Multi-Agent Analysis of Industrial Networks:

A South African Bio-Energy Case Study

René Malan

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Declaration

I know the meaning of plagiarism and declare that all the work in the document, save for that which is properly acknowledged, is my own.

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Abstract

Industrial networks are complex structures consisting of multiple interacting enterprises, differing in nature, each with independent (often conflicting) objectives, producing numerous, possibly competing products. These networks play an important role in meeting basic human needs and contributing to economic prosperity through generation, manufacture and distribution of goods and services. Design of a network to achieve more sustainable business practice requires an understanding of how its structure and function affect its economic, environmental and social performance.

In this thesis it is argued that this understanding can be gained through modelling and simulation of such networks, where existing toolkits include simulators and/or optimisers, as well as an array of "soft systems" approaches, including multi-criteria decision analysis (MCDA). An agent-based simulation-optimisation approach was developed to capture the complexity associated with modelling of industrial networks, including the decision-making process followed by each enterprise, the responsiveness and interplay between the enterprises and the evolution and performance of the network over time.

This modelling approach was applied to a case study network associated with generation of electricity from biomass in the province of kwaZulu-Natal, South Africa. The network includes sugar and paper and pulp mills, the South African power utility and independent power producers. The decision-making criteria of the enterprises and the key performance indicators of the network were both measured by economic (cost and NPV respectively), environmental (CO_2 emissions) and social (electrification of rural communities) factors. The sensitivity of the structure and function of the network to changes in network effects (carbon credits selling price) and enterprise behaviour (decision and risk policies) was tested. It was found that changes in enterprise behaviour had the greatest influence on the structure and functioning of the network, with changes in decision policy having a greater influence than changes in risk policy. From this case study it is concluded that although each network presents custom complexities and uncertainties, the modelling approach developed in this thesis does provide a platform that allows designers, analysts and decision-makers to take into account relevant enterprise and network characteristics.

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Abbreviations

AAU - Assigned Amount Unit

ABM – Agent-based Modelling

CDM - Clean Development Mechanism

CER - Certified Emission Reductions

DSS – Decision Support System

EAOC - Equivalent Annual Operating Cost

ERU – Emissions Reductions Units

EWO - Enterprise-wide optimisation

GHG – Green House Gas

IPP – Independent Power Producer

KZN – kwaZulu-Natal

lCER - Long-term Certified Emission Reductions

MOO – Multiple Objective Optimisation

NPV – Net Present Value

RE – Resource Efficiency

REE - Rural Electrification Equivalent

RMU - Removal Unit

SCM - Supply Chain Management

tCER - Temporary Certified Emission Reductions

UNFCCC - United Nations Framework Convention on Climate Change

1 Introduction

1.1 Background

Industrial networks play an important role in meeting basic human needs and contributing to economic prosperity through generation, manufacture and distribution of goods and services. Such networks are complex structures consisting of multiple interacting enterprises, differing in nature, each with independent (often conflicting) objectives, producing numerous, possibly competing products. Examples of such networks are the networks created by the enterprises associated with the energy supply sector (parts of which form the focus of this study).

The operation of enterprises comprising an industrial network not only influences economic activities, it also impacts the natural environment, through the consumption of raw materials and generation of waste; and could potentially contribute to social upliftment through job creation and improvement of quality of life. This has led to leaders in the global business arena assigning more significance to the term sustainability. Bakshi and Fiksel (2003) suggests that this shift in thinking is due to recognition by leaders that profitability alone is not a sufficient measure of success, and that non-financial concerns associated with sustainability should also be included as fundamental drivers in long term shareholder value. Indeed it has been suggested by Beamon (1998) and Bakshi and Fiksel (2003) that failure to recognise these strategic issues could threaten the very survival of an enterprise. Consequently, understanding the behaviour of enterprises in industrial networks, and hence the structure and functioning of these networks, is vital in the drive towards more sustainable business practice.

In an increasingly competitive world market, enterprises today are striving towards improved performance through improved efficiency and responsiveness. It has been identified that this improvement will only occur if both the network and the individual enterprises comprising the network are designed appropriately, and the allocation of resources is performed effectively (Shah 2005). The challenges associated with this are discussed next.

Industrial networks could consist of a few enterprises or they could span multiple value chains across several continents (Riddalls et al. 2000). As such, the entities comprising a network could typically be separate organisations such as government institutions, or enterprises in the manufacturing and retail industrial or even consumers. All these organisations contribute to the functioning and behaviour of the industrial network by setting standards and incentives, providing information, setting rules of interaction and providing supply and demand for network outputs. The allocation of resources is thus a task performed by multiple enterprises and hence decision-makers. The interplay between these enterprises and decision-makers creates a network which is dynamic in that the links between enterprises are continuously changing, thus requiring the inclusions of learning and adaptation as enterprise attributes. In this study the terms learning and adaptation are used to describe a system that is able to adapt to increase its performance over time based on previous experience (Holland 1995). Capturing these attributes in a model will require learning and adaptation algorithms, the inclusion of which could potentially be challenging from a computational and mathematical viewpoint (Valluria and Croson 2005).

In addition, the interactions between the enterprises and the resulting behaviour of the network may contain uncertainties and non-linearities. As such, modelling of industrial networks presents the added challenge of understanding how the inclusion of non-linearity and uncertainty influence the decision-making processes and resulting network behaviour.

Finally, enterprises could join and leave the network at any time. As such, information relating to the network resides across a multitude of enterprises, is dynamic and ever changing. It follows that collection of reliable, up to date data in a timely and efficient manner may be limiting from a technological viewpoint.

From these challenges, it is evident that capturing this full complexity in an attempt to model the behaviour of existing networks, or to design new networks, is a formidable task, as identified by Grossmann (2004), *"it will require multi-scale modelling ranging from the atomic level to the enterprise level, as well as the development and improvement of supporting methods for simulation, optimisation, control and information processing."*

It has been identified that traditional organisational theories of business practice are unable to cope with this complexity and that modelling the network as a complex system is critical

(Amaral and Ottino 2004), (Macal et al. 2004),(Peltoniemi and Vuori 2004) and (Kempener 2006a); with the term "complex" used as defined by Amaral and Ottino (2004), "*Complex systems typically have a large number of components which may act according to rules that may change over time and that may not be well understood; the connectivity of the components may be quite plastic and roles may be fluid*". Modelling approaches aimed at understanding the behaviour of industrial networks have been developed in several research fields, including economics (Sterman 2000), chemical engineering (Amaral and Ottino 2004) and management, decision and social sciences (Choi et al. 2001) and (Epstein 1999). These approaches can be classified into two groups; namely "aggregated" and "disaggregated" approaches.

In an aggregated approach to modelling industrial network, the focus is on aggregated flows (energy, material and capital) and decision-making in the network is modelled from the perspective of a single decision-maker, or at least a group of decision-makers who are interested in the overall performance of the network (illustrated in Figure 1.1). In other words, each enterprise is *not* seen as an autonomous, independent entity.

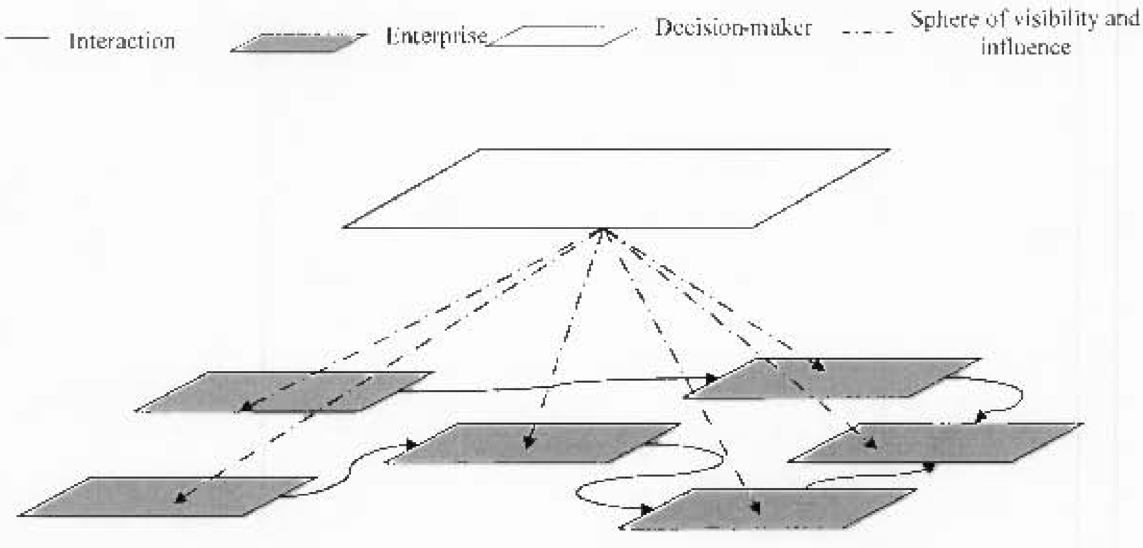

Figure 1.1: Aggregated level of analysis of an industrial network

In the literature, an aggregated approach to analysis of networks is often referred to as system dynamics modelling. This approach is widely used in fields such as process systems engineering (Freppaz et al. 2004), operations research (Camm et al. 1997) and supply chain management (Shah 2004). Here, independent enterprises are not treated as autonomous decision-makers and the models are generally used for the exploration of the overall network performance in light of a clearly defined objective(s). In the cited examples, the level of detail includes overall network optimisation e.g. maximise profit or minimise environmental impact, by considering constraints such as of resource availability, technology alternatives and geographic location. Although it can be argued that such an aggregated view of the functioning of the network may be sufficient for strategic planners or governments interested in optimising the system as a whole, implementing the modelling outcomes may disadvantage some of the enterprises in the network, financially or in terms of constraints placed on their operations (Kempener et al. 2006b). The advantage of such an overall systems approach of the network is that it may assist policy makers and planners to design appropriate instruments (e.g. regulations, taxes, incentives, subsidies, etc.) to promote the achievement of optimal network performance.

In a disaggregated approach the enterprises comprising the network are represented as autonomous entities acting in a self-interested manner. In this network, the decisions are made by multiple decision-makers, as seen in Figure 1.2.

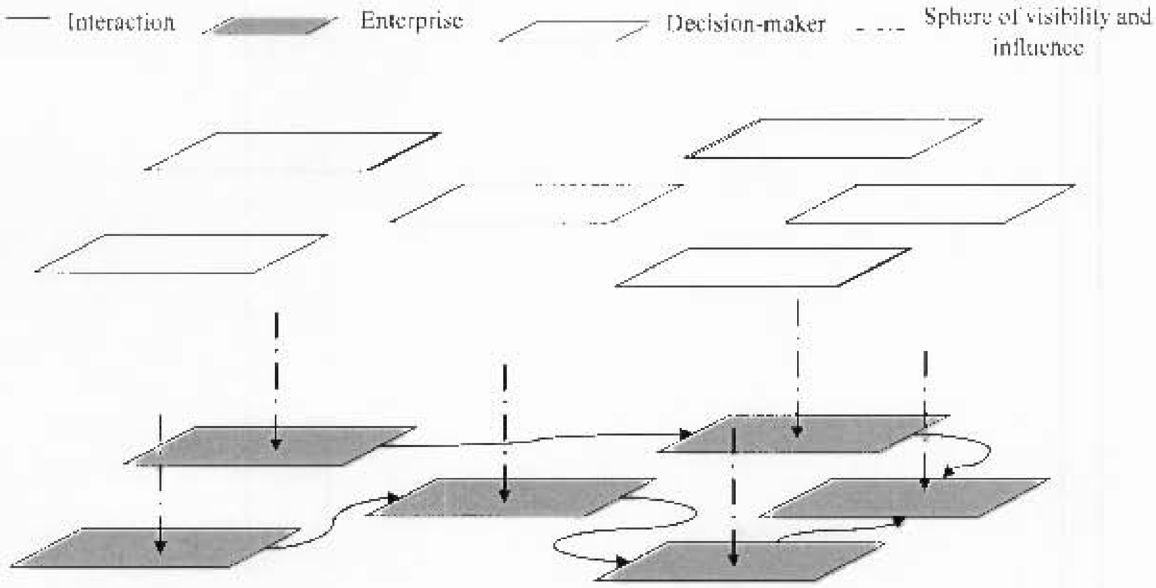

Figure 1.2: Disaggregated level of analysis of an industrial network

In the literature, disaggregated approaches to analysis of networks are often referred to as agent-based modelling (Baumgaertel et al. 2001) and (Choi et al. 2001). Here, the independent enterprises are modelled as autonomous entities, and the behaviour and performance of the network emerges as a result of the interaction between the enterprises. Although modelling enterprises such that they pursue their own interests could lead to a configuration yielding sub-optimal network operation and performance, this approach could provide an understanding of the functioning of "real world" networks. Gaining this understanding and illustrating how this modelling approach could be as a tool to assist all network players to understand network behaviour, and thus support decision-making related to the network in question, is the main aim of this thesis.

It was decided that this aim can best be met in the context of a case study network. The network selected for this purpose is a biomass-energy network in kwaZulu-Natal, South Africa. This specific network forms part of a multi-party research project involving the Departments of Chemical Engineering at the Universities of Cape Town and Sydney, and sponsored by South Africa's electrical utility, Eskom Holdings. The agents identified in this network are the sugar and paper / pulp mills in this region, potential independent power producers and Eskom. Each of these agents should be modelled such that it operates autonomously and makes decisions in light of economic, environmental, and social objectives. In South Africa there is an increased drive towards renewable energy alternatives to diversify sources of energy. The reasons for this are an increase in energy demand, rising oil prices and the environmental issues associated with the burning of fossil fuels. The government targets 10 000 GWh total additional renewable energy generated by 2013, to be produced mainly from biomass, wind, solar and small-scale hydro plants (Anon 2003). The energy generation potential of the kwaZulu-Natal region lie with the biomass from the sugar mills being used as a feedstock for electricity generation. It has been suggested that these mills generate sufficient biomass to be able to export a projected 3 000 GWh over and above their own power requirements of about 700 MWh (Anon 2004a)[1]. A study of such a network at a time when there is still the opportunity to intervene in its development to ensure that this occurs in a profitable and sustainable manner is thus both timely and meaningful.

1.2 Research Objectives

The research objectives for this study are as follows:

1. Propose an analytical framework with which industrial networks can be designed. Determine which characteristics of the network and the enterprises comprising the network can / should be captured by this framework.
2. Use the analytical framework to develop a modelling approach within which the interactions between the enterprises in the network can be represented. In doing so, compare the developed approach to other modelling paradigms and conclude which approach is better suited to the problem at hand.
3. Develop an understanding of the manner in which economic objectives together with environmental and social objectives can be included into the decision-making procedures followed by enterprises today. This understanding must be extended beyond merely including environmental and social objectives as financial externalities.

[1] The total energy target of 10 000 GWh is a cumulative value generated over 10 years (from 2003-2013). If the sugar mills were to produce 3000 GWh each year, from 2003 – 2013, it would add up to 30 000 GWh; three times more than the target.

4. Apply the modelling approach to a case study industrial network. Determine how consideration of economic, environmental and social objectives in decision-making could lead to more sustainable business practices in the future.
5. Analyse the outcomes of the application of the modelling approach developed to the case study network specifically and draw conclusions regarding the implementation of such an approach to industrial networks in general.

1.3 Thesis Structure

This thesis is structured such that the research objectives outlined in the previous section can be address in turn. This was done by considering these objectives from an aggregated and a disaggregated perspective, as seen in Figure 1.3.

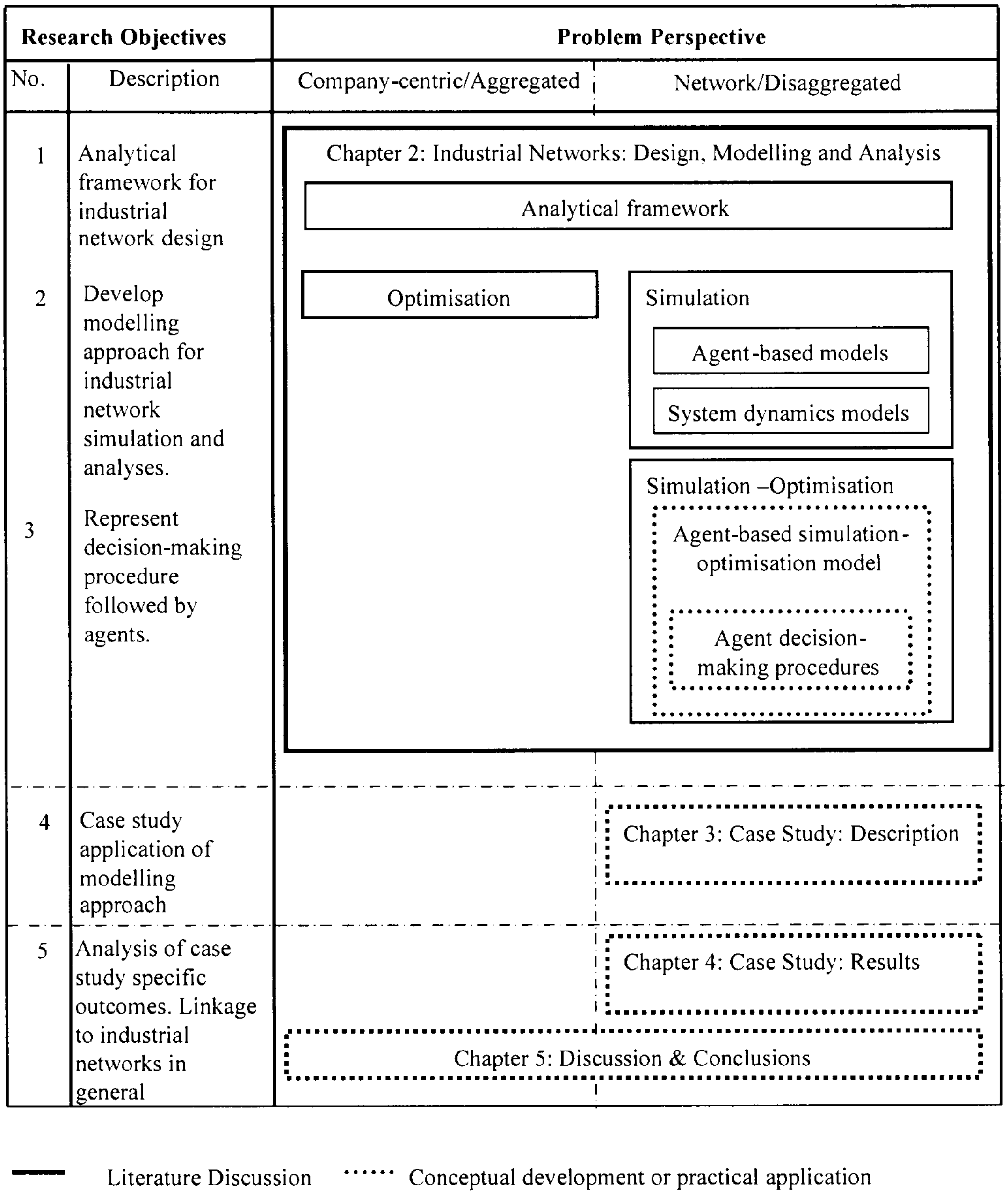

Figure 1.3: Diagrammatic representation of thesis structure

2 Industrial Networks: Design, Modelling and Analysis

This chapter aims at developing an analytical framework and from this a modelling approach for the design, modelling and analysis of industrial networks. As such, the discussion in this chapter is structured to address these aims respectively.

2.1 Analytical Framework

The analytical framework used in this study is based on ideas developed by Kempener et al. (2006c)[2], seen in Figure 2.1. Such a framework is both necessary and attractive as it addresses the challenges of modelling and analysis of the behaviour of industrial networks, as outlined in section 1.1.

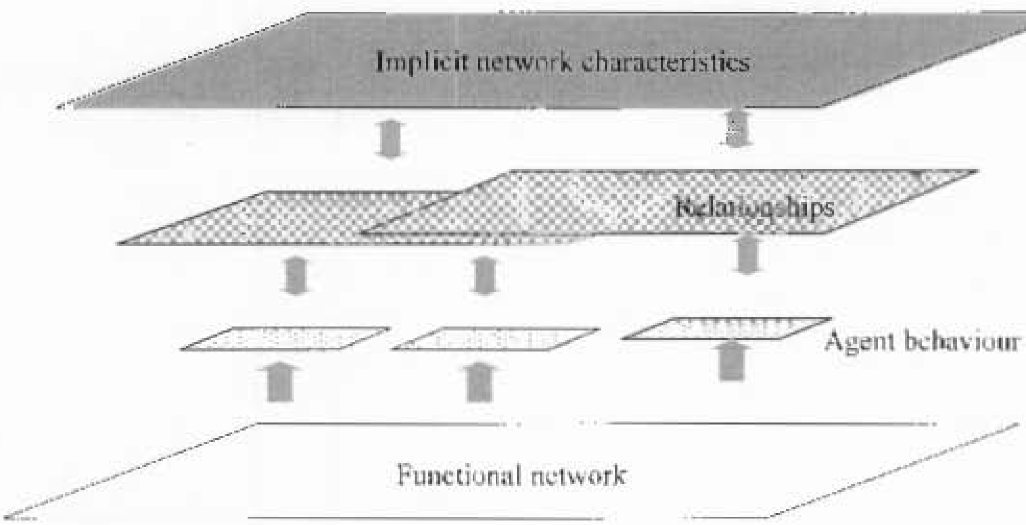

Figure 2.1: Four Level Analytical Framework for Industrial Network Design and Analysis (Kempener et al. 2006c)

2.1.1 Level 1: Functionality

The first level is the so-called "functional" level. This level relates to the exchange of resources (capital, land, labour, material, etc) and services and the information which directly relates to this exchange. Classical and neo-classical economic theories suggest that this rate of

[2] The authors cited as responsible for this work – Kempener, R., B. Cohen, L. Basson and J. Petrie, - form part of a multi-institutional research group, within which the study presented here was also conducted.

exchange is determined by each enterprise in an attempt to maximise its own profit and value/utility, with the prices paid for goods and services relating to resource scarcity (Freppaz et al. 2004).

2.1.2 Level 2: Agent behaviour

Each of the enterprises in a network has its own set of objectives, different long term goals and intentions and has limited access to information regarding the other enterprises and the network as a whole. Therefore, in reality, the exchanges within the functional network between several independent enterprises do not necessarily occur such that each enterprise is able to operate at optimal operating conditions. As such, the second level of the framework includes the decision-making processes which an enterprise employs to effect transformation or transaction of resources within the network; and is thus called "agent behaviour". Evaluation of the consequences of decisions in the face of complexity lies in the field of decision analysis; a literature overview of which is given in Appendix A. It has been suggested that the inclusion of agent-behaviour into the way in which industrial networks are modelled: (i) significantly impacts the performance of both the network as a whole and the enterprises comprising the network, and (ii) results in deviation of real world systems from classical economic models (Kempener et al. 2006c).

2.1.3 Level 3: Relationships Between Enterprises

Granovetter (1985) argues that the functionality of a network is not only dependant on individual agent decision-making, but is also strongly influenced by the relationships between the agents (level 3). Thus, once an enterprise has identified one or more enterprises as potential exchange partners, whether or not the exchange takes place will be determined by relationship factors such as trust and loyalty which have been established over time; and perceptions of status or reliability of the other enterprises in the network. The incorporation of "trust" and "loyalty" considerations into agent-based decision-making forms part of a much larger project (Kempener 2006a).

2.1.4 Level 4: Network Characteristics

A series of network-wide effects influence the decision-making procedure followed by individual enterprises in the network, which in turn influences the exchanges taking place in the network. These effects include (i) policies and legislation, which set the bounds within which enterprises can legitimately trade; (ii) norms and values established within the network, with enterprises that do not conform to these likely to be excluded. The norms and values adopted by an enterprise define how it evaluates different decision alternatives; (iii) societal expectations and how these impact on the "licence to operate" of any enterprise in the network, and hence the evolution of the network as a whole.

As mentioned previously, the incorporation of social awareness into the decision-making procedure of enterprises in a network forms part of a larger project (Kempener 2006a), as such, only the first, second and fourth levels are considered here. Although it is believed that inclusion of these factors would yield additional insights into the performance of both the network as a whole and the enterprises concerned, it falls outside the scope of this thesis.

This then describes the framework within which the formation and functionality of industrial networks are understood within the context of this thesis. Identification of the individual levels of the framework is not a unique or particularly novel exercise in itself, and much literature is available on modelling each of these factors in isolation (Haunschild 1994), (Camm et al. 1997) and (Perea et al. 2000). The challenge addressed in this thesis was the development of an integrated set of tools which may be used to consider all of these levels simultaneously, in such a way that the feedback between the different levels of the model is accounted for. This will allow the user to represent and analyse the behaviour of both the network as a whole and the enterprises that comprise the network. The remainder of this chapter consists of a literature overview of the modelling tools currently used for this purpose, from which an integrated set of tools that allows for modelling and analysis of industrial network is developed.

2.2 Optimisation

The decisions to be made by enterprises in an industrial network often involve selecting from a long list of potential alternatives e.g. which products to manufacture, which technologies to use for this, and at which capacity operation should occur (Biegler and Grossmann 2004). Optimisation techniques are typically used for this purpose as it has been identified that operating at optimal conditions translates into large savings for the enterprise concerned. Optimisation problems are formulated as follows:

$$Min\ Z = \mathrm{f(x,y)}\ \text{s.t.} \begin{cases} h(x,y) = 0 \\ g(x,y) \le 0 \\ x \in X, y \in \{0,1\} \end{cases} \qquad \textbf{[eq. 2.1]}$$

Where $f(x, y)$ is the objective function (e.g. cost), $h(x, y) = 0$ are the equations that describe the performance of the system (e.g. material and energy balances, etc) and $g(x,y) \le 0$ are the constraints of the system. The variables x are continuous and generally correspond to state variables (e.g. flow rates), while y are the discrete variables, which are restricted to take 0–1 values. The discrete variables represent decision variables, e.g. selection of units in a flow sheet (Chakraborty and Linninger 2002), sequencing in planning and scheduling (Grossmann et al. 2002), number of plants to operate and geographic location of these plants (Freppaz et al. 2004).

Historically, in the field of process systems engineering, research interests in optimisation focused primarily on problems that could be evaluated and ranked based on a single metric, e.g. profit (Biegler and Grossmann 2004). Solving such a single-objective optimisation problem involves identifying one solution (vector of values for decision and continuous variables) that maps to the best value of the objective function, while satisfying all of the constraints. An example of such a single objective optimisation problem applied to supply network case study is presented by (Freppaz et al. 2004).

The study of Freppaz et al. (2004) aims at developing a decision support system (DSS)[3] for biomass exploitation for energy production purposes at a regional level. This was done by assessing the possibility of biomass exploitation for both thermal and electric energy

[3]A DSS is defined as *"... any interactive, flexible and adaptable software systems that integrate models, databases and other decision aiding tools, and package them in a way that decision-makers can use" (Zhou et al. In Press).*

production in a given area, while relating this use to efficient and sustainable management of the forests within the same territory. In the DSS an optimisation modelling approach was used to determine the location and optimum sizing of possible plants. This problem was presented as a single objective optimisation aimed at minimising costs while maximising benefits. Environmental considerations were included as constraints on the system (a minimum renewable energy production constraint) and not objectives, which, together with cost considerations drive the decision-making in the system. The sensitivity of the system to the environmental constraint was then tested and an optimum was found. The authors state that *"there are significant benefits to reap by including an environmental constraint on economic performance"*. As such, multi-objective optimisation (MOO) techniques and applications are discussed next.

Techniques for multiple objective optimisation have been developed around the optimisation of cost and waste/energy minimisation, with the recent inclusion of operability issues (Alexander et al. 2000). This has occurred as many enterprises today not only consider economic but also environmental and social objectives when making decisions. For this reason, many of the problems associated with the modelling of industrial networks must be evaluated using multi-objective optimisation. The solution to this class of problem cannot be represented as a single point; instead it is the set of feasible points that represent the trade-off between the various objectives. It is thus up to the decision-maker to select the manner in which to trade-off the various objectives to select the final, single solution to implement. The can be done by exploring the trade-offs between conflicting objectives across the Pareto optimal solution space; defined as a solution whose attributes cannot be simultaneously outperformed by any other solution. An example of this process is a study presented by Glazner and Sgouridis (2005). The aim of this study was to analyse regional freight transportation policies and examine the effect of these policies on a supply network in order to provide insight into a policy-planning process. Transportation in the network occurred between three enterprises in the same region (automotive, food and electronics companies). Region-wide objectives included profit and environmental impact (measured as emissions and landfill affects). The multiple objective optimisation consisted of trading-off the maximisation of profit and the minimisation of environmental impact such that the best policy (Pareto optimum) for the network can be selected.

Even though all of the abovementioned studies include sensitivity analyses, there is no way to determine the dynamic behaviour of the system (as no time dependencies were modelled). The limitation of this modelling configuration is that it does not allow for investigation of the effect of different strategic and tactical decisions over the long or short term. Together with this, both the single and multi-objective optimisations of the economic and environmental objectives of the system were performed from an overall system perspective (in this case a regional perspective). This is also a modelling limitation as there is no way to include the behaviour of independent enterprises each with their own set of goals and objectives.

The first limitation can be tackled by dynamic optimisation[4] of the system. Examples of dynamic optimisation can be found in Biegler et al. (2002) and Bansal et al. (2003), with both studies developing techniques to solve these optimisation problems and then applying these techniques to distillation applications. The main conclusion drawn from these studies is that even for a rather "small" system; dynamic optimisation is computationally very cumbersome and requires a huge amount of coding in packages such as Matlab and Visual Basic.

The second limitation can be tackled by what Grossmann (2005) labels as enterprise-wide optimisation (EWO). EWO involves optimising the operations of supply, manufacturing and distribution activities of a company, which often requires non-linear models. Shapiro (2001) and Grossmann (2005) identify that the major challenge involved in EWO as the integration and coordination of decision-making across the various functions in a company (purchasing, manufacturing, distribution, sales), across various geographically distributed organisations (vendors, facilities and markets), and across various levels of decision-making (strategic, tactical and operational). Grossmann (2005) states that in order to achieve EWO in the process industry, a new generation of computational tools will be required to meet the following challenges:

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[4] Dynamic optimisation of a system consists of it being modelled by making use of differential equations that describe the dynamic behaviour of the system, such as mass and energy balances, and algebraic equations that ensure physical and thermodynamic relations. The objective function is then determined as a function of these differential equations.

