The University of Nottingham

UNITED KINGDOM · CHINA · MALAYSIA

DYNAMIC OPTIMISATION FOR ENERGY EFFICIENCY OF INJECTION MOULDING PROCESS

By

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ABSTRACT

Low carbon economy has emerged as an important task in China since the energy intensity and carbon intensity reduction targets were clearly prescribed in its recent Twelfth Five-Year Plan during 2011-2015. While the largest enterprises have undertaken initial initiative to reduce their energy consumption, small and medium-sized enterprises (SMEs) will need to share the responsibilities in meeting the nation's targets. However, there is no established structure for helping SMEs to reduce their efficiency gap and hence the implementation of energy-saving measures in SMEs still remains patchy. Addressing this issue, this thesis seeks to understand the critical barriers faced by SMEs and aims to develop proprietary methodologies that can facilitate manufacturing SMEs to close their efficiency gap.

Process parameters optimisation is perceived to be an effective "no-cost" strategy which can be conducted by SMEs to realise energy efficiency improvement. A unique design of experiment (DOE) introduced by Dorian Shainin offers a simplistic framework to study process optimisation, but its application is not widespread and being criticised over its working principles. In order to address the inherent limitations of the Shainin's method, it was integrated with the multivariate statistical methods and the signal-response system in the empirical study. The nature of the research aim also requires a theoretical approach to evaluate the economic performance of the energy efficiency investment. Hence, a spreadsheet-based decision support system (file SERP.xlsm) was created via dynamic programming (DP) method.

The main contributions of this thesis can be subdivided into empirical level and theoretical level. At the empirical level, a technically feasible yet economically viable approach called “multi-response dynamic Shainin DOE” was developed. An empirical study on the injection moulding process was presented to examine the validity of this novel integrated methodology. The emphasis has been on the integration of multivariate techniques and signal-response analysis. The former successfully identified the critical factors to energy consumption and moulded parts’ impact performance regardless of the great fluctuation in the impact response. The latter enables the end-user to achieve different performance output based on the particular intent. At the theoretical level, the “DP-based spreadsheet solution” provides a convenient platform to help the rationally-behaved decision makers evaluate the energy efficiency investments. A simple hypothetical case study on the injection moulding industry was illustrated how the decision-making process for equipment replacement can evolve over time.

To sum up, both proprietary methodologies enhance the dynamicity in the optimisation process to support injection moulding industry in closing their efficiency gap. The study at the empirical level was limited by the absence of real industrial case study where it is important to justify the practicality of the proposed methodology. Regarding the theoretical level, the dataset for initial validation on the spreadsheet solution was not available. Finally, it is important to continue the future work on the research limitations in order to increase the cogency of the proprietary methodologies for common use in the industry.

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LIST OF ABBREVIATIONS

ABS	Acrylonitrile butadiene styrene
ANN	Artificial neural network
ANOVA	Analysis of variance
BIP	Binary integer programming
CAE	Computer-aided-engineering
CBR	Case based reasoning
CIS	Charpy impact strength
DE	Differential evolution
DEA	Data envelopment analysis
DOE	Design of experiment
DOF	Degree of freedom
DP	Dynamic programming
DSS	Decision support systems
EA	Evolutionary algorithm
FYP	Five-Year Plan
GA	Genetic algorithm
GDP	Gross domestic product
GHG	Greenhouse gases
GRA	Grey relational analysis
HDPE	High-density polyethylene

IP	Integer programming
ISM	Interpretive structural modelling
LCL	Lower control limit
LDPE	Low-density polyethylene
LP	Linear programming
MFI	Melt flow index
MIP	Mixed integer programming
MP	Mathematical programming
MRDSD	Multi-response dynamic Shainin DOE
MRS	Multiple response statistics
MTCE	Million tonnes coal equivalent
NP	Nonlinear programming
OFAT	One-factor-at-a-time
OLAP	On-line analytical processing
OR	Operations research
ORSA	Operations Research Society of America
PA	Polyamide
PC	Polycarbonate
PMM	Performance measure modelling
POM	Polyoxymethylene
PP	Polypropylene
PS	Polystyrene

PSO	Particle swarm optimisation
PVC	Polyvinyl chloride
RBF	Radial basis function
RECIPE	Reduced Energy Consumption In Plastics Engineering
RFM	Response function modelling
RSM	Response surface method
SA	Simulated annealing
SAE	Self-adaptive evolution
SEC	Specific energy consumption
SERI	Solar Energy Research Institute
SERP	Stochastic equipment replacement problem
SME	Small and medium-sized enterprise
S/N	Signal-to-noise
SOE	State-owned enterprise
SPC	Statistical process control
SQP	Sequential quadratic programming
UCL	Upper control limit
UNIDO	United Nations Industrial Development Organisation
UNNC	University of Nottingham Ningbo China
VBET	Variable Barrier Energy Transfer
VDP	Variable displacement pump
VSD	Variable speed drive

CHAPTER 1

INTRODUCTION

1.1 Research Motivation

To address the 2008 financial crisis, the central government of China publicly pledged to sustain an annual economic growth rate of 8%, which is well known as "baoba" policy[1]. While the economy of China is moving towards recovery, its economic growth model is not sustainable as it is heavily dependent on coal-based energy production. According to the National Bureau of Statistics of China [1], coal-fired power stations had a share of 77.8% of the total electricity generation in 2011, which amounted to 2,474 million tonnes coal equivalent (MTCE). In the long run, there is an undeniable fact that the greenhouse gases (GHG) emitted from the fossil fuels combustion will worsen the climate change issue. While, in the short run, coal burning will augment the urban smog level which in turn causes human health problems. Newly revealed evidence shows that the life expectancies are approximately 5.5 years lower in Northern China due to an increased rate of cardiorespiratory mortality [2]. The main cause is attributed to the long-term exposure to air pollution in this region because of employing winter heating systems fired by coal.

[1] The direct translation of the word "baoba" in English is "maintain eight".

In addition to the environmental and health problems, fossil fuels often encounter issues of resource scarcity and price volatility. Having realised the shortcomings of reliance on fossil fuels, China strives to expand its renewable energy capacity but recent estimates suggest that the renewables will still occupy a small portion of China's primary energy mix until 2035 (see Figure 1.1) [3]. Figure 1.1 implies that the renewable energy sectors are still not mature enough to handle the increasing energy demand in China for the next few decades. For this reason, improving energy efficiency has become an imperative task in China, not only to sustain its economic growth, but also to address global climate change issue. The economic model of this type is often called low carbon economy.

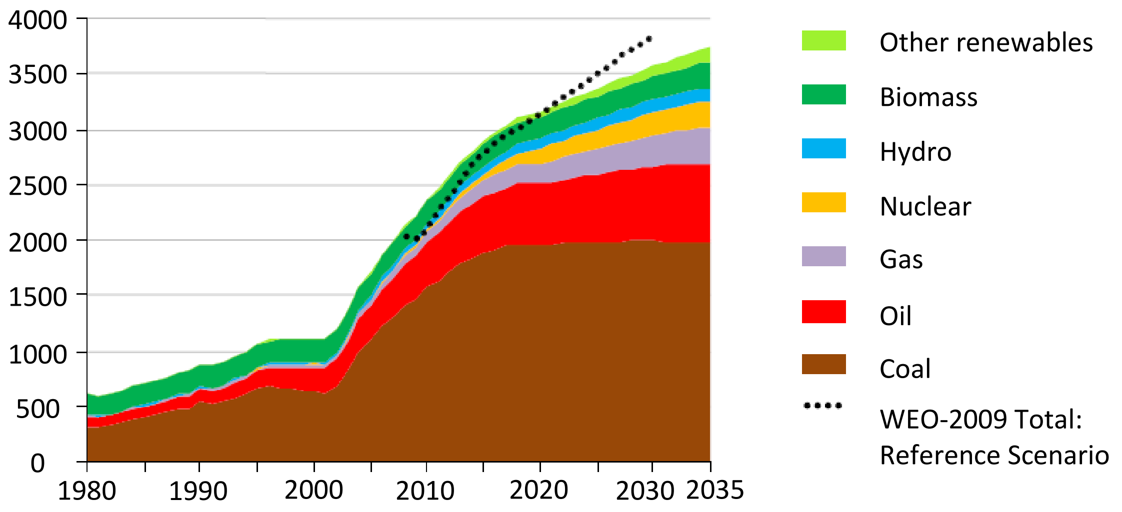

Figure 1.1 – Total primary energy demand in China from 1980 to 2035. Source: [3]

To successfully transform to a low carbon economy, some stringent policy strategies will be required. In this regard, the central government of China has already announced energy intensity reduction targets in its Eleventh Five-Year Plan (11th FYP) during 2006–2010, set to reduce the nation’s energy intensity by 20%. Energy intensity is an important measure of the energy efficiency in a country's economic structure, normally calculated in terms of total energy consumption per unit of gross domestic product (GDP). In order to achieve the target by the end of 2010, it was reported that the Chinese government despatched its negative enforcement mechanisms that culminated in socially and economically disruptive measures such as black-outs, shutting down of residential heating systems and forced closures of inefficient factories [4]. Even so, the eventual reduction rate achieved by 2010 was reportedly 19.1%. Evidently, these short-term measures cannot resolve the root causes of energy inefficiency, nor can they mitigate the nation's energy intensity because they merely reduce the overall energy use without boosting GDP growth concurrently. Even though the previous target has not been met, the central government of China has set another two ambitious goals in its Twelfth Five-Year Plan (12^{th} FYP) for the period of 2011-2015: to further cut the nation's energy intensity by 16%, and for the first time in its FYP, to reduce the nation's carbon intensity[2] by 17% (see Table 1.1).

Table 1.1 – Energy intensity and carbon intensity reduction targets in China's 11^{th} and 12^{th} Five-Year Plan

	11th FYP's (2006-2010) Target	**11th FYP's Actual Result**	**12th FYP's (2011-2015) Target**
Energy intensity (% reduction)	20	19.1	16
Carbon intensity (% reduction)	Not set	N/A	17

[2] Carbon intensity is defined as the amount of carbon by weight emitted per unit of GDP.

During the 11th FYP period, one of the key policies launched by the central government of China is the "Top 1,000 Enterprises Energy Efficiency Programme" (Top-1000 programme). The major target of the Top-1000 programme is to achieve an energy saving of nearly 100 MTCE in five years through the top 1,000 enterprises, which had been reported to have collectively consumed one-third of the nation's total energy usage in 2004 [5]. Strict penalties would be imposed to those participating enterprises that did not fulfil their commitments assigned by the Chinese government. As a result of this policy, China's energy intensity was estimated to have decreased by 46% from 1996 to 2010 although its total industrial energy consumption increased by 134% at the same period [6].

To further optimise the behaviour of energy consumers, a number of market mechanisms have been proposed in the 12th FYP to urge a transition from the energy-intensive and low value-added sectors, such as carbon tax, carbon emissions trading, energy and electricity price reform and so on [4]. While the energy-intensive, large-sized enterprises have undertaken initial initiative to enhance their energy efficiency through the Top-1000 programme during the 11th FYP period, there is greater importance to focus on the less energy-intensive, small and medium-sized enterprises (SMEs), so as to achieve the energy intensity and carbon intensity reduction targets set in the 12th FYP. The industrial structure in China is primarily made up of SMEs. Based on the data given by the National Bureau of Statistics of China [1], around 94.8% of the above-scale industrial enterprises[3] are categorised as SMEs. Enterprises that fit this category in China are vital to its economy as they

[3] Above-scale industrial enterprises refer to those who own annual business revenue of more than 20 million Chinese Yuan.

collectively contribute to approximately 57.7% of the total industrial output value in 2011. In this context, it is important to scrutinise the manufacturing industry as it represents the largest energy consumer in China, accounting for 58% of the total energy usage in 2010 (see Figure 1.2).

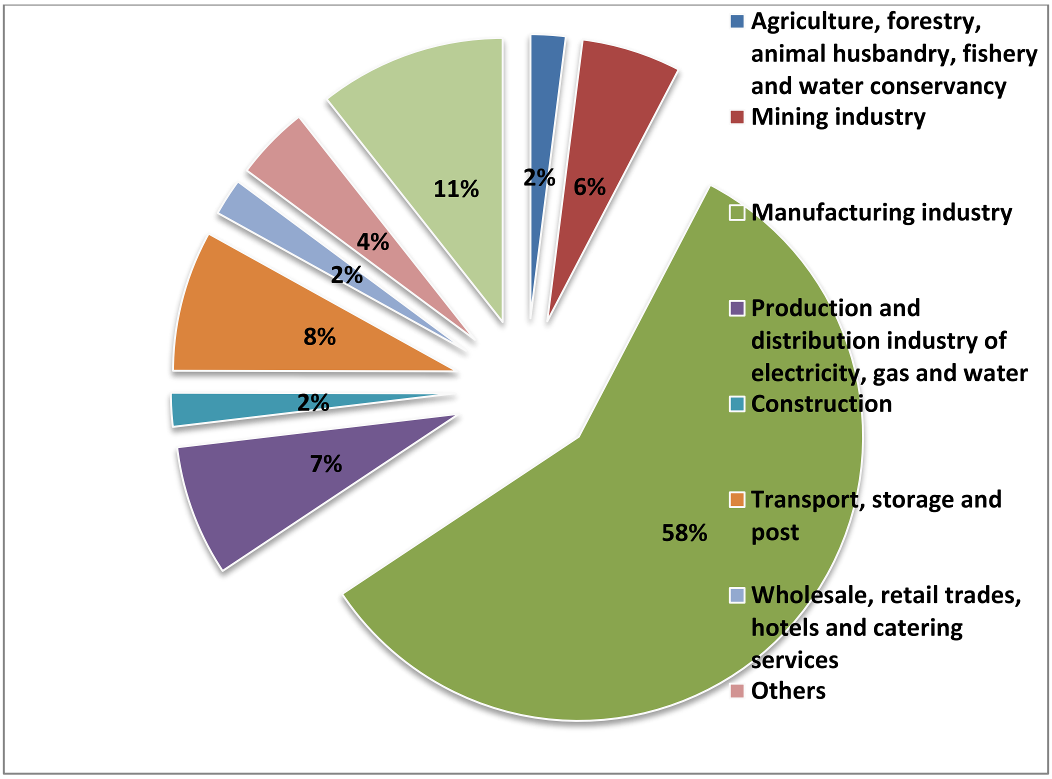

Figure 1.2 – Distribution of China's energy consumption across different sectors in 2010 based on China Statistical Yearbook 2012. Source: [1]

From the perspective of business, the importance of improving energy efficiency is of two fold. First, companies can increase their profit margins via energy saving. Second, companies need to ensure that they comply with the governmental regulations pertaining to energy policies. Nevertheless, the implementation of energy-saving measures in SMEs remains patchy despite the fact that many of the relevant measures are allegedly cost-effective. This phenomenon is termed the "efficiency gap" in the energy efficiency literature which was first proposed by the Solar Energy

Research Institute (SERI) [7]. According to the definition by SERI, the efficiency gap refers to the difference between the levels of investment in energy efficiency that appear to be cost-effective based on engineering-economic models and the levels actually occurring. A number of causes to the efficiency gap are at play, but there is no established structure helping SMEs to initiate pertinent actions. For this reason, closing the efficiency gap in manufacturing SMEs forms the main motivation for this thesis since the longer-term challenges in the energy intensity and carbon intensity reduction targets lie on manufacturing SMEs.

1.2 Research Scope

The scope for this thesis was circumscribed specifically to plastic products industry, which is in conjunction with the previous collaborative project, called "Energy Efficiency in the Regional Ningbo Automotive Industry". This project was conducted by the Division of Engineering at The University of Nottingham Ningbo China (UNNC). The overarching vision was to reduce cost and energy consumption in plastics manufacturing processes, while not reducing the quality of the final product. In summing up this project, the company under research collaboration was more willing to retrofit their existing machines rather than to invest on new machinery due to high initial cost and immature green technology at that time.

In 2010, almost 99.85% of the enterprises in China's plastic products industry were classified as SMEs [8]. In the same year, China overtook Europe as the largest plastics production region in the world (see Figure 1.3) [9], where the total amount of energy consumed by the plastic products industry was up to 20.975 MTCE [1]. Even so, it was reported that plastics consumption per capita in Asia is still much below the levels of mature industrial regions [9]. In this context, China is likely to see greater energy demand in the plastic products industry, while plastics consumption per capita in China is expected to grow with its GDP per capita in the future [10]. From the point of view in business, energy efficiency has become increasingly important in the plastic products industry since energy cost represents the third largest variable cost (after material and direct labour costs), whilst in some companies it is even the second largest variable cost [11]. In addition to the issue of rising energy costs, plastic products industry in China has to deal with more stringent environmental policies as well as the emerging competition from lower wage economies.

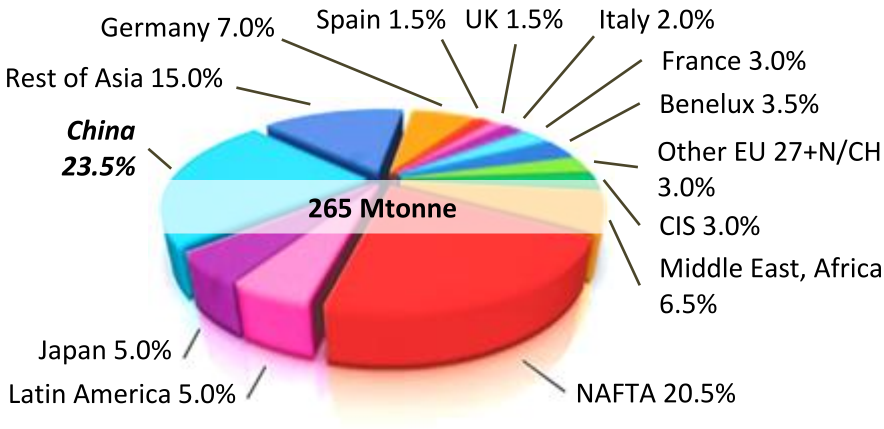

Figure 1.3 – World Plastics Production 2010. Source: PlasticsEurope Market Research Group

Injection moulding is the most commonly practiced method in China given the fact that it has the highest market share (40%) among all types of plastics processing machinery in 2009 [12]. According to China Plastic Machinery Industry Yearbook 2010 [13], the percentages of exported and imported injection moulding machines respectively reached 42.62% and 64.73%, which are also the highest among plastics processing machineries. Furthermore, almost one third of plastic products consumed worldwide are processed by injection moulding [14]. Considering the large scale of injection moulding sector in the plastic products industry, injection moulding was hence selected for the case study in this thesis.

1.3 Research Aim and Objectives

The main aim of this thesis was to develop proprietary methodologies that can facilitate manufacturing SMEs, particularly small and micro enterprises, to close their efficiency gap. The *hypothesis* raised here is that the potentials of a wide range of methodologies developed by the academic community cannot be easily practiced in the environment of SMEs. Following the review of literature, three research questions were posed which shaped the main research work in this thesis:

i. Would there be a strategy with “no-cost investment” that can help manufacturing SMEs to implement energy efficiency project without capital expenditure? (See Section 2.2)
ii. Which optimisation methodology would be the most appropriate solution to address the particular barriers facing SMEs? (See Section 2.4)
iii. How would SMEs determine whether an energy efficiency investment decision can contribute to the economic performance within the company? (See Section 2.5)

To answer the above questions, the research aim was then expanded into eight primary objectives:

i. To investigate the critical barriers that inhibit the implementation of energy efficiency investments which appear to be cost-effective particularly in the environment of SMEs.
ii. To review a wide ranging of available energy-saving measures that can be adopted by the injection moulding industry.
iii. To identify the most appropriate optimisation methodology that can be easily practiced in the environment of SMEs for energy efficiency improvement.
iv. To develop a user-friendly and technically feasible optimisation methodology for which it can be easily practiced at the manufacturing shop floor.
v. To demonstrate and verify the validity of the proposed methodology through the empirical study.
vi. To optimise the energy efficiency during the injection moulding process whilst not deteriorating the quality of moulded parts.
vii. To assist the decision makers in SMEs assess the energy efficiency investments.
viii. To develop a decision support system that can be used interactively by personnel from different levels of expertise.

1.4 Research Approach

In the opening discussion of what strategy is suitably applied by SMEs to handle energy efficiency barriers, the title of this thesis suggests that the "dynamic optimisation" is an effective strategy that will be demonstrated throughout the work. In economics, the term "dynamics" refers to how the companies adjust their resources and capabilities over time to varying circumstances [15]. Albeit inherently temporary, the dynamicity enables the companies to create a competitive advantage in order to stay ahead of the industrial trend and sustain their profitability. In this thesis, the meaning of "dynamic" is more subtle and specifically of two fold. First, it describes the signal-response system in which the response value is adjustable based on particular intent (see Section 3.6). Put another way, the response is said to have a "dynamic" characteristic. Second, it refers to the dynamic programming (DP) method that will be applied to create a spreadsheet-based decision support system (see Section 2.5). The term "dynamic" reflects the fact that the decisions are interrelated and subject to change over time. The former was used to address the first two research questions in an empirical way, while the latter was used to deal with the third research question theoretically.

1.4.1 Empirical-level approach

Optimising the process parameters is perceived to be a useful technique for enhancing the environmental attributes of manufacturing processes [16]. While there are a wide variety of optimisation methodologies, a unique design of experiment (DOE) introduced by Dorian Shainin was adopted in this study (see Subsection 3.2.3). Despite the fact that Shainin's method is not widespread and being criticised over its working principles, it can be developed into a more widely-used strategy in process optimisation due to its ease of implementation. Addressing its inherent limitations, the multivariate statistical methods and the signal-response system were integrated into Shainin DOE. This novel integrated methodology is named as "*multi-response dynamic Shainin DOE*" (MRDSD) in this thesis. This study needs to overcome the multi-response problems effectively since reduction in process energy use does not necessarily imply a good product quality. To verify the proposed methodology, it was applied to reduce the energy consumption during injection moulding process with the assurance of impact performance. The inclusion of signal-response system is a promising approach in dealing with the trade-off situations based on different optimisation objectives.

1.4.2 Theoretical-level approach

Although process optimisation can be treated as a cost-effective alternative to improve the energy efficiency of manufacturing processes, it results in possible machine downtime and production disruption. Consequently, the companies might not be willing to adopt this approach due to the unforeseen risks and economic losses. In addition, whether this approach can outperform the benefits brought by the capital investment in energy-efficient equipment remains unclear. Due to the constraints on time and cognitive ability, the upper management is often satisfied with the status quo and hence the potential cost savings could easily be overlooked, especially when the decision-making process is often in a top-down fashion. In this context, this thesis proposes to create a spreadsheet-based decision support system (DSS) via dynamic programming, which is called “*DP-based spreadsheet solution*” in this thesis. Due to the persistent absence of DP software packages, an Excel-based solution (file SERP.xlsm) was developed to solve the problem under consideration. Nevertheless, decision makers may not simply base their investment decisions on the DP solution. The reason is that the decision-making process is not only affected from the economic perspective but also from the behavioural perspective (see Subsection 2.2.2).

1.5 Thesis Structure

The whole thesis is comprised of six chapters and one appendix. Following the introductory chapter, the remaining chapters are summarised as follows:

Chapter 2 provides a detailed review of the literature in order to identify the research needs and directions for this thesis. It first presents the much cited works regarding the barriers to energy efficiency. Subsequently, a range of energy-saving measures are reviewed before selecting the most implementable method in SMEs. This is followed by the study of various types of optimisation methodology and decision support system, in an attempt to address the barriers faced by SMEs in closing their efficiency gap.

Chapter 3 explicitly demonstrates the development of MRDSD. At the beginning, it carefully analyses the pros and cons in different kinds of experimental design. Next, the procedures in developing the proposed methodology through the integration of the multivariate statistical methods and the signal response system are clearly presented.

Chapter 4 presents an empirical study to verify the validity of MRDSD. To summarise, this chapter clearly describes the experimentation set-up, selection of quality response and material, list of important variables, and the experimental outcomes. In short conclusion, the proposed methodology has proved to be an effective "no-cost investment" strategy.

Chapter 5 primarily illustrates the formulation of DP model for solving the stochastic equipment replacement problem and the development of the corresponding Excel-based solution. A simple hypothetical example is demonstrated and the probable behaviours of the decision makers are discussed.

Chapter 6 concludes the overall thesis work and summarises the findings from the research objectives. The main knowledge contributions are presented and some future studies are discussed in response to the limitations found in the empirical-level and the theoretical-level approach.

CHAPTER 2

REVIEW OF LITERATURE

2.1 Introduction

Energy efficiency has become an inevitable topic in China due to the launch of its Twelfth Five-Year Plan that emphasises the energy intensity and carbon intensity reduction targets. This policy has prompted many companies into action but there is no established structure to support SMEs in taking appropriate actions. In order to understand the main causes to the efficiency gap, this chapter first looks into the much cited literature regarding the barriers to energy efficiency in SMEs. The main highlight of this section is to identify the research needs and directions for this thesis. To do so, a range of energy saving measures for plastic injection moulding was reviewed. Some discussions were provided in selecting the energy saving option. To further assist decision makers in SMEs in decision management for energy efficiency investment, this section also presents the literature concerning decision support systems and operations research.

2.2 Barriers to Energy Efficiency in SMEs

Although there is abundant empirical and theoretical literature studying the barriers encountered in industrial energy efficiency, there is no consensus on which is the most crucial barrier. The most probable explanation is that those studies were performed across different sectors, firm sizes or geographical regions. For example, Nagesha and Balachandra [17] identified limited financial resources and rational behaviour of business owner as the primary barriers to small industry (specifically foundry, brick and tile industry) in India. On the other hand, Thollander et al. [18] found that low priority of the energy efficiency issue is the major barrier among the manufacturing SMEs in Sweden. In particular to the Chinese context, Shi et al. [19] concluded that lack of economic incentive policies and lax environmental enforcement are the most important barriers to energy-efficient production in SMEs.

A wide-ranging of energy efficiency barriers has been extensively discussed in the literature. Describing all these barriers that have appeared from time to time will be an “exhausting” enumeration process. The main objective of this section is not to create another piece of puzzle to the literature in this field, but to review the much cited literature so as to scrutinise the potential barriers at a macroscopic level. Taking into account the research aim, a prerequisite in this section is to distinguish different categories of SMEs in China and to understand the definition of SMEs in a more explicit way.

2.2.1 Classification and definition of SMEs

On 18th June 2011, the Ministry of Industry and Information Technology, the National Bureau of Statistics, the National Development and Reform Commission, and the Ministry of Commerce jointly promulgated China’s Regulations on the

Standards for Classification of Small and Medium-sized Enterprises [20]. In this classification system, SMEs are divided into three categories: medium, small, and micro. The upper and lower limit standards for each category are specified according to different industries. The particular standards for manufacturing industries are as follows:

Table 2.1 – Classification standards for manufacturing SMEs in China [20]

	Upper limit	Medium	Small	Micro
Manufacturing industry	Staff headcount < 1,000 or, annual revenue < 400m Yuan	Staff headcount ≥ 300 and, annual revenue ≥ 20m Yuan	Staff headcount ≥ 20 and, annual revenue ≥ 3m Yuan	Staff headcount < 20 or, annual revenue < 3m Yuan

While it is compulsory to follow the conventional thresholds of staff headcount and annual revenue, the definition of SMEs also needs to take into account whether an enterprise is autonomous, a partner or linked [21]. This will provide a more realistic criterion to determine which category a particular enterprise falls within. Enterprises are considered autonomous if they are totally independent or they have a holding of less than 25% in other enterprises, or less than 25% of their holding is owned by others. There are exceptions for this 25% threshold such as universities, institutional investors, public investment corporations and non-profit research centres. Put another way, enterprises may still be considered autonomous even if more than 25% of their holding is owned by the stated organisations. The holding threshold for a partner enterprise is between 25% and 50%. When determining the SME status of a partner enterprise, a proportion of the other enterprise's staff headcount and financial details must be added. Exceeding the 50% threshold indicates that an enterprise is linked. For this case, all 100% of the linked enterprise's data must be added in determining the SME status. For example, if enterprise A owns 51% of B, while C has a holding of 33% in A, the calculation for determining the status of enterprise A will be equal to 100% of A plus 100% of B plus 33% of C. The definition and calculation for these three different types of enterprise are summarised in Table 2.2.

Table 2.2 – Definition and calculation for an autonomous, a partner and a linked enterprise

Type	Definition	Calculation
Autonomous	▪ Owns a holding of less than 25% in other enterprises ▪ Less than 25% is owned by other enterprises	The autonomous enterprise's data remains unchanged
Partner	▪ Owns a holding of 25% to 50% in other enterprises ▪ 25% to 50% is owned by other enterprises	The proportion which reflects the percentage of the partner enterprise's holding must be added
Linked	▪ Owns a holding of more than 50% in other enterprises ▪ More than 50% is owned by other enterprises	All 100% of the linked enterprise's data must be included

2.2.2 Perspectives of barriers

Despite the growing importance of energy efficiency investments, various types of barriers have reportedly inhibited companies from implementing these investments. According to the report prepared by Sorrell et al. [22], all these barriers to energy efficiency investments can be generally viewed from the economic, behavioural, and organisational perspectives, as clearly displayed in Figure 2.1. These perspectives are further explained as follows.

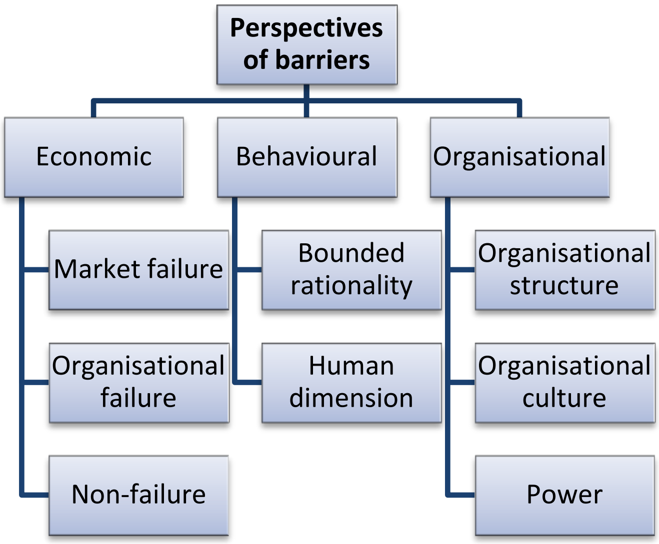

Figure 2.1 – Characterisation for the perspectives of barriers to energy efficiency improvement

2.2.2.1 Economic perspective

Jaffe and Stavins [23] as well as Golove and Eto [24] distinguished between the market barriers and market failures under the economic perspective. Based on their definition, the market barriers represent any factor which explains why energy efficiency technologies are neglected at a reasonable cost whereas the market failures refer to those market barriers which inhibit the market functioning and provide a justification for public policy intervention. One particular form of the market failures is information asymmetry where one party has better information access than the others [22]. Hannon et al. [4] pointed out that the economic market failures will be a long-term challenge in Chinese SMEs as the conservative bank-lending policies and governmental policies favour state-owned enterprises (SOEs).

The concept of market barriers is subsequently subdivided into organisational failure and non-failure by Sorrell et al. [22]. The presence of organisational failure explains the influence of organisational structure on the end-use energy efficiency which could be mitigated through managerial tools. Two broad categories of organisational failure are (i) principal-agent relationships within organisations, and (ii) split incentives within organisations. A principal-agent relationship arises when the interests of the principal (e.g., the shareholders) rely on the agent (e.g., the financial department). For example, the principal may impose stringent payback criteria on certain energy efficiency investment while the agent is responsible to comparing and evaluating its relative economic performance. Non-failure describes the rational behaviour of the organisation on energy efficiency investments by considering the payback rate, capital budget and hidden cost. As described by Eyre [25], when customers are facing with two options, one with low capital costs and the other one with unclear operating costs, they may rationally go for the low capital option.

2.2.2.2 Behavioural perspective

From the behavioural perspective, the theory of bounded rationality portrays a more factual interpretation of human behaviour. This theory was first introduced by Herbert Simon in his work in 1955 [26]. He pointed out that given the limited cognitive capacity of humans, it is difficult for decision makers to identify and evaluate all the possible alternatives. More explicitly, a number of assumptions which form the basis of bounded rationality can be summarised as follows [27]:

i. It is impossible to enumerate all possible events and estimate the probabilities of all events.
ii. Decision makers' preferences are not rational in terms of benefit maximisation.
iii. Decisions spread out over time and sub-decisions are mutually dependent.
iv. Attention and available information are vital in delimiting problems and strongly affects the subsequent decisions.

Bounded rationality is often cited as one of the reasons for why energy efficiency measures have been overlooked. The reason is that organisations will tend to make satisfactory decisions based on experience or practice, instead of devoting more time and effort for the optimal solution due to the constraints on time, attention, resources as well as relevant expertise [22]. As a “solution” to bounded rationality, every organisation has a set of rules which specifies the routines for coordinating activities and managing decisions [28]. Even so, rules can be mistakenly obeyed or violated because of misjudgement on special incidents. In conjunction with the theory of bounded rationality, Kahneman and Tversky [29] presented the concept of loss aversion and risk aversion which explains the human's preference to circumventing losses and risks rather than acquiring gains.

Another important concept from the behavioural perspective is the human dimension which relies more on social psychology rather than economics. Three important examples listed in the report of Sorrell et al. [22] are the form of information, credibility and inertia. The effectiveness of information is not only affected by the information search costs but also the form of dissemination. For example, the information might not be explicit enough for the companies to fully understand and utilise it. Credibility of the source is the further dimension of information where the companies may find the information inconceivable or irrelevant. Inertia describes the phenomenon of reluctance to change in the individuals or companies. As stated by Stern and Aronson [28] (*p. 69*), "people resist change because they are committed to what they have been doing".

2.2.2.3 Organisational perspective

Three particular concepts stemming from the organisational perspective are the organisational structure, organisational culture and power. Differences in organisational structure are reflected in the allocation of responsibilities which in turns impacts the organisations' decision making capabilities [30]. For example, financial department might not have adequate capability to process information pertaining to energy efficiency and thus they may reject a potential investment. One of the key factors for a successful energy management is the creation of an organisational culture with real interest from the top-level management [31]. Without commitment from the top-level management, it is difficult to raise the company awareness in order to sustain a long-term achievement. For example, setting up a reward programme within the company will lead the staff to become more proactive in taking actions for energy efficiency improvement. Power here refers to the authorisation of energy-related duties within an organisation. The barrier to energy efficiency might be a by-product of diverse roles assumed by individual departments where one department has more power than the other one [32]. It is not uncommon to see that energy management is often regarded as a peripheral agenda which is assigned to engineering or maintenance department, the status of which is normally low within a company hierarchy. These departments might not have sufficient power to initiate an immediate action for adopting energy-saving measures.

2.2.3 Barriers under economic theories

The classification of barriers becomes more obfuscated when some of them can overlap in multiple perspectives. For example, Kostka et al. [33] carried out a survey based on questionnaires completed by 479 SMEs in Zhejiang Province, informational barrier was found to be the most crucial factor inhibiting energy efficiency improvement in SMEs. They defined the informational barrier as "lack of information and high transaction costs which hinder SMEs from adopting energy-efficient investments and technologies" [33] (*p. 5*). This explanation lies somewhat between the economic and behavioural perspectives because lack of information is categorised as market failure; whereas the theory of transaction cost economics explains that the existence of transaction cost is caused by bounded rationality (see Subsection 2.2.3.3).

Some studies even suggest that the barriers are interrelated. For example, Wang et al. [34] employed interpretive structural modelling (ISM) to analyse the interrelationships among energy efficiency barriers in China. They developed an ISM hierarchy to clearly illustrate these interrelationships and rank them accordingly. Based on their findings, barriers of highest importance were also found in overlapping perspectives such as lack of awareness (economic and behavioural) and lack of strategic planning (behavioural and organisational).

Many studies have attempted to improve the explanation of barriers to energy efficiency by applying a number of economic theories. The four main theories found in the literature are neoclassical economics, agency theory, transaction cost economics, and behavioural economics [35]. This subsection is intended to understand these four different theories underlying the barriers to energy efficiency.

2.2.3.1 Neoclassical economics

Neoclassical economics covers a broad definition that has changed over time. In general, Dequech [36] claims that this theory can be characterised by the combination of the following features:

i. It does not challenge the assumption of rationality about human decision-making process and makes use of utility maximisation as the criterion of rationality.
ii. It emphasises on equilibrium.
iii. It disregards the existence of uncertainty.

Utility here refers to the perceived value of a good based on the decision makers' preferences and attitudes towards risk, but the determination of utility functions is usually difficult and subjective [37]. There are a number of existing utility functions that can be utilised for decision analysis, such as expected utility, cardinal utility, and ordinal utility.

2.2.3.2 Agency theory

Agency theory is used to explain the principal-agent problem such as that mentioned in Subsection 2.2.2.1. This theory additionally encompasses information costs and opportunism in the neoclassical economics [35]. According to this theory, the agencies sometimes act opportunistically with information asymmetries in order to maximise their own benefits rather than those of the principals.

2.2.3.3 Transaction cost economics

The theory of transaction cost economics originated from the book "The Economic Institutions of Capitalism" (1985) authored by Oliver Williamson. This theory differs from the neoclassical economics in the fact that the former contains the behavioural assumptions [38]. Under this theory, human rationality is inherently bounded and therefore additional costs are unavoidably incurred when making an economic decision. The transaction cost might be used for gathering information, assuming risk, reaching decision, and so on. This theory is often applied to explain some behavioural phenomena, not necessarily associated with the evident cases of undertaking transaction.

2.2.3.4 Behavioural economics

Behavioural economics rightly argues that decision-making is not only confined to the concept of bounded rationality but also systematically biased and descriptive [35]. For example, prospect theory suggests that individuals tend to be risk averse with respect to gains which gives rise to an asymmetrical S-shaped curve for the hypothetical value functions when evaluating outcomes, as illustrated in Figure 2.2 [39]. This theory was advanced by Daniel Kahneman and Amos Tversky where the former had received Nobel Prize in Economic Sciences in 2002 by virtue of this theory. The main contribution of prospect theory is to describe and predict the "distorted" human behaviour rather than to characterise the rationally optimal behaviour.

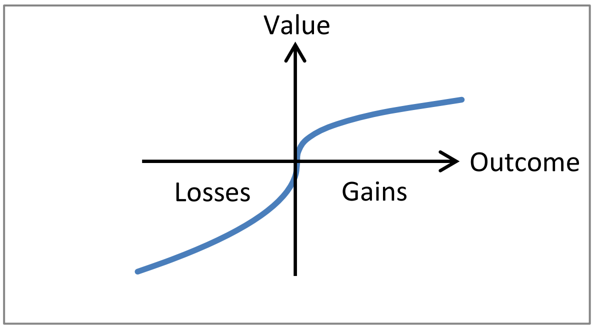

Figure 2.2 – Hypothetical value functions for gains and losses. Source: [39]

2.2.4 General taxonomy of barriers to energy efficiency

Due to the blurring boundaries between neoclassical economics and agency theory, both theories will be combined as NA theory in this thesis. Likewise, due to the proximity between transaction cost economics and behavioural economics, the term TB theory is given to represent these two similar theories. In this sense, NA theory and TB theory can be distinguished from each other on a more distinctive basis.

