Investigation on Integration of Sustainable Manufacturing and Mathematical Programming for Technology Selection and Capacity Planning

A thesis submitted for the degree of
Doctor of Philosophy

By

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January 2016

Abstract

Concerns about energy supply and climate change have been driving companies towards more sustainable manufacturing while they are looking on the economic side as well. One practicable task to achieve sustainability in manufacturing is choosing more sustainable technologies among available technologies.

Combination of two functions of 'Technology Selection' and 'Capacity Planning' is not usually addressed in the research literature. The importance of integrated decisions on technology selection and capacity planning at such strategic level is therefore essentially important. This is supported by justifications in some selected manufacturing areas particularly concerning economies of the scale and accumulated knowledge.

Furthermore, manufacturing firms are working in a global competitive environment that is changing in a continuous way. Strategic design of systems under such circumstances requires a carefully modelled approach to deal with the complexity of uncertainties.

The overall project aims are to develop an integrated methodological approach to solving the combined 'technology selection' and 'capacity planning' problems in manufacturing sector. The approach will also incorporate the multi-perspective concept of sustainability, while taking uncertainties into account.

A framework consisting of four modules is proposed. Problem structuring module adopts an Ontology method to map the technology mix combinations and to capture input data. 'Optimisation for Sustainable Manufacturing' module addresses the optimisation of technology selection and capacity planning decisions in an integrated way using Goal, Mixed Integer Programming method. The model developed takes the multi-criteria aspect of sustainability development into account. Three criteria, namely a) Environmental (e.g. Energy consumption and Emissions), b) Economics, and c) Technical (e.g. Quality) are involved. 'Normalisation algorithm by comparison with the best value' method is adopted in this research in order to facilitate a systematic comparison among various criteria. The economic evaluation is based on 'Life-Cycle Analysis' approach. The 'Present Value (PV)' method is adopted to address 'Time Value of Money', while taking both 'Inflation' and 'Market Return' into account in order to make the proposed model more realistic. A mathematical model to represent the total PV of each technology investment, including both capital and running costs, is developed.

‘Sensitivity Analysis’ module addresses the uncertainty element of the problem. A controlled set of re-optimisation runs, which is guided by a tool coded in Visual Basic for Applications (*VBA*), is developed to perform intensive sensitivity analyses. It is aimed to deal with the uncertainty element of the problem.

Within ‘Solution Structuring’ module, two knowledge structuring schemes, namely Decision Tree and Interactive Slider Diagram, are proposed to deal with the large size of solution sets generated by the “Sensitivity Analysis” module. An innovative, hybrid, Supervised and Unsupervised Machine Learning algorithm is developed to generate a decision tree that aims to structure the solution set. The unsupervised learning stage is implemented using DBSCAN algorithm, while the supervised learning element adopts C4.5 algorithm.

The methodological approach is tested and validated using an exemplar case study on coating processes in an automotive company. The case is characterised by three operations, twelve possible technology mix states, both capital budget and environmental limits, and 243 different sensitivity analysis experiments. The painting systems are evaluated and compared based on their quality, technology life-cycle costs, and their potential VOC (Volatile Organic Compounds) emissions into the air.

Acknowledgements

The greatest adorations to God, not only because of his permanent support through my entire life, but moreover because he is worthy of worship and praise.

First and foremost, I would like to express my sincere gratitude to my supervisor Professor Kai Cheng for his continuous support and help of my PhD study and research, for his patience, motivation, enthusiasm, and immense knowledge. His guidance helps me in all the time of research and writing of this thesis.

Also, I would like to thank Dr Richard Bateman, my second supervisor for his help.

My sincere thanks also go to Dr. M. Jahangirian for his help and advice. I would especially like to thank all my office mates and friends who made this journey enjoyable, Dr Madani, Dr. Abbas Zadeh, Dr. Behjati, Dr. Samira Saravi, Dr. Soheil Hasanzadeh, Dr. Kiara Wang and Yasmin Akar.

I would like to thank to Mr Mostafa for his priceless help regarding data collection.

A special thanks to my family and my family in law. Words cannot express how I am grateful to have such a wonderful family. I want to say a big thanks to my lovely parents for all of the sacrifices that they have done for me. I also like to say thank you to my kind brother, Mohsen, who was always an emotional support.

Last but not the least I would like to thank my beloved husband, Mansour for supporting and encouraging me throughout the process.

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Abbreviations

cc	Capital Cost
DBSCAN	Density-based Spatial Clustering of Applications with Noise
DEA	Data Envelopment Analysis
GP	Goal Programming
IP	Integer Programming
LCA	Life Cycle Assessment
LP	Linear Programming
MCDM	Multi-Criteria Decision Making
MOP	Multi-Objective Programming
NLP	Non-Linear Programming
NPV	Net Present Value
NPW	Net Present Worth
PV	Present Value
rc	Running Cost
RL	Reinforcement Learning
RoR	Rate of Return
SP	Stocastic Programming
TDIDT	Top-Down Induction of Decision Trees
VOC	Volatile Organic Compounds

Chapter 1 Introduction

This chapter provides a short description of the effects of sustainability on manufacturing industries, and how it could motivate to development of a comprehensive methodological approach to achieving scientific understanding of sustainable manufacturing particularly linked to manufacturing technology selection and capacity planning. This approach is concerned with selecting the best available techniques while taking account of three aspects; environmental, technical and economic. This chapter, followed by aims, objectives and scope of the research, sets the scene and scope of the dissertation.

1.1 Sustainability in manufacturing systems

Sustainable development is defined in a report of the United Nations World Commission 1987 as “a development that meets the needs of the present without compromising the ability of future generation to meet their own needs” (Brundtland, 1987). An important sector to sustainability is manufacturing, because of its high volume of resource consumption, introduction of new products every year, increasing volume of emissions and energy through product life cycles (Ocampo & Clark, 2015).
Manufacturing industries are now responsible for the impact of their products and processes. All these issues lead to manufacturing companies to have the growing interests in sustainability.

Sustainable manufacturing is normally investigated in three dimensions; environmental, economic growth and social well-being, known as the triple-bottom line (Gimenez, et al., 2012), however, these dimensions can be more focused or even just investigated based on one dimension. On the other hand sustainability is achieved when the interest of the government, customers, suppliers, competitors, employees and consumers, are satisfied (Theyel & Hofmann, 2012). Figure 1-1 shows three dimensions of sustainability (Jovane, et al., 2008). Jovane, et al (2008) believes sustainability at the macro level is based on the environment as a fundamental need economy to be a tool to meet social requirements.

The challenge and responsibilities rise among designers and engineers in how to make a balance among multiple conflicting goals to remain competitive. The integration of environmental aspects into the process needs a technical approach as well as economic selection and decision making framework, which reflect the company or government environmental policy (Devanathan, et al., 2010).

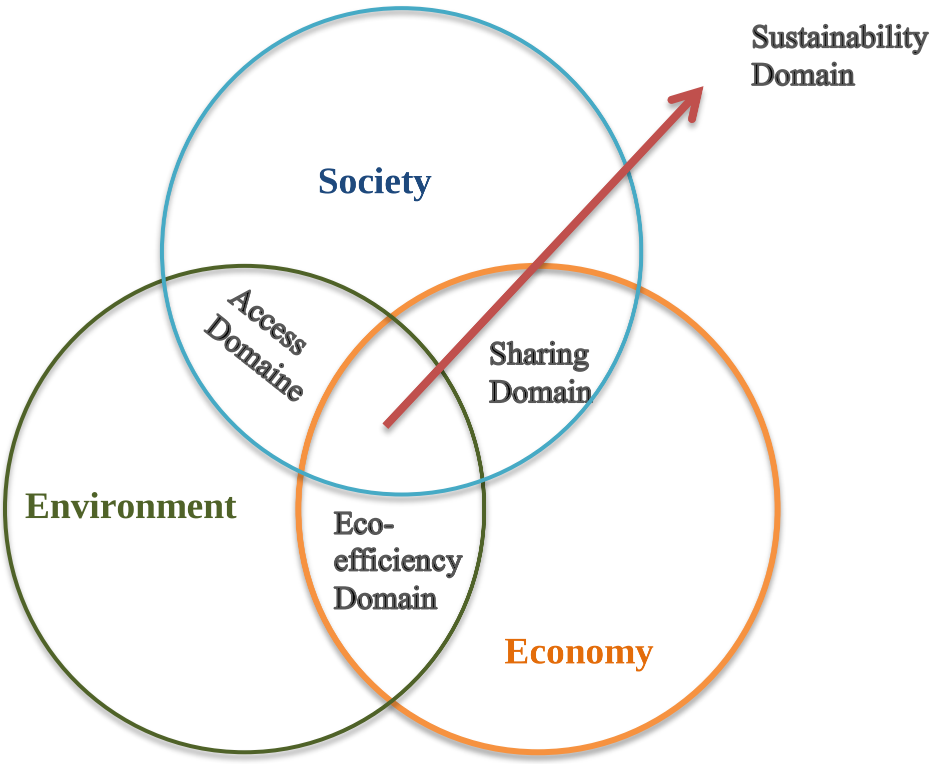


Figure 1-1 Fundamental of sustainable development (Jovane, et al., 2008)

1.2 Research background and motivation

Concerns about energy supply and climate change have been pushing companies towards choosing more sustainable technologies while they are looking on the economic sides as well. Primarily, production processes are the main concern of the legislation. The solutions to environmental damage can be in pursuit of investment in machinery and equipment to remove pollution or contaminants based on the principle of ‘polluter pays’.

The other motivation point is competition among industries to make progress on environmental issues to improve environmental performance, since inability to move forward on environmental initiatives can result in a loss of competitiveness in the market.

Based on the above background there are two approaches to achieve sustainability while there are conflicting issues that should be dealt with in order to have a best available technique and also have an optimum level of production capacity for each technology:

1. Technology selection
2. Capacity planning

1.2.1 Technology selection

By changing attitudes, manufacturing companies toward environmental sustainability are moving from reactive approach to proactive approach. As well as product related issues, there is focus on the process or system issues too. Because sustainable manufacturing process and system design have become important, decisions on the process and systems have very important influence on the environment. As a result, a proactive way to minimise environmental effects is integrating the environmental aspects, as well as economic aspects in the existing process. The integration of all these aspects into the process development requires decision-making framework.

A buyer of manufacturing technology is now encountered with a large number of options. The decision of which technology to select, makes decision more complex since technology performance is specified by a large number of parameters. “Technology selection and justification involve decision-makings that are critical to the profitability and growth of a company in the increasing competitive global scenario” (Chan, et al., 2000).

Technology selection is one of the most challenging subset of decision making ground that manufacturing industries are faced with. A company should select and invest in a technology field from different technology alternatives with comparative advantage and conflicting criteria in a complicated environment. Technology selection is based on the renewal of existing technology resources to remain competitive. Selection of key technologies helps industries to get new opportunities to achieve their advantages in a competitive environment. Although technology selection is a multi-criteria decision making challenge, but it is necessary to be considered different aspects of criteria for example potential benefit, risk and costs, to find the most suitable one. In addition decision maker should be aware of facing with other challenges like the rising cost of technological development, and a variety of technical options, which makes the task of accessing suitable technologies more difficult.

1.2.2 Capacity planning

The design and operation of a production facility need numerous decisions; including capacity planning for determining maximum production levels for each product type.
Capacity planning is the calculation of the number of tools needed to manufacture predicted by product demands. Difference between customer demands and capacity results in inefficiency, therefore the aim of capacity planning is to minimize the discrepancy. Capacity planning can be managed by introducing or utilizing new technologies, equipment or number of workers or machines.

Capacity planning has been subject to the uncertainties, especially when more than one technology is available. This type of model should be more capable when encounter with the conflicting criteria of comprehensibility. Therefore capacity planning is a major strategic decision in manufacturing. These strategic decisions should be made when confronted with uncertainty, which arise with realisations of demand, price and technology information.

1.3 Aims and objectives of the research

This PhD research aims to investigate the sustainable manufacturing approach to the technology selection and capacity planning with the focus on underlying both qualitative and quantitative issues.
The distinct objectives of the research are to:

- Develop a research framework for technology selection and capacity planning
- Develop a Mixed Integer-Linear Goal programing model for technology selection and capacity planning
- Conduct sensitivity analysis to deal with uncertainty
- Validate the developed methodology in an appropriate manufacturing setting

1.4 Scope of the research

The scope of the research and challenges problem addressed in this research is characterised as follows:

a. It is defined in the context of manufacturing systems.
b. The system is composed of a number of operations.
c. The research involves ‘Technology Selection’ for each operation as the main function to be addressed, while a mixture of different technologies is also acceptable. Technology selection in this research means selecting the right technology to the critical goals of the company.
d. ‘Capacity Planning’ for each selected technology does also need to be addressed in order to meet the demands.
e. There exist uncertainties in some of the data associated with the problem.
f. ‘Sustainability’ of the system should drive the research methodology.

1.5 Dissertation structure

Chapter 2 presents a cited literature review of technology selection and its application for in sustainable manufacturing. Existing literature on sustainable manufacturing and decision making, as well as mathematical programming and ontology and knowledge representation schemes are reviewed.

Chapter 3 focused on development of the general research architecture for technology selection and capacity planning toward sustainable manufacturing. In this chapter manufacturing challenges corresponding integrated decision, such as technology selection and capacity planning are addressed, whereas sustainability criteria is considered as well.

Chapter 4 presents mixed integer linear goal programming model for technology selection to solve the integrated technology selection and capacity planning towards sustainable manufacturing. Sensitivity analysis is also developed in order to encounter with uncertainty.

Chapter 5 highlights two knowledge structuring schemes: 1) decision tree, and 2) interactive slider diagram based on the sensitivity analysis in order to manage massive data generated by sensitivity analysis. The detail of these algorithms is described in this chapter.

Chapter 6 uses the car painting system as a case study to further evaluated and validated the developed methodology and framework.

Chapter 7 concludes the methodological approach as well as a contribution to knowledge which is resulted from this research. This chapter also presents recommendations for future works.

Figure 1.1 provides an overview of the thesis structures and scope with chapters listed above.

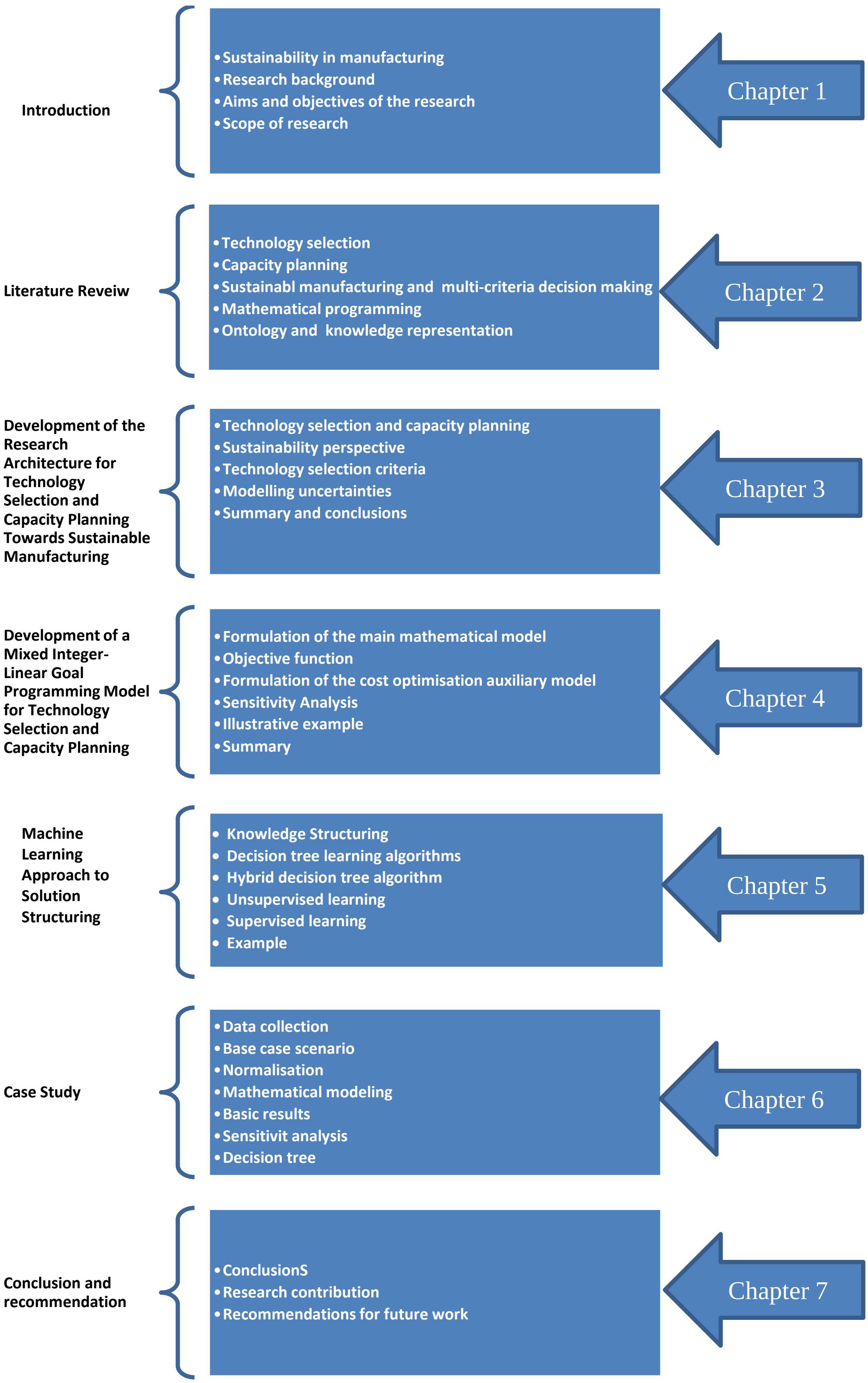


Figure 1-2 the thesis structure

Chapter 2 **Literature Review**

2.1 **Introduction**

In today's world, industries are faced with internal and external force regarding sustainable development. New technologies try to reduce time and increase quality regardless of the fact that they have to be considered about emission limits and energy consumption. Therefore, achieving sustainability requires a holistic view on products and also manufacturing processes to have a balanced consideration to the multidimensional and complexity of the nature of the sustainable development targets.

Having established a baseline for environmental performance or limitation as well as economic restriction for an industry has direct effects on technology selection and capacity planning. It is important to consider all technical aspects of technology such as price, environmental burden as well as capacity which is expected and actual capacity of each technology.

In addition to the above aspects of sustainability, the research scope of sustainable development requires comprehensiveness; therefore there is a need to construct a knowledge platform to “enable us to replace the current piecemeal approach with one that can develop and apply comprehensive solutions to these problems’’ (Komiyama & Takeuchi, 2006). Consequently structuring knowledge is an important task of sustainability science, which deals with complex and evolving problems. As the problems of sustainable development, by their nature, relate to a different supplier or technologies, the problem-solving process needs the collaboration between them. One of the key technologies for knowledge structuring and organizing a conceptual platform is ontology engineering, because “ontology is characterized as a tool for supporting thinking” (Kumazawa & Saito, 2009).

This chapter presents a review of the previous research done on the technology selection movement toward sustainable manufacturing based on mathematical programming supported by knowledge representation.

The literature is related to the mathematical programming and its relevant subclasses such as linear programming, integer programming goal programming, stochastic programming and sensitivity analysis.

2.2 Technology selection

In 1990 manufacturing companies were facing with more and more competitive market characterized by demand uncertainty, increased customization, and quick response (Chen, et al., 2002). As a result, in recent years there is a need to formulate demands and model technology selection in order to have flexible technology.

Basically, there are two types of factors which contribute to the demand uncertainty by considering capacity and technology choices. The first is a random component that is modelled as an additive or multiplicative to complement a predictable demand pattern help to incorporate dynamic factors such as seasonality, trends, etc. The second factor of uncertainty is related to the demand pattern, which is used to define the evolution of demand over the product life or the planning perspective. The distinguisher character which can of these two factors is the behavior of uncertainty over the time. There are two ways to model uncertainty demand; first approach is defined to let the components to be varied with time and being also independent, therefore demand history does not provide any information regarding future demand; these types of models when combined with a suitable predictable component can describe a variety of stochastic dynamic demands. The second approach is based on the dependency of the demand on time; these types of dependencies are inspired by success of product, since demand for successful products is consistent and high in successive periods. It is obvious that understanding the sources of uncertainty is useful to develop appropriate strategies to manage demand uncertainty (Chen, et al., 2002).

Most of the research done is dealing with the first approach, and results are based on the independence assumption. For instance Fine and Freund (1990) develop a model which is considered the optimal mix in flexible and nonflexible technology for static and uncertain demands. They formulate technology-capacity problem in two stages; First stage is dealing with investment decision in flexible and non-flexible technologies. Second stage focuses on the capacity allocation after understanding the demand.

(Chakravarty, 1989) Also used two-product problem in a different way, which prices and shortage costs are not specified, but role of rationing is considered.

Most of the researches based on technology selection indicate the uncertainty of the demand is stochastic demand and is not dependent on the time; in addition, these models ignore the economic sides which are one of the most important sides of sustainability (Chen, et al., 2002).

Technology and supplier selection have received considerable attention for its important influence on sustainable development. Environmental, social and economic dimensions aspects of sustainability must be considered to select a well-rounded sustainable supplier or technology, which include the process of supplier evaluation and selection (Govindan, et al., 2015). Technological alternatives are assessed according to their economic and environmental performance. Shen, et al.,(2011) Believe technology selection is multi-criteria-decision making, their model for technology selection is composed of two parts; (1) making a technology model based on critical economic or industrial factors, and (2) identification of important technology fields. Therefore, several decision making support tools have been developed for structuring and supporting supplier selection. The decision models become more complex since several new dimensions brought in sustainable supplier selection. The decisions include more intangible dimensions such as reputation and social impact (Govindan, et al., 2015).

2.3 Capacity planning

When the demand changes capacity planning is needed. Capacity planning is defined as a process to determine the capacity required for a manufacturing industry. Effective capacity planning happens when a company is capable to handle constraints such as quality problems, delay and demand in a limited period of time. However an inconsistency between capacity and demand cause inefficiency for both under-utilizes resources or unfulfilled customers, generally the aim of capacity planning is minimizing this type of discrepancy. Basically, the demand for a company's capacity is varied based on the changes in decreasing or increasing of the quantity products.

In typical inventory decision problems, capacity is assumed to be unconstrained in order to meet the demand. However capacity planning is considered as a tool to face with uncertain demand. Hence, capacity planning models are an extension of inventory planning models (Shin, et al., 2015). A flexible capacity decision model is proposed by (Netessine & Rudi, 2002) in this model interaction of each different class of demands are an influential factor for determining the optimal capacity allocation decision. Another model is developed for flexible capacity planning for two substitutable products by (Bish, et al., 2009), moreover the dynamic between the level of substitutability and capacity decision is investigated by (Bish & Suwandechochaib, 2010). A two-stage model, which uses hybrid capacity planning which combine analytical modelling and allocation heuristics together, is developed by (Roy, et al., 2011).

2.4 Sustainable manufacturing and multi-criteria decision making

Developing sustainable products is based on having a vision to foresee interrelations between a product's characteristics and its economic, social and environment impacts. To support sustainability task an extensive range of design methods has been developed.

When product characteristics are defined, design engineers determine product properties. The product structure influences the product life cycle and its ability to optimise the procedure in early design phases (Buchert, et al., 2015). Therefore, the integration of sustainability aspects based on product design involves continuing quantitative assessment of the product along with its manufacturing process (Arena, et al., 2013). Life cycle assessment (LCA) which is used currently to assess sustainability of the products requires a big and detailed amount of information about a product which is usually not available; however simplified LCA methods only cover environmental aspects. (Millet, et al., 2007). Therefore, quantitative oriented methods are used to address sustainability issues in process design stages.

So developing a method to address following three subjects is very important (Buchert, et al., 2015):

1) Engineering design methodology: a systematic approach for developing sustainable products.

2) Multi-criteria assessment: an approach to determine which manufacturing method is more sustainable in comparison with other methods.

3) Life cycle evaluation: a methodology is developed on how to assess the whole lifecycle of a product considering economy, environment and social dimensions.

Developing sustainable design requires attention to multiple criteria of sustainability target at the same time (e.g. Reduction of energy used against higher technology cost), therefore conflicting of the requirement can result in an over constrained design space consequently developing multi- criteria decision making is necessary.

Multi-criteria decision making problems contain a fundamental feasible solution and several objectives to be assessed with feasible solutions (Buchert, et al., 2015). In general, for multi- criteria decision making problems there is no generic solution approach and clear-cut concept of definition, and different approaches depending on the decision of decision maker based on the underlying problem.

Multi-criteria decision making (MCDM) methods have become more and more popular in decision-making for sustainable design because of the multi-dimensionality of the sustainability goals and the complexity of socio-economic and biophysical systems (Wang, et al., 2009). MCDM is a tool to evaluate problems where, is faced with several alternatives and finding optimal solutions are needed, while there are several conflicting criteria. The advantage of using MCDM is addressing questions concerning sustainable development, when ecological, economic, social and technical objectives are involved (Antunes, et al., 2006). Multi- criteria, methods provide an influential framework for policy analysis in the context of sustainable development, because of their ability to achieve the goals of accounting for multiple dimensions of sustainability problems.

Multi-criteria decision making consists of ranking alternatives based on the legitimate synthesis of the criteria (Arrow & Raynaud, 1986). Generally, there is not a solution for optimizing all aspects of the problem at the same time, but this method can help to improve quality of decision by making the criteria more explicit, rational and efficient.
A decision maker needs to choose among quantifiable or non-quantifiable and multiple criteria. The objectives are generally conflicting consequently; the solution is dependent on the preferences of decision-maker. (Pohekar & Ramachandran, 2004). Applications of MCDM are in the fields of integrated manufacturing systems, evaluations of technology investment, water management in agriculture and energy planning. A set of

multi-criteria methods have been developed by (Bana & Carlos, 1990), (Janssen & Munda, 1999) and (De Montis, et al., 2000). Pohekar & Ramachandran, 2004 specified a list of classification of MCDM methods by their application areas.

The purpose of using multi criteria decision making in sustainable manufacturing is to minimize negative environmental impacts, conserve energy and natural resources, while economic and technology sides are also considered. multi- criteria decision making is investigated in three dimensions: economic, environmental and technical.

2.4.1 Four dimensional system approach

When manufacturing changes raw material to products, emission and environmental wastes are generated from consumption of energy and material. Therefore, sustainable manufacturing has attracted attention in recent years for reducing the environmental impact and improving the economic performance of manufacturing industries by attention to the process design. Traditionally, process design has been evaluated by technical and micro-economic attention to ensure that new plants are good enough to fulfil the purpose, and maximize economic returns to an industry. However, now it is becoming clearer that modern plant cannot be designed based on the only these two dimensions. The other dimensions of sustainability, environmental and social aspect, should be included in the process of design. Figure 2-1 shows a paradigm for sustainable manufacturing (Westkamper, et al., 2001).

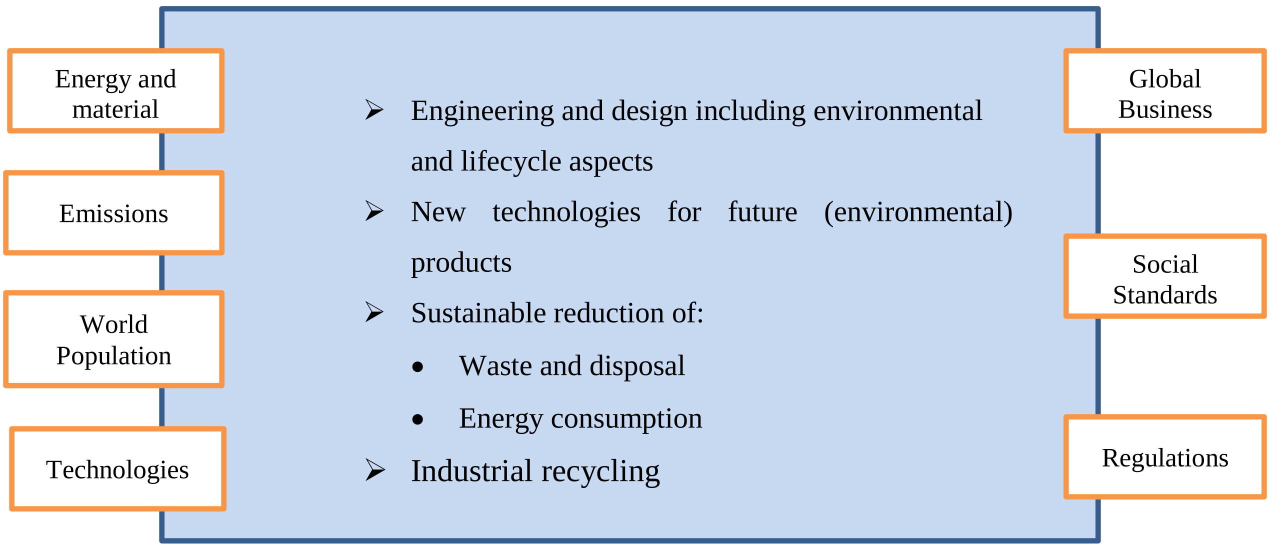


Figure 2-1 A model for sustainable industrial manufacturing (Westkamper, et al., 2001)

2.4.1.1 Economic dimension

Today’s life is dependent on economic and, economy dominates the environment and technology. The British government’s definition of sustainable development includes the aim of a ‘high level of economic growth’ (Deter, 1999). Therefore economy plays a big role in sustainable development.

Net Present Value (NPV) is widely used by economics. In finance NPV or NPW (net present worth) is defined as the summation of the present value of income and outcome of cash flow over a period of time. NPV is used for capital budgeting and also measures the excess or shortfall of cash flow, when financing charges are met. NPV method is an approach to assess the possibility of a project.

Benefits of using NPW are increasing in order to awareness or understanding to improve decision making.

Investment cost also is important to make decision, since it comprises all costs relating to the cost of mechanical equipment, installation of technology. Operation and maintenance cost are excluded from investment cost and they are calculated separately, however, they are important to make a decision too. Operation and maintenance costs consist of two parts; first include employee wages, cost of material and energy, another is maintenance cost to avoid failures of operation suspension. Operation and maintenance cost are also divided into fixed and variable costs (Wang, et al., 2009). The economic sustainability of different power parks are evaluated by means of NPV by (Quaia, et al., 2015).

2.4.1.2 Environmental dimension

Environmental consideration can be treated as an objective to be balanced against other objectives (Allen & Rosslelot, 1996). This need, creating environmental performance measures. Allen, (1992) believes that the deficiency of metrics to support objective environmental assessment is one of the main barriers to developing effective pollution prevention and design for environment approach. Moreover, lack of a general necessary value system for environmental impact assessment makes the environmental impact of a design difficult to assess.

When emission of a single pollutant is the most significant environmental concern affecting a design, the mass of pollutant released to the environment can be used as an indicator for environmental impact (Rossiter & Kumana, 1994). This method has been used by (Diwekar, 1995). In case of having more than one chemical source of environmental concern, environmental evaluation turns into more complicated. One way to solve this complexity is to use the release inventory directly as a set of indicators; this approach is used when there are only a few pollutants that are involved. COX, NOX and SOX are used as a three environmental emission source to be minimized for chemical plants by (Chang & Hwang, 1996). The approach becomes difficult to manage when upstream emissions are considered. In these cases it is necessary to summarize the information into a small number of indicators to optimize and rank alternatives.

It should be always a balanced between all of the demands on the forthcoming products. This means that environmental criteria must be balanced with all other requirements such as economic, quality, material, safety and so on (Luttropp & Lagerstedt, 2006). Because up to now environmental criteria are not the only priority, all environmental action should be related to all the elements in design without allowing them to dominate. Environmentally friendly design requires the coordination of several databases, for example, environmental impact metrics, data management, design optimization and etc., (Mizuki, et al., 1996) and (Bovea & Pérez-Belis, 2012).

Integrating environmental criteria into decision making is a necessary and an initial step to move toward sustainable development. Integration of environmental management with decision making process to convert the resource into usable products is called environmental operation management (Gupta & Sharma, 1996).So far, regardless of the direct impact and important role of environmental management on the manufacturing operations, much of the research has done is based on anecdotal evidence, that apparently remind managers to be aware of environmental impacts within a wide choice of different technology, and little attention to the environmental performance as a competitive dimension for different technologies. Environmental technologies are defined as any production methods, equipment or product design that can limit or reduce the negative impacts of the process or product on environment; therefore it is accepted as an important base for sustainable development in environmental performance. Environmental technologies can reduce operation costs, and can create competitive advantages.

2.4.1.3 Technical dimension

The basis dimension of sustainability is the technology which is employed in manufacturing. However, it is difficult to determine the sustainability performance of manufacturing as both material and energy consumption of the process is determined by requirements of manufacturing processes (Yuan, et al., 2012). Improvement of technological process led to improve the sustainability performance of manufacturing industry by reducing energy and material.