- modelling challenge – development of mathematical programming and logic-based models that can be integrated to capture the complexity of many operations.
- multi-scale optimisation challenge – how to integrate long term strategic decisions with medium to short term tactical and operational decisions.
- uncertainty challenge – development of effective programming tools to account for stochastic variations in the model.
- algorithmic and computational challenge – how to solve the above mentioned three problems with efficient algorithms and modelling platforms.

Even though EWO proves to be a very promising area of research in both the process systems and operational research communities, it is limited as it does not present a solution to the investigation of supply network dynamics over a period of time.

Enterprises in industrial networks also have to deal with a dynamically changing operating environment. As such, although the methods and tools discussed above do provide answers to optimal operating conditions; the impact of these solutions on the behaviour of the network can only be assessed by using simulation (Riddalls et al. 2000), as discussed in the next section.

2.3 Simulation

A simulation model is considered as a set of rules that define how the system being modelled will change or perform in the future, given its present state (Woodwell 1998). Such an approach is useful for modelling industrial networks as the behaviour and dynamic performance of both the network as a whole and each enterprise in the network can be captured as a function of (i) enterprise functionality (level 1 of analytical framework), (ii) decision-making procedure followed by each enterprise (level 2 of analytical framework), (iii) network characteristics (level 4 of analytical framework). It was previously identified that approaches to modelling networks can be classified into two main groups - namely, aggregated and disaggregated approaches. An aggregated approach typically involves representing the system through a system dynamics model (Woodwell 1998) and (Schieritz and Grobler 2003a), whereas a disaggregated system is modelled by using an agent-based approach (Swaminathan et al. 1998), (Axtell et al. 2002) and (Borshchev and Filippov 2004). These approaches are discussed in sections 2.3.1 and 2.3.2 respectively.

2.3.1 Systems Dynamics Models

This field of study was initially called industrial dynamics and developed from the work of Forrester (1961); who defined it as "*the study of the information feedback characteristics of industrial activity to show how organisational structure, amplification (in policies), and time delays (in decision and actions) interact to influence the success of the enterprise It treats the interactions between the flows of information, money, orders, materials, personnel, and capital equipment in a company, an industry, or a national economy*". Applying a system dynamics modelling approach to an industrial network would entail representing the system in terms of stocks (e.g. of material, energy, etc) and flows (capital, information, etc) between the stocks. Scholl (2001) argues that the primary assumption of a system dynamics approach is that the feedback characteristics, and hence the internal causal structure of a system, determine its dynamic tendencies and that it is not a single decision or external disturbances that are responsible for the system's behaviour, but the structure within which the decisions are made.

The range of system dynamics applications is broad and includes corporate planning and policy design (Forrester 1961), economic systems (Sterman 2000), urban and social systems (Forrester 1969), ecological systems (Woodwell 1998), etc. As the focus of this study is gaining an understanding of how the structure and functioning of an industrial network influences its performance, only applications of system dynamics models addressing this issue were investigated. An example of this is the study presented by (Akkermans 2001).

(Akkermans 2001) applies a system dynamics model to represent an inter-organisational network. The aim of this study was to encourage collaborative supply chain management in the electronics industry. The supply network consists of four enterprises located in close proximity and sharing a history of collaboration. The author aims at investigating policies that would increase the flexibility of the supply network. Stocks and flows were used to map the goods flows, capacity acquisition, utilisation flows and planning and order flows. The main findings were: (i) the interrelations across departments in an enterprise (production, logistics and design) have the potential to improve the performance of the supply network; (ii) more efficient sharing of information, and thus interrelations across the enterprises could increase production output.

2.3.2 Agent-Based Models

Research interest in agent-based modelling (ABM) developed from the fields of artificial intelligence and object-oriented programming (Jennings 2001) and currently spans a wide range of disciplines; including social science (Epstein 1999), economics (Tesfatsion 2003), industrial ecology (Axtell et al. 2002), supply chain management (Swaminathan et al. 1998), (Baumgaertel et al. 2001) and (Julka et al. 2002a) and distributed computing (Jennings 2001).

As a result, there is no universally accepted definition of what ABM is. For the purpose of this study, the term agent-based modelling is used as defined by Parunak et al. (1998); *"A model that consists of a set of agents that encapsulate the behaviours of the various individuals that make up the system and model execution consists of emulating these behaviours. In terms of agent-based modelling, every agent is given a set of rules according to which it interacts with other agents, this interaction then generates the overall system behaviour".*

These is still much disagreement as to what properties an entity should possess to be called an agent, with many of the agent properties found in literature used to a greater or lesser extent, depending on research field and the purpose of the agent. Consequently, only the agent properties that are required to accurately model the behaviour of enterprises in an industrial network are highlighted. These properties have been adapted from (Schieritz and Milling 2003b), (Gjerdrum et al. 2001) and are as follows;

- Autonomy: Ability to act without direct external intervention, thus the agent has control over its actions and internal state.
- Social ability: Ability to interact with the environment[5] and with other agents either by coordination, cooperation or competition
- Proactive: Ability to take initiative in order to achieve goals.
- Reactive: Ability to react to changes in the environment
- Situatedness: An agent is embedded in its environment and can sense and act on it.
- Learning: Ability to increase performance over time based on previous experience

[5] In an agent-based model, the environment refers to the modelling platform through which the entities interact with each other.

- Intelligent: Having human-like attributes, i.e. beliefs, goals and intentions
- Rational: Designed to accomplish well-defined tasks by choosing actions based on internal goals.

Even though these properties are sufficient to capture the behaviour of a single enterprise, industrial networks typically consist of more than one enterprise. Consequently, an ABM of such a system will require more than one agent. Such a system is often referred to as a multi-agent system; described as a system in which it is assumed that there are a fixed set of rules and also a fixed set of agents upon which these rules act (Ostrom et al. 1994). According to Jennings et al. (1998) multi-agent systems have four characteristics:

- Each agent possesses incomplete information, or capabilities for solving a given problem, thus each agent has a limited viewpoint
- There is no global system control over distributed resources, expertise, intelligence and processing capabilities
- Data is widely dispersed among the agents
- Computation is asynchronous
- The agents interact with each other in an open and uncertain environment

An example of an application in which the agent properties and multi-agent attributes discussed above are used, in the form of an agent-based model, is the study presented by Julka et al. (2002a). The reason this study was selected is that the focus of this thesis is to develop an understanding of how to represent and analyse the behaviour of both an industrial network and the enterprises that comprise this network; and only applications of ABM addressing this issue were investigated.

The aim of this two-part paper was to develop an agent-based framework for supply chain management (Julka et al. 2002a), and to illustrate the practical application of this framework by means of a case study example (Julka et al. 2002b). The purpose of the developed framework is to allow the user to model, monitor and manage a supply chain or supply chain network in the form of a decision support system (DSS). In these papers, the difference between a supply chain and a supply chain network is that the former deals with a particular enterprise and its supply chain whereas the latter deals with a number of enterprises interacting in a specific business environment. As such, the term 'supply network' is seen as equivalent to the term industrial network as defined in this thesis.

The framework included dispersed information required for the functioning of an enterprise and made use of objects and agents to model the supply chain/network. Even though objects are similar to agents in that they are defined as *"computational entities that encapsulate some state, are able to perform actions, or methods on this state, and communicate by message passing"* (Jennings 2001); they differ from agents significantly in that they are not autonomous entities. From this it follows that the material and information in the supply chain/network were modelled as objects whereas each enterprise was modelled as an agent; with the objects exchanged between agents. The manner in which a supply chain/network could then be monitored and managed through the use of this DSS is that the user could configure different scenarios and compare the effect of different operating policies and decisions on predefined key performance indicators. This framework was developed such that it could provide decision support at various levels of the supply chain through tracking of these performance indicators. These levels include the (i) cluster level, defined as a number of enterprises in a business environment forming a supply chain network/industrial network (ii) inter-enterprise level, dealing with a particular enterprise and its supply chain and (iii) intra-enterprise level which deals with the supply chain activities within an enterprise.

In the second paper, the authors demonstrate the practical application of this DSS to a petroleum refinery supply chain/network application; called the Petroleum Refinery Integrated Supply chain Modeller and Simulator (PRISMS). The agents in this model are (i) refinery departments - namely, procurement, sales, logistics, storage and operations; (ii) oil suppliers; (iii) third-party logistics providers (3PLs) and (iv) an oil exchange company. The material and information flowing between these agents were modelled as the exchange of objects between agents. The user "creates" a refinery supply chain/network by specifying the active agents, refinery details (e.g. location, operational constraints, production policy, etc), planning parameters (e.g. time, inventory, yields) and simulation details (number of days for which the refinery supply chain/network must be simulated). Once the simulation is complete, the responses and results recorded are the messages, events and data associated with the respective agents. The messages tagged with a simulation time, the procurement cycle number that they belong to and the communicating agents. These results could then by used by decision-makers to plot key performance indicators (e.g. production profiles and supply-demand curves). The sensitivity of this system to different decision variables was explored, namely, impact of a change in policy of the refinery, effect of demand fluctuation and impact of change in refinery plant configuration. It is important to note that the framework developed in this study is similar to the analytical framework used in this thesis. The refinery supply chain/network creation captures the functionality (level 1) of the enterprises involved. The evaluation of refinery policy changes and plant configuration captures the agent behaviour (level 2) whereas the investigation of demand fluctuation captures the network characteristics (level 4) of the framework.

In terms of industrial networks, this study is important as it illustrates how ABM can be used to model the performance of the network as a whole (cluster level), while still capturing the interactions between the enterprises that comprise the network (inter-enterprise level) together with modelling the operation and behaviour of each enterprise (intra-enterprise level). In terms of comparing agent-based and traditional system dynamics approaches to modelling industrial networks, this study is important as the authors conclude that "...in contrast to traditional modelling techniques which make use of mathematical programming for this problem, an agent-based approach is more versatile and can easily capture the qualitative as well as the transactional nature of the supply chain".

2.3.3 System Dynamics vs. Agent-Based Models

It has been illustrated in sections 2.3.1 and 2.3.2 that both system dynamics and agent-based models could be used to model the behaviour of multiple enterprises in a supply network. However, the choice of modelling approach results in practitioners defining problems differently, including the desired information which is to be gathered from the modelling exercise, following different implementation procedures (model structure and area of focus) and using different criteria to evaluate the results. As such, it is important that the modelling approach most suited to the problem at hand is selected and applied where this is determined by the outputs that the modeller desires from the modelling exercise. With regard to modelling and analyses of industrial networks, this section aims at; (i) discussing the difference between agent-based and system dynamics models and (ii) determining under which conditions the use of one modelling approach above another will yield additional insights into the problem at hand. The following questions were constructed to address both of these issues, the answers of which comprise the remainder of this section:

- Is the behaviour of enterprises *event driven* or is it *continuous*?
- Is the outcome of the model dependent on or influenced by the degree of *model flexibility*?
- Are the enterprises that comprise the network required to display evolutionary (*learning and adaptation*) behaviour?
- Is it important to understand the effect of *stochastic events* on the model structure and outcome?
- Do *model dynamics* or *model assumptions* have a greater influence on the outcomes of the modelling exercise?
- Does the modeller possess accurate and sufficient *knowledge and information* about the enterprises in the network and the network as a whole?
- Are there *independent decision-makers* present in the network to be modelled?

As the interactions of enterprises in an agent-based model are modelled in an *event driven* manner, the handling of time is a *continuous* process populated by discrete events (Schieritz and Grobler 2003a) and (Gu and Tang 2005). A system dynamics model consists of feedback loops representing overall system structure; the structure is thus predetermined, predefined and fixed. A feedback loop is a time dependent differential equation; therefore the handling of time is always continuous[6]. Delays have a major influence and occur frequently in industrial networks i.e. delays in production, ordering, lead times, etc. As a system dynamics model is continuous, representing these pure delays is difficult, but possible, by making use of

[6] Feedback loops in geographically spatial models are not only time dependent, but also include partial differential equations (spatially dependent) (Heimgartner 2001)

exponential delays which approximate pure delays (Riddalls et al. 2000). An agent-based model allows for inclusion of delays as events. As such, for the purpose of modelling networks in which delays occur, these models are preferred above system dynamics models.

Model flexibility addresses the question of control versus emergence. In the case of industrial networks, the difference between control and emergence is how much of the network structure and configuration the modeller controls (by predefining the interactions and links between the enterprises in the network) and how much is not controlled by the modeller and emerges from the interaction between autonomous agents. In a system dynamics model, every possible enterprise has to be included into the model and linked to its potential trading partners in advance. Therefore, in terms of network structure and configuration, there is little model flexibility but a high degree of control. The advantage of such an approach is that the level of detail makes it consistent with the "global" perspective required by governments or strategic planners who may be interested in investigating the structure and configuration of the network as a whole when under a high degree of control. It is important to note that defining this structure beforehand can be cumbersome if the system being modelled has a high degree of complexity. In this case an agent-based model is recommended as it allows for network structure and configuration to emerge from the relatively simple and localised activities of its agents, therefore offering a high degree of flexibility but little overall control (Choi et al. 2001)

In industrial networks consisting of multiple interacting enterprises, *learning and adaptation* are requirements of the enterprises to be modelled, e.g. a retail enterprise in the "real world" will learn and adapt to select suppliers which offer the best quality products and the lowest cost. An adaptive system is defined as a system that emerges over time into a coherent form, and adapts or organises itself without any singular entity deliberately managing or controlling it (Holland 1995). An agent-based approach presents a major advantage above a system dynamics approach with regards to learning and adaptation. The reason for this is that entities in an agent-based model are modelled such that they are autonomous and distinguishable from each other, whereas the entities in a system dynamics model are not autonomous and are indistinguishable from each other.

In many industrial networks, *stochastic events* have a major influence on the results of the model, e.g. unplanned power outages. Agent-based models are event driven whereas system dynamics models operate in continuous time. As such, stochastic events are easier to implement in an agent based framework. Rahmandad and Sterman (2004) suggests that applying an agent-based model to a network is more helpful than a system dynamics model in applications where it is important to understand the impact of stochastic events on the range of likely outcomes

When modelling an industrial network one of the important questions regarding the outcome of the modelling exercise is in terms of *model dynamics* versus *model assumptions.* The interactions between enterprises in such a network are complex, with complexity used as defined by Amaral et al. (2004), "*Complex systems typically have a large number of components which may act according to rules that may change over time and that may not be well understood; the connectivity of the components may be quite plastic and roles may be fluid*". In such systems, the model outcomes may be as complex to understand as the system they are modelling. Even with as few as three variables, a complex system can be extremely sensitive to small perturbations in either initial conditions or model structure, thus small changes can lead to very different results (Janssen 2002). This problem has been identified by Axelrod (1997); "*Although the assumptions may be simple, the consequences may not at all be obvious*"; and also by Forrester (1994); "*In a complex system the cause of a difficulty may lie far back in time from the symptoms, or in a completely different and remote part of the system*".

The behaviour of the system in an agent-based model emerging, rather than being intricately designed and controlled by a static system of feedback loops, can be difficult to interpret, understand and place confidence in as the complexity of the model grows. Therefore if the modeller is required to make exact correlations between cause and effect, thus having a precise understanding of the model dynamics, it might be more beneficial to use a system dynamics approach. On the other hand, as suggested by Janssen (2002), for system dynamics models; "*The scientific understanding necessary to define the problem sufficiently well to meaningfully apply optimal control techniques is either too costly or altogether impossible to achieve*". This is where agent-based models have much to offer. It is evident that the modeller will have to decide beforehand which attributes of the system are most important; selecting either an agent-based approach yielding model flexibility, complexity and a high level of detail, or opting for a system dynamics approach offering certainty and exact interpretation of causal relationships.

A modeller must possess a certain amount of *knowledge and information* of the network to be modelled. If a system dynamics approach is adopted, the modeller must possess knowledge and information regarding the links and interactions of every enterprise in the network. This will require having expert consensus regarding the feedback structure between the enterprises in the network and if the structure of the network is not captured sufficiently, the resulting insights may be faulty (Scholl 2001). In other words the modeller has to think in terms of structural dependencies and provide quantitative data to ensure that the model is credible. In contrast to this, agent-based models use the individual as the primary unit of analysis, thus requiring little or no knowledge about global interdependencies. As stated by Borshchev et al. (2004), *"you may know nothing or very little about how things affect each other at the aggregate level, or what the global sequence of operations are... but if you have some perception of how the individual participants of the process behave, you can construct the agent-based model and then obtain the global behaviour"*.

In industrial networks consisting of interdependent multiple enterprises with conflicting goals and distributed interests, the decision-making is performed by *independent decision-makers*. The decision structure adopted by enterprises in system dynamics and agent-based models has been illustrated in Figure 1.1 and 1.2 respectively. From this, it is evident that system dynamics and agent-based models differ fundamentally in the manner by which the relationships among enterprises are modelled and the level at which they focus their attention (Parunak et al. 1998). The decision structure of enterprises in both types of models is based on ideas proposed in (Ostrom et al. 1994), (Jennings 2001),(Schieritz 2002), (Macal et al. 2004), (Borshchev and Filippov 2004), (Desmeulles et al. 2006); and is discussed below.

In a system dynamics model, the decision structure of an enterprise is described by the following:

- Preferences - preferences are predictions about the future, e.g. future allocation of resources, price and growth predictions, etc.

- Past experience - examples of past experiences could be a record an enterprise keeps with regards to previous suppliers, raw material quantities, prices, etc.
- Present condition - examples of present conditions could be current processing capacity of raw materials, amount of product produced, capital flow, etc.
- Constraints on operation - constraints are typically associated with the present conditions. Examples being constraints of capacity, raw material purchased, etc.

It is important to note that modelling enterprises in a network by making use of a system dynamics approach means that the network as a whole is modelled in terms of stocks and flows and the independent enterprises in the network are not modelled explicitly. As such, the behaviour and decision structure of an enterprise can not influence that of another enterprise or the subsequent decision to be made in the following time interval. In terms of industrial networks, one of the disadvantages of this configuration and decision structure is that the "human dimension" of the problem can not be modelled. The reason for this is that there is no place in the model where the behaviour of independent decision-makers can be included, as is the case with in ABM (Pahl-Wostl 2002).

Enterprises in an agent-based modelling approach are situated in an environment over which they exercise partial control and only have a limited sphere of visibility. The agents can sense changes in the environment and act upon them through sensors and effectors respectively (Jennings 2001). As such, each agent can adopt and apply a tailored decision structure to determine the best course of action. The decision structure of a specific agent is based on localised preferences, past experience, present conditions and constraints and observation of the actions of the other agents within the system through the common environment. The decision output then not only influences the decisions of other agents in the system, but also the decisions to be made in the next time interval. In this manner all of the agents in the system act autonomously and are distinguishable from one another. It is evident that the functionality agent-based models offer, in terms of autonomous agents, enables the modeller to integrate behavioural aspects into the analysis of an industrial network. Moreover, modelling the enterprises as autonomous agents allows for the inclusion of optimisation at the enterprise level, whereas if the enterprises are not autonomous agents optimisation can only be performed at a network level. In a network where each enterprise has independent goals and objectives, an approach favouring optimisation at the enterprise level, as opposed to the network level, is ideal. Although it can be argued that a network perspective is sufficient for strategic planners or governments interested in optimising the network as a whole, implementing the modelling outcomes may disadvantage some of the enterprises in the network, financially or in terms of constraints placed on their operations.

From the above argument, it is thus concluded that if the enterprises to be modelled are indistinguishable, there is little benefit of modelling the network in an agent-based manner. If the enterprises to be modelled are unique in terms of acting autonomously, interacting with other enterprises by coordination, cooperation or competition, and learn and adapt as time progresses, then an agent-based model will be simpler and more beneficial to implement. In industrial networks consisting of multiple, interacting enterprises, each with its own set of goals and objectives, a modelling approach allowing for the inclusion of the autonomous behaviour of each enterprise will be beneficial. As such, it is concluded that ABM is better suited to model and represent industrial networks when compared with system dynamics models.

Having determined which modelling approach to apply to industrial networks, the question of analysing the outcomes is addressed next.

2.4 Simulation-Optimisation

Simulation is a useful tool to evaluate "what-if" scenarios, as it gives a comprehensive view of the behaviour of the network and the enterprises that comprise the network under different operating conditions; but simulating the network does not allow the modeller to include optimisation routines. Modelling industrial networks comprising multiple enterprises will require optimisation routines as each enterprise has its own set of goals and objectives. Modelling such a network by making use of optimisation routines only will yield optimal operating conditions for each of the enterprises, but little insight will be gained into the dynamic behaviour of the network under these operating conditions. Subsequently, a need for combination of simulation and optimisation procedures has been identified (Fu 2002) and (April et al. 2005).

A combinatory simulation-optimisation model can be executed as either of the following two configurations, (i) optimisation for a simulation, in which the optimiser is an add-on to an underlying simulation engine, (ii) simulation for optimisation, in which a simulation is the add-on to an optimisation engine. These alternatives are illustrated in Figure 2.2. The left hand diagram is concerned with discrete event simulators and can be found in commercial software used in areas such as inventory control systems (Gjerdrum et al. 2001) and supply chain applications (Ding et al. 2004). The right hand diagram is concerned with stochastic programming in which the scenarios are (mainly) generated by a Monte Carlo simulation[7], with the primary application being in the field of financial planning (Fu 2002) and (Lee et al. 2005).

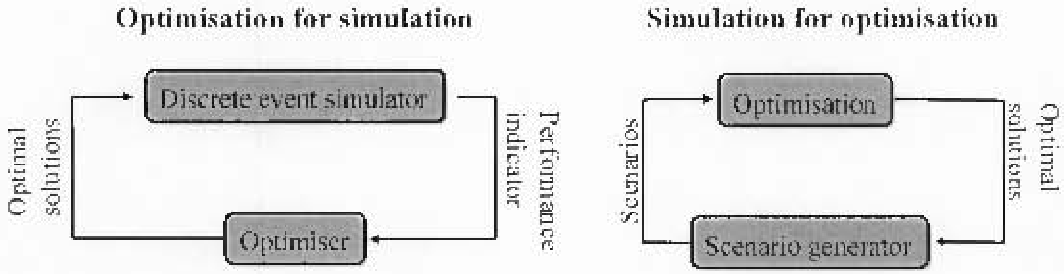

Figure 2.2: Combined optimisation and simulation techniques

The choice of configuration is dependent on the required model outcome. Ding et al. (2004) present an example of an "optimisation for simulation" modelling procedure. In this study, a decision support tool (named ONE – *O*ptimisation methodologies for *N*etworked *E*nterprises) was developed that allowed for assessment, design and optimisation of supply networks with respect to economic, environmental and social decision criteria together with explicit inclusion of uncertainty and risk. This tool focused on decision-making at strategic and tactical levels, with the former involving long terms decisions about resource acquisition and process and capacity planning, whereas the latter involves medium to short term decisions about resource allocation and process refinement. An object-oriented modelling environment was used in which a multi-objective optimisation was performed first, thus yielding optimum operating

[7] A Monte Carlo simulation is a process which randomly generates values for uncertain variables repeatedly to simulate a model.

conditions which were then fed into a simulation engine to determine the key performance indicators of the supply network. The application of this tool was illustrated by means of a case study in which the profitability and responsiveness of enterprises in a supply network was improved by redesigning its production-distribution network.

Such an approach illustrates how simulation-optimisation could be used for modelling industrial networks as it allows for both optimisation of operating conditions and subsequent inclusion of these conditions into the simulator to determine the dynamic behaviour of the supply network. However, it is noted that the optimal operating conditions, which were determined by the multi-objective optimisation, were calculated by assuming a single network decision-maker. The different enterprises in this study were not modelled as independent, autonomous entities. As stated by the authors, the ONE tool *"allows a holistic approach with a continuous view on the whole network"*. As such, it is concluded that such an approach would not be sufficient for the purpose of the study presented in this thesis. The reason for this is, as identified in Chapter 1, in order to model the behaviour of industrial networks effectively, an approach that allows for the inclusions of multiple, autonomous enterprises is required.

Lee et al. (2005) present an example of a "simulation for optimisation" modelling procedure. In this study a framework was developed to allow for multi-objective optimisation together with simulation of time dependent variables. The main aim of this study was the evaluation and selection of an optimal set of inventory policies for two case study problems. This was achieved by generating a set of inventory policies (through simulation) and then finding an optimum policy from this set based on the concept of Pareto optimality[8] (optimisation).

The focus of the study presented in Lee (2005) is to find a set of optimal solutions given a set of multiple objectives. For the purpose of modelling industrial networks as described in this thesis, such an approach is not sufficient as it does not allow for analysis of the dynamic behaviour of the network.

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[8] A Pareto optimal solution is defined as a solution whose attributes cannot be simultaneously outperformed by any other solution.

2.5 Conclusions

From the literature discussion in this chapter it is concluded that there is a weight of evidence that supports the assertion that an agent-based simulation-optimisation modelling approach is the tool best suited for design, modelling and analyses industrial networks. This conclusion is drawn based on the following:

- The literature analysed suggested that for complex systems applications, a disaggregated level of analysis is superior to an aggregated level of analyses. The reason being enterprises modelled as unique, autonomously, interacting entities in a system closely approximate "real world" industrial networks. Whereas the system modelled by means of a system dynamics approach considers the network as a whole and focuses on aggregated flows, resulting in enterprises being indistinguishable from one another. A disaggregated approach to the modelling of industrial networks is typically implemented by making use of an agent-based model; whereas an aggregated approach makes use of a system dynamics model.
- In order to analyse the dynamic behaviour and the performance of both the network and the enterprises comprising the network as a function of time, a simulation engine was required.
- Competitive enterprises typically strive towards maximising profit or minimising cost. Capturing this behaviour is done by optimisation of this objective. In many cases enterprises not only consider economic but also environmental and social objectives, thus requiring multiple objective optimisation procedures.

The next chapter illustrates a case study application of this modelling approach.

3 Case Study: Description

3.1 Motivation and Scope

In South Africa there is an increased drive towards renewable energy alternatives to diversify sources of energy. The reasons for this are an increase in energy demand, rising oil prices and the environmental issues associated with the burning of fossil fuels. The government targets 10 000 GWh total additional renewable energy generated by 2013, to be produced mainly from biomass, wind, solar and small-scale hydro plants (Wiesne and Purchase 2004).

For the purpose of this study, a biomass-energy network in kwaZulu-Natal, South Africa, was used as a case study industrial network. This case study forms part of a large contract-research project for Eskom Holdings, South Africa's state-owned electrical utility company, being undertaken jointly by the Universities of Cape Town and Sydney. The energy generation potential of this region lies with the biomass from the sugar mills being used as a feedstock for electricity generation. It has been suggested that these mills generate sufficient biomass to be able to export a projected 3 000 GWh over and above their own power requirements of about 700 MWh. This value could theoretically be increased to 5 500 GWh if field residues (trash and tops) are added. It is noted, however, that the collection of this residue over the large harvesting area may not be feasible as it represents in itself an energy demand (Anon 2004a). The total energy target of 10 000 GWh is a cumulative value, to be generated over 10 years (from 2003-2013). If the sugar mills were to produce 3 000 GWh each year, from 2003 – 2013, it would add up to 30 000 GWh; three times more than the target. The target is also a cumulative value across all renewable sources. It is evident that the target was not set at high value and that the sugar industry has great potential to contribute, and better, this value. The reason this has not been realised is due to the substantial difference between the cost of producing electricity from biomass sources when compared with Eskom's current electricity price, mainly based on the cost of electricity production from coal and nuclear sources (Wiesne and Purchase 2004). In recent years, economic incentives have been making this difference smaller. It is recognised that two emerging financial mechanisms will contribute to the economics of these alternatives, being the premium at which green[9] electricity may be sold, and the Clean Development Mechanism (CDM)[10] of the Kyoto Protocol. The green electricity market is one which has become established in many developed countries and is starting to find a place in the South African market (Winkler 2005)[11].

Whilst biomass is not necessarily the most promising option among the renewable technologies with respect to profitability or capacity, the industrial networks associated with electricity generation from biomass present an interesting alternative to diversify the energy alternatives in South Africa – one that can be made operational in relatively short order. Together with this, these networks serve as exemplars of many of the features of industrial networks: they consist of many enterprises which differ in nature (from individual farmers to large enterprises); the networks can produce multiple, possibly competing, energy products (steam, electricity, bio-fuels) together with the possibility of some of the biomass being diverted to non-energy products (e.g. paper fibre). A study of such a network at a time when there is still the opportunity to intervene in its development, to ensure that this occurs in a sustainable manner, is thus both timely and meaningful.

This chapter aims to address the following research questions and aims:

1. Make use of the analytical framework and modelling approach developed in Chapter 2 to design and analyse the case study network. This should be done such that the interactions between enterprises are captured together with representation of the decision-making procedure followed by each enterprise.
2. Discuss the functional (capital, energy and material flows) and behavioural interactions included in the modelled enterprises.

[9] For the remainder of this report "green" electricity will be used to refer to electricity generated from renewable sources.

[10] Refer to Appendix B for detailed discussion of the workings of this mechanism.

[11] An example of the growth in interest and importance of renewable energy in South Africa is the recent release of the bio-fuels energy policy by the Department of Mineral and Energy, see www.dme.gov.za/pdfs/energy/renewable.

3. Illustrate how financial, environmental and social factors could be employed as: (i) multiple decision criteria for each enterprise and (ii) as key performance indicators to track the dynamic behaviour of the network
4. Investigate the effect of including both model structure and data uncertainties.
5. Determine which policies and regulations could be used by either the government or the private sector to encourage investment in the green electricity market. Determine whether these policies and regulations lead to practices that sufficiently contribute towards the renewable energy target and thus further the drive towards more sustainable business practice in South Africa.
6. Determine the sensitivity of this network to changes in these policies and regulations.

Although the developed framework was applied to a specific biomass-energy network, it is believed that the results obtained will not only yield insights into the structure and functioning of this network, but will also lead to a better understanding of the dynamics and complexity associated with representing and modelling generic industrial networks with a view to improving their contribution to more sustainable business practice.

3.2 Network Constituents

The enterprises[12] included in the network are: (i) sugar mills, (ii) independent power producers (IPP), (iii) Eskom and (iv) paper and pulp mills.

Selection of actual enterprises in a particular region for the case study (rather than an abstract case study) allowed for existing information to be used and facilitated the exploration of rules and scenarios which potentially reflect those which would be faced by real enterprises. Even though the focus was on a regional level, it included those stakeholders which also play a role on a national level, such as the government, electricity-using industry, households, international markets, etc. These factors were not included as agents but rather as external

[12] It is recognised that these enterprises do not represent the entire range of enterprises that could potentially form part of an industrial network in kwaZulu-Natal, e.g. green power trading companies. For the purpose of this study, it was assumed that they are sufficiently diverse in operation and behaviour to illustrate the use of an agent-based simulation-optimisation modelling approach for an industrial network.

inputs that influence the agents in the network[13], e.g. policy interventions, electricity demand projections, resource availability, etc

The products and wastes currently produced by the **sugar mills** are sugar, molasses, cane juice, bagasse and tops and trash. From this list, sugar is the only commercially significant product manufactured, thus exposing the mills to fluctuations in the world sugar market. An over supply of sugar has led to many mills considering by-products to increase their earnings (Wiesne and Purchase 2004).

