SUSTAINABILITY CONSIDERATION IN MACHINING OF 2½D MILLED FEATURES

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requirements of University of Greenwich
for the Degree of Doctor of Philosophy

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DECLARATION

"I certify that this work has not been accepted in substance for any degree, and is not concurrently being submitted for any degree other than that of Doctor of Philosophy being studied at University of Greenwich. I also declare that this work is the result of my own investigations except where otherwise identified by references and that I have not plagiarised the work of others."

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LIST OF PUBLICATIONS

Zhang, T., Owodunni, O.O., and Gao, J., 2011. Energy-efficient Toolpath Strategy for End Milling Operation, in: Proceedings of 9th International Conference on Manufacturing Research, Glasgow, UK, pp: 199-205

Owodunni, O.O., Zhang, T., and Gao, J., 2013. Energy Consideration in Machining Operations - Towards Explanatory Models for Optimisation, in: Proceedings of 11th Global Conference on Sustainable Manufacturing, Berlin, Germany, pp: 158-163

Zhang,T., Owodunni, O.O, and Gao, J., 2015, Scenarios in multi-objective optimisation of process parameters for sustainable machining, Procedia CIRP, Volume 26, pp: 373-378

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GLOSSARY

A - cross sectional area of the undeformed chip

ACO – ant colony algorithm

AE - auxiliary energy consumption

ae – width of cut

ap – depth of cut

A_{tm} – theoretical minimal shearing area

C – cost

C_e – energy cost

C_l – labour cost

C_t – tool cost

d – diameter of cutting tool

DE - direct energy consumption

DOE – design of experiment

E - energy consumption

$E_{auxiliary}$ – energy consumption for auxiliary function

$E_{machining}$ – energy consumption for machining operation

ER – energy efficiency ratio

$ER_{machining}$ – energy efficiency for machining operation

$ER_{process}$ – energy efficiency for machining process

E_{setup} – energy consumption for machining setup

E_{total} – total energy consumption

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f – feed rate

F - Feed rate m/r

F_a - axial force

F_c - cutting force

F_r - radial cutting force

F_t - tangential cutting force

F_{tm} – theoretical minimal shearing force

F_x - cutting force for X axis

F_y - cutting force for Y axis

F_z – feed rate per tooth

GA – genetic algorithm

H - chip thickness

IE - indirect energy consumption

K_t - cutting force co-efficient

MRR - material removal rate

MRR_z – material removal rate per tooth

n – spindle speed

P - power consumption

P_0 – idle power consumption

$P_{auxiliary}$ – power consumption for auxiliary function

$P_{constant}$ – constant power consumption

$P_{machinig}$ – power consumption for machining operation

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$P_{spindle}$ – power consumption for spindle

P_{total} – total power consumption

R_a – surface roughness

R_e – electricity rate

R_l – labour rate

R_t – tool rate

SCE - specific constant energy consumption

SEC - specific energy consumption

SPE - specific process energy consumption

TE – theoretical energy comsumption

T_l – tool life

T_{lr} – reference tool life

T_m – machining time

TME - theoretical minimal energy consumption

TSE - total specific energy consumption

T_{setup} – setup time

T_{tc} – total changing time

T_{total} – total time consumption

V_c - cutting speed

V_m – material removal volume

z – number of cutting flutes

τ – shear strength

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ϕ – rotational angle

η_s – signal noise ratio

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TECHNICAL TERMS

Sustainability of manufacturing

Sustainability issues related to manufacturing process, including: economic, environmental, social factors.

Sustainability performance

Overall sustainability performance for manufacturing process, including: economic performance such as cost, time and quality, environmental performance such as energy consumption, impact of cutting fluid and material waste, and social performance such as safety issues.

Sustainability considerations

In this thesis, sustainability considerations means the manufacturing processes that consider multiple criterions from economic, environmental, social aspects.

Sustainable manufacturing process

In this thesis, sustainable manufacturing process refers to the manufacturing process with sustainability considerations.

Sustainable machining

In this thesis, sustainable machining means the machining process with the considerations of specific criterions such as cost, time, surface roughness, energy consumption, cutting force, power and tool life.

Sustainability improvement

Methods for improving sustainability performance of manufacturing process or machining operations.

Framework for machining optimisation

Generic methodology for improving machining performance by selecting optimal process parameters.

ABSTRACT

At present, sustainable manufacturing process has been widely demanded by manufacturing industry to address the financial pressure from increasing energy price and the political pressure from legislation on reduction of environmental impact. The motivation of this research is to reduce the environmental impact caused by high energy demand and consumption on the manufacturing process.

This research addresses important issues related to the environmental impact of manufacturing operations. Through a review of literature and industrial practices, the following requirements have been identified: (i) *Sustainability performance measures* which can be used to effectively identify potential inefficiency, and recommend ways of improvement; (ii) *Optimisation of existing manufacturing process* which take energy as an additional factor in the optimisation of machining processes; and (iii) *Developmen*t *of new machining processes and technologies* that move closer to the theoretical boundaries of energy efficiency.

To address the above requirements, this project developed a set of energy prediction models and energy efficiency metrics to measure the energy usage during machining processes. The results show that energy consumption in machining $2^1/_2$D milled features can be improved by optimising the use of existing machining processes and by designing new machining processes and technologies.

The characteristics of machining operations with energy considerations have been investigated using graphical multivariate data analysis techniques. A direct search method was used to conduct the optimisation procedure. This study showed that energy consumption decreases monotonically as process parameters (depth of cut, width of cut, spindle speed and feed rate) increase, and can be minimised up to 75% for machining Aluminium 7075-T6 by using Haas TM 1CE Vertical milling machine (maximum spindle speed 4,000rpm) without conflicting with cost and time under the constraints of spindle speed, cutting force and surface roughness.

Typical optimisation methods have been found which can give similar results, and methods of opening up the reasoning process have been identified which enable practitioners to have more confidence in their results. An optimisation method has been proposed and tested for selecting optimal process parameters for a typical CNC milling

operation resulting in the reduction of energy consumption. A scenario-based method has been developed to provide a comprehensive solution for decision makers to solve machining optimisation problems with sustainability considerations.

An energy-efficient profiling toolpath strategy has also been developed to improve energy efficiency for $2^{1}/_{2}$D milled features. It was found that further reduction in energy consumption could be achieved compared to conventional cutting strategies.

Finally, the developed methodologies can be integrated as a comprehensive framework into existing machining process improvement procedures to help process planners and manufacturing practitioners to improve the sustainability of manufacturing processes.

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CHAPTER 1: INTRODUCTION

This chapter aims to introduce the research field of this thesis. It will firstly describe the background and motivation that prompted this research, including the challenges and requirements of environmental impact to be faced in the manufacturing domain. A summarised review of current sustainable manufacturing research will be analysed to define the research questions. Based on the research questions, the research aim and objectives will be set to further explain the tasks of this thesis and to identify the scope and potential contributions which could be made by this research. The research methodology will then be discussed to explain the plan on how to answer the research questions. Finally, the structure of this thesis will be outlined.

1.1 Motivation: Energy Issues in Manufacturing Industry

The motivation of this research is to reduce the environmental impact caused by high energy demand and consumption on the manufacturing process.

Manufacturing is playing an extremely important role in national economic development. The rapid development of manufacturing demands a large amount of energy and resources which placed huge environmental and economic burden. Energy consumption was selected to be the investigation objective because of the increasing demand of energy and the greenhouse gas emissions. From manufacturing enterprises' point of view, large energy consumption will also cause extra economic burden.

The earliest research relating to the limitations of natural resources can be traced back to the 1970s, when Meadows et al. (1972) published a report named "The Limits to Growth". In this report, the Club of Rome predicted that natural resources are going to run low due to the exponential increase of the world's population. According to the research of the International Energy Agency (2009), the total energy demand in 2030 will increase to 19,000 million tonnes of oil equivalent (Mtoe), which is 270% more than the energy demand in 1980 (7,000 Mtoe), and 80% of energy will be generated from non-renewable fossil fuels (see Figure 1.1). The impact of this high energy demand is not sustainable due to environmental reasons (such as climate change, carbon dioxide emission), economic reasons (such as increasing energy prices) and social awareness. The increase in energy consumption and energy prices has become a global problem for both developed and developing countries which is still not being properly solved.

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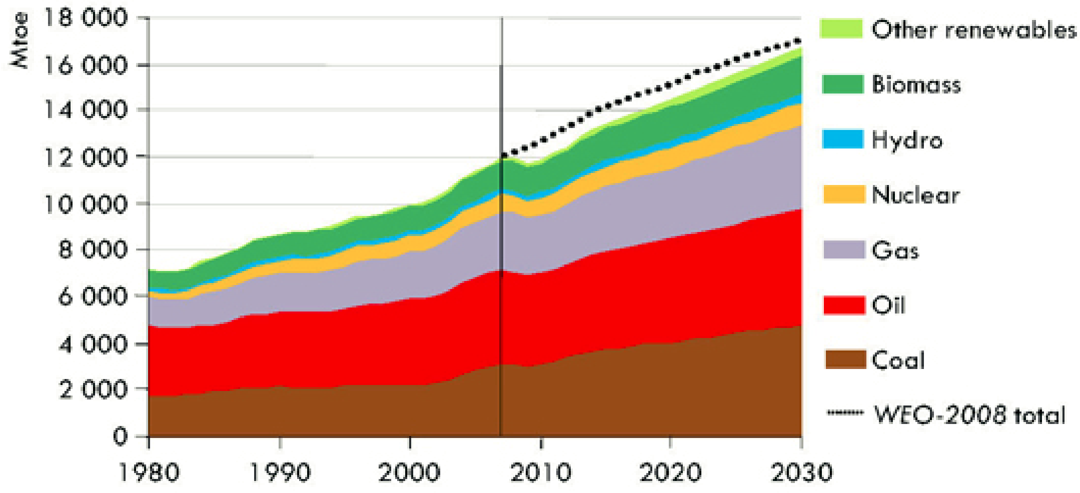

Figure 1.1 World Primary Energy Demand by Fuel (IEA, 2009)

For developed countries, such as the United Kingdom (UK), although the total amount of electricity consumption has not significantly changed in the last decade, energy prices have risen rapidly. Compared to 2002, industrial coal and gas, which are the major electricity generation fuels, increased prices in 2012 by 54% and 122% respectively. In 2012, electricity prices were 94% higher than in 2002. Since 2001, the UK government started to charge Climate Change Levy (CCL) and the rate started to rise annually in line with inflation from 2007 (UK Department of Energy & Climate Change, 2013). This rise in industrial electricity prices also happened in other EU15 and G7 countries, such as Japan and Germany (shown in Figure 1.2, additional data can be found in the Appendix).

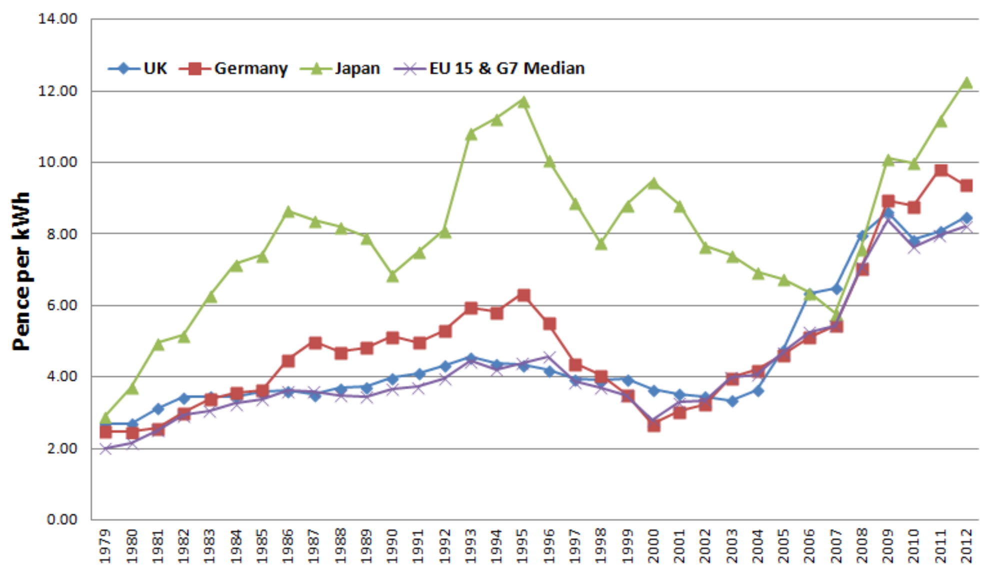

Figure 1.2 Industrial Energy Price for Developed Countries (UK Department of Energy & Climate Change, 2013)

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For developing countries, such as China, who are playing the role of the "Workshop of the world", the energy consumption for industry and manufacturing accounts for over 70% of total energy consumption and has increased rapidly and continuously in the past decade. The energy consumption of industry increased 140% in 2011 compared to 2002 (see Figure 1.3).

Meanwhile, the increase in energy consumption is not the only problem experienced in developing countries, the electricity supplied in developing countries is much worse in fuel type and energy use efficiency than those in developed countries, so more damage will be created in the global environment. The composition of energy production in China in 2010 showed that over 90% of energy was generated from non-renewable natural sources. In addition, electricity generation efficiency was only 42.43%. This inevitably will cause the problem that the carbon intensity of electricity production in China is much higher than developed countries (see Figure 1.4).

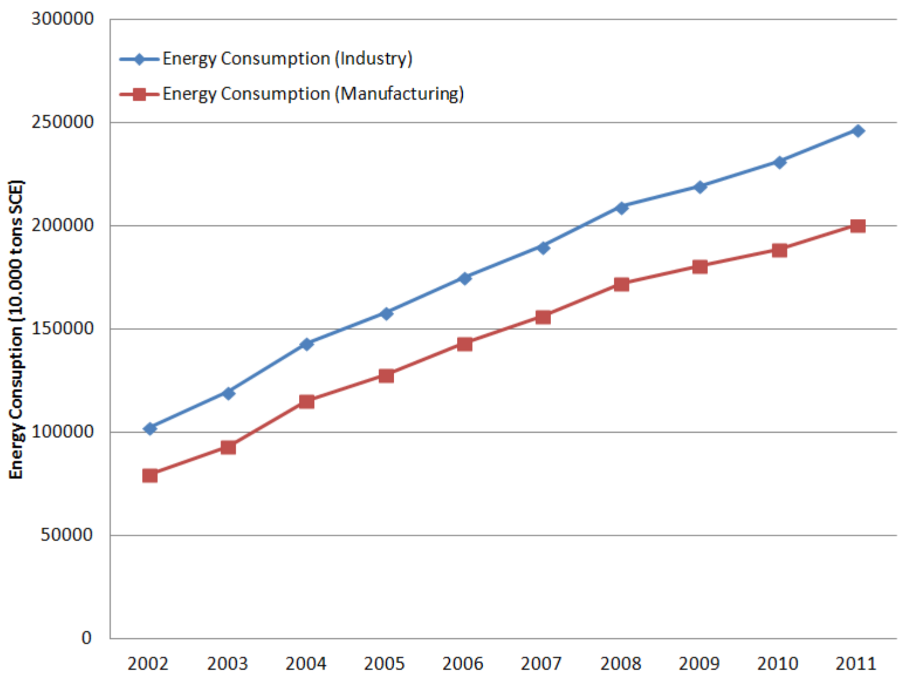

Figure 1.3 Energy consumption of industry and manufacturing in China, 2002 to 2011 (National Bureau of Statistics of China, 2011)

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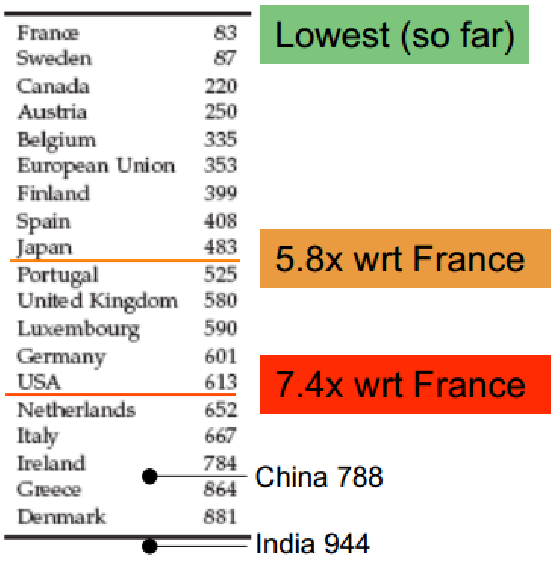

Unit: gCO2/kWh of electricity or 0.001 MTon/MWh

Figure 1.4 Carbon intensity of electricity production (Dornfeld, 2010)

These issues, focussed on energy consumption in manufacturing industry, provide motivations for conducting this research, specifically looking at developing methodologies, technologies, knowledge and tools to evaluate and improve the sustainability performance of manufacturing processes.

1.2 Activities and Issues in Energy-efficient Manufacturing

Traditionally, manufacturing organisations have attempted to produce products of higher quality at lower cost in shorter time scales. The increasing pressures from environmental considerations and cost of energy bring the new requirements and challenges for companies seeking new operating strategies to remain competitive and create more profit.

As part of the field of environmentally-friendly management, the minimisation of energy consumption in manufacturing applications is a complex research subject covering a wide range of manufacturing activities. In terms of the product life cycle, environmental impact can be reduced across the whole product life cycle at the stages of product design, manufacturing, distribution/logistics, product use and product end of life. In addition, from the perspective of the organisation of the system, environmental impact can be considered at multiple levels, such as factory, department, production line, work cell, machine tool, discrete part, manufacturing feature and unit operation/process level (Duflou et al., 2012, Deshpande et al. 2011a, 2011b).

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A lot of research has already been conducted to address the problem of energy consumption at different levels of an organisation by many research groups such as the Laboratory for Manufacturing and Sustainability (UC Berkeley, US), the Centre for Sustainable Manufacturing and Recycling Technologies (Loughborough University, UK), the Joint German-Australian Research Group (TU Braunschweig, Germany, University of New South Wales, Australia) and the Institute for Sustainable Manufacturing (University of Kentucky, US). From their work, three issues have been identified as part of a grand challenge for energy-efficient manufacturing:

- The development of performance measures for sustainable manufacturing;
- The improvement of performance in sustainable manufacturing through the optimisation of existing processes and technologies; and
- The improvement of performance in sustainable manufacturing through the development of new processes and technologies.

1.2.1 Research Activities and Issues Relating to Performance Measures for Sustainable Manufacturing

The aim of the research described in section 1.2.1 is to develop prediction models to evaluate the energy performance of manufacturing processes. Although some energy audit models and energy-efficient metric have been proposed to help measure and evaluate the energy usage, these models and metrics still have some identifiable limitations.

Firstly, most of the models proposed are empirical models which lack scientific explanations. Some are too simple and not informative enough and relate only to the material removal rate (e.g. Gutowski et al., 2006), these models cannot be widely applied in other machining systems.

Secondly, most of the proposed informative models are for turning operations only (e.g. Rajemi et al, 2010). It is difficult to find a reliable model to calculate the energy consumption for milled or freeform features.

Thirdly, the definition of energy efficiency has problems and can cause bias. According to the existing energy efficiency definition, some advanced machine tools have worse energy efficiency than manual machines because auxiliary functions cost more energy (Kordonowy, 2001). In addition, even if auxiliary energy consumption can be reduced

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to zero and all of the energy is consumed by machining operations. This does not mean that the efficiency is 100%.

1.2.2 Research Activities and Issues Relating to the Improvement of Performance in Sustainable Manufacturing through Optimisation of Existing Machining Processes and Technology

Environmental challenges, such as energy considerations, provide new challenges in applying the results of optimisation and process planning research. However, as identified by Roy et al. (2008), most academic optimisation results have not been used by industry because practitioners mostly prefer to select optimal parameters based on expert experience. The reasoning behind practices on optimisation is not clear and needs to be uncovered.

In addition, there are also some issues in the multi-objective optimisation results. Most of the multi-objective machining optimisation research into energy considerations reviewed only used *priori* techniques which will combine the objectives together based on decision makers' preferences (e.g. Sheng and Srinivasan, 1995). The optimal results achieved by using these methods are a unique optimal plan, but not a set of feasible solutions. It is, therefore, necessary to investigate the optimal solutions of multi-objective machining optimisation with energy considerations by using *posteriori* techniques.

In this context, it is important to develop a comprehensive method to achieve a sustainable manufacturing process by selecting optimal process parameters.

1.2.3 Research Activities and Issues relating to the Improvement of Performance in Sustainable Manufacturing through Development of New Machining Processes and Technologies

Instead of the improvement of current manufacturing processes, the aim of develop new energy-efficient machining strategies is to develop new concepts and machining strategies to minimise energy consumption for the machining operation. However, these strategies also have limitations and currently are still not able to replace conventional strategies. For example, most of these research contributions are related to the coolant strategies or using different cutting tools (e.g. Campatelli, 2009, Klocke et al., 2014 and Blau et al., 2014). Although these research contributions can reduce the energy consumptions, the inherent inefficiency of existing machining processes which is

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caused by the cutting technology, is still not properly solved. In this case, it is really important to develop a new energy-efficient strategy to further minimise the energy consumption and improve the energy efficiency of the existing cutting process. A new proposed energy-efficient strategy should also give direction to the research of new technologies for tool design, toolpath strategy and machining technology.

1.2.4 Summary of Research Activities in Sustainable Manufacturing

The summary of major researchers, and their research activities and contributions in sustainable manufacturing are listed in Table 1.1, and the details will be explained in the Chapter 2 Literature Review.

Table 1.1 Research Contributions in Sustainable Manufacturing

Major Researchers	Research Activities in Sustainable Manufacturing			Key Research Contributions
	Sustainability Measures	Machining Optimisation	New Strategies	
Dornfeld et al.	✓		✓	Energy prediction and energy-efficient toolpath strategy
Rahimifard et al.	✓			Measures of energy consumption and energy efficiency
Jawahir et al.		✓	✓	Machining optimisation and sustainable machining strategies
Rajemi and Mativenga	✓	✓		Energy prediction and minimisation by selecting optimal process parameters
Gutowski et al.	✓			Measures of energy consumption
Sheng et al.	✓		✓	Measures of overall sustainability performance and development of new process planning methods
Kara et al.	✓			Energy prediction
Herrmann et al.	✓			Measures of energy consumption and energy efficiency
Newman et al.	✓			Measures of energy consumptions and process improvement
Avram et al.		✓		Multi-criteria decision making method for sustainability improvement
Pusavec et al.			✓	New lubricant system
Mori et al.		✓		Energy minimisation
Blau et al.			✓	New lubricant system
Klocke et al.			✓	New coolant strategy
This Project	✓	✓	✓	

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1.3 Research Questions

This research is an attempt to answer the following main research questions:

What methods can be applied to obtain a sustainable manufacturing process by improving the energy efficiency in the machining operation?

The main research questions can be further divided into three aspects which correspond with the identified issues in section 1.2.

The research question of section 1.2.1 is:

- ***What method should be used to measure and evaluate the performance of energy use for the machining process?***

The research questions of section 1.2.2 are:

- ***What method should be used to optimise the energy consumption of machining operations based on a comprehensive understanding of how energy affects machining optimisation as an additional factor to traditional factors of cost, time and quality?***
- ***Which method is the most suitable optimisation method from varieties of options?***

The research question of section 1.2.3 is:

- ***What method should be used to reduce energy consumption for existing machining methods through applying energy-efficient strategies?***

1.4 Aim and Objectives

Based on the formulated research questions, the aim and objectives of this research can be clearly set as below.

The aim of this research is to provide systematic methods and tools to measure and evaluate the energy use performance, and reduce the energy consumption for machining operations thus to achieve sustainable manufacturing processes.

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The objectives of this research include:

- To identify the gap in current research contributions by conducting a comprehensive literature review on the topic of energy-efficient design and manufacturing to investigate the current research achievements and problems.
- The development of energy prediction models and energy efficient metrics which can be used to measure and evaluate energy consumption of machining process.
- The characterisation of machining operation with energy considerations will be investigated to provide a comprehensive understanding of the machining operation and uncover the interaction of different variables.
- The development of a numerical experimentation rig to investigate the reasoning behind the results obtained in applying typical optimisation methods. Optimisation procedures will be carried out to determine the optimal process parameters with energy considerations.
- Development of a scenario-based framework to solve machining optimisation problems especially when multiple objectives need to be considered.
- An energy efficient machining strategy, which is carried out based on optimisation of process parameters, will be proposed to further improve energy efficiency for $2^1/_2$D milled features.
- A comprehensive framework which integrates the above research findings will be developed for decision makers to improve sustainability performance of their manufacturing process.

1.5 Research Scope

The research scope of this thesis can be determined and presented in Figure 1.5. The detail of research scope is explained as below:

- Firstly, only unit process level energy which is the energy consumed during the machining process was considered in this thesis. The machining type only refers to conventional machining process. Other shape/feature forming methods like net shape manufacturing and 3D printing were not considered.

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- Secondly, only $2^1/_2$D milled features were considered in this research. But principles and developed research methodology can be extended to other features, workpiece material and machining operations.
- Thirdly, only optimisation is considered not multi-criteria decision making. The output of this research such as the characterisation of the machining operation and analysis of objectives will not directly give any decisions when multiple objectives need to be considered. But the output can be used as the suggestion and basis of understanding to help users to make the decision.

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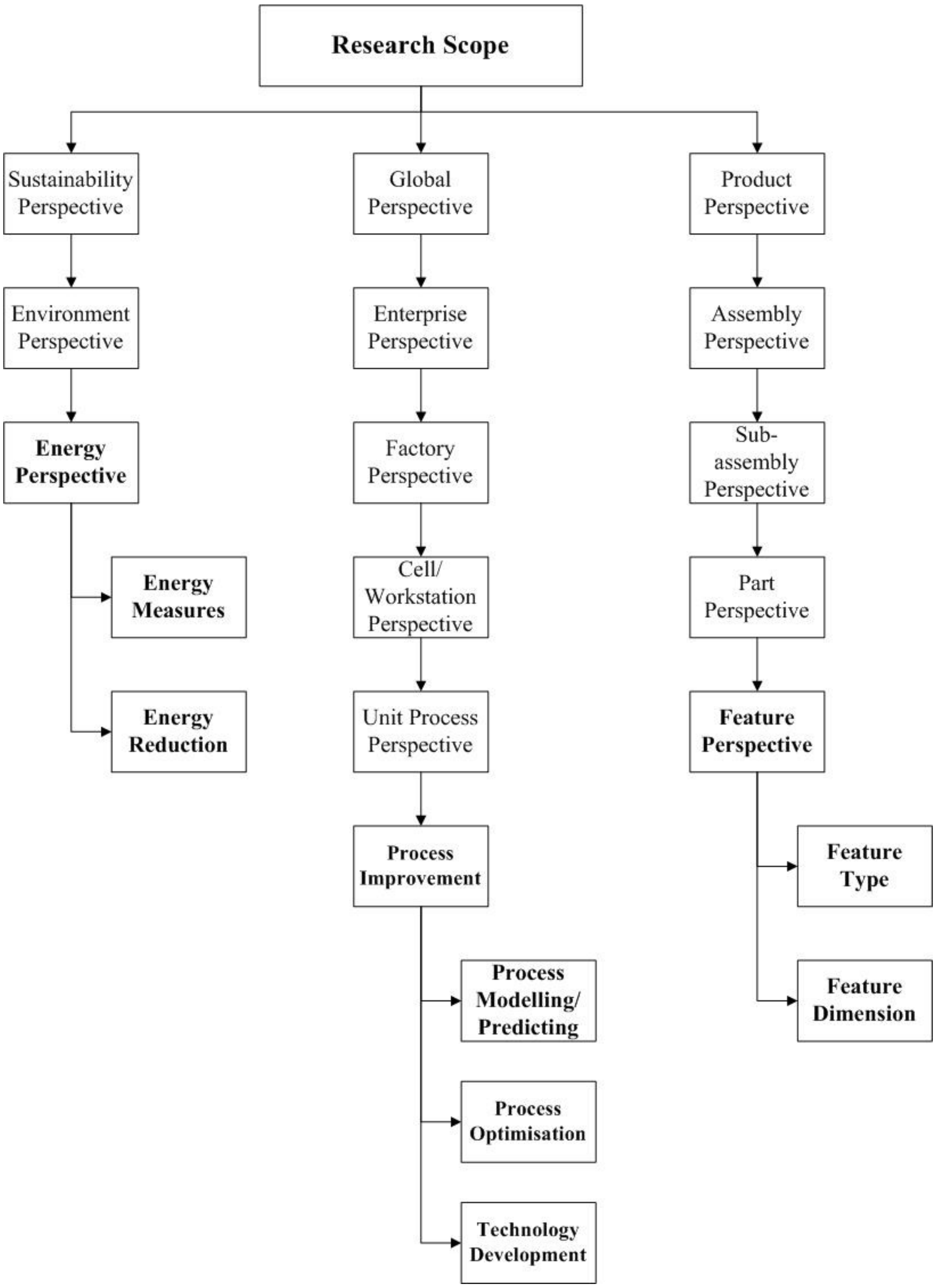

Figure 1.5 Research Scope of this Thesis

1.6 Research Methodology

The aim of this section is to design a scientific research methodology for carrying out the research based on the characteristic of the project. According to the nature of this research, which is exploratory and explanatory research including quantitative and qualitative analysis, a three-phase research methodology has been developed. Figure 1.6 shows the model used for the research methodology.

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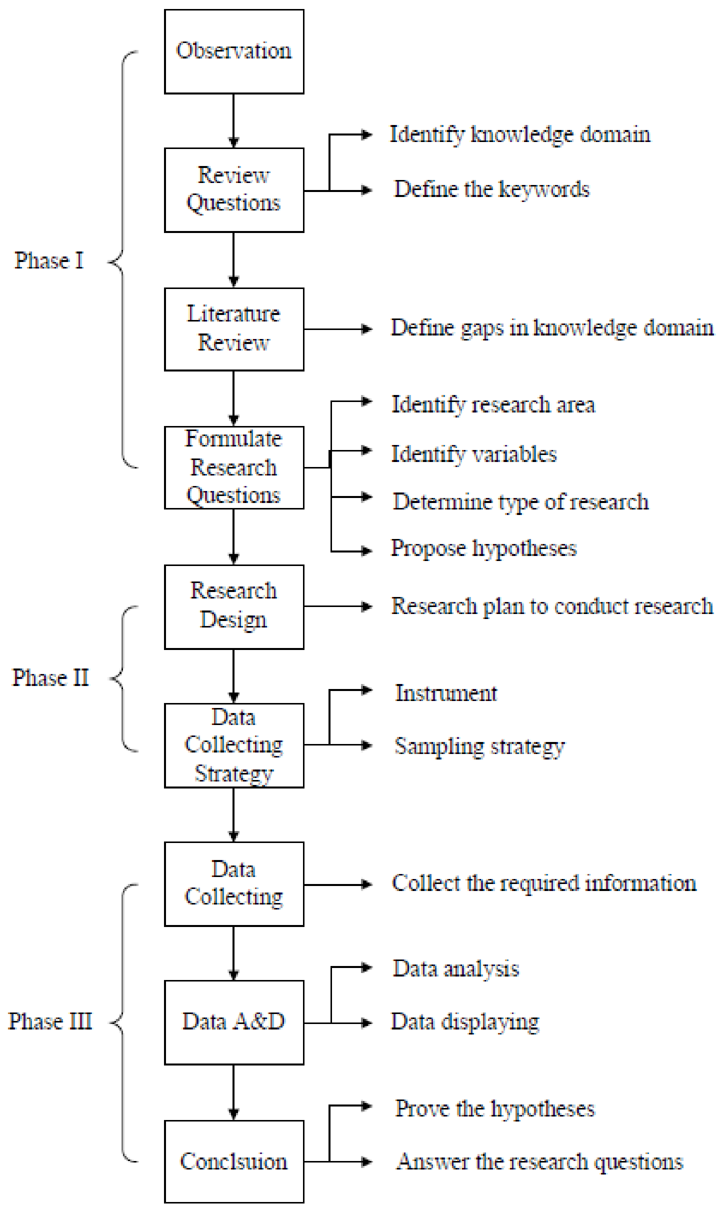

Figure 1.6 Developed Process of Research Methodology

Based on the developed steps in Figure 1.6, the methods of how the research questions will be answered can be presented. According to issues identified from literature review, the research can be divided into three stages. The following output will be delivered for each stage:

- Stage 1 Performance measures: new metrics for measuring energy consumption and energy efficiency.
- Stage 2 Optimisation of existing processes and technology: a comprehensive framework for selecting optimal process parameters with energy considerations.

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- Stage 3 development of new processes and technology: new energy-efficient machining strategy (a profiling toolpath strategy) was proposed based on end milling operation

The result of Stage 1 will be implemented to carry out the result in Stage 2, and the result achieved in Stage 2 will be the foundation of stage 3. The design of the thesis is listed as below:

Stage 1: Performance measures

The aim of this stage is to develop a reliable method to measure and predict the energy consumption performance of the machining operation system. The specific tasks include: mathematical modelling, design of energy efficiency metrics and experimental verification.

The metrics for measuring energy consumption and efficiency will be built based on existing machining science theories.

Physical experiments will be conducted to collect data (power consumption and cutting force) by using developed force and power measurement system on a CNC milling machine. The collected data will be used to determine cutting force coefficient, and then validate mathematical models. The developed prediction model and energy efficiency metrics will be used to conduct the following stages.

Stage 2: Improvement of performance in sustainable manufacturing through optimisation of existing processes and technology

The aim of this stage is to develop a comprehensive framework for selecting optimal process parameters with energy considerations. The specific tasks include: characterisation of machining operation by considering energy as an additional factor to the conventional criteria, investigate optimisation algorithms and provide an optimal solution for minimising energy consumption, develop solution scenarios for solving multiple-objective cases and design the optimisation framework.

Numerical experiments will be conducted by using MATLAB simulation based on the verified mathematical models to collect more data for carrying out the analysis.

Multivariate data analysis techniques such as contour plot, plot matrix and tabular method will be used to analyse the data.

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Typical machining optimisation methods (such as Taguchi method, Genetic Algorithm, Direct Search method and Ant Colony method) will be investigated and applied to conduct the optimisation procedures.

Stage 3: Improvement of performance in sustainable manufacturing through development of new processes and technology

The aim of this stage is to develop an energy-efficient machining strategy which can further reduce the energy consumption for machining operation. The specific tasks include: propose the new strategy, discuss implementing conditions (feature type and dimension) and carry out case study to show the improvement.

A profiling toolpath strategy will be proposed to get close to the theoretical limitation in energy consumption for achieving a feature.

1.7 Structure of Thesis

Chapter 2 - Literature Review: This chapter describes the relevant existing published research works in the research area of sustainable development, sustainable manufacturing and energy-efficient machining technologies and strategies.

Chapter 3 - Development of Predictive Models and Energy Efficiency Metrics for Machining Operation and the Experimental Verification: In this chapter, an energy prediction model will be built based on cutting force model. Experiments will be conducted to determine the coefficients and verify the energy prediction model. New energy efficiency metrics will be proposed to measure the energy use performance and identify the inefficiency of machining operation. Case studies for machining a particular feature will be carried out to discuss the results obtained by using the new proposed metrics.

Chapter 4 - Energy Characterisation and Minimisation by Selecting Optimal Process Parameters: In this chapter, energy consumption of machining operation will be characterised and investigated. A systematic research methodology will be proposed for uncovering the reasons behind results obtained when energy is considered in machining optimisation. An optimisation procedure will be conducted to show the improvement of energy consumption and energy efficiency by implementing optimal process parameters.

Chapter 5 - Multiple Objectives Optimisation for Sustainable Machining: In this chapter, a multiple objective optimisation method will be introduced as part of optimisation framework for machining optimisation by developing a problem-solution scenarios system.

Chapter 6 - Energy-efficient Cutting Strategy - A Profiling Toolpath Strategy for End Milling Operation: In this chapter, an energy-efficient profiling toolpath strategy will be proposed for forming $2^{1}/_{2}$D milled feature which can further reduce the energy consumption and improve the energy efficiency for machining process. Implementing conditions of different feature shapes will also be discussed.

Chapter 7 - Development of Framework for Machining Optimisation with Sustainability Consideration: In this chapter, a comprehensive framework which integrates the research findings in the previous chapters will be introduced to provide a systematic tool for decision makers to improve sustainability performance of their manufacturing process. Case studies will also be carried out to demonstrate how the proposed framework can be implemented.

Chapter 8 - Conclusion and Further Work: This chapter states the conclusion of current research achievements, limitations and problems. Further work plan is also outlined to address the current problems.

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CHAPTER 2: LITERATURE REVIEW

The aim of this chapter is to review currently published literature based on the identified issues in Chapter 1. This chapter will describe the key elements of the research including theoretical foundations, current research status and contributions. After a systematic review, the research gaps will be identified in order to lead the research directions, formulate research questions and define the research scope.

The aim of this research is to provide a systematic methodology for achieving a sustainable manufacturing process by minimising the energy consumption and improving the energy efficiency. Therefore, this review of literature seeks to identify gaps in the methods currently employed for measuring and minimising energy consumption. The scope of the literature review can be divided into four stages. Firstly, the literature review begins with the investigation of the general concepts relating to sustainable manufacturing and the identification of important energy consumption issues. The second stage focuses on the research output relating to how to measure energy consumption and efficiency at unit process level. The third stage focuses on the research on optimisation of process parameters with energy considerations including: optimisation methods, optimisation frameworks and energy related optimisation. The final stage will investigate the energy minimisation methods through development of new processes and technology. Gaps in above areas will be identified after the review.

Various sources and materials were used during this literature review, including academic reference books, published journals, conference papers, PhD theses and other research materials. The sources for searching literature include the University of Greenwich library electronic catalogue and e-library on-line databases, including Elsevier Science Direct, Compendex and Springer Link. Other Internet resources (e.g. Google Scholar) and library catalogue (British Library) were also used. The key areas for this literature review in this thesis include:

- Sustainable manufacturing
- Energy efficient machining and manufacturing
- Machining optimisation

2.1 Concepts of Sustainable Manufacturing

Sustainable development has become an important approach to address the challenges from economic development, environmental protection and social development. The

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concerns of environmental development have emerged since early 1980's in response to the increased awareness and concern over the environmental impact of economic growth and global expansion of business and trade.

The term sustainability was first defined in the Brundtland report, which stated: "Sustainable development meets the needs of the present without compromising the abilities of future generations to meet their own needs" (Alting and Jorgensen, 1993). The meaning of Sustainable Life Cycle Management (LCM)/ Life Cycle Assessment (LCA) is to reduce the environmental impact throughout the product life cycle. Current industrial production and consumption have undergone experienced changes, such as: an increase in manufacturer responsibility, pollution and waste problems and non-renewable resource issues. Based on this general concept, the research for achieving sustainability can be conducted from different points of view (Alting and Legarth, 1995, Alting, 1996, Westkämper et al., 2001).

The development of assessment methods for the impact on the environment has been a concern of sustainability. Researchers have developed different methods based on their investigations which are mainly using two procedures: Environment Impact Assessment (EIA) to evaluate planned projects (e.g. technological process) and Life Cycle Assessment (LCA). Five profiles were considered to assess the environmental impact including: raw material, energy, waste, product, and packaging (Fijal, 2007). The effect on the resource and energy efficiency of production was considered by both academic and industrial researchers to minimise the cost and environmental impact (Dimitroff-Regatschnig and Schnitzer, 1998).

The research area of sustainable manufacturing, which aims to address environmental problems, has become a necessary and important part of the manufacturing process. Sustainable manufacturing calls for the design and manufacture of the product life cycle for minimum environmental impact and maximum resource utilisation. Sustainable manufacturing is part of sustainable development (Leahu-Aluas, 2010). At the 1992 U.N. Conference on Environment and Development (UNCED, 1992) held in Rio de Janeiro, sustainable production was introduced and adopted for the transition towards and achieving sustainable development. As sustainability is becoming an expected business practice by both large and small companies, sustainable manufacturing is defined as developed and implemented by manufacturing companies and their networks of suppliers and customers. The US Department of Commerce (DOC) adapted the

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definition of sustainable manufacturing as "the creation of manufacturing products that use materials and processes that minimise negative environmental impacts, conserve energy and natural resources, are safe for employees, communities, and consumers and are economically sound" (Trade, 2010).

Researchers at the University of Kentucky described sustainable manufacturing as the 6R approach at product-level. 6R is short for remanufacturing, redesign, recover, recycle, reuse and reduce, which is shown in Figure 2.1. In view of sustainable production technologies, there are some methods which improve sustainability performance, including: reduce machining processes energy consumption, minimise waste generation (e.g. generate less waste, increase the reusage or recycling waste), effectively use resources, use recyclable materials or reuse machine-tool components at the end of life-cycle, improve the cooling lubrication fluids (CLF) strategy, and adopt LCA methods. The main natural resources of concern in production technologies are material, coolant/lubrication, water and energy (Jawahir, 2007, Pusavec et al., 2010a & 2010b, Kopac, 2009, Jayal et al., 2010).

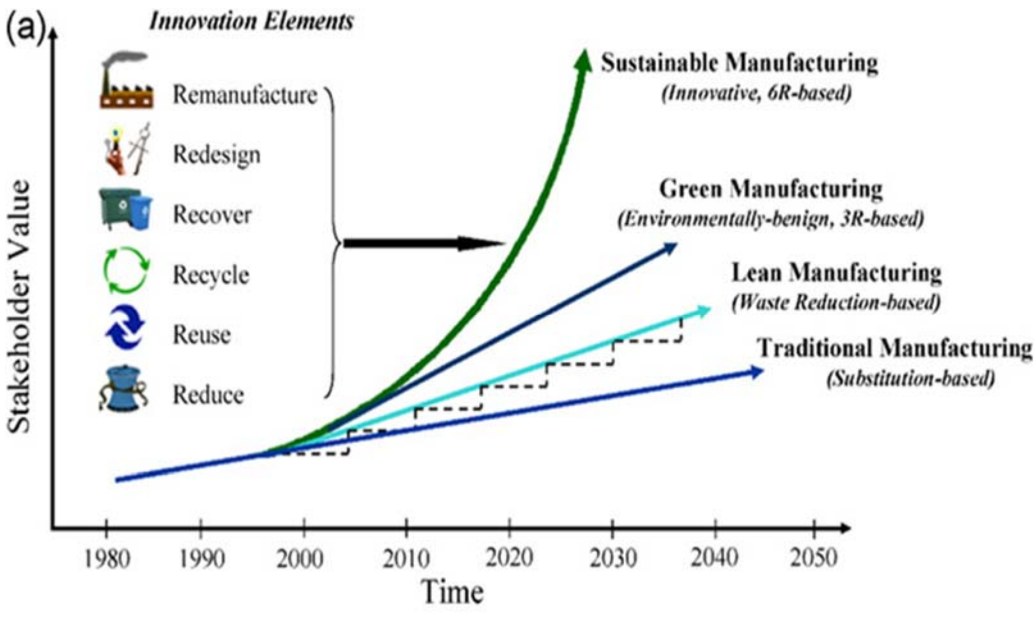

Figure 2.1 Sustainable Directed Production (Jawahir, 2007)

World Technology (WTEC) Division organised a study panel and have started to conduct research relating to Environmentally Benign Manufacturing (EBM) since 2000. The aim of their research is to investigate and develop new methods and technologies to reduce the environmental impact and maximise the benefits to industry. Manufacturing can be considered as an open system which is consisted with the flows of various

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resources, products, waste and pollution. By taking the system view of manufacturing and the track of Product Life Cycle (PLC), the manufacturing system can be divided into four stages: raw materials production, manufacturing, use phase and end-of-life phase; this is shown as a closed system in Figure 2.2 (Gutowski et al., 2001, Krishnan et al., 2009).

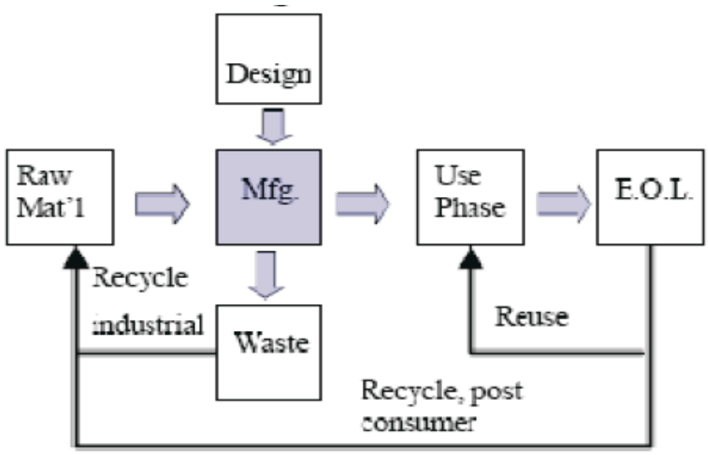

Figure 2.2 Manufacturing and Product Life Cycle (Gutowski, 2001)

The machining process is a major manufacturing process which involves a number of sustainable factors and has significant potential for reducing environmental impact. Three elements are involved in the machining process, including material, cutting or machining tool, and cutting fluid.

Research contributions in energy consumption for machining operations can be mainly divided into two scenarios. One scenario is at the machine tool system level where research mainly focuses on the energy measurement and energy efficiency for the machining tool. The second scenario is the machining process and operation level which focuses on the impact of process planning on energy consumption. The concept of the Machine Tool System (MTS) is considered as traditional machines endowed with numerical control part and able to conduct different types of mechanical work on different faces of the same work-piece. The MTS must have two basic functions which are machining function (material removal function) and the auxiliary function (support/control function). Many research contributions have been conducted to investigate the energy consumption of each section, and develop new methods and strategies based on different sections (e.g. machining operation, process parameter, cutting tool and tool-path strategy etc.) to reduce the energy consumption.

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Duflou et al. (2012) summarised the potential energy improvement aspects at unit process level. One aspect is to develop methodologies for determination/measurement of energy usage performance. The specific tasks include develop equations or prediction models to determine the theoretical minimal energy requirement and calculate the energy consumption, and develop metrics for identifying potential inefficiency, suggesting the improvement direction and comparing the performances of external benchmarking. The other aspect is to develop new machining strategies to reduce energy consumption during machining activities. From machine tool manufacturers' points of view, implementation of energy-efficient machine tool components (e.g. drivers, pump, spindle etc.) can effectively reduce the energy usage. However, it does not mean the real energy efficiency for the process can be improved. The other direction for reducing energy consumption for machining process is the optimisation of process control. It can be realised by optimising the planning of existing process (e.g. optimise process parameters) and by designing new processes/technologies (e.g. change coolant type, change cutting strategies, select efficient machine tool and cutters).

2.1.1 International Standards of Environmental and Energy Management

Cascio et al. (1996) developed an overall framework of the environmental management as the ISO 14000 family of standards (see Figure 2.3). It specifies the requirements for the establishment of an energy management system from organisation and product aspects.

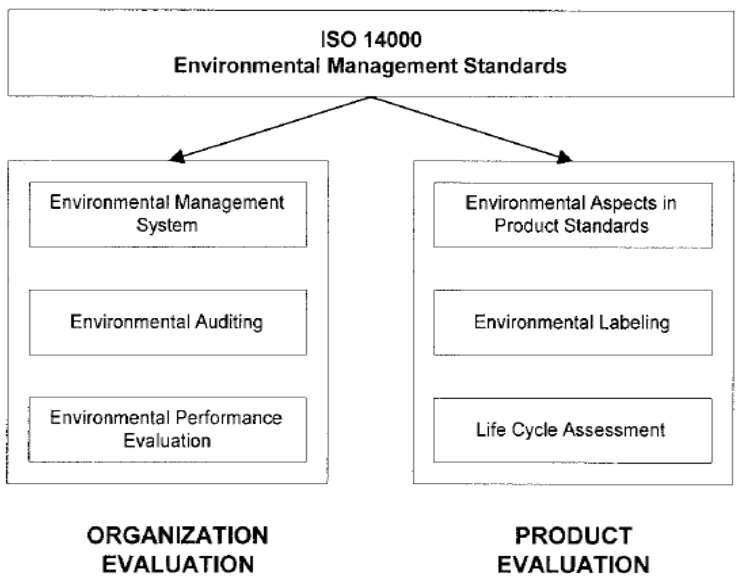

Figure 2.3 ISO 14000 Family of Standards for Environmental Management (Cascio et al., 1996)

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ISO 14000 series standards are designed to provide management tools for company/organisations to manage, improve and assess environmental performance. For environmental and economic benefits, it can be implemented by following a PLAN-DO-CHECK-ACT (PDCA) cycle (ISO, 2009).

A new environmental standard ISO 14955 was introduced by Newman et al. (2012) (Environmental evaluation of machine tools) is currently being developed by ISO/TC 39/WG 12 to improve energy efficiency by implementing unified methods for measuring, evaluating and reducing energy consumption. Upcoming standard ISO 14955 consists of four major parts which are:

- ISO 14955-1: 2014 Eco-design methodology for machine tools (has already been published).
- ISO 14955-2: Methods of testing of energy consumption of machine tools and functional modules.
- ISO 14955-3: Test pieces/test procedures and parameters for energy consumption on metal cutting machine tools.
- ISO 14955-4: Test pieces/test procedures and parameters for energy consumption on metal forming machine tools.

Specific to general energy management, new ISO standard, ISO 50001:2011 (Energy management systems - Requirements with guidance for use) was released by ISO in June 2011 after the ISO 9001 (Quality Management System) and ISO 14001 (Environmental Management System). The aim of ISO 50001 is to provide management strategies to public and private sector organisations to improve energy performance (including energy efficiency, use, and consumption) and reduce costs (ISO, 2011). Implementation of ISO 50001 also followed a PDCA approach (see Figure 2.4).

The steps of the PDCA cycle of ISO 50001 can be briefly described as follows:

Plan: establishing targets and action plans.

Do: implementing established plans and undertaking improvement measures.

Check: monitoring and reviewing the established targets (e.g. energy performance), and collecting new suggestions via energy audits.

Act: evaluating the current energy performance, and then establishing new strategies and optimisation process to further improve the energy performance.

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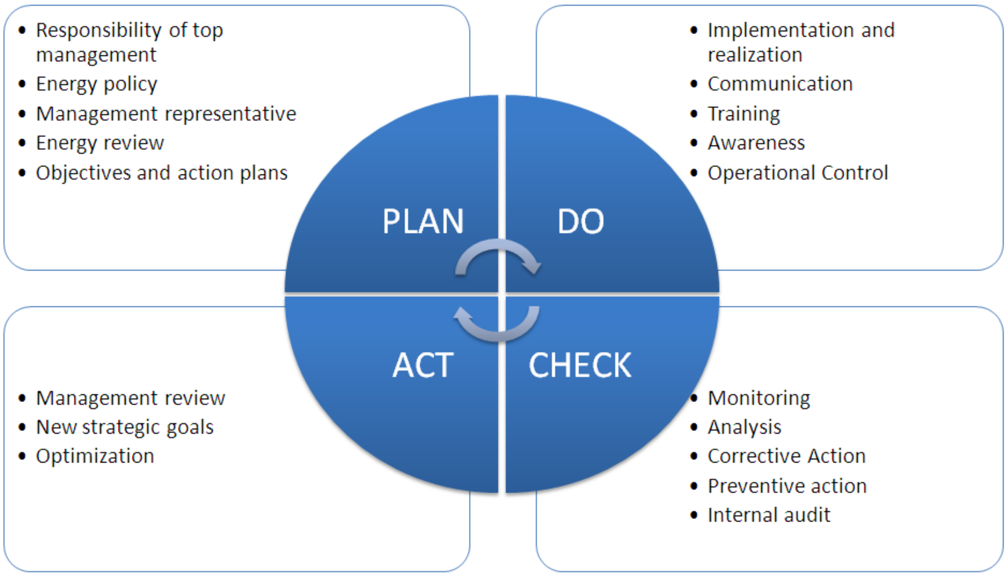

Figure 2.4 The Four Phases of the PDCA Circle for Implementing ISO 50001 (ISO, 2011)

Nowadays, ISO 50001 has been applied to guide the manufacturing process in some EU countries (e.g. Germany). Apart from the direct saving though the reduction of energy consumption, companies who have ISO 50001 certificate can also have reduction in Renewable Energies Act (Erneuerbare-Energien-Gesetz, EEG) (Kahlenborn et al., 2012).

2.2 Cutting Force Models

To mathematically build the energy or power consumption model for machining operation, cutting force models were investigated. The cutting force is considered as one of the main performance estimators during the machining process. Research into the cutting force is a typical topic in machining which has been conducted over ten decades. The effects of the cutting force include: extreme conditions in the machining process, determining the spindle power requirements and bearings loads, causing the deflection of the part, tool or machining structure, and the energy transfer in the machining system.

Figure 2.5 shows the process parameters of the end milling operation. Where, ap is depth of cut, ae is width of cut, n is spindle speed, fz is feed rate per tooth, Vf is feed rate and Vc is cutting speed.

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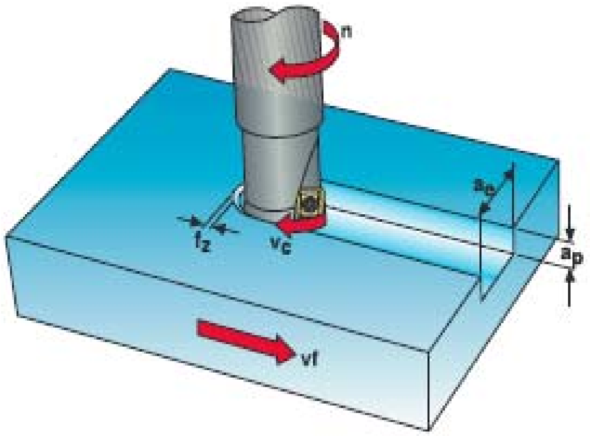

Figure 2.5 Process Parameters of End Milling Operation (SECO Tools, 2012)

2.2.1 Investigation of Cutting Force Models

Many different cutting force models have been suggested by a number of authors throughout the 20th century. At the beginning of the century, a model was proposed as a direct relation between cutting forces and the chip cross sectional area (Kronenberg 1966, Ehmann et al. 1997, Waldorf et al. 1998) such that:

$$F_C = K_s \cdot A \tag{2.1}$$

Where, K_s is specific cutting pressure, A is the area cross sectional area of the undeformed chip, F_C is the force acting at the cutting speed direction (tangential force). This model considered that the relationship between force and area is linear.

However, it was found that K_s is not a constant, but a function of process parameters (e.g. chip thickness and tool rake angle). Kronenberg (1966) introduced a more accurate method to calculate K_s.

$$K_s = K_s^{'} \cdot h^{-c} \tag{2.2}$$

where $K_s^{'}$ and *c* are coefficients and *h* is chip thickness.

The milling operation has its characteristics such as variation on the undeformed chip thickness and interrupted cut. The cutting force model of milling is different from cutting force models of the other machining operations. A model considering the chip thickness and depth of cut is accepted and widely used by current researchers to predict cutting force (Martelotti, 1941, Altintas and Yellowley, 1989, Tlusty, 2000, Lai, 2000, Coelho et al. 2003).

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$$F_T = K_S \cdot a_p \cdot h(\phi) \tag{2.3}$$

$$h(\phi) = f_z \, sin \, \phi \tag{2.4}$$

$$F_R = r \cdot F_T \tag{2.5}$$

where F_T is tangential force, F_R is radial force, a_p is axial depth of cut, $h(\phi)$ is instantaneous value of chip thickness, f_z is feed per tooth, and ϕ is rotational angle which is related to diameter of tool and width of cut. According to the total force Equation 2.6

$$F_x^2 + F_y^2 = F_T^2 + F_R^2 \tag{2.6}$$

The force for conventional up-milling in the X and Y directions can be given as Equation 2.7.

$$\begin{cases} F_x(\phi) = F_T \, cos \, \phi + F_R \, sin \, \phi \\ F_y(\phi) = F_R \, cos \, \phi - F_T \, sin \, \phi \end{cases} \tag{2.7}$$

The rotational force model can be further developed in three dimension spaces, which consider the Z direction and is shown in Equation 2.8 (Zaman et al., 2006).

$$\begin{cases} F_T = K_T \cdot a_p \cdot h(\phi) \\ F_R = K_R \cdot a_p \cdot h(\phi) \\ F_a = K_a \cdot a_p \cdot h(\phi) \end{cases} \tag{2.8}$$

where F_a is the axial force.

Among these cutting forces components, the tangential force which is also called the main cutting force is considered to contribute most of the power consumption. In this case, the value of the tangential force is used in the theoretical calculation of machining operation energy consumption. The instantaneous tangential force can be generated as in Equation 2.9.

$$dF_T = K_T \cdot a_p \cdot f_z \cdot \sin d\phi \tag{2.9}$$

where F_T is tangential force N, K_T is cutting force coefficient $\mathrm{N/mm^2}$, a_p is depth of cut, f_z is feed per tooth mm/tooth, ϕ is tool rotated angle (after the width of cut is completely engaged to the material), and f_z is related to feed rate, number of teeth and spindle speed. ϕ is rotational angle which is related to the width of cut and diameter of the tool. The relationships are shown as equation 2.10 and 2.11.

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$$f_z = \frac{f}{n \cdot z} \tag{2.10}$$

$$\phi = \phi_{out} - \phi_{in} = \cos^{-1}\left(\frac{d - 2a_e}{d}\right) \tag{2.11}$$

where f is feed rate mm/min, n is spindle speed rpm, d is diameter of tool mm, a_e is width of cut mm, and z is number of cutting flutes for milling cutters. Based on these equations, tangential force in end milling operation is related to depth of cut, width of cut, diameter of tool, workpiece material, feed rate, spindle speed and number of flutes. The instantaneous tangential force can be integrated as in Equation 2.12.

$$F_T = \int_{\phi_{in}}^{\phi_{out}} K_T \cdot a_p \cdot \frac{f}{nz} \cdot \sin\phi \, d\phi \tag{2.12}$$

$$F_T = K_T \cdot a_p \cdot \frac{f}{nz} \cdot (\cos\phi_{in} - \cos\phi_{out})$$

Based on equation 2.12, when the tool is fully engaged in the material such that $\phi_{in} = 0$, the tangential force of milling can be represented in Equation 2.13.

$$F_T = K_T \cdot a_p \cdot \frac{f}{nz} \cdot \left(1 - \frac{d-2a_e}{d}\right) \tag{2.13}$$

$$F_T = \frac{2K_T \cdot a_p \cdot f \cdot a_e}{nzd}$$

Equation 2.13 can be further simplified and represented in Equation 2.15 (Tlusty, 2000).

$$MRR = a_p \cdot a_e \cdot f \tag{2.14}$$

$$F_T = \frac{2K_T \cdot MRR}{nzd} \tag{2.15}$$

where, K_T is cutting force coefficient, N/mm^2. Based on the cutting force Equation 2.15, the tangential force is in proportion to depth of cut, width of cut and feed rate, and in reverse proportion to spindle speed and number of teeth.

In addition to conventional cutting force models, there are also a lot of research contributions used numerical modelling methods to predict cutting force for machining operations (Ozel and Althan, 2000, Saffar et al., 2008, Jin and Altintas, 2012). One of most common methods is Finite Element Modelling method. The goal of finite element method is to analyse and simulate machining process by considering the deformations, stress and strains in the workpiece and the load on the cutting tool under the specific

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machining process parameters. Usually, 2D/3D models of machining operation will be created by using existing commercial FEA software (e.g. DEForm and Abaqus), and the cutting force will be automatically simulated after defined the criterions in material mechanical properties, frictions on chip-tool interface and so on. Three approaches are used for meshing the finite element model which are Lagrangian, Eulerian and Arbitrary Lagrangian Eulerian (Arrozola et al., 2013, Mackerle, 1999).

The accuracy of the finite element analysis is related to the accuracy of the material mechanical properties, such as flow stress. The mostly accepted material constitutive model was introduced by Johnson and Cook (1983) and shown in Equation 2.16.

$$\sigma = (A + B\varepsilon^n)\left(1 + C\ln\frac{\dot{\varepsilon}}{\dot{\varepsilon_0}}\right)\left[1 - \left(\frac{T-T_r}{T_m-T_r}\right)^m\right] \qquad (2.16)$$

where, σ is the equivalent flow stress, MPa or N/mm^2, ε is the equivalent plastic strain, $\dot{\varepsilon}$ is equivalent plastic strain rate, s^{-1}, $\dot{\varepsilon_0}$ is the reference equivalent plastic strain, T is the workpiece temperature, ℃, T_r is the room temperature, ℃, T_m is the material melting temperature, ℃, A is yield strength of the material, MPa, B is strain hardening modulus, MPa, C is strain rate sensitivity, m is thermal softening coefficient, and n is hardening coefficient.

The friction on the chip-tool interface can be represented by Equation 2.17.

$$\mathrm{m} = \frac{\tau}{k} \qquad (2.17)$$

where, m is shear friction factor, τ is friction shear stress, k is workpiece material flow stress.

However, the problem for implementing finite element modelling is that there are too many variables, such as temperatures, need to be considered. In addition, the implementation of FEA modelling method also requires operators to have a very good knowledge in metal cutting theory. Compared to conventional modelling method, it requires more complex validation process and time, and is not easy to be implemented in practice. Meanwhile, the accuracy of the model and simulation depends on the algorithms of the software. In this case, in this thesis conventional cutting force modelling method will be selected to predict cutting force and build energy prediction models.

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2.2.2 Investigation of Cutting Force Coefficient

The cutting force coefficient is one of the key components of the cutting force model. Early researchers considered the value of the coefficient to be approximately a constant for different materials, as was explained in section 2.1.1. The unit of cutting force coefficient is N/mm^2 or $W \cdot sec/cm^3$. Tlusty (2000) provided constant values of cutting force coefficients for different workpiece materials which are shown in Table 2.1.

Table 2.1: Cutting Coefficients of Common Workpiece Materials (Tlusy, 2000)

Material	K_S
Grey cast iron HBN 200	1500
Carbon steel 1020 N	2100
Carbon Steel 1035	2300
Carbon Steel 1045	2600
Stainless steel 302	2700
Alloy steel 4140/5140	2800
Al 7075-T6	850

However, the accuracy of this model has always been questioned in that the cutting coefficient is not a constant even for the same workpiece material. Based on Equation 2.8, some researchers (Wan et al., 2010, Dang et al., 2010) have conducted experiments to determine the values of cutting force coefficients for the end milling operation (see Figure 2.6).

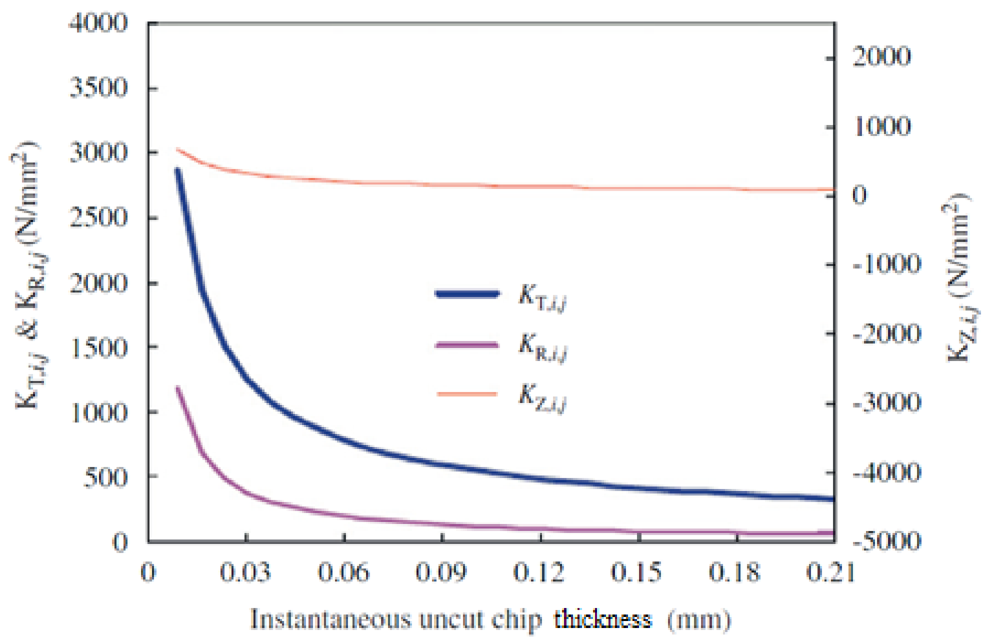

Figure 2.6 Cutting Force Coefficients (Wan et al., 2010)

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From Figure 2.6, it can be found that the cutting force coefficient *Kz* for axial force is close to zero which means the axial force in end milling operation is also close to zero. The coefficient of tangential and radial directions can change significantly (e.g. K_T is from 3000 to 400). However, when the uncut chip thickness is changed from 0.03mm to 0.21mm, the trend of tangential and radial coefficient flattens (e.g. K_T is from 1000 to 500). It means the cutting force co-efficient can be considered as a constant in particular range of the uncut chip thickness or can be chosen by building up co-efficient data based on uncut chip thickness. However, the value of cutting force coefficient may also be affected by other factors like different machine tools, different cutting tools (e.g. type and material), temperature, cutting fluid and lubrication strategies, and still need to be further investigated.

To accurately predict cutting force, the cutting force coefficient K_T can be considered as a function of process parameters and generated by using a regression method based on experimental measurement. The mathematical expressions of the cutting force and the cutting force coefficient are shown in Equations 2.18 and 2.19.

$$K_T = f(a_p, a_e, d, z, f_z, n) = C_0 \cdot a_p^{C_1} \cdot a_e^{C_2} \cdot d^{C_3} \cdot z^{C_4} \cdot f_z^{\ C_5} \cdot n^{C_6} \tag{2.18}$$

$$F_T = 2C_0 \cdot a_p^{C_1} \cdot a_e^{C_2} \cdot d^{C_3} \cdot z^{C_4} \cdot f_z^{\ C_5} \cdot n^{C_6} \cdot a_p \cdot f_z \cdot a_e/(nzd) \tag{2.19}$$

where, C_0 to C_6 are cutting force constants which are determined by the experimental values of force or power.

2.2.4 Summary of Cutting Force Modelling

This section introduced the modelling method for predicting the tangential cutting force for end milling operation. The modelling method in this section has been developed based on machining theory which is related to the workpiece material and the machining process parameters. However, this model still has some limitations. As a very complex process, there are too many variables involved during the machining process and some of them are still not quantitatively determined by the current machining science research. So the modelling methods of cutting force have different complexities. Ideally, the more complex the model is and the more variables are considered, the more accurate the model will be. However, as a consequence, the increasing complexity will bring the problems of flexibility and validity which means the proposed model can only be used under particular conditions (e.g. specific

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machining tools, machining cutters and workpiece materials) and mean that it is very difficult to verify. Also the improvement of accuracy may be very small and not necessary in the practical machining processes.

2.3 Measurement of Energy Consumption and Energy Efficiency

In the early stages of machining research, energy consumption was not considered as a unique objective and always represented as power consumption. However, the power consumption is not able to directly reflect the energy consumption of the machining process. With the increasing demand for environmental awareness, quantitatively predicting energy consumed during machining operation has become necessary for academic researchers and practitioners.

2.3.1 Measurement of Energy Consumption for Machining Process

One of the earliest pieces of research which reported the issues of energy efficiency in numerically controlled machine tools was carried out by Filippi et al. (1981). They conducted experiments to collect the data on the power consumption of ten different machine tools in various operations. Based on their experimental results, the energy efficiencies (mean power over installed power) of tested machine tools were almost all less than 50% and the productive time only accounted for 60% of the available time. This finding identified the potential to improve the energy efficiency of machine tool by designing advanced multi-functional machine tools. They also suggested that it is necessary to set up a power/energy measurement device on the machine tool in order to help to avoid the high power usage.

The earliest research which clearly identified issues of environmental impact at machining process level was conducted by the researchers from the Consortium on Green Design and Manufacturing (CGDM), University of California at Berkeley in 1990s. Munoz and Sheng (1995) proposed a mathematical model with the consideration of material, energy and time consumption. Two main loss streams were introduced: primary mass loss which consisted of chip generation in the machining process, and catalytic mass losses which consisted of the waste stream of cutting fluid and the expended tools. It is one of the earliest contributions to provide a systematic tool to measure the energy consumption and environmental impact of the machining process.

Researchers from MIT firstly conducted research to systematically measure energy efficiency of machine tool system. Kordonowy (2001) conducted a series of

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experiments for different types of milling machine under Gutowski's supervision and the results were shown in energy break charts in his thesis. Figure 2.7 shows the energy consumption for a milling process. The energy consumed for machining operation just accounted for 48% of total energy consumption. Idling energy consumption which was presented as constant set-up time accounted for 27% of total energy consumption. This finding further accurately showed the energy usage performance of the machine tool system.

