high. This is because the demand for biogas is very high when the transaction in the IES just starts. After some simulation cycle, it can be seen that biogas usage reach maximum point and declines afterwards, this is as a result of steady demand. The fluctuation in the usage of biogas is linked to the demand variation from the buyers according to normal distribution with mean and standard deviation. At the end of each simulation cycle, the market is saturated. Saturation in the market referred to when all demand is satisfied and the program has reached the end of the simulation period The two peaks in the graph indicate maximum/minimum peak which corresponds to maximum and minimum biogas usage respectively. CHP2 biogas increase steadily until the 25th simulation cycle when the usage reach the pick (2800m^3/month) and have a sharp decrease. Throughout the simulation cycle, CHP3 biogas usage is the highest over the simulation cycle and has average usage of approximately 1,600m^3/month. The biogas usage of the CHP1 is relatively stationary, fluctuating between 250m^3/month and 700m^3/month. After the 30th the simulation cycle decreases because the market is saturated, although at some cycle we may have high usage.

For the AD plants, Figure 4-7 shows that the steam requirement is relatively low at the beginning of the simulation except for AD1 which has high requirement from the beginning but dropped to lower value and picked up again. As mentioned above, the fluctuation in the usage of process steam is also linked to its total demand in the IES. It can be seen that AD2 has highest usage of process steam over the simulation period while AD3 usage is the lowest. The fluctuation in the market can be linked to market (IES) saturation as it can be seen that at the end of the 30th simulation cycle each of the plant process steam decreases. It is clear that there are many fluctuations in these figures. This is as a result of the decision strategies adopted by buyers and sellers.

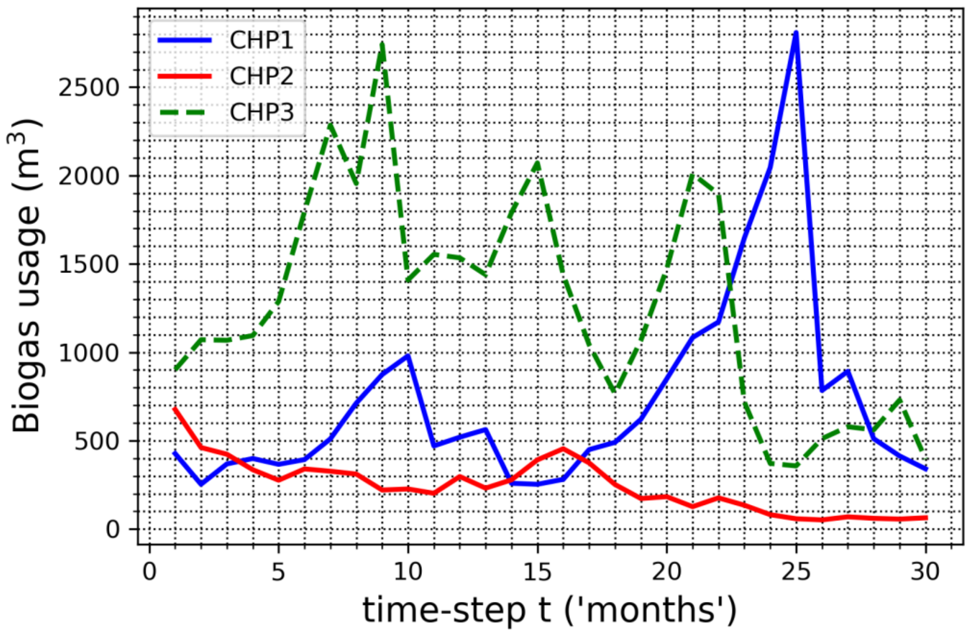


Figure 4-6: Biogas usage per month by combined heat and power (CHP) as buyer of biogas from sellers (market seller or anaerobic digestion)

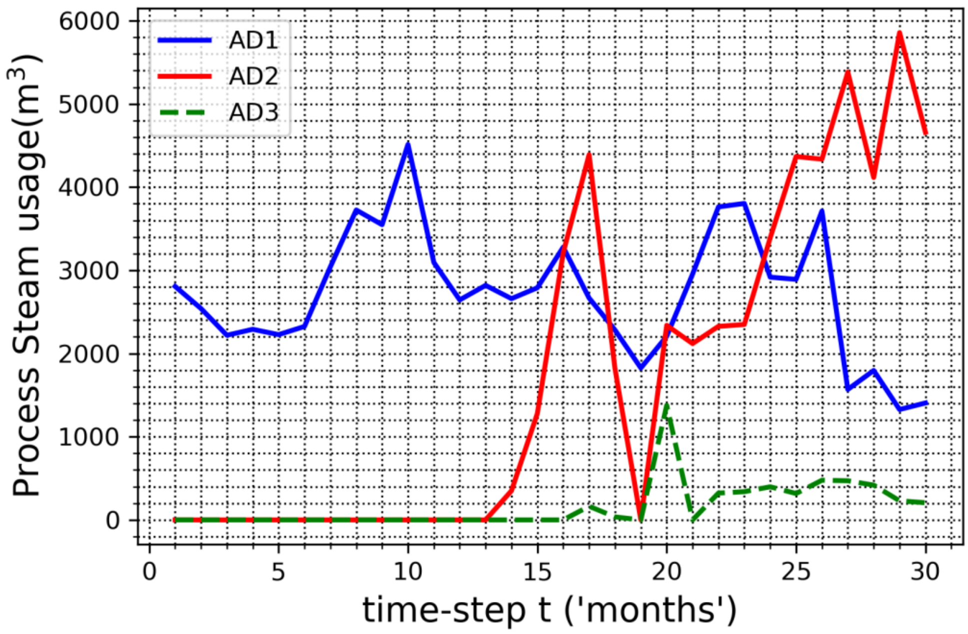


Figure 4-7: Process steam usage per month by Anaerobic Digestion (AD as buyer of process steam from sellers (market seller or CHP)

It is generally accepted that single realization of a stochastic process usually generates illustrative information that is not representative of the general system behaviour. So the simulation was run fifty times to generate average demand and the error over 30 steps. Some statistical characteristics, such as average, standard deviation and correlation coefficient, were obtained from these random variables. The statistics are shown in Table 4-6 and Table 4-7 and plotted in Figure 4-8 and Figure 4-9. Fifty simulation runs were carried out to assess the effect of the initial conditions for all the agent. Figure 4-8 show the average process usage by anaerobic digestion (AD1) while Figure 4-9 show the average biogas usage by CHP1. The other average usage for the remaining anaerobic digestion (AD2 and AD3) and combined heat and power (CHP2 and CHP3) plants are shown in the Appendix A.3.

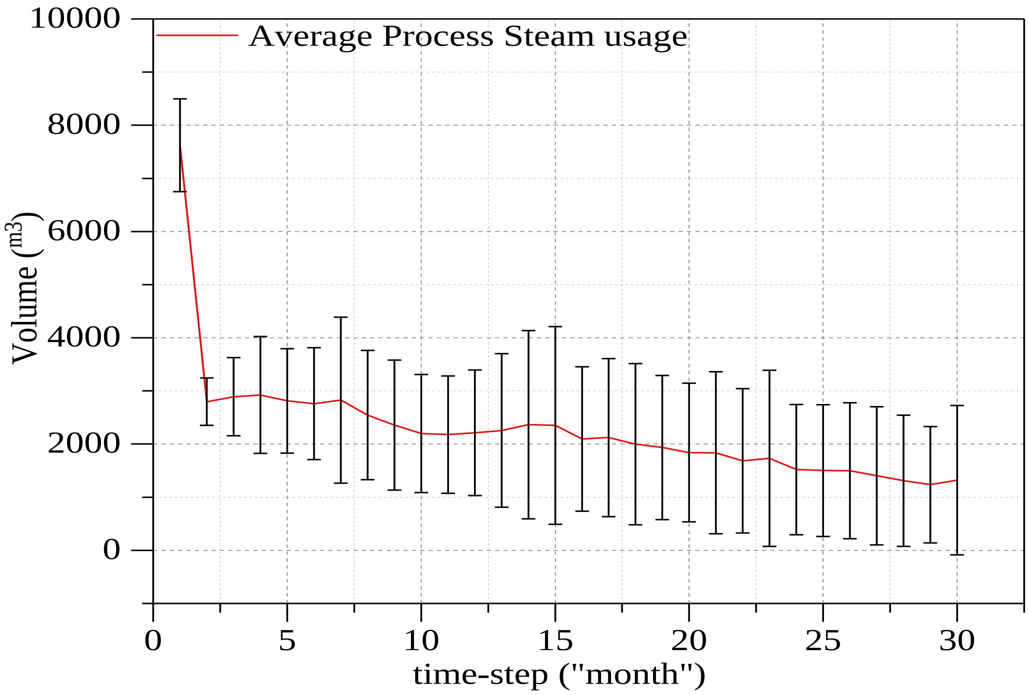


Figure 4-8: Average Process Steam usage by anaerobic digestion plant (AD1)

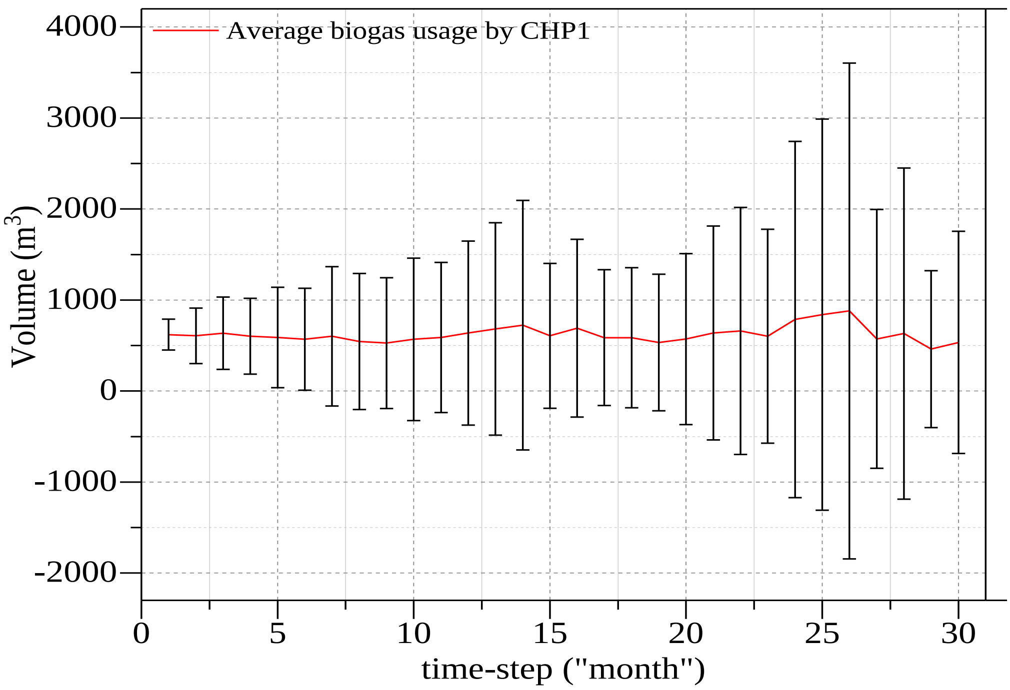


Figure 4-9: Average Biogas usage by combined heat and power plant (CHP1)

It can be seen that the average biogas usage of the factory CHP2 is 749.37 m^3/month, which is the highest one among the factories that uses biogas in the IES, followed by the factory CHP1 (622.64/ m^3/month). The CHP3 factory has the lowest biogas usage (576.78 m^3/month). The skewness and kurtosis of the resulting data is also included in the statistical characteristic tables. These two statistical analysis are used to further establish proper understanding of our simulation results. Skewness is the extent to which the data are not symmetrical. The skewness value can be positive, negative, or undefined. As shown in Table 4-6 and Table 4-7, the skewness is either positive or negative. For example, biogas usage skewness is 1.289 for CHP1, -0.118 for CHP2 and 1.053 for CHP3. Kurtosis on the other hand indicates how the tails of a distribution differ from the normal distribution. This is use to understand the characteristics of our result output. It is either a positive (right tail), negative (left tail) or zero (no tail) kurtosis. Thus we can explain that for the simulation is either positively or negatively skewed and normally distributed. The confidence interval (CI) is also shown in Table 4-6 and Table 4-7. The confidence interval shows the upper and lower bound for each of the agents, e.g., the upper bound for process steam usage and price is 2657.12m^3.

Table 4-6: Statistical characteristics of combined heat and power plants

	CHP1			CHP2			CHP3		
	Biogas usage	Process steam price		Biogas usage	Process steam price		Biogas usage	Process steam price	
		Risk-based	Random		Risk-based	Random		Risk-based	Random
Average (\month)	622.64	0.718	0.729	749.37	0.718	0.810	576.58	0.719	0.813
Standard deviation	90.10	0.108	0.045	124.16	0.004	0.167	155.85	0.005	0.079
Confidence interval	588.99	.0716	0.720	0.703	0.717	0.8371	242.93	0.718	0.7971
	656.30	0.721	0.738	0.795	0.719	0.9032	782.42	0.720	0.8283
Skewness	1.289	0.378	0.675	-0.118	-0.270	0.339	1.053	-0.180	-0.344
Kurtosis	2.089	0.661	0.292	-0.748	0.821	-1.362	0.366	-0.820	-0.875

Table 4-7: Statistical characteristics of Anaerobic digestion plants

	AD1			AD2			AD3		
	Process Steam usage	Biogas price		Process Steam usage	Biogas price		Process Steam usage	Biogas price	
		Risk-based	Random		Risk-based	Random		Risk-based	Random
Average (\month)	2228.78	4.21	5.78	367.10	4.594	8.027	258.71	4.353	8.003
Standard deviation	1147.11	0.01885	1.519	241.54	0.004	2.409	91.22	0.02138	2.532
Confidence interval	1800.44	4.204	5.478	276.90	4.594	7.549	224.64	4.349	7.680
	2657.12	4.218	6.081	457.29	4.596	8.505	292.77	4.357	8.786
Skewness	3.772	0.042	0.190	0.052	0.594	-0.133	-0.264	0.757	-0.595
Kurtosis	1.7799	0.667	-1.516	-1.102	-0.843	-1.573	-0.370	0.543	-0.860

4.6.1.2 Price evolution in the industrial ecosystem

The price evolution of process steam and biogas for Type I decision strategy by the selling/buying agents are shown in Figure 4-10 to Figure 4-13. Figure 4-10 and Figure 4-11 show the result of a single simulation run based on sellers agent randomly changing the price of its output and the buyers purchased the product by choosing the sellers at random without considering any factors (e.g. price). As shown in Figure 4-10, CHP1 has the highest price of 1.4 unit price/m^3 in period 21st. the maximum pick for CHP2 is in period 81th while CHP1 maximum peak is in 85th period. Figure 4-11 shows the price of biogas for each of the sellers. AD2 has the highest price (8 unit price/m^3). This value is the highest compare to the other factory selling agents (AD1 and AD3). As can be seen from these two figures, the price of either process steam or biogas reach as low as zero in some periods. In reality the price can be zero, and below zero. This is because there can be a cost for disposal of byproduct to the buying company. An example of such is solid recovered fuels (SRF) derived from municipal solid waste (MSW) (Garg *et al.* 2009).

In reality seller always have some knowledge about the market and evaluate the risk involved in making a price change at any period. Figure 4-12 and Figure 4-13 shows the single run simulation for a risk based price setting for process steam and biogas or by envisaging the risk involved in making a price change at any period. Figure 4-11 shows the price evolution of all the factory selling agent in the park. At the beginning of the simulation CHP1 has the highest price (0.75 unit price/m^3) while CHP2 has the lowest (0.70 unit price/m^3) for process steam. Each agent evaluate the market and changes it price over the period until around period 35 when there is a match in all the price. The reason for this is as a result of saturation in the market and any further raising of the price may result in the seller not able to sell adequately. Figure 4-13 shows the price of biogas in unit price/m^3. The average biogas price in the market is about 3.5 unit price/m^3. It can be seen that each of the sellers maintain almost the same price over the period. This is as result of careful evaluation by each sellers before making any changes in price.

In order to test if there is any difference between the values obtained from the random price settings and the risk based ones. We conducted a normal distribution test (Z-test) to ascertain if there is any statistical differences between the two seller decision strategies (SDS1 and SDS2) used. A Z-test is any statistical test for which the distribution of the test statistic under the null hypothesis can be approximated by a normal distribution. The null hypothesis is a general statement that there is no relationship between two measured phenomena. It is observed that there is no significant difference between SD1 and SD2 i.e., the two output data are generated from the same mean and standard deviation (Gaussian distribution), thereby having the same variances and shapes. Although the random price settings cannot be used in real life while the second decision strategy (risk based – best price) is more realistic and can be use by the decision makers managing the industrial ecosystem. As a seller the best decision strategy to use in setting price is the risk based while for buyers, selecting seller based on best price strategy is recommended.

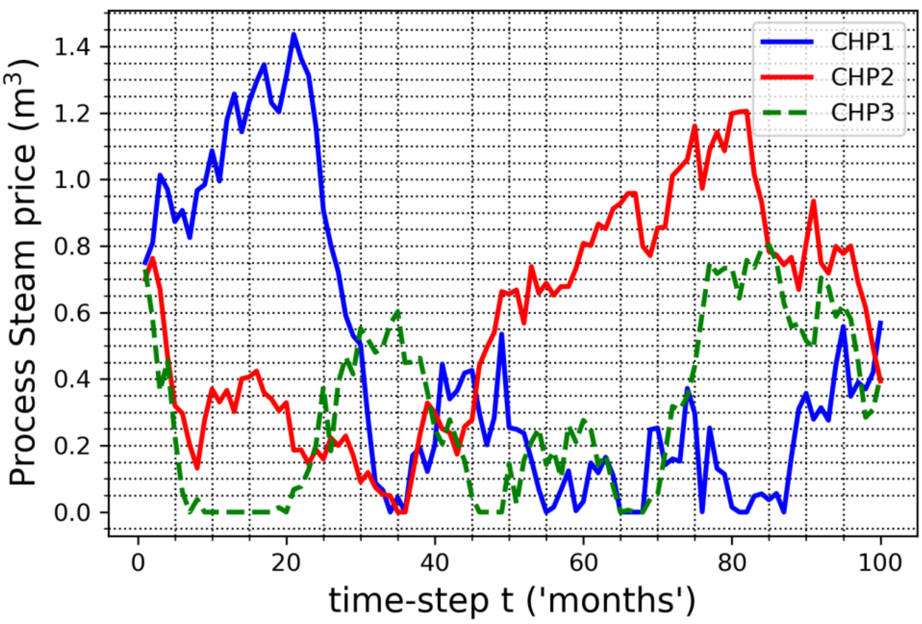


Figure 4-10: Process Steam price/ m^3 (Type I decision strategy)

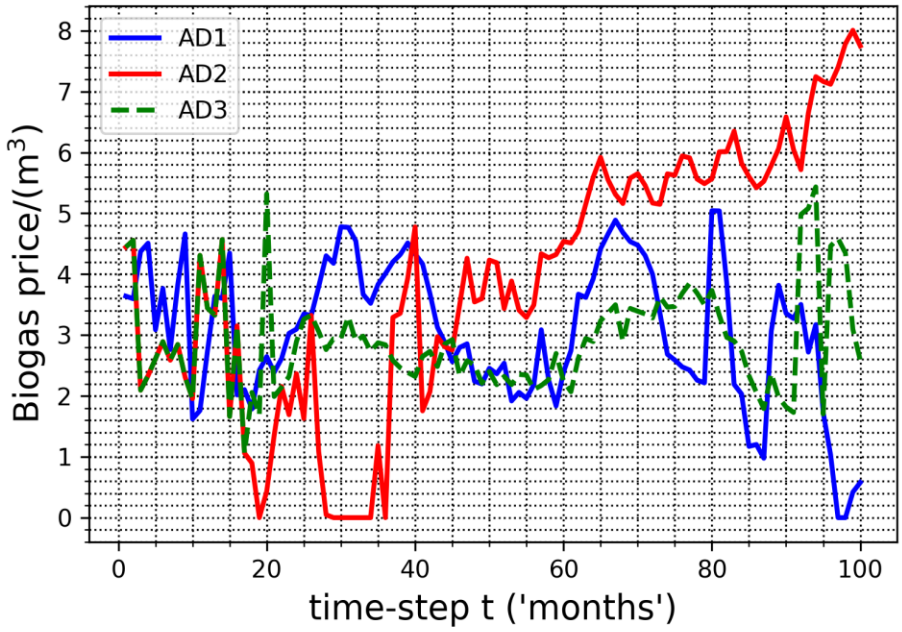


Figure 4-11: Biogas price/m^3 (Type I decision strategy)

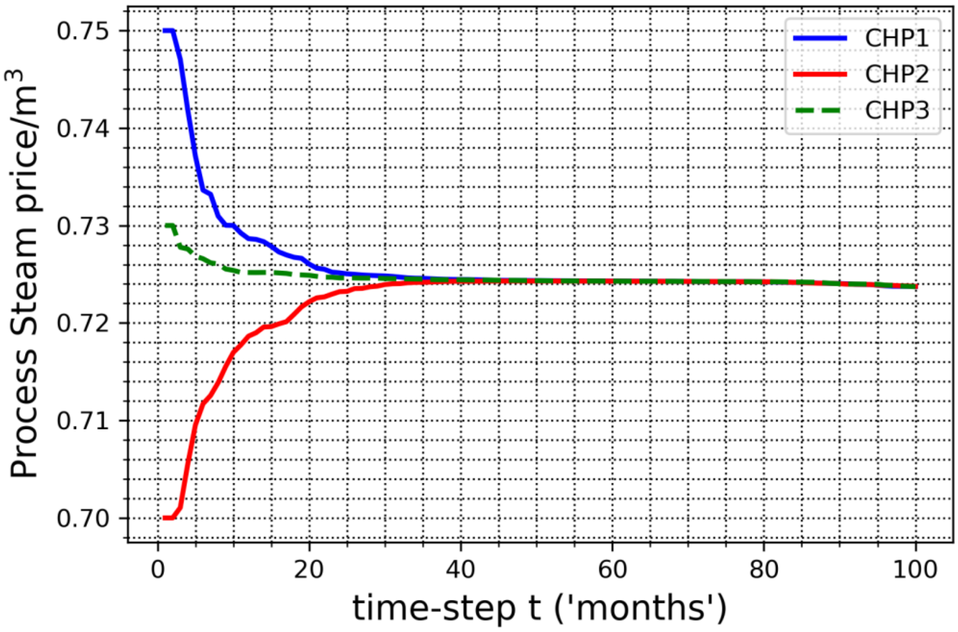


Figure 4-12: Process Steam price/m^3 (Type II decision strategy)