Cane juice is expressed from the sugar cane and through a series of cleaning and concentration steps is converted into sugar and molasses. In order to produce bio-ethanol from cane juice, only juice purification steps are needed, whereas if both bio-ethanol and sugar are produced, a sugar mill with all its additional processing steps is needed. If ethanol production is considered as an alternative, then the diversion of cane juice away from sugar production is the most viable alternative (Anon 2003).

The molasses produced by the mills is used as an animal feed supplement and as a substrate for yeast, alcohol and lysine production. If all of the molasses is diverted from its current use and used for bio-ethanol production, a total of 2.3% of the national gasoline consumption could be substituted with ethanol (Anon 2003).

Bagasse is the fibrous cane residue left after shredding and pressing to extract the sugar-rich juice from the sugarcane. The mills currently combust this bagasse inefficiently to generate the steam and power necessary for processing cane. This is done as even inefficient burning of bagasse is cheaper than disposal. The reason for the current situation of inefficient combustion rather than efficient combustion for electricity generation is that there is surplus bagasse available for the mills to meet their steam demand[14] and thus the original mills were not designed to generate electricity for export. Consequently, bagasse could potentially be used as

[13] See section 3.4.3.

[14] A typical mill in KZN averages about 300 t/h cane. It is estimated, with conversion efficiencies and moisture content, at this throughput the boiler steam is just over 160 t/h (Wiesne and Purchase 2004).

a feedstock for electricity generation, although some competition already exists for the resource.

Independent Power Producers (IPP): Given the potential deregulation of the electricity sector and the government's drive towards establishment of independent power producers, these agents were considered in the model. The biomass energy network potentially represents a suitable niche market for foreign companies to enter the South African energy market as IPPs.

Eskom generation: Electricity generation in South Africa is dominated by Eskom, a wholly state-owned utility currently operating 24 power stations and supplying 95% of South Africa's and about two thirds of Africa's electricity. Almost 90 % of this electricity is generated in coal-fired power stations, 5 % by a nuclear plant and a further 5 % is provided by hydroelectric and pumped storage schemes[15]. Eskom also owns and operates the national electricity grid[16]. Needless to say, the inclusion of Eskom in the formulation of this network is necessary as they are the main player in the electricity market and own most of the existing infrastructure. In this study, the only electricity generation technology included in the Eskom agent was co-firing bagasse and coal into an existing power station. The closest existing power station is the Majuba plant, located just across the KZN border in Mpumalanga.

Paper and pulp mills: Paper and pulp mills in South Africa are synonymous with the companies Mondi and Sappi; apart from some finishing mills they own all of the mills (Anon 2004a). The bagasse used in the paper production process is purchased from sugar mills in close proximity. Although these two paper mills are not considered to be potential green electricity generators in this study, they were included in the network as they serve as competition to both independent power producers and Eskom for the acquisition of the bagasse.

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[15] http://www.eskom.co.za

[16] http://www.dme.gov.za/energy/electricity.stm#top

In the study, the energy generation capabilities of the network lie with one or a combination of the following alternatives: (i) the sugar mills invest in either a new technology or a technology upgrade that will include (green) electricity generation, for commercial purposes, as one of the products of cane milling, (ii) Eskom generation and/or an IPP purchase bagasse from the sugar mills and invest in the most viable technology to generate (green) electricity. The technology options available to the sugar mills and the IPP considered here are a choice between combustion and gasification. The only technology option available to Eskom is combustion through co-firing bagasse and coal into an existing coal-fired power station. The potential energy recovery route from sugarcane and the technology options available to each enterprise can be seen in Figure 3.1. The conversion process from cane into final products illustrated in the sugar mills was adapted from (Maurice 1989). The technology data relevant to this case study are discussed in section 3.4.2.

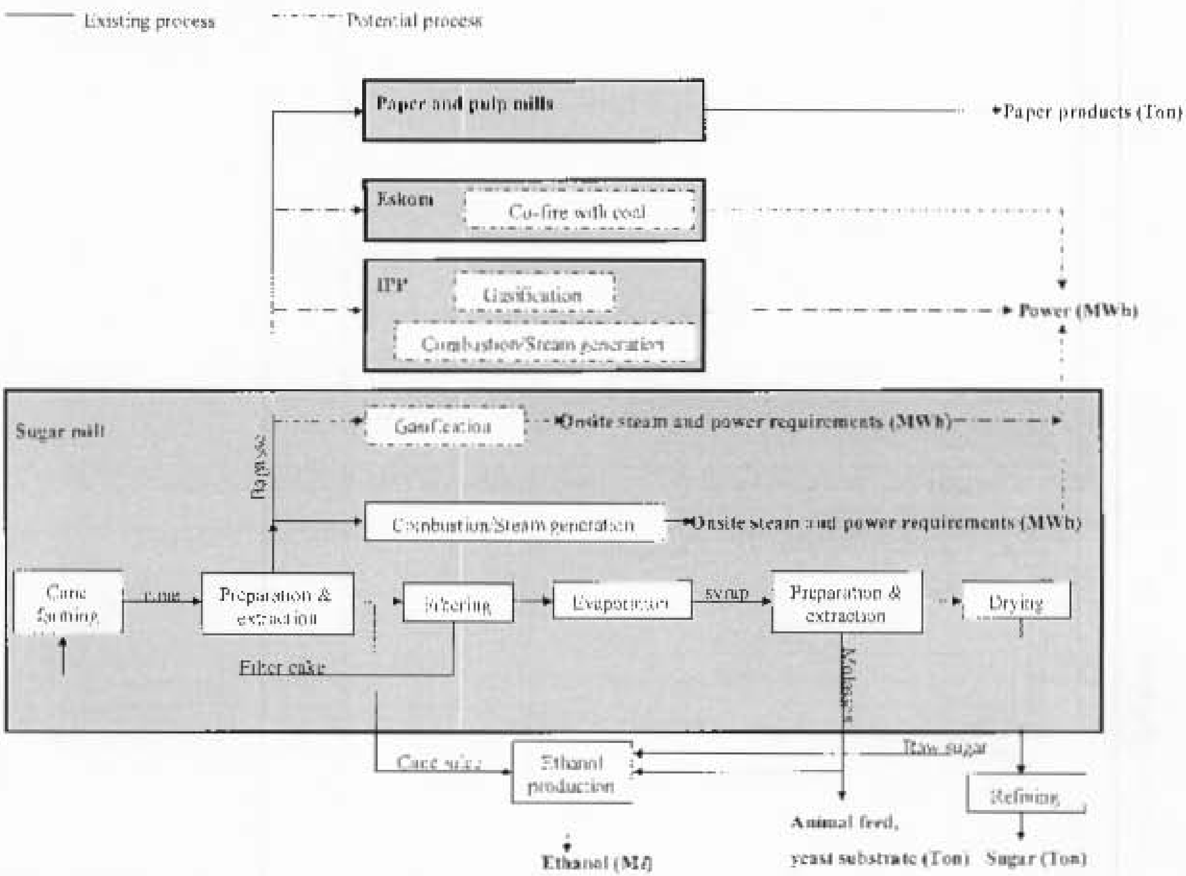


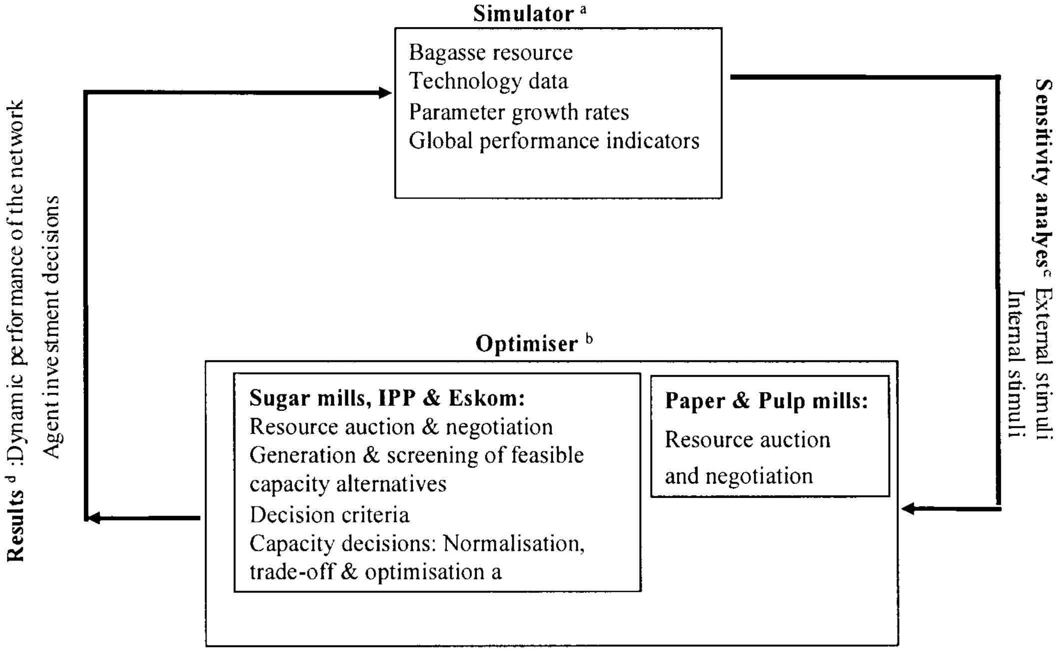
Figure 3.1: Flow sheet of processing options for products and by-products from sugar mills

3.3 Modelling Approach

The biomass-energy network was modelled by making use of an "optimisation for simulation" procedure applied within a multi-agent framework. Each enterprise was modelled as an individual agent, with the agents interacting in a modelling environment. A simulation engine with an embedded optimiser methodology was selected as: (i) simulation allows for representation of the dynamic behaviour of the network under different operating regimes but does not yield optimal solutions; (ii) optimisation procedures yield optimal solutions, but offer no insight with regard to the dynamic behaviour[17] of the network under different operating regimes.

The software package used for this purpose is the proprietary modelling tool, AnyLogic© (XJtechnologies 2005). The primary benefit of AnyLogic that is offers the user the capability to create models using several different modelling methodologies, including discrete event, system dynamics and agent-based modelling. The models can be created by using both object-oriented visual tools together with Java code. Models can also be customised to extend their capabilities. Applying this modelling tool to the case study network is illustrated by a model structure diagram, see Figure 3.2.

[17] Dynamic optimisation does yield insights into the dynamic behaviour of the network, but this falls outside the scope of this study.



[a] Discussed in section 3.4

[b] Discussed in section 3.5

[c] Discussed in Chapter 4

[d] Discussed in Chapter 4

Figure 3.2: Diagrammatic representation of the model structure

In order to investigate the sensitivity of the network and the robustness of the model structure proposed in Figure 3.2, a base case scenario was developed. The assumptions made and the manner in which these values were determined is discussed in the sections to follow. The base case values determined in each of the sections are tabulated at the end of the respective section.

3.4 Simulator: Representation of Network Dynamics

3.4.1 Bagasse Resource

As bagasse is a product of cane milling, its availability and location is dependent on the production season and location of the sugar mills. Of the 14 sugar mills in South Africa, 12 are located in kwaZulu-Natal with most of these being situated along the coast[18]. The other two

[18] A diagrammatic representation of these locations can be seen in Appendix C.

mills are situated in Mpumalanga and are thus removed from the rest of the mills with their raw sugar transported to Maputo, whereas all other mills send their (raw) sugar to Durban. The majority of the mills are owned by Illovo Sugar Ltd and Tongaat-Hulett Ltd. Illovo owns five mills, having sold one of its mills (KwaDukuza, formerly Gledhow) to Umvoti Transport (Pty) Ltd in March 2005 and Tongaat-Hulett controls four mills. The remaining two mills are owned by the UCL Company Ltd and the black economic empowerment (BEE) group Ushukela Milling (Pty) Ltd (Anon 2004b). In the study as presented here, all of the sugar mills were aggregated into a single agent; therefore the independent mills are made indistinguishable from one another. Such an approach allows for a depth of issues to be considered with detailed information, rather than having to work with a large amount of data and cover a superficial breadth of issues. Furthermore, it is suggested that the agent and object-oriented manner in which the model is configured readily allows for inclusion of more agents once a working model is complete and the resulting dynamics have been understood.

As the agricultural production of cane is a seasonal activity, bagasse availability is limited to certain months of the year depending on the mill from which the bagasse is sourced. The majority of the sugar mills are in production from beginning of March or April, reaching peak production around July and finishing in November or December. Power is required all year round, so the question arises how potential power generators should best operate. The alternatives available to an enterprise wanting to enter the power market are as follows:

- substitution of bagasse in the off season with another fuel source.
- storage of bagasse throughout the harvesting season for use in the off season. Although bagasse can be stored, indirectly, by converting it to a gaseous product, this option may not be particularly attractive as it would involve costs for storage and encounter issues associated with bagasse decomposition.
- shutting down operations from December to March.

For the purpose of this study, the third alternative was selected. As the sugar mills are aggregated into a single agent, the monthly bagasse variability was determined by assuming an average value across all of the mills. In terms of base-load power generation, this seasonality is a problem. However, for the purposes of demonstrating the features of the network, and the underlying modelling approach, this complication was ignored at this time.

The initial bagasse price was set at R15.2/MWh, being the amount for which the sugar mills can sell the bagasse to the pulp and paper industry as fibre (Anon 2004b). Even though bagasse is currently sold to the paper and pulp industry on a mass basis, this initial bagasse price is expressed here on an energy basis to allow for consistency. The sugar mills have process heat (steam) requirements. It has been estimated 20% of bagasse produced is currently used for this purpose (Anon, 2007). These assumptions, along with the location and distance assumptions used as a base case can be seen in Table 3.1.

Table 3.1: Base case: Bagasse resource

Input	Unit	Sugar mills	IPP	Eskom	P&P
Bagasse availability	Ton/month	See Table C2	-	-	-
Production time	months/year	9	9	9	9
Initial bagasse price	R/MWh	-	-	-	15.2
Steam Demand	%	20	-	-	-
Location	-	Sezela, KZN	Durban, KZN	Majuba, Mpumalanga	Felixton & Stanger, KZN
Distance	Km	0	50	500	60 & 40

3.4.2 Technology data

Combustion and gasification were modelled as technology options available to both the sugar mill and IPP agents, whereas the Eskom agent only had co-firing of bagasse and coal and subsequent combustion as a technology option available to it. Combustion of bagasse (or co-combustion of biomass and coal) for electricity generation purposes occurs in a boiler, where the heat of combustion is transferred into high pressure steam. This high pressure steam drives a turbine and electricity is produced from an electrical generator attached to the turbine.

Gasification of biomass is a thermo-chemical process that converts biomass into a combustible gas. Electricity generation by using this gas is made possible by combining a gasifier with a gas turbine.

In this study it was assumed that the conversion efficiency[19] of each of these technologies is a function of generation size (MW). These efficiencies together with the CO_2 emitted by electricity generation through the use of these technologies[20] can be seen in Table 3.2. The operation and maintenance costs of each of these technologies can be found in Appendix C.

Table 3.2: Technical data for combustion and gasification technologies

	Combustion	**Gasification**
Capacity	**Efficiency**	
MW	%	
5	27	33
25	30	36
50	32	38
100	34	40
200	36	42
Capacity	**CO_2 Emission**	
MW	**ton CO_2/ ton Bagasse**	
5-200	0.707	0.707

[19] The conversion efficiency of a technology is defined as how efficiently that technology can be used to convert a raw material resource, in this case bagasse, into final product – in this case electricity.

[20] The data for ton CO_2 / ton bagasse was derived from EPA (1996) and Wardrop (2002), which suggest that bagasse burnt in a sugar mill, using a spreader stoker boiler, produces 1560 lb/ton of CO_2, which is the equivalent to 0.707 ton CO_2/ton bagasse. This number only includes CO_2 emission from the conversion of bagasse to electricity, in a stationary combustion or gasification plant, and does therefore not include emission from transport or any other process.

3.4.3 Parameter Growth Rates

When the electricity market is considered, it is noted that electricity demand, raw material cost, prices, and other costs experience changing rates as time progresses, with these values based on predictions and estimations. The remainder of this section discusses these rates.

Electricity demand growth projections are made based on figures obtained from the National Integrated Resource Plan (Anon 2004c); with this value assumed to be 2.5% p.a. The initial demand for green electricity was set at 2% of the total electricity demand in KZN (Anon 2004a). The raw material growth included is the bagasse resource, with this value assumed to be 2.5% p.a., as estimated by the Department of Minerals and Energy (Anon 2004a). The price growth included is an increase in both the green electricity and the carbon credits selling prices. Based on predictions made by the Department of Minerals and Energy (Anon 2004a); the green electricity price was assumed to experience a 2.5 % growth rate p.a. The initial green electricity price was set at R250 /MWh, as predicted by (Anon 2004c). According to the United Nations Framework Convention on Climate Change (UNFCCC)[21], the market value of carbon credits transacted in 2004 was EUR 245m and it is estimated that more than EUR 620m worth of credits were transacted in 2005. This market is expected to grow substantially, with banks, brokers, funds and private traders participating. For this reason, it was assumed that the carbon credits selling price will grow at a rate of 10% p.a.[22], with an initial value of R30/MWh[23]. As a result of the instability and rapid growth of the fuel prices in South Africa, it is assumed that the (road) transport costs will increase by 5% p.a. The initial value of transportation cost as predicted by the World Bank[24] is 0.13 R/ton/km. The timber price in South Africa was assumed to experience a 2.5% growth in the future with an initial value of

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[21] See the UNFCCC website at http://cdm.unfccc.int

[22] It is estimated that the carbon credits selling price will rise to 22 US$/t-$CO_2$, which corresponds to 21% growth p.a. (Matsuhashi et al. 2004). However, this estimate is based on ratification of the Kyoto protocol by the USA; therefore a more conservative growth rate was set.

[23] Including technology efficiencies and conversion rates, it was approximated that one ton of CO_2 is equivalent to 1 MWh of electricity produced from biomass sources (Goldblatt et al. 2001). It is recognised that the expression of carbon credits in the unit R/MWh is not standard. The reason this was done is to maintain consistency throughout the model.

[24] See www.worldbank.com

R250/ton (Anon 2005a). From this discussion, the base case values of all the abovementioned growth rates and initial values can be seen in Table 3.3.

Table 3.3: Base case: Parameter growth rates and initial values

Input		Unit	Network
Demand:			
	Initial value	GWh	275
	Growth rate	% p.a	2.5
Bagasse:			
	Initial value	ton/month	Table C 2
	Growth rate	% p.a	2.5
Electricity price:			
	Initial value	R/MWh	250
	Growth rate	% p.a	2.5
Carbon credits selling price:			
	Initial value	R/MWh	30
	Growth rate	% p.a	10
Transport cost:			
	Initial value	R/ton/km	0.13
	Growth rate	% p.a	5
Timber Price:			
	Initial value	R/ton	250
	Growth rate	% p.a	2.5

These growth rates and initial values were modelled as inputs to the simulation engine. Subsequently, they impact the performance of the enterprises and the network as time progresses. For this reason, indicators tracking the performance of the network were required. These indicators are discussed in the section to follow.

3.4.4 Global Performance Indicators

One of the aims of this study was to investigate the manner in which the modelling approach assumed influenced the performance of an industrial network. For this reason, indicators were developed to track the performance of the network. These indicators also provide a means to determine the robustness and flexibility of the network when faced with external and internal stimuli. Furthermore, it was required that these indicators not only reflect the economic performance of the network, but also drive towards enterprises adopting more sustainable business practices. Consequently, economic, environmental and social indicators were selected as key performance measures for the network.

The economic performance indicator was selected such that it included both the net present value (NPV) of the network and total availability of bagasse. The NPV is typically used to analyse the profitability of an investment alternative. When comparing investment alternatives, the NPV is used as follows; (i) if the NPV of the network is greater than zero (Rand), the investment with the larger NPV is more favourable, (ii) if the NPV is below zero (Rand), the investment rates unfavourably, (iii) if an investment has a zero NPV, its cash flows are sufficient to repay the cost of the investment and provide a return equal to the discount value. Thus, from an economic perspective, a project with a zero NPV breaks even.

Even though the NPV is typically used to evaluate investment alternatives, the NPV was included as a performance measure of the network as it is a direct indication of the monetary value of the network when compared with IRR, which is a percentage. Consequently, the economic performance indicator is calculated as follows:

$$Econ_{sys} = \frac{NPV}{\sum_{n=1}^{N} m_{bag,sys}} \qquad \textbf{[eq.3.1]}$$

Where NPV (Rand) is the net present worth of the network, N is project life time (years) and $m_{bag,\ sys}$ (ton Bagasse /year) is the total availability of bagasse in the network. The bagasse resource was included as it allows for the economic performance of the network to be measured as a function of the resource efficiency, in terms of conversion of raw materials into profit.

One of the aims of this study was to investigate the manner in which renewable energy projects could lead to enterprises adopting more sustainable business practices in the future. For the purpose of this study, the carbon trading market (in terms of the sales of carbon credits) was identified as the main driver encouraging investment in renewable energy projects in South Africa. As such, resource efficiency (RE) was selected as the environmental indicator, with this number indicating of the amount of emissions released per MWh of electricity generated. Even though this study only takes into account CO_2 emissions as a contributor to the RE, other gases have been identified by the Kyoto protocol as also having global warming potentials (see Appendix B). The CO_2 emissions released during electricity generation is dependent on the efficiency of the conversion technology[25]. The RE is thus indicative of the amount CO_2 emitted per MWh electricity generated, with low and high values of this variable equal to good and poor environmental performance respectively. The RE is calculated as follows:

$$RE = \sum_{n=1}^{N} \left(\frac{\sum \left(\dot{m}_{CO_2,Tr} + \dot{m}_{CO_2,P} \right)_a}{m_{bag,sys}} \right) \qquad \text{[eq. 3.2]}$$

Where $m_{CO2,Tr}$ and $m_{CO2,P}$ are the amounts of CO_2 released due to transport and production respectively, N is the project lifetime, a denotes all the agents and $m_{bag,sys}$ is the total availability of bagasse.

The bagasse resource is included as it allows for the environmental performance of the network to be measured as a function of the resource efficiency, in terms of conversion of raw materials efficiently into a final product such that the least amount of CO_2 is emitted.

When it comes to analysing the value of the potential network in terms of its contribution to social upliftment, the choice of indicators is many and varied. For the purpose of this study, the social indicator was derived from the contribution of the network to direct electricity provision to off-grid communities. This indicator is expressed as the number of non-electrified houses that would be electrified if a generation facility was erected in a specific region. This criterion is called the rural electrification equivalent (REE), which was defined as part of the larger multi-party Eskom-funded project, with

$$REE = \sum_{i=0}^{i=N} \sum_{r=1}^{R} \alpha_r \frac{P_{\sup ply,r}}{P_{demand,r_i}} \qquad \text{[eq.3.3]}$$

Where N represents the project lifetime, r the geographical regions, P_{demand} and P_{supply} the electricity demand and supply and α is the priority factor in region r respectively.

[25] The efficiencies of the conversion technologies utilised by all the agents can see in Table 3.2.

The regions in KZN follow the boundaries of the district municipalities (see Appendix C for a map). As the sugar mills were aggregated into a single agent, the location of this agent was set as that of the Sezela mill. It was assumed that the IPP is located in Durban, as this region has the highest electricity demand. As previously discussed, the only alternative available to the Eskom agent is assumed to be co-firing of bagasse and coal into an existing facility. The facility was selected to be the Majuba plant in Mpumalanga, which is closest to the cane growing belt. The district municipalities, corresponding electricity demand and electrification priority of the agents is show in Table 3.4.

Table 3.4: Energy demand, electrification priority and municipal districts for each agent

Agent	District Municipality	Total number of households	Un-electricified households	Un-electricfied/total number of households	Normalised priority factor
Sugar mill	Ugu	1.51E+05	7.83E+04	0.52	0.65
IPP	eThekwini	7.87E+05	1.59E+05	0.20	0.25
Eskom	Amajuba	9.67E+04	2.66E+04	0.28	0.34

As illustrated in Table 3.4, the agents are not all located in districts of equal electricity demand. It is important to note that this demand is measured by the number of households that are un-electrified in a district. An electrification priority factor was defined such that an agent erecting a facility in a region of higher electricity demand is a better performer upon consideration of the social criteria. The reason this was done was that the social criteria was measured in terms of contribution to social upliftment; the more un-electrified houses are electrified, the better this contribution. In order to accurately measure the contribution by each agent, it was necessary to normalise this factor such that it is directly comparable with the best and worst performers in KZN. This normalisation was performed on a linear scale with the best and worst performers being the Umkhanyakude and the eThekwini districts respectively (see Appendix C for complete table).

By making use of the indicators developed in eq. 3.1, 3.2, 3.3, the performance of the network could thus be tracked in terms of economic, environmental and social indicators.

3.5 Optimiser: Individual agent decision-making process

A logical flow diagram of the technology and capacity decisions made by each agent can be seen in Figure 3.3. The diagram is discussed under the headings (indicated as dashed lines in Figure 3.3); (i) resource auction and negotiation, (ii) generation and screening of feasible capacity alternatives, (iii) normalisation, trade-off & optimisation of feasible capacity alternatives.

Together with the base case values presented in Table 3.1, 3.2 and 3.3, a number of constants were required to determine both the performance indicators of the network and the decision criteria of each agent. For the purpose of this study, profit margin was used as an indicator of an enterprises policy and its ability to control costs and represents the net income of an enterprise as a percentage of its revenue. Even though competitive strategy and product mix cause profit margin to vary among different enterprises, the base case value for this percentage was set at 20% for all the enterprises in the network. This was done as the most important unit of measure in this study, and thus main product from the network, was considered to be energy. The minimum acceptable rate of return base case value was set at 20%. The contract period is the time for which the contracts were set up and the resources locked in. It is important to note the difference between contract period and project lifetime. In this study the contract period was assumed to be short term contracts, i.e. 3 years. The project lifetime is defined as the number of years for which a technology will be operable and financially feasible before being upgraded or replaced, i.e. 20 years. The manner in which these values were used in the model is explained in the sections to follow.

Table 3.5: Base case: Constants

Input	Unit	All Agents
Profit Margin	%	20
Minimum acceptable internal rate of return	%	20
Disount rate	%	6.5
Contract length	years	3

All of the numbered steps described in sections 3.5.1, 3.5.2, 3.5.3 and 3.5.4 refer to Figure 3.3.

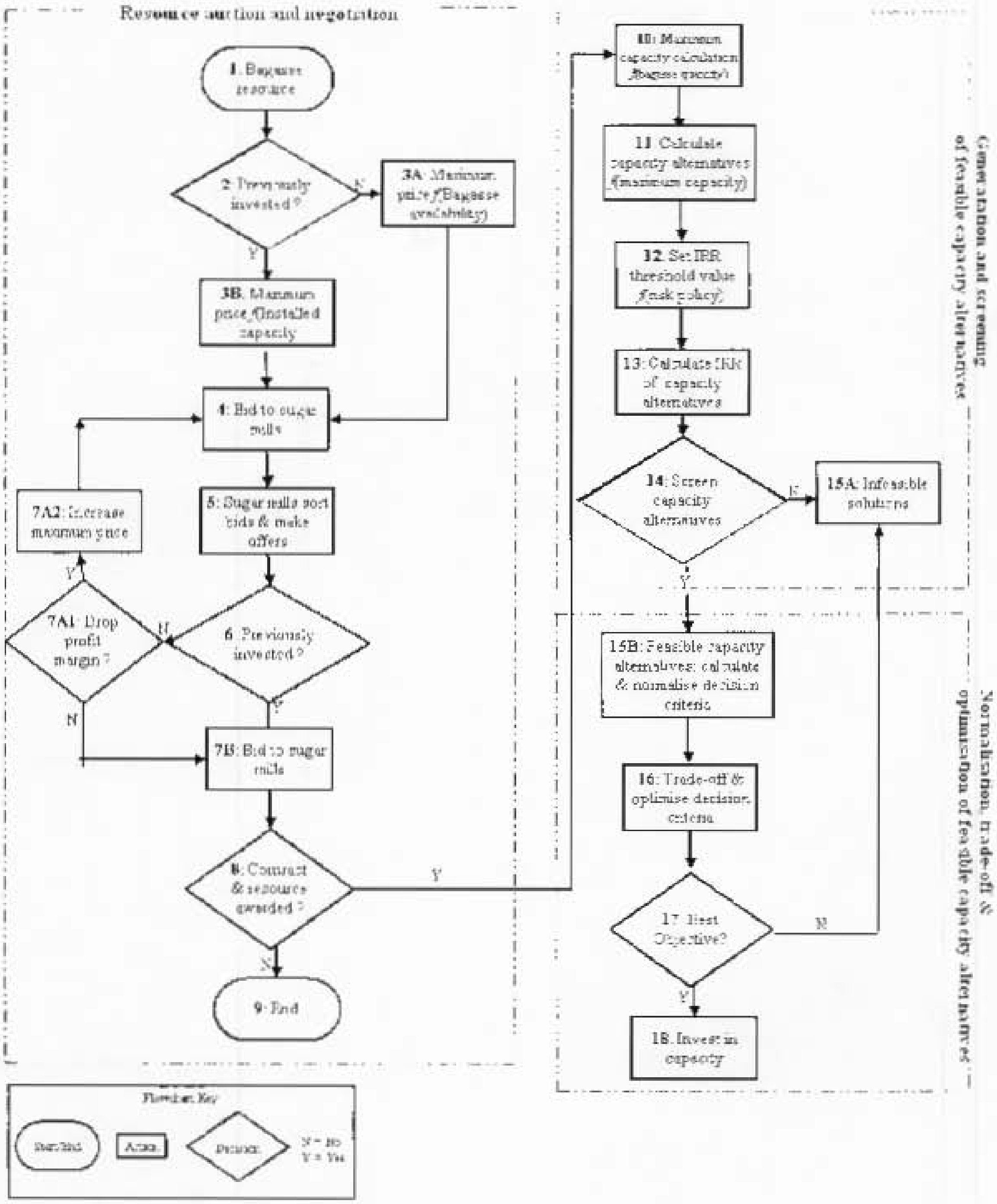

Figure 3.3: Logical flow diagram of individual agent decision-making procedure

3.5.1 Resource Auction and Negotiation

As bagasse is generated by the sugar mills, it can be said that it is "owned" by them; hence decisions made by the mills will determine the availability of bagasse for other uses, including Eskom Holding, independent power producers, and as a feedstock for paper manufacture (step **1**). In this study bagasse is auctioned off by the sugar mill agent. This auctioning process was set to occur every time the contract period expires. In this study this contract length was set at 3 years. As such, bagasse is auctioned off every three years to the highest bidder. The first decision faced by the agent in this process (step **2**) is a decision regarding the maximum price it is willing to offer the mills in return for bagasse. This price is based on a profitability calculation of operating a potential generation facility. This calculation is performed by determining the raw material costs when the profit is zero, i.e.

$$I = E \qquad \textbf{[eq. 3.4]}$$

Where I is the income (R), E is the expenses (R)

And;

$$I = PC * (EP + CCP) \qquad \textbf{[eq. 3.5]}$$

Where PC is the possible production capacity (MWh), EP is the electricity price (R/MWh) and CCP is the carbon credits price (R/MWh). If an agent had not previously invested in a generation facility, the possible production capacity is dependent on bagasse availability (step **3A**). If an agent had previously invested in a generation facility, the possible production capacity is dependent on the actual installed capacity (step **3B**).