Technical feasibility and implementation of technologies are the fundamental of this study that cause several requirements:

- Definition of minimum requirements
- Technical description of the process (efficiency, operating stage)
- Technical description of alternative products or technologies
- Selection of potential systems
- Optimization strategies

Generally, the study begins with the objective definition for technical requirements for example: the minimum requirements. Table 2-1 shows a list of technical criteria considered in the manufacturing area like paint shop.

The other important characteristic of the technology is establishment of alternative technologies, which are based on the technically conceivable of existing technologies.

Table 2-1 Technical requirements for automotive painting

Criteria	Requirement
Product	Material, Layout, Design, Quality
Process Engineering	Process technology (process, cycle times, flexibility, etc.), Production capacity, Logistics (integration of surface technology in production process), Process safety, Application technology (efficiency, layer thickness), Drying technology (convection, IR, UV, air drying, etc.), Degree of automation (fully automated, partially automated, manual), Paint recycling external treatment
Painting systems	Conventional solvents (water based, powder coating), application recyclability, rework ability

The comparison of alternative technologies, their advantages and disadvantages in different scales do not give consistent results. Therefore, there is a need for quantitative method to assess the technologies. Some methods that contribute to the technology assessment are:

1. Technology assessment: is an institutional analysis to evaluate the design of engineering or technology development (Loveridge, 2009).
2. Value analysis: is a solving method for complex problems which are not fully or not described by algorithm. It includes the behaviour and management of the system element, their simultaneous mutual influence with aim of optimization results. As a whole it is a business management method for cost minimization (Ordoobadi & Mulvaney, 2001).
3. Holistic Utility Analysis (HUA): It is a comprehensive method that investigates three dimensions, including technology, environment and economy. Therefore, it is a good analytical development method (Finkbeiner, et al., 2010).

2.4.1.4 Social dimension

Social dimension of sustainability has been not considered as much as other dimensions of sustainability (Cuthill, 2009), (Vavik & Keitsch, 2010). There are various opinions about what issues to be evaluated (Murphy, 2012). The literature suggests about having a greater look at the linkage between social and environmental dimensions (Gough, et al., 2008) and (Littig & Griessler, 2005).

With reference to Brundtland definition of sustainability, "Development that meets the needs of the present without compromising the ability of future generations to meet their own needs" (Brundtland, 1987), social development is the integration of people's needs with bio-physical environment management goals through economic development (Vallance, et al., 2011). This definition includes; changing the quality of growth; meeting vital needs such as jobs, food, energy, water and sanitation, reorienting technology, merging environment and economics in decision making, orientation of international economic relations.

Another social aspect of sustainability is that only when people's basic needs are satisfied, they can be concerned about biophysical environmental activities (Crabtree, 2005), for example building energy efficient houses for people who are faced with the immediate needs for food, is meaningless. Therefore it is unrealistic to expect people to care about their environment when they are unsafe, without food, job, house and etc.

To summarize; society has influenced sustainability, and how sustainability is important for a society is dependent on the economic and social growth of the society. So sustainability horizon is different from one society to the other society.

2.5 **Mathematical programming**

Management science is known by its ability to use mathematical models in order to provide guidelines for managers to make effective decisions by having the current information, or even if current information is not enough, to make a decision ask for more information. The essence of management science is the model-building approach, which is an effort to identify the most important factors which have effects on the decision to implement them in a mathematical abstraction. Models are simplified of the real world. Mathematical models in order to support management decisions should be simple and easy to use, while they have to provide a complete representation of the decision environment by integrating all the required elements to characterise the problem under study, which is not an easy job. Through on these efforts to design mathematical model management science provide guidelines for managers to understand of the consequences of their actions.

The mathematical programming goal is a process synthesis optimisation to find the best combination of process units.

Mathematical programming and linear programming, particularly, is one of the most used branches of management science. Mathematical programming deals with the optimum allocation of limited resources among activities, subjected to the set of constraints enforced by nature of the problem under study. The constraints may reflect financial, marketing, operational, technological or many other considerations. Generally a mathematical programming is defined as a mathematical representation for planning the best possible allocation of scarce resources.

There are numerous numbers of published mathematical programming formulations. A common characteristic of these formulations is using of cost minimization as the objective to optimize. Generally mathematical programming formulations try to use a total cost minimization approach, which include capital costs in the objective function (Dunn, et al., 1995) (Srinivas & El-Halwagi, 1993). However, they do not include the opportunity of improving economic performance. In table 2-2 six MP techniques are brought for detailed review. In the following sections, LP, IP, GP, and SP are reviewed as subsets of Mathematical Programing.

Table 2-2 Mathematical Programing

Technique	Usage	Literature
Linear programming (LP)	• The mathematical optimization method to achieve the optimum result in a given mathematical model, when there is a number of requirements based on linear relationships	a) Simple LP: (Chen, et al., 2011), (Lin, et al., 2011) b) Fuzzy LP: (Yucel & Güneri, 2011) (Amin, et al., 2011), (Lin, 2012) c) Multi-objective LP (MOLP): (Ozkok & Tiryaki, 2011), (Yucel & Güneri, 2011) d) Mixed integer LP (Amin & Zhang, 2012), (Toloo & Nalchigar, 2011)
Nonlinear programming (NLP)	• Some of objectives or constraints are nonlinear • There are two directions (Chai, et al., 2013): 1. Simple utilization of NLP 2. Mixed integer NLP formulations	(Hsu, et al., 2010), (Razmi & Rafiei, 2010), (Rezaie & Davoodi, 2012)
Data Envelopment Analysis (DEA)	• Non parametric Mathematical methods • Used to evaluate the relative efficiency of entities for decision making • Can be used as a performance measurement to evaluate the relative efficiency of decision-making units based on multiple inputs and output	(Aliakbarpoor & Izadkhah, 2012), (Cooper, et al., 2011)
Multi-objective programming (MOP)	• Decision making problem when there are conflicting objectives • Recently, research on fuzzy multi-objective linear programming become mainstream direction • It can be linear or non-linear • Mixed integer non-linear MOP is a common type of MOP	(Adeyefa & Luhandjula, 2011), (Haleh & Hamidi, 2011), (Yeh & Chuang, 2011)
Goal programming	• Is type of optimization methods • Is an extension of MOLP to multiple and conflicting objectives • Each of objectives are given a goal value to be achieved	(Büyüközkan & Berkol , 2011), (Kull & Talluri, 2008)
Stochastic programming (SP)	• Framework for modelling uncertainty optimization problems	(Kara, 2011), (Kull & Talluri, 2008)

2.5.1 Linear programming

A linear programming is defined as a problem of maximizing or minimizing a linear function subject to linear constraints. The constraints may be equalities or inequalities. Simple linear problems have got two or three constraints, therefore they can be solved by graphing the set of points in the plane that satisfies all the constraints and finding the set of the point which maximize or minimize the value of the objective function.

Not all linear programming problems are easy to solve. There might be many variables and also many constraints.

Linear programming may face with difficulties to solve practical problems, because of their limitations, especially in the processes that have many parameters that must be identified based on experience or observations.

Linear programming is used widely in microeconomics and company management, like production planning, transportation, technology selection, and so on. However, most companies are looking to maximize profits or minimize cost with limited resources, so there are many issues that should be determined to solve by linear programming. For example (Kannan, et al., 2013) use fuzzy technique to analyse the importance of multiple criteria to determine the best green suppliers and then use multi-objective linear programing to formulate different constraints such as quality control, capacity, and other objectives. The objective of the mathematical model is maximizing the total value of purchasing and minimizing the total cost of purchasing. In addition (Ng, 2008) proposed a weighted linear program for the multi-criteria supplier selection problem.

Simple Linear programing can be solved by two algorithms; first Simplex algorithm and second Criss-cross algorithm.

2.5.2 Integer programming

Integer programming is a type of mathematical programming that some or all of the variables are restricted to be integers. Integer linear programming is a term which refers to linear objective function and constraints. This restriction increases the number of problems that can be modelled. In addition, it makes the models more difficult to solve (Taha, 2011).

As a whole there are two applications of integer variables:

1. When only integer variables are needed in order to represent the integer quantities, for example quantity of human resources.
2. When integer variables signify decisions and only should take the value 0 or 1.

Based on the above applications, linear integer programming is used widely in production planning, scheduling in transportation networks, Telecommunications networks and Cellular networks.

(Hong, et al., 2005) Developed a mixed-integer linear programing model to select optimal number of suppliers and optimal order quantities to maximize profits, this model can be used in technology selection as well. Kilic (2013) uses mixed integer linear programing to determine the supplier and the quantities of products to be produced and from the related supplier in the air filter sector.

Integer linear programming is solved widely by branch and bound methods.

2.5.3 Goal programming

Linear programming study can be used when only there is a single overriding objective, for instance minimizing cost. However, in reality, focusing on only one objective is not true always and studios are looking for a variety of other objectives, e.g., increase profit, decrease environmental emission, and reduce energy consumption. A way to overcome toward several objectives simultaneously is using Goal programing.

The goal programming fundamental approach is providing a specific numeric goal for each objective; formulate an objective function for each objective, then looking for a solution to minimize the sum of the deviations of the objective functions for their respective goals.

Goal programming is a subset of multi-objective optimization, which is an extension of linear programming to do multiple and conflicting objective measure.

The major strength of goal programming is its ability and simplicity of being easy to use. Linear goal programmes can be solved by linear programming software as a single linear programme or as a series of connected linear programmes. Goal programing is mostly used to provide the optimum solution when there are varying amount of resources and priorities of the goals.

(Taha, 2011) Presented two algorithms for solving goal programing, both algorithms are based on the multiple goals by a single objective function. These two methods do not usually give the same solutions and none of them is superior to the other, since these methods entail distinct decision making preference. The first method is weights method, which the single objective function is the weighted sum of the function representing the goal of the problem. Second method is the pre-emptive method which prioritizing the goals based on their importance, and then model optimizes the goals one at a time in order of priority in a manner that does not degrade a higher-priority solution.

The most direct employment of GP as a decision tool is in (Kull & Talluri, 2008); GP is used as a decision tool for supplier selection in the presence of risk measures and product life cycle considerations. (Sharma & Balan, 2013) Use goal programing model to identify the best performing supplier among weighted supplier.

2.5.4 Stochastic programming

Stochastic programming is defined as mathematical programming with a set of uncertain parameters, which are normally described by discrete distributions (Birge & Louveaux, 1997). Uncertainty is usually characterized by a probability distribution on the parameters. Uncertainty in practice can be from the outcomes of the data to specific probability distributions, for example the set of possible demands for the next few weeks.

The fundamental idea behind stochastic programming is its ability to take correct action after the realization of a scenario has taken place (Grossmann & Guillén-Gosálbez, 2010). Stochastic programs are solved by a number of stages. Between each stage, there is some uncertainty to decide and then choose an action to optimize existing objective and also an expectation of the future objectives. The most common type of stochastic programs is two-stage models. With a two-stage problem, some decisions are made on the first stage, when more information is found; in stage 2 decisions involve variables that can be adjusted based on the realization of the scenarios.

One application of stochastic programming is that its ability to solve problems where some of the decisions can be delayed later when the experience with the primary decision has eliminated some or all of the uncertainty in the problems. This is stated as stochastic programming with recourse since corrective action is made later to compensate for any undesirable outcomes with the initial decisions (Hillier & Lieberman, 2015). A multi-product supplier selection that has stochastic demand developed by (Yang, et al., 2011).

2.5.5 Sensitivity analysis

Sensitivity analysis is an important step in optimisation models in general and in multi-criteria decision making models in particular. Uncertainty in input data makes sensitivity analysis important for optimisation models. When it comes to multi-criteria decision making, however, the problem becomes even more complicated due to the fact that one is mostly dealing with conflicting criteria; hence an optimum solution is not achievable. Under these circumstances, sensitivity analysis will help to find satisfactorily good solutions when parameters change. An extensive research is conducted on sensitivity analysis for operations research and management science model like linear programming. For example (Wendell, 1992)has done a tolerance approach to manage variations in the parameters of more than one term at a same time, when he also considered sensitivity analysis as a post optimality step as well. The main goal of sensitivity analysis is to identify if the best alternative progresses the design objectives enough or not.

Some aspects of the process design are subject to considerable uncertainty. The impact of uncertainties associated with technical factors and economic and environmental performance is examined by (Diwekar, 1995). A sensitivity analysis is done by (Govindan, et al., 2015) As a most important method of selecting a supplier that has the best environmental performance.

2.6 Ontology-based modelling and analysis

The ontology based analysis provides a comprehensive framework for describing system component relationships, to help users to understand the complexity of the system. As a whole ontology refers to explicit specification of a conceptualization (Sharman & Kishore, 2007). Ontology offers a chance to utilize and unify framework to embody objects and concepts, relationships and definitions.

Ontology has a strong role in the development of semantic web, because it has ability to represent of a shared conceptualization of a particular domain and also capturing knowledge about concepts in the domain and relationships among concepts (Gruber, 1993).

Recent studies show that future systems will be knowledge-driven, by emphasizing the need to develop integrated tools to extract existing knowledge and transform it to the new and more useable knowledge. This goal is achievable by defining a comprehensive ontology to consider the desired product or process aspects.

Ontologies can be considered as a collection of classes of objects like entity-relationship models from the community or object-oriented class (Ding, 2001), on the other hand, ontologies are a theory of reality which describe the kinds and structures of objects, properties, events, processes and relations in reality. An ontology-based framework for sustainable factories is developed by (Gagliardo, et al., 2015), this model intended to develop a include factory framework to includes data and process necessary for energy and environmental assessment in order to support sustainable design of factory entities. A recommendation system for anti-diabetic medication is designed by (Chen, et al., 2012) for doctors to recommend suitable medicine.

2.6.1 Ontology and knowledge representation

"Ontologies are used to represent human knowledge in a machine understandable format" (Gobin, 2012). Ontologies also capture knowledge of concepts in the domain and relationships among these concepts (Horridge, et al., 2004). Relations can be hierarchical between classes, subclasses, supper classes and slots which describe properties of classes and instances, axioms and rules between classes.

An ontology defines a common vocabulary for those who want to share information on a domain. It includes machine-interpretable definitions of basic concepts in the domain and relation among them (Noy & McGuinness, 2001). The goal of ontology is "to formalize domain of knowledge in a generic way and provide a common agreed understanding of a domain, which may be used and shared by applications and groups (Aufaure, et al., 2006)". The most important advantage of using ontology is being good at demonstrating and utilization of relations.

Based on the job done by (Noy & McGuinness, 2001), developing an ontology includes; defining classes, arranging the classes in a taxonomic hierarchy, defining of slots filling the values for slots for instances.

There are seven steps for developing ontologies:

I. Determine the domain and scope of the ontology
II. Consider reusing existing ontologies
III. Enumerate important terms in the ontology
IV. Define the classes and the class hierarchy
V. Define the properties of classes—slots
VI. Define the facets of the slots
VII. Create instances

In the following section the reasons of using ontologies are described.

According to (Noy & McGuinness, 2001) There are five important reasons for using ontology:

- "To share common understanding of the structure of information among people or software agents".
- "To enable reuse of domain knowledge".
- "To make domain assumptions explicit".
- "To separate domain knowledge from the operational knowledge".
- "To analyses domain knowledge".

2.6.1.1 Ontology- based decision making system

"Ontology is a unique form of representing knowledge applied in various domains" (Smirnov & Chandra, 2000). Chang, et al (2012) Used ontology to define a set of data and structure to share knowledge, manage reuse of data and help designers to make decisions by considering economic, environmental and technical criteria. (Sadeghi Niaraki & Kim, 2009) developed a decision hierarchical framework to provide the basic rules for evaluation in the multi-criteria decision methods. (Pandit & Zhu, 2007) use ontology to integrate heterogeneous systems, the ontological framework is used to support decision making ontology in order to select transformations.

Most of the systems which have been developed, use ontology to represent and exchange knowledge, ease confusion to provide a knowledge base for decision support systems in particular areas. In this research an ontology-based method developed to provide a decision support to illustrate relationships for users, and to provide a knowledge base system to make decisions more scientifically. Figure 2-2 represent working processes of ontology-based decision making based on (Chang, et al., 2010) works.

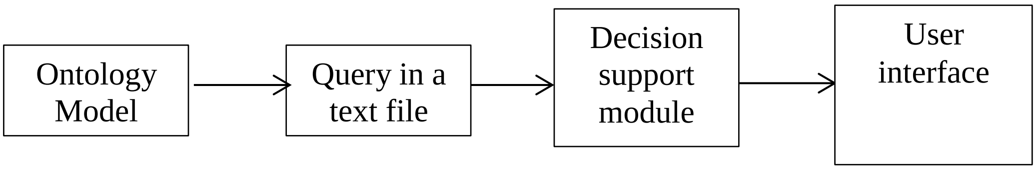


Figure 2-2 Working process of ontology-based decision making (Chang, et al., 2010)

2.6.1.2 Ontology editors

Ontology is the fundamental of this research, and should be built by an ontology editor. Lambrix, et al., (2003) compared four ontology editors: protégé- 2000, Chimaera, DAG-Edit and OilEd. Among these four ontology editors Protégé-2000 compared with other editors has a better user interface, easy to use and configurable tool for knowledge extraction. However protégé-2000 is the old version of protégé but up to now the latest version has its advantages of the old version. Based on a survey done by (Michael, 2002) Among 94 ontology editors in terms of 11 characteristics, such as base language, web support, graph view and other characteristics, Protégé has more advantages than others.

Protégé is a free, open source editor, which has ability to be a knowledge acquisition system (Noy & McGuinness, 2001). The ontology developed by Protégé can be imported or exported in RDF, RDFS, OWL, OIL, DAML+ XML, and CLIPS or UML. Protégé also allows visualizing ontologies with AT&T's highly sophisticated Graphviz visualization software like OntoViz and TGViz. Moreover, there is some plug-ins to extend ontology construction, check axiom and integration functions. In this study ontologies are built by protégé to represent the relationship, concepts and properties for the available automotive paint shops.

2.6.2 Knowledge representation schemes

Knowledge representation schemes are tools to encode and store knowledge in a knowledge base (Rosenberg, 1986). This representation can be in different forms, based on the type of problem which is needed to solve.

Knowledge representation schemes generally is categorised into two groups: knowledge structuring schemes and implementation schemes. First groups are used to organize knowledge that have some common theme or have a same goal point. The second group is used to represent domain knowledge within a computer system. Knowledge representation is described in terms of its roles by (Davis, et al., 1993):

1. It can be used as a tool that can determine the effects by thinking instead of acting
2. A set of ontological commitments
3. A part of intelligent reasoning expressed in terms of recommended inference
4. It is a medium for practically well-organized computation
5. It is a medium of human expression

Therefore, knowledge representation is defined as a multidisciplinary subject that combines techniques of logic, ontology and computation.

The challenges of knowledge modelling and representation are investigated from two points of view by (Chandrasegaran, et al., 2013):

A. Coding of design and process knowledge at different stages of design in order to have a better quality design
B. The capture, use and communication of knowledge between teams and organizations.

The use of ontologies can be helpful in means of integrating unstructured information and knowledge and provide a richer conceptualisation of a complex domain (Rezugi, et al., 2011). Ontology is a fundamental concept that lets the designers to represent a specific domain in terms of axiomatic definition and taxonomic structure. Ontology as a structured concept covers process, objects and attributes of the domain along with complex relations.

As mentioned in previous sections, designing a sustainable manufacturing process has shifted in the design process to support early design decisions. During design, designers need to know whether they should do more evaluation of information or generate new possible solution, negotiate changes in criterion features and missions, breakdown the problem into sub problems, or get conclusion and document results (Chandrasegaran, et al., 2013). Recent research is looking to develop a methodology to design decisions, for example, design a methodology for selection of product design projects (Wei & Chang, 2008). A decision support system in the knowledge representation form uses utility theory to deliver a mathematical tool to capture designer's preferences, and also construct decision support to make a decision (Fernandez, et al., 2005); in addition because of complexity of system which is tied with constraints, designer might fail to estimate the effect of each change on the other variables. Therefore a knowledge based model for product and manufacturing process that encompass key attribute for decision making regarding sustainability development (such as energy consumption and material cost) is needed.

2.6.3 Machine learning

Machine learning is a subclass of computer science that investigates the construction of algorithms that can learn from data and make prediction. These types of algorithms work by building a model from example inputs to make data driven predictions or decisions, instead of following static program instructions.

Machine learning is working closely with computational statistics, which is expert in prediction making. Machine learning also has a strong relation with mathematical optimisation to take its methods, theory and application domains. Machine learning when is applied in industries, might be referred to predictive analytics or predictive modelling.

Tom M. Mitchell defines machine learning as: "A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E" (Mitchell, 2007), therefore machine learning is more operational rather than being cognitive based on this definition.

2.6.3.1 Machine learning types

Machine learning algorithms based on their nature of learning are usually categorized into three categories. These categories are (Russell & Norving, 2003):

- Supervised learning
- Unsupervised learning
- Reinforcement learning

The definition and usage of each category are coming in following.

2.6.3.1.1 Supervised learning

Supervised learning is a general learning method, which inferring a function from training data, training data is a set of data which is used to know if there is any predictive relationships, training data is a set of training examples. Basically, in supervised learning each example consists of an input object and output value as a pair. The infrared function produced by supervised learning algorithm is called a classifier if the output is discrete, or regression function if the output is continues.

Supervised learning is used commonly in training neural networks and decision trees. Both of these techniques are based on the information given by the pre-determined classifications.

2.6.3.1.2 Unsupervised learning

Unsupervised learning looks more difficult than supervised learning, since the goal is to learn computer to do something without teaching how to do it. There are two approaches to unsupervised learning; the first is to teach the algorithm by using some sort of reward system to indicate success, this type of training is used for the decision problem framework, since the aim is to maximize rewards not classification. The second type is named clustering, which finds similarities in the training data. The main concern of cluster analysis is to group objects and their attributes into clusters that each individual element in a cluster has a high degree of natural association among themselves and very little natural association between clusters (Selim, et al., 1998).

2.6.3.1.3 Reinforcement learning

Basically, in RL standard method, a learning agent repeatedly observes the state of its environment, and then it chooses how to perform, by doing an action the state of its environment is changed, therefore agent gets a payoff instantly. Positives are rewards and negatives are punishments. Reinforcement learning algorithms are different from supervised learning in case of that correct input/outputs are not given in supervised learning.

2.7 **Summary**

In this chapter, the present situation of sustainable manufacturing and its difficulties are stated. The basic knowledge and development of mathematical programming is introduced in Section 2.4. Mathematical programming is playing a vital role to develop our model in order to find an optimum technology when environmental, technical and economic criteria are conflicting. Computer-based approaches are used to facilitate this research to explore the ontology-based method for technology selection for a sustainable manufacturing. Ontology and machine learning schemes are represented in section 2.5.

From the literature review, it can be concluded that there are the following research needs which provide the motivation for the focus of this work.

1. To achieve environmentally sound product design goals, environmental criteria should be integrated into process design with economic and technical restrictions. This issue requires a systematic decision making for integrated process design; to deal with these conflicting criteria a systematic decision making framework is needed. This system should have the ability to trade-off and comparison among environmental performance, economic and technical restrictions.
2. Using ontology to represent and exchange knowledge, increases the clarity, and provides a knowledge base to support decision making. In order to facilitate the system thinking and ease of relation understanding, an ontology-based method is used.
3. As mentioned earlier in section 2.2 and 2.3 up to now there is no comprehensive framework to integrate technology selection and capacity planning and this is one of

the knowledge gaps. In this research there is the need for an integrated model to select the best available technology, while an integration of different technologies is also acceptable. Simultaneously an optimum level of production capacity for each technology is needed.

Chapter 3 Development of the Research Framework for Technology Selection and Capacity Planning Towards Sustainable Manufacturing

3.1 Introduction

Today's manufacturing systems face many challenges, amongst which are;

a) To enable integrated decisions (e.g. technology selection and capacity planning)
b) To achieve sustainable manufacturing
c) To deal with dynamism and uncertainty about the environment

Isolated decision making within manufacturing systems, especially at the strategic levels leads to conflicts, inefficiency, or at the least it could produce a sub-optimal solution. For example, two types of decisions, namely technology selection and capacity planning to have some elements in common. But they have been addressed in the literature largely in an isolated way. Integrated strategic decisions provides a better result, while it generates a larger, more complex problem to solve.

New technologies, such as powder-based painting systems in automotive manufacturing, are becoming widespread that are offering more environmentally friendly solutions, or higher quality products, or energy efficiency. It is, however, less likely that these benefits come all at once, at least not together with a lower capital price of the technology. Thus, the question is how to optimize such a multi-criteria decision on the choice of technology.

On the other hand, manufacturing firms are working in an environment that is changing on a continuous manner. For instance, demand for products is affected by many factors such as population, substitute products, price, competition, and so on. Such a complexity is a recipe for dynamism and uncertainty.

We address all the above three challenges in this research and provide solutions accordingly. This chapter aims to present a general architecture of the proposed methodology. The general design of the proposed framework, including the selection of methods and algorithms is described in this chapter. Some general algorithms, such as normalization, cost structures and economic evaluation, are also explained. Further details about optimization models, sensitivity analysis, and solution structuring are described later in chapters four and five.

3.2 Technology selection and capacity planning

There are two perspectives to the technology selection problem. a) A zero-one selection where a technology is either selected or rejected, b) A combined use of different technologies, or so-called ‘technology mix’, which allows the split of capacity among different technologies.

Technology mix perspective is not usually addressed in widely studied scenarios in recent years. For example, the study presented in (Van de Kaa, et al., 2014) aims to analyze the data to select one dominant technology out of five available alternatives. The authors use fuzzy Analytic Hierarchy Process method to achieve their aim. (Onar, et al., 2015) Concentrates on the selection of the appropriate wind energy technology. The problem is constructed as a multi-expert multi-criteria decision making problem. At (Ren & Lutzen, 2015)VIKOR was used to evaluate and prioritize three alternative technologies out of which one technology is selected. The study by (Evans, 2013) aims to adopt an approach where both experts and non-experts can use historical decision information to support the evaluation and selection of an optimal manufacturing technology. This form of approach is based on the logic in which a decision maker would irrationally recall previous decisions to identify relationships with new problem cases. In all these types of studies, the problem is actually treated like a rather simple 0-1 decision type of scenario, where a technology is either selected or rejected. Just a fraction of these studies provide an approach with an aim to contribute to manufacturing sustainability. Yet in reality, more complex scenarios are happening.

In line with the inception of globalisation age, the emergence of global manufacturing corporations with several plants located around the world started off decades ago and is still on the rise. While some of the decisions in such a structure are made de-centrally, the importance of integrated decisions at some strategic levels, such as technology selection and capacity planning, is still evident. Such an integrated decision is supported by justifications in the areas of economies of scale and accumulated knowledge-base.

The driving force of these decisions is multi-faceted. Manufacturing technologies are subject to a continual improvement process, especially in the context of sustainable development. Technologies have a limited life-cycle and need to be replaced. Further, increasing demand for an existing product would require capacity expansion, while new product development could justify new technologies as well as capacity acquisition.

In this research, a model is developed with an integrated view to solve both problems ‘Technology Selection’ and ‘Capacity Planning’ simultaneously. The general scenario targeted in this research assumes that the firm’s management is going to make a decision on:

“How much of capacity from which technology to acquire?”

In order to meet demands and in accordance with a number of criteria. A technology mix would enable an appropriate level of trade-off amongst conflicting criteria, such as cost, quality, and emissions. Managers might face this type of decisions in various industries and in different stages of their business, either to establish a new plant, or to expand on existing facilities, or even to replace the old technologies.

Existing studies rarely look at this combined problem of ‘Technology Selection’ and ‘Capacity Planning’ in an integrated way. (Filomena, et al., 2014) address technology selection and capacity investment under uncertainty for an electricity generation problem in a game theory-based competitive environment. The study focuses on cost evaluation against a portfolio of technologies and does not address multi-criteria nature of decisions or sustainability analysis.

3.3 **Sustainability perspective**

Manufacturing plays a key role in the realisation of sustainable development. Manufacturing systems make a significant contribution in creating wealth, jobs, as well as pollution. Thus the concepts of 'sustainable manufacturing' and 'sustainable technologies' are key in achieving sustainable development. When it comes to sustainable technologies, however, there is another very important dimension to consider, namely 'Technical' aspects and specifications. In fact, the major global challenges that the manufacturing sector is facing today need to be addressed in the multifaceted context of economy, society, environment and technology (ESET) (Jovane et al., 2008). Figure 3.1 illustrates a conceptual model of manufacturing performances from these four dimensions.

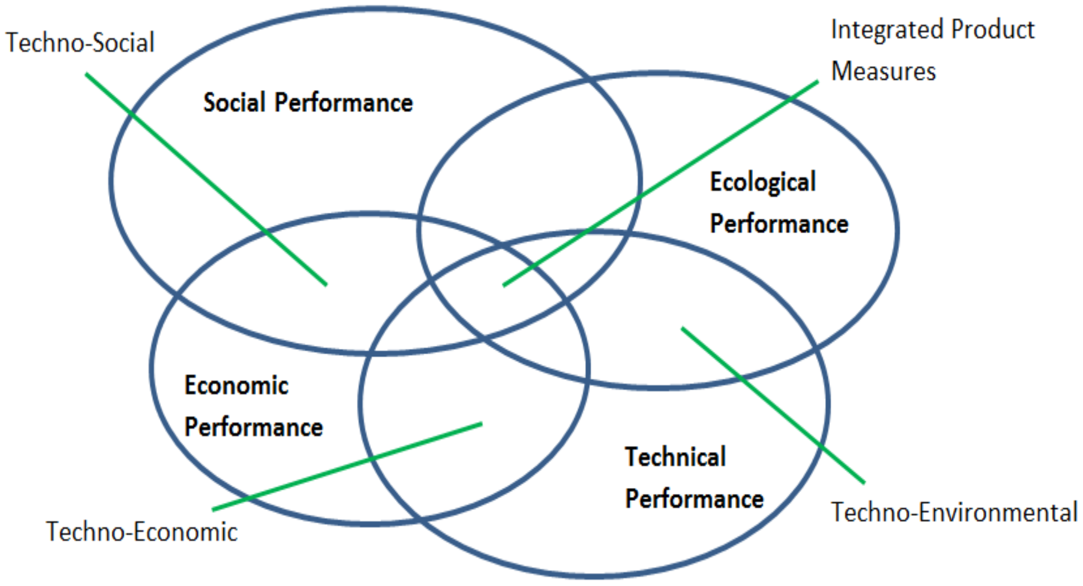


Figure 3-1 Sustainable Manufacturing (Kiritsis, 2007)

A drive for sustainable technologies generally leads to ways that reduce the consumption of resources. Three major initiatives to achieve such objective have been identified (Westkamper, 2007) .Miniaturization of products, technical components and machines is the first initiative. The substitution of hardware by software constitutes the second initiative. Finally, the implementation of technical intelligence throughout the process has the potential to reduce waste.

One major aspect of this research is to observe the 'Sustainability' of manufacturing systems in the course of technology selection. The proposed methodology should drive the selection of more sustainable technologies. This objective can be achieved through an optimisation algorithm in which sustainability criteria are involved along with other selection criteria. In the next section, a discussion of selection criteria is presented.

3.4 Technology selection criteria

Inspired by the fundamentals of sustainability theory in the context of manufacturing, our approach to the problem 'technology selection and capacity planning' considers three criteria, namely

a) Environmental (e.g. Emissions)
b) Economic
c) Technical (e.g. quality)

These three criteria are largely in conflicting positions. Environmentally friendly technologies could come as pricey, because they may require advanced components to reduce the scale of emissions. Similar argument is true with quality and cost criteria. This gives rise to the multi-criteria decision making challenge, which is addressed later in the thesis.

It is assumed that there exist regulations on controlling the environmental emissions for industries, making them keep their emissions generation at a certain level. This restriction is treated as a constraint in the proposed model.

Modelling the economic aspect of the problem is more complicated. The cost structure includes both capital and operational elements, latter of which should be considered over a time horizon. Thus, a total life-cycle costing method is proposed. The concept of 'Time Value of Money' is addressed through a discounted cash-flow method that is 'Present Value (PV)' analysis. Further, the effect of *inflation rates* is considered, making the proposed model more realistic. Figure 3.2 presents this research's triangular perspective to sustainable manufacturing.