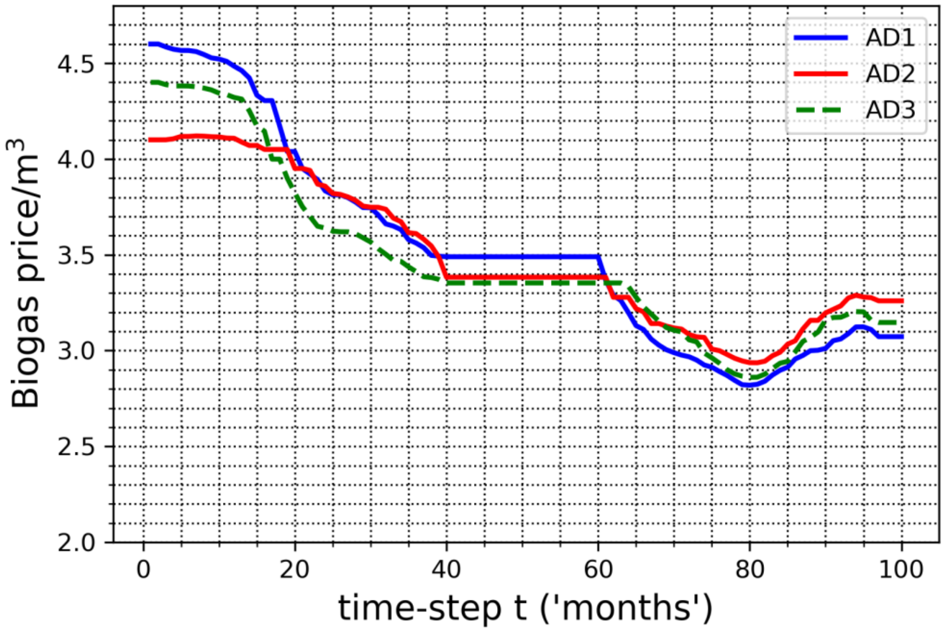
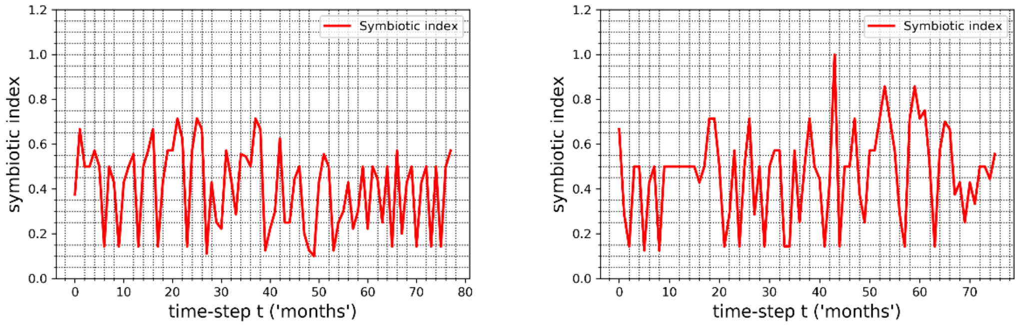


Figure 4-13: Biogas price/ m^3 (Type II decision strategy)

4.6.1.3 Buyer-Seller Symbiotic Relationship

The results of 100 simulation run of buyer – seller relationship frequency in the market transaction are shown in Figure 4-14. We used the metric Symbiotic Relationship Index (SRI) developed in section 3.6.3 to determine the symbiotic index and present graphical representation of how frequent a buyer agent make a deal with a seller agent. Figure 4-14 (a) and (b) show that there is strong symbiotic relationship between the internal agents (anaerobic digestion and the combined heat and power plants). However, due to the fact that there is only single material/product exchange in this case study, the frequency of fluctuation of the metric, SRI is seen to be quick. Type I decision strategy is used by the seller/buyer in Figure 4-14 (a) Type II is used in Figure 4-14 (b). As can be seen, there is no clear distinction from the two graphs. The maximum SRI in Figure 4-14 (a) is approximately 0.7 while it is 1.0 (perfect symbiosis) in Figure 4-14 (b). It is literarily impossible to have a perfect symbiosis in real life except when we have an isolated system. The average Symbiotic Relationship Index is 0.45 and 0.5 for Type I and Type II decision strategies respectively. These values indicate symbiotic relationship that exist between the factories in sharing resources and pointed out that over some periods, exchange of material/product were established by the external agents. With this developed metric, it can be concluded that the frequency of transaction between the factory agents in sharing resources are effective ways to improve the sustainability of an industrial ecosystem system. Please note that our focus is on the companies interacting in the industrial ecosystems. This is because industrial ecosystem focuses more on the synergy that exist between partnering companies than external supplies.



(a) Type 1 (b) Type II

Figure 4-14: Symbiotic Relationship Index (SRI) of the Industrial ecosystem (IES)

4.7 Conclusions

While cooperative resource exchange has been widely studied in the literature, few studies had investigated strategies and mechanisms to understand the complexity of an industrial ecosystems. This chapter fills the gap, by pilot testing the developed agent based model in this research work. In particular we developed decision criteria from buyers' and sellers' perspectives. We noted that the traditional approach to buyers' selection is to select suppliers solely on the basis of the price among other selection criteria (e.g. quality, delivery, rejection, capacities, rating and flexibility) for many years. Although, with the time passing on, price is not only a sufficient measure or criterion for supplier selection. In particular, we focus on price evolution in the industrial ecosystems and describe the "Strategic characteristics" refers to the strategies the agent will use to reach the objective of selling or buying. The simulation was run using just two different types of small scale process plants: anaerobic digestion plant, and a combined heat and power plant. Each of the factory types made up three distinct factories as the main agents in the industrial ecosystem. The output of Réseau single input single output *(SISO)* demand curve was tested on two different types of decision strategies, Type I and Type II. The observed demand time series displayed significantly different characteristics for each of the buyers. The simulation output and the analysis confirmed that the decision strategy chosen by the agents affects their behaviour at any period in the industrial ecosystem and shows that there is a level of symbiotic relationship between the factory agents (anaerobic digestion and combined heat and power plants). It is observed that the Symbiotic Relationship Index (SRI) will increase if the number of resource exchange increases. This case study is used to test the developed Réseau agent-based model. At the current state of development of the model, the results are promising, yet, réseau still needs further improvement. This is because at this stage of réseau, it can only be used to simulate single input single output industrial ecosystem. In real life what exist is multiple input multiple output industrial ecosystem

Chapter 5
Agent-Based Model of Multiple Input Multiple Output (MIMO) Industrial Ecosystem

5.1 Introduction

In order to address the issue of sustainable environment integration of energy industries and uncertainty inherent in industrial ecosystem, Réseau agent-based model has been developed to gain a better understanding of agents dynamic behaviour. We present the application of the modified Réseau agent-based model to simulate large scale industrial ecosystem focusing on the matching of demand and supply due to fluctuation that may occur. Owing to the short fall in the initially developed model which only accommodates agents with single input single output, we further modify it so as to allow thousands of agents and also enable agents to have multiple input and multiple outputs.

To further demonstrate the effectiveness and robustness of Réseau and gain more insights, we model an industrial ecosystem consisting of factories with multiple input multiple output. Each of the factory has two or more input and can produce one main product and two or more by-products.

Figure 5-1 shows the potential structure of the multiple input multiple output industrial ecosystem conducted in this chapter. It includes three different factories; (1) Bio-refinery plant (BIO) (2) Combined heat and power plant (CHP); and 3) Anaerobic digestion plant (AD). The AD plants convert organic waste to biogas and generate some residual waste. It uses some process steam and electricity to heat up the digester. CHP plant can use biogas as a replacement for coal, while generating electricity and process steam as its main output. It should be noted that fuel switching (i.e., biogas as a replacement for coal cannot be undertaken easily and that is beyond the scope of this work. The Bio-refinery plants main output is ethanol and generate lignin pellet, waste water as its by-product. These three candidate plants formed the internal environment of the industrial ecosystem while the market sellers and buyers formed the external environment of the park where raw material can be purchased or finished good can be absorbed without any capacity limitation.

The internal environment consists three different stages. Each stage is made up of three different firms that produces same output but use different input raw materials. Stage A include three different anaerobic digestion (AD) plants that produce biogas as their main products. To produce biogas, the firms requires either cattle feedlot manure or food and bio-solids (Appels *et al.* 2011; Gonela and Zhang 2014). Stage B also consist three different combined heat and plants that produces electricity and process steam (heat) as its output. Lastly, stage C is made up of bio-refinery plants that generates ethanol as their main output.

Each firm in the all the stages and the market seller observed a stochastic demand over time, distributed according to Gaussian distribution with a given mean and standard deviation. In this work, the Réseau is used to simulate the interaction between companies, market buyers and sellers in the IES so as to understand the dynamic behaviour of all the candidates in the park particularly the process plants. This section that follows presents the detail configurations of each of the agents (companies, market buyers and sellers) in the IES for this case study.

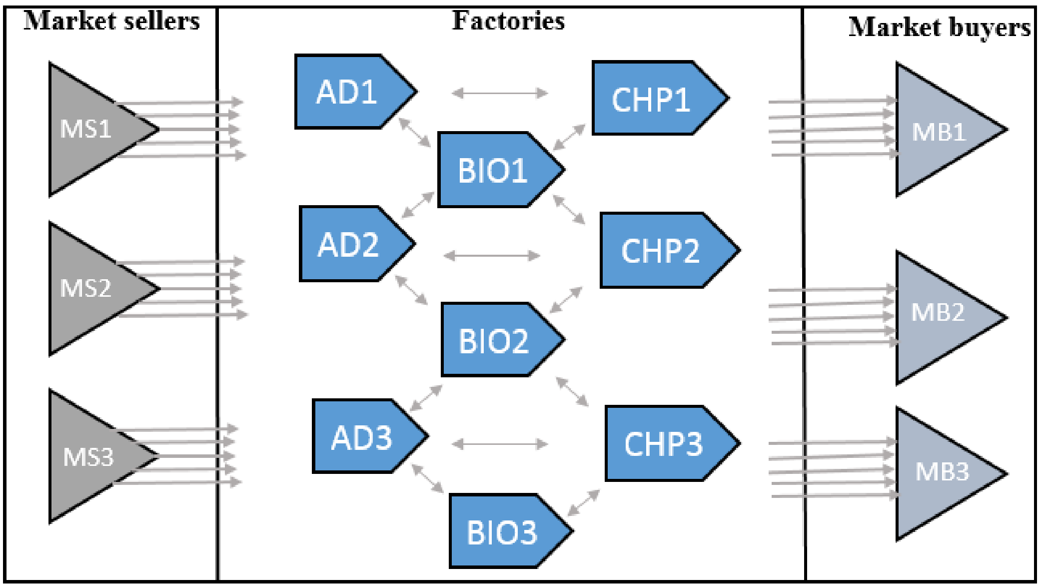


Figure 5-1: Case study of multiple input multiple output *(MIMO)* industrial ecosystem

5.2 Anaerobic Digestion (AD) Plant

The AD plants form the core part in the industrial ecosystem. As discussed in the other two process plant types above, we also have three different AD plants: AD1: 0.3 million tons of food and bio-solid wastes AD2: 0.2 million tons of food and bio-solid waste, AD3: 0.16 million tons of food and waste. Figure 5-2 shows the input and output products of the AD plant. The configuration of the anaerobic digestion plants in the IES can be seen in Table 5-1.

Figure 5-2: Input and output products of the AD plant.

The following assumptions are made for the AD plant in the IES:

1. Process steam and electricity are obtained from the CHP plants while electricity may also be gotten from the market sellers.
2. Food and bio-solid wastes can be obtained from the market sellers
3. DDG is obtained from the bio-refinery plants.
4. Biogas can be sold to market buyers or CHP plants.
5. Bio-fertilizers can be sold to the market buyers.
6. The assumption is that the generated waste has no economic values.

Table 5-1: Configuration of combined heat power, Anaerobic digestion and Bio-refinery plants

Plant Type	Capacity	Output product		Input product	
		Product	Potential input to plant	Product	Potential output from plant
Anaerobic digestion plant	0.2 – 0.3 million tons of food and bio-solid waste	Biogas	Combined heat and power	Food and bio-waste	-
				Electricity	Combined heat and power
				Steam	Combined heat and power
				DDG	Bio-refinery
Combined heat and power	60 – 90 MW electricity	Electricity	Anaerobic digestion, Bio-refinery	Biogas	Anaerobic digestion
		Steam		Lignin pellets	Bio-refinery
Bio-refinery	20 – 40 MMGY of corn based ethanol	Ethanol	-	Corn, corn stover	-
	5 – 10 MMGY of cellulosic based ethanol	DDG	Anaerobic digestion	Electricity	Combined heat and power
		Lignin pellets	Combined heat and power	Steam	Combined heat and power

5.3 Combined Heat and Power (CHP) Plant

In the IES, we have three different combined heat and power plants: CHP 1, CHP 2 and CHP 3. Each of the CHP plant use biogas as input fuel to generate electricity and process steam. The focus is mainly on biogas as input, however, the combustion technology being used in the CHP plants is co-combustion of a combination of lignite, biogas and lignin pellets. The difference between these three factories/plants is in their capacity and the electricity/heat ratio being generated: CHP 1, CHP 2 and CHP 3 are 99 MW, 65 MW, 52.8 MW respectively. The electricity/heat efficiency for all the three plants are CHP 1: 0.33/0.49, 0.35 /0.40 and 0.33/0.52. The assumption is that all the CHP plants are heat driven and their overall efficiencies are 70%, 90% and 90% respectively. Figure 5-3 represents the input-output of any of the CHP plants and the configuration in the IES can be found in Table 5-1.

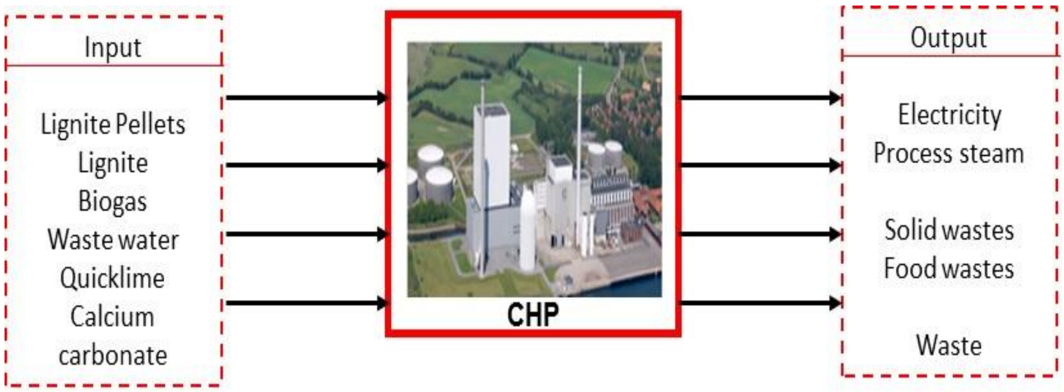


Figure 5-3: Input and output products of the CHP plant.

The following assumptions are made for the CHP plants in the IES

1. Lignin pellet, lignite, can be obtained from the market (market sellers) as much as required.
2. The output product, electricity can be sold to bio-refinery and AD plants in the IES and to the market (market buyers).
3. The output product, process steam can be sold to the bio-refinery plant, the AD plant and to market buyers. It is assumed that technology is available to produce process steam at desired temperature and pressure and it costs same for all.
4. Lignin pellets from the bio-refinery plants can also be used in the combustion of boilers in the CHP plants.

5. The source of wastewater for treatment unit can be from any of the bio-refinery plants, and/or the market sellers.
6. Biogas can be purchased from the AD plants.

5.4 Bio-refinery Plant

The three main bio-refinery concepts in existence are the (a) lignocellulose feedstock (LCF) bio-refinery, (b) the whole-crop bio-refinery, (c) and the green bio-refinery (Kamm and Kamm 2004). This work focuses on the LCF bio-refinery systems classified by Gonela and Zhang (2014) as a hybrid type of bio-refinery plant. The three bio-refinery plants produce a combination of first generation (corn based) and second generation (cellulosic based) bioethanol. Cellulosic based bio-ethanol consit of product output such as corn stover, wheat straw and barley straw which depends on the availability of bioethanol in nearby areas. Although the second generation bio-refinery plant technology is not yet matured, it proved more profitable (Gonela and Zhang 2014). In the IES, there are three different bio-refinery plants having different production capacities: BIO1, BIO2 and BIO3. The capacity of the first bio-refinery, BIO1 plant is assumed to be 50 million gallon per year (MMGY) of ethanol, the second bio-refinery (BIO2) capacity is 27 MMGY of ethanol and the last one, BIO3 has capacity of 33 MMGY. Figure 5-4 shows the input and output products of the bio-refinery plants while the configuration in the IES is indicated in Table 5-1.

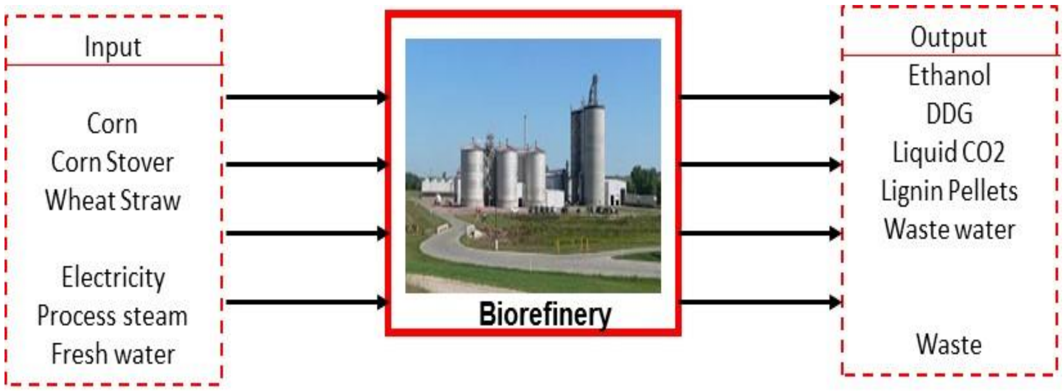


Figure 5-4: Input and output products of the bio-refinery plant.

The following assumptions are made for the bio-refinery plant in BBIES:

1. Raw materials, corn, corn stover and wheat straw are purchased from market (infinite source) and can be procured as much as required.
2. Electricity and process steam are procured from the CHP plants resulting in less capital investment for boilers and zero consumption of fossil fuel or from the market sellers.
3. Distilled dry grain (DDG) can be sold to AD plants.
4. Final products (ethanol) and by-products (DDG, lignin pellets, and liquid CO_2) can be sold to the market (infinite sink). Lignin pellets can also be sold to CHP plants for co-combustion.
5. All the wastes generated are disposed.

5.5 Simulation scenarios

The scenarios in this Chapter is builds on those in Chapter 4. We defined the simulation scenarios by changing the decision strategies developed in section 3.6. The output of the simulation is dependent on the decision made by buyer and seller in the trading transaction that occur in the industrial ecosystem. To investigate the behaviour of the agents in the IES towards variation in demand and price fluctuation, we consider in this chapter four different decision strategy types, illustrated in Table 5-2 There are four different decision strategies types; Strategy Type I, II III and IV. Strategy Type I is BDS1/SD1 decision strategy combination while Strategy Type II is BDS1/SDS2 decision strategy combination. To explain this, for example, Strategy Type III (STIII) is decision combination rule in which buyer select seller(s) from a list of *n* – number of seller by considering the best price while each sellers adjust its selling price per period considering the risk (cost-effect) involved in changing the material, m, price. The demand of each firm at each time period t was drawn at random Each firm in all the stages and the market seller observed a stochastic demand over time, distributed according to Gaussian distribution with a given m mean and s standard deviation. Thus, s controlled the environmental uncertainty: the higher the standard deviation, the higher the uncertainty.

5.6 Simulation Results and Discussion

This section focuses on the results obtained in simulating an industrial ecosystem with factory agents that can use multiple inputs and generates multiple output as indicated in configuration of the case study in Figure 5-1 The simulation outputs of the case study further demonstrate the effectiveness of our proposed methodology. The simulation was carried in two different ways. Firstly, the simulation was done to determine the behaviour and how each factory make decision operating in the standalone mode. Standalone mode means each factory only buys from the market selling or sells to the market buying agents in IES while other factory agents are absent. The second simulation was carried out with presence of all the factory agents in the IES. Thereby possible symbiotic relationship can occur between the agents and/or the market agents.

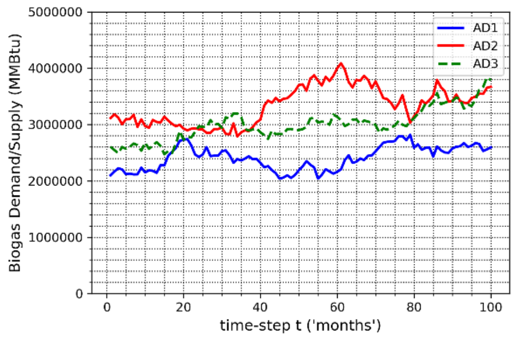
5.6.1 Demand and Supply response

The results of a single simulation run for the generation of demand/supply for all the factory agents in the industrial ecosystem are shown in Figure 5-5 - Figure 5-9. Each of the figures, for example Figure 5-5 is divided into Figure 5-5 (a) - (c). The division shows the different demand/supply curve for the different decision strategy types used during the simulation. Note that one simulation cycle stands for a time period of one month. As stated in section 3.6.1and 3.6.2, we used two different decision rules from the buyer and seller agent. For the buyer agent, we considered the random and risk based decision strategies while random and best price are used as the decision making strategies for the sellers. The combination of the decision gives different simulation results. As seen in Table 5-2, there are four (I – IV) decision strategy types that are used to access the behaviour of the agents in the IES. For example, using ST I, the buyer enters into market, purchased randomly (random price of materials) while the sellers changes its price randomly according to the market price history. The figure can be explain as follow that there is synergy that occur within the ecosystem and the agents freely interact with each other to exchange resources.

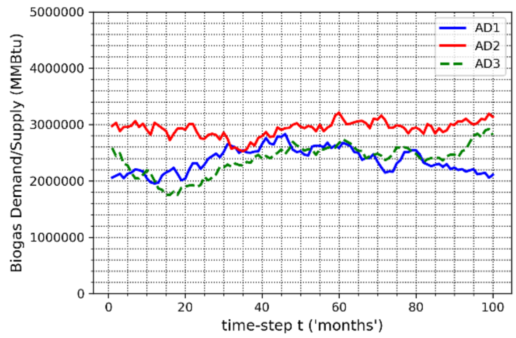
Table 5-2: Buyer/Seller decision strategy types

		Seller	
		SDS1	SDS2
Buyer	BDS1	**ST I**	**ST II**
	BDS2	**ST IV**	**ST III**

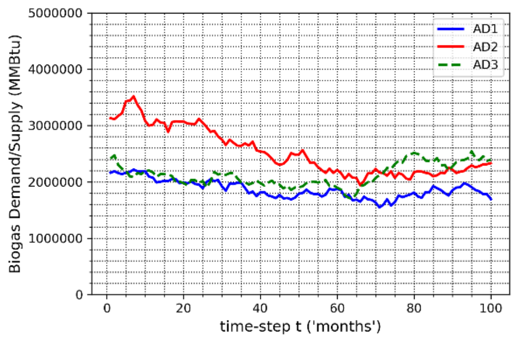
Figure 5-15 shows the symbiotic relationship that exist between the three combined heat and power plants as buyers (CHP1, CHP2, CHP3) and the anaerobic digesters as the sellers (AD1, AD2 and AD3). Figure 5-5 shows the biogas consumption (volume) of the three combined heat and power plants (agents) in the IES. It can be seen that the average demand and supply for the three CHP plants is 2.6 x 10^6 MMBtu over the period. When the simulation starts, the biogas usage for the three CHP plants is approximately the same for the four different decision strategy types by the buyer-seller agents. This is because the initial input parameters are the same at the beginning of the simulation runs. After some simulation cycle, it can be seen that biogas usage reaches maximum point and declines afterwards. The fluctuation in the total usage of biogas is linked to saturation in the biogas usage in the IES and it is also being affected by the decision strategy type the agents are using during the market transaction. In comparison to the contribution of the selling agents in the IES, agent AD2 supplies are the highest over the period except in Figure 5-5(d) where AD3 supplies more from the 40th simulation cycle onward. The average supply of biogas in the IES is 2.25 x 10^6, 2.3 x 10^6, 2.5 x 10^6 MMBtu over the period for agents AD1, AD3 and AD2 respectively.