While the barriers to energy efficiency are frequently reinterpreted in numerous ways by different researchers, Sorrell et al. [35] alleged in their more recent report that most of the barriers can be generally subdivided into six types, i.e., risk, imperfect information, hidden costs, access to capital, split incentives, and bounded rationality. This report was prepared for the United Nations Industrial Development Organisation (UNIDO), which has collectively studied 160 works regarding energy efficiency, drawn from both academic and 'grey' literature. On the basis of this comprehensive report, the contributory mechanisms for each of the six specified barriers are elaborated in Table 2.3 in accordance to NA theory and TB theory.

Table 2.3 – Taxonomy of barriers to energy efficiency based on economic theories

Barriers	Descriptions
Risk	NA theory: ▪ Energy-efficient technologies carry higher technical risk caused by unfamiliarity; the probable technical disruption might result in a high discount rate for the relevant investment. ▪ Energy efficiency investments are considered as irreversible because they are usually associated with building renovation, equipment installation or staff retraining. ▪ Energy efficiency investments do not reflect high rate of return due to uncertainties over the potential benefit.

Table 2.3 (*continued*)

Barriers	Descriptions
Risk	TB theory: ▪ Perceptions of risk are viewed differently by individuals and therefore the decision may deviate from the rational economic models.
Imperfect information	NA theory: ▪ Insufficient information leads to underestimation of the benefit that can be brought by the energy efficiency investments. ▪ The asymmetric or ambiguous information within energy service market[4] is difficult to detect by the end-users and the underlying search cost is relatively high. TB theory: ▪ The transaction costs involved in the acquisition of information might not be considered in the engineering-economic models. The relevant costs can be high due to incapability to process information or inadequate credibility of the source. ▪ While energy efficiency investments can have the characteristics of search goods, experience goods or credence goods[5], in most cases they are regarded as the credence goods.
Hidden costs	NA theory: ▪ General overhead cost of energy management is considered as an important obstacle to the energy efficiency investments. ▪ Some energy-efficient technologies may lead to production disruption, retraining of staff or additional maintenance cost. TB theory: ▪ There is transaction costs associated with searching for opportunities, seeking approval for capital investment, tendering for renovation, and so on. Transaction costs may decline over time as a result of learning effects within the organisation.
Access to capital	NA theory: ▪ SMEs often deal with difficulties in raising additional funds internally or externally because they have less credit-worthiness. ▪ Asymmetric situation possibly exists between the risks and rewards of energy efficiency investments.

[4] Energy service market refers to the sector which provides a wide range of solutions for energy-related business.

[5] Search goods: consumers understand the product quality to a certain extent before making the procurement decision; experience goods: consumers only realise the product quality after the use; credence goods: consumers are unclear about the product quality even after the use.

Table 2.3 (*continued*)

Barriers	Descriptions
Access to capital	NA theory: ▪ Companies sometimes are reluctant to borrow money from the loan finance as a result of perceived risk in increasing the debt/equity ratio known as "gearing". TB theory: ▪ Fund raising from either internal or external sources may incur additional transaction costs. ▪ Cost savings from energy efficiency investments are presumed to be small and hence they are not prioritised by top management.
Split incentives	NA theory: ▪ Departments within an organisation may overlook energy efficiency improvement simply because they are not in charge of energy management. ▪ The incentive structure in SMEs is more inclined to investments with rapid capital payback. TB theory: ▪ The energy efficiency investments may be dealt by individuals or departments who only aim at minimising the investment costs but lack the relevant knowledge. ▪ The presence of transaction costs is likely to reduce the incentive for energy efficiency improvement.
Bounded rationality	NA theory: ▪ The concept of bounded rationality, which is opposed to the rationality assumption about human decision-making process, is beyond the boundaries of NA theory. TB theory: ▪ Non-optimal decisions are made due to the constraints on time, attention, resources and the ability to process information. ▪ The decision for making an investment relies heavily on the strategic objectives of the organisation; consequently the energy efficiency improvement might not be prioritised. ▪ Organisations tend to solve problems by following existing rules or routines rather than developing a new method. ▪ Individuals or companies are reluctant to change the status quo due to cognitive dissonance[6], loss aversion or risk aversion.

[6] A phenomenal theory proposed by Leon Festinger in his book named "A Theory of Cognitive Dissonance" (1957), which states that human has an intention to maintain internal consistency which can give rise to irrational behaviour.

2.2.5 Discussions on the barriers to SMEs

In this section, barriers to energy efficiency are classified into three perspectives (economic, behavioural, and organisational) and interpreted using two different combinations of economic theories (NA theory and TB theory). These classifications and interpretations suggest that companies do not simply make their investment decisions concerning energy efficiency based on economic factors. The TB theory has frequently been used to explain the existence of different barriers from the behavioural and organisational perspective. It would seem that unless relevant investments show high rates of return, a wide range of barriers may inhibit the company from realising energy efficiency improvement. This argument is plausible especially in the environment of SMEs where the investment costs could easily outweigh the saving potentials since their energy intensity is comparatively low.

Continual investment is necessary for a company to compete in the marketplace [40]. With fewer internal assets than medium-sized enterprises, small and micro enterprises are far less capable of making capital investments on energy efficiency improvement. In addition, small and micro enterprises are at an apparent disadvantage in competing for bank loans because larger enterprises usually have a better record for debt repayment. Nonetheless, investment does not necessarily mean acquisition of fixed assets with high capital costs. What remains questionable is the extent to which such investment costs would be willingly assumed by SMEs. The answer to this question is subjective according to utility theory (see Subsection 2.2.3.1) and might not be unanimous across different sectors, regions, and company sizes of SMEs category. In this context, the first research question arises here is:

would there be a strategy with "no-cost investment" that can help manufacturing SMEs to implement energy efficiency project without capital expenditure? Perhaps an ideal "no-cost investment" would not occur because hidden costs generally coexist alongside any action or decision based on NA theory and TB theory. These costs might include loss from production disruption or cost from hiring research personnel to conduct rigorous research on the cost-effectiveness of various investments. Small and micro enterprises could have been aware of the potentials of smaller energy efficiency projects, however, the number of staff is limited and their working time is often preoccupied with meeting production demand and maintaining product quality [41]. As a consequence of limited access to capital, expertise and time, small and micro enterprises tend to "behave rationally" and place energy efficiency projects at low priority.

In practical terms, small and micro enterprises could benefit enormously from the collaboration with external research institutions such as universities as discussed in [42] by the author. This collaboration allows for comprehensive data collection and analysis because research institutions usually have sufficient research personnel, time resource and laboratory equipment. However, decision makers might have an early perception that this collaboration might not result in financial returns. Addressing this issue, this thesis assumes the role as "research institution" and aims to generate proprietary solutions to small and micro enterprises. The outcomes will then be disseminated to show that potential improvement in both economic and environmental performance can be achieved by means of "no-cost investment".

2.3 Energy-saving Measures for Plastic Injection Moulding

This section provides more information about the injection moulding process and discusses the key factors that affect the overall energy consumption. An injection moulding machine fundamentally consists of drive system, injection system, clamping system, mould system and control system. Injection moulding is known to be an intricate, nonlinear process, therefore the control system must be equipped with robust sensor or transducer technology [43]. A high-quality control system is capable of self-diagnosing and justifying the root causes of faulty operation. In fact, the advancement of injection moulding technology is mainly attributed to the ever-enhancing control capability [44].

In general, one complete injection moulding process cycle can be divided into three distinct stages [45]:

i. Plasticisation stage (screw recovery) where the plastic pellets are being melted and mixed inside the heating barrel by the shear action of the reciprocating screw.
ii. Filling stage where the molten material is injected with a specified shot size into the closed mould unit under high injection pressure.
iii. Packing and cooling stage where additional material is packed into the mould cavity to compensate for the volumetric shrinkage during solidification.

Injection moulding is thus considered as an energy-intensive process, since it converts the solid plastic pellets into thermally homogeneous melt and then re-solidifies the material by a series of operations [46]. When practiced in an industrial scale, injection moulding is required to meet a wide range of requirements where the efficiency of which is highly dependent on various factors. In general, energy consumption during injection moulding process can be seen as a complex function of machinery, part design, plastic material, production rate, mould design, and process parameters. A range of energy-saving measures are reviewed in order to identify where and how improvements in energy efficiency can be made by the injection moulding industry.

2.3.1 Development of energy-saving machinery

There are two internationally recognised ways to designate the plastic injection moulding machines generally operated nowadays — the clamping tonnage and shot capacity [45]. The clamping tonnage, usually rated in tons, is the largest force that can be supplied by the machine to close the mould halves together. For example, Demag Systec 160-840 is a machine model which possesses a maximum clamping tonnage of 160 tons and a shot capacity of 840 units. While the injection moulding application is expanding, there appears to be a growing competition among machine manufacturers worldwide. In order to survive in the existing market, subjects such as computer integrated injection moulding, shortened cycle time, improved product quality, higher part complexity, and simplified mould changeover must always be prioritised [47]. Nowadays, when environmental compatibility issue becomes a hot topic, injection moulding machine manufacturers are also required to accommodate energy-efficient technology in their latest machine design. According to a European project, Reduced Energy Consumption In Plastics Engineering (RECIPE) [48], almost 59% of the overall energy usage in a typical injection moulding plant can be attributed to the machinery as shown in Figure 2.3.

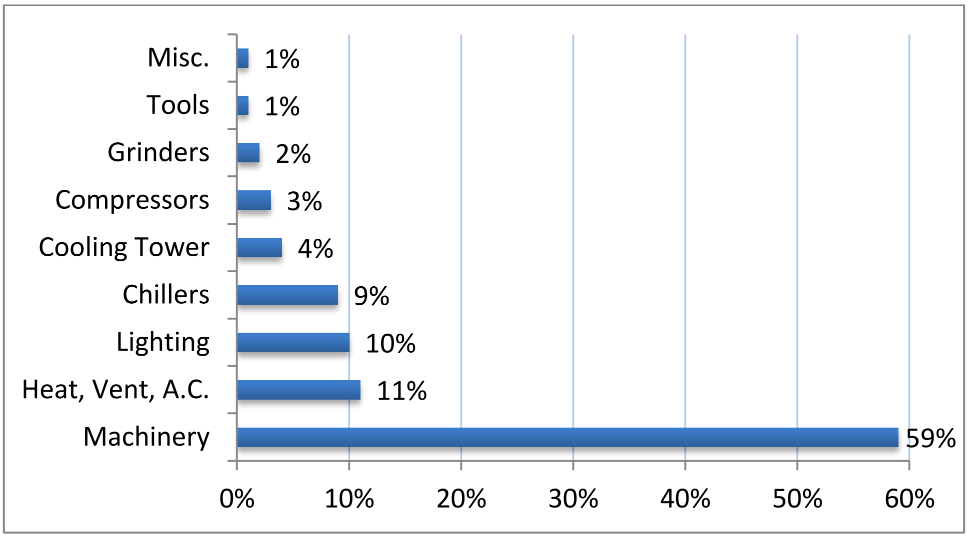

Figure 2.3 – Energy usage distribution in a typical injection moulding plant. Source: [48]

2.3.1.1 Energy-saving drive systems

Drive system is the primary energy consumer within an injection moulding machine as most energy are consumed by the drive unit during processing [48]. The drive unit delivers the necessary power for the operation of the injection and clamping units. A conventional hydraulic machine is highly inefficient because its hydraulic fluid operation is driven continuously at a fixed rate. The flow rate is simply manipulated by hydraulic oil re-circulation through pressure relief valves. Excessive fluid is throttled back to the hydraulic tanks, adding up energy waste and cooling system workload [48]. Energy requirements for different stages in one complete injection moulding cycle fluctuate to a large extent. As a result, there is considerable amount of energy wasted from the conventional machine due to the fluctuating load demand is not accommodated accordingly. Choosing a hydraulically driven machine based on the peak load demand will result in large energy consumption. Therefore, installing an accumulator in the machine can handle the surging load demand during processing and mitigate the need of a larger hydraulic system [49].

The introduction of variable displacement pump (VDP) and variable speed drive (VSD) enable the machine operation to match with the varying load demand. In VDP system, the volume of fluid being pumped can be adjusted accordingly, reducing overflow losses. Whereas, VSD can alter the motor speed in accordance to the variable load and thus optimise the pump rate [48]. Other benefits of retrofitting old machines with VDP/VSD or purchasing new machines which contain VDP/VSD include reduced noise level, better process control as well as less overheating problems in the hydraulic system.

In recent years, servo-driven machines have largely replaced conventional hydraulic machines owing to better energy efficiency. The servo drive does not require pilot flow or minimum system pressure and it does not consume energy in idling mode [50]. It receives command signal from the closed-loop speed controller and then transmits the signal to the hydraulic pump in order to produce hydraulic flow correspondingly. Further advantages of servo-drive system encompass faster response, longer equipment life and higher control precision. However, the servo-driven machine is relatively more expensive and thus it is more feasible to be employed in precision injection moulding for manufacturing high-end plastic products [51].

In hydraulically driven machines, electric pumps transfer energy to hydraulic fluid which is then transformed into useful mechanical work. Obviously, hydraulically driven machines have inherent inefficiencies attributed to several transfers of energy together with friction losses inside the hydraulic circuits. The launch of all-electric machines becomes the best energy-saving solution because the use of direct-drive technology greatly reduces idling loss and eliminates consumables such as hydraulic oil and filters [48]. According to the case studies presented in Cléirigh's report [52] for Plastics Ireland, the percentage reduction in energy consumption can be up to 66% when a hydraulic machine is replaced with an all-electric machine. Moreover, many machine manufacturers claim that all-electric machines offer better start-up, higher precision, faster response, and lower noise level in comparison to hydraulic machines. However, the price of all-electric machines is generally higher than that of hydraulic machines. The introduction of hybrid machines hence fits into a niche market at an intermediate cost. A common hybrid machine features a hydraulic drive in the clamping system and a servo drive in the injection system [48]. The screw recovery stage consumes most energy in one complete cycle, thus "electrifying" the screw movement would provide the greatest savings in designing a hybrid machine [53].

2.3.1.2 Energy-saving injection and clamping systems

The secondary form of energy consumed by injection moulding machine is the process heat. Depending on the type of drive system, barrel heating accounts for 20-50% of the energy input to the machine operation [54]. Hence, improving injection system can be treated as another alternative to energy-saving. First, screw design can be optimised to obtain homogeneous melt at uniform and lowest possible melt temperature, reducing specific energy consumption [55]. For example, Myers et al. [56] introduced a new injection screw design called Variable Barrier Energy Transfer (VBET) screw which possesses a unique flight geometry that can maximise the conductive melting mechanism. Second, insulating the heating barrel can achieve an energy saving of up to 15% without significant capital expenditure [57]. Energy can be lost easily as heat from the exposed barrel surfaces to the surrounding environment during injection moulding process. Therefore, a well-insulated heating barrel assembly not only reduces energy waste, but also enhance the start-up process, melt temperature control, and operational safety. In order to reduce the heat loss due to the physical contact between barrel surface and heater bands, Xaloy® Corporation designed a new barrel heating technology with non-contact induction called nXheat™, which allows direct heating through an interposed layer of thermal insulation [58].

In the aspect of the clamping system, the toggle clamp design is claimed to be able to offer an energy saving of up to 10% compared to direct hydraulic clamps, as a result of shorter cylinder stroke for mould movement [55]. Another main advantage of using toggle clamp is its capability of “self-locking” once mechanically extended. Nevertheless, the use of toggle mechanism can shorten the mould life because large clamp force is occasionally exerted on the mould unit [55]. Consequently, toggle operated clamp is often used in the small and medium-sized injection moulding machines. Direct hydraulic clamp is still preferred in particular for large-tonnage machines in spite of large initial cost and oil leakage problem since it offers higher manoeuvrability. Jiao et al. [59] demonstrated a novel clamp design, specifically an internal circulation direct hydraulic two-platen clamping system, which has several advantages over toggle clamp design such as simpler mechanical structure, higher energy efficiency, higher moulding precision, and stronger mould adaptability.

2.3.2 Improvements in part design and plastic material

The part design has a direct relation to the selection of machine size as designated in clamping tonnage and shot capacity, which in turns results in an immense influence on the overall energy usage. The tonnage requirement is decided according to the required cavity pressure and the projected area of the mould cavity. A safety factor of about 10 to 20% is usually required in order to ensure no flashing (melt leakage) occurs at the parting-line area [46]. On the other hand, the shot capacity is determined by the product of the maximum injection pressure and the maximum injection volume [45]. Furthermore, the cooling time heavily relies on the part wall thickness. Some researchers [60, 61] thereby suggest that the minimisation of energy consumption during injection moulding process should be initiated at the product design stage. They developed a framework to estimate the necessary energy for producing an injection moulded part before going into real production.

With regard to processing material, different types of plastic material have dissimilar properties like thermal conductivity, thermal diffusivity, temperature dependent viscosity, heat of crystallisation, rheological behaviour, characteristic cooling time, and thus different specific energy requirement for processing. For example, Figure 2.4 illustrates the characteristic cooling time and melt flow index (MFI) for different plastic material by assuming a wall thickness of 2 mm. MFI is a parameter empirically defined by the amount of plastic that can be extruded by the plunger driven by a weight through the heated die opening, with a standard opening of 2.095 mm and a length of 8 mm, usually expressed in grams per 10 minutes [62]. Viscosity of polymeric melt has an inversely-proportional relationship with MFI. In other words, materials with low MFI demand larger injection force by the screw to fill into the mould cavity because viscosity is the resistance to flow. Given the growing demand on energy efficiency, some advanced materials that require lower specific energy requirement have been developed. For examples, Dow® Post-metallocene Linear Low Density Polyethylene (P-mLLDPE) [63] which requires lower back pressure and Makrolon® series [64] which permits faster cycling with low viscosity.

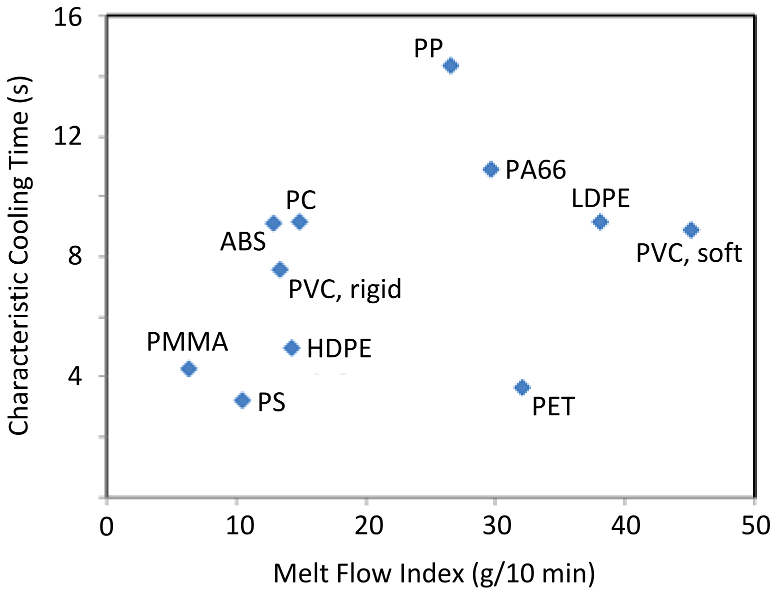

Figure 2.4 – Comparison of the melt flow index and the characteristic cooling time for different types of plastic materials with a wall thickness of 2 mm. Source: [65]

2.3.3 Maximisation of production rate

Specific energy consumption (SEC), commonly calculated in unit of kWh/kg, is a useful measure to compare the efficiency of different machines with the similar task [66]. It is defined as the necessary input energy per unit mass of processing material. The measurement and monitoring of SEC can be conducted at either machine level or site level [48]. Machine SEC refers to the specific energy usage of a single machine unit while site SEC is a more comprehensive energy usage measurement for the whole manufacturing plant, including auxiliary equipment, building heating and lighting as well as other utilities. Several examples of auxiliary equipment that augment the power requirement for injection moulding process are dehumidifiers, granulators, conveyors and robotics.

One frequent assertion about the reduction in SEC has been that higher production rate will result in lower SEC because the fixed energy demand is being amortised over a larger production volume. Gutowski et al. [67] deduced a general empirical equation to express the relationship between SEC and production rate as shown below:

$$\mathrm{SEC} = \frac{P_f}{\dot{m}} + p_v \tag{2.1}$$

where $\dot{m}$ = production rate, kg/h;

P_f = fixed power, kW;

and p_v = variable energy per unit mass, kWh/kg.

Equation 2.1 shows that production rate not only serves as an indicator of productivity, but also affects the SEC value. In general, the term P_f is required to support the operation of the equipment features, while p_v represents the physics of the actual production process. For hydraulic injection moulding machine, P_f is the minimum power required to maintain the operation of hydraulic system, cooling system and other idling equipment; whereas p_v indicates the average energy being consumed per unit mass of processing material, which is closely related to the part design and plastic material. Qureshi et al. [68] conducted an empirical study to quantify Equation 2.1 by examining the energy consumption of hydraulic injection moulding machine. Their model successfully predicted the machine SEC value with an accuracy of up to 90%.

On the other hand, Kent [11] generated a benchmark based on an investigation of 114 standard hydraulic injection moulding machines of different sizes as displayed in Figure 2.5. The curve is a power law best fit to the data distribution which clearly illustrates that machine SEC generally reduces with increasing production rate. Nevertheless, simply comparing SEC values for assessing energy efficiency is a great pitfall because these values can be easily affected by the variation in production volume [11]. For example, RECIPE [69] learned that small-sized machines would lead to higher site SEC in comparison to large and medium-sized machines because larger machines offer higher production volume, resulting in lower SEC value. For this reason, it is vital to distinguish between the "temporary savings" and the "genuine efficiency". The category of product is a decisive factor on the production rate. Technical or precision parts with tight tolerance limits are normally associated with longer cycle time, and hence higher SEC. In contrast, general purpose items are usually fabricated in fast process cycle with lower SEC.

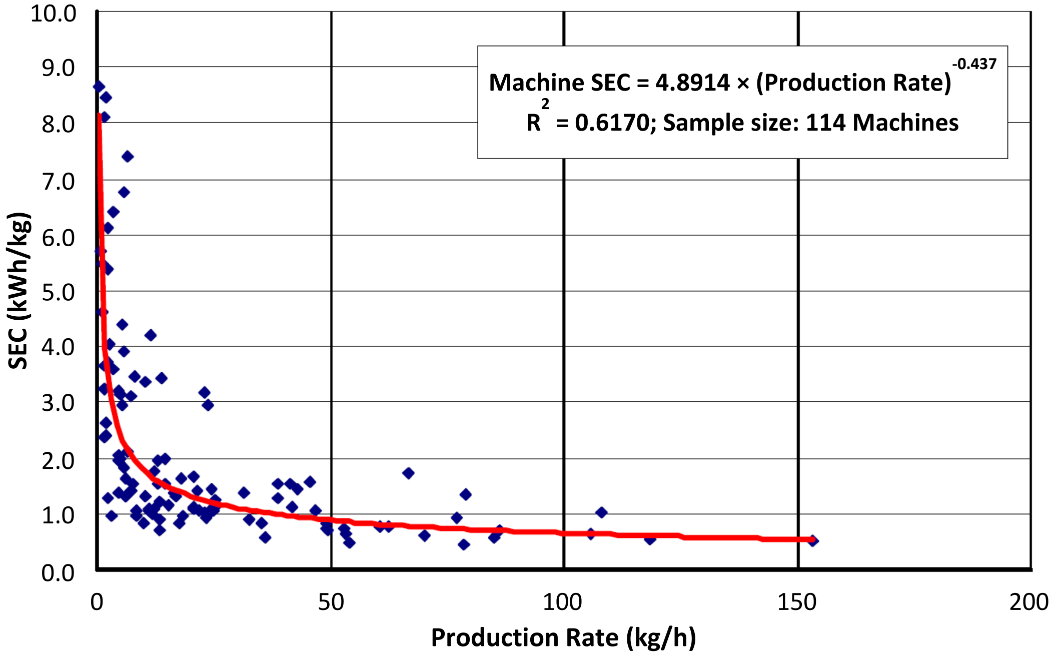

Figure 2.5 – Machine SEC vs. production rate for injection moulding. Source: [11]

2.3.4 Optimisation of mould design and process parameters

The influence of mould design and process parameters on the specific energy requirement of injection moulding process is not negligible [70]. There is a great potential to realise energy saving through the optimisation of mould design and process parameters. Optimisation of mould design normally takes place at the early stage of an injection moulding plan because making modification after the mould fabrication often entails a high expense. Comparatively, optimisation of process parameters is inexpensive and can be performed whenever necessary.

2.3.4.1 Mould design

Injection moulding with well-designed lightweight mould is normally more efficient than the heavy duty mould [71]. Mould design variables such as the gating system, sprue geometry, and runner layout are significant to the overall energy usage. In every injection moulding cycle, the molten material is being injected into the mould cavity through a narrow entrance called gate. Sprue is a tapered channel where the melt first enters the mould from the injection nozzle. Runner system is needed particularly in the multi-cavity mould at which the melt is distributed from the sprue into multiple cavities. There are two kinds of runner system: cold runner system and hot runner system. The major discrepancy between these two systems is that the molten material remains in the hot runner system until the next shot, whereas in the cold runner system, the unwanted runner part will be formed together with the final moulding. Although the hot runner tooling is more expensive, it reduces the necessary shot weight, which in turn lowers the overall energy consumption [46]. The cooling system configuration is also an integral part of the mould unit where the channel design will dictate the cooling efficiency.

2.3.4.2 Process parameters

Process parameters affect the specific energy requirement to a certain extent but little research work has been carried out in this area [54]. Injection moulding is always regarded as a complex manufacturing process since it involves numerous parameters that affect the quality of the final product. Chen and Turng [72] suggest that all important parameters could be classified into three distinctive levels: level 1 for machine variables, level 2 for process variables, and level 3 for quality variables (see Table 2.4).

Table 2.4 – Classification of variables for injection moulding process. Source: [72]

Variables and Level	Examples
Level 1 – Machine variables	Temperature: i. Barrel temperature (in several zones) ii. Nozzle temperature iii. Coolant temperature Pressure: i. Pack/hold pressure ii. Back (recovery) pressure iii. Maximum injection pressure Sequence and Motion: i. Clamp/fill/pack/hold/recovery/eject switchover point ii. Injection (ram) speed (constant or profiled) iii. Screw (rotation) speed iv. Shot volume and cushion (via screw displacement)
Level 2 – Process variables	Melt temperature (in the nozzle, runner, or mould cavity) Melt pressure (in the nozzle, cavity) Melt-front advancement Maximum shear stress Rate of heat dissipation and cooling
Level 3 – Quality variables	Part weight and part thickness Dimensional conformity (shrinkage and warpage) Sink marks Appearance and strength at the weld lines Other aesthetic defects: burn marks, gate blushes, surface texture

Machine variables are independently controllable as they can be fine-tuned at the control panel unit within an acceptable range. When all settings have been carefully checked and optimised, the machine can be switched to fully automatic mode for long production run. Process variables are the combined result of machine variables, processing material, machine and mould configuration. Profitability of the manufacturers is largely determined by the quality variables which are the final responses from both machine and process variables.

Changing the process parameters of manufacturing operations has been identified as a technically and economically viable technique to reduce the environmental impact in terms of energy consumption [16]. This requires an empirical study to understand the relationships between process parameters, energy consumption, as well as the desirable quality responses. Merely reducing energy consumption without considering the product qualities is totally impractical. Nevertheless, there is insufficient quantitative information regarding the relationships among machine, process, and quality variables for injection moulding [72]. Studying the capricious interrelationships among these variables is a complicated process because the process dynamics could be governed by a set of equations. In addition, the quality variables in terms of aesthetic features are difficult to measure quantitatively.

2.3.5 Energy Management Programme

In addition to process parameters optimisation, there are many low-cost practices that can be implemented by the injection moulding industry to reduce energy consumption during processing, e.g., regularly checking cooling pipework, utilising heat recovery, reviewing mould performance and carry out routine maintenance. As most of these energy saving opportunities are mostly technical in nature, Figure 2.6 illustrates that energy management programme will bring greater improvement potentials in a long-term policy. According to the definition from the "Dictionary of Energy Efficiency Technologies" [73], energy management creates an energy awareness within an organisation and provides tools for reducing its energy consumption to a lower level. There are specific case studies well documented and promulgated to facilitate energy management in the plastic products industry [48, 57, 71, 74]. Generally, the key elements of a successful energy management programme include [31, 48, 57, 73]:

i. Commitment from the top management and well-developed strategies
ii. Capital and operating budgets in relation to energy management
iii. Delegation of responsibility to the well-trained personnel
iv. Reporting and communication throughout all levels of the organisation
v. Review and internal recognition for the project achievement
vi. Continuous energy monitoring and assessment of energy efficiency investments

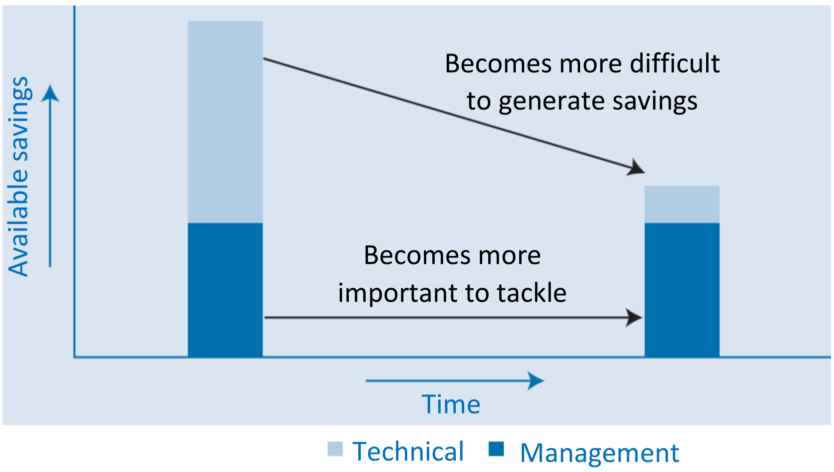

Figure 2.6 – Energy savings potential against time. Source: [57]

2.4 Optimisation of Injection Moulding Process

After scrutinising various energy-saving measures in Section 2.3, the first insight implies that energy efficiency may be improved through process parameters optimisation as a “no-cost investment” strategy. This lead to the second research question: *which optimisation methodology would be the most appropriate solution to address the particular barriers facing SMEs?* Various types of optimisation methodologies have been adopted by researchers to improve the quality of product or system. There is unlikely to be one best method that fits into all kinds of situation since each optimisation method has its own strengths and weaknesses. As a consequence, one of the main difficulties in the optimisation process is to select an appropriate method for a particular problem. The correct selection will heavily depend upon the nature of problem and the conditions of the end-users. This section aims to identify a technically feasible yet economically viable approach that can overcome the “rational behaviour” of the end-users in reducing energy consumption. Prior to selecting the most suitable method, a literature review on the recent optimisation methods is presented, particularly in the field of injection moulding process.

2.4.1 Review of optimisation methodologies

The injection moulding operation can be divided into three stages: first, running the injection moulding machine; second, utilising a prescribed set of parameters for a particular plastic material and mould unit to produce satisfactory parts; third, optimising the operation so as to achieve better product quality and higher productivity [46]. Without adequate expertise, trial-and-error and one-factor-at-a-time (OFAT) approaches are commonly applied at the shop floor for process optimisation. These approaches use unsystematic guesswork based on past experiences or suppliers' recommendations until the desired result is achieved. At best, it gives satisfactory outcomes with several attempts but it does not provide insight into the root causes of the problem.

In comparison to the trial-and-error or OFAT approach, design of experiment (DOE) is definitely a more organised method for conducting experimental study in determining the optimal solution. DOE is a series of experimentation where changes are purposely made to the input variables so that corresponding data can be collected and analysed by statistical methods, resulting in valid and objective conclusions [75]. Full factorial design, fractional factorial design, orthogonal design and Latin hypercube design are some classical examples of DOE (see more details in Subsection 3.2.1). For example, Annicchiarico et al. [76] employed half fractional factorial design to minimise the shrinkage problem whilst maximising the part mass in micro injection moulding. Taguchi method is a special form of DOE which basically makes use of orthogonal arrays and signal-to-noise (S/N) ratios to innovate and reinterpret the classical approach (see more details in Subsection 3.2.2). Orthogonal arrays can greatly reduce the number of experiments induced by the number of variables and their associated levels; while S/N ratios act as performance measures where the response means are compared to the variation. For example, Öktem [77] made use of Taguchi orthogonal arrays and analysis of variance (ANOVA) to investigate the effect of the process parameters on the shrinkage problems during injection moulding process.

In terms of analytical approach, a number of mathematical models have been established to describe various characteristics of injection moulding process such as filling and heating stage [46]. However, a general comprehensive mathematical model which can satisfy different operational conditions is not available due to the complexity of this process [78]. Therefore, computer-aided-engineering (CAE) simulation tools like C-Mold and Moldflow are often adopted by researchers to optimise injection moulding process. CAE simulation allows engineers to quickly modify the input parameters, run the simulation and then analyse the possible outcomes. Despite the fact that CAE simulation can minimise resource expenditure and production disruption, it can be a tedious and computationally costly task since iterative runs are often needed to achieve the best possible results. For that reason, researchers have integrated various optimisation methodologies with CAE tools to optimise injection moulding process.

Dang [79] divided the simulation-based optimisation methods into direct discrete methods and metamodel-based methods as shown in Figure 2.7. According to his definition, direct discrete optimisation is an approach where explicit objective functions are formulated; whereas metamodelling optimisation is an approach where objective functions are approximated into a form of low order polynomials with acceptable accuracy. In direct approach, both gradient-based and non-gradient based optimisation techniques have been applied to optimise injection moulding process. For example, Turng and Peic [80] employed a gradient-based local optimisation algorithm called sequential quadratic programming (SQP) to search for the optimal point based on the steepest descent scheme. In some cases, genetic algorithm (GA) has been combined with gradient-based technique for process optimisation because GA is known to be a global optimisation algorithm while gradient approach tends to reach a local optimum. For example, Lam et al. [81] used GA/gradient hybrid method to optimise injection moulding conditions and showed that hybrid approach has better performance than the GA method alone.

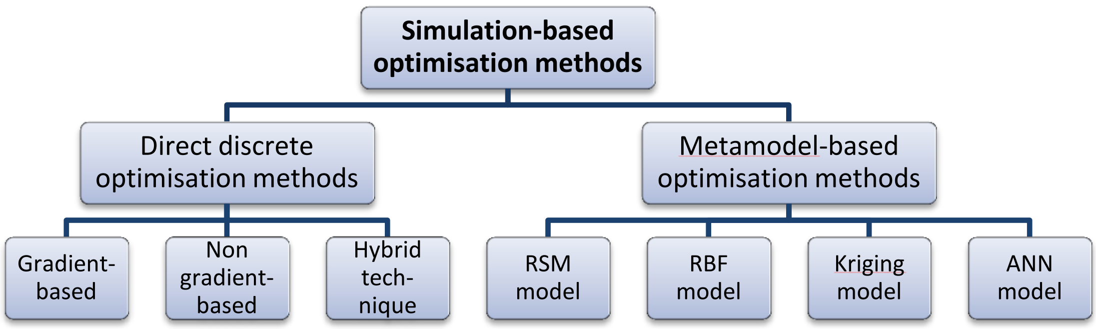

Figure 2.7 – Classification of simulation-based optimisation methods. Source: [79]

Metamodelling methods include response surface method (RSM), radial basis function (RBF), Kriging model and artificial neural network (ANN). Metamodels, also known as surrogate models, are used to shorten the computation time by approximating the simulation outcomes as closely as possible. For example, in order to minimise the warpage problem in injection moulded parts, Kurtaran and Erzurumlu [82] applied RSM model in conjunction with GA while Gao and Wang [83] adopted Kriging model to replace the time-consuming Moldflow analysis. Li et al. [84] used RBF model to improve the packing profile of injection moulding process in order to obtain a moulded part with better shrinkage evenness. Altan [85] generated an ANN model which can accurately predict the shrinkage problem in injection moulded parts. Nevertheless, employing surrogate models can still be too costly because they are built based on the data obtained from previous simulations or experiments [86]. For example, ANN application requires considerable amount of training data from the real experiments for better estimations. The accuracy of surrogate models may need to be sacrificed in order to alleviate the computational effort, reducing the effectiveness of the surrogate models.

Along with GA, self-adaptive evolution (SAE) and differential evolution (DE) are characterised as evolutionary algorithms (EAs), which mimic the Darwinian evolution in a way to evolve better solutions through genetic operations such as survival of the fittest (selection), recombination (crossover) and mutation [87]. Unlike those EAs, particle swarm optimisation (PSO) does not use crossover operators to exchange information but it is still regarded as EAs because it is population-based, fitness-oriented and variation-driven [88]. Although integrating CAE simulation with EAs facilitates engineers in searching for optimal solutions, they are sometimes considered as not computationally efficient because a standard EA requires an adequate amount of fitness evaluations to achieve an optimal solution. Addressing this issue, Chen et al. [89] made use of Kriging model to replace the CAE simulation as the fitness function of PSO algorithm, and they were able to reduce computational cost effectively. All these EAs are also regarded as global optimisation algorithms which are capable of searching for global optimum with the presence of multiple local optima. Simulated annealing (SA) is another global optimisation technique that originates from the analogy with the physical annealing process in which the energy is the objective function and the temperature is the control variable [90]. Turng and Peic [80] compared various global (i.e., SAE, DE, SA) and local (i.e., SQP) optimisation algorithms in terms of computational efficiency and effectiveness for injection moulding process.

Other well-known methods that have been used for optimising plastic injection moulding process include case based reasoning (CBR), grey relational analysis (GRA) and fuzzy logic [91]. The fundamental idea of employing CBR is to solve a new problem based on the most similar case stored in the case library. As such, the performance of CBR system deeply relies on the accuracy in case retrieval. Zhao et al. [92] employed CBR to identify the initial process parameters for injection moulding. In GRA, an uncertain problem is managed with the use of grey relational coefficients which express the level of correlation between the desirable and actual experimental outcomes [93]. The optimal levels of process parameters can be obtained through the computation of the grey relational grade that corresponds to the performance characteristics. For example, Shen et al. [94] performed the Moldflow analysis in conjunction with GRA to find out the minimal warpage range for micro-injection moulding process.

The adoption of fuzzy logic in industrial applications is generally attributed to two reasons [95]: first, it can deal with functional nonlinearities which are subjected to difficult mathematical modelling; second, it can strongly imitate the experience of a human operator. Chiang and Chang [96] integrated GRA with fuzzy logic (known as “grey-fuzzy logic”) to optimise multiple performance characteristics when manufacturing cell phone shell via injection moulding process. It is worth noting that fuzzy logic together with other methodologies such as GA and ANN are often termed as soft computing in the field of computer science, which exploit the tolerance for imprecision, uncertainty to achieve tractability and low solution cost [97]. Soft computing could deal with optimisation problems in an approximate way to human reasoning. In contrast, hard computing requires a precisely stated mathematical model which is usually not available in the real world problems.

Table 2.5 summarises all the above-mentioned works in chronological order where the optimisation methodologies, targeted product qualities and key results are presented concisely.