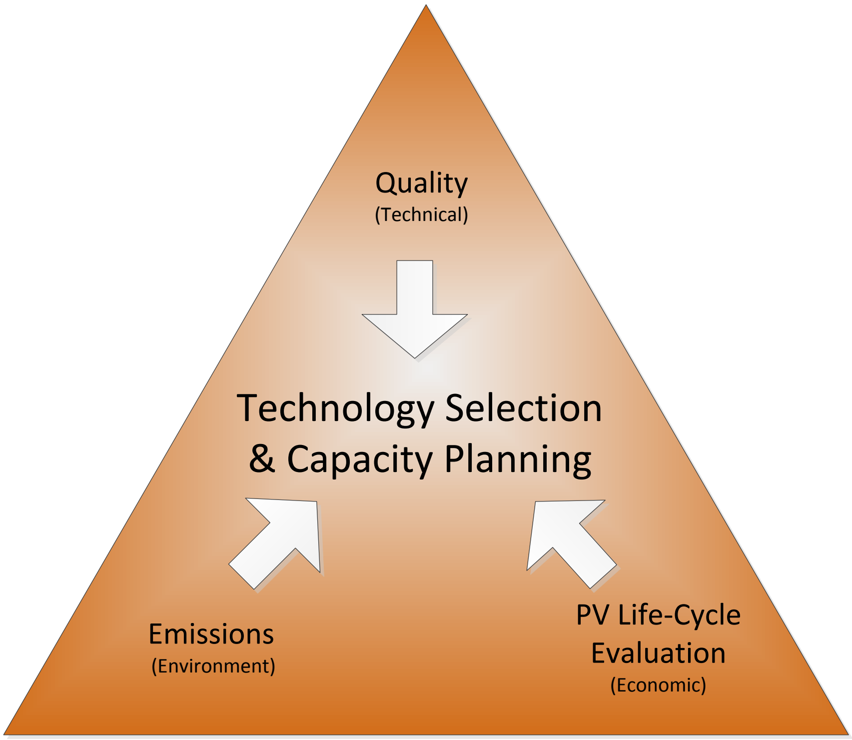


Figure 3-2 A triangular perspective to 'Technology Selection and Capacity Planning'

3.5 Modelling uncertainties

Every decision faces some uncertainties, the level of which becomes intensive where the decision has a long prospect in the future. It is assumed that the decision-making is happening in a time window through which the new circumstances might occur, e.g. prices change or criteria priorities are shifted, on the basis of which it requires the decision to be revised or adapted. Some of these uncertainties are taken into account in this research, which in turn introduce a great deal of complexity into the model.

Dealing with uncertainty constitutes one of the biggest challenges in an optimisation approach. Very few studies take uncertainty into account and use a set of methods called 'Non-Deterministic or *Stochastic'* in general. On the other hand, the mainstream literature tends to assume that all data are certain and use the methods called '*Deterministic*'. Non-deterministic models have to deal with a much larger set of data, which require high level of computational resources. Some methods use approximations to reduce the problem into a manageable size.

3.5.1 Types of uncertainties:

There are three types of uncertainties that are addressed in this research, as follows:

Uncertainty factors with virtually no control over: Perhaps the most important uncontrollable factor associated with this type of uncertainty is;

a) Demand

This factor has a key role in capacity planning decisions. It is, however, assumed that there exists some information about future demand based on historical records or other types of sources such as expert opinions.

Uncertainty factors with some level of flexibility: The other possibility is that although some of the parameters used in the model are beyond the user's control, they might still be influenced by the user's power, e.g. through negotiations, or give the decision maker a certain level of flexibility with the parameter value. Here are the most important ones that fall into this category:

a) Purchasing price of the technology
b) Regulatory limits

Controllable parameters: In addition, the technology selection and capacity planning problem are characterised by some parameters within the decision maker's control that could have impacts on the final results. Therefore, it is important to identify the sensitivity of the model results to the deviations on these parameters. Some of these parameters are:

a) *Criteria weights(the criteria are not all eaqually important, so allocating weights give them relative priority in the decision)*
b) *Rate of return (RoR)*
c) *Budget limit*

3.6 **Proposed research framework**

A framework consisting of ten major steps in four modules is proposed (figure 3.3). The framework puts an emphasis on facilitation of communication with users; hence two modules of 'Problem Structuring' and 'Solution Structuring' are developed to facilitate problem formulation and solution representation, respectively. 'Ontology', which compartmentalises the variables needed for some set of computations and establishes the relationships between them, plays a key role in the former module.

Module 'Optimisation for Sustainable Manufacturing' addresses the optimisation of technology selection and capacity planning decisions in an integrated model. It also takes the multi-criteria aspect of sustainability in the model developed.

'Sensitivity Analysis' module is designed to deal with the uncertainty associated with the model through scenario generations and model re-optimisations.

As a part of the 'Solution Structuring' module, the results, which constitute a large number of solution sets, are then processed using Machine Learning techniques and translated into two solution formats, namely a) decision trees, and b) interactive slider diagram.

The next sections describe the general functionalities of the above four modules as well as some algorithms developed. Further details are presented later in Chapters Four and Five.

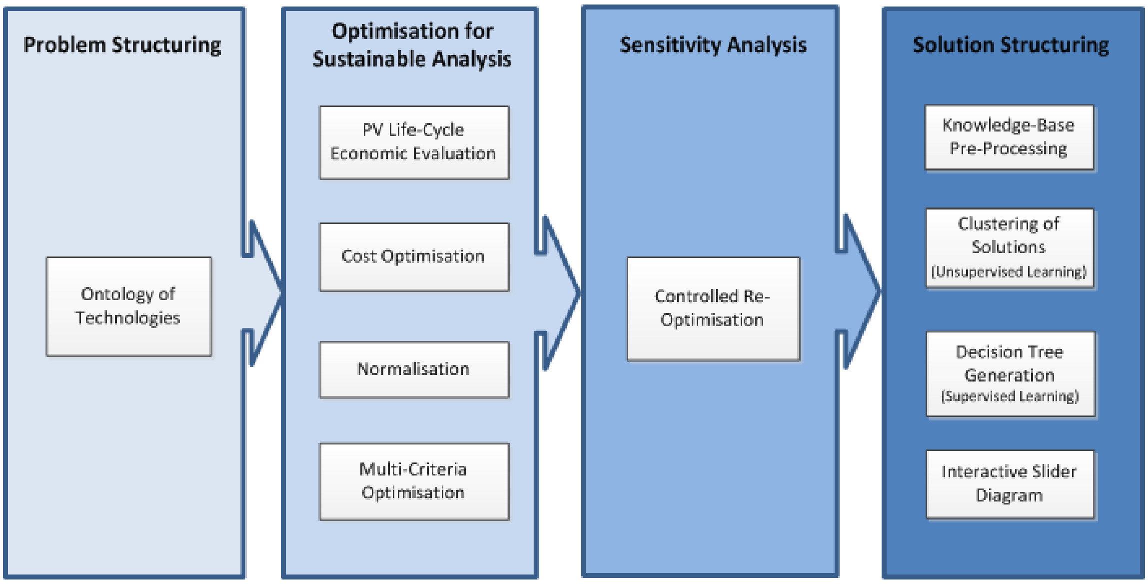


Figure 3-3 General architecture of an integrated optimisation approach to technology selection and capacity planning

3.6.1 Problem structuring

Decision for choosing technology often needs to be made with respect to several aspects, for example energy consumption, demand, environment impacts, etc. it is a big challenge for designers to consider all the constraints and relations at the same time and make a balance among these parameters especially when they are not familiar with the process and available technologies. Ontology can take care of this problem, however it is not well developed yet.

An ontology is an approach to deal with the structure of reality. For instance ontology provides terms and definition of concepts that are important in terms of objects, processes, entities, etc.

In reality, developing ontology is defining classes, arranging classes, subclasses and subclasses, slots and specifying values for slots, and input or edit of the slots (Natalya & McGuiness, 2001).

There are seven steps based on the Noy and McGuinness (2001) report as shown in Figure 3.4.

In the first step the purpose, scope and requirements are defined. The aim of ontology is capturing domain of knowledge and share information in a domain of interest. Therefore the requirements the proposed ontology should be specified based on the intended applications.

In the second step is class and concepts categorisation. The classes and relations among them and also their subclasses are formed as a tree structure.

After class, concepts and relation are defined in ontology model; new design alternatives can be generated. A new design alternative is a new instance corresponding class in the ontology.

In Protégé query tab is realized through searching instances according query needs. To query the knowledge in ontology, data reasoning based on JTP reasoner.

After all steps done, designers can use ontologies to make and add new design alternatives into the knowledge base, they can infer new knowledge by the relations exist in ontology.

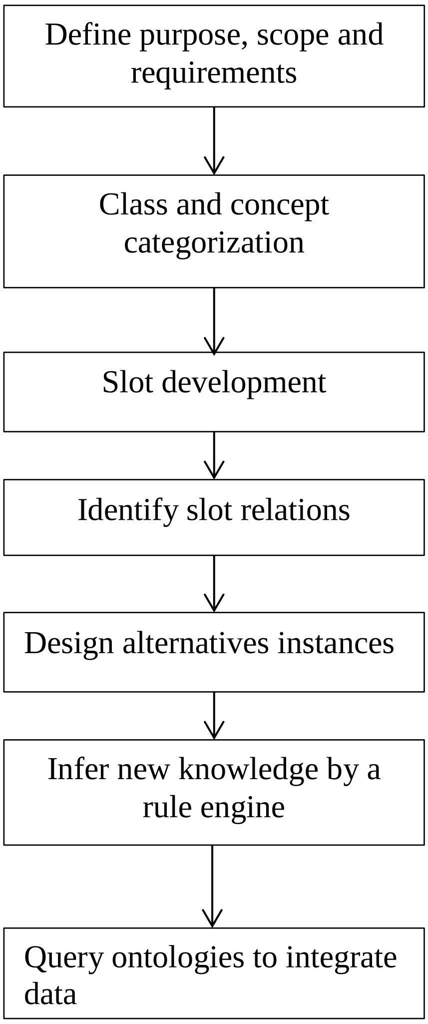


Figure 3-4 Ontology development flowchart

3.6.2 Optimisation for sustainable analysis

System analysis and design for achieving sustainability is a challenging task. Multi-objective decision making is fundamental to the solution approach. Analytical methods are adopted to conduct optimisation of the design task.

This module consists of four steps, namely a) PV life cycle economic evaluation, b) cost optimisation, c) normalisation, and d) multi-criteria optimisation, as described in the next sections.

3.6.2.1 PV Life-Cycle economic evaluation

Economic evaluation of design alternatives has always played a major role in decision making. Various levels of detail and evaluation methods have been used before. Due to historical and ever increasingly vital importance of the cost factor, this research attempts to present a highly detailed economic evaluation algorithm based on 'Present Value (PV)' method.

Technology investments are characterised by both initial capital spending and annual running costs. The real value of money is changed throughout time, due to the effects of *'Inflation'* and *'Market Return'*. PV method transforms all annual costs into their equivalent present values in a way that can be treated in the model similar to the initial capital part of an investment. Then various investments are evaluated based on their total equivalent present value. The details of the PV modelling in this research are described in the next sections (Fabrycky, et al., 1998):

- *Cost structure*

Two major cost categories for each technology investment are defined in this research:

a. **Capital costs (cc):** Mainly includes 'purchase cost' of one unit of technology.
b. **Running costs (rc):** Includes five sub-categories, namely i) materials, ii) labour, iii) energy, iv) rework, and v) maintenance. These cost items need to be discounted over the life of the technology (e.g. 20 years) and transformed into present value. The running cost formulae is presented below:

$$\boldsymbol{MT_{ij} = [x_{ij} \times mt_{ij} \times (1 + rw_{ij})]} \qquad \forall\, \boldsymbol{i, j}$$

$$\boldsymbol{L_{ij} = [x_{ij} \times l_{ij} \times (1 + rw_{ij})]} \qquad \forall\, \boldsymbol{i, j}$$

$$\boldsymbol{E_{ij} = [x_{ij} \times e_{ij} \times (1 + rw_{ij})]} \qquad \forall\, \boldsymbol{i, j}$$

$$\boldsymbol{MA_{ij} = y_{ij} \times ma_{ij}} \qquad \forall\, \boldsymbol{i, j}$$

Where

$\boldsymbol{MT_{ij}}$ = cost of materials per one year production by technology j for operation i,

$\boldsymbol{mt_{ij}}$ = cost of materials per unit of product produced by technology j for operation i,

$\boldsymbol{L_{ij}}$ = cost of labour per one year production by technology j for operation i,

$\boldsymbol{l_{ij}}$ = cost of labour per unit of product produced by technology j for operation i,

$\boldsymbol{E_{ij}}$ = cost of energy per one year production by technology j for operation i,

$\boldsymbol{e_{ij}}$ = cost of energy per unit of product produced by technology j for operation i,

$\boldsymbol{MA_{ij}}$ = cost of maintenance per one year production by technology j for operation i,

$\boldsymbol{ma_{ij}}$ = cost of maintenance per unit of technology j for operation i,

$\boldsymbol{rw_{ij}}$ = percentage of rework associated with technology j for operation i,

$\boldsymbol{x_{ij}}$ = capacity volume required for technology j of operation i;

$\boldsymbol{y_{ij}}$ = Number of units required for technology j of operation i;

- *The effect of inflation:*

In the real world, where price inflations exist, the expenses will rise from one year to the next at the rate known as 'Inflation Rate'. In a simple word, a cost item c will rise to $c(1 + ri)$ next year, where ri represents the rate of inflation. Therefore, the annual running costs will actually rise in real term in the form of a geometric series (Table 3.1). Furthermore, the inflation rates actually vary with regards to different cost items, namely materials, labour, energy, and maintenance. In this research, the effect of inflation for each cost item is taken into account using different inflation rates.

Table 3-1 Geometric series representing the effect of inflation (Fabrycky, et al., 1998)

Year	1	2	3	…	t
Cost	rc	rc	rc	…	rc
Inflated Cost	rc x (1+ri)	rc x $(1+ri)^2$	rc x $(1+ri)^3$	…	rc x $(1+ri)^t$

- *The effect of market return:*

Market return is a profit on an investment, also called return on investment (ROI). It is a measure of investment performance. The effect of market return is involved when dealing with cash flows over time. Market return is represented by the Rate of Return (RoR) in a sense that every pound invested at time zero should grow over time at a rate RoR when used in a business. In other words, every pound spent at time one would be worth 1/(1+RoR) at time zero. The equivalence value of running costs at time zero when considering the effect of market return can be shown in Table 3.2.

Table 3-2 The effect of market return on investment rate on annual running costs (Fabrycky, et al., 1998)

Year	1	2	3	…	t
Cost	rc	rc	rc	…	rc
Equivalent Cost at year 0 (effect of market return)	$\frac{rc}{(1+RoR)}$	$\frac{rc}{(1+RoR)^2}$	$\frac{rc}{(1+RoR)^3}$	…	$\frac{rc}{(1+RoR)^t}$

- *Present Value (PV) model:*

The PV model of annual running cost rc when considering the combined effects of inflation and market return can be shown in the form of a new geometric series as follows:

$$\frac{\boldsymbol{rc}\,(\mathbf{1}+\boldsymbol{ri})}{(\mathbf{1}+\boldsymbol{rr})},\frac{\boldsymbol{rc}\,(\mathbf{1}+\boldsymbol{ri})^{\mathbf{2}}}{(\mathbf{1}+\boldsymbol{rr})^{\mathbf{2}}},\frac{\boldsymbol{rc}\,(\mathbf{1}+\boldsymbol{ri})^{\mathbf{3}}}{(\mathbf{1}+\boldsymbol{rr})^{\mathbf{3}}},\ldots$$

Or

$$\boldsymbol{rc}\times\boldsymbol{dr}\quad,\quad\boldsymbol{rc}\times\boldsymbol{dr}^{\mathbf{2}}\quad,\quad\boldsymbol{rc}\times\boldsymbol{dr}^{\mathbf{3}}\quad,\ldots$$

Where $dr(=\frac{(1+ri)}{(1+rr)})$ represents the combined discounting effects of both inflation rate and return on investment.

The summation of the series terms, which represents the equivalent present value of all running costs of the technology j for operation i, is calculated using the following formulae:

$$\boldsymbol{Running\ Cost\ Present\ Value}=\boldsymbol{rc}_{\boldsymbol{ij}}\times\boldsymbol{dr}\times(\frac{\mathbf{1}-\boldsymbol{dr}^{\boldsymbol{t}_{\boldsymbol{ij}}}}{\mathbf{1}-\boldsymbol{dr}})$$ (Fabrycky, et al., 1998)

Where t_{ij} refers to the life period of the technology j for operation i.

Finally, the total PV of each technology investment, including both capital and running costs, can be calculated as follows:

$$\boldsymbol{PV}_{\boldsymbol{ij}}=\boldsymbol{cc}_{\boldsymbol{ij}}+[\boldsymbol{MT}_{\boldsymbol{ij}}\times\boldsymbol{dr}\times\left(\frac{\mathbf{1}-\boldsymbol{dr}^{\boldsymbol{t}_{\boldsymbol{ij}}}}{\mathbf{1}-\boldsymbol{dr}}\right)+[\boldsymbol{L}_{\boldsymbol{ij}}\times\boldsymbol{dr}\times\left(\frac{\mathbf{1}-\boldsymbol{dr}^{\boldsymbol{t}_{\boldsymbol{ij}}}}{\mathbf{1}-\boldsymbol{dr}}\right)+[\boldsymbol{E}_{\boldsymbol{ij}}\times\boldsymbol{dr}\times\left(\frac{\mathbf{1}-\boldsymbol{dr}^{\boldsymbol{t}_{\boldsymbol{ij}}}}{\mathbf{1}-\boldsymbol{dr}}\right)+[\boldsymbol{MA}_{\boldsymbol{ij}}\times\boldsymbol{dr}\times\left(\frac{\mathbf{1}-\boldsymbol{dr}^{\boldsymbol{t}_{\boldsymbol{ij}}}}{\mathbf{1}-\boldsymbol{dr}}\right)]$$ (Fabrycky, et al., 1998)

3.6.2.2 Cost optimisation

This part of the proposed framework is particularly responsible for finding the total cost goal for the purpose of normalisation as described later in the next section. The cost optimisation model is similar to the main model assuming there is only one criterion to consider, namely cost. A Linear Programming (LP) model is developed to solve this problem. The details of the cost optimisation model are explained later in chapter four.

3.6.2.3 Normalisation

One of the first steps in a multi-criteria approach is to normalise the effects of various criteria. In normalisation, impact potentials and resource consumptions are expressed on a common scale by relating them to a common reference, to enable a comparable assessment across impact categories (Wenzel, et al., 2001) .All potential impacts are converted intthe same unitsts to facilitate a systematic comparison. To compare different impact potentials, an evaluation should be based on the seriousness of the impact, which is assessed by a set of weighting factors.

All the three criteria mentioned earlier in section 3.4 require normalisation transformations in order to enable a comparable evaluation of the various scenarios. Common normalisation algorithms convert various scales into a unique scale for all the criteria scores. ‘Normalisation algorithm by comparison with the best value’ method is adopted in this research. This method can be formulated in two ways, as presented below, assuming that the criterion is to be minimised.

$$Normalised\ Score = 1 - \frac{criteria\ value\ for\ a\ specific\ alternative - Min.\ criteria\ value\ across\ all\ the\ alternatives}{Min.\ criteria\ value\ across\ all\ the\ alternatives}$$

$$Normalised\ Score = \frac{Min.\ criteria\ value\ across\ all\ the\ alternatives}{criteria\ value\ for\ a\ specific\ alternative}$$

Our initial experimentations showed very close results generated by both transformations. The first formula was, however, preferred in this research due to the fact that the second one turned the linear model into a non-linear one, which compromises on the efficiency and effectiveness of the solution.

Normalisation algorithm requires a target (or best) value for each criterion. In the current research, the best criteria value across different technologies for a specific operation is used as the target value for normalisation calculations. The normalised transformation of the best value is set to ‘1’ based on the above formula.

There are, however, some complications involving the technology mix nature of the problem. Technology mix makes both optimisation and normalisation algorithms more complicated, because the number of alternatives is numerous. Each alternative could involve a mixed use of several technologies per operation. Under such circumstances, calculations in normalisation algorithms are carried out per each technology mix rather than per each individual technology.

Assuming all the three criteria values are to be minimised in the context of this research, the following normalisation formulae are proposed.

- *Normalised environmental impact measure:*

It is calculated based on the following formulae, as presented above.

$$NE_i = 1 - \frac{\sum_j (e_{ij} \times x_{ij}) - Min_j(e_{ij}) \times D_i}{Min_j(e_{ij}) \times D_i} \qquad \forall\, i$$

Where NE_i denotes the normalised environmental impact value associated with operation i ($NE_i \in \{0,1\}$ with 1 being the least environmental impact), e_{ij} denotes raw environmental impact value associated with technology j for operation i, x_{ij} denotes the capacity acquisition of technology j for operation i, and D_i denotes the level of demand for operation i. It is important to note that the environmental impacts of technologies are compared for each operation rather than across all operations. Therefore, $Min_j(e_{ij})$ is referred to the minimum environmental impact value across technologies available for operation j.

- *Normalised technical measure:*

Assuming that technical scores are allocated in a way that best scenario will get a lower score, the normalised score, similar to the environmental measure, is calculated based on the following formulae:

$$NT_i = 1 - \frac{\sum_j (t_{ij} \times x_{ij}) - Min_j(t_{ij}) \times D_i}{Min_j(t_{ij}) \times D_i} \qquad \forall\, i$$

Where NT_i denotes the normalised technical (quality) value associated with operation i ($NT_i \in \{0,1\}$ with 1 being the highest technical index), and t_{ij} denotes raw technical value – such as quality rejection rate - associated with technology j for operation i. It is important to note that t_{ij} represents a variable that is to be minimised.

- *Normalised economic measure:*

As for the economic measure, the *best value* cannot be obtained as straightforward as it was with the other two criteria. This is due to the fact that the cost structure of each technology is more complicated and consists of several elements, as described earlier in section 3.6.2.1. Therefore the minimum total cost value needs to be obtained. This is carried out using an auxiliary model called 'Cost Optimisation', as discussed earlier in 3.6.2.2. The cost optimisation is carried out through a separate mathematical model that finds the minimum total cost across all the operations. Therefore, the normalised economic score is calculated based on the following formulae;

$$NC = 1 - \frac{tc - tc^*}{tc^*}$$

Where NC refers to the normalised economic value ($NC \leq 1$ with 1 being the lowest total cost), tc refers to the total cost associated with each technology combination scenario across all operations, and tc^* refers to the minimum total cost across all operations.

3.6.2.4 Multi-criteria optimisation

This element of the research framework is responsible for the actual multi-criteria optimisation of technology selection and capacity planning for a sustainable manufacturing. The problem addressed in this research is characterised by a number of complexities, namely:

- Multi-criteria nature of sustainability perspective, where different types of criteria (both quantitative and qualitative) are taken into account.
- The 'technology mix' approach to the problem. This makes optimisation algorithms more complicated compared to the situation where there are only two

states; ‘selection’ or ‘no selection’. Instead, a numerous number of combinatorial scenarios need to be considered in this research.

- The model is to work under uncertainty. Problem-solving approaches under uncertainty face a huge complication, dealing with uncertain data.

To the best of our knowledge, no previous studies have addressed all the above major challenges simultaneously. This research adopts a group of methods and algorithms to tackle these challenges. The main approach used in this research is ‘Mathematical Programming’, which is a general term for a suit of methods. More specifically, a Goal Mixed Integer/Linear Programming method is used, where Goal Programming model is responsible for multi-criteria optimisation and the Mixed Integer/Linear Programming model deals with an integrated optimisation of technology selection and capacity planning. Further details about the Multi-Criteria Optimisation module can be found in chapter four.

3.6.3 Sensitivity analysis

Decisions are made in a highly uncertain environment. This means that the results might not be valid by the time the decisions are to be implemented. Also, the decision-making might be happening in a time window through which the new circumstances might occur, on the basis of which it requires the decision to be revised or adapted. There are several ways to deal with uncertainty. A related field is sensitivity analysis. With sensitivity analysis one can ascertain the impact of the uncertainty with respect to the parameters’ values on the quality of the optimum solution. Uncertainty analysis and sensitivity analysis are essential parts of analyses for complex systems.

The proposed approach to high variability situations in this research is to predict possible scenarios in advance and pre-plan for each. The focus of this research is on sampling-based sensitivity analysis, which is an effective and widely used approach (Helton, 2008).

There is a very important property of the Linear Programming (LP) models that is called ‘Duality’. Knowledge of the duality provides interesting economic and sensitivity analysis insights to the problem. The optimisation model developed in this research is, however, essentially of a mixed Integer/Linear Programming type, which does not allow the applicability of duality. Therefore, a controlled re-optimisation approach was adopted where the original model is re-optimised for a set of sampled input data. Each re-optimisation episode is characterised by one set of input data against one set of output results. The re - optimisation module uses the same method as used in the original optimisation step. A software tool is designed to control the re-optimisation process in an efficient way. Further details on this module are presented in chapter four.

3.6.4 Solution structuring

Sensitivity analysis module provides rich pieces of knowledge for decision makers in a form of scenario-solution pairs in the scale of hundreds or perhaps thousands. Such a massive knowledge, however, needs to be structured in an abstract way, yet scientifically sound to represent the knowledge originally generated.

This research adopts *'Machine Learning'* approach to the solution structuring stage of the framework. More specifically, two types of knowledge structuring are suggested, including:

i) Decision tree
ii) Interactive slider diagram

These representation schemes provide decision-maker with a variety of methods to structure the solution set. Decision tree is a widely-used and effective knowledge representation scheme. The generation of the most precise, yet smallest decision tree out of a large number of solution instances (thousands) is scientifically a very hard problem. *'Machine Learning'* in general and a combination of *'Clustering'* and *'Classification'* algorithms are applied in this research to generate the best decision tree.

Further details on the algorithms can be found later in chapter five.

3.7 Conclusions

In this research, a model is developed with an integrated view to solve two problems 'Technology Selection' and 'Capacity Planning' simultaneously. A *'technology mix'* decision is allowed, which enables an appropriate level of trade-off amongst conflicting criteria, such as cost, quality, and emissions. A framework consisting of ten major steps in four modules is proposed, namely a) Problem Structuring, b) Multi-Criteria Optimisation, c) Sensitivity Analysis, and d) Solution Structuring.

One major aspect of this research is to observe the *'Sustainability'* of manufacturing systems in the course of technology selection. The proposed methodology should drive the selection of more sustainable technologies. This objective is achieved through an optimisation algorithm in which sustainability criteria are involved along with other selection criteria. Three criteria are considered, including a) Environmental (e.g. Emissions), b) Economic, and c) Technical (e.g. quality).

'Normalisation algorithm by comparison with the best value' method is adopted in this research in order to facilitate a systematic comparison among various criteria. Calculations in normalisation algorithms are carried out per each *technology mix* rather than per each individual technology.

A total life-cycle costing method is proposed. The concept of *'Time Value of Money'* is addressed through a discounted cash-flow method that is *'Present Value (PV)'* analysis. Further, the effect of both *inflation rate* and *market return* are considered, making the proposed model more realistic. A mathematical model to represent the total PV of each technology investment, including both capital and running costs, is developed.

A variety of uncertainties are taken into account in this research, which in turn introduces a great deal of complexity into the model.

In summary, the main characteristics of the proposed framework are:

- An integration of technology selection and capacity planning functions.
- Tackling uncertainty
- Addressing multi-operation problems
- Considering the effects of inflation and market return
- Total life-cycle economic evaluation
- Sustainability perspectives
- Decision tree-based solution structuring
- Technological constraints (incompatible technologies)

Chapter 4 Development of a Mixed Integer-Linear Goal Programming Model for Technology Selection and Capacity Planning

4.1 Introduction

The problem addressed in this research can be regarded as an optimisation one where two sub-problems, namely technology selection and capacity planning, are solved in an integrated way. The objective, however, is multi-faceted mainly due to the multi-disciplinary characteristic of the sustainability science.

Mathematical programming allows the problem-solving approach to incorporate usual resource constraints as well as other types of constraints, such as technological incompatibilities. The theoretical foundation of mathematical programming supports a sound solution approach to the problem.

Some assumptions might, however, be established when working with a solution approach in general and with a mathematical programming approach in particular. The assumption established in the proposed model is as follows:

- Manufacturing technologies are supplied in discrete capacity levels. For instance, each unit of a specific car paint shop technology could be supplied in a capacity level of 250,000 cars per year.

This chapter aims to present the development of a mathematical model for solving the integrated ‘technology selection’ and ‘capacity planning’ problem towards sustainable manufacturing. A method to conduct intensive, controlled sensitivity analyses is also developed. The proposed methods are illustrated with a small example. A flowchart of the optimisation module steps is demonstrated in Figure 4.1.

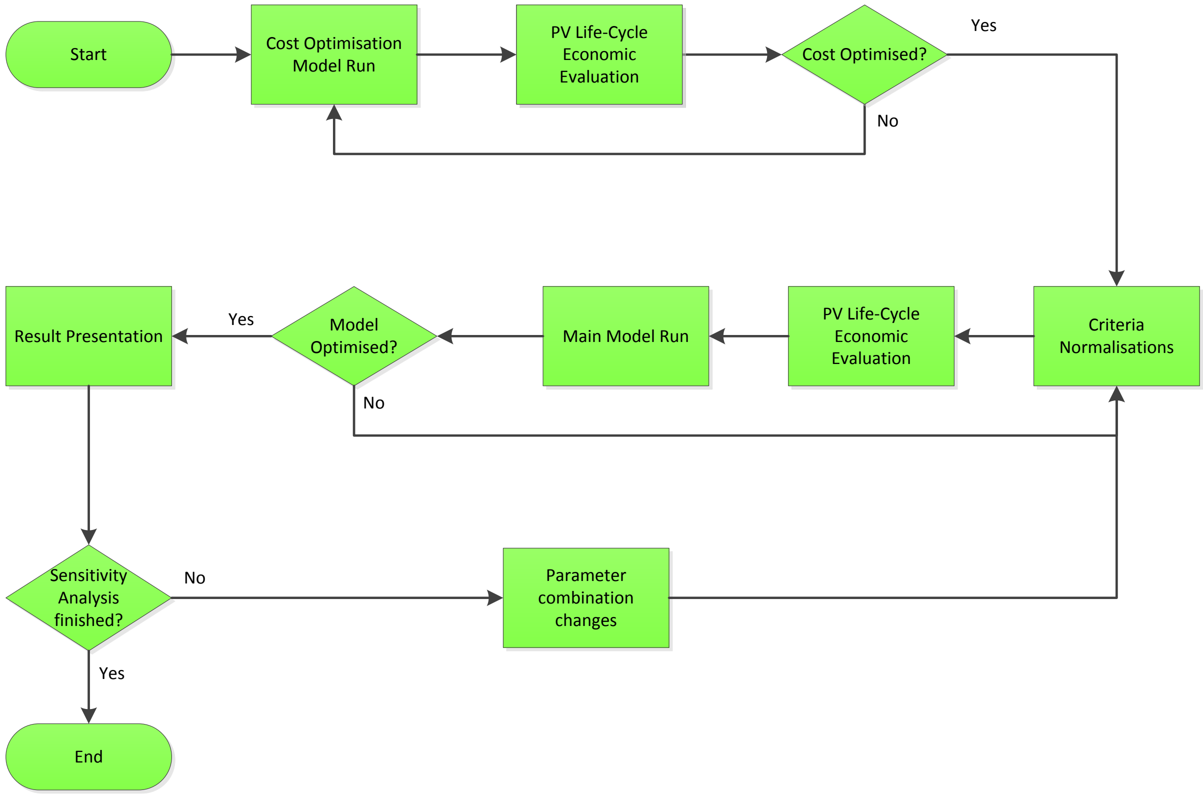


Figure 4-1 Flowchart of the optimisation module steps

4.2 Problem definition and formulation

Mathematical programming, and especially linear programming, is one of the best developed and most used branches of management science. When the mathematical representation uses linear functions exclusively, a linear-programming model is created (Bradley, et al., 1977). Mathematical modelling in general and Goal Mixed Integer/Linear Programming in particular is used to solve both ‘Technology Selection’ and ‘Capacity Planning’ problems in this research.

A mathematical model has three main components: a) Decision Variables, b) Objective Function, and c) Constraints.

4.2.1 Decision variables

Decision variables represent the entities about which a decision is going to be made. Solving a mathematical model means finding the best numerical values for these decision variables in the presence of constraints.

Decision variables defined for the problem addressed in this research are as follows:

Decision Variables	**x_{ij}: Capacity volume required for technology j of operation i;** **y_{ij}: Number of units required for technology j of operation i;** **d_c: Deviation from goal on economic criteria** **d_{ie}: Deviation from goal on environmental impacts criteria with regards to the ith operation** **d_{it}: Deviation from goal on technical (quality) criteria with regards to the ith operation**

x_{ij} and y_{ij} represent the key variables to solve the technology selection and capacity planning problems. The other three variables - namelyd_c, d_{ie}, and d_{it} – take care of multi-criteria aspect of goal programming method. A combination of different technologies can also be accepted. This is important when there is a budget limit.

4.2.2 Objective function

In the mathematical models, the goal is to maximise or minimise a quantity such as profit, cost, number of employees, customer satisfaction, etc. The maximisation or minimisation of the quantity is known as objective. Objective function highlights the fact that the objective is a function of decision variables.