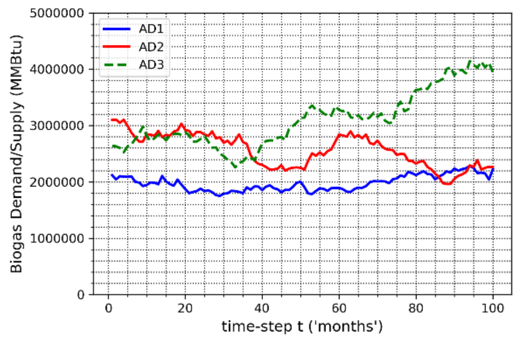
(a) ST I



(b) ST IV



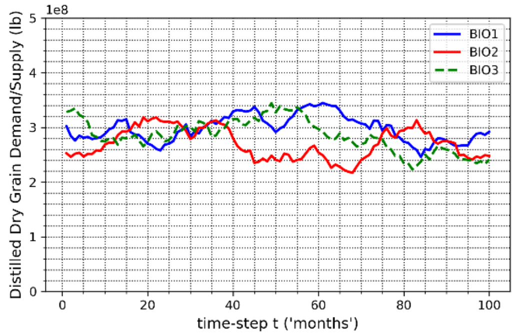
(c) ST III



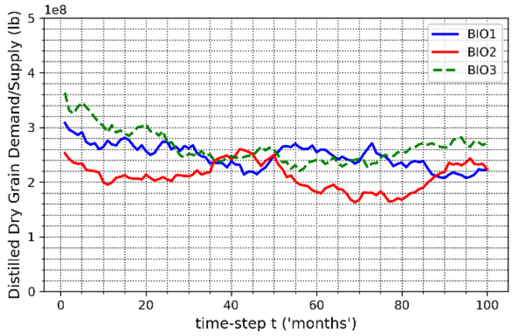
(d) ST II

Figure 5-5: Average biogas demand/supply

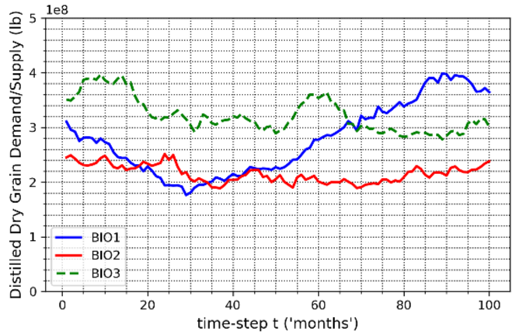
The potential symbiotic links of finished goods and by-products is shown in Figure 5-15. The assumptions made under bio-refinery plant configuration in section 5.4, suggest that bio-refinery plants have the potentials to synergized with both the anaerobic digestions and combined heat and power plant agents. Figure 5-6 and Figure 5-7 show the demand/supply curve that exist between the three bio-refinery plants as the seller agents (BIO1, BIO2, BIO3) while the anaerobic digestion plants (AD1, AD2 and AD3) and combined heat and power plants (CHP1, CHP2, CHP3) as the buying agents. Figure 5-6 shows the distilled dry grain (DDG) sold out per month by bio-refinery agents to the anaerobic digestion agents. In Figure 5-6, agent with name BIO2 can be seen to supply the least DDG for the four different decision making rules. This is as a result of the agents (BIO2) having the lowest production capacity compared to the other two bio-refinery agents in the park. Apart from this, the input/output ratio for agent BIO2 is comparably low also. It can also be seen that an average of 2.7 x 10^8 lb of DDG is sold in the market over the entire period. It can be seen that when the simulation starts, the BIO2 sales of DDG is stable as shown in Figure 5-6 (a) – (c) throughout the simulation period. For the other two bio-refinery agents, the supply of DDG fluctuates but the peaks are considerably lower at any given intervals. The bio-refinery agents also have a strong symbiotic link with combined heat and power plant as shown in Figure 5-7. The lignin pellet average demand/supply for the three CHP plants is 0.5 x 10^6 tons over the period. It can be seen that when the simulation starts, the lignin pellet usage for the three CHP plants is approximately high and diminished towards the end of the simulation runs. After some simulation cycle, it can be seen that lignin pellet usage reaches the maximum point and declines afterwards. The fluctuation in the total usage of lignin pellet is linked to saturation in its usage in the IES and it is also being affected by the decision strategy type the agents are using during the market transaction. The average supply of lignin pellet in the IES is 0.6 x 10^6, 0.53 x 10^6, 0.52 x 10^6 tons over the period for bio-refinery agent BIO1, BIO2 and BIO3 respectively. From the aforementioned, it can be seen that there is a strong SRF in selling by-products between the bio-refinery as seller agents, combined and power plant and anaerobic digestion type as the buyer agents in the IES. This is in line with (Gonela and Zhang 2014).



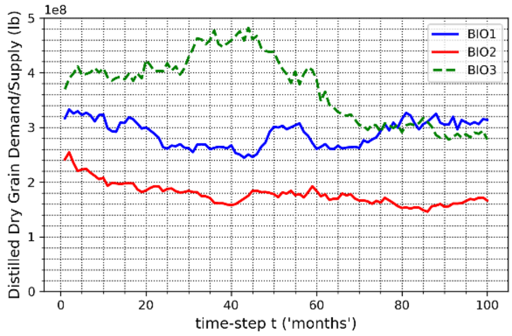
(a) ST I



(b) ST IV

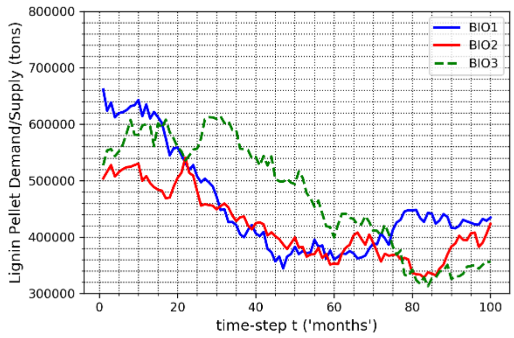


(c) ST III

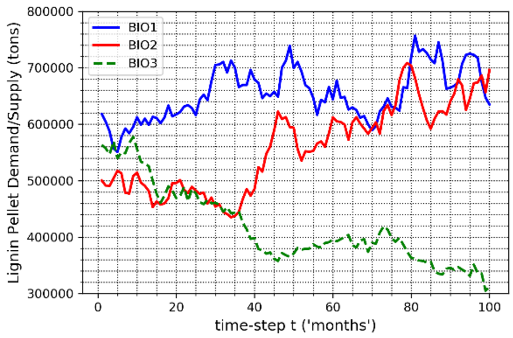


(d) ST II

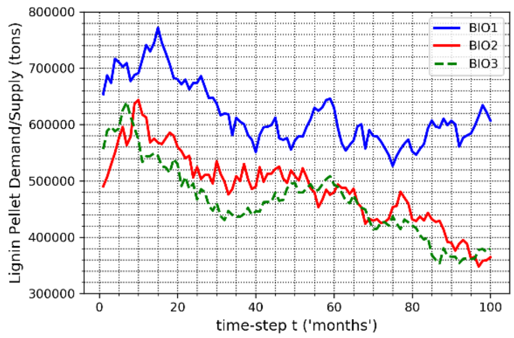
Figure 5-6: Average distilled dry grain demand/supply



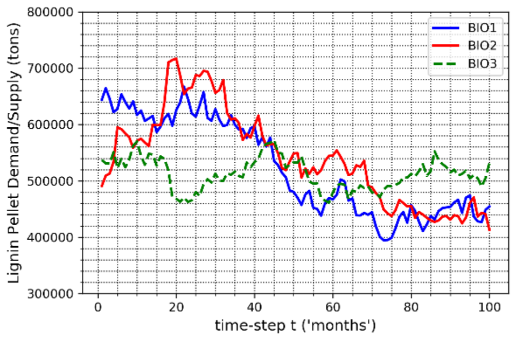
(a) ST I



(b) ST IV



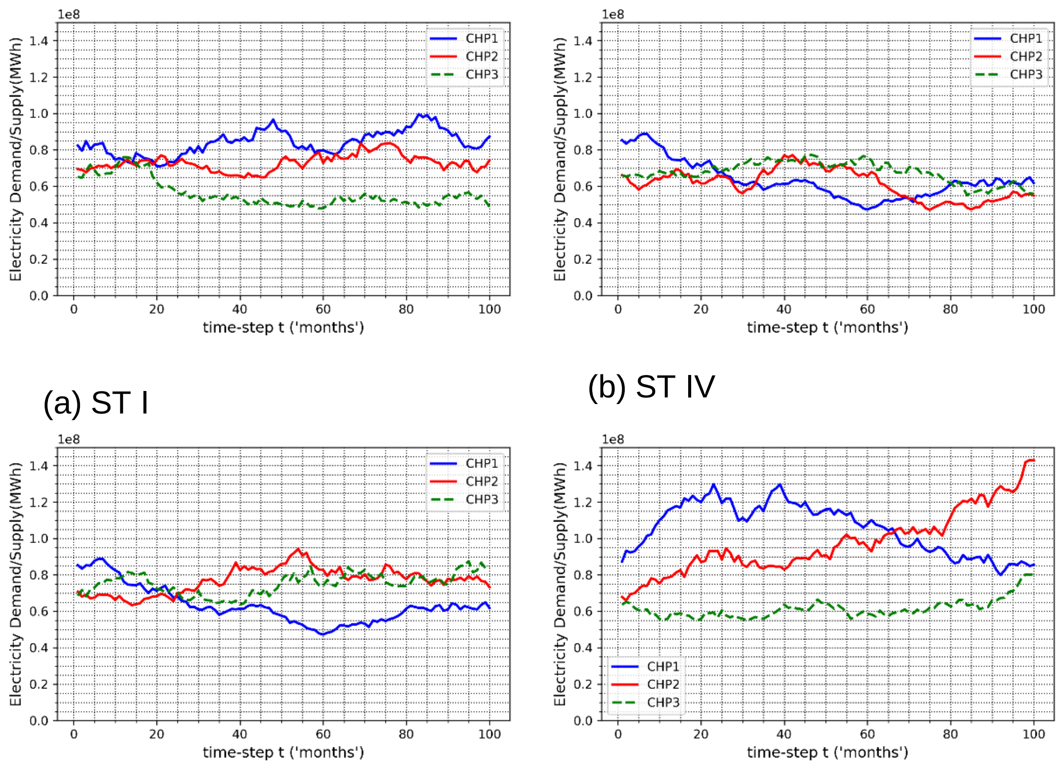
(c) ST III



(d) ST II

Figure 5-7: Average lignin-pellet demand/supply

The combined heat and power plant agents as indicated in section 5.3 have the potentials to synergise with bio-refinery, anaerobic digestion and the market buyer agents. Figure 5-8 shows the average electricity sold to the bio-refinery agents by all the three CHP agents during the transaction period while Figure 5-9 show the process steam demand/supply for the simulation period. The impact of the CHP plants on the supply of electricity and process steam to the bio-refinery plants is high based on the symbiotic index shown in Figure 5-15. Based on synergy that occur internally in the IES, it suggests that the bio-refinery agent will transact more with the external agents if the CHP plants are not part of the agents in the internal part of the industrial ecosystem. As shown in Figure 5-8, the supply is randomly distributed and the maximum supply is 0.85 MWh by agent CHP1 in all the figures except in Figure 5-8 (d) where agent CHP2 supply reach 0.73 MWh while the minimum supply is about 0.6 MWh in all the four figures. In Figure 5-9 average process steam supplied by agent CHP3 is the highest all the simulation period except in (d) where CHP2 supplied more to the bio-refinery agents. However, in all the decision strategy types, agent CHP1 supplies the list and this is as a result of the low output of steam been generated.



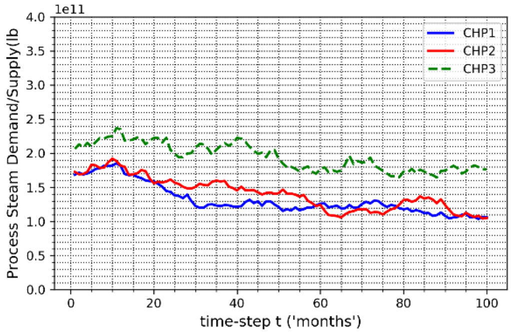
(a) ST I

(b) ST IV

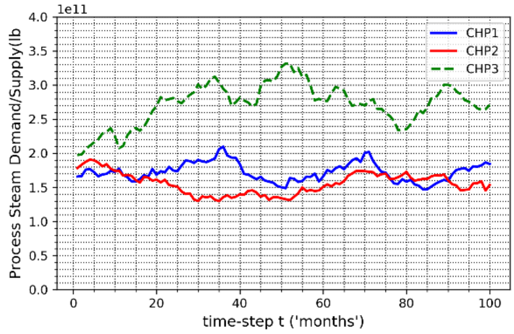
(c) ST III

(d) ST II

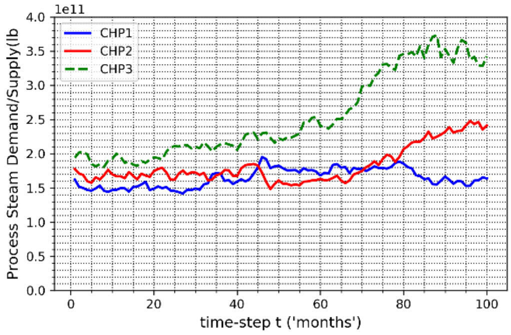
Figure 5-8: Average electricity demand/supply



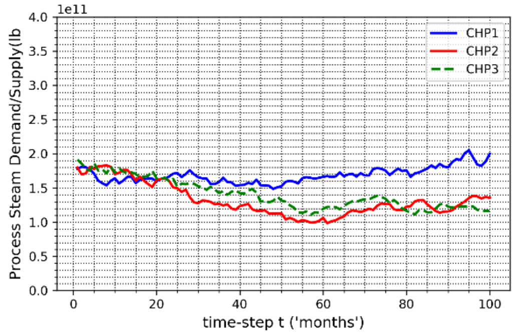
(a) ST I



(b) ST IV



(c) ST III



(d) ST II

Figure 5-9: Average process steam demand/supply

5.6.2 Price evolution of agents in the industrial ecosystem

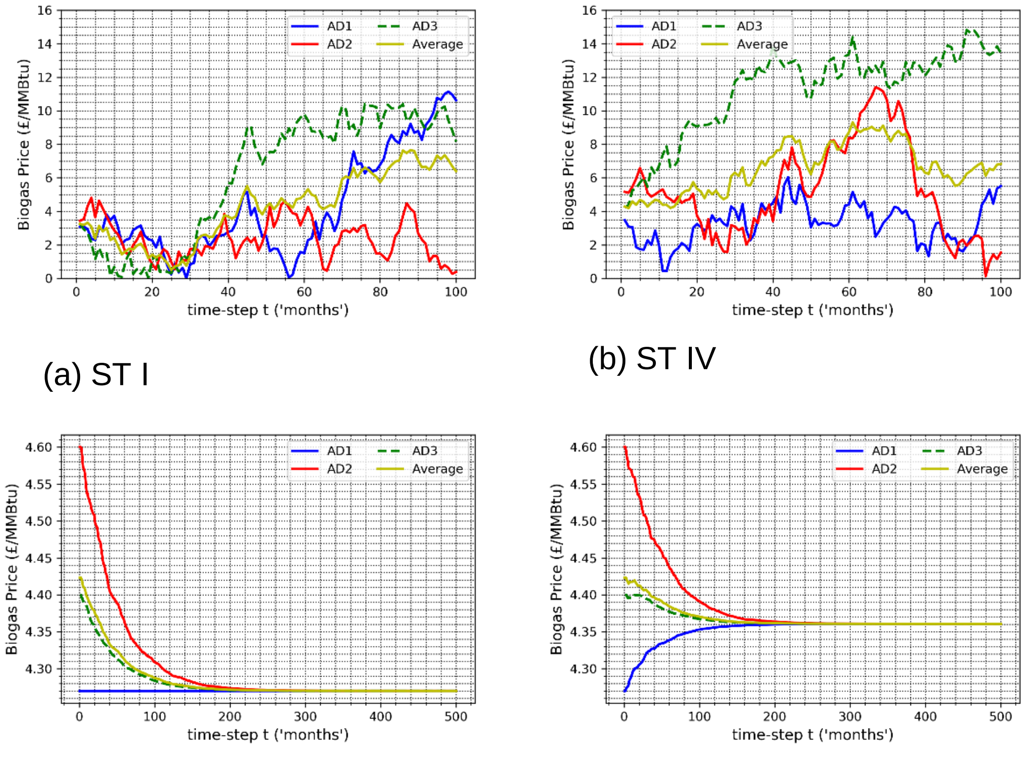
Figure 5-10 to Figure 5-14present the price evolution of the material exchange in the IES for each of the factory agents. Each figure is divided into four different decision strategy types as used in the simulation. The decision strategies implemented in this case study are; ST I, ST II, ST III, and ST IV (see Table 5-2). For the price variation, the number of simulation run done for ST I and ST IV is different from the other two decision strategy types. As shown in Figure 5-10 to Figure 5-14 we carried out 100 runs for ST I and ST IV while 500 simulation runs was done for ST III and ST II. The reason for this difference is to show that over a long period time the price converge to a point in ST III and ST II. As pointed out in section 3.6.2, sellers can change price either randomly or envisaged the risk involved in changing its price, while five different decision making strategies are proposed for the buyers. Although only two (random and best price) of the buyers' decision strategies are used in this case study.

The price evolution for the biogas from the three anaerobic digestion plants (Figure 5-10). This is the only material exchange for these process plants. As it can be seen the seller decision in changing the price has effect on the buyer and vice- versa. From Figure 5-10 (a) and (b) in where the decision strategy is ST I and ST IV respectively, the price of biogas fluctuates and reaches as high as £14/MMBtu. In reality, this cannot be used for decision making by business owners. Figure 5-10 (c) and (d) on the other hand, can be linked to what happens in real life. At the beginning of the simulation runs, each of the agents in the IES the decision strategies applied, the price changes and moves towards equilibrium over time. The price of biogas flattens out at period 160th in both Figure 5-10 (c) and (d) and remain the same till the end of the simulation run. The equilibrium price for all the three agents based on Figure 5-10 (c) is 4.28 MMBtu while it is £4.36 MMBtu The reason for the flatten out is as a result of the decision strategy used by the sellers (risk based) that forced the market price to move towards equilibrium when any change will mean less sales for the selling agent. However, there is little difference between the ST II and ST III. For the ST III, the equilibrium price shift towards the agent with the lowest price in the IES, while there is random shift at every period before equilibrium is reached in the ST II.

The possible material that the bio-refineries can exchange are lignin pellet and distilled dry grain while process steam and electricity are the exchange materials for the combined heat and power plants. The price evolution for these two factory types; CHPs and BIOs are shown in Figure 5-11 and Figure 5-12 for the CHPs while Figure 5-13 and Figure 5-14.

Figure 5-11 and Figure 5-12show the price variation for electricity and process steam under four different decision strategy types by the sellers and buyers. In this case, the combined heat and power plants are the selling agents while bio-refinery and anaerobic digestion plants are the buying agents in the industrial ecosystem. The ST I and ST IV decision rules as pointed earlier are not realistic and this indicated in the graph. The minimum average price of electricity as can be seen is approximately £ 0 MWh and the maximum reaches as high as £ 0.09 MWh in Figure 5-11(a) while the maximum value in Figure 5-11(b) is £0.08 MWh. For Figure 5-11(c) and (d), show a constant value after a period of time as expected. The electricity price is £0.049 MWh from the 60th period, in Figure 5-11(c) however, the value is £0.053 MWh. As can be seen, the price of all the selling agents did conform to the average price recorded from the market history.

The price variation for the distilled dry grain and lignin pellet as the materials exchange by the bio-refinery plants are shown in Figure 5-13 and Figure 5-14 From the assumption made in the beginning of this case study, each of the bio-refinery plants can sells lignin pellet to the combined heat and power plants and distilled dry grain to the anaerobic digestions plants. As always the case, the seller (bio-refinery plants), act as offensive player while the buyer act as the defensive players. From Figure 5-13(a) and b) in where the decision strategy is ST I and ST IV respectively, the price of DDG fluctuate and reach as high as £0.16/lb for the ST I decision rule while it is around £0.056/lb. In the other two decision rules, the price reach as high as £0.18/lb before reaching converging and the price (£0.082/lb)is maintained throughout the simulation. In case of the lignin pellet price variation, the average price in the market fluctuate and reach a maximum value of £ 24/ton. For our decision strategies that is close to reality i.e.; ST II and ST III, the price of lignin pellet is almost the same after from 140th period in both cases. The value in case of the STII is £6.2/ton while it is £6.16/ton for the ST III.