Table 2.5 – Recent studies on process parameters optimisation for injection moulding

Year and Authors	Methods	Targeted qualities (plastic material)	Results and discussion
2002, Turng & Peic [80]	Fractional factorial DOE, SQP, SAE, DE, SA	Linear or volumetric shrinkage of the test bar and cycle time (HDPE)	▪ SAE showed better optimum compared to SQP in the first test. ▪ DE and SA were capable of reaching the optimum in the second test.
2004, Shen et al. [94]	Taguchi DOE, GRA	Part warpage of micro-injection moulding (PP, PC, PS, POM)	▪ PS material is the most suitable material used in micro-injection moulding.
2006, Chiang & Chang [96]	GRA, fuzzy logic, orthogonal DOE	Welding line strength, shrinkage and warpage of mobile phone cover (PC/ABS)	▪ Multiple targeted qualities were effectively improved together through the grey-fuzzy logic approach. ▪ Mould temperature and injection pressure were found to be noticeable.
2006, Kurtaran & Erzurumlu [82]	Full factorial DOE, RSM, GA	Part warpage of bus ceiling lamp base (ABS)	▪ Warpage was improved by about 46%. ▪ Packing pressure is the most influential parameter to warpage.

Table 2.5 (*continued*)

Year and Authors	Methods	Targeted qualities (plastic material)	Results and discussion
2006, Lam et al. [81]	GA/gradient hybrid approach	Maximum shear stress and maximum cooling time of office tray (PP)	▪ Minimising maximum shear stress required a high melt temperature and a long injection time. ▪ Minimising maximum cooling time required a low mould temperature and a long injection time.
2009, Gao & Wang [83]	Kriging model, Latin hypercube DOE, SQP	Part warpage of mobile phone cover (PC/ABS)	▪ Warpage was reduced by 38%. ▪ Injection time is the most critical factor. ▪ Too short the packing time causes quality problem, conversely, it results in energy and material waste.
2010, Altan [85]	Taguchi DOE, ANN	Shrinkage of the rectangular-shaped specimens (PP/PS)	▪ Packing pressure and melt temperature were found to be the most significant parameters for the PP and PS moulded parts respectively. ▪ The generated ANN model is an efficient predictive tool for shrinkage.
2010, Chen et al. [89]	Kriging model, PSO	Deflection of printer upper cover along length direction and maximum injection pressure (PC)	▪ Trade-off behaviour between deflection and maximum injection pressure existed. ▪ The difference percentage between predicted results and simulation solutions was no more than 3.3%.
2010, Li et al. [84]	RBF	Shrinkage evenness of the rectangular slab (HDPE)	▪ Stronger global exploration performance could be improved by increasing the infill data properly. ▪ An optimal packing profile was obtained which should be first constant and then ramped down.
2011, Zhao et al. [92]	CBR, empirical model, fuzzy logic	Aesthetic defects of plastic part (PP)	▪ Optimum process parameters were obtained to produce a satisfactory part without heavy dependence on the experience of skilled operators.
2012, Öktem [77]	Taguchi DOE, mathe-matical and regression modelling	Volumetric shrinkage of DVD-ROM cover (ABS)	▪ Melt temperature is the most statistically significant process parameter on the shrinkage.

Table 2.5 (*continued*)

Year and Authors	Methods	Targeted qualities (plastic material)	Results and discussion
2013, Annicchia-rico et al. [76]	Fractional factorial DOE, desirability functions	Part shrinkage and part mass of micro-mould specimen (POM)	▪ The optimised values were compromising results between shrinkage minimisation and mass maximisation. ▪ Melt temperature, mould temperature and packing pressure were important parameters.

2.4.2 Particular optimisation studies related to energy consumption

A review of literature in the previous subsection has revealed that optimisation of injection moulding process has brought improvement in terms of product quality, cycle time or even associated computational time. However, energy consumption is seldom taken into consideration or seen as a by-product in the optimisation work. For example, Yin et al. [98] showed that lower part warpage can be obtained by increasing the packing pressure and packing time, meanwhile the energy consumption and production cycle were constrained in a particular range from the economic perspective. Ferreira et al. [99] utilised the mould design variables to optimise the cycle time, material waste, and pressure drop in injection moulding where all these targeted responses are directly correlated to the overall energy usage. Alternatively, Dawson et al. [100] introduced the use of energy monitoring in problem diagnosis and process quality control for injection moulding. They suggested that the variations in power and current provide valuable insight into the process and machine conditions which are likely to affect the qualities of the final product.

In the field of injection moulding, primarily focusing on energy reduction via aforementioned optimisation methodologies is not a novel practice. For example, Fernandes et al. [101] employed EA to optimise multiple responses in injection moulding, encompassing energy consumption in terms of maximum cavity pressure and pressure work. They concluded that all selected responses cannot be optimised at the same time. Nevertheless, a trade-off solution can be achieved based on the concept of Pareto frontiers. Lin [102] employed Taguchi DOE, single-factor experiment and ANN to optimise energy consumption with surface quality assurance. However, his work only took account of the injection parameters and the energy usage during injection stage. Pang [103] made use of CAE tools such as SolidWorks, Rhinoceros and Moldex3D along with analytical software such as Minitab and MATLAB to identify an optimal set of process parameters, which can minimise the part warpage and energy consumption concurrently. The main deficiency found in his work is the absence of empirical validation for the numerical results. A more recent study is provided by Lu et al. [104] in which the Taguchi method, ANOVA and the integration of ANN with GA-based lexicographic method were utilised to reduce the energy usage with pre-determined quality requirement. Their methodology successfully achieved energy saving in a laboratory scale test without unwanted deviation from the targeted part weight.

2.4.3 Discussions on the selection of optimisation method

Even though there is an abundant literature related to the process parameters optimisation for injection moulding process, energy consumption is frequently overlooked in these optimisation studies. Some studies had made use of simulation-based optimisation methods together with software packages to optimise energy consumption. In relation to the hypothesis made in the introductory chapter (see p. 8), these methodologies are regarded as “over-academic” and too sophisticated to be applied in the milieu of SMEs. Simulation-based experiments are more suitable to be employed in laboratory tests or large manufacturing enterprises where research personnel, software packages and pertinent equipment are readily available. The efficacy of simulation-based experiments will be much reduced if it entails high computational costs. Eventually, the numerical results need to be validated through empirical studies.

Recall that the problem at hand is how SMEs optimally and responsibly respond to the energy efficiency issue with “no-cost investment”. While barriers faced by SMEs are already multifaceted, the rationally-behaved decision makers tend to economise their time resources in order to focus on other strategic objectives rather than sophisticated optimisation problems. As such, SMEs might be more willing to optimise the process parameters based on their past experience, organisational procedures and routines. In this sense, empirical study via DOE will be a more direct approach to be practiced in SMEs. This forms the main aim in this thesis, which is to establish proprietary methodologies that can help SMEs to close their efficiency gap, since they might not devote more time to foster the relevant skills. The empirical-level approach with a well-articulated theoretical framework is explicitly developed and demonstrated in Chapter 3.

2.5 Decision Management for Energy Efficiency Investments

The preceding section thus far explores that “no-cost investment” strategy via process parameters optimisation could be considered as an alternative to realise energy efficiency improvement. Nonetheless, whether the “no-cost investment” is best suited to the company and can outperform the capital investment in energy-efficient equipment, remains an open question. On the other hand, the energy-efficient equipment has no guarantee for better economic performance because equipment replacement is often coupled with high initial expense, long payback time and unforeseen technical risk. This yields the third research question pertaining to the decision management: *how would SMEs determine whether an energy efficiency investment decision can contribute to the economic performance within the company?* This question is significant in actual practice because decision makers in SMEs may only pay particular attention to energy efficiency investments if the potential cost savings can be clearly examined. Problems of this type are commonly called equipment replacement problems in the operations research community. Small and micro enterprises might not know how to conduct a proper cost assessment for making an economically viable decision. This section thus looks over the literature of decision support systems and operations research in an attempt to solve the problem under consideration.

2.5.1 A brief retrospective of decision support systems

Decision management is a complex task that needs some logic thinking techniques to deal with considerable amount of information. In the past few decades, economists, psychologists, operations researchers and management scientists have studied this topic from different perspectives. However, when dealing with “too much” information, the theory of bounded rationality (see Subsection 2.2.2.2) suggests that a surplus of information will result in a deficit of attention. This phenomenon puts an emphasis on the organisation’s ability to process information and make judgement for important decisions. In this regard, Simon et al. [105] pointed out that human decision-making process can be done by or in cooperation with intelligent machines in the information age. It implies that organisations nowadays have to build their competitive positions by figuring out how to integrate decision support systems (DSS) for decision making and problem solving. By definition, DSS is an interactive computer-based system or subsystem intended to help decision makers complete the decision-making process [106]. Making use of DSS is not only concerned with how to acquire the necessary information, how to perform the calculations, but more importantly to accurately evaluate the probabilities and potential output of the future events. Power [107] conducted a retrospective of DSS and he categorised DSS into five distinct types: model-driven DSS, data-driven DSS, communications-driven DSS, document-driven DSS, and knowledge-driven DSS. These different forms of DSS are briefly explained as follows [108]:

i. Model-driven DSS emphasises access to and manipulation of a quantitative model, especially algebraic, financial, optimisation or simulation models. It normally uses mathematical models to provide decision support.

ii. Data-driven DSS emphasises access to and manipulation of time-series internal data and occasionally external and real-time data. It is usually more data-intensive than the model-driven DSS.

iii. Communications-driven DSS uses network and communications technologies to recognise and solve decision-relevant collaboration problem. In this system, communication technologies are the dominant component.

iv. Document-driven DSS uses computer storage and processing technologies for document retrieval and analysis. Large document database may include hypertext documents, images, sounds and videos.

v. Knowledge-driven DSS is a man-machine system which consists of knowledge about a particular domain. This system can suggest or recommend actions to decision makers.

In 1960s, researchers began systematically making use of DSS to assist decision management. For example, Scott-Morton [109] developed a Management Decision System to help marketing and production managers coordinate production planning for laundry equipment. Scott-Morton's system was a form of model-driven DSS which studied how computers and analytical models could provide decision support to managers. Model-driven DSS normally does not require large database because it only uses limited data and parameters provided by the decision makers in solving a problem [110]. The advent of personal computers has made potential development of model-driven DSS at a reasonably low cost such as spreadsheet-based DSS.

Addressing the issue of disparate, multi-oriented and time variant data resources, Devlin and Murphy [111] first promoted the concept of data warehouse system. However, it was not until 1992 that the definition of data warehouse was clarified when Bill Inmon, who is known as the "father of the data warehouse", published a book called "Building the Data Warehouse" [112]. Data warehouse acts as the central repositories of integrated data which allows data from disparate sources to be accessed and tailored to a specific setting by retrieval tools. Setting up a sophisticated data-driven DSS often leads to a need of building a data warehouse. One solution to analyse the accumulated historical DSS data in a large data warehouse is making use of on-line analytical processing (OLAP). OLAP software provides fast, consistent and interactive access to multidimensional data, it can be used to discover trends, analyse critical factors and perform statistical analysis [108].

Another powerful tool that emerged in the early 1990s for building DSS is data mining. Data mining, also known as database exploration, is applied to identify patterns in data and infer rules from them [108]. Following the introduction of data warehouse, OLAP and data mining, the rapid development of World Wide Web has promoted the demand of web-based DSS. Web-based DSS has reduced technological barriers and allows geographically dispersed companies to make decision-relevant information concurrently at a comparatively low expense. According to Power [108], web-based DSS can be model-driven, data-driven, communications-driven, document-drive, knowledge-driven, or a hybrid.

2.5.2 Review of operations research methods

The introduction of operations research (OR) can be traced back to the World War II period when there was an exigent need to allocate limited resources to numerous military operations [113, 114]. According to the Operations Research Society of America (ORSA), “Operations research is concerned with scientifically deciding how to best design and operate man-machine systems, usually under conditions requiring the allocation of scarce resources.” In broad sense, OR techniques can be viewed as a collection of mathematical models and techniques used to solve complex management problems [114]. The process normally begins by carefully observing and studying a given problem, then the mathematical models which closely resemble the situation of the problem is constructed. To a certain extent, some forms of assumption or constraint are required in order to simplify the computational process, leading to a suboptimal solution. The next step is to validate the OR solution with some practical studies and it is followed by modification when necessary.

The application of operations research has been widely applied in different industries to coordinate the decision-making process within an organisation. One important feature of OR is its broad viewpoint in the context of mathematics, statistics, economics, engineering, computer science, business administration, and even the psychological sciences [113]. Consequently, a comprehensive OR study usually requires an interdisciplinary team approach which is commonly referred to as “OR teams”. Given the complexity and uncertainty in real world problems, it is unlikely to ascertain particular OR solution to be the best solution because many unforeseen conditions might take place. Rather than keep optimising the solution, "satisficing" is a more practical strategy to achieving a satisfactorily suboptimal solution. The term "satisficing", introduced by Herbert Simon [115], describes the behaviour of decision makers in seeking a "good enough" solution when the ideal solution is improbable to be achieved.

In order to select an appropriate decision management tool, it is necessary to review the fundamental concepts of operations research and the relevant methods. Two generic OR methods applied in the manufacturing field are mathematical programming (MP) and dynamic programming (DP). A variety of methods can be collectively categorised as MP methods where the relationships between decision variables are described precisely through mathematical formulation. On the other hand, DP is a mathematical technique used for optimising a sequence of interrelated sub-problems. More details for these two OR methods are further elaborated in the following subsections.

2.5.2.1 Mathematical programming

Mathematical programming is defined as a family of optimisation techniques which can either maximise or minimise a given algebraic objective function for a number of decision variables [116]. These objective functions are usually subjected to some specified constraints. The three most common MP techniques are linear programming, nonlinear programming and integer programming.

i. Linear programming (LP)

As its name suggests, the mathematical formulation for LP model must be consisted of linear objective functions subject to linear inequalities, which are generally of the form

$$A_i x \geq b_i \qquad i = 1, 2, \dots m \tag{2.2}$$

where x represents the variables and A_i is the coefficient vector for the constraint b_i [117]. A normal optimisation criterion for LP problems is to either maximise or minimise the objective functions in which all the constraints must be satisfied. Approximations and assumptions are generally required to simplify the LP model so that it can be solved without great difficulty. An algebraic procedure called the simplex method is effective in solving large LP problems where sophisticated software packages are available. However, not all types of problem can be solved by LP method even with the most reasonable approximations. Another main limitation of this method is that all the mathematical coefficients must be deterministic.

ii. Nonlinear programming (NP)

When the approximations and assumptions do not hold true for LP model, NP method can be used to reflect the problem more accurately. NP can deal with maximisation or minimisation of a nonlinear objective function over a set of values delimited by several nonlinear equalities or inequalities [118]. In contrast to LP method, NP not only solves problems deterministically but also stochastically and heuristically. The heuristic strategies are used whenever the former two techniques fail to solve some highly complicated optimisation problems. There is no single method that can solve different types of NP problem like the simplex method for LP. Nevertheless, there are some powerful software packages such as MINOS being developed to solve enormous NP problems with great computational feasibility.

iii. Integer programming (IP)

In many practical problems, the decision variables are required to be integer values such as the number of people or machines. The introduction of IP method solves these problems where one or a subset of variables in the mathematical model are restricted to assume only integer or discrete values [119]. In general, IP method can be subdivided into linear and nonlinear approach. Mixed integer programming (MIP) is needed in some settings for which only some of the variables are restricted to be integers. Alternatively, if IP model is confined to only binary variables (or 0-1 variables), it is specifically called binary integer programming (BIP). Computer codes for building IP models are commonly available in MP software packages. However, the algorithms used for solving IP are generally less efficient than the simplex method [113]. The consistency and computational efficiency of IP models will become lower when the number of integer variables increases.

2.5.2.2 Dynamic programming

When decision makers are required to make a sequence of interrelated decisions, DP method provides a procedural framework for determining the optimal combination of decisions after the original problem is converted into multistage sub-problems. Therefore, DP can be viewed as a recursive technique used to optimise the trajectory of the decision-making process rather than to find an optimum point [120]. In general, DP problems can be divided into deterministic problems and stochastic problems. In deterministic problems, the state of each stage is completely determined by the state and decision made at the previous stage [113]. The “state” here refers to various possible conditions in which the problem might be at each particular stage. The DP model tends to become computationally intractable when the number of state increases tremendously. Consequently, approximations or assumptions are frequently established in order to simplify the DP model. The main challenge in DP community lies in the fact that there is a persistent absence of commercial software packages for building and solving DP models. Although some DP problems can be solved by software packages such as LINGO, it can only handle relatively small and simple problems [116]. The DP models generated for real-world problems are usually consisted of specifically designed models rather than general framework. This makes it difficult to develop a general computer program that can solve all different types of DP problem [121]. Despite this difficulty, DP method has been widely applied to solve a variety of problems such as equipment replacement policy, capital resource allocation and batch replenishment problem. For example, Zhou et al. [122] designed a DP based procedure to help manufacturers select energy saving options at different stages.

2.5.3 Research opportunity in decision management

The invention of decision support technologies is intended to provide managerial support in decision making and problem solving, it will continue to evolve in the future [123]. Recall that the objective of this section is to find a proper decision management tool to help small and micro enterprises assess the energy efficiency investments, provided that the “no-cost investment” might be a more cost-effective alternative. Addressing this issue, model-driven DSS will be a more understandable and easily built system using the information that reflects the situations of the enterprise. In this regard, spreadsheet package is the simplest technology which can be employed for building model-driven DSS. By definition, spreadsheet is a collection of cells displayed on a computer screen whose values can be changed and analysed [124]. For example, Microsoft Excel is probably the most ubiquitous and easily accessible spreadsheet package even in the environment of SMEs. DSS that uses spreadsheet package to provide decision support is generally termed a spreadsheet-based DSS [125]. The most evident advantage in using spreadsheet-based DSS is the ease of which it can be implemented interactively by staff from all levels, including personnel with low level of expertise. As such, the design of the user interface is important to the success of a spreadsheet-based DSS so that it is accessible to non-technical personnel.

In making a financial decision, a decision maker needs to concern about the decision made at earlier stage will influence the situations of subsequent stages. Actual manufacturing environments are dynamic and have many interacting elements, as a consequence, the interrelationships between decision variables usually cannot be expressed analytically with well-behaved functions [126]. In consideration of the intertwined sub-actions, the dynamic programming method in the operations research seems to provide an appropriate option in designing the spreadsheet-based DSS. First, DP model allows the problem to be subdivided into multiple stages which are interrelated and associated with probabilities. Second, DP model can contain a number of states that describe various possible situations at every stage. It should be noted here that a model-driven DSS is not totally the same as OR-based decision making system. According to Power and Sharda [127], the two characteristics that differentiate a model-driven DSS from the OR special decision study are:

i. A model-driven DSS is made accessible to a non-technical specialist such as a manager through a user-friendly interface.
ii. A specific DSS is designed for repeated use in the same or a similar decision situation.

There is a promising research opportunity in creating a spreadsheet-based DSS via DP method for helping small and micro enterprises assess the energy efficiency investment. This system can be created in accordance to the specific circumstances of the problem and can be modified when necessary. The pertinent development of the decision support system, called "DP-based spreadsheet solution" in this thesis, is explicitly presented in Chapter 5 for solving stochastic equipment replacement problem.

2.6 Chapter Conclusions

This study is specifically aimed at reducing the efficiency gap in SMEs, especially the small and micro enterprises. A review of literature shows that the existence of efficiency gap can be explained from the economic, behavioural, and organisational perspectives. In general, barriers to energy efficiency improvement are consisted of at least six factors, including risk, imperfect information, hidden costs, access to capital, split incentives, and bounded rationality. These barriers can be interpreted by two different combinations of economic theories, which are NA theory (neoclassical economics and agency theory) and TB theory (transaction cost economics and behavioural economics). In short, there appears to be no conclusive answer for which barrier is the most critical factor. Unless the energy efficiency investments show high rates of return, less energy-intensive SMEs might not be willing to invest in energy efficiency projects due to the presence of various barriers. To address these barriers, a "no-cost investment" strategy was proposed for which the manufacturing SMEs can implement energy efficiency project without capital expenditure.

After reviewing a range of energy-saving measures for plastic injection moulding, process parameters optimisation was identified as a "no-cost investment" model that can help SMEs reduce process energy usage without high expense. There is a rich literature concerning process parameters optimisation in the field of injection moulding. However, relatively little research exist to take energy consumption into account. In fact, most of these optimisation methodologies proposed by different researchers downplay the environment of SMEs. That is, those methodologies are “over-academic” and too sophisticated to be implemented by SMEs because they have neither sufficient access to expertise nor equipment. In this context, DOE method has been considered as a technically and economically viable approach for SMEs. To achieve the research aim, a simple and valid methodology that can improve the process energy efficiency without trading off the product quality must be established.

Nevertheless, the efficacy of this “no-cost investment” strategy does not necessarily outweigh the capital investment in energy-efficiency technologies. Consequently, decision makers in SMEs need to conduct a proper cost assessment for making an economically viable decision. However, they might be incapable of processing too much information and make a proper judgement owing to the phenomenon of bounded rationality. For this reason, a spreadsheet-based decision support system was proposed in this thesis in order to facilitate the decision makers in SMEs assess the energy efficiency investment.

CHAPTER 3

MULTI-RESPONSE DYNAMIC SHAININ DOE

3.1 Introduction

The main objective of this chapter is to further explore the second research question. In doing so, a user-friendly, non-resource-intensive, and statically valid optimisation methodology based on design of experiment was established. The proposed methodology mainly relies on the philosophy lying behind the Shainin® System where the core objective is to create a simplistic and cost-effective experimental study. In other words, the methodology can be easily practiced by the operating personnel in SMEs with minimal training time and resource expenditures. To address the inherent limitations of the Shainin approach, it was integrated with the elements of the multivariate statistical methods and the signal-response system. This novel integrated methodology is called "multi-response dynamic Shainin DOE" (MRDSD) in this thesis, where the term "dynamic" refers to the signal-response system.

3.2 Design of Experiment

Design of experiment (DOE) consists of a series of experiments for investigating the influence of factors on the response variables and thereby identifying the optimal solution for the problem under study. DOE is relatively quick and easy to use for the development of new processes in which historical data are absent [128]. In general, there are three kinds of DOEs: classical DOE, Taguchi DOE and Shainin DOE. Classical DOE and Taguchi DOE have been extensively discussed and are easily accessible throughout the literature. In contrast, Shainin DOE is not well documented and receives scarce attention in the literature. The two main reasons are that Shainin DOE is legally protected and the originator did not publish any definitive book about the relevant method [129-131]. The most effective DOE method is subjected to considerable debate among the scholars. The debate remains inconclusive following the distinctive standpoints from the advocates of these three different DOEs. The method selection is unlikely to be proper if the inherent limitations of each method and the nature of problem are not well understood. Therefore, the objective of this section is to deliver the fundamental principles lying behind these DOEs and clarify why Shainin DOE can be developed into a more widely-used strategy in the milieu of SMEs.

3.2.1 Classical DOE

The classical approach is credited to Sir Ronald Fisher who first applied factorial experiments in the field of agriculture in 1920s. Factorial experiments can be divided into full factorial design and fractional factorial design. Full factorial experiments examine all possible combinations of every given level for a set of factors. The total number of full factorial experiments can be calculated by n^k where n is the number of levels and k is the number of factors. Because the total number of experiments will increase exponentially as the number of factors increases, it will become more practical and cost-effective to carry out fractional factorial experiments. For example, half factorial designs 2^{k-1} require only half of the treatments from their full factorial counterparts. Treatments (also known as "runs") here refer to particular combinations of factor levels in a design of experiment.

Despite that the number of experiments can be reduced, the main disadvantage of using fractional factorial designs is that the "confounding effects" exist between the individual factors and their corresponding higher-order interactions. For example, considering a full factorial design which accommodates three factors (A, B, C) and two levels (+: high level; $-$: low level) as displayed in Table 3.1, there is a total of eight experimental runs ($2^3 = 8$). Hence, its half factorial counterpart will only require four of the total runs. One question arises here is: which four of the treatments should be selected in order to maintain the validity of experimental outcomes?

Table 3.1 – Contrasts for a 2^3 full factorial design

Run	Treat-ment	Contrast						
		A	B	C	AB	AC	BC	ABC
1	(1)	−	−	−	+	+	+	−
2	a	+	−	−	−	−	+	+
3	ab	+	+	−	+	−	−	−
4	b	−	+	−	−	+	−	+
5	bc	−	+	+	−	−	+	−
6	c	−	−	+	+	−	−	+
7	ac	+	−	+	−	+	−	−
8	abc	+	+	+	+	+	+	+

The treatments selection is determined by the “defining contrast” which is generally of the highest-order interaction [128]. The highest-order interaction is selected because it is usually insignificant to the problems. The contrast for every individual effect and interaction is given in Table 3.1. Provided that the ABC interaction is selected to be the defining contrast, its corresponding contrast is given by “a + b + c + abc – (1) – ab – bc – ac”. Herein, either the plus-sign terms or the minus-sign terms can be taken as the treatments for the half factorial experiment. Normally, the plus-sign terms are chosen because of easier computational work. In this case, the chosen treatments are therefore “a, b, c, abc”. Now, the confounding effects can be clearly observed from the rows of Table 3.1 in grey highlight where contrast A is exactly the same as contrast BC, so is contrast B with contrast AC and contrast C with contrast AB. As such, using fractional factorial experiments will result in a confusing circumstance about whether the main effect is caused by individual factor or its higher-order alias. More details on the principles of factorial experiments can be found in the references [75, 132].

Several common forms of the classical DOE include the completely randomised design, the randomised block design, and the Latin square design. The statistical tools such as ANOVA and regression analysis are often employed to analyse the data obtained from the experiments. Classical DOE normally uses two-level designs so that the critical factors can be identified earlier during the investigation [133]. Higher-level designs associated with some powerful tools such as RSM can be used to examine the nonlinear response function if the nonlinearity is significant. Put another way, classical DOE is more inclined to a sequential and iterative nature of process learning. Another major disadvantage of using the classical DOE is that there is a need for non-technical specialists to learn the statistical knowledge and understand the concepts underlying the experimental designs before implementing it. Although the classical approach becomes more feasible nowadays with the aid of statistical software, the training time needed by the practitioners for thorough understanding is relatively long [134].

3.2.2 Taguchi DOE

Taguchi methodology was initiated by Genichi Taguchi in 1950s and has been largely employed for quality control in industrial sector. Taguchi [135] introduced a quality philosophy which describes that a reduction in the variation of product quality will reduce the loss imparted to society. Taguchi method is also called robust engineering as its primary objective is to minimise the effect of noise or uncontrollable factors in the quality control process. In other words, it helps engineers to identify an optimal combination of control factors that can enhance the functional robustness of the system. Ueno [136] presented a detailed case study about robust engineering for injection moulding process.

There are three sequential phases in the Taguchi method: system design, parameter design and tolerance design. System design is a conceptual phase where engineering knowledge is needed to build a prototype with minimal deviation from the desirable values. Parameter design aims to identify an optimal set of process parameters that can minimise the variation caused by noise factors with the use of orthogonal arrays and signal-to-noise (S/N) ratios. Finally, tolerance design makes use of narrower tolerance ranges for variation reduction when the parameter design does not satisfactorily achieve the target.

Orthogonal array is an experimental design which can perform a balanced investigation for chosen factors at all available levels while not necessary to carry out a full factorial experiment. More explicitly, two factors are said to be orthogonal if all their level settings have the same amount of runs. There are eighteen orthogonal arrays designed by Taguchi that have been widely used for experimentation such as L_8 (2^7), L_9 (3^4), L_{16} (2^{15}), L_{32} ($2^1 \times 4^9$) and so on [137]. The letter "L" in the notation of the form "L_m (n^k)" indicates that orthogonal arrays are actually generalised Latin square design whereas the letters m, n, k, represent the number of experiments, number of levels, and number of factors respectively. Orthogonal arrays are adopted mainly because the number of experiments can be greatly reduced even though there are many factors being taken into consideration. For this reason, more factor levels are urged to be deployed in Taguchi DOE so as to investigate the probable existence of nonlinearity [128]. In S/N ratios, the signal indicates the desirable mean value whereas the noise represents the measure of variability. Three of the most common mathematical expressions for S/N ratios are the "nominal-the-best (NTB)", "smaller-the-better (STB)", and "larger-the-better (LTB)". For example, S/N ratio for the NTB case is as shown below:

$$\mathrm{S/N} = 10 \log_{10} \frac{\bar{x}}{s^2} \tag{3.1}$$

where $\bar{x}$ and s^2 denote the sample mean and sample variance respectively.

Nair et al. [138] present considerable debate over the cogency of Taguchi DOE. Ironically, the major academic criticisms received by the Taguchi method are the use of orthogonal arrays and S/N ratios. Firstly, orthogonal arrays are criticised as being unscientific because they neglect the interaction effects [138]. Orthogonal designs are even more simplified than the common fractional factorial experiments and thus severely downplay the “confounding effects”. Unless the interaction effects are confirmed being unimportant, results from the orthogonal arrays can be misleading. Secondly, the use of S/N ratios is arguably invalid since the response mean and variance are stochastically independent of each other [139]. Combining the mean value and the measure of variation into a single objective function makes it difficult to distinguish whether the relevant factor is influential to the mean or the variation. In comparison, classical DOE performs these calculations in a separate way, giving a more statistically sound result.

3.2.3 Shainin DOE

As the Shainin® System[7] is legally protected under Shainin LLC[8] by its founder Dorian Shainin, there are two particular ways to learn about this methodology: (i) attend to Shainin's consultancy services; (ii) study the book authored by Keki R. Bhote and his son Adi K. Bhote [134]. Keki R. Bhote joined Motorola as a development engineer and adopted Shainin's consultancy services for a considerable period of time. He

[7] Under particular terms of use, the copyright or trademark symbol is labelled for every specific terminology in Shainin System but only for the first time the relevant term appears.
[8] Disclaimer: This research has no any connection, financial or otherwise with Shainin LLC. All related discussions and borrowed ideas pertaining to Shainin DOE are based on the definitive book by Bhote and Bhote [134] unless otherwise specified.

played an important role for Motorola in winning the first Malcolm Baldrige National Quality Award in 1988 — a formal recognition of performance excellence for U.S. organisations. The father-son pair later were authorised to publish a book that explicitly discusses about the Shainin methodology. According to their contention, Shainin DOE is a simpler yet more powerful DOE strategy in comparison to the classical DOE and Taguchi DOE. The key concept lying behind the Shainin approach is the Pareto principle which describes that the variation problems in quality control are attributed to the "vital few" factors, not the "trivial many" [134]. Red X® is the term given to the most critical factor while Pink X™ and Pale Pink X™ correspond to the second-most and third-most important factor respectively [140]. Shainin devised a screening experiment called Variables Search™ to find out these factors from a list of suspected variables. The listed variables are ranked in the order of importance so that the key factors can be identified as earlier as possible without additional waste of time and material. Since the number of key variables is usually no more than four, another important feature of the Shainin approach is the emphasis on the use of full factorial experiments so as to get rid of "confounding effects".

The main advantage of using Shainin DOE is that it enables high involvement of staff from all levels because it does not need to deal with complicated statistical operations [134]. In contrast to the classical DOE and Taguchi DOE, the necessary training time for Shainin DOE is relatively short. In addition, Shainin DOE is more cost-effective because it requires a comparatively small sample size using the "best" and "worst" parts made from two opposite groups of set values [130] (see p. 82 and p. 88 in Section 3.3 concerning the use of small sample size). Despite the fact that

Shainin DOE is not well-known, some case studies [141-144] prove that this approach is less costly and can be easily executed in the environment of industry. Nevertheless, Shainin approach is being criticised for its effectiveness being exaggerated from the academic perspective.

First of all, since Shainin DOE is legally trademarked, there is lack of specific dissemination of the relevant approach and the only definitive book written by Bhote and Bhote [134] is claimed to be hyperbolic and heavily biased [130, 131]. In spite of Shainin's own claim about his method's usefulness, Ledolter and Swersey [145] argue that variables search is statistically inefficient compared to the fractional factorial designs because it relies on engineering judgement a priori in arranging the rank of listed variables. The time needed for the variables search can be lengthy if the order of importance is not correctly ranked. Contrary to the advantage, Steiner et al. [130] makes a persuasive claim that there is a risk of using small sample size to identify the dominant factors because the sampling error or systematic error can result in an occurrence of outliers. Logothetis [146] states that Shainin DOE is only applicable to medium-to-high volume processes at which a high level of quality and stability has already been achieved. Another major drawback of Shainin DOE is that it does not characterise the relationships between important factors and quality responses [147]. This method merely attempts to identify the key factors of the quality problems but the improvement potentials cannot be observed and exploited.

3.2.4 Discussions on the selection of DOE

Owing to various conditions, certain methodology that works well for one process is not necessarily suitable to the other processes. The factors that influence the decision of using a specific DOE strategy include the nature of problem, degree of optimisation required, time and cost constraints [133]. Based on the overview in the preceding subsections, some conclusions are drawn towards each approach. Firstly, classical DOE has the highest statistical validity with the aid of some statistical tools. As a result, it is also the most difficult approach as it involves complex statistics knowledge. Unless the statistical software is accessible and the necessary training time is short, it will not be widely practiced at the factory shop floor. Secondly, Taguchi DOE will be recommended only if the robustness to noise factors and small tolerance settings are prioritised in the study. If the interaction effects are significant to the process, the effectiveness of the Taguchi method will be greatly reduced due to the presence of the confounding effects. Lastly, Shainin DOE is the most easily understood method and therefore the associated training time is relatively short. The root causes can be readily identified with the use of a screening experiment called variables search. However, this tool also receives criticisms over its working principles. In Section 3.3, several major drawbacks concerning the variables search highlighted in the literature are being debated as implausible.

Table 3.2 provides some important comparisons for rapid identification of the most appropriate DOE strategy for a specific purpose.

Table 3.2 – Important comparisons for three different kinds of DOE

Type of DOE	Classical DOE	Taguchi DOE	Shainin DOE
Ease of implementation	Low	Medium	High
Sample size	Large	Medium	Small
Statistical validity	High	Low	Medium
Training time	Long	Medium	Short
Engineering judgement required	No	No	Yes
Factor-response relationship	Yes	No	No
Identification of root causes	Yes	No	Yes
Presence of confounding effects	Yes/No[9]	Yes	No
Rapid process understanding	No	Yes	Yes
Robustness to noise factors	No	Yes	No
Screening experiment	No	No	Yes
Tolerance settings	No	Yes	No

Recall that the specific objective in this thesis is to improve the energy efficiency of injection moulding process in the environment of SMEs. Injection moulding is a medium-to-high volume manufacturing process where interrupting the production run for conducting experiment may seem impractical. Therefore, the DOE strategy must be user-friendly with relatively short implementation time. Classical DOE is statistically sophisticated and hence it is not suitable for the stated objective, because SMEs especially small and micro enterprises might have limited access to expertise or reluctance to learn. The interrelationships among variables are important for the injection moulding process. Since Taguchi DOE does not take interaction effects into account, it is also not recommended in this study. Under these circumstances, Shainin DOE seems to provide the best solution for the stated objective as it allegedly has high ease of implementation and short training time. The

[9] For classical DOE, the occurrence of confounding effects depends upon the types of the chosen factorial experiments. Confounding effects are precluded in the full factorial experiments.

following sections will further discuss the dispute over the inherent limitations of Shainin DOE and demonstrate how it can be developed into a more useful strategy.

3.3 Variables Search

Shainin advocates using full factorial experiments in order to avoid the confounding effects. As mentioned in Subsection 3.2.1, full factorial designs will not be practicable provided that too many factors are taken into consideration. Therefore, Shainin introduces four useful tools to eliminate the unimportant factors. These tools include the Multi-vari Chart™, Components Search™, Paired Comparisons™ and Variables Search™ [134]. Multi-vari chart is used to investigate the pattern of variation whether it is positional, cyclical or temporal. In analysing the multi-vari chart, simple values like the mean and the range are used to identify the type of variation in abundant dataset [142]. Components search and paired comparisons are similar to each other where the good parts and bad parts are coupled together to observe the potential sources of variation. The good and bad parts are selected based on the corresponding parameters for the problem [142]. The main difference between both tools is that components search is only suitably applied for elements which can be disassembled and reassembled, whereas paired comparisons can be used for any other circumstances. Lastly, the main function of variables search is to identify the most critical factors from a list of suspected variables. Variables search is generally divided into four main phases. The main focus of this section is to explicitly discuss the working principles behind the variables search since the doctrines established in the book by Bhote and Bhote [134] do not provide thorough knowledge background.

3.3.1 Phase one: List of variables and test of significance

In the Shainin terminology, Green Y® refers to the quality characteristic that is important to the customer [140]. To ensure customer satisfaction, it is vital to determine the Red X factor and put it into right level in order to achieve a desirable Green Y value. Given that the few key factors are not readily identified, a list of suspected variables can be suggested based on engineering knowledge, past experiences, references from the literature or perhaps a brainstorming session. As noted earlier, these variables are arranged in descending order of importance so as to complete the search process as fast as possible. The number of experiments in the next phase will be increased if the ranking of variables is not adequately correct. Nevertheless, the variables "prearrangement" provides an early idea on the dominant causes to the Green Y.

Shainin emphasises the need to conduct an economical design of experiment using small sample size. Therefore, each variable is only assigned to two levels, i.e., "best level (+)" and "marginal level (–)", which are perceived to contribute to either targeted or deviated Green Y value respectively [134]. Two types of experiment are performed in the phase one: all-best experiment, where all variables are set at their best levels; and all-marginal experiment, where all variables are swapped to their marginal levels. The advantage of using these two opposite combinations of set values is that the Green Y values will be substantially different and hence the key factors can be more identifiable with small sample sizes [130]. Both types of experiment are repeated twice and the sequence of running all these six experiments should be randomised. The randomisation can reduce the biased readings caused by noise or uncontrollable factors [134].

The test of significance exploited in this phase is the $D_m: \bar{d}$ ratio test where D_m is the difference between the medians of the output values from the all-best and all-marginal experiments whereas $\bar{d}$ is the average range of these two different types of experiment. This test allows the end-users to check whether the correct variables with the correct levels have been selected. According to the test criterion, if the absolute value of $D_m: \bar{d}$ ratio is greater than or equal to 1.25:1, it indicates that variables search can proceed to the next phase. Otherwise, it is necessary to revise and rectify the list of variables. This procedure is similar to the hypothesis testing for which it is used to implicitly assume the conformity of the test results to a specified value.

However, the test criterion of $\left|D_m: \bar{d}\right| \geq 1.25{:}1$ is not adequately persuasive based on the decision limits set in the phase two which will be discussed later. This situation is illustrated in Figure 3.1 where there might be an overlapping region between the “best” and “marginal” values, as indicated by the grey region between the blue and red dotted lines. If certain observation value falls within this region, it will become difficult to determine whether it is a “best” value or a “marginal” value. In order to make these two separate regions more distinguishable, the test criterion for $D_m: \bar{d}$ ratio will be readjusted in the next subsection.

