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An innovative method for process planning for sustainable manufacturing

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An Innovative Method for Process Planning for Sustainable Manufacturing

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ABSTRACT

The goal of this thesis is to address the urgent industrial need for energy efficient Computer Numerical Control machining systems by developing effective empirical energy consumption models and optimisation approaches for energy efficient machining processes.

In the thesis, a comprehensive literature survey has been conducted to identify industrial needs, the state-of-the-art energy consumption modelling and optimisation methods. Related research has been analysed and benchmarked. Based on the survey, research gaps have been identified.

To develop effective energy consumption models is an essential step to achieve sustainable machining processes. Based on literature survey, it is recognised that there is a lack of models suitable for various types of machining processes, in particular, milling processes. In this thesis, based on Main Effect and Interaction Plots techniques, qualitative analysis has been made to establish relationships between critical machining parameters (including spindle speed, feed rate, depth of cut and width of cut) and the energy required for machining. Effective energy consumption models that can be configurable for various machining processes have been developed. Two different model structures are proposed according to the model selection criteria used.

Application of sensible optimisation methods will be imperative for implementing energy efficient machining processes. In this thesis, based on the energy consumption models, two optimisation methods have been developed to identify optimal machining parameters to achieve the minimum energy consumption during machining processes.

It is concluded that new and effective models and optimisation methods have been developed in the thesis. Future research directions have been summarised in the thesis.

Keywords: Sustainable Manufacturing, Energy Consumption, Optimisation, Milling Process, Modelling

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List of Abbreviations

a_e	Width of Cut
ANOVA	Analysis of Variance
a_p	Depth of Cut
CE	Cutting Energy
CNC	Computer Numerical Control
D	Tool Diameter
DE	Direct Energy
f	Feed Rate
GA	Genetic Algorithm
lb	Lower Bound
LSM	Least Squares Method
MINLP	Mixed Integer Nonlinear Programming
N	Number of Tool Teeth
PS	Pattern Search
PSO	Particle Swarm Optimisation
R^2	Coefficient of Determination
RMSE	Root-Mean-Square Error
RSM	Response Surface Methodology
R-sq adj	Adjusted Coefficient of Determination
S	Spindle Speed
SA	Simulated Annealing
SEC	Specific Energy For Cutting
SS_{res}	Sum Of Squares Of Residuals
SS_{tot}	Total Sum Of Squares
Sz	Feed Per Tooth
up	Upper Bound
v_c	Cutting Speed

Chapter 1: Introduction, Motivation and Outline

1.1 Introduction and Motivation

Manufacturing is the backbone of economies in industrialised nations (Rao 2011). The increase in energy demand, with the associated environmental and economic aspects, has been a worldwide concern in recent decades, and the manufacturing sector is at spotlight of energy usage. According to U.S. EIA (2010), this sector was responsible for approximately one-third of the primary energy usage and 38% of CO_2 emissions globally. Moreover, government leaders are increasingly aware of the urgent need to make better use of world's energy resources. A series of policies, commitments and guidelines on lifecycle energy/carbon-related management have been launched towards a reduction in greenhouses emissions, which have encouraged and supported efficiency improvements by industrial firms (Geller *et al*. 2006). Therefore, a reduction in energy demand of production systems is of prime importance.

Since the third industrial revolution, in the early 1970s, Computer Numerical Control (CNC) machines and machining became predominant in industry, especially in high-precision automotive and aerospace sectors. Furthermore, according to Liu *et al.* (2013), CNC machines are identified as the basis energy-consuming devices in manufacturing systems. For this reason, CNC machine and machining processes have been the focus of research communities all over the world.

Machining process planning is the stage that defines the operation sequences and the appropriate machine tools, cutting tools and machining parameters, which greatly determines the quality and energy consumption of production. The success of machining operations depends on the selection of machining parameters via process planning, which is usually done based on the planner engineer or operator's experience and/or handbooks recommendations. However, it is not easy to choose the optimal parameters in order to obtain the best machining performance, even for experienced machinists.

Currently, the global scenario highlights the urgent need for energy savings as well as more sustainable manufacturing processes. This scenario together to the wide use of CNC machines in the industry sector, the high impact of those on the energy demanded by production systems and the current way that machining process planning is decided, demonstrate that studies on optimisation of CNC machining operations yet in the planning stage is imperative and urgent.

To date, some energy consumption modelling and optimisation approaches for the process planning stage for CNC machining processes have been developed – this will be further described in the following chapters. However, CNC machining processes are complex in terms of various machining parameters, tooling selection, machining strategies and operations. For this reason, knowledge gaps are still existent indicating that effective modelling and optimisation approaches need to be employed to achieve better solutions for the problems.

In addition, as the world, industry and customer requirements would embrace more sustainable best practices and industrial regulations, approaches for process planning optimisation must comply with the energy-saving objectives and constraints imposed by the sustainable trends. As a consequence, more effective energy consumption modelling and optimisation algorithms, techniques, solvers and methods are imperative to be developed.

A common issue found in existing research in this area is the applicability of models and optimisation approaches, and also the reproducibility. Usually, those are either too complex or too specific to a particular experiment. This fact also describes the challenge within this research area itself, once machining processes are wide and the existent operations have many particular specifications, which make it difficult for one single model to be generalised to all operations.

Thus, in response to this scenario, this research is motivated to accomplish with effective predictive energy consumption models for milling operations, which can aid in the machining planning stage to achieve sustainability during production. Moreover, based on the empirical models, optimisation approaches to support energy efficient process planning should be also developed. The research issue found in this area will be addressed by the developed models and approaches that are easy to be adopted by industry and can be replicated and extended to different cases.

1.2 Aim and Objectives

The primary goal of this thesis is to develop empirical modelling and an optimisation approach for CNC machining processes. Case studies are carried out with the main goal to validate the developed research. Furthermore, this research focuses on a detailed development of an empirical model for energy consumption, and further an optimisation approach to identify the best machining cutting parameters for milling processes.

The main aim of this thesis is divided into the following three objectives:

I. To conduct comprehensive literature surveys on the research areas to identify the research status, gaps and further directions.

II. To develop a statistical technique-based predictive energy consumption model for qualitative analysis of a set of machining operations experimental data so as to provide an effective means for machinists to determine the machining variables during process planning qualitatively in order to achieve energy saving during productions.

III. To develop optimisation approaches and compare performance and results of the two different optimisation approaches so as to facilitate machinists to achieve the minimisation of energy consumption quantitatively.

1.3 Thesis Outline

The logical flow of the research work reported within the thesis has a top-down structure, where the development presented in one chapter are predecessors of the development carried out in the following chapter (and chapters) as illustrated in Figure 1-1.

The outline of the presented research work is given chapter by chapter in the order as they appear in the thesis.

Chapter 2: This chapter provides the essential background and literature review of the research area of this thesis. Only the necessary background is provided here. Such background starts with a survey of key aspects that lead the research development trends related to the manufacturing sector and CNC machines in this sector. Then, a comprehensive survey of research development related to energy consumption and efficiency of machine tools is presented, followed by an overview of the need for modelling and optimisation of machining processes. The literature survey is finalised by presenting the research approaches on energy consumption modelling of machining processes. Part of this chapter is presented in (Moreira et al 2015).

Chapter 3: This chapter presents the predictive energy consumption model and the empirical modelling framework designed based on the modelling process carried out in this thesis. It starts with a literature survey on CNC milling processes and empirical modelling, in addition to a background of modelling methods. Subsequently, the methodology brings the details and steps used to achieve the aim of this chapter: to propose a modelling framework and a predictive model for energy consumption as a result of its implementation. Followed by a detailed model development, including qualitative analysis. After that, the results and discussion are presented, and, finally, the chapter conclusions.

Chapter 4: In this chapter, the predictive model, developed in Chapter 4, will be used for the optimisation approach proposed to find optimal values for cutting parameters with the objective to minimise the energy required by cutting processes. The chapter begins with a literature survey on optimisation approaches related to machining processes, including methods applied, optimisation goals and decision variables. Then, the methodology brings the details and steps used to achieve the aim of this chapter. Followed by the implementation of the optimisation problem, its results and discussion, and, finally, the conclusions.

Chapter 5: Conclusions and further work. The research is concluded, the research contributions are highlighted, and the future research is outlined.

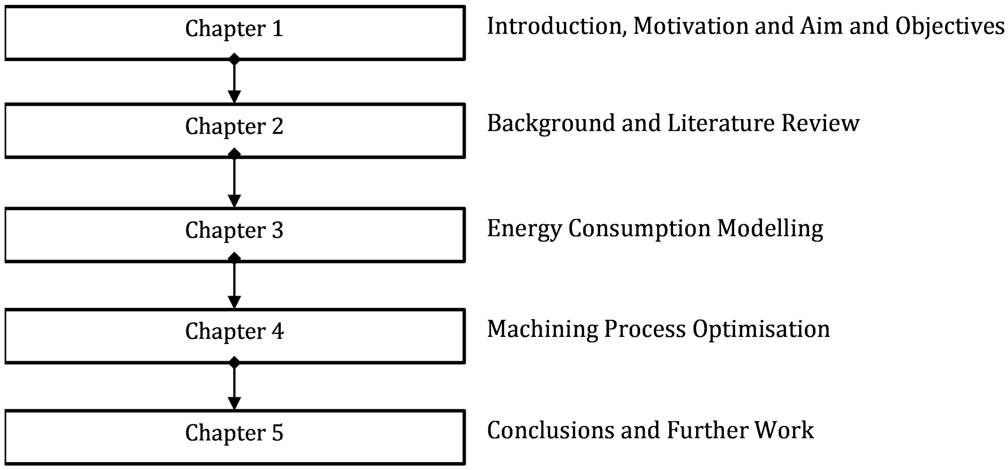

Figure 1-1: Schematic diagram of the logical flow of chapter’s dependency in the thesis.

1.4 Boundaries of Case Study

In this work, sustainability in manufacturing systems is enhanced on the process planning stage by implementing the energy consumption modelling and optimisation approaches hereby presented. Furthermore, case studies for the implementation of the modelling methodology and optimisation approach proposed are used to validate the research. Regardless the fact the specific operation, the methodology proposed can be replicated and extended to different cases and operations in future.

Chapter 2: Background and Literature Review

2.1 Research Background

2.1.1 Manufacturing Industry Trends on Energy Efficiency

According to a report published by BP Energy Outlook 2035 (2014), primary energy demand will increase by 41% between 2012 and 2035, with growth averaging 1.5% per year. The 2002-2012 decade recorded the largest ever growth of energy consumption in volume terms over any ten-year period.

This report clearly suggests that energy consumption is a factor of high concern for the upcoming years. Responsible for one-third of the total primary energy consumption in the world (EIA 2010), manufacturing companies have been under increasing pressure to provide more sustainable production systems.

From the economical perspective, rises in energy, raw materials and wages price are three important factors that justify the urgent need for smarter and more energy efficient processes in manufacturing industries. Furthermore, to remain competitive in a global manufacturing scale, manufacturing companies need to be aligned with legal and environmental regulations. In addition, to comply with new customer and market requirements. Customer environment awareness has led to a green consumer behaviour, in which individuals consider environmental or social issues while making purchasing or non-purchasing decisions (Peattie 1992). This describes the increasing trend for greener products. Therefore, companies are striving to improve productivity and quality, while maintaining a clean and sustainable environment (Gupta *et al.* 2015).

Sustainability can be implemented in the manufacturing sector in different manners. In industries where machine tools are the core of manufacturing processes, the adoption of sustainable techniques such as reduction of manufacturing steps by employing advanced or alternative techniques, use of eco-friendly lubricants and more sustainable lubricant techniques while machining, minimum waste of material and the energy consumption reduction are of great importance to achieve eco-friendly machining processes (Gupta *et al.* 2015).

Leading countries in the manufacturing sector, such as China, Germany, the US and Japan have reported a high significance of the energy consumption of their manufacturing sector. China, which presents the fastest economic growth rate recently, emerged as the key contributor to the growth of energy consumption over the last decade. Moreover, in this country, the manufacturing sector is responsible for approximately 50% of the entire electricity produced and generates at least 26% of the total CO_2 emissions (Tang *et al.* 2006). The industrial production in China increased 6% in July of 2015 over the same month in the previous year. It has averaged 12.84% annual growth from 1990 until 2015 (China statistical yearbook 2014). Together, the U.S. and China account for over one-third of global greenhouse gas emissions (White House fact-sheet 2014). As the world's third largest emitter, India is coming under increasing pressure to comply with commitments and targets (India's NAPCC 2008). Moreover, the industry sector in Germany consumes around 46% of the country's overall energy (König 2010). For comparison, in 2013, the industry sector accounted for 25.1% of the final energy consumption in Europe.

According to IEA's World Energy Outlook (2014), effective policy commitment to energy efficiency is essential. In addition, without this policy commitment, international efforts to help and assist developing countries will not be able to fully succeed (Janssen 2010). A number of policies and agreements have been launched by governments in the past decades, Table 2-1 brings a few important commitments and initiatives related to climate change and energy efficiency that affect the manufacturing sector, established in recent years.

Table 2-1: Recent policies, commitments and initiatives for energy saving.

Country/Region	**Content**
Worldwide	"United Nations Climate Change Conference Paris COP21" (2015): keep the rise in temperature below 2°C per year (COP21 2015).
Europe	"2030 Framework" (2014): new energy efficiency target of 27% or greater by 2030 (European Commission 2014).
China and USA	"US-China Clean Energy Research Center (CERC)" (2014): 150 million USD - CERC primarily researches advanced coal technologies, electric vehicles, and enhanced energy efficiency (Climate nexus 2014).
Germany	"Energy Concept 2050" (2010): Greenhouse gas emissions should have been reduced by 40% by 2020, 55% by 2030 and at least by 80% by 2050 (Climate Action Plan 2050 2015).
India	"National Mission for Enhanced Energy Efficiency" (2008): an initiative to address national problems of inefficient energy use (India's NAPCC 2008).
China	"Premier Wen Jiabao speech" (2008): target to reduce energy consumption for every 10,000 yuan (1,298 U.S. dollars) of GDP by 20% by 2010, while

	pollutant discharge should drop by 10% (Chow 2008).
United Kingdom	"CRC Energy Efficiency Scheme" (2007): is a mandatory carbon emission reporting and pricing scheme to cover large public and private sector organisations (Carbon Trust 2015).

From Table 2-1, it can be seen that countries must continue to apply efforts to reduce energy consumption and that energy efficiency is a spotlighted topic.

According to CIMA (2010), the manufacturing sector is seen as a source of stronger and more sustainable growth. As a major source of energy consumption in manufacturing systems, CNC machines can be an important key to promoting more sustainability in this sector. For this reason, different research approaches for CNC machines and machining processes have been carried out and appeared to be of great value to support the challenges faced by the industry sector.

2.1.2 CNC Machines in the Manufacturing Industry Sector

Production systems can be divided into two main energy consuming sources: transportation and transformation of raw material. The third industrial revolution, on the early 1970s, landmarked the migration from manual production to automated systems, in which machines controlled by computer hardware and software have become predominant to enhance productivity and/or quality of machining processes. Moreover, with the rise of employment costs and the economy slowdown of most western countries in the same decade, CNC machines become predominant in manufacturing processes, displacing older technologies such as hydraulic tracers and manual machining (CNC cookbook 2015).

Nowadays, there are different types of CNC machines which can be found on a small scale to a large manufacturing companies. It can be used in industries for removing materials, where machining operations such as turning, milling, drilling, boring and so on are performed; for transforming materials, where the machining processes are performed on thin metal plates and machines perform processes such as bending, shearing, plasma cutting, punching, laser cutting, forming, welding, etc., in addition to, Electro-Discharge Machining (EDM) industries, where sparks burn the material to be removed.

Research in machine technology, machine and product design, process planning and machining strategies have been achieved in past years. Nevertheless, the requirements that machining processes have to meet change accordingly to new environmental and energy efficiency aspects, as well as to the economic scenario, as previously mentioned. Such requirements make the need for continuous improvements of machining equipment, process planning and machining strategies towards sustainability to be imperative.

In this regard, an important action was taken by the International Organization for Standardization (ISO) to develop the standard *Environmental evaluation of machine tools* (ISO14955-1 2014). The standard includes three main parts: 1) eco-design methodology for machine tools; 2) methods for testing of energy consumption of machine tools and functional modules; and, 3) test pieces/test procedures and parameters for energy consumption on metal cutting machine tools. This ISO shows that different approaches can be adopted to improve the performance of machine tools.

In the last years, various research projects have been addressed to improve CNC machining processes, which are commonly evaluated in terms of energy consumption, productivity and surface quality. Table 2-2 lists some topics and related research work on the field.

Table 2-2: Research topics on energy consumption of machining.

Research topic	**Related work**

Eco-design of machine equipment/product.	Braungart et al. (2007), Lopes De Lacalle et al. (2011), Kok-Soo and Sheng (2010), Rossi et al. (2013)
Analysis of machining parameter/machining configuration.	Newman et al. (2012), Rajemi et al. (2010), Xue et al. (2010)
Machining operation sequence/tool path optimisation.	Qudeiri et al. (2007), Lazoglu et al. (2009), Kong et al. (2011)
Machining behaviour/motion evaluation.	Avram and Xirouchakis (2011), Lv et al. (2015), Tang (2012)
Machining monitoring.	Wang (2013), Segreto et al. (2013), Behrendt (2013), Hu et al (2012)
Multi-objective optimisation of machining parameters.	Wang et al. (2015), Yan and Li (2013)
Cloud manufacturing.	Wang (2013), Xu (2012)

According to Lv *et al.* (2015), accurate characterization of the energy consumed by machining processes is a starting point to improve manufacturing energy efficiency and reduce their associated environmental impacts. Therefore, it is of utmost importance to comprehend how energy consumption factor in machining processes has been addressed in order to enhance the energy efficiency in production systems.

2.2 Literature Review

2.2.1 Research topics on energy consumption of CNC machines

Energy consumption is a topic of concern in the boardroom and of significant research interest in the last five years (O'Driscoll and O'Donnell 2013). By integrating energy consumption criteria into a process planning and operating structures, a reduction in process energy demand is to be expected. Consequently, energy modelling of machine tools operations for energy consumption prediction is of prime importance. In the last years, the great amount of publications in this area has shown that lots of effort have been applied to the development of research with respect to the energy consumed by CNC machining processes. For that, different approaches were found and categorised into two stages of the *Product Life Cycle Energy Efficiency Enhancement*, see Table 2-3.

Table 2-3: Research approaches related to energy efficiency of machining.