Multi-criteria mathematical modelling approaches face the challenge of dealing with several objectives of different scales. Furthermore, some of the objectives might be in conflict with each other, such as cost and quality. Goal Programming (GP) is the type of method to deal with such situations. In a GP model, 'Goals' are set for each criterion as the targets. Then, the ultimate objective is set to minimise total deviations from the goals. This ensures that the model will find the best possible solution. Prior to that, however, normalisation of the measures as well as weighting of the criteria needs to be taken into account. Therefore, the objective function in this research is formulated as follows:

Objective Function	$\boldsymbol{Minimise\ f(d) = (n \times w_c \times d_c) + (w_e \times \sum_{i=1}^{n} d_{ie}) + (w_t \times \sum_{i=1}^{n} d_{it})}$

Where n denotes the number of operations, and w_c,w_e , and w_t denote the relative weight assigned to total cost, environmental impacts, and quality criteria, respectively.

4.2.3 Constraints

Constraints represent some limitations on resources such as money, labour and material or to represent relationships between decision variables, these constraints are set by personal conversation with experts.

In this research, nine sets of constraints are presented below:

4.2.3.1 Technical goal constraints

Represent relationship between decision variables and the goal on technical criteria. One such constraint is developed for each operation. Technical goal constraints are formulated in this research as follows (technical goal constraints are defined as quality problems here):

Technical Goal Constraints	$\boldsymbol{NT_i + d_{it} = 1}$	$\boldsymbol{\forall\ i = 1, \dots, n}$

Where NT_i denotes normalised technical value associated with operation i as presented earlier in section 3.6.2.3.

4.2.3.2 Environment goal constraints

Represent relationship between decision variables and the goal on environmental impacts criteria. One such constraint is developed for each operation. Environmental goal constraints are formulated in this research as follows:

Environmental Goal Constraints	$\boldsymbol{NE_i + d_{ie} = 1}$	$\forall\, \boldsymbol{i = 1, \ldots, n}$

Where NE_i denotes normalised environmental impact value associated with operation i as presented earlier in section 3.6.2.3.

4.2.3.3 Economic goal constraint

Represent relationship between decision variables and the goal on economic criteria. One such constraint is developed for all operations. Economic goal constraint is formulated in this research as follows:

Economic Goal Constraint	$\boldsymbol{NC + d_c = 1}$

Where NC denotes normalised economic value associated with operation i as presented earlier in section 3.6.2.3.

4.2.3.4 Technology unit constraints

As mentioned earlier in section 4.1, it is assumed that manufacturing technologies are supplied in discrete capacity levels, so-called ‘Technology Unit’. This means that the demand for total capacity requirement is met by a number of technology units from each technology type. The technology unit constraints establish a logical relationship between capacity volume decision variables (x_{ij}) and technology unit decision variables

(y_{ij}). The model should assume that y_{ij} is an integer variable, because it is the number of unit required.

It is important to point out that any fraction of one technology unit should be treated as one full unit. For instance, if the mathematical model finds a solution as 2.3 units of technology, it will round it up to 3 units. Therefore, the capital cost of three units is taken into account. The constraint formula ensures that this condition is met.

Technology unit constraints are formulated in this research as follows:

Technology Unit Constraints	$\frac{\boldsymbol{x_{ij}}}{\boldsymbol{u_{ij}}} \leq \boldsymbol{y_{ij}}$

Where $\boldsymbol{u_{ij}}$ denotes the unit capacity of technology j for operation i.

4.2.3.5 Demand constraints

As suggested earlier in the research scope, new capacities can be acquired from a combination of different technologies, a concept that is called 'Technology Mix'. Demand constraints ensure that the total capacity acquired from the technology mix meets the demand for each operation. Demand constraints are formulated in this research as follows:

Demand Constraints	$\sum_{j=1}^{m} \boldsymbol{x_{ij}} = \boldsymbol{D_i}$	$\forall\ \boldsymbol{i = 1, \dots, n}$

Where D_i refers to the demand level for operation i.

4.2.3.6 Environmental impacts limit constraint

Regulatory bodies in national and international levels (for example EU Industrial Emissions Directive) set out emission limits on selected pollutants for certain activities, such as large combustion plants, waste incineration and co-incineration plants, solvent using activities and titanium dioxide production. As an example, the EU Paints Directive sets out the limitation of emissions of volatile organic compounds due to the use of organic solvents in decorative paints and varnishes and vehicle refinishing products. As a result, such limits are enforced for related industries, where decisions, such as technology selection, are made to comply with these limits.

Environmental impact limit constraint in this research, as formulated below, assumes that each production unit, for instance, painting of a car, generates a certain emission level.

Environmental Impact Limit Constraint	$\sum_{i=1}^{n}\sum_{j=1}^{m}(e_{ij} \times x_{ij}) \leq L$

Where e_{ij} refers to the annual amounts of environmental impact resulted from technology j for operation i, and L refers to the annual limit set out by regulatory bodies.

4.2.3.7 Capital budget limit constraint

A technology selection decision is normally constrained by a capital budget limit, which in turn would lead to a trade-off decision in terms of some other criteria, such as quality and environmental impacts. It should be pointed out that the capital budget applies to the purchase price of the technologies and is not allocated to the running costs.

Capital budget limit constraint is formulated in this research as follows:

Capital Budget Limit Constraint	$\sum_{i=1}^{n}\sum_{j=1}^{m}(CP_{ij} \times y_{ij}) \leq B$

Where CP_{ij} refers to the capital price of one capacity unit of technology j for operation$i$, and B refers to the total capital budget limit set out by the management.

4.2.3.8 Technological constraints

This type of constraints represents some restrictions associated with specific technologies. For instance, there might be incompatibility constraint between two technologies j and j' for operations i and i'. For instance Water base primer cannot use with Solvent base coat.

Technological incompatibility constraints are formulated in this research as follows:

Technological Incompatibility Constraints	$y_{ij} \times y_{i'j'} = 0$	$\exists\ [(i,j),(i',j')] \in P$

Where P includes the set of incompatible technologies j and j' for operations i and i'. This innovative formulation ensures that both these incompatible technologies would not be selected together.

4.2.3.9 Variable constraints

This type of constraints ensures that the decision variables take values in an acceptable range, normally non-negative. All the decision variables defined earlier in section 4.2.1 should be non-negative. This applies to the goal deviation variables too due to the fact that the normalisation algorithm proposed in this research does not allow criteria values beyond their goal value, which is ‘one’.

Furthermore, some variables might be required to take integer values only, such as the technology units in the context of this research. Such a restriction in a mathematical programming model normally results in making the problem hard to solve. The more number of integer variables, the more complicated the solution process would be. Therefore, it is recommended to develop a model with the least number of integer variables, if any. Thus, in the current research, $\boldsymbol{x_{ij}}$, namely capacity volume required for technology j of operation i, is not defined as an integer variable. This is because $\boldsymbol{x_{ij}}$ takes grand values, in a scale of thousands or even more. Therefore, non-integer values can easily be rounded down or up in practice without a major impact on the final results. Variable constraints are formulated in this research as follows:

Variable Constraints	$\boldsymbol{x_{ij} \geq 0 \quad \forall\, i, j}$ $\boldsymbol{y_{ij} \geq 0 \quad \forall\, i, j}$ $\boldsymbol{d_c \geq 0}$ $\boldsymbol{d_{ie} \geq 0 \quad \forall\, i}$ $\boldsymbol{d_{it} \geq 0 \quad \forall\, i}$ $\boldsymbol{y_{ij}\colon Integer \quad \forall\, i, j}$

4.3 Formulation of the cost optimisation auxiliary model

As explained earlier in section 3.6.2.3, the normalisation algorithm requires a total cost goal value. An innovative algorithm is proposed in this research to identify this goal value. First, it is suggested to use the minimum total cost as the goal value. This is in harmony with goal value setting suggested for the other two criteria, namely technical and environmental impacts. Then a cost optimisation model is developed to find the minimum total cost.

It is claimed that the minimum total cost can be found through a cost optimisation mathematical model that is somehow similar to the main mathematical model, as explained earlier in section 4.2, but with cost as the only criterion to consider. All the elements associated with the other criteria in the main model do actually compromise on the economic outcome. In other words, taking out the effects of other criteria in the main model is believed to generate the most economically viable solution.

A major difference between the main model and the cost optimisation auxiliary one is on the fact that the auxiliary model is of a single-criterion type. This means that there is no need to use Goal Programming method within the auxiliary model. The effect is a different objective function and no need for goal constraints. The cost optimisation model is of a Linear Mixed Integer Programming type. Accordingly, the formulation of the cost optimisation auxiliary model is proposed as follows:

Decision Variables	x_{ij}: **Capacity volume required for technology j of operation i;** y_{ij}: **Number of units required for technology j of operation i;**
Objective Function	$\boldsymbol{Minimise\ tc = \sum_i \sum_j \left(cc_{ij} + \left[MT_{ij} \times dr \times \left(\frac{1-dr^{t_{ij}}}{1-dr}\right)\right] + \left[L_{ij} \times dr \times \left(\frac{1-dr^{t_{ij}}}{1-dr}\right)\right] + \left[E_{ij} \times dr \times \left(\frac{1-dr^{t_{ij}}}{1-dr}\right)\right] + \left[MA_{ij} \times dr \times \left(\frac{1-dr^{t_{ij}}}{1-dr}\right)\right]\right)}$
Technology Unit Constraints	$\boldsymbol{\frac{x_{ij}}{u_{ij}} \leq y_{ij}}$
Demand Constraints	$\boldsymbol{\sum_{j=1}^{m} x_{ij} = D_i \qquad \forall\ i = 1, \ldots, n}$
Capital Budget Limit Constraint	$\boldsymbol{\sum_{i=1}^{n} \sum_{j=1}^{m} (CP_{ij} \times y_{ij}) \leq B}$

The result of this model is a solution associated with the minimum cost, tc^*, which is then used in the cost normalisation formulae presented earlier in section 3.6.2.3.

It is important to point out that any changes to the environmental data or quality data or criteria weights would have no effects on this model. More precisely, the results of this model will be valid as long as the data in the model, namely a) economic data, b) demand, c) capital budget limit, or d) technological constraints, are not changed. In case any of these four groups of data do change, the auxiliary model needs to be re-run. This is the topic of the next section, namely 'Sensitivity Analysis'.

4.4 **Sensitivity analysis**

One popular method to do certain types of sensitivity analyses in mathematical programming is called 'Duality'. It provides a streamlined way to conduct sensitivity analyses without a need to do several re-runs of the model. While this makes duality an efficient method, there are three main drawbacks associated with it, namely;

a) Duality can be used for certain types of sensitivity analyses, including analysis on the objective function coefficient values and constraint limits. But it cannot be used for changes to the, for instance, constraint coefficients.
b) The results of duality method will be valid only for a limited threshold changes to the parameters. Any changes beyond those thresholds will require a model re-run.
c) Duality can be used only for non-integer models where Simplex method is applicable.

However, in our model, where some of the variables are forced to be integer, duality cannot be adopted. Furthermore, our research is going to address various types of sensitivity analyses in an extensive scale, most probably beyond the duality threshold limits. Therefore, the proposed approach to conduct sensitivity analysis and tackling all the uncertainties cited earlier in section 3.5 is through a controlled set of re-optimisation runs, which is guided by a tool developed in this research and coded in Visual Basic for Applications (VBA). The VBA program code is presented in Appendix D.

4.4.1 Parameters

Our model and VBA tool allows for conducting sensitivity analyses on all the parameters mentioned earlier in section 3.5, which are found to be the most important ones in the context of the problem addressed in this research. These parameters are;

a) Capacity demand for operations
b) Purchasing price of the technologies
c) Regulatory limits
d) Criteria weights
e) Rate of return (RoR)
f) Budget limit

4.4.2 Re-optimisation method

Re-optimisation method uses the same mathematical model developed earlier in section 4.2. Parameters' value ranges are identified by the user. Then all the possible combinations of parameter values are worked out by the VBA tool, which will subsequently re-run the original model in a controlled fashion based on each combination. Results are generated for each combination. The results might not show a difference compared to the baseline, in which case an implication would be that the model is not sensitive to that specific change in parameters. Otherwise, a new set of results are generated. This controlled model re-run is repeated for every combination. Figure 4.2 exhibits the proposed sensitivity analysis process.

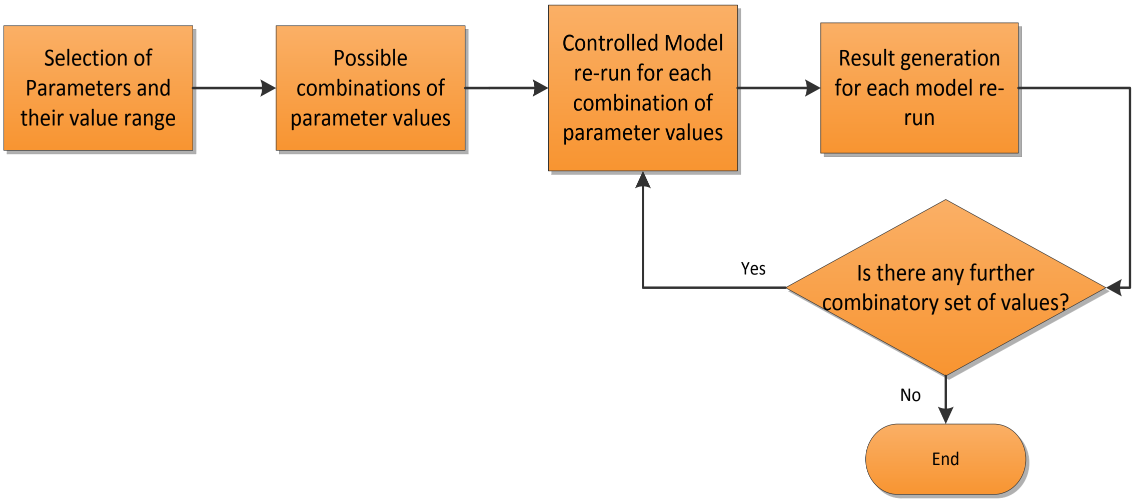


Figure 4-2 Proposed sensitivity analysis process

Each parameter set is associated with its own result set, forming what is known as a 'Solution Example'. A number of such examples, also known as a 'Solution Set', are produced by the VBA tool and then are fed into the Solution Structuring module, which is described in detail later in chapter five. An illustration of a solution set is shown in Figure 4.3.

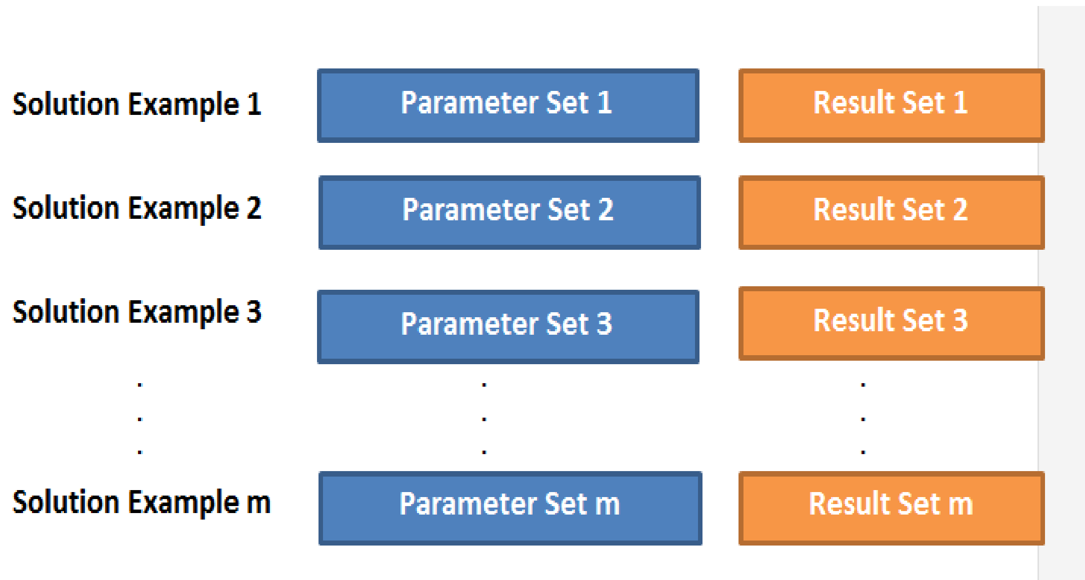


Figure 4-3 An illustration of a 'Solution Set'

4.5 **Illustrative example**

A small illustrative example is presented in Appendix A, to elaborate on the development of a) the cost optimisation model, b) the main model, and c) sensitivity analysis.

4.6 **Summary**

Two mathematical models are developed, one as the main model to solve the main problem addressed in this research, and the second one as the auxiliary model to identify the best solution in terms of the total cost only.

The main model adopts Goal Mixed Integer/Linear Programming to solve both ‘Technology Selection’ and ‘Capacity Planning’ problems. The model consists of five types of decision variables, two of which to solve the twin integrated problem above mentioned, and the other three to deal with the multi-criteria aspect of the sustainability perspective.

The objective is set to minimise total deviations from the goals. Normalisation of the measures as well as weighting of the criteria are incorporated in the objective function. Nine sets of constraints are developed in this research, three of which are concerned with goal constraints, and the other six include technology unit constraints, demand constraints, environmental impact limit constraint, capital budget limit constraint, technological constraints, and variable constraints.

The auxiliary model aims to find the economic criteria goal for normalisation purpose. A linear programming model is developed to find the minimum total cost. It is somehow similar to the main mathematical model, but with cost as the only criterion to consider.

A controlled set of re-optimisation runs, which is guided by a tool coded in Visual Basic for Applications (VBA), is developed to perform intensive sensitivity analyses. It is aimed to address the uncertainty element of the problem.

The working of the proposed methodology is illustrated based on a small example that includes three operations with 2 to 3 technology options for each. Both the main model and the auxiliary model are developed and then are run using What'sBest software.

Chapter 5 **Machine Learning Approach to Solution Structuring**

5.1 **Knowledge structuring**

The scale of the results and knowledge generated by the sensitivity analysis tool is large. Hundreds or thousands of parameter combinations will have to be defined, each of which requires one solution set generated by our model and the software tool. What we are facing here is the transformation, or generalisation, of the massive number of solution sets into a format that can be handled and adopted easily by decision makers. An appropriate knowledge structuring scheme needs to be developed that allows decision makers to handle the massive scale of the knowledge-base.

The nature of knowledge in this context represents a set of information across various fields, namely *manufacturing technologies, production planning, environmental, technical, economic and management priorities*. All these information are reflected in the solution set (Figure 5.1)

Ontologies are explicit formal specifications of the terms in a domain and the relations among them (Gruber, 1993). Ontologies allow the development of a knowledge representation capable of integrating information across various scientific disciplines. This will also facilitate the collaboration between different disciplines.

This research adopts two knowledge structuring schemes, namely a) Decision Tree, and b) Interactive Slider Diagram. Novel algorithms are developed to build decision trees and interactive slider diagrams based on the results of sensitivity analyses generated. The details of these algorithms are described in this chapter.

5.2 **Decision tree generation**

A decision tree is a classifier expressed as a recursive partition of the instance space. The decision tree consists of nodes linked together in a hierarchical way. The terminal nodes in a tree are also called '*decision nodes*' or '*leaves*'. Each internal node splits the instance space into two or more sub-spaces according to a certain discrete function of the input attribute values. Each leaf is assigned to one class representing the most appropriate target value (Rokach & Maimon, 2008).

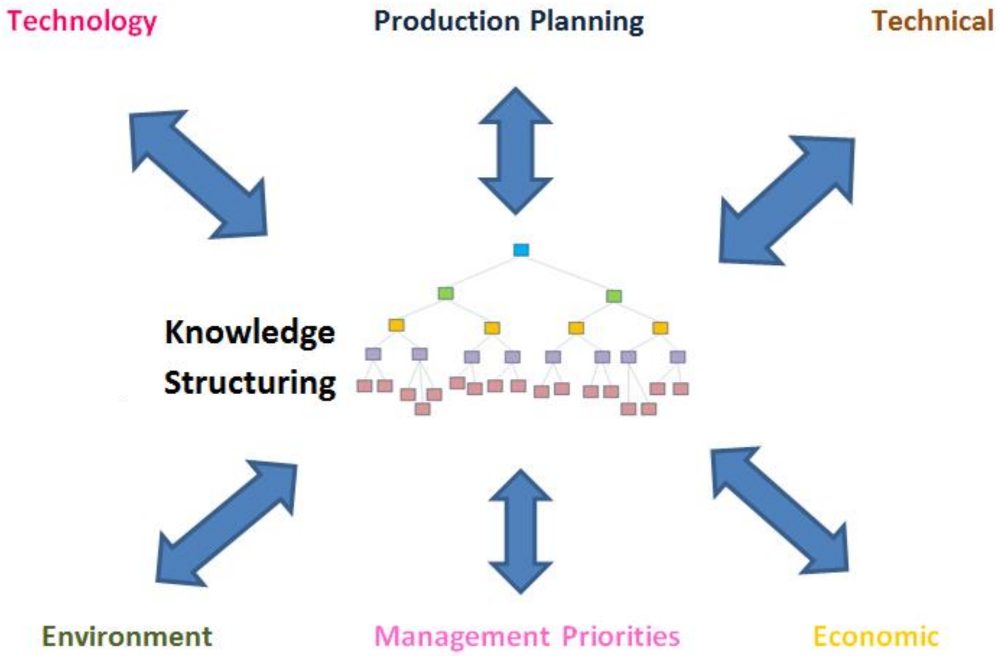


Figure 5-1 Proposed ontology framework to represent solution knowledge in the context of technology selection in a sustainable manufacturing

Decision tree is a widely-used and effective knowledge representation scheme. There exist three criteria to evaluate the goodness of a decision tree generation algorithm, namely a) its correctness to predict the class of an unseen example, b) its completeness, in a sense that the tree can cover all the possible examples, and c) the size of the tree, in terms of the number of its nodes. The generation of the most correct, most complete, yet smallest decision tree out of a large number of solution instances (thousands) is scientifically a very hard problem.

'Decision Tree' scheme was found appropriate for the problem addressed in this research because;

a) It can easily be understood by people,
b) It can reduce the size of a knowledge-base in an optimised way, using Machine Learning algorithms.
c) It prioritises the sensitivity level of various parameters against the model results.

A tree can be learned by splitting the database into subsets based on an attribute value test. This process is repeated on each derived subset in a recursive manner called recursive partitioning. The recursion is completed when the subset at a node has all the same value of the target variable, or when splitting no longer adds value to the predictions. This process of *top-down induction of decision trees* (TDIDT) is an example of a greedy algorithm, and it is by far the most common strategy for learning decision trees from data.

There are two key, conflicting criteria to evaluate the goodness of a decision tree, namely a) correctness, b) tree size. An ideal situation is to generate a decision tree that is the smallest and the most correct one. In a realistic situation, there needs to be a trade-off between these two criteria. There are techniques known as 'Decision Tree Learning', a branch of Machine Learning approach that uses specific algorithms to generate decision trees.

5.3 **Decision tree learning algorithms**

Machine Learning is a class of algorithms that is data-driven. In other words, it is the data that tells what the "good answer" is. For example, a hypothetical non-machine learning algorithm for truck shape recognition in images would try to define what a truck is (rectangular shape of a specific size with round shapes as wheels underneath, etc.). A machine learning algorithm, however, would not have such coded definition; instead it 'learns by examples', which means the algorithm is given a set of images of trucks and non-trucks and a good algorithm will eventually learn and be able to predict whether or not an unseen image is a truck.

This particular example of pattern recognition is '*supervised*', which means that the examples must be tagged with information about its category or so-called 'Class'. In the above case, the class would reflect the information as to whether an example is a truck or not.

On the other hand, in an *'unsupervised'* algorithm the examples are not tagged with 'Class' data. This means that the data are not classified. In such a case, the algorithm itself cannot 'discover' what a truck is, but it can try to 'cluster' the data into different groups. For example, it can distinguish that trucks are very different from balls, which are very different from humans. Good algorithm will eventually learn and be able to predict whether or not an unseen image is a truck.

This particular example of pattern recognition is ‘supervised’, which means that the examples must be tagged with information about its category or so-called ‘Class’. In the above case, the class would reflect the information as to whether an example is a truck or not.

On the other hand, in an ‘unsupervised’ algorithm the examples are not tagged with ‘Class’ data. This means that the data are not classified. In such a case, the algorithm itself cannot ‘discover’ what a truck is, but it can try to ‘cluster’ the data into different groups. For example, it can distinguish that trucks are very different from balls, which are very different from humans.

5.4 Proposed hybrid decision tree algorithm

In the current research, both supervised and unsupervised learning algorithms are used. Figure 5.2 exhibits the flowchart that represents sequential steps developed in this research to carry out solution structuring.

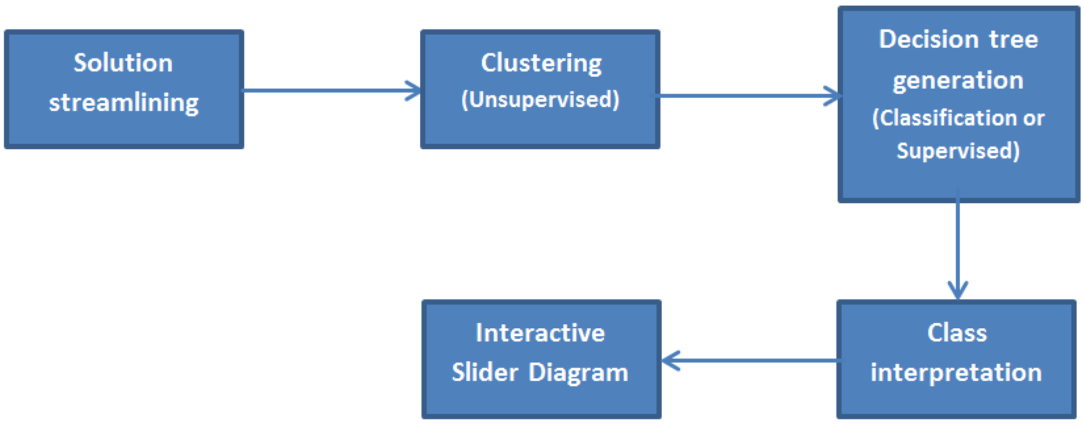


Figure 5-2 Flowchart of the proposed solution structuring module

The result of sensitivity analysis in terms of solution representation can be shown in Figure 5.3. Each solution example, as illustrated in the figure, is formed of a pair of value sets, first of which is called ‘parameter value set’ and the second is called ‘technology value set’.

As parameter values change, the technological values will be calculated accordingly using the optimisation module. Sensitivity analysis module in this research will produce a massive number of solution examples to handle modelling uncertainties, as shown in Figure 5.4. Each row in this figure can be named as one training example.

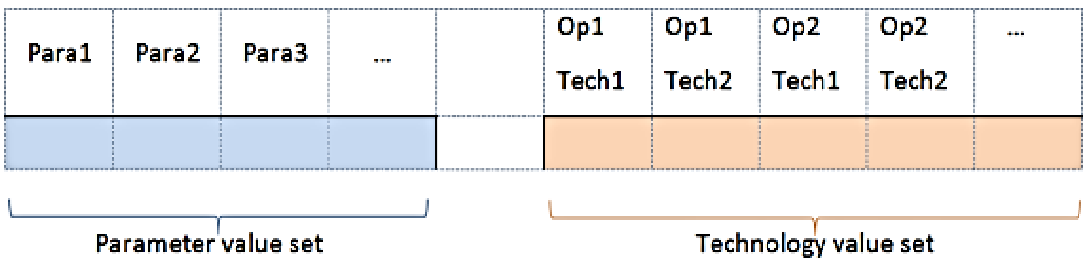


Figure 5-3 One solution example

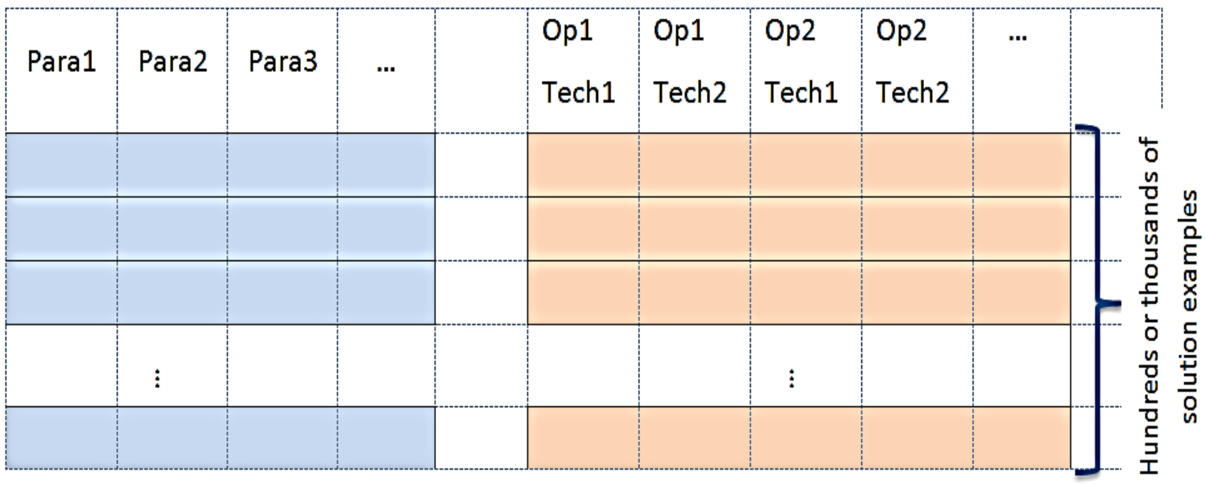


Figure 5-4 An illustration of the population of solution examples generated by the sensitivity analysis tool

The objective of this stage of research is to learn a reasonably small decision tree out of the massive number of training examples at the highest accuracy level. Machine learning algorithms do not necessarily generate 100% accurate rules, although it is the target. This is because machine learning algorithms are normally supposed to generalise, which would result in some inaccuracies.

In order to be able to use supervised learning methods, the examples must include information about the category of the examples or so-called ‘Class’. In this case, the class would normally be the solution part of the training example. However, in our research the solution part consists of a number of data fields (technology data) rather than a single data field that represents a ‘class’. This causes some complications if using supervised learning. A multi-step hybrid algorithm is proposed in this research, in which the unsupervised learning method is first used to cluster solution examples, before a supervised learning algorithm can be applied. The details of this hybrid algorithm are presented in the next sections.

5.5 **Unsupervised learning (Clustering)**

A sensitivity analysis experiment is normally resulted in a number of similarly patterned solution examples. This is because some parameter changes might have no impacts on the results. In such cases, especially where there are a large number of sensitivity analyses involved, patterns can be recognised to streamline solution structuring. Each recognised pattern is allocated a class number, which will then be used for supervised learning.

The process of pattern recognition within the sensitivity analysis results is driven by a method called ‘Unsupervised Learning’, or so-called ‘Clustering’. This method looks for similarities or patterns in the examples and clusters them accordingly. Before that, however, a *‘solution streamlining’* step is carried out on the solution examples to simplify the clustering process. This step aims to reduce the size of the examples based on the mathematical relationships between them. For instance, in a solution set illustrated in table 5.1, the capacity volume of various technologies for each operation are defined as dependent variables, as shown below:

$$Op1Tech1 + Op1Tech2 = Demand1$$

$$Op2Tech1 + Op2Tech2 + Op2Tech3 = Demand2$$

$$Op3Tech1 + Op3Tech2 = Demand3$$

Table 5-1 An example of pattern recognition in the 'Technology value set' part

Budget Limit (m)	Economic Weight	Demand 1	Demand 2	Demand 3	Op1 Tech 1	Op1 Tech 2	Op2 Tech 1	Op2 Tech 2	Op2 Tech 3	Op3 Tech 1	Op3 Tech 2
27	5	190,000	190,000	290,000	26,070	163,930	30,000	160,000	0	290,000	0
30	5	190,000	190,000	290,000	26,070	163,930	30,000	160,000	0	290,000	0
33	5	190,000	190,000	290,000	26,070	163,930	30,000	160,000	0	290,000	0
27	3	190,000	190,000	300,000	50,000	140,000	0	190,000	0	300,000	0
30	3	190,000	190,000	300,000	50,000	140,000	0	190,000	0	300,000	0
33	3	190,000	190,000	300,000	50,000	140,000	0	190,000	0	300,000	0

As a result, one column out of each operation can be removed randomly, as shown in Table 5.2.

The aim of clustering is to recognise similarity patterns. For instance, two patterns can be recognised in the technology part (orange-coloured) of the solution set illustrated in table 5.2. In fact, repetitions are noticeable in this part. The pattern recognisable is that the production capacities allocated to the different technologies do not change in response to different budget limits as long as the other parameters are the same. This means that the results are not sensitive to the scale of budget limit shift shown in the Table 5.2.