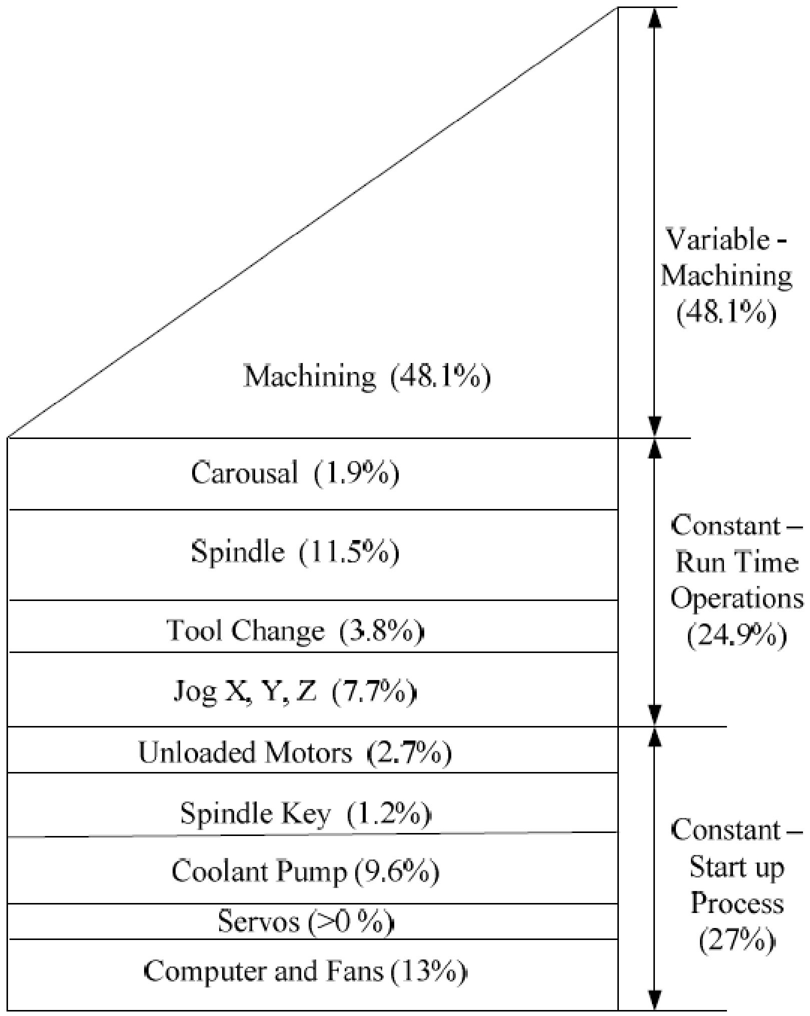

Figure 2.7 Energy Consumption Chart for a Milling Process: 1988 Cincinnati Milacron Automated Milling Machine with a 6.0 kW Spindle Motor (Kordonowy, 2001)

Based on the results of energy usage of machine tool, Dahmus and Gutowski (2004) analysed the machining operation at machine tool system level from the view of environmental impact. Figure 2.8 shows the specific material flow, energy consumption

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and waste generation during machining system. Since machining is a material removal process, most of the environmental impact and energy consumption stem from the material removal process. The specific energy consumption (energy used over material removed) was proposed to evaluate the performance of machine tools. Four different milling machines were measured and compared. The comparison result shows that specific energy consumption is different for different machine tools and workpiece materials. The environmental impact of machining operation can be possibly reduced by minimising the energy consumption during material removal process and associated processes, such as material production and cutting fluid preparation.

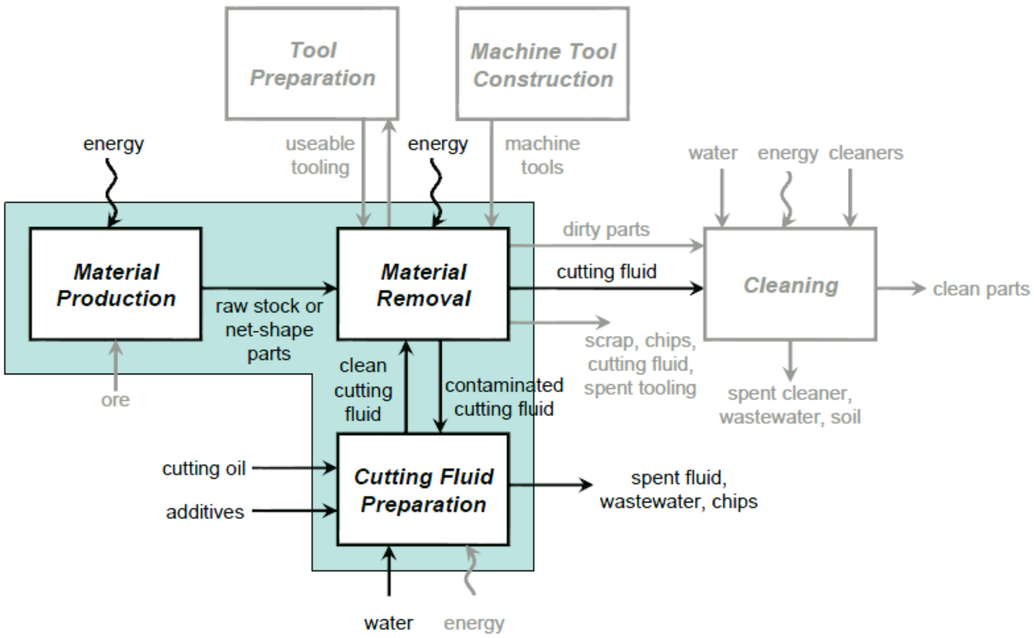

Figure 2.8 Energy Consumption in Machining System (Dahmus and Gutowski, 2004)

Gutowski et al. (2005) identified the energy use for current manufacturing industry was not very effective. Toyota Motor Corporation was taken as an example. Based on the energy use breakdown for machining (shown in Figure 2.9), the energy use for machining operation just accounted for 14.8% of total energy use, and 85.2% of the energy consumed as constant energy required for non-value added operations (e.g. centrifuge, coolant, oil pump). This finding shows that even for a modern, highly automated, mass production environment, there are potentials to reduce the energy consumption by improving the efficiency of both machining technology and auxiliary equipment.

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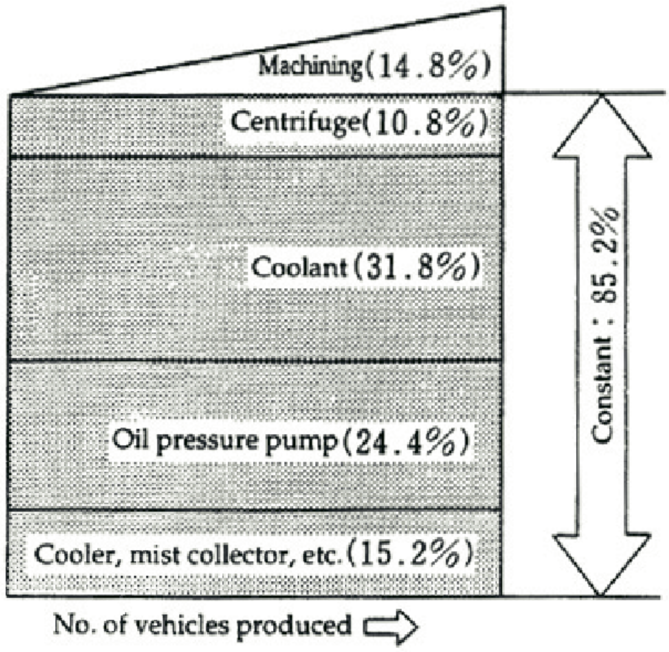

Figure 2.9 Energy Breakdowns for Machining in Toyota (Gutowski et al., 2005)

To better support the research of Environmentally Benign Manufacturing and measure the environmental impact of manufacturing process, Gutowski et al. (2006) proposed an energy prediction model to calculate the electrical energy for manufacturing processes. The total power consumption of the manufacturing process can be divided into two parts: idle power and power for machining operation. Idle power comes from auxiliary equipments. Power for machining operation can be calculated by material removal rate multiplying the specific energy consumption constant (energy use/material removed, shown in Equation 2.20).

$$P = P_0 + MRR \times K \tag{2.20}$$

where, P_0 is idle power, K is specific energy consumption, MRR is material removal rate.

In addition, they also proposed a metric to measure the energy loss of the machine tool system.

$$E_{lost} = E_{in} - E_{out} \tag{2.21}$$

where, E_{lost} is energy lost which can show the potential for improvement of the system, E_{in} and E_{out} are the input and output energy.

The current research which investigated the energy consumption for machining usually used simplified equation (Kara & Li, 2011, Anderberg et al., 2012):

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$$SEC = C_0 + \frac{C_1}{MRR} \tag{2.22}$$

Or

$$P = SEC \cdot MRR$$

where, SEC is specific energy consumption

For end milling operation, material removal rate is related to depth of cut (mm), width of cut (mm) and feed rate (mm/min). However, the problem of this model has some limitations:

- Material removal rate is a dependent variable which consists of other dependent variable. These independent variables are considered as equally important, which is doubtful. Energy consumption should be different from "light" or "heavy" machining (identified by Newman et al., 2012).
- MRR does not consider all the process parameters and cause prediction models cannot respond to other process parameters.
- The concept of specific energy consumption is determined by experiments which is lack of physical theory and sometimes is dimensionless.

In this case, to further investigate the characteristics of energy consumption during the machining process, more complex energy prediction model needs to be developed based on machining theory.

Many research contributions have been conducted to develop more informative models to calculate energy consumption for turning operation based on Gutowski's result. Manchester researcher Rajemi and Mativenga (Rajemi et al, 2010, Mativenga et al, 2011) proposed a comprehensive model to predict energy consumption for dry turning operations by considering depth of cut, feed rate and cutting speed. Guo et al. (2012) further extend the Gutowski's energy prediction model in details for turning operation (shown in Equation 2.23).

$$TSE = SPE + SCE = C_0 \cdot v_c^{\alpha} \cdot f^{\beta} \cdot a_p^{r} \cdot D^{\varphi} + \frac{C_1}{v_c \cdot f \cdot a_p} \tag{2.23}$$

Where, TSE is total specific energy, SPE is specific process energy, SCE is specific constant energy, D is final workpiece diameter mm, Vc is cutting speed m/min, f is feed rate mm/r, α, β, γ, φ, C_0 and C_1 is are coefficients.

The energy prediction models in specific energy consumption from existing research publications are shown in Table 2.2 for various type of workpiece materials (such as mild steel 1020 and AISI 1018) and machining operations (turning and milling).

Table 2.2 Energy Prediction Models from Existing Publications

Researchers	Operation	Workpiece Material	Models
Kara and Li (2011)	Turning	Mild Steel 1020	SEC=2.378+2.273/MRR
	Milling		SEC=2.830+1.344/MRR
Diaz et al. (2012)	Milling	AISI 1018	E/V=1.475+1556/MRR
Guo et al. (2012)	Turning	Steel	$TSE = 1.9205 V_c^{0.4486} f^{-6851} a_p^{-0.8214} D^{-0.8040} + \frac{85.4442}{V_c f a_p}$

2.3.2 Measurement of Energy Efficiency for Manufacturing Process

Since energy label has already been applied to choose the more efficient products and cut the cost for household appliances in Europe (e.g. refrigerator, washing machine, air conditioners etc.), Herrmann et al. (2007) proposed a concept about the initiation of energy labels for production machine which can facilitate the energy efficiency of machine tool through transparency and performance of different machines. The implication of energy labels for machine tools can stimulate the enforcement of energy efficiency. Herrmann and Thiede (2009) investigated the energy efficiency at manufacturing process level. They discussed the energy consumption in three different layers (production process and machine, production system and technical building services) in terms of what objectives should be achieved and how to achieve the objectives. The energy efficiency was defined as:

$$Energy\ Efficiency = \frac{productive\ output\ of\ production\ system}{total\ energy\ input\ of\ production\ system} \quad (2.24)$$

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A 5-step simulation approach was developed to foster the energy efficiency of manufacturing, improve the energy efficiency and help to reduce energy cost (electricity) which is especially suitable for small and medium sized enterprises (SME).

Kara and Li (2011) developed an empirical model to describe the relationship between energy consumption and process variables for material processes (e.g. tool conditions, workpiece material, cutting parameter and cutting environment) based on Gutowski's energy consumption framework. They selected specific energy consumption (SEC, energy consumption of machine tool for removing 1 cm^3 material, which is related to two machine coefficients and material removal rate) to evaluate different machining process. The value of SEC can be generated based on the experimental results. When material removal rate is over 1 cm^3/s, the SEC value is almost a constant. The model was tested by comparing the predicted energy and experimental measurement of four different machine tools (turning and milling) and different cut environment (wet and dry). The accuracy of proposed model is between 91.95% - 97.63%. Li et al. (2012) further carried out a case study to evaluate the resource efficiency of CNC grinding process at unit process level. An integrated approach was proposed to evaluate the eco-efficiency of unit manufacturing process which is defined as:

$$Eco - Efficiency = \frac{product\ or\ service\ value}{environmental\ impact} \tag{2.25}$$

The result shows that higher material removal rate can lead to less energy consumption, but will degrade the surface roughness. In addition, the use of CBN grinding wheel can further improve both surface roughness and environmental impact compared to Al_2O_3 grinding wheel.

Behrendt et al. (2012) proposed a method to measure and analyse the energy consumption for machine tools. A standardised test procedure was developed to assess the energy performance of machine tools. The procedure includes three steps which are standby power (idle mode), component power (spindle, axis movement) and machining power. A series of experiments were conducted under various cutting conditions and machine tools to compare and characterise the energy consumption for the machine tools. The results of this research can identify the potential for energy usage to optimise and help to establish standard rules (e.g. energy labelling system) for the machine tools.

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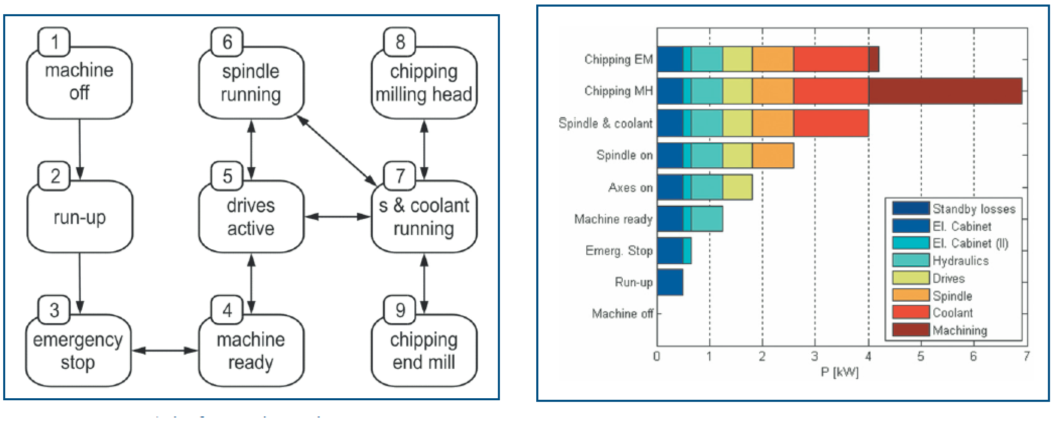
A modelling framework was proposed by Dietmair and Verl (2009) which can accurately predict the total energy consumption for machining tools based on the specifically investigations of elements of efficiency in manufacturing processes and existing models for calculating energy efficiency. The elements of energy were introduced to calculate the energy efficiency. The power consumptions for 9 states during milling operation were observed. Figure 2.10 shows the framework map of nine states and the specific energy consumption for each state. Acceleration and deceleration were contributed to the peak power requirement during end milling chipping and machining head chipping states. Based on the application of the model, the energy efficiency for machine operation is very low (just account for 20% of the entire operation). This efficiency can be improved by optimising the cutting parameters, reducing the acceleration and deceleration effects and reducing the auxiliary power (e.g. coolant, idling). This result can enable manufacturers and operators of machines to include energy consumption into their considerations in an objective way to accurately forecast cost, formulate strategies and set up working plan.



(a) (b)

Figure 2.10 Energy Consumption for Each State (Dietmair and Verl, 2009)

Rahimifard et al. (2010) proposed a model for calculating the embodied product energy used at manufacturing process level. The embodied product energy can be defined as the sum of direct energy (DE) and indirect energy (IE). Indirect energy is energy consumed by the environment in which production takes place (e.g. lighting and heating, shown as Equation 2.26). The direct energy is defined as the sum of theoretical energy (TE) and Auxiliary Energy (AE).TE is the minimum energy required to achieve the manufacturing process and AE is that required to achieve supporting functions (e.g. coolant usage). Efficiency ratios (ER) were defined at the process level (shown as

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Equation 2.26), product level (shown as Equation 2.27) and at the production system level (shown as Equation 2.28). The proposed energy efficiency metrics provided great transparency on energy inefficiencies and identified that the energy efficiency of manufacturing can be improved by minimising the auxiliary energy. The example showed that 20–50% reduction of energy consumption can be achieved through combined improvements in production and product design.

$$Embodied\ Product\ Energy = DE + IE = TE + AE + IE \quad (2.26)$$

$$ER_{process} = TE/(TE + AE) \quad (2.27)$$

$$ER_{product} = TE/(TE + AE + IE) \quad (2.28)$$

$$ER_{production} = DE/(TE + AE + IE) \quad (2.29)$$

2.3.3 Issues of Energy Consumption and Energy Efficiency Measurement

Though the academic research has proposed some energy audit models and energy efficiency metric to help measure and evaluate the energy usage, these models and metrics have some limitations which can cause confusion. The following issues can be identified:

- Firstly, most of the models proposed are empirical models which lack scientific explanations. Some of the models are too simple and not informative enough which are just related to material removal rate (MRR). So these models cannot be generally applied in the machining processes which contain more process parameters.
- Secondly, the definition of energy efficiency has problems. According to the existing proposed energy efficiency definition, the energy efficiency of some advanced machine tools may be worse than manual machines because of auxiliary functions require more energy. In addition, from Equation 2.26, if the auxiliary energy can be reduced to zero (TE=DE), the energy efficiency of machining process will be 100%. These conclusions disagree with the general principle that using 100% energy for machining operation does not mean the energy efficiency is 100% too.

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2.4 Introduction of the Nature of Machining Optimisation

The reason for conducting the optimisation procedure in machining operations is to improve the performance in sustainable manufacturing through optimisation of existing processes. One of benefits is the optimisation operation can achieve improvement without adding extra resource and materials or changing the current techniques. In this case, it is an easy, efficient and cheap method to improve the existing manufacturing process.

Before the determination of optimal process parameters, it is necessary to specifically introduce the nature of machining optimisation which can provide a clear and solid theory foundation for the following analysis and discussion. Also it can help the users to have a comprehensive understanding about how the optimisation procedures conduct and how the optimal result can be achieved. According to the definition of optimisation, machining optimisation problem is a multivariable optimisation with no/equality/inequality constraints (Rao, 2009). The following sections will specifically introduce the basic concepts of machining optimisation.

2.4.1 Nature of Search Space

Search space, which is also called design space or objective function space in mathematical optimisation, is the most fundamental concept for an optimisation problem. It can be explained as a domain which is consisted with all the possible solutions. According to modelling method of machining operation, the objectives are represented as a function in terms of independent variables.

Without regarding to the impact of constraints, the original search space of machining optimisation is a multi-dimensional space located in a positive interval of the coordinate. The level of dimensions will be determined by the number of independent variables. Figure 2.11a to 2.11c show the original searching space for 3/4/5 variables situations. Each point in search space represents a combination of independent variables.

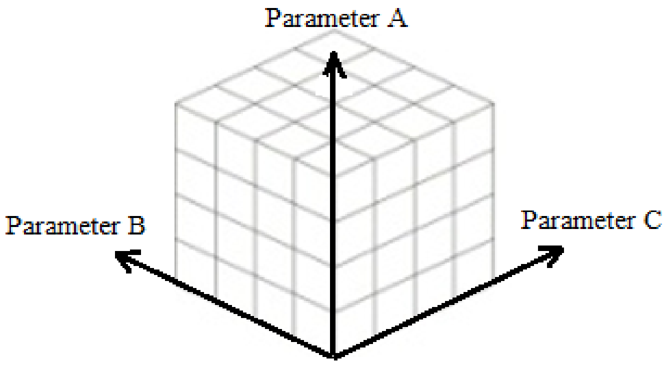

Figure 2.11a 3D Searching Space

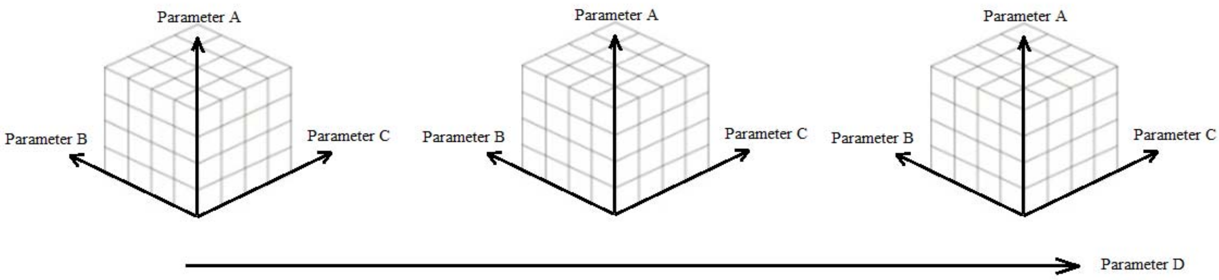

Figure 2.11b 4D Search Space

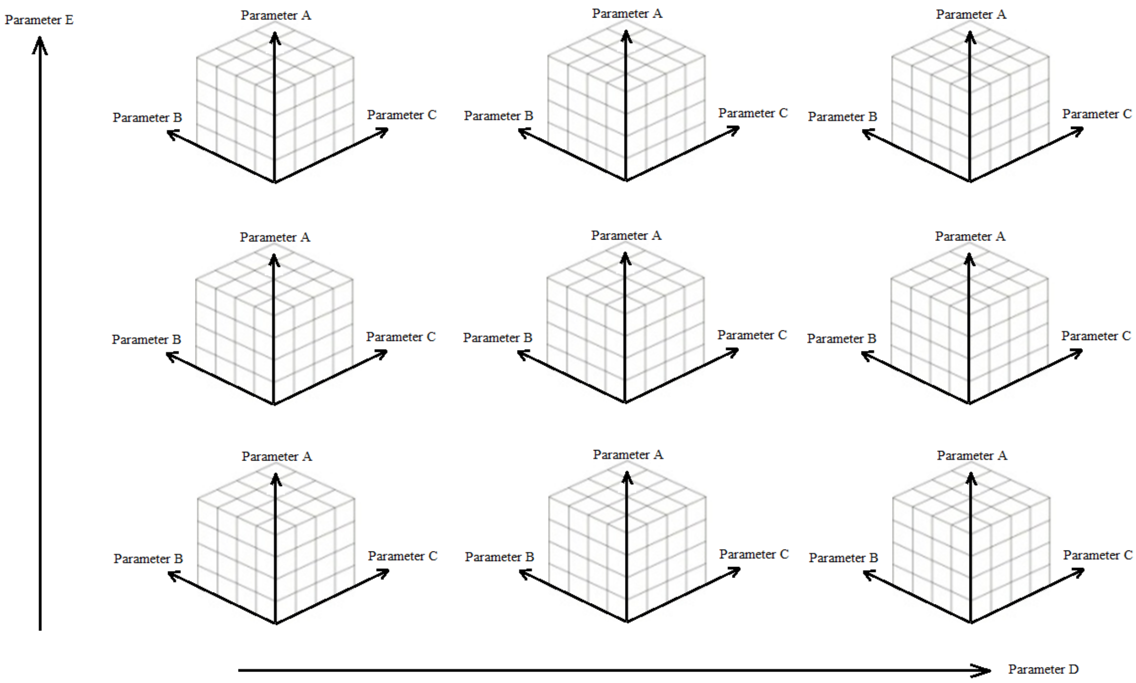

Figure 2.11c 5D Searching Space

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In addition, the size of the search space is not only determined by number of independent variables but also related to the accuracies based on technical conditions. The search space of end milling operation, when four process variables (depth of cut, width of cut, feed rate per tooth and spindle speed) are considered, is the same as Figure 2.11b. The original search space is a 4D search space (see Figure 2.11b), which is a linear array of a 3D cube. However, because of the accuracy of variables should be reasonable and meaningful in practice and limited by technical conditions (e.g. the accuracy of depth and width of cut should be 0.01mm, spindle speed should be 1rpm), the total number of the results in search space is finite and countable.

From Figure 2.11a to Figure 2.11c, it can also identify that the search space will be expanded when more variables are added. Each additional parameter will increase one dimension of the search space. The consequence of additional dimension is that the number of total points will be geometrically increased. The more parameters are considered, the larger the search space will be, and the more complex the machining optimisation will be.

2.4.2 Nature of Variables

Variable is another important factor for machining optimisation. It will be used to mathematically represent the quantity of the physical phenomenon. Statistically, variables can be divided into two groups: dependent variable and independent variable. Independent variables are the basic elements of the mathematical model. It can be also called input variable or design variable. The values of independent variables exist independently and are not directly affected by each other. The dependent variable is also called "response variable" or "output variable" which is the response of the independent variable.

Table 2.2 shows the independent variables and dependent variables for end milling operation. Usually independent variables have physical range/constraints, for example width of cut *ae* is not possible to exceed the cutting tool diameter *d*, depth of cut *ap* should not be chosen large than the length of cutting edge, spindle speed n is not possible to exceed the machine spindle design maximum speed.

The independent variables can also be separated into two groups. The first group comes from the machining process plan including depth of cut, width of cut, feed rate and spindle speed. This type of independent variable usually can be observed from NC code

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and determined by practitioners or process planners. The value ranges of these variables are contributed to the machine tools and machining tools. This range is comparably wide, e.g. the range of spindle speed is from 0 to thousands (conventional machining) or tens of thousands (high speed machining). The second group variable is the variable determined from the dimension of machining tools including diameter of the cutter and number of cutting flutes. The value ranges of these parameters are much narrow than the first group, because dimension of machining tool are usually standard for all machining tool manufacturers. For example, the diameter of end milling cutter for conventional machining is from 1 to 30 mm, and number of flutes is from two to four (Hanita, 2005, WNT, 2012).

Dependent variables are the machining performances that people can observe from the machining operation. The values of dependent variables are corresponding to independent variables (design vector) which can be presented as objective function/mathematical models.

Table 2.3 Independent Variables and Dependent Variables for End Milling Operation.

Independent Variables	Dependent Variables
Depth of cut: ap (mm)	Energy
Width of cut: ae (mm)	Cost
Feed rate: fz (mm/tooth)	Time
Spindle speed: n (rev/min)	Material Removal Rate
Diameter of tool: d (mm)	Tool Life
Number of flutes: z (mm)	Torque
	Cutting Force
	Power
	Surface Finishing
	Cutting Speed
	Feed Rate

2.4.3 Nature of Objectives and Constraints

Based on the functions, variables can be further separated into two groups as well: objectives and constraints. A good objective should be a dependent variable consists of all the independent variables. The conventional objectives for machining operation are

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cost, time, surface roughness, and tool life. From the environmental aspect, energy consumption is a new objective for the machining operation.

Apart from the objective functions, to accurately determine the optimal results, constraints should be considered to satisfy for a meaningful optimisation of the machining process. The function of constraints is to refine the results by reducing the searching space. Jha et al. (1994) and Tandon et al. (2002) claimed that there are two types of constraints. The first type constraints are obvious from the machine tool capabilities. The other type constraints are derived from product requirements such as surface finish, force-bearing capacity of the tool and so on. For cutting force, it is directly related to several constraints including maximum loading on feeding mechanism constraint, bending stress constraint and fatigue constraint. So they can be simplified as a cutting force constraint in this research. Tandon et al. (2002) also mentioned some constraints can be redundant and neglected in some situation, and different constraints may not be all active at the same time. Practically, horsepower limitation may be the active constraint for rough milling, and, surface finish may be the active constraint for finish milling. In addition, because of the nature of the machining optimisation itself, the value of all the variables should not be less than zero which gives a natural limitation of the search space.

Based on the classification of variables in section 2.4.2, the constraints of machining optimisation can be divided into three levels:

- Level 1: Boundary/side constraints (physical constraints of independent variables). This type of constraint is the physical limitation of the independent variables. They are usually determined by the machine tools and cutting tools. The first level constraints will confine the search space as a close scope.
- Level 2: Behaviour constraints from capability of machine tool/cutting tool (physical constraints of dependent variables). This type of constraints is the physical limitations of dependent variables which contribute to the design of the machine tool, for example, the power of the machine tool and torque of spindle. However, this type of constraint can be redundant by the other constraints. It may/may not affect level 1.
- Level 3: Behaviour constraints from manufacturing requirements (constraints determined by decision makers). This type of constraint is usually determined by

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operators' requirements, e.g. quality, cutting speed, tool life and so on. This type of variable is the dominated constraints which can further refine the search space to find the optimal solution. Although level 3 and level 2 are all behaviour constraints, most of the time level 3 is possible to overlap level 2.

2.5 Introduction of the General Machining Optimisation Methods

A lot of optimisation methods have been applied to optimise machining process. Roy et al. (2008) comprehensively classified the existing optimisation methods applied in engineering design optimisation (shown in Figure 2.12).

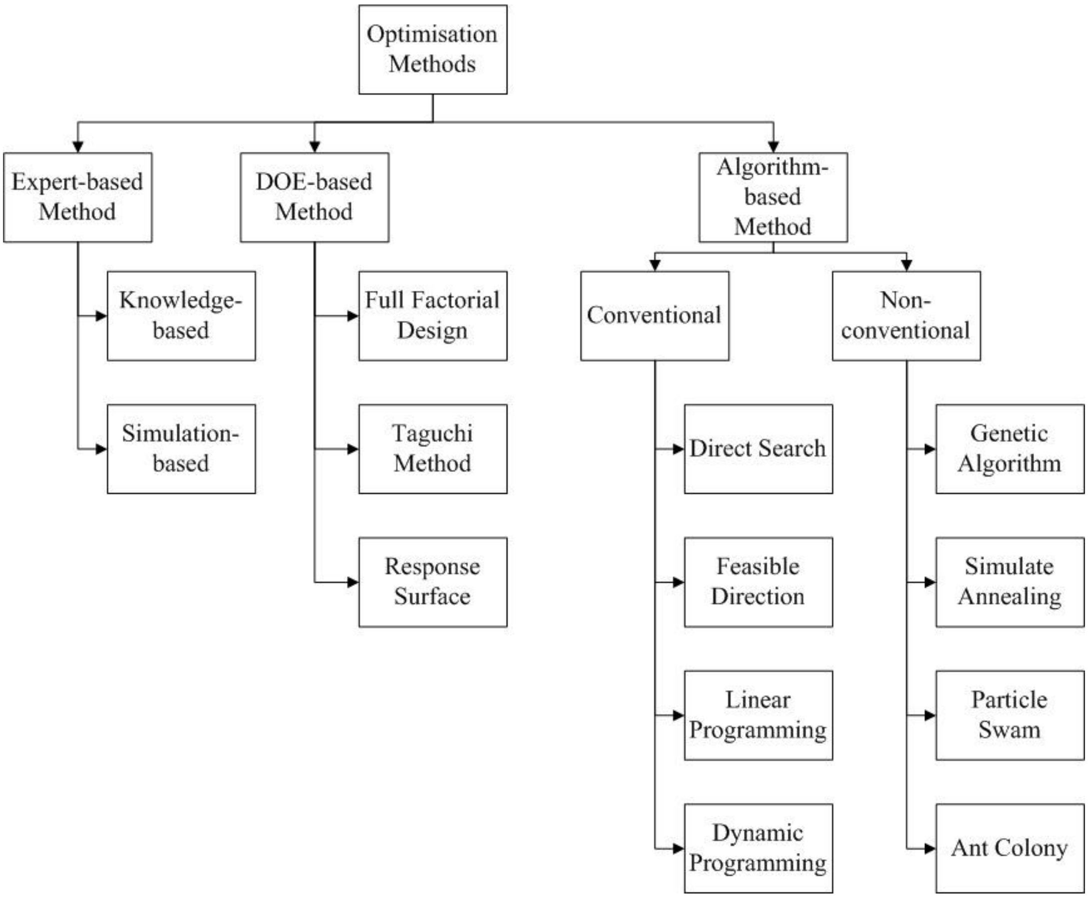

Figure 2.12 Classification of Existing Optimisation Methods (Roy et al., 2008)

Research contributions of machining optimisation have been reviewed and concluded by many. From machining optimisation perspective, two stages of optimisation method were described for general machining operation (Mukherjee and Ray, 2006, Aggarwal and Singh, 2005, Ganesan et al., 2011, Dhavaman and Alwarsamy, 2011, Mahesh et al., 2012):

1. Modelling of input-output and in-process parameter relationship.

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2. Determination of optimal or near-optimal cutting condition or cutting parameters.

Typical Mathematical Optimisation Procedures:

1) Build up mathematical objective function (or functions).
2) Define constrains
3) Implement mathematical algorithms
4) Get the optimal or near optimal results

They classified the input-output and in-process parameter relationship modelling methods and listed as below.

- **Statistical Regression Technique** is an easy modelling method which is commonly used for describing the functional relationship of input and output variables. But this method has some shortcomings. It is usually dimensionless and cannot show the non-linear complex relationship between the variables.
- **Artificial neural network (ANN)** is multi-variable, dynamic, non-linear modelling method. It can handle complex cases, but is only used when regression techniques failed to provide an adequate model. The problem of ANN is that the modelling parameters cannot describe non-linear relationships between them, and the accuracy is depended on volume of data set.
- **Fuzzy set theory** is suitable for the situation that subjective knowledge or options is expected as a key role in defining the objective function. But it is depended on the users or experts' knowledge.

2.5.1 Expert-based Optimisation Methods

In the early stage of manufacturing operation, the modern concept of "Optimise optimisation, optimal, optimum" was not applied by practitioners. However, good experienced technicians could manufacture the products for different requirements based on their experiences. For example: quality (e.g. for different price, good quality for high price, bad quality for cheap price), energy (e.g. according to the physical state), resources (e.g. workpiece and fuel), productivity (e.g. quantity of products, deadline for the work) and cost (e.g. cutting tool wear). This method can be summarised as "Expert-based Optimisation" which is still being widely used in practical manufacturing and design process (Roy et al, 2008). The principle of this type of optimisation method is it

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usually determines the optimal plan based on expert judgement and experiences (knowledge-based), or simulation results (simulation-based). These experiences and simulation results of machining performance can be considered as qualitative models for describing the relationship between independent variables (process parameters) and objectives.

The advantage of this method is that the decision makers do not require additional skills and can quickly have an optimal result. Expert-based method can allow the practitioners to control the process based on their knowledge or simulation result, so that they will be confident about the optimal result. Although this type of method can always achieve a better result compared to original process, it may not be able to achieve the best solution. The optimal results will be different if the operators are different. In addition, the influences of process parameters and are also not able to be quantitatively represented.

2.5.2 Experiment-based Optimisation Methods

To address the problem of "Expert-based optimisation", "Experiment-based optimisation" was developed. Experiment-based optimisation is also called Design of Experiment (DOE) method. As the name, DOE method is a structured and organised method mainly based on experimental measurement to determine the relationship between the process parameters and find out the best combination. The fundamental concepts for designing experiment were proposed by Fisher (1926 and 1935) to deal with the applications of statistical methods. The typical DOE methods are Full Factorial Design method, Taguchi method and Response Surface method. To implement DOE methods, large amount of test data will be firstly collected by conducting experiments and "failure models" will be built based on collected data to show the boundaries of search space. Then the optimal process parameters can be selected within the refined search space.

Taguchi method is one of the typical DOE methods which was firstly brought by Genichi Taguchi in 1950s and systematically introduced by Ross (1988) to improve product and process design. As a fractional factor design method, Taguchi method can significantly reduce the time and resource needed compared to conventional DOE methods. In addition, because it can be easily implemented and has a good applicability, the Taguchi method has been widely used in machining optimisation research to determine important process parameters. Taguchi's Orthogonal Arrays (OA) provide a set of well-balanced experiments by reasonably reducing experiment numbers, and

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Taguchi signal-to-noise ratio (S/N) is used to evaluate the impacts of the variables by considering the average value and standard deviation. The S/N ratio in this research is to represent energy which is required to be minimised. So Lower-the-better (LB) criteria should be chosen. The equation for calculating Taguchi S/N for LB is shown in Equation 2.30.

$$\eta_s = -10log\left(\frac{1}{n}\sum_{i=1}^{n} Y_i^2\right) \tag{2.30}$$

where, η_s is S/N ratio, n is number of experiments and Y_i is value of energy consumption for the machining operation.

In addition, DOE methods are not only used to build regression models, but also allowed to use mathematical models to generate prediction results. The advantages of DOE method are:

- It is a direct optimisation method that is easy to be understood and implemented.
- Compared with expert-based optimisation, it can quantitatively show the relationship between the objective (e.g. cost, time, energy...) and the process parameters (e.g. depth of cut, width of cut, spindle speed and feed rate).
- The optimal result is the real optimal result.

However, the problems of DOE method are:

- It is an expensive method (which is the same as expert-based method), because it will consume energy and resource. This consumption could be significant when the number of experiments is large.
- The experiments could take a long time.
- The accuracy of the optimal result is depended on the number and level of variables. If there are too many variables or too many levels, the number of experiments will be a lot which is not acceptable (because of the cost and time).
- Usually, it is difficult to put constraints to control the results.

2.5.3 Algorithm-based Optimisation Methods

To achieve more accurate optimal result, mathematical optimisation theory started to be applied in machining optimisation. With the development of algebra, especially after

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Newton and Leibniz created the theory of calculus which can be used to determine the extreme points of functions by conducting differentiation, optimisation theory was further developed and had a new form. By implementing algorithm-based optimisation methods, mathematical optimisation models need to be firstly built to describe the relationships between input process parameters (independent variables) and output objectives (dependent variables). The general mathematical optimisation models are shown as below:

Objective function:

$$\min/\max f(x)$$

Constraints:

$$g_i(x) \leq 0 \quad i = 1,2,\cdots,m$$

$$h_j(x) = 0 \quad j = 1,2,\cdots,n$$

where, $g_i(x)$ are inequality constraints and $h_j(x)$ are equality constraints

Based on the algorithm operation functions, algorithm-based method can be further divided into conventional and non-conventional methods.

The conventional methods are usually developed based on the ground principle of mathematical optimisation theory. This type of method is similar as simulating common sense knowledge of optimisation and DOE methods in mathematical form. For example, feasible direction/gradient method is similar as providing an artificial searching direction. Direct search is similar as full factorial design method that creates grids to represent all the individuals in the search space. However, conventional methods also have some limitation. The search space of the machining operation is a complex and multi-dimensional space when multiple process parameters need to be considered. It still requires a lot of work and computations to implement conventional methods for achieving an overall optimal result.

In this case, new non-conventional optimisations (e.g. Evolution Computing or Meta-Heuristic search algorithms) have become popular in machining optimisation. This type of algorithm is usually inspired by some improvement behaviour in nature or physical phenomenon.

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The general steps of meta-heuristic algorithms are: (1) Randomisation: randomly select initial individual or population to generate the starting point or starting set of points. (2) Reproduction: based on selected individuals to generate representative points by using algorithms which can rapidly explore the search space or Pareto set. (3) Evolution: Select and keep the best individual. According to these characteristics, heuristic algorithms are widely used to solve parameter optimisation problem, especially when the search space is very large and complex. The advantage of non-conventional methods is they can locate the optimal results faster than the conventional method. Two typical algorithms are introduced as below:

Genetic algorithm (GA) was firstly introduced by American researcher, Holland from the University of Michigan, in early 1970s (Holland, 1975). GA is a stochastic search combinatorial optimisation method. A population of candidate solutions is maintained. At first, the initial population is generated randomly or with heuristic rules to generate good solutions to the problem. With a fitness function, the individuals are evaluated to determine how well they solve the problem. The individuals with higher fitness values are selected as parents of the next generation. Then, the crossover and mutation operators are used to generate new individuals. The function of crossover is to rapidly explore a search space and mutation is to provide a small amount of random search. Then new individuals are evaluated with the fitness function. GA iterates over many cycles of selection, crossover and mutation until the termination criterion is satisfied. In general, as the algorithm executes, solutions in the population become fitter and fitter until they finally converge to the optimal solution.

Ant colony optimisation (ACO) is another meta-heuristic algorithm which is developed by Dorigo and his associates in early 1990s based on the cooperative behaviour of real ant colonies to determine the shortest path from their nest to a food source (Colorni et al., 1992, Dorigo et al., 1996). The basic principle of ACO is that if the design variables of the optimisation problem are independent with each other, the multivariate machining optimisation can be represented as several one variable optimisations. The structure of ACO can be presented as a multi-layered graph in Figure 2.13. For implementing ACO, the number of layers is equal to the number of design variables and number of nodes in each layer is equal to the number of discrete value of the design variable.

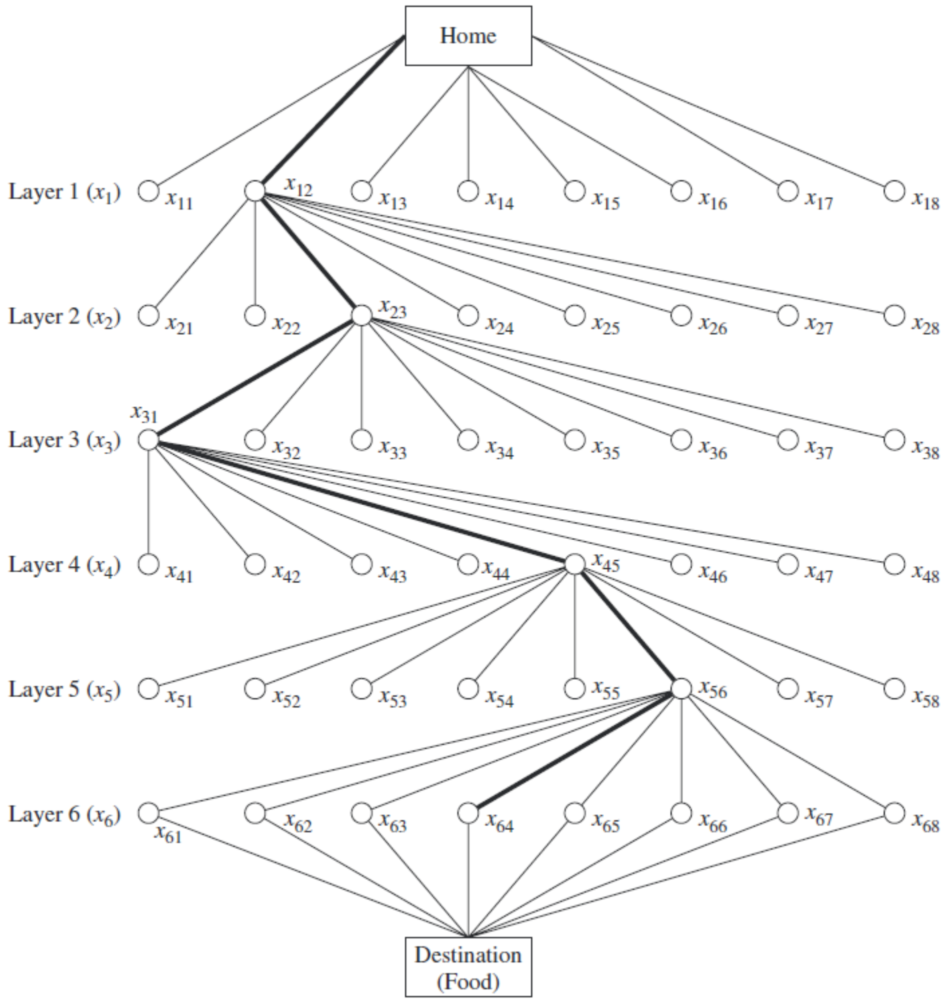

Figure 2.13 Graphical representation of ant colony algorithm (Rao, 2009)

However, the problems of meta-heuristic algorithms are:

- Characteristics of machining operation are not able to be clearly displayed.
- The basic principle of optimisation theory is embedded into the algorithms which cannot be easily discovered.
- The technical terms applied in the optimisation algorithms are too abstract to be understood by practitioners. They are not able to link these terms to machining terms.

So the consequence of above problems is these optimisation methods are more like "black box" tools. In practice, most of academic optimisation results have not been used by industry because practitioners do not understand how the results are obtained from optimisation methods and trust the optimal results. They still prefer to select optimal process parameters based on expert experience.

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2.6 Improvement through the Optimisation of Existing Machining Processes

Research of improving machining performance by selecting optimal process parameters has been conducted for over 100 years since Taylor published his tool life equations in the early 1900s (Taylor, 1907). He developed a series of equations to predict tool life by considering process parameters. The results showed that the optimal cutting speed exists to decide the optimal material removal rate to maximise the cutting tool life and minimise the cost. Since then, a great number of research have been carried out to improve the performance of machining from different aspects (e.g. objectives, optimisation methods). This section introduces research contributions in this area, and discusses their advantages and limitations.

2.6.1 General Machining Optimisation

Early researchers (1950s to 1970s) proposed optimal suggestion based on analysis of machining variables. The optimisation process usually followed procedures of (1) data collection through conducting physical experiments, (2) mathematical modelling (3) analysing the mathematical equation, and (4) proposing optimal solutions.

One of the earliest traceable research was conducted by Brewer and Rueda (1963) which proposed a monograph technique to optimise cutting force and tool life with the consideration of a group of independent variables (cutting speed, feed rate, depth of cut etc.) for variety types of materials. The results showed that for non-ferrous materials which have good machining ability, the best cutting conditions are regarded as the high material removal rate which machine will permit. For difficult-to-machine material the range of feasible parameter is more restricted than non-ferrous material.

Crookall (1969) proposed a concept of performance-envelope to represent the permissible and desirable operation regions of machining based on the characteristics of machining cost and time with the constraints of machining tool capability (power), cutting tool failure, and surface roughness. Koren (1978) optimised the flank wear for steel turning operation based on Taylor's tool life equation. The theoretical and experimental results are graphically compared and represented how cutting speed affects flank wear when the machining time and cutting distance is increasing. It showed higher cutting speed will reduce the tool life.

Lau (1987) and Enparatza (1991) from University of Manchester conducted the research for the optimisation of cutting parameters and tool selections for end milling operation.

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The research involved the investigations of the factors which could affect the cutting performance such as tool life and cutting force. Enparantza (1991) developed a tool selection module for end milling operation and conducted an optimisation procedure of cutting conditions by considering economic criteria. The optimisation procedure was based on a general search method and the result showed that the machining cost can be minimised by selecting optimal cutting speed. The optimisation procedure also showed how constraints (tool life, cutting force, machining power and tool deflection) reduce the search space. He also identified that the optimum point should line on the constraints (boundary between feasible and unfeasible region). However, his result has some shortcoming because other machining parameters were considered as constant (e.g. diameter of tool, number of flutes). In real machining operation, the interaction of these parameters is very important and cannot be ignored.

Tolouei-Rad and Bidhendi (1997) investigated optimisation of machining parameters for general milling operation. They identified that the optimisation of end milling is a non-convex, non-linear, multi-variable and multi-constrained problem according to the developed optimisation models. In addition, they used "profit rate" as a new objective to combine the previous two objectives machining cost and process time which actually convert the problem from multi-objective to single-objective. A feasible direction method was selected and graphically demonstrated how to achieve the optimal results. A case study of machining a multiple-feature component showed that up to 350% improvement in profit rate can be achieved from machining data handbook recommendations.

Khan et al. (1997) described the problem of using traditional optimisation methods (e.g. expert-based, Calculus method and Gradient method) to select optimal machining conditions which have limited ability to solve non-convex problem. Optimisation models for machining operation are usually non-linear. In this case, new non-conventional algorithms which can solve global optimisation for non-linear and non-convex solution space are required (e.g. genetic algorithm and simulated annealing). Optimisation procedures were conducted by using genetic algorithm (GA), simulated annealing (SA) and continuous simulated annealing (CSA) to optimise cost for turning operation based on different prediction models. Comparison results between traditional algorithms (sequential unconstrained minimisation technique and generalised reduced gradient) and non-conventional algorithms showed that non-conventional algorithms were more reliable and easy to be implemented. SA can give high precision and easy to

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be programmed (few hundred lines of code), but it requires more computing time. For GA, the precision depends on the number of bits to represent each variable, but the computing time is much shorter than SA. Another inspiration from this paper is the dimension of the machined feature (e.g. depth of feature) should be considered as size constraints for optimisation model.

Meng et al. (2000) used direct search methods to optimise cutting conditions for turning operation. A mathematical model of specific cost (cost per unit volume) was built by using a variable flow stress machining theory. Both mathematical prediction and experimental test results showed that the specific cost continuously decreased with the increase of width of cut. The equations of constraints including plastic deformation, machine tool torque and power, tool life values and build up edge formation were also modelled based on machining theory to avoid the problem that empirical models always contain lots of constants and coefficients which are not readily available. The author also claimed that when applying direct search methods (grid search) to carry out optimisation process, there is no need to check all the points in the search region (d-f plane) but just check the points next to the constraints curve. This finding can be applied to reduce the experiment works in data collecting. In addition, the result also showed that the optimal specific cost is on the boundary of feasible searching region. They also claimed that the tool manufacturer recommendations do not consider the process constraints.

Owodunni et al. (2007) investigated optimum cutting conditions for STEP-NC turned features by using direct search algorithm. 10×10 grids were created on ap-f (depth of cut and feed rate plane) to represent the cost of operation. The optimal value was selected within the feasible direction by considering the constraints of maximum tool force, machine power/torque workpiece deflection. The results proved that the constraints will control the value of optimum parameters for turning operation. For the feature which does not have a deflection constraint, the optimum depth of cut is only determined by machine tool power.

Onwubolu (2005) used term "Tribes" which is the same as Particle Swarm Optimisation (PSO) to select optimal cutting conditions for face milling and end milling operations. The comparison result with GA by considering comprehensive criteria (cutting force, material removal rate, surface roughness and time) showed that the optimal results

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achieved by using both algorithms are similar. It means the proposed Tribe algorithm is an efficient, effective, and competitive method compared to GA.

Baskar et al. (2005, 2006) conducted optimisation of machining parameters for milling operation based on maximum profit rate. Four non-conventional methods (ACO, GA, PSO and Tabu Search) were introduced and compared with handbook recommendations and method of feasible direction. The results showed that significant improvements can be achieved in profit rate from handbook recommendations (283% to 440%) and method of feasible direction (0.92% to 54%). Among the four methods, the optimal results achieved from PSO were better than the other algorithms. However, the difference between GA and PSO was less than 5%. These comparison results proved that there was a significant potential improvement for using optimal cutting conditions. In addition, the optimal results for different algorithms are not different a lot. Further research was carried out by Bharathi Raja and Baskar (2010) to find out which non-conventional algorithm (SA, GA and PSO) is the robust and versatile for optimising machining cost, surface finishing and production time of turning operation. The comparison result of SA, GA and PSO showed that the performance of PSO was also better than GA and SA, but was not very significant.

Researchers from University of Maribor (Cus et al., 2006), also implemented PSO to optimise machining time of high speed end milling. The simulated result showed that PSO was faster than GA and SA. Up to 30% reduction of machining time was observed. The following research of Cus and Zuperl (2009) mentioned that evolution algorithm (GA, SPO) was more convenient for solving multi-objective optimisation problem. The example of optimising material removal rate and machining time showed that by using PSO, up to 20% of machining time can be reduced and 28% of MRR can be improved. However, there was no evidence showed that PSO had significant advantages than other algorithms.

Wang et al. (2005) proposed an approach to select the optimal processing parameters for minimising production time for multi-pass milling. The optimisation was conducted by using GA, SA, hybrid of GA and SA (GSA) and proposed parallel genetic simulated annealing (PGSA). The results of comparison between geometric programming (GP), parallel genetic algorithm (PGA) and PGSA showed that although the optimisation result of PGSA was almost the same as PGA, the calculation time can be significantly reduced.

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Pan et al. (2009) used DOE method to investigate the tool life for milling Aluminium 7050. The coefficients of Taylor's basic tool life equation were determined by using multi-linear regression method based on the experimental result. The optimisation procedure was also conducted based on the verified equation to select the optimal depth of cut and feed rate by maximising tool life. The result shows that the machining performance can be possibly improved by selecting the optimal combination of cutting parameters.

2.6.2 Machining Optimisation with Energy Considerations

One of the earliest contributions to optimise machining process parameters with consideration of environmental impacts is by Sheng et al. in mid of 1990s. They conducted a series of research which considered environmental factors as one of the key issues in machining operations. Munoz and Sheng (1995) developed a model by considering material, energy and time consumption. Two main loss streams were introduced: primary mass loss which consisted of chip generation in the machining process, and catalytic mass losses which consisted of the waste stream of cutting fluid and the expended tools.

Sheng et al. (1995) developed an environmentally conscious, feature-based, multi-objective process planning method, which was beyond the traditional methods that just considered economic criteria. This new process planning method estimated the process mechanics, tool life and fluid flow, process energy, machining time and the mass flow of component waste streams (shown in Figure 2.14). These waste streams can be weighted by environmental factors such as toxicity, carcinogenicity, irritation, reactivity and flammability. A prioritisation equation was built with the consideration of cutting parameters and the waste weight model to evaluate the performance of new process plans by considering process energy, machining time, quality and waste stream mass. Thus the specific values of energy and waste can be calculated.

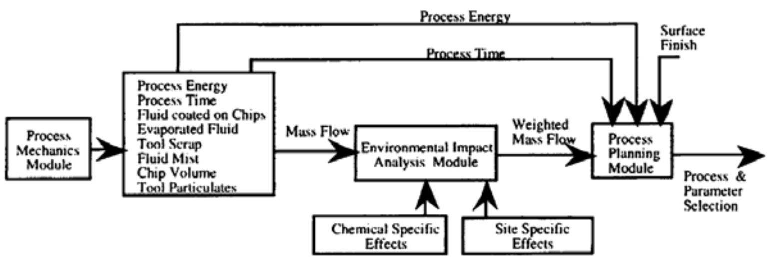

Figure 2.14 The Map of Decision Making System (Sheng et al., 1995)

Srinivasan et al. (1995) developed a scoring system called Health Hazard Score (HHS) which can quantitatively show the environmental impact based on the chemical effect on human health and safety (e.g. toxicity, carcinogenicity, dermal and eye irritation, flammability etc). Later on, Gune and Peng (1995) complemented the model by adding two additional factors: the effect of waste stream on exposure route, and the effect of site-specific conditions on waste containment and handling.

Srinivasan and Sheng (1995, 1999a, 1999b) applied the environmental process planning method to machine parts with hierarchical features. They proposed a process planning system in which environmental criteria such as process energy and mass flow of waste streams are considered in addition to traditional criteria such as production rate and quality. The multi-objective optimisation process proposed uses an overall utility which is a weighted sum of the different criteria. The system developed allows optimal selection of a process path sequencing the machining operations of interacting feature volumes. The other contribution of this research is that they developed a feature-based micro and macro planning methods. For the different dimensions of the feature, different machining operation or different operation sequences can be selected based on the energy and waste values. The micro-planning method was used to machine intra-feature (e.g. step hole), and the macro-planning method was used to machine the part which has interactive features. In this research, they further developed the process planning model, and more details were given. Figure 2.15 shows the task sequence for environmentally-conscious process planning.

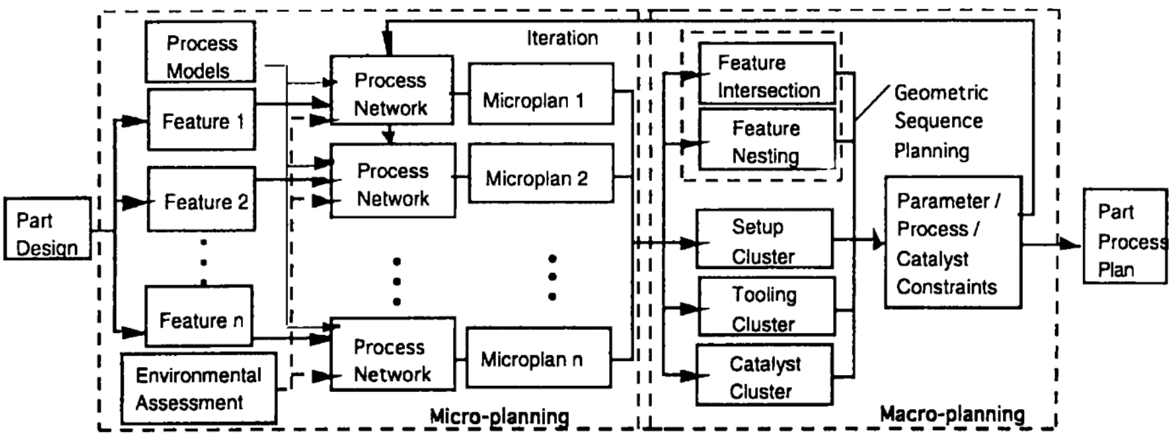

Figure 2.15 Environmentally-Conscious Process Planning System (Srinivasan and Sheng, 1995)

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The micro-planning section integrated the different dimensions at the feature level to optimise the process plan in process, parameters, cutting fluid and tool selection. Srinivasan and Sheng (1999a) specifically built up the calculation models of these factors. The process energy model of machining operation is related to cutting force, cutting velocity and process time. The process time can be generated by material removal volume and material removal rate. The quality referred to surface roughness which is related to feed and diameter of cutting tool. The waste stream mass is related to tool wear, chip generation and usage of cutting fluid. The models and process planning method were also implemented into 3D solid modelling software Pro/Engineer, and a case study of machining a part was given to theoretically verify the function of the new computer aided micro-planning system.

Srinivasan and Sheng (1999b) introduced a macro-planning method which focused more on the "global" context. The macro-planning method started with the aggregation of features (micro-planning), and then generated the feature clusters or sub-clusters by considering the feature interaction situations (geometric interactions and process based interactions). For geometric interactions situation, energy consumption was calculated based on the removal volume for different sequences to achieve the feature. Then the system prioritisations of each sequence can be calculated and compared to choose the optimal region. The process based interactions can be divided into tool interactions, cutting fluid interactions and set up interactions. Thus, the optimisation of process interaction is based on minimising the tool change time, cutting fluid use and setup time. The arrangement of clusters or sub-clusters was evaluated by micro-planning method. Then the machining sequences of all the clusters or sub-clusters would be re-ordered based on the optimised prioritisation.

By combining unit process models, hazard evaluation and system simulation, Sheng et al. (1997) developed a model which can predict capability of energy consumption, waste flows and exposure risks over a planning horizon. The case studies were conducted in process parameters sensitivity, cutting fluid selection and process changes to demonstrate the application of the methodology in machining system. The final decision can be showed in a spider chart to compare the environmental burden of different strategies based on the calculation result by using this multi-objective model. It further improved the new process planning system. Sheng et al. (1998) developed a multi-criteria hazard (MCH) method to evaluate environmental impact manufacturing process. Different manufacturing process plans could be compared based on MCH

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weigh in terms of energy consumption, waste flow, processing time and health issues. This is one of the earliest research work contributed to improve the sustainability of machining process.

Krishnan and Sheng (2000) integrated this environmentally conscious process planning as an agent into a Java based CAD tool called WebCAD and can be applied for CNC machining. A case study was conducted to show that the environmental macro-planning which was generated by using WebCAD can reduce 4.5% of total energy consumption and 47.2% of fluid coated on a chip than conventional macro-planning system. This result further verified the effectiveness of environmentally conscious process planning system. However, research of Sheng et al. also has some shortcomings. First of all, the process planning method is based on the improvement of energy consumption and environment affect, but none of the research investigated the energy efficiency for specific machining. Secondly, the improved process plan with sustainability consideration did not consider optimisation of process parameters. So the optimised result might not be the best solution. Thirdly, energy consumption in these researches just considered for the machining operation which just accounts for small part of total energy consumption for manufacturing process.

Researcher from University of Manchester Rajemi et al. (2010) conducted research on the minimisation of energy consumption by optimising cutting parameters for dry turning operations. A prediction model was developed to calculate energy consumed in dry turning operations. The proposed model also included explicit expressions for components of the Auxiliary Energy (AE) such as machine set up energy, energy for tool change and energy embodied in the tool and made explicit the machining parameters such as feed rate, cutting velocity and tool life. This informative mathematical model made it possible to carry out an optimisation procedure which minimises the turning energy with respect to the cutting conditions (e.g. tool life). They also identified that optimising energy footprint in machining was a trade-off between the use of rapid machining to reduce cycle times and the use of the cutting tool at conservative speeds to maintain longer machining activity.

Further experimental verification of Rajemi et al.'s model was conducted by Mativenga and Rajemi (2011) to test the tool breakage constraints, power constraint and optimise the cutting variables. The experiment compared the energy and cost between optimal result and the suggested values from cutting tool catalogue. The experimental results

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proved that, based on minimum energy criterion, the optimum tool life can be used to constrain and optimise other cutting variables. The total energy consumption and cost based on machining parameters from a tool supplier catalogue is not efficient and economic. By optimising feed rate, cutting velocity and depth of cut with minimum energy and cost criteria, the energy consumption and cost can be significantly reduced (up to 64% can be saved). Both criteria can get the same trend of optimisation, and the results are same. This research proved that energy footprint can be used as the criteria to optimise cutting parameters for machining operation.

Mori Seiki Co. Ltd in Japan conducted a study to improve the energy efficiency for machine tool (Mori et al. 2011). The study focused on the energy consumption during the machining operation (e.g. drilling, end milling and face milling), which can be further divided into three states: non cutting state, cutting state and positioning state. A variable which is equal to energy consumption divided by material removal volume was defined to evaluate the improvement. The result proved that the energy consumption can be reduced by choosing suitable cutting parameters, toolpath and machining strategies, and shortening the process time. The results also showed that cutting performance can be improved by adjusting cutting speed, feed rate, depth and width of cut. Up to 66% power consumption for milling operation can be reduced by selecting high level of cutting conditions within a value range which does not compromise tool life and surface finish. The machining time also can be shortened with a significant increase in material removal rate (up to 333% material removal rate can be increased by selecting optimum cutting parameters). Oda et al. (2012) further carried out experiments for energy efficiency improvement in ball end milling on a 5-axis machine tool. They reported that up to 50% improvement of power consumption can be achieved by applying optimised cutting conditions (higher cutting speed, higher feed rate and smaller tool-workpiece inclined angle).

Newman et al. (2012) investigated energy-efficient process planning for end milling. Experiments were conducted to compare the power consumption for different loading cutting conditions. The results showed that when keeping material removal rate as a constant, light cutting condition (small depth of cut, large feed rate) consumed less power than high cutting condition (large depth of cut, small feed rate). However, up to 6% total power can be saved for slotting aluminium. It means increase of cutting force from increasing feed rate is less than increasing depth of cut. This conclusion can be also drawn from empirical cutting force equation that the cutting force coefficient of

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feed rate is smaller than the cutting force coefficient of depth of cut. This result also proved that the specific energy consumption models (e.g. Kara et al., 2011 and Diaz et al., 2012) which were just related to MRR were not informative enough. However, the experimental comparison and multi-feature test showed that the improvements of power consumption are only 6% and 1.7%. This result needs to be further extended by considering other energy minimisation methods to draw decision makers' attention to the energy consumption.

2.6.3 Multiple Objectives Machining Optimisation

The consideration of the improvement of machining operation in term of sustainability is actually a multiple objective optimisation or multiple criteria selection problem. In practical machining process, these criteria or objectives could be either conflicting or non-conflicting. However, when the multiple objectives considered are conflicting, it usually require decision makers to have clear preferences. The challenge of current research is how preference of decision makers can be accurately and effectively represented.

Chong and Zak (2007) gave a description of multi-objective engineering optimisation problems. Compared to the single objective optimisation problems which only have one objective function, most engineering problems require designers to consider more than one objective which may be in conflict with each other. It means the improvement in one objective may lead to deterioration in other objectives. Multi-objective problems in which the objectives are conflicting may have no unique optimal solution.

The purpose of multi-objective optimisation (MOO) is to assist decision makers select the optimal plan or make a better decision. Marler and Arora (2004) conducted a survey of current nonlinear multi-objective optimisation methods for engineering use. They reported that the current methods can be divided into three major categories based on the preference type of decision maker, which is priori articulation, posteriori articulation and no articulation. They also claimed that no single approach is superior. The selection of optimisation method must depend on the type of information provided, the decision maker's preferences, the solution requirements and the availability of software.

Multi-objective optimisation problems are also referred to as multi-criteria or vector optimisation problems. A multi-objective optimisation problem can be as follows:

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Find a decision variable that satisfies the given constraints and optimises a vector function whose components are objective functions. In general, there are three different types of multi-objective optimisation problems:

- Minimise all the objectives functions.
- Maximise all the objective functions.
- Minimise some and maximise others.

For the implementation in machining optimisation, the MOO methods can be divided into two categories based on the techniques applied which are Priori techniques and Posterior techniques (because the optimisation methods applied for solving no articulation of preferences problems are just simplification of Priori techniques). The basic principle of priori techniques is to convert MOO problems to single-objective optimisation by combining different objectives functions as a single objective function. The optimal result will be displayed as a unique solution. On the other hand, posterior techniques (e.g. evolutionary computation techniques) will present a set of feasible solutions for the decision makers to choose. This set of feasible solutions is called Pareto optimal set and can be represented as a Pareto front.

For using priori techniques, Malakooti et al. (1990) proposed a method for assessing the weights of the importance of different criteria on machinability including production rate, operation cost, product quality, tool life, surface roughness, accuracy, temperature, power/force/torque, vibration and noise. A machinability function was developed which can combine different process outputs together. The weights of the importance of these objectives can be calculated and evaluated according to decision maker's preference. Based on this method, Cus and Balic (2003) optimised cutting speed and feed rate by using genetic algorithm. A unique optimal plan was achieved for end milling operation with the consideration of production rate, operation cost and surface roughness. The work was extended in Cus and Zuper's further publications (Zuper and Cus, 2003, Cus and Zuper, 2006 and 2009) by using different optimisation methods for turning and end milling operation. Tolouei-Rad and Bidhendi (1996) investigated optimisation of machining parameters for conventional milling operation. Profit rate was utilised to combine machining cost and process time. A case study of machining a multiple-feature component showed that up to 350% improvement can be achieved compared to recommendations from Machining Data Handbook.

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On using posteriori techniques, Sardinas et al. (2006) used genetic algorithm to optimise production rate and cost for turning operation. Pareto front was used to represent the feasible optimal results. Kapat and Ozel (2007) used neural network and particle swarm algorithm to optimise three conflicting cases: surface roughness and productivity, material removal rate and tool life, and surface roughness and surface residual stress. Three sets of Pareto fronts were plotted to show the optimal results for each case. Pareto fronts were also used to show the optimal results of two conflicting objectives such as surface roughness and tool wear by Roy and Mehnen (2008), and material removal rate and tool wear by Yang and Natarajan (2010) for turning operation.

For optimising machining operation with energy considerations, Sheng and Srinivasan (1995a, 1995b) developed an environmentally conscious multi-objective process planning method. This new process planning method estimated the process mechanics, tool life, fluid flow, process energy, machining time and the mass flow of component waste streams. These waste streams can be weighted by environmental factors such as toxicity, carcinogenicity, irritation, reactivity and flammability. Thus the process and parameter can be selected based on objectives including process energy, process time, surface finish and weighted mass flow. Mativenga and Rajemi (2011) carried out a research to optimise energy consumption for turning operation. They also reported that the optimal cost can be achieved with optimal energy by using identical optimal process parameters.

Avram et al. (2011) developed a multi-criteria decision method for assessing the sustainability of machine tool systems. The proposed method seeks to find one or several satisfactory solutions among a set of possible solutions by considering different criteria. An interpretation table (Table 2.3) of the weighting methods of different criteria was built to capture preference information of the decision makers. Then the overall performance of different process plans/cutting strategies can be calculated and selected with the corresponding requirements. So the decision makers can easily select the optimal alternative based on the overall rate in both machining process level and machine tool system level.

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Table 2.4 Weighting of Different Criteria (Avram et al., 2011)

Scale value	Interpretation
1	Equally preferred
3	Moderately preferred
5	Strongly preferred
7	Very strongly preferred
9	Extremely preferred
2, 4, 6, 8	Halfway between the integers on either side
Reciprocals of above	In comparing criteria i and j, if i is 3 compared to j, then j is 1/3 compared to i

2.6.4 Summary: Issues of Machining Optimisation Research

Machining optimisation has been considered for over 100 years. However, there are still some issues existing in current machining optimisation research.

Firstly, although characterisations of machining operation for energy consumption (e.g. Kara et al., 2011 and Diaz et al., 2012) and conventional objectives (e.g. cost, time, quality, tool life and surface roughness, Meng, 2000) have been presented in early research, there still lacks of understandings of the relationship between different criteria (e.g. conflicting or non-conflicting). It will cause problems (e.g. how to get the optimal results and why the optimal results look like in such form) when multiple objectives need to be considered during machining optimisation.

Secondly, the link between modern optimisation methods and optimisation theory is missing or embedded into algorithms functions. As identified by Roy et al (2008), most of academic optimisation results have not been used by industry because practitioners mostly prefer to select optimal parameters based on expert experience. To solve this problem, the optimisation process needs to be uncovered or transparent to make the practitioners to understand and accept the optimal results, and implement optimal results in practice. The following requirements need to be addressed to achieve this goal:

- The optimisation procedure must be based on a comprehensive understanding of the nature of problem (e.g. search space, variables, constraints).
- The primary objective (energy) must be related to the conventional objectives such as cost, time and quality which the practitioners are familiar with and interested in.
- The optimisation method adopted must be suitable for the machining problem and conform to practitioners' knowledge or obvious general principle.

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- The optimisation results must be easily visualised, so that decision makers can rapidly find the optimal result and have confidence in the obtained optimal results.