Product Life Cycle Energy Efficiency Enhancement Approaches		

1. **Production Design stage**	Product design strategies	• Strategies for more sustainable part design
		  • Waste material reduction
		  • Easy-to-perform shapes

	Machine tool innovation design	• New mechanical parts technologies • New parts design • New controllers
	Machine tool auxiliary components innovation design	• Cooling systems strategies/technology • Chip conveyor manners • New cutting tools (shape, technology, material)

2. **Production Execution stage**	Non-productive machining	• Reduction of idle time:
		  • Tool path topology/strategy
		  • Process planning and scheduling strategies

	Machining performance	• Strategies for cutting:
		  • Tool path geometry
		  • Number of passes
		  • Tool selection
		  • Machining cutting parameters selection

The *Production design stage,* shown in Table 2-3, is aimed at implementing sustainability through the new design of machine components and auxiliar components, for further information refer to (Braungart *et al.* 2007). The second stage *Production Execution* focuses on refining the strategies to enhance the performance of machining processes, using the resources (machine, tools, product design, etc.) currently available, for further information refer to (Avram, O. I. and Xirouchakis, P. 2011). Despite the divergence in focus, both research directions are complementing and converge to the same impact on the future of manufacturing: more efficient production processes.

Some topics and respective related work published recently are presented in Table 2-4.

Table 2-4: Research publications topics on energy consumption and efficiency of machining.

Research topic	Related work
1. Eco-design of machine equipment or product.	Braungart *et al.* (2007), Lopes De Lacalle *et al.* (2011), Kok-Soo and Sheng (2010), Rossi *et al.* (2013)
2. Analysis of machining parameter, machining configuration.	Newman *et al.* (2012), Rajemi *et al.* (2010), Xue *et al.* (2010)
3. Machining operation sequence, tool path optimisation.	Qudeiri *et al.* (2007), Lazoglu *et al.* (2009), Kong *et al.* (2011)
4. Machining behaviour, motion evaluation.	Avram and Xirouchakis (2011), Lv *et al. (2015), Tang (2012)*
5. Machining monitoring.	Wang (2013), Segreto *et al.* (2013), Behrendt (2013), Hu et al (2012)
6. Multi-objective optimisation of machining parameters.	Wang *et al.* (2015), Yan and Li 2013)
7. Cloud manufacturing.	Wang (2013), Xu (2012)

The scope of this research project is limited to investigations within the Production Execution stage - the execution stage is investigated in order to support the development of smarter approaches to aid in the process planning phase of machining processes. Many research work has been published in the past years in which researchers' goals are to achieve better machining performance as well as an understanding of CNC machining operations. The work summarised in Table 2-4 from Topics 2 to 7 are, mainly, within the stage 2, Production Execution. Nonetheless, in Topic 1 some related work on the Production Design stage is provided. In addition, findings from research on stage 2 may support research & development on the topics from stage 1.

Furthermore, understanding the relationship between inputs (machining variables) and outputs (e.g., energy consumption) can be taken as a preliminary topic for the development of the research topics listed in Table 2-4.

In such topic, a behaviour of a chosen output is studied by the selection of different input variables. The knowledge construction process lies on the relationship modelled between independent and dependent variables – input and output, respectively. In other words, machining variables (usually 2 up to 4) are chosen for experimental designs, in which the behaviour of the output (energy consumption) variable will be observed or measured during the experimental tests. The measurements obtained, together to the experimental design, allow a relationship and analysis to be drawn.

2.2.2 Need for Modelling and Optimisation of Machining Processes

In the current manufacturing environment, many large industries use highly automated and computer-controlled machines as their strategy to adapt to the ever-changing competitive market requirements (Rao 2011). Due to the high capital and manufacturing costs, besides the legal and environmental aspects, there is an urgent need to operate these machines as efficiently as possible in order to obtain the required payback, as well as to attend the overall requirements of such dynamic and globalised market.

Furthermore, according to (Rao 2011, Newman 2012), the success of manufacturing processes depends on the selection of the optimum process parameters. This step is of paramount importance for defining the quality of the machined part, shop floor productivity and production costs. Despite its role in the output of manufacturing processes, the selection of process parameters is still done based on machinists' experiences and machining handbooks.

Consequently, considering the significance of such step together to the economic, legal, social and environmental aspects in which the manufacturing sector has to deal with, may researchers have been addressing this problem in order to provide more intelligent and sustainable solutions that can support this decision-making process. However, (Shunmugam and Narendran 2000, Rao 2011) highlights that modelling and optimisation of process parameters of any manufacturing process are not an easy task, and some aspects have to be considered, such as knowledge of manufacturing process, empirical equations to develop realistic constraints, development of an effective optimisation criteria, as well as knowledge of mathematical and numerical modelling and optimisation techniques.

It is known that the performance of machining processes is affected by many factors and a single parameter change can influence the process in a complex way. Because of the many variables and the complex (see Figure 2-1 for a detailed variables network scheme) and stochastic nature of the process, achieving the optimal performance, even for a highly experienced and skilled machinist is rarely possible (Rao 2011).

In this thesis, the focus of modelling and optimisation of machining process lies on finding the optimum machining cutting parameters that generate the lowest energy consumption for the machining process. Thus, in the next section, a comprehensive survey of the research approaches on energy consumption modelling of machining processes is provided.

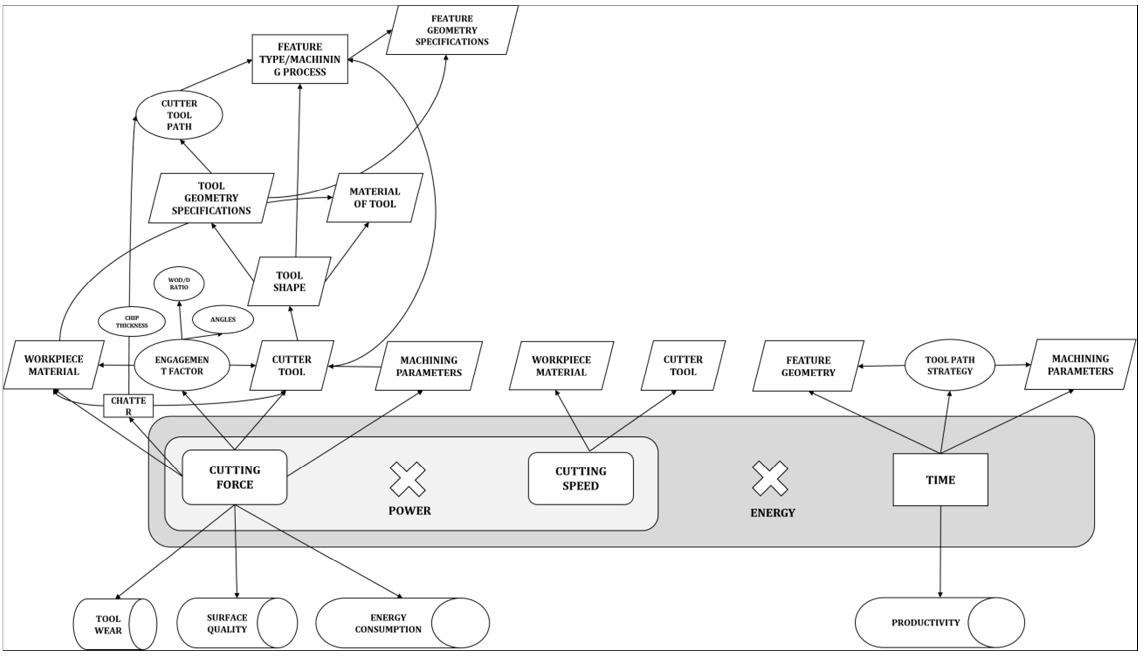

Figure 2-1: Variables network Banyan tree of machining operations. (Source: Author)

2.2.3 Research Approaches on Energy Consumption Modelling of Machining Processes

Investigations on ways to increase the energy efficiency of machining have lied on the energy consumption modelling approach used for such processes. Energy consumption models are used to describe the relationship between a part to be machined and the energy demanded by the machine to do the job, which according to (Rao 2011), is the first step for process parameter optimisation. The relationship described by a model can be a function of different aspects (or variables), which varies according to the approach and strategies used.

Although the main goal is equivalent – to enhance the energy consumption efficiency of machining process – modelling approaches and strategies differ according to different modelling purposes, resources available, process specifications, as well as models' application. However, the literature shows there are two main approaches commonly applied: empirical and mechanistic approaches. These represent the roots of several research branches, characterised by the use of different methods and techniques for modelling.

A classification of the existent approaches and calculation structures for developing and applying, respectively, the energy consumption models and its analysis is provided in Table 2-5. In Table 2-5, the inputs for developing the model and for running the calculations are described. Moreover, an analysis based on the advantages and disadvantages of each approach is presented.

The decision to choose the best modelling approach depends on the modelling reason as well as the application of the model. Hence, different purposes for developing an energy consumption model lead to the selection of different methods and calculations structures. It is essential that the question '*Why/What for modelling*' is answered prior to defining '*How to model*'. Therefore, it is critical that prior to selecting the modelling approach to be used, the modelling whys and wherefores and its application are well clear. This includes specifying which type of energy consumption would be modelled (if total or specific), and, if total, define the energy consumption decomposition within a machining process.

Table 2-5: Approaches and structures related to energy consumption models.

	Type	Description	Advantages	Disadvantages
APPROACHES	1. Empirical modelling	Energy consumption (EC) model is developed using statistical techniques to fit an equation to data obtained from experimental tests. This method has been used for the direct energy (DE) – required by the entire machine tool system (*MTS*) – or limited to the cutting process (*SEC*) – specific energy for cutting. The inputs for the equation are usually the machining parameters such as depth of cut (a_p), width of cut (a_e), feed rate (f) and cutting speed (v_c)	- With the use of coefficients, it can be adaptive to different workpiece materials/cutter tool. - Usually, presents good accuracy.	- It requires running several experiments and accurate data measurements to be developed. - Some models are limited to the conditions used in experiments.

		Development inputs - experimental data.	- Practical for the decision maker in the planning stage.	- Some models have coefficients that require experiments to be obtained.
		Calculation input: - machining parameters.	- Can be easily created if data is available.	
	2. Mechanistic modelling	EC model considers the cutting force (usually as the main spindle's torque), cutting speed and time, to estimate the energy required to remove the unwanted material.	- It can be used to process for different machining shapes (features) with the same tool.	- The model validation process requires experimental tests.
		The inputs depend on the mechanistic model developed, but, in general, it requires the uncut chip cross-sectional area (A), rake angle (α), depth of cut (a_p), number of tool flutes (Z) and workpiece material's hardness.	- More robust than empirical.	- Lack of flexibility with different cutter tool geometries.
		Development inputs: - machining parameters.		
		Calculation input: - machining parameters.		
STRUCTURE	A. Machining-state based modelling (analytical)	The machining process is divided into operational states. EC model is the sum of each states' energy consumption – which is equal to the power required times the time.	- It's structure is useful for optimisation of machining operational states – reducing idle and monitoring machining efficiency and performance.	- It depends on additional equations to estimate the EC of operational states.
		The inputs vary according to the equations used for each operational state - empirical or mechanistic.	- Provide detailing information for machining process for a better understanding and planning.	- It takes a little bit longer to give a response.
	B. NC code based modelling	The model structure is based on the information extracted from the NC Code generated to run a machining process.	- This structure allows 'modularization' of the machining process, for	- Differences in NC Codes

		example, toolpath can be a configurable and optimised variable.	generation can be a limitation.
	The inputs vary according to the equations used for each operational state - empirical or mechanistic.	- Flexible: Several inputs can be taken, which means different formulas can be used depending on the desired output or process.	
		- Easy to be implemented in cloud platforms.	- Requires generation of NC code for running calculations.

The two approaches presented in Table 2-5, i.e., empirical and mechanistic, have strengths and weaknesses and also require different resources for obtaining the outputs required for developing the model. For the mechanistic approach, for example, a dynamometer for measuring the cutting force during the machining process is usually necessary for data collection and/or model validation. In this approach, the power required by the machining process is a function of the machining forces involved in the material removal process and the machining speed.

Based on the above two approaches, detailed energy consumption models for both the entire machine tool (DE) and specific energy consumption (SEC) of CNC machining processes have been developed. The related work is summarised in Table 2-6.

Table 2-6: Energy consumption models.

Author	Type	Machining Model
1 (Wang et al. *2014)*	*DE*	$E(M_i) = E(M_i)_{idle} + E(M_i)_{.working} + E(M_i)_{.toolchange} + E(M_i)_{.set-up}$
2 (Peng et al. *2013)*	*DE*	$E = \sum_{i=1}^{n} Estatei = \sum_{i=1}^{n}\sum_{j=1}^{m} E_{state_i,component_j} = \sum_{i=1}^{n}\sum_{j=1}^{m} P_{state_i component_j} \cdot t_i$

3	*(Balogun and Mativenga 2013)*	*DE*	$E = P_b \cdot t_b + (P_b + P_r) \cdot t_r + P_{air} \cdot t_{air} + (P_b + P_r + P_{cool} + k \cdot v) \cdot t_c$ *Where* P_b, P_r, P_{cool} *and* P_{air} *represent the basic and ready state powers, coolant pumping power and the average power for a non-cutting approach and retract moves over the component, respectively;* t_b, t_r, *and* t_c *are the basic, ready and cutting times respectively;* t_{air} *is the total time duration of the non-cutting moves;* k *(kJ/cm*^{3}*) is the specific cutting energy;* v *(cm*^{3}*/s) is the rate of material processing.*
4	*(Newman et al. 2012)*	*SEC*	$e = \frac{P}{f.h.D}$ *Where* P *is the power demanded;* f *and* h *are feed rate and depth of cut, respectively; and* D *is the total volume removed.*
5	*(He et al. 2012)*	*DE*	$E_{total} = E_{spindle} + E_{feed} + E_{tool} + E_{cool} + E_{fix}$ *This can be expanded to:* $E_{total} = \int_{t_{me}}^{t_{ms}} P_m dt + \int_{t_{ce}}^{t_{cs}} P_c\, dt + \sum_{i=1}^{m} \int_{t_{fs}}^{t_{fe}} P_i dt + P_{tool} t_{tool} + P_{cool}(t_{coe} - t_{cos}) + (P_{servo} + P_{fan})(t_e - t_s)$
6	*(Avram and Xirouchakis 2011)*	*SEC*	$E_{DE} = E_{aY} + E_{SY} + E_{dY} + E_{run} + E_{cut}$ *This can be expanded to:* $E_{DE} = \int_{t'_0}^{t'_1} P_{aY} dt + \int_{t'_1}^{t'_2} P_{SY} dt + \int_{t'_2}^{t'_3} P_{dY} dt + \int_{t'_0}^{t'_3} P_{run} dt + \int_{t'_1}^{t'_2} P_c dt$
7	*(Mori et al. 2011)*	*SEC*	$\eta = -10\, log \frac{\sum_{i-1}^{n}}{n}$ *Where* y_i *(Wh/cc) is the power consumption per material removal unit, and* n *is the number of experiments per condition.*
8	*(Kong et al. 2011)*	*DE*	$E_{machine} = E_{const} + E_{run-time-transient} + E_{run-time-steady} + E_{cut}$ *The total energy consumption required by a machining process was divided into four types: constant, run-time-transient, run-time-ready and cut.*

		SEC	$E_{cut} = K_{cut} \cdot w \cdot b \cdot z^p \cdot v_f^{1-p} \cdot n^p$	*Where vf is the feed rate,* n *is the rotational speed of the spindle,* w *is the width of cut,* b *is the depth of cut,* z *is the number of flutes of a cutter, and* p *and* K_{cut} *are empirically determined fitting constants.*
9	*(Diaz et al. 2011)*	*DE*	$E = P_{avg} * \Delta t = (P_{cut} + P_{air}) * \Delta t$	*Where* P_{avg} *is the average power demand and* Δt *is the processing time.* P_{cut} *and* P_{air} *are the cutting and air power, respectively.*
		SEC	$e_{cut} = k * \frac{1}{MRR} + b$	*Where* k *is the machines constant,* MRR *is the material removal rate and* b *represents the steady-state specific energy.*
10	*(Li and Kara 2011)*	*SEC*	$SEC = C_0 + \frac{C_1}{MRR}$	*Where* C_0 *is the coefficient of the inverse model,* C_1 *is the coefficient of the predictor, and* MRR *is the material removal rate.*
11	*(Draganesco et al. 2003)*	*SEC*	$E_{cs} = \frac{P_c}{60\eta Z}$	*Where* P_c *is the necessary cutting power at main spindle (kW),* Z *the material removal rate (cm³/min) and* E_{cs} *the specific consumed energy (kWh/cm³).*
12	*(Li et al. 2013)*	*SEC*	$SEC = k_0 + k_1 \cdot n/MRR + k_2/MRR$	*Where* k_0 *is the specific energy requirement in cutting operations,* k_1 *is the specific coefficient of the spindle motor,* k_2 *is the constant coefficient of machine tools and equals the sum of standby power and the spindle motor's specific coefficient;* n *is the spindle speed in rpm.*

Ehmann *et al.* (1997) traced the historical evolution of research in machining process modelling and found that, in general, analytical models do not accurately predict the dynamic forces. Mechanistic and numerical methods are of more recent origin and rely on empirical models and computer simulation techniques. The latter include both mechanistic and finite element methods. It was concluded that a combination of these methods is typically needed to obtain a working model and that mechanistic models showed the most predictive power compared to other methods. For this reason, most current research is steered towards the mechanistic force models (Kadi *et al.* 2014). Nonetheless, such modelling process usually requires specific equipment and a great effort is required for providing a very specific output. In this thesis, empirical modelling was the selected approach due to the favourable trade-off when taking into account development time, resources available and demanded output.

This shows that in spite of empirical models have been widely applied, the modelling procedures need to be revised and improved in order to provide more models that describes the process more precisely and realistically. Hence, next section will describe the empirical modelling process carried out in this thesis based on face milling experimental data.

Chapter 3: Energy Consumption Modelling

3.1 Aim and Objective and Chapter Organisation

The aim of this chapter is to develop an empirical model for energy consumption as a function of machining parameters by combining different statistical techniques and methods for both qualitative and quantitative analysis. For that, an empirical model development framework is proposed, which shows the steps for achieving the aim above. As a result, the best-fit energy consumption model for milling operations is achieved.

This chapter is organised as follows: Section 3.2 provides the introduction and background. Section 3.3 presents the methodology carried out for the energy consumption model development. Followed by the model development details shown in Section 3.4. Finally, the results and discussion are provided in Section 3.5, followed by the chapter conclusions in Section 3.6.

3.2 Introduction and Background

In the modern industry sector the goal is to be able to produce with the lowest energy consumption and cost, highest quality and within the shortest time. These can be described as efficient and sustainable processes. CNC machining processes are at the spotlight of efficiency enhancement, and, furthermore, milling is the second most common method (after turning) for metal cutting (Bernardos and Vosniakos 2002). This operation is further described in the next section.

3.2.1 Milling Operations

In CNC machining, milling is the machining process in which the unwanted metal is removed by a rotating multiple cutter tool in order to obtain the final shape desired. As the cutter rotates, each cutter tooth (or flute) removes a small amount of material from the advancing work for each spindle revolution. Milling is the second most common method for metal cutting (Bernardos and Vosniakos 2002).