The clustering algorithm then allocates 'cluster number' to each pattern. This allows the application of supervised learning in the next step. The outcome of the clustering algorithm is shown in Table 5.3.

Table 5-2 Solution streamlining and Pattern Recognition

Budget Limit	Economic Weight	Demand 1	Demand 2	Demand 3	Op1 Tech 1	Op2 Tech 1	Op2 Tech 2	Op3 Tech 1
27000000	5	190,000	190,000	290,000	26,070	30,000	160,000	290,000
30000000	5	190,000	190,000	290,000	26,070	30,000	160,000	290,000
33000000	5	190,000	190,000	290,000	26,070	30,000	160,000	290,000
27000000	3	190,000	190,000	300,000	50,000	0	190,000	300,000
30000000	3	190,000	190,000	300,000	50,000	0	190,000	300,000
33000000	3	190,000	190,000	300,000	50,000	0	190,000	300,000

Table 5-3 The solution set after clustering

Budget Limit	Economic Weight	Demand 1	Demand 2	Demand 3	Cluster no.
27000000	5	190,000	190,000	290,000	1
30000000	5	190,000	190,000	290,000	1
33000000	5	190,000	190,000	290,000	1
27000000	3	190,000	190,000	300,000	2
30000000	3	190,000	190,000	300,000	2
33000000	3	190,000	190,000	300,000	2

5.5.1 Density-based spatial clustering of applications with noise (DBSCAN) method

DBSCAN, proposed in 1996 (Ester, et al., 1996), is a density-based clustering method that identifies high-density group of examples that are close together, while distinguishing outlier points that lie alone in low-density regions. DBSCAN has proved one of the most commonly used clustering algorithms and also one of the most cited ones in scientific literature (Microsoft Academic Search, 2015). Unlike some other methods, DBSCAN does not require one to specify the number of clusters in the data a priori. Such a characteristic makes this method less parametric.

DBSCAN requires two parameters with descriptions as follows:

a) ε (epsilon): It represents neighbourhood radius. In general, small values of ε are preferable, and as a rule of thumb only a small fraction of points should be within this distance of each other. Trial and error is a common method that can be used to find the appropriate value for epsilon.

b) MinPts: It represents the minimum number of points required to build a dense region or cluster. Larger values are usually better for data sets with noise and will yield more significant clusters. The larger the data set, the larger the value of MinPts should be chosen. In the context of this research, the level of noise could be low.

This research adopts DBSCAN method. The parameters are obtained through a process based on trial and error runs.

5.6 Supervised learning (Classification)

Supervised learning works based on a 'Class' attribute already in the data set, hence called 'Classification'. It aims to infer generalised rules or other simple types of knowledge structures such as decision trees.

The aims of supervised learning in this research are two-fold:

1) *To generate the optimum representation for the solution set:* This is a generalised form of representation that connects various combinatorial parameter values to different set of solutions at the highest correctness rate acceptable.
2) *To predict what class an unseen point belongs to:* An unseen point for the exemplary case presented earlier in table 5.3 can be shown in table 5.4. As shown, the economic weight for this new point is 3.5 while all other attribute values are similar to an existing point. A function of the supervised learning algorithm is to predict the best possible cluster (or class) for this unseen point.

Table 5-4 An example of unseen point

Budget Limit	Economic Weight	Demand 1	Demand 2	Demand 3	Cluster no.
27000000	3.5	190,000	190,000	300,000	???

This algorithm is applied to the result of 'Unsupervised Learning' step developed earlier in the previous section. A simple decision tree generated out of the dataset illustrated earlier in table 5.3 is shown in Figure 5.5.

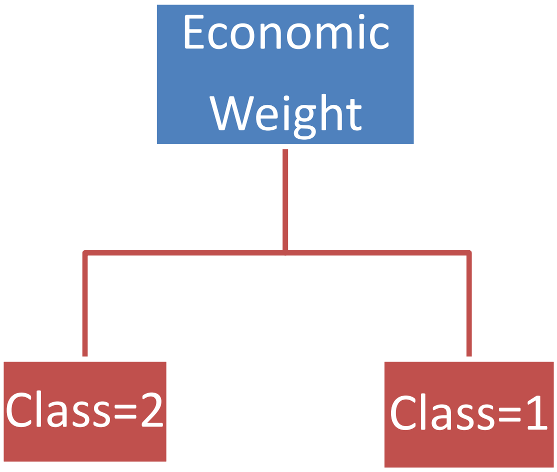


Figure 5-5 A possible decision tree for the dataset in Table 5.3

This tree is complete, which means it covers all the six examples. The tree is also 100% correct in a sense that it correctly predicts all the two classes. But, perhaps the most important advantage is that the tree learning method has generated a much simpler representation of the knowledge compared to the original dataset.

Different classification methods can generate different trees that might vary in terms of attributes, size, and correctness. For example, another tree is shown in Figure 5.6, which uses a different attribute as classifier, namely demand3. This tree is also 100% complete and 100% correct.

Both these trees constitute optimum solutions in tree generation algorithm in terms of the size, completeness and correctness.

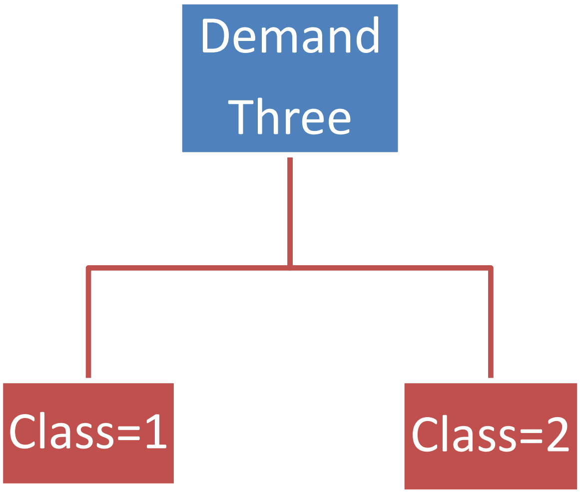
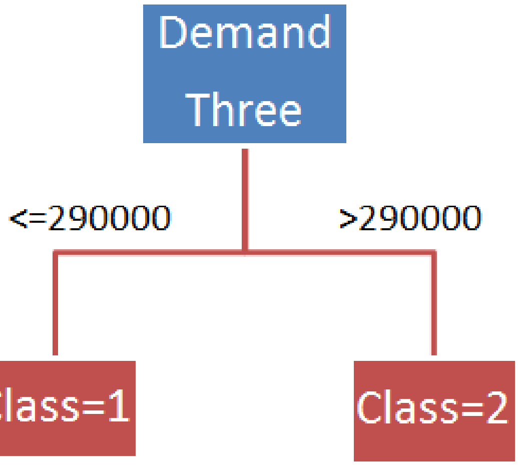


Figure 5-6 An alternative tree for the dataset in Table 5.3

The last step is to replace the tree leaves with their equivalent solution set as obtained earlier by the unsupervised learning (Table 5.2). Figure 5.7 represents the outcome of this step.



Op1 Tech 1	Op2 Tech 1	Op2 Tech 2	Op3 Tech 1
26,070	30,000	160,000	290,000

Op1 Tech 1	Op2 Tech 1	Op2 Tech 2	Op3 Tech 1
50,000	0	190,000	300,000

Figure 5-7 Decision tree generated for the dataset in Table 5.3

5.4.1. C4.5 Method

C4.5 method was developed by Quinlan in 1993 as a decision tree generation algorithm. It is an extension of an earlier method called ID3. Both C4.5 and ID3 have been amongst the most popular decision tree generator algorithms available.
At each node of the tree, C4.5 chooses the attribute of the data that most effectively splits its set of examples into subsets enriched in one class or the other. The splitting criterion is the normalized information gain (difference in entropy). The attribute with the highest normalized information gain is chosen to make the decision. The C4.5 algorithm then recurs on the smaller sublists.

One key parameter in C4.5 is the 'minimum number of instances per leaf'. This parameter determines how big and consequently how correct the generated tree will be. The bigger the tree, the more correct it will be, and vice versa. However, bigger trees would generally make it difficult to follow by decision makers. Thus, there needs to be a trade-off between size and correctness of a tree. For example, a threshold can be defined for the correctness of a tree.

J48, a Java implementation of C4.5 method in the Weka data-mining software tool, was used in this research to conduct supervised learning.

5.7 Illustrative example

The results of the example presented earlier in section 4.5 were fed into the solution structuring module. Unsupervised learning was conducted using DBSCAN method with parameters set at Epsilon=0.2 and MinPoint=3 and was implemented in the Weka software tool. One technology option of each operation was removed randomly. Eighteen clusters (or patterns) were recognised and a unique cluster number was allocated to each cluster. A sample of the clustering result consisting of 24 solution examples are shown in Appendix B.

Supervised learning was conducted using C4.5 algorithm with two parameter values 'Min. number of instances per leaf' set at 3 and 4 and was implemented in Weka software tool, as shown in Appendix B respectively.

5.8 **Interactive slider diagram representation**

An alternative way to represent the sensitivity analysis results is suggested here by using an interactive slider diagram, which is developed in a spreadsheet platform. The slider diagram is linked to the decision tree and illustrates its result in a histogram format interactively. The slider diagram exhibits the model results (technology mix) against the input parameter values. It is interactive in a sense that every change to the parameter values is reflected onto the results on a real-time basis.

While decision trees allow the recognition of general patterns in the solution set, interactive slider diagram works based on a point-to-point approach where each input data point identifies one solution point.

5.9 **Summary**

Two knowledge structuring schemes, namely Decision Tree and Interactive Slider Diagram, are proposed to deal with the massive size of solution sets generated by the sensitivity analysis module.

Machine learning approach in general, and a hybrid supervised and unsupervised learning algorithm in particular, is developed to generate a decision tree that aims to structure problem solution set. The unsupervised learning method is first used to cluster solution examples, before a supervised learning algorithm can be applied to generate a decision tree. The unsupervised learning stage is implemented using DBSCAN algorithm, while the supervised learning element adopts C4.5 algorithm. The algorithm's parameters are obtained through a process based on trial and error runs.

The working of the proposed decision tree generation algorithms is illustrated based on the same example presented in chapter four.

Finally, an alternative way to represent the sensitivity analyses results is suggested by using an interactive slider diagram, which is linked to the decision tree and illustrates its result in a histogram format interactively. The slider diagram exhibits the model results (technology mix) against the input parameter values.

Chapter 6 **Case Study on Automotive Painting Systems**

6.1 Introduction

To validate the proposed methodology in chapters 3, 4, and 5, defining an appropriate case study is necessary. Since this research deals with technology selection the case study should consist of different operations that each or some of them can be replaced by another compatible technology. Therefore, automotive coating is chosen because of having variety of available technologies.

This chapter starts with an introduction about automotive industry, particularly specified in coating section, followed by environmental strategy, industry's economic condition of the painting process structure in Iran, followed by implementing methodologies and analysing findings.

6.1.1 Automotive industry

Automotive manufacturing is one of the largest industries in the world. According to the European Motor Manufacturers Association (ACEA), 17.2 million cars, vans, truck and buses are manufactured in Europe per year with a turnover of 452 Billion EURO. By this large amount of demand for passenger car, there are strong competitions among automotive manufacturing companies. Moreover, external pressures from governments by their rules have affected these industries. For example Clean Air Act (CAA) has changed the basic method of vehicle coating in the United States, to reduce amount of VOC emissions in painting processes. VOCs, volatile organic compounds have hazardous effects to the atmosphere.

6.1.2 Environmental effects

The automotive painting is considered as an emission intensive process among all manufacturing stages of an automotive. Around 90% of VOC emission of car manufacturing belongs to the painting activities (Rivera & Reyes-Carrillo, 2014).

Environmental emission of paint shop included emission to air, water and soil. Air emission includes; VOCs, SO_x, NO_x, CO, and CO_2. Table 6-1 shows The European Emission limit value of the SE Directive (Directive 1999/13/EC).

The energy which is required for coating of a car is between 5-15 GJ, dependant on the size of car and painting methods. Painting processes, including surface preparation, paint application and drying, that consume around 48 to 60% of the energy of automotive assembly section (Rivera & Reyes-Carrillo, 2014).

Table 6-1 Emission limit values for vehicle coating (EC, 2009)

Activity	**Annual production**	**Emission limit**	
Vehicle coating	>5000	New installations	Existing installations
		45 g/m^2 or 1,3 kg/body + 33 g/m^2	60 g/m^2 or 1,9 kg/body + 41 g/m^2
	≤5000	90 g/m^2 or 1,5 kg/body + 70 g/m	90 g/m^2 or 1,5 kg/body + 70 g/m^2

The need for low/solvent free, and less energy consuming painting systems, is very important for automotive manufacturing companies. However, when production cost aspects are come into account the conflicting issues is noticeable.

6.2 Automotive painting at Pars Khodro

Founded in 1956, in Iran under Jeep licence to manufacture and assemble different types of Jeep. In 1973 Pars Khodro started to cooperate with General Motors. In 1980, after Iran revolution cooperation with GM has been interrupted and Pars Khodro started to work with Japanese companies like Nissan. Recently Pars khodro is manufacturing some French automotive as well.

In recent years, many innovative developments in painting process have been introduced. Moreover, environmental pressure of government with respect to the solvent emissions is another consideration of Pars Khodro to comply. Although new technologies and government pressures are pushing organizations to meet the criteria, but existing plants and operation are also parts of potential improvements.

6.2.1 Process flow and structure

Automotive assembly plant has 3 areas: Body Shop, Paint Shop, and assembly. as shown in Figure 6-1 Each of these areas have their own different processes.

Figure 6-1 Three components of automotive assembly plant

The automotive paint shop is complex, multi-stage operation and high consumption of energy. As said before, it is a source of air pollution known as the VOC. Moreover automotive coating is expensive in terms of capital investments and high material costs. The exact cost of paint materials is dependent on the colour, application methods and chemical formulation. The coating material cost is half of the cost of automotive painting.

The coating process is consisting of several stages as shown in Figure 6-2. First of all body-in-white is dipped in cleaning baths to remove oil and other substances. This process, including alkaline degreasing, neutral detergent, phosphating is used to make the metal surface property better for painting. Then bodies go through painting processes. The most commonly applied coating techniques are solvent based system. E-coat process is given an electrostatic charge by paint spray and helps that coat applied on the total car body. Ovens are used for drying processes. After painting, the body is checked to be sure the paint is applied all over of the body.

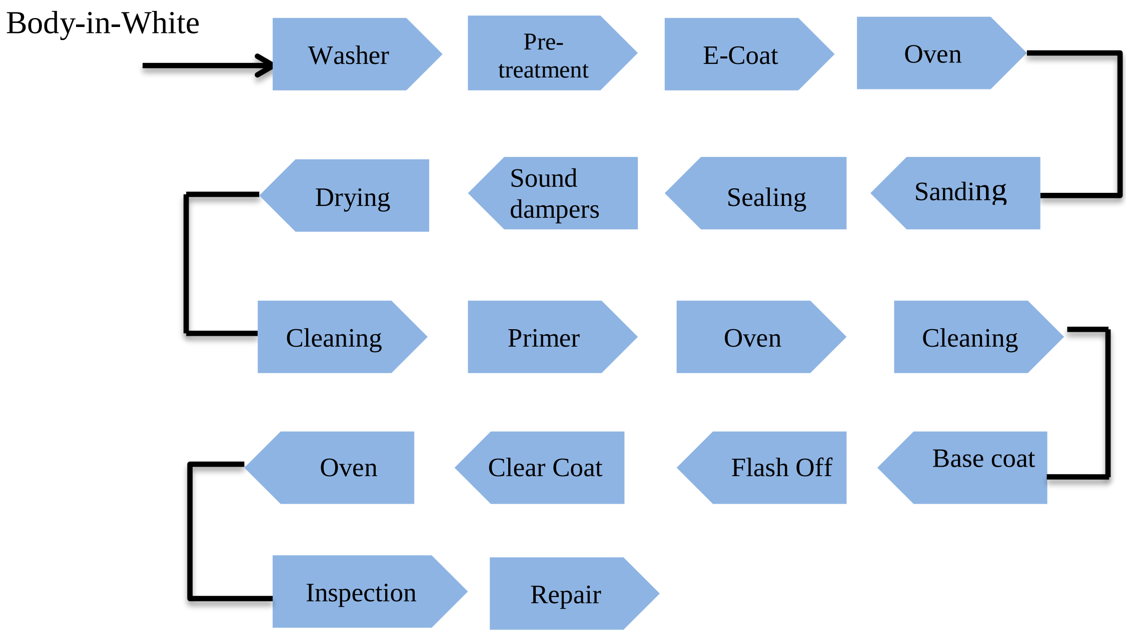


Figure 6-2 Automotive paint-shops process steps (Streiberger & Dossel, 2008)

6.2.2 Existing painting process and technologies

Table 6-2 shows different technology of painting systems that can be compatible with each other and used by the automotive industries (Prendi, et al., 2006). The painting processes with water-based clear coat results in reduction of big amount of the VOCs emissions compared with conventional procedures that use solvent-based products. Powder clear coat leads energy, saving about 10% in comparison with other methods of clear coat. Powder polyester resins are cheaper than waterborne alternatives in surface primer process. The combination of water-based and powder slurry produces very low VOC emission by experience.

Due to the conflicting issues decision making for new coating lines or replacement equipment should consider following aspects:

- environmental aspects
- costs
- quality and
- process reliability

Table 6-2 The possible combination of coating methods, http://eippcb.jrc.ec.europa.eu/reference/sts.html

Primer	Base coat	Clear Coat
SB	WB	SB
SB with Booth air abatement	SB	SB with booth air
WB	SB with booth air abatement	

Primer	Base Coat	Clear Coat
SB	WB	WB
WB		Powder
None		Powder slurry
Powder Primer		

Painting process is very complex and completely integrated operation consisting of several interdependent steps. Therefore, because each step influences other steps, decision making about one step can effect on other parts of the system. Moreover, some combinations of systems might be incompatible with the others. Since pre-treatment and e-coat application technologies are the same for the almost coating processes, they are intentionally excluded.

6.2.2.1 Waterborne coating

A waterborne painting has been introduced to the automotive industry since 1980. Water-based coating is based on polyester, acrylate, alkyd, melamine and epoxy resins. Waterborne coating contains solvents as a solubiliser to improve the properties of the wet film layer. Primers, clear coat and base coat can be solvent-based or powder based.

Waterborne basecoat is generally low cost, in liquid form and they contain VOCs amount from zero to 12%. However, there are some disadvantages of using a waterborne coating, for example, water could be trapped under the surface skin during dehydration in heated flash stage. Economically material costs of waterborne paints are up to 20% higher than solvent based paints.

6.2.2.2 Solvent-borne coating

Solvent-borne paints have the ability to be used in all stages of the painting process on plastics or metals. Solvent based coating materials are classified as polycondensation- e.g. phenol/urea/melamine resin, polymerisation (e.g. polyesters-, acrylate resin, alkyd resins) and polyaddition-laquers (e.g. epoxy or PU lacquers).

Solvent-borne painting methods compared to the waterborne painting methods, consume 15% lower energy because of effective flash- off of solvent-borne systems. Curing time for solvent-borne painting is shorter than the time is needed for waterborne systems.

6.2.2.3 Powder coating

Powder coatings are solvent-free coating systems that are suitable for metal surfaces. Powder coating materials are based on acrylic resins with an acid or anhydride. They can be applied in primer or clear coat. The most important characteristic of powder coating is that its zero VOC emission and no needs for water use for particulate abatement. Powder coating materials can be reused up to 97%. Energy requirement for powder coating is lower than waterborne material and also solvent-based technology.

The main concern of using powder technology is difficulty of control of the film thickness, since the thickness that is created is usually more than necessary.

From economics point of view, changing from existing technology to retrofitting powder technology, has high capital costs, since powder technology is quite different technology and wants a general refit of facilities, materials and equipment. Although reduction of operation costs in comparison with water-based and solvent-based methods is achievable.

6.2.2.4 Powder slurry coating

Powder slurries are powder coating dispersed in water, therefore it has properties of both water-borne and powder coatings, but chemical formulation of powder slurries is closer to powder coatings. On environmental aspects, a significant reduction of VOC emission is achievable by replacing the conventional component of the wet-on-wet of the clear coat stage. However, controlling of booth temperature and humidity to meet quality criteria is difficult. A thinner film is easier to achieve in comparison with powder coating. Powder slurry requires a forced flash-off, since water must evaporate from wet film to baking it.

Powder slurry coating like powder coating has surface quality problems, for example thick films and poor flow during cure leads to ‘orange peel’. Another problem of using powder paint is high usage of material is achieved only if recycling of overspray is done.

6.3 **Data collection**

As a part of the assessment of components and systems, the product lifecycle in terms of economic data(manufacturing costs), environmental data (emissions, raw materials, energy consumption, exhaust air) and engineering data(system parameter) are collected. Based on economics, environmental and technical dimensions of sustainability a big amount of data is required. Definitely collecting of these data is not an easy job and cannot be collected from one source. Most of the economic and technical data are collected from Pars khodro. Environmental data (emission) are collected from GaBi. GaBi is chosen because of its capability to model products and systems from a life cycle viewpoint. Inputs for this case study include material and energy and outputs are emissions.

6.4 **Base case scenario**

The baseline scenario is defined as three dimensional points of view of a painting process which include:

- The economic life cycle (NPV)
- The environmental life cycle (emissions, waste)
- The technical lifecycle (efficiency, paint job)

Size of the problem and available information are control factors for selection of the process models but limited to primer, base coat and clear coat painting processes. Table 6-3 summarizes the basic conditions required to compare automotive painting systems. The goal of optimization in three areas (technology, economy, and environment) for the automotive coating systems is to investigate the changes in holistic optimum. This optimisation allows the decision makers to develop new potential painting systems to be analysed and interpreted. Table 6-4 present basic data associated with each candidate technology.

Table 6-3 Basic conditions required for comparing automotive coating systems

Subject	Condition
Goal	• evaluate current automotive painting systems and possible coating systems in multi-dimensional conditions, when priorities criteria is possible to select prospective technology • capacity planning, when there is a possibility to add another or several coating line to the current coating line
Dimensions	• technology: efficiency of each component, relation of each machine with each other, line arrangement, compatibility of systems components • environmental: primary energy, VOC emission • economic: machinery cost, resource and material cost

Table 6-4 Technologies' basic data

Operation	Technology	Capacity Unit (Cars/Year)[1]	Price of Capacity Unit[1]	Running Cost (Per car)[1]				Maintenance Cost (Per Year)[1]	Environmental Impact (g Per m^2)	Technical Fault
				Materials	Labour	Energy[1,2]	Rework (%)			
Primer	**Solvent Base**	**190000**	**120,000,000,000**	162203	9473	63175	0.15	**4,500,000,000**	**12**	23
	Water Base	**150000**	**160,000,000,000**	170313	7200	72651	0.17	**8,000,000,000**	**9**	25
	Powder Primer	**100000**	**130,000,000,000**	202754	10800	5300	0.9	**6,500,000,000**	**1**	25
Base Coat	**Water Base**	**190000**	**300,000,000,000**	283856	3789	84736	0.20	**15,000,000,000**	**14**	18
	Solvent Base	**190,000**	**569,373,688,000**	892120	3789	73684	0.34	**28,500,000,000**	**24**	16
	Solvent Base with booth air abatement	**190,000**	**569,340,725,000**	770466	5684	79600	0.37	**28,462,000,000**	**28.8**	20
Clear Coat	**Water Base**	**150,000**	**599,000,000,000**	1038104	4800	66580	0.12	**29,950,000,000**	**8**	19
	Powder slurry	**100,000**	**419,538,507,000**	999174	10800	54000	0.15	**20,976,900,000**	**1**	15
	Powder	**100,000**	**323,538,507,000**	5677130	10800	52105	0.18	**16,276,900,000**	**1**	15
	Solvent Base with booth air	**190,000**	**299,670,362,000**	425784	5684	57895	0.15	**10,500,000,000**	**10**	18

[1]Personal communication, Pars Khodroo Iran, 2015
[2]GaBi 2015

6.4.1 Technical dimension

In order to make all systems comparable, all the systems under evaluation must be based on similar conditions.

Table 6-5 Basic technical data for car painting (Pars khodro, 2015)

Description	Unit	Value
Production time	H/day	16
Working day	Per year	250
Oven time	Hr/day	20
Car weight	kg	300
Coating surface	m^2	25

6.4.2 Environmental dimension

For investigating environmental dimension relevant energy usage, material flow and VOCs emission is needed. Table 6-6 shows energy consumption, material used, and VOC emission for Pars khodro Painting process, which is solvent based.

Table 6-6 Basic environmental data for Pars khodro coting system

Description		Unit	Value
Primary energy (per 1kg)	Primer	MJ	1.902
	Basecoat		3.29
	Clear coat		2.839903727
Material	Primer	Lit(per car)	1.5
	Basecoat		2.89
	Clear coat		10
VOC emission	Primer	g/m^2	12
	Basecoat		24
	Clear coat		10

6.4.3 Economic dimension

The other dimension of this study is economic dimension, which its data are fundamental of Net Present Value (NPV) and cost optimisation model. These data include:

- Capital cost (cc): purchase cost
- Running cost (rc): including materials, labour, energy, rework, maintenance

These costs should be discounted over the life of technology and transformed into present value.

6.4.4 Criteria weights and general data

Criteria weights, as set by the management, as well as general data are presented in Table 6-7.

Table 6-7 Criteria weights and general data

Criteria	Economic	Environment	Technical
Weight	4	2	1

Capital Budget Limit	Emission Limit (g/m^2)	Rate of Return (RoR)	Life-Cycle Period (Years)
£2.6b	45	11%	20

Cost Items	Materials	Labour	Energy	Maintenance
Rate of Inflation (ri)	11%	20%	20%	15%

Operation	1	2	3
Demand	250k	300k	400k

6.5 Problem structuring (ontology)

In order to define and give our problem structure ontology is developed. Ontology is used to promote capture of design knowledge and reusing the knowledge design selection. Ontology in this research is developed to locate the proper information and the relationships between each operation and technologies to offer users a compatible combination.

The aim of using ontology is to formalize domain of knowledge in a generic way and develop a common understanding of a domain that can be shared and used by users (Chang, et al., 2008). Ontology compered to with data bases is more flexible and skilled to capture and manage knowledge about concepts and their relationship (Horridge, et al., 2011).

The ontology presented here can be used to capture manufacturing aspects of different coating methods of automotive and their relations along with how they can be compatible with each other in addition to their limitations. This ontology is used as central ontology. In the following sections, ontology's hierarchy, important classes and their relations are described.

6.5.1 Ontology hierarchy and important classes

Protégé is used as a tool to develop ontology. The hierarchy of the ontology classes is shown in Figure 6-4.

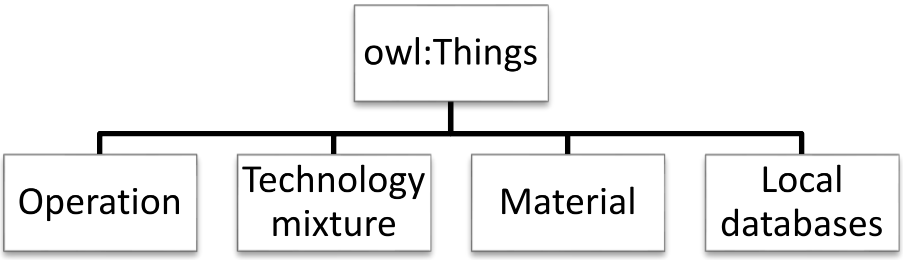


Figure 6-3 Hierarchy of the ontology

The operation class is consisted of available technologies which exist for three main operations of coating:

- Primer
- Base coat
- Clear coat

Each of these classes is divided into their subclasses in the ontology model. Figure 6-5 shows the representation method to categorize the concepts.

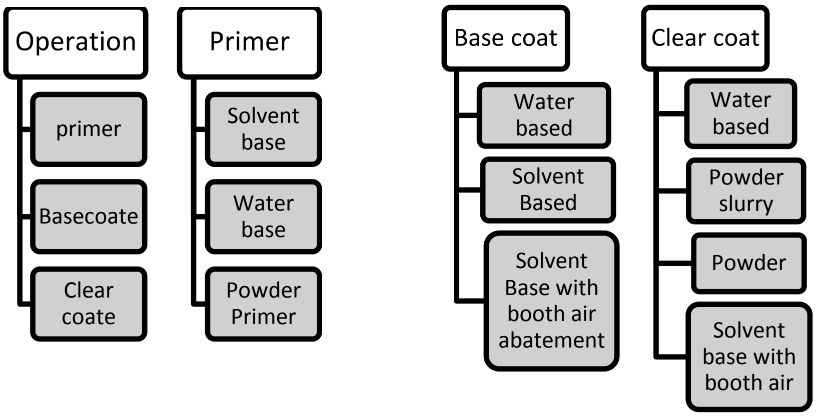


Figure 6-4 Hierarchy classification of technologies in painting ontology

Technology mixture class is classified into combination of coating technologies that exist or the combination of them is possible. There are 17 possible coating systems in this ontology. This class is made after each combination is created in the form of individual.

Material class is consisted of different material used for each technology.

Figure 6-7 shows classes in the automotive coating Process.

Energy consumption cost per painting a car, environmental impact (VOC amount produced per car), technology cost, material cost per each car for each technology are defined by data type properties for each individual. "Datatype properties describe relationships between an individual and data values" (Horridge, 2004).

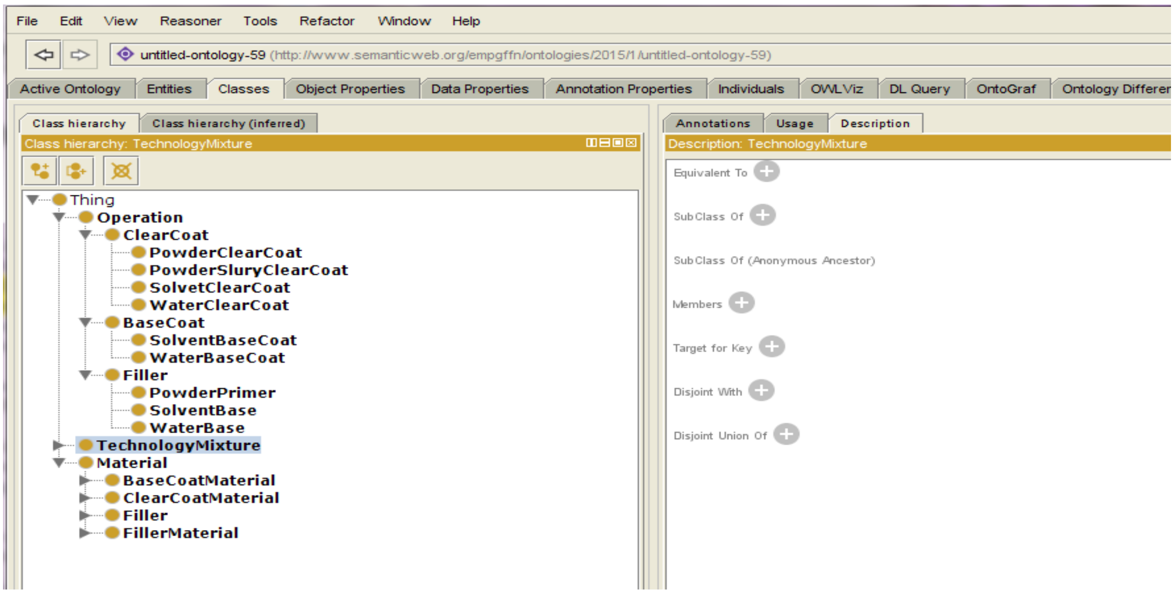


Figure 6-5 Classes of the automotive coating ontology

Figure 6-7 shows technologies mixture and their relationships with operations which are linked together. By clicking on each line with the object properties that linked the classes are shown. For instance, in Figure 6.7 technology 1&2 are expanded to demonstrate its operations, and on the object property line is clicked to show the relationship types.