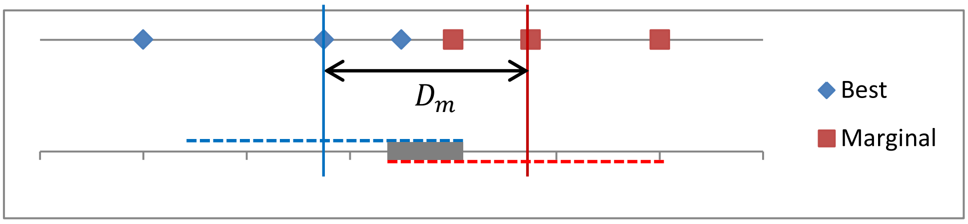

Figure 3.1 – Illustration of the probable blurring region in the test of significance

3.3.2 Phase two: Separation of unimportant factors

The main purpose of the phase two is to separate the important variables from the unimportant ones using the decision limits. The decision limits resemble the construction of control limits for univariate control charts in statistical process control (SPC). Let m represent the median values, the decision limits are calculated by

$$\mathrm{DL}_{\mathrm{B/M}} = m_{\mathrm{B/M}} \pm t_{\alpha/2,4}\frac{\bar{d}}{d_2} \tag{3.2}$$

where the subscript B or M represents the all-best or all-marginal experiments correspondingly. The t-distribution is used because the population variance is unknown. In order to produce a non-biased result, one less degree of freedom (DOF) is taken from each type of experiment; hence there are a total of four DOFs in this case. From the t-distribution table, the t-value for a 95% two-sided confidence interval with four DOFs is equal to 2.776.

The process standard deviation is estimated by dividing the average range $\bar{d}$ by the statistical constant d_2 because small sample size is used. When sampling from a normally distributed population, the relative range $W = R/\sigma$ is correlated to the sample size [128]. The statistical constant d_2 represents the mean value of the relative range W. The exact value of d_2 for Equation 3.2 is somewhat confusing since there appear two different values from the literature. According to the table of "Factors for Constructing Variables Control Charts" (see Appendix 1), the value of d_2 is equal to 1.693 based on three observations[10]. On the other hand, Bhote and Bhote [134] adopted an alternative value of 1.81 in their book but they did not exemplify any relevant source for this specific value. For this reason, the value of 1.693 was suggested to be employed in this study. To redefine the $D_m{:}\,\bar{d}$ ratio in the phase one, it can be noted from Figure 3.1 that the D_m value must be no less than the total distance of the given decision limits (Equation 3.2), so that the boundaries of the "best region" and the "marginal region" will not be overlapping. This implies that the minimum D_m value must be twice as much as the latter portion of Equation 3.2, that is[11], $\left|D_m{:}\,\bar{d}\right| \geq 3.28$.

By following the order of importance, the first variable in the all-best experiment is swapped from its best level to its marginal level. Likewise, in the all-marginal experiment, the first variable is swapped from its marginal level to its best level. If the output response lies outside the decision limits, it confirms that the first variable and its associated interaction effects are significant to the targeted Green Y. Otherwise, this variable can be deemed as unimportant and eliminated from the list of variables. The pair of opposite tests is rerun for the subsequent variables in the list until two or three important variables are identified. Clearly, the number of

[10] Since the average range $\bar{d}$ is used, there are three observations for each type of experiment respectively.
[11] Given $D_m \geq 2\left(t_{\alpha/2,4}\bar{d}/d_2\right)$, thus, $D_m{:}\,\bar{d} \geq 2(2.776/1.693) = 3.28$ (see Appendix 1 for the value of d_2)

experiments in the phase two heavily depends on how well the listed variables are ranked in the phase one.

3.3.3 Phase three: Capping run

Capping run serves as a validation stage to verify that all the important variables identified from the separation phase are truly dominant to the Green Y. In the first validation test, all the important variables in the all-best experiment are maintained at their best levels while the rest are adjusted to their marginal levels. The second validation test is totally contrary to the first test where all variables are swapped to their opposite levels. For the capping run case, if the outcomes do not lie within the decision limits given by Equation 3.2, it indicates that the search of important variables is not yet accomplished. In consequence, phase two has to be rerun for the subsequent variables in the list until another important variable is spotted. Usually, there will be no more than four variables found to be significant [134]. If no results fall outside the decision limits in the next capping run, it confirms that all the unimportant variables have been successfully separated from the list.

3.3.4 Phase four: Factorial analysis

The function of the factorial analysis is to quantify the main effect of each important variable and the interaction effects among them. This phase does not require any new physical experiment, the factorial analysis is carried out based on the data generated from the previous phases [134]. At the end of this phase, the Red X, Pink X and Pale Pink X would be readily identified. Shainin also recommends using an interaction plot to check whether or not the interaction between important variables does exist. If the lines in the interaction plot are parallel to each other, this depicts that there is no interaction between variables. However, the interaction plot is limited in describing to which extent the parallelity between variables can be considered as "no interaction". In addition, this graphical tool is seen as redundant work since the interaction effects are already quantified and examined in the factorial analysis. Hence, it is suggested that the interaction plot is exempted in this study, further simplifying the proposed methodology.

3.3.5 Discussions on the variables search

As discussed in Subsection 3.2.3, Shainin DOE receives several criticisms despite the claims of its advantages over the other methods. An overview of variables search in this section however finds that some of the arguments do not seem plausible. First of all, the variables search will be less efficient than the fractional factorial experiments if the engineering judgement does not offer satisfactory outcomes [145]. The necessary number of experimental runs in the variables search will be increased if the order of importance is not arranged well. Nevertheless, the variables "prearrangement" provides early and useful clues in identifying any significant cause to the desirable or deviated Green Y values. In comparison, it is required to complete all the treatments given in the fractional factorial designs before running factorial analysis. Moreover, fractional factorial experiments are effective only if the interaction effects are totally insignificant.

Secondly, small sample size does not guarantee the correctness of results due to the possible occurrence of outliers [130]. This situation is in fact mitigated by the use of median values instead of the mean values in the variables search. In some cases, the outliers are unlikely to be pinpointed and thus the resulting average range $\bar{d}$ will be too wide. If that happens, the $D_m{:}\,\bar{d}$ ratio test in the phase one will certainly be rejected if $\bar{d}$ value is too large. As such, it is necessary to rerun the phase one until the test criterion is satisfied. In the phase two, although the occurrence of outliers will cause misperception about the significance of the relevant variables, the pair of opposite tests can ensure that at least one of the two tests will not have an outlier problem. The reason is that the probability of outlier occurrence is small, and thus the probability of two consecutive outliers occurring is much smaller. Moreover, the capping run stage will further examine the results obtained from the separation phase, assuring the correctness of the variables search process.

Thirdly, some researchers [131, 146] criticise Shainin DOE for being statistically invalid. However, this section has demonstrated that the variables search process actually contains some statistical concepts. The test of significance (phase one) and the decision limits (phase two) are correspondingly analogous to the hypothesis testing and control chart monitoring. Additionally, the capping run will validate the test results and the factorial analysis will quantify the main effects on the targeted Green Y. Shainin's main idea is to create a methodology which can be easily understood and implemented by the end-users, therefore the statistical tools are transformed into four-phase procedures in the variables search. This step-by-step framework allows the staff from all levels to practice a “simple-and-valid” experimental technique.

3.4 Integration of the Multivariate Statistics

The decision limits (Equation 3.2 on p. 84) used in the phase two of variables search address process monitoring from the univariate perspective, that is, only one response will be taken into consideration. In present days, multivariate analyses are playing more important roles in quality engineering practice because very often there is more than one response needed to be controlled simultaneously. Statistical methods used for simultaneous process monitoring of multiple responses are collectively known as multivariate statistics [148]. In fact, the word “multivariate” not only gives the meaning of “many variables”, but also implies that these variables might be correlated [149]. If the targeted responses are not independent of each other, using univariate analysis to control these responses separately may yield an erroneous result. This situation will be explained and illustrated in Subsection 3.4.2. In this regard, although Shainin DOE can readily identify the underlying causes for a single response, there is a need to bridge its gap in the field of multi-response study.

This section aims to integrate Shainin’s variables search with the multivariate statistical methods. However, the major difficulties in the application of multivariate statistics are that it usually involves complex mathematical formulae and difficult-to-interpret results. Even with the advent of advanced computing power nowadays, the complicated multivariate problems can be resolved within seconds, the necessary operating skills, training time, and access to software packages might not be available in the environment of SMEs. Multivariate statistics can be more widely practiced if the relevant methods are easily understood and implemented. For this reason, Hotelling's T^2 statistic is tailored to bivariate statistic in this study where two highly prioritised responses will be taken into account. This section starts with a literature review regarding multi-response optimisation study by means of DOE. Next, some mathematically rigorous multivariate techniques documented in the statistical literature are overviewed before integrating some appropriate multivariate methods into the variables search. At last, three generalised outcomes that might be attained from the "bivariate variables search" are clearly discussed.

3.4.1 Multi-response optimisation via DOE

Design of experiment has been largely applied for solving single-response problems. An effective multi-response optimisation methodology can be demanding, therefore, engineering judgement is often included to solve such complex problems. For example, Reddy et al. [150] applied Taguchi DOE to separately determine the optimal levels of control factors for multiple responses. They suggested using engineering judgement to resolve the trade-off situations if found. However, the engineering knowledge is often subjective in nature and contradictory results could be reached by different engineers [151]. To deal with the uncertainty in engineering judgement, weight assignment has been adopted by many researchers to define the relative importance of each response. For example, Besseris [152] devised a weighted multi-response optimisation method based on Taguchi's orthogonal arrays and super-ranking concept which can reduce multiple characteristics to a single response. Nevertheless, assignment of the weighting terms also relies on the engineers' subjective judgment and hence it leads to a certain degree of ambiguity when selecting weight. Another reported technique of decreasing the uncertainty caused by engineering judgement is data envelopment analysis (DEA). Liao and Chen [153] utilised DEA based ranking approach to optimise multi-response problem via Taguchi method. The DEA approach has somewhat low practicality at the factory shop floor since it involves many mathematical models.

Logothetis and Haigh [154] as well as Pignatello [155] incorporated regression analysis with the Taguchi method to optimise multiple responses in a multiple-univariate or one-response-at-a-time manner. This approach does not solve the problem in an efficient way, nor does it take into account the possible correlations among the responses. Overlooking these correlations may easily lead to an incorrect judgment because the variation in one response might have a direct influence to the variation in the other response. Furthermore, the critical factors found in the univariate approach might not be as same as that found in the multivariate approach [156]. Hsieh et al. [157] employed the regression analysis and desirability function to optimise the multi-response problem with the use of Taguchi's dynamic system (see Section 3.6 for more details on Taguchi's dynamic system). Desirability function, which represents the degree of achieving a particular target within the interval [0,1], is a useful technique for analysing the multi-response problem [158]. Similarly, the main disadvantage of this technique is that it requires some advance knowledge in mathematical formulation. Thus, it cannot be easily understood and practiced at the factory shop floor.

Some researchers also apply soft computing methods for multi-response optimisation. Li et al. [159] designed an integrated method via ANN, GA, and desirability function to optimise the manufacturing process associated with multiple responses. ANN was used to build the fitness function for predicting the response value whereas GA was used to identify the optimal combination of parameters based on the fitness function. Antony et al. [160] proposed a four-phase procedure to solve multi-response problem through the use of neuro-fuzzy model and Taguchi DOE. They made use of neuro-fuzzy model to convert multiple S/N ratios into a single performance index called multiple response statistics (MRS) in a way to determine the optimal level for each factor. Using soft computing simulation methods enables engineers to conduct experiments without interrupting the production run. However, as discussed previously in Subsection 2.4.3, the simulation-based experiments might not be suitable to SMEs where research personnel and necessary software are not readily available.

In selecting a multi-response optimisation method, the users should understand the principles and limitations lying behind the method [156]. Most of the aforementioned studies utilise Taguchi DOE to deal with multi-response problems. As presented in Subsection 3.2.2, there are two main inherent limitations in the Taguchi method: (i) the existence of confounding effects when using orthogonal arrays; (ii) S/N ratios are claimed to be statistically incorrect. In the following subsections, a proprietary optimisation methodology for the empirical study is developed based on the elements of multivariate techniques and Shainin DOE.

3.4.2 Multivariate statistical methods

In comparison to other well-known methods such as DOE, RSM and regression analysis, multivariate statistical methods are much less known in quality engineering [149]. One of the major concerns in the application of multivariate statistics is that non-statisticians may find it difficult to understand and analyse the multivariate data due to the mathematical complexity. Therefore, simplifying the multivariate statistical methods will usually be of great help particularly to the non-statisticians. First of all, it is essential to understand why monitoring multiple responses individually through univariate approach might yield erroneous outcomes. This situation is illustrated in Figure 3.2 and further explained as follows.

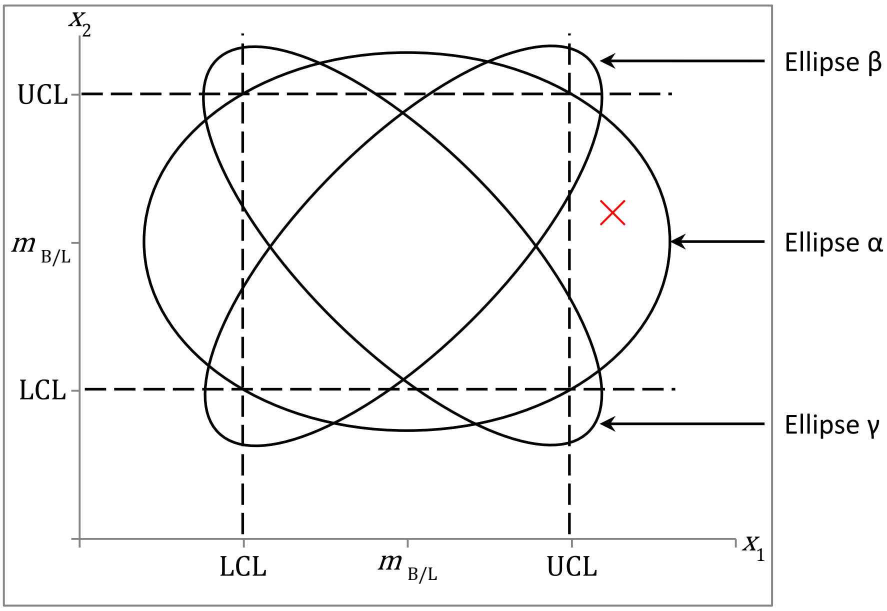

Figure 3.2 – Elliptical control region for two quality characteristics

Suppose that two quality responses x_1 and x_2 are taken into consideration. If both characteristics are monitored individually, the control region will be a two-dimensional plot in a rectangular shape. The boundaries for this rectangular region are basically formed by the control limits of these two different characteristics. In this case, the observation is said to be in control if it falls within the control region. However, the observation is sometimes misleading since an actual control region for two characteristics are reported to be elliptic in nature [128] (see explanation in Subsection 3.4.3.1). For example, when the control region is Ellipse α, the observation point X in Figure 3.2 is considered as in control even though it lies outside the rectangular region. Put another way, the multivariate control region can identify an out-of-control state for certain observation while the individual control regions do not. Notice that the major and minor axes of Ellipse α are parallel to the corresponding plot axes, this implies that both characteristics are independent of each other and the covariance between them is equal to zero [128]. If the two characteristics are positively correlated, a large portion of the observations will fall within the control region of Ellipse β. On the contrary, if the two characteristics are negatively correlated, the shape of the control region will be similar to that of Ellipse γ. Clearly, the multivariate control region will be more effective in detecting the out-of-control states when the correlation between responses cannot be neglected.

Harold Hotelling is considered as a pioneer in the field of multivariate statistics with his well-recognised paper in 1947 [161], where he constructed multivariate control charts based on T^2 distribution. As stated by Jackson [162] (*p. 21*), any application of multivariate quality control is required to fulfil four conditions: (i) to check whether the process is in control; (ii) to specify the overall Type I error, that is, the probability of an observation lying outside the control limits when the process is set at the standard level; (iii) to take into account the correlations among the responses under consideration; (iv) to identify the assignable causes to the out-of-control states. Hotelling's T^2 control chart is a common way to check the first condition, that is, whether or not the multivariate data is under control.

In order to construct the Hotelling's T^2 control chart, it is a prerequisite to understand the Student's t-distribution. Suppose that a random sample of size n has a sample mean $\bar{x}$ and a sample variance s^2, and is normally distributed with a population mean μ and an unknown variance σ^2, it is known that its sampling distribution with $n-1$ degrees of freedom is given by

$$\frac{\bar{x}-\mu}{s/\sqrt{n}} \sim t_{n-1}. \tag{3.3}$$

Equation 3.3 forms the basis of Hotelling's T^2 distribution where its multivariate counterpart can be expressed as

$$t^2 = (\bar{x}-\mu)^2/(s^2/n) = n(\bar{x}-\mu)(s^2)^{-1}(\bar{x}-\mu). \tag{3.4}$$

When t^2 is generalised to p characteristics, there appears two column vectors[12] in Equation 3.4, that is $(\bar{\mathbf{x}}-\boldsymbol{\mu})$. By transposing the first column vector into row vector, this yields an inner product (or scalar product) as follows:

$$T^2 = n(\bar{\mathbf{x}}-\boldsymbol{\mu})^T\mathbf{S}^{-1}(\bar{\mathbf{x}}-\boldsymbol{\mu}) \tag{3.5}$$

where $\mathbf{S}$ is represented by the following matrix equation:

[12] A column vector indicates the dimension of a matrix system with m rows and 1 column, the notation of which is m×1. On the other hand, a row vector has a notation of 1×m.

$$\mathbf{S} = \frac{1}{n}\sum_{i=1}^{n}(\mathbf{x}_i - \bar{\mathbf{X}})(\mathbf{x}_i - \bar{\mathbf{X}})^T. \tag{3.6}$$

After computing Equation 3.6, the symmetrical matrix of variance-covariance for p characteristics will look as below:

$$\mathbf{S} = \begin{bmatrix} s_1^2 & s_{12} & \cdots & s_{1p} \\ s_{12} & s_2^2 & \cdots & s_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ s_{1p} & s_{2p} & \cdots & s_p^2 \end{bmatrix} \tag{3.7}$$

where the sample variance for i-th characteristic with n observations is given by

$$s_i^2 = \frac{1}{n}\sum_{k=1}^{n}(x_{ik} - \bar{x}_i)^2; \tag{3.8}$$

and the covariance between i-th and j-th characteristics is calculated from

$$s_{ij} = \frac{1}{n}\sum_{k=1}^{n}(x_{ik} - \bar{x}_i)\left(x_{jk} - \bar{x}_j\right). \tag{3.9}$$

For small sample sizes where $n < 30$, the sample size n in Equation 3.8 and Equation 3.9 should be replaced with $n - 1$ in order to obtain an unbiased statistical result and to better estimate the population.

Hotelling's T^2 statistic given by Equation 3.5 can be seen as a measure of the distance between the responses' values and their means. After computing the T^2 values, one can check whether the process is in control by establishing a control limit. Besides that, the correlations between the responses are taken into account in the form of variance-covariance matrix. As such, it can be said that Hotelling's T^2 statistic satisfies the first three conditions described by Jackson [162]. However, the fourth condition which is in relation to the interpretation of the out-of-control states is much more difficult to handle especially when the number of responses increases.

More details in determining the control limits and interpreting the out-of-control states will be presented as follows.

3.4.2.1 Determination of the upper control limits

Hotelling's T^2 distribution has the same shape as the *F*-distribution [149], that is,

$$T^2 \sim \frac{p(n-1)}{n-p} F_{\alpha,p,n-p} \tag{3.10}$$

where $F_{\alpha,p,n-p}$ denotes that the proportion to the right on the *F*-distribution is α, with p DOFs in the numerator and $n-p$ DOFs in the denominator. Equation 3.10 acts as the upper control limits (UCL) in the multivariate control charts, which is important for hypothesis testing. The lower control limits (LCL) is usually set to zero because the observation values close to mean will lead to a very small T^2 value.

Alt [163] showed that when m samples of size n are used to estimate the mean and standard deviation, Equation 3.10 can be modified into the following form:

$$\mathrm{UCL} = \frac{p(m-1)(n-1)}{mn-m-p+1} F_{\alpha,p,mn-m-p+1}. \tag{3.11}$$

Generally there are two distinct phases in using the multivariate control charts for process monitoring. Equation 3.11 is used as the UCL in the phase one where the objective is to obtain a set of in-control signals so that a more robust control limits can be set up in the phase two for future monitoring process [164]. Therefore, phase one is sometimes known as "retrospective analysis". The UCL used in the phase two is slightly different from Equation 3.11 where it is multiplied by a factor of $(m+1/m-1)$, it yields

$$\mathrm{UCL} = \frac{p(m+1)(n-1)}{mn-m-p+1} F_{\alpha,p,mn-m-p+1}. \tag{3.12}$$

Lowry and Montgomery [165] show that the *F*-approximated UCL will be approaching the chi-square value χ_p^2 when a large number of samples is used. On the other hand, if the number of samples is small, Tracy et al. [166] point out that it can easily lead to incorrect judgement with the use of *F*-UCL. Therefore, they developed a special T^2 statistic for individual observations (the subgroup size is 1, that is, $n = 1$) based on the beta distribution, as given by

$$\mathrm{UCL} = \frac{(m-1)^2}{m} \beta_{\alpha,p/2,(m-p-1)/2} \tag{3.13}$$

where $\beta_{\alpha,p/2,(m-p-1)/2}$ represents the upper α percentile of a beta distribution with parameters $p/2$ and $(m-p-1)/2$. If the beta distribution table is not readily available, it can be calculated from the relationship between the beta distribution and the *F*-distribution as shown below:

$$\beta_{\alpha,p/2,(m-p-1)/2} = \frac{(p/(m-p-1))F_{\alpha,p,m-p-1}}{1+(p/(m-p-1))F_{\alpha,p,m-p-1}} \tag{3.14}$$

3.4.2.2 Interpretation of the out-of-control states

If the Hotelling's T^2 value for certain multivariate observation calculated by Equation 3.5 exceeds the given UCL, it indicates that the process is out of control. One question arises here that is how to interpret which of the p characteristics (or which subset of them) has caused the out-of-control signal. Many researchers address these problems and develop a variety of approaches for interpreting the assignable causes to the out-of-control states, however, a general method like Hotelling's T^2 is still not available [167]. Some of the popular interpretation methods are reviewed as follows in chronological order.

In 1987, Murphy [168] proposed a method to investigate the out-of-control signal by dividing it into two partitions, that is,

$$\bar{x}^* = \left(\bar{x}^{*(1)}, \bar{x}^{*(2)}\right) \tag{3.15}$$

where $\bar{x}^{*(1)}$ represents p_1 subset of the p characteristics which is suspected to have caused the signal and $\bar{x}^{*(2)}$ contains the remaining p_2 characteristics. In his method, a T_p^2 value and a T_{p1}^2 value are calculated based on $\bar{x}^*$ and $\bar{x}^{*(1)}$ respectively, and then the difference $D = T_p^2 - T_{p1}^2$ is considered. If D value is large, the hypothesis for which the p_1 subset has caused the out-of-control state is rejected. According to the paper by Das [169], this method does not perform well when the characteristics have a highly negative correlation.

In 1991, Doganaksoy et al. [170] proposed using the univariate t-statistic to rank the most possible characteristics that have caused the out-of-control state, which is defined by

$$t = \left(\bar{x}_{i,new} - \bar{x}_{i,ref}\right)\left[s_{ii}\left(n_{new}^{-1} + n_{ref}^{-1}\right)\right]^{-1/2} \tag{3.16}$$

where $\bar{x}_{i,new}$ and $\bar{x}_{i,ref}$ represent the sample mean and reference sample mean of the i-th characteristic respectively; s_{ii} indicates the estimated variance of the characteristic from the reference sample, and n is the sample size. Das [169] pointed out that the effectiveness of this method will reduce if the correlation between characteristics is low.

In 1995, Mason, Tracy and Young [171, 172] devised a cause selecting procedure by decomposing the T^2 statistic into p independent components, each of which can reflect its corresponding contribution to the overall T^2 statistic. Often referred as "MYT decomposition method" in the statistical literature, the general decomposition of the T^2 statistic for p characteristics is given by

$$T^2 = T_1^2 + T_{2.1}^2 + \cdots + T_{p.1,2,\ldots,p-1}^2. \tag{3.17}$$

The first term in Equation 3.17 is unconditional term whereas the rest are conditional terms. More specifically, one of the p characteristics can be randomly selected as unconditional term. Subsequently, any of the $(p-1)$ remaining characteristics is selected to condition on the first selected characteristic. This procedure is repeated by selecting any of the $(p-2)$ remaining characteristics to condition on the first two selected characteristics, and so on. Eventually, there will be $p!$ different partitions that can yield the same overall T^2 statistic. The main disadvantage of MYT decomposition method is the numerous computations involved in the conditional terms especially when the number of characteristics is large [173]. In addition, this method does not perform well when the correlation between characteristics is high [169].

In 1996, Runger et al. [174] provided a relatively simpler approach by considering all subsets of characteristics. In their method, the T^2 statistic is decomposed into two components in which the contribution of each individual characteristic can be defined by

$$D_i = T^2 - T_i^2, \qquad i = 1, 2, \ldots p \tag{3.18}$$

where T_i^2 gives the statistic value for all characteristics except the i-th one. Larger the D_i value denotes that the corresponding characteristic is more significant in a given multivariate observation. The main advantage of using this decomposition method is that the calculations can be easily performed using standard software packages [164].

3.4.3 Bivariate variables search

As can be seen from Equation 3.5, computing Hotelling's T^2 value requires the knowledge of matrix algebra, it will become more computationally complex when dealing with more characteristics. As such, the multivariate analysis is effective only if it is not restricted from the computing power. However, one important objective of using variables search is to establish an empirical study which can be easily applied and understood by non-statisticians. Therefore, variables search integrated with the multivariate analysis should be easy to understand and conduct, especially for the end-users in SMEs. Considering the computation of bivariate T^2 statistic is not too complex, this study will thus only take two highly prioritised responses into account. In this case, the order of importance for the list of variables will be ranked according to the primary response. Although both quality responses are not prioritised equivalently, the bivariate variables search will be designed in a way that the perplexed weighting terms are precluded.

3.4.3.1 Calculating the bivariate T^2 value

Given that two responses x_1 and x_2 are under investigation, where sample variances are indicated by s_1^2 and s_2^2 respectively, and the covariance between them is denoted by s_{12}, the bivariate T^2 value under these conditions is as shown below (see Appendix 2 for formula derivation):

$$T^2 = \frac{n}{s_1^2 s_2^2 - s_{12}^2}\left[s_2^2(\bar{x}_1 - \mu_1)^2 + s_1^2(\bar{x}_2 - \mu_2)^2 - 2s_{12}(\bar{x}_1 - \mu_1)(\bar{x}_2 - \mu_2)\right]. \quad (3.19)$$

Note that if Equation 3.19 is depicted graphically, it will look akin to the control ellipses as shown in Figure 3.2 depending on the sign of covariance. There are four transformation steps to incorporate Equation 3.19 with the elements of Shainin DOE:

i. The sample means $\bar{x}_1$ is substituted by y_1, which represents the primary Green Y value obtained in the separation stage; whereas $\bar{x}_2$ is substituted by y_2 which is of secondary importance.
ii. The population means μ is replaced with the medians m from the all-best or all-marginal experiments.
iii. The sample variances s^2 are approximated by $\left(\bar{d}/1.693\right)^2$ for a sample size of three as explained in Subsection 3.3.2.
iv. The covariance s_{12}^2 is replaced with the adjusted covariance s_{12}^*.

This yields the bivariate T^2 value as follows:

$$T^2 = \frac{3(1.693)^2}{\bar{d}_1^2\bar{d}_2^2 - (1.693)^4 {s_{12}^*}^2}\left[\bar{d}_2^2(y_1 - m_1)^2 + \bar{d}_1^2(y_2 - m_2)^2 - 2(1.693)^2 s_{12}^*(y_1 - m_1)(y_2 - m_2)\right]_{\mathrm{B/M}} \quad (3.20)$$

Note that the adjusted covariance s_{12}^{*} is computed from

$$s_{12}^{*} = \pm|\bar{s}_{12}| \tag{3.21}$$

where $\bar{s}_{12}$ corresponds to the average covariance from both types of experiment. The adjusted covariance is employed here because the covariance computed from a small sample might lead to an incorrect perception about the actual relationship between responses. The use of adjusted covariance will help redefine the sign of covariance based on the outcomes from the all-best and all-marginal experiments. More specifically, s_{12}^{*} will be given a "+"sign if both responses are found to have a positive relationship, that is, the variations in both responses are in the same direction. Otherwise, a "–" sign is assigned to s_{12}^{*} when a negative relationship is spotted. This adjustment is statistically rational because covariance is significant in defining the directions of variation but limited in describing the relatedness between responses [175].

3.4.3.2 Determining the upper control limit

The *F*-distribution, beta distribution or chi-square value is not appropriate to be utilised as the UCL for the bivariate variables search. The main reasons are, with the use of small sample size, the *F*-UCL value will be too large whereas the *β*-UCL and chi-square values will be too small. Using these control limits will easily lead to judgement error when the T^2 value is neither too large nor too small. A brief comparison between the *F*-UCL, *β*-UCL and chi-square values is provided in Table 3.3, given that $\alpha = 0.01$, 0.05 and $p = 2$. *F*-UCL values are computed based on Equation

3.10 whereas *B*-UCL values are computed based on Equation 3.13 and Equation 3.14. On the other hand, chi-square values are directly determined from the chi-square distribution table.

Table 3.3 – Different multivariate UCL values for $\alpha = 0.01$, 0.05 and $p = 2$

n	$\alpha = 0.01$			$\alpha = 0.05$		
	F-UCL	*B*-UCL	chi-square	*F*-UCL	*B*-UCL	chi-square
1			9.21			5.99
2			9.21			5.99
3	19998.00		9.21	798.00		5.99
4	297.00	2.25	9.21	57.00	2.24	5.99
5	82.19	3.17	9.21	25.47	3.04	5.99

Clearly, there is a necessity to establish a suitable control limit for the bivariate variables search. To do so, Equation 3.20 is used to determine the UCL by taking the squared distance at which the lower or higher end of the decision limits (Equation 3.2) is reached by one response whereas the other one is located at the median level. In other words, one response is assumed to be nearly out of control from the univariate perspective whilst the other one has perfectly reached the median value. The in-control range is hence said to be equivalent to a 95% two-sided confidence interval with four DOFs in the *t*-distribution table. In this case, the final form of the UCL for the bivariate variables search is given by (see Appendix 2 for formula derivation):

$$\mathrm{UCL} = \frac{3(2.776)^2 \bar{d}_1^2 \bar{d}_2^2}{\bar{d}_1^2 \bar{d}_2^2 - (1.693)^4 \bar{s}_{12}^2}. \tag{3.22}$$

Equation 3.22 represents the bivariate counterpart of univariate UCL, whose value relies on the average range $\bar{d}$ of the all-best and all-marginal experiments. In the separation stage (phase two), if both T^2 value from the pair of opposite tests fall below the computed UCL, this indicates that the relevant variable and its associated interaction effects, are confirmed as unimportant and hence it can be eliminated from the list. Conversely, if any T^2 value lies above the UCL, it implies that the process is out of control and the relevant variable is presumed to be significant to the bivariate statistic. While for the capping run stage (phase three), if the T^2 value falls below the UCL, it confirms that the separation stage is successful and all the significant factors have been identified.

3.4.3.3 Interpreting the out-of-control state

Next, the interpretation method provided by Runger et al. [174] is modified here for interpreting which characteristic has contributed more to the out-of-control state. This modification allows the end-users to use simpler calculation work in analysing the bivariate statistic. Based on Equation 3.4, T_i^2 is reinterpreted as the statistic value for the i-th characteristic, that is,

$$T_i^2 = \frac{n(\bar{x}_i - \mu_i)^2}{s_i^2}, \qquad i = 1,2. \tag{3.23}$$

After integrating Equation 3.23 with the elements of Shainin DOE through the similar transformation procedures of Equation 3.19, it becomes

$$T_i^2 = \frac{3(1.693)^2(y_i - m_i)^2}{\bar{d}_i^2}, \qquad i = 1,2. \tag{3.24}$$

Suppose that y_i is approaching the lower or higher end of the corresponding decision limits (Equation 3.2), Equation 3.24 will be approximated to a value of 23.12 (see details in Appendix 2). If the computed T_i^2 value is larger than this specified value, it implies that the relevant variable and its associated interaction effects are significant to y_i from the univariate perspective. At first glance, a larger T_i^2 value indicates a more significant contribution from response y_i to particular bivariate statistic. However, simply comparing the difference between T_i^2 values may not yield a reliable result. The reason is that the relative contributions of different characteristics to the overall T^2 value will not be equivalent since they have dissimilar $D_m\colon \bar{d}$ ratio (see Subsection 3.3.1). To determine the relative importance between y_1 and y_2, the calculation of $T_1\colon T_2$ ratio is derived from Equation 3.24 as follows:

$$\frac{T_1}{T_2} = \left|\left(\frac{y_1 - m_1}{\bar{d}_1}\right)\left(\frac{\bar{d}_2}{y_2 - m_2}\right)\right|_{\mathrm{B/M}}. \tag{3.25}$$

When an out-of-control state occurs, assume that the observation values y_i in the all-best experiment will be approaching the median values of the all-marginal experiment, or vice-versa, the decision limits for the $T_1\colon T_2$ ratio test can hence be approximated by

$$T_{\mathrm{DL},1} \sim \frac{|D_m\colon\bar{d}|_1}{|D_m\colon\bar{d}|_2} \quad \text{and} \qquad T_{\mathrm{DL},2} \sim \frac{|D_m\colon\bar{d}|_2}{|D_m\colon\bar{d}|_1}. \tag{3.26}$$

Clearly, the $T_1\colon T_2$ ratio test is not applicable for the in-control situation. Provided that $\left|D_m\colon \bar{d}\right|_1$ is larger than $\left|D_m\colon \bar{d}\right|_2$, there are three possible outcomes that can be deduced from the $T_1\colon T_2$ ratio test:

i. If $T_1 : T_2 > T_{\mathrm{DL},1}$, it indicates that the primary response y_1 is the dominant response to the bivariate statistic.

ii. If $T_{\mathrm{DL},1} > T_1 : T_2 > T_{\mathrm{DL},2}$, it indicates that the relative importance of y_1 and y_2 is somewhat equivalent.

iii. If $T_1 : T_2 < T_{\mathrm{DL},2}$, the relevant variable along with its associated interaction effects can be eliminated from the list because the secondary response y_2 is more important to the bivariate statistic, unless further investigation on y_2 is interested.

Notice that when $\left|D_m : \bar{d}\right|_1$ is smaller than $\left|D_m : \bar{d}\right|_2$, y_1 is the dominant response if $T_1 : T_2 > T_{\mathrm{DL},2}$, contrariwise, y_2 is the dominant response if $T_1 : T_2 < T_{\mathrm{DL},1}$.

3.4.4 Generalised outcomes of bivariate variables search

Optimisation of multi-response problems does not necessarily produce a solution in which all targeted responses are satisfactorily optimised. In general, there will be three possible outcomes that can be achieved from the bivariate variables search, that are, win-win solution, trade-off situation and no conflict, as expounded below:

i. Win-win solution can be achieved when all targeted responses can be optimised simultaneously provided that the correlation between responses does not make them contradict with each other. This type of correlation is termed “favourable correlation” in this study. Normally, all responses will satisfy the tests of significance with the initial combination of all-best and all-marginal settings.

ii. Trade-off situation refers to the case where the potential improvement for particular response will be compromised by the deterioration of the other response. In such case, the responses are said to have an "adverse correlation". The test criterion for the tests of significance might not be met initially and the most likely factors need to be switched from their best level to the marginal level, and vice versa.

iii. No conflict occurs when each response has a completely different set of significant factors. Hence, all targeted responses can be optimised independently.

3.5 Full Factorial Designs

An important step in Shainin DOE is to include all the significant variables identified from the variables search process in the full factorial experiment. Shainin advocates using the full factorial designs mainly because it does not confound the main effects of individual variables with the corresponding interaction effects. This study suggests using the 2^k full factorial designs in which only two levels will be assigned to each variable. Although two-level factorial designs will only consider the linear effects in the factor-response relationship, it will work quite well when the nonlinearity is not significant. Moreover, full factorial experiment with two-level designs is more economical and feasible from a business point of view.

Two important principles of experimental design should be emphasised when running the factorial experiment, that are, randomisation and replication [132, 134].

The randomisation can minimise the biased results caused by noise or uncontrollable factors such as ambient temperature and humidity. In other words, the experimenter can ensure the analytical work is less affected by the uncontrolled changes during the course of the experiment. For some variables which are hard to manipulate, they can be restricted to only one or few changes in the randomisation process. By replication it means each treatment in the experimental design should be carried out for more than one time, depending on the available cost and time. The average value will provide a more accurate result to the experimenter.

Recall that one of the major disadvantages in the Shainin approach is that it does not characterise the relationships between factors and responses (see Subsection 3.2.3). Addressing this issue, the signal-response system will also be integrated into Shainin DOE as further discussed in Section 3.6. The signal-response system enables the end-users to achieve a range of output values by changing the level of a specified factor called signal factor. In this regard, the Red X factor is treated as the signal factor whereas other significant factors are made as the control factors. The number of level for the signal factor is assigned according to the need of study. On the other hand, the control factors are accommodated in an inner array with two-level designs: "+" sign for higher level and "–" sign for lower level. Note that it should not be confused with the "best level (+)" and "marginal level (–)" used in the variables search process. The level settings for the inner array do not necessarily follow the previous settings used in the variables search. At least, new potential level settings should be tested in order to further examine the achievable optimal solution. Table 3.4 displays a modified full factorial designs when two control factors are accommodated and four levels are assigned to the signal factor in the signal-response analysis.

Table 3.4 – Full factorial designs for the signal-response system

Run	Control factor		Signal factor, A			
	B	C	I	II	III	IV
1	–	–				
2	+	–				
3	–	+				
4	+	+				

3.6 Signal-Response System

The two general types of the signal-response system are the measurement system and the multiple target system [132, 176]. Measurement system is an estimation process for certain quantity of interest which may include sampling, sample preparation, calibration and actual measurement process. For example, the Charpy impact tester is a form of measurement system. On the other hand, multiple target system is a system whose response value can be manipulated by adjusting the level of a signal factor. Injection moulding machine is classified as a multiple target system where the qualities of interest in the moulded parts can be varied through process settings.

Given the varying demands in many optimisation studies, there is an increasing importance to incorporate the concept of the signal-response system. The signal response system is sometimes known as the "dynamic system" because the response value is adjustable according to the particular intent of different period. In contrast, the simple response system is considered as a "static system" where the targeted response is set to achieve a specified value as closely as possible. An ideal signal-response relationship can be described by a simple linear regression model as follows [177]:

$$y = \beta M + \epsilon \quad (3.27)$$

where y and M represent the response and signal factor respectively while β indicates the system sensitivity and ϵ denotes the random error. The random error is assumed to be normally distributed with a zero mean and an error variance σ^2, that is, $\epsilon \sim N(0, \sigma^2)$. The error variance is also known as the system dispersion. Depending on the circumstances, the system sensitivity can be as large as possible, as small as possible, or as close to target value as possible. On the other hand, small system dispersion is always desirable because it implies a more consistent outcome. Wasserman [178] considered the influence of control factors on the system sensitivity and system dispersion as illustrated in Figure 3.3, Equation 3.27 was thus re-expressed as

$$y = \beta(x)M + \epsilon(x). \quad (3.28)$$

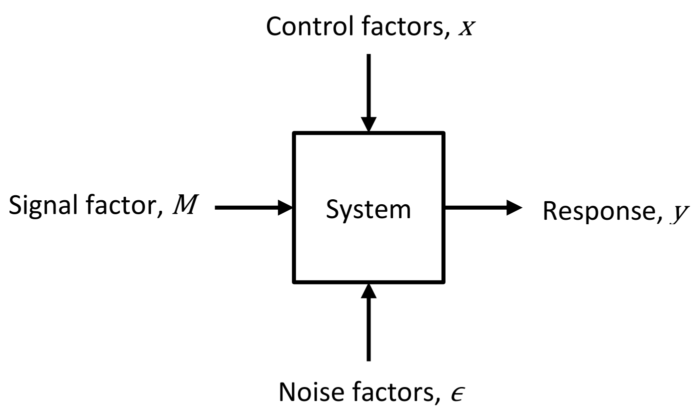

Figure 3.3 – An illustration of the signal-response system

A critical step in evaluating the signal-response relationship is to select a suitable performance measure for a given problem. There are two distinctive types of modelling strategy: performance measure modelling (PMM) and response function modelling (RFM). More details on these two modelling strategies are provided in the following subsections based on the work of Miller and Wu [176].