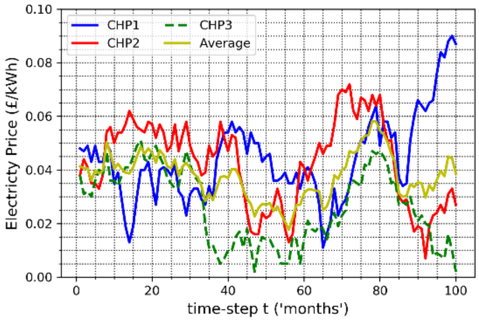
(a) ST I

(b) ST IV

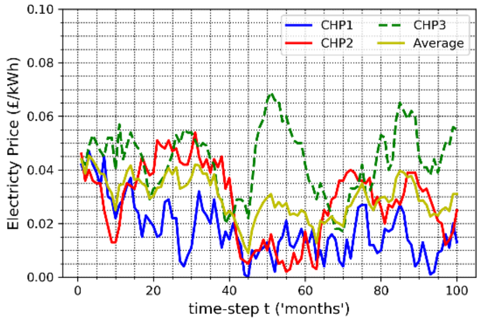
(c) ST III

(d) ST II

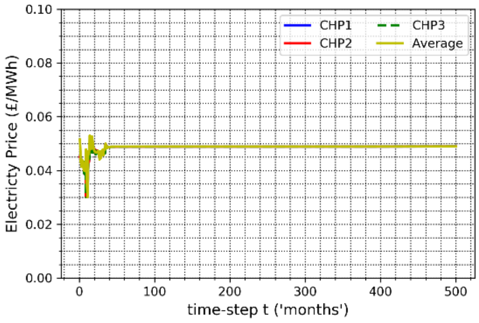
Figure 5-10: Biogas price variation under different seller-buyer decision strategy types



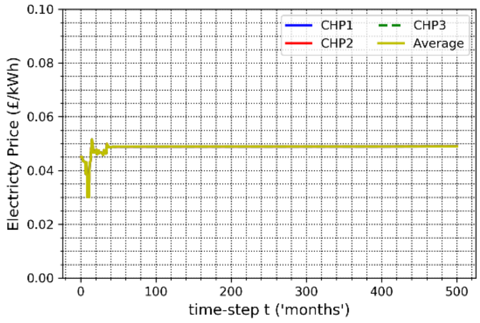
(a) ST I



(b) ST IV

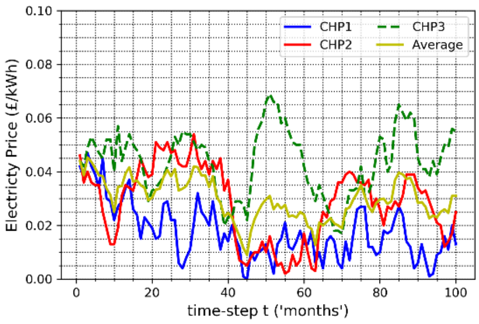


(c) ST III

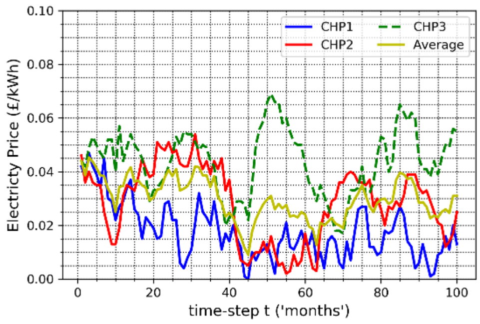


(d) ST II

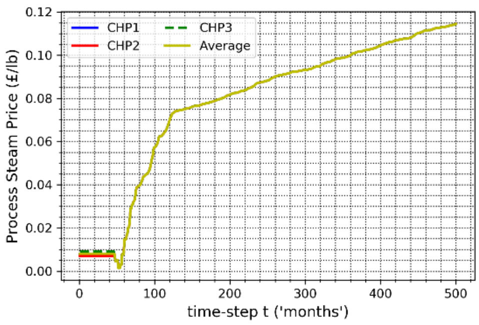
Figure 5-11: Electricity price variation under different seller-buyer decision strategy types



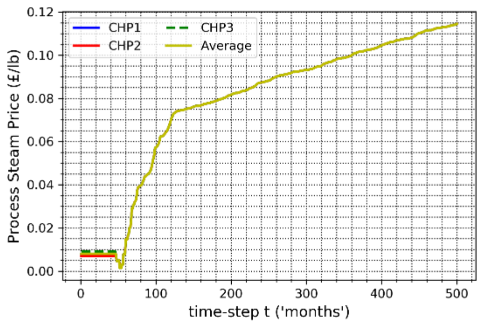
(a) ST I



(b) ST IV

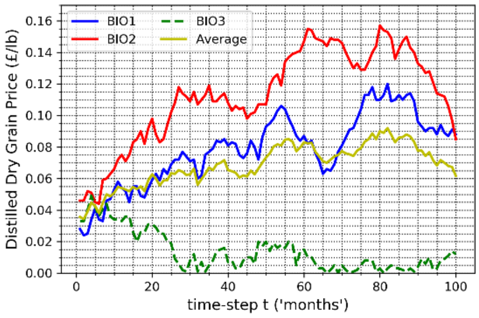


(c) ST III

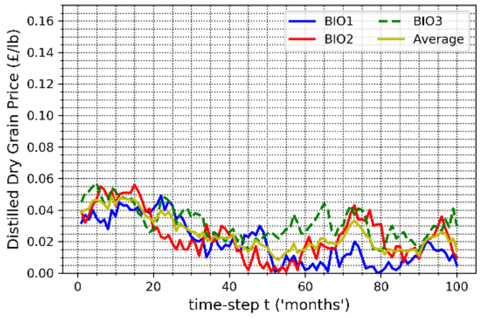


(d) ST II

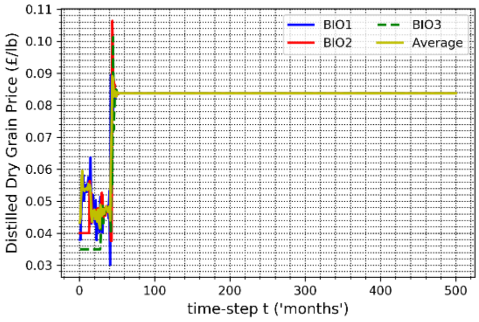
Figure 5-12: Process steam price variation under different seller-buyer decision strategy types



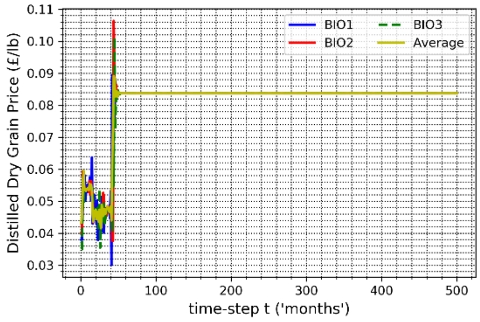
(a) ST I



(b) ST IV

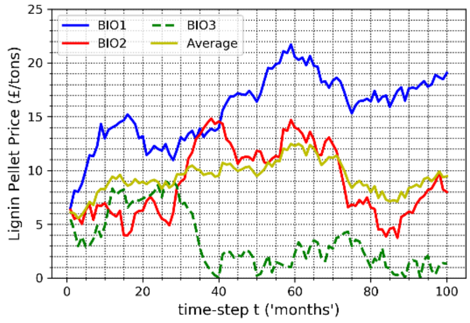


(c) ST III

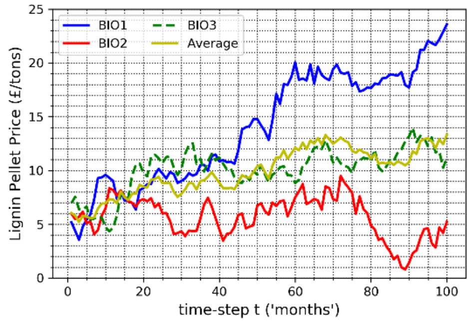


(d) ST II

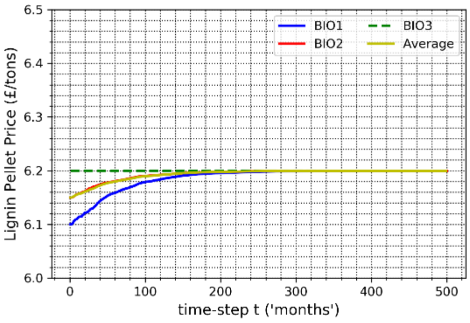
Figure 5-13: DDG price variation under different seller-buyer decision strategy types



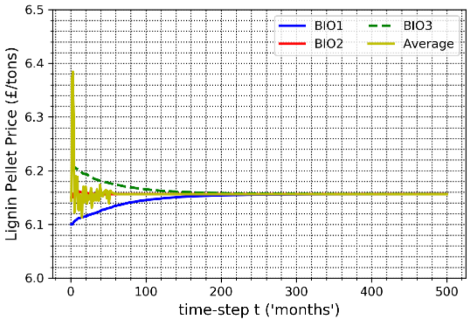
(a) ST I



(b) ST IV



(c) ST III

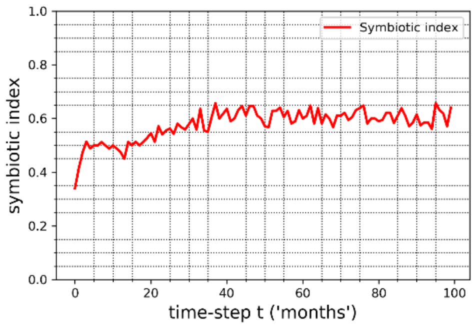


(d) ST II

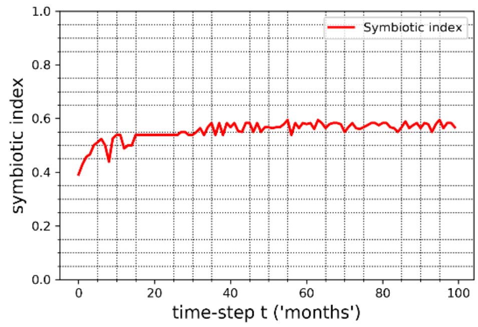
Figure 5-14: Lignin pellet price variation under different seller-buyer decision strategy types

5.7 Buyer-Seller Symbiotic Relationship

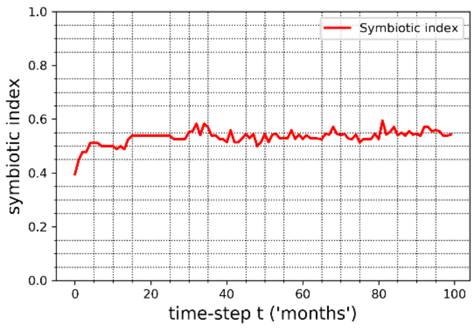
Based on the metric developed in section 3.6.3, Symbiotic Relationship Index (SRI) , we present the pictorial representation of the index for the simulation runs carried out. In order to identify changes of symbiosis in and Industrial ecosystem, Figure 5-15 shows the Symbiotic Relationship Index (SRI) for each of the decision strategy types. As it can be seen in Figure 5-15, the ability of the proposed indicator to detect total absence or presence of symbiosis in an IES. As expected during the beginning of the simulation, the SRI value is close to 0.2, this indicates absence of symbiosis in the IES. This can be seen at the beginning of each of the simulation runs. While the simulation is on the SRI value grow significantly which indicates an increase in the transaction relationship between the different factories. It can be seen in the figure that the symbiotic relationship grow considerably from the 10th period and this was maintained till the end of the simulation. The maximum value of the index as can be seen in the figure is about 0.62 in Figure 5-15 (a) and (b) while the maximum value for the other two is 0.6. These values indicate that there is considerable symbiotic relationship that exist with all the factory agents in the IES.



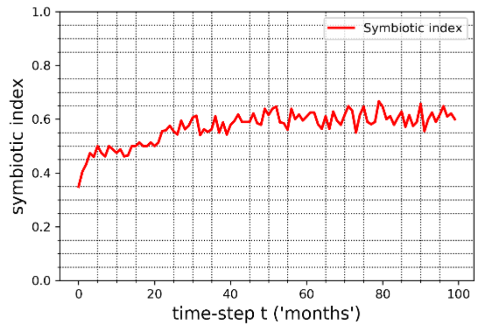
(a) ST I



(b) ST IV



(c) ST III



(d) ST II

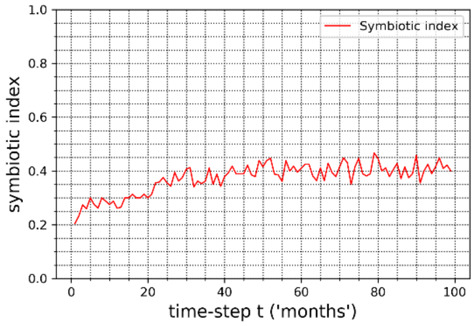
Figure 5-15: Symbiotic Relationship Index (SRI) of the Industrial ecosystem (IES)

5.8 Sensitivity Analysis

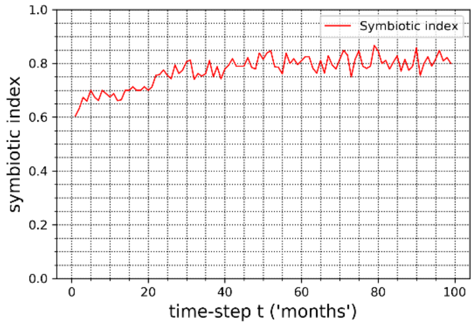
In order to gain some insight to the behaviour of the factory agents in the IES, this section conducts the following sensitivity analyses: (1) the effect of increasing the selling price of products by the factory agents on the Symbiotic Relationship Index, SRI. (2) the impact of market sellers increasing selling price on SRI.

Sensitivity analysis is conducted to determine the effect of factories selling their products in the IES at higher price compare to the market sellers. At the start of the simulation, the input values for the price of biogas, steam, electricity were changed for only the factory agents and we simulate using ST III. An increase in the range of 5% – 10% is added to the initial input value, thus making the factory agents price higher in the IES compare to the market seller agents while other parameters remain the same. Figure 5-16 (a and b) presents the result of sensitivity analysis by making the product price of the factory agents to be higher in the IES. It suggests that the symbiotic relationship index decreases (average of 0.37) while it increases for the market sellers (average of 0.77); i.e., the buyers tend to form synergy with the market sellers than with the factory agents. We conducted another sensitivity analysis, this time we make the market sellers have the high selling price at the start of the simulation for each time-steps while other input parameters remain unchanged as before. Figure 5-16 (c and d) show the impact of market sellers selling at higher price throughout the simulation run. The effect of this on the IES suggests that the factory agents SRI to the buyers increases to 0.72 on average while the SRI for the market sellers to the buyers decreases to 0.40. This is like a self-sufficient system that does not required external source of supply but in reality this cannot happen because waste will always be generated.

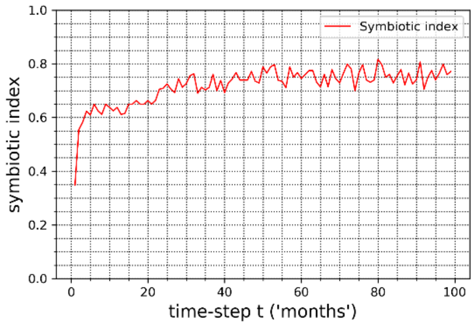
In summary, the results show that price variation has considerable impact on the configuration of industrial ecosystem. It also suggests that to improve the relationships that exit between various parties in the IES, there must be price regulation and this is one of the reasons why agents are able to learn from their history as well as market history.



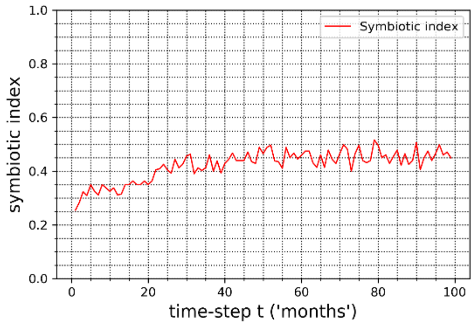
(a) SRI decreases between factory agents and buyers



(b) SRI increases between market sellers and buyers



(c) SRI increases between factory agents and buyers



(d) SRI decreases between market sellers and buyers

Figure 5-16: Sensitivity analysis on the effect of high/low price

5.9 Conclusions

Agent-based modelling technique has proven to be an effective tool that can be used to express the evolution of eco-industrial systems. We can predict or simulate the price variation or forecast demand and supply time series by using this modelling technique, which are difficult to be determined using deterministic calculations of supply and demand. Increasing the product categories, extending industrial chains and creating new industrial chains through utilizing wastes and by-products can create a comprehensive factory symbiotic community, which has a higher sustainability. The results demonstrated that the Réseau agent-based model allowed for investigation of the different behaviour exhibited by the different agents in exchange of materials in the industrial park. The simulation showed an enhanced robustness of the IES results compared to the case study in Chapter 4.

This more complex case study demonstrated realistic demand time series that are generated for decision strategies ST II and ST III. Though the price curve for such strategies are not too realistic as they converge to a single value. In all, we observed that the risk based seller decision strategy developed in this work provides significantly more realistic demand and supply time series. This is independent on whether buyer choses the seller randomly or based on best price. This is the result of the risk-based price being linked to the market average only. In reality, it will also depend on manufacturing costs.

In conclusion, the findings in this chapter suggest that agent-based modelling is a promising tool that can be used to simulate industrial ecosystem in order to examine the behaviour of agents in the park in response to demand and supply variation.

Chapter 6
Impact of Multi-Period Contractual Mechanism on Demand Time series

6.1 Introduction

The shift from economy that heavily depends on fossil fuels to one that is powered solely by renewable energy has been accelerating in recent years, bolstered by mounting concerns over climate change and falling prices of solar and wind energy (Obama 2017). Another future challenges seems to be the management of the integration of fluctuations in the electricity production from combined heat and power units (Lund 2005). Also the intermittent and unpredictable features of the renewable generations e.g. wind power raise challenges to energy provider to balance its production and consumption. The use of renewable energy sources have proven to bring about a reduction in the reliability of electricity generation (Lund *et al.* 2010). In order to match the supply against the demand in industrial ecosystem consisting of energy provider unit like combined heat and power plant and other energy consumer players, there is urgent need to either enhance the park system flexibility or mitigate the variability in the CHP units output. Large-scale integration of wind power into the electricity generation from CHP units may be use to address this challenge of designing integrated regulation strategies of overall energy systems.

As mentioned in the previous chapters, industrial symbiosis concerns with resource exchanges between network of organization towards achieving sustainable development, however, there is little or now work on techniques or strategies that strenghten IS. This chpater fills this gap by introducing the concept of contract in the industrial ecosystem. At off-peak hours in the winter, CHP covers a large portion of the power demand, resulting in a heavy curtailment of wind power. To increase the flexibility in the heat generated from a CHP operations, electrical heat boilers can be turned on to use the wasted wind power or by replacing part of the heat production from CHP units by heat accumulator) (Chen *et al.* 2015). This will correspondingly reduce CHP power production when wind power is abundant and the CHP is put on when the wind power is low considerably. This paradigm shift from the use of fossil fuel to energy system that depend solely on renewable source can further be driven by demand response (DR). The US Department of Energy defined DR as “a tariff or program established to motivate changes in electric use by end-use consumers, in response to changes in the price of electricity over time, or to give incentive payments designed to induce lower electricity use at times of high market prices or when grid reliability is jeopardized" (Qdr 2006).

In order to push independent firms to pursue self-integration with another, proper supply contracts should be adopted (Giannoccaro and Pontrandolfo 2004). The assumption of this modelling design is that a full spot market cannot become dominant in the future since it is only responsible to augment the fluctuation in the main supplier. An example of a spot market can be such as e.g. supplying combined heat and power plant that can be used for wind power to mitigate the fluctuation in electricity supply. In such systems, wind power plants will often operate on electricity spot markets by storing energy when electricity prices are low and producing electricity when prices are high. In this chapter we focus on simulating the emergence of an industrial ecosystem with possibility of analysing the effect of contractual agreement between agents on the formation of a stable symbiotic relationship with fixed price over the contract period. The contractual mechanism is setup in this work between the combined and heat power plant and the wind turbine agents. This is just to investigate the essence of contracts mechanism in fostering industrial symbiosis in a network of organization that are sharing resources.

The above problem is viewed as a complex system. Following the results obtained in chapter 5 some improvement of Réseau agent-based model is identified, such as the possibility of including a contractual agreement between agents. In order to push independent factory to pursue self-integration with another, proper supply contracts should be adopted (Giannoccaro and Pontrandolfo 2004). The assumption of this modelling design is that a full spot market would become dominant in the future. An example of a spot market can be such as e.g. wind power that can be used for supplying combined heat and power plant to mitigate the fluctuation in electricity supply.

.

Réseau was used to carry out simulation analysis to investigate the interaction of stable symbiotic relationship in the IES. In particular we simulate the problem using two different scenarios. We look into the interaction of combined heat and power integrated with units of wind power plants to serve as an anchor plant in the industrial ecosystem as a major provider of electricity and/or heat if required at any point in time. The objective is to gain insights the behaviour of the respective agents in the IES, in two different settings, one defined by the absence of contract in the industrial synergy and the other where the proposed contractual mechanism is adopted only by companies involved with short or long contract scheme. By this, we examine the degree of effect of contract agreement in fostering the synergy that exist between different participating firms in the industrial ecosystem. This problem is demonstrated using a case study with two scenarios; with or without scenarios.

6.2 Case study and agents identification

As discussed in Section 1.4, one of the objectives of this thesis is to simulate the behaviour of agents in industrial ecosystem. In this case study, we investigate how contract scheme affect the behaviour of agents in the IES. Here we use we used data referring to real case study discussed in (Gonela and Zhang 2014). The firms (factories) formed the internal environment of the park while the market buyers and sellers occupied the external environment. The external environment is an infinite source or sink, where raw material can be purchased or finished good can be absorbed without any capacity limitation.

The internal environment consist of three different factory agent types; anaerobic digestion plant (AD), combined heat and power plant (CHP), and bio-refinery plant (BIO). Each factory agent type is made up of three different firms that produces same output but use different input raw material. The ADs include three different plant (AD1, AD2, and AD3) that produce biogas as their main products. To produce biogas, the firms requires either cattle feedlot manure or food and bio-solids (Appels *et al.* 2011; Gonela and Zhang 2014). The CHPs in this case study is modification of the one presented in section Chapter 5. The difference is the combination of CHP's and wind turbine for the generation of electricity and process steam (heat) as its output. The integration in this case is necessary in order to reduce excess production of electricity and proper management of heat demand. The integration of CHP and wind power is subject to fluctuations in electricity production (Lund and

Clark 2002). Wind turbines depend on the wind, and CHP depends on the heat demand. The wind agents only relate/transacts with the CHP agents by entering into a contract for a valid contracting period. Also electricity/process steam are considered as one entity and can be obtained from the combined heat and power plant (CHP). The food and bio-solids can be obtained only from the market sellers while the electricity/process steam can either be obtained from CHP or market sellers. The ecosystem also consist of three different bio-refinery (BIO1, BIO2, and BIO3) plants. The main output is ethanol while lignin pellet and distilled dry grain are generated as by-products.

The biogas output of the AD factories can either be sold to the CHP factories or directly to the market buyers. The CHP plants uses biogas as its main input to generate electricity/process steam and can also be in contract with wind agents to forestall any interruption in generation of electricity. The output of the CHP's firm can either be sold to the firms in stage A or directly to the market buyers. The stage C consist of bio-refinery plants. The bio-refinery plants generate ethanol as its final output and required electricity as one of its major inputs. The configuration of all the factories used in this case study are the same as presented in Chapter 5 except that the combined heat and power plants (CHPs) are in contractual agreement with wind turbine agents (local suppliers). The wind turbines serve as spot market to when local demand of electricity from the CHPs is more than their generation.

All the factories and the market seller in the industrial ecosystem observed a stochastic final buyer demand over time, distributed according to Gaussian distribution with a given mean, m and standard deviation, s.

6.2.1 Plant configurations

As mentioned earlier, the configuration of other factory agents are as described in section 6.2.1 of Chapter 5, therefore we will discuss the configuration of only the wind turbines in this section as additional agents in the ecosystem. The contractual agreement between the wind power and the combined heat and power plants are also discussed.

6.2.1.1 Wind turbine power output

Wind power is one of the world's fastest growing renewable energy sources (Ma *et al.* 2009). Wind energy is distinctive in nature by its lack of pollutant emissions and fossil fuel usage as discussed in Wang and Singh (2009) as well as by its low land-use requirements. High penetration of wind power has greatly challenged the way the power system has been operated. On one hand, wind power is sustainable and has zero carbon emissions. On the other hand, wind power is intermittent and very difficult to predict. Wind turbines work by converting the kinetic energy in the wind first into rotational kinetic energy in the turbine and then electrical energy that will be use to meet the demand. The energy available for conversion mainly depends on the wind speed and the swept area of the turbine. A block diagram of the working principle of wind power can be represented as shown in Figure 6-1.

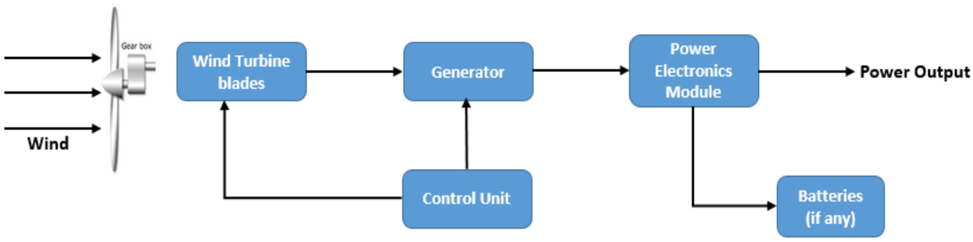


Figure 6-1: Block diagram of wind power generation systems

One of the most important future challenges seems to be the management of the integration of fluctuations in the electricity production from renewable energy sources and the electricity production from CHP units. Planning is key in other to know the expected power and energy output of each wind turbine to able to understand its economic viability.

The power obtained from the wind turbine at the average speed which can be supplied to the CHP unit based on contract can be calculated as:

$$P_{wt} = \frac{1}{2}\eta_{wt}\rho_{air}A_{wt}C_{p,wt}V^3 \qquad (10)$$

Where P_{wt} is the wind turbine power, ρ_{air} is the density of air in kg/m^3, η_{wt} is efficiency of the wind turbine, V is the wind velocity in m/s^2, and $C_{p,wt}$ is power coefficient (Ozlu and Dincer 2015). An example of CHP-wind integration is the Danish energy policy where the installed CHP produced about 50% of both the electricity and heat demand while 15% of electricity is produced by wind (Lund and Clark 2002).