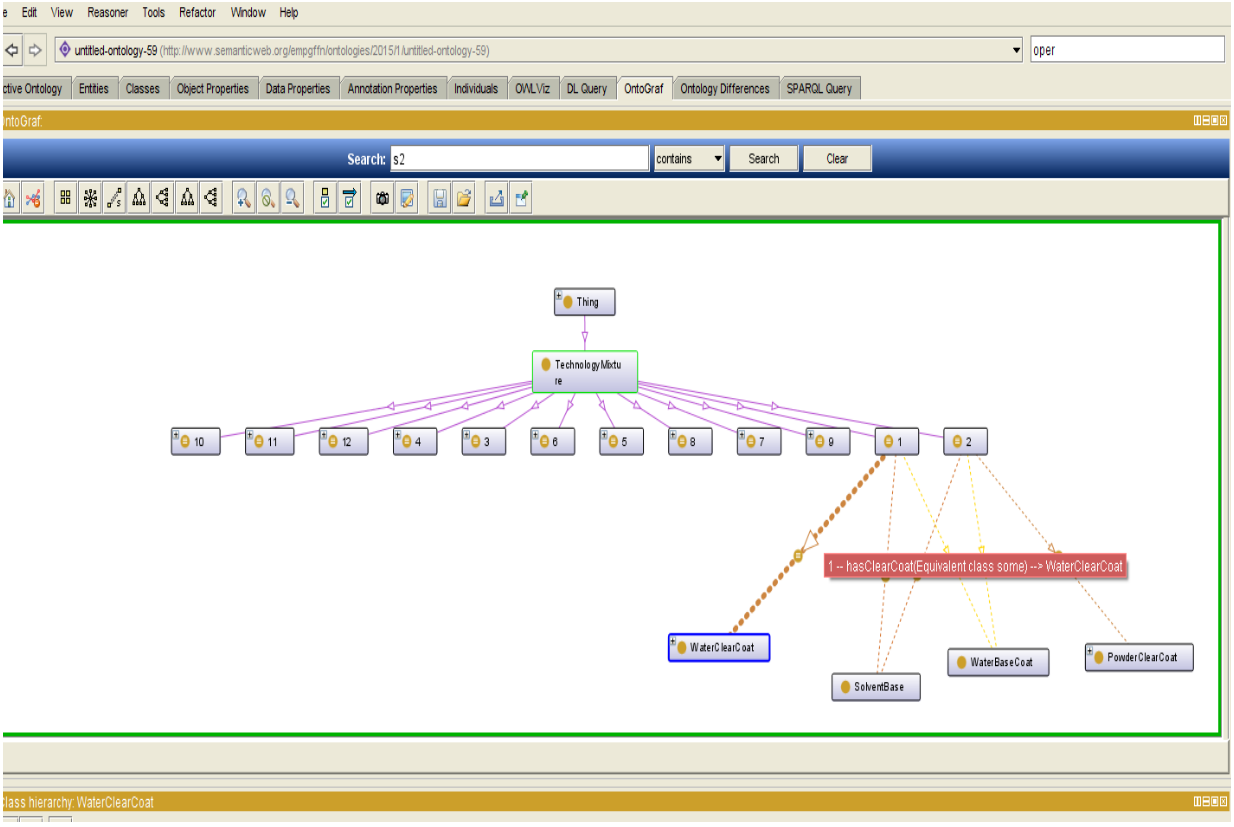


Figure 6-6 Schematic view of the automotive paint shop ontology

6.6 Normalisation

Normalisation is necessary in order to give different standards of the optimisation factors a comparable value.

All the three criteria mentioned above, environmental, technical and economic, require normalisation in order to enable a conversion to single-criteria Linear Programming model. Normalisation takes the range [0, 1] for all the criteria with 1 being the highest score. Table 6.8 includes the technologies' normalised measures.

The cost optimisation model was developed, as presented in table 6-8, and was run using What'sBest software. The minimum total cost was obtained as 14,700,036,966. This figure is used for the purpose of the normalising economic measure in the main model.

Table 6-8 Technologies' normalised measures

Operation	Normalised Economic Measure (NC_{ij})	Normalised Environmental Impact Measure (NE_{ij})	Normalised Technical Measure (NT_{ij})
1	-0.03	-1.85	0.93558744
2		1.00	0.875
3		1.00	0.99999887

6.7 Mathematical model

The main mathematical model is developed, as presented in Appendix C and was run using What's Best software. The main model results are presented in table 6-9.

6.8 Sensitivity analysis

Five key parameters and three different values per parameter were chosen to test the sensitivity analysis algorithm. The list of key parameters and their value ranges are presented in Table 6-10.

Table 6-9 Main model results

Operation	Technology	Production Mix	No. of Technology Units
Primer	SB	150,000	1
	WB	1	0
	Powder	100,000	1
Base Coat	WB	300,000	2
	SB	0	0
	SB with booth air abatement	0	0
Clear Coat	WB	0	0
	Powder Slurry	400,000	4
	Powder	0	0
	SB with booth air abatement	0	0

Table 6-10 Key parameters and their range of values

Key Parameter	Range of Values
Budget Limit	23b, 26b, 29b
Economic Weight	3, 4, 5
Demand 1	230k, 250k, 270k
Demand 2	280k, 300k, 320k
Demand 3	380k, 400k, 420k

The number of all combinations of various parameter values work out as 243 (= 3 ×3×3×3×3). The full results of the intensive sensitivity analysis are shown in Appendix E.

Pre-processing: Base Coat operation was removed fully, because there is a clear pattern that is technology ‘Water Base’ is the best option in all conditions. Also, Powder technology at Primer operation was removed, because its capacity can be identified from the other two technologies. As for Clear Coat operation, a clear pattern is that the technology Solvent Base with booth air is not selected at any condition. Finally, Powder technology on the Clear Coat operation was removed, because its capacity can be identified from the other two technologies.

Unsupervised learning was conducted using DBSCAN method with parameters set at Epsilon=0.3 and MinPoint=2 and was implemented in the Weka software tool. One to two technology options of each operation were removed. Eighteen clusters (or patterns) were recognised and a unique cluster number was allocated to each cluster. There are three examples that were not clustered. The results of clustering are shown in Appendix D.

Supervised learning was conducted using C4.5 algorithm with parameter values ‘Min. number of instances per leaf’ set at 3 and 4 and was implemented in Weka software tool, as shown in Figures 6-7 and 6-8. The quality of generated decision trees is demonstrated in Table 6-13 based on two measures, namely ‘Tree Size’ and ‘incorrectly classified instances’.

What can be implied from both trees is that:

1. The first tree which is bigger with 67 nodes, represent 90.5% correct inference. The second tree represents 80% correctness. So if the correctness threshold is set on 75%, then second tree is acceptable too.
2. Technology 2 of operation 1, technology 2 and 3 of operation 2, technology 1 of operation 3 and technology 4 of operation 3 are subjected by the other technologies any are not selected.
3. the descending order of parameters with regard to the sensitivity on the final results is ‘Demand 3’, ‘Demand 1 and Budget Limit’, and ‘Economic Weight and ‘Demand 2’.

Table 6-11 The quality of two generated decision trees

Min. number of instances per leaf	Tree size(No. of nodes)	Incorrectly Classified Instances
3	67	9.5%
4	41	20%

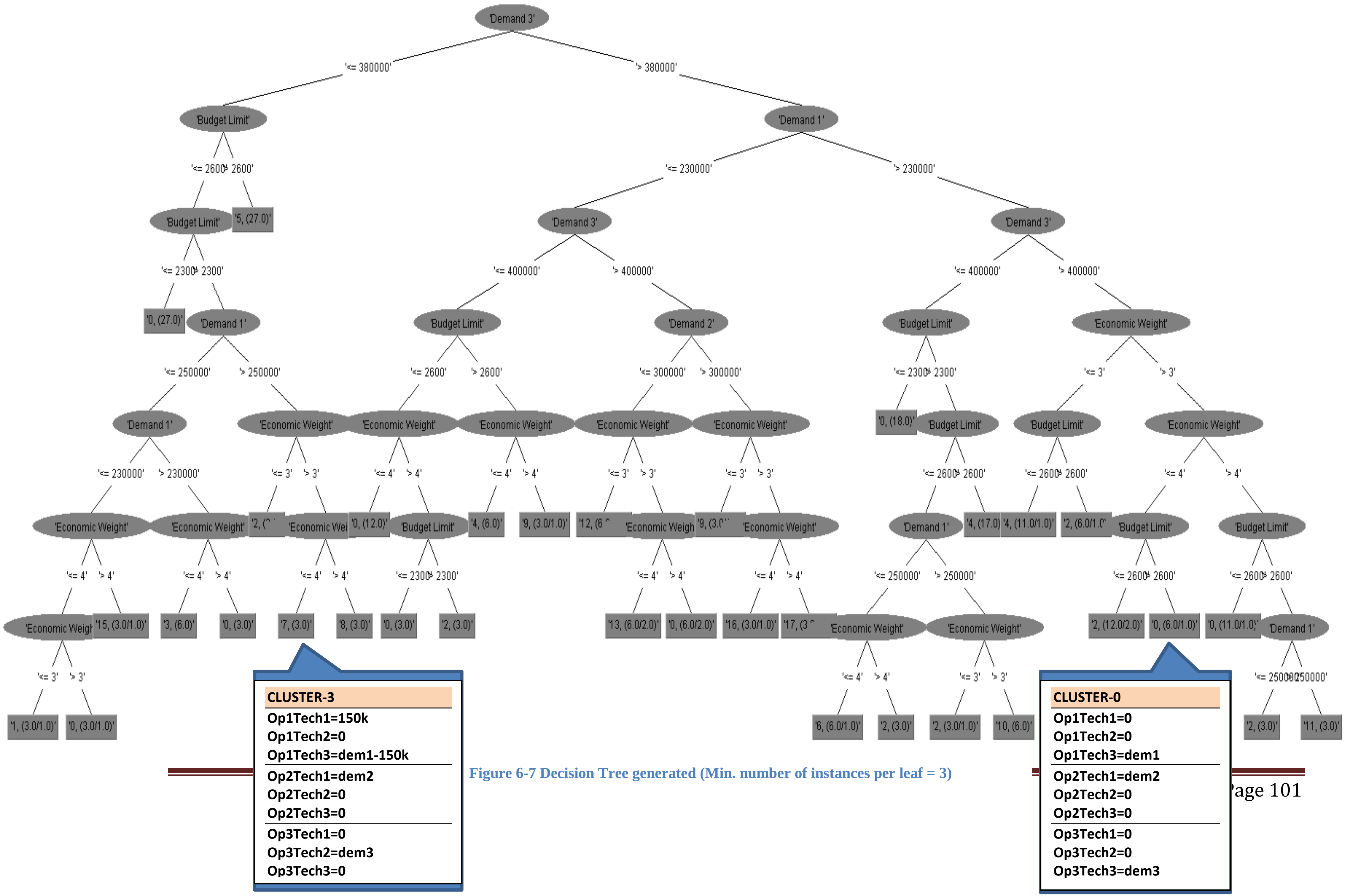


Figure 6-7 Decision Tree generated (Min. number of instances per leaf = 3)

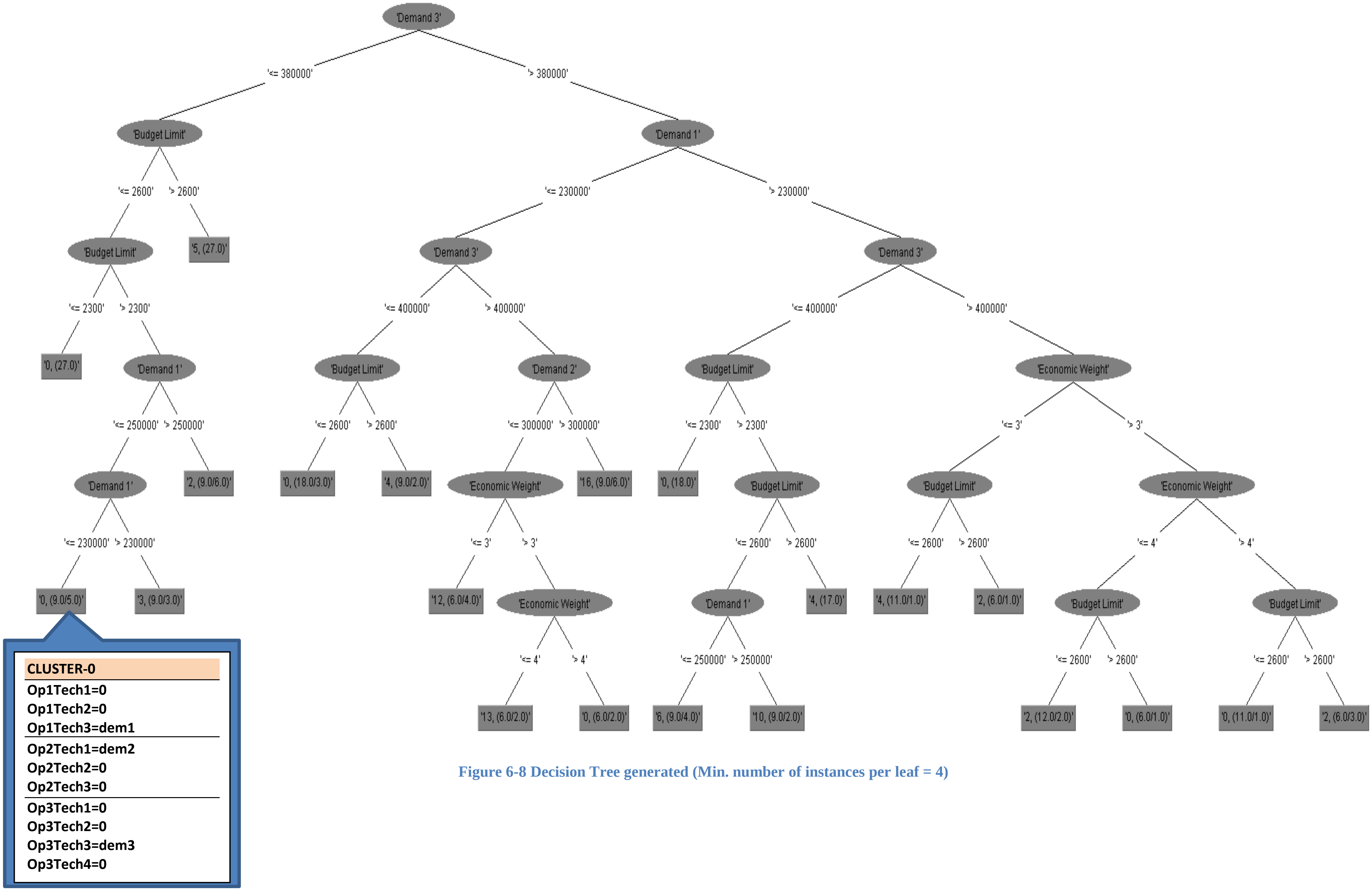


Figure 6-8 Decision Tree generated (Min. number of instances per leaf = 4)

6.9 Interactive slider diagram representation

Figure 6.10 and 6.11 show interactive slider diagram, which is developed in excel platform. The slider diagram demonstrates the model results against the input values. The Interactive slider diagram's inputs are Budget limit, Economic weight, and Demands 1, 2 and 3. The out puts are total costs of each technology.

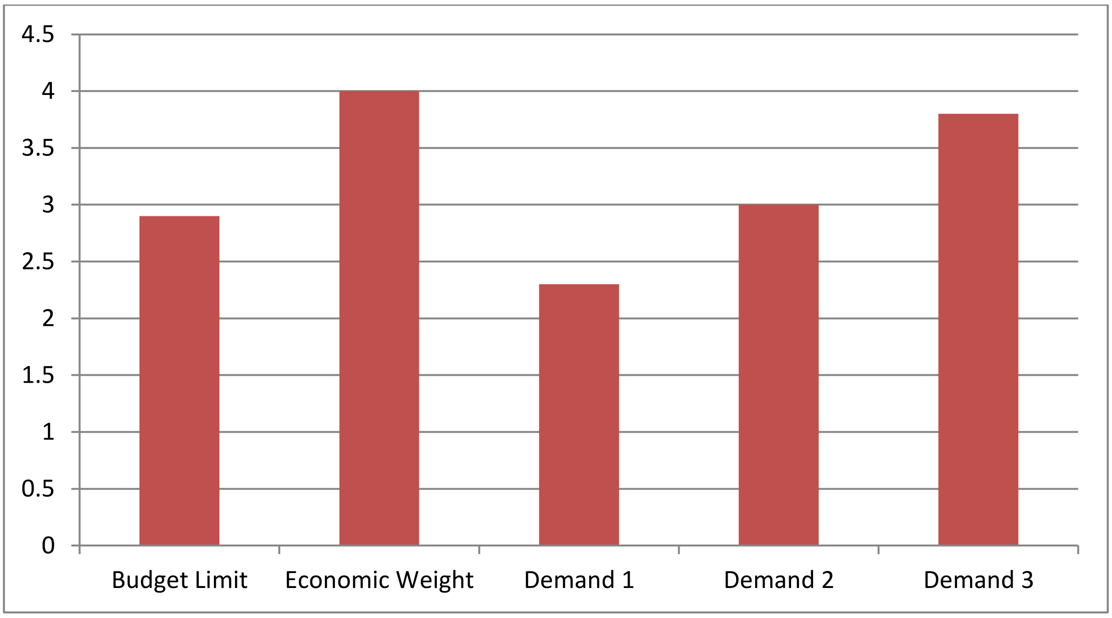


Figure 6-9 Input interactive slider diagram

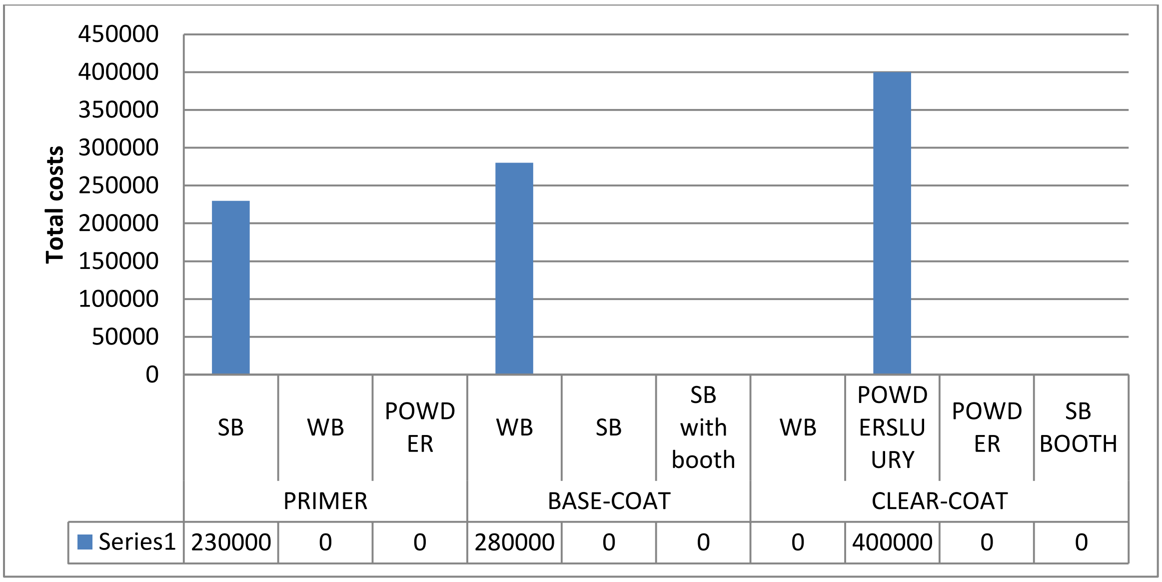


Figure 6-10 Output interactive slider diagram

6.10 **Conclusion**

In this chapter, the automotive coating technologies are implemented as a case study by methodology to validate the methodology in real environment. Ontology is used to give structure and shows available alternatives. Normalisation is done to facilitate the case study a systematic comparison among various criteria. The mathematical model is developed to solve the integrated technology selection and capacity planning based on the demand in Appendix C. Results are provided in table 6.9. Based on the results 1 unit of Solvent Base and 1 unit of Powder Base technology of Primer operation is needed to meet the demand. 2 units of Water Base technology for Base Coat operation is needed and 4 units of Powder Slurry technology for Clear Coat operation is required. Sensitivity analysis is done for five key parameters and three different values per parameter. Based on the sensitivity analysis results clustering is conducted using DBSCAN methods and then unsupervised learning was done by C4.5 algorithm. At the end the developed interactive slider diagram is used as an alternative way to represent sensitivity analysis results.

Chapter 7 **Conclusions and Recommendations for Future Work**

Achieving sustainability in manufacturing needs a general view that spans not only the product, but also the manufacturing process. Therefore process design and particularly the technology selection are playing an important role in the realisation of a sustainable manufacturing. This research focused on the development of a novel methodology based on mathematical programming for sustainable technology selection and capacity planning simultaneously, and designing a set of algorithms based on machine learning for solution structuring under uncertainty.

7.1 **Fulfilment of the project objectives**

As outlined in the Introduction chapter, there were four fundamental objectives in this research to be met, namely:

- *Develop a research framework for technology selection and capacity planning*
  This objective is covered by chapters three and four, where a general architecture of the methodology, an integrated mathematical programming method as well as all the proposed algorithms are developed and explained.
- *Develop a Mixed Integer-Linear Goal programing model for technology selection and capacity planning*
  This objective is covered by chapter four, where two mathematical models are developed. The main model use Goal Mixed Integer/Linear Programming to solve ‘Technology Selection’ and ‘Capacity Planning’ problems. The auxiliary model is used to find the economic criteria goal for normalisation. A linear programming model is developed for this purpose.
- *Conduct sensitivity analysis to deal with uncertainty*
  Sensitivity analysis is conducted through a tool coded in Visual Basic for Applications (VBA),inorder to address the uncertainty elements of the problem in chapter four.
- *Validate the developed methodology in an appropriate manufacturing setting*

This objective is met This objective is met through a case study in chapter six where the proposed methodology is tested and validated based in an automotive company painting process. The case is characterised by three operations, twelve possible technology mix states, both capital budget and environmental limits, and 243 different sensitivity analysis experiments.

7.2 Conclusions and research contribution

No previous studies were found in the literature that looks at an integrated supplier selection and capacity planning functions with an aim to achieve sustainable manufacturing under uncertainty. This research achieved the development a comprehensive methodology to address such a very complicated problem and provided its validation through a case study in the automotive industry. The methodology has broad applications and is not limited in terms of the type of manufacturing industry.

Significant contributions this research has been able to extend to the body of knowledge are as follows:

a) The design of a novel research architecture consisting of four modules in ten different major steps that work together to solve the problem addressed.
b) The development of an integrated mathematical model using Mixed Integer, Goal Programming method to solve both ‘Technology Selection’ and ‘Capacity Planning’ functions simultaneously in a manufacturing setting with a multi-criteria perspective of sustainability. The model incorporates a number of original capabilities that deal with multi-operational settings, technological incompatibilities, and technology unit calculations.
c) The development of an innovative way to carry out solution structuring consisting of a suit of algorithms based on Machine Learning approach in general, and a combination of ‘Unsupervised Learning’ and ‘Supervised Learning’ methods in particular. This will result in a decision tree structure of the solution sets.

7.3 Limitations

While this research makes any efforts to address complexities of the real world, such as decision making under multi-criteria and uncertain circumstances, no research can offer an all-inclusive methodology. This research is no exception, hence the following limitations apply:

- The proposed methodology does not take the pre-installed technologies into account when these technologies are to work alongside the new selected technologies.
- The ontology component is working on an off-line mode in connection with the main model.

7.4 Recommendation for future work

Some avenues for further research are suggested in line with the achievements made in this research, as follows:

1. To integrate the ontology component into the optimisation model, in a way that these two parts of the whole system could communicate automatically. One potential outcome of such integration is that the incompatibility of technologies could be evaluated through ontology.
2. From practical implementation point of view, the methodology can be converted into integrated software with a user friendly interface, which can be shared through technology suppliers to get exact information and give reliable decision solution to the user.
3. The methodology which is developed in this research is implemented in the process design stage of manufacturing phase of Life Cycle Assessment. This model has the ability to be implemented in the recycling /reuse phase of the LCA as well, with more research about recycling, adjusting the parameters, and adding or removing some parameters based on the nature of reuse or recycling concept.
4. Report research feedback to the automotive company and make the model more tangible according to the available market criteria or requirements.

7.5 Overall benefits of the research outcome

The outcome of the research is a unique method to integrate decisions for technology selection and capacity planning. This method covers technology selection and capacity planning together, while the other methods are designed just for only technology selection or capacity planning. In addition the designed framework has the ability to deal with sustainability issues such as economic and environmental. Moreover uncertainty is considered in the developed method. All these aspects of the developed method make this research a novel approach for designing or optimisation of a manufacturing system.

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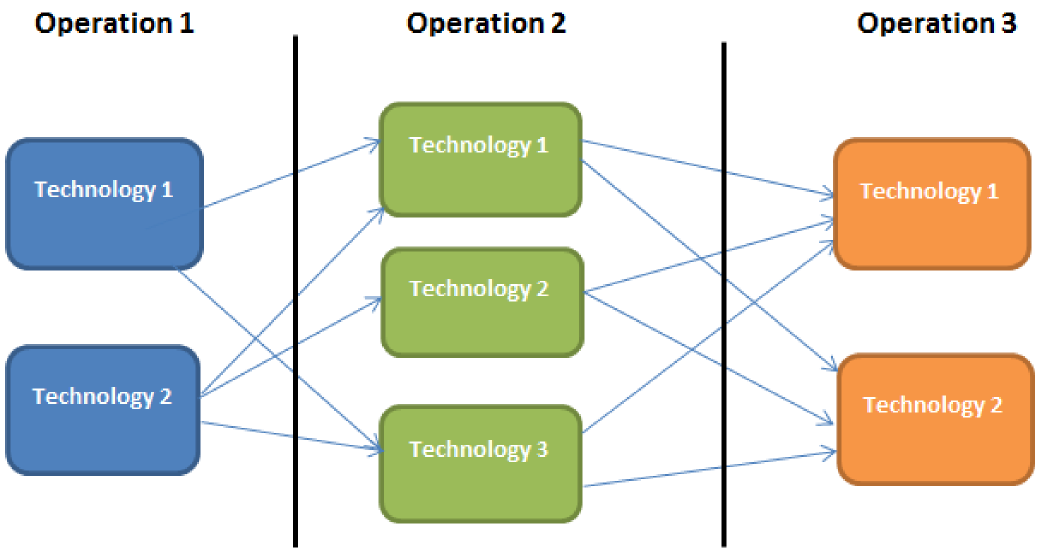
Appendix A: Illustrative example for development of a mixed integer-linear goal programming

A small illustrative example is presented to elaborate on the development of a) the cost optimisation model, b) the main model, and c) sensitivity analysis.

System composition

The example includes three sequential operations, each of which can be performed with a number of candidate technologies, as depicted below.



An exemplary system composition of operations and candidate technologies

Technological constraint:

As it can be seen from the diagram above, technology 1 of operation 1 and technology 2 of operation 2 are incompatible and cannot be adopted together.

Criteria weights and general data:

Criteria weights, as set by the management, base on the management preference and government ruls. General data are presented below as well.

Criteria	Economic	Environment	Technical
Weight	4	2	1

Capital Budget Limit	Emission Limit (Units per Year)	Rate of Return (rr)	Life-Cycle Period (Years)
£27m	70m	11%	20

Cost Items	Materials	Labour	Energy	Maintenance
Rate of Inflation (ri)	+4%	+3%	+3%	+5%

Operation	1	2	3
Demand	200k	200k	300k

Technology basic data:

Following tables present basic data associated with each candidate technology and technologies' normalised measures.

Technologies' basic data

Operation	Technology	Capacity Unit (Cars/Year)	Price of Capacity Unit	Running Cost (Per car)				Maintenance Cost (Per Year)	Environmental Impact (Units Per Car)	Technical Faults [0,1]
				Materials	Labour	Energy	Rework (%)			
1	1	50,000	2,200,000	5	2	1	5%	25,000	95	0.8
	2	70,000	1,800,000	3	1	5	6%	30,000	91	0.85
2	1	60,000	2,300,000	2	2	6	5%	25,000	95	0.7
	2	80,000	3,000,000	4	2	5	5%	30,000	85	0.8
	3	90,000	3,200,000	8	16	6	7%	35,000	80	0.9
3	1	110,000	3,300,000	3	10	5	6%	40,000	87	0.85
	2	120,000	3,500,000	9.5	10	9	3%	50,000	76	0.92

Technologies' normalised measures

Operation	Normalised Economic Measure (NC_{ij})	Normalised Environmental Impact Measure (NE_{ij})	Normalised Technical Measure (NT_{ij})
1	1.0	0.96	1
2		0.86	0.94
3		0.86	1

Cost optimisation model

Decision Variables	x_{ij}: **Capacity volume required for technology j of operation i;** y_{ij}: **Number of units required for technology j of operation i;**
Objective Function	$\boldsymbol{Minimise\ tc = \sum_i \sum_j PV_{ij}}$
Technology Unit Constraints	$\frac{x_{11}-1}{50000} \leq y_{11}$ $\quad \frac{x_{21}-1}{70000} \leq y_{21}$ $\frac{x_{12}-1}{60000} \leq y_{12}$ $\quad \frac{x_{22}-1}{80000} \leq y_{22}$ $\quad \frac{x_{32}-1}{90000} \leq y_{32}$ $\frac{x_{31}-1}{110000} \leq y_{31}$ $\quad \frac{x_{32}-1}{120000} \leq y_{32}$
Demand Constraints	$x_{11} + x_{12} = 200000$ $x_{21} + x_{22} + x_{23} = 200000$ $x_{31} + x_{32} = 300000$
Capital Budget Limit Constraint	$(2,200,000 \times y_{11} + 1,800,000 \times y_{12} + 2,300,000 \times y_{21} + 3,000,000 \times y_{22} + 3,200,000 \times y_{23} + 3,300,000 \times y_{31} + 3,500,000 \times y_{32}) \leq 27,000,000$
Technological Incompatibility Constraints	$y_{11} \times y_{22} = 0$
Variable Constraints	$x_{ij} \geq 0 \quad \forall\, i,j$ $y_{ij} \geq 0 \quad \forall\, i,j$ $y_{ij}: Integer \quad \forall\, i,j$

Where

$$PV_{11} = \mathbf{2,200,000} \times \boldsymbol{y_{11}} + \left[\mathbf{5} \times \boldsymbol{x_{11}} \times (\mathbf{1} + \mathbf{0.05}) \times \frac{\mathbf{1.04}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.04}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.04}}{\mathbf{1.11}}}\right)\right] + \left[\mathbf{2} \times \boldsymbol{x_{11}} \times (\mathbf{1} + \mathbf{0.05}) \times \frac{\mathbf{1.03}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.03}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.03}}{\mathbf{1.11}}}\right)\right] + \left[\mathbf{1} \times \boldsymbol{x_{11}} \times (\mathbf{1} + \mathbf{0.05}) \times \frac{\mathbf{1.03}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.03}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.03}}{\mathbf{1.11}}}\right)\right] + \left[\mathbf{25000} \times \boldsymbol{y_{11}} \times \frac{\mathbf{1.05}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.05}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.05}}{\mathbf{1.11}}}\right)\right]$$

$$PV_{12} = \mathbf{1,800,000} \times \boldsymbol{y_{12}} + \left[\mathbf{3} \times \boldsymbol{x_{12}} \times (\mathbf{1} + \mathbf{0.06}) \times \frac{\mathbf{1.04}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.04}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.04}}{\mathbf{1.11}}}\right)\right] + \left[\mathbf{1} \times \boldsymbol{x_{12}} \times (\mathbf{1} + \mathbf{0.06}) \times \frac{\mathbf{1.03}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.03}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.03}}{\mathbf{1.11}}}\right)\right] + \left[\mathbf{5} \times \boldsymbol{x_{12}} \times (\mathbf{1} + \mathbf{0.06}) \times \frac{\mathbf{1.03}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.03}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.03}}{\mathbf{1.11}}}\right)\right] + \left[\mathbf{30000} \times \boldsymbol{y_{12}} \times \frac{\mathbf{1.05}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.05}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.05}}{\mathbf{1.11}}}\right)\right]$$

$$PV_{21} = \mathbf{2,300,000} \times \boldsymbol{y_{21}} + \left[\mathbf{2} \times \boldsymbol{x_{21}} \times (\mathbf{1} + \mathbf{0.05}) \times \frac{\mathbf{1.04}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.04}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.04}}{\mathbf{1.11}}}\right)\right] + \left[\mathbf{2} \times \boldsymbol{x_{21}} \times (\mathbf{1} + \mathbf{0.05}) \times \frac{\mathbf{1.03}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.03}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.03}}{\mathbf{1.11}}}\right)\right] + \left[\mathbf{6} \times \boldsymbol{x_{21}} \times (\mathbf{1} + \mathbf{0.05}) \times \frac{\mathbf{1.03}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.03}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.03}}{\mathbf{1.11}}}\right)\right] + \left[\mathbf{25000} \times \boldsymbol{y_{21}} \times \frac{\mathbf{1.05}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.05}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.05}}{\mathbf{1.11}}}\right)\right]$$

$$PV_{22} = \mathbf{3,000,000} \times \boldsymbol{y_{22}} + \left[\mathbf{4} \times \boldsymbol{x_{22}} \times (\mathbf{1} + \mathbf{0.05}) \times \frac{\mathbf{1.04}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.04}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.04}}{\mathbf{1.11}}}\right)\right] + \left[\mathbf{2} \times \boldsymbol{x_{22}} \times (\mathbf{1} + \mathbf{0.05}) \times \frac{\mathbf{1.03}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.03}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.03}}{\mathbf{1.11}}}\right)\right]$$
$$+ \left[\mathbf{5} \times \boldsymbol{x_{22}} \times (\mathbf{1} + \mathbf{0.05}) \times \frac{\mathbf{1.03}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.03}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.03}}{\mathbf{1.11}}}\right)\right] + \left[\mathbf{30000} \times \boldsymbol{y_{22}} \times \frac{\mathbf{1.05}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.05}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.05}}{\mathbf{1.11}}}\right)\right]$$

$$PV_{23} = \mathbf{3,200,000} \times \boldsymbol{y_{23}} + \left[\mathbf{8} \times \boldsymbol{x_{23}} \times (\mathbf{1} + \mathbf{0.07}) \times \frac{\mathbf{1.04}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.04}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.04}}{\mathbf{1.11}}}\right)\right] + \left[\mathbf{16} \times \boldsymbol{x_{23}} \times (\mathbf{1} + \mathbf{0.07}) \times \frac{\mathbf{1.03}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.03}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.03}}{\mathbf{1.11}}}\right)\right]$$
$$+ \left[\mathbf{6} \times \boldsymbol{x_{23}} \times (\mathbf{1} + \mathbf{0.07}) \times \frac{\mathbf{1.03}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.03}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.03}}{\mathbf{1.11}}}\right)\right] + \left[\mathbf{35000} \times \boldsymbol{y_{23}} \times \frac{\mathbf{1.05}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.05}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.05}}{\mathbf{1.11}}}\right)\right]$$

$$PV_{31} = \mathbf{3,300,000} \times \boldsymbol{y_{31}} + \left[\mathbf{3} \times \boldsymbol{x_{31}} \times (\mathbf{1} + \mathbf{0.06}) \times \frac{\mathbf{1.04}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.04}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.04}}{\mathbf{1.11}}}\right)\right] + \left[\mathbf{10} \times \boldsymbol{x_{31}} \times (\mathbf{1} + \mathbf{0.06}) \times \frac{\mathbf{1.03}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.03}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.03}}{\mathbf{1.11}}}\right)\right]$$
$$+ \left[\mathbf{5} \times \boldsymbol{x_{31}} \times (\mathbf{1} + \mathbf{0.06}) \times \frac{\mathbf{1.03}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.03}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.03}}{\mathbf{1.11}}}\right)\right] + \left[\mathbf{40000} \times \boldsymbol{y_{31}} \times \frac{\mathbf{1.05}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.05}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.05}}{\mathbf{1.11}}}\right)\right]$$

$$PV_{32} = \mathbf{3,500,000} \times \boldsymbol{y_{32}} + \left[\mathbf{9.5} \times \boldsymbol{x_{32}} \times (\mathbf{1} + \mathbf{0.03}) \times \frac{\mathbf{1.04}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.04}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.04}}{\mathbf{1.11}}}\right)\right]$$
$$+ \left[\mathbf{10} \times \boldsymbol{x_{32}} \times (\mathbf{1} + \mathbf{0.03}) \times \frac{\mathbf{1.03}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.03}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.03}}{\mathbf{1.11}}}\right)\right] + \left[\mathbf{9} \times \boldsymbol{x_{32}} \times (\mathbf{1} + \mathbf{0.03}) \times \frac{\mathbf{1.03}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.03}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.03}}{\mathbf{1.11}}}\right)\right]$$
$$+ \left[\mathbf{50000} \times \boldsymbol{y_{32}} \times \frac{\mathbf{1.05}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.05}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.05}}{\mathbf{1.11}}}\right)\right]$$