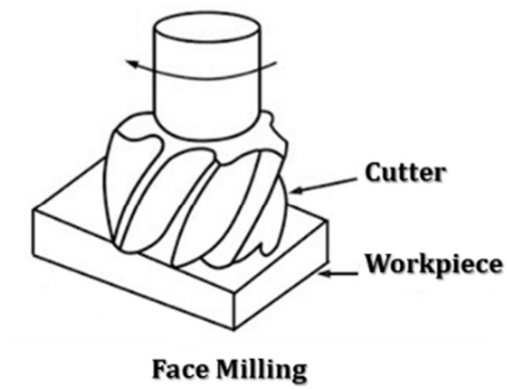

Figure 3-1: Face milling operation.

Face milling operations are used to obtain the final height of a machined part. It can be described as a process of removing material by feeding the workpiece past a rotating multi-point cutter to generate a surface (Shunmugam et al 2000).

Figure 3-1 shows a milling operation. Some independent and dependent variables for milling processes that have been applied in research publications can be seen in Table 3-1.

Table 3-1: Example of variables used in machining experimental designs.

Machining process experimental variables	
Independent Variables	Dependent Variables
• Feed per tooth (S_Z) • Feed rate (f) • Cutting speed (v_c) • Spindle speed (S) • Depth of cut (a_p) • Width of cut (a_e) • Tool diameter (D) • Number of tool flute (N) • Tool Helix angle • Tool Rake angle • Tool engagement • Cutting tool path	• Total energy consumption (TEC) • Specific energy consumption (SEC) • Cutting force (CF) • Surface finish (SF) • Productivity (time) (P) • Material hardness (MHar) • Tool wear (TWea) • Tool vibration (TVib) • Residual Stress

3.2.2 Empirical Modelling

The empirical approach for modelling machining process outputs has been frequently adopted and proved to deliver accurate models. A framework for the empirical modelling process is described in Figure 3-2.

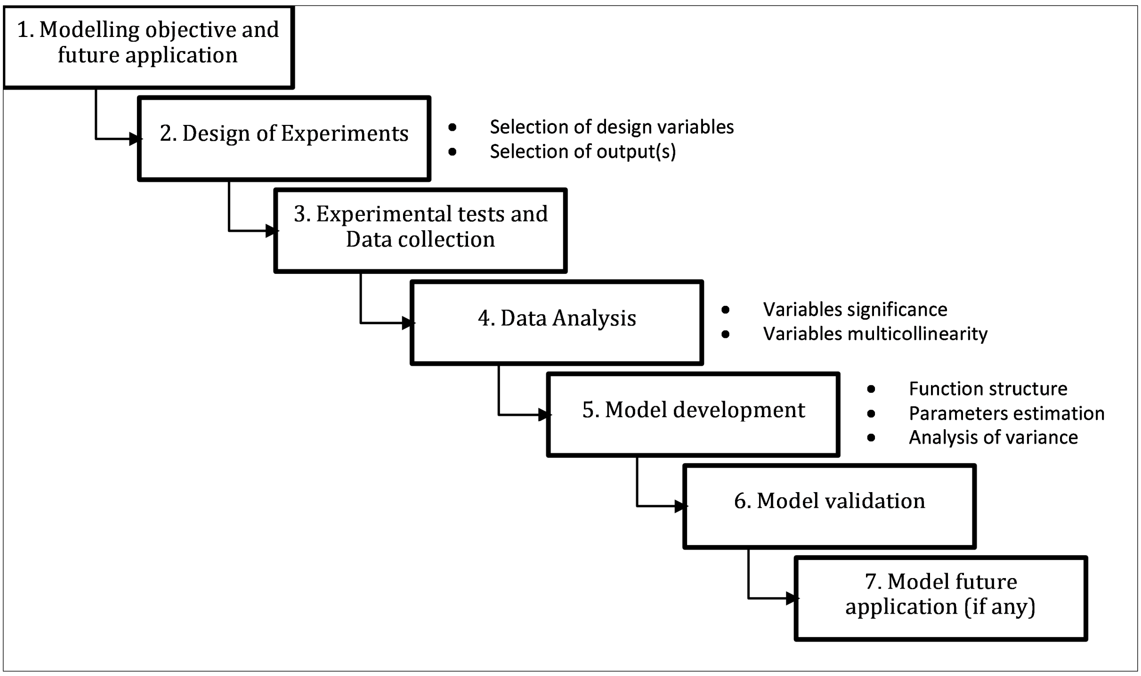

Figure 3-2: Empirical modelling process. (Source: Author)

Several methods and techniques have been used in each of the stages comprised in the empirical modelling process. The selection of the methods to be used depends on the modelling objectives. Some methods that have been employed, its stage of application and related work are shown in Table 3-2.

Table 3-2: Methods and techniques of empirical modelling.

Stage	Method/Technique	Related Work
Design of experiment	Taguchi DoE	(Peng and Xu 2013), (Camposeco-Negrete 2013), (Nalbant *et al.* 2007), (Yan and Li 2013)
Data analysis & treatment	ANOVA, Main effect analysis, Interaction plots, CoMoS, Canonical Analysis, Taguchi Signal-to-Noise ratio, Grey relational analysis	(Morri *et al* 2011), (Li and Kara 2011), (Li *et al.* 2013), (Bhattacharya *et al.* 2009), (Nalbant *et al.* 2007), (Camposeco-Negrete 2013)
Model development	Regression analysis, Curve fitting, Response Surface Methodology, Artificial Neural Network, Taguchi Signal-to-Noise, Fuzzy sets, Least Squares Method	(Li and Kara 2011), (Diaz *et al.* 2011), (Wang S. *et al.* 2014), (Calvanese *et al*. 2013)
Model analysis	ANOVA, Sensitivity analysis	(Winter *et al.* 2013), (Lee *et al.* 1998)

In this work, the empirical approach was chosen for the energy consumption model development. The selected techniques and methods employed during the modelling process are further described in the following sections.

3.2.3 Statistical Techniques for Data Analysis

The data analysis stage of the empirical modelling process is an essential step for further exploring the existent and non-existent relationships between machining parameters and the response analysed – machining energy consumption. This analysis provides important information that should be known prior to the modelling stage, such as potential multicollinearity between independent variables, the degree of significance of machining variables to the outputs under analysis and so on.

In this thesis, the techniques chosen for analysing the data collection are main effect analysis and the interaction plots. The choice is due to their simplicity and efficiency in obtaining the desired information before starting with the modelling stage.

3.2.3.1 Main Effect Analysis

This statistical technique is commonly used to examine differences between level means for one or more factors within a data range. The main effect is existent when different levels of a factor affect the response differently. A main effects plot graphs of the response mean for each factor level connected by a line (Minitab 2016). With this technique, the significance of the mean of the independent variables spindle speed (S), feed rate (f), depth of cut (a_e) and width of cut (a_p) on the cutting energy consumption will be investigated.

3.2.3.2 Interaction Plots

Interaction plots are employed to study the multicollinearity (or covariance) between factors when analysing a specific response. It is used to visualise possible interactions. Parallel lines in an interaction plot suggest that there is no interaction between factors. Moreover, the greater the difference in slope between the lines, the higher the degree of interaction.

However, the statistical significance of possible interactions cannot be obtained from this method. This drawback can be minimised by using a statistical technique, such as main effect analysis, before generating the interaction plots in order to visualise the significant multicollinearities that can be further analysed using the interaction plots.

In this work, main effect analysis is used to filter the significant multicollinearities between the independent variables and then, interaction plots will be applied to further explore those.

3.2.4 Statistical Techniques for Data Modelling

The modelling stage is comprised of two main steps: model structure and parameter estimation. Several methods can be applied to obtain the desired model, as mentioned in the previous section. In this work, two methodologies for the modelling stage were chosen for comparison sake, that is, response surface methodology and curve fitting with least squares method. The details of each technique and the reason for selection are provided in the following sub-sections.

3.2.4.1 Response Surface Methodology (RSM)

RSM is an extensively used technique for modelling and optimisation problems in engineering. It is a collection of statistical and mathematical methods that describe response(s) as a function of inputs process parameters. In manufacturing, RSM is used to model and optimise processes from data collected through experimental tests (Rao 2011).

In the RSM, all the input process parameters are assumed to be measurable and the corresponding responses can be expressed as follows:

$$y = f\left(x_1, \quad x_2, \quad \ldots, \quad x_k\right) + \varepsilon \tag{3.1}$$

where y is the response, f is the unknown function of response, $x_1, \quad x_2, \quad \ldots, \quad x_k$ denote the independent parameters (or variables) respectively, k is the number of independent (or input) variables and, finally, ε is the statistical error that represents other sources of variability not accounted for f. It is generally assumed that ε has a normal distribution with mean zero and unit variance (Boyaci and Bas 2006).

Moreover, in this methodology, it is assumed that the independent variables are continuous and controllable by experiments with minor errors. It also requires that a suitable approximation for the relationship between independent variables and responses is found. RSM quadratic model is a second-order regression model and is given as:

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^{\,2} + \sum_{i=1}^{k-1} \sum_{j>i}^{k} \beta_{ij} x_i x_j \tag{3.2}$$

where y is the response and x_i and x_j are the coded levels of k independent variables. And β_0, β_i, β_{ii} and β_{ij} are the regression coefficients for constant, linear, quadratic and interaction terms, respectively.

The system of equations given above is solved using the standard linear least squares method (LSM). The RSM contains other three types of modelling, which are linear, interaction and pure quadratic. The linear type is comprised of intercept and linear terms. Then the interaction one has intercept, linear and interaction terms, and, finally, pure quadratic presents intercept, linear and squared terms only.

The reason for selecting the RSM lies on its advantages compared to classical experimental methods, in which one variable at a time is used, and also due to its capability of providing a large amount of information from a limited number of experiments. In addition, it considers the interaction effect of the input variables on the response. Also, the empirical model developed by this methodology can be used to obtain information about the machining process.

However, the major drawback of this technique is to fit the data to a second order polynomial. It cannot be secured that all responses containing curvature would be well accommodated by a second order polynomial. Nonetheless, to overcome this, the data can be treated and converted to a form that a second order model would be of good fitness, such as using logarithmic transformation.

3.2.4.2 Curve Fitting

Curve fitting, also known as regression analysis, is used to find the best-fit line or curve for a series of data points. The curve fit produces an equation that allows finding points anywhere along the curve. Thus it makes curve fitting as a simple and effective technique useful for manufacturing process data description, parameter estimation and control. Consequently, in this work, this technique was chosen for data collection prescription, in order to find the best fit model for the relationship between independent variables (the machining parameters: Spindle speed, feed rate, depth of cut and width of cut) and the outputs (energy consumption).

3.2.4.3 Least Squares Method (LSM)

One of the applications of the least squares method (LSM) or method of least squares is parameter estimation. Basically, this method optimality criterion is to minimise the sum of squares of residuals between actual observed outputs and output values of the numerical model , built from an experimental data, such as in the case study developed in this thesis.

Linear LSM is applied for estimating the parameters in the RSM and Curve fitting modelling methodologies chosen in this work. For the RSM case, the matrix notation of the RSM model, which is solved using the standard linear LSM, is expressed as:

$$
\begin{gathered}
y = X\beta + \varepsilon \\
\underbrace{\begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix}}_{y} = \underbrace{\begin{bmatrix} 1 & x_{11} & x_{12} & \cdots & x_{1k} \\ 1 & x_{21} & x_{22} & \cdots & x_{2k} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & x_{n1} & x_{n2} & \cdots & x_{nk} \end{bmatrix}}_{X} \underbrace{\begin{pmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_k \end{pmatrix}}_{\beta} + \underbrace{\begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{pmatrix}}_{\varepsilon}
\end{gathered}
\tag{3.3}
$$

In LSM, it is assumed that random errors are identically distributed with a zero mean and a common unknown variance and that they are independent of each other. The difference between the observed and the fitted value ($\hat{y}$) for the ith observation $\varepsilon_i = y_i - \hat{y}_i$ is called the residual and an estimate of the corresponding ε_i. Following the method optimality criterion, β_i is estimated considering the minimised sum of the squares of the residuals, or sum of squares of the errors, denoted by SSE, and described as:

$$SSE = \sum_{i=1}^{n} \varepsilon_i^2 = \sum \left(y_i - \hat{y}_i \right)^2 \tag{3.4}$$

After the regression coefficients are obtained, the estimated energy consumption can be easily calculated using the model.

3.2.5 Statistical Techniques for Analysis of Model Performance

3.2.5.1 Root Mean Square Error (RMSE)

This technique is frequently employed in model evaluation studies to describe the differences between values predicted by a model and the values actually observed. In other words, the RMSE represents the sample standard deviation of the differences between the predicted and measured values.

The RMSE of estimated values $\hat{y}_i$ for experiment i of an actual measure variable y_i is computed for n different predictions as the square root of the mean of the squares of the deviations:

$$RMSE = \sqrt{\frac{SS_{res}}{n}} \tag{3.5}$$

where the sum of squares of residuals is given as:

$$SS_{res} = \sum_{i=1}^{n} \left(\hat{y}_i - y_i \right)^2 \tag{3.6}$$

Thus,

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(\hat{y}_i - y_i\right)^2}{n}} \tag{3.7}$$

For the RMSE value, the closer to zero, the less the sum of errors, thus, the better the model is. The selection of RSME to evaluate the models presented in this work is that according to (Chai 2014) this technique is more appropriate to use when the model errors follow a normal distribution. Consequently, this method will be used to evaluate the different models developed using RSM later in this Chapters.

3.2.5.2 Coefficient of Determination (R^2)

This statistical coefficient is commonly applied to evaluate how well the observed outcomes are replicated by the statistic model developed. The coefficient is obtained by solving:

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \tag{3.8}$$

INSERT FORMULA FOR R2 ADJUSTED TO DO

Where SS_{tot} is described as the total sum of squares:

$$SS_{tot} = \sum_{i=1}^{n}\left(\hat{y}_i - \overline{y}\right)^2 \tag{3.9}$$

where $\overline{y}$ is the mean value of y.

R-squared presents two fields: ordinary (unadjusted) and adjusted. The former supposes that every independent variable in the model explains the variation in the dependent variable, whereas the latter gives the percentage of variation explained y only those independent variables that in reality affect the dependent variable. Furthermore, (Investopedia 2015) states that

> ”the adjusted R-squared compares the descriptive power of regression models that include diverse numbers of predictors. Every predictor added to the model increases R^2 and never decreases it. Thus, a model with more terms may seem to have a better fit just for the fact that is has more terms, while the adjusted R-squared compensates for the addition of variables and only increases if the new term enhances the model above what would be obtained by probability and decreases when a predictor enhances the model less than what is predicted by chance. In an overfitting condition, an incorrectly high value of R-squared, which leads to a decreased ability to predict, is obtained. This is not the case with the adjusted R-squared.”

The equation for the adjusted R2 is given as:

$$\bar{R}^2 = 1 - \frac{\left(1 - R^2\right)\left(N - 1\right)}{N - p - 1}$$

Where N and p are number of samples and numbers of terms in the model, respectively. The better the regression fits the data in comparison to the simple average, the closer the value of R^2 and/or $\bar{R}^2$ is to 1.

3.3 Methodology

The methodology to achieve the aim presented in this chapter has been carried out for quantitative and qualitative analysis. Statistical techniques are used to analyse and build the basis understanding of the experimental data collected from milling experiments, such as Main effect analysis and Interaction plots. Furthermore, Curve fitting is used to aid in the selection of the model structure and modelling methodology.

After that, Response Surface Methodology (RSM) is employed to develop the empirical energy consumption models and estimate its parameters using Least Squares Method (LSM). Moreover, statistical techniques such as Root mean sum of errors (RMSE) and

Coefficients of determination (R^2) are applied to analyse the models obtained with RSM and to select the best fit model to be used in its further application – optimisation algorithm to obtain the best machining parameters in order to achieve the least energy consumption. The framework of the energy consumption model development carried in this theses is shown in Figure 3-3.

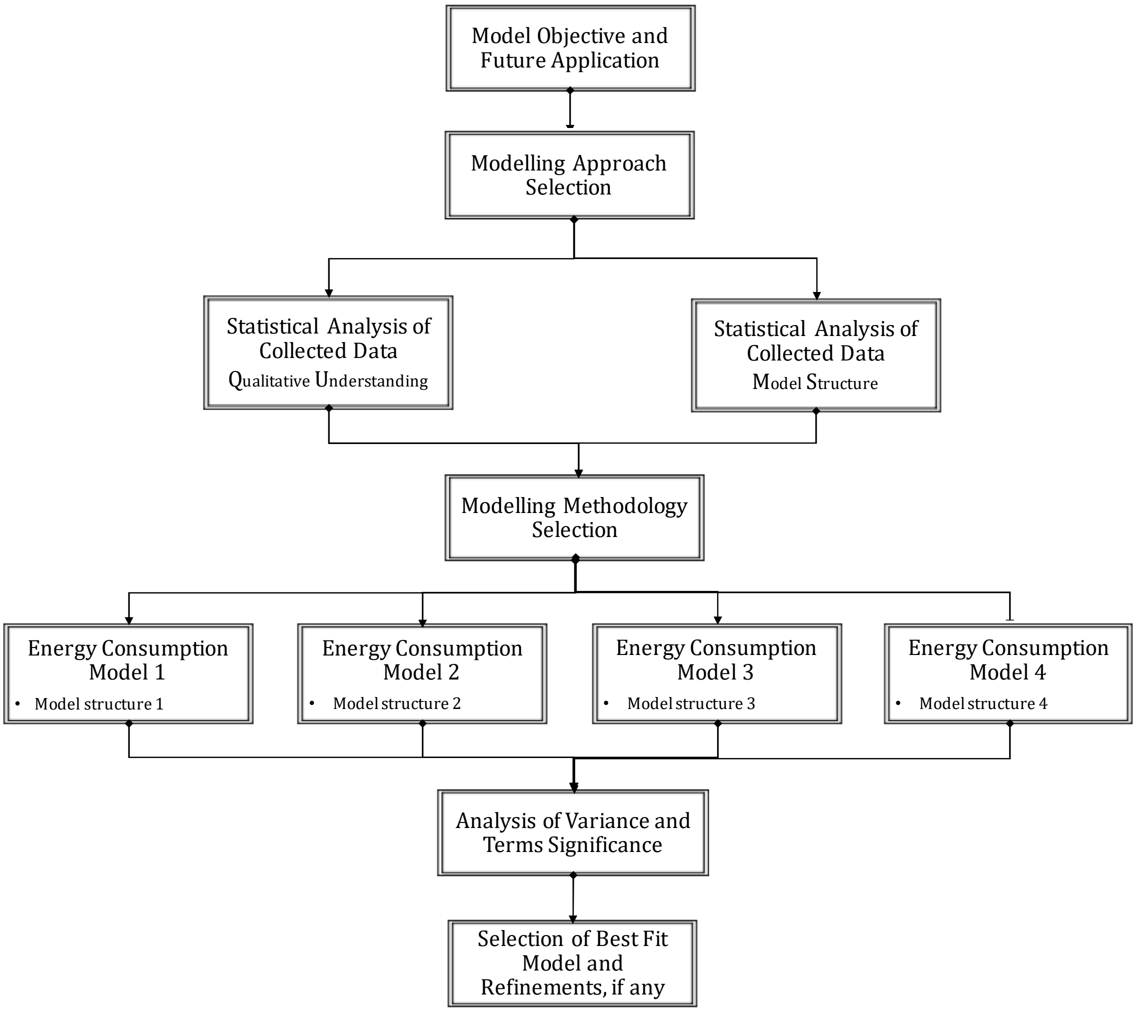

Figure 3-3: Empirical model development framework. (Source: Author)

3.4 Energy Consumption Model Development

As according to the model development framework provided in Figure 3-3, the first step of the modelling process is to define the reason(s) for developing the model and its future application if any. The former definition – why modelling – decides the design (input) variables and the response (output) variables to be represented by the model. In this thesis, the modelling objective is to describe the specific energy consumption – or machining energy – of a milling process as a function of the cutting parameters (input variables): spindle speed (S), feed rate (f), depth of cut (a_p) and width of cut (a_e). This model is to be applied to an optimisation approach, targeting to find the optimum machining parameters to obtain the least energy consumption, this way, proposing to enhance the sustainability within machining process.