The diagram in Figure 6-2 and Figure 6-3 show the actual energy produced in each 1-hour time interval for two out of the ten wind agents used in this work, in the course of the year 2001 and 2005, 2006 and 2010, by all wind turbines installed in Aviemore situated within the Cairngorms National Park in the Highlands of Scotland, England. This is equivalent to the time behaviour of the effective electric power, averaged over the same time span. The reading is at the network input, that is net of all production efficiencies. The recording shows a peak of 1.6 MWh for the Aviemore turbines and 6.25 MWh Carborne in some period of the years.

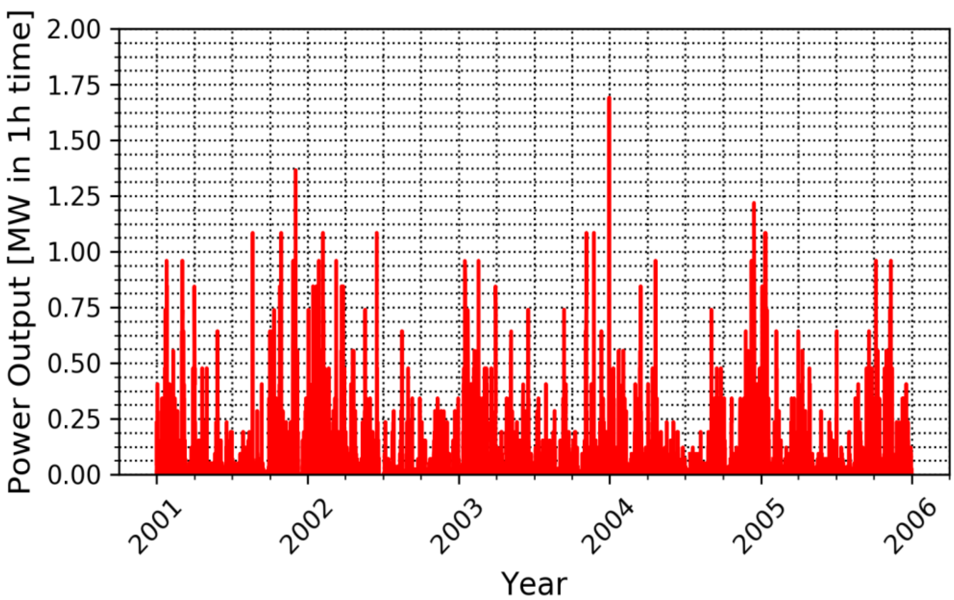


Figure 6-2: 2001 - 2005 Aviemore weekly wind generation

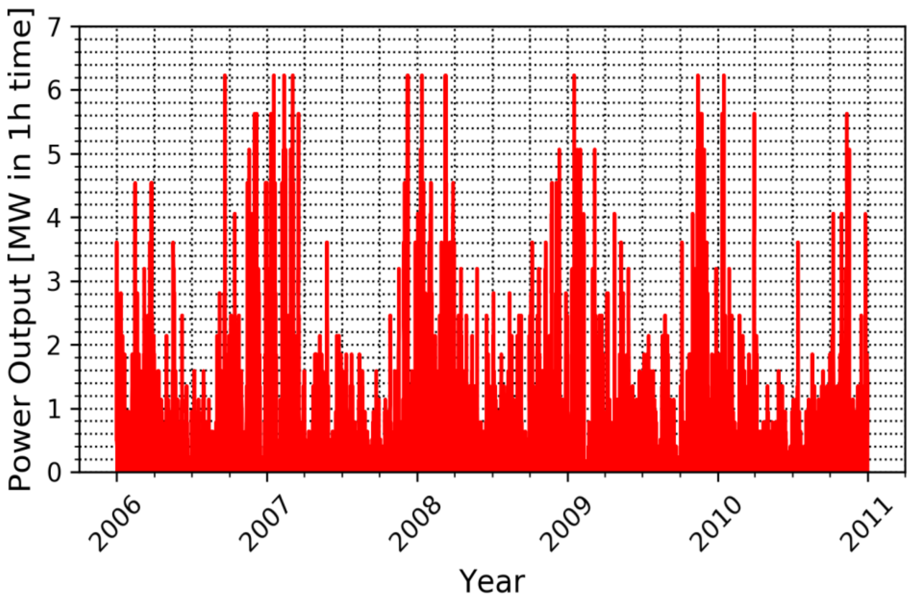


Figure 6-3 : 2006 - 2010 Aviemore weekly wind generation

6.3 Simulation scenarios

In order to verify the role of contracts in an industrial ecosystem, we consider two different contractual agreement between two generic firms to form symbiotic relationship.

Scenario 1 (*Baseline or without contract*)

Scenario 1 correspond to situation of the industrial development, where companies that are in the industrial ecosystem form synergy (material, by-product, waste) with the other companies without having any contractual agreement before and after the synergy. Thus any company can decide to opt out of the synergy at any point in time without any implication. As indicated in the case study, the wind turbines are expected to make up for the short in supply of electricity by the combined heat and power plants to the local demand but with no guarantee to supply at any time. This scenario aim to represent an unstable IES.

Scenario 1 (*with contract*)

Scenario 2 aim at representing a stable IES where the synergy between companies that have contractual agreement has a perfect Symbiotic Relationship Index (SRI = 1). This scenario correspond to situation of the industrial development, where companies that are in the industrial ecosystem form synergy (material, by-product, waste) with the other companies by entering into contractual agreement. A contractual agreement is a business agreement which explicitly states a fixed duration that the contract will be in effect. Thus, a buyer – seller contract agreement cannot at any time be renege until the expiration, or end date, of the contract. Any company that decide to opt out of the contract agreement before the contract end will have to abide by the contract terms. The contract length or period for each signing parties is not fixed, i.e. Each of the wind agents can have the same or different contract length. The signing parties used in this scenario is combined heat and power plants and the wind turbine plants. Three different combined heat and power plants sign contract with ten different wind turbines in the industrial ecosystem with different contract length. The wind turbines (agents) are meant to fill the short fall in supply of electricity in the park.

Both scenarios are simulated for 100 periods for three different simulation (30,50, and 100) time steps. The input data for all the companies (Bio-refineries, Combined heat and power plants, anaerobic digestion plants) are obtained from (Gonela and Zhang 2014; Gonela 2013). The input data for the wind turbines are UK data obtained between year 2001 to 2010 (Met Office 2010). The data is separated into year 2001 – 2005 and 2005 – 2010. The input data for the all the wind turbine used for this case study can be found in https://github.com/ganiyuajisegiri/reseauWindmultipleContract.

6.4 Simulation Results and Discussion

In this section we discuss the results from the two different scenarios modelled. We simulated the two scenarios (scenario 1 and scenario 2) for simulated run of 30, 50, 100 time-steps and replicated each simulated run for 100 times so as to give statistical significance results. We make comparison between outputs of the same scenario and also between the two scenarios.

The symbiotic relationship index (SRI), mean profit, mean average profit was computed at the end of the simulation time.

6.4.1 Scenario 1 (Baseline or without contract)

Model results are shown in Table 6-1 and Figure 6-4 to Figure 6-7 for the baseline or without contract case where all the wind turbine agents as without contract deal with any of the combined heat and power plant agents in the industrial ecosystem. Table 6-1 shows mean average profit of all the wind agents for different time-steps (30, 50 and 100) having *'without contract'* with the combined heat and power plants in the industrial ecosystem. Figure 6-4 shows the results for the mean profit for 30 time-steps, Figure 6-5 shows the results for the mean profit for 50 time-steps, and Figure 6-6 shows the results for the mean profit for 100 time-steps. The mean profit time series exhibited in the figures can be explained as follows. At the beginning of the transaction, all the wind agents starts with the same initial profit. This can be seen in all the three graphs. However, we observed different mean profit growth for each agents throughout the simulation run. This is because the decisions to buy in the ecosystem solely depend on the buyers and wind agents not in any contract with buyers. The buyers can buy using any of the decision strategies discussed in section 3.6.1. For example, in the case of wind turbine (wind4), it has the highest mean profit growth of £/MWh 950,000 in Figure 6-4 while it has one of the lowest values (£/MWh 50,000) in Figure 6-6. While wind9 has a flat profit from start to the end of the simulation in all the simulation time-steps. This is as a result of using wind9 like a dummy plant, i.e., it exit in the network but switched-off without supply electricity.

As can be seen from the mean average profit presented in Table 6-1, we find out that there is significant difference between the three different simulation time-steps. This is due to the number of time each wind agents sells during the transaction periods. A wind agents that supply more electricity over the length of the period is expected to have high mean average profit. Wind4, wind8 and wind3 have the highest mean average profit of £/MWh 529783.85 £/MWh 684697.03 and £/MWh 875058.35 for the three different simulation time-steps respectively.

Figure 6-7 shows a graphical representation of the mean average profit of four out of all the ten wind turbine agents. it can be seen that the volume of sales or number of times the wind agents is in synergy with a buyer during a simulation period that determine how high its profit will be. This invariably means the longer the synergy the more benefit it is for the partnering companies in the industrial ecosystem.

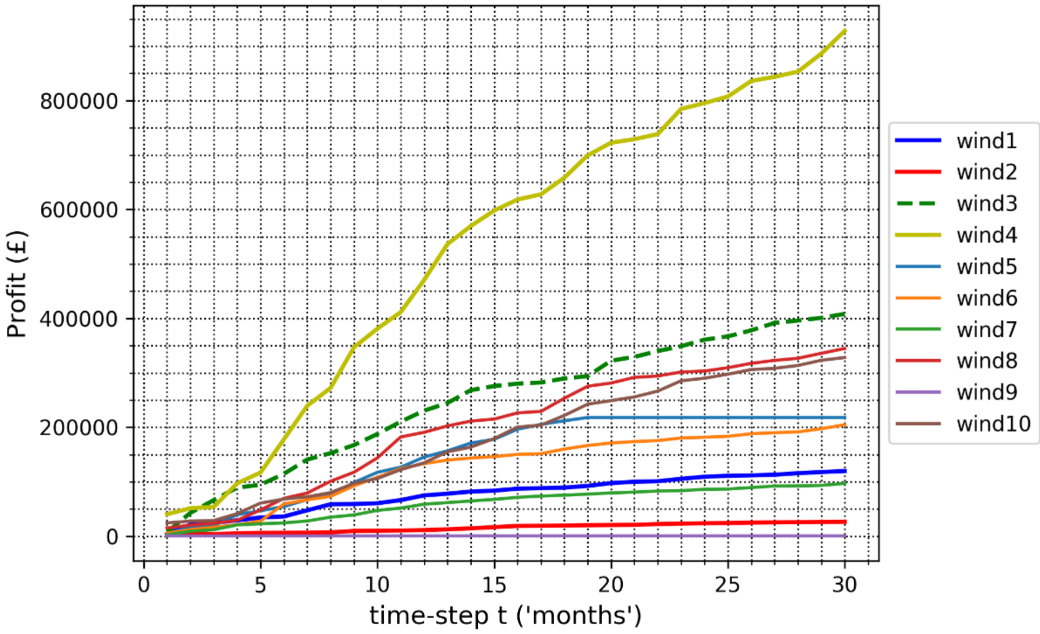


Figure 6-4: Mean (100 – simulation runs) profit over 30 time-steps on the ***'without contract'*** scenario case for all the wind turbine agent in the industrial ecosystem

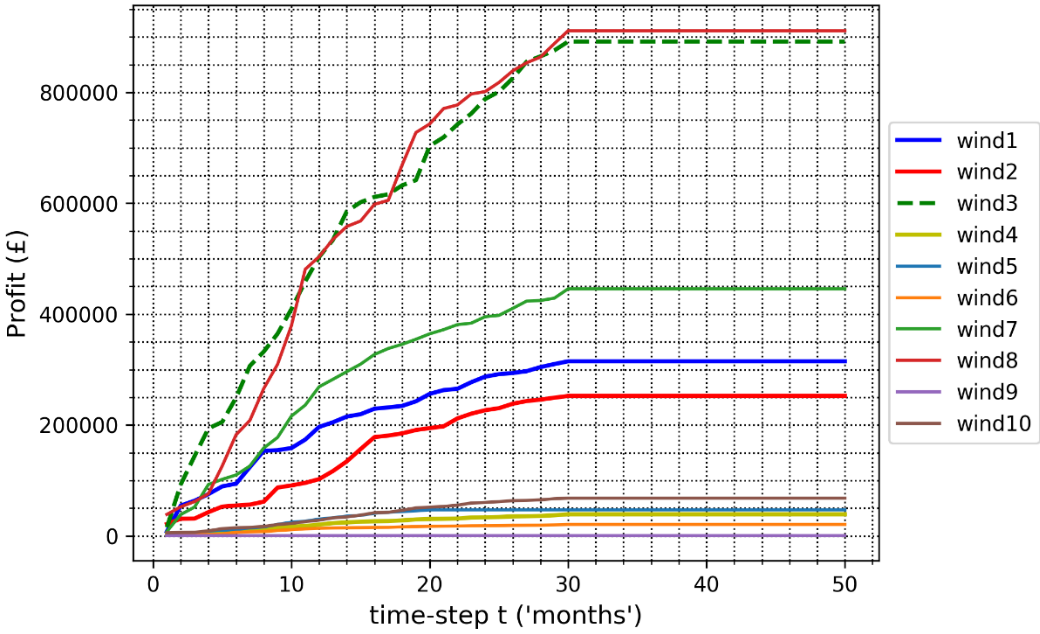


Figure 6-5: Mean (100 – simulation runs) profit over 50 time-steps on the ***'without contract'*** scenario case for all the wind turbine agent in the industrial ecosystem

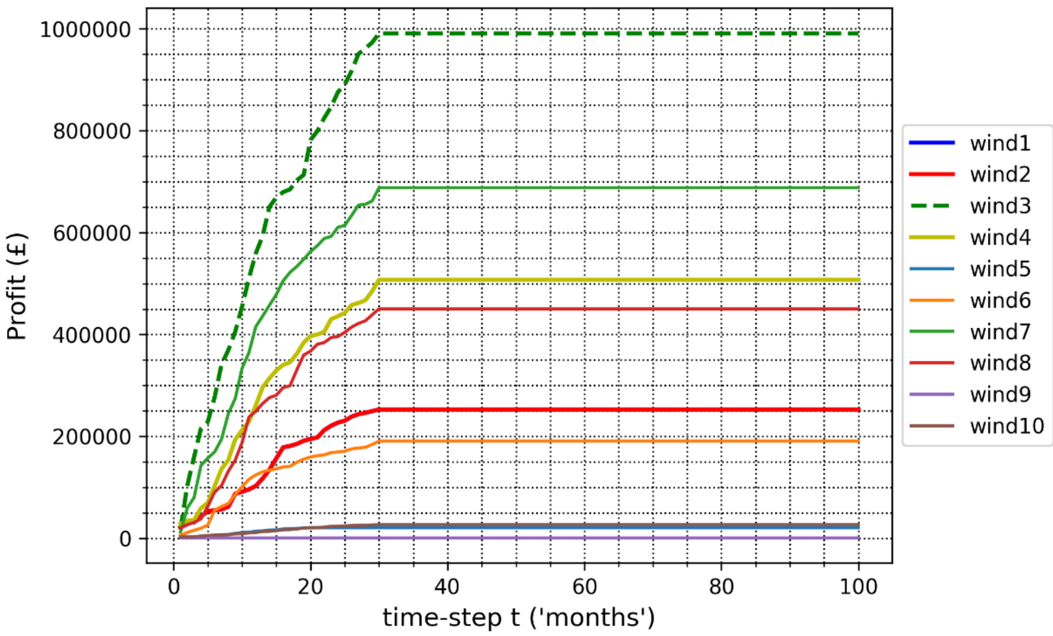
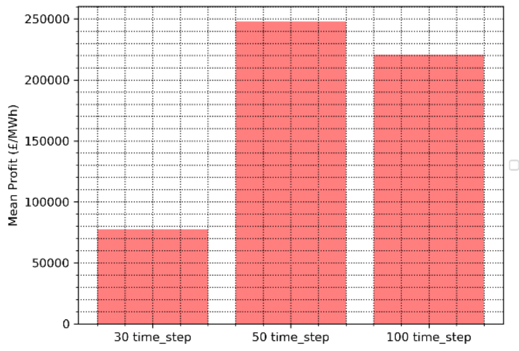
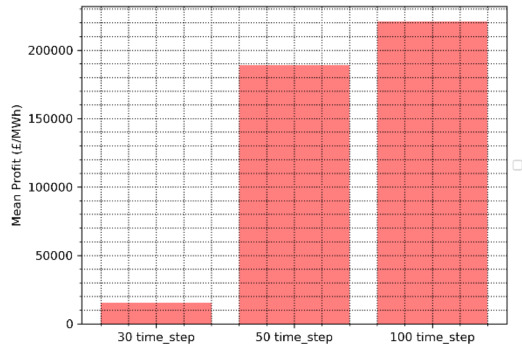


Figure 6-6: Mean (100 – simulation runs) profit over 100 time-steps on the ***'without contract'*** scenario case for all the wind turbine agent in the industrial ecosystem

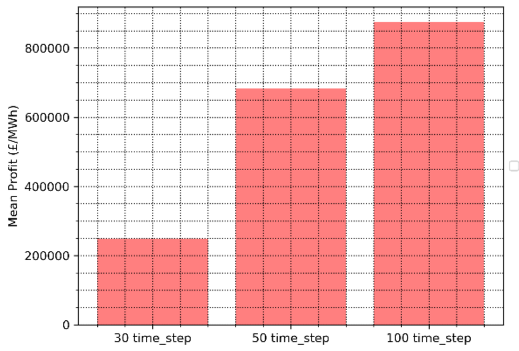
Table 6-1: Mean average profit of all the wind agents for different time-steps (30, 50 and 100) having ***'without contract'*** with the combined heat and power plants in the industrial ecosystem.

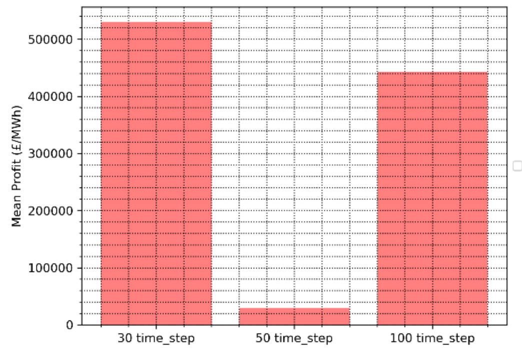
Agent name	Mean average profit for 30 time-steps	Mean average profit for 50 time-steps	Mean average profit for 100 time-steps
Wind1	77361.14	247804.68	220863.33
Wind2	15686.33	188749.27	220863.33
Wind3	249467.49	683208.23	875058.35
Wind4	529783.85	29406.02	442898.21
Wind5	151688.85	38362.16	18903.05
Wind6	127920.00	16289.11	169353.07
Wind7	60275.07	343725.07	609284.07
Wind8	202171.44	684697.03	394310.32
Wind9	939.00	939.00	939.00
Wind10	181836.51	50199.13	23288.78





(a) Wind turbine 1 (Wind1) (b) Wind turbine 2 (Wind2)





(c) Wind turbine 3 (Wind3) (d) Wind turbine 4 (Wind4)

Figure 6-7: Mean average profit of four different wind agents for different time-steps (30, 50 and 100) having ***'without contract'*** with the combined heat and power plants.

6.4.2 Scenario 2 (*with contract*)

The results for this scenario (with contract) are shown in Table 6-2 and c, where we consider fostering of symbiotic relationships with contractual agreement between partnering companies. We ran the simulation in the same way as the baseline (without contract) settings. Table 6-2 shows the mean average profit of all the wind agents for different time-steps (30, 50 and 100) having *'with contract'* with the combined heat and power plants in the industrial ecosystem. Figure 6-8 shows the results for the mean profit for 30 time-steps, Figure 6-9 shows the results for the mean profit for 50 time-steps, and Figure 6-10 shows the results for the mean profit for 100 time-steps.

All the results obtained in this scenario correspond to the trend observed in the baseline settings. However, it shows that contractual agreement foster and lead to perfect symbiotic relationships among buyers and sellers in the industrial ecosystem. As usual, each wind agents starts with the same initial amount at the beginning of the simulation. The growth in profit is therefore different per agent as till the end of the simulation. We maintained the contract length for wind4, wind7 and wind8 agents and maintained for others for the three different simulation runs (30, 50, 100 time-steps). It can be seen from the figure that the mean profit of these three agents are the highest in Figure 6-8 to Figure 6-10 with mean values as shown in Table 6-2. The high profit growths for these three agents can be explained as follows. The contract length for these there agents is more than for others, thereby stay longer in the synergy than other wind agents.

Figure 6-11 shows a graphical representation of the mean average profit of four out of all the ten wind turbine agents. it can be seen that the volume of sales or number of times the wind agents is in synergy with a buyer during a simulation period that determine how high its profit will be. For the three different simulation run, wind4, wind7 and wind8 has the highest values of mean average profit in that order.