3.6.1 Performance Measure Modelling

The main procedures of running the PMM approach are as follows:

i. For each combination of control factor levels, the performance measure value is computed based on the response values obtained from different combinations of signal and noise factor levels.
ii. The performance measure values obtained in the first stage is modelled as a function of the control factors. The optimal combination of control factor levels is then determined from the fitted model.

Taguchi's dynamic parameter design is a clear example of PMM approach. The performance measure applied in this system is the dynamic signal-to-noise ratio, which converts the system sensitivity β and the system dispersion σ^2 into a single performance measure, as given by

$$\mathrm{S/N} = \ln\left(\frac{\beta^2}{\sigma^2}\right). \tag{3.29}$$

After computing the dynamic S/N ratio based on the response values, the second stage involves the adjustment of the sensitivity β, which is computed as a function of the control factors. Taguchi [177] suggested using the appropriate levels of the significant control factors to maximise the dynamic S/N ratio. The main purpose of doing so is to ensure the system being robust over the uncontrollable factors. However, the maximisation of this ratio has an effect of maximising β^2 as well as minimising σ^2. Even though the latter effect is considered necessary, the former effect might result in an unwanted result that is outside the specification limits. Further discussions on the limitations of the dynamic S/N ratio in optimising the signal-response system can be found in [179].

According to Miller and Wu [176], the major drawback found in the PMM approach is that direct modelling of the performance measure only provides information on how control factors influence the overall performance of the system. It does not provide useful clues on how these factors influence the signal-response relationship and hence the information for further system improvement is missing. For this reason, the PMM approach is not suitable to be adopted in this study.

3.6.2 Response Function Modelling

Miller and Wu [176] introduced a more powerful modelling strategy called RFM which does not suffer from the limitation in the PMM approach. RFM approach makes use of response values to characterise the signal-response relationship as a function of the control and noise factors. Likewise, this approach can be stated in a two-stage procedure:

i. For every combination of control and noise factor levels, a regression model is fitted into the response values over a range of signal factor levels.

ii. Separate fitted models are derived for the system sensitivity β and the system dispersion σ^2 as functions of the control and noise factors. Then, the performance measure is computed with respect to these models and the optimal control factor settings can thus be determined.

Depending on the essential features of the signal-response relationship, the general polynomial regression models for the first stage can be written as follows [179]:

$$f(M, d, \epsilon) = \beta_0(d, \epsilon) + \beta_1(d, \epsilon)M + \cdots + \beta_r(d, \epsilon)M^r. \tag{3.30}$$

In the second stage, the fitted models for the system sensitivity β and the system dispersion σ^2 are constructed based on the average main effects of the control and noise factors as well as their interactions. Through the use of ANOVA, the system dispersion σ^2 can be divided into lack-of-fit component ${\sigma_l}^2$ and pure error component ${\sigma_p}^2$ for further analysis. This may yield the response values with the least variability if the optimal control factors are used.

In comparison to PMM, RFM provides useful information on how to manipulate the control factors so as to further improve the system performance. Therefore, RFM approach is integrated into Shainin DOE to add dynamicity in the optimisation study. Perhaps a more important concern is the inclusion of RFM analysis will complicate the proposed methodology and hence reduce the practicality at the factory shop floor. However, the regression modelling techniques used for estimating the system sensitivity and system dispersion will not augment too much complexity in conducting the analytical work. Because in general the regression analysis and ANOVA can be easily performed by means of Microsoft Excel tools or statistical software such as Minitab or SPSS.

3.7 Chapter Conclusions

To sum up this chapter, a stepwise optimisation methodology named as "multi-response dynamic Shainin DOE" (MRDSD) was developed for the empirical study, which contains several significant features such as simplicity, novelty, validity, and usefulness. First of all, Shainin DOE was adopted mainly because it offers a more cost-effective and user-friendly strategy in comparison to the classical DOE and Taguchi DOE. Secondly, Shainin DOE was innovated with two useful techniques due to its inherent limitations: (i) a novel bivariate variables search was devised based on the multivariate statistical methods; (ii) the signal-response system was integrated into Shainin DOE to enhance the dynamicity in the optimisation process. Thirdly, in the aspect of statistical validity, it has been explained that variables search contains statistical rigor through the use of the test of significance, separation process, capping run, and factorial analysis. The proposed bivariate variables search can readily identify the dominant factors to two highly prioritised responses. The univariate decision limit may not be able to satisfy this criterion because it does not consider the correlation between responses. In addition, this approach does not suffer from the potential ambiguity in selecting the weighting terms as seen in the conventional multi-response optimisation study. Lastly, this novel integrated methodology will be exceptionally useful for non-statisticians to conduct multi-response optimisation without dealing with complex computational work. The step-by-step procedures as illustrated in Figure 3.4 can be easily understood and implemented by the operating personnel with limited statistical knowledge.

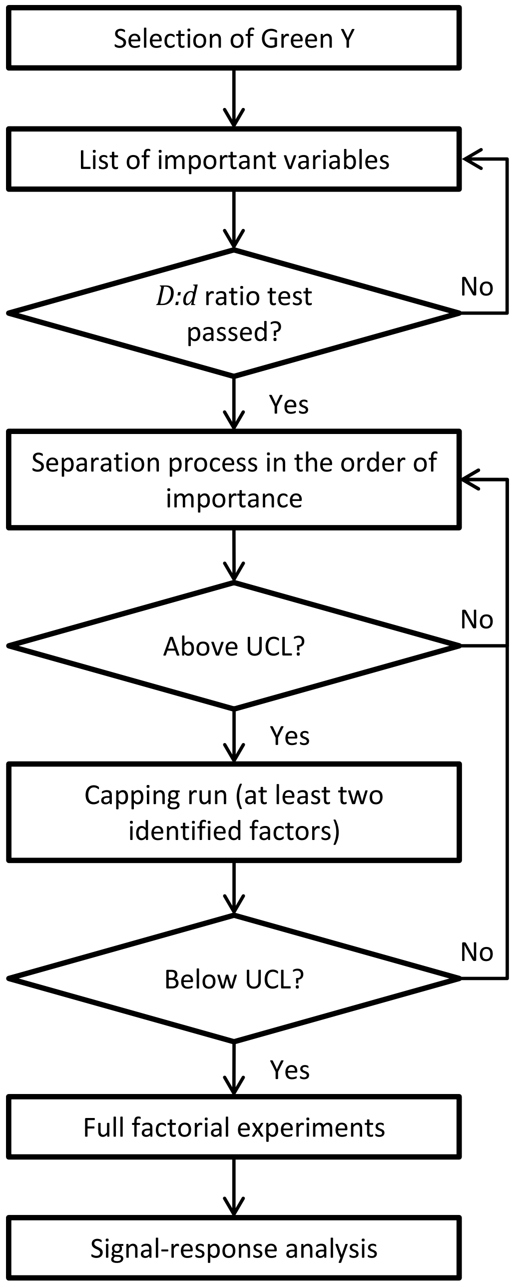

Figure 3.4 – The framework of multi-response dynamic Shainin DOE

CHAPTER 4

EMPIRICAL STUDY AND ANALYSIS

4.1 Introduction

Having described and explained the proposed optimisation methodology (MRDSD) in the previous chapter, this chapter presents an empirical study on the injection moulding process in the laboratory scale, so that some valid results can be generated before disseminating the potential solution to SMEs. Through the use of bivariate variables search, factors such as barrel temperature, mould temperature and cooling time were found to be significant to both qualities of interest: specific energy consumption and Charpy impact strength in polypropylene parts. This study showed that regardless of great fluctuations in impact strength data, the proposed methodology successfully identified the critical factors based on the multivariate techniques. In addition, the signal-response analysis via response function modelling demonstrated that the end-user could achieve different performance output targets specified by the customer or the manufacturer's intent.

4.2 Experimentation Apparatus and Set-up

The main objective of this empirical study is to optimise the energy efficiency of the injection moulding process through the proposed empirical-level approach (MRDSD), while not affecting the targeted quality of the final product. An energy balance approach is useful in studying the energy efficiency of different systems in the injection moulding machine. For example, this approach can be used to determine the pressure losses from the drive system, friction and heat losses from the injection system, or momentum transfer losses from the mould system. However, such level of detail was not required in this laboratory-scale study because the energy measurement was directly taken at the power supply terminal for the injection moulding machine [40, 46]. This is a measurement of the total energy consumption by the whole machine unit. Energy balance approach is more suitable for medium to larger manufacturing sites. In place of the energy balance, the energy efficiency during processing was estimated in terms of specific energy consumption (see Subsection 2.3.3).

The first step in this empirical study was to set up an energy monitoring system on the injection moulding machine. At the factory shop floor, a non-invasive sub-metering system can be employed to estimate the energy consumption of the production machines [71]. In this study, a simple data logger system was set up on the injection moulding machine for energy measurement. To set up the data logger system, a three-phase, four-wire power transducer (input: 380V, 5A) and three current transformers were installed on the main power switch of the machine as shown in Figure 4.1. A three-phase, four-wire power transducer was required because the machine was connected to a three-phase AC power supply terminal. The voltage ports of the power transducer were directly connected to the power supply, while the current was converted to an acceptable range by the current transformers (200A/5A) before being transferred to the power transducer through wires coiled around the current ports. With these wire connections, the power transducer is able to transform the instantaneous power measurement into a voltage signal. The power transducer used here is the WB9128 series made by Mianyang Weibo Electronic Co., Ltd where the maximum rated output voltage signal is 5V. The output voltage signal is delivered to the Grant SquirrelView 2020-1F8 data logger. The Squirrel 2020 series data logger is a computer-linked data acquisition system which can take up to 20 readings per second on one channel.

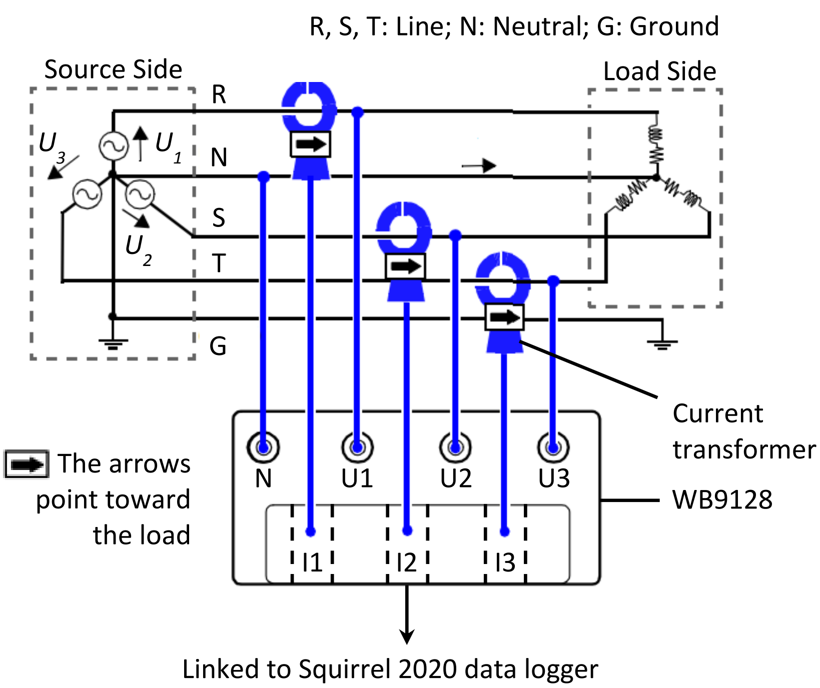

Figure 4.1 – The three-phase four-wire electrical connections in the energy monitoring system

The injection moulding machine adopted in this study was a Haitian Mars Series MA1200/370 model, featuring a dynamic servo-drive system and an externally installed mould cooling system. The built-in power supply for the mould cooler is directly connected to the same power supply terminal for the machine. It indicates that the energy consumed by the mould cooler is also measured by the energy monitoring system concurrently. Figure 4.2 displays the set-up of the energy monitoring system on the Haitian machine. Although servo system offers better energy efficiency in comparison to conventional drive system, it does not imply that there is no room to further improve the energy efficiency. There is still a possibility to generate energy saving through process parameters optimisation. Table 4.1 lists out some of the important technical specifications of the Haitian machine employed in the experiment.

Figure 4.2 – Set-up of the energy monitoring system on Haitian Mars Series MA1200/370 injection moulding machine

Table 4.1 – Technical specifications of Haitian Mars Series MA1200/370 and mould cooler

Machine Property	**Unit**	**Value**
Clamp tonnage	kN	1200
Clearance distance between tie bars	mm	410 × 410
Shot size	cm^3	214
Injection pressure	MPa	171
Injection rate (PS)	g/s	117
Heater power	kW	9.75
Pump motor power	kW	13
Mould cooler power	kW	6

Assume that the injection moulding machine is a balanced three-phase system, the total power dissipated in the three-phase system is the sum of the powers dissipated in its three phases [180]. As such, the output voltage signal from the power transducer can be reconverted into an actual power reading according to Equation 4.1 based on the user manual of the power transducer:

$$P = \frac{U_{out}}{U_{max}} (3UI \cos\theta)/1000 \qquad (4.1)$$

where P = instantaneous power consumption, kW;

U_{out} = output voltage from power transducer, V;

U_{max} = maximum rated output voltage of power transducer (5V);

U = phase voltage to injection moulding machine (380V);

I = maximum rated input current of current transformer (200A);

and $\cos\theta$ = power factor ($\theta = 0.1$).

The computation of energy consumption is executed through SquirrelView software by accumulating the power readings taken in every second over several injection moulding cycles. The energy data can then be directly downloaded to the computer via an electrical cable for further analysis.

4.3 Selection of Green Y and Material

Recall that the first procedure in the proposed methodology is to define the Green Y, which represents the quality response that must be optimised. Specific energy consumption (SEC), in unit of kWh/kg, was treated as the primary response y_1 in this study. Each time the parametric settings were changed, five moulded parts along with their associated energy data were collected and the corresponding mass of the five moulded parts was measured. Notice that the energy data collection was only started when two conditions were satisfied: (i) the machine settings had reached a steady state; (ii) the "soak period" was not too lengthy. The moulded parts made before the steady state must be discarded since they might not truly reflect the effects of the particular parametric settings. "Soak period" refers to the duration in which the injection screw stays with the newly charged material after the plasticisation process. During this "soak period", additional melting is generated due to conductive heating from the heated barrel. This results in the formation of melt film which can affect the subsequent feeding performance because thicker melt film will reduce the shear rates [46].

Another important objective of this empirical study is to verify the validity of the proposed methodology in using small sample size. As stated in Subsection 3.3.5, small sample size may lead to incorrect outcomes due to the possible occurrence of outliers. For this reason, the Charpy impact strength (CIS) was chosen as the secondary response y_2. The results obtained from the Charpy impact test are often widely scattered even with the most careful test procedures because impact strength is not an inherent material property [181]. Given such circumstance of great fluctuations in impact data, it is useful to examine the validity and applicability of the proposed methodology.

The mould unit employed here was a four-cavity type B ISO mould which can produce 80mm × 10mm × 4mm impact test bars as shown in Figure 4.3. This type of test bars is called "type 1 test specimens" according to ISO 179-1:2010 [182]. Before running the Charpy impact test, the test specimens were conditioned for at least 16 hours at a room temperature of 23±2°C and a relative humidity of 50±2% in accordance to ISO 291:2008 [183]. The Charpy impact test was performed according to ISO 179-1/1eA [182]. The term "1eA" indicates that the type 1 test specimen is subject to edgewise (e) impact test with a notch tip radius of 0.25±0.05mm (A). The CIS results were computed by dividing the energy required to break the notched specimen by the surface area at the notch section in unit of kJ/m^2. Due to the high variation in CIS data, all twenty specimens cut from the five collected moulded parts were tested, and the arithmetic mean of the CIS results was calculated and taken as the final value. Nevertheless, the CIS results cannot be directly applied to the part design because it does not represent the true energy required to break the specimen, but only a measure of the notch sensitivity in different plastic materials [184].

Polypropylene (PP) material was chosen since it is commonly used more than any other single polymer in the automobile parts which usually require an excellent impact strength [185]. The particular type of the plastic material used in this study was impact copolymer PP7684KN supplied by ExxonMobil™, which is designed for small and large injection moulded parts. The pertinent datasheet for this plastic material is provided in Appendix 3.

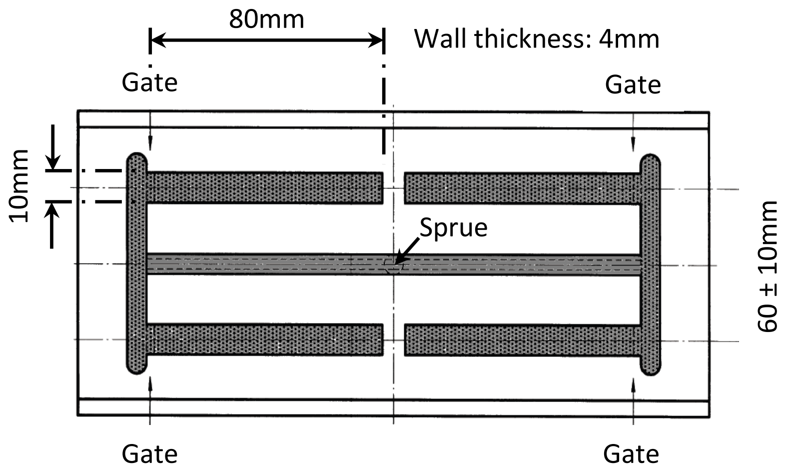

Figure 4.3 – Feature of the four-cavity type B ISO mould

4.4 Determination of Important Variables

The main purpose of this section is to determine a list of important variables for SEC and then rank them in the order of importance. To do this, some studies with particular relation to the energy usage of injection moulding process were reviewed and this provides a useful basis for "engineering judgement". The relevant research was pioneered by Nunn and Ackerman [186] where they formulated a thermodynamic model which divides the main energy usage into melting and filling stage. Thiriez [187] suggests adding the heat of fusion in the Nunn-Ackerman model for semi-crystalline polymer because the additional energy needed to transform the crystalline structure into fluidic melt is not negligible. Based on these two studies, Ribeiro et al. [188] further expand the thermodynamic model in a more empirical way, which also includes the idling power, cooling power, cooling time, and the efficiency index for melting and filling stage:

$$E_{min} = \frac{mc_p(T_m - T_{amb}) + \lambda m H_F + \bar{p} V_{inj}}{\varepsilon} + t_c(P_{idle} + P_{cool}) \tag{4.2}$$

where m = mass of injection shot;

c_p = specific heat of the polymer;

T_m = melt temperature;

T_{amb} = ambient temperature;

λ = degree of crystallisation;

H_F = heat of fusion for 100% crystalline polymer;

$\bar{p}$ = average injection pressure;

V_{inj} = shot volume;

ε = efficiency index for melting and filling;

t_c = cooling time;

P_{idle} = machine power in idle;

and P_{cool} = average power consumption of the cooler.

The cooling time dominates in one complete cycle of injection moulding process. It can vary from few seconds to several minutes depending upon the processing material, part thickness and type of product. Insufficient cooling time can result in dimensional defects such as ejector imprints and increased after-shrinkage [189]. Conversely, excess cooling time causes energy waste due to machine idling.

Therefore, it is essential to determine an economically acceptable cooling time without degrading the moulded parts. Stelson [190] studies all the available equations for estimating the cooling time for injection moulding process and concludes that the most theoretically correct formula for a plate-like part is given by

$$t_c = \frac{a^2}{\pi^2 \alpha} \ln\left[c\left(\frac{T_m - T_f}{T_e - T_f}\right)\right] \tag{4.3}$$

where a = part thickness;

α = thermal diffusivity of the polymer;

T_m = melt temperature;

T_f = mould temperature;

T_e = ejection temperature;

and c $= \begin{cases} 4/\pi \\ 8/\pi^2 \end{cases}$ based on mid-plane temperature or average temperature.

In view of the above studies, process parameters such as melt temperature, mould temperature, cooling time and injection pressure were highlighted as important factors to energy consumption. Other parameters such as screw rotational speed, back pressure and injection speed might have impact on SEC to a certain extent; therefore they were also included in the experimental study. The order of importance was arranged in accordance to the time profile of the listed variables because energy consumption has a linear relationship with the processing time. Barrel temperature and mould temperature were ranked at the top of the list since the heating barrel and mould cooler keep operating during the whole process. Next, cooling time was ranked at the third place as it is always dominant in one complete process cycle. The plasticisation stage normally takes longer time and presumably consumes more energy in comparison to the injection stage. Hence, screw rotational speed and back pressure were ranked ahead of injection speed and injection pressure. The following subsections provide more details on the corresponding “best (+)” and “marginal (–)” levels for each variable listed above.

4.4.1 Barrel temperature

In this study, the term “barrel temperature” is used instead of “melt temperature” because the setting values on the machine can only be regarded as a reference, but not the actual temperature of the melt inside the barrel. If the barrel temperature is set too low, it increases the melt viscosity and thereby results in pressure losses. In addition, the friction induced during injection even causes a steeper rise in melt temperature, leading to local thermal overloads and a risk of mechanical damage in the material [45]. If the barrel temperature is set too high, it will result in thermal degradation, higher dimensional variation and poorer mechanical properties [189].

There are five separate zones in the heating barrel of a Haitian MA1200/370 machine: feed zone, transition zone, metering zone, nozzle and long nozzle. The melt formation mostly occurs at the transition zone as a result of the shear action and conductive heat transfer, while the screw rotates and compresses the plastic pellets against the inside wall of the heating barrel. The molten material builds up in the metering zone and is ready for injection into the mould cavity through the nozzle. When setting the barrel temperature, it is advisable to gradually increase the temperature values as the melt travels along the screw unit [185]. The temperature profile for PP material as shown in Figure 4.4 was adopted as the reference. The lowest temperature range values (as indicated by the red line in Figure 4.4) were set as the best level because lower barrel temperature results in lower energy consumption. Since the melt temperature of PP material generally ranges from 220°C to 280°C [189], the extreme value of 280°C was taken as the marginal level. For PP mouldings, the impact strength will deteriorate when the melt temperature goes up [46]. The best and marginal values applied in the five separate zones are clearly tabulated in Table 4.2.

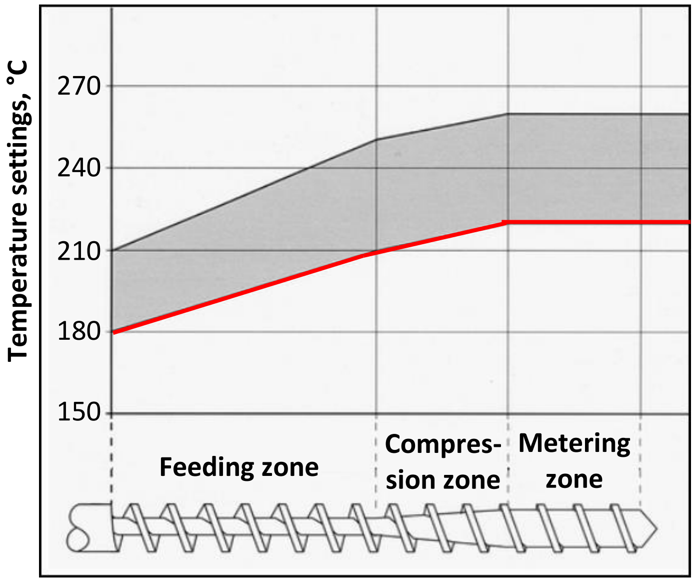

Figure 4.4 – Barrel temperature profile for high crystallinity polypropylene material. Source: [185]

Table 4.2 – The best and marginal values for barrel temperature in the five separate zones of Haitian machine

Barrel zone	**Feed zone**	**Transition**	**Metering**	**Nozzle**	**Long nozzle**
Best (+)	190°C	210°C	220°C	220°C	220°C
Marginal (–)	250°C	270°C	280°C	280°C	280°C

4.4.2 Mould temperature

The lowest mould temperature that can be provided by the mould cooler adopted in this study is no less than the temperature of the input water. The average temperature of the input cooling water was approximately 22°C during the empirical study. Therefore, the lowest range of mould temperature was 25-30°C because the water will be slightly heated up inside the mould cooler. The mould temperature range suggested for PP material lies within 40-80°C according to the user manual of Haitian machine [191]. Since higher mould temperature requires higher energy demand, 40°C was taken as the best level while 80°C was treated as the marginal level. Regarding the mechanical properties, lower mould temperature can bring higher impact strength in PP mouldings because the material can cool more rapidly and form a finer crystalline structure [46].

4.4.3 Cooling time

As can be seen from Figure 4.5, the cycle time can be separated into filling time (t_f), packing time (t_p), cooling time (t_c) and recovery time (t_r). Although the cooling process begins right after the material filling into the mould, the manipulation of cooling time only starts after the packing stage. Theoretically, the minimum cooling time can be calculated using Equation 4.3. Given that the thermal diffusivity of PP material is approximately 0.096mm^2s^{-1} and the ejection temperature is set at 60°C, the necessary cooling time based on average temperature is approximately equal to 30s. Using shorter cooling time can help reduce energy loss due to machine idling. In order to examine the minimum achievable cooling time, half of the estimated cooling time, i.e. 15s, was used as the best level whilst 30s was set as the marginal level instead.

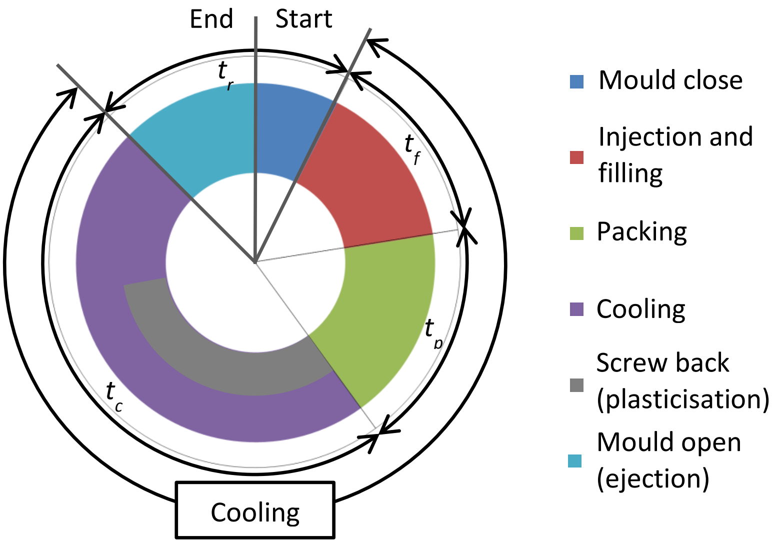

Figure 4.5 – Breakdown of cycle time for injection moulding process. Adapted from: [192]

4.4.4 Screw rotational speed and back pressure

After the packing stage, the reciprocating screw rotates and returns to the "screwed back" position. This process is known as screw recovery where new batch of plastic pellets are being loaded, melted and then re-accumulated at the screw front. Screw rotational speed should be adjusted as fast as necessary so that the plasticisation process can be accommodated within the cooling stage. The highest value of screw rotational speed that can be set on the machine is 99rpm. Faster rotational speed consumes more energy as it requires higher power to generate faster rotational motion. If the screw rotational speed is set too high, it not only causes entrapped air and unmelted material in the moulded parts [189], but might also result in mechanical damage to the machine. Therefore, an average value of 50rpm was used as the best level while a higher value of 75rpm was set as the marginal level.

Back pressure is needed to achieve a sufficient level of melt homogeneity during plasticisation stage. If the back pressure is too high, it will bring a risk of thermal degradation due to frictional heating [45]. According to the Haitian machine manufacturer's recommendation, it is not necessary to apply the back pressure for processing the pure PP material unless under poor melting conditions. For this reason, the best level was set at 0bar whereas the marginal level was set at 10bar since the energy usage increases directly with the back pressure.

4.4.5 Injection speed and injection pressure

Injection speed is the average speed of the melt as it passes through the critical cross-sectional area. The critical portion of the test specimens is the one on which the impact test will be conducted. The injection speed was calculated according to Equation 4.4 based on ISO 294-1:1998 [193].

$$v_i = \frac{V_M}{nAt_i} \tag{4.4}$$

where v_i = injection speed, mm/s;

V_M = cavity volume, mm^3;

n = number of cavities;

A = critical cross-sectional area, mm^2;

and t_i = injection time, s.

The mould unit has four cavities, and the cavity volume, critical cross-sectional area can be calculated based on Figure 4.3. By assuming an injection time of 0.5s, an injection speed of approximately 15mm/s was obtained from the calculation. As higher injection speed consumes more energy, the injection speed was doubled and used as the marginal level, i.e. 30mm/s. If the injection speed is set too fast, it will result in voids and thermal degradation which in turn affect the mechanical properties [189].

The injection pressure should be set at an appropriate level so that the injection speed limit can be reached, otherwise, the actual injection time will remain unaltered even though changes are made to the injection speed [189]. In this study, an injection pressure of 15bar was used as the best level while the marginal level was set at 30bar because higher injection pressure would result in higher energy consumption. If the injection pressure is set too high, it could lead to thermal degradation and burn marks on the finished part due to frictional heating on the material when passing through the gate [45].

4.4.6 Packing pressure and packing time

During the packing stage, there is usually a residual amount of molten material left at the screw front. This is called the melt cushion which exerts certain amount of pressure on the solidifying material inside the mould, enabling material packing as well as preventing backflow. The energy consumption during the packing stage was reportedly small (only up to 5%) [48, 70]. For this reason, packing pressure and packing time were excluded from the list of variables. However, it is still necessary to set the packing parameters correctly so as to avoid sink marks, flashing or other visible defects. Packing pressure is adjusted to about 60% of the required injection pressure whereas packing time is set at nearly 30% of the cycle time [189].

4.4.7 Summary of important variables

In brief, seven variables were suspected to be significant towards reducing SEC. Following the order of importance, they are, respectively: barrel temperature, mould temperature, cooling time, screw rotational speed, back pressure, injection speed, and injection pressure. Each process variable was assigned to a "best (+)" level and a "marginal (–)" level for PP material based on the literature, datasheet, equipment user manual or manufacturer's recommendation. The eventual list of variables is summarised in Table 4.3 along with the corresponding best and marginal values. The influence of ambient factors (or noise factors) was precluded in this study as the injection moulding process was carried out at a room temperature of 20±1°C and a relative humidity of 68±2%.

Table 4.3 – List of variables for SEC in descending order of importance

Rank	Variables	Values (for PP material)		
		Unit	Best (+)	Marginal (–)
1	Barrel temperature (BT)	°C	220	280
2	Mould temperature (MT)	°C	40	80
3	Cooling time (CT)	s	15	30
4	Screw rotational speed (SS)	rpm	50	75
5	Back pressure (BP)	bar	0	10
6	Injection speed (IS)	mm/s	15	30
7	Injection pressure (IP)	bar	15	30

4.5 Results and Discussions for Bivariate Variables Search

After highlighting all the suspected variables, the next procedure is to carry out the bivariate variables search process based on the procedural and theoretical frameworks as established in Section 3.3 and Section 3.4. At the end of this section, the significant factors to both SEC and CIS would be readily identified before proceeding to the full factorial experiment and the signal-response analysis.

4.5.1 Tests of significance

As mentioned in Section 4.3, SEC was labelled as y_1 as it represents the more desirable response whereas CIS was denoted by y_2. The bivariate variables search was started by carrying out three all-best and three all-marginal experiments in a randomised order. The results from these two types of experiments are respectively displayed in Table 4.4 and Table 4.5. Notice that the random orders for running the all-best and all-marginal experiments are indicated in parentheses for convenient reading.

Table 4.4 – Results of all-best experiments

Run	Variables							y_1	y_2
	BT	MT	CT	SS	BP	IS	IP	SEC, kWh/kg	CIS, kJ/m^2
1(1)	+	+	+	+	+	+	+	0.6008	6.1250
2(4)	+	+	+	+	+	+	+	0.6545	6.7219
3(6)	+	+	+	+	+	+	+	0.6448	6.7016
Median								0.6448	6.7016
Range								0.0537	0.5969

Table 4.5 – Results of all-marginal experiments

Run	Variables							y_1 SEC, kWh/kg	y_2 CIS, kJ/m^2
	BT	MT	CT	SS	BP	IS	IP		
4(2)	–	–	–	–	–	–	–	1.1106	4.0813
5(3)	–	–	–	–	–	–	–	1.1579	4.1625
6(5)	–	–	–	–	–	–	–	1.1440	4.5953
Median								1.1440	4.1625
Range								0.0473	0.5140

For y_1, the difference between the medians D_m was equal to 0.4992kWh/kg and the average range $\bar{d}$ was equal to 0.0505kWh/kg. Thus, the value of $\left|D_m:\bar{d}\right|_1$ was equal to 9.89:1, which was far greater than 3.28:1, indicating that there was no necessity to rectify the list of variables in Table 4.3. On the other hand, the D_m for y_2 was equal to 2.5391kJ/m^2 whereas $\bar{d}$ was equal to 0.5555kJ/m^2. Hence the value of $\left|D_m:\bar{d}\right|_2$ was equal to 4.57:1, which implied that both responses have the similar best and marginal levels for the listed variables. In other words, SEC and CIS were found to have a favourable correlation because a decrease in SEC will lead to a proportional increase in CIS. Therefore, it can be expected to achieve a win-win solution (as discussed in Subsection 3.4.4) provided that both responses have the same significant factors. Otherwise, there will be no conflict if they have totally different set of significant factors.

4.5.2 Separation process

In this phase, the covariance s_{12} for the all-best and all-marginal experiments was first calculated based on Equation 3.9 (see p. 96) with a sample size of $n-1$.

Subsequently, the average covariance was calculated and the resultant value was adjusted to a "–" sign since both responses were found to have a negative relationship. The calculation of the adjusted covariance s_{12}^{*} is shown in Table 4.6.

Table 4.6 – Calculation of the adjusted covariance

Type of experiment	s_{12}
All-best	0.01278
All-marginal	0.00136
Average covariance, $\bar{s}_{12}$	0.00707
Adjusted covariance, s_{12}^{*}	-0.00707

Next, a pair of opposite tests was carried out by swapping the level of variables according to the order of importance. The measurement data for both responses are provided in Table 4.7. To separate the unimportant variables from the list, a Hotelling's T^2-chart was set up with the following four steps:

i. T^2 values were computed according to Equation 3.20 (see p. 102).
ii. The upper control limit was determined based on Equation 3.22 (see p. 104).
iii. The contribution of each response T_i^2 was estimated according to Equation 3.24 (see p. 105).
iv. The $T_1\!:T_2$ ratio test was established by calculating the range of T_{DL} based on Equation 3.26 (see p. 106).

Since $\left|D_m\!:\bar{d}\right|_1$ was larger than $\left|D_m\!:\bar{d}\right|_2$ in the tests of significance, if $T_1\!:T_2 < T_{\mathrm{DL},2}$, it indicates that the relevant variable along with its associated interaction effects is negligible on y_1 (refer to Subsection 3.4.3.3 for detailed explanation). Table 4.8 clearly displays the calculation results for the separation phase.

Table 4.7 – Measurement data in the separation phase

Run	Variables							y_1	y_2
	BT	MT	CT	SS	BP	IS	IP	SEC, kWh/kg	CIS, kJ/m^2
7	–	+	+	+	+	+	+	0.8012	5.4719
8	+	–	–	–	–	–	–	1.0761	6.5641
9	+	–	+	+	+	+	+	0.7530	5.2000
10	–	+	–	–	–	–	–	1.0741	4.9753
11	+	+	–	+	+	+	+	0.7908	4.4188
12	–	–	+	–	–	–	–	0.8825	5.5266

Table 4.8 – Bivariate T^2-chart for the separation phase

Run	Hotelling's T^2	UCL	Out-of-control	Contributions				Importance of y_1
				T_1^2	T_2^2	$T_1{:}T_2$	T_{DL}	
7	82.49	48.35	✓	82.48	42.14	1.40	0.46-2.16	✓
8	217.7	48.35	✓	15.55	160.7	0.31	0.46-2.16	✘
9	63.49	48.35	✓	39.47	62.84	0.79	0.46-2.16	✓
10	20.34	48.35	✘	16.47	18.41	0.95	0.46-2.16	N/A
11	145.3	48.35	✓	71.87	145.2	0.70	0.46-2.16	✓
12	260.3	48.35	✓	230.6	51.86	2.11	0.46-2.16	✓

In Table 4.8, the resultant T^2 values from Run 7 and Run 8 show that barrel temperature was presumed to be significant to both responses. However, the $T_1{:}T_2$ ratio in Run 8 was less than $T_{\mathrm{DL},2}$ which implies that the contribution of y_1 was not significant enough. It can also be noted in Run 8 for the T_1^2 value of which was less than 23.12, denoting that y_1 actually lied within its univariate decision limit. Next, the significance of mould temperature could not be confirmed because one T^2 value (Run 10) fell below the UCL. Therefore, the opposite tests were rerun for the next important variable, i.e. cooling time, before going into the capping run phase. Since both T^2 values obtained in Run 11 and Run 12 were found above the UCL, it could be confirmed that cooling time was a significant factor to both responses. Overall, the contribution of y_1 can be said as potent as that generated by y_2 as most $T_1\!:T_2$ ratios were found inside the T_{DL} range.

4.5.3 Capping run

In the previous phase, barrel temperature, mould temperature and cooling time were presumed to be significant to both responses. The capping run phase was performed to validate the importance of these variables where the resultant values are given in Table 4.9. Subsequently, the corresponding T^2 values were computed as shown in Table 4.10. Both T^2 values were found below the UCL and this confirmed that these three variables were important to both responses. Here, it could be said that the order of importance was arranged satisfactorily since all three important variables were ranked at the top of the list. The remaining four variables can thus be eliminated from the list when running the full factorial experiments. Because both responses have a favourable correlation with the same key factors, a win-win solution can be achieved at the end of the experimental study.

Table 4.9 – Measurement data in the capping run

Run	Variables							y_1	y_2
	BT	MT	CT	SS	BP	IS	IP	SEC, kWh/kg	CIS, kJ/m^2
13	+	+	+	–	–	–	–	0.6539	5.9719
14	–	–	–	+	+	+	+	1.0981	4.6125

Table 4.10 – Bivariate T^2-chart for the capping run

Run	Hotelling's T^2	UCL	Out-of-control	Contributions				Importance of y_1
				T_1^2	T_2^2	$T_1\!:T_2$	T_{DL}	
13	25.47	48.35	✘	14.84	0.28	7.29	0.46-2.16	N/A
14	7.53	48.35	✘	5.64	7.10	0.89	0.46-2.16	N/A

4.5.4 Factorial analysis

After having identified the key factors, factorial analysis was carried out to quantify the main effects of each factor and the interactions among them. All data generated from the previous phases were utilised in the factorial analysis. As can be seen in Table 4.11, cooling time was identified as the Red X factor for SEC while barrel temperature and mould temperature were the Pink X and Pale Pink X factor respectively.