And;

$$E = PC * (OC + D * TC + BC) \qquad \textbf{[eq. 3.6]}$$

Where OC is the operation and maintenance costs (R/MWh), D is the distance of the agent from the bagasse resource (km), TC is the transportation costs[26] (R/MWh/km), BC is the cost

[26] It is assumed that transport only occurs by road. Therefore this cost was estimated by considering fuel efficiency for a certain type and weight of truck.

of purchasing the bagasse (R/MWh). Bagasse will be purchased on a mass basis. It is thus important to remember that expressing this mass basis as an energy basis involved technology efficiencies. Technology efficiency is in turn a function of both technology type and size (MW), i.e. the larger the potential facility, the more efficient the conversion process will be (see Table 3.2).

As the profit tends towards zero, the maximum price each agent is willing to pay for the bagasse resource is equal to *BC*. Consequently, from eqs. 3.4, 3.5 & 3.6, the only unknown is the maximum price the agent would be willing to pay for bagasse (BC). In this manner each agents is thus able to determine what the maximum price is it would be willing to pay for bagasse. Even though the bagasse is owned by the sugar mill agent, it also determines a maximum price it would be willing to offer for this resource. The reason for this is that the sugar mill agent is then able to compare the potential profitability of installing a generation facility with the alternative of selling bagasse to the other agents in the network.

Each agent then uses this maximum price it is willing to pay for bagasse and makes an offer to the sugar mill agent (step **4**). The sugar mill agent sorts these bids in descending order and informs each agent of its success or failure in acquiring bagasse (all agents are then aware of the bidding amounts of the other agents, step **5**). Each agent then enters into a negotiation process with the sugar mill agent. This occurs as follows:

If an agent had previously invested in a generation facility (step **6**) and it is able to further drop its profit margin, it will adjust its bid so as to make a better offer to the sugar mill agent, as it will have a significant interest in obtaining the bagasse so as to not be left with idle capital infrastructure. An agent can lower its profit margin until its expenses do not amount to more than its income (step **7A1**). The adjusted maximum price an agent would be willing to pay for the bagasse (step **7A2**) is then calculated by considering the first offer it made to the sugar mill agent (current maximum price, x) and the maximum price the sugar mill agent calculated it would be willing to pay for the bagasse (y). The logic of the price adjustment each agent performs is then as follows:

If $y > x$

Adjusted maximum price = $x*\left(\frac{y-x}{y}+1\right)$ [eq. 3.7]

From eg.3.7, it is not evident that this price adjustment is based on a percentage increase. This will be explained by a hypothetical example. The IPP offers a sugar mill R 90/ MWh for bagasse (x) (the calculation of this value was explained previously in this section). The sugar mill uses MCDA techniques (see section 3.5.3 & 3.5.4 to follow) to determine what is the price equivalent of the profit it will be able to generate from investing in a generation facility itself R 100 / MWh (y). The IPP will adjust its price 10%, as determined by eg. 3.7[27].

If $y <= x$; no further price adjustment will occur and the agent will continue bidding at its current maximum price, namely x. If the value of the adjusted bid is still not high enough to secure the bagasse resource, the agent will fail to secure the resource and consequently posses a stranded asset. This state is undesirable for any agent in the network.

An agent will not alter its original offer if: (i) it was the top bidder, (ii) it has not invested in a technology previously (step **6**), or (iii) it would not longer be profitable if it has to lower its profit margin further.

After this procedure has been completed, the agents then make an offer to the sugar mill agent in an attempt to secure bagasse (step **7B**). Bagasse is awarded to the agents in order of highest bidder until either the bagasse resource has been depleted or the available resource is no longer sufficient to meet the needs of a specific agent (step **8**). If the latter is the case, the remaining bagasse is "lost" from the system for that year [28] (step **9**).

3.5.2 Generation and Screening of Feasible Capacity Alternatives

To allow for selection of an optimal capacity for installation, a procedure by which a set of capacity alternatives were generated and then screened was developed. Each agent generates this set by calculation of a maximum possible capacity alternative. This value is dependent on,

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[27] The sugar mills defaults to selling bagasse if its price equivalent of the profit it will be able to generate from investing in a generation facility is equalled.

[28] The storage of bagasse, or its energy value, from one year to the next, is not included in this study.

(i) the amount of bagasse secured in the bid, (ii) the technology options available to the agents and the (iii) electricity demand in the region.

Item one was discussed in section 3.5.1. The technology options available to the sugar mill and the IPP agents are either a combustion or gasification facility. The technology option available to Eskom is limited to co-firing bagasse together with coal into an existing pulverised coal boiler / steam turbine combination. The electricity demand in a region is a function of both the demand in KZN and the number of households that are un-electrified in the specific region. The region each agent is located in and the corresponding demand in that region can be found in Appendix C.

The maximum possible capacity for each agent is determined by comparing the electricity demand in the municipal district and the amount of bagasse the agent is able to secure in the bid (step **10**). Depending on this outcome, the maximum possible capacity is either limited by electricity demand or by bagasse availability. Consequently, the set of capacity alternatives is known, with zero and the maximum possible capacity used as the upper and lower bounds respectively (step **11**). Each agent is thus able to consider this set of alternatives when making a decision regarding investment in a generation facility.

An economic profitability process was used to screen this set of possible capacities. Even though enterprises today take into account economic, environmental and social objectives when considering projects, economic profitability still remains the key factor driving investments in new ventures. An economic screening process was performed by comparing the rate of return (IRR) of each alternative with the risk policy adopted by the agent (steps **12 - 13**). This risk policy was determined by the minimum acceptable IRR[29]. It is important to note that the minimum acceptable IRR is determined for an investment alternative over the project life time (20 years) and not over the contract period (3 years) of that alternative. A high risk agent will adopt a low minimum acceptable IRR whereas a risk averse agent will demand a

[29] This is but one method through which risk can be incorporated into investment analysis. See (Goldblatt et al. 2001) for a discussion of risk analysis of clean development mechanism projects in South Africa.

high minimum acceptable IRR[30]. This value was then used as a threshold value; with projects yielding IRR values below this threshold not considered further as feasible alternatives. Even though the NPV and IRR are interrelated, the IRR was preferred for the economic screening process of the agents as it was easier to identify a minimum acceptable threshold value in terms of percentage return on investment over the project life time, when compared with identifying a monetory (Rand) threshold value as given by the NPV. Figure 3.4 illustrates the screening process performed by the sugar mill agent, in the third year of a simulation (performed with base case values), when considering capacity alternatives for gasification generation.

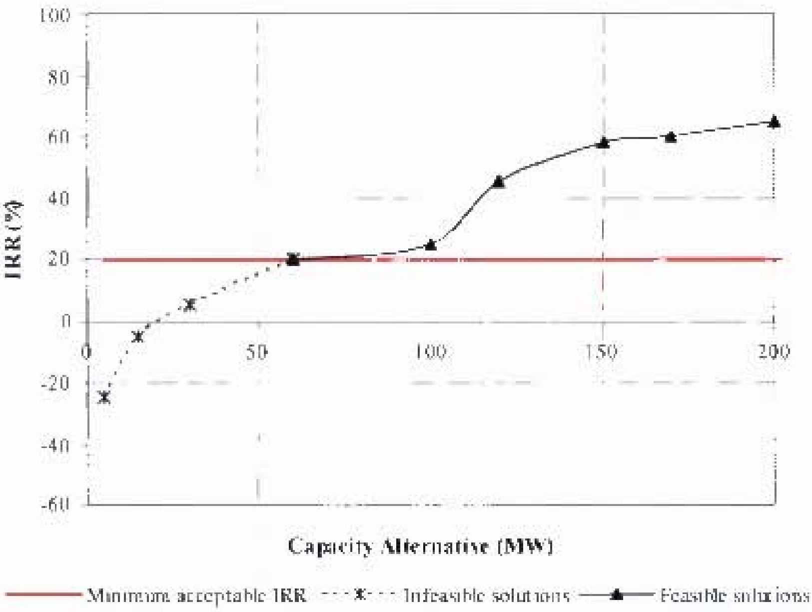

Figure 3.4: Internal rate of return screening process for a set of capacity alternatives

The red line indicates the minimum acceptable IRR, with all capacity alternatives yielding IRRs lower than this value regarded as infeasible solutions. In this manner the infeasible and feasible capacity alternatives were determined (step 14). The infeasible solutions were further

[30] For the remainder of this report, the term 'high risk agent' will be used to refer to agents who will adopt a low minimum acceptable IRR whereas the term 'risk averse agent' will refer to agents who demand a high minimum acceptable IRR. It should be noted, in some cases, this terminology might not align with the investment notion of 'high risk, high return'.

disregarded from the system (step **15A**). An optimal value was then selected from the set of feasible alternatives to determine the technology type and size of the generation facility to be installed. The optimal value was determined by; (i) calculating the economic, environmental and social decision criteria of each alternative, (ii) trading-off these criteria against each other and selecting the alternative with the best objective. These procedures are discussed in sections 3.5.3 and 3.5.4 to follow.

3.5.3 Decision Criteria

Economic evaluation of equipment alternatives is based on capital costs, operating and maintenance costs and equipment life expectancy (Turton et al. 1998). The economic criterion was developed such that it captured all of these factors. One of the following methods could be used for this purpose, namely (i) capitalised cost method; (ii) equivalent annual operating cost method.

The first method makes use of capital costs and an equivalent capitalised operating cost. The equivalent capitalised operating cost can be calculated by converting the operating cost into an equivalent capital cost (ECC). Therefore the capital cost and the yearly operating costs are lumped into a single cash amount. This amount could then be used to compare different equipment alternatives, with the alternative with the lowest ECC the most favourable. The second method amortises the capital cost over the operating life to establish a yearly cost; which is added to the operating costs to yield the equivalent annual operating cost (EAOC).

Although both methods take into account the time value of money, it was decided to make use of the second method to account for the economic criterion of each agent. The reason for this was that a sensitivity analysis of both external and internal stimuli was performed. The stimuli mainly influence the operating cost of a technology (e.g. carbon credits selling price). The capital cost of a technology is dependent only on technology type, capacity and efficiency. As such, an economic criterion capturing the effect of the sensitivity analyses directly (as opposed to indirectly in the form of an equivalent value) was desired. For each year, the EAOC was calculated; this value was then summed over the project life time, to yield a total lifetime cost, as seen in eq 3.8:

[eq.3.8]

$$EAOC = \sum_{i=0}^{i=N} (Ap + Ac)$$

Where

Ap is the annual operating costs, Ac is the annualised capital cost (= $C*Ar$), C the total capital cost of constructing a generation facility, Ar is the annuity rate, Dr the discount rate, N the project lifetime (years).

With Ar calculated as follows:

$$Ar = \frac{Dr(1+Dr)^N}{(1+Dr)^N - 1} \qquad \textbf{[eq.3.9]}$$

The environmental criterion of each agent is represented by the resource efficiency (RE_{local}). This value was calculated in a similar fashion to the global environmental performance indicator (RE_{system}, see [eq. 3.2), namely, it is a measure of how efficiently bagasse is converted into electricity such that the least amount of CO_2 is emitted. Each agent makes use of the following equation to perform this calculation:

$$RE_{local} = \frac{\sum_{i=0}^{i=N} m_{CO_2,Tr} + m_{CO_2,P}}{\sum_{i=0}^{i=N} EP} \qquad \textbf{[eq. 3.10]}$$

Where $m_{CO2,Tr}$ and $m_{CO2,P}$ are the amounts of CO_2 released due to transport and production respectively. EP is the electricity production (MWh) of all the agents and N is the project lifetime. From eq.3.10 the following should be noted:

(i) the CO_2 emissions for any particular investment decision were projected over the project life time, as, once the decision is taken, these emissions are merely a function of design parameters, which are fixed.

(ii) CO_2 emissions are expressed as a function of the electricity production of the network. This was done so that the emissions of different technologies could be compared against each other, in terms of energy output. This could then capture the effect of difference in technology efficiencies and economies of scale (i.e. the bigger the facility, the more efficient it will be, see Table 3.2).

The social criterion of each agent is represented by the rural electrification equivalent (REE). This value was calculated in a similar fashion to the global social performance indicators (REE, see eq. 3.3), namely, it is a measure of the contribution of the network to electricity provision to off-grid communities. The indicator was taken to be the number of non-electrified houses that would be electrified if a generation facility was erected in a specific region, and can be calculated as follows;

$$REE = \sum_{i=0}^{N} \alpha_r \frac{P_{supply,r}}{P_{demand,r}} \qquad \textbf{[eq. 3.11]}$$

Where N represents the project life time, r the geographical regions, P_{demand} and P_{supply} the electricity demand and supply and α is the priority factor in region r respectively.

As discussed in section 3.4.4, the regions in KZN follow the boundaries of the district municipalities (see Appendix C for a geographical map). The manner by which the priority factor of each region is determined is also discussed in this section.

By making use of eq. 3.8, 3.9, 3.10 & 3.11 each agent is thus able to calculate its performance relative to economic, environmental and social criteria respectively (step **15B**). Performance in these criteria were then normalised and traded-off to enable each agent to make the optimal investment decision. This procedure is discussed in the section to follow.

3.5.4 Capacity Decisions: Normalisation, Trade-off and Optimisation

One of the objectives of this study was to determine how economic factors together with environmental and social factors influence the decision-making procedure of agents within this network. This understanding must be extended beyond merely including environmental and social factors as financial externalities. The paragraphs to follow elaborate on this by: (i) discussing the disadvantages of including environmental and social factors as financial externalities; (ii) offering an alternative means to include these factors into the decision-making procedure followed by enterprises.

Environmental and social factors are included as externalities by monetisation of these factors and then typically performing single or multiple objective optimisations. It is important to note that both the environmental and social externalities are expressed in terms of monetary units. This monetisation of externalities is typically done in the form of emissions taxes for the environmental externality and political capital for the social externality (Glazner and Sgouridis 2005). The difficulties experienced with this monetisation of the environmental and social objectives are in terms of magnitude; as illustrated in Figure 3.5.

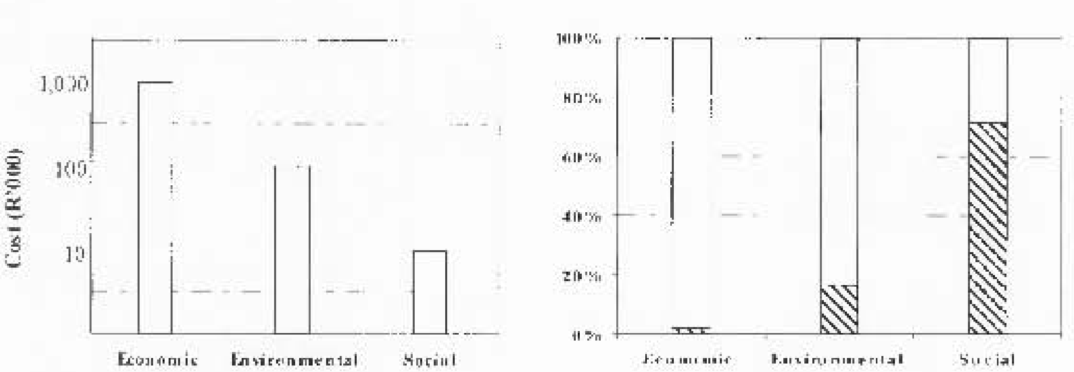

Figure 3.5: Scaling problem experienced by monetisation of economic, environmental and social objectives

The hypothetical scenario seen in Figure 3.5 is used for illustrative purpose only, so as to show the sensitivity of the three factors to a change in an external stimulus. A change in this stimulus translates to a R1000 decrease in value of all three of the factors. As a result of the difference of the order of magnitude between the three factors, the effect of the R1000 change (and thus the external stimuli) is vastly different. The social factor changes in excess of 60% whereas the environmental and economic factors change by 17% and 1.5% respectively. Consequently, the factor with the largest order of magnitude is the least sensitive to changes in these stimuli.

The problem with difference in scale of decision criteria explained above is not only relevant when all of the criteria are expressed in terms of monetary units. If the economic criterion is expressed in South African Rand for example, the environmental criterion in ton CO_2 and the social criterion in number of rural houses electrified, the scaling problem previously explained would be experienced not only in terms of possible difference in scale but also in difference of unit. As such, it is evident that an alternative means to include environmental and social criteria into the decision-making process of agents is required. Even though it is recognised that there is an entire body of literature devoted[31] to costing externalities, these approaches fall outside the scope of this thesis and will not be presented here. Instead the focus will be on a single approach and the difficulties and methodologies associated with taking this approach in practice will be discussed.

The alternative means by which environmental and social criteria are included as decision criteria without being expressed as externalities will be discussed under the following headings: (i) normalisation of economic, environmental and social decision criteria (step **15B**), (ii) setting preferences for each criterion through which the weighted sum of the normalised criteria can be calculated (step **16**), (iii) determination of the best objective through optimisation of the weighted sum of the normalised criteria (step **17**) (iii) selecting the capacity corresponding to this optimum (step **18**).

In this study, normalisation of the decision criteria eliminates both the unit and scale difference between the criteria[32]; and was performed by constructing value functions. The construction of value functions translates the performances of the capacity alternatives into a value score on an interval scale, thus indicating a decision-makers/enterprises preference for a particular level of performance.

This was done was by firstly selecting two performance scores which represent the best (X_j^*) and the worst (X_{j*}) situation in each decision criterion. It is common practice to scale, with the best score generally allocated a value score of 1 and the worst score a value of 0 (Belton and Stewart 2002). These performance limits were determined by time-dependent figures derived from a global optimisation model of the physical system and the feasible technology options

[31] See Pearce (2001) for overview.

[32] Normalisation can also be used when units are commensurate – the aim of normalisation is to provide context, and to reduce the number of degrees of freedom, thereby making analysis simpler.

(Beck 2006)[33]. And secondly determining the value score ($v(X_j)$) of each criterion (X_j). For the purpose of this study, a linear value function[34] was used, as illustrated in Figure 3.6.

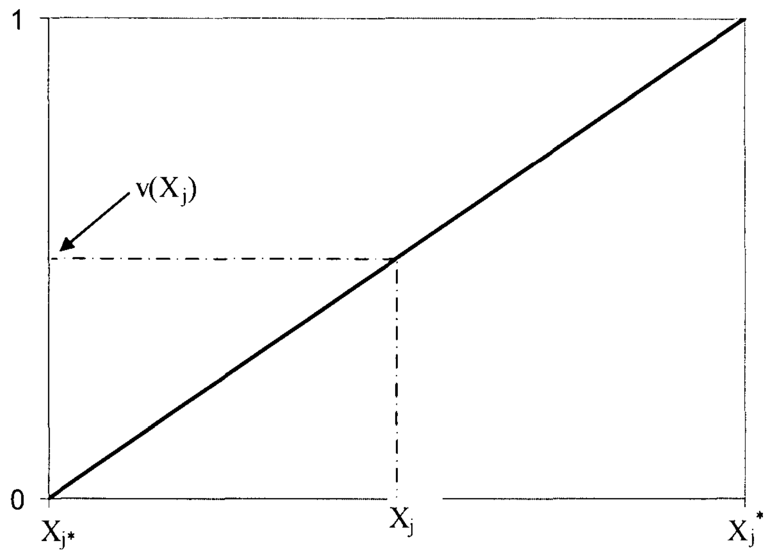

Figure 3.6: Diagrammatic representation of the translation of performance scores to a value basis

Consequently, the performance scores of the three decision criteria were all represented as a value between 0 and 1. As such, they are directly comparable and can be traded off. This was done by calculating the weighted sum of the normalised criteria ($V(x_j)$) (often referred to as the additive aggregation function (Belton and Stewart 2002) as follows:

$$V(x_j) = \sum_{j=1}^{n} w_j v_j(x_j) \qquad \text{[eq. 3.12]}$$

[33] See Appendix C for description of these models.

[34] Common shapes for value functions are linear, concave, convex, sigmoidal or step. Linear value functions suggest that changes in performance are valued equally throughout. Concave and convex functions are used when this is not the case. Step or sigmoidal functions are constructed when a particular value in the range over which the value functions is defined has a particular significance (Belton et al. 2002). See Appendix A for diagrammatic representation of these functions.

With w_j is the preference setting (or weighting) adopted by each enterprise and $v_j(x_j)$ the value score as explained above.

The weighting selected by each enterprise should reflect the trade-offs the decision-makers find acceptable. In practice the weightings preference an agent expresses towards certain decision criteria should be determined by interviewing the stakeholders. In this study the focus was not on the determination of stakeholder preferences but rather on developing an agent-based modelling approach for industrial networks. As such, the base case weighting values for these stakeholder preferences were each set at 33.3% for the economic, environmental and social criteria i.e. the decision-maker is preferentially indifferent to these criteria. A sensitivity analysis on these weightings was performed, as discussed in section 4.2.3.

By making use of the procedure explained above, each enterprise was thus able to calculate an additive aggregation function for all feasible capacity alternatives. The additive aggregation function with the highest value in the set of feasible capacity alternates was the selected as the optimum aggregation function and the technology and capacity alternative corresponding to this value was set as the optimal capacity to be installed. As awarded, bagasse was then locked into the agents and their proposed technologies and installed capacities for the period of time for which the bagasse contracts were set up by the sugar mills. Once the contract length (three years) had expired, the entire procedure was repeated and the resource re-allocated. The bagasse resource is only locked into a certain agent, and thus a certain technology, for the contract length period. It is important to note that in such a case, the project life time, i.e. the pay back period of the investment; is longer than contract period, and an agent could possibly lose the resource to higher bidders during this time. Even though it is recognised that such a scenario presents high risks for potential investors, the model was configured in this manner as the allocation of resources for the carbon trading market is uncertain due to rapid changes and developments occurring in this market in the past few years[35]. In other words it was assumed that the sugar mills are unlikely to set up medium to long term contracts (10 years – 20 years) with potential bagasse buyers due to the volatility of the carbon trading market. The

[35] See the UNFCCC website at http://cdm.unfccc.int

management of the risks associated with this model configuration was not included in this study.

In this manner a simulation-optimisation agent-based model can be used to model and analyse the behaviour of an industrial network. A discussion and analysis of the resulting dynamics of such an application are presented in the next chapter.

4 Case Study: Results

As suggested by Rahmandad and Sterman (2004), the outcomes of agent-based models are difficult to validate. One means by which model validation can be done is by setting an overall system goal prior to modelling and analysis and evaluating if the network is able to reach this goal or not. As the network used for this study consisted of constructing possible scenarios and agents that could potentially arise from the energy generation capability in the kwaZulu-Natal region, where no such network exists at present, no benchmarks were set against which a result can be deemed "good" or "bad". Although an extensive sensitivity analysis is not a means by which a model can be validated, it was assumed that such an analysis would yield insights into the "correctness" of the model through the trends and behaviours that arise from configuring the agents, and hence the network, in a certain manner. The results of this analysis illustrate: (i) the dynamic performance of the network as a function of changes in external and internal stimuli and (ii) individual agent behaviour; in terms of capacity investment decisions, also as a function of changes in external and internal stimuli. Before the results of this analysis are presented in section 4.2, the behaviour of the network and the agents at the base case values is first shown in section 4.1. It is important to note that the figures illustrated in the remainder of the chapter are results obtained from the agent-based simulation-optimisation model as presented in Chapter 3. As such, the discussions and conclusions refer to an industrial network configured in this manner. The results as presented here are subject to cost estimations[36], model assumptions[37] and decision criteria[38] as defined in this study.

4.1 Base Case results

The base case values assumed for the variables and parameters in this study are presented in Table 3.1, 3.3 and 3.5. The logic flow diagram of the manner in which the model is executed can be seen in Figure 4.1.

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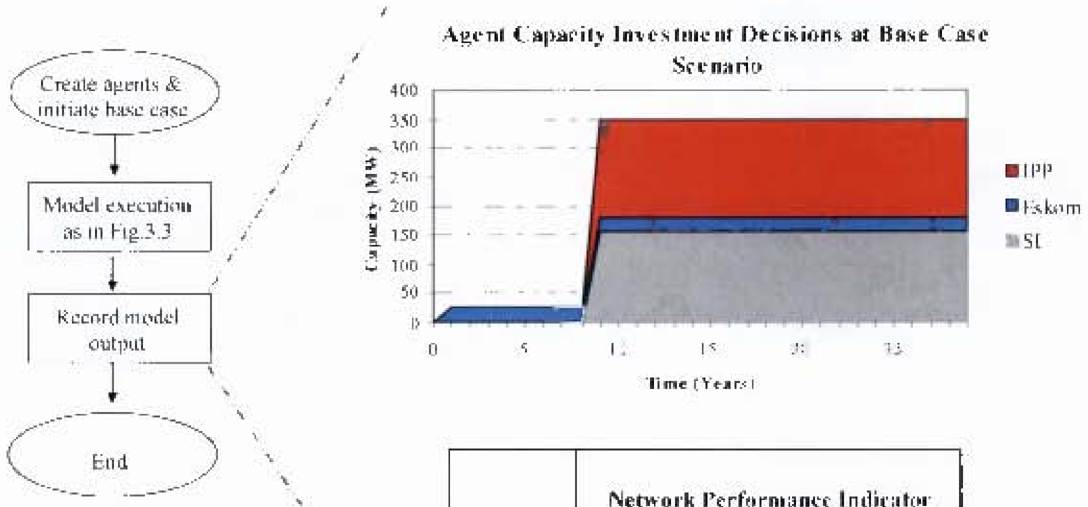
[36] See Appendix C

[37] See base case discussed in chapter 3

[38] Measured by the economic, environmental and social criteria discussed in section 3.5.3



	Network Performance Indicator		
Simulation Time (years)	Economic	Environmental	Social
30	0.26	0.8	0.25

Figure 4.1: Logical flow diagram of model execution for base case scenario

From this output both the agent capacity investment decisions can be seen as a function of time as well as the performance of the network over the project life time (30 years). It can be seen that the Eskom agent selects to invest in a small generation facility as of time zero whereas the sugar mill and IPP agents only invest at later times in bigger facilities. In addition, it can be seen that the overall economic and social network performance are similar and perform poorly (0.26 and 0.25 respectively) for the base case scenario. The environmental performance of the network is higher for the base case scenario (0.8). Note, all scores are on a "value" basis of "0" to "1", as a consequence of the normalisation. These results will be discussed in context of the sensitivity analysis results presented in the following section.

4.2 Sensitivity Analysis

The sensitivity and dynamic behaviour of the network as a whole and that of the individual agents, with regard to changes in external and internal stimuli, were investigated. The external stimulus explored was the selling price of carbon credits and the internal stimuli were the decision and risk policies adopted by each agent. The ranges for these stimuli can be seen in

Table **4.1**; with the reason for each range selection discussed in the results section of each respective variation, presented in the sections to follow.

Table 4.1: Variables and ranges used for sensitivity analyses

	External stimulus	**Internal stimuli**			
	Carbon credits selling price (R/MWh)	Minimum acceptable internal Rate of return (%)	Economic weighting (%)	Environmental weighting (%)	Social weighting (%)
Range	0-150	0-30	See Table 4.3		

A logical flow diagram of the manner in which the sensitivity analysis was performed, together with an example of the typical model output, can be seen in Figure 4.2.

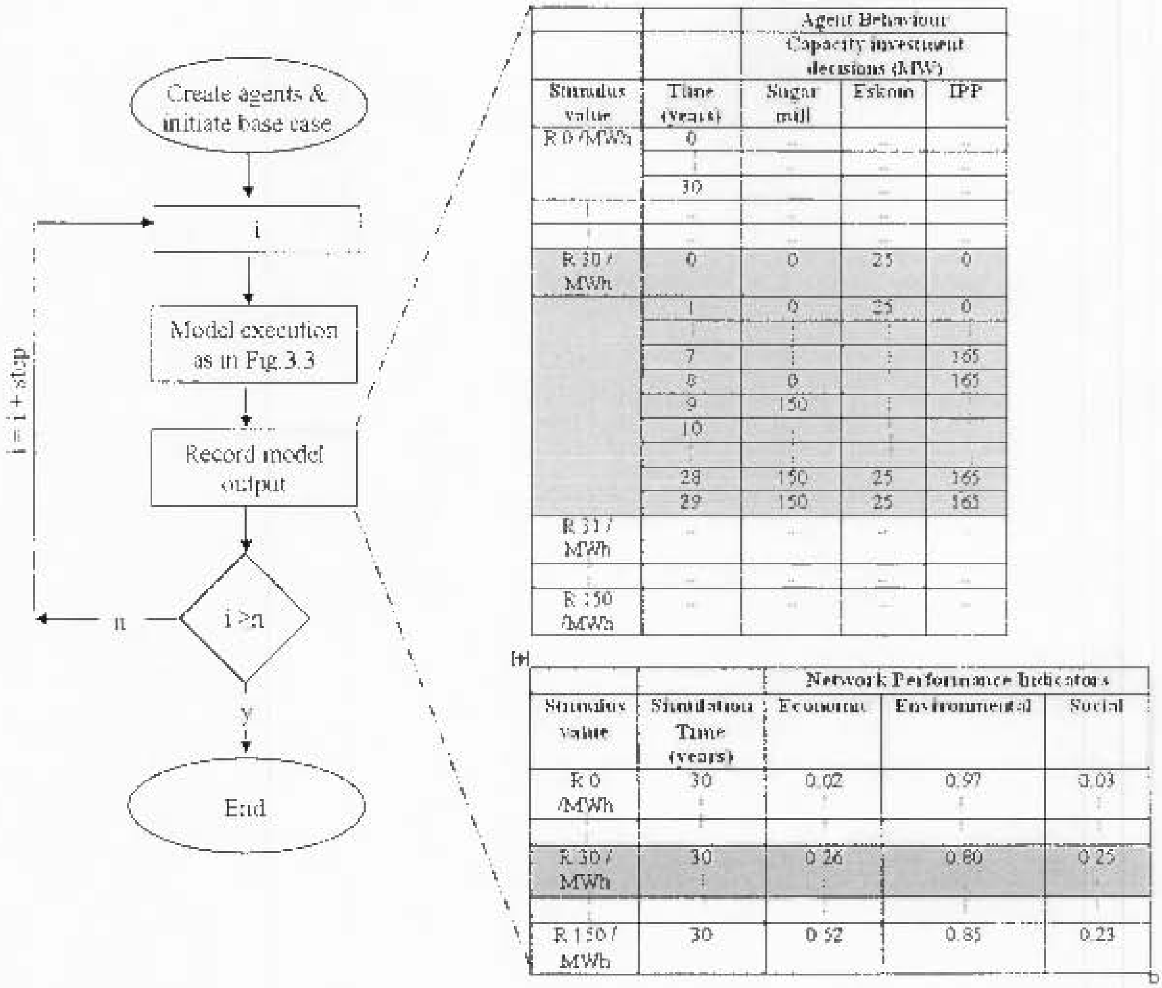


Figure 4.2: Logical flow diagram of sensitivity analysis procedure

From this diagram, it is important to note the following:

- *i* denotes the input of a stimulus, e.g. value of the carbon credits selling price.
- *n* denotes the upper bound of the range in which the stimulus is varied, e.g. R 150/MWh for the carbon credits selling price.
- *step* denotes the size of the step in which the stimulus was varied, e.g. the carbon credits selling price was varied from 0 to 150 in a step size of 1.
- the variables were tested independently, i.e. as the value of the variable in question (e.g. carbon credits selling price) was varied, all of the variables remained constant at values determined by the base case scenario.