Main model

Decision Variables	$\boldsymbol{x_{ij}}$: **Capacity volume required for technology $\boldsymbol{j}$ of operation $\boldsymbol{i}$;** $\boldsymbol{y_{ij}}$: **Number of units required for technology $\boldsymbol{j}$ of operation $\boldsymbol{i}$;** $\boldsymbol{d_c}$: **Deviation from goal on economic criteria** $\boldsymbol{d_{ie}}$: **Deviation from goal on environmental impacts criteria with regards to the $\boldsymbol{i}$th operation** $\boldsymbol{i = 1, \ldots, 3}$ $\boldsymbol{d_{it}}$: **Deviation from goal on technical (quality) criteria with regards to the $\boldsymbol{i}$th operation** $\boldsymbol{i = 1, \ldots, 3}$
Objective Function	$\boldsymbol{Minimise\ f(d) = (3 \times 4 \times d_c + 2 \times (d_{1e} + d_{2e} + d_{3e}) + 1 \times (d_{1t} + d_{2t} + d_{3t})}$,

Technical Goal Constraints	$\left(1-\frac{0.8x_{11}+0.85x_{12}-(200,000\times 0.8)}{(200,000\times 0.8)}\right)+d_{1t}=1$ $\left(1-\frac{0.7x_{21}+0.8x_{22}+0.9x_{23}-(200,000\times 0.7)}{(200,000\times 0.7)}\right)+d_{2t}=1$ $\left(1-\frac{0.85x_{31}+0.92x_{32}-(300,000\times 0.85)}{(300,000\times 0.85)}\right)+d_{3t}=1$
Environment Goal Constraints	$\left(1-\frac{95x_{11}+91x_{12}-(200,000\times 91)}{(200,000\times 91)}\right)+d_{1e}=1$ $\left(1-\frac{95x_{21}+85x_{22}+80x_{23}-(200,000\times 80)}{(200,000\times 80)}\right)+d_{2e}=1$ $\left(1-\frac{87x_{31}+76x_{32}-(300,000\times 76)}{(300,000\times 76)}\right)+d_{3e}=1$
Economic Goal Constraint	$\left(1-\frac{\sum_i\sum_j PV_{ij}-310,612,604}{310,612,604}\right)+d_c=1$
Technology Unit Constraints	$\frac{x_{11}-1}{50000}\le y_{11}$ $\quad \frac{x_{21}-1}{70000}\le y_{21}$ $\frac{x_{12}-1}{60000}\le y_{12}$ $\quad \frac{x_{22}-1}{80000}\le y_{22}$ $\quad \frac{x_{32}-1}{90000}\le y_{32}$ $\frac{x_{31}-1}{110000}\le y_{31}$ $\quad \frac{x_{32}-1}{120000}\le y_{32}$

Demand Constraints	$x_{11} + x_{12} = 200000$ $x_{21} + x_{22} + x_{23} = 200000$ $x_{31} + x_{32} = 300000$
Capital Budget Limit Constraint	$(2,200,000 \times y_{11} + 1,800,000 \times y_{12} + 2,300,000 \times y_{21} + 3,000,000 \times y_{22} + 3,200,000 \times y_{23} + 3,300,000 \times y_{31} + 3,500,000 \times y_{32}) \leq 27,000,000$
Technological Incompatibility Constraints	$y_{11} \times y_{22} = 0$
Variable Constraints	$x_{ij} \geq 0 \quad \forall\, i,j$ $y_{ij} \geq 0 \quad \forall\, i,j$ $y_{ij}: Integer \quad \forall\, i,j$

Main model's result

Operation	Technology	Production Mix	No. of Capacity Units to Purchase	Purchase Cost	PV
1	1	0	0	0	0
	2	200,000	3	5,400,000	26,046,025
2	1	120,000	2	4,600,000	17,984,199
	2	80,000	1	3,000,000	12,862,093
	3	0	0	0	0
3	1	300,000	3	9,900,000	69,286,467
	2	0	0	0	0
Total				22,900,000	126,178,762
Total capital cost				£22,900,000	
Total environmental impacts (units per year)				62,500,000	

Sensitivity Analysis Results

We choose 5 key parameters and two to three different values per parameter to test our sensitivity analysis algorithm. The list of key parameters and their value ranges are presented

Key Parameter	Range of Values
Budget Limit	27m, 30m, 33m
Economic Weight	3, 4, 5
Demand 1	190k, 200k
Demand 2	190k, 200k, 210k
Demand 3	290k, 300k, 310k

The number of all combinations of various parameter values work out as 157 (=3×2×3×3×3). A sample of the intensive sensitivity analysis results consisting of 24 solution examples is shown in folloing Figure.

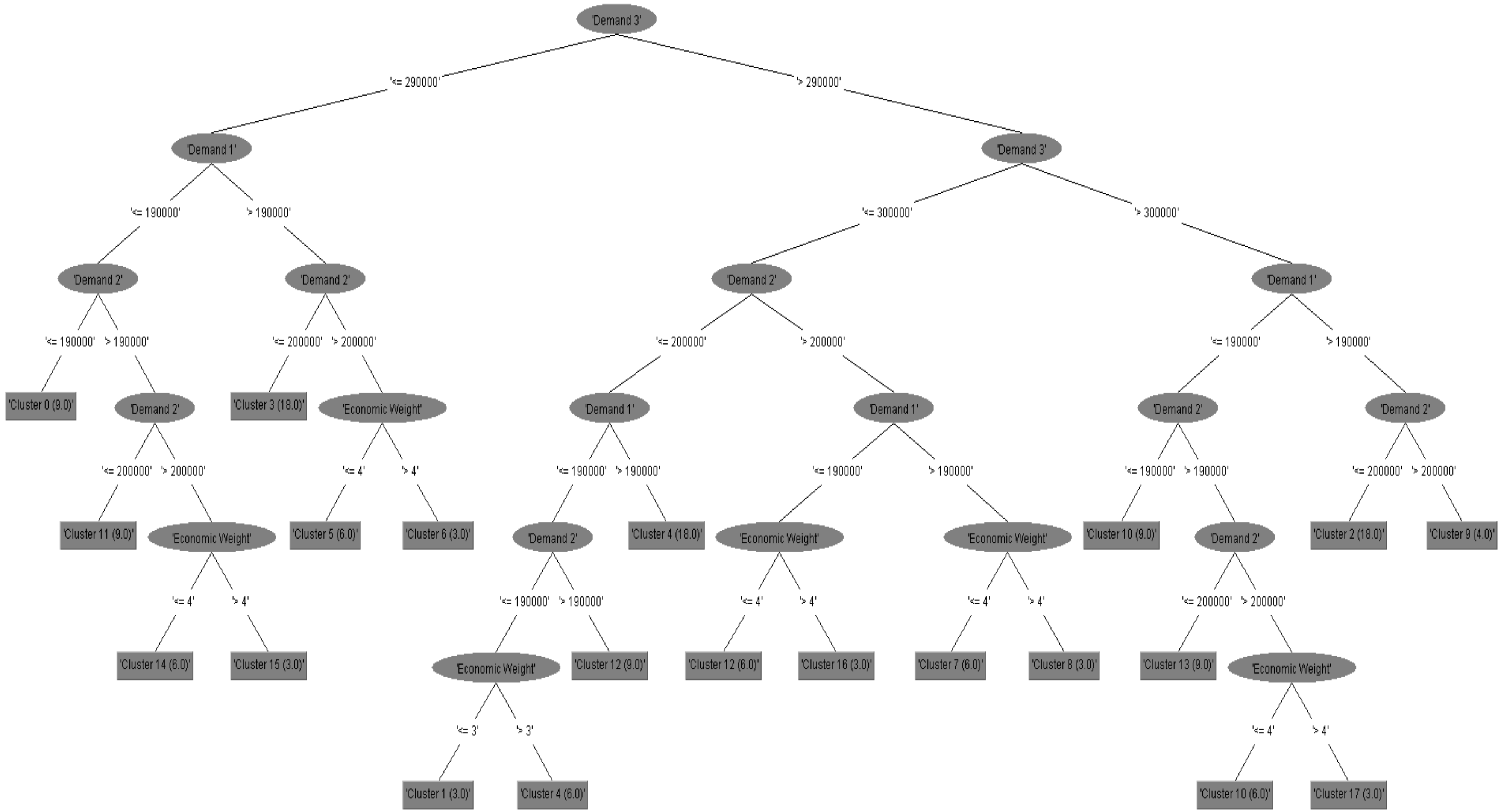
						Operation 1		Operation 2			Operation 3	
Solution no.	Budget Limit	Economic Weight	Demand 1	Demand 2	Demand 3	Tech 1	Tech 2	Tech 1	Tech 2	Tech 3	Tech 1	Tech 2
1	27000000	3	190,000	190,000	290,000	26070	163930	30000	160000	0	290000	0
2	30000000	3	190,000	190,000	290,000	26070	163930	30000	160000	0	290000	0
3	33000000	3	190,000	190,000	290,000	26070	163930	30000	160000	0	290000	0
4	27000000	4	190,000	190,000	290,000	26070	163930	30000	160000	0	290000	0
5	30000000	4	190,000	190,000	290,000	26070	163930	30000	160000	0	290000	0
6	33000000	4	190,000	190,000	290,000	26070	163930	30000	160000	0	290000	0
7	27000000	5	190,000	190,000	290,000	26070	163930	30000	160000	0	290000	0
8	30000000	5	190,000	190,000	290,000	26070	163930	30000	160000	0	290000	0
9	33000000	5	190,000	190,000	290,000	26070	163930	30000	160000	0	290000	0
10	27000000	3	190,000	190,000	300,000	50000	140000	0	190000	0	300000	0
11	30000000	3	190,000	190,000	300,000	50000	140000	0	190000	0	300000	0
12	33000000	3	190,000	190,000	300,000	50000	140000	0	190000	0	300000	0
13	27000000	4	190,000	190,000	300,000	0	190000	118695	71305	0	300000	0
14	30000000	4	190,000	190,000	300,000	0	190000	118695	71305	0	300000	0
15	33000000	4	190,000	190,000	300,000	0	190000	118695	71305	0	300000	0
16	27000000	5	190,000	190,000	300,000	0	190000	118695	71305	0	300000	0
17	30000000	5	190,000	190,000	300,000	0	190000	118695	71305	0	300000	0
18	33000000	5	190,000	190,000	300,000	0	190000	118695	71305	0	300000	0
19	27000000	3	190,000	190,000	310,000	50000	140000	60000	130000	0	310000	0
20	30000000	3	190,000	190,000	310,000	50000	140000	60000	130000	0	310000	0
21	33000000	3	190,000	190,000	310,000	50000	140000	60000	130000	0	310000	0
22	27000000	4	190,000	190,000	310,000	50000	140000	60000	130000	0	310000	0
23	30000000	4	190,000	190,000	310,000	50000	140000	60000	130000	0	310000	0
24	33000000	4	190,000	190,000	310,000	50000	140000	60000	130000	0	310000	0

A sample of intensive sensitivity analysis results

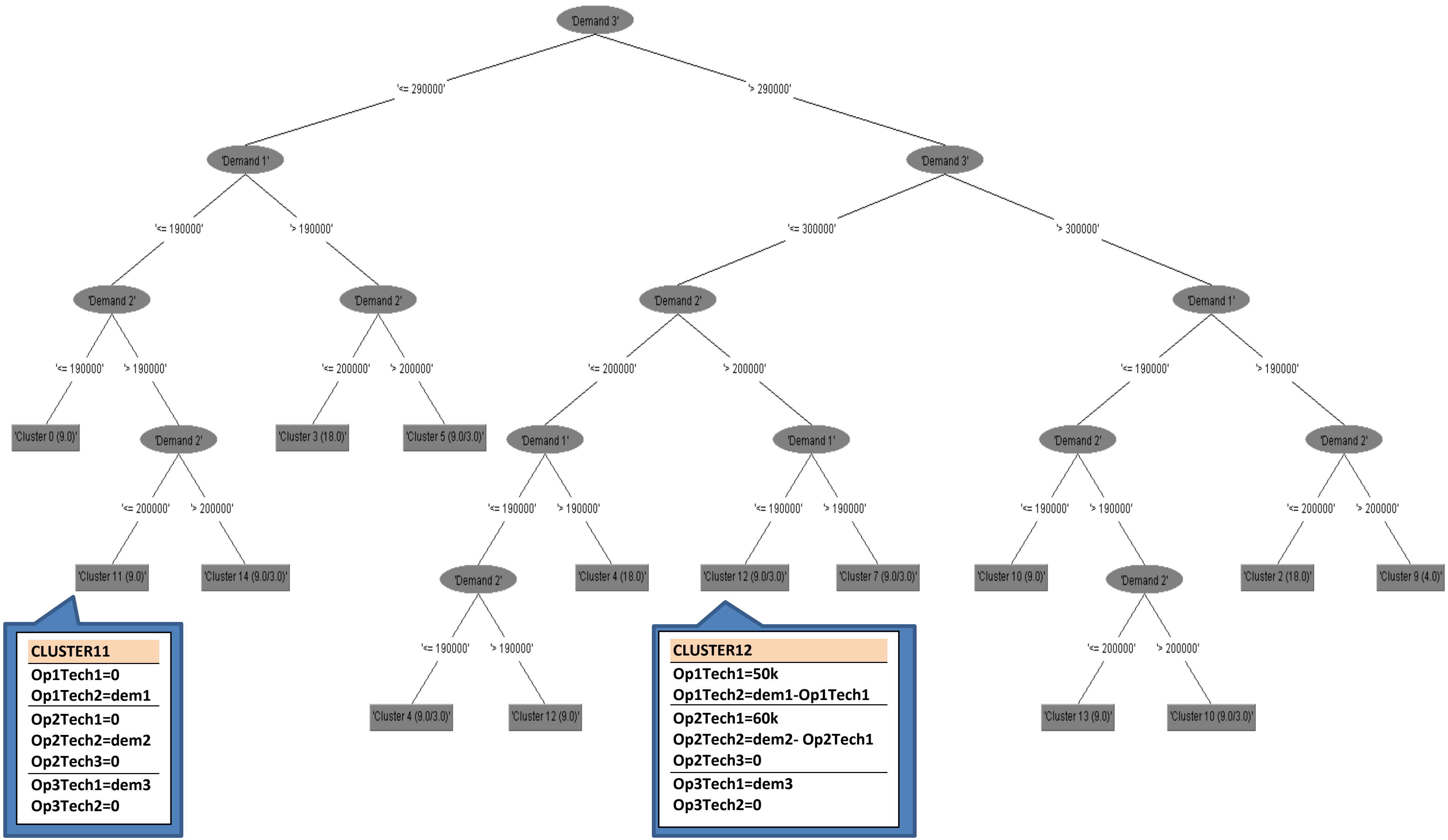
Appendix B: Machine learning approach to solution structuring

Solution no.	Budget Limit	Economic Weight	Demand 1	Demand 2	Demand 3	Operation 1 Tech 1	Operation 1 Tech 2	Operation 2 Tech 1	Operation 2 Tech 2	Operation 2 Tech 3	Operation 3 Tech 1	Operation 3 Tech 2	Cluster No.
1	27000000	3	190,000	190,000	290,000	26070	163930	30000	160000	0	290000	0	0
2	30000000	3	190,000	190,000	290,000	26070	163930	30000	160000	0	290000	0	0
3	33000000	3	190,000	190,000	290,000	26070	163930	30000	160000	0	290000	0	0
4	27000000	4	190,000	190,000	290,000	26070	163930	30000	160000	0	290000	0	0
5	30000000	4	190,000	190,000	290,000	26070	163930	30000	160000	0	290000	0	0
6	33000000	4	190,000	190,000	290,000	26070	163930	30000	160000	0	290000	0	0
7	27000000	5	190,000	190,000	290,000	26070	163930	30000	160000	0	290000	0	0
8	30000000	5	190,000	190,000	290,000	26070	163930	30000	160000	0	290000	0	0
9	33000000	5	190,000	190,000	290,000	26070	163930	30000	160000	0	290000	0	0
10	27000000	3	190,000	190,000	300,000	50000	140000	0	190000	0	300000	0	1
11	30000000	3	190,000	190,000	300,000	50000	140000	0	190000	0	300000	0	1
12	33000000	3	190,000	190,000	300,000	50000	140000	0	190000	0	300000	0	1
13	27000000	4	190,000	190,000	300,000	0	190000	118695	71305	0	300000	0	4
14	30000000	4	190,000	190,000	300,000	0	190000	118695	71305	0	300000	0	4
15	33000000	4	190,000	190,000	300,000	0	190000	118695	71305	0	300000	0	4
16	27000000	5	190,000	190,000	300,000	0	190000	118695	71305	0	300000	0	4
17	30000000	5	190,000	190,000	300,000	0	190000	118695	71305	0	300000	0	4
18	33000000	5	190,000	190,000	300,000	0	190000	118695	71305	0	300000	0	4
19	27000000	3	190,000	190,000	310,000	50000	140000	60000	130000	0	310000	0	10
20	30000000	3	190,000	190,000	310,000	50000	140000	60000	130000	0	310000	0	10
21	33000000	3	190,000	190,000	310,000	50000	140000	60000	130000	0	310000	0	10
22	27000000	4	190,000	190,000	310,000	50000	140000	60000	130000	0	310000	0	10
23	30000000	4	190,000	190,000	310,000	50000	140000	60000	130000	0	310000	0	10
24	33000000	4	190,000	190,000	310,000	50000	140000	60000	130000	0	310000	0	10

A sample of unsupervised learning results illustrating the clustering of 24 solution examples



Decision tree generated by J48 method with 'Min. number of instances per leaf = 3'



Decision tree generated by J48 method with 'Min. number of instances per leaf = 4'

What can be implied from both trees is that;

1) Technology 3 of operation 2 and technology 2 of operation 3 are dominated by the other technologies and are not selected at any circumstances studied.
2) ‘Budget limit’ parameter does not exist in any of the two trees. This means that the budget limit change in the range specified has no effects on the final result.
3) The descending order of parameters in terms of sensitivity on the final results is ‘demand 3’, ‘demand 1’, ‘demand 2’, and ‘economic weight’. This can be drawn from the position of parameters in the hierarchy.
4) The first tree is bigger (41 nodes and 21 leaves), but represents a 100% correct inference. On the other hand, the second tree is smaller (29 nodes and 15 leaves), while it represents a less correct knowledge of 88.535%. If the correctness threshold is set at minimum 85%, then the second tree would still be acceptable.
5) The only difference between two trees is that the second one, which is smaller, has actually removed the ‘economic weight’ nodes, which was less effective compared to ‘demands’. This obviously has made this smaller tree less correct by about 11.5%.

Appendix C: Case study model

Cost optimisation model

Decision Variables	$\boldsymbol{x_{ij}}$: Capacity volume required for technology $\boldsymbol{j}$ of operation $\boldsymbol{i}$; $\boldsymbol{y_{ij}}$: Number of units required for technology $\boldsymbol{j}$ of operation $\boldsymbol{i}$;
Objective Function	$\boldsymbol{Minimise\ tc = \sum_i \sum_j PV_{ij}}$
Technology Unit Constraints	$\frac{x_{11}-1}{190000} \leq y_{11}$ $\quad \frac{x_{12}-1}{150000} \leq y_{12}$ $\quad \frac{x_{13}-1}{100000} \leq y_{13}$ $\frac{x_{21}-1}{190000} \leq y_{21}$ $\quad \frac{x_{22}-1}{190000} \leq y_{22}$ $\quad \frac{x_{23}-1}{190000} \leq y_{23}$ $\frac{x_{31}-1}{150000} \leq y_{31}$ $\quad \frac{x_{32}-1}{100000} \leq y_{32}$ $\quad \frac{x_{33}-1}{100000} \leq y_{33}$ $\quad \frac{x_{34}-1}{190000} \leq y_{34}$
Demand Constraints	$x_{11} + x_{12} + x_{13} = 250000$ $x_{21} + x_{22} + x_{23} = 300000$ $x_{31} + x_{32} + x_{33} + x_{34} = 400000$
Capital Budget Limit Constraint	$(120 \times y_{11} + 160 \times y_{12} + 130 \times y_{13} + 300 \times y_{21} + 569.373688 \times y_{22} + 569.340725 \times y_{23} + 599 \times y_{31} + 419.538507 \times y_{32} + 323.538507 \times y_{33} + 299.670362 \times y_{34}) \leq 2,600$
Variable Constraints	$x_{ij} \geq 0 \quad \forall\, i, j$ $y_{ij} \geq 0 \quad \forall\, i, j$ $y_{ij}: Integer \quad \forall\, i, j$

Where

$$PV_{11} = \mathbf{2,200,000} \times \boldsymbol{y_{11}} + \left[\mathbf{5} \times \boldsymbol{x_{11}} \times (\mathbf{1} + \mathbf{0.05}) \times \frac{\mathbf{1.04}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.04}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.04}}{\mathbf{1.11}}}\right)\right] + \left[\mathbf{2} \times \boldsymbol{x_{11}} \times (\mathbf{1} + \mathbf{0.05}) \times \frac{\mathbf{1.03}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.03}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.03}}{\mathbf{1.11}}}\right)\right]$$
$$+ \left[\mathbf{1} \times \boldsymbol{x_{11}} \times (\mathbf{1} + \mathbf{0.05}) \times \frac{\mathbf{1.03}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.03}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.03}}{\mathbf{1.11}}}\right)\right] + \left[\mathbf{25000} \times \boldsymbol{y_{11}} \times \frac{\mathbf{1.05}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.05}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.05}}{\mathbf{1.11}}}\right)\right]$$

$$PV_{12} = \mathbf{1,800,000} \times \boldsymbol{y_{12}} + \left[\mathbf{3} \times \boldsymbol{x_{12}} \times (\mathbf{1} + \mathbf{0.06}) \times \frac{\mathbf{1.04}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.04}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.04}}{\mathbf{1.11}}}\right)\right] + \left[\mathbf{1} \times \boldsymbol{x_{12}} \times (\mathbf{1} + \mathbf{0.06}) \times \frac{\mathbf{1.03}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.03}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.03}}{\mathbf{1.11}}}\right)\right]$$
$$+ \left[\mathbf{5} \times \boldsymbol{x_{12}} \times (\mathbf{1} + \mathbf{0.06}) \times \frac{\mathbf{1.03}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.03}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.03}}{\mathbf{1.11}}}\right)\right] + \left[\mathbf{30000} \times \boldsymbol{y_{12}} \times \frac{\mathbf{1.05}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.05}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.05}}{\mathbf{1.11}}}\right)\right]$$

$$PV_{21} = \mathbf{2,300,000} \times \boldsymbol{y_{21}} + \left[\mathbf{2} \times \boldsymbol{x_{21}} \times (\mathbf{1} + \mathbf{0.05}) \times \frac{\mathbf{1.04}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.04}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.04}}{\mathbf{1.11}}}\right)\right] + \left[\mathbf{2} \times \boldsymbol{x_{21}} \times (\mathbf{1} + \mathbf{0.05}) \times \frac{\mathbf{1.03}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.03}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.03}}{\mathbf{1.11}}}\right)\right]$$
$$+ \left[\mathbf{6} \times \boldsymbol{x_{21}} \times (\mathbf{1} + \mathbf{0.05}) \times \frac{\mathbf{1.03}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.03}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.03}}{\mathbf{1.11}}}\right)\right] + \left[\mathbf{25000} \times \boldsymbol{y_{21}} \times \frac{\mathbf{1.05}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.05}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.05}}{\mathbf{1.11}}}\right)\right]$$

$$PV_{22} = \mathbf{3,000,000} \times \boldsymbol{y_{22}} + \left[\mathbf{4} \times \boldsymbol{x_{22}} \times (\mathbf{1} + \mathbf{0.05}) \times \frac{\mathbf{1.04}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.04}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.04}}{\mathbf{1.11}}}\right)\right] + \left[\mathbf{2} \times \boldsymbol{x_{22}} \times (\mathbf{1} + \mathbf{0.05}) \times \frac{\mathbf{1.03}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.03}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.03}}{\mathbf{1.11}}}\right)\right]$$
$$+ \left[\mathbf{5} \times \boldsymbol{x_{22}} \times (\mathbf{1} + \mathbf{0.05}) \times \frac{\mathbf{1.03}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.03}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.03}}{\mathbf{1.11}}}\right)\right] + \left[\mathbf{30000} \times \boldsymbol{y_{22}} \times \frac{\mathbf{1.05}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.05}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.05}}{\mathbf{1.11}}}\right)\right]$$

$$PV_{23} = \mathbf{3,200,000} \times \boldsymbol{y_{23}} + \left[\mathbf{8} \times \boldsymbol{x_{23}} \times (\mathbf{1} + \mathbf{0.07}) \times \frac{\mathbf{1.04}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.04}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.04}}{\mathbf{1.11}}}\right)\right] + \left[\mathbf{16} \times \boldsymbol{x_{23}} \times (\mathbf{1} + \mathbf{0.07}) \times \frac{\mathbf{1.03}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.03}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.03}}{\mathbf{1.11}}}\right)\right]$$
$$+ \left[\mathbf{6} \times \boldsymbol{x_{23}} \times (\mathbf{1} + \mathbf{0.07}) \times \frac{\mathbf{1.03}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.03}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.03}}{\mathbf{1.11}}}\right)\right] + \left[\mathbf{35000} \times \boldsymbol{y_{23}} \times \frac{\mathbf{1.05}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.05}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.05}}{\mathbf{1.11}}}\right)\right]$$

$$PV_{31} = \mathbf{3,300,000} \times \boldsymbol{y_{31}} + \left[\mathbf{3} \times \boldsymbol{x_{31}} \times (\mathbf{1} + \mathbf{0.06}) \times \frac{\mathbf{1.04}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.04}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.04}}{\mathbf{1.11}}}\right)\right] + \left[\mathbf{10} \times \boldsymbol{x_{31}} \times (\mathbf{1} + \mathbf{0.06}) \times \frac{\mathbf{1.03}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.03}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.03}}{\mathbf{1.11}}}\right)\right]$$
$$+ \left[\mathbf{5} \times \boldsymbol{x_{31}} \times (\mathbf{1} + \mathbf{0.06}) \times \frac{\mathbf{1.03}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.03}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.03}}{\mathbf{1.11}}}\right)\right] + \left[\mathbf{40000} \times \boldsymbol{y_{31}} \times \frac{\mathbf{1.05}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.05}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.05}}{\mathbf{1.11}}}\right)\right]$$

$$PV_{32} = \mathbf{3,500,000} \times \boldsymbol{y_{32}} + \left[\mathbf{9.5} \times \boldsymbol{x_{32}} \times (\mathbf{1} + \mathbf{0.03}) \times \frac{\mathbf{1.04}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.04}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.04}}{\mathbf{1.11}}}\right)\right] + \left[\mathbf{10} \times \boldsymbol{x_{32}} \times (\mathbf{1} + \mathbf{0.03}) \times \frac{\mathbf{1.03}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.03}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.03}}{\mathbf{1.11}}}\right)\right]$$

$$+ \left[\mathbf{9} \times \boldsymbol{x_{32}} \times (\mathbf{1} + \mathbf{0.03}) \times \frac{\mathbf{1.03}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.03}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.03}}{\mathbf{1.11}}}\right)\right] + \left[\mathbf{50000} \times \boldsymbol{y_{32}} \times \frac{\mathbf{1.05}}{\mathbf{1.11}} \times \left(\frac{\mathbf{1} - \left(\frac{\mathbf{1.05}}{\mathbf{1.11}}\right)^{\mathbf{20}}}{\mathbf{1} - \frac{\mathbf{1.05}}{\mathbf{1.11}}}\right)\right]$$

Main mathematical model

Decision Variables	x_{ij}: Capacity volume required for technology j of operation i; y_{ij}: Number of units required for technology j of operation i; d_c: Deviation from goal on economic criteria d_{ie}: Deviation from goal on environmental impacts criteria with regards to the ith operation $i = 1, \dots, 3$ d_{it}: Deviation from goal on technical (quality) criteria with regards to the ith operation $i = 1, \dots, 3$
Objective Function	$\boldsymbol{Minimise}\ f(d) = 4 \times 3 \times d_c + 2 \times (d_{1e} + d_{2e} + d_{3e}) + 1 \times (d_{1t} + d_{2t} + d_{3t})$,
Technical Goal Constraints	$\left(1 - \frac{0.8x_{11} + 0.85x_{12} - (200,000 \times 0.8)}{(200,000 \times 0.8)}\right) + d_{1t} = 1$ $\left(1 - \frac{0.7x_{21} + 0.8x_{22} + 0.9x_{23} - (200,000 \times 0.7)}{(200,000 \times 0.7)}\right) + d_{2t} = 1$ $\left(1 - \frac{0.85x_{31} + 0.92x_{32} - (300,000 \times 0.85)}{(300,000 \times 0.85)}\right) + d_{3t} = 1$
Environment Goal Constraints	$\left(1 - \frac{95x_{11} + 91x_{12} - (200,000 \times 91)}{(200,000 \times 91)}\right) + d_{1e} = 1$ $\left(1 - \frac{95x_{21} + 85x_{22} + 80x_{23} - (200,000 \times 80)}{(200,000 \times 80)}\right) + d_{2e} = 1$ $\left(1 - \frac{87x_{31} + 76x_{32} - (300,000 \times 76)}{(300,000 \times 76)}\right) + d_{3e} = 1$
Economic Goal Constraint	$\left(1 - \frac{\sum_i \sum_j PV_{ij} - 310,612,604}{310,612,604}\right) + d_c = 1$
Technology Unit Constraints	$\frac{x_{11} - 1}{190000} \le y_{11}$ $\frac{x_{12} - 1}{150000} \le y_{12}$ $\frac{x_{13} - 1}{100000} \le y_{13}$ $\frac{x_{21} - 1}{190000} \le y_{21}$ $\frac{x_{22} - 1}{190000} \le y_{22}$ $\frac{x_{23} - 1}{190000} \le y_{23}$ $\frac{x_{31} - 1}{150000} \le y_{31}$ $\frac{x_{32} - 1}{100000} \le y_{32}$ $\frac{x_{33} - 1}{100000} \le y_{33}$ $\frac{x_{34} - 1}{190000} \le y_{34}$