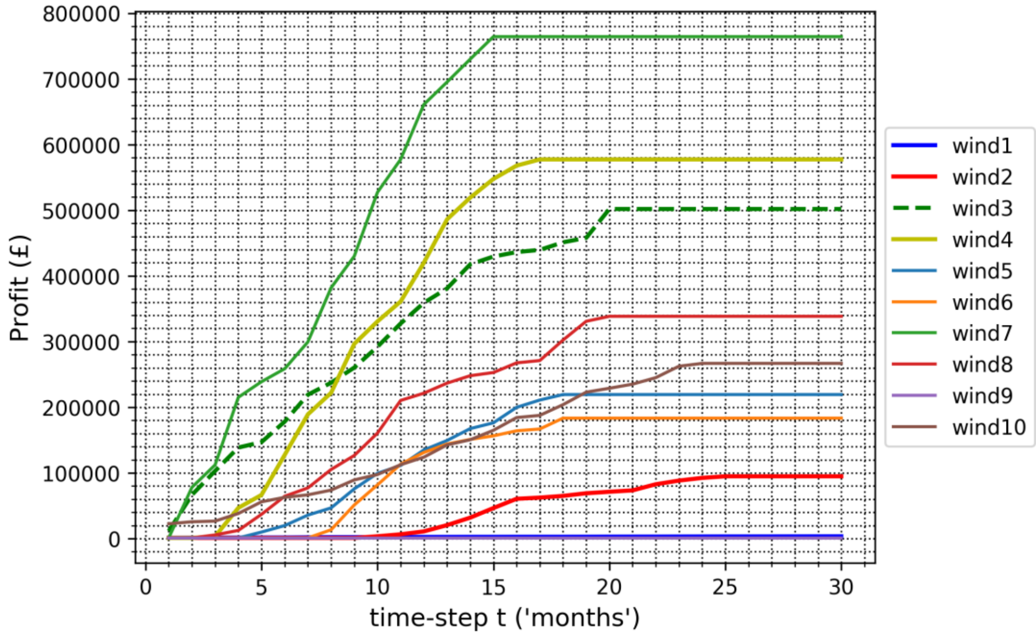


Figure 6-8: Mean (100 – simulation runs) profit over 30 time-steps on the ***'with contract'*** scenario case for all the wind turbine agent in the industrial ecosystem

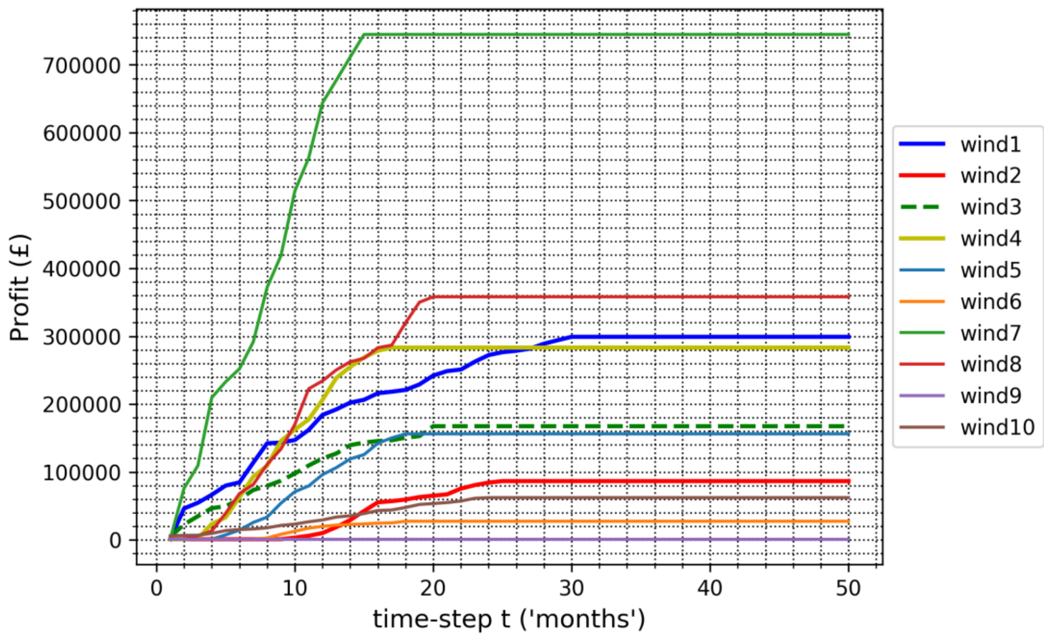


Figure 6-9: Mean (100 – simulation runs) profit over 50 time-steps on ***'with contract'*** scenario case for all the wind turbine agent in the industrial ecosystem

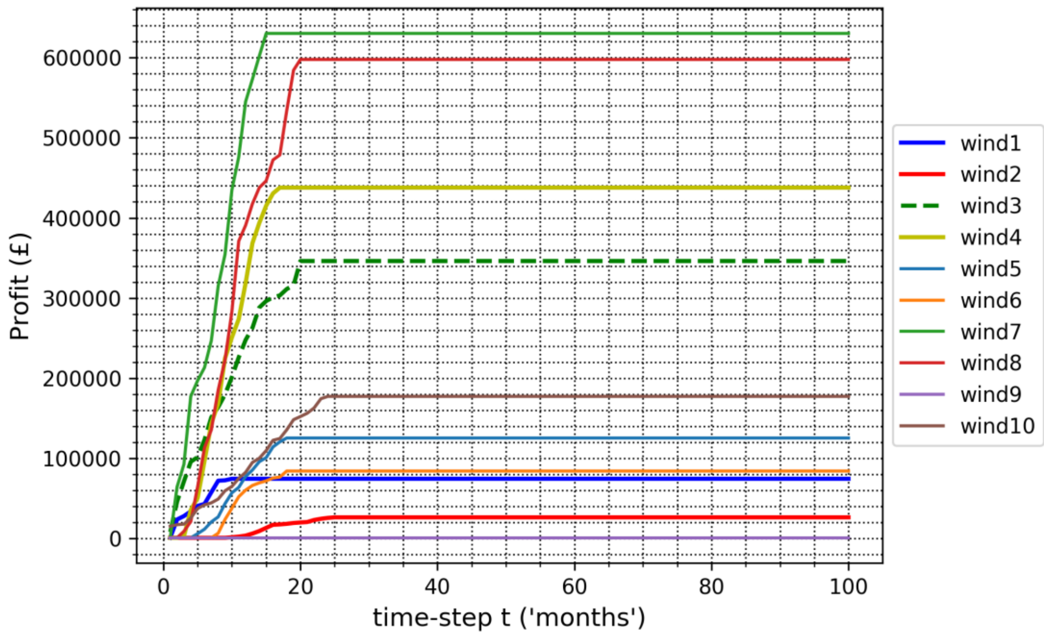
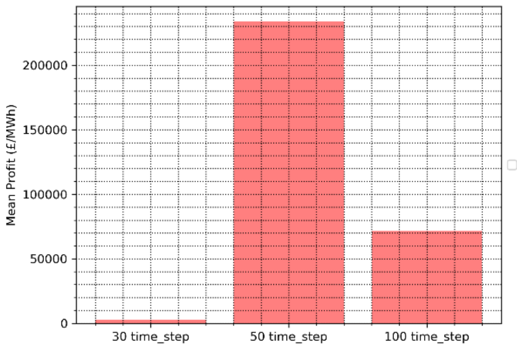


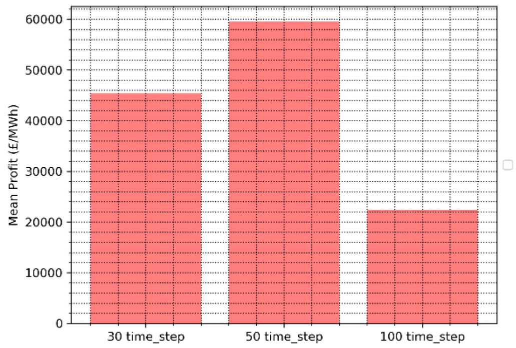
Figure 6-10: Mean (100 – simulation runs) profit over 100 time-steps on the ***'with contract'*** scenario case for all the wind turbine agent in the industrial ecosystem

Table 6-2: Mean average profit of all the wind agents for different time-steps (30, 50 and 100) having ***'contract deal'*** with the combined heat and power plants in the industrial ecosystem.

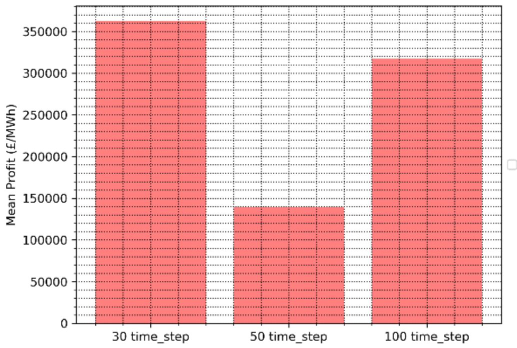
Agent name	**Mean average profit for 30 time-steps**	**Mean average profit for 50 time-steps**	**Mean average profit for 100 time-steps**
Wind1	2543.99	233825.31	71589.26
Wind2	45404.18	59546.64	22432.21
Wind3	362438.80	139674.00	317393.20
Wind4	408964.00	233866.40	399498.10
Wind5	143066.90	123658.40	112403.70
Wind6	118784.85	21796.90	75395.23
Wind7	581172.40	637714.60	584901.00
Wind8	221822.20	284103.70	535808.40
Wind9	939.00	939.00	939.00
Wind10	163020.80	47901.72	156703.80



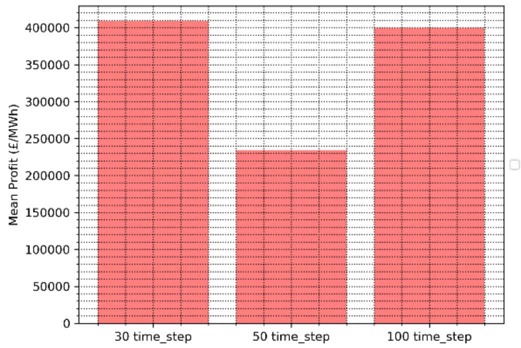
(a) Wind turbine 1 (Wind1)



(b) Wind turbine 2 (Wind2)



(c) Wind turbine 3 (Wind3)

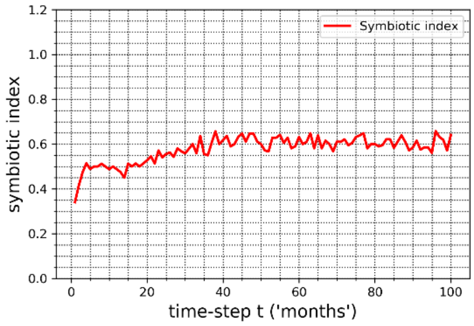


(d) Wind turbine 4 (Wind4)

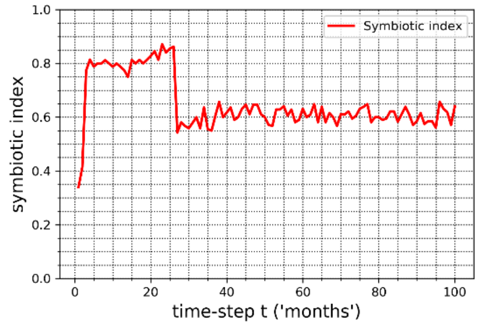
Figure 6-11: Mean average profit of four different wind agents for different time-steps (30, 50 and 100) having ***'contract deal'*** with the combined heat and power plants.

To further look at the effect of contract on the synergy that exist in the ecosystem, we tested the robustness of the results by comparing the two scenario together. We compared the results achieved in the contract and baseline settings using the Symbiotic Relationship Index. Figure 6-12, shows the Symbiotic Relationship Index for the Baseline (without contract) and Scenario 2 (with contract). The contract length for scenario 2 is changed for three different simulation to see the effect of contract in the ecosystem, each simulated for 100 time-steps and repeated for 100 runs to obtained an average value. We notice that the use of the contract increase the number of symbiotic relationships in scenario 2 compared to the baseline settings. On average the Symbiotic Relationship Index is 0.60 (60%) for the baseline while is 0.82(82%) for Scenario 2. Note that SRI of 1.0 indicate a perfect symbiosis which is not attainable in real life. This can be seen from Figure 6-12 and can be explained that for the period where the agents and the combined heat power plant entered into contractual agreement there is perfect collaboration and supply of electricity is constant. On average, the Symbiotic Relationship

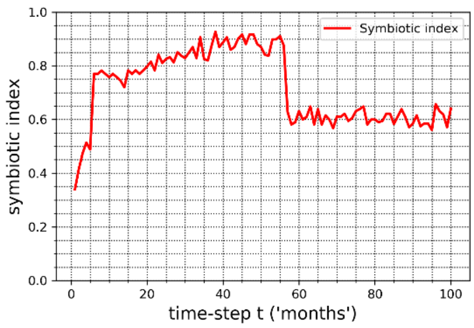
Index increases by about 37% within the contracting period compared to the Baseline settings. The results presented in this scenario test our simulation model, which indeed is able to reproduce the empirical observations and the details identified in the literature.



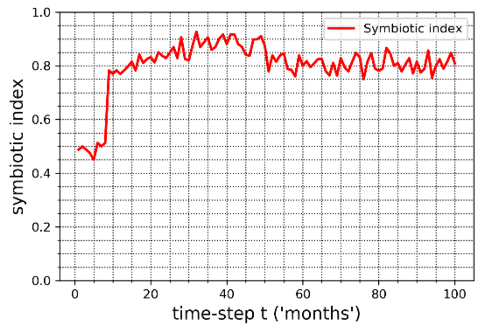
(a) Scenario 1 (*Baseline or without contract)*



(b) Scenario 2 *(with contract)* average contract length of 24 time-steps



(c) Scenario 2 *(with contract)* average contract length of 50 time-steps.



(d) Scenario 2 *(with contract)* average contract length of 90 time-steps

Figure 6-12: Symbiotic Relationship Index (SRI) of the industrial ecosystem. (a) Scenario 1 (Baseline or without contract); (b) Scenario 2 (with contract) average contract length of 24 time-steps; (c) Scenario 2 (with contract) average contract length of 50 time-steps, and (d) Scenario 2 (with contract) average contract length of 90 time-steps.

6.5 Conclusion

Several research works have been carried out to investigate how independent agents should cooperate to pursue a symbiotic relationships, few studies have developed the framework and the strategies to promote a win-win industrial ecosystem, i.e., the benefit of all the entities in the industrial ecosystem is increased in the case the presence of contract versus absence of contract. We introduced the adoption of contractual agreement to rule the symbiotic relationships between the entities in the industrial ecosystem. Agent-based modelling has been used to simulate the interaction that exist within the agents using two scenarios; with or without contracts. The results showed that the industrial ecosystem is more stable and the Symbiosis Relationship Index (the ratio between internal and external transaction) increased significantly when long duration contracts are available. The simulation analysis established that adoption of contract agreement in industrial ecosystem promote industrial symbiosis network.

Chapter 7
Summary and Conclusions

7.1 Summary of work

This work developed agent-based model called Réseau. The model is used for the interaction of different agents; factory, market seller and buyer in an industrial ecosystem. Réseau is constructed to gain insight in the complexity of ecosystem using the principles of industrial symbiosis (IS) where materials and energy flow and the related supply-demand match for each output products (finished goods, by-products, useful waste) becoming primary input for entirely new processes that are co-located in or within the same vicinity. Variation in economic drivers e.g., price, demand and supply are used to express the dynamic of an industrial ecosystem.

Chapter 3 gives a working detail of the methodology adopted using ODD to describe it and an example procedure is used in demonstrating the model. Chapter 4 focused on the application of the methodology to an industrial ecosystem consisting of single input single output *(SISO)* to investigate the behaviour of the agents towards price changes over time. This is to establish a base line for our model before using the model to solve a more complex IES; multiple input multiple output *(MIMO)*. This chapter explored the behaviour of agents in an eco-industrial park network using the developed model and revealed some preliminary conclusions. From this analysis it was found that the decision strategy chosen by the agents affect their behaviour at any period in the eco-industrial park. The simulation analysis confirmed that there is a level of symbiotic relationship between the factory agents (anaerobic digestion and combined heat and power plants) but the Symbiotic Relationship Index (SRI) will increase if the number of resource exchange increases. Utilizing this modelling framework to investigate the behaviour and interaction of many autonomous entities, or agents in IES over time allows for a quantitative discussion of benefit and adequate judgement for policy makers and industry.

Based on the shortcomings revealed in Chapter 5 we modified the model to allow N numbers of agents (N > 3) and also enable agents to have MIMO also exploring price, demand and supply variation as the decision strategy to investigate the behaviour of each agent in the IES in sharing resources for a win – win collaboration. Chapter 6 builds further on the previous modelling attempt and migrates the model to incorporate a contracting mechanism that promotes industrial symbiosis. This is the most detailed agent based model of the industrial ecosystem constructed to date. This objective function is a valuable tool for policy-makers and it is capable of influencing policy decisions on facility construction in order to achieve net benefits for producers as well as society. Overall, we have contributed to the SHAREBOX project by developing a new agent-based moodel called Réseau, used it to simulate industrial ecosystems to generate demand and supply time series. Also, as part of our involvement in SHAREBOX project University of Leeds, we are presently working with SHAREBOX project University of Strathclyde to integrate Réseau and MERIT together. Merit is an optimization tool that supports the development of new and renewable energy schemes by searching for matches between user specified demand profiles and possible supply technologies when deployed separately and in any combination. The system has in-built knowledge about typical energy demands and the different possible supplies. The integration will be incorporated as part of the decision tool on SHAREBOX online platform that can deliver next generation industrial symbiosis through a smart platform to effectively and confidently share resources with other companies.

7.2 Conclusions

While different studies on resources exchange in industrial network had been discussed in many literature, few studies have investigated the complexity of eco-industrial system and the effect of economic drivers (e.g., price). The study fills this gap by exploring the use of agent-based modelling (ABM), a bottom-up approach method, to the design of an industrial ecosystem in order to gain insight into their response to any changes in internal and external decision criteria e.g., price variation in the market. Agent-based models provide us with a flexible framework to explore ideas and capture some of the behaviour of eco-industrial network. However, we must be very cautious about extrapolating from what is still a highly simplified model (i.e., we keep the process model simple using input-output model integrated in the agent-based model) to the behaviour of a real eco-industrial park. This research work focuses on the application of a simulation tool within industrial ecosystem to unravel the complexity of eco-industrial system and generate demand and supply time series as this data is important but typically difficult to obtain. The research is conducted in four steps.

Firstly, agent based model of industrial ecosystem is developed. Python (an object-oriented programming language) is used to develop the model. The main goal is to improve the economic performance of the industrial actors and at the same time attaining a win – win condition. A comprehensive case study is developed and the important managerial insights findings from the research work are:

- Agent-based modelling can be employed to model eco-industrial systems in order to understand how the systems evolved over time.

- Prediction or simulation of different economic indices such as profit, price variation, supply and demand fluctuations can be obtained by using this modelling technique, which are difficult to determine using deterministic calculations of supply and demand.

- The risk based seller decision strategy developed in this work provides significantly more realistic demand and supply time series. This is independent on whether buyer choses the seller randomly or based on best price.

- Combined heat and power plants act as a focal plant for all other plants in the park as it provides electricity and process steam.

- The findings of this study strongly suggest that the industrial plants (agents) in the ecosystem should collaborate as there is strong symbiotic relationship between them thus leading to economic benefit and full utilization of the natural resources.

- The simulation analysis confirmed that there is a level of symbiotic relationship among the agents (e.g. anaerobic digestion and combined heat and power plants).

- As the number of resource exchange increases the Symbiotic Relationship Index (SRI) will increase. Note that perfect symbiosis (SRI = 1) cannot be attain in real life.

- Variation in the price of the resources overtime is a factor that needs to be considered

- The generated supply and demand will be used in SHAREBOX project to support technology selection for energy based identification of feasible IS project.

7.3 Recommendations

7.3.1 Recommendation for future work

Recommendations for further work on this topic include detail analysis of the mathematical expression of the objectives of agents (factory, market seller, market buyers, local seller and buyer) in the ecosystem and reformulation of their different decision rules. Agent-based modelling is suitable for the simulation of industrial ecosystem, yet there are little or no available data from the different companies that may likely participate in the synergy. The data needed to generate the demand and supply curve can be predicted accurately if additional learning methods apart from agent learning from history are implemented in Réseau. This will enable Réseau to make accurate prediction of the demand and supply time series for proper decision making.

The traditional approach to buyers' selection has been to select suppliers solely on the basis of price (Pal *et al.* 2013) among other selection criteria (e.g. quality, delivery, rejection, capacities, rating and flexibility) for many years. As shown in this work, one of the drivers over integration decision of companies is the economic return which fluctuates according to prices of resources over time, however, there are other drivers like quality. Investigating the other drives (e.g. quality, delivery, rejection, capacities, rating and flexibility) using complex adaptive systems will be a way of extending this study. Lastly, an improvement on the input-output model adopted for the production chain of buyers will be new direction for this research work.

In the last chapter of implementing Réseau, the analysis confirmed that a contract fosters the emergence of eco-industrial parks. This mechanism modifies how the symbiotic economic gives a win-win among the agents (Combined heat and power plant and wind turbine) engaging in contract, thereby enhancing their motivation to establish a synergy. An extension of this study can be the incorporation of other renewable resources and make a comparison of the one that has improved economic benefit among the different renewable resources while forming synergy in the industrial ecosystem.

7.3.2 Recommendations for Implementation

Based on the case studies in this research work , it is recommended that industrial entities strongly consider the use of agent-based modelling of eco-industrial park in order to understand their complexity and establish the benefits of eco-industrial integration. Such tools would underpin improvements in the economics and environmental performance of operations, proactively making improvements to processing in the eventual scenario of greater legislation on emissions of contaminants to air, water and land. In addition, this work serves to instruct policy-makers on the effect of price, demand and supply fluctuations to express the dynamic of IS/IES systems. More importantly, to estimate the impact of the different decision criteria between the demanding and supplying agents.

List of References

AISSANI, L., A. LACASSAGNE, J. B. BAHERS and S. L. FÉON. 2019. Life cycle assessment of industrial symbiosis: A critical review of relevant reference scenarios.

AKANDE, S. and G. AJISEGIRI. Performance Measure of Multipurpose Machine From Single Machine Units.

ALBINO, V., E. DIETZENBACHER and S. KÜHTZ. 2003. Analysing materials and energy flows in an industrial district using an enterprise input–output model. *Economic Systems Research,* **15**(4), pp.457-480.

ALBINO, V., L. FRACCASCIA and I. GIANNOCCARO. 2016. Exploring the role of contracts to support the emergence of self-organized industrial symbiosis networks: an agent-based simulation study. *Journal of cleaner production,* **112**, pp.4353-4366.

ALLENBY, B. R. and D. J. RICHARDS. 1994. *The greening of industrial ecosystems.* National Academies.

APPELS, L., J. LAUWERS, J. DEGRÈVE, L. HELSEN, B. LIEVENS, K. WILLEMS, J. VAN IMPE and R. DEWIL. 2011. Anaerobic digestion in global bio-energy production: Potential and research challenges. *Renewable and Sustainable Energy Reviews,* **15**(9), pp.4295-4301.

ASHTON, W. S. J. J. O. I. E. 2009. The structure, function, and evolution of a regional industrial ecosystem. **13**(2), pp.228-246.

AVISO, K. B., R. R. TAN, A. B. CULABA and J. B. CRUZ JR. 2011. Fuzzy input–output model for optimizing eco-industrial supply chains under water footprint constraints. *Journal of Cleaner Production,* **19**(2-3), pp.187-196.

AXELROD, R. M. 1997. *The complexity of cooperation: Agent-based models of competition and collaboration.* Princeton University Press.

AYRES, R. U., L. W. AYRES, P. FRANKL and L. W. AYRES. 1996. Industrial ecology: towards closing the materials cycle.

BAAS, L. W. and F. A. J. J. O. C. P. BOONS. 2004. An industrial ecology project in practice: exploring the boundaries of decision-making levels in regional industrial systems. **12**(8-10), pp.1073-1085.

BALCI, O. 1994. Validation, verification, and testing techniques throughout the life cycle of a simulation study. *Annals of operations research,* **53**(1), pp.121-173.

BATTEN, D. F. 2009. Fostering Industrial Symbiosis With Agent-Based Simulation and Participatory Modeling. *Journal of Industrial Ecology,* **13**(2), pp.197-213.

BERGLUND, M. and P. BÖRJESSON. 2006. Assessment of energy performance in the life-cycle of biogas production. *Biomass and Bioenergy,* **30**(3), pp.254-266.

BICHRAOUI, N., B. GUILLAUME and A. HALOG. 2013. Agent-based Modelling Simulation for the Development of an Industrial Symbiosis - Preliminary Results. *Procedia Environmental Sciences,* **17**, pp.195-204.

BOIX, M., L. MONTASTRUC, M. RAMOS, O. GENTILHOMME and S. DOMENECH. 2017. Benefits analysis of optimal design of eco-industrial parks through life cycle indicators. *27th European Symposium on Computer Aided Process Engineering, Pt B,* **40b**, pp.1951-1956.

BONABEAU, E. 2002. Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences of the United States of America,* **99**, pp.7280-7287.

BOONS, F. and M. BERENDS. 2001. Stretching the boundary: the possibilities of flexibility as an organizational capability in industrial ecology. *Business strategy and the environment,* **10**(2), pp.115-124.

BORSHCHEV, A. and A. FILIPPOV. 2004. From system dynamics and discrete event to practical agent based modeling: reasons, techniques, tools. *In: Proceedings of the 22nd international conference of the system dynamics society*.

BRUNDTLAND, G. H. 1987. *Report of the World Commission on environment and development:" our common future.".* United Nations.

BRUNNER, P. and H. RECHBERGER. Practical Handbook of Material Flow Analysis, 2004. *New York: Lewis,* **317**.

BURSTRÖM, F. and J. KORHONEN. 2001. Municipalities and industrial ecology: reconsidering municipal environmental management. *Sustainable Development,* **9**(1), pp.36-46.