The empirical modelling approach was selected for the model development, as mentioned previously. Thus, the energy consumption model can be obtained by following the empirical model development framework proposed in Figure 3-3.

3.4.1 Experimental Data Collection

In this work, the model development is based on experimental data published in (Yan and Li 2013), obtained from measurements of a machining process. The experimental data is the result of a fractional factorial design using Taguchi orthogonal array L27, for a three level four factors design of experiments, see Table 3-3 for factors and levels details. For more details about Taguchi Design of Experiments (DoE) please refer to (Roy 2001). The 27 experimental tests were performed on a CNC micromachining centre (Hurco CNC BMC-20LR Vertical Machining Centre) with 5.6kW spindle power and a maximum speed of 6000 rpm.

Table 3-3: Input variables and its levels.

N	**FACTOR**	**LEVEL**		
		A	**B**	**C**
1	Spindle (S) [rpm]	1000	1500	2000
2	Feed (f) [mm/min]	200	250	300
3	Depth (a_p) [mm]	0.2	0.3	0.4
4	Width (a_e) [mm]	5	10	15

The machining process details are provided in Table 3-4. The power measurement system consisted of a three-phase power sensor WB9128-1 and the sampling frequency was set to be 10 Hz.

Table 3-4: Machining process details.

M.	Specifications	
Cutter	Tool material:	Carbide
	Diameter (D):	24mm
	Number of teeth (N):	3 teeth
Workpiece	Material:	Medium carbon steel (C45)
Feature	Milling:	Face Milling

The results of the 27 experimental sets and the respective cutting energy measurements are used to implement the empirical model development framework proposed in this work. Firstly, the data is analysed using statistical techniques in order to build the understanding and knowledge necessary regarding the performance of the machining process, including the significance of the selected machining parameters (input variables) on the cutting energy demanded, and to investigate the existence of covariance between these input variables. Next section will present a qualitative analysis based on statistical results of the data collected.

3.4.2 Data Analysis One: Qualitative Understanding

The qualitative analysis based on statistics is necessary to form the understanding of the machining process based on the results of the experimental tests. Two statistics techniques are employed in this section: main effect analysis and interaction plots. The former provides information to understand the significance of the machining parameters on the mean cutting energy demanded, and the latter gives the plots that show the covariance behaviour between those independent variables.

3.4.2.1 Main Effect Analysis

Minitab software was used to develop the main effect analysis on the experimental data collection. The experimental design and the cutting energy required by each experiment, measured during the experiments, were used as inputs for the calculation of the effect of each factor on the mean cutting energy. Figure 3-4 shows the effect of each level of the four factors (S, f, a_p and a_e) on the mean Cutting Energy (CE), in kJ, analysed individually.

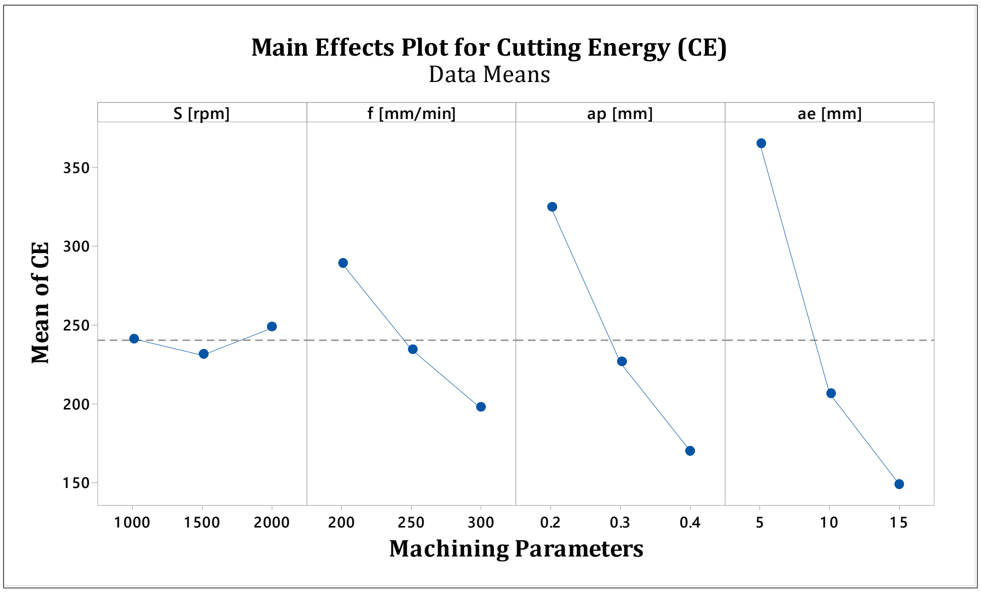

Figure 3-4: Main effects of input variables on Cutting Energy (CE).

In general, the plots in Figure 3-4 show that all factors affect the cutting energy required during the machining process, once the lines are not horizontal. Furthermore, it also suggests that the mean response is affected differently by each factor, for example, spindle speed shows a lower effect on the mean CE for its different levels when compared to other factors.

An analysis of the main effects plot of each factor is provided as follows:

- Factor 1: Spindle speed (S)

There is a decrease of approximately 5% in the mean CE from the first (1000 rpm) to the second level (1500rpm). Then, the response CE showed an increase of, approximately, 10% from the second to the third, and highest, level (2000 rpm). Considering that the smaller the better, i.e. the smaller the mean CE the better the result is, 1500 rpm (second level) appears to be the best spindle speed value, *ceteris paribus*. In the machining operation perspective, the spindle speed may not have presented a substantial effect on the mean CE due to the characteristic of the machining operation – face milling. From the experimental design, the cutter tool did not have a great engagement onto the workpiece (levels of depth of cut are 0.2, 0.3 and 0.4). Even though the workpiece's material, medium carbon steel (C45), is a considerably hard to machine material, a significant change despite the level of spindle speed was not seen. In addition to, the results suggest that when on level 2000 rpm, a greater amount of energy was required, but with less efficiency.

- Factor 2: Feed rate (*f*)

The mean CE presented significant changes for the three levels of feed rate. Moreover, it shows to be inversely proportional to the increase of feed rate levels. The lowest level of feed rate (200mm/min) required a CE, approximately, 27% higher than the mean CE of the medium level (250mm/min). Then, the CE drops approx. 20% further, with the increase of feed rate to the highest level (300mm/min). Considering that the smaller the better for the response under analysis, the highest level of feed rate – 300mm/min – showed to be the optimal level, *ceteris paribus*. For the face milling operation, feed rate plays an important role on the total machining time, once in this process the cutter tool is continuously fed onto the workpiece. From the results, it can be seen that the trade-off between the load applied to the machine axis, which comes from the material removal process when the cutter tool is engaged onto the workpiece, and the total time for cutting due to the increase in feed rate levels is positive in terms of mean CE.

- Factor 3: Depth of cut (a_p)

The main effect plot of depth of cut shows significant drops on the mean CE with the increase in levels, despite the fact that the level's interval is 0.1 mm. The most substantial drop is seen from the first to second levels, in which the latter shows 44% less mean CE than the former. Furthermore, the third level shows the lowest mean CE, which is 25%

lower than the second level. Consequently, it suggests that a_p = 0.4 mm is the optimum level of depth, considering that the smaller the mean CE the better, and all the factors kept constant. In the machining planning stage, the depth of cut defines the number of passes necessary for the total material removal process, which has a direct impact on the total time for cutting, as well as on the total load applied to the machine axis and the main spindle. The results from the main effect plot suggests that for the levels of depth given, the higher loads on axis and main spindle due to the increase in depth are not as significant as the time for cutting (the higher the depth, the less the number of passes to finish the part, thus, the less the time for finishing the part), thus, show a positive trade off in terms of mean CE for the face milling operation.

- Factor 4: Width of cut (a_e)

In the width of cut plot, the most significant effect is seen from the first to the second level, 5 mm to 10 mm, respectively, in which the mean CE decreases from approximately 380 kJ to 205 kJ – a drop of 46%. These two values of width correspond to, approximately, 20 and 40% of the tool diameter, respectively. Another decrease is noticed from the second to the third level (15 mm, approx. 2/3 of tool engagement), which represents the lowest mean CE. For this reason, the third level of a_e is shown to be the optimal value, *ceteris paribus*. Moreover, this factor is found to present the most substantial effect on the mean CE, based on the highest and lowest mean CE values and the effects due to changes in width levels. Planning engineers and machinist operators define the width of cut to decide how much the cutter tool will engage onto the workpiece radially. For face milling processes, this variable plays a crucial role on the final tool path, total load on the feed table and main spindle, in addition, it can have a significant impact on the total cutting time – the latter will depend on the workpiece geometry (or volume of material to be removed) and selection of tool path strategy.

In summary, from this analysis, it can be concluded that the changes in S did not substantially affect the mean energy required for cutting and that the second level 1500 rpm is shown to demand the lowest mean CE. Besides that, the overall effect of the factors f, a_p and a_e on the response mean CE is that the latter decreases with the increase in the factors' level. Moreover, the width of cut is the most significant factor in terms of the mean cutting energy. These conclusions draw the understanding scenario of cutting process in face milling operations.

The next section will present the results and analysis for the interaction plot, which shows the interrelationship between the machining parameters based on the results obtained from the experimental tests.

3.4.2.2 Interaction Plot Analysis

The interaction plots in Figure 3-5 provide valuable information for understanding the behaviour of responses considering the relationship between different factors. The plot displays the three levels of one factor on the x-axis, on each column, together to a different line for each level of the compared factor, on each row. In addition, the mean CE values are displayed on the y-axis of each row.

The interaction plots show that there are multicollinearities between input variables on the plots II, III and VI, which correspond to the covariance between machining parameters spindle and depth of cut, spindle speed and width of cut, and, finally, depth of cut and width of cut. The latter presents a lower level of interaction when compared to the former ones.

In plot I. $S*f$, the lines the describe the feed levels vs the spindle speed levels (x-axis) show that the behaviour of mean CE is similar when the levels of each factor vary in level – note that the lines are in parallel.

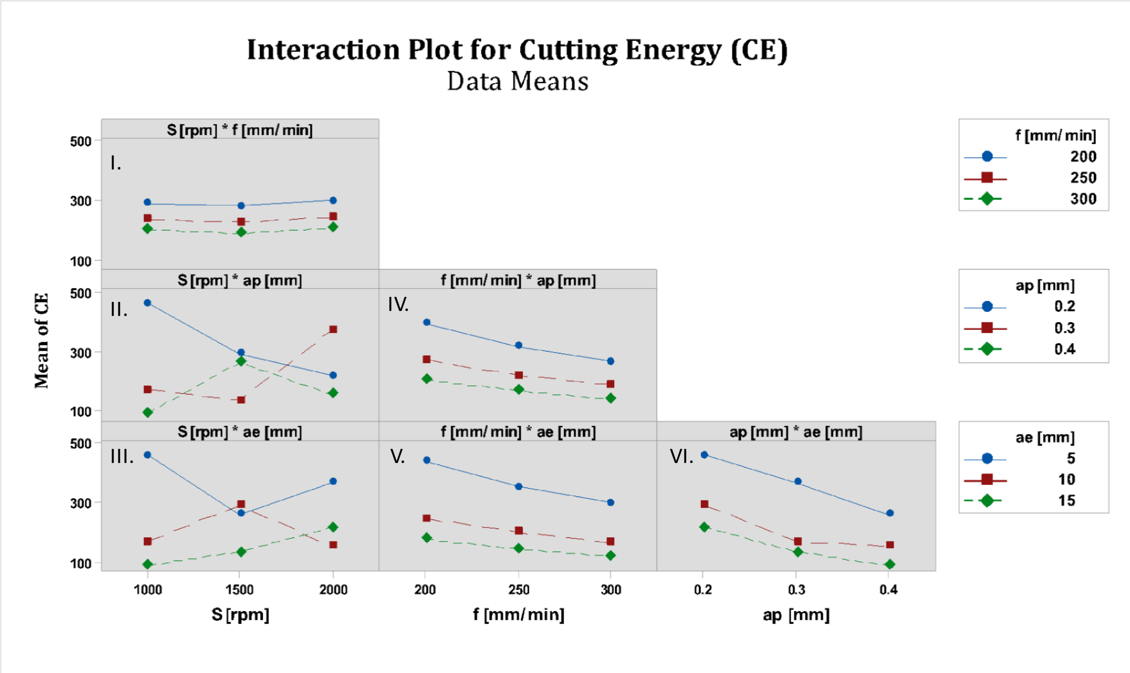

Figure 3-5: Interaction plots of input variables and mean CE.

Moreover, this behaviour suggests that there is no covariance between those variables. Furthermore, this means that if the spindle speed is changed does not affect the mean CE for any value of feed rate, and vice-versa. Also, the graph suggests that the *sweet spot* in terms of energy consumption is found when spindle speed is 1500 rpm and feed rate is 300 mm/min, for the face milling processes carried out in the experiments. This is due to such cutting parameters combination requires the least energy consumption for machining the part.

Alike behaviour can be seen in plots IV and V, which stand for $f*a_p$ and $f*a_e$, respectively. However, the plots show that the lines present not an entire linear parallel behaviour, which suggests there is some interaction, which will be better understood later from the mathematical analysis. Such behaviour found for $f * a_p$ interaction may be explained by the small values of the depths' levels, that did not cause significant difference in the load carried by the machine axis (which feeds the cutter tool on the workpiece) and, thus, did not influence the mean response from the feed factor when changing the levels of depth, and vice-versa. Plot IV also suggests that the highest levels of f and a_p, together, gives the optimal mean response.

For the plot V, in which feed rate and width of cut show low correlation, the results obtained are not as expected. In general, for face milling processes, the percentage of engagement of the cutter tool onto the workpiece (described by the width of cut together to depth of cut) should have a significant effect on the total load on the machine axis, which would be described by a strong relationship between a_e and f. However, once more the experimental values for this factors may have lowered such interaction level. Nonetheless, the interaction terms to be modelled on the next section will show such relationship in mathematical terms. This will clarify and complement this analysis.

The strong relationships described in plots II and III which represent $S * a_p$ and $S * a_e$, respectively, can be explained by the different loads in the main spindle speed. In *b*, it can be seen that locking the first level of a_p – blue line – and increasing the spindle speed, the mean CE decreases. Then, locking the second level of a_p – red line – and increasing the spindle speed, the mean CE decreases when spindle reaches its second speed level, followed by a substantial rise from the second to the third speed level. This rise can be explained by the lack of efficiency of the machine tool when increasing the spindle speed to the third level 2000 rpm, which is one-third of its maximum limit. The best combination of these factors, according to the smallest mean CE, is shown to be $a_p = 0.4$ mm and $S = 1000$ rpm.

Plot III shows how spindle speed and width of cut interact. The strong interaction between these variables is suggested by the crossing lines of a_e levels. When locking the first level of a_e – blue line – and increasing the spindle speed, the mean CE presents a decrease till second speed level, and then an increase to the third level – this increase is believed to be lack of efficiency of the machine tool when operating on these levels. Then, locking the second level of a_e – red line – and increasing the spindle speed, the mean CE increases when spindle reaches its second speed level, then falls with the 2000 rpm speed. It suggests that the highest speed presents a better performance when the width is set to be 10 mm, compared to the average speed. The third level of a_e shows that the mean CE increases according to the spindle speed, and that the lowest mean CE is achieved when a_p = 15 mm and S = 1000 rpm. This final observation states that despite the higher load on the main spindle due to the greater cutter tool engagement, the optimal speed and width are the lowest and the highest levels, respectively, and that not necessarily a faster spindle speed is the best, as commonly assumed by machinists.

The relationship between depth and width of cut (a_p*a_e), displayed in plot VI, showed some interaction in both second levels – red line. This interaction will be further investigated later in this Chapter.

3.4.3 Data Analysis Two: Model Structure

The decision about the model structure is very important when modelling a data set. In this work, Curve fitting statistical technique was chosen to support the decision making upon the model structure that suits best the experimental data collection.

For that, specific samples from the data set – presented in Appendix A – were strategically selected in order to build the mathematical model for each design variable – S, f, a_p and a_e, individually – against the respective cutting energy consumption measured.

The results obtained from Curve fitting are displayed in Figure 3-6 to Figure 3-9, where the effect of spindle speed, feed rate, depth and width of cut, respectively, on the cutting energy, ceteris paribus, are shown – level A of the other factors were locked. From the graphs shown in those figures, the relationship between each machining parameter *vs* cutting energy could be mathematically described. The resultant models of cutting energy as a function of input variables, individually, can be seen from (3.10) to (3.13).