Demand Constraints	$x_{11} + x_{12} + x_{13} = 250000$ $x_{21} + x_{22} + x_{23} = 300000$ $x_{31} + x_{32} + x_{33} + x_{34} = 400000$
Capital Budget Limit Constraint	$(120 \times y_{11} + 160 \times y_{12} + 130 \times y_{13} + 300 \times y_{21} + 569.373688 \times y_{22} + 569.340725 \times y_{23} + 599 \times y_{31} + 419.538507 \times y_{32} + 323.538507 \times y_{33} + 299.670362 \times y_{34}) \leq 2,600$
Environmental Impact Limit Constraint	$(12 \times x_{11} + 9 \times x_{12} + 1 \times x_{13} + 14 \times x_{21} + 24 \times x_{22} + 28.8 \times x_{23} + 8 \times x_{31} + 1 \times x_{32} + 1 \times x_{33} + 10 \times x_{34}) \leq \frac{(250{,}000+300{,}000+400{,}000)}{3}$
Technological Incompatibility Constraints	$y_{11} \times y_{21} = 0$ $\quad y_{11} \times y_{23} = 0$ $\quad y_{12} \times y_{22} = 0$ $\quad y_{13} \times y_{22} = 0$ $y_{13} \times y_{23} = 0$ $\quad y_{21} \times y_{34} = 0$ $\quad y_{22} \times y_{31} = 0$ $\quad y_{22} \times y_{32} = 0$ $y_{22} \times y_{33} = 0$ $\quad y_{23} \times y_{31} = 0$ $\quad y_{23} \times y_{32} = 0$ $\quad y_{23} \times y_{33} = 0$
Variable Constraints	$x_{ij} \geq 0 \quad \forall\, i,j$ $\quad y_{ij} \geq 0 \quad \forall\, i,j$ $d_{ie} \geq 0 \quad \forall\, i$ $\quad d_{it} \geq 0 \quad \forall\, i$ $\quad d_c \geq 0$ $y_{ij}: Integer \quad \forall\, i,j$

Appendix D: The VBA program code of controlled re-optimisation tool developed for the purpose of intensive sensitivity analyses

```
Sub Macro2()

    'This macro performs intensive sensitivity analysis

    'Count1 to count5 are Loop counters and are integers
    Dim Count1 As Integer
    Dim Count2 As Integer
    Dim Count3 As Integer
    Dim Count4 As Integer
    Dim Count5 As Integer
    'TableRow is the row number of result cells, and is integer
    Dim TableRow As Integer

    Sheets("Model").Select
    'Set Demand1 initial value
    Range("K62") = 210000
    'Set row number initial value
    TableRow = 2

    'Demand1 loop
    For Count1 = 1 To 3
        'Set Demand2 initial value
        Range("L62") = 260000
        'set demand1 value
        Range("K62") = Range("K62") + 20000

        'Demand2 loop
        For Count2 = 1 To 3
        'Set Demand3 initial value
```

```
Range("M62") = 360000
'Set Demand2 value
Range("L62") = Range("L62") + 20000

'Demand3 loop
For Count3 = 1 To 3
'Set Economic Weight initial value
Range("K39") = 2
'Set Demand3 value
Range("M62") = Range("M62") + 20000

'Economic Weight loop
For Count4 = 1 To 3
'Set Budget Limit initial value
Range("K44") = 2000000000
'Set Economic Weight value
Range("K39") = Range("K39") + 1

'Budget Limit loop
For Count5 = 1 To 3
'Set Budget Limit value
Range("K44") = Range("K44") + 300000000

'Solve the main model
Application.Run macro:="WBUsers.wbSolve"

Sheets("Model").Select

'set the result row
TableRow = TableRow + 1
'Capture the result values
Cells(TableRow, 17) = Range("E30")
Cells(TableRow, 18) = Range("K39")
```

```
        Cells(TableRow, 19) = Range("E23")
        Cells(TableRow, 20) = Range("E24")
        Cells(TableRow, 21) = Range("E25")
        Cells(TableRow, 22) = Range("K9")
        Cells(TableRow, 23) = Range("K10")
        Cells(TableRow, 24) = Range("K11")
        Cells(TableRow, 25) = Range("K12")
        Cells(TableRow, 26) = Range("K13")
        Cells(TableRow, 27) = Range("K14")
        Cells(TableRow, 28) = Range("K15")
        Cells(TableRow, 29) = Range("K16")
        Cells(TableRow, 30) = Range("K17")
        Cells(TableRow, 31) = Range("K18")
        Cells(TableRow, 32) = Range("B3")
        Cells(TableRow, 33) = Range("D2")
        Cells(TableRow, 34) = Range("C35")

        Next Count5

        Next Count4

        Next Count3

        Next Count2

    Next Count1

End Sub
```

Appendix E: Case study solution set with the result of unsupervised learning

No.	Budget Limit	Economic Weight	Demand 1	Demand 2	Demand 3	Operation1			Operation2			Operation3				Class
						Tech1	Tech2	Tech3	Tech1	Tech2	Tech3	Tech1	Tech2	Tech3	Tech4	
1	2300	3	230000	280000	380000	0	0	230,000	280,000	0	0	0	0	380,000	0	0,
2	2600	3	230000	280000	380000	130,000	0	100,000	280,000	0	0	0	380,000	0	0	1,
3	2900	3	230000	280000	380000	0	0	230,000	280,000	0	0	0	380,000	0	0	5,
4	2300	4	230000	280000	380000	0	0	230,000	280,000	0	0	0	0	380,000	0	0,
5	2600	4	230000	280000	380000	0	0	230,000	280,000	0	0	0	0	380,000	0	0,
6	2900	4	230000	280000	380000	0	0	230,000	280,000	0	0	0	380,000	0	0	5,
7	2300	5	230000	280000	380000	0	0	230,000	280,000	0	0	0	0	380,000	0	0,
8	2600	5	230000	280000	380000	230,000	0	0	280,000	0	0	0	300,000	80,000	0	15,
9	2900	5	230000	280000	380000	0	0	230,000	280,000	0	0	0	380,000	0	0	5,
10	2300	3	230000	280000	400000	0	0	230,000	280,000	0	0	0	0	400,000	0	0,
11	2600	3	230000	280000	400000	0	0	230,000	280,000	0	0	0	0	400,000	0	0,
12	2900	3	230000	280000	400000	0	0	230,000	280,000	0	0	0	400,000	0	0	4,
13	2300	4	230000	280000	400000	0	0	230,000	280,000	0	0	0	0	400,000	0	0,
14	2600	4	230000	280000	400000	0	0	230,000	280,000	0	0	0	0	400,000	0	0,
15	2900	4	230000	280000	400000	0	0	230,000	280,000	0	0	0	400,000	0	0	4,
16	2300	5	230000	280000	400000	0	0	230,000	280,000	0	0	0	0	400,000	0	0,
17	2600	5	230000	280000	400000	0	0	230,000	280,000	0	0	0	300,000	100,000	0	2,
18	2900	5	230000	280000	400000	230,000	0	0	280,000	0	0	0	400,000	0	0	9,
19	2300	3	230000	280000	420000	230,000	0	0	280,000	0	0	0	400,000	0	0	9,
20	2600	3	230000	280000	420000	130,000	0	100,000	280,000	0	0	0	100,000	320,000	0	12,
21	2900	3	230000	280000	420000	0	130,000	100,000	280,000	0	0	0	400,000	20,000	0	13,
22	2300	4	230000	280000	420000	0	130,000	100,000	280,000	0	0	0	400,000	20,000	0	13,
23	2600	4	230000	280000	420000	0	130,000	100,000	280,000	0	0	0	400,000	20,000	0	13,
24	2900	4	230000	280000	420000	0	0	230,000	280,000	0	0	0	0	420,000	0	0,
25	2300	5	230000	280000	420000	0	0	230,000	280,000	0	0	0	0	420,000	0	0,
26	2600	5	230000	280000	420000	0	0	230,000	280,000	0	0	0	0	420,000	0	0,
27	2900	5	230000	280000	420000	0	0	230,000	280,000	0	0	0	300,000	120,000	0	2,
28	2300	3	230000	300000	380000	0	0	230,000	300,000	0	0	0	0	380,000	0	0,
29	2600	3	230000	300000	380000	130,000	0	100,000	300,000	0	0	0	380,000	0	0	1,
30	2900	3	230000	300000	380000	0	0	230,000	300,000	0	0	0	380,000	0	0	5,

31	2300	4	230000	300000	380000	0	0	230,000	300,000	0	0	0	0	380,000	0	0,
32	2600	4	230000	300000	380000	130,000	0	100,000	300,000	0	0	0	380,000	0	0	1,
33	2900	4	230000	300000	380000	0	0	230,000	300,000	0	0	0	380,000	0	0	5,
34	2300	5	230000	300000	380000	0	0	230,000	300,000	0	0	0	0	380,000	0	0,
35	2600	5	230000	300000	380000	0	0	230,000	300,000	0	0	0	0	380,000	0	0,
36	2900	5	230000	300000	380000	0	0	230,000	300,000	0	0	0	380,000	0	0	5,
37	2300	3	230000	300000	400000	0	0	230,000	300,000	0	0	0	0	400,000	0	0,
38	2600	3	230000	300000	400000	0	0	230,000	300,000	0	0	0	0	400,000	0	0,
39	2900	3	230000	300000	400000	0	0	230,000	300,000	0	0	0	400,000	0	0	4,
40	2300	4	230000	300000	400000	0	0	230,000	300,000	0	0	0	0	400,000	0	0,
41	2600	4	230000	300000	400000	0	0	230,000	300,000	0	0	0	0	400,000	0	0,
42	2900	4	230000	300000	400000	0	0	230,000	300,000	0	0	0	400,000	0	0	4,
43	2300	5	230000	300000	400000	0	0	230,000	300,000	0	0	0	0	400,000	0	0,
44	2600	5	230000	300000	400000	0	0	230,000	300,000	0	0	0	300,000	100,000	0	2,
45	2900	5	230000	300000	400000	0	0	230,000	300,000	0	0	0	400,000	0	0	4,
46	2300	3	230000	300000	420000	0	0	230,000	300,000	0	0	0	400,000	0	0	4,
47	2600	3	230000	300000	420000	130,000	0	100,000	300,000	0	0	0	100,000	320,000	0	12,
48	2900	3	230000	300000	420000	0	130,000	100,000	300,000	0	0	0	400,000	20,000	0	13,
49	2300	4	230000	300000	420000	0	130,000	100,000	300,000	0	0	0	400,000	20,000	0	13,
50	2600	4	230000	300000	420000	0	130,000	100,000	300,000	0	0	0	400,000	20,000	0	13,
51	2900	4	230000	300000	420000	0	0	230,000	300,000	0	0	0	0	420,000	0	0,
52	2300	5	230000	300000	420000	0	0	230,000	300,000	0	0	0	0	420,000	0	0,
53	2600	5	230000	300000	420000	0	0	230,000	300,000	0	0	0	0	420,000	0	0,
54	2900	5	230000	300000	420000	0	0	230,000	300,000	0	0	0	300,000	120,000	0	2,
55	2300	3	230000	320000	380000	0	0	230,000	320,000	0	0	0	0	380,000	0	0,
56	2600	3	230000	320000	380000	0	0	230,000	320,000	0	0	0	0	380,000	0	0,

57	2900	3	230000	320000	380000	0	0	230,000	320,000	0	0	0	380,000	0	0	5,
58	2300	4	230000	320000	380000	0	0	230,000	320,000	0	0	0	0	380,000	0	0,
59	2600	4	230000	320000	380000	0	0	230,000	320,000	0	0	0	0	380,000	0	0,
60	2900	4	230000	320000	380000	0	0	230,000	320,000	0	0	0	380,000	0	0	5,
61	2300	5	230000	320000	380000	0	0	230,000	320,000	0	0	0	0	380,000	0	0,
62	2600	5	230000	320000	380000	230,000	0	0	320,000	0	0	0	300,000	80,000	0	15,
63	2900	5	230000	320000	380000	0	0	230,000	320,000	0	0	0	380,000	0	0	5,
64	2300	3	230000	320000	400000	0	0	230,000	320,000	0	0	0	0	400,000	0	0,
65	2600	3	230000	320000	400000	0	0	230,000	320,000	0	0	0	0	400,000	0	0,
66	2900	3	230000	320000	400000	0	0	230,000	320,000	0	0	0	400,000	0	0	4,
67	2300	4	230000	320000	400000	0	0	230,000	320,000	0	0	0	0	400,000	0	0,
68	2600	4	230000	320000	400000	0	0	230,000	320,000	0	0	0	0	400,000	0	0,
69	2900	4	230000	320000	400000	0	0	230,000	320,000	0	0	0	400,000	0	0	4,
70	2300	5	230000	320000	400000	0	0	230,000	320,000	0	0	0	0	400,000	0	0,
71	2600	5	230000	320000	400000	0	0	230,000	320,000	0	0	0	300,000	100,000	0	2,
72	2900	5	230000	320000	400000	230,000	0	0	320,000	0	0	0	400,000	0	0	9,
73	2300	3	230000	320000	420000	230,000	0	0	320,000	0	0	0	400,000	0	0	9,
74	2600	3	230000	320000	420000	230,000	0	0	320,000	0	0	0	400,000	0	0	9,
75	2900	3	230000	320000	420000	30,000	0	200,000	320,000	0	0	0	100,000	320,000	0	16,
76	2300	4	230000	320000	420000	30,000	0	200,000	320,000	0	0	0	100,000	320,000	0	16,
77	2600	4	230000	320000	420000	30,000	0	200,000	320,000	0	0	0	100,000	320,000	0	16,
78	2900	4	230000	320000	420000	30,000	0	200,000	320,000	0	0	0	200,000	220,000	0	17,
79	2300	5	230000	320000	420000	30,000	0	200,000	320,000	0	0	0	200,000	220,000	0	17,
80	2600	5	230000	320000	420000	30,000	0	200,000	320,000	0	0	0	200,000	220,000	0	17,
81	2900	5	230000	320000	420000	0	0	230,000	320,000	0	0	0	0	420,000	0	0,
82	2300	3	250000	280000	380000	0	0	250,000	280,000	0	0	0	0	380,000	0	0,
83	2600	3	250000	280000	380000	150,000	0	100,000	280,000	0	0	0	380,000	0	0	3,
84	2900	3	250000	280000	380000	0	0	250,000	280,000	0	0	0	380,000	0	0	5,

85	2300	4	250000	280000	380000	0	0	250,000	280,000	0	0	0	0	380,000	0	0,
86	2600	4	250000	280000	380000	150,000	0	100,000	280,000	0	0	0	380,000	0	0	3,
87	2900	4	250000	280000	380000	0	0	250,000	280,000	0	0	0	380,000	0	0	5,
88	2300	5	250000	280000	380000	0	0	250,000	280,000	0	0	0	0	380,000	0	0,
89	2600	5	250000	280000	380000	0	0	250,000	280,000	0	0	0	0	380,000	0	0,
90	2900	5	250000	280000	380000	0	0	250,000	280,000	0	0	0	380,000	0	0	5,
91	2300	3	250000	280000	400000	0	0	250,000	280,000	0	0	0	0	400,000	0	0,
92	2600	3	250000	280000	400000	0	0	250,000	280,000	0	0	0	300,000	100,000	0	2,
93	2900	3	250000	280000	400000	0	0	250,000	280,000	0	0	0	400,000	0	0	4,
94	2300	4	250000	280000	400000	0	0	250,000	280,000	0	0	0	0	400,000	0	0,
95	2600	4	250000	280000	400000	0	150,000	100,000	280,000	0	0	0	400,000	0	0	6,
96	2900	4	250000	280000	400000	0	0	250,000	280,000	0	0	0	400,000	0	0	4,
97	2300	5	250000	280000	400000	0	0	250,000	280,000	0	0	0	0	400,000	0	0,
98	2600	5	250000	280000	400000	0	0	250,000	280,000	0	0	0	300,000	100,000	0	2,
99	2900	5	250000	280000	400000	0	0	250,000	280,000	0	0	0	400,000	0	0	4,
100	2300	3	250000	280000	420000	0	0	250,000	280,000	0	0	0	400,000	0	0	4,
101	2600	3	250000	280000	420000	0	150,000	100,000	280,000	0	0	0	0	420,000	0	0,
102	2900	3	250000	280000	420000	0	0	250,000	280,000	0	0	0	300,000	120,000	0	2,
103	2300	4	250000	280000	420000	0	0	250,000	280,000	0	0	0	300,000	120,000	0	2,
104	2600	4	250000	280000	420000	0	0	250,000	280,000	0	0	0	300,000	120,000	0	2,
105	2900	4	250000	280000	420000	0	0	250,000	280,000	0	0	0	0	420,000	0	0,
106	2300	5	250000	280000	420000	0	0	250,000	280,000	0	0	0	0	420,000	0	0,
107	2600	5	250000	280000	420000	0	0	250,000	280,000	0	0	0	0	420,000	0	0,
108	2900	5	250000	280000	420000	0	0	250,000	280,000	0	0	0	300,000	120,000	0	2,
109	2300	3	250000	300000	380000	0	0	250,000	300,000	0	0	0	0	380,000	0	0,
110	2600	3	250000	300000	380000	150,000	0	100,000	300,000	0	0	0	380,000	0	0	3,
111	2900	3	250000	300000	380000	0	0	250,000	300,000	0	0	0	380,000	0	0	5,
112	2300	4	250000	300000	380000	0	0	250,000	300,000	0	0	0	0	380,000	0	0,

113	2600	4	250000	300000	380000	150,000	0	100,000	300,000	0	0	0	380,000	0	0	3,
114	2900	4	250000	300000	380000	0	0	250,000	300,000	0	0	0	380,000	0	0	5,
115	2300	5	250000	300000	380000	0	0	250,000	300,000	0	0	0	0	380,000	0	0,
116	2600	5	250000	300000	380000	0	0	250,000	300,000	0	0	0	0	380,000	0	0,
117	2900	5	250000	300000	380000	0	0	250,000	300,000	0	0	0	380,000	0	0	5,
118	2300	3	250000	300000	400000	0	0	250,000	300,000	0	0	0	0	400,000	0	0,
119	2600	3	250000	300000	400000	0	150,000	100,000	300,000	0	0	0	400,000	0	0	6,
120	2900	3	250000	300000	400000	0	0	250,000	300,000	0	0	0	400,000	0	0	4,
121	2300	4	250000	300000	400000	0	0	250,000	300,000	0	0	0	0	400,000	0	0,
122	2600	4	250000	300000	400000	0	150,000	100,000	300,000	0	0	0	400,000	0	0	6,
123	2900	4	250000	300000	400000	0	0	250,000	300,000	0	0	0	400,000	0	0	4,
124	2300	5	250000	300000	400000	0	0	250,000	300,000	0	0	0	0	400,000	0	0,
125	2600	5	250000	300000	400000	0	0	250,000	300,000	0	0	0	300,000	100,000	0	2,
126	2900	5	250000	300000	400000	0	0	250,000	300,000	0	0	0	400,000	0	0	4,
127	2300	3	250000	300000	420000	0	0	250,000	300,000	0	0	0	400,000	0	0	4,
128	2600	3	250000	300000	420000	0	0	250,000	300,000	0	0	0	400,000	0	0	4,
129	2900	3	250000	300000	420000	0	0	250,000	300,000	0	0	0	300,000	120,000	0	2,
130	2300	4	250000	300000	420000	0	0	250,000	300,000	0	0	0	300,000	120,000	0	2,
131	2600	4	250000	300000	420000	0	0	250,000	300,000	0	0	0	300,000	120,000	0	2,
132	2900	4	250000	300000	420000	0	0	250,000	300,000	0	0	0	0	420,000	0	0,
133	2300	5	250000	300000	420000	0	0	250,000	300,000	0	0	0	0	420,000	0	0,
134	2600	5	250000	300000	420000	0	0	250,000	300,000	0	0	0	0	420,000	0	0,
135	2900	5	250000	300000	420000	0	0	250,000	300,000	0	0	0	300,000	120,000	0	2,
136	2300	3	250000	320000	380000	0	0	250,000	320,000	0	0	0	0	380,000	0	0,
137	2600	3	250000	320000	380000	150,000	0	100,000	320,000	0	0	0	380,000	0	0	3,
138	2900	3	250000	320000	380000	0	0	250,000	320,000	0	0	0	380,000	0	0	5,
139	2300	4	250000	320000	380000	0	0	250,000	320,000	0	0	0	0	380,000	0	0,
140	2600	4	250000	320000	380000	150,000	0	100,000	320,000	0	0	0	380,000	0	0	3,

141	2900	4	250000	320000	380000	0	0	250,000	320,000	0	0	0	380,000	0	0	5,
142	2300	5	250000	320000	380000	0	0	250,000	320,000	0	0	0	0	380,000	0	0,
143	2600	5	250000	320000	380000	0	0	250,000	320,000	0	0	0	0	380,000	0	0,
144	2900	5	250000	320000	380000	0	0	250,000	320,000	0	0	0	380,000	0	0	5,
145	2300	3	250000	320000	400000	0	0	250,000	320,000	0	0	0	0	400,000	0	0,
146	2600	3	250000	320000	400000	0	150,000	100,000	320,000	0	0	0	400,000	0	0	6,
147	2900	3	250000	320000	400000	0	0	250,000	320,000	0	0	0	400,000	0	0	4,
148	2300	4	250000	320000	400000	0	0	250,000	320,000	0	0	0	0	400,000	0	0,
149	2600	4	250000	320000	400000	0	150,000	100,000	320,000	0	0	0	400,000	0	0	6,
150	2900	4	250000	320000	400000	0	0	250,000	320,000	0	0	0	400,000	0	0	4,
151	2300	5	250000	320000	400000	0	0	250,000	320,000	0	0	0	0	400,000	0	0,
152	2600	5	250000	320000	400000	0	0	250,000	320,000	0	0	0	300,000	100,000	0	2,
153	2900	5	250000	320000	400000	0	0	250,000	320,000	0	0	0	400,000	0	0	4,
154	2300	3	250000	320000	420000	0	0	250,000	320,000	0	0	0	400,000	0	0	4,
155	2600	3	250000	320000	420000	0	0	250,000	320,000	0	0	0	400,000	0	0	4,
156	2900	3	250000	320000	420000	0	0	250,000	320,000	0	0	0	300,000	120,000	0	2,
157	2300	4	250000	320000	420000	0	0	250,000	320,000	0	0	0	300,000	120,000	0	2,
158	2600	4	250000	320000	420000	0	0	250,000	320,000	0	0	0	300,000	120,000	0	2,
159	2900	4	250000	320000	420000	0	0	250,000	320,000	0	0	0	0	420,000	0	0,
160	2300	5	250000	320000	420000	0	0	250,000	320,000	0	0	0	0	420,000	0	0,
161	2600	5	250000	320000	420000	0	0	250,000	320,000	0	0	0	0	420,000	0	0,
162	2900	5	250000	320000	420000	0	0	250,000	320,000	0	0	0	300,000	120,000	0	2,
163	2300	3	270000	280000	380000	0	0	270,000	280,000	0	0	0	0	380,000	0	0,
164	2600	3	270000	280000	380000	0	0	270,000	280,000	0	0	0	300,000	80,000	0	2,
165	2900	3	270000	280000	380000	0	0	270,000	280,000	0	0	0	380,000	0	0	5,
166	2300	4	270000	280000	380000	0	0	270,000	280,000	0	0	0	0	380,000	0	0,
167	2600	4	270000	280000	380000	170,000	0	100,000	280,000	0	0	0	380,000	0	0	7,
168	2900	4	270000	280000	380000	0	0	270,000	280,000	0	0	0	380,000	0	0	5,

169	2300	5	270000	280000	380000	0	0	270,000	280,000	0	0	0	0	380,000	0	0,
170	2600	5	270000	280000	380000	120,000	150,000	0	280,000	0	0	0	380,000	0	0	8,
171	2900	5	270000	280000	380000	0	0	270,000	280,000	0	0	0	380,000	0	0	5,
172	2300	3	270000	280000	400000	0	0	270,000	280,000	0	0	0	0	400,000	0	0,
173	2600	3	270000	280000	400000	0	0	270,000	280,000	0	0	0	300,000	100,000	0	2,
174	2900	3	270000	280000	400000	270,000	0	0	280,000	0	0	0	400,000	0	0	
175	2300	4	270000	280000	400000	0	0	270,000	280,000	0	0	0	0	400,000	0	0,
176	2600	4	270000	280000	400000	0	270,000	0	280,000	0	0	0	400,000	0	0	10,
177	2900	4	270000	280000	400000	0	0	270,000	280,000	0	0	0	400,000	0	0	4,
178	2300	5	270000	280000	400000	0	0	270,000	280,000	0	0	0	0	400,000	0	0,
179	2600	5	270000	280000	400000	0	270,000	0	280,000	0	0	0	400,000	0	0	10,
180	2900	5	270000	280000	400000	0	0	270,000	280,000	0	0	0	400,000	0	0	4,
181	2300	3	270000	280000	420000	0	0	270,000	280,000	0	0	0	400,000	0	0	4,
182	2600	3	270000	280000	420000	0	0	270,000	280,000	0	0	0	400,000	0	0	4,
183	2900	3	270000	280000	420000	0	0	270,000	280,000	0	0	0	300,000	120,000	0	2,
184	2300	4	270000	280000	420000	0	0	270,000	280,000	0	0	0	300,000	120,000	0	2,
185	2600	4	270000	280000	420000	0	0	270,000	280,000	0	0	0	300,000	120,000	0	2,
186	2900	4	270000	280000	420000	0	0	270,000	280,000	0	0	0	0	420,000	0	0,
187	2300	5	270000	280000	420000	0	0	270,000	280,000	0	0	0	0	420,000	0	0,
188	2600	5	270000	280000	420000	0	0	270,000	280,000	0	0	0	0	420,000	0	0,
189	2900	5	270000	280000	420000	70,000	0	200,000	280,000	0	0	0	300,000	120,000	0	11,
190	2300	3	270000	300000	380000	0	0	270,000	300,000	0	0	0	0	380,000	0	0,
191	2600	3	270000	300000	380000	0	0	270,000	300,000	0	0	0	300,000	80,000	0	2,
192	2900	3	270000	300000	380000	0	0	270,000	300,000	0	0	0	380,000	0	0	5,
193	2300	4	270000	300000	380000	0	0	270,000	300,000	0	0	0	0	380,000	0	0,
194	2600	4	270000	300000	380000	170,000	0	100,000	300,000	0	0	0	380,000	0	0	7,
195	2900	4	270000	300000	380000	0	0	270,000	300,000	0	0	0	380,000	0	0	5,
196	2300	5	270000	300000	380000	0	0	270,000	300,000	0	0	0	0	380,000	0	0,

197	2600	5	270000	300000	380000	120,000	150,000	0	300,000	0	0	0	380,000	0	0	8,
198	2900	5	270000	300000	380000	0	0	270,000	300,000	0	0	0	380,000	0	0	5,
199	2300	3	270000	300000	400000	0	0	270,000	300,000	0	0	0	0	400,000	0	0,
200	2600	3	270000	300000	400000	0	270,000	0	300,000	0	0	0	400,000	0	0	10,
201	2900	3	270000	300000	400000	0	0	270,000	300,000	0	0	0	400,000	0	0	4,
202	2300	4	270000	300000	400000	0	0	270,000	300,000	0	0	0	0	400,000	0	0,
203	2600	4	270000	300000	400000	0	270,000	0	300,000	0	0	0	400,000	0	0	10,
204	2900	4	270000	300000	400000	0	0	270,000	300,000	0	0	0	400,000	0	0	4,
205	2300	5	270000	300000	400000	0	0	270,000	300,000	0	0	0	0	400,000	0	0,
206	2600	5	270000	300000	400000	0	270,000	0	300,000	0	0	0	400,000	0	0	10,
207	2900	5	270000	300000	400000	0	0	270,000	300,000	0	0	0	400,000	0	0	4,
208	2300	3	270000	300000	420000	0	0	270,000	300,000	0	0	0	400,000	0	0	4,
209	2600	3	270000	300000	420000	0	0	270,000	300,000	0	0	0	400,000	0	0	4,
210	2900	3	270000	300000	420000	0	0	270,000	300,000	0	0	0	300,000	120,000	0	2,
211	2300	4	270000	300000	420000	0	0	270,000	300,000	0	0	0	300,000	120,000	0	2,
212	2600	4	270000	300000	420000	0	0	270,000	300,000	0	0	0	300,000	120,000	0	2,
213	2900	4	270000	300000	420000	0	0	270,000	300,000	0	0	0	0	420,000	0	0,
214	2300	5	270000	300000	420000	0	0	270,000	300,000	0	0	0	0	420,000	0	0,
215	2600	5	270000	300000	420000	0	0	270,000	300,000	0	0	0	0	420,000	0	0,
216	2900	5	270000	300000	420000	70,000	0	200,000	300,000	0	0	0	300,000	120,000	0	11,
217	2300	3	270000	320000	380000	0	0	270,000	320,000	0	0	0	0	380,000	0	0,
218	2600	3	270000	320000	380000	0	0	270,000	320,000	0	0	0	300,000	80,000	0	2,
219	2900	3	270000	320000	380000	0	0	270,000	320,000	0	0	0	380,000	0	0	5,
220	2300	4	270000	320000	380000	0	0	270,000	320,000	0	0	0	0	380,000	0	0,
221	2600	4	270000	320000	380000	170,000	0	100,000	320,000	0	0	0	380,000	0	0	7,
222	2900	4	270000	320000	380000	0	0	270,000	320,000	0	0	0	380,000	0	0	5,
223	2300	5	270000	320000	380000	0	0	270,000	320,000	0	0	0	0	380,000	0	0,
224	2600	5	270000	320000	380000	120,000	150,000	0	320,000	0	0	0	380,000	0	0	8,

225	2900	5	270000	320000	380000	0	0	270,000	320,000	0	0	0	380,000	0	0	5,
226	2300	3	270000	320000	400000	0	0	270,000	320,000	0	0	0	0	400,000	0	0,
227	2600	3	270000	320000	400000	0	0	270,000	320,000	0	0	0	300,000	100,000	0	2,
228	2900	3	270000	320000	400000	0	0	270,000	320,000	0	0	0	400,000	0	0	4,
229	2300	4	270000	320000	400000	0	0	270,000	320,000	0	0	0	0	400,000	0	0,
230	2600	4	270000	320000	400000	0	270,000	0	320,000	0	0	0	400,000	0	0	10,
231	2900	4	270000	320000	400000	0	0	270,000	320,000	0	0	0	400,000	0	0	4,
232	2300	5	270000	320000	400000	0	0	270,000	320,000	0	0	0	0	400,000	0	0,
233	2600	5	270000	320000	400000	0	270,000	0	320,000	0	0	0	400,000	0	0	10,
234	2900	5	270000	320000	400000	0	0	270,000	320,000	0	0	0	400,000	0	0	4,
235	2300	3	270000	320000	420000	0	0	270,000	320,000	0	0	0	400,000	0	0	4,
236	2600	3	270000	320000	420000	0	270,000	0	320,000	0	0	150,000	100,000	170,000	0	14,
237	2900	3	270000	320000	420000	0	270,000	0	320,000	0	0	150,000	100,000	170,000	0	14,
238	2300	4	270000	320000	420000	0	270,000	0	320,000	0	0	150,000	100,000	170,000	0	14,
239	2600	4	270000	320000	420000	0	270,000	0	320,000	0	0	150,000	100,000	170,000	0	14,
240	2900	4	270000	320000	420000	0	0	270,000	320,000	0	0	0	300,000	120,000	0	2,
241	2300	5	270000	320000	420000	0	0	270,000	320,000	0	0	0	300,000	120,000	0	2,
242	2600	5	270000	320000	420000	0	0	270,000	320,000	0	0	150,000	0	270,000	0	0,
243	2900	5	270000	320000	420000	70,000	0	200,000	320,000	0	0	0	300,000	120,000	0	11,

Appendix F: A List of Publications Arising from the PhD Research

Nejadi, F., Cheng, K.,f (2015) 'Ontology-based modelling and analysis of the automotive coating system for sustainable manufacturing', *25th International Conference on Flexible Automation and Intelligent Manufacturing,* Wolverhampton, West Midlands, United Kingdom

Nejadi, F., Cheng, K., (2016), 'Towards a comprehensive framework for technology selection and capacity planning for sustainable manufacturing'. European Scientific Journal (ESJ), (in press).