- The behaviour of the network and the agents was tested for a 30 year time period in the model execution step.
- The shaded area shown in the model output is for illustrative purpose only.
- The sensitivity of the network was measured by economic, environmental and social performance indicators.
- The dynamic behaviour by the agents was measured by the capacity investment decisions as a function of time
- In this study, uncertainty is dealt with in a simplistic manner by performing several "what-if" studies, as illustrated by the sensitivity analyses. Even though the objectives of this study do *not* include an extensive uncertainty analysis, it is recognised that a more rigorous approach to the consideration of uncertainty could potentially yield more insight into the sensitivity of the network to small changes in internal and external stimuli.

In this manner the sensitivity of the network to changes in external and internal stimuli was tested. The results of these analyses are discussed in the remainder of this section.

4.2.1 Carbon Credits Selling Price

The studies reviewed by the National Strategy Study for the **carbon credits** selling price in South Africa predict a price range from under R20 /ton CO_2 to over R70/ton CO_2 (Goldblatt et al. 2001). Due to the rapid growth of the carbon credits market[39] and the time in which the Goldblatt study was performed (2001), it is assumed that a value of R70/MWh[40] is a conservative estimate. For this reason the carbon credit selling price was varied between a negative future (one in which the carbon market does not develop, i.e. the carbon credits selling price is R 0 /MWh) and positive a future (i.e. a selling price of R150 /MWh). The performance of the network as a function of this variation is illustrated in Figure 4.3.

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[39] http://cdm.unfccc.int/Projects/registered

[40] Including technology efficiencies and conversion rates, it was approximated that one ton of CO_2 is equivalent to 1 MWh of electricity produced from biomass sources (Goldblatt et al. 2001).

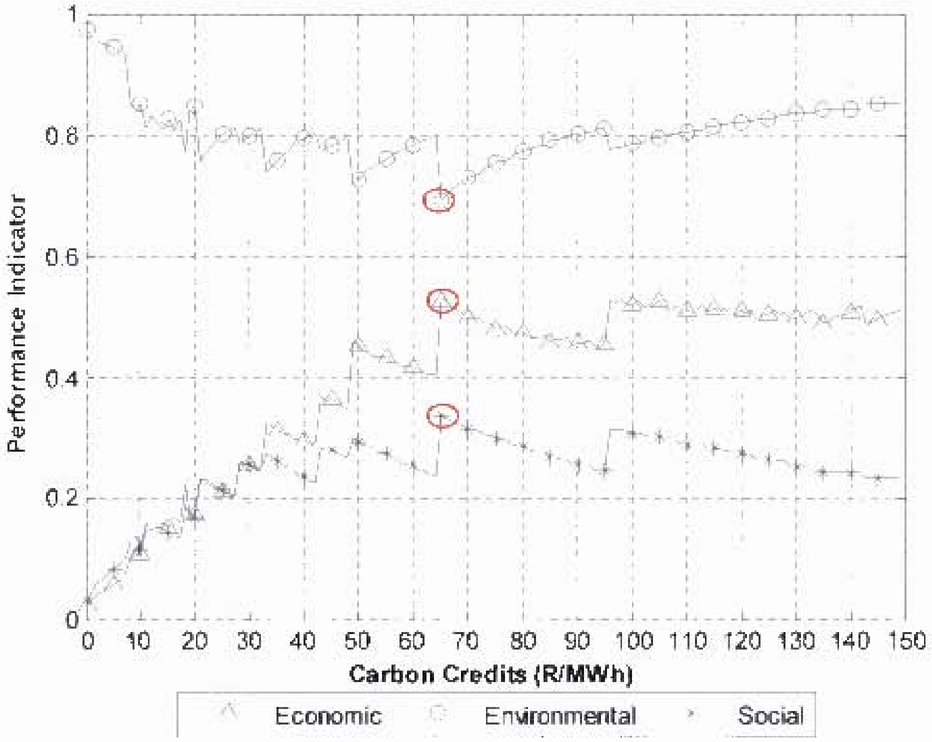


Figure 4.3: Performance of the network vs. carbon credits selling price

As indicated by Figure 4.3, the performance of the network for all values of carbon credits selling price between R0 /MWh and R150/ MWh was tested. It is important to remember that these performance scores were normalised with respect to the "best" and worst" network performance derived from a global optimisation model of the physical system and the feasible technology options (see Appendix C for model description). Therefore their magnitude indicates how they compare with the "best" and "worst" network performance. It is evident that the performance of the environmental indicator is closest to that of the "best" network performance throughout the simulation. This is due to the following:

i. life cycle considerations relating to the carbon footprint of sugar cane production and bagasse conversion have not been taken into account. The environmental indicator thus only measures CO_2 emissions without comparing this value to "business as usual" operation by the sugar mills. Consequently, the smaller (to minimise production emissions) and more favourably located (to minimise transport emissions) the CDM project the better the environmental performance of the network. As such, for low carbon credits selling prices, erection of generation facilities will only happen on a small scale (MW). For these reasons, the environmental performance of the network is best for low carbon credits selling prices

ii. the aggregated configuration of the sugar mills leads to less emission from transportation when compared with modelling the mills at different geographical locations.

It can also be seen that the indicators measuring network performance display non-uniform/saw tooth pattern behaviour. The reason for this is changes in network configuration as time progresses. It is important to note that the performance scores of the network shown in this figure are cumulative values over the 30 year project lifetime. If the performance of the network every year was to be represented, this figure would require a third dimension, i.e. a time axis. This was not done to show the performance of the network as a whole, but for each enterprise that comprises the network, as illustrated in Figure 4.4 and Figure **4.5**. As such, changes in network configuration with time will be addressed in the discussion of these two figures.

The other trends observed in Figure 4.3 are as the carbon credits selling price increases the: (i) economic and social performance increases to a maximum performance after which the performance tends to level out, and (ii) environmental performance decreases to a minimum performance followed by a gradual increase.

The extreme performance scores of the three indicators are shown by the red circles in Figure 4.3. It is evident that even though the network performs best economically and socially at a carbon credits selling price of R65 R/MWh, its environmental performance is at its worst value at this price. It is important to note that the network performance emerges as a result of the individual agent behaviour. As such, if results are considered in a "top down" manner (e.g. from the perspective of potential CDM partners or a government institution), these three indicators should be traded off against each other to determine what the performance of the network is at a specific carbon credits selling price. In practice this would be done by assigning weightings to each performance indicator; with these weightings indicative of stakeholder preferences. The manner in which such weightings can be assigned was discussed in section 3.5.4.

The reason for the non-uniform/saw tooth behaviour of the performance indicators is due to changes in network configuration as the value of the carbon credits selling price and time is varied. A change in network configuration could otherwise be worded as: (i) when the agents make investment decisions (years) and (ii) what size capacity the agents decide to install (MW). These configuration changes can by explained by investigating the capacity/time profiles of all the agents in the network as a function of carbon credits selling price, as illustrated in Figure 4.4 and Figure 4.5. It is important to note that the colour bar indicates the size (MW) of the capacity investment decisions.

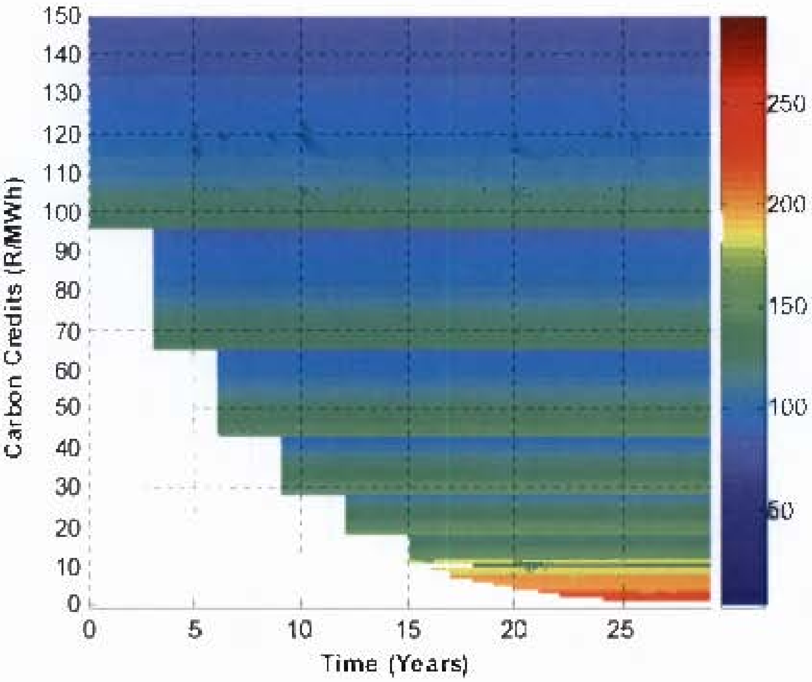


Figure 4.4: Installed capacity of the sugar mill agent vs. time and carbon credits selling price

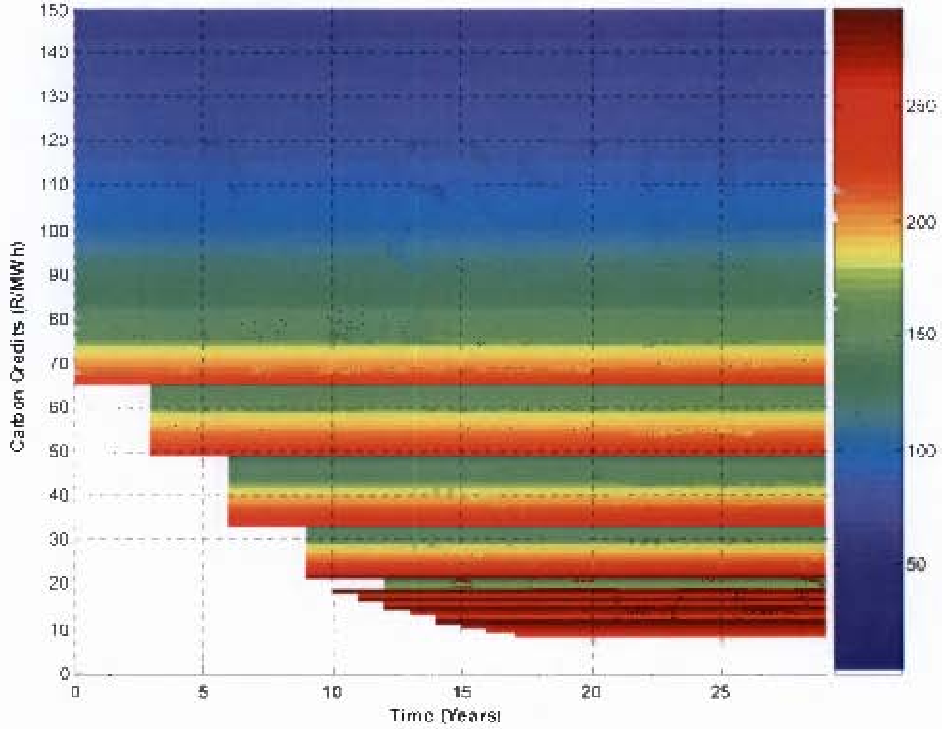


Figure 4.5: Installed capacity of an IPP agent vs. time and carbon credits selling price

The capacity profile of the Eskom agent was found to be relatively uniform with this agent making positive investment decisions as of time zero and the capacity only ranging between 5 MW and 25 MW throughout the simulation time. The reason for this is due to the location of this agent (500km from the bagasse resource). Although a large plant would be desirable in terms of the social criterion (measured as an ability to supply electricity to off-grid communities[41]), transportation enough bagasse to construct such a plant would be economically infeasible (in terms of costs) and environmentally undesirable (in terms of emissions). Of course, there is the value of bio-energy supply to the Eskom grid, either as new capacity, or to off-set poor performing coal stations. The life cycle benefits of such options were not considered here.

[41] Even though in reality Eskom own the grid, and could thus export electricity to this grid, only electricity supply to off-grid communities was considered.

The trends observed in Figure 4.4 and Figure **4.5** are:

(i) as time progresses, the carbon credits selling price at which the sugar mill and IPP agents make positive investment decisions decreases in a step like fashion. The reason for this is that the carbon credits price was modelled such that it experienced a 10% growth rate p.a. (this is the rate assumed for the base case scenario, see section 3.4.3),

(ii) the higher the carbon credits selling price the earlier an agent will invest in a smaller generation facility. The reason for this is the increase in profitability as the selling price of carbon credits increases.

(iii) at any time, the capacity the agents invest decreases as the carbon credits selling price increases. The can be seen looking at time = 10 years. The capacity the IPP agent decides to install decreases from 250 MW to 150 MW for a price increase of R 21/MWh to R31/MWh. The capacity of the sugar mill agent decides to install decreases from 150 MW to 90 M0 for a price increase of R 31/MWh to R41/MWh. The reason for this is as the incentive increases to transport bagasse over a long distance, the Eskom agent will install larger capacity, this leads to less bagasse available to the other agents, hence them installing smaller capacities.

The sugar mills were aggregated into a single agent; therefore the individual mills were indistinguishable from one another in the model. It was found that this configuration led to agents not only making positive investment decisions relatively early on (as illustrated by the behaviour of the Eskom agent), but also installing large capacities (as illustrated by the sugar mill (Figure 4.4) and IPP (Figure 4.5) agents). The reasons for this are; (i) the spatial co-ordinates of the sugar mill agent are set at a single location and the bagasse resource summed over all of the mills and (ii) it was assumed that the aggregated configuration of the mills was controlled by a single decision-maker. It is evident that the behaviour of the IPP agent is less uniform when compared with that of the sugar mill agent, this can be seen in Figure 4.4 and Figure **4.5** as: (i) the capacity of the IPP agent varies from a maximum of 260 MW (CDM price between R9 /MWh and R19 /MWh and time between 10 and 30 years) to a minimum of 60 MW (CDM price > R110 /MWh), whereas (ii) the capacity of the sugar mill agent varies from a maximum of 220 MW (CDM price between R3/MWh and R 5/ MWh and time between 22 and 30 years) to a minimum of 100 MW (CDM price > R130 MWh). From this non-uniform behaviour of the IPP agent it can be concluded that it is more sensitive to changes in the carbon credits selling price. The reason is that the IPP was modelled such that the sale of electricity generated from bagasse together with selling carbon credits through the clean development mechanism is its core business. As such, small changes in the carbon credits selling price could greatly affect the profitability of such an enterprise. This is not the case for the sugar mill and Eskom agents as they were modelled such that sugar sales[42] and sale of electricity generated from fossil fuels are their respective core businesses. In the interest of both the government and potential CDM partners, it would be desirable to know what the behaviour of the agents are at the present day value of the carbon credits selling price together with the behaviour of the network over a whole range of prices. The governmental interest would mainly be around energy output, whereas potential CDM partners would be interested in the carbon credits selling prices at which the enterprises involved consider investment in generation facilities economically, environmentally and socially feasible. These two topics are discussed in the remainder of this section.

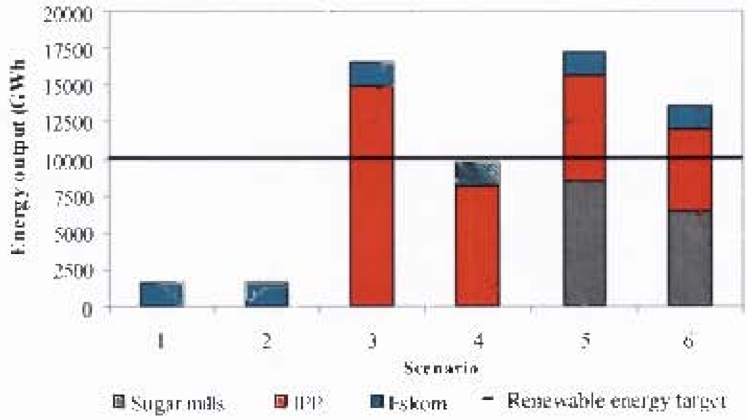
The current day value used for the carbon credits selling price is 30 R/MWh. This value is indicative of world trends in the carbon credit market (see Appendix B). In the simulation model, at time zero (present day); given the base case assumptions, the decision procedures adopted by each agent, and the manner in which the carbon market was modelled, the following carbon credits selling price scenarios were constructed; (i) current price, (ii) doubling, (iii) tripling (iv) quadrupling of the current price, and (v) price at which the sugar mill, IPP and Eskom agents first invest in a generation facility. These scenarios can be seen in Table 4.2.

[42] In this study it was assumed that the sugar market does not collapse and thus sugar sales remain profitable for the mills. Current trends in the sugar market suggest that this may not be the case in the future,(Wiesne and Purchase 2004), this was not considered here.

Table 4.2: Carbon credits selling price scenario's investigated

Scenario	Description	Value (R/MWh)	% increase in current day carbon credits price
1	Current day price& price at Eskom's first investment	30	0
2	Double today's price	60	100
3	Price at IPP's first investment	65	117
4	Tripple today's price	90	200
5	Price at sugar mill's first investment	97	223
6	Four times today's price	120	300

In Figure 4.4 and Figure 4.5 it can be seen that at time zero, the minimum carbon credits selling price at which positive investment decisions were made by the sugar mill, IPP and Eskom agents occur at 97 R/MWh, 65 R/MWh and 30 R/MWh respectively. Prior to discussing this result, the energy output of the network at the respective carbon credits selling prices was investigated; this is illustrated in Figure 4.6.



Scenario	% increase or decrease in renewable energy target
1	-84
2	-84
3	65
4	-3
5	72
6	36

Figure 4.6: Energy output as a function of carbon credits price scenarios during the period 2003 – 2013

From Table 4.2 and Figure 4.6 it can be concluded that:

i. If an enterprise today were considering investment in a facility to convert bagasse into green electricity, and if such a facility displayed characteristics similar to a sugar mill or an IPP, then the carbon credits selling price would have to undergo growth rate of 223% (scenario 5) and 117% (scenario 3) respectively before such projects become viable. The Eskom agent was modelled such that only co-firing of bagasse and coal into an existing boiler was included as an investment alternative. This alternative would therefore not involve a large amount of initial capital to erect a new generation facility, resulting in the associated cost being marginal when compared with the economic gain presented by a relatively small carbon credits selling price. Consequently, the results indicate if the carbon credits selling price were to remain at a present day value (scenario 1) or increase by 100% (scenario 2), the only agent active in the green electricity market would be the Eskom agent.

ii. Investment decisions are not only made based on economic but also environmental and social objectives. Nevertheless, it is concluded that the reason the sugar mill agent only erects a generation facility if the carbon credits selling price increases by 223% (scenario 5) and 300% (scenario 6) above the current day price is that the profit the mills can generate from selling the bagasse to both Eskom and an IPP is greater than the profit they are able to acquire from erection of a generation facility and subsequent sale of green electricity and carbon credits.

iii. The energy output of the network is greatest at a carbon credits selling price of R 97 / MWh (scenario 5). This result is contrary to intuitive "feel" that the greater the incentive encouraging investment in renewable energy projects (scenario 6) the greater the energy output from such projects. The reason for this is that the incentive is financial (as the carbon credits are measured by R/MWh) and the decision procedure applied by the agents includes not only financial gains but also environmental and social gains. As such, a greater financial incentive might not lead to a higher energy output due to the adverse environmental effect of a larger generation facility (in terms of CO_2 emissions from transportation and production). This same effect can be seen when comparing scenario 3 and 4.

iv. If the carbon credits selling price were to remain at a present day value or undergo a 100% increase, the energy output of the network is such that it is 84% lower than the renewable energy target[43]. From a governmental perspective, the energy target can

[43] The target is a cumulative value over a 10 year period. It was assumed that no agents undertook capacity upgrades to increase the energy output of their original generation facilities during this period.

easily be reached when the carbon credits price is at R65 / MWh (investments only by Eskom and the IPP agents), or at R97/ MWh and R120 / MWh (investments by the sugar mill, Eskom and the IPP agents).

From the perspective of potential CDM partners, it would be desirable to know for which values of the carbon credits selling price would investments in a generation facility occur and for which values not; irrespective of whom the investors are. As such, the boundary line between a positive (invest in a generation facility) and negative (do not invest in a generation facility) decision can be seen in Figure 4.7; with the grey area indicating the former and the white area the latter. This boundary line was constructed by investigating the earliest time in which the respective agents made positive investment decisions.

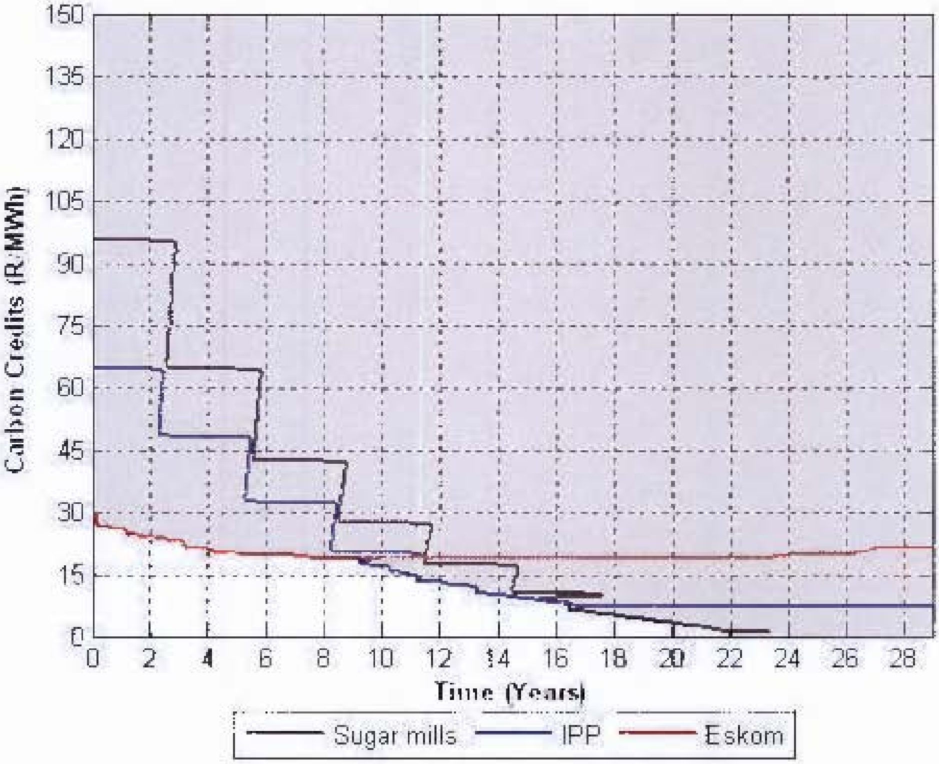


Figure 4.7: Investment decisions of all agents vs. time and carbon credits selling price

Figure 4.7 was adapted as a contour plot from the capacity profiles of the sugar mill (Figure 4.4), IPP (Figure 4.5) and the Eskom agent. The important thing to notice is that when plotted as a function of carbon credits selling price and time, the shaded section (positive investment decisions) occupies a much bigger area than the white section (negative investment decisions). As such, for the conditions defined in this study, it can be concluded that from a model structure perspective, the fewer decision-makers and less diverse the agents in the network, the less sensitive the agents, and hence their investment decisions, will be to the carbon credits selling price. From the perspective of potential CDM partners this is favourable as, once a CDM generation facility has been erected, it is economically, environmentally and socially viable for a large range of carbon credits selling prices. Therefore sudden changes in the carbon market would not have detrimental effect on profitability, provided the minimum carbon price selling price is achieved.

4.2.2 Risk Policy

There are many risks associated with investment in new projects. These risks could be the unknown future behaviour of the economy, the uncertain price and demand for green electricity or the stability of the carbon credits market. Enterprises today have no given formula to commensurate risk with return; it is largely a judgement call established for each enterprise by upper management (Peters et al. 2003). Even though only financial risk was included in this study, it is recognised that there are many other types of risk enterprises have to consider when investing in business ventures[44]. The financial **risk policy** adopted by an agent was captured by the minimum acceptable internal rate of return (IRR) value.

For the purpose of this study, risk commensuration was included by modelling enterprises willing to take high risks such that they adopt a low minimum acceptable IRR whereas enterprises that are risk averse demand a high minimum acceptable IRR. As such, the risk policy adopted by each agent was varied as an internal stimulus (between 10% and 30%) to ascertain its effect on both the performance of the network as a whole and the behaviour of each agent. The results of this variation are presented and discussed in the remainder of this section.

[44] See Crouchy and Galai (2001) for comprehensive review the different types of risk associated with investment in new projects. In the study risk management methods and tools are also presented.

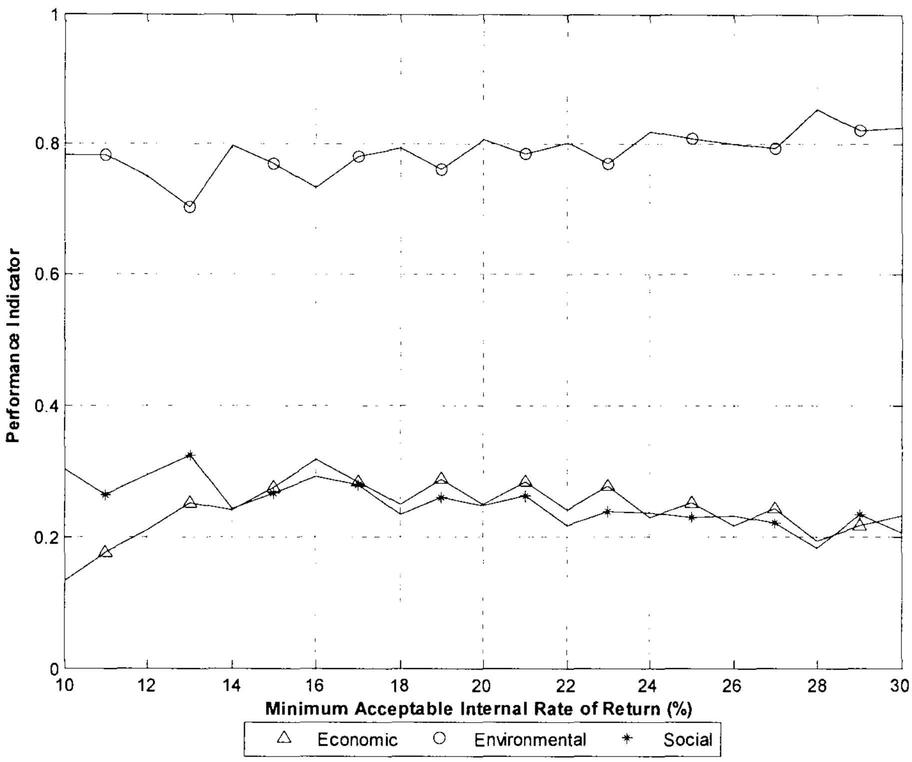


Figure 4.8: Performance of the network vs. minimum acceptable IRR

The performance indicators were normalised with respect to figures derived from an optimisation model of the physical system and the feasible technology options (see Appendix C). Therefore their magnitude indicates how well they compare with the performance of the optimally configured network. As seen in Figure 4.8, the environmental indicator compares most favourably throughout the simulation. This trend is due to the exclusion of life cycle consideration into the formulation of the agents together with the aggregated configuration of the sugar mills, both of which are discussed in section 4.2.1.

It is evident from Figure 4.8 that the performance of the network (measured by all three indicators) does not vary greatly with a change in minimum acceptable IRR. Notwithstanding this apparent "insensitivity" of the network to changes in minimum acceptable IRR, and hence to the financial risk policies adopted by the agents, there are values for which the economic, environmental and social performance of the network is at a maximum and minimum. These points correspond to an IRR value of 13% and 28%. At 13% the economic performance of the network is at an average value (when compared with the network performance over the entire range of IRR values); the social network performance is at a maximum whereas the environmental performance is at its worst value. The reason for this is that the lower the minimum acceptable IRR, the higher risk an agent is willing to take, thus the bigger the capacity it will install. This is desirable from a social and economic perspective as bigger capacities lead to more profit generated by the sale of electricity and carbon credits and greater supply of electricity to off-grid communities. This is not desirable from an environmental perspective due to an increase in production and transport emissions from a larger generation facility[45]. Conversely, at 28% the environmental performance of the network is at a maximum value whereas the social and economic performances are at minimum values. The reason for this is that the agents are risk averse and will not invest in large generation facilities. From these findings it is evident that the performance of the network is a function of the individual agent risk policies and corresponding investment capacity decisions, which are illustrated in Figure 4.9 and Figure 4.10. It is important to note that the colour bar indicates the size (MW) of the positive capacity investment decisions.

[45] In reality, if a large biomass-electricity generation plant were to be erected, there will be life cycle benefits of carbon capture by biomass, hence leading to carbon neutrality. Together with this, the derived electricity will substitute for new (small) coal plants, hence improving overall carbon footprint. These factors were not taken into account in this study.