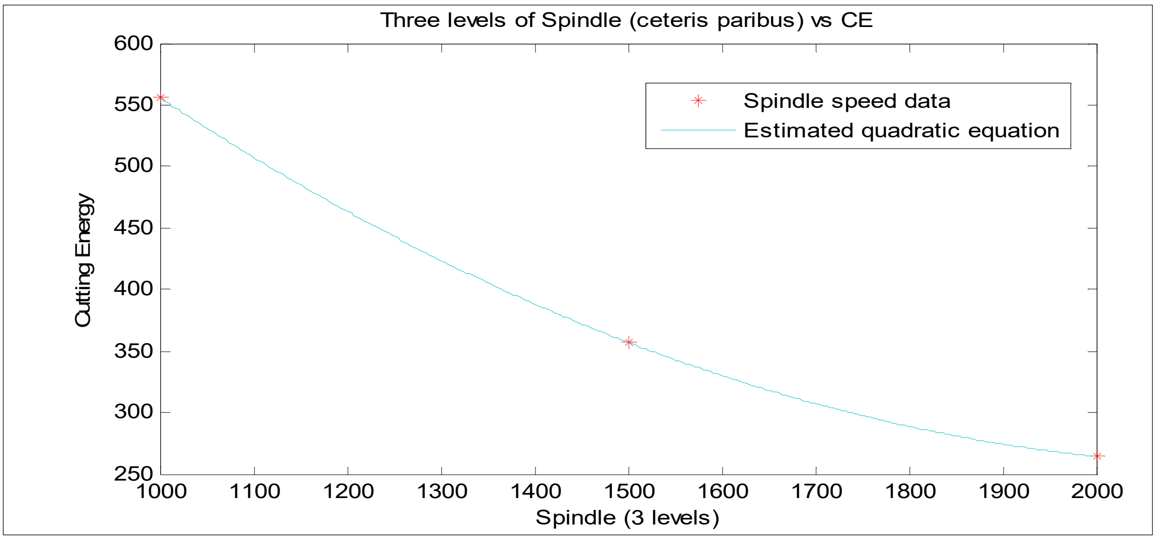

Figure 3-6: Effect of Spindle speed on Cutting energy.

$$CE(S) = 0.00021 * S^2 - 0.93 * S + 1300 \tag{3.10}$$

The norm of residuals, which is the measure of the deviation between the correlation and the data, of (3.10) is 5.934x10^{-13}.

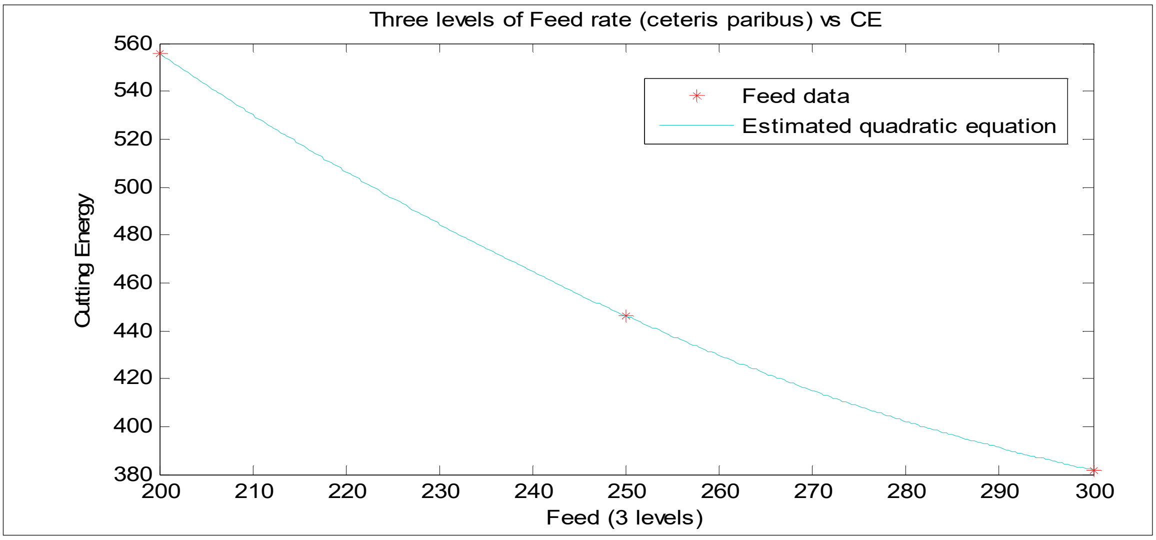

Figure 3-7: Effect of Feed rate on Cutting energy.

$$CE(f) = 0.0091 * f^2 - 6.3 * f + 1400 \tag{3.11}$$

The norm of residuals of (3.11) is 6.653x10^{-13}.

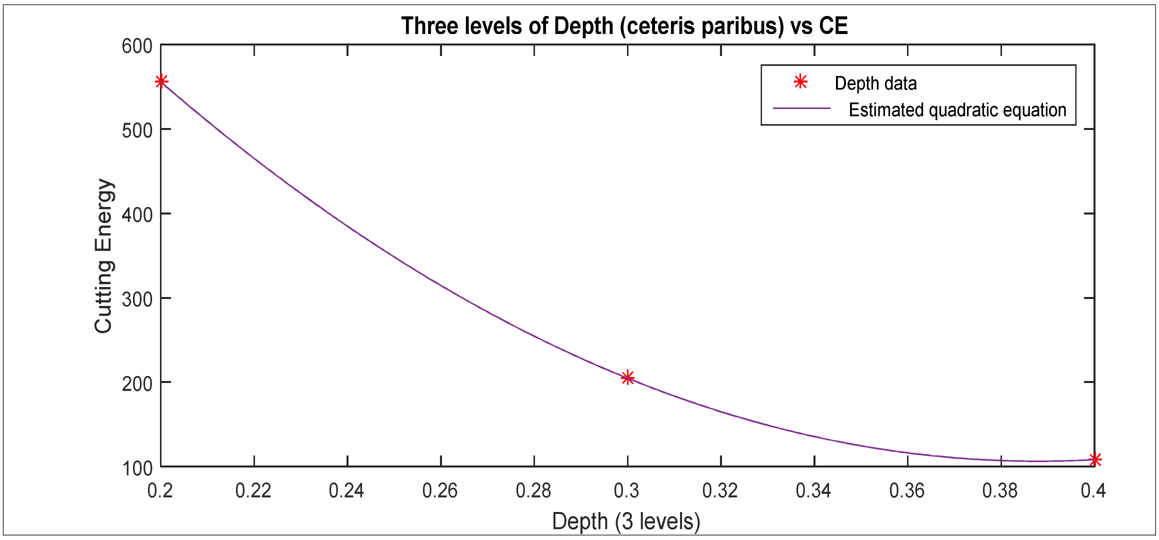

Figure 3-8: Effect of Depth of cut on Cutting energy.

$$CE(a_p) = 1300 * a_p{}^2 - 9900 * a_p + 200 \tag{3.12}$$

The norm of residuals of (3.12) is 1.594x10^{-12}.

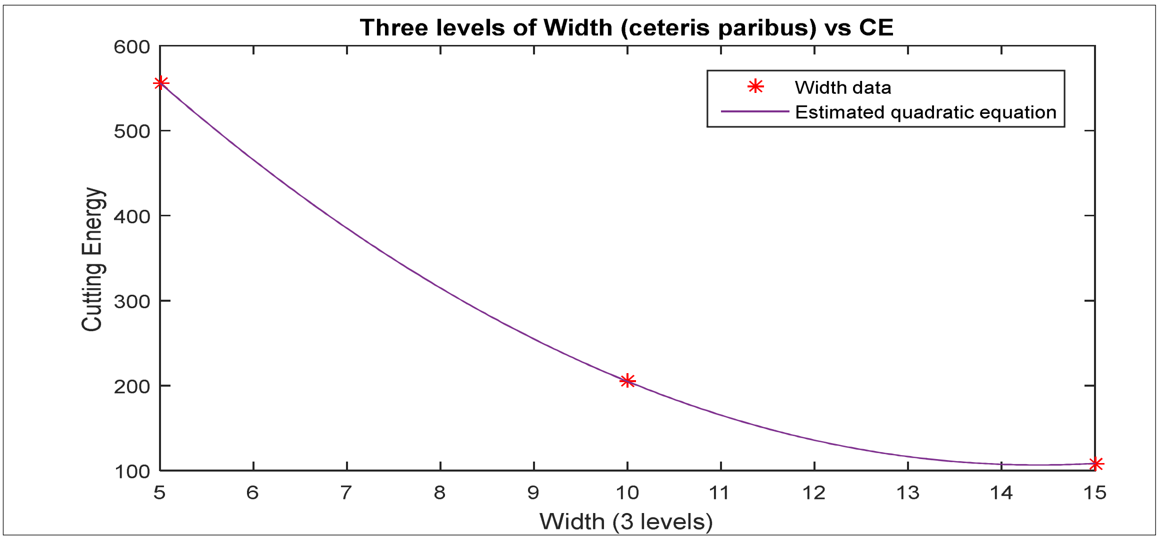

Figure 3-9: Effect of Width of cut on Cutting energy.

$$CE(a_e) = 5.1 * a_e^2 - 1500 * a_e + 1200 \tag{3.13}$$

The norm of residuals of (3.13) is 5.155x10-13. The norm of residuals have demonstrated a very good polynomial fit. However, it is important to note that the fact that only three levels per factor were selected influenced for obtaining such results. This observation suggests that three points only are not enough for obtaining a realistic curve fitting. Furthermore, this reflects directly on the quality of the experimental design – but this is not scope of analysis at this moment.

Applying the superposition SUM of the polynomial equations from (3.10) to (3.13), the model that describes the cutting energy as a function of the machining parameters can be obtained and is given as:

$$\begin{aligned} CE(S, f, a_p, a_e) = {} & 0.00021 * S^2 + 0.0091 * f^2 + 1300 * a_p^2 + 5.1 * a_e^2 \\ & -0.93 * S - 6.3 * f - 9900 * a_p - 1500 * a_e + 4100 \end{aligned} \tag{3.14}$$

In matrix form, this model can be presented given as:

$$CE\left(S, f, a_p, a_e\right) = \begin{bmatrix} 1 & S & f & a_p & a_e & S^2 & f^2 & a_p{}^2 & a_e{}^2 \end{bmatrix} * \begin{bmatrix} 4100 \\ -0.93 \\ -6.3 \\ -9900 \\ -1500 \\ 0.00021 \\ 0.0091 \\ 1300 \\ 5.1 \end{bmatrix} + \left[\varepsilon\right] \tag{3.15}$$

The CE model (3.14) obtained from Curve fitting analysis built an acceptable model structure that shows how the energy consumption can be modelled based on the four three-level factors fractional experimental design, with an interval of confidence of 95%. Furthermore, the coefficient of each term defines the significance of the variables. But it is important to note the difference of values between the levels of each input variable.

It can be seen that (3.15) is comprised of squared, linear and constant terms. Such structure is equivalent to the pure quadratic function from the RSM. Consequently, the obtained model suggests that RSM would be a good selection for the model development using experimental data collection used in this work.

Nonetheless, the qualitative analysis performed previously showed the existence of covariance between the input variables. Such multicollinearities should not be disregarded in the CE mathematical model due to its impact on the final estimated value, which will be crucial for the decision making later when utilised on the optimisation approach. Although the curve fitting used did not mathematically mensurate those interactions, it is known that RSM can model data considering the interaction between factors. Thus, the next section will show the implementation of RSM to develop different models for describing $CE\left(S, f, a_p, a_e\right)$. Furthermore, an appraisal of the obtained models based on the adjusted coefficient of determination (adj R-sq) and RMSE is provided, as well as a model refinement is proposed considering the findings from the qualitative analysis and significance of terms coefficients.

Again, it is important to note that the results obtained are not very realistic because only three data points could be used from the data range available, in which any second order polynomial could be fitted in. However, this analysis focuses on a framework of statistical analysis that can be later expanded to a larger data set.

3.4.4 Energy Consumption Models and Performance Analysis

3.4.4.1 Estimated Models for Cutting Energy

According to the statistical analysis performed, a pure quadratic RSM model should provide a good description of the cutting energy in terms of spindle speed, feed rate, depth of cut and width of cut. Although, the qualitative analysis showed that it is worth considering the interaction between these input variables. Consequently, for comparison sake, the four modelling types from the RSM (linear, interaction, pure quadratic and quadratic) will be developed and evaluated. For the selection of the best fit, the future application of the desired model is also taken into account.

a. Model One: RSM linear

Using MATLAB/Simulink *rstool*, which is able to read the experimental data and model it into the selected model structure, the linear model that fits the DoE of cutting energy (CE) in terms of S, f, a_p and a_e was found to be as in (3.16), with five terms in total (intercept + first order terms).

$$CE_{linear}(S, f, a_p, a_e) = 908.45 + 0.0073 * S - 0.922 * f - 775 * a_p - 21.6 * a_e \tag{3.16}$$

The equation organised in matrices is shown in (3.17). This way provides a better visualisation of the coefficients estimated for this model type.

$$CE_{\text{linear}}\left(S,f,a_p,a_e\right)=\begin{bmatrix}1 & S & f & a_p & a_e\end{bmatrix}*\begin{bmatrix}908.45\\0.0073\\-0.922\\-775\\-21.6\end{bmatrix}+\left[\varepsilon\right] \tag{3.17}$$

b. Model Two: RSM interaction

The RSM interaction function obtained is given as in (3.18). The model is comprised of eleven terms: intercept, linear and interaction terms.

$$\begin{aligned}&CE_{\text{interaction}}(S,f,a_p,a_e)=1427+0.23*S-2.6256*f\\&-1121.5*a_p-117.9*a_e-3.13e-5*S*f-1.081*S*a_p\\&+0.018*S*a_e+3.049*f*a_p+0.0836*f*a_e+143.08*a_p*a_e\end{aligned} \tag{3.18}$$

In matrix, it can be organised as:

$$\begin{aligned}&CE_{\text{interact}}\left(S,f,a_p,a_e\right)=\\&\begin{bmatrix}1 & S & f & a_p & a_e & S*f & S*a_p & S*a_e & f*a_p & f*a_e & a_p*a_e\end{bmatrix}*\begin{bmatrix}1427.1\\0.23\\-2.63\\-1124.5\\-117.9\\-3.13e-5\\-1.081\\0.018\\3.049\\0.0836\\143.08\end{bmatrix}+\left[\varepsilon\right]\end{aligned} \tag{3.19}$$

c. Model Three: RSM pure quadratic

As described previously, the pure quadratic model structure contains the intercept, linear and squared terms. The CE model obtained is comprised of nine terms and is given as:

$$CE_{\text{pure\_quad}}(S,f,a_p,a_e) = 1587.4 - 0.157*S - 2.73*f - 2051.4*a_p$$
$$-61.94*a_e + 0.0000547*S^2 + 0.0036*f^2 + 2127.3*a_p{}^2 + 2.0165*a_e{}^2 \tag{3.20}$$

$$CE_{\text{pure\_quad}}\left(S,f,a_p,a_e\right) =$$
$$\begin{bmatrix} 1 & S & f & a_p & a_e & S^2 & f^2 & a_p{}^2 & a_p{}^2 \end{bmatrix} * \begin{bmatrix} 1587.4 \\ -0.157 \\ -2.73 \\ -2051.4 \\ -61.94 \\ 5.47e-5 \\ 0.0036 \\ 2127.3 \\ 2.0165 \end{bmatrix} + \left[\varepsilon\right] \tag{3.21}$$

d. Model Four: RSM quadratic

The experimental dataset used in this work is not large enough to develop a quadratic RSM model using MATLAB/Simulink *rstool*, however, Minitab software could do so by removing the interaction term a_p*a_e, once the coefficient β for this term could not be estimated by LSM due to not enough data – which reason is the use of fractional factorial design for running the experimental tests. This way, the coded RSM quadratic model obtained for the cutting energy is given as:

$$CE_{\text{quad}}(S,f,a_p,a_e) = 155.27 + 3.64*S - 46.10*f - 94.17*a_p - 91.73*a_e$$
$$-0.78*S*f + 32.68*S*a_p - 33.34*S*a_e + 15.25*f*a_p + 20.89*f*a_e \tag{3.22}$$
$$+13.67*S^2 + 9.03*f^2 + 37.94*a_p{}^2 + 66.75*a_e{}^2$$

Transforming (3.22) into matrices structure, it becomes:

$$CE_{\text{quad}}\left(S, f, a_p, a_e\right) = [\varepsilon] + \begin{bmatrix} 1 & S & f & a_p & a_e & S*f & S*a_p & S*a_e & f*a_p & f*a_e & S^2 & f^2 & a_p^{\,2} & a_e^{\,2} \end{bmatrix} * \begin{bmatrix} 155.27 \\ 3.64 \\ -46.1 \\ -94.17 \\ -91.73 \\ 13.67 \\ 9.03 \\ 37.94 \\ 66.75 \\ -0.78 \\ 32.68 \\ -33.34 \\ 15.25 \\ 20.89 \end{bmatrix} \quad (3.23)$$

The uncoded coefficients for the RSM quadratic can be given as:

$$CE_{\text{quad}}\left(S, f, a_p, a_e\right) = [\varepsilon] + \begin{bmatrix} 1 & S & f & a_p & a_e & S*f & S*a_p & S*a_e & f*a_p & f*a_e & S^2 & f^2 & a_p^{\,2} & a_e^{\,2} \end{bmatrix} * \begin{bmatrix} 2318 \\ -0.2116 \\ -4.431 \\ -4.961 \\ -72.63 \\ 5.5e-5 \\ 0.00361 \\ 3794 \\ 2.67 \\ -3.1e-5 \\ 0.6535 \\ -0.01334 \\ 3.049 \\ 0.08357 \end{bmatrix} \quad (3.24)$$

For the selection of the best model, firstly, two criteria were defined in order to evaluate those which are: sum of residuals and accuracy of estimation, to be determined by R^2;

RMSE; and, number of terms in the model. The latter criteria will have a lower analytical weight on the decision-making process, once the goodness of fit is assumed to be more important than the computational time required by the optimisation algorithm – further application of the selected model – which can be influenced by the number of terms.

3.4.4.2 Analysis of Variance of Models and Model Selection

Consequently, the four models obtained using RSM were evaluated using the two statistic methods adjusted R-squared and RMSE using MATLAB/Simulink, the results are shown in Table 3-5. The experimental tests sets from the 27 samples were used as input for the models, and the estimated values were compared to the actual (measured) values.

Table 3-5: ANOVA of RSM models developed.

Model Type	R-sq adj	RMSE	No of Terms
Linear	0.8840	36.0173	5
Interaction	0.9634	17.8792	11
Pure quadratic	0.9407	23.9226	9
Quadratic	0.9955	9.2497	14

The quadratic structure for the model is found to provide the most accurate model, note that it has the higher R-sq adjusted, 0.9955.

Adjusted R-squared was used because this performance statistical indicator takes into account the number of terms of each model, this way, providing a more realistic model fitness value.

The results presented in Table 3-5 suggests that the RSM quadratic proposed the best fit model for estimating the energy consumption based on the experimental data, regardless the fact that the interaction coefficient of the term $a_p * a_e$ could not be estimated due to limited size of data and, consequently, it had to be removed from the model structure.

The number of terms contained in the model is also a criterion considered in the model appraisal, although this is not as important as the model fitness. Considering that the best-fit model contains fourteen terms, which can be considered as a large number of terms when the exhaustive search takes place, for example, the qualitative analysis built in the previous section, together to the p-value calculated for the models' terms, will be used to refine the model. This process evaluates the model in a way that only the significant terms will be kept, i.e. it checks the terms that do not have a significant effect on the estimated response: cutting energy.