Thirdly, too many different optimisation methods have been applied in machining optimisation. These methods are developed based on different background and now have been widely used in machining operation. The comparison between these methods showed that in some circumstance, there is no significant difference in the performance (e.g. accuracy) of these methods. So it is difficult to tell which one is the "best". Also there is lack of understanding about how these methods function to achieve the optimal results.

Fourthly, the process of understanding machining operation in terms of the nature of machining operation and optimisation takes a long time. There is no comprehensive framework or guideline to help the users (both academic and industry) who do not have good knowledge about machining optimisation to scientifically determine the optimal machining parameters.

Finally, sustainability awareness brings new requirements for existing multi-objective machining optimisation research. In carrying out the review of current research contributions, the following problems can be identified:

- For priori techniques, decision maker's preferences are required to determine the weight for each objective or directly combine the objectives together. However, priori techniques are not suitable for the cases that the decision makers' preferences are not clear, or optimising objectives are not able to be reasonably combined.
- For posteriori techniques, Pareto front is usually employed to present the optimal results for the problems when two conflicting objectives need to be considered. However, when there are more than 2 objectives, multiple Pareto fronts are required to present the optimal results for every two objectives. These multiple Pareto fronts are difficult to understand, and analysis process is complex and inefficient.
- Most multi-objective machining optimisation research with energy considerations reviewed only used priori techniques. The optimal results achieved by using these methods are a unique optimal plan, but not a set of feasible solutions. So, it is necessary to investigate the optimal solutions of

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multi-objective machining optimisation with energy considerations by using posteriori techniques.

2.7 Improvement through the Development of New Processes and Technologies

Beyond optimisation of existing machining process, further reduction of energy consumption can be achieved through the development of energy efficient industrial processes and technology. This need is being addressed through ongoing energy efficient manufacturing research as part of a wider field of sustainable manufacturing.

Dahmus and Gutowski (2004) identified factors (e.g. such as material production, cutting fluid usage and material removal) which affect energy consumption during machining operation. Energy consumption from cutting fluid usage is reduced by minimising (i.e. Minimal Quantity Lubrication, MQL) or eliminating (i.e. dry machining) the quantity of coolant used during machining, hence reducing the energy used during machining as well as pollution and harmful health effects from additives in coolants (Yalcin et al, 2009).

The minimisation or complete reduction of the usage of cutting fluid and lubrication (CLF) in machining process has been investigated to reduce the energy consumption and environmental impact to achieve the goal of sustainable manufacturing. By abandoning conventional cooling lubricants and coolant strategies, and applying the advanced strategies of dry machining or minimum quantity lubrication (MQL), the cost of the machining process can be significantly reduced. Dry machining and MQL are the key technologies to reduce the cost and improve the overall performance of cutting operation through cooling lubrication. Implementing dry machining cannot be simply accomplished by switching off the coolant supply pump. The cooling lubricant has some important functions that include:

- Cooling lubricants can reduce the friction, thus reduce the generation of heat and dissipate the generated heat.
- Cooling lubricants can remove the chips to clean the tools, work pieces and fixtures.
- The tool life can be increased and the cutting force can be reduced.

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Research of CLF for different strategies and application conditions can reduce the environmental impact by reducing energy consumption and waste generation, and improving the economics and efficiency performance (Hands et al., 1996, Weinert et al., 2004).

Minimal Quantity Lubrication (MQL) is a new method between dry and wet machining. An experiment conducted by Rahman et al (2002) to evaluate the effect of MQL in milling showed that MQL (8.5 ml/h) could drastically save more coolant than the traditional flood cooling method (42000 ml/h). Braga et al (2002) applied MQL during an experiment of drilling of aluminium-silicon alloys. The result showed that both machining precision of hole (37.5% of roughness was reduced for diamond coated tools, and 66.7% for uncoated tools) and tool life (25% of the feed force was reduced) are improved. Kishawy et al (2005) applied MQL during the high-speed machining of A356 aluminium alloy, further proving that MQL can replace the flood method and improve dry machining (30% of cutting force was reduced).

Dry machining eliminates the use of cutting fluid during machining, thus completely avoiding the energy consumption and environmental damage from coolant use. Without the use of coolant, the cutting force and heat generated will be considerably high and lead to rapid wear/failure of cutting tools. Kustas et al (1997) used nanocoatings on cutting tools, and tested the machining result by comparing with traditional tools, reaching the conclusion that the nanocoated cutting tools can greatly reduce the cutting force (33%) and wear during machining however, dry machining is not suitable for all conditions. It is difficult to use for grinding operation or machining specific materials (aluminium and aluminium alloy).

Campatelli conducted an experiment for three different lubrication strategies: flooded, MQL and dry for turning operation of AISI 1040 steel based on Gutowski's work (Campatelli, 2009). The energy consumption was evaluated from the analysis of the cutting force along the cutting and feed direction (tangential and radius) for using different lubrication strategies. According to the experiment result of energy, tool life and emission, the overall performance of MQL is better than dry and flooded strategies (15% energy saved, 25% tool life increased).

New CLF technologies (e.g. cryogenic machining and high pressure jet assisted machining, HPJAM) were investigated to alternate conventional CLF methods by the

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researchers from Kentucky. The new technologies can increase the productivity (improve material removal rate), tool life (lower abrasion, chemical wear), surface quality, and reduce the cutting force, thus achieve the goal of sustainability (lower energy consumption, environment impact and machining cost) (Jawahir et al., 2007, Pusavec et al., 2010a, 2010b, Kopac 2009, Jayal, 2010).

New type of lubricant supplies were introduced at 12th Global Conference on Sustainable Manufacturing by Klocke et al. (2014) and Blau et al. (2014) by considering high pressure lubricant supply and Cryogenic cooling method. These additional coolant supplied may cause the increase of total power consumption, but lower temperatures can reduce flank wear and break the limits of conventional machining/coolant strategies by massively increasing cutting speed without harming the tool life. Thus it will significantly reduce the machining time, and the total energy consumption will be reduced too.

Apart from coolant strategies, optimising toolpath or cutting tool utilisation is another way to achieve an energy-efficient machining process. Researchers from Laboratory of Manufacturing and Sustainability (LMAS) conducted the research in minimising the energy consumption in machining operation based on improving the machine tool performance, optimising cutting parameters and toolpath strategies. Vijayarahavan and Dornfeld (2010) presented a software-based approach to monitor the energy consumption for machine tools and help to make decision based on multi-level/scale temporal analysis. Diaz et al. (2010) researched on energy minimisation of end milling operation. The research was conducted based on an understanding of the direction of table travel where more energy is used on machine tools. The effects of the orientation of toolpath were investigated for various toolpath strategies on energy consumption. The energy consumption per unit was determined and optimised based on cutting parameters (e.g. feed rate). Then the kinetic energy recovery system (KERS) was used to improve the production efficiency. 5% to 25% of power consumption can be saved. A unified monitoring scheme was used to capture the energy flow which can easily and effectively integrate various disparate elements and analyzed the sampled data. Through the three approaches, the energy efficiency for precision manufacturing can be easily improved.

Further research was conducted to verify Diaz's research. Life-cycle Assessment (LCA) of two types of end milling machines (Bridgeport Manual Mill, low automation and the

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Mori Seiki Dura Vertical 5060, high automation) was carried out based on energy demand and CO_2 emissions. The results showed that the energy requirement to manufacture high automation machine is much higher (100,000MJ) than low automation machine (18,000MJ). In this case, the different design of machining tool will consume different amount of energy (Diaz et al, 2010a). In addition to implementing machine tool design changes, energy consumption for using a machine tool could also be reduced through selecting process parameter. A total energy consumption model for the machine tool operation was proposed based on power demand (Diaz et al., 2010b). The energy consumption for machine tool can be classified into three categories: constant, variable and cutting energy. Constant energy (CE) comes from auxiliary equipment (e.g. computer panel, light fixture and coolant pump). Cutting energy is the energy consumed during machining operation, and depends on cutting parameters (e.g. feed rate, spindle speed, width of cut, depth of cut, and number of flutes of the cutter). Variable energy comes from the spindle motor, which also has two states: steady state (spindle drives under a specified value) and transient state (spindle accelerating or decelerating). Figure 2.16 shows the processing time and energy consumption for different toolpath strategies to produce a pocket feature based on this proposed model. It shows that the energy consumption and processing time for different toolpath are different, and where more energy is used in machine tools.

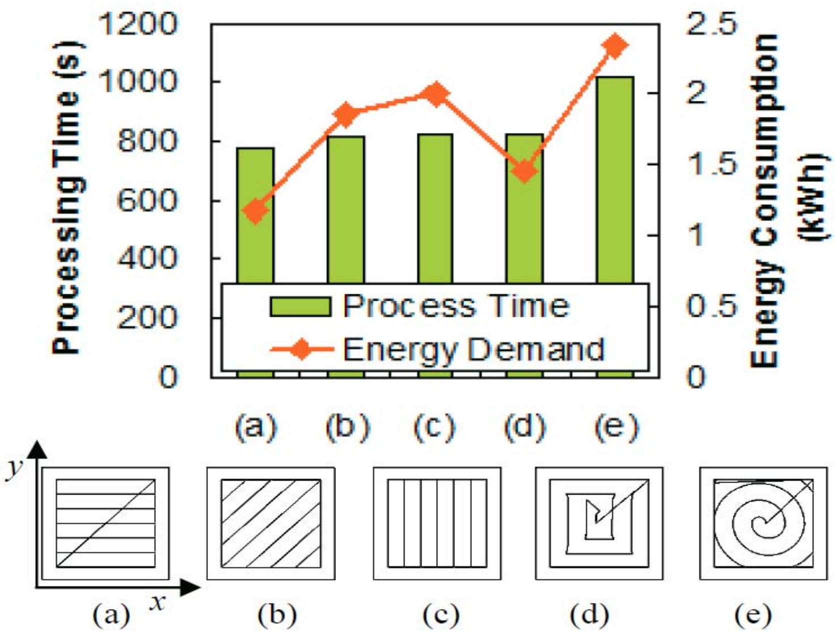

Figure 2.16 Processing Time and Energy Consumption of Various Tool Paths (Daiz et al. 2010a)

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Schultheiss et al. (2013) proposed an approach to increase cutting tool utilisation for milling and turning operation which can significantly increase cutting tool utilisation thus increase the sustainability of the machining process. By swapping the major and minor cutting edge (for milling operation) or reversing feed direction (for turning operation), the tool life can be possibly increased 50%-100% without harming surface roughness. This increase of tool life cannot only reduce the cost of cutting tool purchase, but also reduce the energy consumption for changing the cutting tool.

Advanced Manufacturing Research Group of TechSolve, US conducted the research to assess the energy consumption efficiency for discrete part manufacturing at machining level (Deshoande et al. 2011a, 2011b). An energy monitoring system called "Smart Energy Monitor" was built up based on National Instruments LabView. The energy consumption of a discrete part can be specifically represented at feature level. Potential energy savings can be achieved by improving the machine tool system, thus achieve the goal of energy-efficient machining and sustainability. However, this research did not provide the sustainable suggestions by considering the optimisation of process parameters and the improvement of machine tools. In addition, the implication of this system requires using specific hardware like power sensors to collect the data, which will increase the operating cost and cannot be widely implemented.

In summary, instead of the improvement of current manufacturing strategy, the aim of developing new energy-efficient machining strategies is to implement new concepts and machining strategies to minimise energy consumption for the machining operation. However, these strategies also have limitations and currently are still not able to replace conventional strategies. For example, most of these research contributions are related to the coolant strategies or using different cutting tools. Although these research contributions can reduce the energy consumptions, the inherent inefficiency of existing machining process which is caused by the cutting technology is still not solved. In this case, it is really important to develop a new energy-efficient toolpath strategy from the knowledge of machining science which can further minimise the energy consumption and improve the energy efficiency of the existing cutting process. The new proposed energy-efficient strategy should be able to identify the potential improvement to the theoretical limitation, and give the direction to the new research of technology for tool design, toolpath strategy and machining technology.

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2.8 Industrial Survey

The survey of industrial practice was also conducted in this research through factory visit, industrial exhibitions visit, informal interview and secondary findings from other literature survey conducted. The aim of industrial survey is to observe how the manufacturing process operates in practice and the current situation of practical manufacturing process. The tasks of the industrial survey focus on the following area:

- Awareness of energy issues in machining operation
- Energy usage and energy efficiency measurement
- Determination of selection of process parameters
- Machining improvement
- Existing tools applied in practice
- Capability of CAM software

The specific interview questions are listed as below:

- What methods are used to determine process parameters in the machining operations?
- What criteria do the practitioners concern in practice?
- Do you think energy should be considered as an important criterion? If yes, do you know the relationship between energy and other criteria?
- Are there any methods used to improve the machining process? If yes, what are they?
- What tools have been used to decide the machining process?

The scale of the visited industry companies covered a broad range including large/medium/small machining workshops, industrial/academic machining laboratories, and machine/machining tool manufacturers. Over 40 people have been interviewed including experienced/young shop floor practitioners, apprentices, sales managers, line managers, facility managers, designers and technical engineers and machining science students and researchers.

The results of industry survey showed that:

- Most of practitioners consider cost (total cost and tool cost) and quality (surface roughness) issues, but do not have awareness of the energy issue. One of the possible reasons is that it is difficult to directly feel the energy consumption during the machining operation.

- It is difficult to measure energy consumption in practical manufacturing environment. One reason is laboratory measurement system is difficult to setup because of the power supply wires and cables in the workshop are integrated and set up together. The second reason is practitioners do not like to be disrupted when they have started machining jobs.
- The process parameters applied in practical machining process are not optimal. Usually, the process parameters are determined based on practitioners' experiences or selected from machining handbook/cutting tool catalogue. Once the process parameters are determined, they are seldom changed.
- Most of the interviewed practitioners lacked the knowledge of machining optimisation. It is one of the reasons they do not trust and accept academic optimisation results. Compared to academic optimal results, they prefer to trust traditional sources (such as machining handbook, cutting tool catalogue, experiences and experiment results. Some companies even buy NC code from third part process planning company).
- The most common improvement method used by practitioners is to improve the productivity via increasing more shifts. One of the reasons is that they do not want to change the process plan. Compared to changing process plan, they prefer to keep a stable process which is easy to predict the outputs and control the inventory/orders.
- The process planning capability of existing CAM software is very limited which is more like an integrated machining library (machining handbook, cutting tool catalogue). Separate from CAM software, some big cutting tool manufacturers (such as Sandvic) developed feed/speed calculator (online version or mobile applications) to determine process parameters. However, most of the calculators are just simple software based on machining science equations. The function is very simple usually related to cutting tool dimensions and cutting speed, and request to manually input the cutting process parameters.
- Finally, there are lots of barriers existing which cause the academic achievements are very difficult to implement in practice. For example, even potential improvements exists in current manufacturing process, almost all of the industries do not want to take a risk to implement new methods/techniques and

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prefer to use conservative methods. Another major problem is most of the companies do not have extra budget (small and medium enterprises) or will (larger/national enterprises) to purchase an energy-efficient process planning system.

From the result of Anderberg's research (2012) in Figure 2.17, the cost of energy only accounts for a very small portion of total cost (less than 1%). This result will cause the negative influence that industry may ignore the importance of energy issues. In this context, it is necessary to explore other research directions in energy consumption to emphasise the importance of energy minimisation, such as:

- What the energy efficiency is in machining operation?
- How energy affects the other considerations (e.g. cost and quality)?

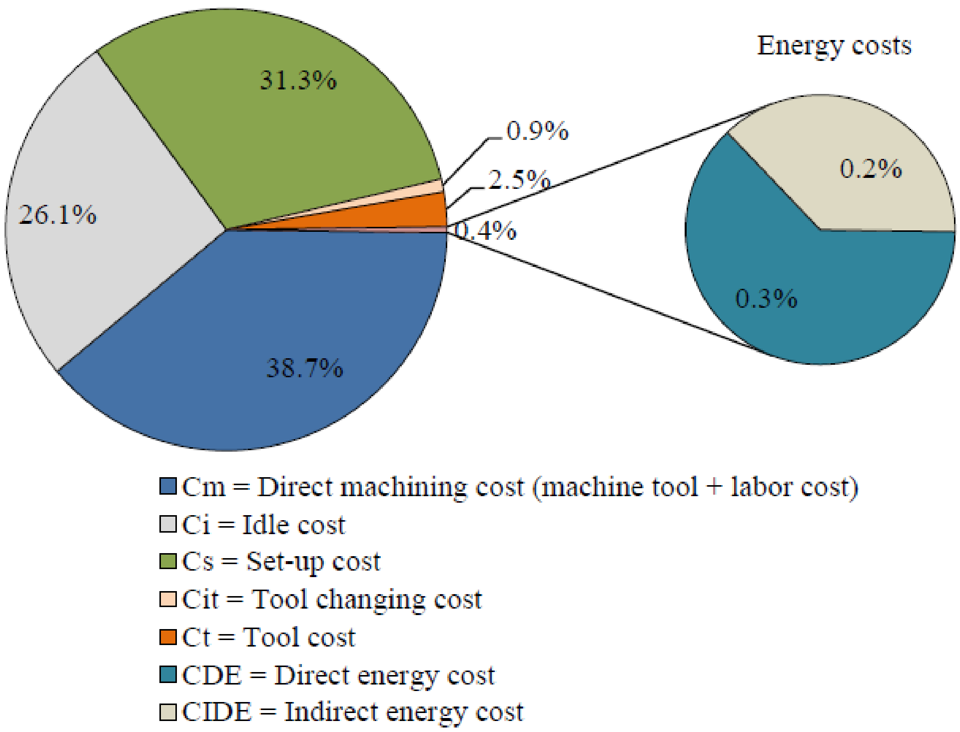

Figure 2.17 Proportion between Cost Components for Machining Process (Anderberg, 2012)

In summary, the issues raised from industry survey are also related to two categories which are similar as the issues identified from literature survey:

- Energy/energy efficiency measurement method needs to be developed for practitioners to better understand the importance of energy consumption. It can

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provide a reason why it is important to pay attention to energy consumption, and provide tools to evaluate their current processes.

- Improvement methods need to be developed for practitioners to improve their machining process. Apart from the human factors, it also needs to consider the factors including: preferences, habits and capability of different users, and form of implementation. So the optimal results can be understood, trusted and accepted by practitioners.

2.9 Summary of Literature Review

In the chapter of literature review, the research contributions of the related area have been investigated in order to identify the issues/gaps of current research and development. Issues of current practical machining process have also been identified based on industry survey which is the same as the issues identified from literature survey. The research questions can be formulated to address the issues raised from literature and industrial survey. According to the investigation of current research in sustainable manufacturing, energy measures for manufacturing process, machining optimisation and energy-efficient machining strategies, the following tasks have been completed and summarised:

Firstly, general concepts of sustainable manufacturing have been introduced to define the research area and describe the current trends in research area. Research of energy consumption/efficiency in manufacturing mainly focuses on how to reduce energy consumption. Reducing energy consumption can be achieved through the development of energy efficient industrial processes and technologies. This need is being addressed through ongoing energy efficient manufacturing research as part of a wider field of sustainable manufacturing.

Secondly, the review of how to measure the energy consumption and energy efficiency for the manufacturing process has been continuously carried out. The major shortcoming of these contributions is that the energy efficiency metrics do not uncover the inherent inefficiencies in the machining process and suggest the direction to achieve better energy efficiency. Though the academic research has proposed some energy audit models and energy efficiency metric to help measure and evaluate the energy usage, these models and metrics have some limitations (e.g. not informative enough) and problems (e.g. against the common sense).

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Thirdly, the review of machining optimisation have been carried out to introduce the existing machining optimisation methods and commonly accepted optimisation procedure which will be used to guide the optimisation based on energy considerations to reduce the energy consumption and improve energy efficiency. However, too many different optimisation methods have been applied in machining optimisation. The optimal results obtained from these research contributions are not transparent enough and most of academic optimisation results have not been used in industry. Although the environmental challenge provides a new opportunity to apply the results of decades of optimisation and process planning research, under this circumstance introducing energy as an additional criterion will bring more complexity of existing machining problems.

Fourthly, sustainability awareness brings new requirements for existing multi-objective machining optimisation research. Most multi-objective machining optimisation research with energy considerations reviewed only used priori techniques to convert multi-objective optimisation to single-objective optimisation problem. The optimal results achieved by using these methods are a unique optimal plan, but not a set of feasible solutions. So, it is necessary to investigate the optimal solutions of multi-objective machining optimisation with energy considerations by using posteriori techniques.

Finally, new energy-efficient machining strategies have been reviewed to introduce the important technologies and significant contributions in the area which can improve the energy efficiency. Energy consumption during machining was grouped as that due to material production, cutting fluid usage and material removal. Reduction of energy from material production aims at utilising materials requiring less energy at the primary production stage, producing less negative effects on the environment and having good recycling properties. Energy consumption from cutting fluid usage is reduced by minimising or eliminating the quantity of coolant used during machining, hence reducing the energy used during machining as well as pollution and harmful health effects from additives in coolants. However, the inherent inefficiency of existing machining process which is caused by the cutting technology is still not properly solved. The new proposed energy-efficient strategy should show direction to the research of new technologies for tool design, toolpath strategy and machining technology.

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CHAPTER 3: DEVELOPMENT OF PREDICTIVE MODELS AND ENERGY EFFICIENCY METRICS FOR MACHINING OPERATION AND THE EXPERIMENTAL VALIDATION

The aim of this chapter is to introduce the mathematical models for machining operation such as cutting force, power, time, energy, cost, tool life and surface roughness. Mathematical expressions have been modelled based on machining theories and common empirical methods. An energy prediction model has been built based on cutting force model. Experiments are conducted to determine the coefficients and verify the energy prediction model. These mathematical expressions will be used to analyse the characteristics of machining operations for the following chapters.

3.1 Modelling of Prediction Model for End Milling Operation

In this section, a theoretical energy prediction model for end milling operation will be built based on machining science theories and other researchers' publications in regarding to power, time and tool life.

3.1.1 Power Consumption Model for Machining Operation

The power consumption to remove a volume of material depends on the force needed to carry out the operation and the cutting velocity at which the operation is being conducted. In this context, theoretically the cutting velocity component in the axial direction is zero, and the component in the radial direction is insignificant compared to the component in the tangential direction (similar conclusion can be drawn from Wan et al., 2010, see Figure 2.6). Therefore, the power consumption for machining operations can be represented in Equation 3.1 with the tangential cutting force based on Equation 2.15 multiplied by cutting velocity.

$$P_{machining} = \frac{F_T \cdot V_c}{60} \tag{3.1}$$

where, V_c is cutting velocity m/min, where, K_T is cutting force coefficient, N/mm^2.

$$V_C = \frac{\pi d n}{1000} \tag{3.2}$$

As the cutting force model shown in Chapter 2, the cutting force is related to the instantaneous cut thickness, depth of cut and feed rate, the power consumption for machining operation can be generated as following steps:

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$$P_{machining} = \frac{K_T \cdot a_p \cdot f \cdot \int_{\phi_{in}}^{\phi_{out}} \sin\phi \, d\phi}{nz} \cdot \frac{\pi dn}{6 \times 10^4} \tag{3.3}$$

$$P_{machining} = \frac{\pi \cdot K_T \cdot a_p \cdot f \cdot d}{6 \times 10^7 z} (\cos\phi_{in} - \cos\phi_{out}) \tag{3.4}$$

When the tool is completely engaged, the power consumption model for machining operation can be represented in Equation 3.5.

$$P_{machining} = \frac{2\pi \cdot K_T \cdot a_p \cdot a_e \cdot f \cdot d}{6 \times 10^4 z \cdot d} = \frac{\pi \cdot K_T \cdot MRR}{3 \times 10^4 z}$$

$$P_{machining} == \frac{\pi \cdot MRR \cdot C_0 \cdot a_p^{C_1} \cdot a_e^{C_2} \cdot d^{C_3} \cdot z^{C_4} \cdot f_z^{\ C_5} \cdot n^{C_6}}{3 \times 10^4 z} \tag{3.5}$$

where, P_M is the power consumption for end milling operation W, MRR is material removal rate mm^3/min.

However, the total power consumed during machining process also need consider the component of auxiliary functions including spindle driven servo motor, NC control pad, computer and fans, lighting, coolant pumper motor etc. The investigation of power consumptions of each component will be shown in the following sections of experimental results.

$$P_{total} = P_{machining} + P_{auxiliary} \tag{3.6}$$

$$P_{auxiliary} = P_{constant} + P_{variable}$$

The auxiliary power consumption can be further divided into two parts which are constant power consumption and variable power consumption. Constant power consumption contributes to the functions which consume constant power such as NC control pad, coolant pump driven motor and lighting. The variable power consumption contributes to the functions that the power consumption changes with the increase/decrease with the process parameters (e.g. feed rate and spindle speed), such as spindle driven servo motor and workbench driven motor.

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3.1.2 Time Consumption for Machining Operation

Total time consumption for machining process can be expressed:

$$t_{total} = t_m + t_{setup} + t_{tool} \tag{3.7}$$

Where t_m is machining time min, t_{setup} is setup time min, t_{tool} is tool changing time, and can be represented as:

$$t_m = \frac{V_m}{MRR}$$

$$t_{setup} = n_s \cdot t_s \tag{3.8}$$

$$t_{tool} = n_{tool} \cdot t_{tc} = \frac{t_{tc} \cdot t_m}{T_l} \tag{3.9}$$

Where, n_s is number of setup times, n_{tool} is number of tool changing times, t_{tc} is tool changing time min/change, t_s is setup time min/setup, T_l is tool life min. So the total time consumption can be represented as:

$$t_{total} = t_m + t_{setup} + t_{tc}\frac{t_m}{T_l} \tag{3.10}$$

3.1.3 Modelling of Tool Life

Tool life depends on a lot of cutting variables. The most significant variables affecting tool life are work piece material, tool material, tool shape, cutting speed, feed rate and depth of cut. Taylor's equation was widely used to calculate tool life in machining operation. Taylor (1907) is the early pioneer of the research of tool life. The basic Taylor's equation is shown in Equation 3.11.

$$VT^u = C \tag{3.11}$$

where, V is cutting speed, T is tool life, C is a tool life coefficient, u depends on different tool materials.

This basic equation is easy to use and only has one variable (cutting speed). But it is not very accurate. In this case, based on the basic equation, the extended Taylor's equation was developed. Extended Taylor equation can be represented by considering cutting speed, feed rate and depth of cut (Enparantza, 1991):

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$$T = \frac{C}{V^m \cdot f^p \cdot a_p^q} \tag{3.12}$$

where, f is feed rate, a_p is depth of cut, m, p and q are constants.

Among these three factors, cutting speed is the most important factor, then the second one is feed rate and the impact of depth of cut is the least. In Enparantza's research, feed rate is fixed, a_p is related to diameter of tool and very small, the basic equation will be suitable for end milling operation. The specific application can be represented as a simple Taylor equation as below:

$$V_C \cdot T_L^u \quad = V_{CR} \cdot T_{LR}^u \tag{3.13}$$

where, V_{CR} is reference cutting speed, T_{LR} is reference tool life. Then,

$$\frac{V_C}{V_{CR}} = \left(\frac{T_{LR}}{T_L}\right)^u$$

$$T_L = T_{LR} \cdot \left(\frac{V_{CR}}{V_C}\right)^{-u} \tag{3.14}$$

Where,

$$\begin{cases} u = 0.25 \sim 0.3 & Carbide \\ u = 0.5 \sim 0.7 & Ceramics \\ u \cong 0.125 & High\ Speed\ Steel \end{cases}$$

Pan et al. (2009) developed a tool life prediction model for milling Aluminium 7075-T6 series aeronautical aluminium by using multi-linear regression. The model considered the impact of cutting speed and feed per tooth which is:

$$T_l = \frac{41078687}{V_c^{1.546} \cdot f_z^{0.473}}$$

3.1.4 Energy Consumption Model for Machining Operation

The energy consumption model for end milling operation can be represented as Equation 3.15:

$$E_{machining} = P_{machining} \cdot t_m \tag{3.15}$$

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Where, tm is time consumption for machining process in seconds. Time consumption can be approximately calculated by material removal volume divided by material removal rate.

$$t_m = \frac{60V_m}{MRR} \tag{3.16}$$

Based on the equation 3.4, 3.7 and 3.8, the energy consumption model can be concluded as equation 3.17.

$$E_{machining} = \frac{\pi \cdot K_T \cdot MRR}{3 \times 10^4 z} \cdot \frac{60V_m}{MRR}$$

$$E_{machining} = \frac{2\pi K_T V_m}{10^3 z} \tag{3.17}$$

where, $E_{machining}$ is the energy consumption for machining operation J, V_m is material removal volume mm^3. Based on equation 3.17, the energy consumption for a machining operation is in proportion to material removal volume and reverse proportion to the number of flutes.

The total energy consumption for machining process can be expressed as in Equation 3.18:

$$E_{total} = E_{machining} + E_{auxiliary} + E_{setup} + E_{toolchange} \tag{3.18}$$

The expressions of each component are shown as below:

$$E_{auxiliary} = t_m \cdot \left(P_{constant} + P_{spindle}\right)$$

$$E_{setup} = t_s \cdot P_{constant}$$

$$E_{toolchange} = t_{tc} \frac{t_m}{T_l} \cdot P_{constant} \tag{3.19}$$

where, $P_{constant}$ is the power consumed by the functional component which requires constant power such as control pad, coolant pump, lighting etc. $P_{spindle}$ is the power consumed by the spindle. It depends on the spindle speed applied during machining.

So the total process energy consumption is:

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$$E_{total} = \frac{2\pi V_m \cdot C_0 \cdot a_p^{C_1} \cdot a_e^{C_2} \cdot d^{C_3} \cdot z^{C_4} \cdot f^{C_5} \cdot n^{C_6}}{z \cdot 10^3} + t_m \cdot \left(P_{constant} + P_{spindle}\right) + t_s \cdot P_{constant} + t_{tc} \frac{t_m}{T_l} \cdot P_{constant} \quad (3.20)$$

3.2 Cost, Surface Roughness and Chatter

Additional models such as cost and surface will also be introduced in this section for carrying out the following research of sustainability improvement with the consideration of energy consumption. In addition, chatter as an important factor in machining operation will also be discussed.

3.2.1 Modelling of Cost with Energy Considerations

The cost of end milling operation is determined by three main factors, which are labour, energy and tool. As expressed in Equation 3.21, the cost, C of end milling operation can be determined as the sum of labour cost C_L, energy cost C_E, and cost of cutting tool C_T..

$$C = C_L + C_E + C_T \quad (3.21)$$

where, C_L - labour cost, C_L - Energy cost, C_T- tool cost

The most important variable to affect the tool cost is tool life. Tool life is the standard to evaluate the performance of the cutting tool. It can be defined as "cutting time required to each tool-life criteria" (Lamond and Sodhi, 1997). It is directly related to the efficiency and cost of machining operation. The relationship is shown as Equation 3.22.

$$C_T = R_T \frac{t_m}{t_L} \quad (3.22)$$

where, R_T – tool rate, equals to tool price or tool resharpening cost divided by tool life, t_L- tool life.

$$R_T = \frac{Tool\ Price}{T_L} \quad or \quad \frac{Tool\ Resharpening\ Cost}{T_L} \quad (3.23)$$

Labour cost in machining process, is related to total time consumed and labour rate. Total time can be determined as the sum of machining time, setup time and tool change time. The expression of labour cost is shown as Equation 3.24.

$$C_L = R_L \cdot t_{total} \quad (3.24)$$

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where, R_L is labour rate.

Energy consumption in the machining process is basically equal to electricity consumption for machine. The energy consumption is related to electricity rate, energy consumption for the machining operation and machining efficiency. Thus, the energy cost can be represented in Equation 3.25.

$$C_E = R_E \cdot E_T \tag{3.25}$$

where, R_E is electricity rate, E_T is total energy consumption

3.2.2 Modelling of Surface Roughness for End Milling Operation

Surface finish is one of the common criteria to evaluate the quality of the machining operation. Early researchers used simplified geometric model to predict the average surface roughness. For example, Enparantza (1991) used:

$$R_a = \frac{f_n^2}{32R}$$

where, *fn* is feed per revolution.

Tolouei-Rad and Bidhendi (1997) used:

$$R_a = \frac{318 f_z^2}{4d}$$

To accurately predict surface finish, empirical equation has been widely used in current machining research. A statistical model has been generated by carrying out multiple regression analysis based on the experimental data. Equation 3.26 shows a typical empirical equation with the consideration of depth of cut, width of cut, feed per tooth and cutting speed. The reason why this model selected is because of it considered more process parameters than the previous models and has a better accuracy because of the surface roughness constants will be determined based on experiment data by using statistic techniques (Pan et al., 2008).

$$R_a = C_0 V_c^{C_1} f_z^{C_2} a_e^{C_3} a_p^{C_4} \tag{3.26}$$

`

According to the validated data from Pan et al. (2008) to investigate surface roughness for milling Aluminium 7075-T6, a statistical model can be generated as below (R-square is 96%):

$$R_a = 2384.4887 V_c^{-1.45061} f_z^{0.491583} a_e^{0.907896}$$

3.2.3 Chatter in Machining Operation

Chatter is another important factor in machining operation which can affect the accuracy of product (such as surface roughness), force variation, and reduce tool life and machine life. The same as other factors, chatter will also be affected by process parameters including depth of cut, width of cut, spindle speed and feed rate. The increase of process parameters will increase the chatter of machine.

One of methods can effectively reduce chatter is to reduce the cutting force by adjusting process parameters such as spindle speed, depth and width of cut, or improving the stability of cutting tools. Enparantz (1991) claimed that at low cutting velocities, the end milling operation actually stabilises cutting. The shorter the wave length (velocity/frequency), the greater the likelihood of damping will be produced. The limiting cutting velocity can be calculated as the following equation:

$$V_{chat} = \left[\frac{2\pi \times 60}{1000}\right] \times f_n \times \lambda_{min} \qquad (3.27)$$

where, fn is machine tool nature frequency, and λ_{min} is minimal wave length.

3.3 Experimental Verification of Energy Prediction Model

To verify and improve the proposed energy prediction models and get accurate data, primary experiment was conducted to measure the power consumptions and cutting forces. Experiments were carried out on a HAAS TM-1CE 3-axis vertical milling machine. The capability of the machine tool is shown in Table 3.1. The power consumptions are measured by a FLUKE 435 Power Quality Analyser (see Figure 3.1).

The aims of the experiment are to measure the power consumption of each machine tool section, and compare the power consumption by using different cutting parameters. To control the errors in measures and make sure the measures are reproducible and repeatable, the validation process will be conducted twice. The data collected from primary measure will be used to generate the energy prediction model.

Table 3.1 HAAS TM-1CE Basic Specification

Manufacturer	Haas
Type	TM 1CE (Vertical)
Number of Axes	3
Tool Station	0
Spindle	1
Motor Power	5.6 KW
Spindle Speed	4,000 RPM

Figure 3.1 Laboratory Power Measurement System

Further experiments were conducted based on the measurement of tangential cutting force to verify the developed model. The cutting forces were captured by a force measurement system consisting of a Kistler 9367C, force measurement unit, charge amplifier, an NI 9205 Analog input/Digital output module and DAQs software system (see Figure 3.2). The results of experimental measures and theoretical predictions (based on the data collected from primary experiments) were compared to validate and check the accuracies of the prediction models.

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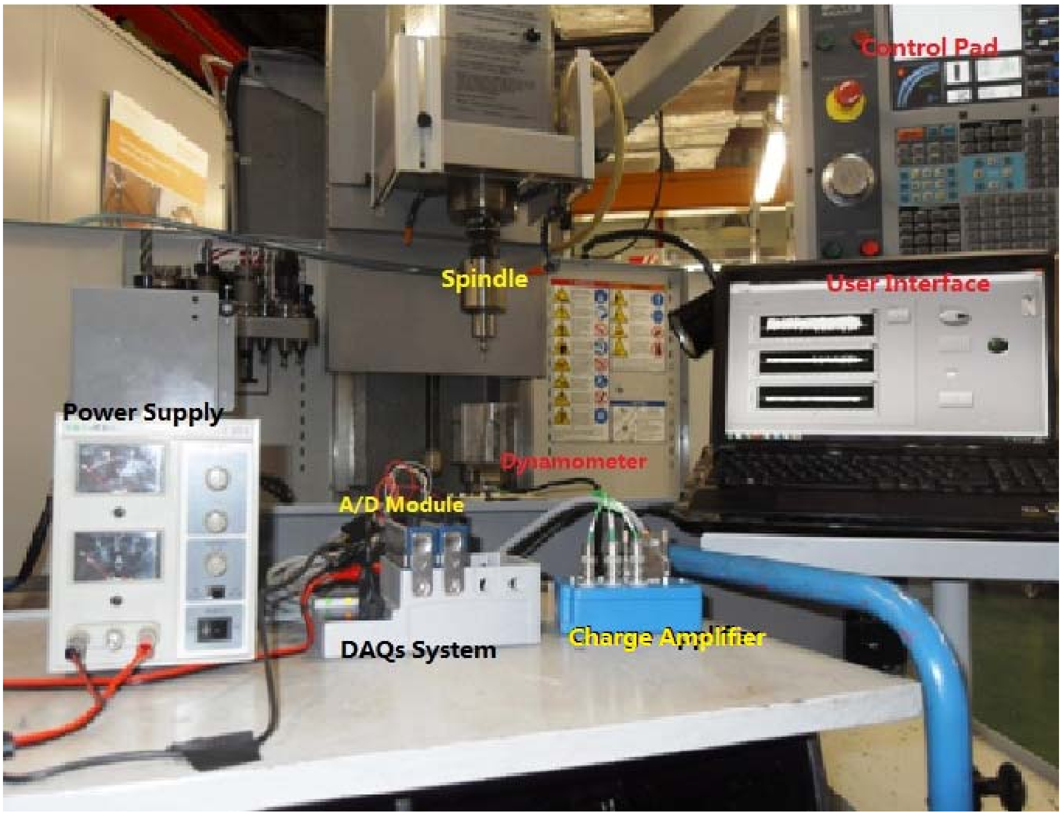

Figure 3.2 Cutting Force Measurement System

Then the extended power measurements were conducted by using different dimensions of cutters and range of process parameters as a Reproducibility and Repeatability (R&R) study to further analyse and evaluate the errors and accuracy of the measurement system, and make sure the measurement system and methods are acceptable for the intended use.

3.3.1 Power Measurement for Auxiliary Functions

Based on the measurement of power consumption, the power consumption via auxiliary functions can be determined. For the tested machine tool, the idle power consumption (power on) is 237.1W, the power consumption for the coolant pump is 60.48W, the power consumption of computer and fan is 74.54W. The power consumption for spindle speed has a linear relationship with spindle speed. The detailed results are shown in Table 3.2 and Figure 3.3 that the active power for spindle driver is 11.62W and the power consumption will increase in proportion to the increase in spindle speed.

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Table 3.2 Power Consumption for Different Spindle speed

Spindle Speed (RPM)	Power Consumption (W)
500	61.64
1000	83.53
1500	144.02
2000	174.58
2500	223.00
3000	261.14
3500	299.70
4000	352.52

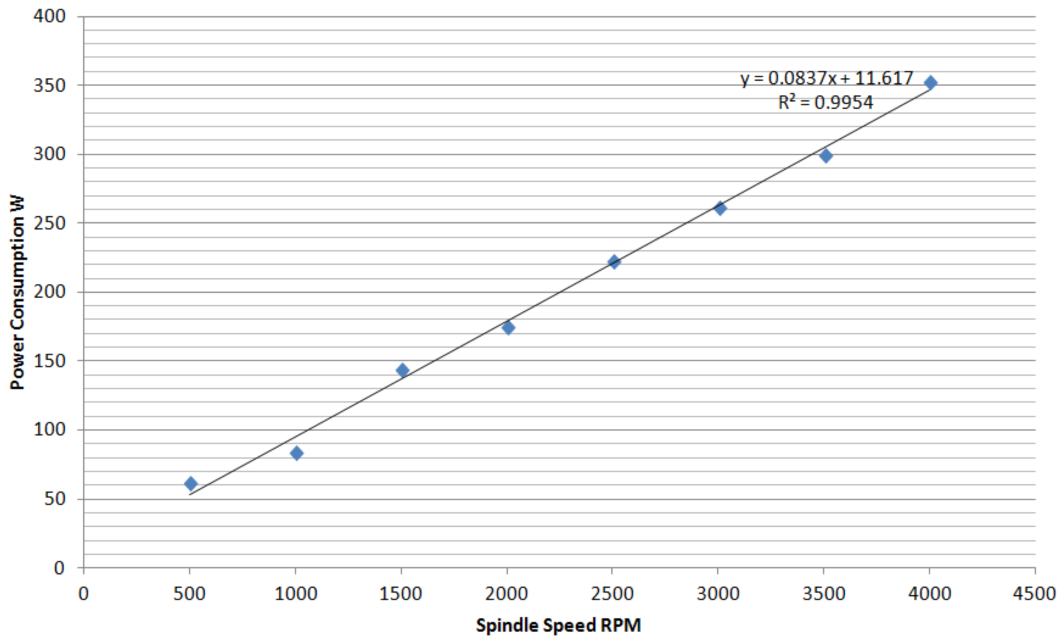

Figure 3.3 Plot of Power Consumption with the Increase in Spindle Speed

3.3.2 Primary Power Measurement for Machining Operation

Three different cutting tools were used which are 10mm 2 flutes end mill, 10mm 3 flutes end mill and 16mm 3 flutes end mill. The work piece material is Aluminium 7075-T6. Different process parameters were applied to capture primary data of power consumption by using power measurement system in Figure 3.1. The results were used to determine the coefficient of the developed model. The detailed experimental plan and measurement data is shown in Table 3.3.

The theoretical power consumption of the above process parameters can be calculated based on the constant value in Table 2.1. The comparison results between the theoretical calculation and experimental measurement are shown in Table 3.4. The theoretical value and experimental value of power consumption for different parameters are compared with the accuracy which is equal to the ratio between experimental value and

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theoretical value. According to the modelling process of power consumption in section 3.1, it is really important to determine the cutting force coefficient K_T. Based on Equation 3.5, the experimental values of tangential cutting force co-efficient and uncut chip thickness were calculated and shown as well in Figure 3.4 and Figure 3.5. The accuracies between theoretical and experimental values in power can be calculated by using the following Equation 3.28. The range of accuracy is between 67.44% and 85.38%.

$$Accuracy = 1 - \%error = 1 - \frac{error}{Actural\,Value} \times 100\% \qquad (3.28)$$

Table 3.3: Primary Experiment Parameters for Power Measurement

No.	d (mm)	z	a_p (mm)	a_e (mm)	feed (mm/tooth)	n (rpm)	Total Power (W)	Auxiliary Power (W)	Machining (W)
1	10	3	1	10	100	1000	481.925	447.040	34.885
2	10	2	1	10	100	1000	489.436	447.300	42.137
3	10	3	1	10	200	1000	495.700	443.967	51.733
4	16	3	1	10	100	1000	502.571	447.700	54.871
5	10	3	1	5	100	1000	469.641	445.125	24.516
6	10	3	1	5	200	1000	479.754	443.967	35.780
7	10	3	1	5	100	2000	552.125	525.700	26.425

Table 3.4: Comparison of Theoretical and Experimental Result

No.	Theoretical (W)	Experiment (W)	Accuracy	K_T	h_C (mm)
1	26.167	34.885	75%	999.89	0.067
2	32.708	42.1367	77.62%	805.16	0.1
3	34.889	51.7333	67.44%	741.40	0.133
4	41.867	54.8714	76.3%	982.97	0.067
5	20.933	24.5159	85.38%	1405.37	0.033
6	26.167	35.78	73.13%	1025.54	0.067
7	31.4	26.425	81.17%	1514.81	0.017

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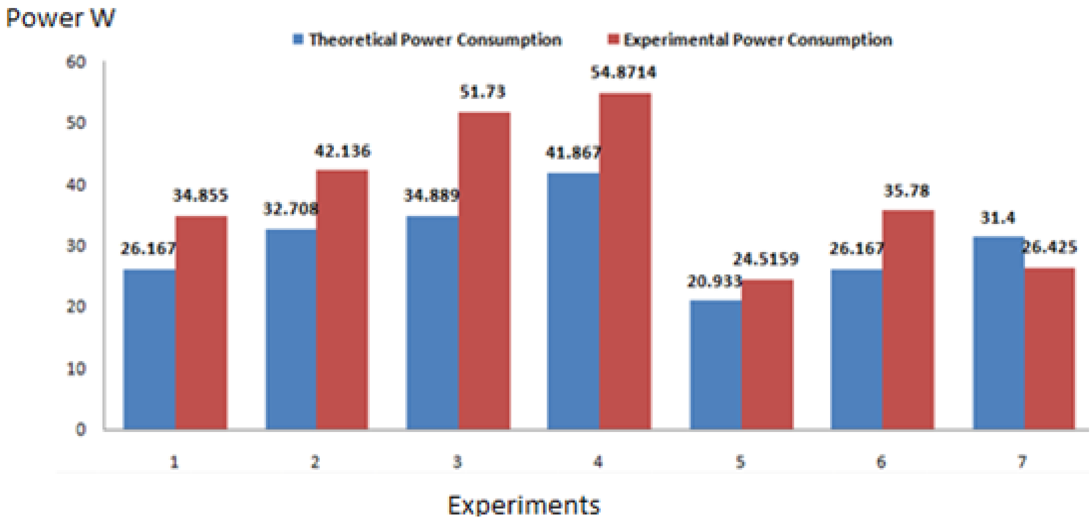

Figure 3.4 Comparison of Power Consumption for Theoretical and Experimental

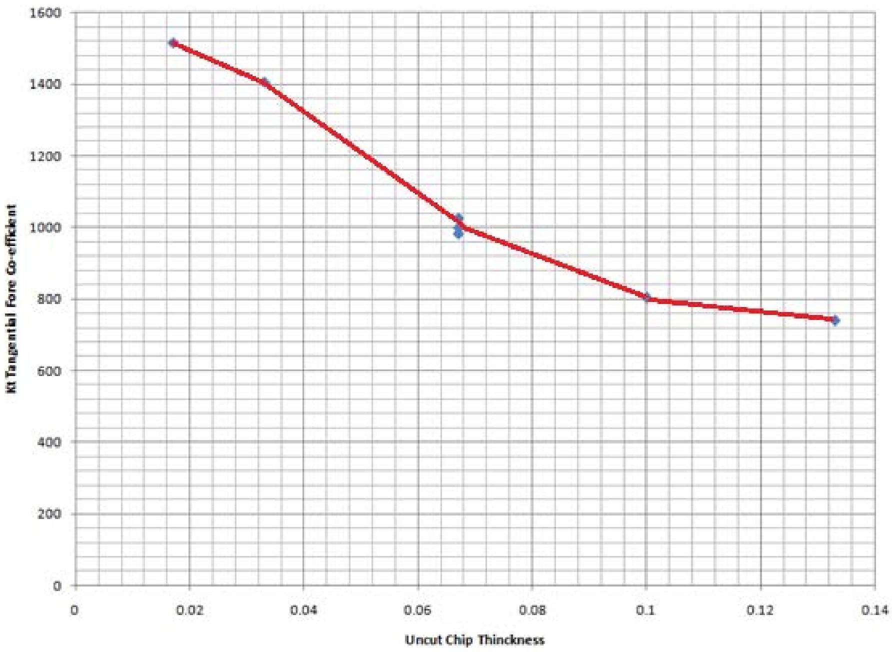

Figure 3.5 Tangential Cutting Force Co-efficient of Experimental Results for Machining Aluminium 7075-T6

The cutting coefficients for different operations are totally different (e.g. the co-efficient of operation 3 is less than half of that for operation 7) and prove that the cutting force coefficient is not constant. According to the experiment results presented in Figure 3.5, when the uncut chip thickness is over 0.03mm, the trend of K_T curve flattens (from 1045 to 741 N/mm^2). This result is very similar to the experimental data from literatures (Wan et al., 2009, Dang et al., 2010) and the values are also similar. Two keys observations can be made from this result.

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Firstly, the values of K_T are similar by using same cutting strategies on different machine tools with the uncut chip thickness. The differences could be caused by the accuracy of the measuring system or circumstances (e.g. temperature).

Secondly, the curve of K_T can be divided into two linear stages. One is the rapidly decreasing stage where the uncut chip thickness is from 0 to 0.03mm. The other one is the flattening stage where the uncut chip thickness is over 0.03mm.

According to these two observations, following suggestions can be proposed to commonly apply the developed cutting force model.

- K_T can be considered as a constant between small range of uncut chip thickness. This method can be applied to the situation that, the uncut chip thickness will not hugely change for the different cutting parameters.
- The value of K_T can be considered as in a range. When using K_T to calculate, the force and energy are also shown as a range. The sensitivity or accuracy will be given to verify the value.
- The value of K_T can be generated as two functions which are related to uncut chip thickness. Since chip thickness is related to feed rate, spindle speed, number of flute and rotated angle, the K_T can be represented as $K_T = f(a_p, n, z, f)$. The function can be generated by conducting experiments and using multi-regression method.

  $$K_T = f\left(a_p, a_e, d, z, f_z, n\right) = C_0 \cdot a_p^{C_1} \cdot a_e^{C_2} \cdot d^{C_3} \cdot z^{C_4} \cdot f_z{}^{C_5} \cdot n^{C_6}$$

  where, $C_0 \sim C_6$ are coefficient
- Manual of coefficients can be developed by conducting more experiments to generate more values in different conditions.

By using regression analysis, the coefficients for flat end milling operation of Aluminium 7075-T6 were determined (presented in Table 3.5).

Table 3.5 Cutting Force Coefficients for Flat End Milling Operation (Workpiece material: Aluminium 7075-T6)

C_0	C_1	C_2	C_3	C_4	C_5	C_6
1611.2282	0.01249	-0.0778	-0.59213	1.45596	-0.20856	-0.20856

`

3.3.3 Verification Experiments

The aim of conducting validation expeirments is to validate the developed energy model. Two measurement systems (force and power) were used to capture the experimental data of cutting force and power consumption for the machining process. Comparison of the tangiental cutting force and the energy consumption of the experimental measurement and the theorical prediction is shown in the following paragragh in this section.

Figure 3.6 shows the comparing results between the experimental measurement and the theoretical prediction by using 2 flutes 10mm end mills in conventional milling. From the figure, the experimental measurement fits very well with the calculation results. The accuracy of selected range is up to 91.5%. This result proves that the theoretical tangential cutting force model is fairly accurate and can be used to predict the energy consumption for end milling operation.

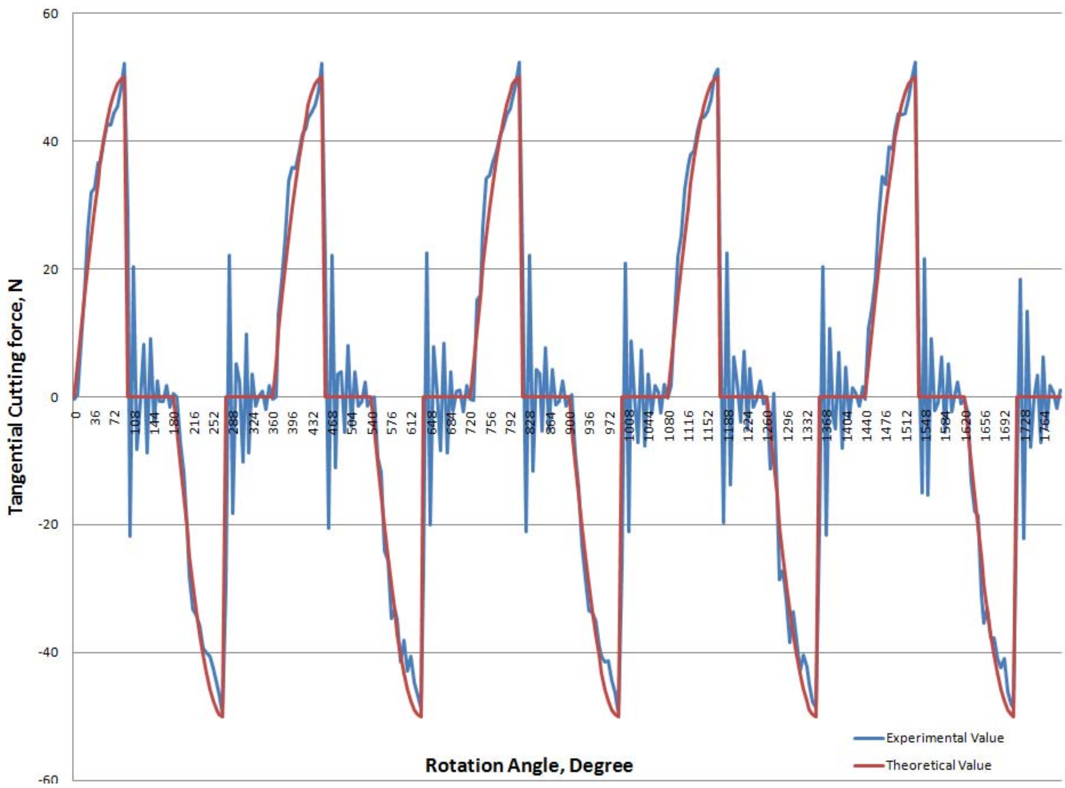

Figure 3.6 Comparison of Tangential Cutting Force between Theoretical Calculation and Experimental Measurement

Extended power measurement tests were conducted to further validate the developed model. 3 different cutting tools were selected which are 8 mm/4 flutes, 10 mm/3 flutes and 12 mm/ 2 flutes. Each tool was used 9 times by using different process parameters

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based on Taguchi design of experiment method. Totally 27 results were captured and shown in detail in Table 3.6. Figure 3.7 shows the comparison of the tangetial cutting force of the experimental measurement and the theoritical prediciton. From the figure, the experimental measurement also fits very well with the theoretical prediction. The average accuracy of total 27 tests is up to 95%. This result further proves that the accuracy of the developed energy prediction model is very good.

Table 3.6: Experimental Verification based on Power Measurement

No.	d (mm)	z	a_p (mm)	a_e (mm)	feed (mm/tooth)	n (rpm)	Prediction (W)	Measurement (W)	Accuracy
1	8	4	1	4	0.01	1000	463.552	436.7	94.207%
2	8	4	1	6	0.02	2000	574.873	560.3	97.465%
3	8	4	1	8	0.03	3000	711.537	697.8	98.069%
4	8	4	2	4	0.03	2000	607.617	570.3	93.858%
5	8	4	2	6	0.01	3000	680.323	629.6	92.544%
6	8	4	2	8	0.02	1000	509.808	450.1	88.288%
7	8	4	3	4	0.02	3000	726.14	701.4	96.593%
8	8	4	3	6	0.03	1000	542.165	470.4	86.763%
9	8	4	3	8	0.01	2000	621.168	536.7	86.402%
10	10	3	1	5	0.01	1000	461.148	450.7	97.734%
11	10	3	1	7.5	0.02	2000	564.406	560.7	99.343%
12	10	3	1	10	0.03	3000	685.609	680.3	99.226%
13	10	3	2	5	0.03	2000	587.591	565.4	96.223%
14	10	3	2	7.5	0.01	3000	663.507	620.3	93.488%
15	10	3	2	10	0.02	1000	493.901	448.6	90.828%
16	10	3	3	5	0.02	3000	695.949	632.7	90.912%
17	10	3	3	7.5	0.03	1000	516.812	450.0	87.072%
18	10	3	3	10	0.01	2000	597.186	520.4	87.142%
19	12	2	1	6	0.01	1000	458.749	450	98.093%
20	12	2	1	9	0.02	2000	553.959	550.5	99.376%
21	12	2	1	12	0.03	3000	659.729	674.5	97.810%
22	12	2	2	6	0.03	2000	567.604	565.1	99.559%
23	12	2	2	9	0.01	3000	646.722	620.5	95.945%
24	12	2	2	12	0.02	1000	478.024	447.5	93.615%
25	12	2	3	6	0.02	3000	665.814	657.6	98.766%
26	12	2	3	9	0.03	1000	491.508	456.8	92.939%
27	12	2	3	12	0.01	2000	573.250	547.6	95.525%
The average accuracy of 27 tests is 94.362%									

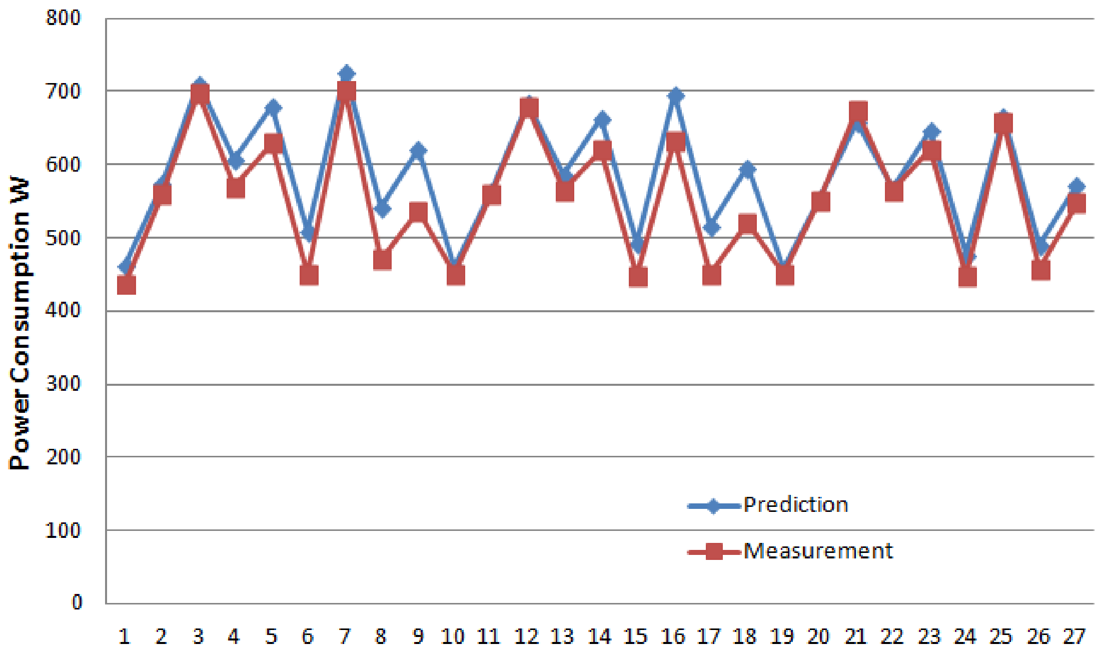

Figure 3.7 Comparison of Power Consumption between Theoretical Prediction and Experimental Measurement

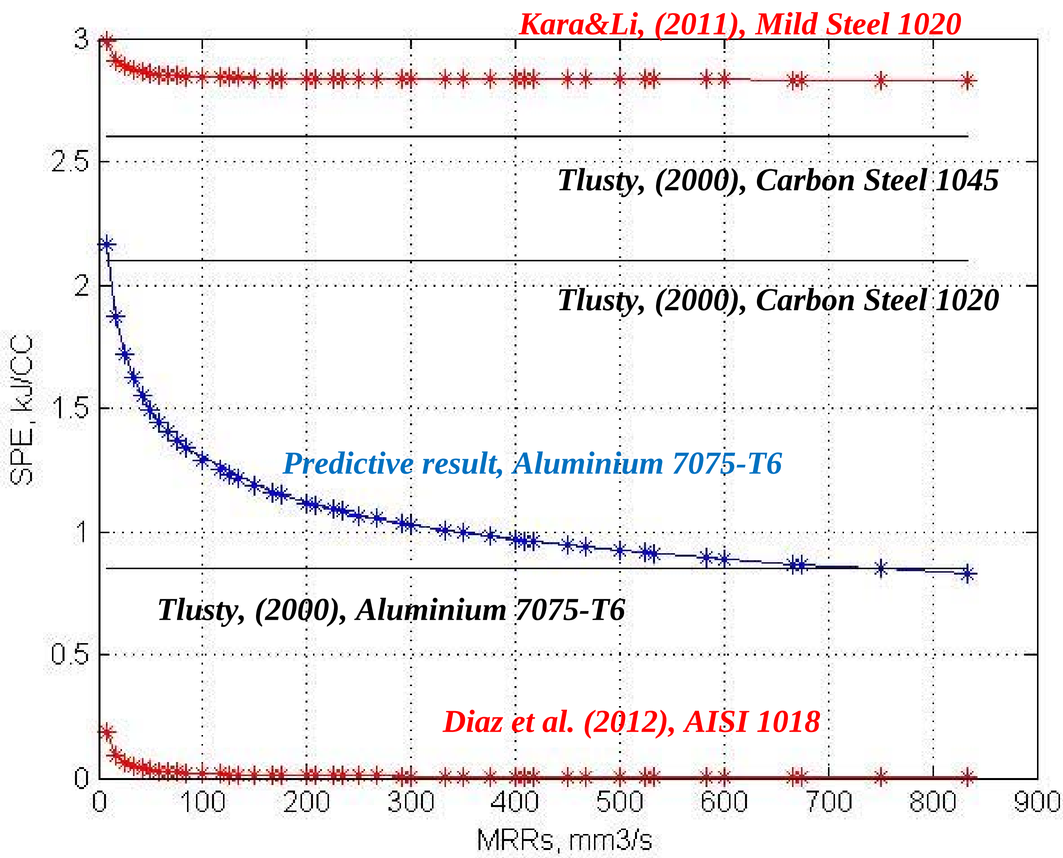

Figure 3.8 Comparison of Power Consumption between Proposed Model and Existed Publications

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Comparison of predictive result by using developed model, suggested results from textbook and predictive results achieved by using existing models from literature in specific energy consumption for various materials are presented in Figure 3.8. The results firstly showed that, with the increase of material removal rate, predictive specific energy consumption of Aluminium 7075-T6 is close to the constant value of same material published in machining science textbook (Tlusty, 2000, 850 N/mm^2). The predictive results achieved by using Kara and Li's model (2011, mild steel 1020) are a little higher than Tlusty's suggested value (approximately 25%). But the predictive results by using Diaz et al.'s model are much smaller than Tlusty's suggested value. Finally, the characterisation of different conventional materials, such as Aluminium and Mild/low carbon Steel are almost same which is monotonously decreases with the increase of material removal rate (MRR).

In addition, the comparison results with other predictive models in different materials can also show general character of specific energy consumption. The specific energy can be reduced by increasing MRR. This finding can further prove that the results achieved by proposed predictive model can be generally implemented for different materials and machine tools.

3.4 Development of New Energy Efficiency Metrics for Machining Operation

According to the issues identified from literature, the major shortcoming of energy efficiency measures for the machining operation is that the inherent inefficiencies of energy consumption in the machining operation have not been considered. The existing energy efficiency metrics do not uncover the inherent inefficiencies in the machining process. To address this shortcoming, new metrics are required to uncover this inherent inefficiency.

The radical difference in Equation 2.26 and the definition of energy efficiency ratio at the manufacturing process level in the work of other researchers (e.g. Rahimifard et al, 2010) is that in these other works Energy Ratio (ER) is defined as ratio of theoretical energy consumption (TE) and direct energy consumption (DE). DE is a sum of TE and auxiliary energy, AE (energy consumption for functions such as coolants, control panel). Hence in existing work, ER for the process can be expressed as in Equation 3.29.

$$ER = TE/(TE + AE) \tag{3.29}$$

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where, *ER* is energy efficiency for machining process, *AE* is auxiliary energy consumption.

The implication of Equation 3.28 is that it is possible to realise an efficiency ratio close to 1 (i.e. 100%) if improved technology makes most of the auxiliary functions unnecessary (e.g. through dry machining) without making any radical improvement in the efficiency of the machining operation itself. However, using 100% energy for machining operation does not mean the energy efficiency of machining operation can reach 100% too. Thus, the measurement of energy efficiency in current work as depicted by Equation 2.26 can only measure the energy efficiency within an existing technology and cannot uncover the inherent inefficiency in the process.

Cullen and Allwood (2010) identified an issue of energy efficiency that to accurately uncover the global improvement potential from energy efficiency measures, it is necessary to identify the theoretical limits of the existing process. In this case, to accurately evaluate the energy usage performance and uncover the inefficiency of machining process, a new definition of energy efficiency for machining has been proposed in the following section.

3.4.1 Proposed New Definition of Energy Efficiency for Machining Operation

A demonstration of the metal cutting process is shown in Figure 3.9. For a single cut (feed per tooth), the area of theoretical shear plane is smaller than the area of actual shear plane. This inefficiency is caused by the limitation of conventional cutting strategy. It means the tangential cutting force generated by using conventional cutting strategy will be always higher than pure shear force.

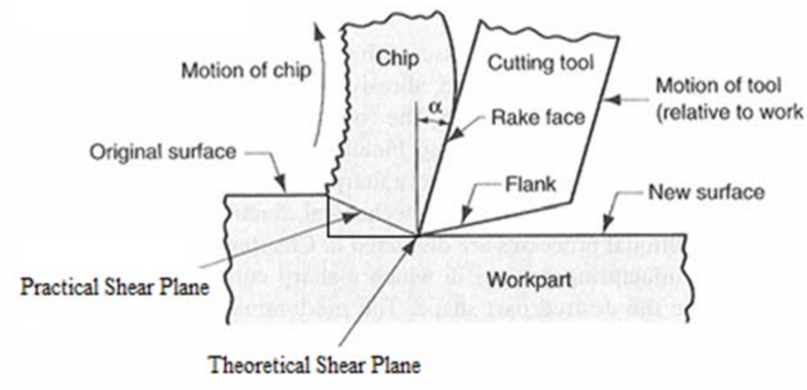

Figure 3.9 Theoretical and Practical Shear Planes of Metal Cutting Process (Lantrip et al., 2003)

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$$dF_{TM} = \tau \cdot dA_{TM} = \tau \cdot a_p \cdot f_z \quad (3.30)$$

where, dF_{TM} is theoretical minimal shearing force for one feed/tooth, dA_{TM} is theoretical shear area for one feed/tooth, τ is shear strength of the workpiece. Table 3.6 shows the value of shear yield strength for cutting typical materials.

Based on equation 3.30, the theoretical minimal cutting force for shearing a plane can be shown in equation 3.31.

$$F_{TM} = \tau \cdot A_{TM} = \tau \cdot L \cdot W \quad (3.31)$$

where, F_{TM} is theoretical minimal shearing force, A_{TM} is shear area of the shear plane, L and W are length and width of the shear plane.

So the *theoretical minimal energy consumption* (TME), which is the theoretical minimal energy requirement to shear a plane, can be represented by the expression in equation 3.32.

$$TME = F_{TM} \times D_s = \tau \cdot A_{TM} \times D_s \quad (3.32)$$

where, TME is theoretical minimal energy consumption for shearing a plane, D_s is cutting tool travelling distance.

The theoretical minimum energy term (TME) is not known to have been used in energy efficiency calculations and its introduction is one of the investigations presented in this research. However, because of the limitation of current machining technology, TME is not possible to be achieved.

Table 3.7 Value of Shear Yield Strength in Cutting (N/mm^2) (Trent, 1984)

Material	Shear Yield Strength
Iron	370
0.13% C Steel	480
Ni-Cr-V Steel	690
Austenitic stainless steel	630
Nickel	420
Copper (annealed)	250
Copper (cold worked)	270
Brass (70/30)	370
Aluminium	97
Magnesium	125
Lead	36

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Table 3.7 showed the values of shear yield stress in cutting for varies of materials. Based on the expression in Equation 3.32, a metric for the energy efficiency (Energy efficiency ratio, ER) in machining operation can be expressed as a ratio of the theoretical minimum energy (TME, as equation 3.32) to the actually machining energy (referred to as theoretical energy, TE, in work of Rahimifard et al, 2010, as equation 3.29) employed during the machining operation. This is expressed as in Equation 3.33.

$$\mathrm{ER}_{\mathrm{machining}} = \frac{TME}{TE} = \frac{TME}{E_{\mathrm{machining}}} \tag{3.33}$$

where, $ER_{machining}$ is energy efficiency for machining operation (cutting), TE is theoretical energy consumption for the machining operation.

So the energy efficiency can be represented in Equation 3.34

$$\mathrm{ER}_{\mathrm{process}} = \frac{TME}{DE} = \frac{TME}{(TE + AE)} = \frac{TME}{Total\ Energy} \tag{3.34}$$

where, $ER_{process}$ is energy efficiency for machining process, DE is direct energy consumption for the machining process, AE is the energy consumption for auxiliary functions. Based on Equations 3.33 and 3.34, the inherent inefficiencies in the machining process can be uncovered by comparing energy efficiencies of current definition and proposed energy efficiency metrics. Further investigation of the energy usage performance for the machining process will be carried out in the following section.

3.4.2 Investigation of Energy Efficiency of Machining Operation

In this section, the investigation of energy efficiency of machining operation will be carried on for milling a step feature ($30\mathrm{mm} \times 30\mathrm{mm} \times 30\mathrm{mm}$). Figure 3.10 shows the shear area of a 2½D step feature. Based on Equation 3.30, the theoretical energy consumption (TME) can be calculated as below:

$$TME = \tau \cdot A_{TM} \times D_s = 97 \times 30 \times (30 + 30) \times \frac{30}{1000} = 5238\,J = 5.238\,kJ$$

The value of TME for these 27 tests is constant (5.238kJ) and play a role as a theoretical limitation of energy consumption for this step feature. The practical energy consumption and energy efficiency has been calculated based on the data captured in Table 3.8 in section 3.3.3. The calculated results are shown in Table 3.7.