Table 4.11 – Results of factorial analysis for SEC

Key Variables			y_1 SEC, kWh/kg				Median
BT	MT	CT					
+	+	+	0.6008	0.6545	0.6448	0.6539	0.6494
–	+	+	0.8012	/	/	/	0.8012
–	–	+	0.8825	/	/	/	0.8825
+	–	+	0.7530	/	/	/	0.7530
+	–	–	1.0761	/	/	/	1.0761
+	+	–	0.7908	/	/	/	0.7908
–	+	–	1.0741	/	/	/	1.0741
–	–	–	1.1106	1.1579	1.1440	1.0981	1.1273

	BT	MT	CT	BT×MT	BT×CT	MT×CT	BT×MT×CT
	+	+	+	+	+	+	+
	–	+	+	–	–	+	–
	–	–	+	+	–	–	+
	+	–	+	–	+	–	–
	+	–	–	–	–	+	+
	+	+	–	+	–	–	–
	–	+	–	–	+	–	+
	–	–	–	+	+	+	–
Mean (+)	0.8173	0.8289	0.7715	0.8625	0.9010	0.9135	0.9205
Mean (–)	0.9713	0.9597	1.0171	0.9261	0.8877	0.8751	0.8681
Effects	-0.1540	-0.1308	-0.2456	-0.0636	0.0133	0.0384	0.0524
	Pink X	Pale Pink X	Red X				

Next, it is worth running the factorial analysis for CIS since it has the same important factors as SEC. The results given in Table 4.12 show that the BT×MT×CT interaction was the Red X factor while the MT×CT interaction and cooling time were the Pink X and Pale Pink X factor respectively. As mentioned in Section 3.2, subjectively overlooking the interaction effects will lead to a wrong interpretation of the experiment outcomes. If fractional factorial designs are used instead, it is necessary to deem whether the individual factor or its corresponding higher-order alias is the real important factor.

Table 4.12 – Results of factorial analysis for CIS

Key Variables			y_2 CIS, kJ/m^2				Median
BT	MT	CT					
+	+	+	6.1250	6.7219	6.7016	5.9719	6.4133
–	+	+	5.4719	/	/	/	5.4719
–	–	+	5.5266	/	/	/	5.5266
+	–	+	5.2000	/	/	/	5.2000
+	–	–	6.5641	/	/	/	6.5641
+	+	–	4.4188	/	/	/	4.4188
–	+	–	4.9753	/	/	/	4.9753
–	–	–	4.0813	4.1625	4.5953	4.6125	4.3789

	BT	MT	CT	BT×MT	BT×CT	MT×CT	BT×MT×CT
	+	+	+	+	+	+	+
	–	+	+	–	–	+	–
	–	–	+	+	–	–	+
	+	–	+	–	+	–	–
	+	–	–	–	–	+	+
	+	+	–	+	–	–	–
	–	+	–	–	+	–	+
	–	–	–	+	+	+	–
Mean (+)	5.6491	5.3198	5.6530	5.1844	5.2419	5.7071	5.8698
Mean (–)	5.0882	5.4174	5.0843	5.5528	5.4954	5.0302	4.8674
Effects	0.5609	-0.0976	0.5687	-0.3684	-0.2535	0.6769	1.0024
			Pale Pink X			Pink X	Red X

4.5.5 Further confirmation experiments

The use of engineering judgement a priori had successfully reduced the necessary number of experiments. In order to verify the validity of the experimental results, some confirmation experiments were conducted to further examine the influence of the unimportant factors to both responses. These trials are not necessary to be carried out at the factory shop floor because it will result in additional use of time and material. The experimental results and the resultant T^2 values are presented respectively in Table 4.13 and Table 4.14.

Table 4.13 – Measurement data in the confirmation experiments

Run	Variables							y_1	y_2
	BT	MT	CT	SS	BP	IS	IP	SEC, kWh/kg	CIS, kJ/m^2
13	+	+	+	–	+	+	+	0.5844	5.8219
14	–	–	–	+	–	–	–	1.1677	4.8266
15	+	+	+	+	–	+	+	0.6382	6.5766
16	–	–	–	–	+	–	–	1.1466	4.8625
17	+	+	+	+	+	–	+	0.6558	6.5438
18	–	–	–	–	–	+	–	1.1733	4.8250
19	+	+	+	+	+	+	–	0.6598	6.8469
20	–	–	–	–	–	–	+	1.1927	3.9141

Table 4.14 – Bivariate T^2-chart for the confirmation experiments

Run	Hotelling's T^2	UCL	Out-of-control	Contributions				Importance of y_1
				T_1^2	T_2^2	$T_1 : T_2$	T_{DL}	
13	120.0	48.35	✓	12.30	21.57	0.76	0.46-2.16	✓
14	44.25	48.35	✘	1.89	12.29	0.39	0.46-2.16	N/A
15	1.98	48.35	✘	0.15	0.44	0.58	0.46-2.16	N/A
16	30.30	48.35	✘	0.02	13.66	0.04	0.46-2.16	N/A
17	0.70	48.35	✘	0.41	0.69	0.77	0.46-2.16	N/A
18	49.62	48.35	✓	2.89	12.23	0.49	0.46-2.16	✓
19	4.84	48.35	✘	0.76	0.59	1.14	0.46-2.16	N/A
20	9.12	48.35	✘	8.00	1.72	2.16	0.46-2.16	N/A

In Table 4.14, out-of-control signals could be observed in Run 13 and Run 18 despite the fact that no value was found outside the univariate decision limits (all the associated T_i^2 values were less than 23.12). For clarity, Run 13 was the all-best experiment except screw rotational speed, whereas Run 18 was the all-marginal experiment except injection speed. The explanation for Run 13 would be exceptionally important since the corresponding T^2 value was much higher than the UCL and the contribution of y_1 could not be ignored. With a favourable correlation, the SEC value is expected to be high while the CIS value is low. However, a relatively low SEC value had caused an out-of-control state in the bivariate statistic. This implies that high screw rotational speed does not consume much energy but it will result in poorer impact strength in the moulded parts. If the univariate decision limits were applied here, it would be unlikely to screen out the out-of-control signal in Run 13. Nevertheless, screw rotational speed and injection speed were not considered in the full factorial experiment since their influence on SEC was not significant (both T_1^2 values were less than 23.12).

4.6 Full Factorial Experiment

From the factorial analysis, cooling time was identified as the most important single factor to both SEC and CIS. Cooling time was thus chosen as the signal factor while barrel temperature and mould temperature were treated as the control factors in the full factorial experiment. The full factorial designs as shown in Table 3.4 (p. 110) was used at this stage. The lowest cooling time employed previously was 15s. Here, the cooling time was varied between 5s and 15s with a 5-second increment in order to determine the minimum achievable cooling time for reducing idle loss. Likewise, for the control factors, a lower barrel temperature of 200°C and a lower mould temperature of 30°C were investigated along with their initial “best levels” used in the bivariate variables search. In every single treatment of the full factorial designs, three SEC measurements were taken so as to obtain a more accurate test result based on the average value. The complete datasheet of the full factorial experiments for SEC is provided in Appendix 4. Obviously, the average SEC goes up when the cooling time increases as can be observed in Table 4.15 and Figure 4.6.

Table 4.15 – Full factorial experiments for SEC in unit of kWh/kg

Row	Control factor		Signal factor: CT, s		
	BT, °C	MT, °C	5	10	15
1	200	30	0.4473	0.5018	0.5688
2	220	30	0.4693	0.5164	0.6047
3	200	40	0.4494	0.5041	0.5752
4	220	40	0.4835	0.5328	0.6119

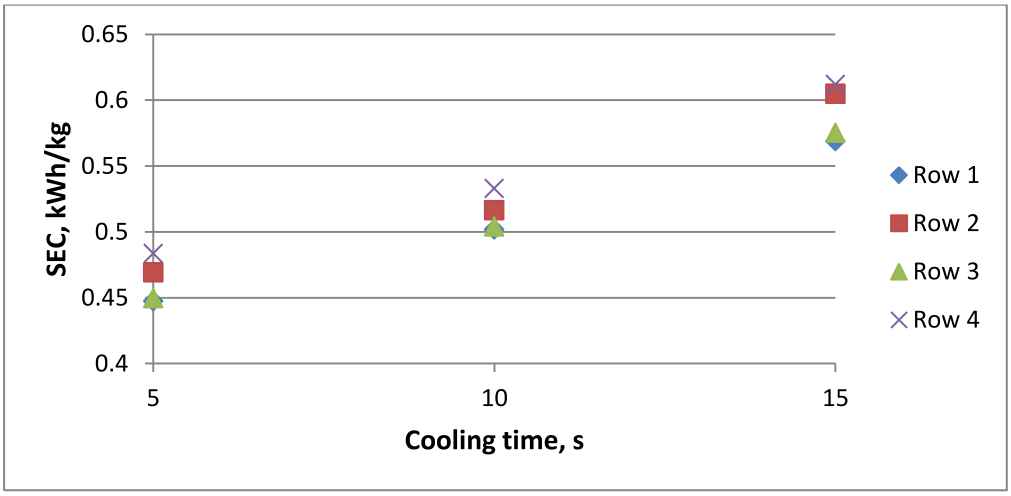

Figure 4.6 – Average SEC values versus cooling time

Next, all twenty specimens moulded from every single treatment were examined in the Charpy impact tests. The complete datasheet of the full factorial experiments for CIS can also be found in Appendix 4. Table 4.16 summarises the arithmetic mean of CIS values whereas Figure 4.7 presents the data distribution of CIS with one standard deviation against cooling time. The findings show that CIS generally decreases with increasing cooling time. This phenomenon could possibly be explained by the fact that the morphology of the crystalline structure grown in the moulded part is highly affected by the temperature history and cooling times [46]. However, there is a gap in the existing literature concerning the relationship between the cooling time and the moulding's impact performance. Minor changes in the cooling time may cause major variations in crystal formation which in turn affects the mechanical properties of the moulded part. The impact performance might be degraded by the internal stresses induced in the moulded part when it is "stuck" inside the mould unit for a longer period.

Table 4.16 – Full factorial experiments for CIS in unit of kJ/m^2

Row	Control factor		Signal factor: CT, s		
	BT, °C	MT, °C	5	10	15
1	200	30	6.3189	5.0804	4.8740
2	220	30	5.8725	5.2925	5.0915
3	200	40	6.2678	5.3449	4.9024
4	220	40	5.8720	5.4867	4.9266

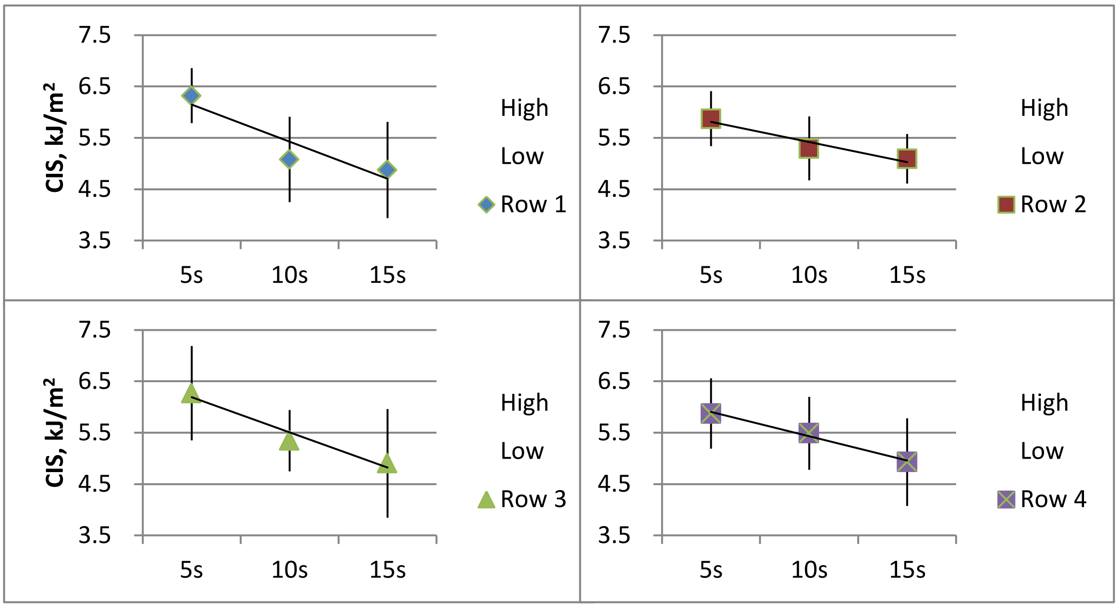

Figure 4.7 – Distribution of CIS values with one standard deviation against cooling time

At the end of this stage, it can be clearly observed from Figure 4.6 and Figure 4.7 that a win-win solution can be simply achieved using a shorter cooling time because it not only reduces SEC value, but also results in higher CIS value at the same time. At first, it might seem that the Row 1 settings provide the most optimal solution as it requires the lowest SEC value while not compromising the CIS performance. However, the signal-response analysis demonstrated in the next section will suggest a different solution based on response function modelling.

4.7 Response Function Modelling Analysis

The first step of RFM analysis involved fitting a suitable regression model for y_1 and y_2 in the full factorial experiments. Since straight lines can be satisfactorily fitted into the response values as illustrated in Figure 4.6 and Figure 4.7, the following simple linear regression models were adopted:

$$y_1 = \beta_{0,y_1} + \beta_{1,y_1} M \tag{4.5}$$

$$y_2 = \beta_{0,y_2} + \beta_{1,y_2} M \tag{4.6}$$

where coefficients β_0 and β_1 characterise the system sensitivity of order 0 and 1 respectively. Through the regression modelling, the values for these coefficients were estimated as given in Table 4.17. In the next step, the main and interaction effects of the control factors on these coefficients were computed. It should be noticed that the symbol "+" and "–" in the RFM analysis denote the higher level and lower level correspondingly.

Table 4.17 – Estimated values for the system sensitivity

Row	Control Factors			Regression Coefficients			
	BT	MT	BT×MT	β_{0,y_1}	β_{1,y_1}	β_{0,y_2}	β_{1,y_2}
1	–	–	+	0.385	0.0121	6.87	-0.144
2	+	–	–	0.395	0.0135	6.20	-0.078
3	–	+	–	0.384	0.0126	6.87	-0.137
4	+	+	+	0.414	0.0128	6.37	-0.095
Mean				0.395	0.0128	6.58	-0.114
BT				0.0200	0.0008	-0.5850	0.0540
MT				0.0090	-0.0001	0.0850	-0.0050
BT×MT				0.0100	-0.0006	0.0850	-0.0120

By averaging out the main and interaction effects, the fitted models of the regression coefficients for y_1 are given by

$$\begin{aligned} \beta_{0,y_1} &= 0.395 + 0.01X_{\mathrm{BT}} + 0.0045X_{\mathrm{MT}} + 0.005X_{\mathrm{BT\times MT}} \\ \beta_{1,y_1} &= 0.0128 + 0.0004X_{\mathrm{BT}} - 0.00005X_{\mathrm{MT}} - 0.0003X_{\mathrm{BT\times MT}} \end{aligned} \tag{4.7}$$

whereas for y_2,

$$\begin{aligned} \beta_{0,y_2} &= 6.58 - 0.2925X_{\mathrm{BT}} + 0.0425X_{\mathrm{MT}} + 0.0425X_{\mathrm{BT\times MT}} \\ \beta_{1,y_2} &= -0.114 + 0.027X_{\mathrm{BT}} - 0.0025X_{\mathrm{MT}} - 0.006X_{\mathrm{BT\times MT}} \end{aligned} \tag{4.8}$$

where $X = -1$ when the corresponding factor is set at lower level; and $X = +1$ when the higher level is used instead.

In order to reduce the variation in CIS data, the system dispersion σ^2 was divided into lack-of-fit component ${\sigma_l}^2$ and pure error component ${\sigma_p}^2$ via ANOVA for further analysis as presented in Table 4.18.

Table 4.18 – Estimated values for the system dispersion in the Charpy impact tests

Row	Control Factors			Lack-of-Fit and Pure Error Component			
	BT	MT	BT×MT	${\sigma_l}^2$	$\ln {\sigma_l}^2$	${\sigma_p}^2$	$\ln {\sigma_p}^2$
1	–	–	+	3.550	1.2669	0.618	-0.4813
2	+	–	–	0.479	-0.7361	0.303	-1.1940
3	–	+	–	0.770	-0.2614	0.774	-0.2562
4	+	+	+	0.102	-2.2828	0.566	-0.5692
Mean					-0.5033		-0.6252
BT					-2.0122		-0.5129
MT					-1.5375		0.4250
BT×MT					-0.0092		0.1999

It is especially important to analyse the pure error component ${\sigma_p}^2$ as it represents the part-to-part variation in the response data. By averaging out the estimated values in Table 4.18, the fitted model for $\ln {\sigma_p}^2$ is given by

$$\ln {\sigma_p}^2 = -0.6252 - 0.2565\mathrm{X}_{\mathrm{BT}} + 0.2125\mathrm{X}_{\mathrm{MT}} + 0.1\mathrm{X}_{\mathrm{BT\times MT}}. \quad (4.9)$$

Table 4.18 shows that the Row 2 settings (BT: 220°C; MT: 30°C) yield the lowest part-to-part variation. This condition can also be observed from Figure 4.7 where the response data in Row 2 show better consistency in comparison to others. The possible explanation for larger variation in CIS response data when using lower barrel temperature (200°C) is the occurrence of inhomogeneous melt and thus the crystal formation in the moulded part is subject to larger variation.

The advantages of including the signal-response system with RFM analysis are explicitly demonstrated in this section. First, the relationships between the key factors and targeted responses can be clearly observed and exploited for quality improvement. From this empirical study, it was found that both SEC and CIS values could be optimised simultaneously using a lower level of cooling time. Second, RFM analysis provided some useful clues on how to manipulate the control factors for improving the system performance. At first sight, Row 1 settings seems to provide the best solution if the purpose is merely to reduce SEC value. However, when the fluctuation in CIS response data is considered, Row 2 settings can provide a more compromising solution where higher barrel temperature can help reduce variation in CIS response data although it requires higher SEC. Furthermore, the regression models can be used to generate result predictions for different levels of signal factor. For example, Row 4 settings are totally the same as those of Run 11 in the variables search (see Table 4.7 on p. 137) except the cooling time. After computing the system sensitivity for SEC according to Equation 4.7, a cooling time of 30s is substituted in Equation 4.5 for estimating the corresponding SEC value. Table 4.19 compares the empirical value from the variables search with the estimated value based on the regression model for SEC. The small percentage difference shows that the regression analysis for SEC is highly accurate.

Table 4.19 – Comparison between the empirical study and the regression model for SEC

	SEC, kWh/kg	
Empirical study	Regression model	% Difference
0.7908	0.7980	0.9

4.8 Conclusions of Experiment

The empirical study demonstrated that the specific energy consumption of the injection moulding process could be optimised concurrently with the moulded part's Charpy impact strength (win-win solution). Through the use of bivariate variables search, cooling time was identified as the most significant factor to both qualities of interest. The derived regression models based on response function modelling method enable the end-users to achieve a range of output performance based on the specific intent. More importantly, this empirical study showed that regardless of great fluctuations in impact strength data, the bivariate variables search was able to identify the critical factors for both responses. The weakness of using univariate decision limits was pointed out through the confirmation experiments, proving the necessity of integrating the multivariate techniques in studying the multi-response problems. The proposed methodology also showed high ease of implementation due to the fact that no sophisticated statistical knowledge was needed for processing data. This allows non-statisticians to easily apply the proposed methodology in the quest for energy efficiency improvement at short notice. Moreover, the optimal solution can be attained with minimal resource expenditures since the proposed methodology only requires small sample size. As a conclusion, MRDSD can be employed as an effective "no-cost investment" strategy in the environment of manufacturing SMEs to reduce their efficiency gap.

CHAPTER 5

DP-BASED SPREADSHEET SOLUTION

5.1 Introduction

Having addressed the first and second research question, this chapter attempts to deal with the third research question in a theoretical way. In short, the primary cause of energy consumption in the manufacturing industry is normally attributed to the production machines. Therefore, replacing the old and inefficient equipment with the energy efficiency technology is the most straightforward method for energy saving. However, there are various barriers that inhibit SMEs from implementing energy efficiency investments such as lack of access to capital or information. Making a financial decision for the energy efficiency investments can be a complicated process due to the stochastic nature of the problem, especially in consideration of the long-term benefit. In order to better manage the decision-making process, this chapter develops a spreadsheet-based decision support system via dynamic programming for solving the stochastic equipment replacement problem. The following sections explain in detail the procedures in developing the spreadsheet solution and these are summarised as follows:

i. Defining and investigating the problem
ii. Formulating the dynamic programming model

iii. Deriving the spreadsheet solution

iv. Exploring large dataset via Markov chains

v. Preparing to implement the solution

5.2 Defining and Investigating the Problem

In SMEs, particularly small and micro enterprises, the cost consideration always dominates in the decision-making process for capital investments. As a result, the capital-intensive energy saving options will easily be negated because of limited access to financial resources. Although decision makers should, in principle, evaluate every available option carefully before making any decision, Stern and Aronson [28] argue that people tend to rationalise and follow their previous decisions related to energy use where this tendency becomes greater for more expensive and irreversible investments (cannot be resold). For the energy efficiency investments, Golove and Eto [24] highlighted that there are at least two key differences from the other investments. First, investments in most energy-efficient equipment are highly illiquid and normally irreversible. Second, energy efficiency investments are often associated with hidden costs or transaction costs which are poorly captured by the engineering-economic analyses, such as costs for searching information, equipment installation costs, and so on. It is therefore imperative to conduct a cost assessment prior to making any financial decision. An effective cost assessment is concerned with collecting information for decision making, performance assessment and future planning [40]. The first thing to recognise in this section is to understand the problem under investigation. To do this, the status quo of the green technologies and the technical cost analysis in particular relation to the injection moulding industry are reviewed in the following subsections.

5.2.1 Status quo of green technologies

The majority of energy consumed by the injection moulding machine during processing is through the drive system [48]. As mentioned in Section 2.3.1.1, the two most prevalent drive systems in the current market are hydraulic servo-drive system and all-electric drive system, which have many advantages over conventional hydraulic or pneumatic drive system. There are also hybrid machines being introduced into the niche market where both hydraulically and electrically driven systems are adopted concurrently. While the selection of drive system may seem very intuitive, the advantages of these three different drive systems are reportedly debatable. The final selection of the drive system often depends on various considerations such as the category of product, technological capability, personal preferences, financial budget as well as local electricity cost [53].

Manufacturers of high-precision, electronic or medical products have a preference for employing all-electric machines which are perceived to offer better repeatability and cleaner operation (oil-free). Many manufacturers are still in favour of hydraulic machines mainly because of their already matured applications, especially for producing large-size parts such as car bumpers. Accumulator-assisted hydraulic machine can deliver a large shot weight into the mould unit under a consistent pressure. In comparison, electric drives are still not suitable for large-sized machines due to the inherent instabilities in the toggle clamp configuration [187]. Moreover, injection moulding that involves multi-material processing requires a multi-barrel injection system which is usually driven and controlled hydraulically [53]. This is a considerably new area to all-electric machines. Lower capital investment is another main reason for using hydraulic machines. Nonetheless, the cost difference between hydraulic machines and all-electric machines had allegedly declined from 40% to 10-20% in recent years [194]. All-electric machines are advocated mainly because they have greater advantage in terms of energy efficiency. However, some machine manufacturers claim that the actual energy savings are exaggerated by comparing the latest all-electric machines with much older hydraulic machines [53]. The electricity cost in different region is reported to have influenced the tendencies in machine selection as well. Manufacturers associated with low electricity cost will show more concerns for increasing production volume rather than improving energy efficiency [53].

5.2.2 Technical cost analysis

Technical cost modelling is an approach to cost estimating in which each of the elements that contribute to the overall cost is estimated individually [46]. Through the technical cost approach, the complexity of the cost analysis problem can be reduced to individual estimates based on the physics of the manufacturing process. In general, the technical cost analysis can be divided into two types of cost elements: variable costs and fixed costs. Variable costs represent those cost elements which are independent of the production volume whereas fixed costs refer to those of which the price per piece of produced part will reduce with the production volume. More details on these elements in the field of injection moulding are further given as follows.

5.2.2.1 Variable cost elements

For most plastics processing enterprises, including injection moulding, the three largest variable cost elements include the material, direct labour and energy [11]. These are also the major costs for operating an injection moulding machine. The operating cost will not remain unchanged over time because it is highly dependent on various factors as explained below.

i. Material cost

The material cost is commonly regardless of production volume unless the material price is given a discount rate by the supplier for a very large purchase order. The part design is not a single factor to the material cost because the scrap losses must also be taken into account. Depending on various situations, scrap losses in the injection moulding process can be resulted from the runner waste, grinding waste, material changes, and oil contamination.

ii. Direct labour cost

Direct labour cost per piece of produced part is very difficult to estimate accurately because it is not always variable. The total cost for the direct labour can be seen as a complex function of the time rate wage, bonus, subsidy, allowance, overtime payment and certainly number of direct labour [46]. The labour productivity is an important factor to largely determine the extent to which such benefits would be willingly paid by the employers.

iii. Energy cost

As described in Subsection 2.3.3, energy use during processing itself can be subdivided into fixed energy and variable energy where the former can be reduced over a large production volume. Normally, the longer a machine is put in service, the lower is its energy efficiency and hence the higher is its variable energy. The economic performance of the equipment will likely differ either considerably or slightly from its initial ratings.

5.2.2.2 Fixed cost elements

Fixed costs are typically consisted of capital investments at one time. For this reason, these costs are amortised over the production volume in a given period of time. Three of the most common fixed cost elements for most plastics production processes are the equipment cost, overhead cost and maintenance cost.

i. Equipment cost

Here, the equipment cost does not only signify the purchase price of the main injection moulding machine, but also the auxiliary equipment such as dehumidifiers and granulators. In terms of energy efficiency investments, the new equipment could be referred to a brand new all-electric machine, servo-driven machine, or retrofitting the existing equipment with the aforementioned green technology such as VBET screw and nXheat™ (see Subsection 2.3.1.2). The new equipment does not necessarily or significantly outperform the existing equipment but SMEs might not have sufficient ability to process these information. As pointed out by Hewett [195], the difficulty in processing information related to energy efficiency investments usually arises from three reasons. First, energy efficiency products and services are purchased very infrequently. Second, if the efficiency ratings of the equipment are considered in the purchase decision, it might be difficult for consumers to evaluate the corresponding performance. Third, the rate of change in energy efficiency technology is rapid relative to the purchase interval.

ii. Overhead cost

Overheads are the indirect costs that usually vary with the production volume. These costs are very also called the transaction costs or the hidden costs. Energy efficiency investments are considered as irreversible because they are usually associated with various transaction costs for processing information. Information is not costless and the search costs can be regarded as a subset of transaction costs that will be incurred when selecting the available green technology in the market. Search costs can be generally divided into cognitive costs (or internal costs) and external costs [196]. Cognitive costs are internal to the purchasers which are influenced by the consumers' ability to cognitively process information. These costs may include costs for sorting information, costs for assuming risk or costs for reaching decisions. On the other hand, external costs are exogenous and beyond purchasers' direct control. For example, external search costs might be incurred for replacing malfunctioned equipment, negotiation with potential suppliers or seeking approval for capital expenditure.

iii. Maintenance cost

The maintenance cost for the equipment is also very difficult to estimate accurately because the maintenance work is often unscheduled [46]. In part, the maintenance cost is incurred in response to the equipment that has malfunctioned. Therefore, the manufacturers are required to investigate the corresponding probability of breaking down the equipment in order to better estimate the maintenance cost. A simple way to estimating maintenance cost is to equally divide the overall cost over a certain period.

5.3 Formulating the Dynamic Programming Model

The main purpose of this section is to reformulate the essence of the problem into a series of algebraic equations via dynamic programming (DP). DP method involves dividing a larger problem into a sequence of interrelated sub-problems. In practice, there appears to be no easy answer to build the DP model because most practical problems are often described in an imprecise and inconsistent way. For this reason, a better approach is to start with a simpler model and then gradually shift towards a more comprehensive model that more closely represents the practical problem [113]. This includes determining such things as the objective functions, reasonable assumptions, appropriate constraints, probability distribution, and possible policy decision. This section starts with the introduction of the fundamental principles underlying the DP method. Subsequently, the formulation of the final DP model will be explicitly discussed. More specifically, the DP model was designed for solving the stochastic equipment replacement problem (SERP) in order to better manage the decision-making process on the energy efficiency investments. All the mathematical notations used in the following DP formulation are self-explanatory.

5.3.1 Characteristics of dynamic programming problems

The principal characteristics of a DP model include the stage, state variables, decision variables, contribution functions and transformation functions. These characteristics were described in Table 5.1 based on the operations research literature [113, 116, 197] by directly analysing the problem under consideration.

Table 5.1 – Characteristics of dynamic programming model associated with problem descriptions

Characteristics of DP model	Descriptions of SERP
i. The problem can be subdivided into $\boldsymbol{T}$ *stages* where a policy decision is required at each stage.	SERP can be divided into a finite number of stages that correspond to the time frame of the problem, e.g., years, quarters or months.
ii. The beginning of each stage is associated with a number of *state variables*, $\boldsymbol{S_t}$, which represent various possible conditions where the problem might be at each particular stage. The subscript $\boldsymbol{t}$ indicates a given stage where $\boldsymbol{t = 1, 2, \ldots, T}$.	In this study, the state variables for SERP are referred to the number of available equipment at each stage. This is the most important evolved idea that has changed the classical equipment replacement problems found in the literature [116, 121, 197], which make use of the "age of the machine" as the state variables.
iii. *Decision variables*, $\boldsymbol{D_t}$ are relevant quantifiable decisions where the respective values are to be determined.	There is either one decision variable or a subset of decision variables at each stage. For example, the operating cost and maintenance cost being considered.
iv. *Contribution functions* $\boldsymbol{C_t(D_t)}$ provide corresponding values via mathematical functions of the given decision variables at each stage.	In SERP, the contribution functions will generate the total estimated cost at each stage.
v. *Transformation functions* $\boldsymbol{S_{t+1}(S_t, D_t)}$ determine how the policy decision transforms the current state to a state associated with the beginning of the next stage.	The number of available equipment is subject to change according to the optimal decision made at each stage.

A common DP model is formed by the networks of these five fundamental elements as illustrated in Figure 5.1. By its nature, DP method is concerned with making a sequence of interrelated decisions that are optimal to the overall problem rather than suboptimal solutions which are only best at particular stage. This is known as the "principle of optimality" in the DP literature, introduced by Bellman [198]

(*Chapter 3*) which states that "An optimal policy has the property that whatever the initial state and initial decision are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision." The DP model is designed to achieve an *optimal value function* $V_t(S_t)$, which is the most desirable total function value from stage t to stage T, given that the state at stage t is S_t. In other words, the optimal decision for each of the remaining stages will only depend on the current state, provided that every previously chosen decision is already an optimal solution.

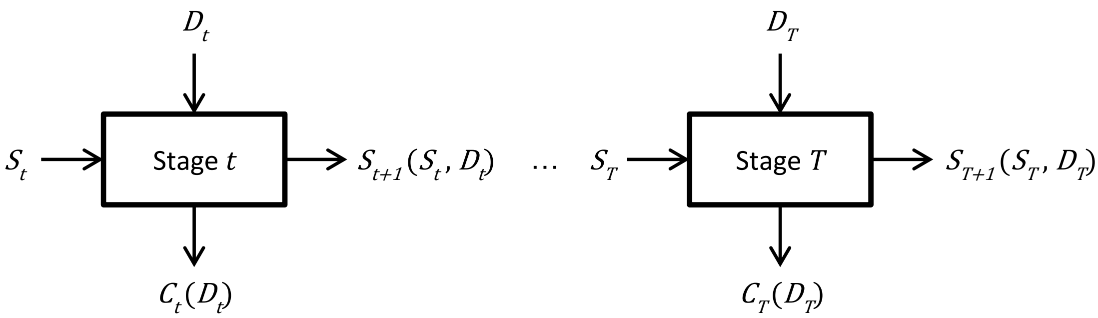

Figure 5.1 – Graphical illustration of a dynamic programming model. Source: [197]

The correctness of a DP model can be examined by proving that every possible state is considered and the principle of optimality is satisfied by a recursive relationship (or called recurrence equation) [197]. DP models can be solved by either forward recursion or backward recursion for which both can reach the same optimum solution. Although the forward approach may seem more mathematically logical, the backward approach is more widely adopted in the DP literature because it is perceived to be more computationally efficient [121]. In backward recursion, the recurrence equation relates the contribution function at stage t to the optimal policy decision at stage $t + 1$. For deterministic problems, the recurrence equation can be written as

$$V_t(S_t) = C_t(S_t, P_t^*) + V_{t+1}(S_{t+1}) \tag{5.1}$$

where P_t^* denotes the optimal policy decision at stage t. Equation 5.1 is widely known as the Bellman's equation or optimality equation in the DP community. The optimality equation shows that if the optimal value at stage $t+1$ is known, it can be solved by moving one stage backwards to add up the value given by the contribution function at stage t. When the backward recursion is used, the stage computations begin from the final stage where a boundary condition needs to be established. The optimal value for the entire DP problem will be yielded at the terminating stage, i.e. the initial stage.

The advantage of using DP method is its ability to achieve an optimum solution by searching through all function values given by every possible state variable. Consequently, the number of necessary computations will grow exponentially as the number of state variables increases. This phenomenon is termed the "curse of dimensionality" by Bellman [199] in 1950s. This reason is often cited for why DP is not practicable for many complex problems. In general, there are three types of curse of dimensionality [200]:

i. State space: If the state variable $S_t = (S_{t1}, S_{t2}, \dots, S_{ti}, \dots, S_{tI})$ possibly has I dimensions and each of them can take up L possible values, there might be a total of L^I different states. This situation can be illustrated by the simple diagram in Figure 5.2 where the node (i, k) denotes the state k at stage i. Assume that each arc represents a recursive relationship that relates a particular state to the next possible state, the number of possible arcs linking the nodes will increase exponentially if each state variable contains more dimensions and values.

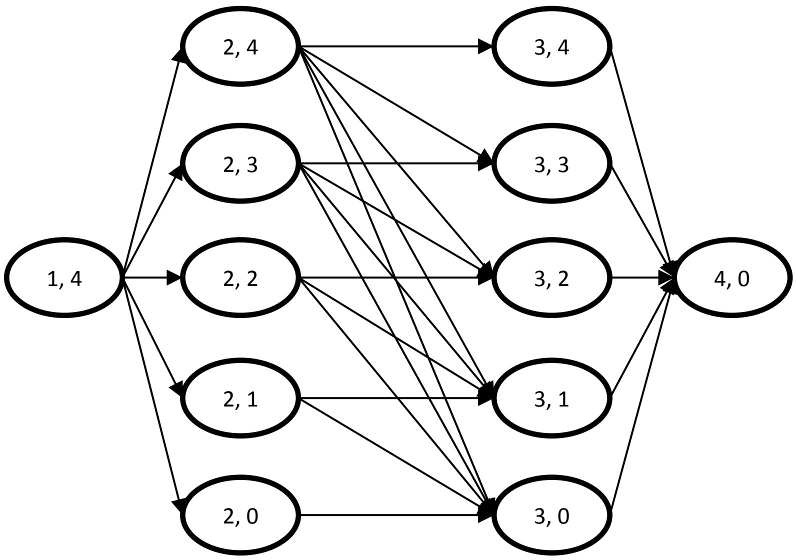

Figure 5.2 – Simple network representation of state space with four stages

ii. Outcome space: If the random variable $W_t = (W_{t1}, W_{t2}, \ldots, W_{tj}, \ldots, W_{tJ})$ might have J dimensions and each of them might result in M values, then there might be a total of M^J outcomes.

iii. Action space: If the decision vector $x_t = (x_{t1}, x_{t2}, \ldots, x_{tk}, \ldots, x_{tK})$ might have K dimensions and each of them might result in N values, then there might be a total of N^K outcomes.

A common difficulty in using DP method is to develop an ideal model that can properly represent a specific problem. From the standpoint of computational efficiency, some approximations and assumptions are required so that the DP computation will become more tractable. Nevertheless, these might shift the model away from the real-world conditions. As such, a practical DP model must be simple enough for computation work yet remains a valid representation of the problem under consideration.

5.3.2 Dynamic programming model for SERP

In this subsection, the overall structure of SERP will become more comprehensible through the mathematical formulation. Suppose that a company is examining the equipment replacement problem over a period of time where it can be divided into T stages $(1, 2, \dots, t, \dots, T)$. The optimal decision is assumed to be made at the beginning of each stage, where the stage can be customised either in years, quarters or months, depending on the need of company. In SERP, decision makers might encounter uncertain situation in which they need to decide whether to buy the new equipment without knowing if the old equipment will break down during the whole period. Although the future situation is unforeseen, it is still possible to estimate the outcomes for certain decision through the use of probability distributions [201].

Certainly, the first order of manufacturing industry is to ensure that the number of equipment can satisfy the production demand that will vary with time. Only after satisfying the demand, the company can decide whether to purchase the new equipment or to keep the old equipment. Ascertaining the appropriate time for a purchase decision is critical in energy efficiency investments due to the rapid change in innovation and price in the technology-oriented market. Decision makers can constantly review the pricing history and predict the price trend of the equipment, or access the relevant information directly from the supplier. The operating cost and maintenance cost of the equipment are also random variables, depending on how long it has stayed in service. Normally, the operating cost and maintenance cost of the existing equipment can be estimated from the data stored in the management information system of the company. On the other hand, the corresponding data for the new equipment can be obtained from the supplier. The main input data that define the DP model for SERP are given and explained as follows. Notice that the notations in bold letters represent the systems of matrices where the superscript N and O denote new equipment and old equipment respectively.

$$\mathbf{a}_t = (a_t^N, a_t^O) \tag{5.2}$$

where a_t^N = demand on the number of new equipment at stage t;

a_t^O = demand on the number of old equipment at stage t;

$$\mathbf{r}_t = (r_t^N, r_t^O) \tag{5.3}$$

where r_t^N = number of new equipment before making any decision at stage t;

r_t^O = number of old equipment before making any decision at stage t;

$$\mathbf{x}_t = (x_t^N, x_t^O) \tag{5.4}$$

where x_t^N = number of new equipment purchased at stage t;

x_t^O = number of old equipment sold at stage t;

$$\mathbf{p}_t = (p_t^N, p_t^O) \tag{5.5}$$

where p_t^N = purchase price of new equipment (positive value[13]) at stage t;

p_t^O = selling price of old equipment (negative value) at stage t;

[13] Positive value indicates the amount to be paid by the company; whereas, negative value indicates the amount to be received by the company.

$$\mathbf{n}_t = (n_t^N, n_t^O) \tag{5.6}$$

where n_t^N = expected operating cost of new equipment at stage t;

n_t^O = expected operating cost of old equipment at stage t;

$$\mathbf{m}_t = (m_t^N, m_t^O) \tag{5.7}$$

where m_t^N = expected maintenance cost of new equipment at stage t;

m_t^O = expected maintenance cost of old equipment at stage t.