3.4.4.2.1 Refining Best Fit Model

Minitab software was used to aid in the refining process by generating the ANOVA table for the RSM quadratic model selected in (3.22). In this analysis of variance, the significance of each term contained in the model is statistically evaluated by p-values. If the p-value is less than (or equal to) α, reject the null hypothesis in favour of the alternative hypothesis. If the p-value is greater than α, do not reject the null hypothesis – the term is significant to the model.The results obtained by ANOVA are displayed in Table 3-6.

Table 3-6: ANOVA of RSM quadratic model.

Term	**Coded Coefficient**	**Uncoded Coefficient**	**p-value**
Constant	155.27	2318	0.000
S	3.64	-0.2116	0.083
f	-46.10	-4.431	0.000
a_p	-94.17	-4.961	0.000
a_e	-91.73	-72.63	0.000
S^2	13.67	0.000055	0.001
f^2	9.03	0.00361	0.019
a_p^2	37.94	3794	0.000
a_e^2	66.75	2.67	0.000
$S*f$	-0.78	-0.000031	0.747

$S*a_p$	32.68	0.6535	0.000
$S*a_e$	-33.34	-0.01334	0.000
$f*a_p$	15.25	3.049	0.000
$f*a_e$	20.89	0.08357	0.000

The coded coefficients were added to Table 3-6, because coded units allow the comparison of the size of the coefficients (on a common scale) to determine which factor has the largest impact on the response.

From the results obtained, it can be seen that two terms presented higher value than α, which is 0.05 – confidence level of analysis is 0.95. These are the linear term for spindle speed (S) and the interaction term *spindle speed*feed rate* $(S*f)$ which p-values are 0.083 and 0.747, respectively.

The analysis carried out in 3.2.1 showed that changes in S levels had no substantial effect on the mean CE (see Figure 3-4), however, it was explained that the reason for that, in the machining process perspective, can be due to the values of depth and width selected, which would not affect the load on the main spindle considerably. Therefore, it is assumed that the results obtained for this term are not enough to make a conclusion upon its removal from the model, thus, this term will be kept.

Nonetheless, the p-value of the term $S*f$ suggests a low statistical significance on the CE, which was also visualised through the interaction plot in section 3.2.1 (see Figure 3-5a). Consequently, this term will be removed from the model for the sake of simplification.

The refined empirical model for the $CE\left(S, f, a_p, a_e\right)$ with 13 significant terms is given as:

$$\begin{aligned}
&CE_{\text{refined_quad}}(S, f, a_p, a_e) = 2329.7 - 0.2194*S - 4.4784*f - 4960.8*a_p \\
&-72.635*a_e + 0.6535*S*a_p - 0.0133*S*a_e + 3.0491*f*a_p \\
&+0.0836*f*a_e + 0.0000547*S^2 + 0.0036*f^2 + 3794.3*a_p{}^2 + 2.67*a_e{}^2
\end{aligned} \tag{3.25}$$

The R-square and RMSE of the refined RSM quadratic CE model are given in Table 3-7. The results show a better accuracy and a lower RMSE of this model compared to the original RSM quadratic.

Table 3-7: ANOVA of refined quadratic energy consumption model.

Model Type	R-sq adj	RMSE	No of Terms
Refined Quadratic	0.9955	5.7269	13

Figure 3-10 shows a plot between the CE estimated by the refined quadratic model, given in (3.25), and the actual values of CE – which were measured from the experimental tests. The experimental design samples were used as input data for calculation. From this graph, the fitness of the refined RSM quadratic model can be visualised.

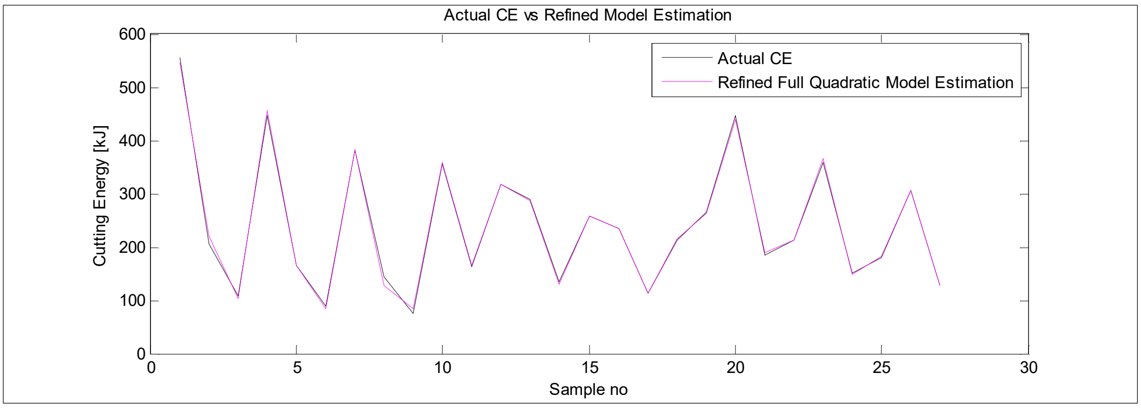

Figure 3-10: Actual CE vs Estimated CE from refined model.

In the next section, the conclusions of this chapter are drawn.

3.5 Conclusions

This chapter presents an empirical modelling framework for machining operations, which was used to develop a case study for milling processes. A predictive energy consumption model was obtained as a result, with R-sq adj and RMSE equal to 0.9955 and 5.7269, respectively.

The qualitative analysis using the Main Effect and Interaction plots techniques was crucial for the knowledge construction process in regards to face milling operations. This analysis revealed that, for milling operations:

- Spindle speed had the lowest effect on the mean CE when switching speed levels, and 1500 rpm was the optimal value, *ceteris paribus*, considering the smaller the CE the better.
- Width of cut has shown as the most significant parameter, showing substantial drops on the mean CE when increasing the levels from A to C.
- Spindle speed presented very low interaction with feed, but a more significant correlation with depth and width of cut.
- Feed and depth presented significant interaction, but no strong interaction between feed and width was found.

The quantitative analysis using Curve fitting supported the selection of RSM as the modelling method for the CE predictive models' development. Furthermore, R-sq adj and RMSE were the decision makers on the best fit model selection and showed to be simple to implement and efficient. Moreover, the *p-value* from ANOVA was a good parameter and validated the findings from the qualitative analysis. It helped in refining the CE model in order to be more efficient for its further application into an optimisation approach.

In summary, the framework proposed provides good guidance when modelling machining operations. Furthermore, the steps of the framework intend to extract the maximum understanding and knowledge from the modelling process, as well as to promote a more critical analysis for the modelling method selection and the best fit estimated model.

In the next chapter, the refined RSM quadratic model will be applied to an optimisation approach to obtain the optimal cutting parameters with the goal to minimise the energy required for the cutting process.

Chapter 4: OPTIMISATION OF CNC MACHINING PROCESSES

4.1 Aim and Objectives and Chapter Organisation

Machining processes cover a wide range of operations, which depends on a series of machining specifications and details, as presented in the previous chapters. Accordingly, a series of optimisation problems have been addressed in order to enhance the performance of different machining operations. Despite the numerous research findings published in the past years, there are still knowledge gaps that must be addressed by further investigations of other optimisation goals.

Energy consumption has been of great concern in the manufacturing industry sector, especially in regards to CNC machining processes, due to the considerable energy demanded by the material removal process performed by CNC machines. Thus, the use of optimisation approaches to aid in the decision making of machining process planning stage is a plausible way to promote sustainability into manufacturing systems.

In this work, an optimisation approach will be described using two different optimisation methods that will be employed to find the optimal machining parameters that require the minimum energy consumption for face milling processes. The estimated energy consumption model developed using RSM, presented in the previous chapter, will be used as the objective function for the optimisation problem.

This chapter is organised as follows: Section 4.2 introduces the research. Section 4.3 presents the background necessary for developing the proposed optimisation approach. After that, Section 4.4 provides the methodology, implementation details of the optimisation problem addressed and the results and discussion. Finally, the conclusions are presented in section 4.5.

4.2 Introduction

A great effort has been developed by the research community worldwide to address complex manufacturing scenarios, which involve environmental, legal, economic and quality requirements. Optimisation methods and algorithms have been noticeably evolved to deal with the complexity of manufacturing problems.

In specific, manufacturing industries have attempted to achieve lower costs of production, higher productivity and better final product quality in manufactured products (Rao 2011). Moreover, manufacturing industries have been increasingly aware of the importance of energy efficiency in their production systems. This aspect together with the forthcoming Industry 4.0, have boosted related research by applying numerical solutions and computational methods, such as simulation and optimisation algorithms, to address sustainability requirements of manufacturing systems.

Based on the empirical modelling process framework developed in Chapter 3, effective optimisation approaches are developed in this chapter. Two optimisation approaches, i.e., Branch and Bound for mixed integer solutions and Genetic Algorithm (GA), are introduced for achieving energy efficiency in CNC machining processes. As a result, optimal machining parameters with the objective of minimising the energy consumption of machining processes are obtained. Comparisons between the two approaches are made.

4.3 Optimisation Problems of CNC Machining Operations

Various optimisation problems have been formulated for different purposes in regards to machining operations. Common objectives for such problems recently seen are productivity, quality, energy consumption and wear of cutter tool. Furthermore, these objectives are designated based on manufacturing or machining aspects such as material removal rate (MRR), surface roughness (Ra), specific energy for cutting (SEC), and so on. These are further described by machining variables and/or intermediate responses that would define the decision variables of the optimisation problem. Frequently used decision variables are machining parameters such as spindle speed, feed rate, depth of cut, width of cut, and/or intermediate responses such as machining cutting force. Accordingly, different solvers and algorithms have been addressing manufacturing optimisation problems. Table 4-1 shows some methods used for machining processes optimisation.

The decision upon which optimisation method to employ for a given single optimisation problem starts with two main points:

- To identify the type of the objective function (linear, quadratic, sum-of-squares, etc.), and,
- To identify the type of the constraints (un-constrained, bound, linear, discrete, etc.). In the case of a multi-objective optimisation problem, please refer to (Hwang and Masud 1979) for more details.

Figure 2-1 presented a network-based scheme that showed the various variables that machining operations depend on. This is why some requirements must be fulfilled before formulation an optimisation problem. Sonmez *et al.* 1999 have highlighted some requirements, these are:

- Knowledge of the machining processes under analysis.
- Empirical (or mechanistic) equations of the objective(s) and constraint(s) to define the optimisation problem.
- Specifications for the CNC machine capabilities.
- Draw an effective optimisation criteria and the problem formulation.
- Knowledge of mathematical and numerical optimisation techniques.

Table 4-1: Related work on the use of optimisation methods for machining processes.

Related Work	**Optimisation Method(s)**	**Objective function(s)**	**Decision Variables**
Wang (2013)	Neural network-based approach	Production rate, Operation cost and Quality	S, f, a_p and a_e
Wang *et al.* 2015	Pattern search (PS), GA and Simulated annealing (SA)	Energy consumption and Productivity	S, v_c, a_p and a_e
Sonmez *et al.* 1999	Dynamic programming and Geometric programming	Production rate	v_c and S_z
Shunmugam (2005)	GA	Total production cost	Number of passes, a_p, S and f
Choi and Yang (1999)	Proposed new algorithm	Tool wear	Cutting force pattern and a_p
Tandon *et al.* 2012	PSO	Machining time	Cutting force, S and f
Wang *et al.* 2015	GA and SA	Production time	v_c and f
Ozcelik *et al.* 2005	GA	Surface roughness	v_c, f and a_p (axial and radial)
Reddy and Rao (2005)	GA	Surface roughness	Tool geometry (*radial angle* and *nose radius*), S and f
Sreeram *et al.* 2006	GA	Tool life	a_p
Baskar *et al.* 2006	GA, Hill climbing algorithm and Memetic	Maximum profit	S and f

	algorithm

Table 4-1 reveals some of the optimisation methods that have been applied to machining processes. It also shows that GA is a commonly chosen method for identifying optimal solutions.

Recently, cutting force (or called machining force) models have been often used as an intermediate response for optimisation purposes. The reason for that is due to cutting force is a response that involves most of the machining variables and settings, and is well correlated to the outputs of machining processes, such as surface finish, the power required (due to load on the main spindle and axis), tool wear and cutting time. Thus, it represents a high potential to promote better performance in CNC operations. A drawback of using cutting force, is the measuring equipment (dynamometer) for CNC machines are usually quite costly.

As objectives and variables have increasingly been seen in optimisation approaches with the goal to enhance the performance of machining processes, the list of optimisation solvers and algorithms have also been progressively developed to overcome the weaknesses of the available methods as well as creating new opportunities to achieve better results benefiting from the innovative mechanisms.

Thus, based on the key identification points described above, two optimisation methods were chosen to carry out the optimisation problem of this work, which are: Branch and Bound for Mixed Integer Problems and GA. A brief background of the optimisation methods selected is provided next.

4.3.1 Mixed Integer Nonlinear Programming

Mixed Integer Nonlinear Programming (MINLP) denotes for mathematical programming with continuous and discrete variables and nonlinearities in the objective function and constraints (see the type of constraints in Table 4-2). In other words, MINLP is an approach that aids in the problem formulation process which it is necessary to optimise an objective function considering a set of decision variables or equations. The general form of an MINLP is given as

$$
\begin{aligned}
&\text{Minimise} \quad f(x) \\
&\text{Subject to: } \mathrm{A}x \leq b \\
&\mathrm{A}eqx = beq \\
&lb \leq x \leq ub \\
&C(x) = d \\
&Ceqx = deq \\
&X_i \ \in \mathbb{R} \\
&X_j \ \in \mathbb{Z}
\end{aligned}
\tag{4.1}
$$

Where $f(x)$ is a scalar function containing the nonlinear objective function, which is subject to given constraints. The type of constraints is shown in Table 4-2.

Table 4-2: Different type of constraints for MINLP.

Type of Constraint	Details
Linear inequalities	A is a $m \times n$ sparse matrix, **b** is a $m \times 1$ vector.
Linear equalities	Aeq is a $k \times n$ sparse matrix, **beq** is a $k \times 1$ vector.
Decision variable bounds	**lb** and **ub** are nx1 vectors, and stand for lower and upper bound, respectively.
Nonlinear inequalities	C is a $u \times 1$ vector of functions containing nonlinear inequality constraints, **d** is a $u \times 1$ vector.
Nonlinear equalities	Ceq is a $v \times 1$ vector of functions containing nonlinear equality constraints, **deq** is a $v \times 1$ vector.
Integer constraints	X_i are decision variables which must be an integer number.
Binary constraints	X_j are decision variables which must be a real number.

The goal of this approach is to minimise the objective function by selecting an optimal value of X that also satisfies all constraints. For more details about this method, please refer to (Lee and Leyffer 2011).

In the case of problems described by MINLP, an improved Branch and Bound (B&B) algorithm for solving mixed integer solutions can be employed as the optimisation method. For more details about B&B please refer to (Borchers and Mitchell 1994).

4.3.2 Genetic Algorithm (GA)

GA is a popular evolutionary algorithm in terms of diversity of applications. This method can solve both constrained and unconstrained optimisation problems, and many of well-known problems have been tried using GA (Yang 2014).

This algorithm works by continuously modifying a population of individual solutions. At each step, it randomly chooses individuals from the current population and uses them to be the parents that will produce the children for the next generation (MathWorks 2016). This characteristic represents the difference from GA to classical algorithms (such as Simplex, B&B, etc.).

The schematic representation of the optimisation procedure of GA algorithms is shown in Figure 4-1.

Genetic Algorithm

Objective function $f(\boldsymbol{x})$, $\boldsymbol{x} = (x_1, ..., x_d)^T$
Encode the solutions into chromosomes (strings)
Define fitness F (eg, $F \propto f(\boldsymbol{x})$ for maximization)
Generate the initial population
Initialize the probabilities of crossover (p_c) and mutation (p_m)
    while (t <Max number of generations)
        Generate new solution by crossover and mutation
        Crossover with a crossover probability p_c
        Mutate with a mutation probability p_m
        Accept the new solutions if their fitness increase
        Select the current best for the next generation (elitism)
        Update $t = t + 1$
    end while
Decode the results and visualization

Figure 4-1: Pseudo code of genetic algorithm.

GA can also be used to solve problems that involve integer-valued variables. This makes this solver a suitable method for the optimisation approach hereby addressed. For a further understanding of the GA procedures and concepts, please refer to (Yang 2014).

4.4 Methodology

The methodology to achieve the goal of this chapter is based on the application of the predictive energy consumption model developed in the previous chapter as the objective function for the optimisation problem. According to the characteristics of the optimisation problem (type of objective function and its goal and type of constraints), two different optimisation methods are selected, i.e., GA and Branch and Bound for mixed integer solutions. After that, the optimisation problem is re-structured to comply with each method's scheme. Then, finally, the optimum machining parameters, suggested by each method, are compared considering the output cutting energy consumption, along with the computation time, this way evaluating the performance of each method. The results obtained are further analysed considering the machining perspective.

4.4.1 Optimisation Problem

4.4.1.1 Problem formulation

The goal of this section is to minimise the energy consumption required by the cutting process performed in face milling operations. This is to be achieved by optimising the estimated CE model in order to obtain the optimal decision variables (or optimised variables). These variables are described as x_1, x_2, x_3 and x_4, which denote for spindle speed, feed rate, depth of cut and width of cut, respectively. Considering the selected refined model $CE_{\text{refined\_quad}}\left(x_1, x_2, x_3, x_4\right)$, obtained in the previous chapter, the general form of the optimisation problem can be expressed as:

$$\begin{cases} \text{Minimise:} & f\left(x_1, x_2, x_3, x_4\right) \\ \text{Subject to:} & g(x_1, x_2, x_3, x_4) \leq 0 \end{cases} \tag{4.2}$$

where the objective function $f(x)$ is the estimated energy consumption model, defined as the refined RSM quadratic model $CE_{\text{refined\_quad}}\left(x_1, x_2, x_3, x_4\right)$ and given in (3.25), and $g(x_1, x_2, x_3, x_4)$ represents the inequality constraint function.

4.4.1.1.1 Objective function analysis

In this chapter, the pure quadratic and the refined quadratic models, presented in Chapter 3, are used as objective functions and separately applied in the optimisation approach. The pure quadratic model was also selected for further investigation of the efficiency of the optimisation methods selected and for comparison sake.