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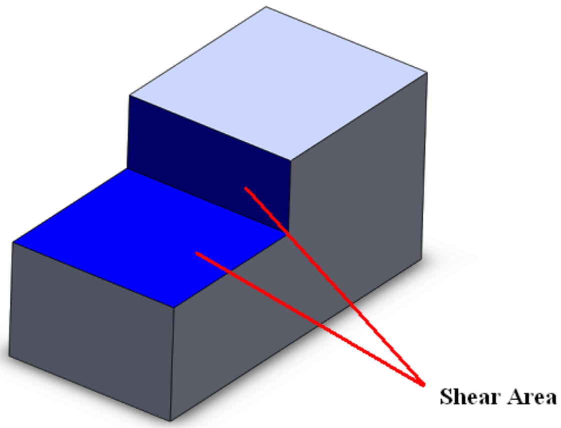

Figure 3.10 Shear Area of a 2½D Step Feature

Table 3.8: Energy Efficiency for the Selected Process Parameters

No.	d	z	a_p	a_e	feed	n	TE (kJ)	DE (kJ)	ER (TE/DE)	ER_m (TME/TE)	ER_p (TME/DE)
1	8	4	1	4	0.01	1000	83.3818	4223.38	1.974%	6.282%	0.124%
2	8	4	1	6	0.02	2000	60.5069	825.508	7.330%	8.657%	0.635%
3	8	4	1	8	0.03	3000	49.9613	364.962	13.69%	10.484%	1.435%
4	8	4	2	4	0.03	2000	57.8815	485.382	11.92%	9.050%	1.079%
5	8	4	2	6	0.01	3000	64.807	604.808	10.72%	8.082%	0.866%
6	8	4	2	8	0.02	1000	68.9647	665.215	10.37%	7.595%	0.787%
7	8	4	3	4	0.02	3000	58.1754	373.176	15.58%	9.004%	1.403%
8	8	4	3	6	0.03	1000	65.1361	455.136	14.313%	8.042%	1.151%
9	8	4	3	8	0.01	2000	69.3149	496.815	13.952%	7.557%	1.054%
10	10	3	1	5	0.01	1000	65.9769	4472.98	1.408%	8.317%	0.117%
11	10	3	1	7.5	0.02	2000	45.6999	855.701	5.341%	11.462%	0.612%
12	10	3	1	10	0.03	3000	37.7349	367.736	10.261%	13.881%	1.424%
13	10	3	2	5	0.03	2000	43.717	493.718	8.855%	11.982%	1.061%
14	10	3	2	7.5	0.01	3000	48.9477	618.949	7.908%	10.701%	0.846%
15	10	3	2	10	0.02	1000	52.088	682.008	7.637%	10.056%	0.768%
16	10	3	3	5	0.02	3000	43.9389	373.94	11.750%	11.921%	1.401%
17	10	3	3	7.5	0.03	1000	49.1962	459.196	10.714%	10.647%	1.141%
18	10	3	3	10	0.01	2000	52.3524	502.353	10.421%	10.005%	1.043%
19	12	2	1	6	0.01	1000	46.3282	5536.33	0.836%	11.306%	0.095%
20	12	2	1	9	0.02	2000	33.6186	1023.62	3.284%	15.581%	0.512%
21	12	2	1	12	0.03	3000	27.7592	417.761	6.645%	18.869%	1.254%
22	12	2	2	6	0.03	2000	32.1598	572.161	5.621%	16.287%	0.915%
23	12	2	2	9	0.01	3000	36.0078	726.010	4.960%	14.547%	0.721%
24	12	2	2	12	0.02	1000	38.3178	803.318	4.770%	13.670%	0.652%
25	12	2	3	6	0.02	3000	32.3231	422.324	7.653%	16.205%	1.240%
26	12	2	3	9	0.03	1000	36.1906	526.191	6.878%	14.473%	0.995%
27	12	2	3	12	0.01	2000	38.5124	578.513	6.657%	13.601%	0.905%

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From Table 3.8, the energy efficiency based on existing definition is between 1% to 15%. These efficiencies approximately fit the range of energy efficiency measured from the previous research contributions for machining operation (Kordonowy, 2001, Gutowski et al., 2005). Energy efficiency based on proposed definition is approximately between 6% to 19% in *ERm* (*TME/TE*) and 0.1% to 1.5% *ERp* (*TME/DE*). Based on the new proposed definition, the energy efficiency is much smaller than the efficiency measured by using the existing definition. It means, though the energy efficiency for machining based on the existing definition is very low, the actual energy usage performance may be even worse. The proposed energy efficiency metrics can help to uncover the inefficiency of the machining process by identifying the theoretical minimal energy consumption for the machining operation. Further evidences to support the conclusion above will be discussed by analysing Figure 3.11a and 3.11b as below.

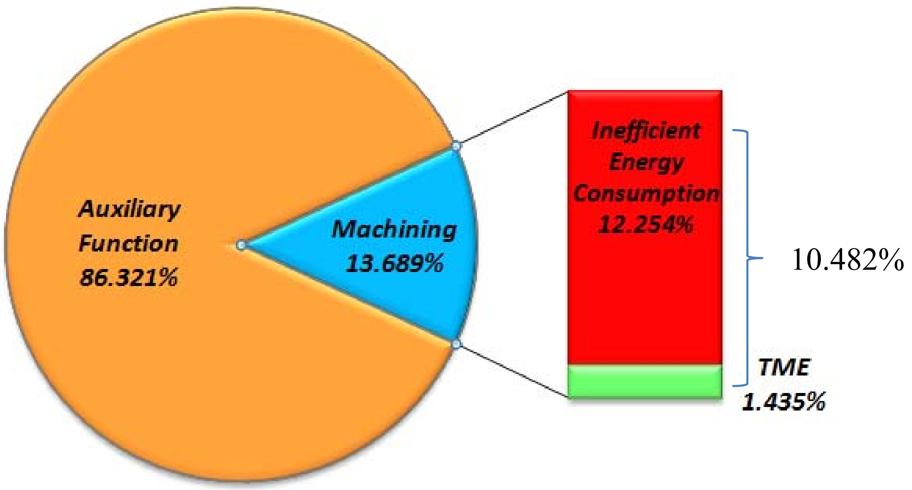

Figure 3.11a Energy Efficiency Chart for No.3 Test

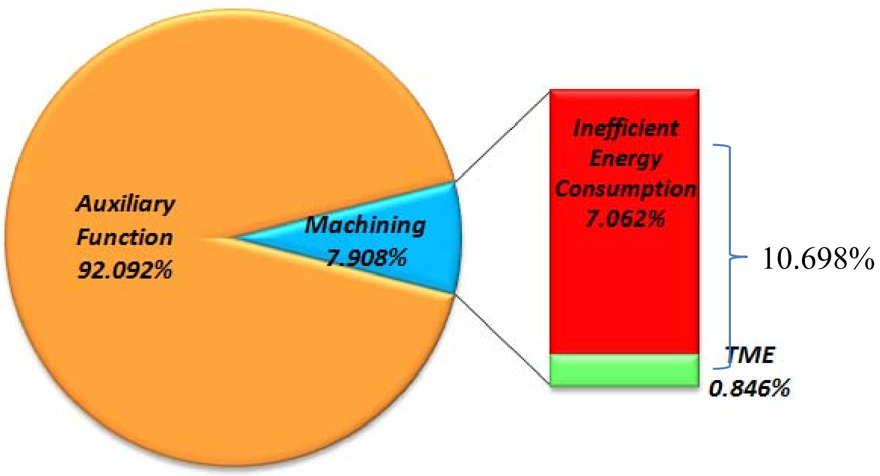

Figure 3.11b Energy Efficiency Chart for No.14 Test

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Figure 3.11a and 3.11b show the energy efficiencies of two selected tests No.3 and No.14. From the figures, it can be found that the theoretical energy consumptions (TE) of test No.3 and test No.14 are similar (49.96kJ and 48.95kJ). However, the energy efficiency of test No.3 is much better than the efficiency of test No.14 (TE/DE, 13.689% to 7.908%, up to 40% improvement). The same conclusion can be drawn by comparing the proposed energy efficiency for machining process which also shows that test No.3 has better energy efficiency than test No.14 (TME/DE, which is 1.435% for test No.3 and 0.846% for test No.14). This conclusion can be verified from the measurement results which showed that test No.3 consumed less energy than test No.14 for achieving the same feature (DE, 364.962kJ for test No.3 and 618.949kJ for test No.14). The reason for this reduction in direct energy consumption is that test No.3 used higher MRR than the MRR used in test No.14, which reduced the machining time, thus reduced the specific energy consumption.

However, the improvement achieved above in energy consumption is almost from the reduction of auxiliary energy consumption. The energy consumptions for machining operation (TE) of two tests are similar (49.961kJ for test No.3 and 48.95kJ for test No.14, test 3 even has higher energy consumption). This similarity can be identified by comparing the new proposed energy efficiency (TME/TE) for machining operation which is 10.482% for test No.3 and 10.698% for test No.14. The function of TME is that it can play an important role in energy efficiency metrics as a boundary line of energy consumption. By comparing the new proposed energy efficiency of machining operation, the potential of energy reduction in TE can be clearly identified. According to selected examples in Figure 3.11a and 3.11b, there is still a huge potential (up to 90%, TE minus TME) for improvement in energy savings in machining. It is necessary to further reduce the theoretical energy consumption and improve the energy efficiency by implementing energy-efficient methods.

3.5 Summary of the Chapter

In this chapter, predictive models for measuring the performance of end milling operation include cutting force, power, time, energy, cost, tool life and surface roughness have been introduced based on machining science theories and common empirical methods. These mathematical expressions will be used to characterise the energy consumption of machining operations in the following chapters.

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Two measurement systems were set up which can measure the cutting force and power consumption for machining operations. Three experiments were conducted to determine the coefficients and verify the energy prediction model.

- Firstly, primary power measurement experiment was conducted to determine the coefficients in the energy prediction model.
- Secondly, cutting force measurement experiment was conducted. Up to 91.5% in accuracy can be achieved based on the comparison between the experimental measurement and theoretical calculation.
- Thirdly, extended power measurement experiment was conducted which showed that up to 95% in overall accuracy of 27 measures can be achieved.
- Finally, comparison of experimental result and results from existing publication and research contributions further showed that the proposed model is accurate and can be generally implemented for different conditions.

According to the above results, it can be determined that the developed energy prediction model is fairly accurate and can be implemented into the following research activities.

In addition, new metrics for measuring energy efficiency of machining operation have been proposed which provided the answers of the research question in the follow aspects:

- A prediction model has been developed to measure the energy consumption of machining operation.
- Energy efficiency metrics have been proposed to uncover the inefficiency of the machining operation.

A case study was carried out to investigate the energy efficiency for machining a small amount of a 2½D milled feature. The results showed that the new proposed energy efficiency metrics cannot only make the same conclusion with the existing energy efficiency metrics. It can also identify the inefficiencies of machining operation which are considerably large (89.5% for test No.3 and 89.3% for test No.14). This conclusion uncovered a huge potential for improvement in energy savings in machining and leads the research to the next stage.

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In addition, although the scope of this thesis only covers 2½ D milled features, the principles and methods of energy consumption and energy efficiency modelling process can be generically applied in other milled features and operations.

First of all, although the cutting force models for different operations are different (different process parameters need to be considered), the basic principle for modelling power (cutting force multiples cutting speed) and energy consumptions (power multiples time) are same.

Secondly, although the machine tools and cutters applied for different operations are different, the components of energy consumption of other milled features and operations are the same as 2½ D milled features. This conclusion can be generated from other researchers publications such as Gutwoski et al. (2006), Diaz et al. (2012), Rajemi et al. (2010), Mativenga et al. (2011), Kare and Li (2011) and Guo et al. (2012).

Finally, proposed theoretical minimal energy consumption is defined based on the energy consumption for shearing a specific area of material which can be generally applied for all machining operations and features as a theoretical limitation for achieving a feature.

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CHAPTER 4: CHARACTERISATION OF ENERGY CONSUMPTION AND ENERGY MINIMISATION BY SELECTING OPTIMAL PROCESS PARAMETERS

The aim of this chapter is to answer the research questions that:

- What are the effects of energy as a new factor to characterise machining operation in addition to conventional factor such as cost, time, cutting force, surface roughness, tool life and power?
- What method can be used to systematically optimise energy consumption?
- What is the reasoning behind algorithms for solving the energy-minimising machining problem?

The characterisations of machining operation with the consideration of conventional criteria have been done by other researchers (Enparatza, 1991, Wan et al., 2010). Energy consumption as an additional criterion is firstly characterised by using graphical multivariate data analysis in this chapter. Then, based on the characterisation of energy consumption, a direct search optimisation method is used as a numerical experimentation rig to investigate the reasoning behind the results obtained in applying Taguchi method, Genetic Algorithm (GA) and Ant colony optimisation (ACO). Finally, a constrained single-objective optimisation procedure is conducted based on energy considerations.

4.1 Characterisation of Energy Consumption in Machining Operation

According to the review of literature, although some degrees of characterisation of machining optimisation problems have been introduced, the nature of the optimisation problem when energy is considered as an additional factor still needs comprehensive investigations. In this section, the characterisation of the energy consumption and other conventional criteria for end milling operation will be introduced by using graphical multivariate data analysis tools.

4.1.1 Design of Numerical Experiment

The data for analysing the characteristics for end milling operation are collected by conducting numerical experiment. Four process parameters depth of cut, width of cut, spindle speed and feed rate are considered as independent variables. The data of energy consumption and other conventional criteria (e.g. cost, time, power, cutting force, tool

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life and surface roughness) will be generated by using the validated machining science equations from Chapter 2 and Chapter 3. The design of numerical experiment is shown in Table 4.1.

Table 4.1: DOE for numerical experiment

Process Parameter	Value Range
Depth of cut ap (mm)	1-5 mm
Width of cut ae (mm)	1-10 mm
Spindle Speed n (rpm)	500-4000 rpm
Feed rate fz (mm/z)	0.01-0.1 mm/tooth
Cutting Tool: 3 flutes carbide flat end mill	
Workpiece material: Aluminium 7075-T6	

4.1.2 Characterisation of Energy Consumption for End Milling Operation

A plot matrix is used to show the energy consumption for the end milling operation with respect to four machining process parameters (see Figure 4.1, the clear presentation of each plot are shown in Appendix V). All four process parameters changed monotonically. The energy consumption of machining operation is characterised by using numerical experiments based on validated prediction model. The independent variables in the expanded figure (ap =1mm, ae=5mm) are feed rate per tooth and spindle speed. The black arrow in the expanded figure points out that with the decrease of spindle speed, the energy consumption curve shifts up (more energy consumed). The result showed that the energy consumption decreases monotonically with the increase of spindle speed and feed rate.

Based on the observation of this characteristic, it can be found that the energy consumptions for end milling specific volume material also decreases constantly with the increase of depth of cut and width of cut. The green arrows point out the direction of energy reduction. It means that the energy consumption decreases monotonically with the increase of process parameters in terms of depth of cut, width of cut, feed rate and spindle speed parameters. It can be concluded that using large machining parameters (e.g. faster spindle speed, larger feed rate and lager cutting volume) within the practical limitations of machining process (e.g. maximal spindle speed, maximal feed rate and diameter of cutting tools) consumes less energy than using small machining parameters.

For example, up to 70% the specific energy consumption can be reduced (17.17kJ/cc to 5.08kJ/cc) when increasing depth of cut from 3mm to 5mm, width of cut from 5mm to 10mm, feed rate from 0.05mm to 0.1mm and spindle speed from 1,000rpm to 4,000rpm.

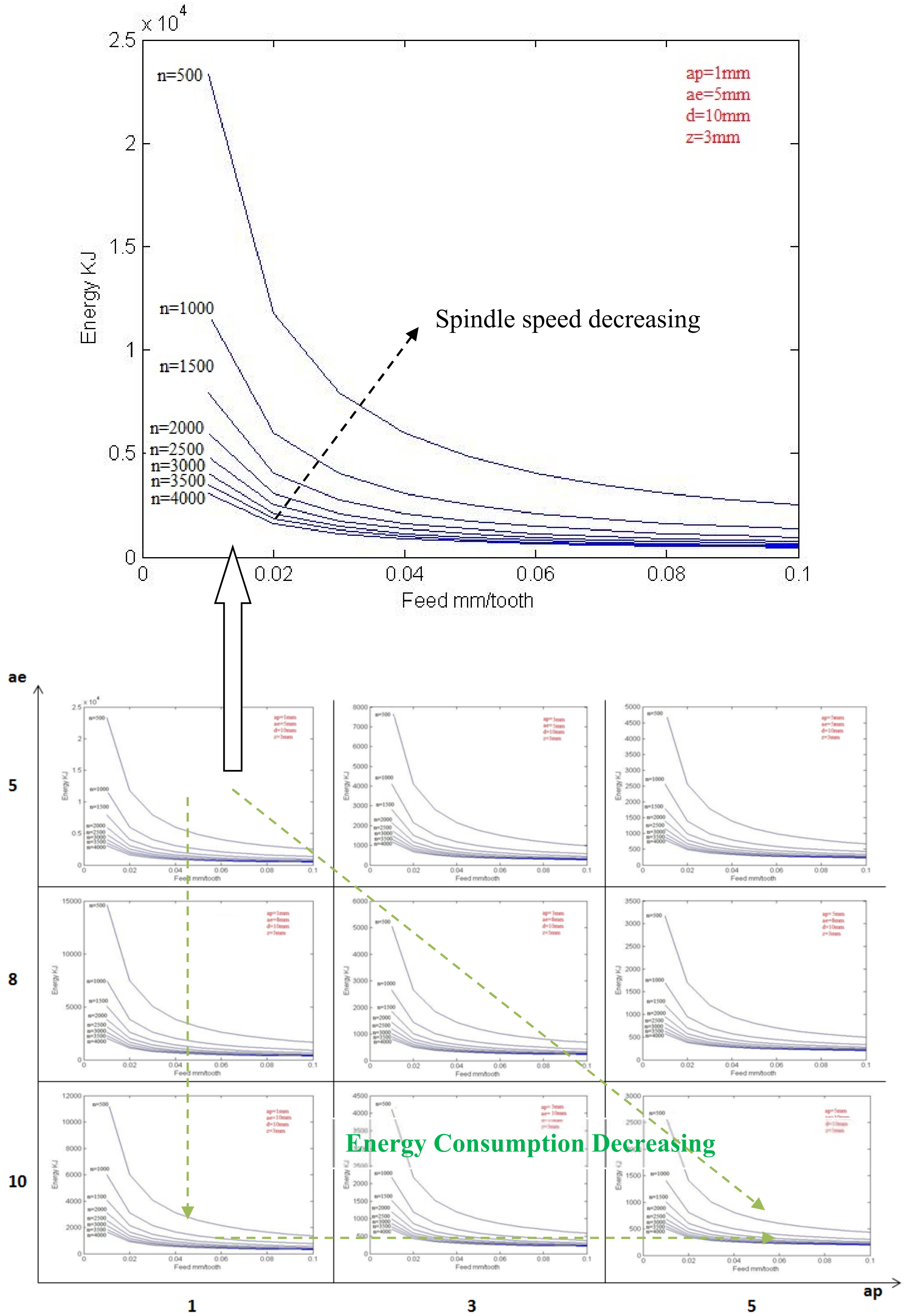

Figure 4.1 Plot Matrix of Energy Consumption based on Process Parameters

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Concluded characteristics of Specific Energy Consumption (SEC, kJ/cc) for end milling operation are shown in Figure 4.2.

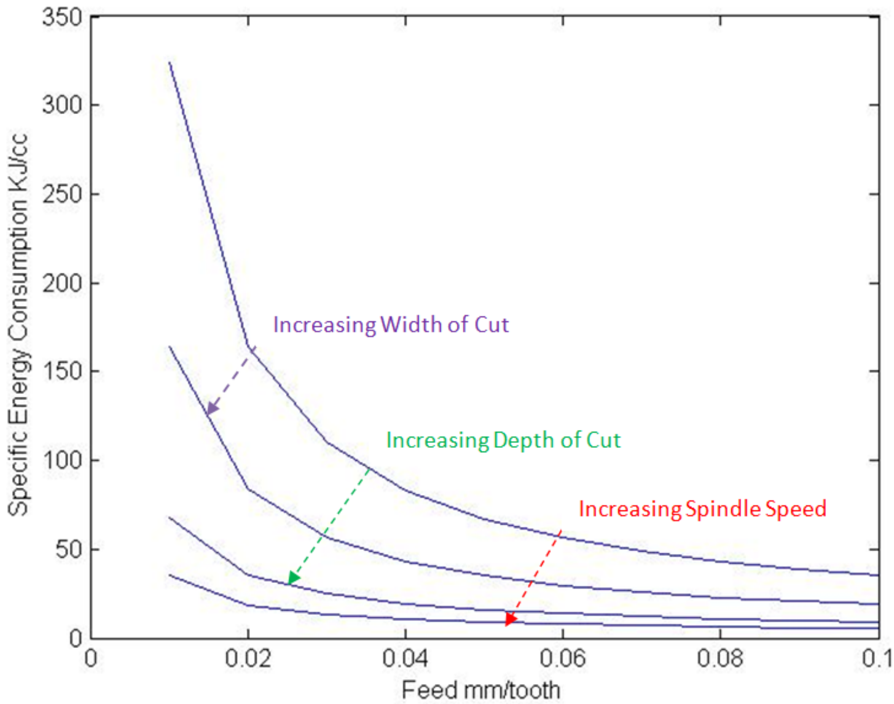

Figure 4.2 Characterisation of Energy Consumption for End Milling Operation

Another observation from Figures 4.1 and 4.2 is that the energy consumption curves are getting flat. It means energy improvement efficiency becomes smaller with continuing increase of process parameters. One of reasons for this observation is that the increase of process parameters can reduce the energy consumption by reducing cutting force and machining time, but it will also increase the power consumption. Another reason is that with the increase of process parameters, tool life will decrease which cause the extra energy consumptions. The results achieved in this section are based on common materials (such as Aluminium and Steel) and conventional machine tools. No turning point was found on the energy plots. However, as mentioned by Professor Wertheim, difficult-to-machine materials may have turning point which is caused by frequent tool change. When applying large process parameters, the minimisation of energy consumption for machining operation will sacrifice the tool life. According to Equations 3.18 and 3.19, the turning point will occur if the energy consumption for tool change is more than the energy consumption for machining operation.

4.1.3 Characterisation of Conventional Criteria for End Milling Operation

Repeating the numerical experiment procedure in section 4.1.2 for other criteria, the characteristics of these criteria (cost, time, surface roughness, cutting force, power, and tool life) can be also displayed as a plot matrix in Figure 4.3. The arrows in the figure show the reducing directions of each criterion as process parameters increase.

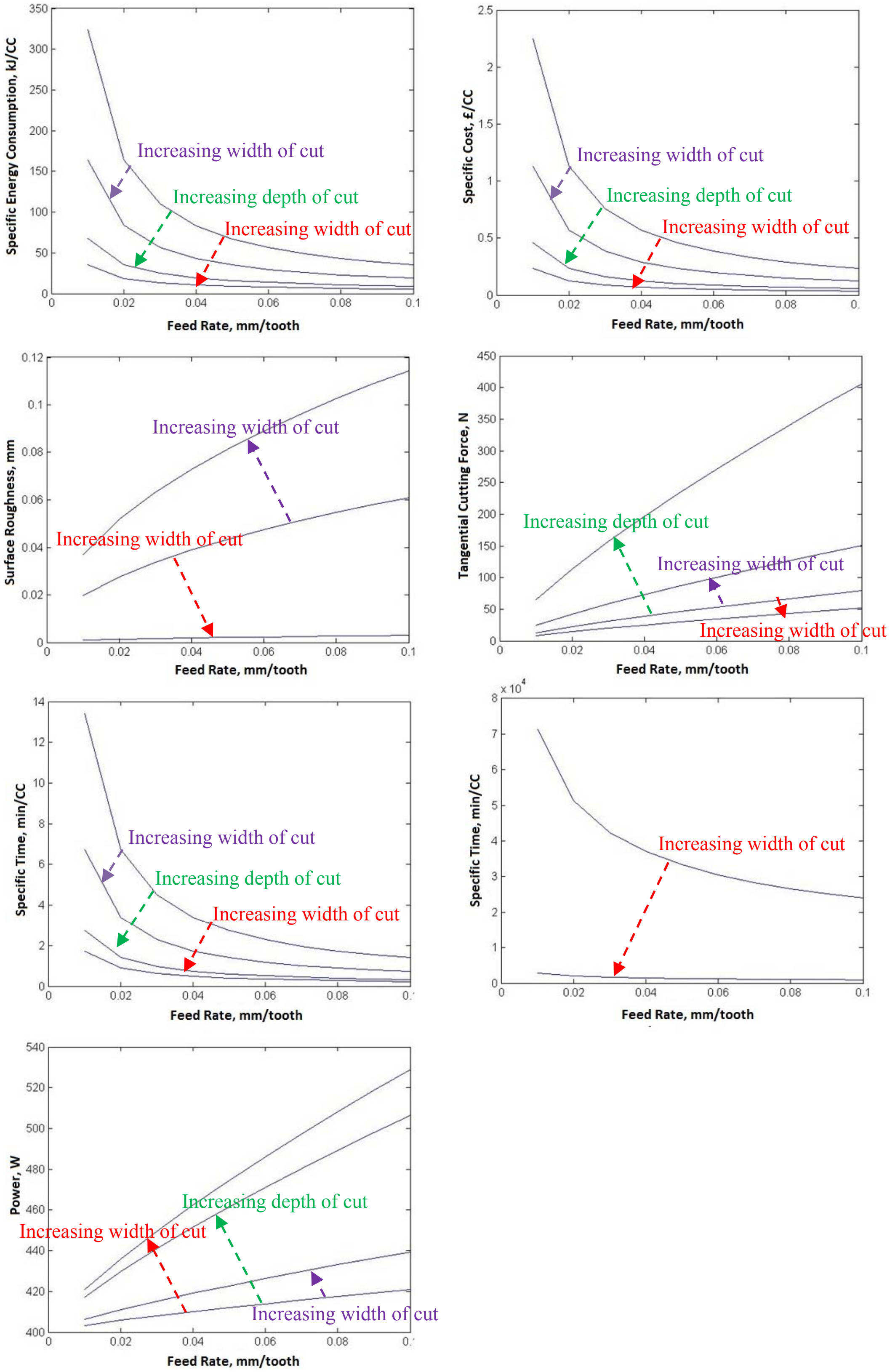

Figure 4.3 Characterisation of Conventional Criteria End Milling Operation

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Figure 4.3 can be summarised and sorted with the independent variables in Figure 4.4. Each single plot in Figure 4.4 shows how the criteria changed with the increase of the corresponding independent variable. The values of X axis are independent variables with constant index. The range of each independent variable is based on the design of experiment in Table 4.1. The values of Y axis are ratios between the all generate results and the first result. So the values of Y axis are all between 0 and 1. For each figure, only one independent variable is selected as the corresponding independent variable and the other parameters are set as constant values.

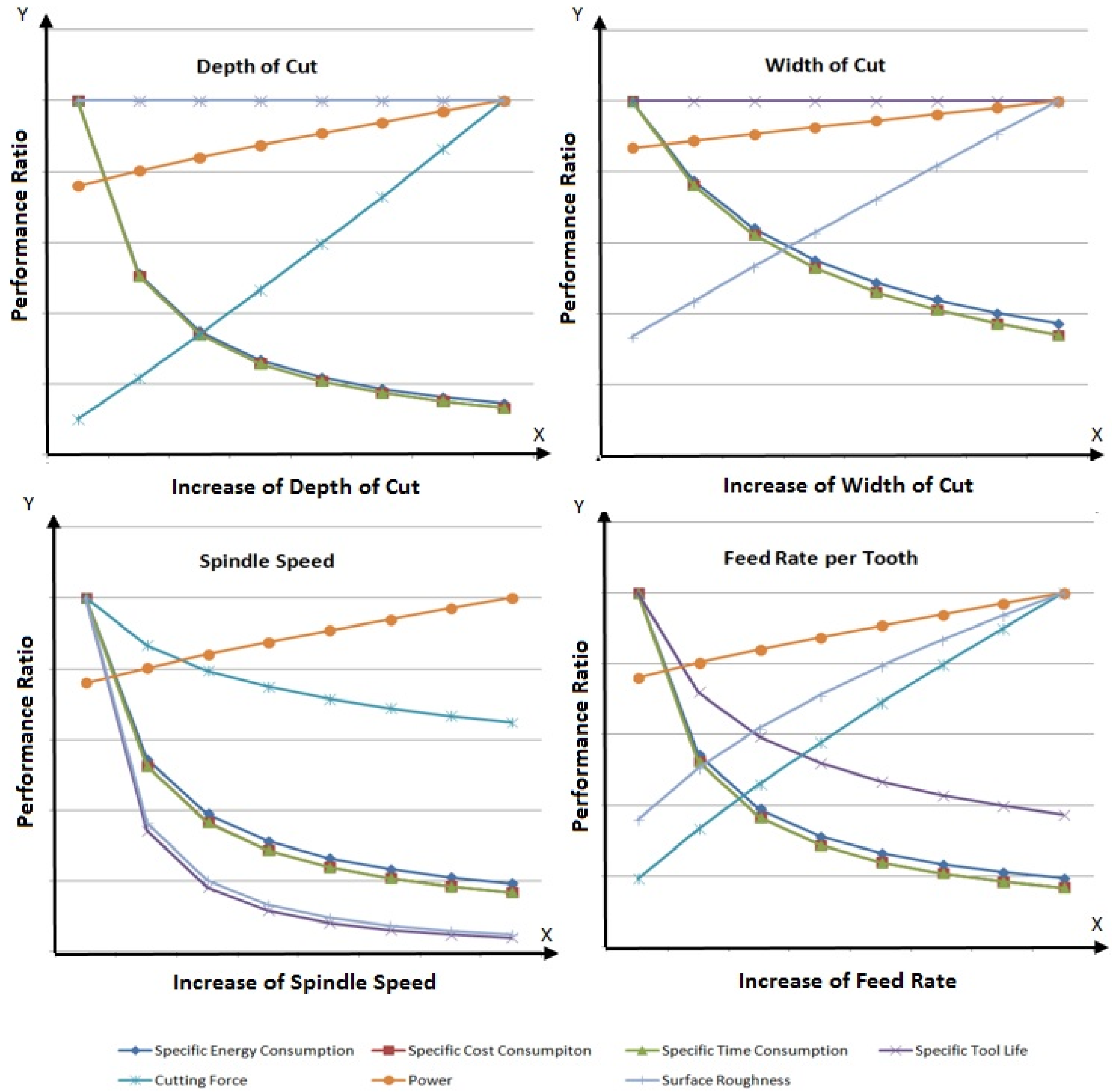

Figure 4.4 Characterisation of End Milling Operation with Respect of Depth of Cut, Width of Cut, Spindle Speed and Feed Rate per Tooth

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Figure 4.4 can clearly identify the characteristics of all the criteria of end milling operation. The same as energy, the other conventional criteria also monotonically changes with the increase of process parameters. The comparison between energy consumption and other criteria showed that energy was non-conflicting with the cost and time for all four independent variables. It was conflicting with cutting force for depth of cut and width of cut, surface roughness for the width of cut and feed rate per tooth, tool life for spindle speed and feed rate per tooth, and power for all four independent variables.

The interacting relationships of these criteria are summarised in Table 4.2. "+" means the machining performance will be improved with the increase of selected process parameters. "-" means the machining performance will be decreased with the increase of selected process parameters. "N/A" in the table means the mathematical models adopted in the analysis are not sensitive with the corresponding independent variable.

Table 4.2 Characterisation of End Milling Operation with the Increase of Process Parameters

	Energy	Cost	Time	Cutting Force	Surface Roughness	Tool Life	Power
ap	+	+	+	-	N/A	N/A	-
ae	+	+	+	-	-	N/A	-
n	+	+	+	+	+	-	-
fz	+	+	+	-	-	-	-

4.1.4 Classification of the Optimisation Objectives based on the Characterisation

According to interaction of criteria (dependent variable) and the changing trend in Table 4.2, the dependent variables can be classified into three groups shown in Table 4.3 as below.

Table 4.3 Three Groups Objectives of Machining Optimisation

Group A	Group B	Group C
The objective will be deteriorated with the increase in independent variables.	The objective will be improved with the increase in independent variables.	The value of the objective will be improved with the increase in some independent variables but be deteriorated with the others.
Power, Tool Life	Energy, Cost, Time	Cutting Force Surface Roughness

`

Group A has two objectives: power and tool life. The objectives in this group will be deteriorated with the increase in process parameters.

Group B has three objectives: energy, cost and time. The objectives in this group will be improved with the increase in process parameters.

Group C has two objectives: cutting force and surface roughness. The objectives in this group will be improved with the increase in some process parameters (e.g. width of cut), but will be deteriorated with the increase of in other independent variables (e.g. spindle speed).

This finding has important influences for the following research about machining optimisation because based on this classification and the interaction of each objective:

- When only one objective is considered, the remaining criteria will be the constraints to refine the search space. The optimal points will be located on the curves of constraints (boundary of refined search space).
- When multiple objectives are considered, it is easy to classify them in two categories: conflicting and non-conflicting category, and select the suitable techniques to solve the problem.

The specific research for this conclusion will be reported in the following chapters.

4.1.4 Analysis of Constraints

Figure 4.5 shows a contour plot of specific energy consumption with the constraint of cutting force (*N*), cutting speed (*Vc, m/min*) and surface roughness (*Ra, μm*).

The coloured arrows in the figure show the directions of reduction of each constraint. From the figure, it is easy to identify that if the constraint of cutting speed is no less than 85 m/min, the constraint of surface roughness will not affect the final optimal result of specific energy consumption. In addition, if the constraint of cutting force is no more than 500N, the upper boundary constraint of spindle speed will be overlapped.

This finding can prove Tandon et al. (2002)'s conclusion that different constraints may not be all active at the same time, and some constraints can be redundant and neglected in some situation. Compared to surface roughness and power, cutting speed and cutting force were the dominant constraints when cutting speed is no more than 85m/min and cutting force is no more than 500N. During rough milling operations, cutting speed and cutting force will be the active constraint. While during finish milling operations, surface roughness will be the active constraint. The behaviour constraints, such as power consumption, will never be reached. So these constraints are redundant and can be neglected in this situation.

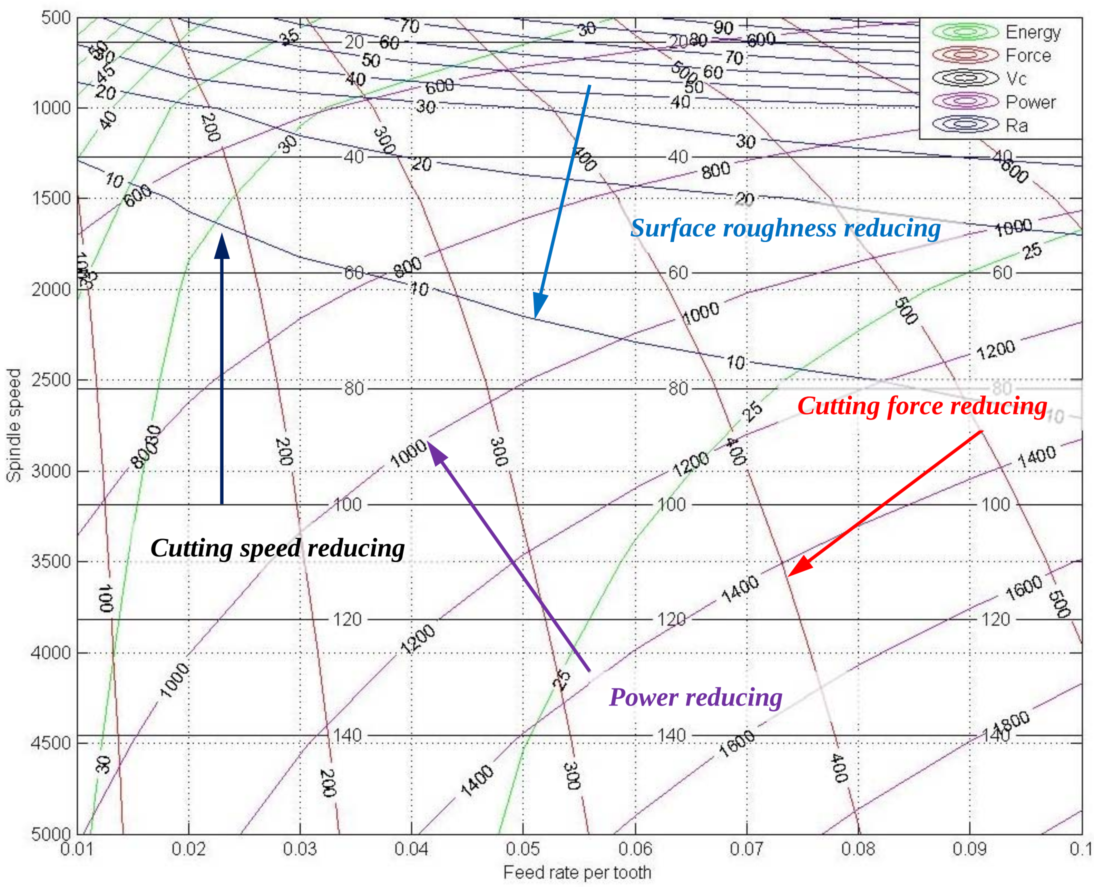

Figure 4.5 Contour Plot of Constraints for End Milling Operation with the Constraints of Cutting Force, Cutting Speed and Surface Roughness

4.1.5 Summary of Characterisation of Machining Operation with Energy Considerations

In this section, the characterisation of machining operation with energy considerations has been investigated by using graphical multivariate data analysis techniques. The results showed that energy consumption decreases monotonically with the increase of process parameters. It is non-conflicting with the cost and time, but conflicting with surface roughness, power requirement, tool life and cutting force. Based on this finding, the criteria of machining optimisation can be divided into two major categories: conflicting and non-conflicting.

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4.2 Explanatory Models for Optimisation Results

The aim of this section is to develop a numerical experimentation test rig based on direct search methods to discover the reasoning behind other typical machining optimisation methods. The reason for choosing direct search method is that it is similar to full factorial design method/Enumeration method within the finite number solutions. The direct search method applied in this research is a grid search method which creates grids based on numbers and levels of independent variables which can represent all the possible solutions. In addition, by graphically presenting the results it is easy to visualise where the optimal point is. In this case, the users can easily understand and accept the optimal result obtained. The developed experimentation rig will be used to explain the reasoning obtained in applying Taguchi methods, Genetic algorithm (GA) and Ant colony algorithm (ACO).

4.2.1 Design of Numerical Experimentation Rig based on Direct Search Method

Table 4.4 shows a 3-level four variables DOE plan. 81 grids (3^4) have been created to represent 81 combinations of process parameters in the search space. The experimentation rig is graphically displayed in Figure 4.6. The label of horizontal axis was removed since it represents the order of samples. The original data after initial multivariate data analysis showed the energy consumption is changing with some pattern which can be displayed as dash squared areas to represent the original searching space of three levels four variables full factor design. Each vertical line of small dash square contains three grids which are corresponding to every three points (increase of spindle speed) in the original energy plot curve. Each horizontal line of small dash line represents the samples with the increase of feed per tooth. Each small dash squared area contains nine grids which are corresponding to every nine points. Nine dash squares can represent the original search space based on the DOE plan.

Table 4.4: 3-Level Design of Experiment

Process Parameter	Level 1	Level 2	Level 3
Depth of cut a_p (mm)	1	3	5
Width of cut a_e (mm)	5	7.5	10
Spindle Speed n (rpm)	500	2250	4000
Feed rate f_z (mm/z)	0.01	0.055	0.1

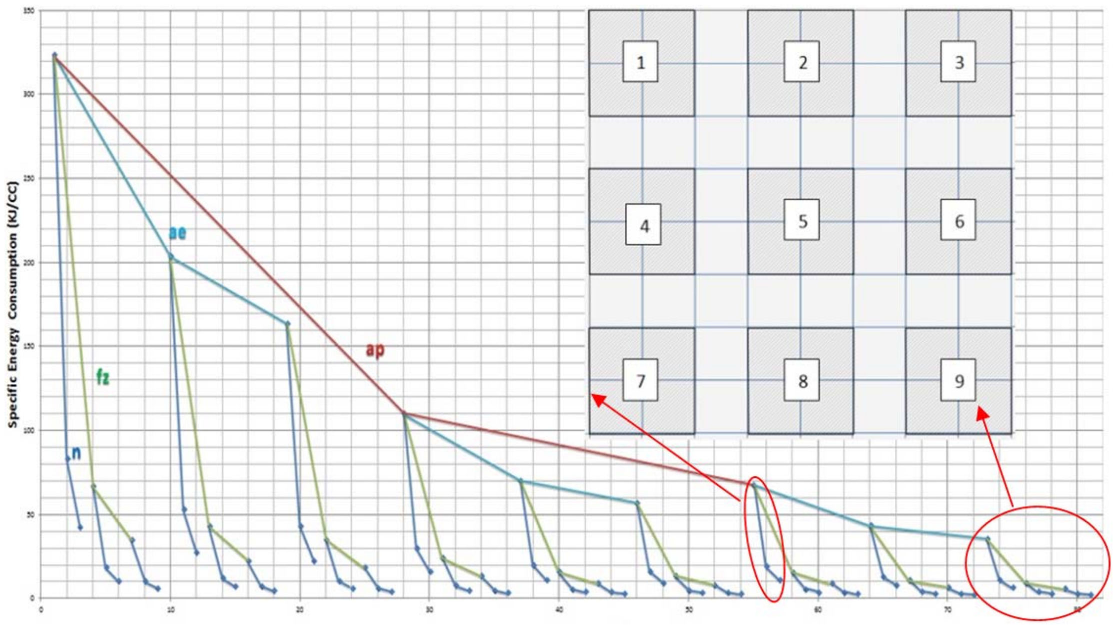

Figure 4.6 Characteristics of Specific Energy Consumption

The highlighted green area in Figure 4.7 shows the data after being sorted with the increase of material removal rate per tooth (*MRRz*). The green band further represents the characteristics of energy consumption discussed in the previous section. The band is getting narrow which means the range of improvement is getting smaller with the increase of *MRRz*. The red curve shows the samples after being organised with the continuing decrease of specific energy consumption.

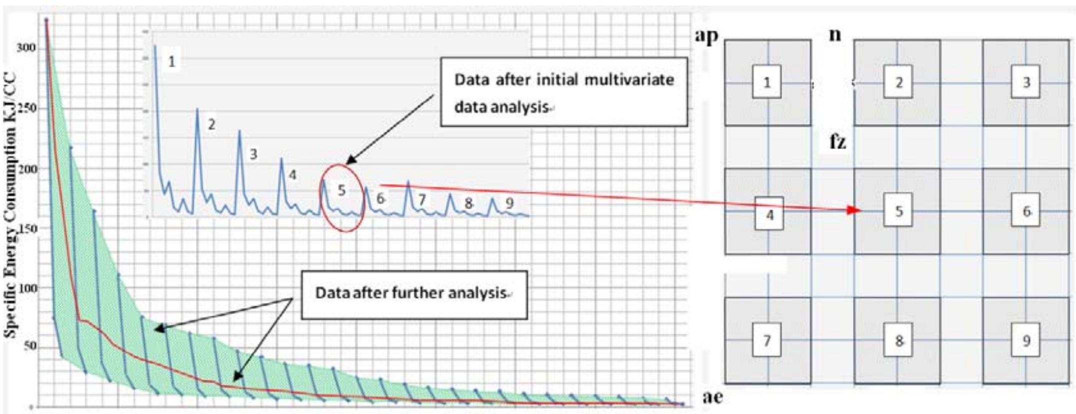

Figure 4.7 Characterisation of Specific Energy Consumption with the Increase of Material Removal Rate per Tooth (MMRz)

Figure 4.8 shows the contour plot matrix which consists of 9 contour plots to represent the designed experimentation rig (4 dimensional search space). Each contour plot is corresponding to a dash block in Figure 4.7. It can also clearly show the characteristics of energy consumption described in Figure 4.7. In addition, 81 points can be found in

Figure 4.6 and the value of each point can also be also evaluated. This contour plot will be used as the examination rig to investigate the other machining optimisation methods in the following sections.

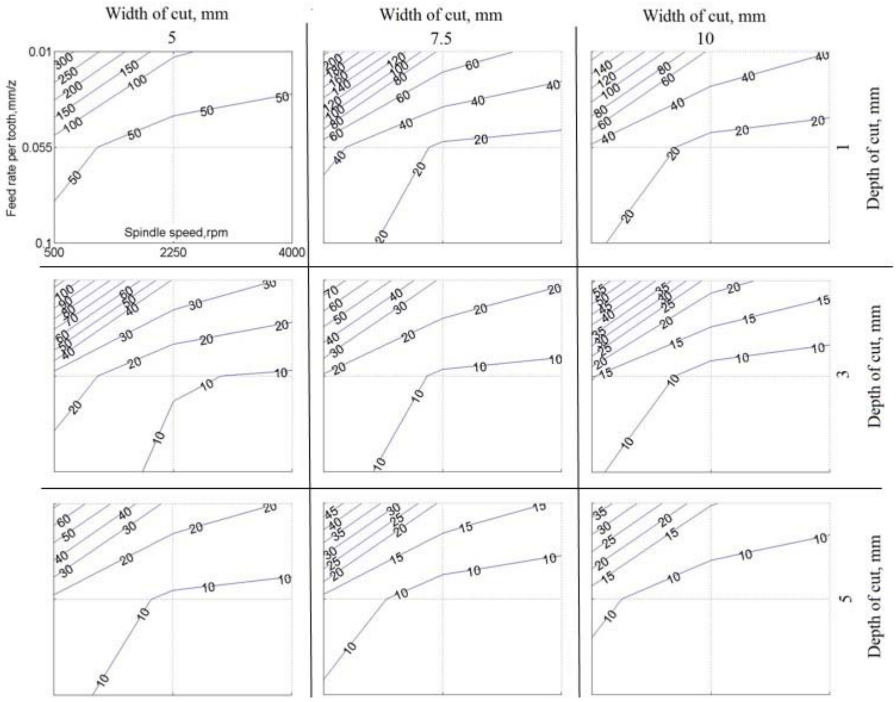

Figure 4.8 Contour Plot Matrix for Experimentation Rig

4.2.2 Investigation of Taguchi Method

Based on the DOE plan in Table 4.4, specific energy consumption of eight Taguchi DOE samples can be shown in Table 4.5 and graphically displayed in the developed contour plot matrix of experimentation rig in Figure 4.9.

Table 4.5: DOE of Taguchi L9 3-level 4 factors

Number	Depth of cut (mm)	Width of cut (mm)	Spindle speed (rpm)	Feed per tooth (mm/tooth)	Specific Energy Consumption (kJ/cc)
1	1	5	500	0.01	336.802
2	1	5	4000	0.1	11.4782
3	1	10	4000	0.01	40.3094
4	1	10	500	0.1	21.4519
5	5	5	4000	0.01	19.244
6	5	5	500	0.1	11.6501
7	5	10	500	0.01	39.0163
8	5	10	4000	0.1	5.084

S/N ratios of energy consumption can be calculated by using Equation 2.24 in Chapter 2. Based on these values, the S/N ratio plot can be created in Figure 4.10 to show the characteristics of process parameters. The first observation obtained from the S/N plot from Figure 4.10 is that depth of cut, width of cut, spindle speed and feed rate all have significant influence on specific energy consumption. In addition, in using the Taguchi method to optimise energy, high level process parameters can achieve better result than the lower level process parameters.

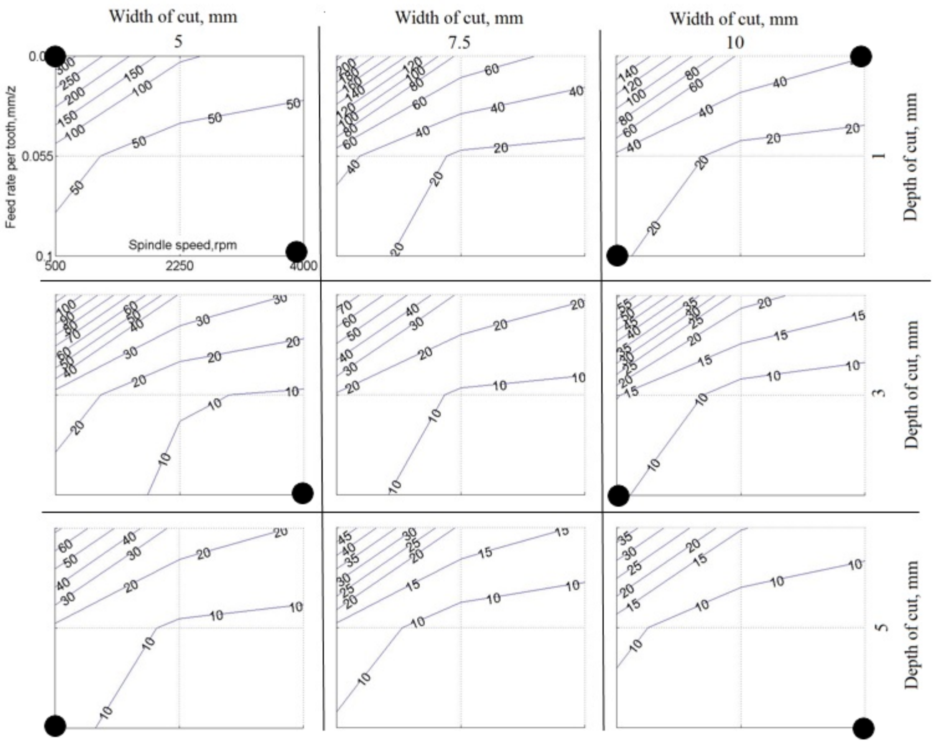

Figure 4.9 Graphical Display of Eight Taguchi Samples in Experimentation Rig

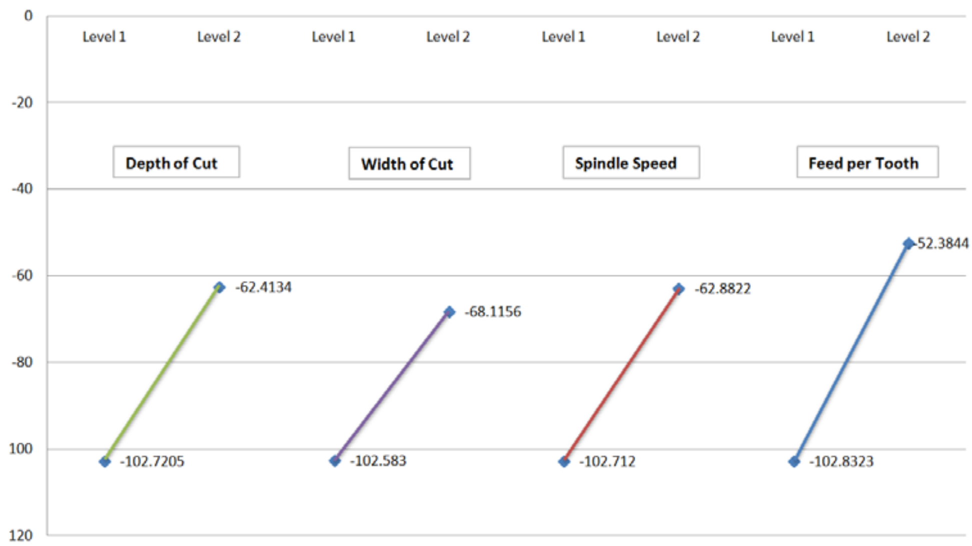

Figure 4.10 S/N Ratio Plots of Process Parameters

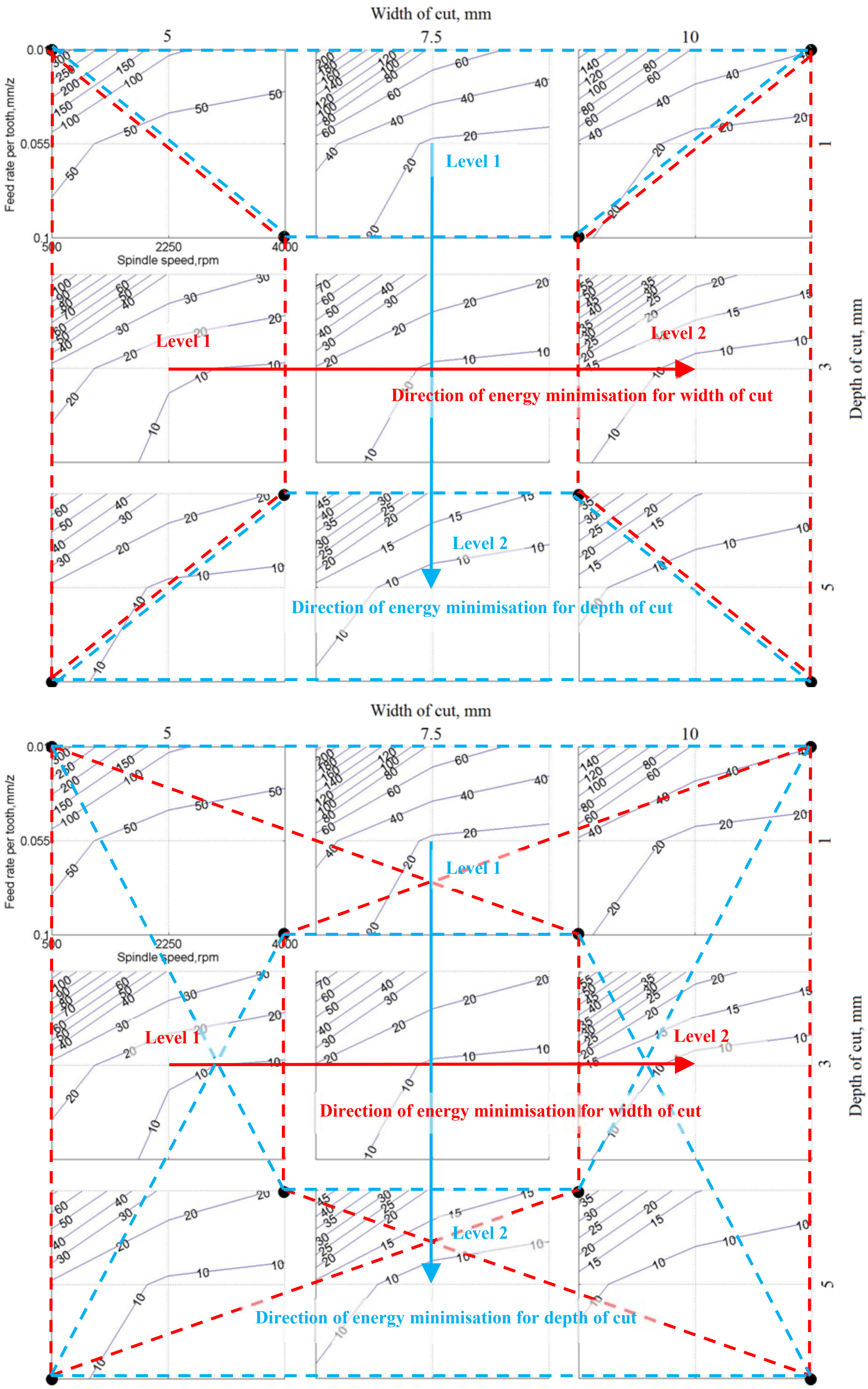

Figure 4.11 Graphical Displays of Taguchi Method in Experimentation Rig

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Figure 4.11 graphically shows how the optimal result was obtained by using Taguchi method. For each design variable, the samples can be classified according to the design levels (shown as the areas framed by dashed lines). The comparison between different levels is actually comparing the average value and standard deviation of different level, then the optimal level will be suggested. The implementation of Taguchi method actually shows the directions of energy minimisation for each process parameter.

To further prove and generalise the results achieved above, a further investigation was conducted with the consideration of increasing levels. An L9 DOE plan has been presented according to Taguchi orthogonal experimental design. Nine out of 81 samples were selected to carry out the analysis. The specific energy consumption values of nine samples are shown in Table 4.6.

Table 4.6: Specific Energy Consumption for Taguchi L9 3 Levels 4 Factors

Number	Depth of cut (mm)	Width of cut (mm)	Spindle speed (rpm)	Feed per tooth (mm/tooth)	Specific Energy Consumption
1	1	5	500	0.01	336.802
2	1	7.5	2250	0.055	16.7368
3	1	10	4000	0.1	7.8894
4	3	5	2250	0.1	7.8868
5	3	7.5	4000	0.01	20.7475
6	3	10	500	0.055	15.1712
7	5	5	4000	0.055	7.1512
8	5	7.5	500	0.1	9.3921
9	5	10	2250	0.01	15.1919

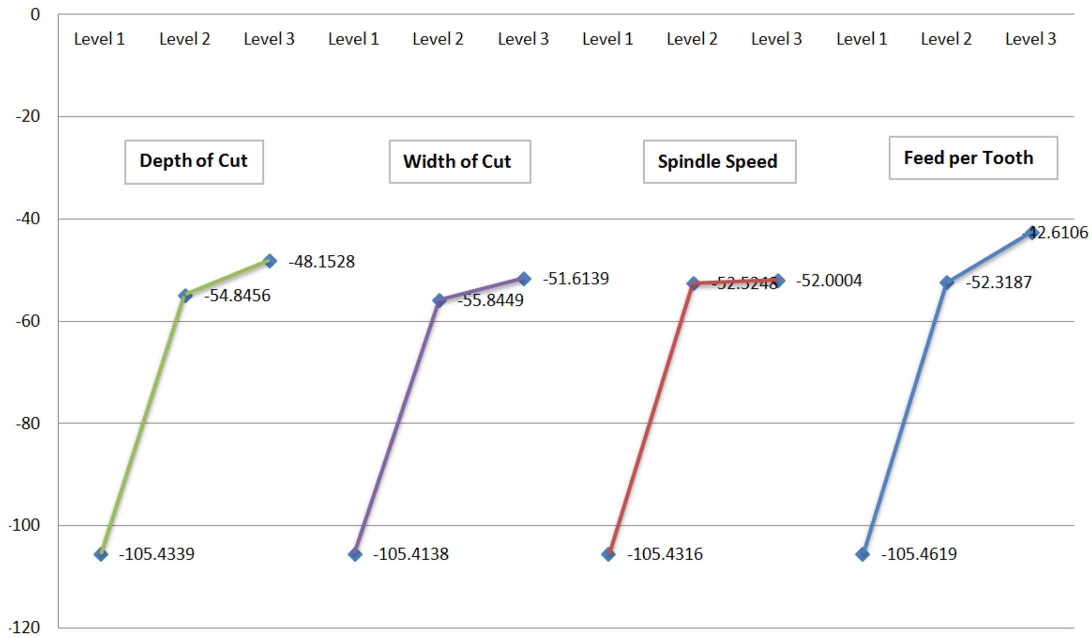

Figure 4.12 S/N Ratio Plots of Process Parameters

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The S/N ratios of energy consumption are shown in Figure 4.12 to show the characteristics of the variables for **three** levels case. From the figure, it can be found that the characterisation of energy consumption for three levels case is the same as two levels case. The additional level does not affect the optimal result. The result of three levels case further proved that the energy consumption when high level values are selected is less than when lower level values are selected. Meanwhile, the additional level can also show the characteristic of energy consumption for the end milling operation identified in section 4.1. The energy improvement efficiency becomes smaller with continued increase in process parameters. Another finding of Taguchi method with respect to the increasing degree of the variables is that for improving the energy consumption it is more efficient to increase the process parameters in the order feed rate, depth of cut, spindle speed and lastly width.

However, as pointed out in the literature, this implementation of the Taguchi method for optimisation is only a first level approximation as it could miss the real optimal value if the optimal point is outside the design search space. For the situations that the selected DOE does not cover the whole search space, the use of Taguchi method will require an iterative approach, in which the experiment is repeated in the vicinity of optimum obtained in a previous step.

4.2.3 Investigation of Genetic Algorithm

The comparison of the basic concepts between GA and machining operation is shown in Table 4.7. Each variable will be considered as a "Chromosome" and the value of the variable will play a role as "Gene". Energy consumption is the fitness value to evaluate the individuals. Process parameters will be randomly selected within the feasible range. The crossover and mutation operators are used to generate new individuals. The function of crossover is to rapidly explore a search space within the initial data range which is the same as changing the combination of process parameters. The function of mutation is to provide a small amount of random search which can expand the search space by extending data range. It is the same as to replace a process parameter with a new value. The function of selection is to compare the results of different combination of process parameters and keep a record of the best combination for further operation. The optimal combination of process parameters can be determined by repeating above operations.

Table 4.7: Concept Comparison between GA and Machining

GA	Machining
Population	Feasible sets of machining process parameters
Individual	A set of machining process parameters
Chromosome	Combination of parameters
Gene	Parameter
Fitness	Optimum value of objective
Selection	Record improved results
Reproduction	Change the combination of machining parameters
Crossover	
Mutation	
Evolution	Generate new optimal results

The following steps presented an example of implementing GA to optimise specific energy consumption. The optimal result can be determined after repeating the algorithm 4 times. The specific optimal procedure can be shown as below:

Step 1: Random selection of starting points (initial population/process parameters). The first step for implementing GA is to select the initial population set. It is difficult to find a completely random selection of starting process parameters in practical machining operation. Even for a novice practitioner who is working on new machining operations (e.g. new material, tool and machine tool) where the best process parameters are not known yet, the selection of the process parameters would be guided by suggestions from machining handbook, tool catalogue or the experience of senior practitioners. A possible explanation of this random selection cannot also be justified by a case of an intelligent machine tool designed to adaptively determine the cutting parameters since database values would usually provide initial values.

The example here shows that the initial population set is located at the beginning of search space. The population size is six. The values of process parameter and objective are shown in Table 4.8a. Current best three optimal results are highlighted and selected to carry out the following steps.

`

Table 4.8a: Individuals of Initial Population

Number	Depth of cut (mm)	Width of cut (mm)	Spindle speed (rpm)	Feed per tooth (mm/tooth)	Specific Energy Consumption (kJ/cc)
1	1	5	500	0.01	336.8022
2	1	5	500	0.055	65.3628
3	1	5	500	0.1	38.0781
4	1	5	2250	0.01	104.8482
5	1	5	2250	0.055	22.8128
6	1	5	4000	0.01	42.9969

Step 2: Generate new individuals by conducting crossover and mutation operation. Based on the initial population, the first generation offspring can be generated by conducting crossover and mutation operations (in Table 4.8b). The mutation factor is value of depth of cut (level 2 replaced level 1). The current best three optimal results are also highlighted and selected to carry out the following steps. In addition, it can be found that the values of spindle speed and feed per tooth at level 1 are eliminated. This process reflects the principle of evolutionary function for implementing GA is "survival of the fittest". The value highlighted in red means the new generated result is worse than the previous generation.

Table 4.8b: Individuals of First Generation

Number	Depth of cut (mm)	Width of cut (mm)	Spindle speed (rpm)	Feed per tooth (mm/tooth)	Specific Energy Consumption (kJ/cc)
Crossover					
7	1	5	4000	0.055	17.4015
8	1	5	2250	0.1	14.5063
9	1	5	4000	0.1	11.4782
Mutation					
10	3	5	2250	0.055	10.7657
11	3	5	500	0.1	16.0496
12	3	5	4000	0.01	28.6516

`

Step 3: Generate second generation offspring, and select and keep the best individual.

The second generation offspring can be generated by repeating the crossover and mutation operation (in Table 4.8c). The mutation factor is width of cut (level 2 replaced level1). After mutation, it can be found that the new generation offspring may not be better than the last generation (as highlighted in red). To keep the new mutation factor, result No.18 was selected to replace No.15 to carry out the further operation.

Table 4.8c: Individuals of Second Generation

Number	Depth of cut (mm)	Width of cut (mm)	Spindle speed (rpm)	Feed per tooth (mm/tooth)	Specific Energy Consumption (kJ/cc)
Crossover					
13	3	5	2250	0.1	7.8868
14	3	5	4000	0.1	6.7837
15	3	5	4000	0.055	8.8558
Mutation					
16	1	7.5	2250	0.1	11.1503
17	1	7.5	4000	0.1	9.0899
18	3	7.5	2250	0.055	8.7112

Step 4: Generate following generation offspring

The third and fourth generation offspring can be generated by repeating crossover, mutation and selection operation. For the third generation, the mutation factor is depth of cut (level 3 replaced level 2). The highlighted green results in Table 4.8d are selected to carry out the following operation. The highlighted red results are worse than the last generation.

Table 4.8d: Individuals of Third Generation

Number	Depth of cut (mm)	Width of cut (mm)	Spindle speed (rpm)	Feed per tooth (mm/tooth)	Specific Energy Consumption (kJ/cc)
Crossover					
19	3	7.5	4000	0.1	5.9647
20	3	7.5	4000	0.055	7.3901
21	3	7.5	2250	0.1	6.7424
Mutation					
22	5	5	4000	0.1	5.8488
23	5	5	2250	0.1	6.5674
24	5	7.5	2250	0.055	7.1111

`

The fourth generation offspring can be generated by repeating the crossover and mutation operation (in Table 4.8e). The mutation factor is width of cut (level 3 replaced level2). The optimal result can be determined which is highlighted. The determined optimal result is the same as the results obtained by using enumeration method and Taguchi method which shows that the energy consumption can be minimised by selecting high level process parameters. In addition, 29 out of 81 samples in total were involved during the optimisation procedure.

Table 4.8e: Individuals of Fourth Generation

Number	Depth of cut (mm)	Width of cut (mm)	Spindle speed (rpm)	Feed per tooth (mm/tooth)	Specific Energy Consumption (kJ/cc)
Crossover					
25	5	7.5	4000	0.1	5.3436
26	5	7.5	2250	0.1	5.8652
Mutation					
27	3	10	4000	0.1	5.5488
28	5	10	2250	0.1	5.5067
29	5	10	4000	0.1	5.0845

Step 5: Determine the optimal result.

The optimal result can be determined after repeating the algorithm four times (graphically shown in Figure 4.13). The green dashed arrow shows the overall search path of implementing GA. However, the results obtained from crossover and mutation operations are not always positive. Defective offspring which are worse than the original generation may occur during the optimisation process. However, the repeated mutation operation can help jump out of previous local search space and eventually find the real optimal specific energy consumption.

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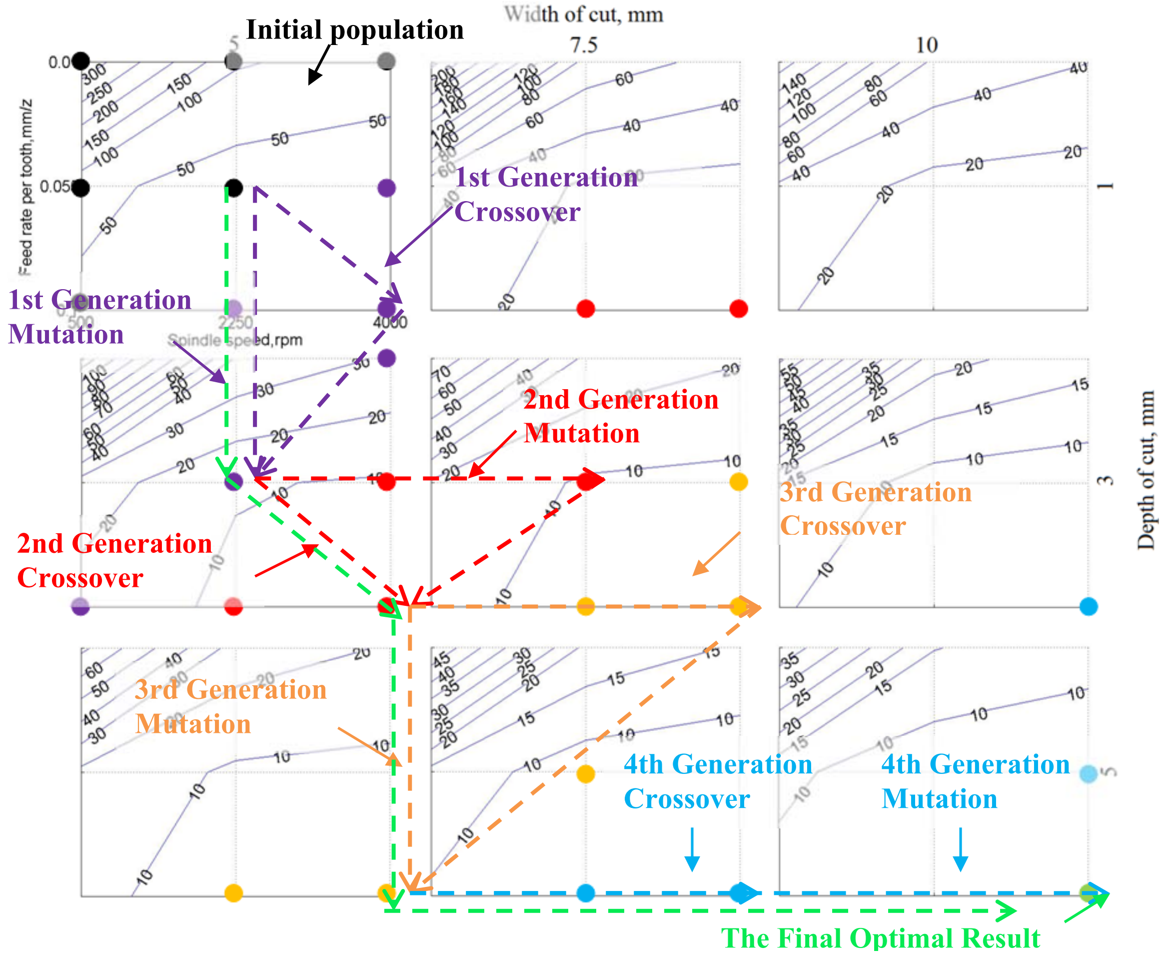

Figure 4.13 Graphical Display of GA in 3-level Experimentation Rig (Manually Generated)

The result above shows a progress for optimising machining process parameters by using GA. However, in practical implementation, the optimisation process is more complex in terms of uncertainty and randomisation. Usually the optimal results will be affected by other factors, such as the size of samples and the position of initial population.