To sum up, the decision variables of this problem can be generically represented by

$$D_t = (\mathbf{a}_t, \mathbf{r}_t, \mathbf{x}_t, \mathbf{p}_t, \mathbf{n}_t, \mathbf{m}_t). \tag{5.8}$$

There are two main sources of uncertainty considered in this problem. First, the probability of breaking down of an old equipment, z_t^O. If failure occurs, the company has an option of salvaging the malfunctioned equipment at g_t^O (negative value). Hence, the expected selling price of the old equipment can be computed by

$$p_t^O = (1 - z_t^O)q_t^O + z_t^O g_t^O, \qquad q_t^O > g_t^O; \tag{5.9}$$

where q_t^O denotes the selling price of an old equipment that is in working condition. Second, the operating cost of the new equipment, n_t^N. This data highly depends on the information provided by the equipment supplier. In consideration of the inexorable properties of degrading efficiency, the operating cost of the new equipment can be estimated by

$$n_t^N = \dot{n}/\eta \tag{5.10}$$

where $\dot{n}$ = initial operating cost of new equipment;

η = efficiency index of new equipment per stage.

A comprehensive DP model must ensure that all possible variables are taken into consideration. However, the classical equipment replacement problems in the DP literature never consider the internal transaction costs (e.g. information search costs). If the DP models do not reflect the existence of these costs, the decision makers may unintentionally overstate the potential investment for a particular technology. For this reason, the DP model here will also take total internal transaction costs into account. Moreover, this DP model will include several types of exogenous information such as random changes to production demands, fluctuation in equipment market prices, variation in operating costs and maintenance costs. The final market prices of the equipment can be fluctuating due to the costs incurred for equipment delivery, installation or removal. The most likely exogenous change to the operating costs is caused by local electricity tariff adjustment. In this thesis, the probable change in operating cost can be internal to the company since the optimisation methodology proposed in Chapter 3 (i.e., MRDSD) can be applied to reduce energy consumption and achieve cost savings. The exogenous information for this DP model is represented by the notation $\hat{E}_t$ and it is assumed to arrive at the beginning of each stage, that is,

$$\hat{E}_t = (\hat{\mathbf{a}}_t, \hat{\mathbf{p}}_t, \hat{\mathbf{n}}_t, \hat{\mathbf{m}}_t) \tag{5.11}$$

where $\hat{\mathbf{a}}_t$ = random change to the demand on the number of equipment at stage t;

$\hat{\mathbf{p}}_t$ = fluctuation in purchase or selling price at stage t;

$\hat{\mathbf{n}}_t$ = variation in operating cost of new or old equipment at stage t;

and $\hat{\mathbf{m}}_t$ = variation in maintenance cost of new or old equipment at stage t.

In summing up, several equations that make up the final decision variables would be

$$\tilde{\mathbf{a}}_t = \mathbf{a}_t + \hat{\mathbf{a}}_t; \tag{5.12}$$

$$\tilde{\mathbf{p}}_t = \mathbf{p}_t + \hat{\mathbf{p}}_t; \tag{5.13}$$

$$\tilde{\mathbf{n}}_t = \mathbf{n}_t + \hat{\mathbf{n}}_t; \tag{5.14}$$

$$\tilde{\mathbf{m}}_t = \mathbf{m}_t + \hat{\mathbf{m}}_t. \tag{5.15}$$

The state variable for this problem is defined by the number of available equipment that remains from the previous stage, which is

$$S_t = (\mathbf{r}_t, \mathbf{x}_t, k_t) \tag{5.16}$$

where k_t indicates the policy decision (or action command) at stage t, that is either to keep the existing equipment or to execute equipment replacement. More specifically, the state variable is determined by

$$S_t = \begin{cases} \mathbf{r}_t, & \text{if kept} \\ (r_t^N, r_t^O - x_t^O), & \text{if replaced} \end{cases} \tag{5.17}$$

where S_t must satisfy two constraints. First, the company is required to ensure the demand on the number of equipment is met, i.e., $S_t \geq \tilde{\mathbf{a}}_t$. Second, old equipment will only be sold provided that $x_t^O \leq r_t^O$, put another way, the company cannot sell more old equipment than what they have. Furthermore, Equation 5.17 implies that any new equipment purchased at stage t can only be used at stage $t + 1$. This assumption is reasonable because the equipment procurement, fabrication and installation procedures normally take time. The transformation function which yields the state for the next stage is thus given by

$$S_{t+1} = \begin{cases} \mathbf{r}_t, & \text{if kept} \\ \bar{\mathbf{r}}_t, & \text{if replaced} \end{cases} \tag{5.18}$$

where $\bar{\mathbf{r}}_t = (r_t^N + x_t^N, r_t^O - x_t^O)$. Because the company can possibly accommodate up to a certain number of equipment, Equation 5.18 must satisfy one assumption, i.e., $S_{t+1} \leq \mathbf{r}_{\max}$.

The contribution function for this DP model is used to calculate the total estimated cost at each stage, which is expressed by

$$C_t\big(S_t, D_t, \hat{E}_t\big) = k_t \mathbf{x}_t \tilde{\mathbf{p}}_t{}^T + \tilde{\mathbf{a}}_t \tilde{\mathbf{n}}_t{}^T + (1 - k_t)\mathbf{r}_t \tilde{\mathbf{m}}_t{}^T + k_t \bar{\mathbf{r}}_t \tilde{\mathbf{m}}_t{}^T \tag{5.19}$$

where $k_t = \begin{cases} 0, & \text{if kept} \\ 1, & \text{if replaced} \end{cases}$

The presence of matrix transpose in Equation 5.19 indicates that this contribution function is written in terms of inner product (or scalar product) of matrices. The first term yields the summation of purchase cost and selling cost if the policy decision is to carry out equipment replacement, i.e., $k_t = 1$. Note that k_t is precluded in the second term, this implies that the policy decision will not influence the total operating cost because it directly relies on the production demand. One important assumption made here is that when there are new and old equipment waiting to be used at certain stage, new equipment will be in priority use for satisfying the demand. Lastly, the third and fourth term give the total maintenance cost for which it is affected by the number of new and old equipment after every policy decision.

Aside from the need of satisfying random demands, the main goal for SERP is set to achieve the minimum expected cost within T stages. Therefore, the optimal value function of the DP model can be written as

$$V_t(S_t) = \min\left(C_t\left(S_t, D_t, \hat{E}_t\right) + \mathbb{E}V_{t+1}(S_{t+1})\right) \tag{5.20}$$

where $\mathbb{E}$ represents the expected value which yields the weighted average of all possible values [200]. Equation 5.20 exhibits the feature of backward recursion. This means that the computation process begins from stage $T+1$, under the assumption that the computational work for all previous stages has been completed. Lastly, the boundary condition for the initial stage can be set as zero, which is

$$V_{T+1}(S_{T+1}) = 0. \tag{5.21}$$

5.3.3 Discussions on the derived DP model

At first sight, the above DP model may appear to be a deterministic DP problem in the sense that, the possible state at a particular stage resulting from the previous decision is predetermined by the state variables at the previous stage. However, the state in this DP problem is not completely determined by the policy decision and state variables from the previous stage. Note that the operating cost of new equipment at each stage will remain unknown until the final DP solution is achieved. Put another way, the company cannot determine the operating cost of new equipment before every optimal decision for equipment replacement is made at each stage. The above DP model can thus be categorised as stochastic problem since it is associated with an uncertainty for what the next state will be.

As mentioned in Table 5.1, the derived DP model differs from the classical equipment replacement problems in terms of the state variable. The state variable employed here is the number of available equipment left from the previous stage, but not the “age of the machine” as proposed in the literature [116, 121, 197]. Although this evolved idea has caused the DP model somewhat more complicated, it can better represent the practical problem. In the manufacturing industry, the production machines are fixed assets that are rarely replaced unless the company is considering a strategic upgrade. Therefore, the company might not have recorded the associated cost for every existing machine at each age. In place of the age details, the company may need to consider the equipment replacement problem from a larger viewpoint based on the number of equipment, where the associated cost can be estimated from the historical data. The only difficulty that will happen in this “evolvement” is the necessity to consider all possible states in the DP computation because the policy decision at each stage is not predetermined. In spite of that, this stochastic DP model does not suffer from the three curses of dimensionality, because the model features relatively small state spaces (a finite number of equipment), only a pair of actions (to keep or to replace), and easily computable expectations (known probability distributions).

Equation 5.20 is a fairly classical optimality equation, but solving it via manual computation is usually a tedious and time-consuming task. As such, the decision makers in SMEs are not necessarily willing to apply the DP model although it can facilitate them in making decision. Fortunately, the advent of multifaceted spreadsheet software can be used as an effective platform for solving DP models

[116, 121]. The development of a specific DP-based spreadsheet solution in response to the derived DP model is expounded in the next section.

5.4 Deriving the Spreadsheet Solution

The main objective of this section is to present the Excel algorithms that form the DP-based spreadsheet solution. Microsoft Excel spreadsheet package is adopted considering the fact that it is ubiquitous and easily accessible even in the environment of SMEs. The development of the final Excel algorithms had undertaken a series of evolvement process to better represent the derived DP model in Section 5.3. In part, some efforts are given to improve the user interface of the spreadsheet solution so as to enable the end-users to implement it without any difficulty.

5.4.1 User interface for the Input Worksheet

The construction of the Excel spreadsheet solution (file SERP.xlsm) begins by setting up the Input Worksheet. There are six important criteria in the Input Worksheet (cells C7:C12) as shown in Figure 5.3. These criteria include the maximum number of stages, T, maximum number of equipment, $\mathbf{r}_{max}$, number of available equipment at stage 1, total internal transaction costs, initial operating cost of new equipment, $\dot{n}$, and efficiency index of new equipment per stage, η. The functions of these criteria will be described whenever they appear in the following formulations.

	A	B	C
6	**Criteria**		
7	**Maximum number of stages, T**		
8	**Maximum number of equipment, $\mathrm{r}_{\max}$**		
9	**Number of available equipment at stage 1**		
10	**Total internal transaction costs**		
11	**Initial operating cost of new equipment, $\dot{n}$**		
12	**Efficiency index of new equipment per stage, η**		

Figure 5.3 – Criteria column in the Input Worksheet

The Input Display Table is where the end-users need to enter the necessary input data for the decision variables (Equation 5.8) and the exogenous information (Equation 5.11) at every stage. The maximum default value for the number of stage is set at 10 initially. The adjustment procedures given in Appendix 6 allow the end-users to flexibly modify the user interface when more than 10 stages will be required. In the Input Worksheet design, yellow cells indicate the input cells where the users have to key in the necessary information, while the white cells represent the calculation cells where the resultant values will be calculated from the input cells. For example, in Figure 5.4, row 22 provides the computed values based on Equation 5.12 with the Excel formula $= \mathrm{SUM(B\$20{:}\,B\$21)}$.

	A	B	C
19	**Demand**		
20	**Demand on the number of equipment, a_t**		
21	**Exogenous change to demand, $\hat{\mathrm{a}}_t$**		
22	**Final demand on the number of equipment, $\tilde{\mathrm{a}}_t$**		

Figure 5.4 – Rows for “demand” calculation in the Input Display Table

5.4.2 Excel algorithms for stage computations

Solving the contribution function (Equation 5.19) and the optimal value function (Equation 5.20) is much more complicated since the stage computations generated by the Excel algorithms have to exhibit the nature of the assumptions or constraints established in the DP model. The stage computations require a form of "lookup table" to find out the optimal value for each possible state. In order to serve this purpose, some of the important Excel functions that make up the algorithms for stage computations are listed and briefly described in Appendix 5.

The combination of INDEX-MATCH function was adopted instead of the HLOOKUP function (or VLOOKUP function) due to two inherent limitations of the latter. First, all data has to be tabulated in a standard table form, this means that the HLOOKUP function is unable to return a value from a different table array. Second, HLOOKUP function uses approximation that is nearest to and less than the lookup value. In this case, HLOOKUP function might give an incorrect result if the data is not arranged in the ascending order, as it stops looking up the remaining values right after the "most approximated" value is identified. For certain cases, the "most approximated" value is not less than the lookup value. As a consequence, this will also result in a false value even if the data is sorted accordingly.

Note that the contribution function (Equation 5.19) is expressed in a compact form by means of matrices. As such, keying the whole optimal value function (Equation 5.20) using Excel functions might be too lengthy to fit into one single cell. In addition, finding and fixing the syntax errors in a long Excel formula can be tedious. Given these considerations, the stage computations for all possible states were subdivided into five worksheets, which are respectively denoted by “p”, “n”, “m”, “Ct” and “Vt”, where each function is clearly described in Table 5.2.

Table 5.2 – Function of each worksheet for stage computations

Worksheet	Descriptions
“p”	To calculate the summation of purchase price (positive) and selling price (negative) at each stage associated with certain policy decision. The calculation is based on the portion $k_t \mathbf{x}_t \tilde{\mathbf{p}}_t{}^T$ in Equation 5.19.
“n”	To calculate the total expected operating cost of new and old equipment at each stage based on the premise that the new equipment will be in priority use. The calculation is based on the portion $\tilde{\mathbf{a}}_t \tilde{\mathbf{n}}_t{}^T$ in Equation 5.19.
“m”	To calculate the total expected maintenance cost of new and old equipment at each stage associated with certain policy decision. The calculation is based on the portion $(1 - k_t)\mathbf{r}_t \tilde{\mathbf{m}}_t{}^T + k_t \bar{\mathbf{r}}_t \tilde{\mathbf{m}}_t{}^T$ in Equation 5.19.
“Ct”	To sum up the calculations from Worksheet “p”, “n” and “m” for every possible state at each stage, and exhibit the backward recursion in the optimal value function. The algorithms in this worksheet also contain the assumptions and constraints that manipulate the stage computations.
“Vt”	To identify the optimal policy decision at each stage which yields the minimum estimated cost for every possible state based on the computed values from Worksheet “Ct”.

Each worksheet for stage computations contains an Input Display Table and a Stage Computations Table. In the Stage Computations Table (starting from row 50 as shown in Figure 5.5), each row describes a possible state where column A, B, C, D respectively indicate the total number of equipment before decision, $\mathbf{r}_t$, number of new equipment, r_t^N, number of old equipment, r_t^O, and action command, k_t (“0” to keep and “1” to replace). The maximum default value for $\mathbf{r}_t$ is set at 10 initially. If

$\mathbf{r}_t > 10$, the end-users are required to modify the user interface according to the adjustment procedures given in Appendix 6.

	A	B	C	D	E
50	**Total number of equipment before decision, $\mathbf{r}_t$**	r_t^N	r_t^O	k_t	
51	0	0	0	0	0
52	0	0	0	1	0

Figure 5.5 – The first three rows in the Stage Computations Table

Recall that the computation process begins from Equation 5.21 in backward recursion. Therefore, column E in the Stage Computations Table which corresponds to the stage $T+1$ is keyed in with a zero value. Subsequently, only the Excel algorithms in cell F51 on each worksheet are presented and described as follows since column F represents the stage T while row 51 denotes the first possible state variable. In Worksheet "p", the algorithm for summing up the purchase price and selling price is written in this manner:

$$= \$\mathrm{D}51 * \mathrm{INDEX}(\$24{:}\$24 * \$27{:}\$27 + \$35{:}\$35 * \$40{:}\$40, \mathrm{MATCH}(\mathrm{F}\$50, \$17{:}\$17, 0)). \tag{5.22}$$

To illustrate the operation of Equation 5.22, suppose that a maximum of four stages is given to the problem as defined in cell C7 under criteria column (see Figure 5.3). A value of "4" will be returned to cell F50 as indicated by the red box in Figure 5.6. Since the action command given in cell D51 is "0", a zero value will be returned to cell F51. If let the action command be defined as "1", the MATCH function will first return the relative position in row 17 (indicated by the green box) that matches the value specified in cell F50. Next, the INDEX function will return the value located at the relative position in row 24 (indicated by the blue box), which corresponds to the number of new equipment purchased, x_t^N. The same procedure will be repeated to return the relevant values from row 27, 35 and 40 for the final purchase price per unit, $\tilde{p}_t^N$, number of old equipment sold, x_t^O, and final selling price per unit, $\tilde{p}_t^O$, respectively. Note that the $ symbol in the Excel algorithm is used to fix either the rows or columns so that they will not be subject to change when the algorithm is being dragged to the following cells. In order to avoid the redundant work, the description for the same INDEX-MATCH function that appears in the following Excel algorithms will not be reiterated.

	A	B	C	D	E	F
17	**Stage, t**	1	2	3	4	5
24	**Number of equipment purchased, x_t^N**					
50	**Total number of equipment before decision, $\mathbf{r}_t$**	r_t^N	r_t^O	k_t	5	4
51	0	0	0	0	0	
52	0	0	0	1	0	

Figure 5.6 – Illustration of stage computations in Worksheet "p"

Recall that the new equipment will be put in priority use whenever there are new and old equipment waiting to be used at certain stage. Therefore, the algorithm in Worksheet "n" for computing the total expected operating cost will look relatively complicated, as given by

$= \mathrm{IF}(\$B51 - \mathrm{INDEX}(\$22{:}\$22, \mathrm{MATCH}(F\$50, \$17{:}\$17, 0)) >= 0,$

$\mathrm{INDEX}(\$22{:}\$22 * \$30{:}\$30, \mathrm{MATCH}(F\$50, \$17{:}\$17, 0)),$

$\mathrm{INDEX}(\$B51 * \$30{:}\$30, \mathrm{MATCH}(F\$50, \$17{:}\$17, 0))) +$

$\mathrm{IF}(\$B51 - \mathrm{INDEX}(\$22{:}\$22, \mathrm{MATCH}(F\$50, \$17{:}\$17, 0)) >= 0, 0,$

$\mathrm{INDEX}((\$22{:}\$22 - \$B51) * \$43{:}\$43, \mathrm{MATCH}(F\$50, \$17{:}\$17, 0))).$ (5.23)

Refer to Figure 5.7, the IF functions in Equation 5.23 will ensure that only new equipment will be used if $r_t^N \geq \tilde{\mathbf{a}}_t$. That is, when the number of new equipment given in cell B51 (indicated by the purple box) is more than or equal to the final demand on the number of equipment (indicated by the blue box). Otherwise, the expected operating cost will be attributed to all new equipment and a necessary number of old equipment (denoted by $\$22{:}\$22 - \$B51$ in Equation 5.23).

	A	B	C	D	E	F
17	**Stage,** t	1	2	3	4	5
22	**Final demand on the number of equipment,** $\tilde{\mathbf{a}}_t$					
50	**Total number of equipment before decision,** $\mathbf{r}_t$	r_t^N	r_t^O	k_t	5	4
51	0	0	0	0	0	
52	0	0	0	1	0	

Figure 5.7 – Illustration of stage computations in Worksheet "n"

Regarding the computation of the total expected maintenance cost, the corresponding algorithm is entered in Worksheet "m" as follows:

$= \mathrm{INDEX}((\$B51 + \$D51 * \$24{:}\$24) * \$33{:}\$33, \mathrm{MATCH}(F\$50, \$17{:}\$17, 0)) +$

$\mathrm{INDEX}((\$C51 - \$D51 * \$35{:}\$35) * \$46{:}\$46, \mathrm{MATCH}(F\$50, \$17{:}\$17, 0)).$ (5.24)

After the stage computations from the three preceding worksheets are done, Worksheet "Ct" will sum up all the resultant values and exhibit the backward recursion by adding the optimal value obtained from the previous stage computations. Moreover, this worksheet also establishes the constraints upon the state variables in a way to manipulate the stage computations. Since the whole algorithm serving these purposes is too lengthy to be explained at one time, it is subdivided into constraint portion and recursion portion here. Firstly, the algorithm for the constraint portion is written in this manner:

$$\begin{aligned} &= \mathrm{IF}((\$\mathrm{A}51 + \mathrm{INDEX}(\$\mathrm{D}51 * (\$24{:}\$24 - \$35{:}\$35), \mathrm{MATCH}(\mathrm{F}\$50, \$17{:}\$17, 0))) \\ &\qquad\qquad > \$\mathrm{C}\$8, 1\mathrm{E}9, \\ &(\mathrm{IF}(\mathrm{OR}(\mathrm{INDEX}(\$22{:}\$22 - (\$\mathrm{A}51 - \$\mathrm{D}51 * \$35{:}\$35), \mathrm{MATCH}(\mathrm{F}\$50, \$17{:}\$17, 0)) > 0, \\ &\mathrm{INDEX}(\$\mathrm{D}51 * \$35{:}\$35 - \$\mathrm{C}51, \mathrm{MATCH}(\mathrm{F}\$50, \$17{:}\$17, 0)) > 0), 1\mathrm{E}9, \ldots \end{aligned} \tag{5.25}$$

The first IF function in Equation 5.25 represents the constraint $\mathbf{r}_{\max} \geq S_{t+1}$ as described in Subsection 5.3.2. This algorithm will return a value of "1+E09" whenever the constraint is not satisfied. That is, when the number of equipment is larger than the maximum number of equipment that can be accommodated by the company, as defined in cell C8 under criteria column (see Figure 5.3). A large positive value is used to indicate an infeasible value in the spreadsheet since the optimal value function is designed to look for the minimum value at each stage. The second IF function is used to set up the constraints $S_t \geq \tilde{\mathbf{a}}_t$ and $x_t^O \leq r_t^O$. The OR function will ensure that a value of "1+E09" will be returned if either of these constraints is not satisfied.

Secondly, the algorithm for the recursion portion is written as follows:

$$\ldots\ (\mathrm{p!\,F51+n!\,F51+m!\,F51+INDEX(Vt!\,E{:}\,E,MATCH((\$A51+INDEX(\$D51} * (\$24{:}\,\$24-\$35{:}\,\$35),\mathrm{MATCH(F\$50,\$17{:}\,\$17,0))),Vt!\,\$A{:}\,\$A,0)} + \mathrm{INDEX(\$B51+\$D51} * \$24{:}\,\$24,\mathrm{MATCH(F\$50,\$17{:}\,\$17,0))} * 2))))). \tag{5.26}$$

Equation 5.26 sums up the previous calculations from Worksheet “p”, “n”, “m”, and exhibits the backward recursion by adding the optimal value at stage 5 with a given state from Worksheet “Vt”. To illustrate the backward recursion, assume that the current state at stage 4 is $\mathbf{r}_4 = (1, 0)$ with action command “0”. In this case, the state variable at stage 5 will remain the same as that of stage 4 since no equipment replacement will be done. Refer to Figure 5.8, cell F55 in Worksheet “Ct” (indicated by the red box) is required to exhibit the recursive relationship with the optimal value computed in Worksheet “Vt”. To do this, the first INDEX-MATCH function in Equation 5.26 is designed to return the optimal value in cell E55 (indicated by the green box) where its relative position has to match with the total value given by the second and third INDEX-MATCH function. In Equation 5.26, the second INDEX-MATCH function yields the relative position for the total number of equipment based on the action command while the third INDEX-MATCH function provides the corresponding number of new equipment. It should be noted that the third INDEX-MATCH function is multiplied by a value of “2”. This will ensure that the correct number of rows will be returned from Worksheet “Vt” because the optimal value for each possible state is displayed once in every two rows (indicated by the blue boxes).

	A	B	C	D	E	F
50	**Total number of equipment before decision, $\mathbf{r}_t$**	r_t^N	r_t^O	k_t	5	4
53	1	0	1	0	0	
54	1	0	1	1	0	
55	1	1	0	0	0	
56	1	1	0	1	0	

(Stage Computations Table in Worksheet "Ct")

50	**Total number of equipment before decision, $\mathbf{r}_t$**	r_t^N	r_t^O	Min	5	4
53	1	0	1	*Min*	0	
54	1	0	1		0	
55	1	1	0	*Min*	0	
56	1	1	0		0	

(Stage Computations Table in Worksheet "Vt")

Figure 5.8 – Illustration of the recursive relationship between Worksheet "Ct" and Worksheet "Vt"

Lastly, the stage computations in Worksheet "Vt" are very simple since its function is only to determine the minimum value out of the two action commands for each possible state from Worksheet "Ct". For example, the algorithm in cell F53 as indicated by the purple box in Figure 5.8 is given by

$$= \mathrm{MIN}(\mathrm{Ct!\,F53{:}\,F54}). \tag{5.27}$$

5.4.3 Excel algorithms for output display

The initial calculation mode for the Excel spreadsheet solution (file SERP.xlsm) is switched to the manual mode. This requires the end-users to press the F9 key to initiate the stage computations. Following the stage computations based on input data, the resultant values will be summarised in the Output Display Table in Output

Worksheet. To illustrate the algorithms for displaying output, suppose that the current state variable at stage 4 is $\mathbf{r}_4 = (0, 1)$.

Refer to Figure 5.9, the algorithm for showing the optimal policy decision at stage 4 is written in cell E26 (indicated by the blue box) in this manner:

$$= \mathrm{IF}(\mathrm{INDEX}(\mathrm{OFFSET}(\mathrm{Ct!\,\$A{:}\,\$A}, 0, \mathrm{MATCH}(\mathrm{E\$17}, \mathrm{Ct!\,\$50{:}\,\$50}, 0) - 1),$$
$$\mathrm{MATCH}(\mathrm{E\$22}, \mathrm{Ct!\,\$A{:}\,\$A}, 0) + \mathrm{E\$23} * 2)$$
$$= \mathrm{INDEX}(\mathrm{OFFSET}(\mathrm{Vt!\,\$A{:}\,\$A}, 0, \mathrm{MATCH}(\mathrm{E\$17}, \mathrm{Vt!\,\$50{:}\,\$50}, 0) - 1),$$
$$\mathrm{MATCH}(\mathrm{E\$22}, \mathrm{Vt!\,\$A{:}\,\$A}, 0) + \mathrm{E\$23} * 2),0,1). \tag{5.28}$$

It should be noticed that both INDEX functions in Equation 5.28 contains the similar algorithms. The only discrepancy is that the former returns the computed values from Worksheet “Ct” (indicated by the red boxes) whereas the latter returns the corresponding optimal values from Worksheet “Vt” (indicated by the green box). If the value in the upper red box is equal to the value in the green box, the IF function will return a value of “0” to the blue box which indicates that the policy decision is “to keep”. Otherwise, a value of “1” will be returned, denoting that the policy decision is “to replace”.

The OFFSET function in Equation 5.28 is used to return a reference range to column A in a specified number of rows and columns. The number of rows is indicated by the value “0” which implies that the reference range is fixed in row; while the number of columns is provided by the first MATCH function. Because the MATCH function returns the relative position of the given stage in Worksheet “Ct” and Worksheet “Vt”, it is required to minus one position in order to obtain the exact number of columns to be returned by the OFFSET function. The second MATCH function returns the relative position of the particular state from the Stage Computations Table.

	A	B	C	D	E	F
50	**Total number of equipment before decision, $\mathbf{r}_t$**	r_t^N	r_t^O	k_t	5	4
53	1	0	1	0	0	
54	1	0	1	1	0	

(Stage Computations Table in Worksheet "Ct")

50	**Total number of equipment before decision, $\mathbf{r}_t$**	r_t^N	r_t^O	*Min*	5	4
53	1	0	1	*Min*	0	
54	1	0	1		0	

(Stage Computations Table in Worksheet "Vt")

16	**Stage**					
17	**Stage, t**	1	2	3	4	5

25	**Optimal policy decision**					
26	**Keep or replace (0 or 1)**					

(Output display table in the Output Worksheet)

Figure 5.9 – Illustration of the algorithm for showing the optimal policy decision

The next step is to determine the state variable at each stage in terms of the number of available equipment as shown in Figure 5.10. The number of old equipment at stage 1 will be provided by the end-user as defined in cell C9 under criteria column (see Figure 5.3). The number of new equipment at stage 1 is presumed to be zero. To determine the state variable at stage 2, the algorithm is written in cell C22 (indicated by the red box) as follows:

$$= \mathrm{IF(B\$26 = 0, B\$22, B\$22 + INDEX(Input!\,\$24{:}\,\$24 -}$$
$$\mathrm{Input!\,\$35{:}\,\$35, MATCH(B\$17, Input!\,\$17{:}\,\$17, 0)))} \quad (5.29)$$

The IF function in Equation 5.29 will maintain the same value as the state variable at stage 1 if the policy decision is to keep, otherwise, the new state variable will be calculated according to the number of equipment purchased and sold. The algorithms for calculating the new state variable is similar to Equation 5.29.

	A	B	C	D	E	F
21	**Number of available equipment (state)**					
22	**Total number, $\mathbf{r}_t$**					
23	**Number of new equipment, r_t^N**	0				
24	**Number of old equipment, r_t^O**					

Figure 5.10 – Rows for displaying the state variable in the Output Display Table

An important aspect of the Output Worksheet is that it creates circular references in the spreadsheet solution which will be clearly demonstrated as follows. Recall that the operating cost of new equipment can only be estimated using Equation 5.10 (on p. 165). The initial operating cost of new equipment and the relevant efficiency index, η, is respectively defined in cell C11 and cell C12 under criteria column (see Figure 5.3). Supposing a new equipment is purchased at stage t, it will only be used at stage $t+1$ with an initial operating cost as suggested by the equipment supplier. At each subsequent stage, its operating cost is estimated to increase by the reciprocal of the efficiency index, i.e., η^{-1}. In fact, the operating cost of new equipment can only be estimated provided that the policy decision for every stage has been completely determined. As a consequence, the circularity occurs because the policy decision is in turn affected by the operating cost of new equipment as illustrated in Figure 5.11. To resolve the circularity in the Excel spreadsheet, the iterative calculation is enabled until the maximum iterations has reached 100 times (default value) or the maximum change is less than the minimum input cost value.

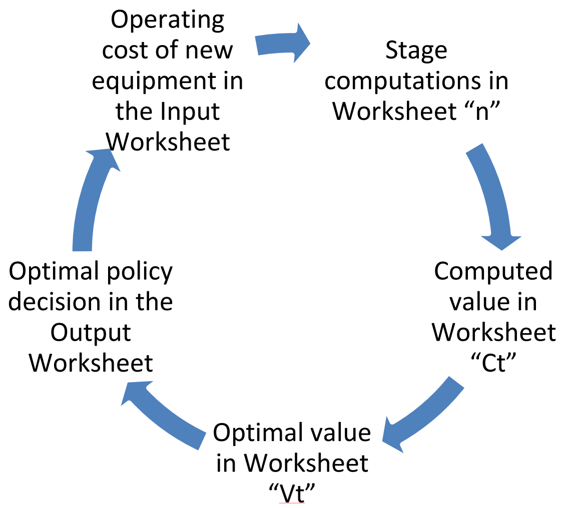

Figure 5.11 – Circular references in the DP-based spreadsheet solution (file SERP.xlsm)

Based on the optimal policy at stage 1, the algorithm for estimating the operating cost of new equipment at stage 2 is written in cell C28 as follows:

$$= \mathrm{IF}(\mathrm{C\$23} = 0, \mathrm{\$C\$11}, (\mathrm{B\$23} * \mathrm{B\$28}/\mathrm{\$C\$12} + (\mathrm{C\$23} - \mathrm{B\$23}) * \mathrm{\$C\$11})/\mathrm{C\$23}). \quad (5.30)$$

The IF function in Equation 5.30 will return the initial operating cost if the number of new equipment at stage 2 is zero. If the value is nonzero, the average operating cost of new equipment at stage 2 will be calculated from the existing new equipment and the newly purchased equipment at stage 1, where the former will be affected by the efficiency index. After the computation of Equation 5.30, the resultant value will be returned to the Input Worksheet for subsequent stage computations so as to determine the optimal policy at stage 2.

Lastly, the algorithm for showing the minimum estimated cost at each stage is the same as the latter INDEX function in Equation 5.28, which returns the corresponding optimal values from Worksheet "Vt". After all the DP stage computations are fully completed, the total estimated cost which includes the total internal transaction cost given in cell C10 under criteria column (see Figure 5.3), will be displayed in cell B31 as shown in Figure 5.12.

	A	B	C	D	E
29	**Minimum estimated cost**				
30	**Minimum estimated cost**				
31	**Total estimated cost (including internal cost)**	0			

Figure 5.12 – Rows for displaying the minimum estimated cost in the Output Display Table

5.4.4 Discussions on the spreadsheet solution

Once the spreadsheet solution is ready, the company can carry out a retrospective test by comparing the hypothetical performance of the DP solution with the historical data. This process of testing is useful to validate the correctness of the DP model. However, a frequent bottleneck in using the DP method is that much of the needed data will not be available for testing the model at the beginning [113]. In particular relation to this study, the shortage of data can be attributed to the low priority placed on the energy efficiency issue or the existing information system is outdated. Usually, a careful validation of the DP solution requires exhaustive practical study for which a considerable amount of time will be needed. This has resulted in a typical question in the DP community, that is, whether to apply the DP solution immediately or to carry out some validating works in advance in order to improve the level of accuracy in the DP model.

In the absence of data validation, the “optimal solution” derived from the DP model is barely a well-approximated suboptimal solution. Supposing the rough dataset is used, the company can get an early idea of what scenario will arise based on the spreadsheet solution. This will increase the confidence of the decision makers in making certain financial decision because the spreadsheet solution allows the end-users to tailor a decision-making process in which the necessary information is unavailable initially. Another implication of using the rough dataset is that the company may need to make a strategic decision in a reasonable period of time, regardless of whether this will affect the ultimate optimum for the problem. As stated in Subsection 2.5.2, “satisficing” is a more practical strategy in the optimisation process if there is little chance to warrant better solution. The company should always consider the cost-benefit balance in the optimisation process. When faced with more information and uncertain situations, the decision makers may negate the final DP solution but they can learn and provide useful ideas that can be used to improve the spreadsheet solution. There is always more to learn and improve, either in the DP model, Excel algorithms, user interface, or the input data.

5.5 Exploring Large Dataset via Markov Chains

The previous discussions thus far have implied that the DP solution is not necessarily the optimal solution because the data for initial investigation might not be available. However, this is not always the case especially when the problem is not that too few data is available but there is an abundant set of data. In this particular study, some of these concerns come from the huge historical data stored in the company information system, such as the operating cost and maintenance cost. To better represent the stochastic nature of the historical data, Markov chains can be applied to provide a more appropriate probability model. A stochastic process is said to be a Markov process if the occurrence of a future state depends only on the current state of the process [121]. The operating cost and maintenance cost in SERP seem to fit this description well, because the equipment condition at certain stage normally impacts the corresponding costs at the subsequent stage. This section begins with some general descriptions of the Markovian properties. Next, the integration of Markov chains into the spreadsheet solution (file SERP.xlsm) is demonstrated.

5.5.1 Introduction to Markov chains

Named after Andrey Markov, the mathematical expression for a Markov chain is usually written as follows [121]:

$$P_{ij} = \mathbf{P}\{X_{t+1} = j | X_t = i\}, \qquad i, j = 1, 2, \dots, w;\ t = 1, 2, \dots, T. \tag{5.31}$$

where the random variables X represent the family of states and t indicates the stage. The conditional probabilities given by Equation 5.31 are also known as the one-step transition probabilities in which a common way of expression is to use the matrix notation as shown below:

$$\mathbf{P} = \begin{array}{c} \text{State} \\ 1 \\ 2 \\ \vdots \\ w \end{array} \begin{array}{c} \begin{array}{cccc} 1 & 2 & \dots & w \end{array} \\ \begin{bmatrix} P_{11} & P_{12} & \dots & P_{1w} \\ P_{21} & P_{22} & \dots & P_{2w} \\ \vdots & \vdots & \ddots & \vdots \\ P_{w1} & P_{w2} & \dots & P_{ww} \end{bmatrix} \end{array} \tag{5.32}$$

In Equation 5.32, the rows denote the state i at stage t while the columns denote the state j at stage $t+1$. It is the matrix notation of this form known as the so-called Markov chain. It should be noticed that $\sum_j P_{ij} = 1$ for $i = 1, 2, \ldots, w$ because the probability of an event can never be more than 1.

In addition to the one-step transition probabilities, there is also an existence of n-step transition probabilities that can be written in terms of Chapman-Kolomogorov equation [121], that is,

$$\mathbf{P}^n = \mathbf{P}^{n-m}\mathbf{P}^m, \qquad 0 < m < n. \tag{5.33}$$

After a sufficient number of transitions, the conditional probabilities in Equation 5.33 will reach a steady state where the state transition will no longer be dependent on the initial state of the system. The conditional probabilities for this situation can be described by

$$\boldsymbol{\pi} = \boldsymbol{\pi}\mathbf{P} \tag{5.34}$$

where $\sum_j \pi_j = 1$. Equation 5.34 implies that the conditional probabilities $\boldsymbol{\pi}$ will remain unaltered even after one transition. For this reason, it is called the steady-state probabilities. The expected number of transitions for the conditional probabilities to reach a steady state can be calculated by

$$\mu_{jj} = \frac{1}{\pi_j}, \qquad j = 1, 2, \ldots, w. \tag{5.35}$$

The Markov chains might contain a considerable number of states but the following subsection will only take account of a finite number of states associated with stationary transition probabilities. The stationary property implies that the transition probabilities will always be the same regardless of the stage or time.

5.5.2 Integration of Markov chains

Suppose that a company has installed a computer-based information system to collect all the necessary data for the old equipment on an on-going basis. Without too much complexity, the equipment condition can be generally classified into three possible states as represented by X_t, that is,

$$X_t = \begin{cases} 1, \text{if the condition is good.} \\ 2, \quad \text{if the condition is fair.} \\ 3, \text{if the condition is poor.} \end{cases} \tag{5.36}$$

Through the statistical analysis on the historical data, the company might have observed how the equipment condition changes from stage to stage. This situation can be transformed into a Markov chain which reflects the conditional probabilities of each possible transition from one state to a particular state:

$$\mathbf{P} = \begin{array}{c} \\ 1 \\ 2 \\ 3 \end{array} \begin{array}{c} \begin{array}{ccc} 1 & 2 & 3 \end{array} \\ \begin{bmatrix} P_{11} & P_{12} & P_{13} \\ P_{21} & P_{22} & P_{23} \\ P_{31} & P_{32} & P_{33} \end{bmatrix} \end{array} \tag{5.37}$$

Equation 5.37 shows that if the equipment condition at stage t is good (state 1), there is a probability of P_{11} it will stay the same at stage $t + 1$, a probability of P_{12} it will become fair (state 2), and a probability of P_{13} it will deteriorate to the poor condition (state 3).