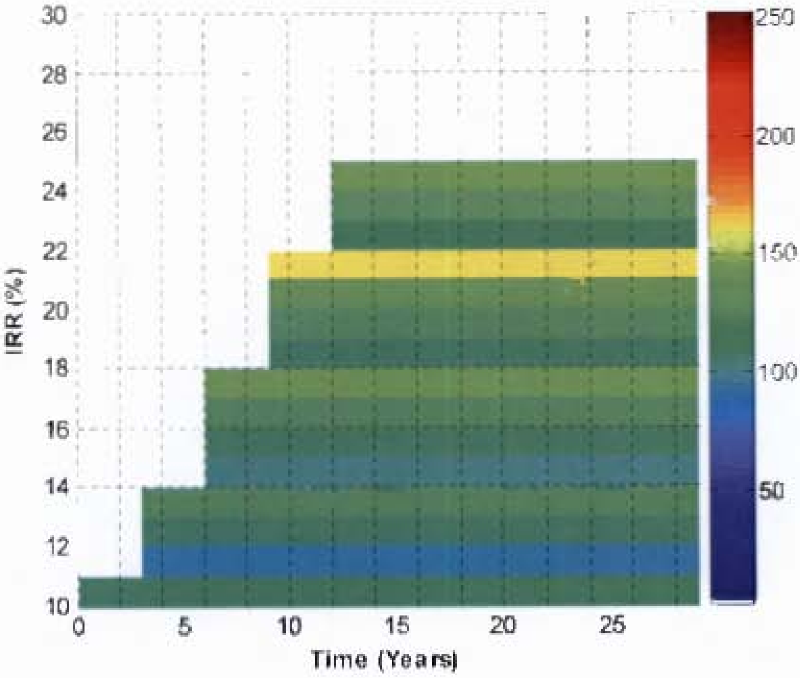


Figure 4.9: Installed capacity of the sugar mill agent vs. time and minimum acceptable IRR

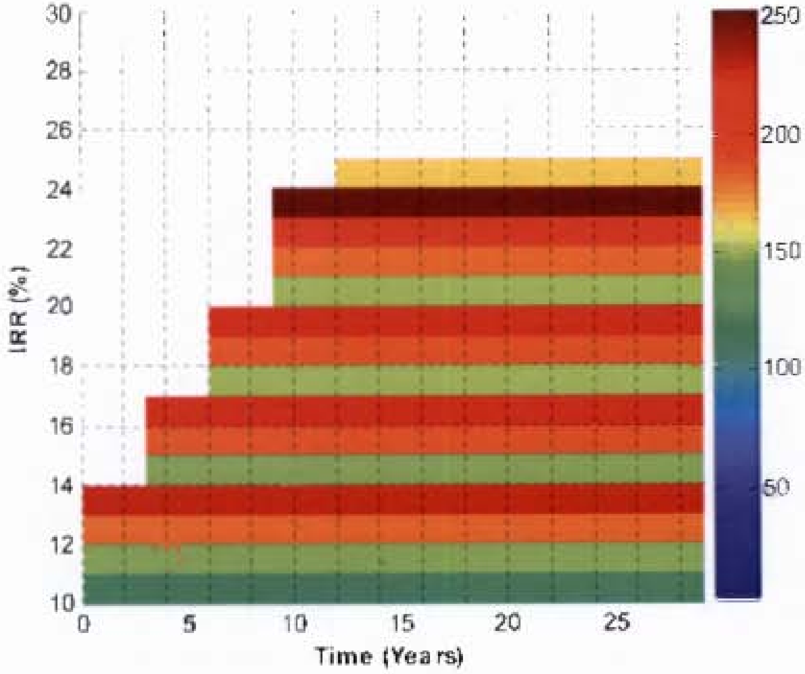


Figure 4.10: Installed capacity for an IPP vs. time and minimum acceptable IRR

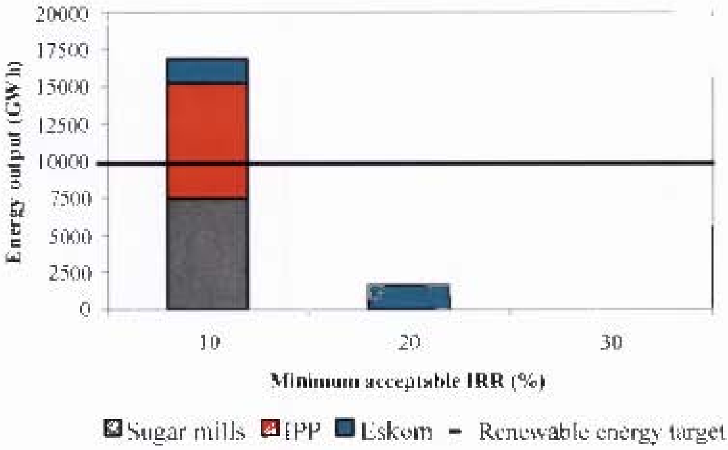
The capacity profile of the Eskom agent is not shown as it was found to be relatively uniform, with this agent making positive investment decisions as of time zero and with the capacity restricted to 25 MW throughout the simulation time. The reason for this is due to the location of this agent (500km from the bagasse source). Although a large plant would be desirable in terms of the social criterion (measured as ability to supply electricity to off-grid communities), transporting enough bagasse to construct such a plant would be economically infeasible (in terms of costs) and environmentally undesirable (in terms of emissions), notwithstanding the benefits of coal substitution and the near-carbon-neutrality from sequestration in biomass.

From Figure 4.9 and Figure 4.10 it can be seen that the more risk averse an agent is the later it will invest in a generation facility. The reason for this is that as time progresses, projects that were not feasible at the outset become economically, environmentally and socially feasible due to the following (i) it was estimated that the carbon credits selling price increases at 10 % p.a. and (ii) the bagasse resource, electricity price and demand increase at 2.5% p.a. (see section 3.4.3).

In the interest of both the government and the enterprises in the network, it would be desirable to know what the behaviour of the agents are in present time as a function of the risk policies adopted, as well as the dynamic behaviour of the network over a whole range risk policies. The governmental interest would mainly be around energy output whereas each agent would be interested in which risk policies yield the best outcome when considering economic, environmental and social objectives. These two topics are discussed in the remainder of this section.

As the interaction between agents in such a network is what ultimately drives the dynamics, the risk policy adopted by one agent would influence the behaviour of the other agents in the network. As such, the minimum acceptable IRR and corresponding capacity investment decisions (as illustrated in Figure 4.9 and Figure 4.10) can not be considered independently. For this reason, scenarios were constructed in which a risk policy is assumed by each agent and behaviour of the network as whole, and of each agent, is tracked. The scenarios considered are: (i) all agents take high risks, IRR = 10%, (ii) all agents are relatively risk averse, IRR =

20%, (iii) all agents are risk averse, IRR = 30%. The resulting energy output of the network and the respective agents can be seen in Figure 4.11.



Minimum acceptable IRR	% increas or decrease in renewable energy target
10	68
20	-84
30	-100

Figure 4.11: Energy output as a function of minimum acceptable IRR scenarios during the period 2003 – 2013

It is important to note that the minimum acceptable IRR is used by the agents to screen capacity alternatives. The capacity decision (MW) made by each agent is determined by calculating the economic, environmental and social criteria of all the feasible capacity alternatives and trading them off against each other (as explained in section 3.5.2). For time equal zero, (indicative of current time), the result of this decision process is what is illustrated in Figure 4.11; from which the following conclusions are drawn:

i. The highest energy output[46] of the network corresponds to all the agents modelled as high risk takers when considering investment decisions (minimum acceptable IRR = 10 %).
ii. The renewable energy target[47] can only be reached by the enterprises in this network if all of them assume a minimum acceptable IRR of 10%. Under these conditions the target will improved upon by 68%, with investments by the sugar mill, Eskom and the IPP agents.

[46] In order to convert capacity, MW, to energy output, GWh, it was assumed that production occurs for 9 months of the year (as explained in section 3.4.1).

[47] The target is a cumulative value over a 10 year period. It was assumed that no agents undertook capacity upgrades to increase the energy output of their original generation facilities during this period.

From the perspective of potential CDM partners and the government, it would be desirable to know for which minimum acceptable IRR values investments in a generation facility would occur and for which values not. As such, the boundary line between a positive (invest in a generation facility) and negative (do not invest in a generation facility) decision can be seen in Figure 4.12; with the grey area indicating the former and the white area the latter. This boundary line was constructed by investigating the earliest time in which the respective agents made positive investment decisions.

Figure 4.12: Investment decisions of all the agents vs. time and minimum acceptable IRR

Figure 4.12 was adapted as a contour plot from the capacity profiles of the sugar mill (Figure 4.4), IPP (Figure 4.10) and the Eskom agent. The following conclusions can be drawn:

i. At present time, the sugar mill agent will invest in a generation facility when the IRR value is the lowest (10%), followed by the IPP agent at 14% and the Eskom agent at 24%. The reason for this is twofold, namely, core business and geographic location.

Sales of electricity and carbon credits from bagasse are not core businesses for the sugar mills and Eskom agents. For these two agents, profit is guaranteed from sugar sales[48] and sale of electricity from fossil fuel sources respectively. Therefore these agents are willing to take higher risks on secondary business ventures. This is not the case for the IPP agent, as it is modelled such that electricity and carbon credits sales from electricity generation from bagasse are its core business. Therefore this agent will only invest when the minimum acceptable IRR is 14%. The reason that generation facilities are only feasible for the Eskom agent at 24% is location (situated 500km from the bagasse source). Even though from a social perspective, erection of a facility at this location is desirable (measured by supply of electricity to off-grid communities in a certain municipal district), it is not desirable from an economic and environmental perspective due to cost and emissions associated with transportation of bagasse over such long distances. To some extent, these negative factors could be mitigated by pre-drying and palletising bagasse, but this was not considered in this study.

ii. When plotted as a function of minimum acceptable IRR and time, the shaded section (positive investment decisions) occupies a much bigger area than the white section (negative investment decisions). As such, for the conditions defined in this study, it can be concluded that the fewer decision-makers and less diverse the agents in the network, the less sensitive the network will be to the risk policies adopted by the respective agents. This is favourable from a "top down" (government) perspective, as sudden changes in the manner in which the agents incorporate risk into their decision-making process would not have a detrimental effect on the behaviour of the network.

4.2.3 Individual Agent Preference Settings

The **decision policy** adopted by each agent was captured by the weightings it prescribed to the different decision criteria. The larger the weighting given to a certain criterion, the more

[48] In this study it was assumed that the sugar market does not collapse and thus sugar sales remain profitable for the mills. Current trends in the sugar market suggest that this may not be the case in the future (see (Wiesne and Purchase 2004))

heavily it will influence the decision to be made (see sections 3.5.4 and 3.5.4). The weighting adopted by each agent, in terms of the economic, environmental and social criteria was investigated. Several scenarios were constructed, each one reflecting a strong, medium or weak preference of the agents towards each of the three criteria. Subsequently, the sensitivity of the network with regard to these settings was determined. It is important to note that even though the preference setting the agents assumed for the three criteria varied from scenario to scenario, (as seen in Table 4.3), within a specific scenario it was assumed that all the agents had the same preference setting.

Table 4.3: Individual agent decision-makers: weighting scenarios explored

		Economic focus			Environmental focus			Social focus		
Scenario	**Base Case**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
$\omega_{economic}$ (%)	33	50	75	100	25	12.5	0	25	12.5	0
$\omega_{environmental}$ (%)	33	25	12.5	0	50	75	100	25	12.5	0
ω_{social} (%)	33	25	12.5	0	25	12.5	0	50	75	100

The decision procedures followed by enterprises typically involve single criteria decision-making aimed at maximising benefits whilst minimising costs (Pohekar and Ramachandran 2004). Even though enterprises today may include economic together with environmental and social criteria in their decision procedures, the importance of the economic criterion is usually much higher than that of social and environmental criteria. The reason that the weighting sensitivity analysis performed in this study allowed both environmental and social criteria to outweigh the economic criterion is that the alternatives available to the agents have already been screened by an economic factor, namely, the minimum acceptable IRR (as discussed in section 3.5.2). Consequently, the set of capacity alternatives available to each agent is economically feasible, as measured by the IRR. The results of this sensitivity analysis can be seen in Figure 4.13. The dashed lines (labelled eco., env. & social base case) represent the behaviour of the network if the agents are modelled with no discernible preference for any of the criteria (each criterion is weighted at 33.3%).

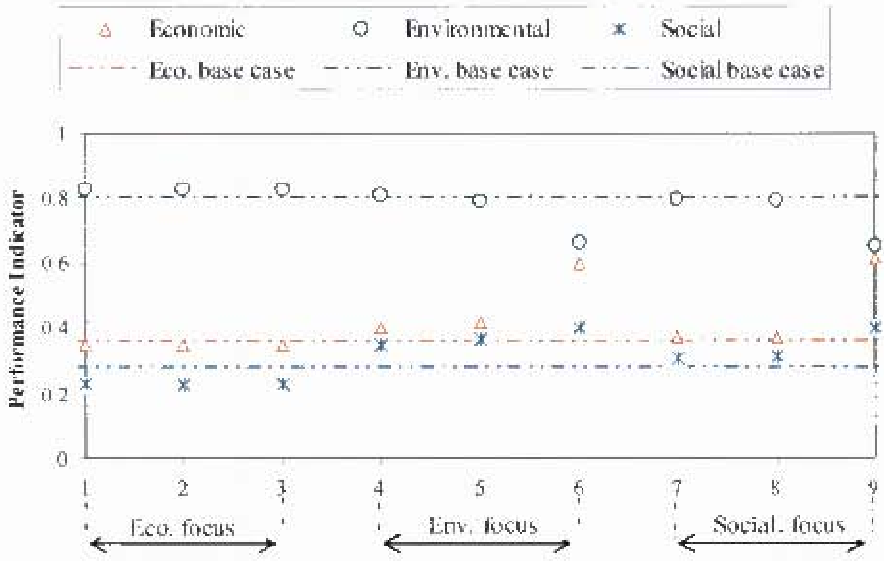


Figure 4.13: Performance of the network vs. weighting preferences of the agents

The environmental performance is consistently higher than both the economic and the social performance. This trend is a result of the performance indicators being normalised with respect to figures derived from an optimisation model of the physical system and the feasible technology options (Appendix C). As such, the magnitude of the performance score indicates how well it compares with that of the optimally configured network. In the optimisation model, the respective mills were modelled such that they are distinguishable and located in different municipal districts (Appendix C). The results presented here follow from the sugar mills modelled as an aggregated agent; this leads to:

(i) fewer emissions from transport when compared with modelling the mills at different geographical locations, resulting in favourable comparison with the environmental performance of the optimally configured network,

(ii) a larger generation facility at a single location compared with several smaller facilities at many locations. The cost of transporting large amounts of bagasse has a more significant impact on the economic performance of the network than the economies of scale[49] included in the cost estimations. As such, the economic

[49] The cost associated with a plant decreases as the size of the plant increases (see Appendix C for costs).

performance indicator does not compare favourably with that of the optimally configured network.

(iii) a smaller number of off-grid communities being supplied with electricity. The agents were modelled such that they are only able to supply electricity to communities in their municipal districts (see section 3.5.3). It follows that the social performance is better the more geographically distributed the agents are. The aggregated sugar mill agent occupies one district whereas modelling the mills as geographically distributed (as is the case with the optimal network configuration) leads to occupation of many districts. Consequently, the social performance indicator does not compare favourably with that of the optimally configured network.

The comparison between each indicator and the base case value will be discussed in relation to the capacity investment decisions (MW) made by each agent when expressed as energy output (in GWh)[50], as illustrated in Figure 4.14.

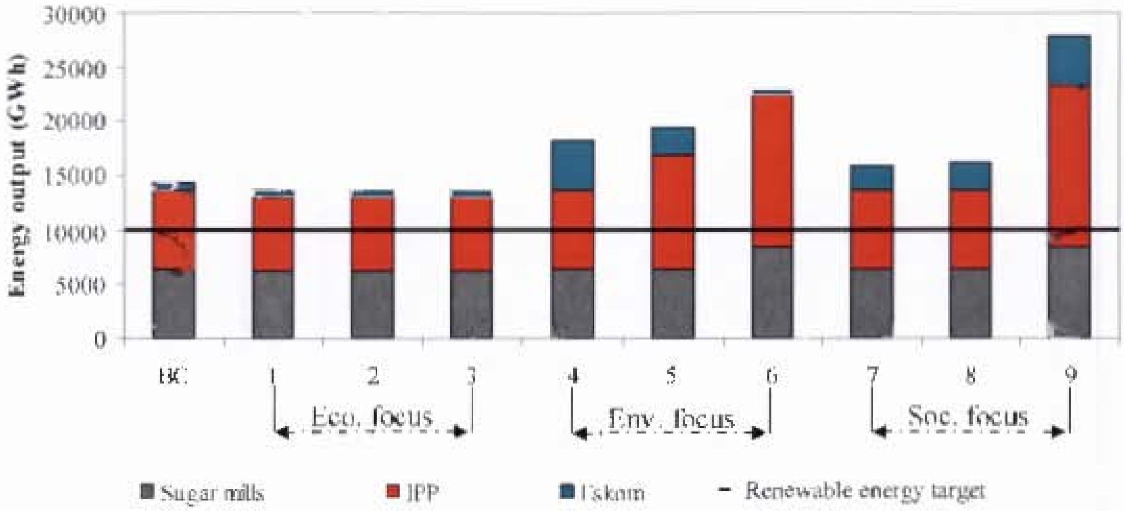


Figure 4.14: Energy output as a function of weighting preferences of the agents during the period 2003 – 2013

[50] To convert MW to GWh a production time had to be assumed, this was taken as 9 months, as explained in section 3.4.1.

The scenario labelled BC indicates the energy output of the model when conditions are set at base case values. The next three items (labelled Eco. focus) represent the capacity decisions made by all the agents and corresponding energy output of the network when the agents are economically rational (i.e. the weighting of the economic criterion is higher that the weightings of the environmental and social criteria). The 1^{st}, 2^{nd} and 3^{de} items represent the agents adopting economic weightings of 50%, 75% and 100% respectively (as shown in Table 4.3). It can be seen that as long as the economic weighting is greater than 50%, the capacity decisions made by all the agents and hence the energy output of the network, are *not* sensitive to a change in this weighting. The reason for this, as explained in section 3.5.2, is that the capacity alternatives available to each agent were screened based on an economic threshold value, (minimum acceptable IRR) to determine a set of feasible capacity alternatives. This set is bounded by the demand in the municipal district the agent is located and bagasse availability. From this set, the optimal capacity (MW) to be installed was determined by trading-off the economic, environmental and social criteria (see section 3.5.4 for detailed explanation). From Figure 4.13 and Figure 4.14 it is evident that both the performance of the network and the capacity decisions made by the agents do not vary as a function of the economic weighting adopted by the agents, above a threshold value. As such, it can be concluded that the economic screening process dampens the sensitivity of the network to changes in economic weighting.

The items labelled "Env. focus" in Figure 4.14 represents the capacity decisions made by all the agents and energy output of the network when the agents are environmentally rational (i.e. the weighting of the environmental criterion is higher than the weightings of the economic and social criteria). The 1^{st}, 2^{nd} and 3^{de} items represent the agents adopting environmental weightings of 50%, 75% and 100% respectively. It can be seen that as long as the environmental weighting the agents assume is greater than 50%, the capacity decisions made by all the agents, and hence the energy output of the network, are sensitive to a change in this weighting. It can be seen that the larger the environmental weighting the bigger the capacity decisions made by the sugar mill and IPP agents and the smaller the capacity decision made by the Eskom agent. The reason the Eskom agent is opting for the smallest possible capacity alternative is that it is located far away from the bagasse source, which is undesirable from an environmental perspective due to transport emissions. It can thus be concluded that the more environmentally rational the agents are modelled, the less influential the Eskom agent will be in this network.

The items labelled "Soc. focus" in Figure 4.14 represents the performance of the network when the agents are socially rational (i.e. the weighting of the social criterion is higher that the weightings of the economic and environmental criteria). The 1st, 2nd and 3de items represent the agents adopting social weightings of 50%, 75% and 100% respectively. It can be seen that as long as the social weighting the agents assume is greater than 50%, the capacity decisions made by all the agents and hence the energy output of the network, are sensitive to a change in this weighting. From scenario 9 it can be seen that if all of the agents prioritise the social criterion the electricity output of the network would be the highest. The reason for this is that the decision criteria used to encourage socially rational agents to invest in technologies is measured by electricity supply to off-grid rural communities. As such, it is concluded that the more socially rational the agents are, the greater the electricity output of the network as a whole.

It was previously noted that the comparison between each indicator and the base case value will be discussed in relation to the capacity investment decisions (MW) made by each agent when expressed as energy output (in MWh). From the preceding discussion it is concluded that: (i) a change in the economic weighting the agents assume, has little or no effect on the energy output of the network, (ii) as the environmental and social weightings increase so the installed capacities of the agents and corresponding energy output of the network increase. This conclusions ties in with the research question aimed at investigating the potential of the biomass energy network in KZN to contribute to the renewable energy target of 10 000 GWh. It is important to note that this target is a cumulative value over a 10 years period from all renewable sources. The total energy output of the network, as a function of the decision policies of the agents was determined, as seen in Table 4.4, this energy output is expressed as a percentage of the renewable energy target.

Table 4.4: Influence of agent decision policy on energy output and renewable energy target

Scenario	Agent rational	% greater than renewable energy target
9	Social	179
6	Environmental	130
5	Environmental	94
4	Environmental	81
8	Social	62
7	Social	59
BC	Neutral	43
1	Economic	36
2	Economic	36
3	Economic	36

The calculations in Table 4.4 are based on the assumption that the generation facilities installed by the agents were not upgraded to a larger size. Given the base case scenario, decision-making procedure and project life time (30 years) as determined by this study, it can be concluded that: (i), the renewable energy target can easily be met by investment in generation facilities by the sugar mills, IPPs and Eskom, (ii) even for the worst performers (indicated by scenario 1-3, when all the agents are economically rational) the renewable energy target is improved upon by 36%, (iii) the target is improved most when the agents are either 100% socially or 100% environmentally rational.

4.3 Model Limitations

Prior to drawing conclusions from the results presented in previous sections, some discussion is offered on the limitations of the existing model.

The network investigated in the case study only considers a subsection of the entire network. Inclusion of other players will change the dynamics which occur in the network. The greatest challenge associated with this is access to information, with regards to cost information of the technologies, agent behaviour (assessment of projects, trading partner selection, bidding strategies for bagasse, length of bagasse contracts, etc) and functional information (flows of materials, information and capital).

The models were created in AnyLogic, a software platform requiring a significant understanding of object orientated programming, including the Java programming language. In addition, the user needs to develop an understanding of the operation of the AnyLogic platform itself. This aspect of the model is an advantage in terms of model flexibility, but a limitation if the modeller is ill equipped to operate, understand and easily use the software platform.

The limitations mentioned above relate to a specific application of the suggested analytical framework. An attempt to model an extended network, with a much broader view, e.g. encompassing the suppliers' suppliers and the customers' customers, is limited in terms of reliability of emerging dynamics. These dynamics, caused by feedback loops, mathematical correlations and interconnection and interaction between the enterprises in the network are data and information dependent. For an extended network, availability of data and information pertaining to every enterprise in the network is very limited. The main question to be answered is whether there is enough reliable data and information available to allow for any of the enterprises in the network to generate realistic and representative results. In other words, will data and information sharing ever occur at such a level to allow for accurate and reliable modelling of the extended network? And if so, how will the modeller tackle model validation and performance measurement? Ideally, model validation can be done by extensive sensitivity tests and the performance measured in terms of achieving global parameters (Rahmandad and Sterman 2004). Model validation is therefore a timely task and system performance measurement will require setting an overall system goal prior to design to determine whether the model is able to reach this goal.

4.4 Conclusions

A biomass-energy network situated in kwaZulu-Natal (KZN), South Africa, was designed and analysed by making use of the agent-based simulation-optimisation modelling approach developed in Chapter 2. The agents included in the network were the existing sugar mills in KZN, a potential independent power producer (IPP), the South African power utility (Eskom) and existing paper and pup mills in KZN. A simulation engine was used to investigate the performance of the network and the behaviour of each agent over a 30 year time period. The network performance was tracked by economic, environmental and social performance indicators. The behaviour of each agent resulted from optimisation and multiple criteria decision-making (MCDM) methods employed as decision-support tools. Given this model configuration, the sensitivity of the network to changes in carbon credits selling price and risk and decision policies was tested. The observations and conclusions drawn from each of these analyses were discussed in this chapter but will be briefly outlined in the remainder of this section. Before this is done it is important to note that the conclusions as presented here are subject to cost estimations, model assumptions and decision criteria as defined in this study.

Influence of carbon credits selling price on network behaviour and agent decisions

The clean development mechanism (CDM), and thus the carbon market, was identified as a mechanism that could be used by either government or the private sector to encourage investment in the green electricity market. One of research aims was to determine how such mechanisms could lead to practices that contribute towards the renewable energy target and thus further the drive towards more sustainable business practice in South Africa. As such, the sensitivity of this network to changes in the carbon credits selling price was determined. Conclusions will firstly be drawn with regard to the sensitivity of the network over a range of carbon credits selling prices, and secondly, with regard to the network performance and agent behaviour at the current-day selling price of carbon credits.

The carbon credits selling price was varied between a negative future (one in which the carbon market does not develop, i.e. the carbon credits selling price is R 0 /MWh) and a positive future (i.e. a selling price of R150 /MWh). From this analysis the following conclusions can be drawn:

i. Irrespective of the selling price of carbon credits, the environmental performance of the network is consistently higher than the economic and social performances (relative to performance the network achieved via a global optimisation model). This is mainly attributed to the life cycle considerations relating to the carbon footprint of sugar cane production and bagasse conversion not being included in the analysis of the environmental performance of the network[51].

ii. The indictors tracking the performance of the network all display non-uniform behaviour when plotted as a function of carbon credits selling price. It was found that these non-uniformities in performance correspond to changes in investment decisions by the agents as a function of carbon credits selling price and time. The main factors influencing these investment decisions are the aggregated manner in which the sugar mills were modelled, the bidding structure through which each agents attempts to secure bagasse, cost assumptions, technology efficiencies, transport and production emissions and the geographic location of the agents.

It is important to note that the current day carbon credits selling price was assumed to be R 30 /MWh and the renewable energy target is a cumulative value of 10 000 GWh from 2003 - 2013. From this analysis the following can be concluded:

i. If the carbon credits selling price were to remain at a present day value, the only agent active in the green electricity market would be the Eskom agent. For this configuration, the most viable generation alternative was found to be co-firing of bagasse and coal into an existing power station. If this were to happen the renewable energy target would not be achievable through electricity generation from bagasse. In fact, the energy generation from such a configuration would be 84% less than the target requires (over the 10 year period).
ii. If a sugar mill or an IPP today were to consider investment in a facility able to convert bagasse into green electricity; the current day carbon credits selling price would have to undergo growth of 223% (to a value of R97 / MWh) and 117% (to a value of R65 / MWh) respectively before such projects become economically, environmentally and socially viable. If this were to happen, the renewable energy target would be improved upon by 72% and 65 % respectively.

[51] This is an important factor to take into consideration in further work, as cane production results in carbon sequestration, which will offset carbon emissions from cane/ bagasse processing for electricity production.

iii. In terms of the renewable energy target, the energy output of the network is greatest at a carbon credits selling price of R 97 / MWh. For this network configuration, the sugar mill and IPP agents both invest in similar size capacities (ranging from 90 MW to 120MW), with the most viable generation alternative being gasification; whereas the Eskom agent will co-fire bagasse (25 MW's worth) and coal into an existing power station. This result is contrary to intuitive "feel" that the greater the incentive encouraging investment in renewable energy projects the greater the energy output from such projects. The reason for this is that the incentive is financial (as the carbon credits are measured by R/MWh) and the decision procedure applied by the agents includes not only financial gains but also environmental and social objectives. As such, a greater financial incentive might not lead to a higher energy output due to the adverse environmental effect of a larger generation facility (in terms of CO_2 emissions from transportation and production).

Influence of the agent risk policy on network behaviour and agent decisions

The risk policy adopted by each agent was captured by setting the minimum acceptable rate of return (IRR) it is willing to accept and comparing this value with to IRR of all the investment alternatives. It is important to note that all the alternatives which yielded IRR's greater than the minimum acceptable IRR were subjected to MCDM methods, including economic, environmental and social criteria, to allow each agent to make an investment decision. The network performance and agent decisions were tested as a function of risk policy by varying the minimum acceptable IRR between bounds. These bounds represent the risk an agent is willing to take; with high values (30%) indicating risk adverse agents and low values indicating risk taking agents (10%). The main conclusions drawn from this analysis are:

i. The highest energy output of the network corresponds to all the agents modelled as high risk takers when considering investment decisions (minimum acceptable IRR = 10 %).

ii. The renewable energy target can only be reached by the enterprises in this network if all of them assume a minimum acceptable IRR of 10%. Under these conditions the target will improved upon by 68% (over the 10 year period), with investments by the sugar mill, Eskom and the IPP agents.

iii. At the present time, the sugar mill agent will invest in a generation facility when the IRR value is the lowest (10%), followed by the IPP agent at 14% and the Eskom agent at 24%. The reason for this is twofold; namely, core business and geographic location. Sales of electricity and carbon credits from bagasse are not core businesses for the sugar mill and Eskom agents, therefore they are willing to take higher risks on secondary business ventures. This is not the case for the IPP agent, as it was modelled such that electricity and carbon credits sales from electricity generation from bagasse is its core business. The reason generation facilities are only feasible for the Eskom agent at 24% is due geographic location (500km from the bagasse source).

iv. When the behaviour of the agent are plotted as a function of minimum acceptable IRR and time, more agents will make positive investment decisions than not. From this it is evident that the fewer decision-makers and less diverse the agents in the network, the less sensitive the network will be to the risk policies adopted by the respective agents. This is favourable from a "top down" (governmental) perspective, as sudden changes in the manner in which the agents incorporate risk into their decision-making process would not have detrimental effect on the behaviour of the network.