Figure 4.14 shows a typical GA implementation by using binary coding method with MATLAB. Additional level was considered to fit the programming requirement. 256 samples were created to represent the search space. The initial population which contains eight individuals was selected at the same position (left corner) as the ideal example shown in Figure 4.13. The green arrow points out how the optimal result was achieved after three generations which is similar to the optimal path shown in Figure 4.13.

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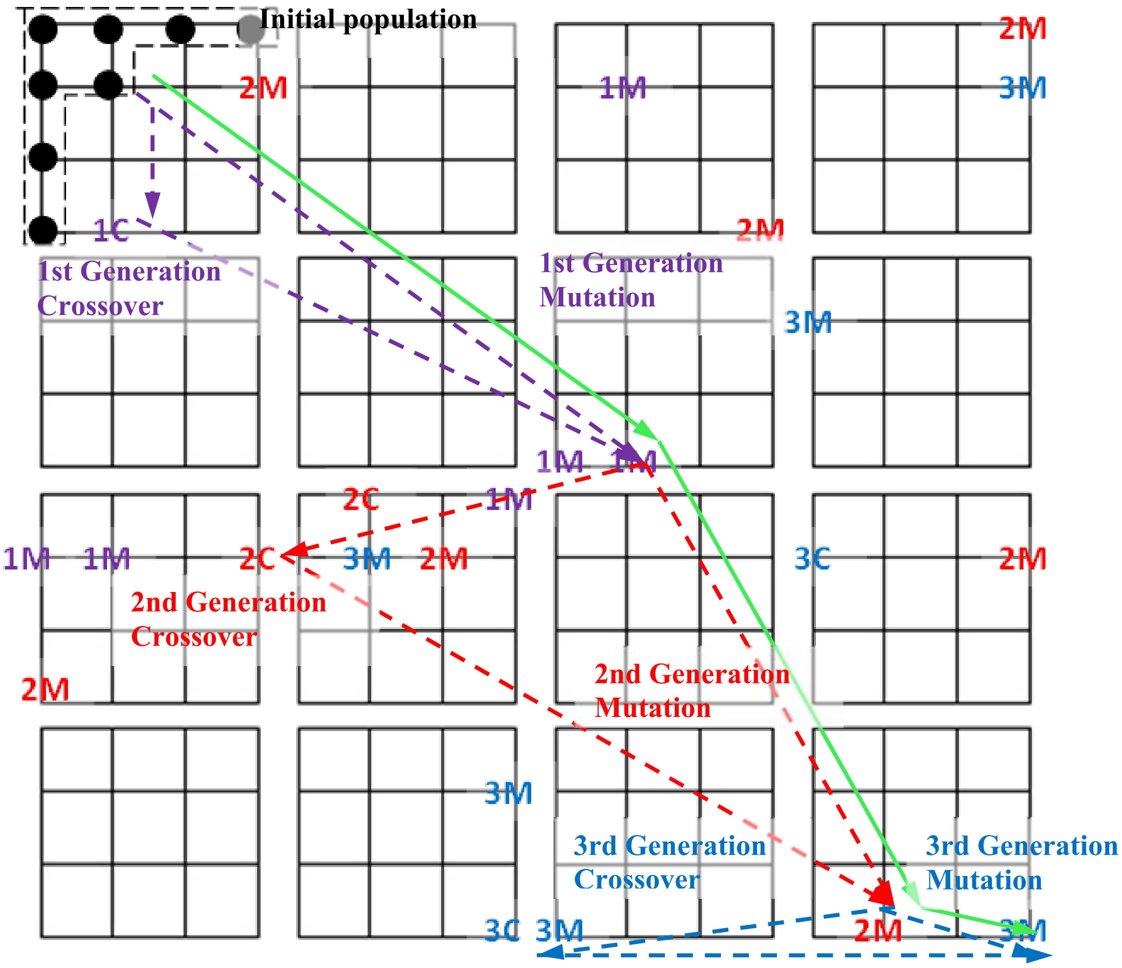

Figure 4.14 Graphical Display of GA in 4-levels Experimentation Rig (Generated by Using Matlab, Initial Population Located at Left Conner of Search Space, Optimal Results Achieved at 3rd Generation)

However, the optimal path of GA is not always positive. Some redundant or negative moves may randomly occur. Although the same optimal results can be achieved by using same settings of process parameters, the optimal path may not be same every time. Figure 4.15 shows a result of repeating the same settings of Figure 4.14. The result shows that the optimal result was achieved after twelve generations. The green arrow points out the overall optimal path after twelve generations which is similar to the optimal path shown in Figure 4.13 and 4.14. However, the black arrow points out the actual optimal path generation by generation which contains many random changes and is different from the optimal path in Figure 4.14.

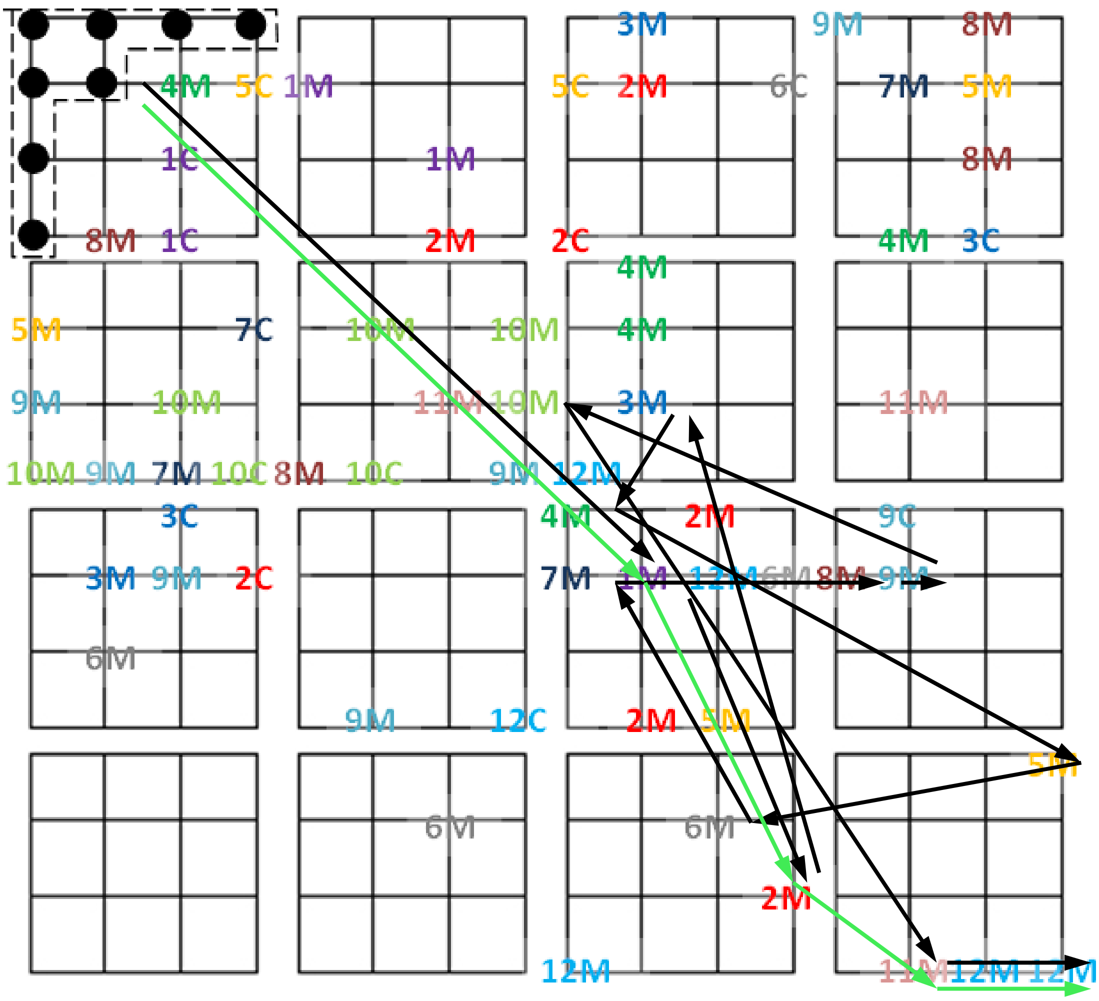

Figure 4.15 Graphical Display of GA in 4-levels Experimentation Rig (Generated by Using Matlab, Initial Population Located at Left Conner of Search Space, Optimal Results Achieved at 12th Generation)

Figure 4.16 shows an example when initial population was selected at different position of search space. The green and black arrows in the figure point out the optimal path that the optimal result was achieved after three generations. Both paths can show the similar characters as the example when the initial population is located at left conner of search space. The result in Figure 4.16 can also identify that even the position of initial population is close to the final optimal point, it cannot guarantee to get the optimal result faster than the further position. In addition, the optimal results of different positions will be same.

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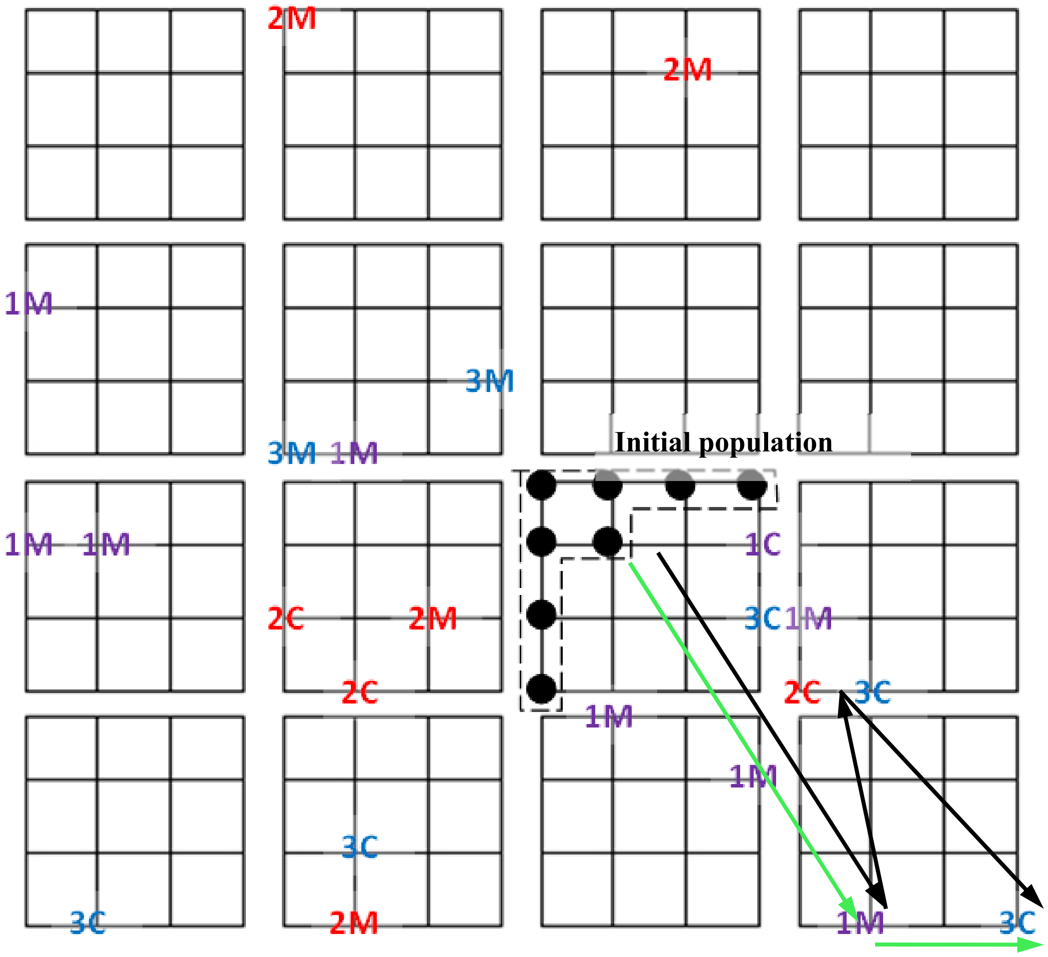

Figure 4.16 Graphical Display of GA in 4-levels Experimentation Rig (Generated by Using Matlab, Initial Population Located at Middle of Search Space, Optimal Results Achieved at 3rd Generation)

Figure 4.17 shows the optimal results of all three examples above and three pure random cases. The comparison result identified that the optimal results of presented examples with different settings are all same, but the optimisation paths are different. This finding can further prove that different settings, such as postition of initial population, will not affect the optimal result but only affect the computation time.

In summary, GA can effectively solve machining optimisation problem according to examples shown above. However, compared to systematic direct search method, GA may not be always effective because of its randomisation. For the example presented of four levels four parameters case, 256 samples were calculated and compared. When using GA, eight individuals were calculated and compared for each generation. After 33 generations ($8 \times 33 = 264$), GA will require more calculations and consume more computing time than systematic direct search method.

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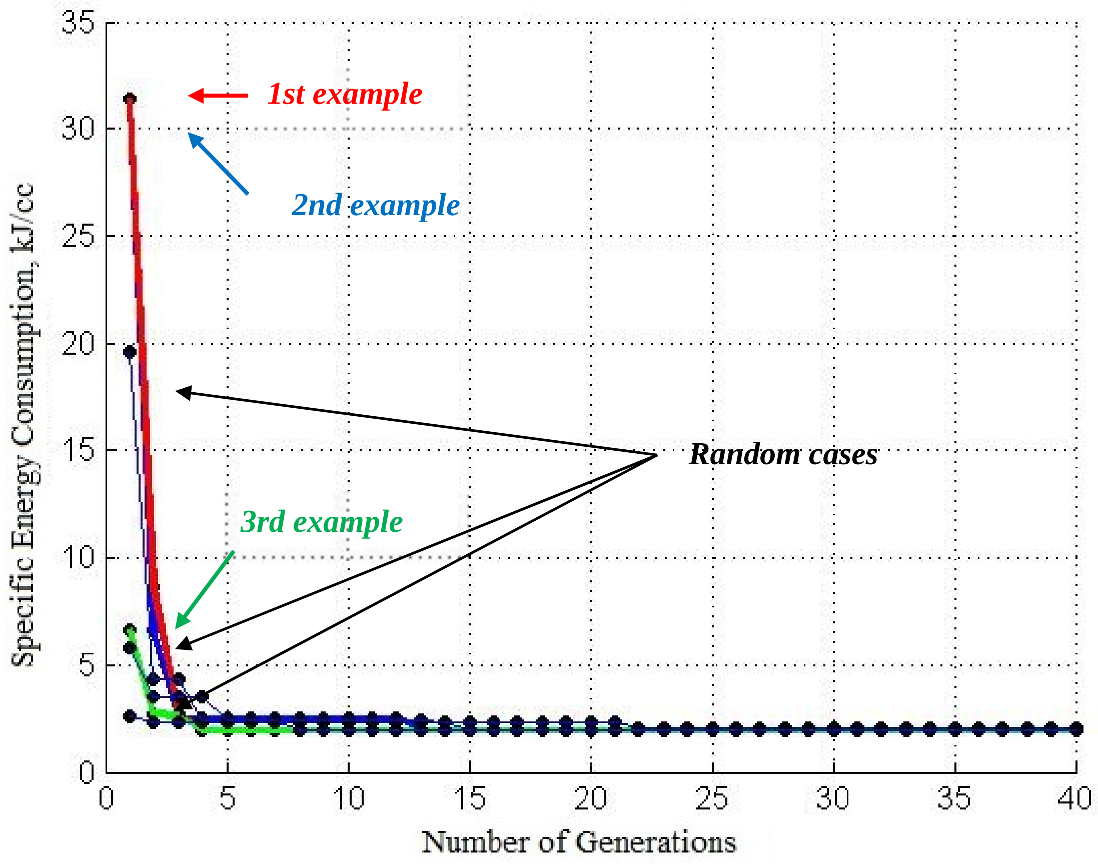

Figure 4.17 Comparison of Optimisation Paths and Results of GA by Running Matlab Program Multiple Times

4.2.4 Investigation of Ant Colony Optimisation (ACO) Method

The specific optimal procedure can be shown as following steps:

Step 1: Determine the Layers and nodes

The first step for implementing ACO is to determine the layers and nodes. According to the characterisation of machining, each process parameter represents a design variable and the number of levels represents the discrete values for each design variable (see Figure 4.18). Four layers have been created based on the design of experiment rig and each layer has three nodes.

Step 2: Determine the optimal node for Layer 1 (spindle speed)

The process parameters and specific energy consumptions of Layer 1 (spindle speed) are shown in Table 4.9a. The result shows that when other process parameters are same, large spindle speed will lead to the optimal energy consumption. So the third level (*n=4000rpm*) is the optimal value for spindle speed and the corresponding node will be the start node for Layer 2.

`

Table 4.9a: Layer 1 Spindle Speed

Number	Depth of cut (mm)	Width of cut (mm)	Spindle speed (rpm)	Feed per tooth (mm/tooth)	Specific Energy Consumption (kJ/cc)
1.1	1	5	500	0.01	336.8022
1.2	1	5	2250	0.01	104.8482
1.3	1	5	4000	0.01	75.7220

Step 3: Determine the optimal node for Layer 2 (feed per tooth)

The process for Layer 2 is the same as Layer 1. The process parameters and specific energy consumptions of Layer 2 (feed per tooth) are shown in Table 4.9b. The result shows that when other process parameters are same, large feed rate will lead to the optimal energy consumption. So the third level (*n=4000rpm, fz=0.1mm/tooth*) is the optimal value for the feed rate and the corresponding node will be the start node for Layer 3.

In addition, before the optimisation started at Layer 2, the spindle speed has already been optimised at Layer 1. So, the result achieved at Layer 2 is the optimal result for both spindle speed and feed rate.

Table 4.9b: Layer 2 Feed per Tooth

Number	Depth of cut (mm)	Width of cut (mm)	Spindle speed (rpm)	Feed per tooth (mm/tooth)	Specific Energy Consumption (kJ/cc)
2.1 (1.3)	1	5	4000	0.01	75.7220
2.2	1	5	4000	0.055	17.4015
2.3	1	5	4000	0.1	11.4782

Step 4: Determine the optimal node for Layer 3 (width of cut)

The same as step 2 and step 3, the process parameters and specific energy consumptions of Layer 3 (width of cut) are shown in Table 4.9c. The result shows that large width of cut will lead to the optimal energy consumption. So the third level (*n=4000rpm, fz=0.1mm/tooth, ae=10mm*) is the optimal value for spindle speed, feed rate, and width of cut, and the corresponding node will be the start node for Layer 4.

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Table 4.9c: Layer 3 Width of Cut

Number	Depth of cut (mm)	Width of cut (mm)	Spindle speed (rpm)	Feed per tooth (mm/tooth)	Specific Energy Consumption (kJ/cc)
3.1 (2.3)	1	5	4000	0.1	11.4782
3.2	1	7.5	4000	0.1	9.0899
3.3	1	10	4000	0.1	7.8894

Step 5: Determine the optimal node for Layer 4 (depth of cut, final optimal result)

Finally, the process parameters and specific energy consumptions of Layer 4 (depth of cut) are shown in Table 4.9d. The result shows that large depth of cut will lead to the optimal energy consumption. So the third level (*n=4000rpm, fz=0.1mm/tooth, ae=10mm, ap=5mm*) is the optimal value for spindle speed, feed rate, width of cut and depth of cut.

Table 4.9d: Layer 4 Depth of Cut

Number	Depth of cut (mm)	Width of cut (mm)	Spindle speed (rpm)	Feed per tooth (mm/tooth)	Specific Energy Consumption (kJ/cc)
4.1 (3.3)	1	10	4000	0.1	7.8894
4.2	3	10	4000	0.1	5.5488
4.3	5	10	4000	0.1	5.0848

The optimal result can be determined after five steps and graphically shown in Figure 4.18. The green dashed arrow shows the search path of implementing ACO which can also clearly show an optimisation path. The optimal result achieved is the same as the results achieved by using other optimisation methods, such as Taguchi method, GA and direct search method (grid search). The optimal result can be gradually achieved layer by layer at the highest value/ level of each designed process parameter.

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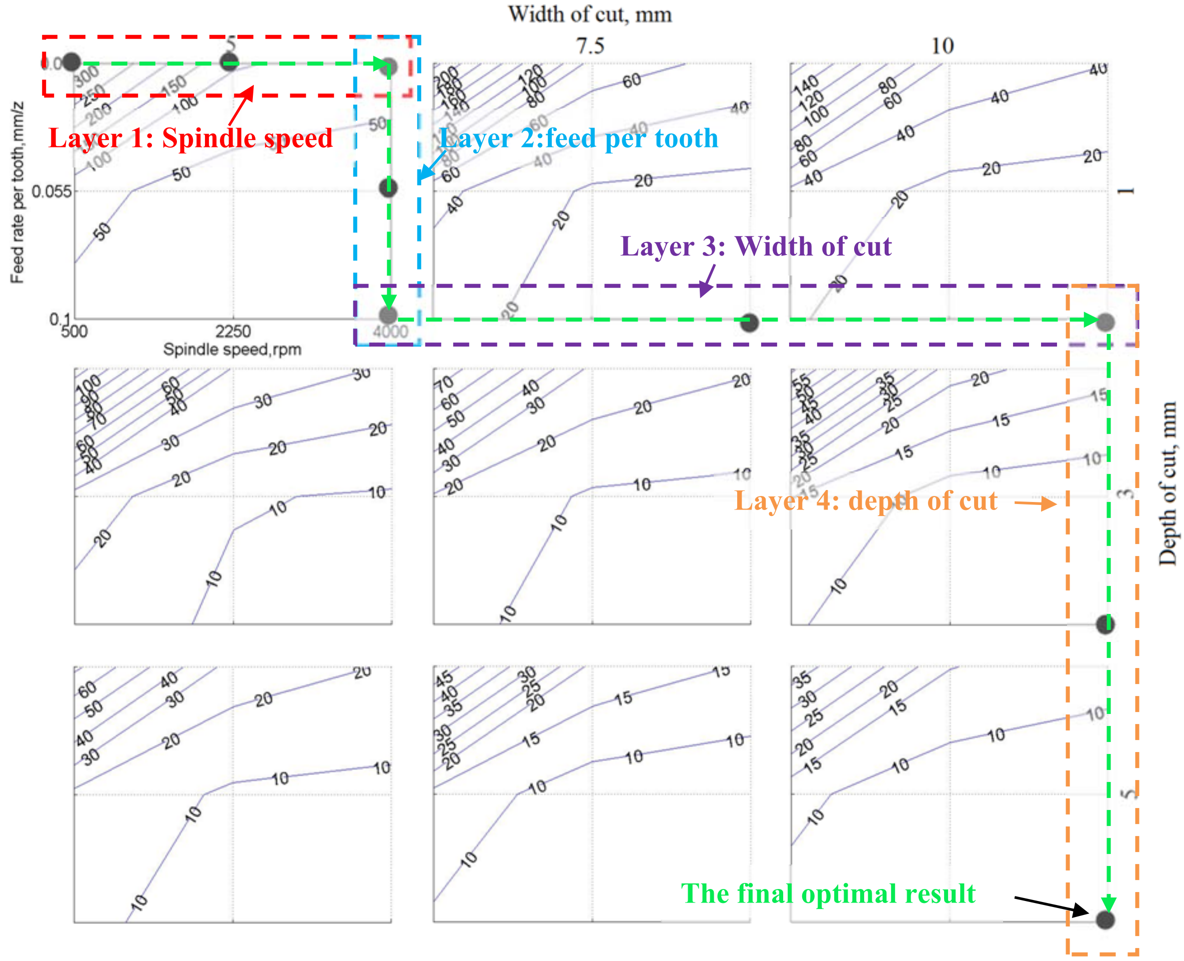

Figure 4.18 Graphical Displays of ACO in Experimentation Rig

4.2.5 Summary of Explanatory Models for Machining Optimisation Methods

In this section, an experimentation rig was built by using direct search method to explain how optimal results are obtained by using Taguchi method, GA and ACO. The basic principles of Taguchi method, GA and ACO have been demonstrated by graphically displaying the procedures of how these optimisation methods operate to achieve the optimal results and explaining the reason why they are faster than the traditional method. The uncovered reasons can provide explicit understanding in machining terms which can also provide confidence to practitioners to trust and implement optimisation results.

The comparison results of an unconstrained single-objective optimisation problem showed that the optimal results obtained by using different methods are same and all of the methods can identify optimising directions. However, the result obtained by using direct search method can easy point out the improvement directions and is much clearer and more convincible.

4.3 Constrained Optimisation Procedure based on Direct Search Method

Based on characterisation of energy consumption machining operation in section 4.1 and unconstrained optimisation procedure in section 4.2, a constrained optimisation procedure has been conducted by using direct search method in this section. 3D contour plots of specific energy consumption (SEC) are shown in Figure 4.19 with the respect of process parameters (depth of cut, width of cut, spindle speed and feed rate per tooth). 3D contour plots of specific energy consumption can clearly show the characteristic of energy consumption. Vertically changed coloured bands represent the distribution of specific energy consumption.

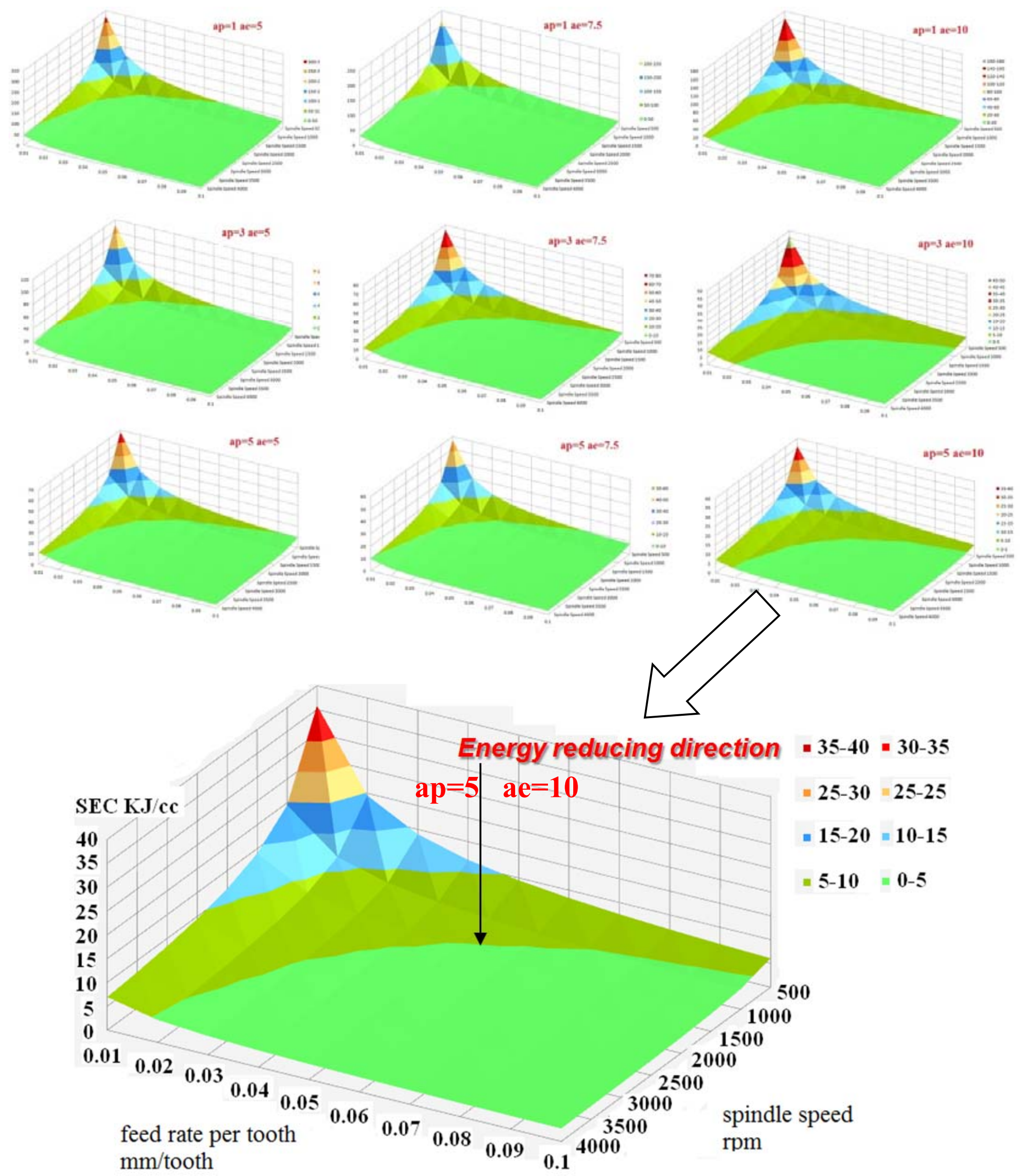

Figure 4.19 3D Contour Plot of Specific Energy Consumption Corresponds to Design of Experimentation Rig

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According to the characterisation of machining optimisation, the optimal result will be located on the boundary of the search space. So the case when depth and width of cut reach the maximal value of the range is shown to demonstrate the optimisation procedure.

4.3.1 Determination of Optimal Specific Energy Consumption

Figure 4.20 shows search space with the constraints of cutting force and surface roughness factor displayed. The green area represents the feasible region of search space when cutting force is no more than 400N and surface roughness is smaller than 0.05mm. So the optimal cutting condition based on energy considerations is the optimal points highlighted in the figure. The comparison result between cutting tool manufacturer's recommendation and optimal result in Table 4.10 shows that up to 75% of improvements in energy consumption (20.695kJ/cc to 5.126kJ/cc), cost (0.142£/cc to 0.036£/cc) and time consumption (50.912sec/cc to 12.778sec/cc) can be achieved by using optimal process parameters under the constraints of spindle speed (4,000 rpm), cutting force (400N) and surface roughness (0.05mm).

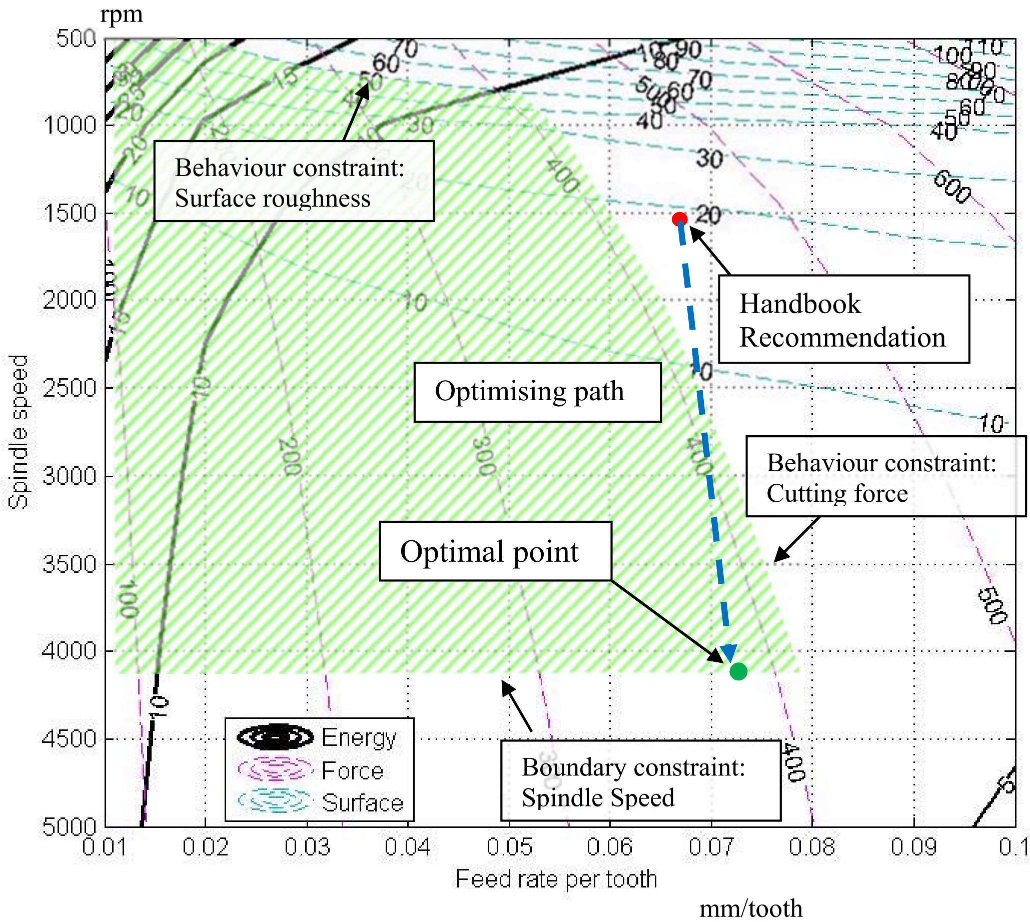

Figure 4.20 Constrained Search Space with Constraints and Optimal Result

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From the figure, it can also be found that the optimal result achieved is actually only affected by cutting force constraints. It means cutting force is the dominant constraint compared to surface roughness in this case study (cutting force 400N, surface roughness 0.05mm). It further proves the conclusion in section 4.1.4 that some constraints can be redundant and neglected in some situation. However, for some particular situations, dominant constraints may be different.

According to the results achieved, the problem of machining optimisation is not a complex problem as reported in the literature (Tolouei-Rad and Bidhendi, 1997). The demonstration above shows that for solving two- variable single-objective optimisation problem, optimal result can be achieved quickly by using MATLAB on a common computer (Sony, Processor - i7 2.00GHz, RAM - 8GB, Hard Drive - 750GB, Operating System - Win 7 Home Premium).

Although it may be argued that the problem will become more complex when more factors are considered (e.g. objectives, constraints, and numbers and levels of independent variable), the extra dimensionality will not change the characteristics of machining optimisation problems. The only issue of complexity of machining optimisation caused by adding levels and accuracy is how the achieved result can be effectively presented and how decision makers can handle large amount of data.

Table 4.10: Comparison of Recommendation and Optimal Process Parameters

Variables	Cutting Tool Manufacturer's Recommendation	Optimal Results	Improvement
ap (mm)	1	5	
ae (mm)	5	10	
n (rpm)	1500	4000	
fz (mm/tooth)	0.067	0.06	
Energy (kJ/cc)	20.695	5.162	75.06%
Cost (£/cc)	0.142	0.036	74.64%
Time (sec/cc)	50.912	12.778	74.90%

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4.3.2 Improvement of Energy Efficiency based on OptimalProcess Parameters

Based on the new energy efficiency metrics proposed in Chapter 3, the energy efficiency of cutting tool manufacturer's recommendation and optimal results can be calculated and shown in Table 4.11, Figures 4.21a and 4.21b. The energy efficiency for implementing recommended values and optimal process parameters are presented in Table 4.11 based on the process parameters in Table 4.10.

Table 4.11: Energy Consumption and Energy Efficiency for Cutting Tool Manufacturer's Recommendation and Optimal Process Parameters

	TME (kJ)	TE (kJ)	DE (kJ)	AE (kJ)	IE (kJ)	ER (TE/DE) ×100%	ER_m (TME/TE) ×100%	ER_p (TME/DE) ×100%
Recommended	5.238	38.920	558.771	519.852	33.682	6.965%	13.459%	0.937%
Optimum	5.238	31.379	139.379	108	26.141	22.513%	16.693%	3.758%

From the figures, it can be found that the energy efficiency of existing definition for implementing optimal process parameters is much better than the result of using the parameters from cutting tool manufacturer's recommendation (22.513% to 6.965%, improvement over 220%). The same conclusion can be determined by comparing the proposed energy efficiency for machining process which also shows that a significant improvement can be achieved (3.758% for optimal process parameters to 0.937% for recommendation).

The additional benefit for implementing optimal result is that it can further reduce the inefficiency of the machining operation. By comparing the energy efficiency of machining operation (theoretical minimal energy consumption/energy consumption for machining operation), the energy efficiencies for implementing optimal result and cutting tool manufacturer's recommendation are 16.693% and 13.459%. Up to 22% reduction of inefficient energy consumption (33.682kJ to 26.141kJ) can be achieved.

According to the analysis of energy efficiency, it can be concluded that the implementation of optimal process parameters cannot only reduce the energy consumption, but also improve the energy efficiency for manufacturing process and machining operation. The improvement of the energy consumption and energy efficiency of the machining process (ER and ER_p) are significant. However, the improvement of the energy efficiency for the machining operation is comparatively small. It means though the optimisation of process parameters can improve the energy use of the existing process, the reduction of inefficient energy consumption of operation is insignificant because of limitation of current machining strategy. It is necessary to develop new process and technologies to further reduce the inefficient energy consumption of machining operation to improve the energy efficiency.

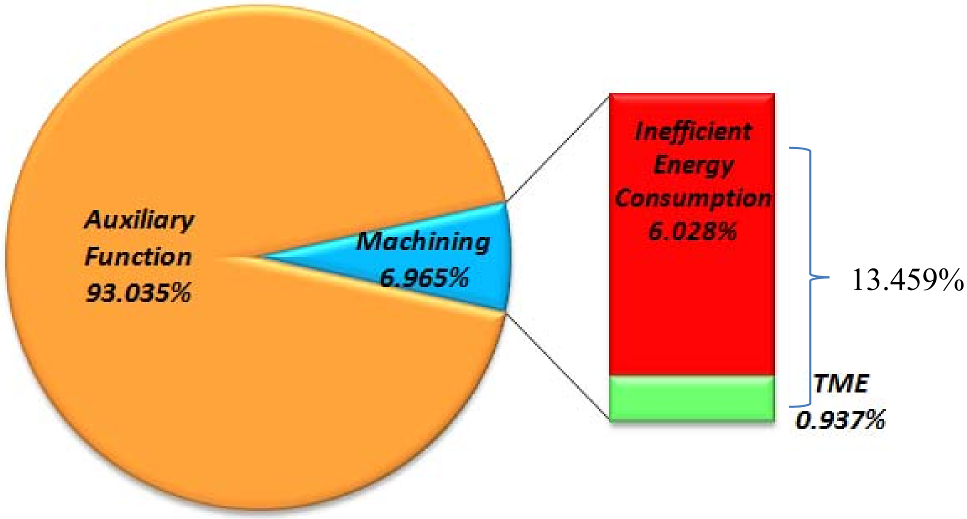

Figure 4.21a Energy Efficiency for Cutting Tool Manufacturer's Recommendation

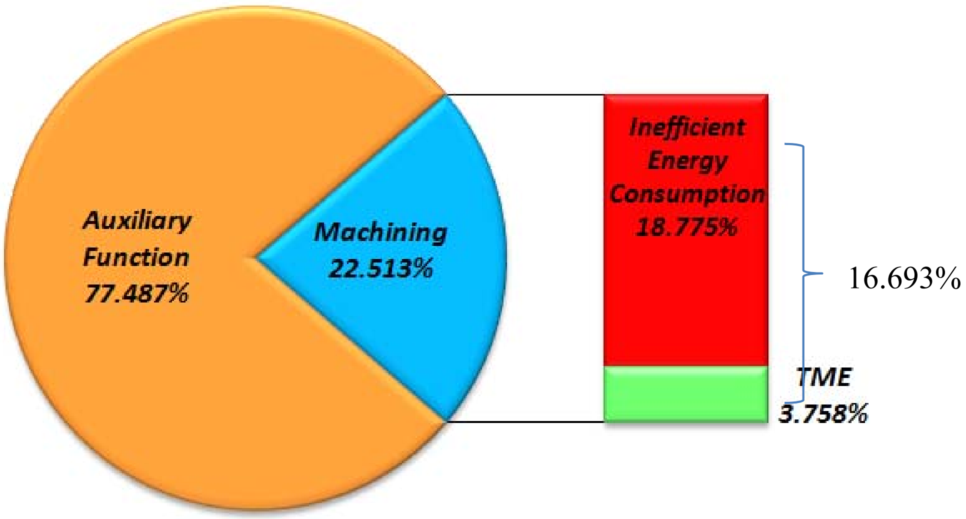

Figure 4.21b Energy Efficiency for Optimal Process Parameters

4.4 Summary of the Chapter

In this chapter, firstly, the characterisation of machining operation with energy considerations has been investigated by using graphical multivariate data analysis techniques. The results showed that energy consumption decreases monotonically with the increase of process parameters.

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Then, a systematic method was proposed for uncovering the reasons behind results obtained when energy is considered in machining optimisation. An experimentation rig was built by using Direct Search method to explain how optimal results are obtained by using Taguchi method, GA and ACO. The uncovered reasons can provide explicit understanding in machining terms. It can also provide confidence to practitioners to trust and implement optimisation results. The comparison results of an unconstrained single-objective optimisation problem showed that the optimal results obtained by using different methods are same and all of the methods can identify optimising directions. However, the result by using direct search method can easy point out the improvement directions and is much clearer and more convincible.

The optimisation result with the constraints of spindle speed (4,000 rpm), cutting force (400N) and surface roughness (0.05mm) for milling Aluminium 7075-T6 (by using Haas TM 1CE Vertical milling machine, maximum spindle speed 4,000rpm and 10mm 3 flutes carbide end mill) showed that up to 75% of improvement of energy, cost and time can be achieved by using optimal process parameters compared to cutting tool manufacturer's recommendation. The implementation of optimal process parameters for the case study shows that over 220% of improvement of energy efficiency (6.965% to 22.513%) for the process, and up to 22% reduction in inefficient energy consumption can be achieved for machining operation.

However, the improvement of the energy efficiency for the machining operation is comparatively small. Reduction of inefficient energy consumption of operation is still not signification because of limitation of current machining strategy. It is necessary to develop new process and technologies to further reduce the inefficient energy consumption to improve the energy efficiency.

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CHAPTER 5: MULTIPLE OBJECTIVES OPTIMISATION FOR SUSTAINABLE MACHINING

Chapter 4 has introduced the nature of machining optimisation and the reasoning behind the obtained optimal results in applying typical optimisation methods. The sustainable machining process needs to consider multiple objectives to fulfil environmental and economic requirements. The problem of solving multi-objective optimisation is that the current implemented optimising tool (Pareto front) is inefficient and difficult to solve machining optimisation problem when the optimisation objectives are more than two. To address this problem, scenarios are introduced in this thesis as part of the optimisation framework for machining optimisation. According to the relationships between objectives, solution scenarios have been developed which contain the problems that fit the descriptions of each scenario and the corresponding solutions.

5.1 Design of the Problem Scenarios

To accurately describe the problems of machining optimisation, the design of a problem scenario will be introduced in this section. The concept of a problem scenario is developed based on the characterisation of the machining operation. Each case represents a combination of considered objectives. These scenarios can be considered as the problem domain which allows decision makers to select the corresponding scenario based on their requirements.

For n objectives, the total number of problem scenarios Ns can be identified by using equation 5.1. The total number of cases is

$$Ns = C_n^0 + C_n^1 + C_n^2 + \cdots C_n^i + \cdots C_n^{n-1} + C_n^n = 2^n \tag{5.1}$$

Where Ns is the number of case studies, n is the number of objectives, and i is the number of objectives considered.

The example shown in this chapter is to investigate an end milling operation with the consideration of the seven objectives: energy, cost, time, power, cutting force, tool life and surface finish. By enumerating the combination of objectives, 128 scenarios in sustainable machining optimisation can be generated and classified in three major scenarios in Figure 5.1. The explanation of each scenario will be introduced in the following section.

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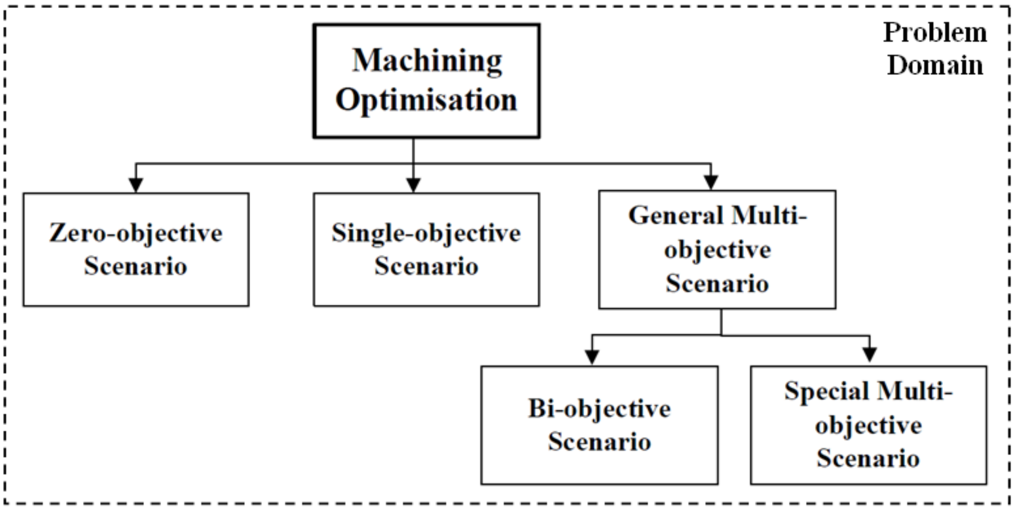

Figure 5.1 Classification of Machining Optimisation Problem Scenarios

The optimisation in practice can be divided into three main scenarios which are zero-objective scenario, single-objective scenario and general multi-objective scenario. The design of each scenario are introduced in the following sections.

5.1.1 Zero-objective Scenario

The definition of a zero-objective scenario is that there is no fixed optimisation objective within the problems in this scenario. Based on the decision makers' understanding of the problem, there are two situations in this scenario:

- The first situation is that decision makers have no idea about how to improve their machining process.
- The second situation is that instead of objectives, decision makers only have some constraints, such as: reduce cost/time/energy by 20%, increase tool life by 10% or improve surface roughness by 30%.

So the main task for this scenario is to describe the problem of machining optimisation (e.g. characteristics of optimisation objectives) and uncover the potential improvement of the current machining process to decision makers. The total number of cases in zero-objective scenario is:

$$N_{zero} = C_n^0 = 1 \tag{5.2}$$

If the number of optimisation objectives is seven, there is only one ($C_7^0 = 1$) scenario in the zero-objective scenario. The solution of zero-objective scenario is to describe the problem of machining optimisation and uncover the potential possibility of the current

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process. The result can be demonstrated by using a non-constrained contour plot to show the states of optimal criteria. Figure 5.2 indicates the solution of a zero-objective scenario with energy, cutting force and surface roughness considerations. It clearly describes the optimisation problem and presents the characterisation of each criterion. So the decision makers can continue to refine their requirements, determine the optimal objectives and select the satisfactory machining plan according to the presented contour plot. In addition, the plotted coloured arrows show the directions of how to minimise the energy consumption. Figures 5.3a to 5.3c clearly shows how the search space is reduced by (a) improving surface roughness by 50% (20μm to 10 μm), (b) reducing cutting force by 30% (450N to 300N), and (c) reducing specific energy consumption by 30% (7.5kJ/cc to 5kJ/cc). The red shadow area represents the original search space and the green shadow area represents the search space after refined.

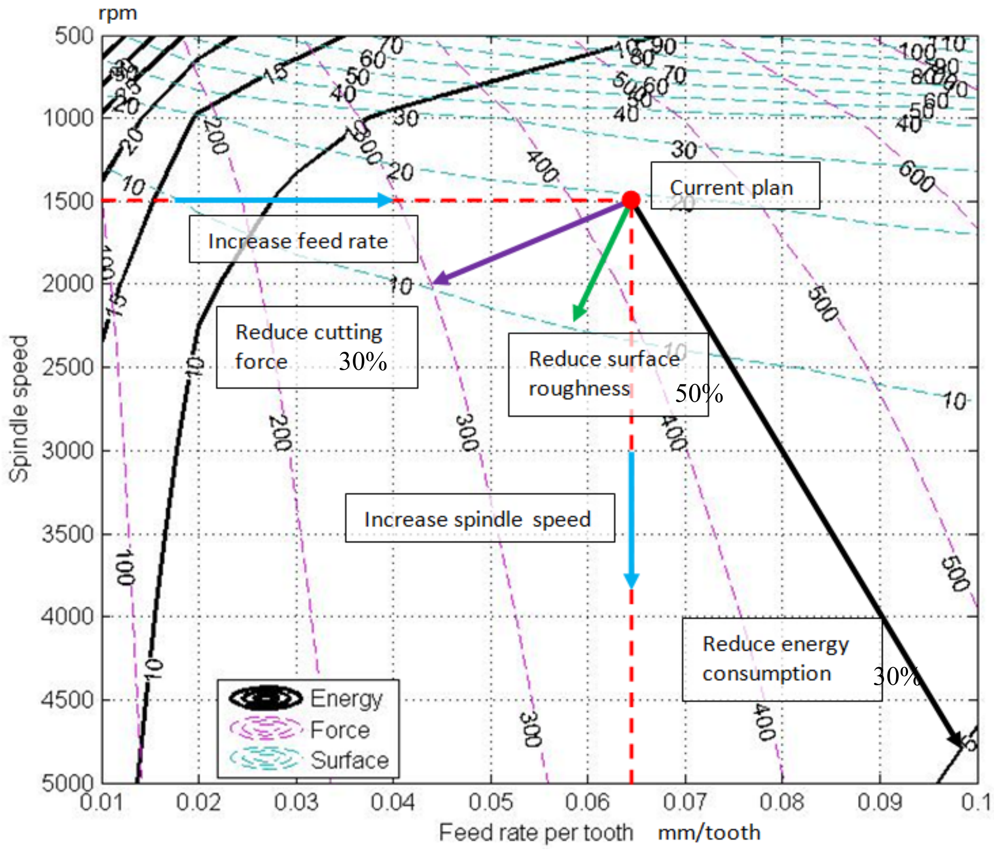

Figure 5.2 Solution of zero-objective scenario

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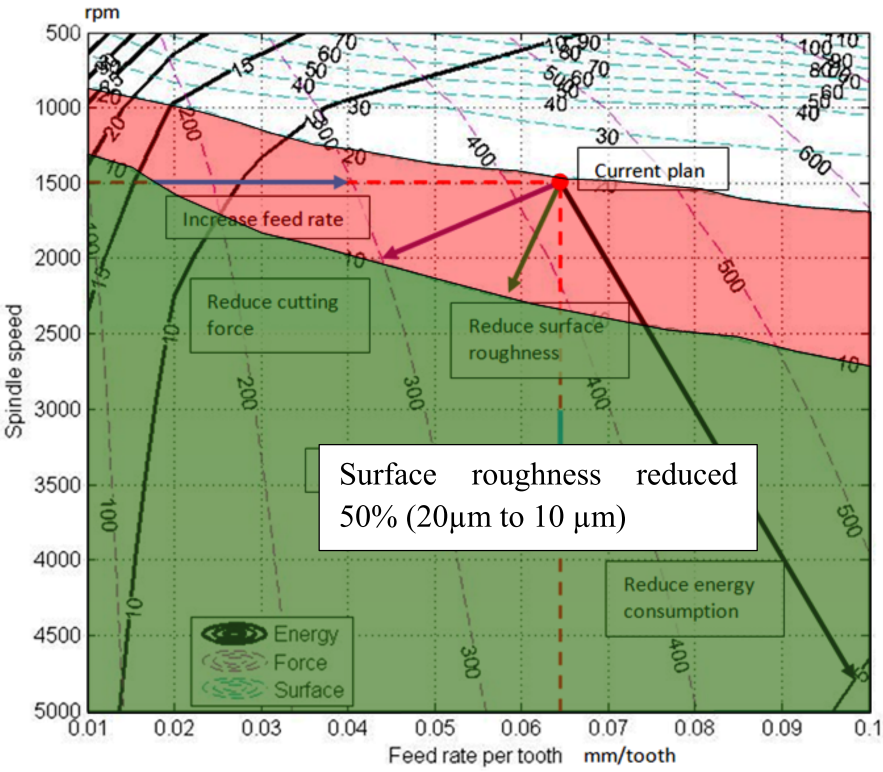

Figure 5.3a Comparison of Search Space via Reducing Surface Roughness by 50%,

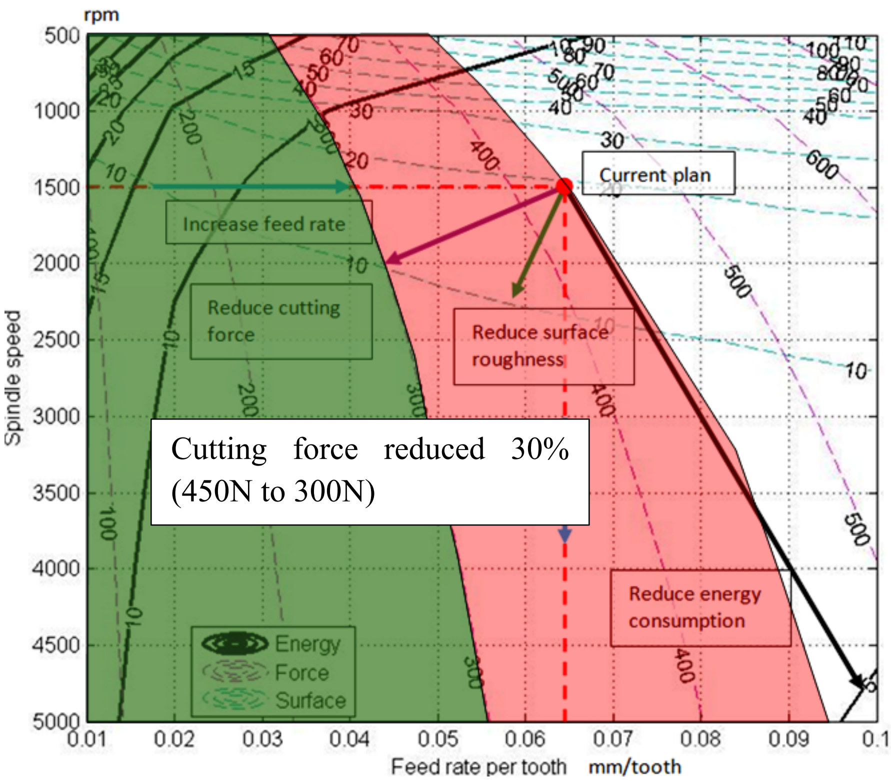

Figure 5.3b Comparison of Search Space via Reducing Cutting Force by 30%

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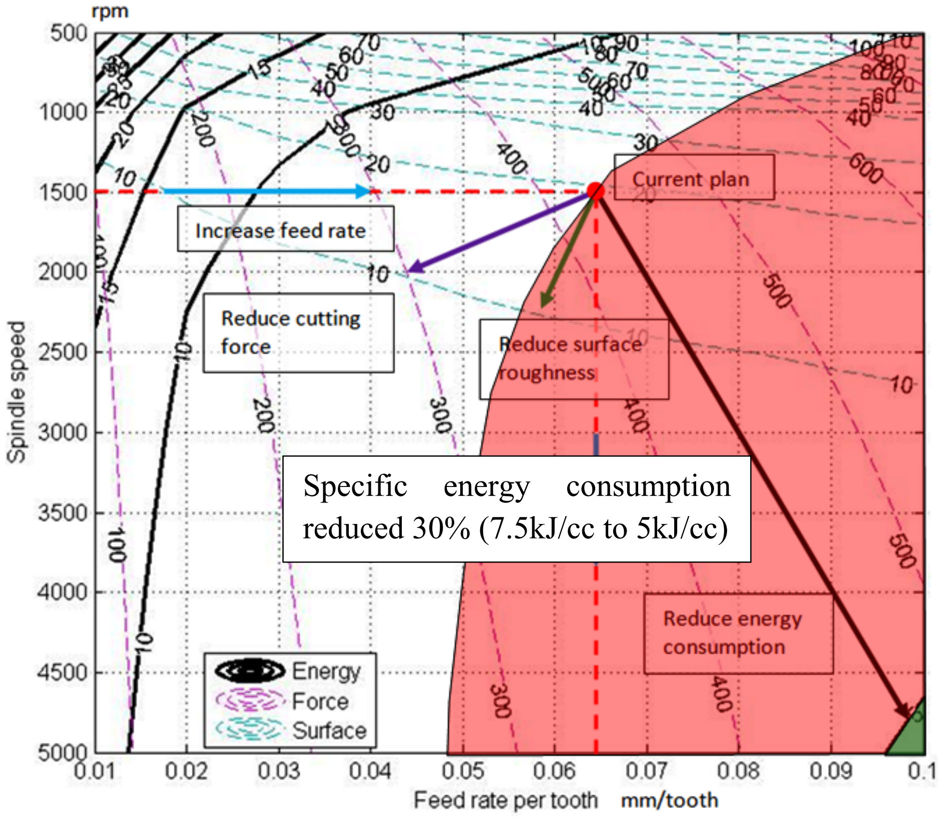

Figure 5.3c Comparison of Search Space via Reducing Specific Energy Consumption by 30%

5.1.2 Single-objective Scenario

The definition of a single-objective scenario is that only one objective function is considered for an optimisation problem. It refers to the practical situation when decision makers have a very clear objective to improve their process based on one specific criterion. The main task in this scenario is to correctly define the constraints to reduce the search space and locate the optimum value.

The total number of cases in a single-objective scenario is:

$$N_{single} = C_n^1 = n \tag{5.3}$$

If the number of optimisation objectives is seven, there are seven ($C_7^1 = 7$) cases in the single-objective scenario. The result can be also demonstrated by a contour plot of the optimal objective. A feasible search space can be indicated with the consideration of constraints. Figure 5.4 indicates the solution of energy minimisation with constraints of cutting force ($\leq 400N$), surface roughness ($\leq 0.05mm$) and spindle speed ($\leq 4000rpm$). The green area represents the constrained feasible region of search space, and the unique optimal result can be determined.

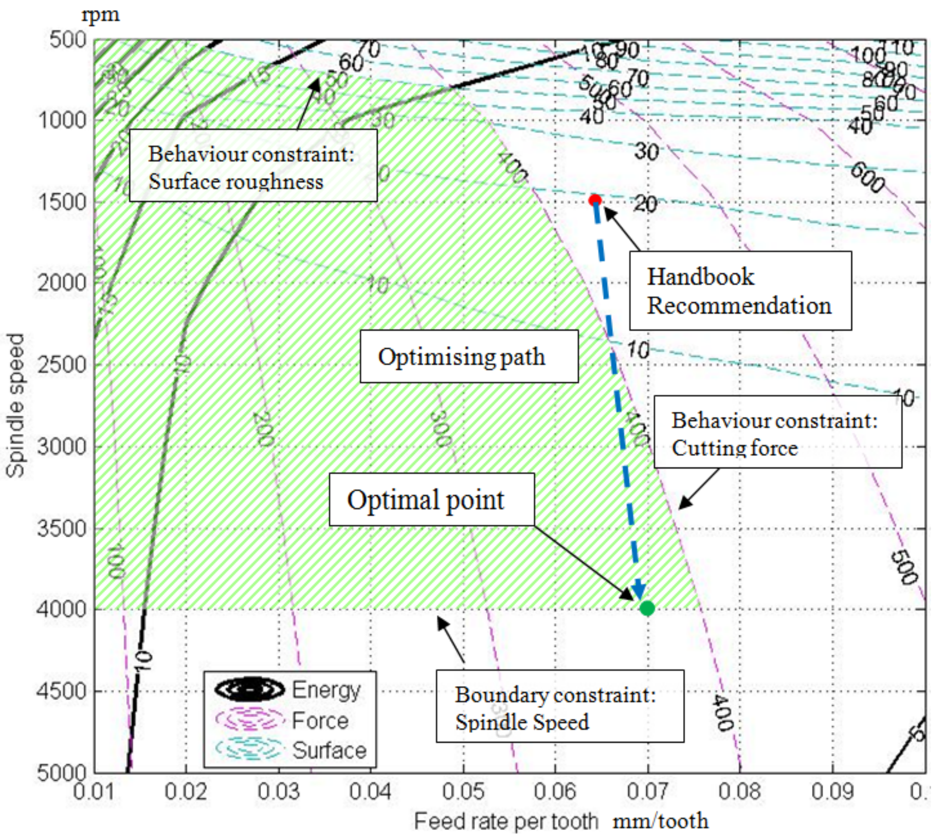

Figure 5.4 Solution of single-objective scenario

The example of energy is specifically shown in section 4.3. The seven objectives are energy, cost, cutting force, surface finishing, tool life, cost and power. A unique optimal solution will be determined in this scenario. The optimal value will be located on the boundary of the constraints. In addition, based on the characteristics of these objectives with the changing of process parameters, they can be divided into three groups as shown in Table 4.3.

5.1.3 Multi-objective Scenario

Generally, a multi-objective scenario consists of a scenario which involves more than one objective function to be optimised simultaneously. According to the number of objectives, a general multi-objective scenario can be further divided into two sub-scenarios:

- Bi-objective scenario
- Special multi-objective scenario

The total number of cases in a multi-objective scenario is:

$$N_{multi} = C_n^2 + \cdots C_n^i + \cdots C_n^{n-1} + C_n^n = 2^n - n - 1 \quad (5.4)$$

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$$N_{bi} = C_n^2 = \frac{2!\,(n-2)!}{n!} \tag{5.5}$$

$$N_{multi} = C_n^3 + \cdots C_n^i + \cdots C_n^{n-1} + C_n^n \tag{5.6}$$

The definition of a bi-objective scenario is that two objectives will be considered in machining optimisation simultaneously. If the number of optimisation objectives is seven, there are 21 ($C_7^2 = 21$) cases in a bi-objective scenario. The solutions of bi-objective scenario can be represented as a single Pareto front.

The definition of a special multi-objective scenario is that more than two objectives will be considered in machining optimisation simultaneously. There are 99 ($C_n^3 + C_n^4 + C_n^5 + C_n^6 + C_n^7 = 99$) cases in this sub-scenario. The solutions of a special multi-objective scenario are usually complex and require multiple Pareto fronts. The more objectives that need to be considered, the more complex the solution will be. The specific analysis will be carried out in the following section.

5.2 Result Analysis for Multi-objective Scenario

Figure 5.5(a) to 5.5(f) show the Pareto fronts of energy consumption with cost, surface roughness, tool life, cutting force, time and power requirement. From the Pareto fronts presented, the optimal result for a bi-objective scenario can be classified into two categories: non-conflicting and conflicting. Figure 5.6 shows a combined Pareto front of all six objectives, the value of the X-axis represents specific energy consumption (SEC) which is selected as a reference objective.

For the scenarios, such as energy and cost/time, the optimal solution will be a unique optimal point (see in Figure 5.6 as a red point). These bi-objective cases with unique optimal points indicate that that the objectives are non-conflicting. Similar findings were also reported by Mativenga and Rajemi (2011) to optimise energy and cost for turning operation. This conclusion can also be drawn from the characterisation of single objective in Chapter 4. This means that the multi-objective analysis in these scenarios can be converted to a single-objective optimisation problem and becomes the earlier results obtained in single objective analysis. These scenarios can be put together as a non-conflicting bi-objective category. The example of a non-conflicting bi-objective category can be found in section 4.3 where the optimal energy consumption was achieved along with the optimal cost and time.

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For the scenarios, such as energy to surface roughness, tool life, cutting force and power, the optimal solutions will be a Pareto front which contains a set of feasible solutions without additional preferences. These scenarios can be put together as a conflicting bi-objective category. According to the plotted Pareto front, decision makers can evaluate their current machining plans and make suitable adjustments based on their preferences.

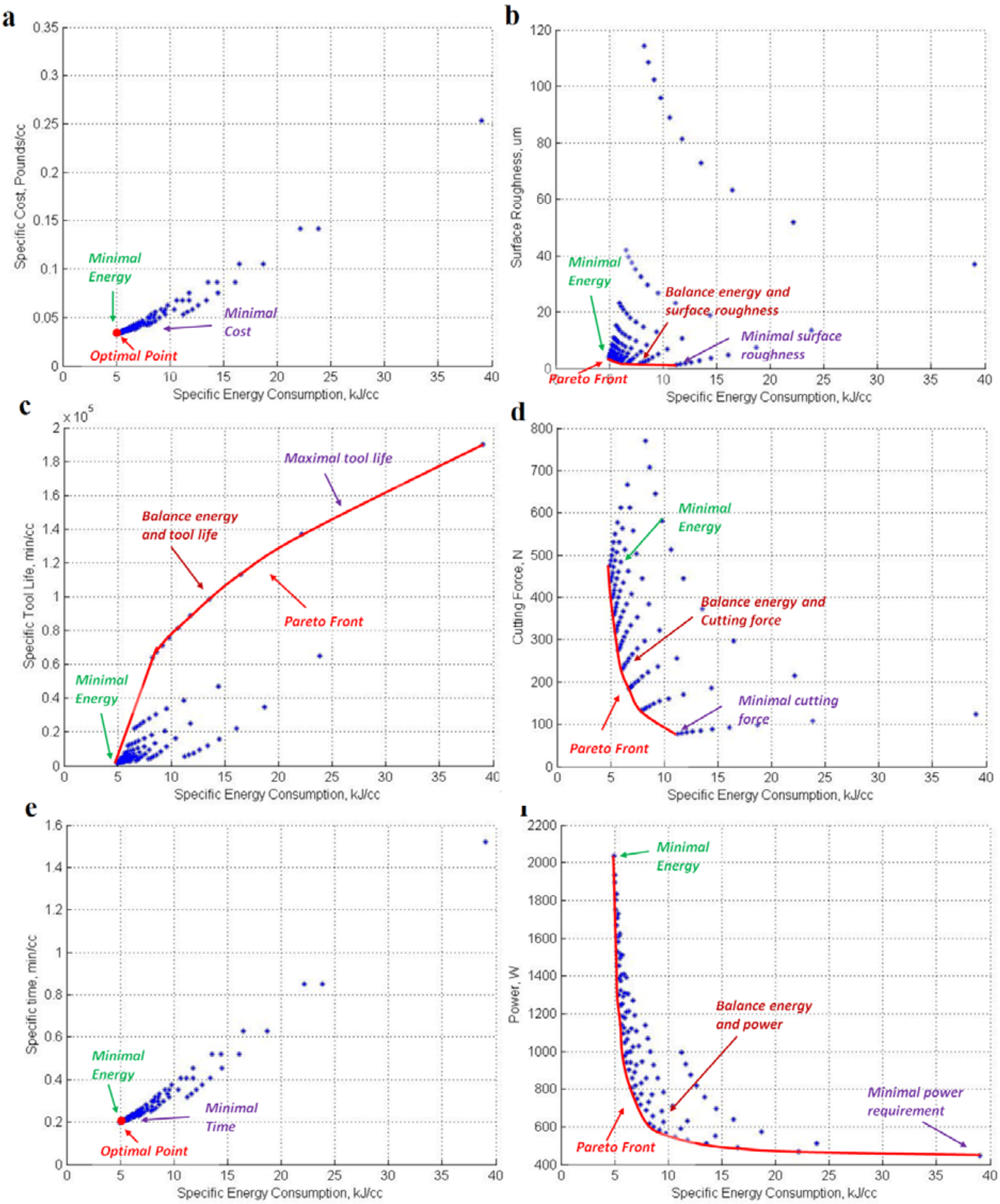

Figure 5.5 Pareto Fronts of (a) Cost, (b) Surface Roughness, (c) Tool Life, (d) Cutting Force, (e) Time, (f) Power against Specific Energy Consumption

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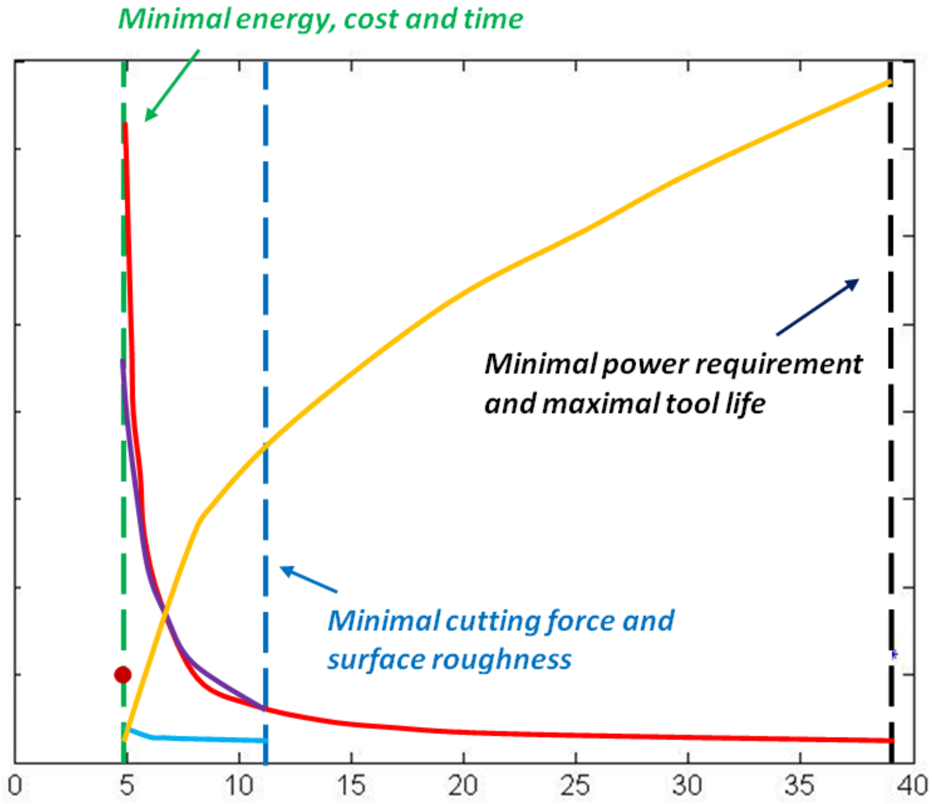

Figure 5.6 Combined Pareto Fronts of Cost, Surface Roughness, Tool Life, Cutting Force, Time and Power.