CAO, K., X. FENG and H. WAN. 2009. Applying agent-based modeling to the evolution of eco-industrial systems. *Ecological Economics,* **68**(11), pp.2868-2876.

CARLEY, K. M. 1996. Validating computational models. *Paper available at http://www. casos. cs. cmu. edu/publications/papers. php*.

CATO, M. S. 2009. *Green economics: an introduction to theory, policy and practice.* Earthscan.

CHASSIN, D. P., S. BEHBOODI, C. CRAWFORD and N. DJILALI. 2015. Agent-based simulation for interconnection-scale renewable integration and demand response studies. *Engineering,* **1**(4), pp.422-435.

CHEESEMAN*, M., P. SWANN, G. HESKETH and S. BARNES. 2005. Adaptive manufacturing scheduling: a flexible and configurable agent-based prototype. *Production Planning & Control,* **16**(5), pp.479-487.

CHEN, X., C. KANG, M. O'MALLEY, Q. XIA, J. BAI, C. LIU, R. SUN, W. WANG and H. LI. 2015. Increasing the flexibility of combined heat and power for wind power integration in China: Modeling and implications. *IEEE Transactions on Power Systems,* **30**(4), pp.1848-1857.

CHERTOW, M. and J. EHRENFELD. 2012. Organizing Self-Organizing Systems. *Journal of Industrial Ecology,* **16**(1), pp.13-27.

CHERTOW, M. R. 2000. Industrial symbiosis: literature and taxonomy. *Annual review of energy and the environment,* **25**(1), pp.313-337.

CHERTOW, M. R. 2004. Industrial symbiosis. *Encyclopedia of energy,* **3**, pp.407-415.

CHERTOW, M. R. 2007. “Uncovering” industrial symbiosis. *Journal of Industrial Ecology,* **11**(1), pp.11-30.

CHRIST, C. F. 1955. A review of input-output analysis. *Input-Output Analysis: An Appraisal.* Princeton University Press, pp.137-182.

COMER, K. W. 2014. *Who Goes First? An Examination of the Impact of Activation on Outcome Behavior in Agent-based Models*. thesis, George Mason University.

COOPER, S. J. and G. P. HAMMOND. 2018. ‘Decarbonising’UK industry: towards a cleaner economy. *Proceedings of the Institution of Civil Engineers–Energy,* **171**(4), pp.147-157.

COTE, R. and J. HALL. 1995. Industrial parks as ecosystems. *Journal of Cleaner production,* **3**(1-2), pp.41-46.

CÔTÉ, R. P. and E. COHEN-ROSENTHAL. 1998. Designing eco-industrial parks: a synthesis of some experiences. *Journal of cleaner production,* **6**(3-4), pp.181-188.

CURRAN, M. A. 1994. *Life cycle assessment*. National Institute of Standards and Technology, Gaithersburg, MD (United States).

DADDI, T., B. NUCCI and F. IRALDO. 2017. Using Life Cycle Assessment (LCA) to measure the environmental benefits of industrial symbiosis in an industrial cluster of SMEs. *Journal of Cleaner Production,* **147**, pp.157-164.

DIJKEMA, G. P. and L. BASSON. 2009. Complexity and industrial ecology. *Journal of Industrial Ecology,* **13**(2), pp.157-164.

DONG, L., H. W. LIANG, L. G. ZHANG, Z. W. LIU, Z. Q. GAO and M. M. HU. 2017. Highlighting regional eco-industrial development: Life cycle benefits of an urban industrial symbiosis and implications in China. *Ecological Modelling,* **361**, pp.164-176.

DUAN, L. S. and J. A. VENTURA. 2019. A Dynamic Supplier Selection and Inventory Management Model for a Serial Supply Chain with a Novel Supplier Price Break Scheme and Flexible Time Periods. *European Journal of Operational Research,* **272**(3), pp.979-998.

EDWARDS, D. W. 2010. *Energy trading & investing: Trading, risk management, and structuring deals in the energy markets.* McGraw-Hill.

EHRENFELD, J. 1995. Industrial Ecology-A strategic framework for product policy and other sustainable practices.

EHRENFELD, J. and N. GERTLER. 1997. Industrial ecology in practice: the evolution of interdependence at Kalundborg. *Journal of industrial Ecology,* **1**(1), pp.67-79.

FELICIO, M., D. AMARAL, K. ESPOSTO and X. G. DURANY. 2016. Industrial symbiosis indicators to manage eco-industrial parks as dynamic systems. *Journal of Cleaner Production,* **118**, pp.54-64.

FIKSEL, J. 2003. Designing resilient, sustainable systems. *Environmental science & technology,* **37**(23), pp.5330-5339.

FINNVEDEN, G., M. Z. HAUSCHILD, T. EKVALL, J. GUINEE, R. HEIJUNGS, S. HELLWEG, A. KOEHLER, D. PENNINGTON and S. SUH. 2009. Recent developments in life cycle assessment. *Journal of environmental management,* **91**(1), pp.1-21.

FRACCASCIA, L. 2019. The impact of technical and economic disruptions in industrial symbiosis relationships: An Enterprise Input-Output approach.

FRACCASCIA, L., V. ALBINO and C. A. GARAVELLI. 2017. Technical efficiency measures of industrial symbiosis networks using enterprise input-output analysis. *International Journal of Production Economics,* **183**, pp.273-286.

FROSCH, R. A. and N. E. GALLOPOULOS. 1989. Strategies for manufacturing. *Scientific American,* **261**(3), pp.144-152.

GARG, A., R. SMITH, D. HILL, P. J. LONGHURST, S. J. T. POLLARD and N. J. SIMMS. 2009. An integrated appraisal of energy recovery options in the United Kingdom using solid recovered fuel derived from municipal solid waste. *Waste Management,* **29**(8), pp.2289-2297.

GELL-MANN, M. 1994. Complex adaptive systems.

GENG, Y., P. ZHANG, R. P. CÔTÉ and T. FUJITA. 2009. Assessment of the national eco-industrial park standard for promoting industrial symbiosis in China. *Journal of Industrial Ecology,* **13**(1), pp.15-26.

GHALI, M. R., J.-M. FRAYRET and C. AHABCHANE. 2017. Agent-Based Model of Self-Organized Industrial Symbiosis.

GIANNOCCARO, H. and P. PONTRANDOLFO. 2004. Supply chain coordination by revenue sharing contract. *International Journal of Production Economics,* **92**(3), pp.297-297.

GIBBS, D. 2003. Trust and networking in inter-firm relations: the case of eco-industrial development. *Local economy,* **18**(3), pp.222-236.

GIBBS, D. 2008. Industrial Symbiosis and Eco-Industrial Development: An Introduction. *Geography Compass,* **2**(4), pp.1138-1154.

GIBBS, D., P. DEUTZ and A. PROCTOR. 2005. Industrial ecology and eco-industrial development: A potential paradigm for local and regional development? *Regional Studies,* **39**(2), pp.171-183.

GLAVIČ, P. and R. LUKMAN. 2007. Review of sustainability terms and their definitions. **15**(18), pp.1875-1885.

GONELA, V. 2013. Stochastic Optimization of Sustainable Industrial Symbiosis Based Hybrid Generation Bioethanol Supply Chains. *A dissertation submitted to the Graduate Faculty of the North Dakota State University of Agriculture and Applied Science*.

GONELA, V. and J. ZHANG. 2014. Design of the optimal industrial symbiosis system to improve bioethanol production. *Journal of Cleaner Production,* **64**, pp.513-534.

GOVINDAN, K., M. N. POPIUC and A. DIABAT. 2013. Overview of coordination contracts within forward and reverse supply chains. *Journal of Cleaner Production,* **47**, pp.319-334.

GRIMM, V., U. BERGER, F. BASTIANSEN, S. ELIASSEN, V. GINOT, J. GISKE, J. GOSS-CUSTARD, T. GRAND, S. K. HEINZ, G. HUSE, A. HUTH, J. U. JEPSEN, C. JØRGENSEN, W. M. MOOIJ, B. MÜLLER, G. PE'ER, C. PIOU, S. F. RAILSBACK, A. M. ROBBINS, M. M. ROBBINS, E. ROSSMANITH, N. RÜGER, E. STRAND, S. SOUISSI, R. A. STILLMAN, R. VABØ, U. VISSER and D. L. DEANGELIS. 2006. A standard protocol for describing individual-based and agent-based models. *Ecological Modelling,* **198**(1), pp.115-126.

GRIMM, V., U. BERGER, D. L. DEANGELIS, J. G. POLHILL, J. GISKE and S. F. RAILSBACK. 2010. The ODD protocol: A review and first update. *Ecological Modelling,* **221**(23), pp.2760-2768.

HAMMOND, G. P. 2007. Industrial energy analysis, thermodynamics and sustainability. *Applied Energy,* **84**(7-8), pp.675-700.

HARDY, C. and T. E. GRAEDEL. 2002. Industrial ecosystems as food webs. *Journal of Industrial Ecology,* **6**(1), pp.29-38.

HEERES, R., W. J. VERMEULEN and F. DE WALLE. 2004. Eco-industrial park initiatives in the USA and the Netherlands: first lessons. *Journal of Cleaner Production,* **12**(8), pp.985-995.

HENDRIKS, C., R. OBERNOSTERER, D. MÜLLER, S. KYTZIA, P. BACCINI and P. H. BRUNNER. 2000. Material flow analysis: a tool to support environmental policy decision making. Case-studies on the city of Vienna and the Swiss lowlands. *Local Environment,* **5**(3), pp.311-328.

HERCZEG, G., R. AKKERMAN and M. Z. J. J. O. C. P. HAUSCHILD. 2018. Supply chain collaboration in industrial symbiosis networks. **171**, pp.1058-1067.

HOLLAND, J. H. 1992. Complex adaptive systems. *Daedalus*, pp.17-30.

HUO, C. H. and L. H. CHAI. 2008. Physical principles and simulations on the structural evolution of eco-industrial systems. **16**(18), pp.1995-2005.

INTERNATIONAL ORGANIZATION FOR STANDARDIZATION. 2006. *Environmental Management: Life Cycle Assessment; Requirements and Guidelines.* ISO.

JACOBSEN, N. B. 2006. Industrial symbiosis in Kalundborg, Denmark: a quantitative assessment of economic and environmental aspects. *Journal of Industrial Ecology,* **10**(1-2), pp.239-255.

JENNINGS, N. R., K. SYCARA and M. WOOLDRIDGE. 1998. A roadmap of agent research and development. *Autonomous agents and multi-agent systems,* **1**(1), pp.7-38.

JIMÉNEZ-GONZÁLEZ, C., S. KIM and M. R. OVERCASH. 2000. Methodology for developing gate-to-gate life cycle inventory information. *The International Journal of Life Cycle Assessment,* **5**(3), pp.153-159.

JOVANE, F., H. YOSHIKAWA, L. ALTING, C. BOËR, E. WESTKAMPER, D. WILLIAMS, M. TSENG, G. SELIGER and A. PACI. 2008. The incoming global technological and industrial revolution towards competitive sustainable manufacturing. *CIRP Annals-Manufacturing Technology,* **57**(2), pp.641-659.

KAMM, B. and M. KAMM. 2004. Principles of biorefineries. *Applied microbiology and biotechnology,* **64**(2), pp.137-145.

KARLSSON, M. and A. WOLF. 2008. Using an optimization model to evaluate the economic benefits of industrial symbiosis in the forest industry. *Journal of Cleaner Production,* **16**(14), pp.1536-1544.

KAUFFMAN, S. 1995. *At Home in the Universe: the Search for Laws of Self Organization and Complexity Viking*. London.

KIM, H., J.-H. RYU and I.-B. LEE. 2012. Development of an agent-based modeling methodology for an industrial byproduct exchange network design. *Industrial & Engineering Chemistry Research,* **51**(33), pp.10860-10868.

KLÖPFFER, W. 1997. Life cycle assessment. *Environmental Science and Pollution Research,* **4**(4), pp.223-228.

KLÜGL, F. 2008. A validation methodology for agent-based simulations. *In: Proceedings of the 2008 ACM symposium on Applied computing*: ACM, pp.39-43.

KOMMISSION, E. 2001. *Economy-wide material flow accounts and derived indicators: a methodological guide.* Office for Official Publ. of the Europ. Comm.

KORHONEN, J. 2000. Industrial ecosystem: using the material and energy flow model of an ecosystem in an industrial system.

KORHONEN, J. 2001a. Co-production of heat and power: an anchor tenant of a regional industrial ecosystem. *Journal of Cleaner Production,* **9**(6), pp.509-517.

KORHONEN, J. 2001b. Four ecosystem principles for an industrial ecosystem. *Journal of Cleaner Production,* **9**(3), pp.253-259.

KORHONEN, J. 2002. Two paths to industrial ecology: applying the product-based and geographical approaches. *Journal of Environmental Planning and Management,* **45**(1), pp.39-57.

KORHONEN, J. 2003. Should we measure corporate social responsibility? **10**(1), pp.25-39.

KORHONEN, J. 2004. Industrial ecology in the strategic sustainable development model: strategic applications of industrial ecology. *Journal of Cleaner Production,* **12**(8), pp.809-823.

KORHONEN, J. and J.-P. SNÄKIN. 2003. Industrial ecosystem evolution of North Karelia heating energy system. *Regional Environmental Change,* **3**(4), pp.128-139.

KORHONEN, J. and J. SNAKIN. 2001. An anchor tenant approach to network management: considering regional material and energy flow networks. *International Journal of Environmental Technology and Management,* **1**(4), pp.444-463.

LANSING, J. S. 2003. Complex adaptive systems. *Annual review of anthropology,* **32**(1), pp.183-204.

LANSING, S., R. B. BOTERO and J. F. MARTIN. 2008. Waste treatment and biogas quality in small-scale agricultural digesters. *Bioresource technology,* **99**(13), pp.5881-5890.

LEONTIEF, W. 1970. Environmental repercussions and the economic structure: an input-output approach. *The review of economics and statistics*, pp.262-271.

LEONTIEF, W. and D. FORD. 1972. Air pollution and the economic structure: empirical results of input-output computations. *Input-output techniques*, pp.9-30.

LEVIN, S. A. 1998. Ecosystems and the Biosphere as Complex Adaptive Systems. *Ecosystems,* **1**(5), pp.431-436.

LIN, X. and K. R. POLENSKE. 1998. Input—output modeling of production processes for business management. *Structural Change and Economic Dynamics,* **9**(2), pp.205-226.

LIU, Q., P. JIANG, J. ZHAO, B. ZHANG, H. BIAN and G. QIAN. 2011. Life cycle assessment of an industrial symbiosis based on energy recovery from dried sludge and used oil. **19**(15), pp.1700-1708.

LOMBARDI, D. and P. LAYBOURN. 2006. Industrial symbiosis in action. *In: Report on the third international industrial symbiosis research symposium, Birmingham, England*.

LORENZ, T. and A. JOST. 2006. Towards an orientation framework in multi-paradigm modeling. *In: Proceedings of the 24th International Conference of the System Dynamics society*: System Dynamics Society Albany, NY, pp.1-18.

LOVINS, A. B., L. H. LOVINS and P. HAWKEN. 1999. A road map for natural capitalism.

LOWE, E. A. 1997. Creating by-product resource exchanges: strategies for eco-industrial parks. *Journal of cleaner production,* **5**(1-2), pp.57-65.

LOWE, E. A. and L. K. EVANS. 1995. Industrial ecology and industrial ecosystems. *Journal of cleaner production,* **3**(1-2), pp.47-53.

LUND, H. 2005. Large-scale integration of wind power into different energy systems. *Energy,* **30**(13), pp.2402-2412.

LUND, H. and W. W. CLARK. 2002. Management of fluctuations in wind power and CHP comparing two possible Danish strategies. *Energy,* **27**(5), pp.471-483.

LUND, H., B. MOLLER, B. V. MATHIESEN and A. DYRELUND. 2010. The role of district heating in future renewable energy systems. *Energy,* **35**(3), pp.1381-1390.

MA, L., S. Y. LUAN, C. W. JIANG, H. L. LIU and Y. ZHANG. 2009. A review on the forecasting of wind speed and generated power. *Renewable & Sustainable Energy Reviews,* **13**(4), pp.915-920.

MARTIN, M., J. IVNER, N. SVENSSON and M. EKLUND. 2009. Classification of Industrial Symbiosis Synergies:: Application in the Biofuels Industry. *In: Industrial Symbiosis and Eco-Industrial Parks*: GIN 2009, p.2394.

MASAD, D. and J. KAZIL. 2015. MESA: an agent-based modeling framework. *In: 14th PYTHON in Science Conference*, pp.53-60.

MATTILA, T. J., S. PAKARINEN and L. SOKKA. 2010. Quantifying the total environmental impacts of an industrial symbiosis-a comparison of process-, hybrid and input− output life cycle assessment. *Environmental science & technology,* **44**(11), pp.4309-4314.

MAYNARD SMITH, J. 1995. Life at the edge of chaos. *The New York review of books,* **42**(2), pp.28-30.

MET OFFICE. 2010. Met Office Integrated Data Archive System (MIDAS) Land and Marine Surface Stations Data (1853-current). NCAS British Atmospheric Data Centre.

MIRATA, M. 2004. Experiences from early stages of a national industrial symbiosis programme in the UK: determinants and coordination challenges. *Journal of Cleaner Production,* **12**(8), pp.967-983.

MIRATA, M. and T. EMTAIRAH. 2005. Industrial symbiosis networks and the contribution to environmental innovation: The case of the Landskrona industrial symbiosis programme. *Journal of Cleaner Production,* **13**(10–11), pp.993-1002.

MIRATA, M. and R. PEARCE. 2006. Industrial symbiosis in the UK. pp.77-105.

NARASIMHAN, R. and S. TALLURI. 2009. Perspectives on risk management in supply chains. *Journal of Operations Management,* **27**(2), pp.114-118.

NILSSON, F. 2005. *Adaptive logistics: using complexity theory to facilitate increased effectiveness in logistics.* Lund University Lund.

NILSSON, F. and V. DARLEY. 2006. On complex adaptive systems and agent-based modelling for improving decision-making in manufacturing and logistics settings: Experiences from a packaging company. **26**(12), pp.1351-1373.

OBAMA, B. 2017. The irreversible momentum of clean energy. *Science,* **355**(6321), pp.126-129.

OZLU, S. and I. DINCER. 2015. Development and analysis of a solar and wind energy based multigeneration system. *Solar Energy,* **122**, pp.1279-1295.

PAL, O., A. K. GUPTA, R. J. I. J. O. S. GARG, MANAGEMENT, ECONOMICS and B. ENGINEERING. 2013. Supplier selection criteria and methods in supply chains: A review. **7**(10), pp.1403-1409.

PARK, H.-S. and S. K. BEHERA. 2014. Methodological aspects of applying eco-efficiency indicators to industrial symbiosis networks. *Journal of Cleaner Production,* **64**, pp.478-485.

POSCHL, M., S. WARD and P. OWENDE. 2010. Evaluation of energy efficiency of various biogas production and utilization pathways. *Applied Energy,* **87**(11), pp.3305-3321.

QDR, Q. 2006. Benefits of demand response in electricity markets and recommendations for achieving them. *US Dept. Energy, Washington, DC, USA, Tech. Rep*.

RAMMEL, C., S. STAGL and H. WILFING. 2007. Managing complex adaptive systems — A co-evolutionary perspective on natural resource management. *Ecological Economics,* **63**(1), pp.9-21.

RAMOS, T. B. and S. CAEIRO. 2010. Meta-performance evaluation of sustainability indicators. *Ecological Indicators,* **10**(2), pp.157-166.

RAO, Y., M. ZHOU, C. CAO, S. TAN, Y. SONG, Z. ZHANG, D. DAI, G. OU, L. ZHANG and X. NIE. 2019. Exploring the quantitive relationship between economic benefit and environmental constraint using an inexact chance-constrained fuzzy programming based industrial structure optimization model. pp.1-22.

REAP, J., F. ROMAN, S. DUNCAN and B. BRAS. 2008. A survey of unresolved problems in life cycle assessment. *The International Journal of Life Cycle Assessment,* **13**(5), pp.374-388.

RICHIARDI, M. G., R. LEOMBRUNI, N. J. SAAM and M. SONNESSA. 2006. A common protocol for agent-based social simulation. *Journal of artificial societies and social simulation,* **9**.

ROBÈRT, K. H., B. SCHMIDT-BLEEK, J. ALOISI DE LARDEREL, G. BASILE, J. L. JANSEN, R. KUEHR, P. PRICE THOMAS, M. SUZUKI, P. HAWKEN and M. WACKERNAGEL. 2002. Strategic sustainable development — selection, design and synergies of applied tools. *Journal of Cleaner Production,* **10**(3), pp.197-214.

ROBINSON, D. T., D. G. BROWN, D. C. PARKER, P. SCHREINEMACHERS, M. A. JANSSEN, M. HUIGEN, H. WITTMER, N. GOTTS, P. PROMBUROM, E. IRWIN, T. BERGER, F. GATZWEILER and C. BARNAUD. 2007. Comparison of empirical methods for building agent-based models in land use science. *Journal of Land Use Science,* **2**(1), pp.31-55.

ROMERO, E. and M. C. RUIZ. 2013. Framework for Applying a Complex Adaptive System Approach to Model the Operation of Eco-Industrial Parks. *Journal of Industrial Ecology,* **17**(5), pp.731-741.

ROMERO, E. and M. C. RUIZ. 2014. Proposal of an agent-based analytical model to convert industrial areas in industrial eco-systems. *Science of the Total Environment,* **468**, pp.394-405.

SAHA, S. and V. MUKHERJEE. 2019. A novel multiobjective chaotic symbiotic organisms search algorithm to solve optimal DG allocation problem in radial distribution system. pe2839.

SAMPER, A. and J. A. SCHWARTZ. 2013. Price Inferences for Sacred versus Secular Goods: Changing the Price of Medicine Influences Perceived Health Risk. *Journal of Consumer Research,* **39**(6), pp.1343-1358.

SCHWARZ, E. J. and K. W. STEININGER. 1997. Implementing nature's lesson: the industrial recycling network enhancing regional development. *Journal of Cleaner Production,* **5**(1), pp.47-56.

SENDRA, C., X. GABARRELL and T. VICENT. 2007. Material flow analysis adapted to an industrial area. *Journal of Cleaner Production,* **15**(17), pp.1706-1715.

SIMEONI, P., G. CIOTTI, C. MATTIA and A. MENEGHETTI. 2019. Integrating industrial waste heat recovery into sustainable smart energy systems.

SINGH, R. K., H. R. MURTY, S. K. GUPTA and A. K. DIKSHIT. 2009. An overview of sustainability assessment methodologies. *Ecological Indicators,* **9**(2), pp.189-212.

SOPHA, B. M., A. M. FET, M. M. KEITSCH and C. HASKINS. 2010. Using Systems Engineering to Create a Framework for Evaluating Industrial Symbiosis Options. *Systems Engineering,* **13**(2), pp.149-160.

SPRINGER, T. M. 1996. Single-family housing transactions: Seller motivations, price, and marketing time. *Journal of Real Estate Finance and Economics,* **13**(3), pp.237-254.

STERMAN, J. D. 2000. *Business dynamics: systems thinking and modeling for a complex world.*

STERN, J. 2012. *The pricing of internationally traded gas.* Oxford University Press.

SUH, S. and S. KAGAWA. 2005. Industrial ecology and input-output economics: an introduction. *Economic Systems Research,* **17**(4), pp.349-364.

SULLIVAN, E. J. and T. M. WEITHERS. 1991. Louis Bachelier: The father of modern option pricing theory. *The Journal of Economic Education,* **22**(2), pp.165-171.