Provided that the statistical analysis has also found that the operating cost and maintenance cost vary with the equipment condition, this will result into two identical Markov chains. Let N_{ij} and M_{ij} represent the average operating cost and maintenance cost given state from i to j, the corresponding Markov chains can be represented by:

$$\mathbf{N} = \begin{array}{c c} & \begin{array}{ccc} 1 & 2 & 3 \end{array} \\ \begin{array}{c} 1 \\ 2 \\ 3 \end{array} & \begin{bmatrix} N_{11} & N_{12} & N_{13} \\ N_{21} & N_{22} & N_{23} \\ N_{31} & N_{32} & N_{33} \end{bmatrix} \end{array}; \qquad \mathbf{M} = \begin{array}{c c} & \begin{array}{ccc} 1 & 2 & 3 \end{array} \\ \begin{array}{c} 1 \\ 2 \\ 3 \end{array} & \begin{bmatrix} M_{11} & M_{12} & M_{13} \\ M_{21} & M_{22} & M_{23} \\ M_{31} & M_{32} & M_{33} \end{bmatrix} \end{array} \quad (5.38)$$

As such, the expected operating cost of old equipment n_t^O and the expected maintenance cost of old equipment m_t^O at each stage can be calculated by

$$n_t^O = [\mathbf{IP}^t][\mathbf{IN}]^T; \qquad m_t^O = [\mathbf{IP}^t][\mathbf{IM}]^T \quad (5.39)$$

where $t = 1, 2, \ldots, T$. It must not be confused here that the index t and T in Equation 5.39 represent the stage and the matrix transpose respectively. The term $\mathbf{I}$ indicates the initial condition of the equipment, that is,

$$\mathbf{I} = \begin{cases} [1 \quad 0 \quad 0], \text{if the condition is good.} \\ [0 \quad 1 \quad 0], \text{ if the condition is fair.} \\ [0 \quad 0 \quad 1], \text{if the condition is poor.} \end{cases} \quad (5.40)$$

5.5.3 Excel algorithms for Markov chains

Concerning the computations, the MMULT function and TRANSPOSE function in Microsoft Excel (see Appendix 5) can be used to compute Equation 5.39. However, there is an absence of an Excel function that can raise a single matrix to the power of

t. In order to conveniently compute the n-step transition probabilities in Equation 5.39, a user defined function was created in the Excel spreadsheet solution (file SERP.xlsm) with syntax "=MPOWER(array, power)" (see Appendix 7 for more details). The computations of Markov chains are resolved in a separate worksheet called Markov Chains Worksheet, where the end-users can enter the necessary data for Markovian properties, such as Equation 5.37 and Equation 5.38, in the arrays as shown in Figure 5.13.

	A	B	C	D	E
6	**Markovian Properties**				
7	**Input Markov chains**	↓→	**Conditional probabilities, P**		
8	**Conditions of the equipment, X_t**		**1**	**2**	**3**
9	**1**				
10	**2**				
11	**3**				
12	**Initial condition of the equipment, I**				

Figure 5.13 – Arrays for Markovian properties in Markov Chains Worksheet

The Excel algorithms for computing Equation 5.39 is written in this manner:

$$= \mathrm{MMULT(MMULT(\$C\$12{:}\,\$E\$12, MPOWER(\$C\$9{:}\,\$E\$11, B\$17)),}$$

$$\mathrm{TRANSPOSE(MMULT(\$C\$12{:}\,\$E\$12, \$F\$9{:}\,\$H\$11))).} \qquad (5.41)$$

After the computations in Markov Chains Worksheet are completed, the resultant values have to be copied to row 41 for n_t^O and row 44 for m_t^O in the Input Worksheet for subsequent DP stage computations. Similarly, Markov Chains Worksheet requires adjustment if the end-users need to handle more than 10 stages in the computations.

5.6 Preparing to Implement the Solution

After an acceptable DP model has been developed and the corresponding spreadsheet solution has been established, the next step is to implement and test the system if the system is to be used repeatedly. In this section, the ability of the DP-based spreadsheet solution to assess the energy efficiency investment is illustrated in a simple hypothetical example.

5.6.1 Hypothetical stochastic equipment replacement problem

Suppose that an injection moulding company needs to determine the replacement policy for the energy-efficient equipment over the next five {5} years. The company currently owns five {5} hydraulic injection moulding machines and the maximum number of equipment that can be accommodated at the shop floor is ten {10}. The current annual energy cost for operating each machine is approximately 100,000 Yuan. It is expected to increase by 5% per year due to machine's aging effect and electricity tariff adjustment. Through the application of MRDSD, the company successfully reduce their annual operating cost by 10% without capital expenditure. The annual maintenance cost for each machine is assumed to be kept at 10,000 Yuan over the five-year period.

According to the efficiency ratings of the all-electric machines, the annual operating cost and annual maintenance cost can be reduced by 50% in spite of the high initial cost and an inexorable efficiency reduction rate of 5%. However, the company cannot simply make the capital investment on the all-electric machines due to limited access to capital resources. Moreover, decision makers often encounter various uncertainties in the practical environment such as hidden costs (internal transaction costs) and random changes to production demand. Therefore, the decision makers can employ the DP-based spreadsheet solution in order to get a better understanding of how investment decisions should evolve over time. The goal is to find the minimum estimated cost that might be incurred throughout the five-year period. For simplicity, all the necessary input data in the spreadsheet are tabulated in Table 5.3 where all the relevant costs are in unit of Chinese Yuan.

Table 5.3 – Input data of the hypothetical case study in the Input Worksheet

Criteria					
Maximum number of stages, T	5	(year)			
Maximum number of equipment, r_{max}	10				
Number of available equipment at stage 1	5				
Total internal transaction costs	10000	(Yuan)			
Initial operating cost of new equipment, $\dot{n}$	50000				
Efficiency index of new equipment per stage, η	0.95				
Stage					
Year	1	2	3	4	5
Demand					
Demand on the number of equipment, a_t	5	5	5	5	5
Exogenous change to demand, $\hat{a}_t$	0	1	1	1	1
Data for new equipment					
Number of equipment purchased, x_t^N	1	2	3	0	0
Purchase price, p_t^N	100000	100000	100000	100000	100000
Fluctuation in purchase price, $\hat{p}_t^N$	5000	5000	5000	10000	10000
Change in operating cost, $\hat{n}_t^N$	0	0	0	0	0
Maintenance cost of new equipment, m_t^N	5000	5000	5000	5000	5000
Change in maintenance cost, $\hat{m}_t^N$	1000	1000	1000	1000	1000

Table 5.3 (*continued*)

Data for old equipment					
Number of equipment sold, x_t^O	0	0	2	3	0
Selling price, q_t^O	-30000	-28000	-26000	-24000	-22000
Salvage value, g_t^O	-15000	-14000	-13000	-12000	-11000
Probability of equipment failure, z_t^O	0.2	0.2	0.25	0.25	0.3
Fluctuation in purchase price, $\hat{p}_t^O$	2000	2000	2000	2000	2000
Operating cost of old equipment, n_t^O	100000	105000	110250	115763	121551
Change in operating cost, $\hat{n}_t^O$	-10000	-10500	-11025	-11576	-12155
Maintenance cost of old equipment, m_t^O	10000	10000	10000	10000	10000
Change in maintenance cost, $\hat{m}_t^O$	2000	2000	2000	2000	2000

The criteria for the iterative calculation were set at 100 for the maximum iterations and 500 for the maximum change. The spreadsheet solution (file SERP.xlsm) only took 11 iterations to complete the stage computations. The resultant values are clearly displayed in Table 5.4.

Table 5.4 – Computed values from the Output Worksheet

Stage					
Year	1	2	3	4	5
Demand					
Final demand on the number of equipment, $\tilde{a}_t$	5	6	6	6	6
Number of available equipment (state)					
Total number, $\mathbf{r}_t$	5	6	8	9	6
Number of new equipment, r_t^N	0	1	3	6	6
Number of old equipment, r_t^O	5	5	5	3	0
Optimal policy decision					
Keep or replace (0 or 1)	1	1	1	1	0
Operating cost of new equipment					
Operating cost of new equipment, n_t^N	50000	50000	50877	51777	54503
Minimum estimated cost					
Minimum estimated cost	2879987	2258987	1448487	652680	363016
Total estimated cost (including internal cost)	2889987				

According to the spreadsheet solution, the optimal policy decision includes purchasing new equipment at the beginning of year 1, 2, and 3, as well as selling old equipment at the beginning of year 4 and 5. In other words, the company should make the capital investment on the all-electric machines although the purchase price is almost the same as the annual operating cost of the existing hydraulic machines. The total estimated cost for the five-year planning horizon is 2.89 million Yuan. It should be noticed that if a value of "1+E09" is returned to the total estimated cost, it implies that the stage computations are infeasible because either of the constraints is not satisfied (see p. 178).

5.6.2 Discussions on the implementation of DP solution

The advantage of the spreadsheet solution is the ease of implementation at which it can be readily used by non-technical personnel. However, it should be concerned that the DP solution generated is only optimal with respect to the derived DP model. There is no guarantee that the DP model can lead to the best possible solution because there are too many uncertainties associated with the real-world problems. In fact, there is not only one single definitive model that can solve a particular problem. Even if the DP model is well formulated and tested, the given outcomes can only be regarded as a good approximation rather than an ideal solution for the problem [113].

Another advantage of the spreadsheet solution is that it allows the end-users to rapidly observe the changes in the DP solution when testing different input data. In doing so, decision makers can assess the potential investment at short notice and increase their confidence in making financial decisions. Nevertheless, the eventual implementation of DP solution will highly rely on the strategic priority of the top management in the company. Because decision makers cannot wait until after the fact to initiate action, this is what makes the spreadsheet solution only a theoretical-level approach. In order to “gloss over” the potential limitations in the theoretical-level approach, it is useful to understand the judgement bias in decision management from the behavioural perspective.

To see this point, the optimal DP solution suggested by the above hypothetical example is to replace the old equipment over the five-year planning period. This implies that the investment in all-electric machines is cost-effective in closing the efficiency gap. Nevertheless, the decision makers might not base their investment decisions on the DP solution. A common way to interpret this bewildering situation can be referred to the utility theory (see Subsection 2.2.3.1). Under this theory, the rate of return from the relevant investment may not outweigh the perceived value of the decision makers’ preferences and attitudes towards risk. Another interpretation for this situation is the phenomenon of bounded rationality (see Subsection 2.2.2.2). Decision makers tend to be risk averse relative to gains when making a capital investment. In this regard, the prospect theory (see Subsection 2.2.3.4) can be applied to approximate the hypothetical value functions about the cognitive bias with respect to gains and losses. This study is not intended to further scrutinise the decision analysis from the behavioural perspective. It is simply beyond the scope of this thesis to analyse it in depth.

5.7 Chapter Conclusions

In summing up this chapter, a theoretical-level approach called "DP-based spreadsheet solution" (file SERP.xlsm) was successfully created using Excel algorithms, in an attempt to help SMEs address the stochastic equipment replacement problem. The advantage of this spreadsheet solution lies in the fact that it is quick and easy to use for personnel from different expertise levels. Although the spreadsheet solution can only be treated as a reference solution, it acts as a convenient tool for running an immediate cost assessment on the potential energy efficiency investments. Through the use of rough dataset, it is important to recognise that the need is for enough relevant information to initiate action. On the other hand, the inclusion of Markovian properties is to better exhibit the stochastic nature of the problem when dealing with huge historical data. The DP solution enables the decision makers to understand how they should base their financial decision on different input data over time, adding dynamicity and flexibility to the capital investment process. Nonetheless, there may still be a judgement bias on decision implementation resulting from the behavioural perspective.

CHAPTER 6

CONCLUSIONS AND OUTLOOK

6.1 Thesis Conclusions

In order to address the three research questions raised in this thesis (see p. 8), an empirical-level approach and a theoretical-level approach were developed for helping manufacturing SMEs, especially small and micro enterprises, in energy saving. The empirical-level approach is consisted of a novel integrated methodology called "multi-response dynamic Shainin DOE" whilst the theoretical-level approach is a spreadsheet-based decision support system based on dynamic programming model. This thesis shows how these two proprietary methodologies can enhance the dynamicity in the optimisation process to support injection moulding industry in closing their efficiency gap. In other words, through the use of these methodologies, manufacturers possess dynamic capabilities to adapt their limited resources over time for energy efficiency improvement. Therefore, it can be concluded that the main research aim was successfully achieved. To see this point clearly, the main findings from the eight primary research objectives (see Section 1.3) which formed the key structure of this thesis are presented as follows:

i. The barriers to energy efficiency can be explained from the economic, behavioural, and organisational perspectives; however, there appears to be no conclusive answer for which barrier is the most critical one among different sectors, firm sizes or geographical regions.

ii. After reviewing a range of energy-saving measures for injection moulding, process parameters optimisation was identified as a potential “no-cost investment” strategy that can be adopted by SMEs.

iii. In comparison to simulation-based methodologies, design of experiment provides a relatively simple, practical, and yet statistically valid tool that may support SMEs to improve their energy efficiency in an economical way.

iv. A stepwise optimisation methodology named as “multi-response dynamic Shainin DOE” was developed, which combines several notable features such as simplicity, novelty, validity, and usefulness.

v. The empirical study demonstrated that regardless of great fluctuations in the response data, the proposed methodology was able to identify the critical factors to the targeted responses.

vi. The inclusion of signal-response system was able to reduce the specific energy consumption during the injection moulding process with the assurance of moulded parts’ impact strength.

vii. A dynamic programming model was specifically designed for solving the stochastic equipment replacement problem which greatly differs from the classic examples found in the DP literature.

viii. A DP-based spreadsheet solution (file SERP.xlsm) with user-friendly interface was created to solve the stage computations involved in the derived DP model.

6.2 Knowledge Contributions

In brief, the key contributions of this thesis can be subdivided into empirical level and theoretical level:

i. *Contribution at the empirical level*

Process parameters optimisation was proposed to be a useful strategy for "no-cost investment" in energy efficiency improvement. However, the research hypothesis (see p. 8) is said to be plausible when most optimisation methodologies developed by the academic community downplays the environment of SMEs. As a consequence, these methods are not easily transferred to industrial practice. In this regard, MRDSD has proved to be a simple and valid methodology that can replace the imprecise routines practiced in SMEs. The originality of the proposed methodology comes from the fact that the inherent limitations of Shainin DOE are resolved by integrating the multivariate statistical methods and the signal-response system into it. The purpose of integrating the multivariate techniques is to replace the univariate decision limits used in the variables search, which have apparent weakness in solving the multivariate problems (see Subsection 3.4.2). Recall that one notable limitation found in the Shainin approach is that the factor-response relationship is overlooked in the analysis (see Subsection 3.2.3). In this regard, the inclusion of signal-response system enhances the dynamicity in the optimisation process. Therefore, the proposed methodology is capable of achieving different output performance based on varying objectives over time. In consideration of the large amount of SMEs in the Chinese context, if this methodology can be disseminated across many enterprises, it can be confidently envisaged that even small improvement in energy efficiency can have a big impact in terms of environmental performance.

ii. *Contribution at the theoretical level*

Although dynamic programming has been widely adopted in solving industrial problems, there is a persistent absence of commercial software packages for solving DP problems. Unless the DP stage computations can be easily and quickly solved, there might not be a wide acceptance among SMEs in using it for making decision and solving problem. The DP-based spreadsheet solution (file SERP.xlsm) developed in Chapter 5 provides a convenient tool for the decision makers in SMEs to understand how investment decisions on energy efficiency technology should evolve over time. This increases the dynamicity in the decision-making process. One main advantage of the spreadsheet solution is the ease with which it can be readily used by personnel from different level of expertise. The derived DP model and the corresponding Excel algorithms extend the existing knowledge with respect to the classic equipment replacement problems in the DP literature. In spite of the acknowledged limitations in the DP solution, there is a great potential in using it to optimise the decision-making process pertaining to energy efficiency investments at short notice.

6.3 Limitations and Future Work

This thesis work provided an initial exploration of an empirical-level approach and a theoretical-level approach that would enable SMEs to close their efficiency gap. Nevertheless, there are some limitations associated with this work that require significant further investigation. Concerning the empirical-level approach, there are two main limitations needed to be addressed in the future:

i. *No industrial case study was conducted based on the empirical-level approach.*
   Although a careful empirical study for statistical validation was carried out, a real case study is important to justify the practicality of the proposed methodology. For example, to examine the degree of acceptance to which it can be persuasively claimed as a "user-friendly" method. This validating procedure must be taken in order to better disseminate the methodology to the potential end-users in SMEs.

ii. *No economic analysis was established to study the economic performance actually achieved.*
   In addition to the ease of implementation, the corresponding economic performance is also vital so that it can lay claim for being "cost effective". While the "no-cost investment" strategy seems possible, it can only be successful if this methodology is not only technically feasible but also economically acceptable. Such economic analysis tends to be more complex in industrial practice since it might encounter economic losses due to

machine downtime and production disruption. For these reasons, future work should be focussed on setting up industrial collaboration, collecting field data, analysing the practicality, and disseminating the useful outcomes in the form of case studies to the relevant industry.

Next, several parts of the theoretical-level approach deserve more comprehensive future studies:

i. *The dataset for initial validation on the DP-based spreadsheet solution (file SERP.xlsm) was not available.*

   As discussed earlier, the real-world problems contain many uncertainties which cannot be completely approximated by the DP model. In consequence, the spreadsheet solution can only offer a reference solution to the decision makers. Through the validation work, it will help to increase the confidence in the decision makers to implement the given outcomes. In consideration of the SMEs' environment, the validation work can be conducted in a university-enterprise collaborative relationship so that the spreadsheet solution can better reflect the real-world problems. At the same time, it is hoped that the end-users will be willing to provide some useful suggestions for further improvement and share their findings with other companies in due course.

ii. *The user interface might not look "smart" enough.*

Not only do all the stage computations involved in the DP model need to be quickly solved, but the spreadsheet solution also needs to enable the potential end-users to easily make use of it. Because SMEs represent the potential end-users of this spreadsheet solution, any difficulty in using it will make it impossible to be widely spread. For this reason, it is important to investigate under what circumstances the features of the spreadsheet solution will encourage or discourage the end-users from using it. This behavioural question has not been extensively studied in the context of spreadsheet-based decision support system.

iii. *The derived DP model is not consisted of a general framework that can solve different types of problem.*

While the DP research community is striving to search for a general class of algorithms that can work reliably on different types of DP problem [200], the DP model derived in this thesis considers a fairly specific equipment replacement problem with a well-articulated structure. At some point, after this specific DP model has undertaken a series of testing and improving process, a set of post-optimality analyses must be conducted to check whether the DP model can solve all the problems of the similar type. Subsequently, the more powerful spreadsheet solution should be disseminated for public use. With certain confidence, it can be envisaged that some algorithmic breakthroughs could possibly form the basis of a patentable work.

iv. *There are many uncertain scenarios which may arise during the decision implementation stage caused by different behaviour of the decision makers.*

This kind of situation can be further examined through “decision analysis” which is also under the area of operations research. Due to the scope governing this thesis work, the decision analysis was inevitably excluded but it is worth further study in the future. This is exceptionally important because the barriers from the behavioural perspective are comparatively less well understood and often tentatively descriptive.

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APPENDICES

Appendix 1

Factors for constructing variables control charts. Source: [164]

Observations in Sample, n	**Chart for Averages**			**Chart for Standard Deviations**						**Chart for Ranges**						
	Factors for Control Limits			**Factors for Center Line**		**Factors for Control Limits**				**Factors for Center Line**		**Factors for Control Limits**				
	A	A_2	A_3	c_4	$1/c_4$	B_3	B_4	B_5	B_6	d_2	$1/d_2$	d_3	D_1	D_2	D_3	D_4
2	2.121	1.880	2.659	0.7979	1.2533	0	3.267	0	2.606	1.128	0.8865	0.853	0	3.686	0	3.267
3	1.732	1.023	1.954	0.8862	1.1284	0	2.568	0	2.276	***1.693***	0.5907	0.888	0	4.358	0	2.574
4	1.500	0.729	1.628	0.9213	1.0854	0	2.266	0	2.088	2.059	0.4857	0.880	0	4.698	0	2.282
5	1.342	0.577	1.427	0.9400	1.0638	0	2.089	0	1.964	2.326	0.4299	0.864	0	4.918	0	2.115
6	1.225	0.483	1.287	0.9515	1.0510	0.030	1.970	0.029	1.874	2.534	0.3946	0.848	0	5.078	0	2.004
7	1.134	0.419	1.182	0.9594	1.0423	0.118	1.882	0.113	1.806	2.704	0.3698	0.833	0.204	5.204	0.076	1.924
8	1.061	0.373	1.099	0.9650	1.0363	0.185	1.815	0.179	1.751	2.847	0.3512	0.820	0.388	5.306	0.136	1.864
9	1.000	0.337	1.032	0.9693	1.0317	0.239	1.761	0.232	1.707	2.970	0.3367	0.808	0.547	5.393	0.184	1.816
10	0.949	0.308	0.975	0.9727	1.0281	0.284	1.716	0.276	1.669	3.078	0.3249	0.797	0.687	5.469	0.223	1.777
11	0.905	0.285	0.927	0.9754	1.0252	0.321	1.679	0.313	1.637	3.173	0.3152	0.787	0.811	5.535	0.256	1.744
12	0.866	0.266	0.886	0.9776	1.0229	0.354	1.646	0.346	1.610	3.258	0.3069	0.778	0.922	5.594	0.283	1.717
13	0.832	0.249	0.850	0.9794	1.0210	0.382	1.618	0.374	1.585	3.336	0.2998	0.770	1.025	5.647	0.307	1.693
14	0.802	0.235	0.817	0.9810	1.0194	0.406	1.594	0.399	1.563	3.407	0.2935	0.763	1.118	5.696	0.328	1.672
15	0.775	0.223	0.789	0.9823	1.0180	0.428	1.572	0.421	1.544	3.472	0.2880	0.756	1.203	5.741	0.347	1.653
16	0.750	0.212	0.763	0.9835	1.0168	0.448	1.552	0.440	1.526	3.532	0.2831	0.750	1.282	5.782	0.363	1.637
17	0.728	0.203	0.739	0.9845	1.0157	0.466	1.534	0.458	1.511	3.588	0.2787	0.744	1.356	5.820	0.378	1.622
18	0.707	0.194	0.718	0.9854	1.0148	0.482	1.518	0.475	1.496	3.640	0.2747	0.739	1.424	5.856	0.391	1.608

(*continued overleaf*)

Observations in Sample, n	Chart for Averages			Chart for Standard Deviations						Chart for Ranges						
	Factors for Control Limits			Factors for Center Line		Factors for Control Limits				Factors for Center Line		Factors for Control Limits				
	A	A_2	A_3	c_4	$1/c_4$	B_3	B_4	B_5	B_6	d_2	$1/d_2$	d_3	D_1	D_2	D_3	D_4
19	0.688	0.187	0.698	0.9862	1.0140	0.497	1.503	0.490	1.483	3.689	0.2711	0.734	1.487	5.891	0.403	1.597
20	0.671	0.180	0.680	0.9869	1.0133	0.510	1.490	0.504	1.470	3.735	0.2677	0.729	1.549	5.921	0.415	1.585
21	0.655	0.173	0.663	0.9876	1.0126	0.523	1.477	0.516	1.459	3.778	0.2647	0.724	1.605	5.951	0.425	1.575
22	0.640	0.167	0.647	0.9882	1.0119	0.534	1.466	0.528	1.448	3.819	0.2618	0.720	1.659	5.979	0.434	1.566
23	0.626	0.162	0.633	0.9887	1.0114	0.545	1.455	0.539	1.438	3.858	0.2592	0.716	1.710	6.006	0.443	1.557
24	0.612	0.157	0.619	0.9892	1.0109	0.555	1.445	0.549	1.429	3.895	0.2567	0.712	1.759	6.031	0.451	1.548
25	0.600	0.153	0.606	0.9896	1.0105	0.565	1.435	0.559	1.420	3.931	0.2544	0.708	1.806	6.056	0.459	1.541

For n > 25.

$$A = \frac{3}{\sqrt{n}} \qquad A_3 = \frac{3}{c_4\sqrt{n}} \qquad c_4 \cong \frac{4(n-1)}{4n-3}$$

$$B_3 = 1 - \frac{3}{c_4\sqrt{2(n-1)}} \qquad B_4 = 1 + \frac{3}{c_4\sqrt{2(n-1)}}$$

$$B_5 = c_4 - \frac{3}{\sqrt{2(n-1)}} \qquad B_6 = c_4 + \frac{3}{\sqrt{2(n-1)}}$$

Appendix 2

Derivation of the bivariate T^2 value

Suppose that there are two responses under investigation, x_1 and x_2, for a sample size of n with sample variances s_1^2 and s_2^2, and the covariance between them is represented by s_{12}. Under these circumstances, Equation 3.5 (p. 95) is expanded into Equation 3.19 (p. 102) as follows:

$$T^2 = n(\bar{\mathbf{x}} - \boldsymbol{\mu})^T \mathbf{S}^{-1} (\bar{\mathbf{x}} - \boldsymbol{\mu})$$

$$= n[\bar{x}_1 - \mu_1 \quad \bar{x}_2 - \mu_2] \begin{bmatrix} s_1^2 & s_{12} \\ s_{12} & s_2^2 \end{bmatrix}^{-1} \begin{bmatrix} \bar{x}_1 - \mu_1 \\ \bar{x}_2 - \mu_2 \end{bmatrix}$$

$$= \frac{n}{s_1^2 s_2^2 - s_{12}^2} [\bar{x}_1 - \mu_1 \quad \bar{x}_2 - \mu_2] \begin{bmatrix} s_2^2 & -s_{12} \\ -s_{12} & s_1^2 \end{bmatrix} \begin{bmatrix} \bar{x}_1 - \mu_1 \\ \bar{x}_2 - \mu_2 \end{bmatrix}$$

$$= \frac{n}{s_1^2 s_2^2 - s_{12}^2} [\bar{x}_1 - \mu_1 \quad \bar{x}_2 - \mu_2] \begin{bmatrix} s_2^2(\bar{x}_1 - \mu_1) - s_{12}(\bar{x}_2 - \mu_2) \\ s_1^2(\bar{x}_2 - \mu_2) - s_{12}(\bar{x}_1 - \mu_1) \end{bmatrix}$$

$$= \frac{n}{s_1^2 s_2^2 - s_{12}^2} [s_2^2(\bar{x}_1 - \mu_1)^2 + s_1^2(\bar{x}_2 - \mu_2)^2 - 2s_{12}(\bar{x}_1 - \mu_1)(\bar{x}_2 - \mu_2)]$$

Derivation of the upper control limit

The upper control limit (UCL) for the bivariate variables search is derived from Equation 3.20 (p. 102), that is,

$$T^2 = \frac{3(1.693)^2}{\bar{d}_1^2 \bar{d}_2^2 - (1.693)^4 {s_{12}^*}^2} \left[\bar{d}_2^2(y_1 - m_1)^2 + \bar{d}_1^2(y_2 - m_2)^2 - 2(1.693)^2 s_{12}^*(y_1 - m_1)(y_2 - m_2)\right]_{\mathrm{B/M}}$$

Let $y_1 = m_1 \pm 2.776\frac{\bar{d}_1}{1.693}$ and $y_2 = m_2$, this gives

$$T^2 = \frac{3(1.693)^2}{\bar{d}_1^2\bar{d}_2^2-(1.693)^4(\bar{s}_{12})^2}\left[\bar{d}_2^2\left(2.776\frac{\bar{d}_1}{1.693}\right)^2\right]$$

After simplifying the above algebraic expression, Equation 3.22 (p. 104) is obtained as given below:

$$\mathrm{UCL} = \frac{3(2.776)^2\bar{d}_1^2\bar{d}_2^2}{\bar{d}_1^2\bar{d}_2^2-(1.693)^4\bar{s}_{12}^2}$$

Determination of the contribution to the T^2 value

The contribution of the particular response to the overall T^2 value is computed according to Equation 3.24 (p. 105). If y_i is replaced with the lower or higher end of the corresponding decision limit, this yields

$$T_i^2 = \frac{3(1.693)^2(y_i-m_i)^2}{\bar{d}_i^2} = \frac{3(1.693)^2(\pm 2.776\bar{d}_i/1.693)^2}{\bar{d}_i^2} = 3(2.776)^2 = 23.12$$

Appendix 3

ExxonMobil™ PP7684KN polypropylene impact copolymer datasheet[14]

Product Description
A high crystallinity, high impact copolymer resin with medium melt flow rate and excellent processing attributes. It is designed for injection moulded small and large appliance parts.

General			
Features	▪ Fast Moulding Cycle	▪ Good Processability	▪ High Stiffness
	▪ Good Heat Aging Resistance	▪ High Impact Resistance	▪ Low Warpage
Uses	▪ Appliances	▪ Crates	▪ Packaging
	▪ Consumer Applications	▪ Industrial Applications	▪ Tool/Tote Box
Appearance	▪ Natural colour		
Form	▪ Pellets		
Processing Method	▪ Compounding	▪ Injection Moulding	

Physical	**Typical Value (English)**	**Typical Value (SI)**	**Test Based On**
Melt Mass-Flow Rate (MFR) (230°C/2.16kg)	20g/10min	20g/10min	ASTM D1238
Density	0.9g/cm^3	0.9g/cm^3	ExxonMobil Method

Mechanical	**Typical Value (English)**	**Typical Value (SI)**	**Test Based On**
Tensile Strength at Yield (51mm/min)	3540psi	24.4MPa	ASTM D638
Tensile Stress at Yield	3520psi	24.3MPa	ISO 527-2/50
Elongation at Yield (51mm/min)	4.4%	4.4%	ASTM D638
Tensile Strain at Yield	3.4%	3.4%	ISO 527-2/50
Tensile Modulus	191000psi	1320MPa	ISO 527-2/1

[14] The information presented on this datasheet was retrieved from www.exxonmobilchemical.com.

Mechanical	Typical Value (English)	Typical Value (SI)	Test Based On
Flexural Modulus - 1% Secant			
1.3mm/min	187000psi	1290MPa	ASTM D790A
13mm/min	214000psi	1480MPa	ASTM D790B
Flexural Modulus (2.0mm/min)	181000psi	1250MPa	ISO 178

Impact	Typical Value (English)	Typical Value (SI)	Test Based On
Notched Izod Impact (23°C)	2.7ft·lb/in	150J/m	ASTM D256A
Notched Izod Impact Strength			ISO 180/1A
-40°C	1.9ft·lb/in^2	4.0kJ/m^2	
-18°C	2.2ft·lb/in^2	4.6kJ/m^2	
23°C	4.0ft·lb/in^2	8.4kJ/m^2	
Charpy Notched Impact Strength			ISO 179/1eA
-30°C	1.9ft·lb/in^2	3.9kJ/m^2	
-20°C	2.3ft·lb/in^2	4.8kJ/m^2	
0°C	3.1ft·lb/in^2	6.6kJ/m^2	
23°C	4.8ft·lb/in^2	10kJ/m^2	
Gardner Impact (-29°C, 3.18mm)	201in·lb	22.7J	ASTM D5420

Thermal	Typical Value (English)	Typical Value (SI)	Test Based On
Heat Deflection Temperature (1.80MPa)	125°F	51.5°C	ISO 75-2/A
Heat Deflection Temperature (0.45MPa)	199°F	93.0°C	ISO 75-2/Bf
Deflection Temperature Under Load at 66psi – Unannealed	221°F	105°C	ASTM D648

Appendix 4

Results of full factorial experiments for SEC in unit of kWh/kg

Row	Control factor		Signal factor, CT (s)		
	BT (°C)	MT (°C)	5	10	15
1	200	30	0.4548	0.4954	0.5605
			0.4745	0.5229	0.5867
			0.4127	0.4871	0.5591
	Average		0.4473	0.5018	0.5688
2	220	30	0.3900	0.5120	0.5595
			0.4777	0.5242	0.6399
			0.5402	0.5131	0.6148
	Average		0.4693	0.5164	0.6047
3	200	40	0.4475	0.4750	0.5760
			0.4712	0.5388	0.6004
			0.4296	0.4984	0.5492
	Average		0.4494	0.5041	0.5752
4	220	40	0.4810	0.4788	0.6382
			0.4976	0.5765	0.5858
			0.4718	0.5432	0.6116
	Average		0.4835	0.5328	0.6119

(Summarised in Table 4.15 on p. 143)

Results of full factorial experiments for CIS in unit of kJ/m^2

Row	Control factor		Signal factor, CT (s)					
	BT (°C)	MT (°C)	5		10		15	
1	200	30	7.4217	6.4338	4.7791	6.2321	5.8875	3.9940
			5.6016	6.5783	6.2033	5.0899	5.1466	4.3854
			5.2033	6.4627	5.6302	4.0498	6.6651	5.0050
			6.2033	5.8589	4.1894	4.4415	5.0616	5.5446
			5.6587	5.5161	5.8016	3.5218	5.5446	5.3738
			6.4627	6.6940	4.3573	4.5257	5.5731	4.4696
			6.6361	7.1007	6.3761	4.4696	5.7158	3.4665
			6.6940	6.3761	6.0883	4.9202	4.4415	4.1894
			6.3473	6.2321	4.4415	5.5161	4.6101	3.5495
			6.5494	6.3473	5.6016	5.3738	5.8302	3.0255
	Average		6.3189		5.0804		4.8740	
	Standard deviation		0.5361		0.8295		0.9369	

(*continued overleaf*)

Row	Control factor		Signal factor, CT (s)					
	BT (°C)	MT (°C)	5		10		15	
2	220	30	5.7158	6.8390	5.8589	4.6663	5.1466	4.6101
			6.3185	6.1170	5.6873	4.8355	4.3294	5.1183
			6.2321	5.8875	6.2609	6.1458	4.8355	5.8016
			6.4916	6.0883	5.7730	6.4338	4.8919	5.8016
			5.3738	6.3185	4.9767	5.2601	4.7227	5.2317
			6.0883	5.7730	6.1745	5.4307	5.8875	5.4022
			6.0022	6.0596	4.8073	4.9767	5.4876	5.7730
			6.0309	4.6382	5.0050	4.7791	4.2453	5.0616
			5.8875	4.9767	4.4977	4.8637	4.8355	5.0899
			5.0616	5.5491	4.7509	4.6663	4.6382	4.9202
	Average		5.8725		5.2925		5.0915	
	Standard deviation		0.5354		0.6223		0.4842	
3	200	40	4.6382	5.5446	5.1466	4.9484	4.7509	6.2321
			5.5446	6.0596	4.5820	5.6016	3.1354	5.3738
			5.4307	7.6854	5.8589	6.4050	4.8637	6.6072
			5.4022	6.8390	4.8355	6.1170	5.4876	5.7730
			6.2897	6.7520	4.4415	5.2601	5.2033	4.0777
			6.0022	6.3473	4.5820	5.3738	5.6587	3.9940
			6.7520	7.2464	4.7791	5.6587	6.6361	3.9661
			6.6651	7.9206	4.6663	5.5446	3.1354	4.3573
			5.2033	7.3632	5.6873	6.3473	3.4112	5.0616
			4.9767	6.6940	5.2601	5.8016	5.5161	4.8073
	Average		6.2678		5.3449		4.9024	
	Standard deviation		0.9207		0.5961		1.0575	
4	220	40	5.3738	5.8875	5.5161	4.5820	5.3453	2.9705
			5.5446	5.7730	4.5538	3.9104	5.5446	5.4876
			5.6302	6.3185	5.4307	5.9735	6.1458	4.9484
			5.2885	6.3473	5.3453	5.4876	4.9484	5.4022
			4.6945	5.3453	6.2609	5.2601	5.7730	3.9383
			6.4916	7.3924	5.4591	6.4338	4.8355	3.8826
			6.3761	6.2321	6.3185	6.0022	5.1466	3.7436
			5.2885	5.5161	5.5446	6.5783	5.4307	3.5218
			5.0050	6.1458	4.9202	5.9735	5.7158	5.2885
			5.6587	7.1298	4.5538	5.6302	5.2885	5.1749
	Average		5.8720		5.4867		4.9266	
	Standard deviation		0.6827		0.7102		0.8530	

(Summarised in Table 4.16 on p. 144)

Appendix 5

Important Excel functions for the spreadsheet solution (file SERP.xlsm)

Excel Function Syntax	Descriptions
=IF(logical_test, [value_if_true], [value_if_false])	The IF function returns one value if the specified condition is met, otherwise, it will return the other value.
=OR(logical1, [logical2], …)	The OR function is combined with the IF function in the spreadsheet algorithms. Thus, it can return one value if any argument is true or the other value only if all arguments are false.
=INDEX(array, row_num, [column_num])	The INDEX function returns a value from a range of cells according to the row and column number indexes.
=MATCH(lookup_value, lookup_array, [match_type])	The MATCH function looks up a specified value in a range of cells, and then returns the relative position of that value in the range. The MATCH function is combined with the INDEX function in the spreadsheet solution. Thus, it can return a value from a range of cells which has matched with the relative position of a specified value in the other range.
=OFFSET(reference, rows, cols, [height], [width])	The OFFSET function returns a reference (either a single cell or a range of cells) to a range that is a given number of rows and columns from a given reference. The number of rows and the number of columns to be returned can be specified by entering “height” and “width”.
=MMULT(array1, array2)	The MMULT function returns the matrix product of two arrays. The resultant matrix product has the same number of rows as “array1” and the same number of columns as “array2”.
=TRANSPOSE(array)	The TRANSPOSE function converts a row of cells as a column of cells, or vice versa. If an array has a dimension of m×n, the resultant matrix will have a dimension of n×m.

Appendix 6

Spreadsheet adjustments for larger problems

The Excel spreadsheet solution (file SERP.xlsm) is set in protected mode initially so that the end-users are neither able to edit the user interface nor can they modify the Excel algorithms. Whenever necessary, the end-users can easily switch from the protected mode to edit mode by clicking "Unprotect Sheet" button on “Review” tab. There are two conditions for which the end-users are required to switch off the protected mode and edit the spreadsheet. First, when the end-users need more than 10 stages since the maximum number of stage is set at 10 initially. In this case, the following modification steps must be performed before running the stage computations:

i. Go to Input Worksheet.

ii. Highlight the last column of cells in the necessary table and drag the fill handle  across the columns as many as are needed, as illustrated in Figure A1.

iii. Click the “Edit Next” button at the top of the Input Display Table to start editing all the necessary tables in the next worksheet.

iv. Repeat step ii and iii until the Output Worksheet has been edited.

	A	B	C		J	K
16	**Stage**					
17	**Stage, t**	1	2		9	10
18	**<Description, e.g., 2015, Q1, Jan>**					

Figure A1 – Spreadsheet adjustment for problems that contain more than 10 stages

Second, the stage computations in the spreadsheet will become infeasible if the total number of equipment before decision is more than 10, i.e., $\mathbf{r}_t > 10$, since the maximum default value is set at 10 initially. In this case, the necessary modification steps before running the stage computations are as follows:

i. Go to Input Worksheet and click the "Insert" button to start editing the Stage Computations Table in Worksheet "p".

ii. Highlight the last row of cells and drag the fill handle across the rows as many as are needed, as illustrated in Figure A2.

iii. Assign the corresponding values to the new rows in column A, B, C, D accordingly.

iv. Click the "Insert Next" button to start editing the Stage Computations Table in the next worksheet.

v. Repeat step ii to iv until Worksheet "Vt" has been edited.

	A	B	C	D	E
50	**Total number of equipment before decision, $\mathbf{r}_t$**	r_t^N	r_t^O	k_t	
181	10	10	0	0	0
182	10	10	0	1	0

Figure A2 – Spreadsheet adjustment for problems that contain more than 10 equipment

Appendix 7

Development of the MPOWER function

There is a necessity to create a new Excel function that can raise a single matrix to the power of t so that the n-step transition probabilities in Equation 5.39 (p. 190) can be conveniently computed. Such a function is named as MPOWER function in this thesis. In order to develop a user defined function in Microsoft Excel, it is required to access the “Developer” tab and open the Visual Basic Editor. The “Developer” tab does not appear on the Excel application ribbon by default. Users can go to the “File” tab and click the “Options” button. Next, choose the “Customize Ribbon” button and click the “Developer” check box to activate the “Developer” tab. To create the MPOWER function, the following code is entered into the new Module:

```
Function MPOWER(rngInp As Range, lngPow As Long) As Variant
Dim i As Long
MPOWER = rngInp
If lngPow > 1 Then
  For i = 2 To lngPow
    MPOWER = Application.WorksheetFunction.MMult(rngInp, MPOWER)
  Next
End If
End Function
```

Having done so, the syntax for the MPOWER function will look in this way:

=MPOWER(array, power)