5.2.1 Optimal Solution for Special Multi-objective Scenario

Normally, a Pareto front is utilised to solve two conflicting objectives optimisation problems. However, Pareto fronts are difficult to understand and inefficient when there are more than two objectives being considered. For example, if five objectives are being considered, there are ten ($C_5^2 = 10$) Pareto fronts which should be plotted to show the relationship between each pair of objectives. The analysis process will be very complex and requires a lot of explanation, and the optimal solution is very difficult to be clearly presented.

However, according to the characterisation of machining optimisation, the objectives are increases or decreases constantly with the increase of process parameters. Every pair of non-conflicting objectives can be considered as a single-objective problem, it can be easily inferred that all the non-conflicting special multi-objective scenarios can be converted to a single objective optimisation.

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Based on the above conclusion, the optimal solution for a special multi-objective scenario can be simplified by carrying out an analysis and combining process with the steps below:

- Characterise the optimising objectives. Identify the relationship between each pair of objectives: Are they conflicting or not conflicting?
- Combine the non-conflicting objectives. The multiple non-conflicting objectives can be combined by using one representative objective (could be any one of them).
- Evaluate the remaining representative objectives. If only one objective remains, then the problem can be classified in a non-conflicting category. Otherwise it can be classified in a conflicting category. The classification and solutions for a special multi-objective scenario are the same as for a bi-objective scenario. So the multi-objective scenario can be generally classified into two categories.

Figure 5.7 shows the analysis process of a general multi-objective machining optimisation. It is clear that the optimal result will be a unique optimal solution if all the objectives are not conflicting with each other. It means the optimal solution of a non-conflicting category is the same as the solution of a single-objective scenario. The optimal result of a conflicting category will be a unique Pareto front which is the same as bi-objective conflicting cases shown in Figure 5.5.

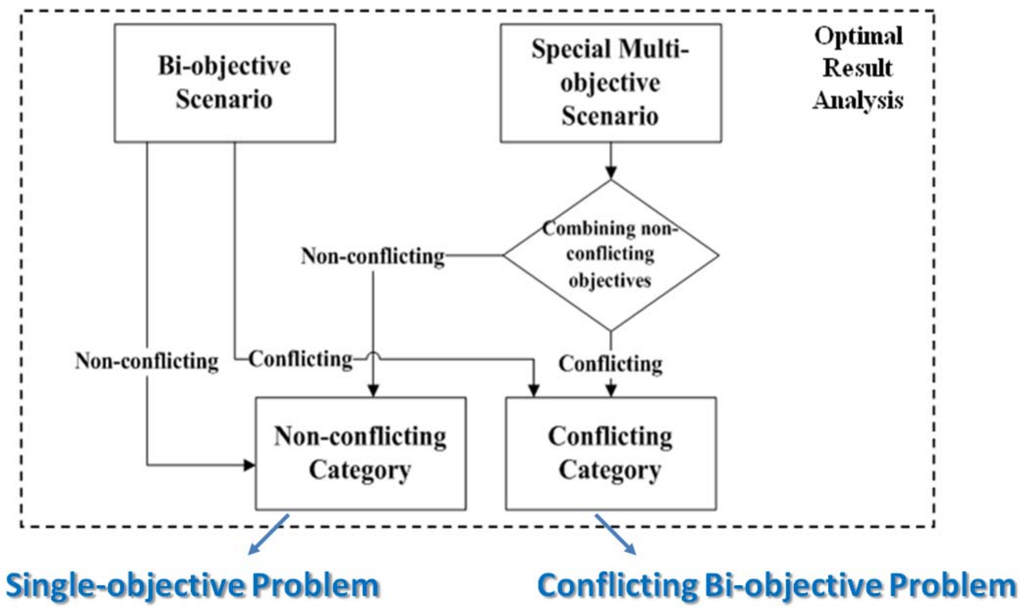

Figure 5.7 Result Analysis of Multi-objective Machining Optimisation

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5.2.2 Classification of Solution Scenario

According to the analysis of optimal results for each problem scenario, the optimal solutions for machining optimisation can be classified into 3 scenarios, which are:

Descriptive scenario. The solutions in this scenario are to address the problems in a zero-objective scenario. The functions of these solutions are to comprehensively describe the problems of machining optimisation for decision makers who do not have explicit optimising objectives, and help them to uncover the potential improvement of their current machining processes. Usually, the solutions in this scenario will be presented as a non-constrained contour plot.

Unique solution scenario. The solutions in this scenario are to address the problems in the single-objective scenario and the non-conflicting category of a multi-objective scenario. The optimising process for this solution scenario can be conducted by using any existing single-objective optimisation algorithms. The solutions in this scenario are a unique optimal solution/result for the problems and can be presented as a constrained contour plot.

Pareto front scenario. The solutions in this scenario are to address the problems in the conflicting category of a multi-objective scenario. The optimal results in this scenario are not a unique optimal result but a set of feasible solutions. The optimal solutions in this scenario can be presented as a single Pareto front.

The proposed solution scenarios in this section can be fused together as a solution domain which will provide the corresponding optimal solution for the scenarios in the problem domain. Figure 5.8 shows the structure of the proposed scenario-based framework for machining optimisation. This framework clearly shows how to solve the machining optimisation problem. It is especially suitable for multi-objective problems, and provides a generic method to address the issues for achieving a sustainable machining process.

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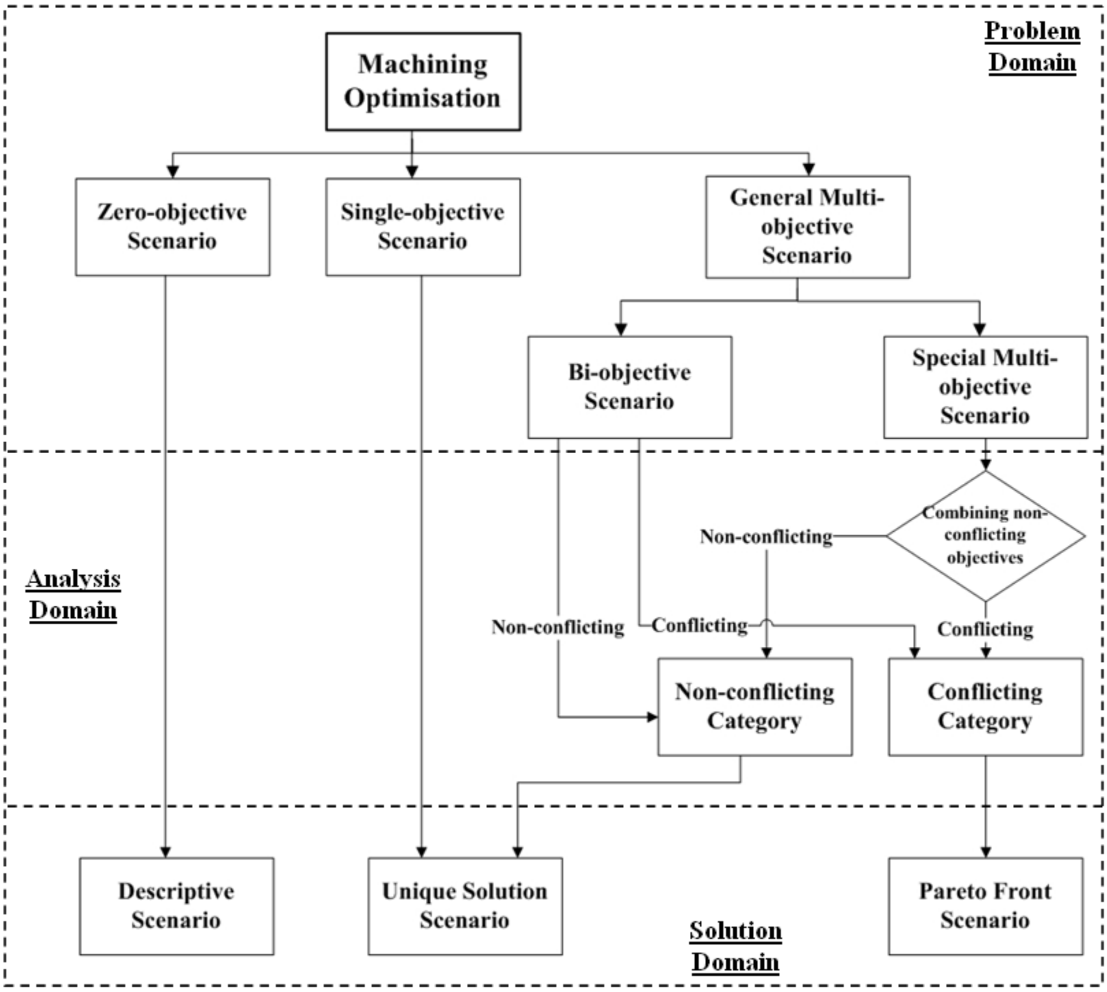

Figure 5.8 Scenario-based Framework for Machining Optimisation

5.2.3 Case Study of Multiple Objectives Optimisation for Implementing Proposed Scenario-based Framework

An example has been produced to demonstrate the process of how to use the proposed method to optimise four conflicting objectives energy, cost, cutting force and surface roughness. By analysing the Pareto fronts of each pair of objectives, energy and cost are not conflicting, and cutting force and surface roughness are not conflicting, so they can be respectively combined and represented by energy and cutting force. Then the optimal result can be plotted as a unique Pareto front as shown in Figure 5.9 where the X axis represents specific energy consumption and Y axis represented cutting force (set as a representative objective). From the figure, decision makers can evaluate their current machining plans and make suitable adjustments based on their preferences, such as minimal cost, minimal surface roughness, and minimum change of process parameters or balance objectives.

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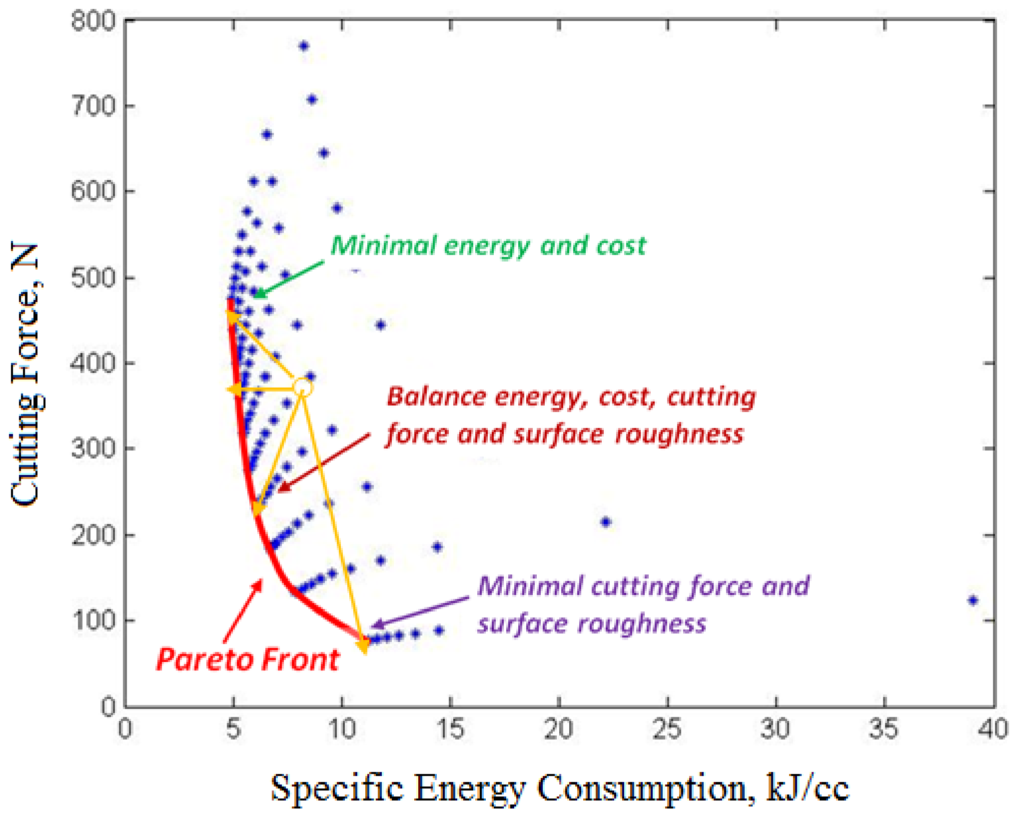

Figure 5.9 Pareto Front for Optimising 4 Objectives: Energy, Cost, Cutting Force and Surface Roughness

5.3 Summary and Discussion

In this chapter, a scenario-based systematic methodology was developed to provide a comprehensive solution for decision makers to solve machining optimisation problems with sustainability considerations.

The problem scenarios have been developed to describe the actual problems of machining optimisation. By enumerating and characterising the problems in sustainable machining operation involving seven objectives including energy, cost, time, power, cutting force, tool life and surface finish, 128 scenarios can be identified and classified into three major problem scenarios: zero-objective, single-objective and general multi-objective scenarios based on the number of objectives considered. Based on the complexity of optimal results (number of Pareto fronts required), the general multi-objective scenarios can be further separated into two sub-scenarios: bi-objective and special objective scenario (optimal objectives more than two).

The solutions for multi-objective scenarios have been investigated by characterising of Pareto fronts of bi-objective sub-scenarios. Based on the analysis, the multiple

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objectives can be divided into two categories: non-conflicting and conflicting category. Non-conflicting multi-objective problems can be converted to a single-objective situation which has a unique solution, and conflicting multi-objective problems can be converted to a set of conflicting bi-objective cases which can be presented as a single Pareto front.

According to the analysis of optimal results, the solutions for machining optimisation can be classified into three solution scenarios which are descriptive scenario (for zero-objective scenario), unique solution scenario (for single-objective scenario and non-conflicting category of multi-objective scenario) and Pareto front scenario (for conflicting category of multi-objective scenario). The proposed solution scenarios can be fused together as a solution domain to provide an optimal solution for the corresponding problem scenarios.

Based on the above results, a scenario-based framework has been proposed for solving general machining optimisation problems. It can provide a generic and systematic methodology for decision makers to better understand their machining processes and address recent challenges from sustainable requirements.

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CHAPTER 6: ENERGY-EFFICIENT CUTTING STRATEGY - A PROFILING TOOLPATH STRATEGY FOR END MILLING OPERATION

The issues of how to improve the sustainability by optimising process parameters have been addressed in Chapter 4 and Chapter 5. The aim of this chapter is to address the issues of how to further reduce the energy consumption for machining operations by developing new machining technologies and strategies. The following research question will be answered in this chapter, which is:

In addition to the optimisation of process parameters, is it possible to further reduce the energy consumption by changing/designing new technologies and processes? If it is possible, what is the maximal improvement can be achieved?

The result presented in this chapter will follow the optimal result obtained in Chapter 4. A profiling toolpath strategy is introduced in this chapter which is energy efficient and cost effective for forming some 2½D features compared to the conventional cutting strategy. The application range for each feature will also be introduced based on the results of the previous chapters on the measurement of energy consumption and cost.

6.1 Introduction: Conventional and Proposed Profiling Toolpath Strategy

The energy efficiency metric developed in Chapter 3 represented a measure that uncovers the inherent inefficiency of existing technology and suggests the direction to improve energy efficiency. Equation 3.17 shows that the energy consumption for machining operations (TE) is related to process parameters and material removal volume. The first aspect has been addressed by conducting the optimisation of process parameters in Chapter 4 which reduced the energy consumption and improved the energy efficiency. The result shows that even when the energy consumption from auxiliary functions can be reduced to zero, the inefficiency still exists. The operation itself is not efficient enough and contains lots of redundant motions. It requires developing new technologies and machining methods to further improve the energy efficiency. There are already many research contributions concerning the development of new energy-efficient methods/technology. However, most of the literature only tends to focus on coolant strategies and tool design, and did not address the inefficiency of the machining process.

Ideally, the absolutely perfect situation in machining should not generate any material waste. However, because of the limitation of technology, waste generation cannot be avoided during the machining process. With the inspiration from the second aspect of Equation 3.17, it is possible to reduce waste and energy consumption by reducing the material removal volume (De Vries, 1992). To address this issue, the research presented in this chapter is an attempt in this direction to further reduce the energy consumption by developing new machining techniques. A new profiling toolpath strategy for the end milling operation that operates outside the boundary of the feature was developed in this chapter to reduce the energy consumption and the inherent inefficiency. The proposed strategy can give a direction to the new research of technology for tool design and toolpath strategy.

6.1.1 Conventional Cutting Strategy for End Milling Operation

In the end milling operation, conventional machining strategies (or conventional toolpath strategies, CTS) will remove the whole feature volume to achieve the shape. Figure 6.1 shows the material removal volume and machining method for conventional machining strategy. The advantages of this method include: low cutting force, low power requirement, less set-up time. In addition, conventional machining strategy can be implemented in machining all types of feature. However, the material removal rate of this method is low. Thus, it will use more time for machining the feature and generate more waste.

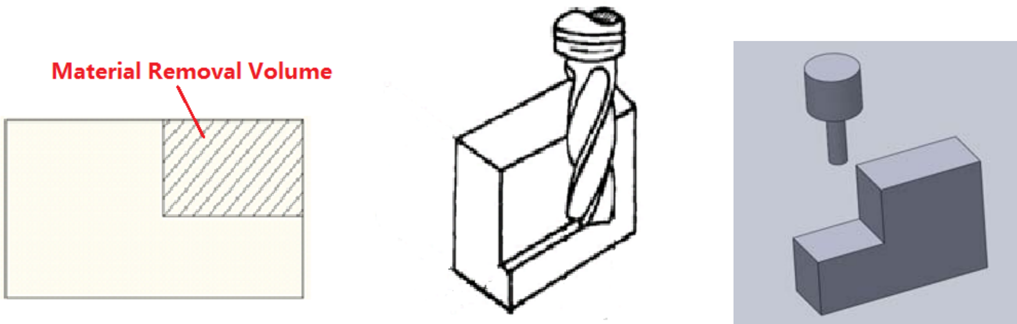

Figure 6.1 Conventional Toolpath Strategy (CTS)

6.1.2 Profiling Toolpath Strategy for End Milling Operation

The proposed energy-efficient machining strategy (profiling toolpath strategy, PTS) uses slotting method (as for conventional toolpath strategy) to conduct machining around the boundary of the feature. Compared to conventional strategy, PTS uses full diameter to cut which can increase the material removal rate. The energy consumption for machining operations can be reduced by shortening the machining time. Figure 6.2

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shows the material removal volume and type of energy machining strategy. However, PTS also has some limitations which are:

- The cutting force will be increased by using full diameter cutting. It will cause spindle vibration, reduce tool life and increase power consumption.
- It may take more set up time than conventional strategy, because of using slotting operation.
- It cannot be implemented for all the features, only specific types of feature are suitable (e.g. deep narrow hole, wide shallow hole, wide deep hole, long shallow slot, long and deep slot, short and shallow slot, short deep slot)

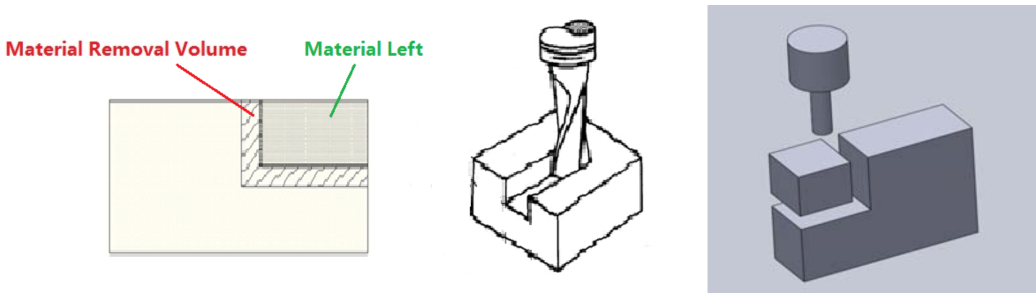
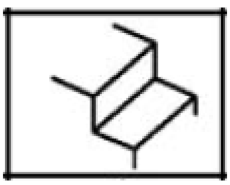


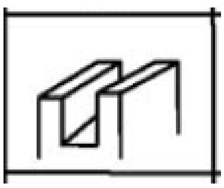
Figure 6.2 Profiling Toolpath Strategy (PTS)

6.2 Investigation of Profiling Toolpath Strategy

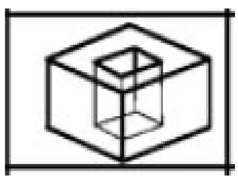
Since the proposed profiling toolpath strategy has a limitation of implementation, four typical features, for which profiling toolpath strategy can be implemented, were selected and investigated from a taxonomy of basic features (Owodunni et al., 2002). Comparison of energy consumption between conventional machining strategy and energy-efficient machining strategy was carried out by conducting numerical simulations. Four features are shown in Figure 6.3, which are step, slot, prismatic hole and round hole. The 3D demonstrations for implementing PTS to machine these four features are shown in Figure 6.4(a) to 6.4(d). The directions of cutting tool movements (rough toolpath) are shown as the red arrows in each figure.



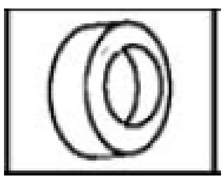
(a) Step



(b) Slot

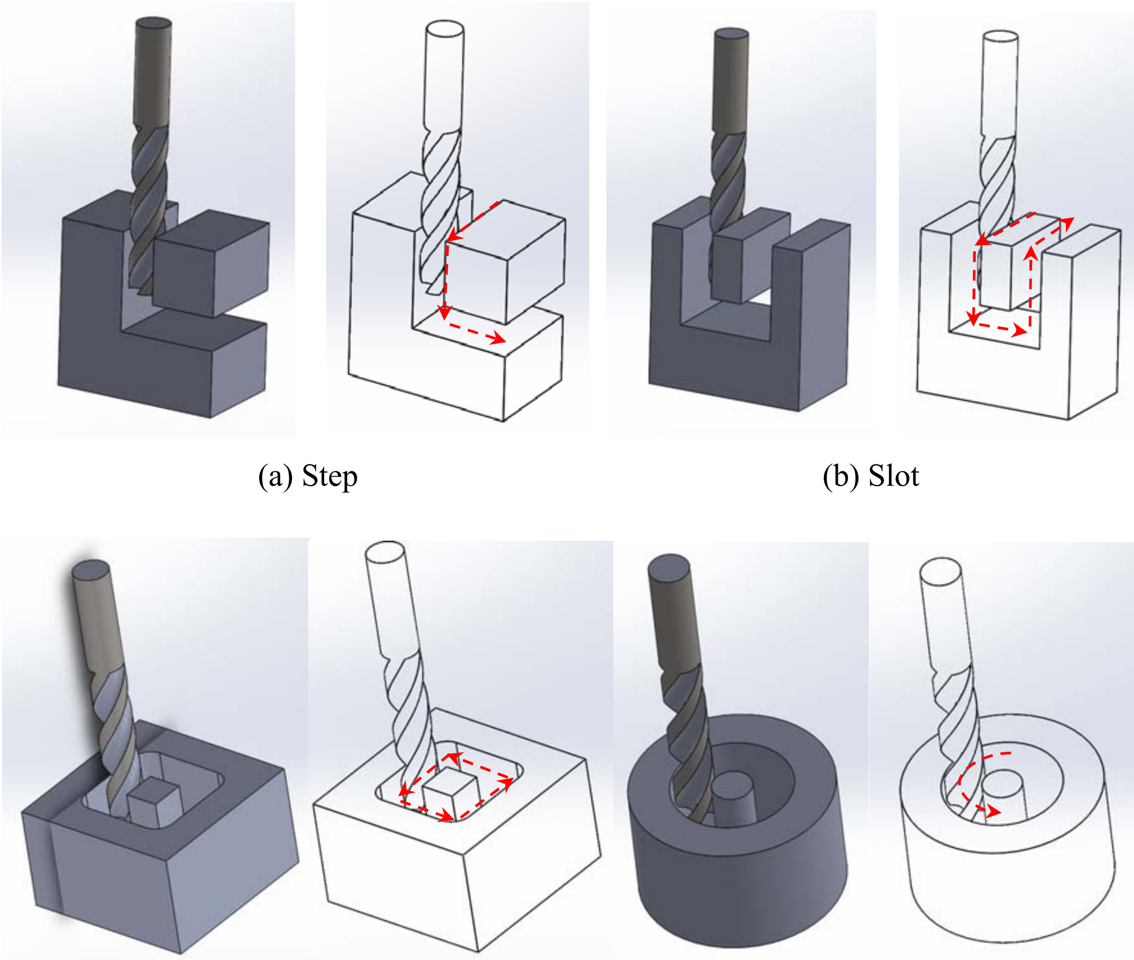


(c) Prismatic Hole



(d) Round Hole

Figure 6.3 Typical 2½ D Milled Features Suitable for PTS



(a) Step (b) Slot

(c) Prismatic Hole (d) Round Hole

Figure 6.4 3D Demonstrations of PTS for Machining 2½ D Milled Features

6.2.1 Material Removal Volume for Conventional End Milling Operation

According to Equation 3.17, the energy consumption for the end milling operation is related to workpiece material, material removal volume and the number of flutes of the cutting tool. For conventional machining strategy, V_m is fixed which is determined by machining feature dimensions. It is not related to the type of feature. In this case, the energy consumption for specific features can be calculated. Material removal volumes of these features are concluded in Equation 6.1.

$$\begin{cases} V_{CTS} = L \cdot H \cdot W \quad (Prismatic\ Feature) \\ V_{CTS} = \dfrac{\pi H \cdot d_H^2}{4} \quad (Round\ Hole) \end{cases} \tag{6.1}$$

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where, V_{CTS} is material removal volume for conventional machining strategy, L is length of feature, H is height of feature, W is width of feature, d_H is diameter of feature. For Step, Slot and Prismatic Hole, the feature shapes are rectangular solids. For Round Hole, the feature shape is a cylinder.

6.2.2 Energy Consumption for Profiling Toolpath Strategy

Compared to conventional machining strategy, the material removal volume of energy-efficient machining strategy is not only related to feature dimensions but to also the diameter of the tool. In this case, even when the volume of the feature is the same (e.g. step, slot and prismatic hole), different types of feature have different toolpaths and hence the toolpath volume, V_m. Material removal volumes of PTS are shown as the following equations.

For Step feature:

$$V_{PTS} = L \cdot d \cdot (H + W - d) \tag{6.2}$$

For Slot feature:

$$V_{PTS} = L \cdot d \cdot (2H + W - 2d) \tag{6.3}$$

For Prismatic hole:

$$V_{PTS} = 2d \cdot H \cdot (L + W - 2d) \tag{6.4}$$

For Round hole:

$$V_{PTS} = \pi H \cdot d \cdot (d_H - d) \tag{6.5}$$

where, d is diameter of tool, mm.

Based on Equation 6.2 to Equation 6.5, if both strategies use the same cutting tool and the same process parameters, the ratio between CTS and PTS can be represented as equation 6.6.

$$Q = \frac{E_{PTS}}{E_{CTS}} = \frac{K_{tPTS} \times V_{PTS}}{K_{tCTS} \times V_{CTS}} \tag{6.6}$$

where, E_{PTS} is energy consumption for energy-efficient machining, E_{CTS} is energy consumption for conventional machining strategy, Q is the ratio between the proposed energy-efficient strategy and conventional strategy. When $Q < 1$ PTS is more efficient, when $Q \geq 1$ conventional machining is more efficient.

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Because the work in this section follows the optimal result obtained in Chapter 4, the process parameters applied to compare conventional strategy and proposed toolpath strategy are the same. In this case, the values of cutting force coefficient Kt for two strategies are the same too. So equation 6.6 can be simplified as:

$$Q = \frac{V_{PTS}}{V_{CTS}}$$

In addition, according to the value of the coefficient in Table 3.5, the coefficient for width of cut is very close to zero. It means that even when the width of cut for two strategies is different, the cutting force coefficient Kt for both strategies is approximately equal.

So the implementation conditions for different features can be theoretically represented as below:

For Step:

$$Q = \frac{V_{PTS}}{V_{CTS}} = \frac{d \times (H + W - d)}{H \times W}$$

When $Q < 1$,

$$d \times (H + W - d) < H \times W$$

$$d \times (W - d) < H \times (W - d)$$

So when $H > d$ and $W > d$, use energy-efficient machining, when $H \leq d$ or $W \leq d$, use conventional machining.

For Slot:

$$Q = \frac{V_{PTS}}{V_{CTS}} = \frac{d \times (2H + W - 2d)}{H \times W}$$

When $Q < 1$,

$$d \times (2H + W - 2d) < H \times W$$

$$d \times (W - 2d) < H \times (W - 2d)$$

So when $H > d$ and $W > 2d$, use energy-efficient machining, when $H \leq d$ or $W \leq 2d$, use conventional machining

For Prismatic hole:

$$Q = \frac{V_{PTS}}{V_{CTS}} = \frac{2d \times (L + W - 2d)}{L \times W}$$

When $Q < 1$,

$$2d \times L + 2d \times (W - 2d) < L \times W$$

$$2d \times (W - 2d) < L \times (W - 2d)$$

So when $D > 2d$ and $W > 2d$, use energy-efficient machining, when $D \leq 2d$ or $W \leq 2d$, use conventional machining.

For Round hole:

$$Q = \frac{V_{PTS}}{V_{CTS}} = \frac{4d \times (d_H - d)}{d_H^2}$$

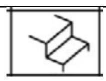
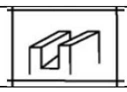
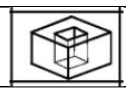
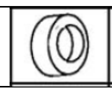
When $Q < 1$,

$$4d \times d_H - 4d^2 < d_H^2$$

$$d_H > 2d$$

So when $d_H > 2d$ use energy-efficient machining, when $d_H \leq 2d$ use conventional machining. Specific conditions for applying PTS are shown in Table 6.1.

Table 6.1: Material Removal Volume and Applying Conditions for PTS

			
$V_m = d \cdot L \cdot (W + H - d)$	$V_m = d \cdot L \cdot (W + 2H - 2d)$	$V_m = d \cdot 2H \cdot (W + L - 2d)$	$V_m = \pi d \cdot H \cdot (d_H - d)$
$H > d, W > d$	$H > 2d, W > 2d$	$H > d, W > 2d$	$d_H > 2d$

6.3 Comparison of Energy Consumption for Conventional Toolpath Strategy and Profiling Toolpath Strategy

According to the developed energy consumption and energy efficiency metrics, the comparison of energy consumption of conventional (CTS) and energy-efficient machine strategy (PTS) can be carried out. There are three groups of parameters, which will be applied for different types of feature. The first group is for step and slot, as shown in Table 6.2a. The length of the feature is a constant value (30mm), and the height and

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width of the feature will change from 0 to 50mm. The second group is for prismatic hole, as shown in Table 6.2b. The height of the feature is a constant value (30mm), and the length and width of the feature will change from 0 to 50mm. The third group is for round hole, as shown in Table 6.2c. The height of the feature is a constant value (30mm) and the diameter of the hole will change from 0 to 50mm. The process parameters will be the same as the optimal result obtained in Chapter 4 and the workpiece material is Al 7075-T6.

Table 6.2a: Process Parameters for Step and Slot

Parameters	Value
Depth of cut	5 mm
Width of cut	10 mm
Tool diameter	10 mm
Number of flutes	3
Feed rate per tooth	0.06 mm/z
Spindle speed	4000 rpm
Height of feature	0-50 mm
Length of feature	30 mm
Width of feature	0-50 mm
Materials	Aluminium 7075-T6

Table 6.2b: Process Parameters for Prismatic Hole

Parameters	Value
Depth of cut	5 mm
Width of cut	10 mm
Tool diameter	10 mm
Number of flutes	3
Feed rate per tooth	0.06 mm/z
Spindle speed	4000 rpm
Height of feature	30 mm
Length of feature	0-50 mm
Width of feature	0-50 mm
Materials	Aluminium 7075-T6

Table 6.2c: Process Parameters for Round Hole

Parameters	Value
Depth of cut	5mm
Width of cut	10mm
Tool diameter	10mm
Number of flutes	3
Feed rate	0.06 mm/z
Spindle speed	4000 rpm
Height of feature	30 mm
Diameter of feature	10-50 mm
Materials	Aluminium 7075-T6

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The comparison result will be shown in graphical form in two steps. The first step will compare the energy consumptions of CTS and PTS for achieving different dimensions of features. The result will be used to determine which strategy is more energy efficient. The comparison in this step will use the following equation.

$$ECD = E_{CTS} - E_{PTS} \tag{6.7}$$

where, ECD is the energy consumption difference between CTS and PTS. If $\mathrm{ECD} > 0$, using PTS is more energy efficient. If $\mathrm{ECD} < 0$, using CTS is more energy efficient. If $\mathrm{ECD} = 0$, the energy consumption of both strategies are the same.

6.3.1 Energy Consumption for Step

Figure 6.5 shows the contour plot of energy consumption difference between implementing CTS and PTS for different dimensions of step features. The X and Y axes represent the ratio between the width/height of the feature and diameter of the cutting tool. The red shadow area shows the result when $\mathrm{ECD} < 0$. The dashed lines (W/d = 1, H/d = 1) represent the judging criteria that when the width and height of the feature is greater than the diameter of the tool (W/d >1 and H/d > 1), PTS is more energy efficient than CTS. Otherwise, CTS is more energy efficient. However, according to the process parameters applied, the red shadow area is not feasible if the width and the height of feature is smaller than the diameter of the tool (W/d <1 or H/d <1). It means PTS is not suitable under such conditions.

Figure 6.6a and 6.6b show the comparison of impact of feature type for implementing CTS and PTS. Shadow areas in Figure 6.6a and 6.6b represent three different feature shapes which have the same area. The blue shadow areas show the situation when width or height of feature is equal to diameter of the tool. It means the machining operation is the same as slotting. The green shadow area shows the case where the width and the height of feature are equal to each other which means the shape of the shadow area is a square.

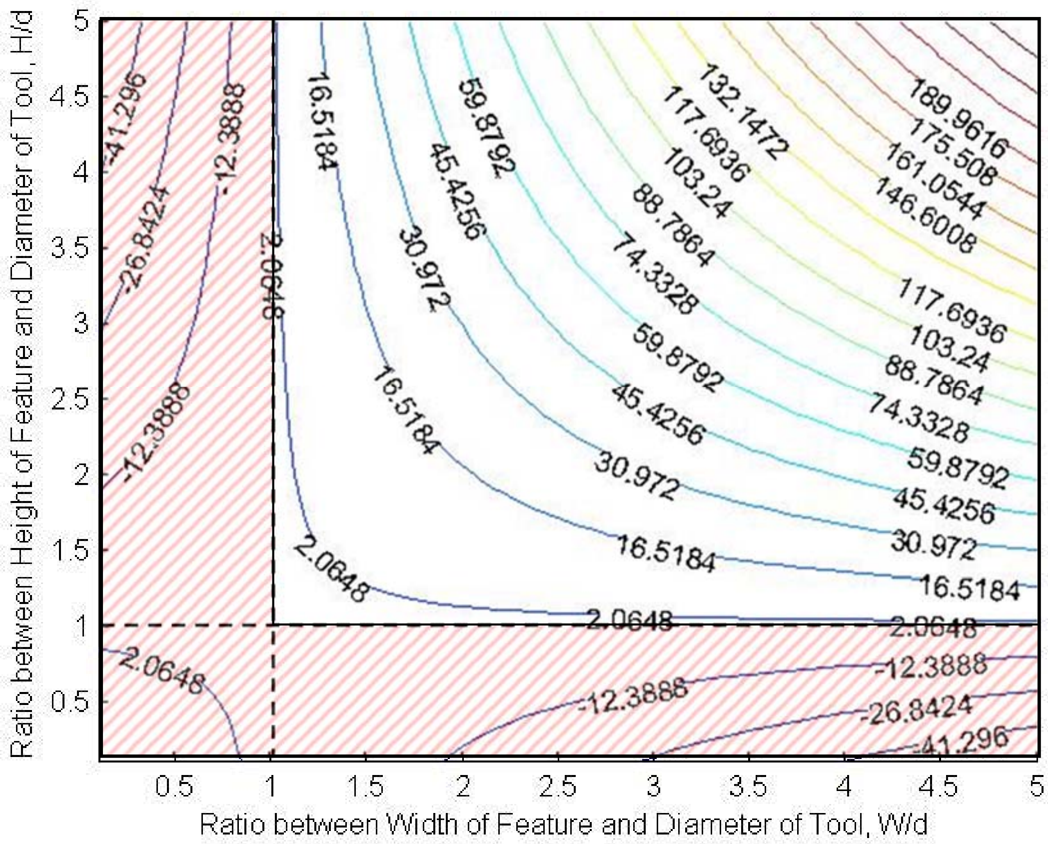

Figure 6.5 Energy Comparison of CTS and PTS for Step Feature

From Figure 6.6a, it can be found that the energy consumption for three shapes are the same (on the same contour). It means when implementing CTS, if the volume of the step features are the same, the energy consumption for achieving the same volume of the features is same. However, for implementing PTS (in Figure 6.6b), the energy consumption for the square is smaller than the rectangle. This is because the material removal volume for the square area is smaller than rectangle area. The red shadow area in Figure 6.6b shows the differences of material removal volume between the square shape and the rectangle shape. The conclusion of findings is that when the cross section area of the features are the same, the closer to 1 for the ratio of the width and the height of the feature (W/H), the less energy will be consumed by using proposed toolpath strategy.

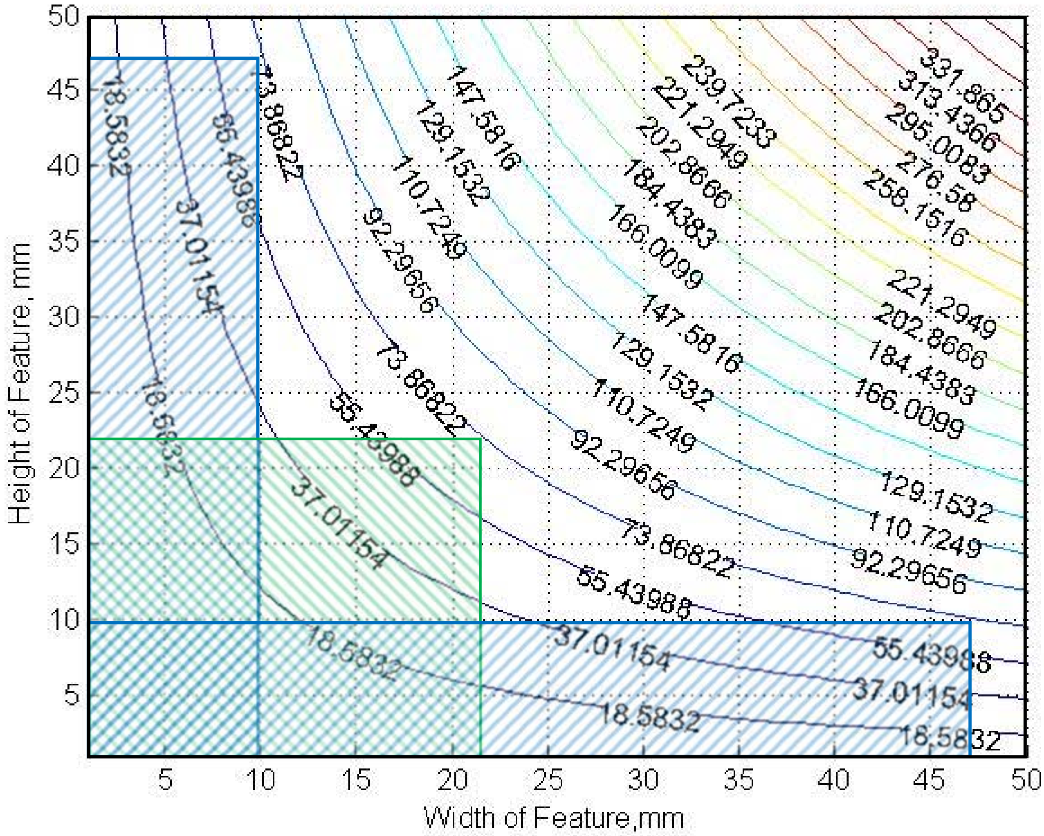

Figure 6.6a Energy Comparison of CTS for Different Step Features

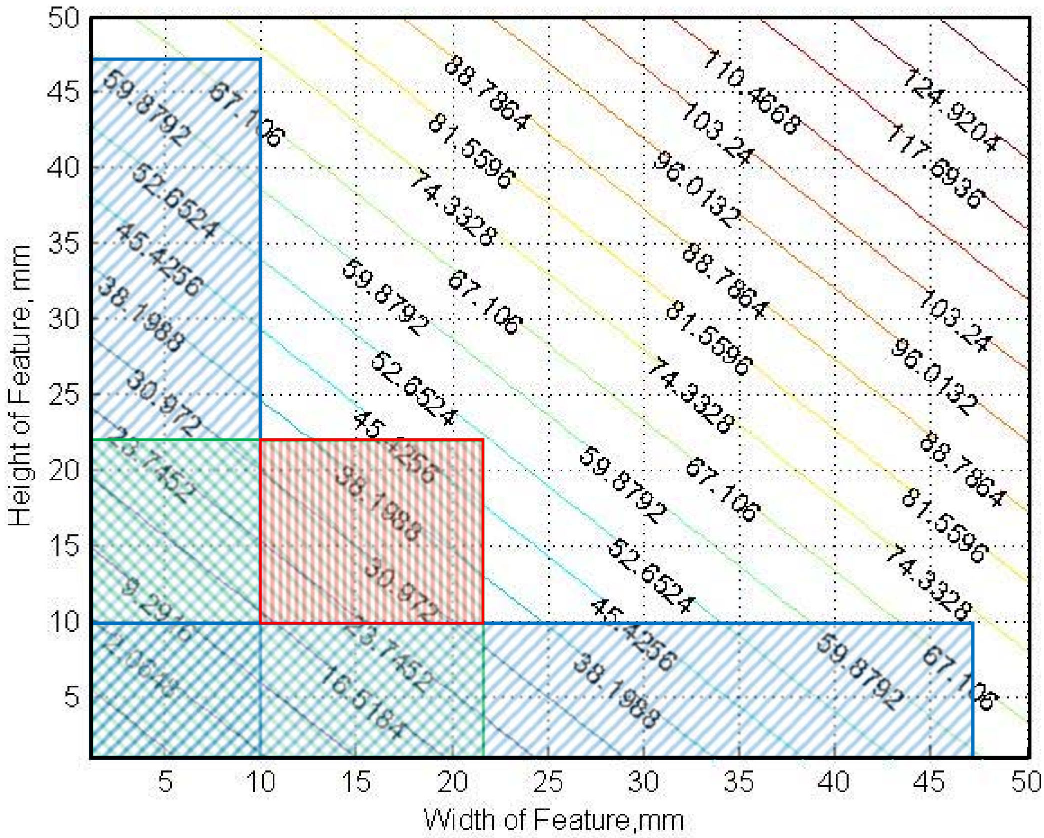

Figure 6.6b Energy Comparison of PTS for Different Step Features

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6.3.2 Energy Consumption for Slot

Figure 6.7 shows the contour plot of energy consumption difference between implementing CTS and PTS for different dimensions of the slot feature. The X and Y axes also represent the ratio between the width/height of the feature and the diameter of the cutting tool. The red shadow area shows the result when ECD < 0. The dashed lines (W/d = 2, H/d = 1) represent the break-even curves which show that when the width of the feature is twice greater than the diameter of the tool, and the height of the feature is greater than the diameter of the tool (W/d >2 and H/d > 1), PTS is more energy efficient than CTS. Otherwise, CTS is more energy efficient. However, according to the process parameters applied, the red shadow area is not feasible if W/d <2 or H/d <1) which means PTS is not suitable under such conditions.

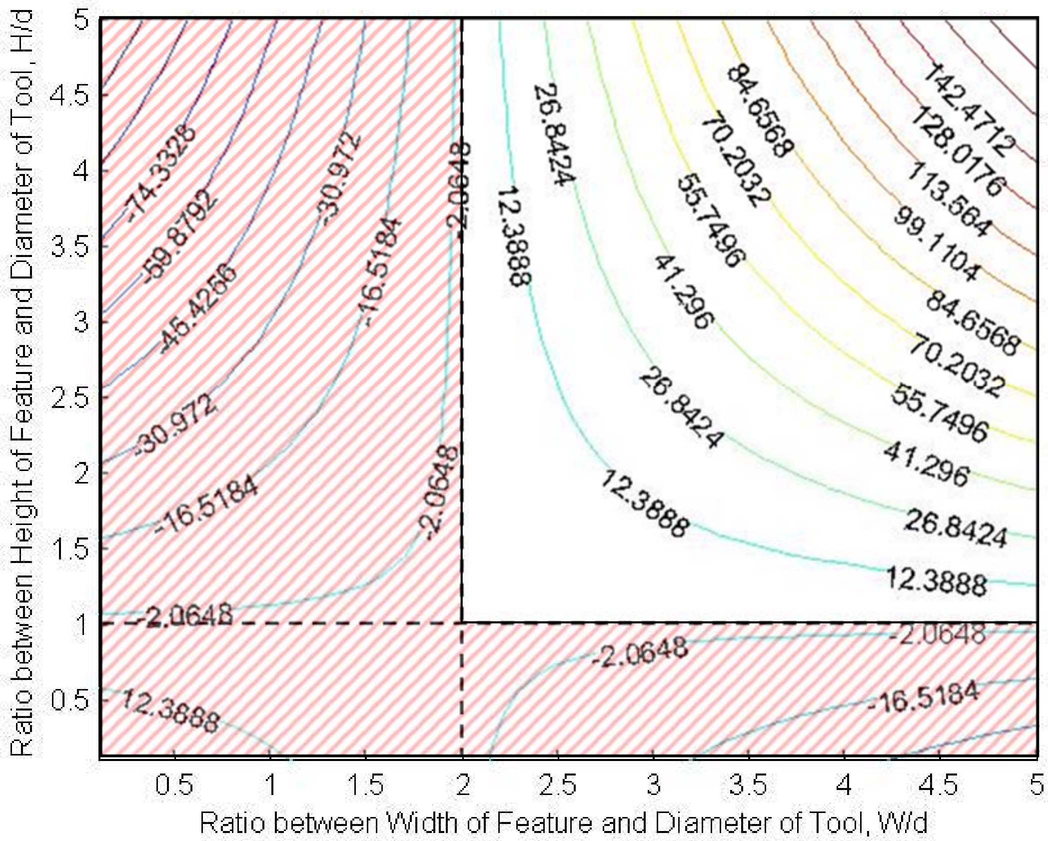

Figure 6.7 Energy Comparison of CTS and PTS for Slot Feature

Figure 6.8a and 6.8b show the comparison of impact of feature type for implementing CTS and PTS. Shadow areas in Figure 6.8a and 6.8b represent three different feature shapes which have the same area. The blue shadow area shows the case where the width of the feature is equal to twice the diameter of the tool. The green shadow area shows the case where the width and height of the feature is equal to each other. The purple area shows the case where the height of the feature is smaller than the width of the feature.

From Figure 6.8a, it can be found that the energy consumption for three shapes are the same. It means when implementing CTS, if the volume of the slot features are the same, the energy consumption for achieving the same volume of the features is the same too. However, for implementing PTS (in Figure 6.8b), the energy consumption is decreasing with the increase in width of feature. It is because the material removal volume for using PTS is reducing with the increase in width of the feature. The conclusion of this finding is that when the feature volume is constant, the greater the width of the feature, the less energy will be consumed by using PTS.

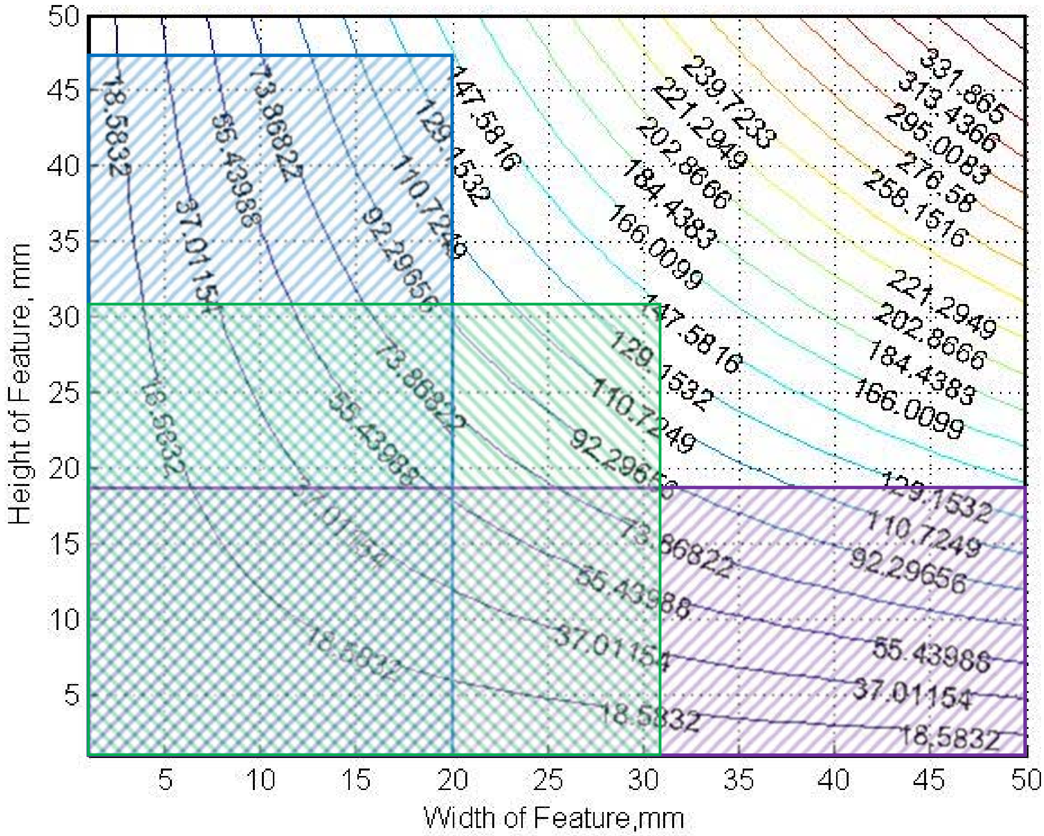

Figure 6.8a Energy Comparison of CTS for Different Slot Features

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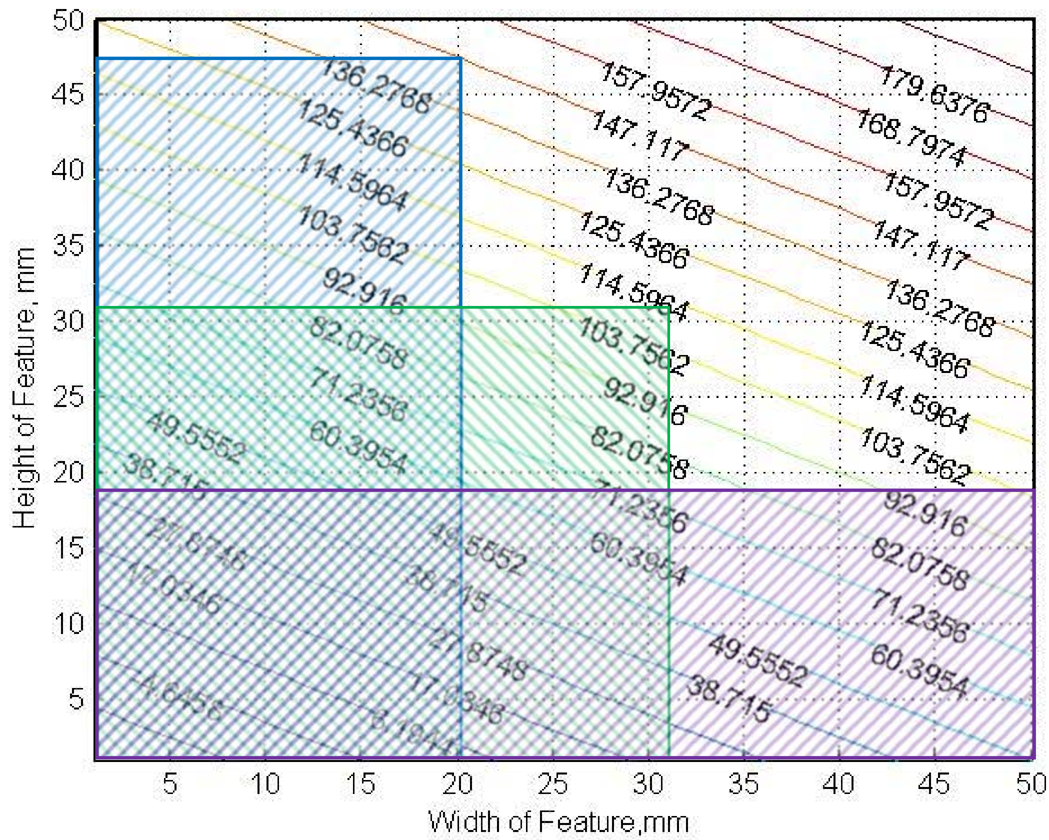

Figure 6.8b Energy Comparison of PTS for Different Slot Features

6.3.3 Energy Consumption for Prismatic Hole

Figure 6.9 shows the contour plot of energy consumption difference between implementing CTS and PTS for different dimensions of prismatic hole. The X and Y axes represent the ratio between the width/length of the feature and the diameter of the cutting tool. The red shadow area shows the result when ECD < 0. The dashed lines (W/d = 2, L/d = 2) represent the judging criteria that when the width and height of the feature is greater than twice the diameter of tool (W/d >2 and L/d > 2), PTS is more energy efficient than CTS. Otherwise, CTS is more energy efficient. However, according to the process parameters applied, the red shadow area is not feasible if the width and height of the feature is smaller than twice the diameter of tool (W/d <2 or L/d <2). It means PTS is not suitable under such conditions.

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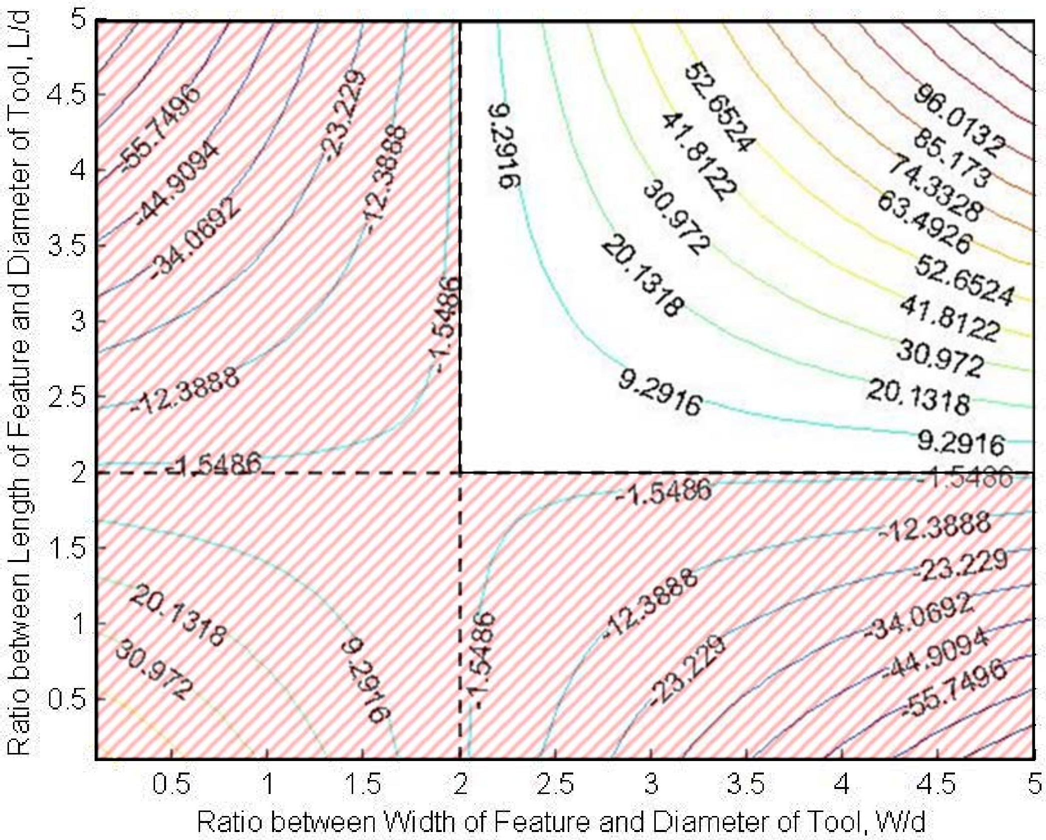

Figure 6.9 Energy Comparison of CTS and PTS for Prismatic Hole

The result of the comparison for different shapes of prismatic hole is almost the same as the result for the step feature. From Figure 6.10a, it can be found that the energy consumption for three shapes are the same. It means when implementing CTS, if the volumes of the prismatic holes are same, the energy consumption for achieving the same volume of the features is the same too.

However, for implementing PTS (in Figure 6.10b), the energy consumption for the square is smaller than the rectangle. This is because the material removal volume for the square area is smaller than for rectangle area. The conclusion of findings is that when the cross section area of the features are same, the closer to 1 for the ratio of width and length of feature (L/H), the less energy will be consumed by using PTS.

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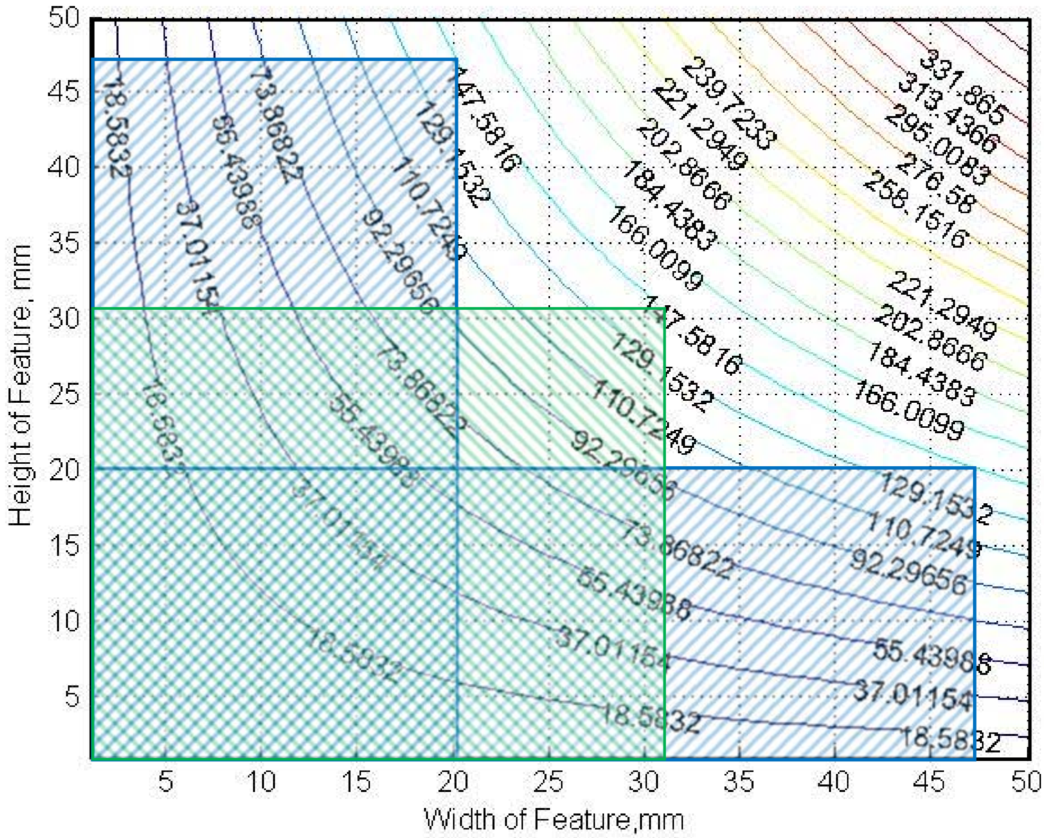

Figure 6.10a Energy Comparison of CTS for Different Shapes of Prismatic Hole

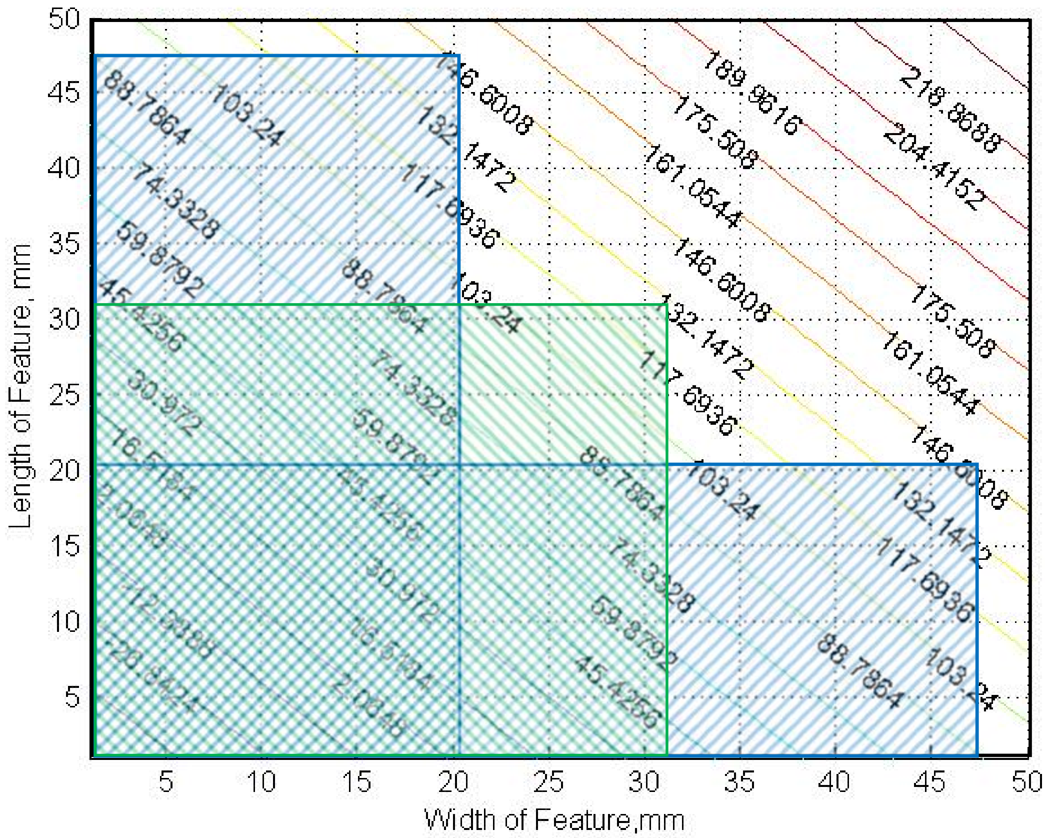

Figure 6.10b Energy Comparison of PTS for Different Shapes of Prismatic Hole

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6.3.4 Energy Consumption for Round Hole

Figure 6.11 shows the plot of energy consumption difference between implementing CTS and PTS for different dimensions of round hole. The X axis represents the diameter of the hole and the Y axis represents the difference in energy consumption between CTS and PTS. The result from Figure 6.11 and Figure 6.12 shows the break-even point occurred on the energy comparison curve when the diameter of the feature was equal to twice of diameter of tool ($d_H = 2d$). When the height of the feature is constant and the diameter of the feature is greater than twice the diameter of tool ($d_H > 2d$), PTS is more energy efficient than CTS. Otherwise, CTS is more energy efficient.

The red shadow area shows that it is not feasible when the diameter of the feature is smaller than twice the diameter of the cutting tool ($d_H < 2d$). It means implementing the proposed profiling tool path strategy is always more energy efficient than conventional toolpath strategy. The larger the feature, the more energy can be saved.

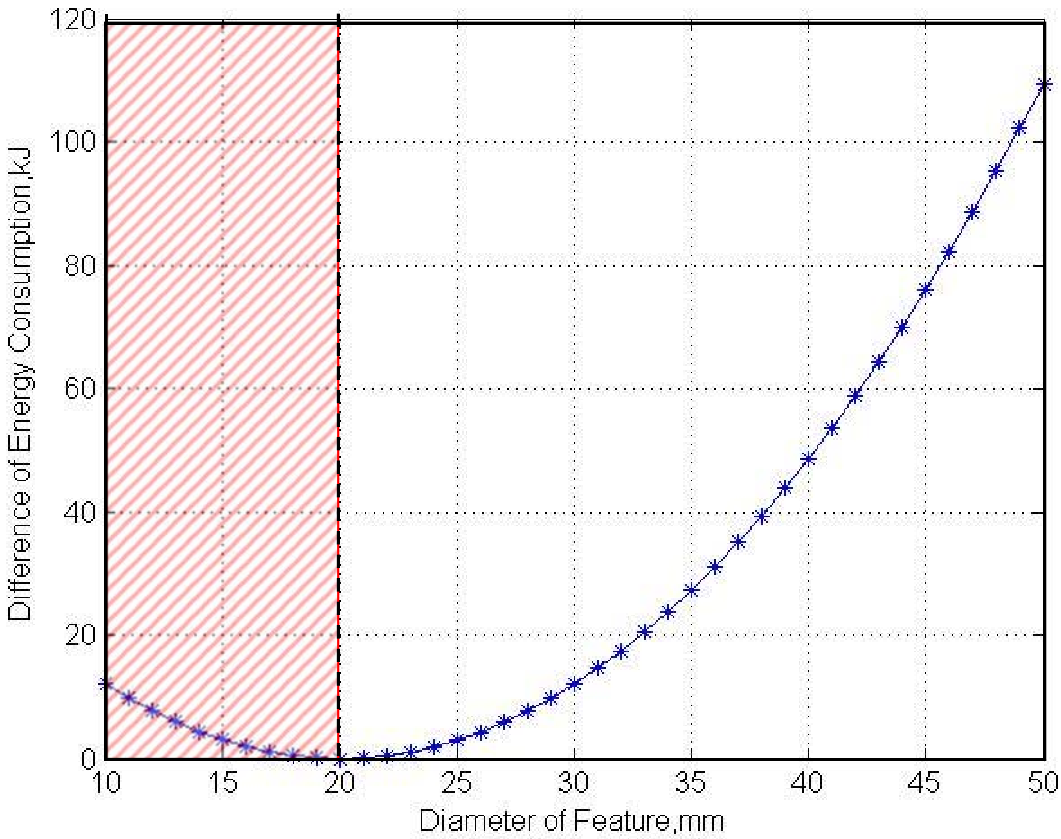

Figure 6.11 Energy Comparison of CTS and PTS for Round Hole

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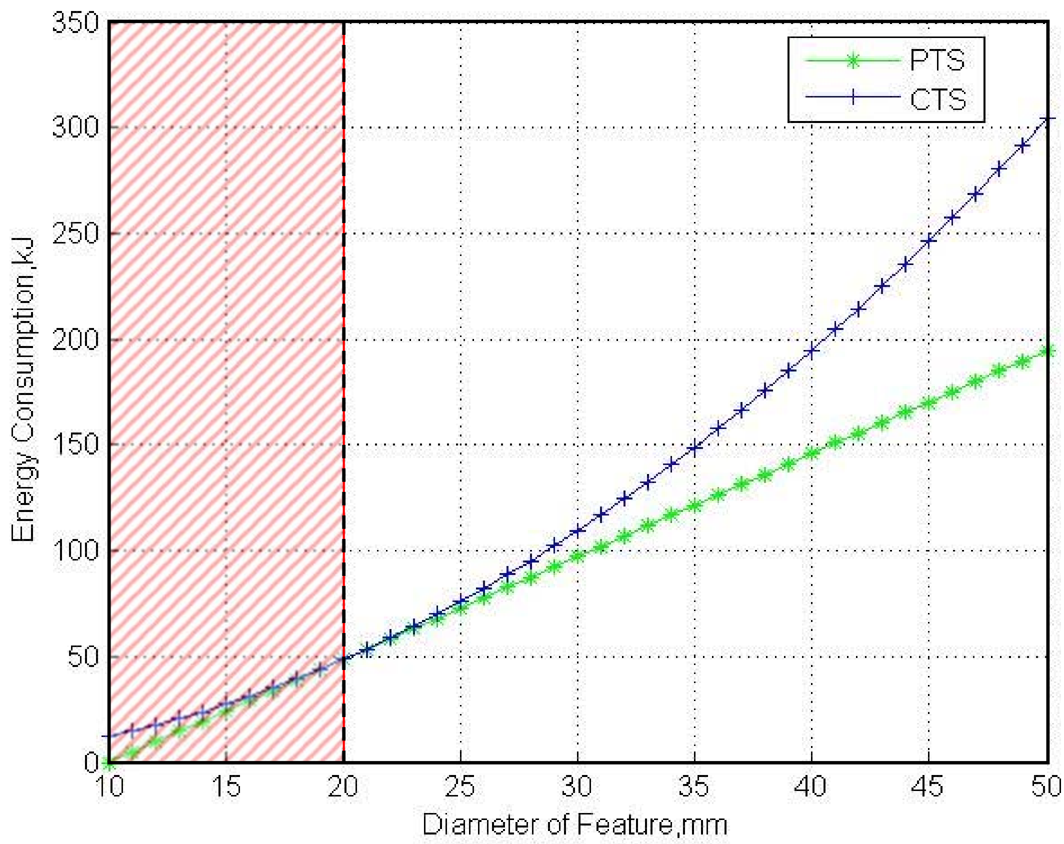

Figure 6.12 Energy Comparison of CTS for Different Shapes of Round Hole

6.3.5 Summary of Energy Comparison Result

The results of energy consumption for both strategies are shown as Figure 6.5 to 6.12. According to the energy consumption comparison curves of these four features, the following conclusions can be drawn:

- For the features of step, slot and prismatic hole, the judging criteria of the CTS and PTS can be identified in energy consumption curves. It means that when the dimensions of the feature are greater than the judging criteria, PTS is feasible and more energy efficient than CTS. Otherwise, when the dimensions of the feature are smaller than the judging criteria, PTS is not feasible to be implemented.
- For round hole, the results showed that when the diameter of the hole is greater than twice of diameter of the cutting tool, PTS is energy efficient than CTS. The larger the feature is, the more energy efficient it is to implement PTS. Otherwise, PTS is not feasible to be implemented.