SUN, L., H. LI, L. DONG, K. FANG, J. REN, Y. GENG, M. FUJII, W. ZHANG, N. ZHANG, Z. LIU and RECYCLING. 2017. Eco-benefits assessment on urban industrial symbiosis based on material flows analysis and emergy evaluation approach: a case of Liuzhou city, China. **119**, pp.78-88.

TAN, R. R., K. B. AVISO, M. A. B. PROMENTILLA, K. D. S. YU and J. R. SANTOS. 2019. Input–Output Models of Industrial Complexes. *Input-Output Models for Sustainable Industrial Systems.* Springer, pp.47-62.

TANG, C. S. 2006. Perspectives in supply chain risk management. *International Journal of Production Economics,* **103**(2), pp.451-488.

TAO, Y., S. EVANS, Z. WEN and M. J. J. O. C. P. MA. 2019. The influence of policy on industrial symbiosis from the Firm's perspective: A framework. **213**, pp.1172-1187.

TIBBS, H. B. 1992. Industrial ecology—an agenda for environmental management. *Pollution prevention review,* **2**(2), pp.167-180.

TIEJUN, D. 2010. Two quantitative indices for the planning and evaluation of eco-industrial parks. *Resources, Conservation and Recycling,* **54**(7), pp.442-448.

UTOMO, D., B. S. S. ONGGO and S. ELDRIDGE. 2016. Deductive and inductive data collection for agent-based modelling: A Comparative Study using a Dairy Supply Chain Case. *In: Social Simulation Conference 2016*.

VAN BERKEL, R. and M. LAFLEUR. 1997. Application of an industrial ecology toolbox for the introduction of industrial ecology in enterprises—II. *Journal of Cleaner Production,* **5**(1–2), pp.27-37.

VAN BERKEL, R., E. WILLEMS and M. LAFLEUR. 1997. Development of an industrial ecology toolbox for the introduction of industrial ecology in enterprises—I. *Journal of Cleaner Production,* **5**(1), pp.11-25.

VEIGA, L. B. E. and A. MAGRINI. 2009. Eco-industrial park development in Rio de Janeiro, Brazil: a tool for sustainable development. *Journal of Cleaner Production,* **17**(7), pp.653-661.

VELENTURF, A. P. 2017. Initiating resource partnerships for industrial symbiosis. **4**(1), pp.117-124.

WANG, L. and C. SINGH. 2009. Multicriteria design of hybrid power generation systems based on a modified particle swarm optimization algorithm. *IEEE Transactions on Energy Conversion,* **24**(1), pp.163-172.

WANG, Y.-J. and Z. MA. 2019. Symbiotic Organisms Search Algorithm Based on Asynchronous Change Learning Strategy. *Recent Developments in Intelligent Computing, Communication and Devices.* Springer, pp.283-290.

WHITING, A. and A. AZAPAGIC. 2014. Life cycle environmental impacts of generating electricity and heat from biogas produced by anaerobic digestion. *Energy,* **70**, pp.181-193.

WOLF, A. and M. KARLSSON. 2008. Evaluating the environmental benefits of industrial symbiosis: discussion and demonstration of a new approach. *Progress in Industrial Ecology, an International Journal,* **5**(5-6), pp.502-517.

YAZAN, D. M. and L. FRACCASCIA. 2019. Sustainable operations of industrial symbiosis: an enterprise input-output model integrated by agent-based simulation. pp.1-23.

YAZAN, D. M., V. A. ROMANO and V. ALBINO. 2016. The design of industrial symbiosis: an input–output approach. *Journal of Cleaner Production,* **129**, pp.537-547.

ZEIGLER, B. P., T. G. KIM and H. PRAEHOFER. 2000. *Theory of modeling and simulation.* Academic press.

ZHANG, Y., S. S. DUAN, J. H. LI, S. SHAO, W. Q. WANG and S. S. ZHANG. 2017. Life cycle assessment of industrial symbiosis in Songmudao chemical industrial park, Dalian, China. *Journal of Cleaner Production,* **158**, pp.192-199.

ZHENG, K. and S. JIA. 2017. Promoting the Opportunity Identification of Industrial Symbiosis: Agent-Based Modeling Inspired by Innovation Diffusion Theory. *Sustainability,* **9**(5), p765.

ZHOU, Z. 2005. *Study on the complex adaptive system of eco-industrial systems*. thesis, Ph. D. Thesis, Department of Chemical Engineering, Beijing: Tsinghua University.

ZITZLER, E. and L. THIELE. 1999. Multiobjective evolutionary algorithms: a comparative case study and the strength Pareto approach. *IEEE transactions on Evolutionary Computation,* **3**(4), pp.257-271.

Appendix

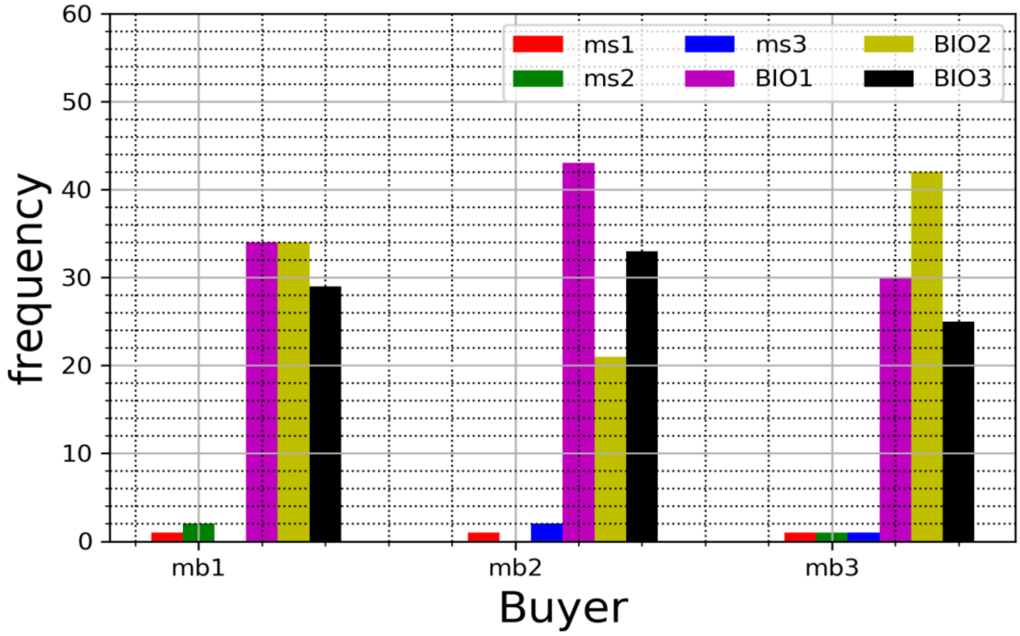
A.1 Agents attributes in an industrial ecosystem

	Factory agent	Market Buyer agent	Market seller agent
Objective	Maximize profit	Meet demand at minimum cost	Supply the factory with materials
Attribute	Price, cost, production capacity, investment, raw material, raw material name, product name, factory name, inventory, raw material demand, production level, demand, supply, location point (x,y) etc.	Infinite demand	Infinite supply of raw materials,
Behaviour	Determine the price of outputs, calculate profit, calculate inventory	Determine the demand and consume products	Supply the raw material, determine price

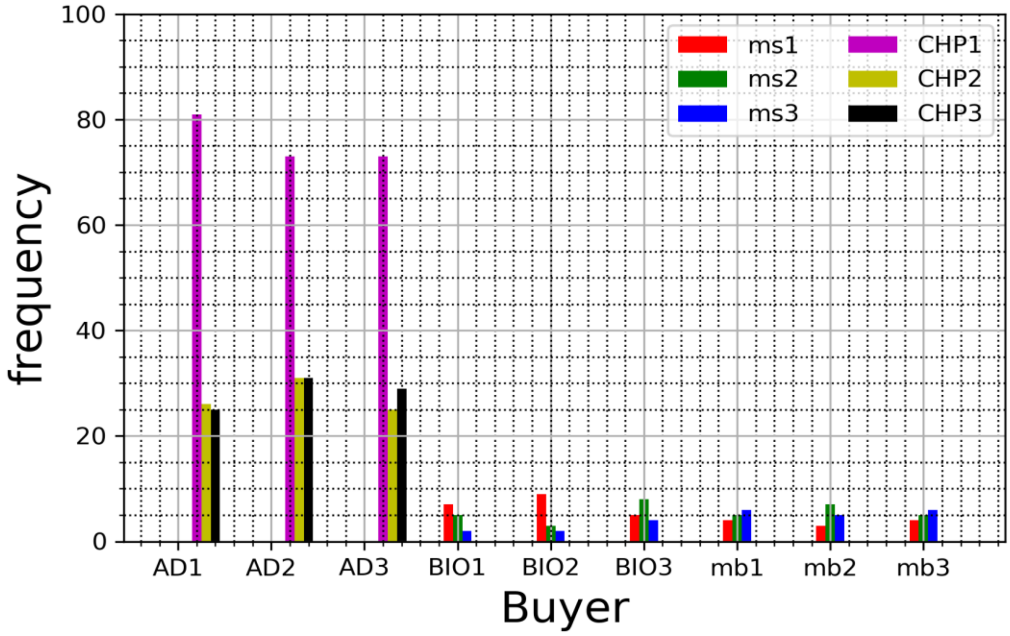
A.2 Sample Input data for single input single output problem

Agent Type	Agent Name	Material Type	Material Name	Material Stock	Qty	Product Type	Product Name	Product Price	Value	Bank Account	Value	X-Co-ord	Value	Y-Co-ord	Value
Factory	CHP1	Rm Name	Biogas	Rm Stock	1710	Prd Name	Heat	Prd price	0.75	Account balance	1084	Xaxis	1	Yaxis	5
Factory	CHP2	Rm Name	Biogas	Rm Stock	2500	Prd Name	Heat	Prd price	0.70	Account balance	1132	Xaxis	2	Yaxis	7
Factory	CHP3	Rm Name	Biogas	Rm Stock	2100	Prd Name	Heat	Prd price	0.73	Account balance	1090	Xaxis	4	Yaxis	4
Factory	AD1	Rm Name	Heat	Rm Stock	405	Prd Name	Biogas	Prd price	4.60	Account balance	1183	Xaxis	1	Yaxis	4
Factory	AD2	Rm Name	Heat	Rm Stock	640	Prd Name	Biogas	Prd price	4.10	Account balance	1062	Xaxis	6	Yaxis	12
Factory	AD2	Rm Name	Heat	Rm Stock	560	Prd Name	Biogas	Prd price	4.40	Account balance	1079	Xaxis	9	Yaxis	4
MSeller	MS1					Prd Name	Biogas	Prd price	4.70	Account balance	10009	Xaxis	2	Yaxis	10
MSeller	MS2					Prd Name	Biogas	Prd price	4.80	Account balance	10002	Xaxis	4	Yaxis	10
Mseller	MS3					Prd Name	Biogas	Prd price	4.75	Account balance	10043	Xaxis	7	Yaxis	7
MBuyer	MB1	Rm Name								Account balance	1146	Xaxis	8	Yaxis	7
MBuyer	MB2	Rm Name								Account balance	1166	Xaxis	1	Yaxis	9
MBuyer	MB3	Rm Name								Account balance	953	Xaxis	8	Yaxis	3

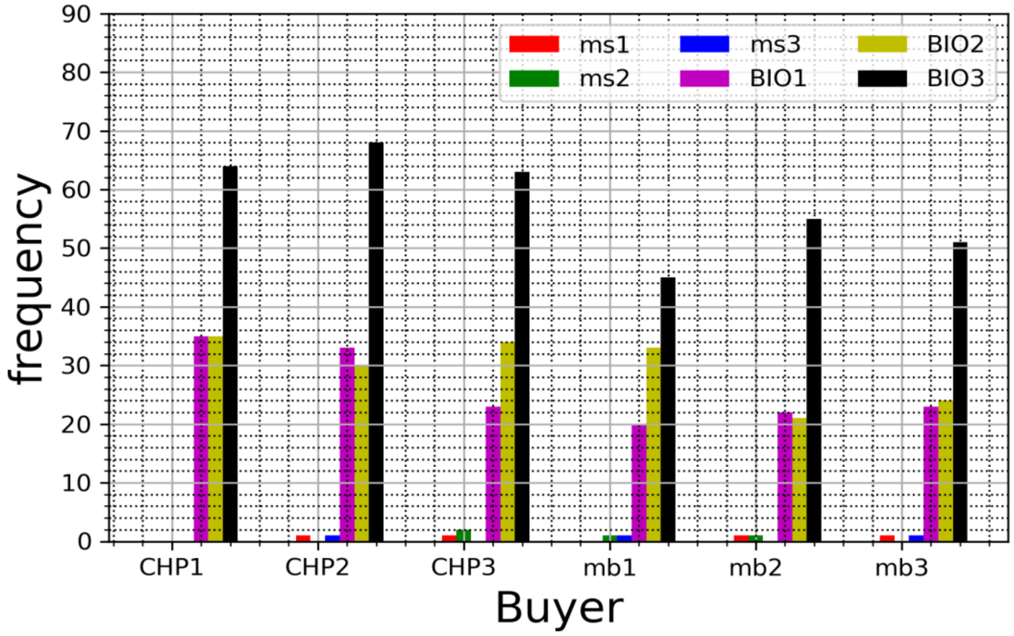
A.3 Sample Input data for single input single output problem



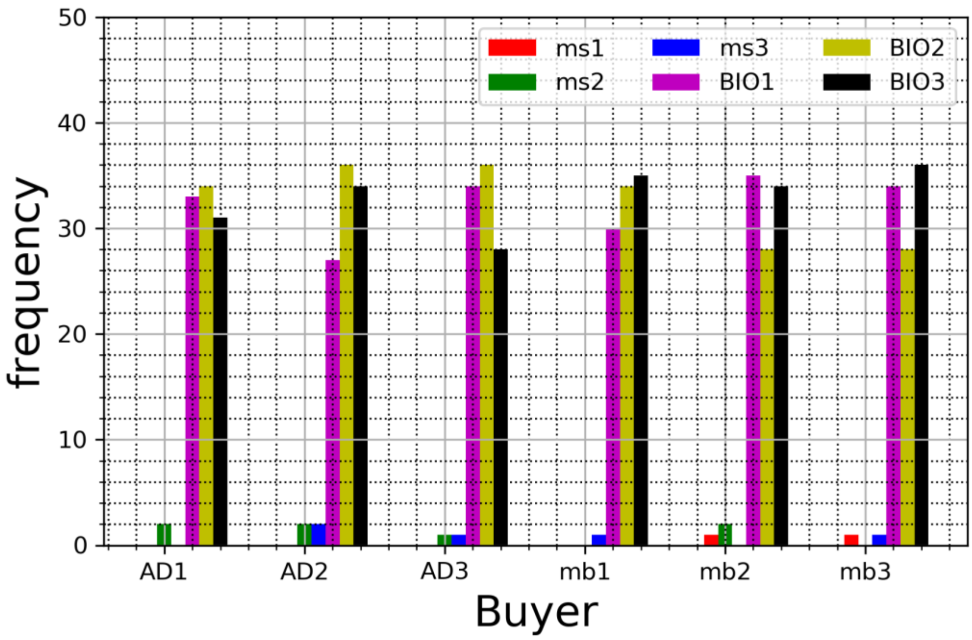
No of times buyers (market buyers) buy ethanol from sellers (market sellers and Bio-refinery). Ethanol is only sold to the external environment of the ecosystem since ethanol is not a by-product



No of times buyers (market buyers and factories) buy ethanol from sellers (market sellers and CHPs). Process steam is a by-product and more of it was bought by ADs compared to other buyers in the ecosystem.

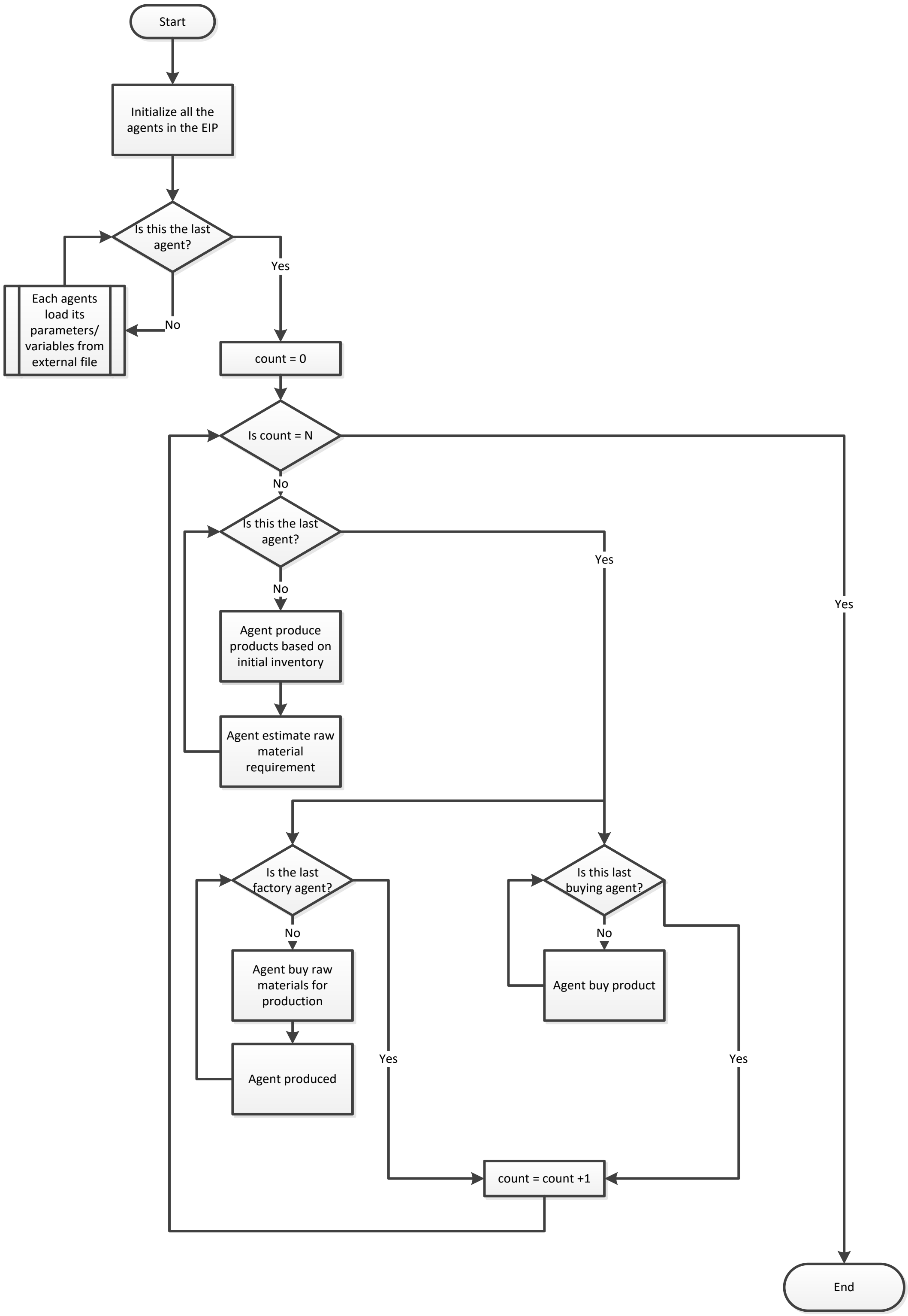


No of times buyers (market buyers and factories) buy lignin pellet from sellers (market sellers and BIOs). Lignin pellet is a by-product from BIOs and more of it was bought by CHPs compared to other buyers in the ecosystem.



No of times buyers (market buyers and factories) buy distilled dry grain (DDG) from sellers (market sellers and BIOs). DDG is a by-product from BIOs and more of it was bought by ADs compared to other buyers in the ecosystem.

A.4 Reseau EIP Logic Flow



Réseau-EIP Model Logic Flow

A.5 Reseau Sample Code

```
=====Reseau.py=====
import xlrd
from reseau.buyer import Buyer
from reseau.seller import Seller
from reseau.factory import Factory
from reseau.history import Histories
from reseau.wind import Wind
from utils.Slate import SLatefilenew, Slatefileclose, Slate,
comment
from utils.reporter import Reporter
from datetime import datetime
import timeit

start =datetime.now()
starttime=timeit.default_timer()
xl_workbook=xlrd.open_workbook("reseau
multipleInputoutputContract.xlsx")
sheet_names = xl_workbook.sheet_names()

SLatefilenew('EIP Output');
Slate("Comments")
DEBUG= False

condition = 'riskbased'
"""seller parameter to make decision on how to set it's selling
price either randomly or riskbased"""

selection_method = 'chepestprice'
"""buyer parameter to make the decision on how to buy from the
seller
 the decision criteria are five. these are:

 random
 cheapestprice
 cost
 trust
 experience"""

class System(object):
 def __init__(self,c):
```

```
self._count=c
self.factories=[]
self.sellers=[]
self.buyers=[]
self.agents=[]
self.winds=[]
self.details=[]
for r in sheet_names:
ab=xl_workbook.sheet_by_name(r)
for t in range(0,ab.nrows):
row = ab.row_values(t)
a=list(filter(None,row))

if a[0] =='finished':
break


elif a[0].lower() =='factory':
agent=Factory(self,a[1])
self.factories.append(agent)
self.buyers.append(agent)
self.sellers.append(agent)
self.agents.append(agent)


elif a[0].lower() =='wind':
agent=Wind(self,a[1])
self.winds.append(agent)
self.agents.append(agent)

elif a[0].lower() =='mseller':
agent=Seller(self,a[1])
self.sellers.append(agent)
self.agents.append(agent)

elif a[0].lower() =='mbuyer':
agent=Buyer(self,a[1])
self.buyers.append(agent)
self.agents.append(agent)
```

```
for i in range(0,len(a)-1,2):
agent.LoadParam(a[i],a[i+1])

for agent in self.buyers:
for contract in agent.contracts:
contract.activated

self.histories=Histories(self)

self.Transactionreporter=Reporter(self.sellers[0].gettransaction("
materialX"),"Transactions")

self.Contractreporter=Reporter(self.winds[0].get_contract("materia
lX"),"Contracts")

@property
def count(self):
return self._count

@count.setter
def count(self,value):
self._count=value

def run(self,step_count=0):
if DEBUG:comment("Market Suppliers")
if DEBUG:comment()
if DEBUG:comment("Market Buyers")
for agent in self.agents:
comment (agent.name)
agent.writeheader()



comment("=========","=========","=========","START
RUN","=========","=========","=========")
for i in range(step_count):
self.cycle()
comment("=========","=========","=========","END
RUN","=========","=========","=========")

#system period
def cycle(self):
self.count+=1
```

```
comment("=========","=========","=========","Cycle",self.count,"==
=======","=========",)
 """Generate buyers and sellers to estimate their """
 for agent in self.agents:
 agent.ProductionStep()
 agent.PredictRequirements(condition)
 for agent in self.buyers:
 agent.ExcecuteContracts()
 for agent in self.buyers:
 agent.BuyRM(self.sellers,selection_method)
 self.histories.collateall()
 for agent in self.agents:
 agent.Report()
 if DEBUG:comment("End of Cycle: ",self.count)

comment("Seller's decision is by ==>", condition,)
comment("Buyer's decision is by ==>", selection_method,)

comment("debug",not True)
sys=System(0)

if __name__ == "__main__":
 sys.run(100)
 Slatefileclose()

stoptime=timeit.default_timer()
stop=datetime.now()
print('Programme runtime is: ', stoptime - starttime)
print('Programme runtime is: ',"--- %s seconds ---" % (stop -start))
```