The two CE models selected are given in (3.20) and (3.25), which are described, respectively, as:

$$\begin{aligned} CE_{\text{pure\_quad}}(S, f, a_p, a_e) = 1587.4 - 0.1567S - 2.7279f \\ -2051.4a_p - 61.944a_e + 0.0000547S^2 \\ +0.0036f^2 + 2127.3a_p^{\;2} + 2.0165a_e^{\;2} \end{aligned}$$

$$\begin{aligned} CE_{\text{refined\_quad}}(S, f, a_p, a_e) = 2329.7 - 0.2194S - 4.4784f \\ -4960.8a_p - 72.635a_e + 0.6535S \cdot a_p \\ -0.0133S \cdot a_e + 3.0491f \cdot a_p + 0.0836f \cdot a_e \\ +0.0000547S^2 + 0.0036f^2 + 3794.3a_p^{\;2} + 2.67a_e^{\;2} \end{aligned}$$

These estimated models describe the energy required for the cutting process as a function of the machining variables spindle speed, feed rate, depth of cut and width of cut, for face milling operations.

- Pure quadratic function analysis

The CE model obtained using RSM pure quadratic structure, shown above, can be expressed in terms of x_i as:

$$CE_{\text{pure\_quad}}(x) = \alpha_0 + \sum_{i=1}^{4} CE_i \qquad (4.3)$$
$$CE_i = \alpha_{i,1}x_i + \alpha_{i,2}x_i^{\,2}$$

where α_0 is the intercept term and x_i is the *i*th optimisation variable and the index $i = 1,2,3,4$ represent spindle speed, feed rate, depth of cut and width of cut, respectively, while $\alpha_{i,0}, \alpha_{i,1}$ and $\alpha_{i,2}$ are the model coefficients, and set according to (3.20). Consequently, (4.3) can be expressed as:

$$\begin{aligned} CE_{\text{pure\_quad}}(x) = 1587.4 - 0.1567x_1 + 0.0000547x_1^2 - 2.7279x_2 + 0.0036x_2^2 \\ -2051.4x_3 + 2127.3x_3^2 - 61.944x_4 + 2.0165x_4^2 \end{aligned} \qquad (4.4)$$

(4.4) shows that the CE model is a sum of four sub models. Each sub model is a quadratic polynomial. Furthermore, it has been realised that each sub model is a convex function because the second x_i derivative of each sub-model in (4.3) generates a positive constant value:

$$\sum_{i=1}^{n} \frac{\partial^2 CE_i}{\partial x_i^{\,2}} = C_i, \qquad C_i \geq 0 \qquad (4.5)$$

where $C_1 = 1.0940\text{e-}04$, $C_2 = 0.0072$, $C_3 = 4.2546\text{e+}03$ and $C_4 = 4.0330$.

Since the sum of convex functions produces a convex function, $CE_{\text{pure\_quad}}(x)$ is a convex function. This observation is of great significance in assisting the selection of the appropriate optimisation solver. Furthermore, this means that the local optimal solution for minimising each sub-model CE_i is the global optimal solution because there is only one solution. Consequently, the optimum value of each variable when obtaining the global solution for minimising (4.4) is the same optimal variables of each submodel case.

In addition, the optimal machining variable denoted x_i^* of CE_i for generating the global minimum can be obtained by satisfying $\frac{dCE_i}{dx_i}=0$, allowed by the convex definition of sub-models.

Accordingly, the results obtained for the pure quadratic function are $x_1^*=1435.1$ in rpm, $x_2^*=379.1667$ in mm/min, $x_3^*=0.9822$ in mm, $x_4^*=15.3583$ in mm, and $CE_{\text{pure\_quad}}(x^*)=\text{-}9.9191$ in kJ. It can be noted that the output cutting energy consumption obtained shows a negative value. Intuitively, this is practically not correct. Nonetheless, this can be explained by the extension of the upper bound constraints, which provided that the optimal variables for feed rate, depth of cut and width of cut values are not located in the range of values used for the model development – not in between the lowest and highest levels of factors. Thus, this result suggests that there is a need to consider constraints where the optimal variables must be located.

4.4.1.1.2 Constraints

In machining processes, the lower and upper bounds, denoted as lb and ub, respectively, of spindle speed and feed rate are usually defined by the minimum and maximum values accepted according to the machining operation. This is along with the machining specifications of the workpiece material and the cutter tool material and shape.

The equations that define the acceptable ranges of speed and feed for a machining process are, respectively:

$$x_1=\frac{1000\times v_c}{\pi\times D} \tag{4.6}$$

$$x_2 = S_z \times N \times x_1 \tag{4.7}$$

where x_1 is given in rpm and x_2 in mm/min. Moreover, v_c and S_z refer the variables cutting speed and feed per tooth, respectively and they are given by machine and tool manufacturers.

However, in this work, the experimental design minimum and maximum levels of each factor (decision variable), addressed in the experimental data in (Yan and Li 2013), will be used as lower and upper bound constraints. Thus, the constraints of this optimisation problem are given as:

$$\text{Constraints:} \quad \begin{Bmatrix} x_1 : & x_2 : & x_3 : & x_4 : \\ x_1 \le 2000 & x_2 \le 300 & x_3 \le 0.4 & x_4 \le 15 \\ x_1 \ge 1000 & x_2 \ge 200 & x_3 \ge 0.2 & x_4 \ge 5 \end{Bmatrix} \tag{4.8}$$

Additionally, the values of spindle speed and feed rate are considered to be positive integer $(x_1, x_2) \in \mathbb{Z}^+$ and x_3 and x_4 are positive real $(x_3, x_4) \in \mathbb{R}^+$.

Therefore, the nonlinearity of the objective function along with the type of constraints: bound constraints with integer and real values, of this optimisation problem, demonstrates that MINLP is a suitable approach to structure the problem formulation, furthermore, that GA and Branch and Bound for solving MINLP solutions are suitable methods for the optimisation approach.

4.4.2 Optimisation of Machining Variables using GA and Branch and Bound for Mixed Integer Solution

The problem formulation presented in the previous subsection showed that MINLP approach can be used for structuring it prior to the optimisation process. Consequently, the mathematical programming structure in MINLP can be expressed as:

$$\begin{aligned}
&\text{Minimise} \quad CE\left(x_1, x_2, x_3, x_4\right) \\
&\text{Subject to}: \\
&1000 \le x_1 \le 2000 \\
&200 \quad \le x_2 \le 300 \\
&0.2 \quad \le x_3 \le 0.4 \\
&5 \qquad \le x_4 \le 15 \\
&x_1, x_2 \ \in \ \mathbb{Z}^+ \\
&x_3, x_4 \in \ \mathbb{R}^+
\end{aligned} \tag{4.9}$$

The structure presented in (4.9) proposes that Branch and Bound for solving mixed integer solutions and GA methods are suitable for addressing this problem. Consequently, these are used to implement the optimisation problem formulation hereby presented. The selection of two different methods is mainly for comparison reasons between the outputs obtained from one gradient-based and one sampling-based method.

Moreover, the CE models selected – pure quadratic and refined quadratic – to be the objective functions and the constraints, defined in the previous subsection, were individually applied to each optimisation method. The choice of implementing these two models is due for further investigations in order to define the trade-offs between the effect of the number of terms in the objective function and the R-square of each model on the optimisation outputs obtained – efficiency of calculation and optimal values found.

Figures X and Y below show the flowchart of each optimisation algorithm implemented – GA and B&B. GA was implemented using the MATLAB/Simulink optimisation tool box. For the implementation of Branch and Bound, the BNB20 algorithm in MATLAB/Simulink was used. This algorithm uses fmincon for solving the sub problems and simple heuristic rules for branching variable selection.

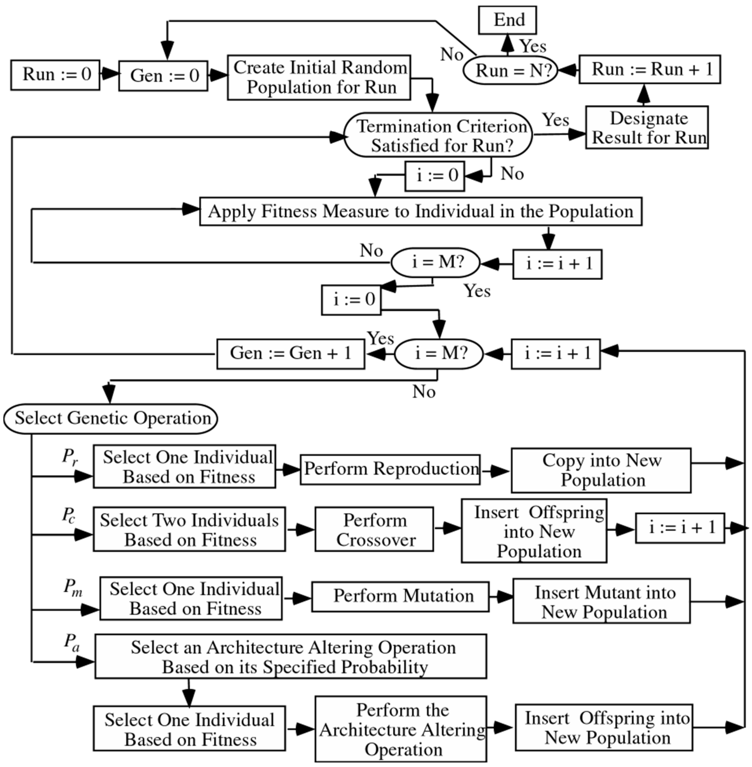

Figure 2 - Genetic Algorithm flowchart.

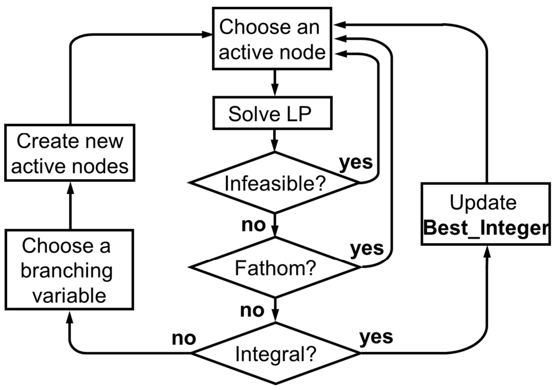

Figure 3 - Branch and Bound flowchart.

Therefore, the results obtained using the problem formulations with the selected models and selected methods are presented in Table 4-3 and Table 4-4.

Table 4-3: Results from GA optimisation where x_1^*, x_2^*, x_3^* and x_4^* are given in rpm, mm/min, mm and mm, respectively.

Estimated Model	No of Terms	R^2	Genetic Algorithm					
			Optimal machining variables				Response	Performance
			x_1^*	x_2^*	x_3^*	x_4^*	CE [kJ]	CT*[s]
Pure quadratic	9	0.9407	1434	250	0.4	15	63.4333	0.671599
Refined quadratic	13	0.995	1147	250	0.4	12.5	63.1018	0.679059

**CT stands for calculation time.*

Table 4-4: Results from Branch and Bound optimisation.

Estimated Model	No of Terms	R^2	Branch and Bound for Mixed Integer					
			Optimal machining variables				Response	Performance
			x_1^*	x_2^*	x_3^*	x_4^*	CE [kJ]	CT*[s]
Pure quadratic	9	0.9407	1433	250	0.4	15	63.4332	0.419749
Refined quadratic	13	0.995	1138	250	0.4	12.5	62.7193	0.436203

**CT stands for calculation time.*

The results displayed in Tables 4-3 and 4-4 showed that the number of terms in the model did not substantially influence on the computational time required for convergence to the optimal solution in either approach. In addition, that there wasn't a significant difference between the optimal response values found using B&B and GA, although, the refined quadratic model suggested a more optimal cutting parameters mix, conclusion taken based on the lowest value obtained for the required cutting energy. Moreover, B&B demonstrated to be more efficient than GA for the optimisation problem addressed in this case study.

In the next section the results will be analysed and discussed.

4.4.3 Results and Discussion

The implementation of the optimisation problem formulated in this case study using the two objective functions and both the optimisation methods selected showed that the number of terms had no significant effect on the computational time for finding the optimal solutions in both methods used. Moreover, the GA approach required a larger time compared to the Brand and Bound. This can be explained due to the nature of the methods used, in which GA is a sampling-based technique while Branch and Bound is a gradient-based technique. The latter converges to the optimum value faster than the former.

Furthermore, Table 4-3 and Table 4-4 showed that the refined CE quadratic model implemented using the Branch and Bound method proposed the optimal results amongst the optimum machining variables found on both methods using the two equations. This was suggested by the lowest response given, $CE = 62.7193$. Consequently, the optimal machining variables for spindle speed, feed rate, depth of cut and width of cut are, respectively, 1138 rpm, 250 mm/min, 0.4 mm and 12.5 mm for face milling operations, as seen in Table 4-4. Moreover, this result unveils the importance of the interaction terms, which are included in the refined CE quadratic model, in the final response, which promotes a more accurate estimation, described by the higher R-sq adj.

In summary, the trade-off between the number of members and the accuracy of the model when considering the computational time showed that accuracy is indeed more significant than the former when selecting the objective function since the most optimal result was found by the estimated refined RSM quadratic model for the cutting energy.

4.5 Conclusions

In this Chapter, a case study for an optimisation problem was addressed. Two estimated models for the cutting energy, developed in the previous Chapter, were employed as objective functions in order to investigate and compare both model structures and optimisation methods selected. The criteria considered are the optimal solution found and the computation time, considering the number of terms and accuracy (defined by R-sq adj) of each model.

During the problem formulation, the objective function analysis carried out was an important step for the problem formulation structuring method and for the constraints definition. It showed that the estimated pure quadratic model is a sum of convex submodels and, therefore, is also a convex model. This way, allowing MINLP to be used as the mathematical representation of the optimisation problem. Furthermore, it proved that the global optimum variables of the entire pure quadratic model are the same as the optimum variable of each of its submodels. In addition, the constraint boundaries were refined in accordance with the experimental design specifications, otherwise, a negative value for the objective function CE could be obtained as an optimal solution – which is inadequate, once negative energy consumption cannot be accepted. This observation emphasised the importance of understanding well the constraints of the optimisation problem.

The investigation on the methods performance as well as the trade-off between the number of terms and the accuracy of the two estimated models selected – pure quadratic and refined quadratic – considering the computational time and quality of output as criteria, showed that accuracy of the model is more important for this case. This is explained by the non-substantial difference between the time required for the search between each objective function when using both methods.

Moreover, Branch and Bound method showed to be more efficient than GA for the problem solved, once it provided the most optimal solution within the shortest time. The optimum machining variables unveiled are: spindle speed=1138 rpm, feed rate=250 mm/min, depth of cut=0.4 mm and width of cut =12.5 mm, for face milling operations. These optimum values give a resultant CE 26% lower than the required if the initial recommended cutting parameters were used – feed rate of 250 mm/min, a spindle speed of 1500 rpm, a cut depth of 0.2 mm and cut width of 10 mm, as given in (Yan and Li 2013).

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Chapter 5: CONCLUSIONS AND FURTHER RESEARCH DIRECTIONS

5.1 Conclusions

The main goal of this thesis is to address the urgent need for more energy efficient machining systems by proposing a framework for empirical modelling of energy consumption during machining processes and, furthermore, to develop an energy consumption optimisation approach. So that, the optimal machining parameters that provide the least energy consumption for machining operations could be obtained. The optimal values provided an estimated energy saving of 26% when compared to the traditionally recommended values.

Knowing that energy consumption modelling of machining processes is an essential step for promoting energy savings, a cautious analysis of experimental data must be taken. Based on this, the modelling process presented was comprised of a series of statistical analysis divided into qualitative and quantitative aspects.

The qualitative analysis, based on Main Effect and Interaction Plots techniques, has provided valuable information for a deeper understanding of the relationships between the machining parameters spindle speed, feed rate, depth of cut and width of cut and the energy required for cutting, on milling operations. The main findings of this analysis are as follows:

- Spindle speed and width of cut appeared as the least and the most significant variables in the mean CE, respectively.
- There was a considerably weak interaction between the variables spindle speed and feed rate, and strong interactions between feed*depth and feed*width.

The quantitative analysis using Curve Fitting was reasonably supportive for the selection of the modelling method to be used. The right choice of the modelling methodology is crucial for the quality of the estimated model. RSM was found to be a suitable method, since the shape of the curve described by the plots of each factor against energy consumption, *ceteris paribus*, presented to be quadratic. Consequently, four estimated models have been developed using the functions available in the RSM tool.

A comparison using R-sq adj and RMSE has showed that the quadratic model, in which all terms are included, presented the highest estimation accuracy and lowest RMSE. This model was further refined considering ANOVA p-value, which demonstrated a low significance of the interaction term Speed*feed in the model, p-value higher than α, as expected, and, consequently, was removed from the model. The coefficients (or parameters) for the new estimated refined RSM quadratic model was obtained using Least Squares Method. The ANOVA results for the refined model presented an R-sq adj equal to 0.9955, which suggests high estimation accuracy.

From the resultant estimated model obtained, the proposed framework provides good guidance when modelling machining operations using the empirical approach. The steps defined in the modelling framework aim to extract the maximum understanding and knowledge of the modelling process, which may bring good contributions to the research and industry communities. In addition, it promotes a more critical analysis for the selection of the modelling method and, furthermore, for the selection of the best fit model.

Two of the models developed using RSM, i.e., pure quadratic and refined quadratic, have been further used as objective functions of the optimisation problem addressed in this thesis. Two steps were considered critical when developing the optimisation approach:

- During the problem formulation, the objective function analysis carried out was an important step for the selection of the problem formulation structuring method and for the constraints definitions. From this analysis, the pure quadratic model is found to be convex because it is comprised of convex sub-models.
- The constraints must be well known and well defined in order to obtain realistic results.

The nonlinear objective function and bound constraints of the optimisation problem suggested the use of Mixed Integer Nonlinear Programming for the mathematical representation of the problem formulation. Furthermore, it indicated that GA and Branch and Bound solver for the mixed integer solutions method are suitable for finding the optimal solution for the optimisation problem.

The results of the investigation carried out considering these two methods and the two selected models have shown that:

- The number of terms in the model did not significantly affect the computation time in both methods.
- The selection of the refined quadratic model as the objective function for the optimisation problem provided better solutions in both methods, compared to the pure quadratic model.
- The method Branch and Bound showed a better performance, faster convergence and the best optimal solution, compared to GA.

Additionally, the optimisation approach has unveiled the optimum machining variables are: spindle speed=1138 rpm, feed rate=250 mm/min, depth of cut=0.4 mm and width of cut =12.5 mm, for the most energy efficient milling operations for the case study. These optimum values give a resultant CE 26% lower than the required if the initial recommended cutting parameters were used.