Influence of the individual agent preference settings on network behaviour and agent decisions

The investment decisions made by the agents were firstly based on their individual risk policies (as discussed previously) and, secondly, on the evaluation and trade-off of economic, environmental and social decision criteria. The decision criteria were traded-off by making use of MCDM methods which included (i) normalisation; with each criterion normalised with respect to the "best" and "worst" network performance derived from a (separate) global optimisation model. This normalisation was performed on a linear scale with the best score allocated a value score of 1 and the worst score a value of 0, (ii) setting a weighting for each criterion; the higher the weighting given to a criterion the more it contributes to the decision to be made, (iii) calculating the weighted sum (often called the additive aggregation function) of the decision criteria, (iv) selecting the alternative with the highest additive aggregation function. This process then encompasses the decision-making procedure followed by each agent. From both a network and agent perspective it would be desirable to know which weightings yield the best performance. The conclusions drawn in this section are with regards to a sensitivity analysis performed on these weightings; and are as follows:

i. The performance of the network and the capacity decisions made by the agents are least affected by the economic weighting adopted by the agents, above a minimum threshold value. The reason for this is that the minimum acceptable IRR screening process dampens the sensitivity of the network to changes in economic weighting.
ii. A change in the economic weighting the agents assume, has little or no effect on the energy output of the network. The more environmentally and socially rational the agents are, the larger the capacity decisions made by them, and hence the larger the energy output of the network.
iii. Even for the base case scenario (all agents assume 33% preferences to all three criteria), the renewable energy target can easily be met by investment in generation facilities by the sugar mills, IPPs and Eskom.
iv. The renewable energy target is improved most when the agents are either 100% socially or 100% environmentally rational.

5 Discussion and Conclusions

Recently there has been much interest in the structure and functioning of industrial networks. These interests are guided not only by a need of enterprises in the network to remain competitive by improved performance, but also such that business activity as a whole can be made more sustainable. As such, it is vital to understand these networks well enough to know how their structure and functioning affect their economic, environmental and social performance. Gaining this understanding was the main goal of this thesis.

Findings and conclusions that address this goal are discussed in this chapter. This is done by consideration of the research objectives outlined in the introductory chapter. Conclusions were drawn with regard to the case study network and extended such that issues relating to design, modelling and analysis of industrial networks in general are addressed. This section is structured such that the research objectives are discussed in sequence.

5.1 Analytical Framework for Industrial Network Design

The first research objective states the following: *Propose an analytical framework with which industrial networks can be designed. Determine which characteristics of the network and the enterprises comprising the network can be captured by this framework.*

In Chapter 2 an analytical framework developed by Kempener et al. (2006c) was proposed, it consists of three levels, namely, functional, agent behaviour and network levels. The first level consists of the exchanges of resources (capital, land, materials, etc) and services and the information which directly relates to this exchange. This level captures the functional characteristics of each enterprise in the network. The second level includes the decision-making procedures an enterprise employs to effect transformation or transaction of resources within the network; and is called "agent behaviour". This level captures the methods and tools used by enterprises as decision aids together with the factors influencing the rationality of enterprises when making such decisions. The third level includes the characteristics of the network that play an important role in the decision-making process followed by each enterprise. This level captures policies and legislation imposed by governments and industry, norms and values to which enterprises must conform such that they are not excluded and societal expectations impacting the "licence to operate" of any enterprise in the network.

Identification of the individual levels of the framework was not a unique or particularly novel exercise in itself, with much literature available on designing each of these levels in isolation. The challenge presented was development of an integrated set of tools which may be used to consider all these levels simultaneously, in such a way that feedback between the different levels of the model is accounted for. This challenge was addressed by the following research objective

5.2 Modelling Approach for Simulation and Analysis of Industrial Networks

The second research objective states the following: *Use the analytical framework to develop a modelling approach with which the interactions between the enterprises in the network can be represented. In doing so, compare the developed approach to other modelling paradigms and conclude which approach is better suited to the problem at hand.*

To capture the feedback between levels 1 and 2 of the analytical framework it was identified that either agent-based or system dynamics approaches could be used to represent the functional and "agent-behaviour" of each enterprise as well as the interactions between the enterprises. The decision of which approach is best suited for this purpose was based on a comparison between them, as presented in Chapter 2. It was found that an agent-based approach is better suited for the following reasons:

i. An agent-based model of a network is modelled in a disaggregated manner, i.e. the enterprises comprising the network are represented as autonomous entities acting in a self interested manner, therefore the decision-making in the network is performed by multiple decision-makers. In a system dynamics model, the system is modelled in an aggregated manner, i.e. a holistic view is adopted where the decision-making in the network is performed by a single decision-maker. As such, an agent-based model of a network more closely approximates "real world" networks which consist of multiple decision-makers.

ii. The interactions between multiple enterprises typically occur as discrete events rather than being continuous over time, e.g., delays in delivery and purchase. Representing such events in a continuous time model, of which the system dynamics modelling paradigm is an example, was found to be more difficult when compared with representing such events in an agent-based model. As such, the event driven nature of agent-based models is preferred when modelling industrial networks.

iii. Another advantage of the event driven nature of agent-based models is that it allows for stochastic events to be easily included into the representation of a network. This is important as uncertain events are a common occurrence in industrial networks (e.g. unplanned power outages).

iv. In a system dynamics model, every enterprise has to be included into the model and linked to its potential trading partners in advance. Defining this structure beforehand can be cumbersome if the network being modelled has a high degree of complexity. In this case an agent-based model is preferred as it allows for complex behaviour to emerge from relatively simple and localised activities of its agents. As such, agent-based models of industrial networks offer a higher degree of model flexibility than system dynamics models.

To capture the interaction between levels 1, 2 and 4 of the analytical framework, it was found that neither simulation nor optimisation of the interactions between enterprises in a network were adequate tools with which analyse the outcome. The reason for this is that although simulation is a useful tool to evaluate "what-if" scenarios and to give a comprehensive view of the behaviour of the network under different operating conditions, it does not yield optimal results. And although optimisation of such networks will yield optimal operating conditions, little insight will be gained into the dynamic behaviour of the network. In light of these concerns, a combinatory simulation-optimisation configuration was selected for the purpose of modelling industrial networks. From this section it can be concluded that an agent-based simulation-optimisation model is best suited for the representation and design of networks.

Having addressed this objective, the next question to be answered concerns the decision-making procedure followed by enterprises. This challenge was addressed by the following research objective.

5.3 Decision-making procedure of Enterprises in Industrial Networks

The third research objective states the following: *Develop an understanding of the manner in which economic objectives together with environmental and social objectives are included into the decision-making procedure followed by enterprises today. This understanding must be extended beyond merely including environmental and social objectives as financial externalities.*

If an enterprise wants to include economic as well as environmental and social decision criteria into its decision-making procedure, multiple criteria decision analysis (MCDA) methods and tools will be required. These tools are used to determine the preferred operating conditions for each enterprise through trade-off of the decision criteria, as reviewed in Chapter 3. In the past, enterprises performed this trade-off procedure by (i) including environmental and social criteria as externalities by monetisation of these criteria, (ii) determination of the preferences of the stakeholders to each criterion.

An example of the first item is inclusion of emission taxes as an environmental externality and political capital as a social externality. The result is that enterprises pay a financial penalty for not meeting environmental and social targets. It should be recognised that when this is done, the monetary value of each criterion could differ in scale; with profit typically an order of magnitude or greater than emission taxes and political capital. As such, trading-off these criteria is problematic, as comparing them directly would result in the criteria with the largest order of magnitude having the greatest influence on the decision to be made. It was found that this problem could be avoided by normalisation of the economic, environmental and social decision criteria. It was suggested that this be done by firstly selecting two performance scores which represent the best and the worst situation, with the best score allocated a value score of 1 and the worst score a value of 0; and secondly determining the value score of each criterion as a function of the best and worst scores. Consequently, the decision criteria could all be represented as a value between zero and one. As such, they are directly comparable and can be traded-off. It was identified that this trade-off procedure should reflect the preferences of the stakeholders; for example, if maximisation of profit is most important to stakeholders when considering investments, the economic criterion should influence the decision the most. It was found that the preferred operating conditions could then be determined by weighting these preferences accordingly and calculating the weighted sum of the normalised criteria. This is a rather simplified form of MCDA, but is adequate for the purposes of this thesis. From this section it can be concluded that a decision-making procedure for enterprises, including economic, environmental and social objectives could be created, based on the model structures and agent-based analysis developed in this thesis. Furthermore, the procedure was developed beyond merely including environmental and social objectives as financial externalities.

In summary, the first three research objectives have thus been met through (i) developing an analytical framework for industrial network design, (ii) from this framework developing a modelling approach with which the behaviour of each enterprise can be represented together with capturing the dynamic behaviour of the network, and finally (iii) developing a decision-making procedure for enterprises in an industrial network that includes economic, environmental and social objectives. As such, the next question to be answered concerns the outcomes when such a modelling approach is applied to a "real world" industrial network. This challenge was addressed by the next research objective.

5.4 Case Study Application of Modelling Approach

The fourth research objective states the following: *Apply the modelling approach developed to a case study industrial network. Determine how inclusion of economic, environmental and social objectives into the decision-making procedure followed by the enterprises in the network could lead to more sustainable business practises in the future.*

In Chapter 3 and 4, a biomass-energy network situated in kwaZulu-Natal (KZN), South Africa, was designed and analysed by using an agent-based simulation-optimisation modelling approach. The agents included were the existing sugar mills in KZN, a potential independent power producer (IPP), the South African power utility (Eskom) and existing paper and pup mills in KZN. A propriety software package, AnyLogic, was used as a simulation engine to investigate the performance of the network and the behaviour of each agent over a 30 time year period. Network performance was tracked by economic, environmental and social indicators. The behaviour of each agent resulted from multiple criteria decision-making (MCDA) methods employed as decision-making tools. The multiple decision criteria included economic as well as environmental and social criteria. It was identified that the outcomes of agent-based models are difficult to validate. One means by which validation can be done is by setting an overall system goal prior to modelling and evaluating if the network is able to reach this goal or not. As the network used in this study consisted of constructing possible scenarios and agents that could potentially arise from the energy generation capability in the KZN region, where no such network consists at present, no benchmarks were set against which a result can be deemed "good" or "bad. Although an extensive sensitivity analysis is not a means by which a model can be validated, it was assumed that such an analysis would yield insights into the "correctness" of the model through trends and behaviours that arise from configuring the agents, and hence the network, in a certain manner. The variables explored in this analysis were proxies for the clean development mechanism and agent decision and risk policies. The reasons for this selection are given below.

One of research objectives was to identify incentives that could lead to practices that sufficiently contribute towards the renewable energy target and thus further the drive towards more sustainable business practice in South Africa. The clean development mechanism (CDM) was identified as a mechanism that could be used by either government or the private sector to encourage investment in renewable energy projects. For this reason the sensitivity of the network to the carbon credits selling price was tested. The main conclusions from this analysis are:

i. If the carbon credits selling price were to remain at a present day value of R 30/ MWh, the only agent active in the green electricity market would be the Eskom agent. For this configuration, a feasible generation alternative is co-firing of bagasse and coal into an existing power station. If this were to happen the renewable energy target of 10 000 GWh over the period 2003 – 2013, would not be achievable through electricity generation from bagasse. In fact, the energy generation from such a configuration would be 84% less than the target requires.
ii. If a sugar mill or an IPP were considering investment in a facility able to convert bagasse into green electricity; the current day carbon credits selling price would have to undergo growth of 223% and 117% respectively before such projects become economically, environmentally and socially feasible. Furthermore, it was found that of

the feasible projects, gasification is preferred above combustion by both enterprises. If this growth in price were to happen, the renewable energy target would be improved upon by 72% and 65 % respectively.

As the enterprises in this network do not operate in isolation, the decision and risk policies assumed by one enterprise influence the behaviour of other enterprises in the network. As such, the sensitivity of the network to these policies was tested.

Risk in this study was modelled as financial risk of potential investment projects. This was captured by means of a minimum acceptable internal rate of return (IRR) on investment that an enterprise demands; with low risk enterprises demanding a high IRR on investments whereas enterprises that are risk averse demand high IRR on investments. The main conclusions from this analysis are that the renewable energy target can only be reached by enterprises in this network if all of them assume a minimum acceptable IRR of 10%. Under these conditions the target will improved upon by 68%, with investments by the sugar mill, Eskom and the IPP agents.

The decision policy adopted by each enterprise was captured by the stakeholder preference settings given to the three decision criteria. As explained previously, the preference settings could then be used to calculate the weighted sum of the normalised criteria such that optimum operating conditions are known. As such, the sensitivity of the network to these preference settings was tested. The main conclusions drawn from this analysis are:

i. The performance of the network and the capacity decisions made by the agents are least affected by the economic weighting adopted by the agents. The reason for this is that the minimum acceptable IRR screening process performed dampens the sensitivity of the network to changes in economic weighting.
ii. The renewable energy target is improved most (179% and 130% respectively) when the agents are either 100% socially or 100% environmentally rational.

From all of the sensitivity analyses discussed previously it was seen that the fewer decision-makers and less diverse the agents in the network, the less sensitive the network will be to the variable in question. This is favourable from a "top down" (governmental) perspective, as sudden changes in the behaviour of the agents would not have a detrimental effect on the behaviour of the network.

In summary, the analytical framework and modelling approach developed was applied to a "real world" industrial network and the sensitivity of this network to changes in network characteristics (i.e. carbon credits selling price) and agent-behaviour (i.e. risk and decision polices of enterprises) was tested and conclusions drawn. The conclusions indicate that when measured as a function of the renewable energy target, the individual agent preference settings have the greatest influence on the network performance and agent behaviour. This is indicated by the greatest increase of the target (179%) when all of the agents are 100% socially rational. The next question to answer is concerned with how these conclusions could be extrapolated to industrial networks in general. This challenge was addressed by the following research objective.

5.5 Extension to Generic Industrial Networks

The fifth research objective states the following: *Analyse the outcomes of the application of the modelling approach developed to the case study network specifically and draw conclusions regarding the implementation of such an approach to industrial networks in general.*

From the application of the modelling approach developed, and thus the analytical framework, to a case study network, the following observations are made with regards to industrial networks in general:

The modelling platform used is a propriety software package called Anylogic®. The **generic nature of the modelling platform** means that it offers the user the capability to create models using several different methodologies, including discrete event, system dynamics and agent-based modelling. The models can be created by using both object-oriented visual tools together with Java code. This allows the user the functionality to customise the platform to extend its capabilities. These factors are major advantages, as the nature of industrial networks is that they are complex structures which operate under a high degree of unpredictability and uncertainty. As such, a tailored modelling tool that offers flexibility to the modeller is preferred. In addition, a generic model can easily be extended to include a greater agent number and also an increase the complexity; this results from the object-oriented/agent-based functionality the platform offers.

The case study illustrates how agent-based simulation-optimisation models can capture **multiple objectives**. This is important if industrial networks, and the enterprises that comprise them, are going to be designed such that business practice as a whole is more sustainable. Anylogic is packaged with OptQuest©, an optimisation software package. This functionality of this package was not used for the purpose of the case study as the optimisations performed were linear and did not require the extensive algorithms designed to search very large solutions spaces filled with non-linearities[52]. It is important to note that the Anylogic offers the user the functionality to include objectives which yield non-linear search spaces, which may often be required in networks, if so desired.

It is believed that the analytical framework and modelling platform proposed in this thesis can be **integrated with a dynamic optimisation**, to give system-wide goals for comparison. This possibility is currently being explored, in the multi-institutional research group within which the study presented here was conducted[53]. This is important as the information relating to the network resides across a multitude of enterprises, is dynamic and ever changing. Each of the enterprises in the network could have different data capturing tools, modelling platforms and methods of analysis to deal with information. As such, a tool that offers the user the ability to integrate with other sources of modelling tool is preferred.

The decision-making process of the enterprises in the case study network illustrates ability of the model to **integrate with multi criteria decision analysis**, which was used for capacity and technology investment decisions. This is important if the enterprises in networks are going to operate under more sustainable business practices. The decision criteria included in this study were economic, environmental and social criteria which were most relevant to the network in

[52] A customised search algorithm was used. This dramatically improved computational time.

[53] This study is being undertaken by Jessica Beck (Beck, 2006).

question. Even though the decision criteria for different networks depend on the structure and functioning of the specific network, the modelling platform is such that more/different criteria could be readily included.

The case study illustrates, as described by the analytical framework, that agent functionality, and behaviour and network characteristics could be included in a model of a network. The model was executed and the structure and functioning of the network, as a function of different operating policies, was known. The modelling tool thus allows decision-makers and analysts to investigate the **effect of different policies on network behaviour** over time. This is important for planning and policy formulation, as decision-makers and analyst thus know what the behaviour of the network is as a function of different policies, ahead of actual implementation of any one policy, and can act accordingly.

In summary, it was illustrated that the analytical framework and modelling platform developed the ability to engage with strategic (planning and policy), tactical (investment) and operational (technology type and size selection) decisions.

5.6 Recommendations for Further Work

The work presented in this thesis could be extended practically in terms of the case study, or theoretically in terms of industrial networks in general. Modelling and analysis tools developed for industrial networks could yield additional insights when considering policy formulation, from a network and enterprise perspective, together with the possibility of being used as a decision support tool for the enterprises involved. Expansion of the work presented here will be discussed in light of these two factors

All of the sugar mills were aggregated into a single agent; therefore the mills were made indistinguishable from one another. Such an approach allowed for a depth of issues to be considered with detailed information, rather than having to work with a large amount of data in which a superficial breadth of issues was covered. Furthermore, it was suggested that the agent and object-oriented manner in which the model was structured readily allows for inclusion of more agents once a working model is complete and the resulting dynamics have been understood. As such, this work could be extended by modelling each of the mills as autonomous and distinguishable agents. A more realistic representation of the actual enterprises in the network will then be known, from which the complexity of the model could be increased. The reason this will yield additional insights is that the functionality and behaviour of each mill could be included. This will allow decision-makers and analysts a more accurate view of what factors influence policy and practice. The main challenges associates with this are interpretation and validation of results.

Uncertainty was dealt with in a simplistic manner by performing several "what-if" studies, as illustrated by the results of the sensitivity analyses as seen in Chapter 4. Further work could include a more rigorous approach to the consideration of uncertainty. There are three possible directions in which uncertainty modelling could be expanded, namely – model form, model parameters and empirical parameters. As the major driving factor of the dynamics in the case study network, and also generic networks, is agent decision-making processes, it is envisaged that uncertainty of the decision structure of agents, and hence model form, would potentially yield more insights into the (i) behaviour of the network and (ii) the sensitivity of the network to changes in internal and external stimuli. The challenges associated with including model form uncertainties are determining which is the dominant factor influencing the model output, as well the identifying how the different factors interact with each other.

In reality, if a large biomass-electricity generation plant were to be erected, there will be life cycle benefits of carbon capture by biomass, hence leading to (potential) carbon neutrality. Together with this, the derived electricity will substitute for new (small) coal plants, hence improving overall carbon footprint. These factors were not taken into account in this study. Further work should include incorporation of life cycle considerations relating to the carbon footprint of sugar cane production and bagasse conversion into electricity.

In summary, from the case study industrial network it can be concluded that a "real world" industrial network can be represented, designed and analysed by using of an agent-based simulation-optimisation modelling approach; within multi-criteria decision analysis tools employed as decision aids. With regard to industrial networks in general, it is concluded that although each individual network presents custom complexities and uncertainties, the analytical framework and modelling approach developed in this study provides a platform that allows designers and analysts the opportunity to take into account relevant enterprise and network characteristics.

The thesis has achieved its overall aim of promoting understanding of how the structure and functioning of industrial networks affect their economic, environmental and social performance. It is envisaged that this knowledge could be used to assist decision-making in the private sector by allowing enterprises to be aware of the implications of their decisions, and to respond more effectively to the challenges posed by the need for more sustainable business practice.

Appendix A: Decision Analysis Discussion

A.1 Literature Overview

As stated by Basson (2004), *"decision analysis (DA) developed in recognition that people are often confronted with difficult decisions characterised by complexity, uncertainty, multiple objectives and the need to consider different perspectives".* Decision analysis initially developed from utility theory (Von Winterfeldt and Edwards 1986) and was first applied to study problems related to oil and gas (Huang et al. 1995) and later moved on to address strategic or policy decisions, typically associated with uncertainties and multiple conflicting objectives (Corner and Kirkwood 1990). Decision analysis methods can be classified as illustrated in Figure 1.1 (adapted from (Zhou et al. *In Press*))

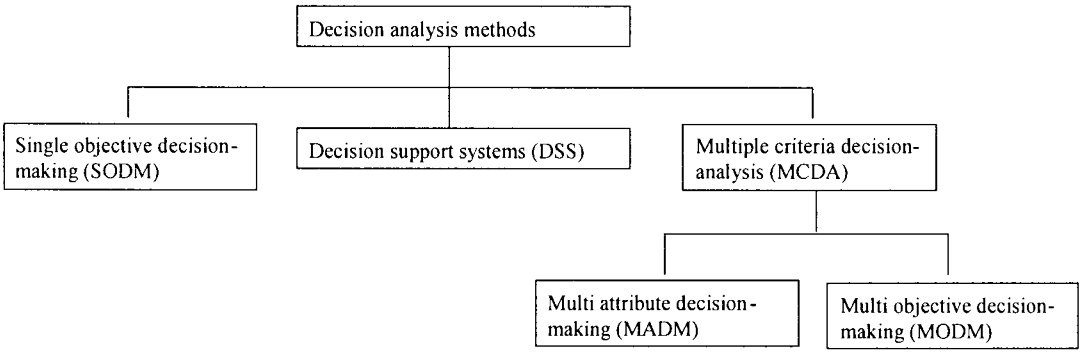


Figure A1: Classification of decision analysis methods

SODM is concerned with evaluation of the available alternatives with uncertain outcomes subject to a single objective (e.g. minimise cost) and one or many constraints. A decision support system (DSS) refers to any interactive, flexible and adaptable software system that integrates models, databases and other decision aiding tools in a packaged tool for decision-makers to use. MCDA allows decision-makers to evaluate alternatives on the basis of several criteria. In such and approach, decisions are made based on trade-offs between a number of criteria that are could be in conflict with each other (Belton and Stewart 2002). Multiple objective decision-making (MODM) and multiple attribute decision-making (MADM) are the two main branches of MCDA (Zhou et al. *In Press*). MODM is concerned with systems in which a set of conflicting objectives is optimised (e.g. minimise cost and environmental impact and maximise social and financial benefit) subject to a set of constraints. MADM refers to making preference decisions by evaluating and prioritising all the alternatives that are characterised by multiple conflicting attributes. The most general MADM methods include: (i) multiple attribute utility theory (MAUT), which allows decision-makers to consider their preferences in the form of multiple attribute utility functions, (ii) analytic hierarchy process (AHP), which is a methodology consisting of structuring, measurement and synthesis, (iii) elimination and choice translating reality methods (ELECTRE I, II, III, IV), which are a family of outranking methods, (iv) preference ranking organization methods for enrichment evaluation (PROMETHEE), which is also a class of outranking methods.

A.2 Value functions

Value functions are constructed by:

(i) selecting two performance scores which represent the best and the worst situation with the best score is generally allocated a value of 1 and the worst score a value of 0.

(ii) selecting the shape of the value function, with common shapes including linear, concave, convex, sigmoid or step value functions, as illustrated in Figure A 2.

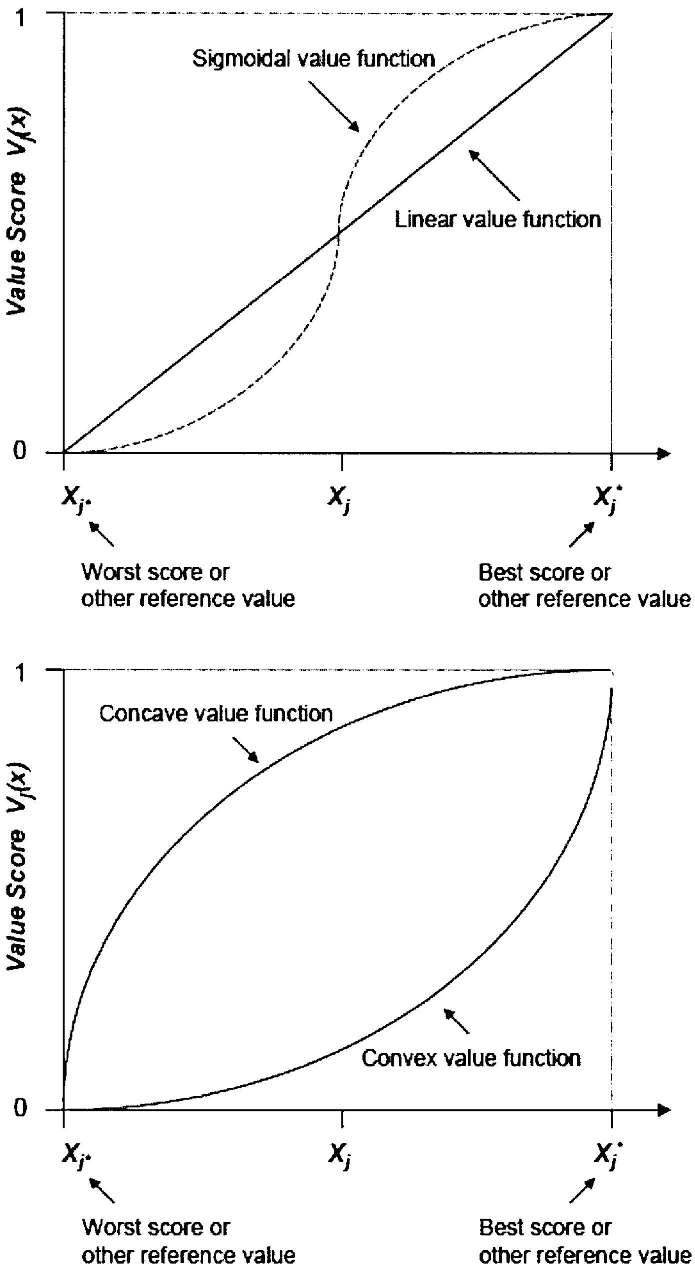


Figure A 2: Examples of shapes of value functions (Basson 2004)

Appendix B: Clean Development Mechanism Discussion

B.1 The Kyoto Protocol

In 1992 the Kyoto Protocol/United Nations Framework Convention on Climate Change (UNFCCC) was signed at the UN Conference on Environment and Development in Rio de Janeiro, Brazil. The UNFCCC commits countries listed in as Annex I parties (industrialised countries) to adopt policies to counter the effect of global climate by reducing Greenhouse Gas (GHG) emissions with the aim of returning emissions to 1990 levels.

Kyoto was adopted in December 1997, with this protocol identifying the mechanisms and compliance systems, but was limited on the details of implementation. 84 countries initially signed the Protocol, indicating an intention to ratify, with only parties who ratify becoming bound to the Protocol. The requirement was that the treaty could only take effect after it had been ratified by 55 countries, representing 55% of the industrialised world's CO_2 output in 1990. Prior to ratification by Russia, sufficient countries had ratified, although these countries only represented 36% of emissions. The Protocol came into effect in February 2005, when Russia ratified the Protocol, bringing the total percentage of Annex I emissions to 61.6%[54]. Once in effect, the Protocol requires that industrialised countries and Eastern European countries in transition have to reduce their emissions in the period from 2008 to 2012 by 5% (compared to the base year 1990). It was identified that these targets could be met by domestic actions and through three mechanisms that encourages compliance through interactions with other countries. These mechanisms are:

- **Joint implementation (JI)** - allows Annex I parties to implement projects that reduce emissions, or remove carbon from the atmosphere in other Annex I parties, in return for emission reduction units (ERUs).
- **Clean Development Mechanism (CDM)** –allows Annex I parties to implement projects that reduce emissions in non-Annex I parties, and in so doing obtain Certified Emission Reductions (CERs), Long-term Certified Emission Reductions (lCERs) and Temporary Certified Emission Reductions (tCERs). A CER is equal to one tonne of

[54] See details at http://cdm.unfccc.int

CO_2 equivalent (CO_2,eq). Both lCER and tCER are Certified Emission Reduction units issued for an afforestation or reforestation project activities.

- **Emissions Trading** - allows Annex I Parties to acquire units from other Annex I Parties. These units may be AAUs, RMUs, ERUs, CERs, tCERs and lCERs. An Assigned Amount Unit (AAU) is a tradable unit of one tonne of $CO_{2,eq}$. A Removal Unit (RMUs) can be obtained by activities that cause a net removal of greenhouse gases.

Irrespective of the mechanism used, the manner in which reduced emissions are measured is through a CO_2 equivalent. As such, the tradable unit in carbon trading schemes is equal to one metric ton of carbon dioxide equivalent (CO2-e). The reason for this is that different gases have different a global warming potential and carbon dioxide equivalents provide a common instrument for trading. Under the Kyoto Protocol, there are six different gases that contribute to this potential, listed in Table B 1(Anon 1996) and (Anon 2001).

Table B 1: Global warming potential of green house gases

Greenhouse Gas	Chemical symbol	Global warming potential
Carbon dioxide	CO_2	1
Methand	CH_4	21
Nitrous oxide	N_2O	296
Hydrofluorocarbons	HFC	12-12,000
Perfluorocarbons	PFC	6,500-9,200
Sulphur hexafluoride	SF_6	23,900

For example, the greenhouse gas reduction activities that are implemented involving methane will yield up to 21 carbon credits per ton of methane reduced. Carbon credits are measured in units of certified emission reductions (CERs), with each CER equivalent to one ton of carbon dioxide reduction. These credits can then be sold on the market at the carbon credits selling price.

Only CDM projects were considered in this study, as it is particularly relevant to South Africa, given that South Africa is classed as a developing country (non-Annex I party). As such, only this mechanism will be further discussed.

In order for a country to host a CDM project it must comply with the following requirements: (i) ratification of the Kyoto Protocol, (ii) identification of a national CDM authority and (iii) must not to be listed as an Annex 1 party.

The CDM was developed based on two key observations:

- Given that global warming is an international concern which is independent of national boundaries, it does not matter where reductions in greenhouse gas emissions take place.
- Industrialised countries generally use advanced and efficient technologies for electricity generation and industrial production, whilst in many developing countries less efficient technologies are used. Improving advanced technology costs much more than replacing obsolete plants, and therefore the cost of reducing one ton of greenhouse gases in developing countries is potentially lower than that in industrialised countries.

Implementation of facilities through the CDM has the potential contribute towards meeting two of the aims of Kyoto Protocol:

- assist industrialised countries in reaching their emissions targets
- support developing countries in moving towards more sustainable futures

The second aim is achieved through the provision of capital, knowledge and technologies, particularly in the fields of renewable energy and energy-efficiency improvement.