`

In addition, energy consumption for implementing PTS is also affected by the shape of the feature. The following observation can be identified:

- For features of step and prismatic hole, the energy consumption for the square is smaller than for the rectangle when the cross section area is constant. When the cross section area of the features are same, the closer to 1 for the ratio of the width and length of the feature (L/H), the less energy will be consumed by using PTS.
- For features of the slot feature, the energy consumption is decreasing with the increase in the width of the feature when the cross section area is constant. When the feature volume is constant, the greater the width of the feature, the less energy will be consumed by using PTS.
- For features of round hole, the larger the diameter of the feature, the more energy can be saved.

The results in development of new energy-efficient machining strategy showed the energy consumption of machining can be possibly reduced on the basis of optimal process parameters. It can further reduce the gap between theoretical minimal energy consumption and practical energy consumption.

6.4 Comparison of Cost and Energy Efficiency for Implementing CTS and PTS

According to the comparison of energy consumption in the previous section 6.3, the comparison of cost and energy efficiency of CTS and PTS has been discussed in this section.

6.4.1 Comparison of Cost between CTS and PTS

The cost of implementing CTS and PTS for step and slot feature is shown in Figures 6.13a to 6.13c, for prismatic hole in Figures 6.14a to 6.14b and for round hole in Figure 6.14. From the figures of comparison of cost for implementing CTS and PTS, it can be found that the cost has the same variation trend as energy consumption for all four features. It means when the PTS is more energy efficient than CTS, it is also more cost effective. This finding further confirms the conclusion in section 4.1.3 that energy consumption and cost are not conflicting with each other (not only for optimal process parameters but also for energy-efficient strategy).

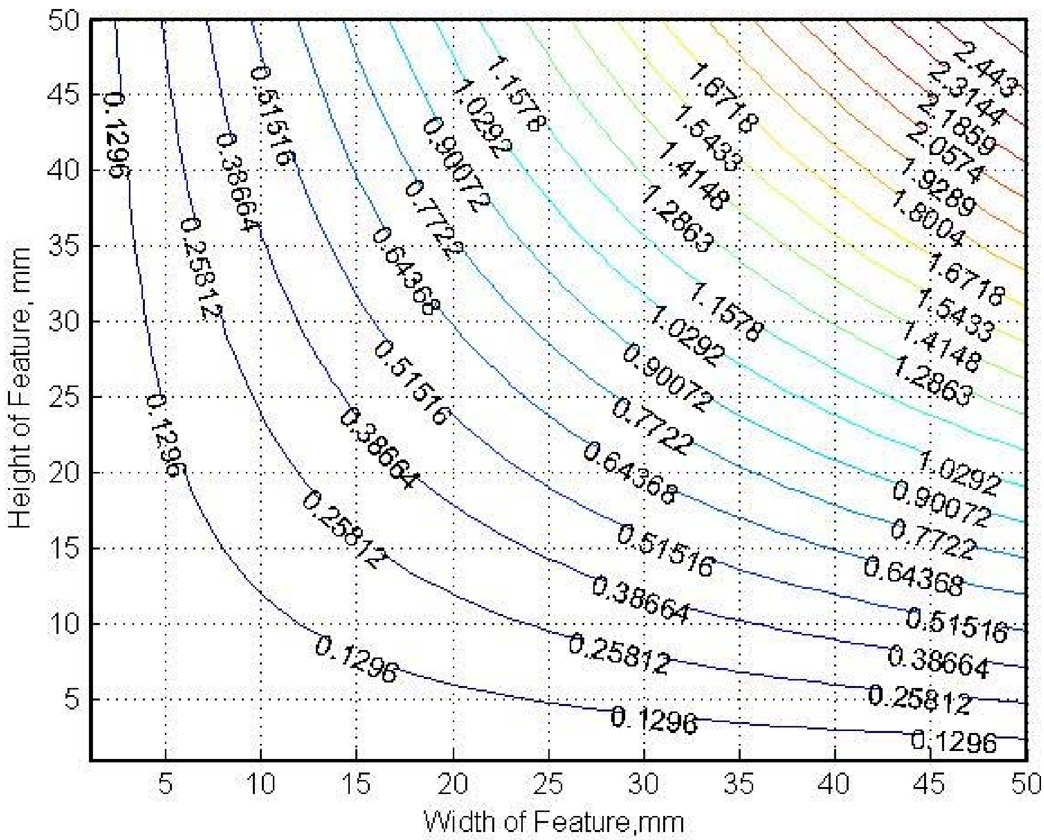

Figure 6.13a Cost of Implementing CTS for Step and Slot Feature

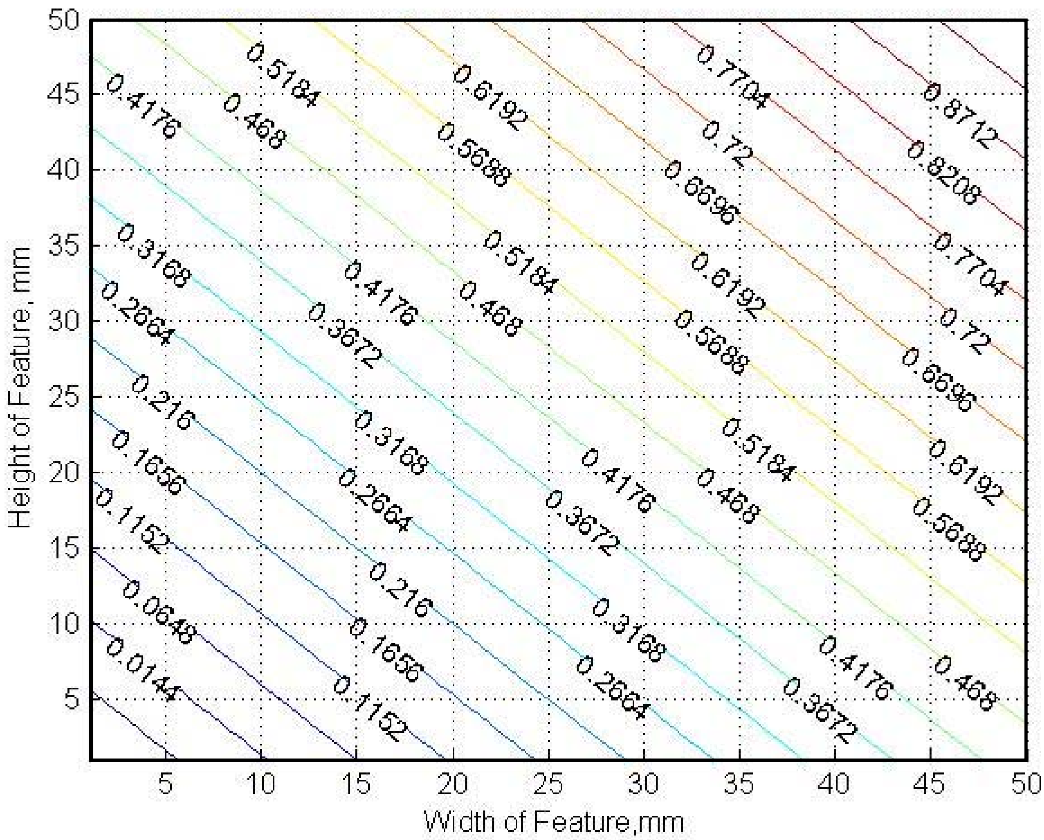

Figure 6.13b Cost of Implementing PTS for Step Feature

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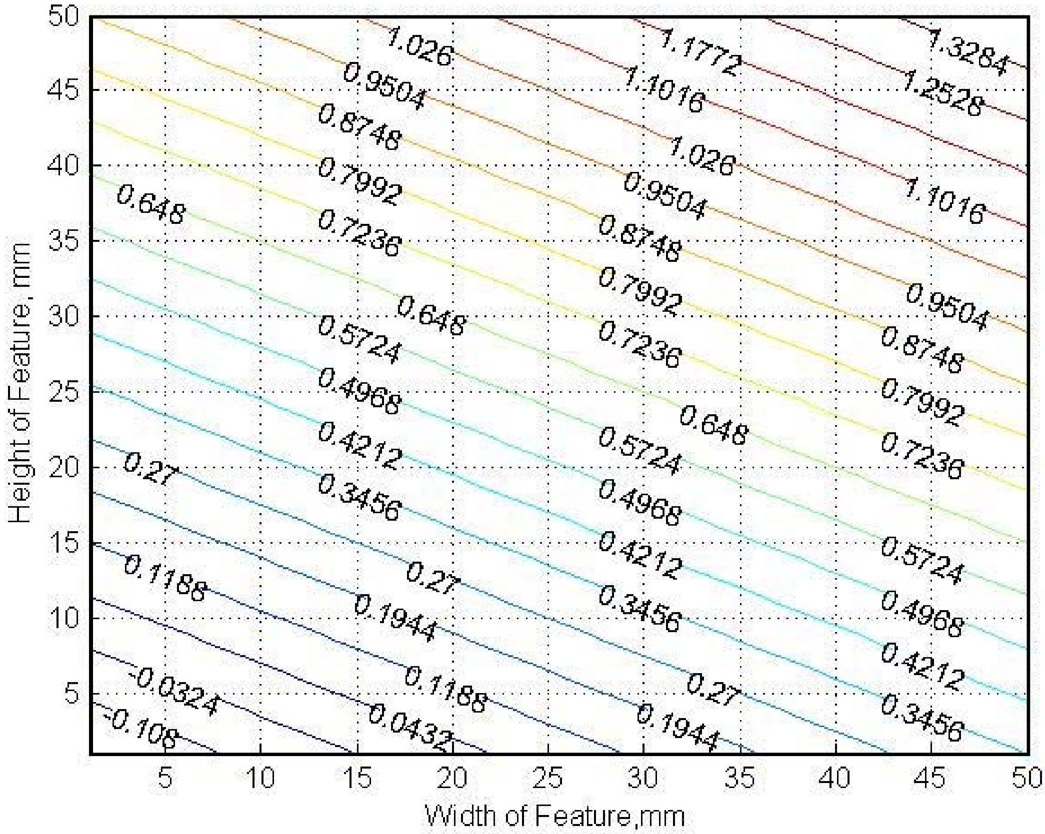

Figure 6.13c Cost of Implementing PTS for Slot Feature

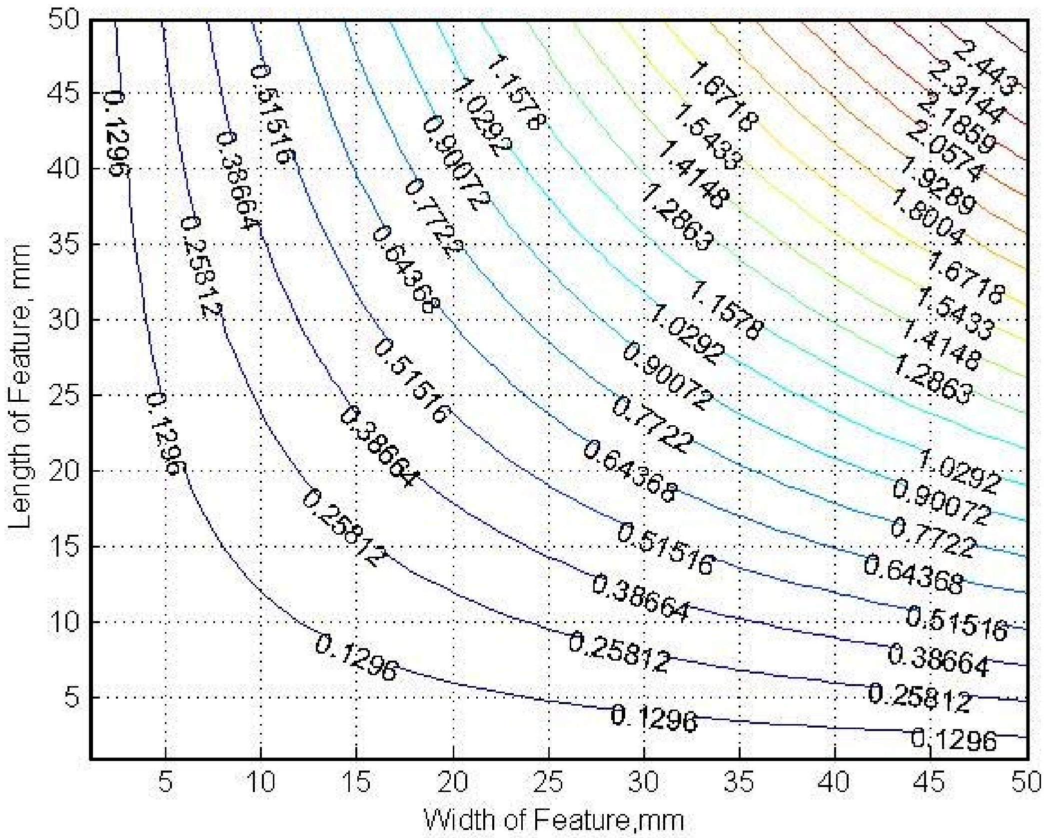

Figure 6.14a Cost of Implementing CTS for Prismatic Hole

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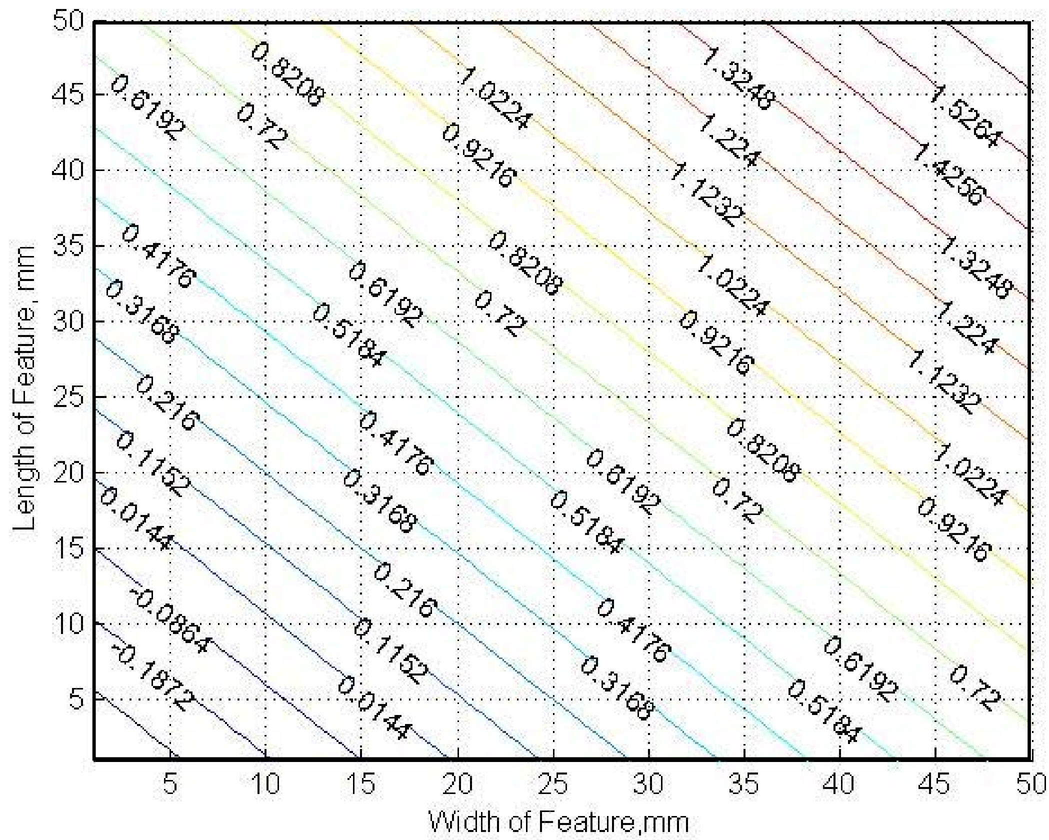

Figure 6.14b Cost of Implementing PTS for Prismatic Hole Feature

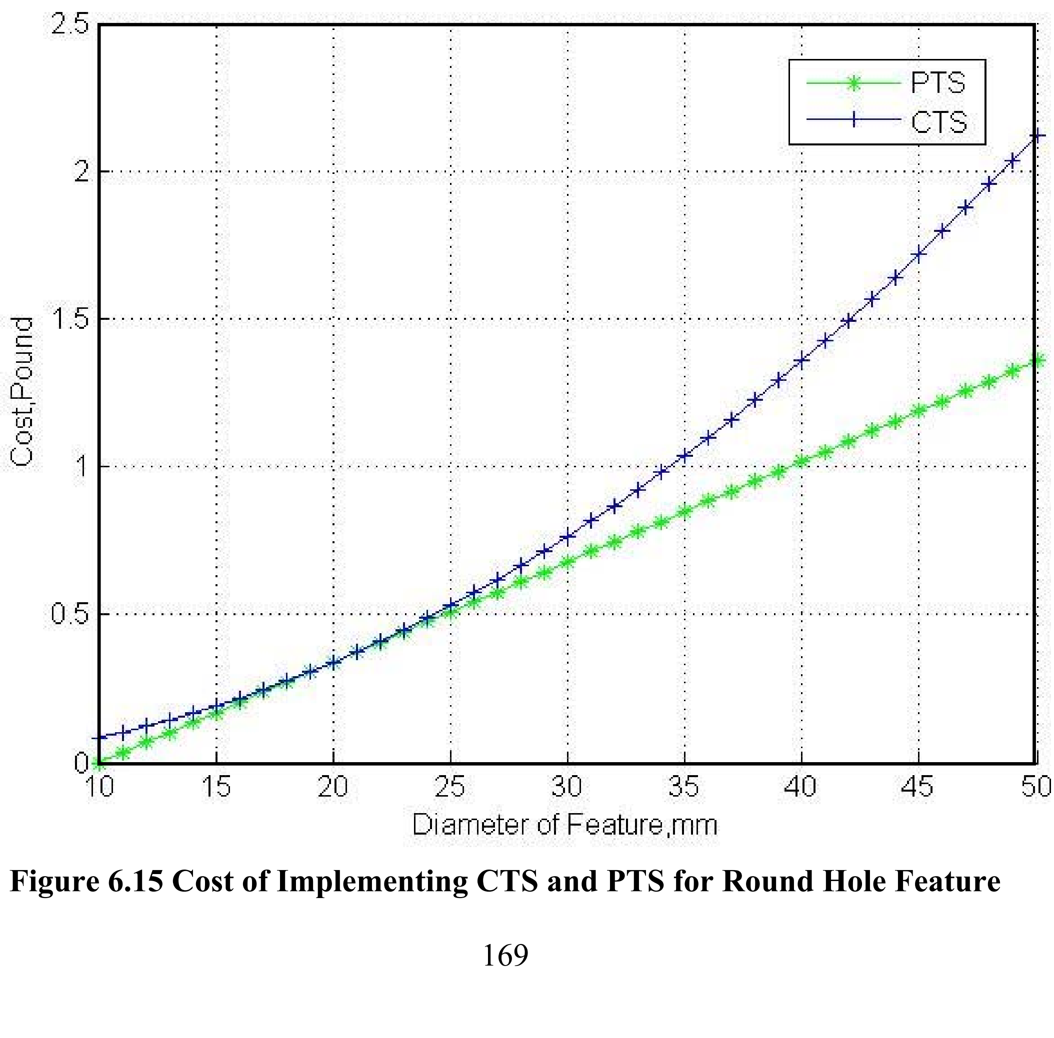

Figure 6.15 Cost of Implementing CTS and PTS for Round Hole Feature

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6.4.2 Comparison of Energy Efficiency for Implementing CTS and PTS

Based on the new energy efficiency metrics proposed in Chapter 3, the energy efficiency of PTS and CTS for step, slot, prismatic hole and round hole can be calculated, and are shown in Table 6.3. The process parameters applied in the calculation are based on the optimal result obtained in Chapter 5.

Table 6.3: Energy Consumption and Energy Efficiency for Implementing CTS and PTS for Different Features

		TME (kJ)	TE (kJ)	DE (kJ)	AE (kJ)	IE (kJ)	ER (TE/DE)	ER_m (TME/TE)	ER_p (TME/DE)
Step	CTS	5.238	31.379	139.379	108	26.141	22.513%	16.693%	3.758%
	PTS	5.238	17.433	117.433	100	12.195	14.845%	30.047%	4.460%
Slot	CTS	7.857	31.379	139.379	108	23.522	22.513%	25.039%	5.637%
	PTS	7.857	24.406	128.406	104	16.549	19.001%	32.194%	6.119%
Prismatic Hole	CTS	10.476	31.379	139.379	108	20.903	22.513%	33.386%	7.516%
	PTS	10.476	27.892	133.892	106	17.416	20.832%	37.559%	7.824%
Round Hole	CTS	9.284	31.379	139.379	108	22.095	22.513%	29.587%	6.661%
	PTS	9.284	26.123	131.109	104.986	16.839	19.925%	35.539%	7.081%

Figure 6.16a and 6.16b show the energy efficiency feature for implementing CTS and PTS for step. From the figures, it can be found that the energy efficiency of existing definition (TE/DE) for implementing PTS for step feature is smaller than the result by using CTS (14.875% for PTS and 22.513% for CTS). However, by comparing the proposed energy efficiency for the machining process (TME/DE), PTS has better energy efficiency (4.460% for PTS and 3.758% for CTS).

Another benefit for implementing PTS is that it can further reduce the inefficiency of the machining operation. By comparing the ratio between TME and TE (energy consumption for machining operation, TME/TE), energy efficiencies for implementing PTS is 30.047% which is higher than the energy efficiency of CTS 16.693%. Up to 54% of inefficient energy consumption can be further reduced.

In addition, implementing PTS can further reduce the energy consumption for the machining operation and auxiliary function. Compared to energy consumption for implementing CTS, up to 16% of direct energy (44.44% of energy consumption for machining operation and 7.41% auxiliary energy consumption) can be reduced by using PTS.

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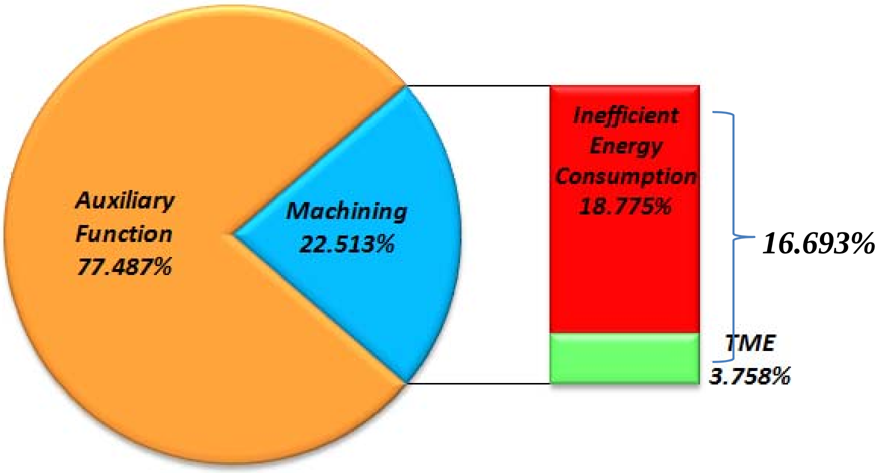

Figure 6.16a Energy Efficiency of CTS for Step Feature

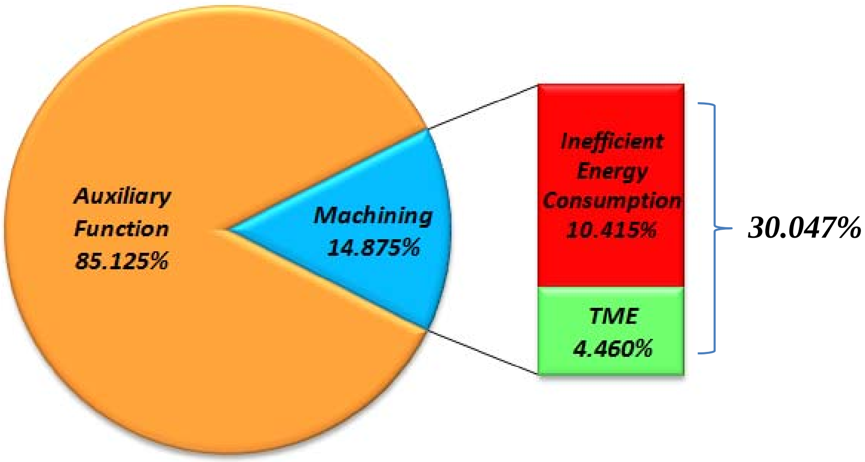

Figure 6.16b Energy Efficiency of PTS for Step Feature

Similar results can be found for the other feature types. Figures 6.17a and 6.17b show the energy efficiency for implementing CTS and PTS for slot feature. Although the energy efficiency of existing definition for implementing PTS for slot feature is smaller than the CTS (19.001% for PTS and 22.513% for CTS), the proposed energy efficiency of the machining process for PTS has better energy efficiency than CTS (6.119% for PTS and 5.637% for CTS). Implementing PTS can further reduce the inefficiency of the machining operation. The energy efficiencies of the machining process for implementing PTS is 32.194% which is higher than CTS 25.039%. Up to 30% of inefficient energy consumption can be further reduced. In addition, implementing PTS can further reduce the energy consumption for the machining operation and auxiliary function. Up to 8% of direct energy (22.22% of energy consumption for the machining operation and 3.70% auxiliary energy consumption) can be reduced by using PTS.

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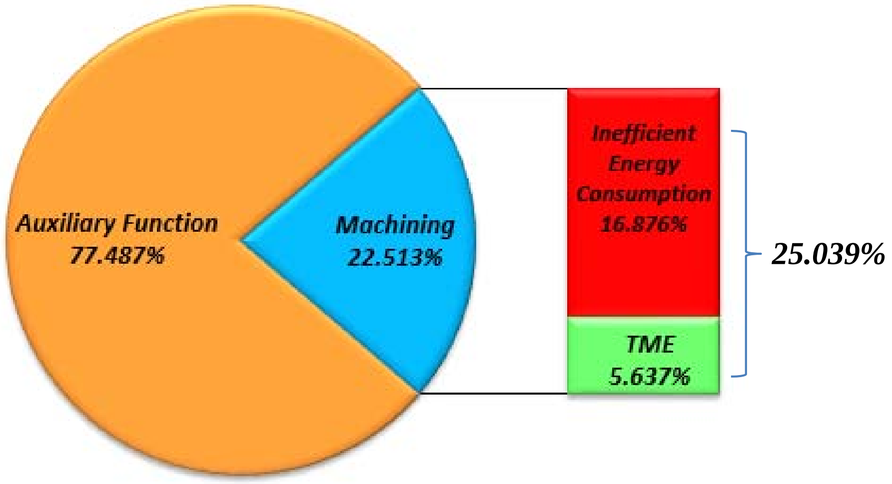

Figure 6.17a Energy Efficiency of CTS for Slot Feature

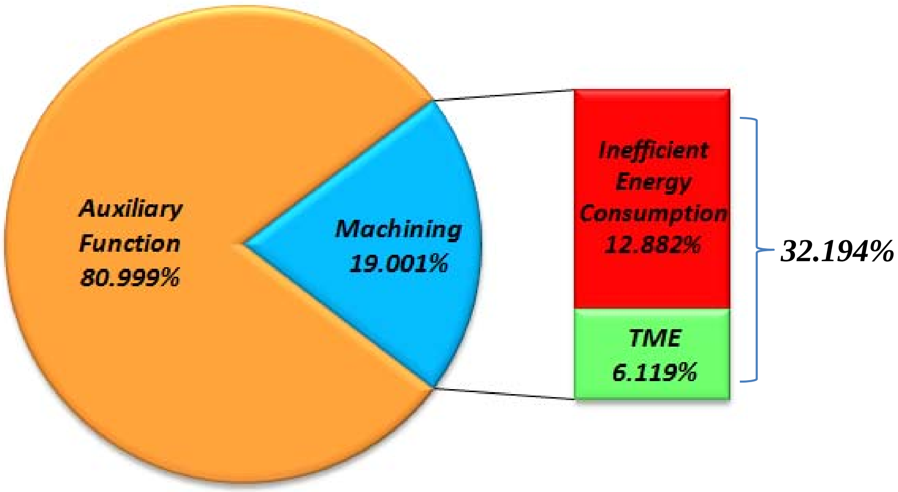

Figure 6.17b Energy Efficiency of PTS for Slot Feature

Figures 6.18a and 6.18b show the energy efficiency for implementing CTS and PTS for prismatic hole. Although the energy efficiency of existing definition for implementing PTS for prismatic hole is smaller than the CTS (20.832% for PTS and 22.513% for CTS), the proposed energy efficiency of the machining process for PTS has better energy efficiency than CTS (7.824% for PTS and 7.516% for CTS). Implementing PTS can further reduce the inefficiency of the machining operation. The energy efficiencies of the machining process for implementing PTS is 37.559% which is higher than CTS 33.386%. Up to 17% of inefficient energy consumption can be further reduced. In addition, implementing PTS can further reduce the energy consumption for the machining operation and auxiliary function. Up to 4% of direct energy (11.11% of

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energy consumption for the machining operation and 1.85% auxiliary energy consumption) can be reduced by using PTS.

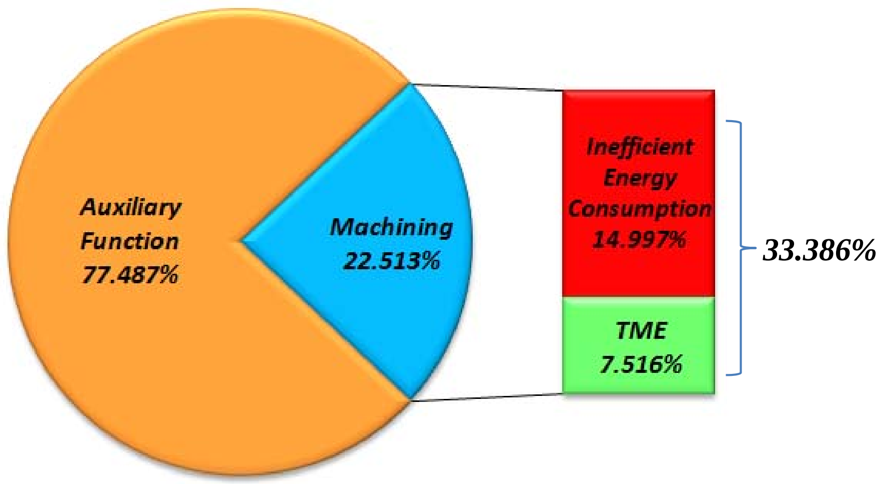

Figure 6.18a Energy Efficiency of CTS for Prismatic Hole

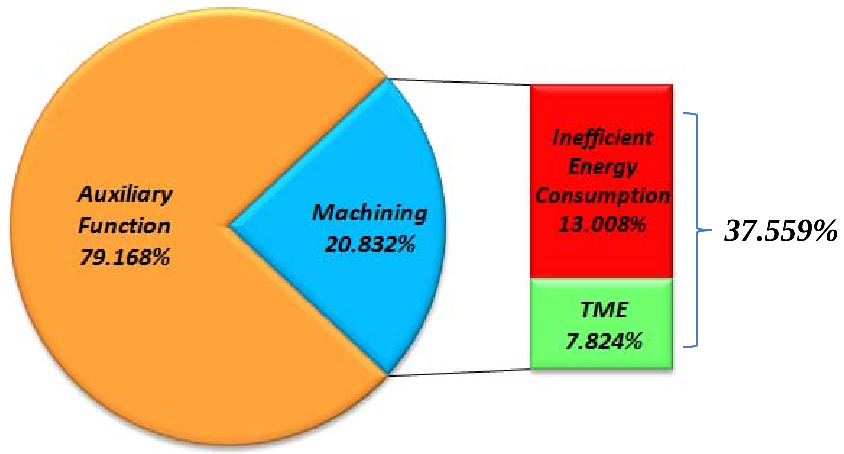

Figure 6.18b Energy Efficiency of PTS for Prismatic Hole

Figure 6.19a and 6.19b show the energy efficiency for implementing CTS and PTS for round hole. Although the energy efficiency of existing definition for implementing PTS for round hole is smaller than for CTS (19.925% for PTS and 22.513% for PTS), the proposed energy efficiency of the machining process for PTS has better energy efficiency than CTS (7.081% for PTS and 6.661% for CTS). Implementing PTS can further reduce the inefficiency of the machining operation. The energy efficiencies of the machining process for implementing PTS is 35.539% which is higher than CTS 29.587%. Up to 24% of inefficient energy consumption can be further reduced. In addition, implementing PTS can further reduce the energy consumption for the machining operation and auxiliary function. Up to 6% of direct energy (16.75% of

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energy consumption for the machining operation and 2.79% auxiliary energy consumption) can be reduced by using PTS.

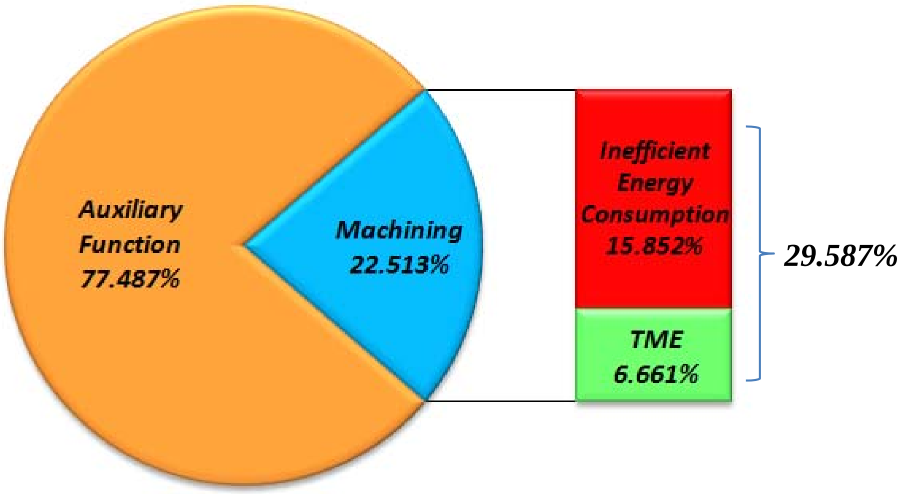

Figure 6.19a Energy Efficiency of CTS for Round Hole

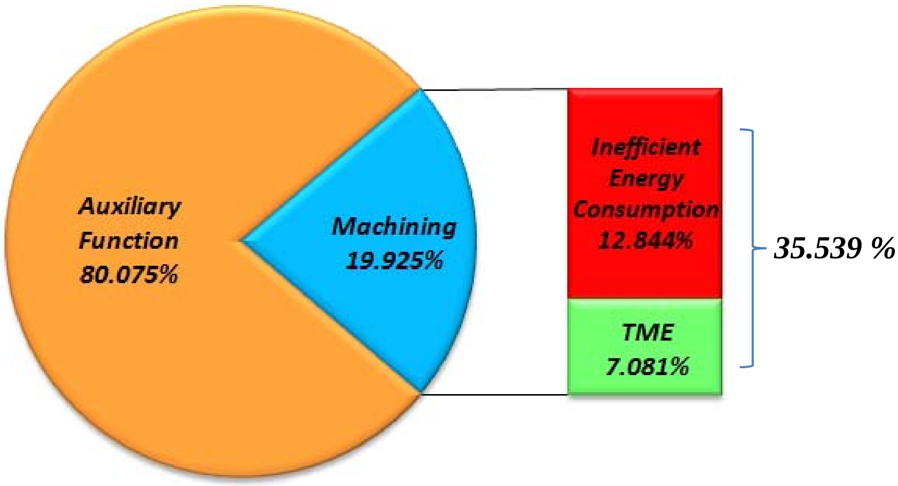

Figure 6.19b Energy Efficiency of PTS for Round Hole

The above results of comparison of energy efficiency showed that implementing PTS cannot only further improve the energy efficiency and reduce the inherent inefficiency of the machining process, but can also reduce the energy consumption for the machining operations (inefficient energy consumption) and auxiliary function. The improvement is related to the area of the machined surface. For the same dimension of material removal volume, the smaller the area of the machined surface, the more energy efficient it is.

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6.5 Summary of the Chapter

In this chapter, an energy efficient profiling toolpath strategy (PTS) has been proposed which can further reduce the energy consumption and improve the energy efficiency for the machining process.

The implementation conditions of PTS for four typical features (step, slot, prismatic hole, and round hole) were specifically analysed. The comparison result between conventional toolpath strategy (CTS) and proposed profiling toolpath strategy (PTS) showed that:

- For the features of step, slot and prismatic hole, break-even curves of the CTS and PTS occurred in energy consumption curves. When the dimensions of the feature are greater than the curves, PTS is feasible and more energy efficient than CTS. Otherwise, PTS is not feasible to be implemented.
- For round hole, when the diameter of the hole is greater than twice the diameter of the cutting tool, PTS is more energy efficient than CTS. The larger the feature, the more energy efficient it is to implement PTS. Otherwise, PTS is not feasible to be implemented.
- For step and prismatic hole, the energy consumption for the square is smaller than for the rectangle when the cross section area is constant. When the cross section areas of the features are same, the closer to 1 for the ratio of width and length of the feature (L/H), the less energy will be consumed by using PTS.
- For slot feature, the energy consumption is decreasing with the increase in width of the feature when the cross section area is constant. When the feature volume is constant, the greater the width of the feature, the less energy will be consumed by using PTS.
- For round hole, the larger the diameter of the hole, the more energy can be saved.

Examples of energy efficiency for implementing PTS and CTS to machine Aluminium 7075-T6 were produced by using the optimal process parameters obtained in Chapter 4. The result showed that although the energy efficiency of existing definition for implementing PTS is smaller than for CTS, the proposed energy efficiency of the machining process for PTS has better energy efficiency than CTS. In addition, implementing PTS can further reduce the inefficiency of the machining operation. For the same dimension of material removal volume, the smaller the area of the machined surface, the more energy efficient it is.

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CHAPTER 7: DEVELOPMENT OF A FRAMEWORK FOR MACHINING OPTIMISATION WITH SUSTAINABILITY CONSIDERATIONS

The previous chapters (Chapter 3 to Chapter 6) have developed mathematical models to measure the sustainability, introduce a systematic process to optimise the process parameters for machining operations, and proposed a new energy-efficient cutting strategy. However, existing research contributions of sustainability improvement are too difficult for decision makers to implement in practical manufacturing processes. This issue raises a research question that:

"What is the best way to implement the developed sustainability improvement methods in practical machining operation to fulfil the requirements from different users?"

To answer the above research question, a framework which integrates the research findings in the previous chapters has been developed in this chapter to provide a tool for decision makers to improve sustainability performance of their manufacturing process.

Demonstrations of how to implement the proposed framework will also be conducted by dealing with practical cases.

7.1 General Methods for Machining Performance Improvement

The determination of product manufacturing plan usually needs to concern multiple objectives. In practice, decision makers may have to improve their manufacturing process to address the prospective challenges of sustainability performance of customer requirements, government/council regulations, national/international standards, and demands for lower energy consumption. For example, to achieve a real sustainable manufacturing process, it must concern the objectives from environmental, economic and social aspects. Unfortunately, without a good understanding of the problem, decision makers are not able to adjust the process parameters quickly to solve emergency requirements (e.g. rush order) from above drivers.

From a practical standpoint, the optimisation task is defined as follows: given a system or process, find the best solution to this process within constraints. This task requires the following elements:

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- An objective function is needed that provides a scalar quantitative performance measure that needs to be minimised or maximised (e.g. system's cost, product quality).
- A predictive model is required that describes the behaviour of the system. For the optimisation problem, this translates into a set of equations and inequalities constraints. These constraints comprise a feasible region that defines limits of performance for the system.
- Variables that appear in the predictive model must be adjusted to satisfy the constraints. This can usually be accomplished with multiple instances of variable values, leading to a feasible region that is determined by a subspace of these variables. In many engineering problems, this subspace can be characterised by a set of decision variables that can be interpreted as degrees of freedom in the process.

The existing methods of selecting optimal process parameters are not transparent and difficult to be implemented. These frameworks have lots of embedded information and require very good knowledge in mathematical modelling and optimisation. It takes a long time to understand what the problem is even for academic researchers. So it is not easy for practical decision makers to understand and use. In addition, the structures of these frameworks are usually very general which only concerns major elements/activity. The details of each element are not clearly identified. It is difficult to directly implement these frameworks to solve a specific machining optimisation problem. Finally, these frameworks are not developed for sustainability improvement purpose.

The framework proposed in this chapter is aiming to provide a comprehensive, step-by-step method to help users from different levels (practitioners, process planning engineers, degree students, and academic researchers) to scientifically and confidently select the optimal results with sustainability consideration.

7.2 General Methods of Machining Optimisation

The method of selecting optimal process parameters is designed based on the four steps introduced in section 7.1. Each step will have several functional elements to answer the corresponding questions from the user. Table 7.1 showed the name of the element and what questions it will answer. The process of how the elements function and connect is shown in Figure 7.1.

`

Step 1: Problem Defining

Element 1: Problem Domain

Based on the requirements, the nature of the problem will be defined by determining what variables need to be considered for the problem, classifying what type the problem is (such as is it single or multiple objective? If it is a multi-objective case, are the objectives conflicting or not conflicting with each other?)

Element 2: Criteria Definition

Determine what criteria need to be optimised (e.g. energy, cost, time and quality). The criteria determination process is actually to determine the objectives of optimisation.

Step 2: Problem Formulation

Element 3: Mathematical Model

Determine what variables should be considered in the optimisation. Which variables are input parameters (independent variables) and which ones are objectives and constraints (dependent variables). The objective functions should be represented in terms of input parameters.

Element 4: Define Constraints

Determine what constraints should be considered to refine the search space.

Step 3: Problem Solution

Element 5: Problem Scenarios

The concept of Problem Scenarios is one of the main contributions of Chapter 5. The function of the test rig is to build a solution set. The solutions in Test Rig are corresponding with the problems in Problem domain. Each solution can link to a unique problem in the problem domain. The solutions in Test Rig will be divided into different scenarios based on the characteristics of objectives.

Element 6: Solution Scenarios

The optimal result can be achieved from Solution Scenarios. For single objective or non-conflicting multi-objective optimisation the optimal result will be a unique solution.

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For conflicting multi-objective optimisation the optimal result will be an optimal solution set.

<u>Step 4: Problem Evaluation</u>

Element 7: Satisfaction Detection

Evaluate the corresponding result or solution set with the decision makers to determine whether or not the optimal result or solution set is accurate or sufficient. Usually for single-objective optimisation and non-conflicting multi-objective optimisation, the optimal result is unique. So they can directly go to the next element. However, for conflicting multi-objective optimisation cases the optimal result is a solution set which has all the feasible results. Unsatisfactory problems here are usually caused by the large number of feasible results. Decision makers should return to Step 2 to refine the problem with more specific requirements.

Element 8: Proposed Result

If the problem is a single-objective or non-conflicting multi-objective optimisation, the unique optimal result will be the proposed result. Otherwise for multi-objective optimisation the proposed result/results will be selected based on users' preferences.

Element 9: Result Validation

This process is to validate the result in practice or based on users' experiences. The process is very similar as Element 7. If the proposed result can pass validation, then it can be applied in practice. If the proposed result fails, it means mathematical models applied in step 2 are not correct. It requires the users to return to step 2 to make the correction of objective functions and constraints.

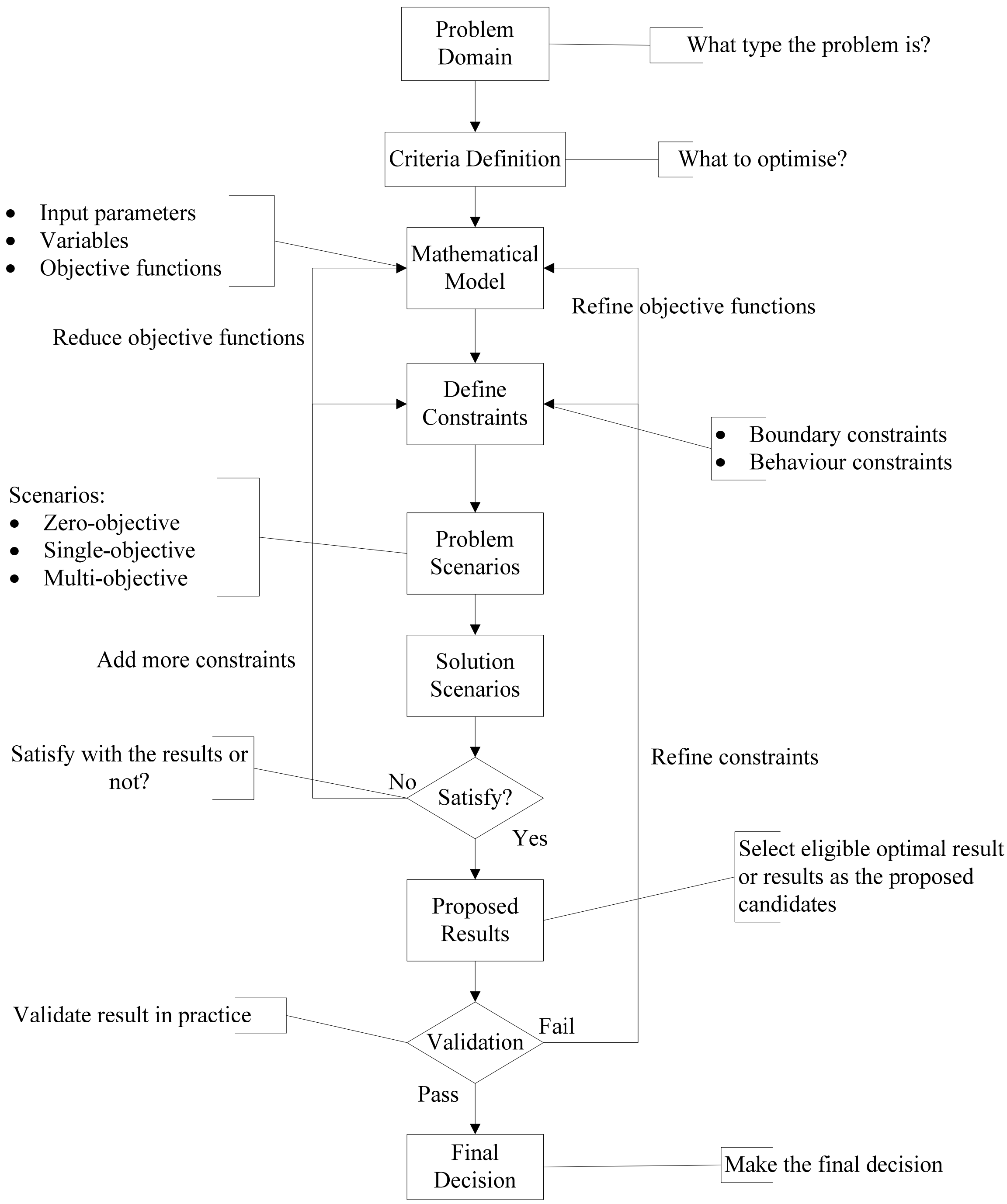

Figure 7.1 General Methods for Machining Optimisation

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Table 7.1 Element of General Optimisation Method and the Corresponding Questions

Step	Name of the Element	Questions
Problem Defining	Problem Domain	What type the problem is?
	Criteria Definition	What is the objective of optimisation?
Problems Formulation	Mathematical Model	What variables are involved in the problem? How can the objectives be represented? What are the dominated variables to influence the objective?
	Define Constraints	What are the technical limitations of the operation? What are the users' requirements?
Optimal result determination	Problem Scenarios	What are the corresponding results to the problems?
	Solution Scenarios	How can we select the optimal process parameters?
Result Evaluation	Satisfaction Detection	Is the solution or solution set good enough?
	Proposed Result	What are the final optimal results?
	Result Validation	Is the optimal result valid?

7.3 Development of Framework for Sustainability Improvement

To address the issue of general machining optimisation framework, a sustainability improvement framework has been proposed in this section which can provide a systematic tool for decision makers to improve sustainability performance of their manufacturing process. The proposed framework is developed based on the research results achieved in the previous chapters and presented in Figure 7.2.

The structure of the proposed framework can be mainly divided into three parts: sustainability performance measures module, improvement of sustainability performance by optimising parameters of existing manufacturing process module and improvement of sustainability performance by implementing energy-efficient machining strategies module, which corresponds to the issues identified of energy-efficient manufacturing in chapter one. The following sub-sections will explain the functions of the elements for each module.

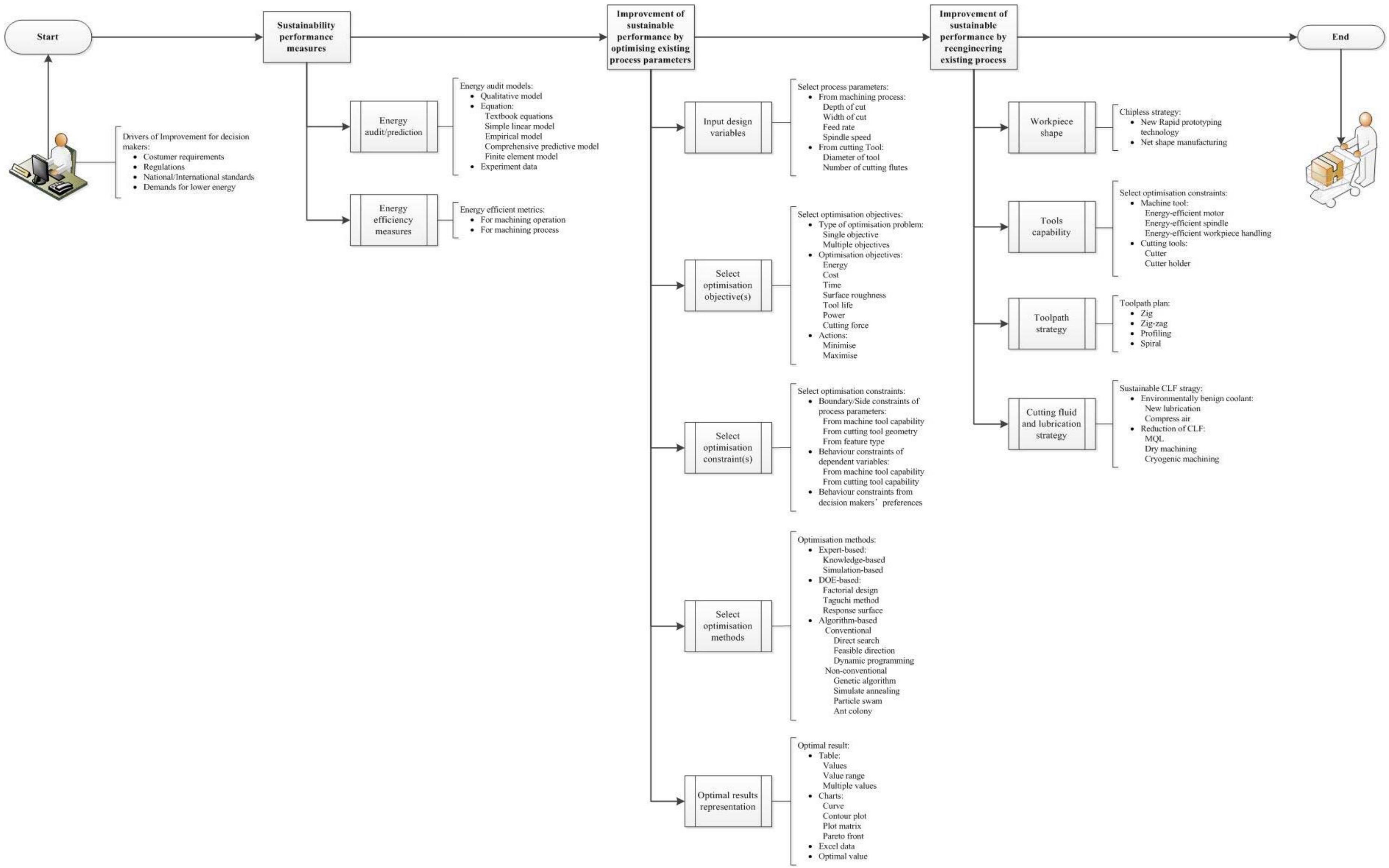

Figure 7.2 Proposed Framework for Sustainability Improvement

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7.3.1 Module of Sustainability Performance Measures

There are two functional elements in this module (see Figure 7.3), which are:

- Energy audit/prediction
- Energy efficiency measures

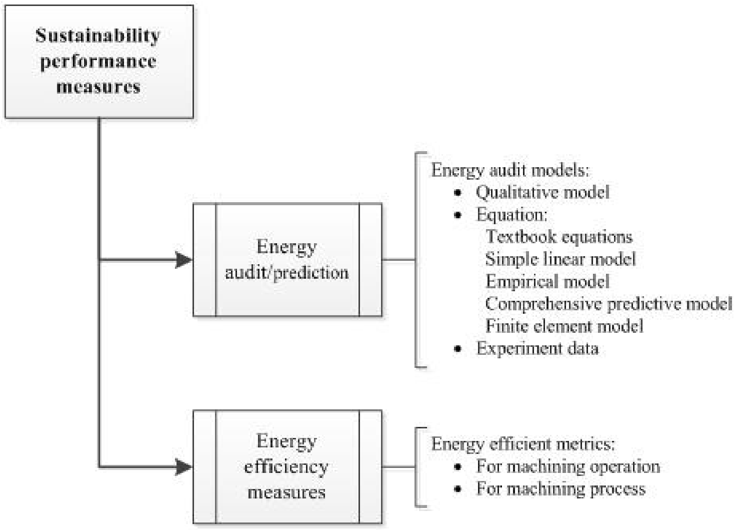

Figure 7.3 Module of Sustainability Performance Measures

The main function of energy audit/prediction is to provide a method for users to measure the energy consumption of their machining processes. For different users, multiple types of models can be selected based on their knowledge level.

- Qualitative model. The models in this type are the experiences or qualitative feelings of practitioners. In practice, practitioners may not be able to quantitatively measure the machining performance. However, they can improve the performance by increasing or decreasing process parameters based on their feelings or experiences. For example, the increase of feed rate can minimise machining time but reduce tool life.
- Equations. The models in this type are equations which are mathematically represented by process parameters and can be implemented to quantitatively predict the machining performance. The accuracy of this type of model is related to the complexity of equations. The more complex the model, the more accurate it will be. However, high accuracy will also cause the difficulty of verification. Typical models in this type are listed as below:

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- Textbook equations (e.g. constant cutting force coefficient/specific energy consumption).
- Simple linear equations (e.g. material removal rate models proposed by Kara, 2011).
- Empirical equations (e.g. the model proposed in Chapter 4).
- Comprehensive predictive model (models consider more independent variables).
- Finite element model

- Experiment/Machining data. The models in this type are the raw data collected/captured during the machining process. The data can be represented into different forms, such as curves, points and tables.

The function of energy efficiency measures at the unit process level is to provide a method to evaluate and represent the efficiency of energy consumption during the machining process. There are two types of energy efficiency metrics (introduced in Chapter 3).

- Energy efficiency for the machining operation.
- Energy efficiency for manufacturing process.

7.3.2 Module of Sustainability Performance Improvement by Optimising Parameters of Existing Manufacturing Process

There are five functional elements in this module (see Figure 7.4), which are:

- Input design variables
- Select optimisation objectives
- Select optimisation constraints
- Select optimisation methods
- Optimal results representing

The main function of design variables is to determine and input the process parameters based on the selected prediction model. There are two types of process parameters:

- Parameters from machining process, including: depth of cut, width of cut, feed rate and spindle speed.
- Parameters from cutting tool, including: diameter of cutter and number of cutting flutes.

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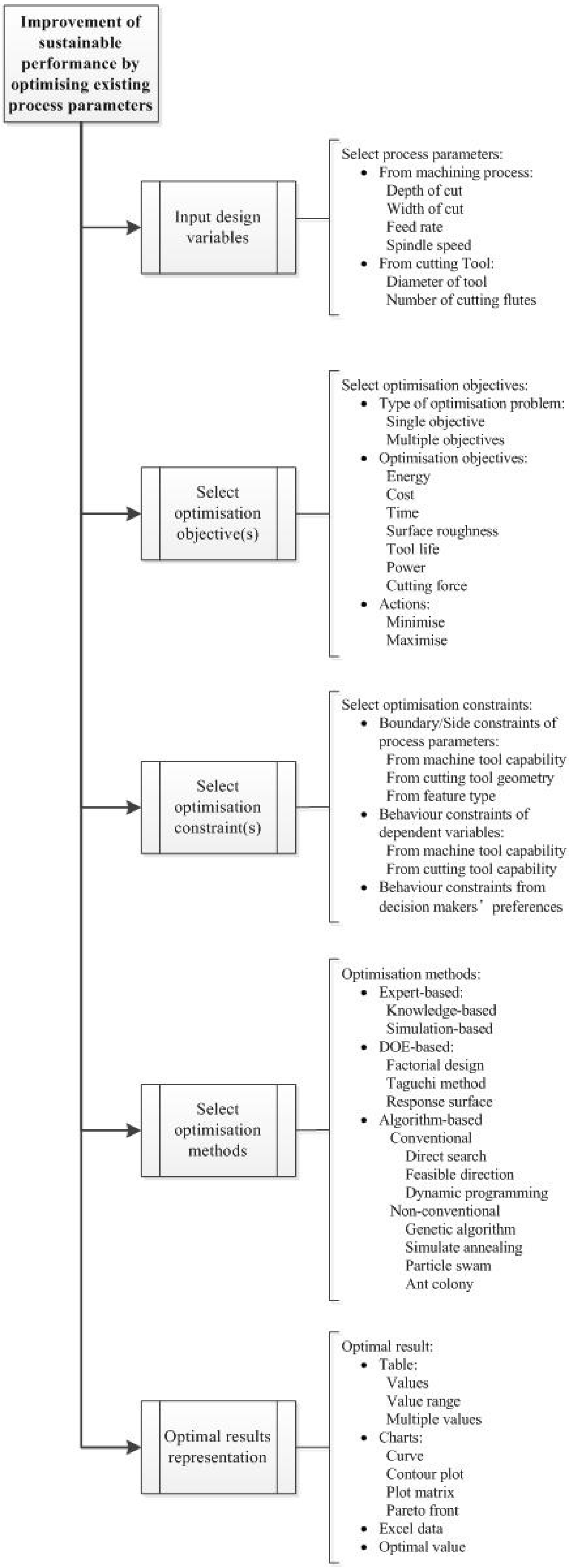

Figure 7.4 Module of Optimisation of Existing Manufacturing Process

The main function of selecting optimisation constraints is to define what problem is going to be solved. The following three steps need to be addressed in this module:

- Determine the type of optimisation problem: Is it a single-objective or multi-objective problem?
- Determine the optimal objective or objectives. The typical objectives include: energy, cost, time, surface roughness, power, tool life and cutting force.
- Determine action of optimisation: minimisation or maximisation.

The main function of selecting optimisation constraints is to refine cutting conditions thus reduce search pace. Optimisation constraints can be selected from the following categories:

- Boundary/side constraints of process parameters. This type of constraint can be selected from:
    - ➢ Machine tool capability, e.g. as spindle speed.
    - ➢ Cutting tool geometry, e.g. number of cutting flutes and diameter of tool.
    - ➢ Machining process, e.g. depth of cut and width of cut.
- Behaviour constraints of dependent variables. This type of constraint can be selected from:
    - ➢ Machine tool capability, e.g. as maximal power allowance.
    - ➢ Cutting tool capability, e.g. maximal cutting force allowance.
- Behaviour constraints from decision makers' preference, e.g. maximal surface roughness, minimal tool life.

The main function of selecting optimisation method is to select an optimisation method to conduct the optimisation procedure. As reported in Chapter 4, the optimal results achieved by using different methods are almost same or showing the same character of the problem. So the decision makers can select any method according to their knowledge and preferences.

The main function of optimisation result representation is to select the best method to represent the optimal results for decision makers to evaluate their current machining plan, and guide them to achieve the optimal results. For different requirements and purpose, the achieved optimal results can be represented as the following types:

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- Tables. Tables are suitable for practitioners to quickly evaluate and select optimal values during practical machining work. Typically, tables should show the following results:
  - Values (for single objective).
  - Feasible value ranges.
  - Multiple values/value range (suitable for multiple objectives scenario).
- Charts. Charts can help decision makers to visualise the characteristics of optimal objective/objectives and determine the optimal results. The typical charts include:
  - Curve. It is suitable for the situation that only one design variable (process parameters) needs to be considered.
  - Contour plot. It is best for the situation that two design variables need to be considered.
  - Plot matrix. It is suitable for the situation that multiple design variables need to be considered.
  - Pareto plot. It is suitable for multi-objectives optimisation situation.
- Excel data. Excel data are similar to tables. But it is suitable for representing large amount of data.
- Optimal value. It is suitable for the situation that decision makers prefer a single direct optimal result.

7.3.3 Module of Sustainability Performance Improvement by Implementing Energy-efficient Machining Strategies

There are four functional elements in this module (see Figure 7.5), which are related to the corresponding energy-efficient cutting strategies. The specific types of these energy-efficient strategies are listed as below:

- Workpiece
- Cutting Tools
- Toolpath
- Cutting fluid and lubricant

The function of this module is just to introduce some energy-efficient technologies published in existing research contributions. Each functional element in this module is independent of each other. Decision makers can select any energy-efficient strategies or

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continue using the conventional strategy based on their preferences and practical manufacturing situations. In addition, in some circumstances multiple strategies can be also applied at the same time.

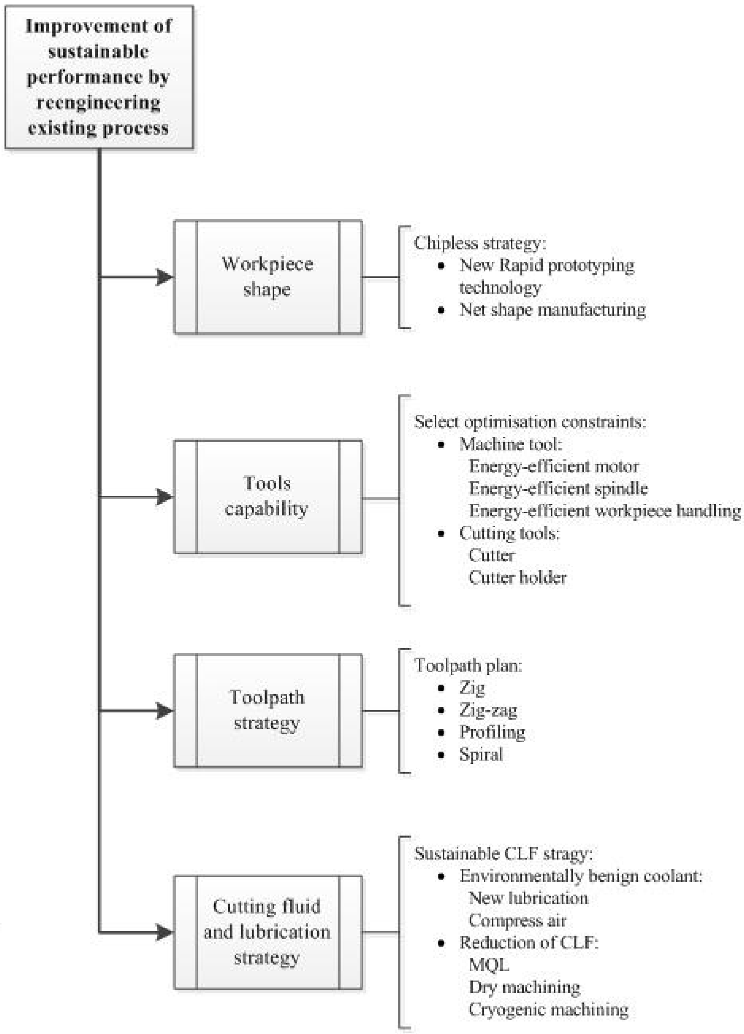

Figure 7.5 Module of Re-engineering Existing Manufacturing Process

Strategies of workpiece shape are mainly focussed on chipless strategies, including: new rapid prototyping strategy and net shape manufacturing.

Strategies of cutting tool capability can be divided into two categories:

- Energy-efficient machine tool. This type of strategy is to use energy-efficient components to replace conventional component on machine tools. The current possible solutions include energy-efficient motor, energy-efficient spindle and energy-efficient workpiece handling system.

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- Energy-efficient cutting tool. This type of strategy is to use energy-efficient cutting tools. Current possible solutions include new design of cutter (shape, material and coating) and cutter holder.

Strategies of toolpath also have two categories:

- Energy-efficient toolpath type. This type of strategies is to select energy-efficient toolpath type based on the shape of workpiece, dimensions of feature and cutting tools and type of machining operation.
- Reduction of redundant movement. This type of strategies is to reduce unnecessary and non-value-added movement. It can be achieved by redesigning the toolpath and reducing the offset.

Strategies of cutting fluid and lubrication can be also divided into two categories:

- Environmentally benign coolant. This type of strategy is to use the environmentally friendly coolant method to replace conventional cutting fluid, such as new type of lubricants and compress air.
- Reduction of the usage of cutting fluid. This type of strategies is to reduce the usage of cutting fluid by implementing new coolant strategies, such as Minimum Quantity Lubrication (MQL), dry machining and Cryogenic machining,

7.4 Implementation of the Framework

The proposed framework can be used on its own as an independent methodology in different formats. Also it can be implemented as part of existing processes in industry. The following sections will introduce the implementation of the proposed framework.

7.4.1 Computer Implementation of the Framework

The framework has been implemented in MATLAB GUI and Microsoft Excel. This type of implementation does not require decision makers to have solid knowledge in machining or machining optimisation.

The user interface (UI) of the MATLAB implementation is shown in Figure 7.6. Decision makers can input the process parameters (value or range) according to their requirements. Contour plots of selected objectives can be graphically displayed at plot

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area. Then the optimal plan can be selected by using existing optimisation methods based on decision makers' preference.

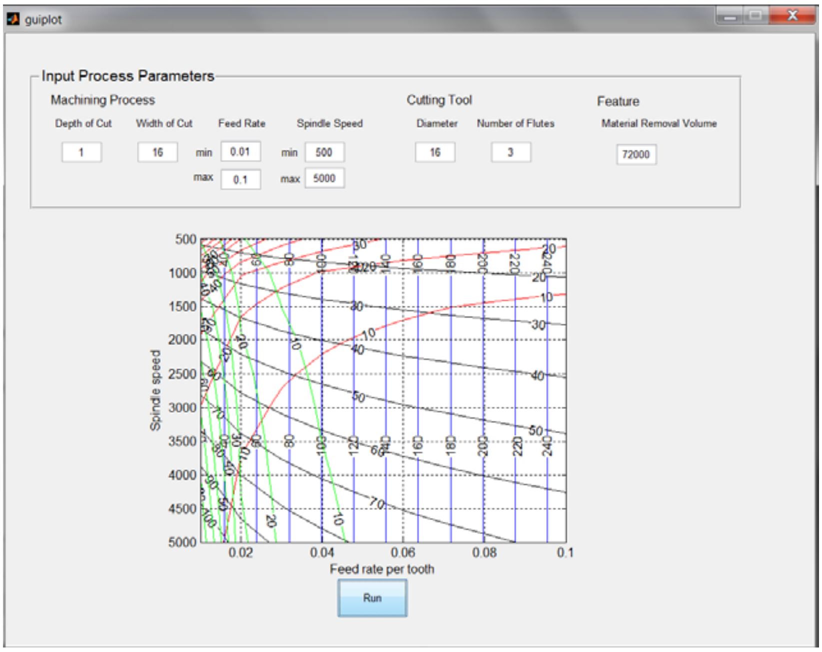
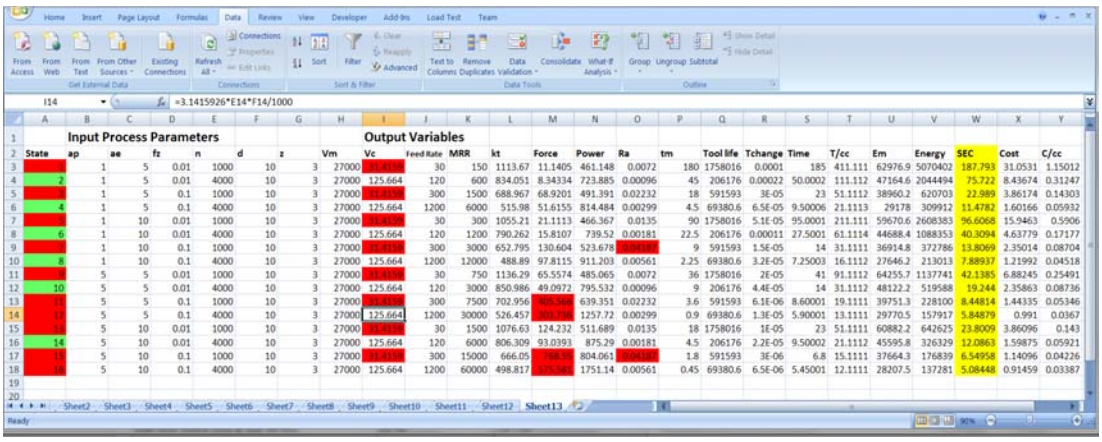


Figure 7.6 User Interface of MATLAB Implementation

Figure 7.7(a) shows an implementation by using Microsoft Excel spreadsheet. Decision makers can manually input the process parameters according to their manufacturing process. Then the corresponding values of each objective and constraint will be automatically generated. The constraints value can be set based on the requirements to reduce search space and displayed in different colours (e.g. use red region to represent non-feasible results, green region to represent feasible results, yellow region to represent target objective), and the optimal plan can be selected within the refined range. The Excel spreadsheet can be also implemented as separated tables for practitioners to use as shown in Figure 7.7(b) (more tabular charts are shown in Appendix III).



	Input Process Parameters							Output Variables																
State	ap	ae	fz	n	d	z	Vm	Vc	Feed Rate	MRR	kt	Force	Power	Ra	tm	Tool life	Tchange	Time	T/cc	Em	Energy	SEC	Cost	C/cc
1	1	5	0.01	1000	10	3	27000	31.4159	30	150	1113.67	11.1405	461.148	0.0072	180	1758016	0.0001	185	411.111	62976.9	5070402	187.793	31.0531	1.15012
2	1	5	0.01	4000	10	3	27000	125.664	120	600	834.051	8.34334	723.885	0.00096	45	206176	0.00022	50.0002	111.112	47164.6	2044494	75.722	8.43674	0.31247
3	1	5	0.1	1000	10	3	27000	31.4159	300	1500	688.967	68.9201	491.391	0.02232	18	591593	3E-05	23	51.1112	38960.2	620703	22.989	3.86174	0.14303
4	1	5	0.1	4000	10	3	27000	125.664	1200	6000	515.98	51.6155	814.484	0.00299	4.5	69380.6	6.5E-05	9.50006	21.1113	29178	309912	11.4782	1.60166	0.05932
5	1	10	0.01	1000	10	3	27000	31.4159	30	300	1055.21	21.1113	466.367	0.0135	90	1758016	5.1E-05	95.0001	211.111	59670.6	2608383	96.6068	15.9463	0.5906
6	1	10	0.01	4000	10	3	27000	125.664	120	1200	790.262	15.8107	739.52	0.00181	22.5	206176	0.00011	27.5001	61.1114	44688.4	1088353	40.3094	4.63779	0.17177
7	1	10	0.1	1000	10	3	27000	31.4159	300	3000	652.795	130.604	523.678	0.04187	9	591593	1.5E-05	14	31.1111	36914.8	372786	13.8069	2.35014	0.08704
8	1	10	0.1	4000	10	3	27000	125.664	1200	12000	488.89	97.8115	911.203	0.00561	2.25	69380.6	3.2E-05	7.25003	16.1112	27646.2	213013	7.88937	1.21992	0.04518
9	5	5	0.01	1000	10	3	27000	31.4159	30	750	1136.29	65.5574	485.065	0.0072	36	1758016	2E-05	41	91.1112	64255.7	1137741	42.1385	6.88245	0.25491
10	5	5	0.01	4000	10	3	27000	125.664	120	3000	850.986	49.0972	795.532	0.00096	9	206176	4.4E-05	14	31.1112	48122.2	519588	19.244	2.35863	0.08736
11	5	5	0.1	1000	10	3	27000	31.4159	300	7500	702.956	405.566	639.351	0.02232	3.6	591593	6.1E-06	8.60001	19.1111	39751.3	228100	8.44814	1.44335	0.05346
12	5	5	0.1	4000	10	3	27000	125.664	1200	30000	526.457	303.736	1257.72	0.00299	0.9	69380.6	1.3E-05	5.90001	13.1111	29770.5	157917	5.84879	0.991	0.0367
13	5	10	0.01	1000	10	3	27000	31.4159	30	1500	1076.63	124.232	511.689	0.0135	18	1758016	1E-05	23	51.1111	60882.2	642625	23.8009	3.86096	0.143
14	5	10	0.01	4000	10	3	27000	125.664	120	6000	806.309	93.0393	875.29	0.00181	4.5	206176	2.2E-05	9.50002	21.1112	45595.8	326329	12.0863	1.59875	0.05921
15	5	10	0.1	1000	10	3	27000	31.4159	300	15000	666.05	768.55	804.061	0.04187	1.8	591593	3E-06	6.8	15.1111	37664.3	176839	6.54958	1.14096	0.04226
16	5	10	0.1	4000	10	3	27000	125.664	1200	60000	498.817	575.581	1751.14	0.00561	0.45	69380.6	6.5E-06	5.45001	12.1111	28207.5	137281	5.08448	0.91459	0.03387

Figure 7.7a Excel Spreadsheet Implementation of Proposed Framework

500	39.01631	22.12691	16.43118	13.55406	11.81146	10.63938	9.795096	9.156737	8.656352	8.253012
1000	23.80092	14.39107	11.19739	9.575239	8.587814	7.920581	7.437849	7.071351	6.782934	6.549579
1500	18.66318	11.75539	9.400355	8.199582	7.466129	6.968936	6.608158	6.333487	6.116764	5.940976
2000	16.06507	10.41224	8.478584	7.489853	6.884381	6.472988	6.173825	5.945602	5.765185	5.618583
2500	14.48987	9.592219	7.912531	7.051782	6.523655	6.164177	5.902339	5.702284	5.543908	5.415042
3000	13.4294	9.036587	7.526939	6.75199	6.275778	5.951187	5.714456	5.533369	5.38985	5.27295
3500	12.66482	8.63357	7.245877	6.532542	6.093655	5.794171	5.575529	5.40812	5.275325	5.167069
4000	12.08625	8.326859	7.030992	6.364105	5.953386	5.672871	5.467907	5.310851	5.186179	5.084477
4500	11.63237	8.084943	6.86077	6.23019	5.841511	5.575853	5.381612	5.23268	5.114387	5.017836
5000	11.26623	7.888788	6.722182	6.120788	5.749845	5.496152	5.310556	5.168178	5.055036	4.962648
n/fz	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09	0.1

Figure 7.7b Tabular Chart Obtained from Excel Spreadsheet: Specific Energy Consumption (kJ/cc) for Constraints of Cutting Force ($Ft \leq$ 400N), Cutting Speed (75m/min $\leq Vc \leq$ 120m/min) and Surface Roughness ($Ra \leq$ 12.5µm)

7.4.2 Implementation of the Framework in CAD/CAM/CAPP Software

The research contributions in this thesis can also be implemented in CAD/CAM/CAPP software tools. For CAD/CAM/CAPP implementation:

- The proposed methodology in energy consumption and energy efficiency measures can be integrated into existing CAD/CAM/CAPP software tools as a function module to calculate the energy consumption and energy efficiency for exiting machining process based on the input process parameters and selected toolpath strategy.
- The proposed methodology in machining optimisation can be integrated into existing CAD/CAM/CAPP software tools as a function module to optimise the existing machining process parameters, uncover the potential improvements and suggest the improvement methods/directions.
- The proposed methodology in developing new energy-efficient strategies can be integrated into existing CAD/CAM/CAPP software tools as a function module to compare the energy consumptions and energy efficiencies for all the available machining plans such as coolant type and toolpath generations.
- The developed algorithm can be embedded into exiting program for calculating machining performance. The analysis can be presented in different forms such as figures, tables or list of recommended process parameters based on the selected criteria/criterions (e.g. energy minimisation).

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7.4.3 Implementation of the Framework for Existing Process Improvement Methods

The proposed framework can also be implemented in some functional elements of existing international standard and process improvement methods.

For PDCA cycle (proposed in ISO 9001/140001/50001)

- Plan: the proposed energy efficiency definition can be used to review the energy performance and develop the new regulation/policy/standard.
- Do: the analysis of energy performance/efficiency can increase the awareness of energy issues in the industry. In addition, the proposed framework itself can be used to train/educate new practitioners/manufacturing process planners/engineering students.
- Check: the proposed measurement and optimisation methods can be used to monitor the energy performance, analyse the factors which will affect the energy consumption and audit the energy consumption for machining operation.
- Act: the proposed improvement method can be used to review the existing manufacturing process by identifying the potential savings and suggest the improvement directions.

For five phases of six sigma tool DMAIC (Define, Measure, Analyse, Improve and Control) or DMADV (Define, Measure, Analyse, Design and Verify):

- Define: general introduction of the proposed framework will clearly state and specify the problem, and identify the solution process.
- Measure: proposed energy performance measures methods can decide what parameters/objectives need to be considered, what is the best way to measure the objectives, what data need to be collected and how to carry out the measurements (physical and numerical experiments).
- Analyse: the introduced characterisation process can identify objective performance (energy, cost, time, etc.) and determine how process parameters affect objectives.
- Improve/design: proposed optimisation method and energy-efficient strategies can be used to reduce the energy consumption of existing manufacturing process or develop a new energy-efficient process.

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- Control/verify: the proposed framework can be used as a tool to control/assess/guide the manufacturing process.

7.4.4 Examples for Demonstrating the Framework

In this section, a test part has been presented to demonstrate the framework proposed (see Figures 7.8). Energy consumptions for each feature can be firstly calculated by using the tools (MATLAB or Excel file) introduced in section 7.4.1. The detailed features of the test component, process parameters and energy consumptions are shown in Tables 7.2.

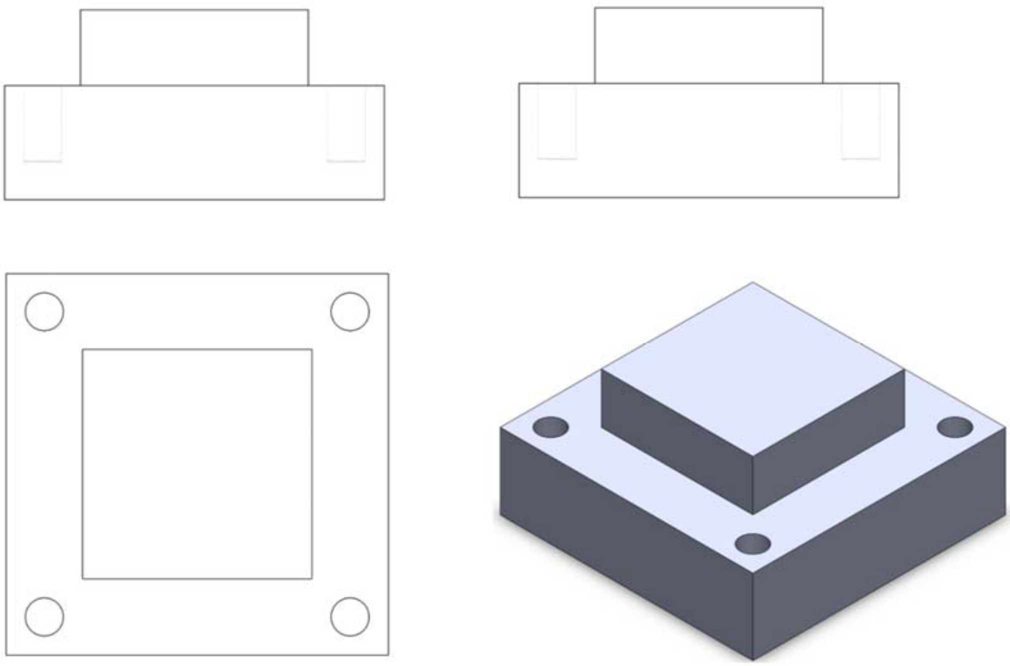

Figure 7.8 Test Component

Table 7.2 Features, Process Parameters and Energy Consumption of Test Component

Feature	Material removal mm^3	Cutting tool	Spindle speed rpm	Feed rate mm/tooth	ae mm	ap mm	Energy kJ	TME kJ	ER
Step: length 100mm, width 20mm, depth 20mm	128,000	16mm end mill 3 flutes	2,000	0.02	8	1	4565.35	1.086	0.024%
Round holes: 4×ϕ10mm, depth 20m	6,283.2	10mm end mill 2 flutes	1,000	0.03	10	1	385.264	0.274	0.071%
Total Energy Consumption							4,950.614	1.36	0.027%

Then the improved results will be carried out by optimising process parameters based on the methods introduced in Chapter 4. The specific optimisation conditions/constraints are:

- Feed rate per tooth: 0.01-0.1 mm/tooth
- Maximum spindle speed 4,000rpm
- Cutting speed no more than 400m/min
- Cutting force no more than 400N

The optimal process parameters and energy consumption are shown in Table 7.3.

Table 7.3 Optimal Process Parameters and Energy Consumption of Test Component

Optimal Results	Spindle speed rpm	Feed rate mm/tooth	ae mm	ap mm	Optimal Energy kJ	Original Energy kJ	Energy Reduction	New ER
Step	4,000	0.1	10	5	281.661	4,565.35	93.830%	0.385%
Holes ϕ10	4,000	0.1	10	2.5	108.725	385.264	71.779%	0.252%
Total energy					390.386	4,950.614	92.114%	0.348%

The result shows that up to 93.830% and 71.779% of reduction in energy for machining step feature and ϕ10 holes, and 92.114% of reduction in total energy consumption can be achieved by implementing optimal process parameters. The energy efficiency can be improved from 0.027% to 0.348%.

Further reduction in energy consumption can be achieved by implementing energy-efficient cutting strategies. The comparison between conventional toolpath strategy (CTS) and proposed energy-efficient toolpath strategy (PTS) has been shown in Table 7.4 for machining a step feature. The result shows that 15.955% of further reduction in energy consumption can be achieved by implementing PTS. The energy efficiency can be improved from 0.385% to 0.459%.

Table 7.4 Energy Reduction by using Energy-efficient Cutting Strategy

Strategy	Feature	Material removal mm^3	Energy kJ	TME kJ	ER (TME/E)
CTS	Step: length 100mm, width 20mm, depth 20mm	128,000	281.661	1.086	0.385%
PTS		121,856	236.720		0.459%
Energy reduction			15.955%		

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In conclusion, the examples shown in this section explained how to implement the proposed framework. Decision makers or shop floor practitioners can easily get the optimal/energy-efficient solutions for real components even without a good knowledge in machining or optimisation. The improved machining process can be achieved by following the step below which is suggested in the proposed framework:

- Define/measure/predict the performance of machining process.
- Improve the performance measure through optimisation of process parameters.
- Further improvement by using new processes/operations/technologies.

However, according to the theoretical limits of machine tool capabilities, characteristics of materials and dimension of features, the improvement for different features/operations/materials will be different. These issues will bring new challenges for the implementation of the proposed framework and need to be further investigated in the future.

7.5 Summary and Discussion

In this chapter, a systematic framework for improving sustainability performance of machining process has been proposed. The idea of such framework can be simply modified by the users based on the understanding of the problem from previous sections. The function of the developed framework is to enable people to set up the measures of machining performance, and improve the performance by optimising process parameters and implementing energy-efficient cutting strategies.

The elements of the framework were determined in section 7.3 according to the research output in Chapter 3 to Chapter 6. The proposed framework can be used on its own as an independent methodology in different formats to fulfil different requirement based on the users' skills and habits such as checklist, manual, guideline and possible computer implementation. Also it can be implemented as part of existing processes in industry, such as PCDA cycle and six sigma.

The results of the framework can be applied in a number of examples as listed below:

- Applying the framework to academic education or professional training. The developed scenarios can be applied to determine what parameters should be used for machining and what problems should be solved. It can be achieved by studying a machining/manufacturing course for undergraduate students and practical apprentices. This is not only a sustainable application/improvements, it

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also has a social impact of educating next generation machining researchers, practitioners and process planers.

- Applying the framework to existing workshop. The benefits can influence many different fields. For example: for the suppliers to make quick decisions when urgent orders come, for apprentices to learn how to choose process parameters, for tool manufacturers to design the tool handbook, for process programmers to decide optimal NC code, for practitioners to improve the performance by developing manuals/application tables.
- Applying the framework to industrial manufacturing. Even if for proprietary reasons, parts details cannot be shared, simple information (e.g. the volume removed, material, the parameters used currently) can be used to determine more optimum parameters or rather present a search space for the practitioners to select from. However, the search space is not unstructured. It looks like a road network that they can personally choose from with their decisions. It is also possible to use the results as a push button at the machine level if the machine tool operators can understand how to achieve the optimal results and take responsibility for their decisions.

Finally, a test part was presented as examples to demonstrate the proposed framework. The process clearly showed how to systematically implement the proposed framework to reduce energy consumptions and improve energy efficiency via optimisation of process parameters and implementation of energy-efficient machining strategy.

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CHAPTER 8: CONCLUSIONS AND FURTHER WORK

This chapter presents the main conclusions of the PhD project and recommendations for future research and development.

8.1 Conclusions of the Project

This research presents a systematic method to measure and evaluate the energy usage performance and reduction in energy consumption, for the manufacturing processes at the unit process level and thus achieves a sustainable machining process.

A literature review was conducted in the scoping phase relating to the environmental impact (energy consumption) of manufacturing operations and improvement methods in the machining performance. Through this review of literature and industrial practices, the requirements of current research contributions are identified in the following:

- ***Sustainability performance measures,*** which can be used to effectively identify potential inefficiencies, recommend ways of improvement, and act as a bench-mark against similar external operations.
- ***Improvement of sustainability by optimising existing processes,*** which takes energy as an additional factor in the optimisation of machining processes and technologies and overcome the multiplicity of the problems in current optimisation methods.
- ***Improvement of sustainability by developing energy-efficient processes and technologies*** that moves closer to the theoretical boundaries of energy efficiency.

According to the above requirements, the research questions of this project can be defined as:

What methods can be applied to attain a sustainable manufacturing process by improving the energy efficiency in the machining operation?

This research question can be further divided into several sub-questions which correspond with the identified requirements of performance measures, optimisation of process parameters and the development of energy-efficient strategies.

The research question of performance measures is:

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- ***What method can be used to measure and evaluate the performance of energy consumed for the machining process?***

The research questions of machining optimisation are:

- ***What methods can be used to optimise the energy consumption of machining operations, based on a comprehensive understanding of how energy affects machining optimisation as a factor in addition to the traditional factors of cost, time and quality?***
- ***Which method is the most suitable of the optimisation methods from the available varieties of options?***

The research question of development of energy-efficient machining strategy is:

- ***What methods can be used to reduce energy consumption for existing machining methods by applying the energy-efficient strategies?***

To answer the research question of performance measures, a set of energy prediction models were developed to measure the energy usage during machining processes. New energy efficiency metrics have been proposed which can accurately evaluate the energy performance of machining operation and point out directions of improvement. The results show that energy consumption in machining operations can be improved by optimising the use of existing processes and by designing new processes and technologies.

To answer the research questions of machining optimisation:

- Characteristics of machining operations along with energy considerations were investigated by using graphical multivariate data analysis techniques.
- A direct search method was used as an experimental rig to investigate the reasoning behind the results obtained in applying Taguchi methods, Genetic algorithm (GA) and Ant Colony Optimisation method (ACO), and to conduct the optimisation procedure. The results have shown that energy consumption decreases constantly as process parameters increase, and up to 75% in energy consumption can be reduced without conflicting with cost and time with the constraints of cutting force, spindle speed and surface roughness. The optimisation process enables practitioners to have more confidence in the optimal results.

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- A scientific framework for solving machining optimisation problems has been proposed based on the characterisation of the machining operation. The proposed framework can be modified by users, based on the understanding of the machining optimisation problems, to solve both single-objective and multi-objective cases. The function of the developed framework is to enable people to set right the machining optimisation problem, identify possible optimisation algorithms and achieve an optimal manufacturing process based on their requirements.

To answer the research question of energy-efficient strategies: an energy-efficient profiling toolpath strategy was developed to improve energy efficiency for $2^{1}/_{2}$D milled features. It was found that further reduction in energy consumption could be achieved compared to conventional cutting strategies. Implementing conditions for different feature type and dimensions was discussed.

Finally, a systematic optimisation framework has been proposed, which can be implemented as an independent methodology in different formats to fulfil differing requirements (e.g. computer implementation) or as part of existing process improvement methods in industry. Decision makers or shop floor practitioners can obtain sustainable solutions for real components even without good knowledge or experience in machining optimisation.

The main achievements of this research are concluded below together with their relation to the initial objectives; this provides the answers for the research questions:

(1) Objective 1: To identify the gap in current research contributions by conducting a comprehensive literature review on the topic of energy-efficient design and manufacturing to investigate the current research achievements and problems.

Corresponding achievements:

- A comprehensive literature review of current research contributions in the field of sustainable manufacturing, energy efficient design and manufacturing and machining optimisation. The gaps of current research have been clearly identified.
- Research questions formulated based on the issues identified from the literature review.

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(2) Objective 2: The development of energy prediction models and energy efficient metrics which can be used to measure and evaluate energy consumption of machining process.

Corresponding achievements:

- A set of energy prediction models have been developed based on the accepted machining science to measure the energy usage during machining processes. Experimental verifications of developed models showed that up to 95% of accuracy can be achieved by using developed prediction models.
- New energy efficiency metrics have been proposed to uncover the inherent inefficiency of machining process and identify the gap between theoretical limitation and existing machining process.

(3) Objective 3: The characterisation of machining operation with energy considerations will be investigated to provide a comprehensive understanding of the machining operation and uncover the interaction of different variables. Corresponding achievements:

- The nature of machining optimisation was investigated by introducing the basic concept of search space, variables, objectives and constraints.
- The characterisation of energy consumption showed that energy consumption of machining operations decreases monotonically with the increase of process parameters. In addition, energy is non-conflicting with the cost and time, but conflicting with surface roughness, power requirement, tool life and cutting force.
- Based on the characteristics, the criteria of machining optimisation can be divided into two major categories: conflicting and non-conflicting.

(4) Objective 4: The development of a numerical experimentation rig to investigate the reasoning behind the results obtained in applying typical optimisation methods. Optimisation procedures will be carried out to determine the optimal process parameters with energy considerations.

Corresponding achievements:

- A direct search method was used as an experimentation rig to investigate the reasoning behind the results obtained in applying typical optimisation methods.

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The basic principles of Taguchi method, GA and ACO have been demonstrated by graphically displaying the procedures of how these optimisation methods operate to achieve the optimal results.

- The optimisation was conducted for milling Aluminium 7075-T6 (by using Haas TM 1CE Vertical milling machine, maximum spindle speed 4,000rpm and 10mm 3 flutes carbide end mill)and the optimisation result with the constraints of spindle speed (4,000 rpm), cutting force (400N) and surface roughness (0.05mm) showed that up to 75% of improvement of energy, cost and time can be achieved by using optimal process parameters (depth of cut, width of cut, spindle speed and feed rate) compared to cutting tool manufacturer's recommendation. The optimisation process enables practitioners to have more confidence in their results.
- The implementation of achieved optimal process parameters for the case study shows that over 220% of improvement of energy efficiency (6.965% to 22.513%) for the process, and up to 22% reduction in inefficient energy consumption can be achieved for machining operation.

Objective 5: Development of a scenario-based framework to solve machining optimisation problems especially when multiple objectives need to be considered.

Corresponding achievements:

- A scientific framework for solving machining optimisation problems has been proposed based on the characterisation of machining operation. The proposed framework provides a generic and systematic methodology for decision makers to better understand machining processes and address recent challenges from sustainable requirements.
- The problem scenarios were built based on the characteristics of optimisation objectives and differing user requirements. These multiple objectives can be divided into two categories: non-conflicting and conflicting category. Non-conflicting multi-objective problems can be converted to a single-objective situation which has a unique solution, and conflicting multi-objective problems can be converted to a set of conflicting bi-objective cases which can be presented as a single Pareto front.
- According to the analysis of optimal results, the solutions for machining optimisation were also built. The optimal solutions can be classified into three

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solution scenarios which are descriptive scenario (for zero-objective scenario), unique solution scenario (for single-objective scenario and non-conflicting category of multi-objective scenario) and Pareto front scenario (for conflicting category of multi-objective scenario).

Objective 6: An energy efficient machining strategy, which is beyond optimisation of process parameters, will be proposed to further improve energy efficiency for $2^1/_2$D milled features.

Corresponding achievements:

- An energy efficient profiling toolpath strategy has been proposed which can further reduce the energy consumption and improve energy efficiency for machining process. Compared to the optimisation of existing process, new energy-efficient strategies can further reduce the gap between theoretical limitation and practical consumptions.
- Implementing conditions for different feature types and dimensions have also been discussed.

Objective 7: A comprehensive framework which integrates the above research findings will be developed for decision makers to improve sustainability performance of their manufacturing process.

Corresponding achievements:

- A systematic framework for improving sustainability performance of machining process has been proposed based on the research output in pervious chapters. The function of the developed framework is to enable people to set up the measures of machining performance, and improve the performance by optimising process parameters and implementing energy-efficient cutting strategies.
- Different forms (e.g. MATLAB GUI and Excel) have been introduced to implement the developed methodology. Decision makers can select the most suitable form (e.g. checklist, manual, guideline and possible computer implementation) based on their skills and habits. Also it can be implemented as part of existing processes in industry, such as PCDA cycle and six sigma.

- A test part was presented as examples to demonstrate the proposed framework. The process clearly showed how to systematically implement the proposed framework to reduce energy consumptions and improve energy efficiency.

8.2 Limitations and Further Work

Although the proposed methodology provides a reliable tool to measure and evaluate energy usage performance and minimise energy consumption and improve energy efficiency for machining operation, there are still some identifiable limitations existing which need to be improved in further work.

8.2.1 Scope and Limitations of the Thesis

The scope and limitations of this thesis are listed as below:

Firstly, the mathematical models applied in this research originated from commonly accepted machining science text books (e.g. Tlusty, 2000). Due to the complexity of experiment and verification, not all of the process parameters were considered in the modelling process. In this case, the accuracy of the models may not be as high as shown in detailed machining science metrics. In addition, because of the limitations of measuring instruments and equipment, some models (e.g. tool life and surface roughness) have come from existing research publications. Therefore, the results obtained from these models may not be as accurate as verified primary models. Meanwhile, not all of the objectives during machining operation are considered, such as chatter, temperature and noise.

Secondly, the profiling toolpath strategy proposed is more like a cutting strategy than a toolpath strategy. This research did not consider the impact of different toolpath strategies (e.g. the orientation of toolpath). The current toolpath generated by CAM software contains a lot of redundant motions which causes lots of unnecessary energy consumptions.

Thirdly, only $2^1/_2$D milled feature were considered in this thesis. Other milled features and operations are not considered in this research.

Fourthly, current research only focuses on the unit process level. However, to successfully implement the concepts of sustainability and developed technology in sustainable manufacturing, it is necessary to extend research to other high level perspectives, such as workstation level, factory level, enterprise level and global level.

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Finally, the research contributions in this thesis only considered machining operations which is only one phase of manufacturing process. It is also necessary to consider other phases of product life cycle, such as product design and development.

8.2.2 Suggestions for Further Work

To address the limitations of this research mentioned in section 8.2.1, the suggestions for further work are listed as below:

Firstly, more investigations and experiments need to be carried out to measure and characterise the sustainability performance of different materials, machine tools and machining operations. More advanced models will be developed to improve the accuracy and generality of the prediction models.

Secondly, the energy efficiency for different type of toolpath needs to be investigated to further reduce the energy consumption and improve energy efficiency. Thus provide a theoretical foundation to improve the toolpath generation functions for CAM software.

Thirdly, to implement the result in common machining process, different feature type/machining operation types need to be investigated, such as 3D freeform features, and turning and drilling operation. In addition, multiple feature cases which combine multiple machining operations also need to be considered, such as turning, drilling, rough machining and finishing, to fulfil the requirements of practical manufacturing. The investigation of energy efficiency can be further extended to investigate the energy requirements and energy efficiency for different manufacturing technologies (e.g. casting, rolling and 3D printing). It can provide a more comprehensive comparison of the energy efficiency for achieving a feature/product by using different manufacturing technologies methods (e.g. conventional techniques or advanced methods).

Fourthly, to better improve the sustainability for manufacturing process, the research area should be extended to the higher levels, such as manufacturing system level, or factory/enterprise level. More aspects of sustainability should be considered (e.g. safety issues, profit issues) to achieve a comprehensive sustainable manufacturing process.

Fifthly, the research contributions of this project should be delivered into proper form which can be easily implemented in the academic and practical area for different levels of users. The possible delivery forms include:

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- Embed result into a module and integrate into new generation energy-efficient machining tools.
- Integrate the result as a mobile/tablet/computer application which can be easily used by practitioners.
- Paper printed tabular catalogue/handbook/guidance.
- Formulate result as a systematic energy labelling system for machining operation/manufacturing process.

Finally, the current research contributions can be extended to other stages in the product life cycle (e.g. product design and development stage). The typical area includes product design and material selection.

- In design stage, the research contributions in sustainability performance (such as energy consumption and energy efficiency) based on different dimensions and types of feature can be used by product designers to analyse and evaluate the sustainability of the current design of product. The research contributions in manufacturing process improvement (including: process parameters optimisation and sustainable manufacturing strategies) can also provide a direction of improvement for product designers to improve their designs.
- In material selection stage, the research contributions in characterisation of workpiece materials can provide a reference for designers to understand the sustainability properties of materials, such as specific energy consumption, specific cost, specific time, power, and quality (surface roughness). So the designers can choose the suitable materials for their designs.

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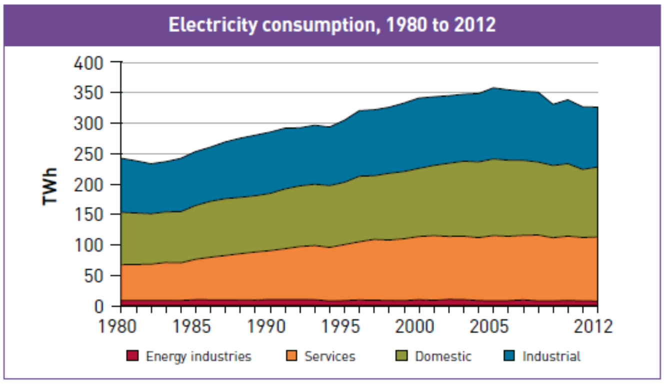
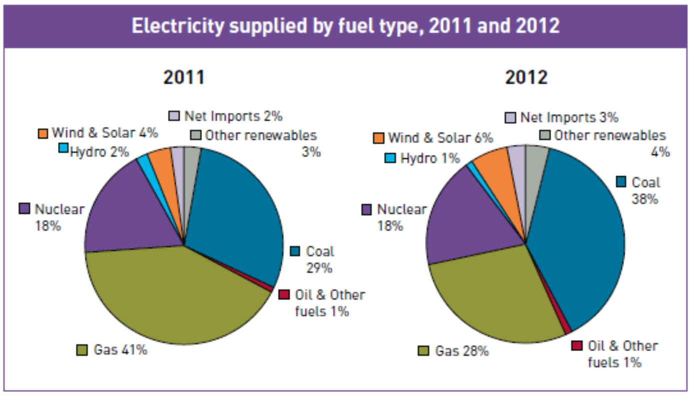
APPENDIX I: Additional Data of Energy Consumption



TWh

	1980	1990	2000	2010	2011	2012
Industrial	88.6	100.6	115.3	104.9	102.7	98.3
Domestic	86.1	93.8	111.8	118.8	111.6	114.7
Services	58.4	80.0	103.5	105.5	103.9	105.1
Energy industries	8.5	10.0	9.7	8.3	7.7	7.4
Total	**241.6**	**284.4**	**340.3**	**337.5**	**325.9**	**325.4**

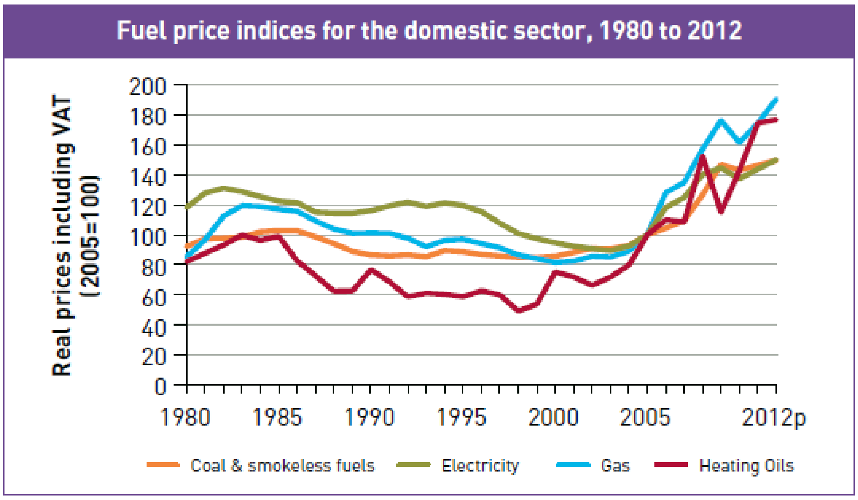
Figure AI.1 UK Electricity Consumption, 1980 to 2012 (UK Department of Energy & Climate Change, 2013)



TWh

	1980	1990	2000	2010	2011	2012
Coal	220.8	213.4	114.7	102.3	103.1	135.9
Oil & other fuels[1]	7.9	19.2	7.3	5.6	4.4	4.4
Gas	–	0.4	138.7	172.5	143.8	98.2
Nuclear	32.3	58.7	78.3	56.4	62.7	63.9
Hydro	3.9	5.2	5.1	3.6	5.7	5.3
Wind & Solar	–	–	0.9	10.2	15.8	20.8
Other renewables	–	–	4.1	10.9	11.8	13.4
Net Imports	–	11.9	14.2	2.7	6.2	12.0
Total electricity available for supply	**264.9**	**308.7**	**371.4**	**364.1**	**353.4**	**353.9**

Figure AI.2 UK Electricity Supplied by Fuel Type, 2011 and 2012 (UK Department of Energy & Climate Change, 2013)



Real prices including VAT, 2005 = 100

	1980	1990	2000	2010	2011	2012
Coal and smokeless fuels.	92.5	86.7	85.8	143.0	146.4	149.5
Electricity	118.3	116.2	94.8	137.3	143.8	149.9
Gas	85.5	101.3	81.7	161.4	174.4	190.3
Heating oils	82.3	76.9	75.3	142.9	174.4	176.6
Domestic prices (fuel & light)	**101.7**	**105.1**	**86.7**	**145.4**	**157.1**	**166.7**

Figure AI.3 UK Fuel Prices, 1980 to 2012 (UK Department of Energy & Climate Change, 2013)

Table AI.1: Energy Consumption of Industry and Manufacturing in China (2002-2011)

Year	Industry	Manufacturing
2002	102181.18	79532.95
2003	119626.63	93163.87
2004	143244.02	115261.44
2005	158058.37	127683.89
2006	175136.64	143051.47
2007	190167.29	156218.8
2008	209302.15	172106.52
2009	219197.16	180595.97
2010	231101.82	188497.25
2011	246440.96	200403.37

Unit: 10,000 tons of SCE (standard coal equivalent 1kg sce=30,000kJ)

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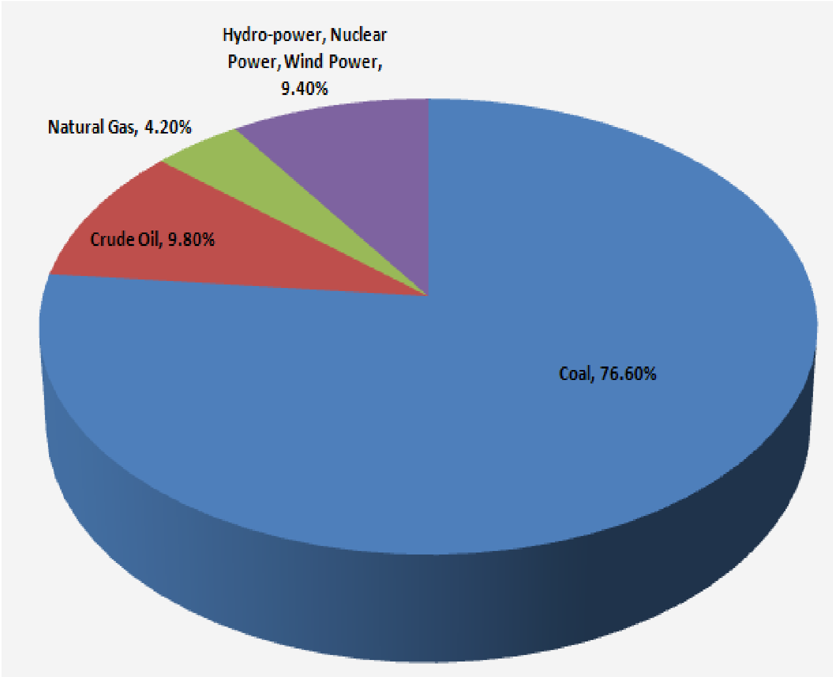

Figure AI.4 Electricity Supplied by Fuel Type in China 2010, (National Bureau of Statistics of China, 2010)

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APPENDIX II: Research Groups in Sustainable Manufacturing

Laboratory for Manufacturing and Sustainability (LMAS), http://lma.berkeley.edu/

Centre for Sustainable Manufacturing and Recycling Technologies, SMART, http://www.centreforsmart.co.uk/

Joint German-Australian Research Group, http://www.sustainable-manufacturing.com/

The Institute for Sustainable Manufacturing, http://www.ism.uky.edu/

APPENDIX III: Tabular Implementation of Proposed Framework

The example below shows a tabular implementation of proposed sustainability improvement framework. The tables can be generated from the Excel spreadsheet presented in section 7.4.1.

Table AIII.1 shows feasible results of specific energy consumption with the constraints of cutting force ($Ft \leq$ 400N, shown in Table AIII.2), cutting speed (75m/min $\leq Vc \leq$ 120m/min, shown in Table AIII.3) and surface roughness ($Ra \leq$ 12.5μm, shown in Table AIII.4). The red region in the tables shows the result of the objective and constraints are not feasible. The green region in the tables shows the feasible results after constrained. Then, practitioners can select the optimal results from the feasible results.

Table AIII.1 Feasible Results of Specific Energy Consumption with Constraints of Cutting Force, Cutting Speed and Surface Roughness

500	39.01631	22.12691	16.43118	13.55406	11.81146	10.63938	9.795096	9.156737	8.656352	8.253012
1000	23.80092	14.39107	11.19739	9.575239	8.587814	7.920581	7.437849	7.071351	6.782934	6.549579
1500	18.66318	11.75539	9.400355	8.199582	7.466129	6.968936	6.608158	6.333487	6.116764	5.940976
2000	16.06507	10.41224	8.478584	7.489853	6.884381	6.472988	6.173825	5.945602	5.765185	5.618583
2500	14.48987	9.592219	7.912531	7.051782	6.523655	6.164177	5.902339	5.702284	5.543908	5.415042
3000	13.4294	9.036587	7.526939	6.75199	6.275778	5.951187	5.714456	5.533369	5.38985	5.27295
3500	12.66482	8.63357	7.245877	6.532542	6.093655	5.794171	5.575529	5.40812	5.275325	5.167069
4000	12.08625	8.326859	7.030992	6.364105	5.953386	5.672871	5.467907	5.310851	5.186179	5.084477
4500	11.63237	8.084943	6.86077	6.23019	5.841511	5.575853	5.381612	5.23268	5.114387	5.017836
5000	11.26623	7.888788	6.722182	6.120788	5.749845	5.496152	5.310556	5.168178	5.055036	4.962648
n(rpm)/ fz(mm/tooth)	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09	0.1

Table AIII.2: Constraint of Cutting Force ($Ft \leq$ 400N)

500	143.5538	248.4631	342.4739	430.0402	513.1065	592.7543	669.6672	744.314	817.0344	888.0853
1000	124.2315	215.0201	296.3771	372.157	444.0426	512.9699	579.5304	644.1298	707.0621	768.5495
1500	114.158	197.5848	272.3448	341.9799	408.0366	471.3747	532.5381	591.8993	649.7285	706.2302
2000	107.51	186.0785	256.4849	322.0649	384.2748	443.9244	501.526	557.4303	611.8919	665.1032
2500	102.6213	177.6171	244.8219	307.4198	366.8008	423.7381	478.7203	532.0826	584.0677	634.8593
3000	98.79238	170.99	235.6874	295.9496	353.1151	407.928	460.8587	512.23	562.2755	611.172
3500	95.66675	165.5801	228.2306	286.5863	341.9431	395.0218	446.2779	496.0238	544.486	591.8355
4000	93.03925	161.0324	221.9622	278.7152	332.5516	384.1725	434.0209	482.4005	529.5316	575.5807
4500	90.7816	157.1249	216.5762	271.952	324.482	374.8503	423.4891	470.6948	516.6822	561.6139
5000	88.80853	153.7099	211.869	266.0413	317.4296	366.7032	414.2849	460.4646	505.4525	549.4076
n(rpm)/ fz(mm/tooth)	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09	0.1

Table AIII.3 Constraint of Cutting Speed (75m/min ≤ *Vc* ≤ 120m/min)

500	15.70796	15.70796	15.70796	15.70796	15.70796	15.70796	15.70796	15.70796	15.70796	15.70796
1000	31.41593	31.41593	31.41593	31.41593	31.41593	31.41593	31.41593	31.41593	31.41593	31.41593
1500	47.12389	47.12389	47.12389	47.12389	47.12389	47.12389	47.12389	47.12389	47.12389	47.12389
2000	62.83185	62.83185	62.83185	62.83185	62.83185	62.83185	62.83185	62.83185	62.83185	62.83185
2500	78.53982	78.53982	78.53982	78.53982	78.53982	78.53982	78.53982	78.53982	78.53982	78.53982
3000	94.24778	94.24778	94.24778	94.24778	94.24778	94.24778	94.24778	94.24778	94.24778	94.24778
3500	109.9557	109.9557	109.9557	109.9557	109.9557	109.9557	109.9557	109.9557	109.9557	109.9557
4000	125.6637	125.6637	125.6637	125.6637	125.6637	125.6637	125.6637	125.6637	125.6637	125.6637
4500	141.3717	141.3717	141.3717	141.3717	141.3717	141.3717	141.3717	141.3717	141.3717	141.3717
5000	157.0796	157.0796	157.0796	157.0796	157.0796	157.0796	157.0796	157.0796	157.0796	157.0796
n(rpm)/ fz(mm/tooth)	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09	0.1

Table AIII.4 Constant of Surface Roughness (*Ra* ≤ 12.5µm)

500	0.0369	0.051881	0.063324	0.072944	0.081401	0.089033	0.096042	0.102558	0.108671	0.114448
1000	0.0135	0.018981	0.023168	0.026688	0.029782	0.032574	0.035139	0.037523	0.039759	0.041873
1500	0.007497	0.010541	0.012866	0.014821	0.016539	0.01809	0.019514	0.020838	0.02208	0.023254
2000	0.004939	0.006945	0.008476	0.009764	0.010896	0.011918	0.012856	0.013728	0.014547	0.01532
2500	0.003573	0.005024	0.006133	0.007064	0.007883	0.008622	0.009301	0.009932	0.010524	0.011083
3000	0.002743	0.003857	0.004707	0.005422	0.006051	0.006618	0.007139	0.007624	0.008078	0.008508
3500	0.002193	0.003084	0.003764	0.004336	0.004839	0.005292	0.005709	0.006096	0.00646	0.006803
4000	0.001807	0.002541	0.003101	0.003572	0.003987	0.00436	0.004704	0.005023	0.005322	0.005605
4500	0.001523	0.002142	0.002614	0.003011	0.00336	0.003676	0.003965	0.004234	0.004486	0.004725
5000	0.001307	0.001838	0.002244	0.002585	0.002884	0.003155	0.003403	0.003634	0.00385	0.004055
n(rpm)/ fz(mm/tooth)	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09	0.1

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APPENDIX IV: Characterisation of Energy Consumption for Different Cutting Tools

The results below show the characterisation of energy consumption for different cutting tools.

Table AIV.1 shows the energy consumption with the constant cutting process parameters *ap*, *ae*, *fz* and n. The result can also been graphically presented in Figure AIV.1. The result shows that the energy consumption of machining operation monotonically reduces with the increase of the diameters of the cutting tools and number of flutes. This characteristic of energy consumption is the same as the characteristic identified in Chapter 3 with the consideration of other process parameters (such as, depth of cut, width of cut, spindle speed and feed rate per tooth). It means for machining a same amount of material, using larger, more flutes cutting tools is more energy efficient.

Table AIV.1: Specific Energy Consumption for Different Cutting Tools (Constant Process Parameters)

8	7.5822	6.0261	5.3175
10	7.4542	5.8722	5.1419
16	7.2341	5.6074	4.8400
20	7.1493	5.5053	4.7236
d/z	2	3	4

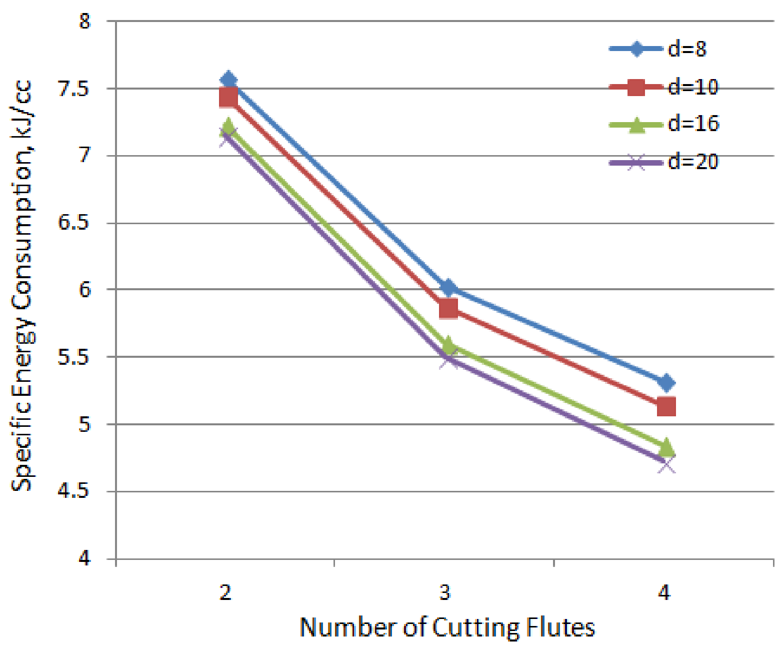

Figure AIV.1 Specific Energy Consumption for Different Cutting Tools (Constant Process Parameters)

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The result is Table AIV.2 and Figure AIV.2 shows the energy consumption of the slotting operation by using different tools with the constant *ap*, *fz* and *n*. The result can further identify more reduction in energy consumption for using larger diameter and more flutes cutting tools.

Table AIV.2: Specific Energy Consumption for Different Cutting Tools (Slotting Operation with Constant *ap, fz* and *n*)

8	5.5583	4.6569	4.2731
10	4.7576	4.0489	3.7521
16	3.5323	3.1076	2.9374
20	3.1142	2.7822	2.6524
d/z	2	3	4

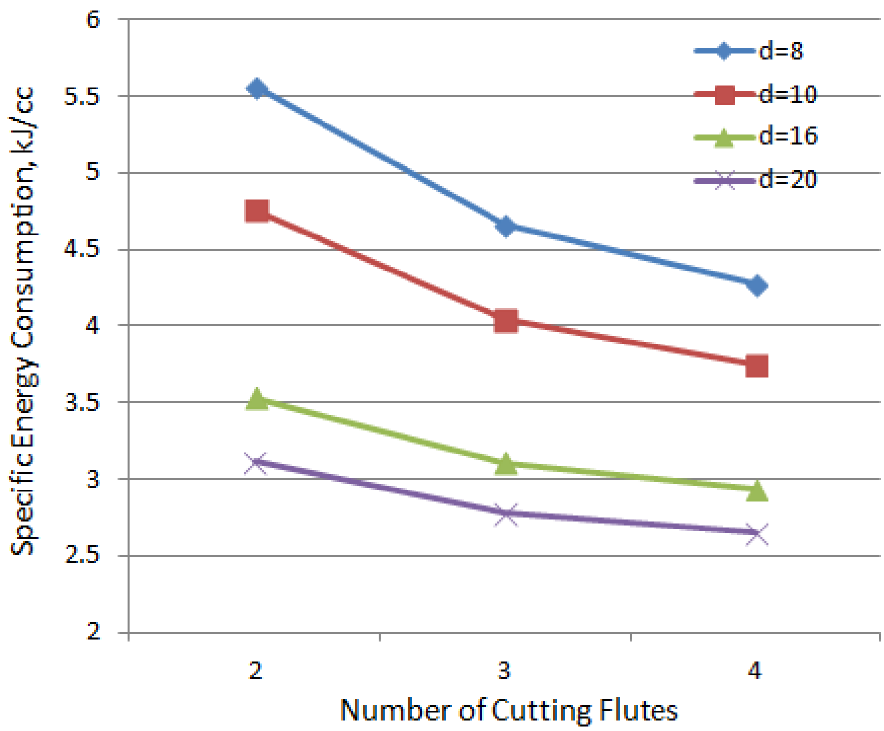

Figure AIV.2 Specific Energy Consumption for Different Cutting Tools (Slotting Operation with the Constant *ap, fz* and *n*)

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APPENDIX V: Additional Figures of Plot Matrix (Figure 4.1)

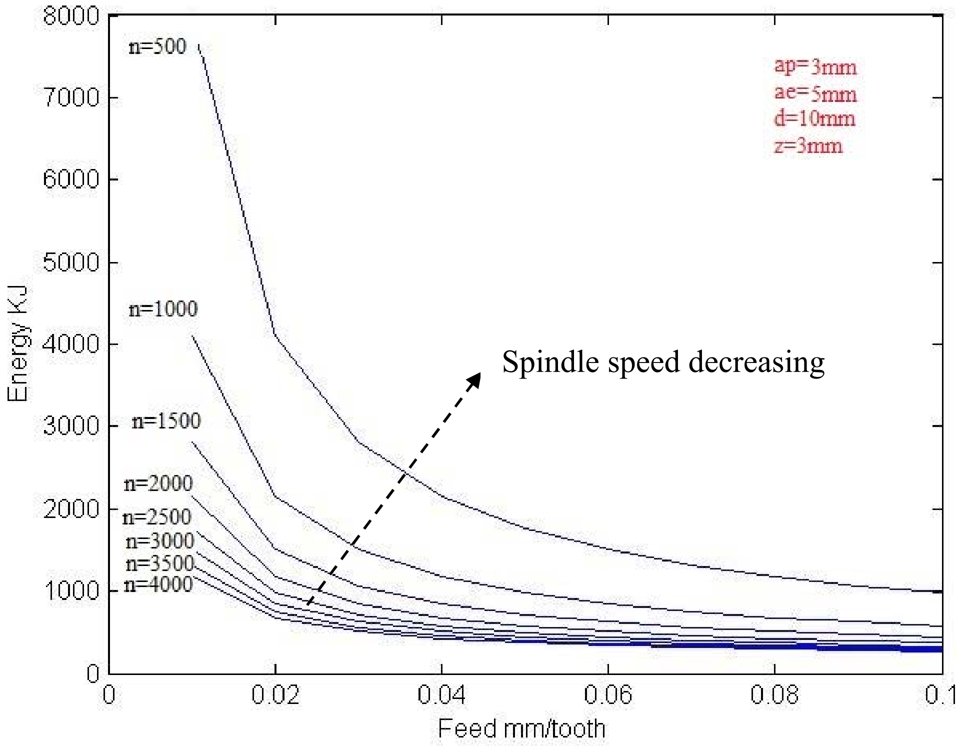

Figure AV.1 ap=3mm, ae=5mm, d=10mm, z=3

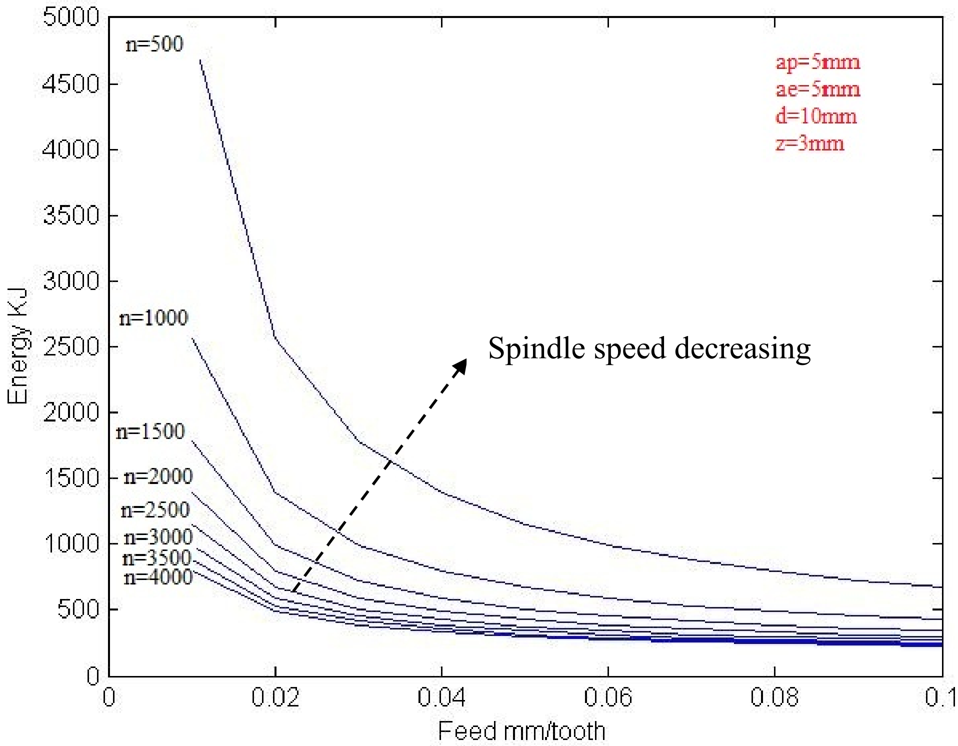

Figure AV.2 ap=5mm, ae=5mm, d=10mm, z=3

`

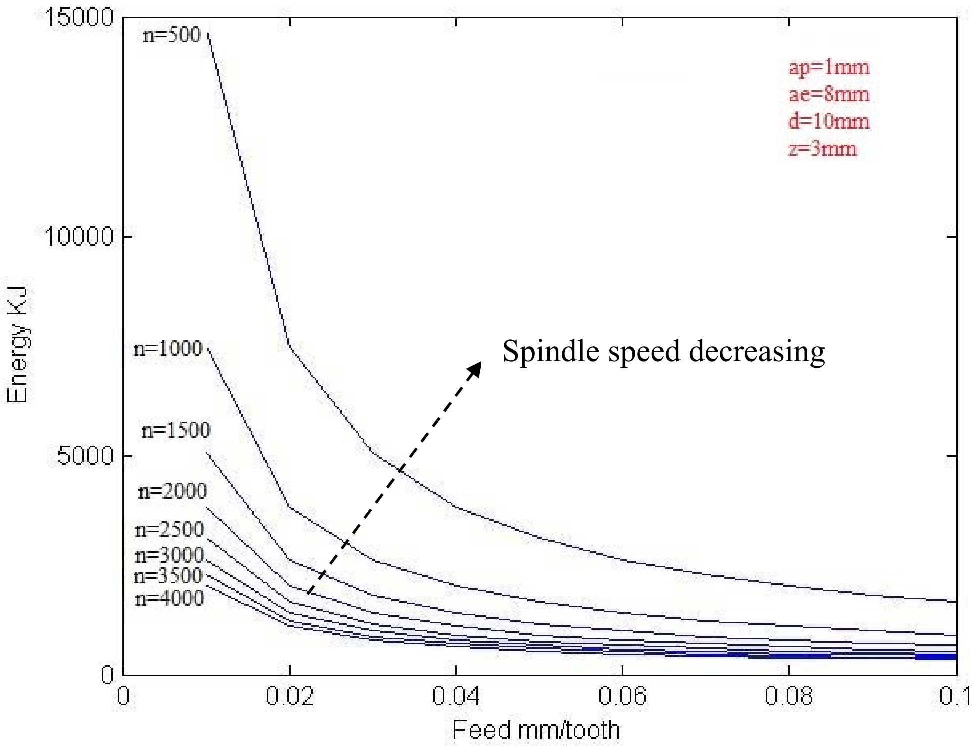

Figure AV.3 ap=1mm, ae=8mm, d=10mm, z=3

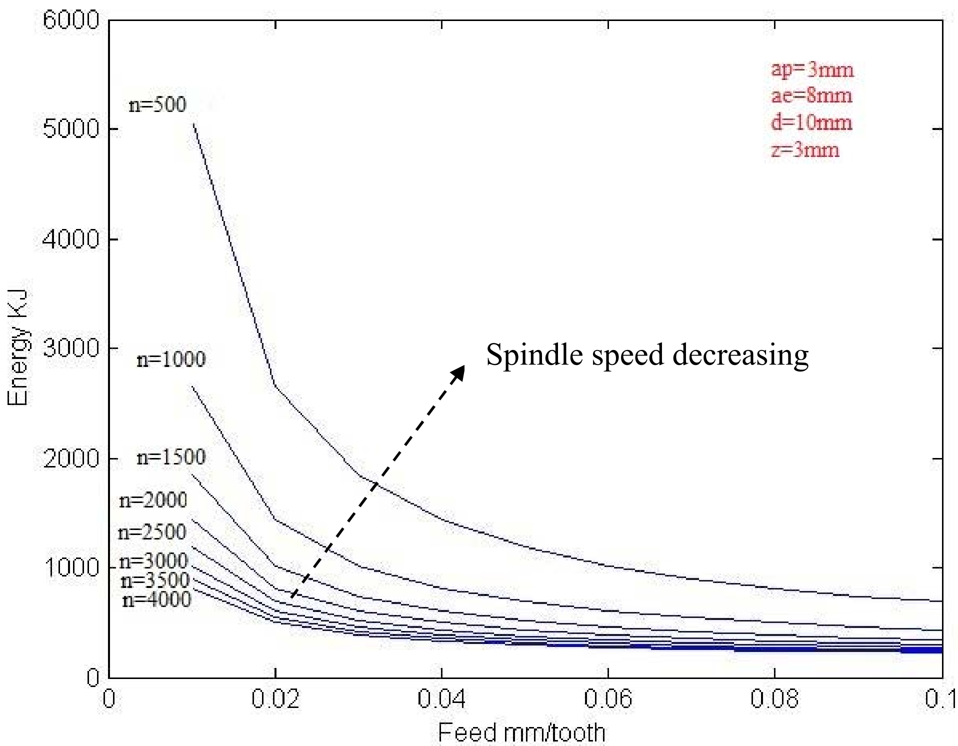

Figure AV.4 ap=3mm, ae=8mm, d=10mm, z=3

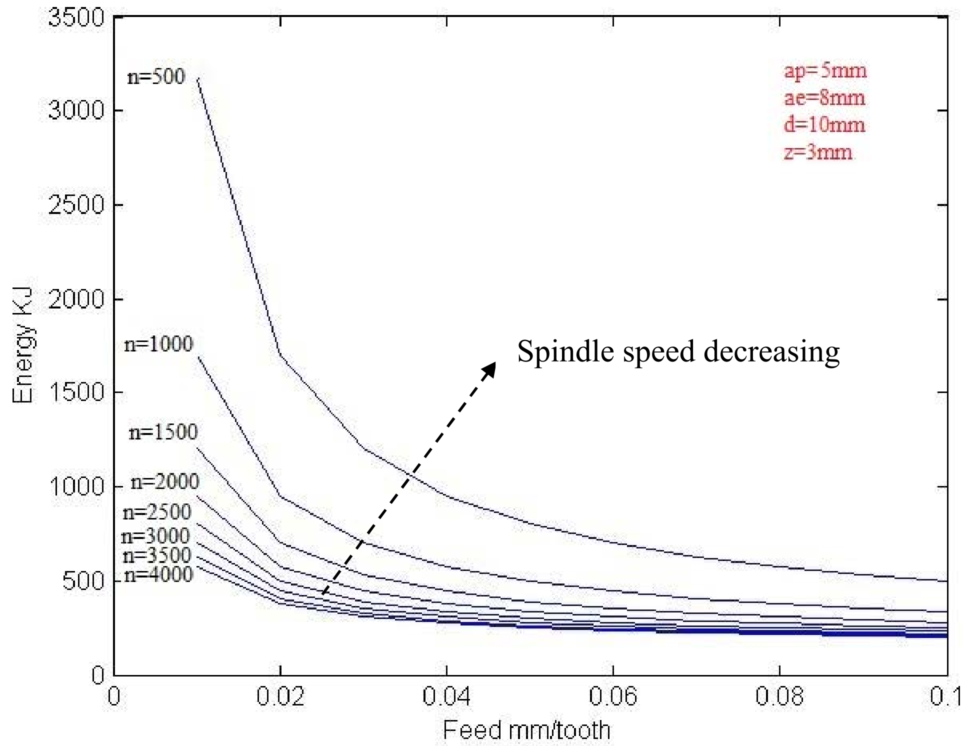

Figure AV.5 ap=5mm, ae=8mm, d=10mm, z=3

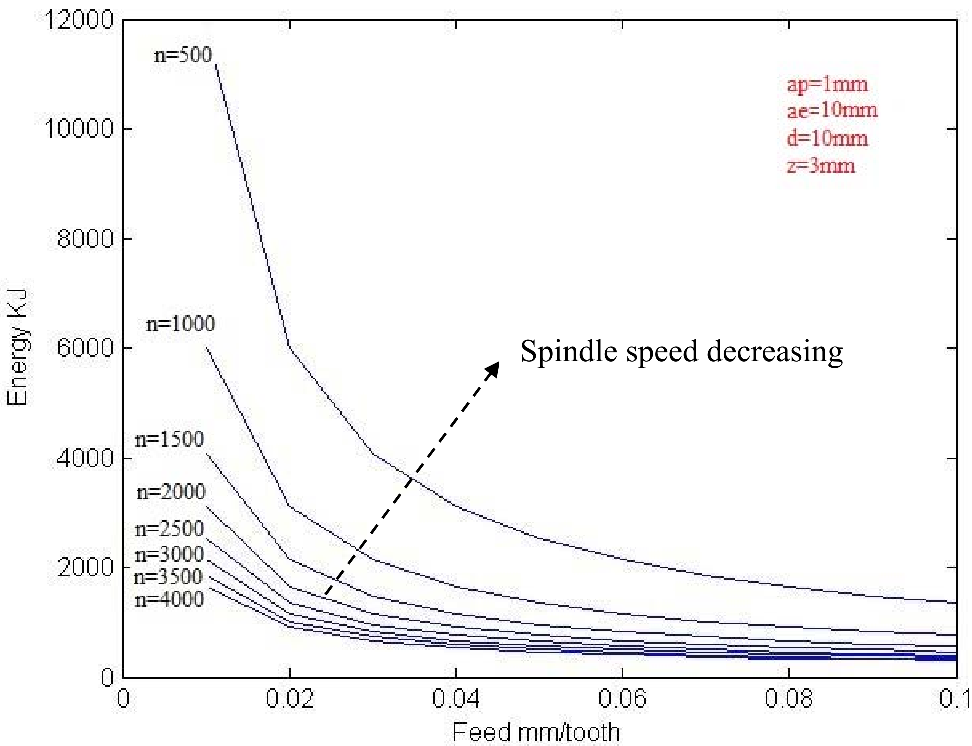

Figure AV.6 ap=1mm, ae=10mm, d=10mm, z=3

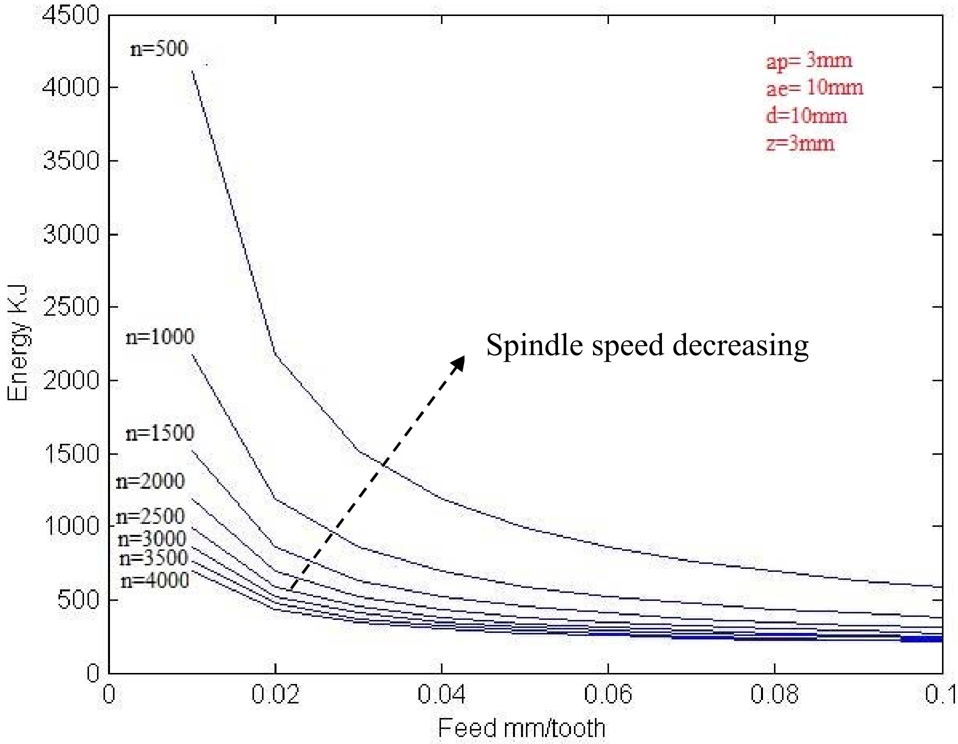

Figure AV.7 ap=3mm, ae=10mm, d=10mm, z=3

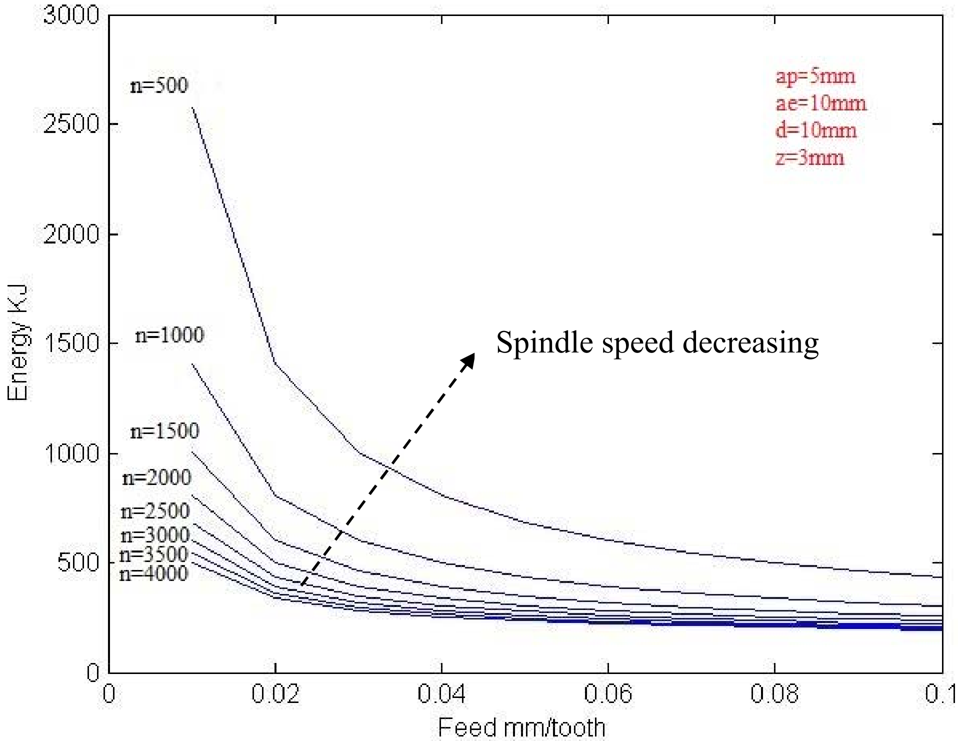

Figure AV.8 ap=5mm, ae=10mm, d=10mm, z=3