B.2 South African CDM Projects

As identified by the UNFCCC, there are currently there are four registered CDM project in South Africa, namely,

The **Rosslyn Brewery Fuel-Switching Project** was registered with the UNFCCC on 29 September 2006 and it a project run by South African Breweries Ltd. The Annex 1 parties were not identified at the time of writing this report. This project consists of industrial fuel switching from coal and petroleum fuels to natural gas, to drive the production processes of the brewery, without extension of capacity and lifetime of the facility. The facility is located near

Rosslyn, north of Pretoria, Gauteng. The amount of reductions generated by this project is 100,941 metric tonnes $CO_{2\,eq}$ per annum.

The **PetroSA Biogas to Energy Project** was registered with the UNFCCC on 29 September 2006 and is a project run by MethCap SPV1 (pty) Ltd. The Annex 1 parties were not identified at the time of writing this report. The project consists of generation of electricity from biogas to drive to production processes. The facility is located near Mosselbay, in the Western Cape. The amount of reductions generated by this project is 29,933 metric tonnes $CO_{2\,eq}$ per annum.

The **Lawley Fuel Switch Project** was registered with the UNFCCC on 6 March 2006 and is a project run by Statkraft Markets BV. The Annex one party is the Netherlands. This project consists of industrial fuel switching from coal and petroleum fuels to natural gas, for thermal fuel used for clay brick baking, without extension of capacity and lifetime of the facility. The facility is located in Lenasia, Johannesburg, Gauteng. The amount of reductions generated by this project is 19,159 metric tonnes $CO_{2\,eq}$ per annum.

The **Kuyasa low-cost urban housing energy upgrade project** was registered with the UNFCCC on 27 August 2005 and is a project run by City of Cape Town. The Annex 1 parties were not identified at the time of writing this report. This project aims at encouraging low cost housing and energy upgrades through the installation of solar water heaters, insulated ceilings and compact fluorescent light in houses in Khayalitcha in the Western Cape. The amount of reductions generated by this project is 6580 metric tonnes $CO_{2\,eq}$ per annum.

Appendix C: Case Study Data

C.1 Combustion and Gasification: Technical Discussion

Table C 1: Capital and operation & maintenance costs for generation technologies

	Combustion		Gasification		Co-fire	
Capacity	Capital costs	Operation & Maintenance costs	Capital costs[a]	Operation & Maintenance costs[b]	Capital costs	Operation & Maintenance costs
MW	Rand	Rand/MWh	Rand	Rand/MWh	Rand	Rand/MWh
3	5.13E+07	47.2	4.36E+07	62.8	2.49E+06	150
4.5	7.34E+07	42.6	6.24E+07	56.7	3.73E+06	150
10	1.44E+08	77.1	1.22E+08	102.6	8.30E+06	150
14	1.90E+08	68.6	1.62E+08	91.3	1.16E+07	150
25	3.30E+08	63.9	2.81E+08	84.9	1.49E+07	150
40	4.51E+08	50.2	3.83E+08	66.8	2.32E+07	150
80	5.18E+08	50.2	4.41E+08	66.8	2.48E+07	150
120	5.96E+08	50.2	5.07E+08	66.8	2.88E+07	150
160	6.86E+08	50.2	5.83E+08	66.8	3.28E+07	150

Notes: a The capital cost of a gasification plant are assumed to be 85% of an equivalent steam plant.

b The operation and maintenance costs of a gasification plant are 133% of an equivalent steam plant (Anon 2005b).

C.2 Location of the Sugar Mills in kwaZulu-Natal

Figure C 1: Location of sugar mills in kwaZulu-Natal Province, South Africa

C.3 Cane and Bagasse Flows in kwaZulu-Natal Sugar Mills

Table C 2: Annual cane delivered and bagasse generated

Mill	Season start (month)	End of season (month)	Season duration (months)	Harvest[a] (t/a)	Bagasse[b] (t/a)	Average harvest (t/month)	Bagasse (t/month)
Amatikulu	Apr	Nov	8	1750000	525000	218750	65625
Union	Mar	Dec	10	777306	233192	77731	23319
Darnall	Apr	Nov	8	1350000	405000	168750	50625
Eston	Mar	Nov	9	1307274	392182	145253	43576
Felixton	May	Nov	7	1894726	568418	270675	81203
Gledhow	Apr	Dec	9	1175622	352687	130625	39188
Maidstone	Apr	Nov	8	1420000	426000	177500	53250
Noordberg	Mar	Dec	10	1614763	484429	161476	48443
Pongola	Mar	Dec	10	1426568	427970	142657	42797
Sezela	Apr	Dec	9	2014283	604285	223809	67143
Umfolozi	Apr	Dec	9	1087606	326282	120845	36254
Umzimkulu	Apr	Dec	9	1136866	341060	126318	37895

Notes: a Average harvest = harvest 2003/2004/ season duration

b Bagasse yield is taken as 30% of cane delivered to mill (Anon 2004a)

C.4 Energy requirement per district council and population group in kwaZulu-Natal

Table C 3: Energy requirement per district council and population group in kwaZulu-Natal

Agent	District Municipality		Black/African	Coloured	Indian/Asian	White	Total	Un-electricified households	Un-electricfied/total energy requirement	Normalised priority factor
Sugar mill	Ugu	Electricity	53787	980	6141	11446	72354	78254	0.52	0.65
		Gas	448	0	8	14	470			
		Paraffin	4773	10	32	5	4820			
		Candles	71055	116	89	51	71311			
		Solar	646	0	4	11	661			
		Other	957	0	7	28	992			
		Total energy requirement					**1.51E+05**			
IPP	eThekwini	Electricity	360492	17814	154411	94588	627305	159440	0.20	0.25
		Gas	1769	34	140	129	2072			
		Paraffin	22168	98	244	21	22531			
		Candles	130703	510	1136	115	132464			
		Solar	1065	20	110	103	1298			
		Other	933	12	63	67	1075			
		Total energy requirement					**7.87E+05**			
Eskom	Amajuba	Electricity	59828	515	3202	6539	70084	26589	0.28	0.34
		Gas	546	0	4	18	568			
		Paraffin	1074	3	3	10	1090			
		Candles	24347	65	18	37	24467			
		Solar	149	0	3	3	155			
		Other	300	0	3	6	309			
		Total energy requirement					**9.67E+04**			
	Umgungundlovu	Electricity	114988	3988	18859	23262	161097	55542	0.26	0.32
		Gas	532	21	32	38	623			
		Paraffin	1482	15	26	7	1530			
		Candles	51758	226	170	60	52214			
		Solar	423	6	7	28	464			
		Other	687	0	9	15	711			
		Total energy requirement					**2.17E+05**			
	Uthukela	Electricity	67806	697	4510	4651	77664	57178	0.42	0.53
		Gas	681	4	4	23	712			
		Paraffin	4166	9	3	4	4182			
		Candles	51335	101	35	22	51493			
		Solar	248	0	0	3	251			
		Other	529	0	0	11	540			
		Total energy requirement					**134842**			

	Umzinyathi	Electricity	17412	416	1706	2337	21871	68242	0.76	0.95
		Gas	354	3	4	3	364			
		Paraffin	3777	7	9	3	3796			
		Candles	62963	102	33	23	63121			
		Solar	333	0	4	0	337			
		Other	617	0	3	4	624			
		Total energy requirement					**9.01E+04**			
	Zululand	Electricity	50958	218	153	4086	55415	89535	0.62	0.77
		Gas	833	0	0	10	843			
		Paraffin	4588	12	0	4	4604			
		Candles	82487	63	7	54	82611			
		Solar	509	0	0	11	520			
		Other	954	0	0	3	957			
		Total energy requirement					**1.45E+05**			
	Umkhanyakude	Electricity	19159	155	98	968	20380	81181	0.80	1.00
		Gas	458	0	0	3	461			
		Paraffin	908	0	0	0	908			
		Candles	78253	42	5	35	78335			
		Solar	589	0	3	3	595			
		Other	882	0	0	0	882			
		Total energy requirement					**1.02E+05**			
	Uthungulu	Electricity	77296	912	2990	8923	90121	81360	0.47	0.59
		Gas	693	0	3	29	725			
		Paraffin	3325	3	4	3	3335			
		Candles	75855	48	7	18	75928			
		Solar	428	3	4	10	445			
		Other	919	0	0	8	927			
		Total energy requirement					**1.71E+05**			
	iLembe	Electricity	46009	535	9312	3481	59337	61052	0.51	0.63
		Gas	482	0	19	0	501			
		Paraffin	2845	22	185	3	3055			
		Candles	56285	69	223	10	56587			
		Solar	265	0	5	4	274			
		Other	613	3	16	3	635			
		Total energy requirement					**1.20E+05**			
	Sisonke	Electricity	21444	1698	267	2379	25788	46452	0.64	0.80
		Gas	239	6	0	4	249			
		Paraffin	3621	34	3	0	3658			
		Candles	41451	529	7	13	42000			
		Solar	167	7	0	0	174			
		Other	357	8	0	6	371			
		Total energy requirement					**7.22E+04**			

Notes: a: source - http://www.statssa.gov.za/census01/html/C2001Interactive.asp

Figure C.2: Map of the district municipalities in kwaZulu-Natal

Note: a: source - http://devplan.kzntl.gov.za/MapsGis/standardMaps.asp

C.5 Time dependent figures used for normalisation of decision criteria

The time dependent figures used for the normalisation of the respective decision criteria were determined by constructing and optimising a functional model of the physical system and the viable technology options available to each agent. The construction and subsequent global optimisation of these models forms part of the work done by the Complex Systems and Sustainability group at the School of Chemical and Bio-molecular Engineering at the University of Sydney and was performed by Jessica Beck (Beck 2006).

In these models agents are presented as nodes with a certain functionality (e.g. an IPP can transform bagasse into electricity) that can be included or excluded from the network to optimise the performance of the network as a whole. The optimisation in this case was performed through the use of a series of simulations (simulation optimisation). The advantage of such an approach includes its relative ease of implementation, compared with agent-based models, and that the results can give an indication of what is technically achievable for the system. Based on this knowledge of preferred overall system performance, the agents will be able to make decisions aligning themselves more closely with the system optimum, and hence for their own benefit. Such models may be set up in various software packages, including spreadsheets, although in this work the Matlab/Simulink modelling environment was chosen as the preferred platform. Matlab/Simulink is a powerful software package, specially designed to handle dynamic optimisation problems, which is one of the main areas of research in the study performed by Beck (2006).

The functional model scope, i.e. the technologies included, is identical to the agent-based model applied in this thesis. To determine the best allocation of bagasse within this network from a global perspective, a range of scenarios were constructed encompassing all possible allocation options for the agents. In each scenario, the flow of bagasse was directed through the system by constructing predefined allocations, as can be seen in Table C 4. The best and worst performance values for all the criteria can be found in Table C 5.

Table C 4: Scenario construction for predefined flow of bagasse through the functional model

Scenario	Description
SM, g	All of the bagasse is gasified by the mills onsite
IPP, g	All of the bagasse is gasified by the IPP (mills still satisfy its power requirement)
cof	All of the bagasse is sent to Eskom of cofiring into a steam boiler
SM, st	All of the bagasse is combusted by the mills in a steam boiler onsite
IPP, st	All of the bagasse is combusted by the IPP in a steam boiler
mix,g	The mills and the IPP each gasify half of the bagasse (the mills still satisfy its power requirement
mix, st	Th mills, Eskom and the IPP each send a third of the bagasse to be combusted in a steam boiler
mix,s &g	The mills and the IPP gasifty 50% and 32.5% of the bagasse respectively. Eskom combustes the 17.5%of the bagasse in a steam boiler

Table C 5: Time dependent figures for the best and worst performance of the network

	Unit	Best value	Worst value
NPV	R/ton.bagasse	49.73	0
RE	CO2/ton.bagasse	0	1.26
REE	-	85.1	0

Higher values of the economic performance measure (NPV/ton Bagasse) are preferred. It was found that this value was the highest when all of the bagasse was gasified by the mills onsite (scenario SM,g). The reasons for this are: (i) transportation and raw material cost were not included in the NPV calculation of the mills as they own the bagasse; (ii) gasification is a more efficient technology than steam generation (Anon 2005b), therefore this technology options allows for larger amounts of bagasse to be converted into electricity. This benefit is enough to offset the higher initial capital outlay.

As the environmental performance measure (RE) is indicative of the amount of CO_2 emitted as a function of bagasse availability, lower values are preferred. The life cycle considerations relating to the carbon footprint of sugar cane production and bagasse conversion were not taken into account. Cane growing and harvesting is driven by sugar production, and while this may change in the future when energy products start playing a dominant role, at the moment the decision whether or not to use bagasse for power generation will not affect harvesting activities, and hence the associated emissions. Bagasse conversion, on the other hand, is assumed to have no emissions as bagasse is a renewable resource, hence carbon neutral, and negligible amounts of fossil fuels would be used in the process. CO_2 emissions from theses sources are thus ignored as they do not influence the decision to invest. Therefore the "best" RE value was set at zero. The "worst" RE factor was determined by constructing the model such that the all of the bagasse was sent to Eskom for co-firing into a steam boiler. The reason for this is that Eskom is located approximately 500 km away from the bagasse source, therefore the CO_2 emissions from transportation will be much higher when compared with the IPP (located approximately 50 km away from the source).

The social performance measure is indicative of the ability of the network to direct electricity provision to off-grid communities. The indicator is taken to be the number of non-electrified houses that would be electrified if a generation facility was erected in a specific region and its power used to electrify local housing. Therefore the higher this value the better the performance of the network. The REE factor was found to be highest when all of the agents were active, as they were then located in different regions and able to contribute to more significantly (scenario $mix_{s,g}$).

References

Akkermans, H. (2001). Emergent Supply Networks: System Dynamics Simulation of Adaptive Supply Agents. Proceedings of the 34th Hawaii International Conference on System Sciences.

Alexander, B., G. Barton, J. Petrie and J. Romagnoli (2000). "Process Synthesis and Optimisation Tools for Environmental Design: Methodology and Structure." Computers & Chemical Engineering **24**: 1195-1200.

Amaral, L. A. N. and J. M. Ottino (2004). "Complex Systems and Networks: Challenges and Opportunities for Chemical and Biological Engineers." Computers & Chemical Engineering **59**: 1653-1666.

Anon (1996). "Background Document: Bagasse Combustion in Sugar Mills, EPA-450/3-77-077, U. S. Environmental Protection Agency." Accessed on: *4 September 2006.* Available at: http://www.epa.gov/ttn/chief.

Anon (2001). "Intergovernmental Panel on Climate Change Third Assessment Report." Accessed on: *4 September 2006.* Available at: http://www.ipcc.ch.

Anon (2003). "Employment Potential of Renewable Energy in South Africa." Accessed on: *23 August 2006.* Available at: www.reeep.org/media/downloadable_documents.

Anon (2004a). "Economic and Financial Calculations and Modelling for the Renewable Energy Strategy Formulation." Accessed on: *15 August 2005.* Available at: Department of Minerals and Energy: www.dme.gov.za.

Anon (2004b). "Assessment of Commercially Exploitable Biomass Resources: Bagasse, Wood & Sawmill Waste and Pulp, in South Africa." Accessed on: *15 August 2005.* Available at: Department of Minerals and Energy: www.dme.gov.za.

Anon (2004c). "National Integrated Resource Plan." Accessed on: *31 July 2006.* Available at: NER, Eskom and ERC: http://www.ner.org.za.

Anon (2005a). "Quarterly Economic and Business Report Pietermaritzburg and Umgungundlovu District." Accessed on: *5 October 2005.* Available at: www.pcb.org.za.

Anon (2005b). Personal Communication with Dennis Williams: Request for Prices on Boilers and Generators. J. Beck, Associated Energy Services (Pty) Ltd.

Anon (2007) "Mauritius Energy Report" Accessed on *31 May 2007.* Available at: http://www.enerdata.fr/enerdatauk/products/reports/mauritius.php4

April, J., M. Better, F. Glover, J. P. Kelly and M. Laguna (2005). Enhancing Business Process Management with Simulation Optimisation. BP Trends Newsletter. **2:** 1-11.

Axelrod, R. (1997). The Complexity of Cooperation, Agent-Based Models of Competition and Collaboration, Princeton University Press.

Axtell, R. L., C. L. Andrews and M. J. Small (2002). "Agent-Based Modelling and Industrial Ecology." Journal of Industrial Ecology **5**(4): 10-13.

Bakshi, B. R. and J. Fiksel (2003). "The Quest for Sustainability: Challenges for Process Systems Engineering." AIChE Journal **49**(6): 1350-1358.

Bansal, V., V. Sakizlis, R. Ross, J. D. Perkins and E. N. Pistikopoulos (2003). "New Algorithms for Mixed-Integer Dynamic Optimisation." Computers & Chemical Engineering **27**(647-668).

Basson, L. (2004). "Context Compensation and Uncertainty in Environmental Decision-making". Department of Chemical Engineering. University of Sydney. Doctoral Thesis

Baumgaertel, H., S. Brueckner, H. V. D. Parunak, R. Vanderbok and J. Wilke, Eds. (2001). Agent Models of Supply Network Dynamics, in The Practice of Supply Chain Management, ed. C. Billington, T. Harrison, H. Lee, and J. Neale. International Series on Operations Research and Management Science, Kluwer.

Beamon, B. M. (1998). "Supply Chain Design and Analysis: Models and Methods." International Journal of Production Economics **55**: 281-294.

Beck, J. M. (2006). "A Framework for the Analyses of Industrial Systems for Sustainability". School of Chemical and Bio-molecular Engineering. University of Sydney, Australia. Doctoral research proposal

Belton, V. and T. J. Stewart (2002). Multiple Criteria Decision Analysis An Integrated Approach. Boston/Dordrecht/London, Kluwer Academic Publishers.

Biegler, L. T., A. M. Cervantes and A. Wachter (2002). "Advances in Simultaneous Strategies for Dynamic Process Optimisation." Chemical Engineering Science **57**: 575-593.

Biegler, L. T. and I. E. Grossmann (2004). "Retrospective on Optimisation." Computers & Chemical Engineering **28**: 1169-1192.

Borshchev, A. (2005). System Dynamics and Applied Agent Based Modelling. International System Dynamics Conference, Boston.

Borshchev, A. and A. Filippov (2004). From System Dynamics and Discrete Event to Practical Agent Based Modelling: Reasons, Techniques and Tools. International Conference of the System Dynamics Society, Palermo, Italy.

Camm, J. D., T. E. Chorman, F. A. Dill, J. R. Evans, C. Sweeny and G. W. Wegryn (1997). "Blending OR/MS, Judgement , and GIS: Restructuring P&G's Supply Chain." Interfaces **27**: 128-142.

Chakraborty, A. and A. A. Linninger (2002). "Plant-Wide Waste Management. 1. Synthesis and Multi-Objective Design." Industrial & Engineering Chemistry Research **41**: 4591-4604.

Choi, T. Y., K. J. Dooley and M. Rungtusanatham (2001). "Supply Networks and Complex Adaptive Systems: Control versus Emergence." Journal of Operations Management **19**: 351-366.

Corner, J. L. and C. W. Kirkwood (1990). "Decision Analysis Applications in the Operations Research Literature: 1970–1989." Operations Research **39**: 206–219.

Crouchy, M. and D. Galai (2001). Risk Management. New York, McGraw Hill.

Desmeulles, G., G. Querrec, P. Redou, S. Kerde´lo, L. Misery, V. Rodin and J. Tisseau (2006). "The Virtual Reality Applied to Biology Understanding: The In Virtuo Experimentation." Expert Systems with Applications **30**: 82-92.

Ding, H., L. Benyoucef, X. Xie, C. Hans and J. Schumacher (2004). "ONE" A New Tool for Supply Chain Network Optimisation and Simulation. Winter Simulation Conference, Washington DC, USA.

Epstein, J. M. (1999). "Agent-Based Computational Models and Generative Social Science." Complexity **4**(5): 41-60.

Forrester, J. W. (1961). Industrial Dynamics. Portland, Productivity Press.

Forrester, J. W. (1969). Urban Dynamics. Waltham, Pegasus Communications.

Forrester, J. W. (1994). "System Dynamics, Systems Thinking, and Soft OR." System Dynamics Review **10**: 86-100.

Freppaz, D., R. Minciardi, M. Robba, M. Rovatti, R. Sacile and A. Taramasso (2004). "Optimising Forest Biomass Exploitation for Energy Supply at a Regional Level." Biomass and Bio-Energy **26**: 15-25.

Fu, M. C. (2002). "Optimisation for Simulation: Theory vs. Practice." INFORMS Journal on Computing **14**: 192-215.

Gjerdrum, J., N. Shah and L. G. Papageorgiou (2001). "A Combined Optimisation and Agent-Based Approach to Supply Chain Modelling and Performance Assessment." Production Planning & Control **12**(1): 81-88.

Glazner, C. and S. Sgouridis (2005). "Optimising Freight Transportation Policies for Sustainability: A Simulation-Based Investigation of Freight Transportation Policy Planning and Supply Chains." Accessed on: *7 November 2005.* Available at: http://www.xjtek.com/files/papers/freighttransportation2005.pdf.

Goldblatt, M., W. Kagi, A. Leuchinger and W. Visser (2001). "South African National Strategy Study on the Clean Development Mechanism. Draft final report. Johannesburg, National Climate Change Committee." Accessed on: *3 September 2005.* Available at: http://siteresources.worldbank.org.

Granovetter, M. (1985). "Economic Action and Social Structure: The Problem of Embeddedness." American Journal of Sociology **91**(3): 481-510.

Grossmann, I. E. (2004). "Challenges in the New Millennium: Product Discovery and Design, Enterprise and Supply Chain Optimisation and Global Life Cycle Assessment." Computers & Chemical Engineering **29**: 29-39.

Grossmann, I. E. (2005). "Enterprise-wide Optimisation: A New Frontier in Process Systems Engineering." AIChe Journal **51**(7): 1846-1857.

Grossmann, I. E., S. A. Van den Heever and I. Harjunkoski (2002). "Discrete Optimisation Methods and their Role in the Integration of Planning and Scheduling." Proceedings of the AIChE Symposium Series No. 326 **98**: 150-168.

Gu, J. and X. Tang (2005). "Meta-Synthesis Approach to Complex System Modelling." European Journal of Operational Research **166**: 597–614.

Haunschild, P. R. (1994). "How Much Is That Company Worth? Inter-organisational Relationships, Uncertainty, and Acquisition Premiums." Administrative Science Quarterly **39**(3): 391-411.

Heimgartner, C. (2001). System Dynamic Modelling of Transport and Land use - A First Model Draft. 1st Swiss Transport Research Conference, Monte Verità / Ascona.

Holland, J. H. (1995). Hidden Order: How Adaptation Builds Complexity, Addison-Wesley, Reading, MA.

Huang, J. P., K. L. Poh and B. W. Ang (1995). "Decision Analysis in Energy and Environmental Modelling." Energy **20**: 843-855.

Janssen, M. A. (2002). Complexity and Ecosystem Management. Northampton, Edward Elgar Publishing Limited.

Jennings, N. R. (2001). "An Agent- Based Approach for Building Complex, Distributed Systems: The Case for an Agent-Based Approach." Communications of the ACM **44**(4): 35-41.

Jennings, N. R., K. Sycara and M. Wooldridge (1998). "A Roadmap of Agent Research and Development." Autonomous Agents and Multi-agent Systems **1**(7-38).

Julka, N., N. Srinivasan and I. Karimi (2002a). "Agent-Based Supply Chain Management: Framework." Computers & Chemical Engineering **26**: 1755-1769.

Julka, N., N. Srinivasan and I. Karimi (2002b). "Agent-Based Supply Chain Management 2: A Refinery Application." Computers &Chemical Engineering **26**: 1771-1781.

Kempener, R. (2006a). "Creating Sustainability in Industrial Networks: A Complex Systems Analysis Using Agent-based Modelling". School of Chemical and Bio-molecular Engineering. University of Sydney, Australia. Doctoral research proposal

Kempener, R., L. Basson, R. Malan, B. Cohen, J. Beck and J. Petrie (2006b). The Use of MCDA to Model Agent Decisions in Complex Industrial Networks. 18th International Conference on Multiple Criteria Decision-making, Chania, Greece.

Kempener, R., B. Cohen, L. Basson and J. Petrie, Eds. (2006c). A Framework for Analysis of Industrial Networks, in: Dynamics of Industrial Ecosystems, B. Davidsdottir & M. Ruth, (eds), in press.

Lee, L. H., S. Teng, E. P. Chew, K. W. Lye and P. Lendermann (2005). Application of Multi-Objective Simulation-Optimisation Techniques to Inventory Management Problems. Winter Simulation Conference, Orlando, USA.

Macal, C. M., G. A. Boyd, R. R. Cirillo, G. Conzelmann, M. J. North, P. R. Thimmapuram and T. D. Veselka (2004). Modelling the Restructured Illinois Electricity Market as a Complex Adaptive System. 24 Annual North American Conference of the USAEE/IAEE Energy, Environment and Economics in a New Era, Washington DC, USA.

Matsuhashi, R., S. Fujisawa, W. Mitamura, Momobayashi Y and Y. Yoshida (2004). "Clean Development Mechanism Projects and Portfolio Risks." Energy **29**: 1579–1588.

Maurice, P. J. (1989). By-products of the Cane Sugar Industry : An Introduction to their Industrial Utilisation. Amsterdam, New York, Elsevier.

Ostrom, E., R. Gardner and J. Walker (1994). Rules, Games and Common-Pool Resources, Ann Arbor: University of Michigan Press.

Pahl-Wostl, C., Ed. (2002). Agent Based Simulation in Integrated Assessment and Resources Management. Lugano, Switzerland, 2nd ed. In: A.E. Rizzoli, A.J. Jakeman (Eds), Integrated Assessment and Decision Support, Proceedings of the 1st Biennial Meeting of the International Environmental Modelling and Software Society, Lugano (Switzerland).

Parunak, H. V. D., R. Savit and R. L. Riolo (1998). "Agent-Based Modelling vs. Equation-Based Modelling: A Case Study and Users' Guide." Proceedings of Workshop on Modelling Agent-Based Systems.

Pearce, D. W. (2001). Energy Policy and Externalities: An Overview. Workshop on Energy Policy and Externalities: the Life Cycle Analysis Approach, Paris, France.

Peltoniemi, M. and E. Vuori (2004). Business Ecosystem as the New Approach to Complex Adaptive Business Environments. eBRF eBusiness Research Forum, Tampere, Finland, Tampere University of Technology.

Perea, E., I. E. Grossmann, E. Ydstie and T. Tahmassebi (2000). "Dynamic Modelling and Classic Contract Theory for Supply Chain Management." Computers & Chemical Engineering **24**: 1143-1149.

Peters, M. S., K. D. Timmerhaus and R. E. West (2003). Plant Design and Economics for Chemical Engineers. New York, McGraw Hill.

Pohekar, S. D. and M. Ramachandran (2004). "Application of Multi-Criteria Decision-making to Sustainable Energy Planning." Renewable and Sustainable Energy Reviews **8**: 365-381.

Rahmandad, H. and J. Sterman (2004). "Heterogeneity and Network Structure in the Dynamics of Diffusion: Comparing Agent-Based and Differential Equation Models." Accessed on: *4 September 2005* Available at: http://esd.mit.edu/WPS/esd-wp-2004-05.pdf.

Riddalls, C. E., S. Bennett and N. S. Tipi (2000). "Modelling the Dynamics of Supply Chains." International Journal of Systems Science **31**: 969-976.

Schieritz, N. (2002). Integrating System Dynamics and Agent-Based Modelling. 20th System Dynamics Conference, Palermo, Italy.

Schieritz, N. and A. Größler (2003a). Emergent Structures in Supply Chains— A Study Integrating Agent-Based and System Dynamics Modelling. 34th Hawaii International Conference on System Sciences, Hawaii.

Schieritz, N. and P. M. Milling (2003b). Modelling the Forest or Modelling the Trees - A Comparison of System Dynamics and Agent-Based Simulation. 2003 System Dynamics Conference, New York City, USA.

Scholl, H. J. (2001). Agent-based and System Dynamics Modelling: A Call for Cross Study and Joint Research. Proceedings of the 34th Hawaii International Conference on System Sciences, Hawaii, USA.

Shah, N. (2004). "Pharmaceutical Supply Chains: Key Issues and Strategies for Optimisation." Computers & Chemical Engineering **28**: 929-941.

Shah, N. (2005). "Process Industry Supply Chains: Advances and Challenges." Computers & Chemical Engineering **29**: 1225-1235.

Shapiro, J. F. (2001). "Beyond Supply Chain Optimisation to Enterprise Optimisation." Accessed on: Available at: www.ascet.com.

Sterman, J. D. (2000). Business Dynamics: Systems Thinking and Modelling for a Complex World. Boston, McGraw-Hill.

Surtees, R. M. (1997). "Electricity Demand Growth in South Africa and the Role of Demand Side Management." Accessed on: *7 October 2005.* Available at: www.ctech.ac.za/conf.

Swaminathan, J. M., S. S. Smith and N. Sadeh (1998). "Modelling Supply Chain Dynamics: A Multi-Agent Approach." Decision Science **29**: 607-632.

Tesfatsion, L. (2003). "Agent-Based Computational Economics: Modelling Economies as Complex Adaptive Systems." Information Sciences **149**: 263-269.

Turton, R., R. C. Bailie, W. B. Whiting and J. A. Shaeiwitz (1998). Analysis, Synthesis, and Design of Chemical Processes. New Jersey, Prentice Hall, PTR.

Valluria, A. and D. C. Croson (2005). "Agent learning in supplier selection models." Decision Support Systems **39**: 219-240.

Von Winterfeldt, D. and W. Edwards (1986). Decision Analysis and Behavioural Research. Cambridge, Cambridge University Press.

Wiesne and Purchase, A. and B. Purchase (2004). "Renewable Energy: An Opportunity for the South African Sugar Industry?" Proceedings of the South African Sugar Technology Association **78**: 39-54.

Winkler (2005). "Renewable Energy Policy in South Africa: Policy Options for Renewable Electricity." Energy Policy **33**(1): 27-38.

Woodwell, J. C. (1998). "A Simulation Model to Illustrate Feedbacks Among Resource Consumption, Production and Factors of Production in Ecological-Economic Systems." Ecological Modelling **112**: 227-247.

XJtechnologies.(2005).Anylogic© v5.3.1 http://www.xjtek.com/

Yoshida., K. Dowaki, Y. Matsumura, R. Matsuhashi, D. Li, H. Ishitani, H. Komiyama (2003). "Comprehensive Comparison of Efficiency and CO_2 Emissions Between Biomass Energy Conversion technologies: Position of Supercritical Water gasification in Biomass Technologies". Biomass and Bioenergy **25**(3): 257 - 272.

Zhou, P., B. W. Ang and K. L. Poh (*In Press*). "Decision Analysis in Energy and Environmental Modelling: An update." Energy.