An important observation from the research developed in this work is in regards to data collection. In this thesis, the modelling process started from the data analysis stage. Nonetheless, when applying the statistical techniques for the quantitative analysis it was noticed that the Design of Experiments (DoE) is a critical step in the empirical modelling for the quality of the estimated model development. The quantitative analysis carried out in this theses showed that the number of levels for each factor (cutting parameter) must meet the mathematical requirements for a realist modelling procedure and, furthermore, it showed that three data points (or levels) are not enough for such analysis. The overall conclusion is that the data collection should be larger (both in terms of levels and sampling number), which is due for the following reasons:

- To avoid numerical problems: limitations were found when describing the interactions of each factor on the mean response CE in mathematical terms. To address this problem, the DoE should contain more samples in which one factor was changed while the others were kept constant.
- To aid in the selection of the model structure: more data points, which would come from more factor levels, would have provided a better picture of the shape of the curve when analysing the data using the Curve Fitting technique. This would provide a more precise structure for the function that can describe the data plotted. In this

work, only three data points were available per factor, in which for such case a seconded order polynomial could be easily fitted.

- To provide a larger range of level per factor: it is important to make sure that the lower and upper bound constraint values defined on the problem formulation are the minimum and maximum values acceptable by the machining process. It's important to note that the larger the level's range, the more variables can be searched by the optimisation method and, consequently, it increases the chance of a convergence to the best optimal solution.

In summary, the experimental set defines the data collection structure (design variables *vs.* response) for analysis. Moreover, the mathematical procedures are all based on this structure (or experimental design Taguchi array). Accordingly, lack of data collection leads to poor modelling procedures, which would develop a low quality estimated model. Furthermore, a low-quality model leads to a non-reliable optimisation process, since the objective function and/or constraints are described by, accurate, but low-quality equations.

Additionally, a non-reliable optimisation process leads to fake optimal solutions, which can cause misunderstanding or, even worse, poor quality machining processes. Therefore, this analysis also suggests that R-squared criteria for describing the model accuracy is an efficient representation in theory. However, if the model is to be applied in practice, it should be validated with real experimental tests, i.e. not only validated based on the comparison between actual measured data and the obtained values from the estimated model, by using the matrix of designed variables as inputs.

5.2 Further work

As further work, the proposed optimal machining variables should be validated through practical experimental tests. Also, it is suggested that different equality and inequality constraints and objectives should be considered in the optimisation problem. In addition, the proposed modelling framework should be applied to develop models for other machining operations, such as end-milling and pocketing, as well as another machining process, such as turning. Furthermore, designing an experiment considering a different type of materials.

Also, the machining processes are described by static variables, which means the current value does not depend on the previous values and is not the most precise approach to consider in such processes, since the dynamics of these, such as heating and vibration, are important aspects to be considered in machining processes. Moreover, the modelling framework could be extended to address more complex model development.

In addition, the predictive model should consider different variables in order to become more realistic, such as cutter tool, workpiece material properties, angle of engagement, etc. And, finally, a smart Design of Experiments should be done to provide the information needed to meet the mathematical requirements for developing an accurate, reliable and realistic model – by selecting more levels or varying dynamically the values of cutting parameters, for example

References

Abu Qudeiri, J., Yamamoto, H., Ramli, R. (2007) 'Optimization of Operation Sequence in CNC Machine Tools Using Genetic Algorithm', *Journal of Advanced Mechanical Design, Systems, and Manufacturing* 1 (2), 272-282.

Avram, O. I. and Xirouchakis, P. (2011) 'Evaluating the use Phase Energy Requirements of a Machine Tool System'*. Journal of Cleaner Production* 19 (6–7), 699-711

Balogun, V. A. and Mativenga, P. T. (2013) 'Modelling of Direct Energy Requirements in Mechanical Machining Processes'*. Journal of Cleaner Production* 41, 179-186

Baskar N, Asokan P, Saravanan R, Prabhaharan G (2006) Selection of optimal machining parameters for multi-tool milling operations using a memetic algorithm. *Journal of Material Process Technology* 174, 239–249

Behrendt, T., Zein, A., and Min, S. (2012) 'Development of an Energy Consumption Monitoring Procedure for Machine Tools'*. CIRP Annals - Manufacturing Technology* 61 (1), 43-46

Bernardos, P.G. and Vosniakos, G.C. (2002) Prediction of surface roughness in CNC face milling using neural networks and Taguchi's design of experiments. *Robotics and Computer-Integrated Manufacturing* 18 (5), 343–354

BP Energy Outlook 2035. [online] http://bp.com/energyoutlook/ (Accessed 05 December 2015)

Borchers, B. and Mitchell, J. E. (1994) 'An Improved Branch and Bound Algorithm for Mixed Integer Nonlinear Programs'*. Computers & Operations Research* 21 (4), 359-367

Boyaci and Bas (2006) Modeling and optimization I: Usability of response surface methodology. *Journal of Food Engineering* 78 (3), 836-845

Braungart, M., McDonough, W., and Bollinger, A. (2007) 'Cradle-to-Cradle Design: Creating Healthy Emissions – a Strategy for Eco-Effective Product and System Design'*. Journal of Cleaner Production* 15 (13–14), 1337-1348

Carbon Trust - CRC Energy Efficiency Scheme. [online] http://www.carbontrust.com/resources/guides/carbon-footprinting-and-reporting/crc-carbon-reduction-commitment (Accessed 07 December 2015)

Camposeco-Negrete, C., Nájera, Juan de Dios Calderón, and Miranda-Valenzuela, J. C. (2016) 'Optimization of Cutting Parameters to Minimize Energy Consumption during Turning of AISI 1018 Steel at Constant Material Removal Rate using Robust Design'*. The International Journal of Advanced Manufacturing Technology* 83 (5-8), 1341-1347

Chai, T. and Draxler, R. R. (2014) 'Root Mean Square Error (RMSE) Or Mean Absolute Error (MAE)?–Arguments Against Avoiding RMSE in the Literature'. *Geoscientific Model Development* 7 (3), 1247-1250

Chartered Institute of Management Accountants (CIMA) (2010) *The global manufacturing sector: current issues.* [online] CIMA sector report ISBN 978-1-85971-674-8, London. http://www.cimaglobal.com/Documents/Thought_leadership_docs/Global_manufacturing_report.pdf (Accessed 07 December 2015)

Choi JG, Yang MY (1999) In-process prediction of cutting depths in end milling. *International Journal of Machine Tools Manufacturing* 39(5), 705–721

Chow, G. C. (2008) 'China's Energy and Environmental Problems and Policies'. *Asia-Pacific Journal of Accounting & Economics* 15 (1), 57-70

Climate Action Plan 2050. [online] http://www.bmub.bund.de/en/topics/climate-energy/climate/details-climate/artikel/scientific-bases-for-the-climate-action-plan-2050-1/ (Accessed 07 December 2015)

Climate Nexus. [online] http://climatenexus.org/learn/international-actions/chinas-climate-and-energy-policy#energy and climate (Accessed 07 December 2015)

CNC Cook book. [online] http://www.cnccookbook.com/CCCNCMachine.htm (Accessed 03 December 2015)

COP21. [online] http://www.cop21.gouv.fr/en/more-details-about-the-agreement/ (Accessed 13 December 2015)

COP21: World awaits landmark climate deal. [online] http://www.bbc.com/news/science-environment-35082895 (Accessed 13 December 2015)

Diaz, N., Redelsheimer, E., and Dornfeld, D. (2011) 'Energy Consumption Characterization and Reduction Strategies for Milling Machine Tool use'. in *Glocalized Solutions for Sustainability in Manufacturing: Proceedings of the 18th CIRP International Conference on Life Cycle Engineering, Technische UniversitÃ¤t Braunschweig, Braunschweig, Germany, may 2nd - 4th, 2011*. ed. by Hesselbach, J. Berlin, Heidelberg: Springer Berlin Heidelberg, 263-267

Draganescu, F., Gheorghe, M., and Doicin, C. V. (2003) 'Models of Machine Tool Efficiency and Specific Consumed Energy'. *Journal of Materials Processing Technology* 141 (1), 9-15

Du, K., Tang, D. and Li, L. (2006) 'On the Developmental Path of Chinese Manufacturing Industry Based on Resource Restraint [J]'. *Jiangsu Social Sciences* 4, 013

Ehmann, K. F., Kapoor, S. G., DeVor, R. E., and Lazoglu, I. (1997) 'Machining Process Modeling: A Review'. *Journal of Manufacturing Science and Engineering* 119 (4), 655-663

European Commission – Energy Efficiency Communication (2014). Energy Efficiency and its contribution to energy security and the 2030 Framework for climate and energy policy [online]. COM(2014) 520 final, Brussels. http://ec.europa.eu/energy/sites/ener/files/documents/2014_energy_efficiency_communication.pdf (Accessed 07 December 2015)

Geller, H., Harrington, P., Rosenfeld, A. H., Tanishima, S., and Unander, F. (2006) 'Polices for Increasing Energy Efficiency: Thirty Years of Experience in OECD Countries'. *Energy Policy* 34 (5), 556-573

Gupta, K., Laubscher, R. F., Davim, J. P., and Jain, N. K. (2016) 'Recent Developments in Sustainable Manufacturing of Gears: A Review'. *Journal of Cleaner Production* 112, Part 4, 3320-3330

Hamieh, T., Kadi, H. E., Deiab, I. M., and Khattab, A. A. (2014) '8th International Conference on Material Sciences, CSM8-ISM5 Predicting Cutting Forces in Aluminum using Polynomial Classifiers'. *Physics Procedia* [online] 55, 237-242. Available from: http://www.sciencedirect.com/science/article/pii/S1875389214000972

He, Y., Liu, F., Wu, T., Zhong, F., and Peng, B. (2012) 'Analysis and Estimation of Energy Consumption for Numerical Control Machining'. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*

Hu, S., Liu, F., He, Y., and Hu, T. (2012) 'An on-Line Approach for Energy Efficiency Monitoring of Machine Tools'. *Journal of Cleaner Production* 27, 133-140

Hwang, C. and Masud, A. S. Md., Multiple Objective Decision Making — Methods and Applications. A State-of-the-Art Survey. In Collaboration with S. R. Paidy and Kwangsun Yoon. Lecture Notes in Economics and Mathematical Systems 164. Berlin-Heidelberg-New York, Springer-Verlag 1979. XII, 351 S., 39 Abb., 35 Tab., DM 35,50, US $19.60. ISBN 3-540-09111-4

India's National Action Plan on Climate Change (NAPCC). [online] http://www.c2es.org/international/key-country-policies/india/climate-plan-summary (Accessed 06 December 2015)

International Energy Agency. (2014) World Energy Outlook 2014 Factsheet - How will global energy markets evolve to 2040?. [online] Fact-sheet, International Energy Agency (IEA), Paris, France. http://www.worldenergyoutlook.org/media/weowebsite/2014/141112_WEO_FactSheets.pdf (Accessed 05 December 2015)

International Organization for Standardization (2014) ISO14955-1:2014: *Environmental evaluation of machine tools*. Geneva, ISO.

Investopedia (2015) What's the difference between r-squared and adjusted r-squared? | Investopedia. [online] Investopedia. http://www.investopedia.com/ask/answers/012615/whats-difference-between-rsquared-and-adjusted-rsquared.asp?ad=dirN&qo=investopediaSiteSearch&qsrc=0&o=40186 (Accessed 23 July 2016)

Janssen, R. (2010) 'Harmonising Energy Efficiency Requirements-Building Foundations for Cooperative Action'. *International Centre for Trade and Sustainable Development, Issue Paper* (14)

Jens, K. (2010) 'Energieeffiziente Produktherstellung'. *Fraunhofer FUTUR Produktionstechnik Für Die Zukunft* 12, 12-13

Jia, S., Tang, R., and Lv, J. (2014) 'Therblig-Based Energy Demand Modeling Methodology of Machining Process to Support Intelligent Manufacturing'. *Journal of Intelligent Manufacturing* 25 (5), 913-931

Kong, D., Choi, S., Yasui, Y., Pavanaskar, S., Dornfeld, D., and Wright, P. (2011) 'Software-Based Tool Path Evaluation for Environmental Sustainability'. *Journal of Manufacturing Systems* 30 (4), 241-247

Lasemi, A., Xue, D., and Gu, P. (2010) 'Recent Development in CNC Machining of Freeform Surfaces: A State-of-the-Art Review'. *Computer-Aided Design* 42 (7), 641-654

Lazoglu, I., Manav, C., and Murtezaoglu, Y. (2009) 'Tool Path Optimization for Free Form Surface Machining'. *CIRP Annals - Manufacturing Technology* 58 (1), 101-104

Lee and Leyffer, S. (2011) Mixed Integer Nonlinear Programming. The IMA Volumes in Mathematics and its Applications. 154 (660). ISBN 978-1-4614-1926-6

Li, L., Yan, J., and Xing, Z. (2013) 'Energy Requirements Evaluation of Milling Machines Based on thermal equilibrium and Empirical Modelling'. *Journal of Cleaner Production* 52, 113-121

Li, W. and Kara, S. (2011) 'An Empirical Model for Predicting Energy Consumption of Manufacturing Processes: A Case of Turning Process'. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture* 225 (9), 1636-1646

Liu, F., Wang, Q., and Liu, G. (2013) 'Content Architecture and Future Trends of Energy Efficiency Research on Machining Systems'. *Chin J Mech Eng* 49 (19), 87-94

Lv, J., Tang, R., Jia, S., and Liu, Y. (2016) 'Experimental Study on Energy Consumption of Computer Numerical Control Machine Tools'. *Journal of Cleaner Production* 112, Part 5, 3864-3874

Moreira, L.C., Li, XX., Li, WD., Lu, X., Fitzpatrick, M.E. (2015) ‘Research Publications on Energy Consumption and Efficiency of Machine Tools: An Overview’. Paper Presented at the *16th International Manufacturing Conference in China.* 22-25 October 2015. Hangzhou, China.

Mori, M., Fujishima, M., Inamasu, Y., and Oda, Y. (2011) 'A Study on Energy Efficiency Improvement for Machine Tools'. *CIRP Annals - Manufacturing Technology* 60 (1), 145-148

Newman, S. T., Nassehi, A., Imani-Asrai, R., and Dhokia, V. (2012) 'Energy Efficient Process Planning for CNC Machining'. *CIRP Journal of Manufacturing Science and Technology* 5 (2), 127-136

O'Driscoll, E. and O'Donnell, G. E. (2013) 'Industrial Power and Energy Metering – a State-of-the-Art Review'. *Journal of Cleaner Production* 41, 53-64

Ozcelik, B., Oktem, H., Kurtaran, H. (2005) Optimum surface roughness in end milling Inconel 718 by coupling neural network model and genetic algorithm. *International Journal of Advanced Manufacturing Technology* 27(3–4), 234–241

Peattie, K. and Charter, M. 'Green Marketing'. *The Marketing Book* 5, 726-755

Peng, T. V. and Xu, X. (2013) 'A Universal Hybrid Energy Consumption Model for CNC Machining Systems'. in *Re-Engineering Manufacturing for Sustainability: Proceedings of the 20th CIRP International Conference on Life Cycle Engineering, Singapore 17-19 April, 2013*. ed. by Nee, C. A. Y. Singapore: Springer Singapore, 251-256

Rajemi, M. F., Mativenga, P. T., and Aramcharoen, A. (2010) 'Sustainable Machining: Selection of Optimum Turning Conditions Based on Minimum Energy Considerations'. *Journal of Cleaner Production* 18 (10–11), 1059-1065

Rao, R. Venkata. (2011) Advanced Modelling and Optimization of Manufacturing Processes. London

Reddy N.S.K., Rao P.V. (2005) Selection of optimum tool geometry and cutting conditions using a surface roughness prediction model for end milling *International Journal of Advanced Manufacturing Technology* 26(11–12), 1202–1210

Roy, R.K. (2001) *Design of experiments using the Taguchi approach: 16 steps to product and process improvement*. John Wiley & Sons.

Shunmugam, M., Reddy, S. B., and Narendran, T. (2000) 'Selection of Optimal Conditions in Multi-Pass Face-Milling using a Genetic Algorithm'. *International Journal of Machine Tools and Manufacture* 40 (3), 401

Sonmez A.I., Baykasoglu A., Dereli T., and Filiz I.H. (1999) Dynamic optimization of multipass milling operations via geometric programming. *International Journal of Advanced Manufacturing Technology* 39, 297–332

Sreeram S, Kumar AS, Rahman M, Zaman MT (2006) Optimization of cutting parameters in micro end milling operations in dry cutting condition using genetic algorithms. *International Journal of Advanced Manufacturing Technology* 30(11–12), 1030–1039

Tandon V., El-Mounayri H., Kishawy H. (2002) NC end milling optimization using evolutionary computation. *International Journal of Machine Tools Manufacturing* 42(5), 595–605

Teti, R., Segreto, T., Simeone, A., and Teti, R. (2013) 'Eighth CIRP Conference on Intelligent Computation in Manufacturing Engineering Multiple Sensor Monitoring in Nickel Alloy Turning for Tool Wear Assessment Via Sensor Fusion'. *Procedia CIRP* [online] 12, 85-90. Available from: http://www.sciencedirect.com/science/article/pii/S2212827113006574

U.S. Energy Information Administration (EIA) (2010) Annual Energy Review 2010. [online] Technical report DOE/EIA-0384(2010), Office of Energy Statistics, U.S. Department of Energy, Washington, DC. http://www.eia.gov/totalenergy/data/annual/archive/038410.pdf (Accessed 03 December 2015)

Wang J. (1993) Multiple objective optimization of machining operations based on neural networks. *International Journal of Advanced Manufacturing Technology* 8, 235–243

Wang, L. (2013) 'Machine Availability Monitoring and Machining Process Planning Towards Cloud Manufacturing'. *CIRP Journal of Manufacturing Science and Technology* 6 (4), 263-273

Wang, S., Lu, X., Li, X. X., and Li, W. D. (2015) 'A Systematic Approach of Process Planning and Scheduling Optimization for Sustainable Machining'. *Journal of Cleaner Production* 87, 914-929

White House. (2014) U.S.-China announcement on climate change and clean energy cooperation. [online] Fact-sheet, the White House, Washington, DC. https://www.whitehouse.gov/the-press-office/2014/11/11/fact-sheet-us-china-joint-announcement-climate-change-and-clean-energy-c (Accessed 04 December 2015)

Xu, X. (2012) 'From Cloud Computing to Cloud Manufacturing'. *Robotics and Computer-Integrated Manufacturing* 28 (1), 75-86

Yan, J. and Li, L. (2013) 'Multi-Objective Optimization of Milling Parameters – the Trade-Offs between Energy, Production Rate and Cutting Quality'. *Journal of Cleaner Production* 52, 462-471

Yang, X.S. (2014) Nature-Inspired Optimization Algorithms. Elsevier Store: 1st Edition. ISBN-9780124167452, Ebook.

Zulaika, J. J., Campa, F. J., and Lopez de Lacalle, L. N. (2011) 'An Integrated process–machine Approach for Designing Productive and Lightweight Milling Machines'. *International Journal of Machine Tools and Manufacture* 51 (7–8), 591-604

APPENDIX A

Table A. 1: Experimental data collection, given in (Yan and Li 2013).

Sampl e No	Spindle speed (*S*) [rpm]	Feed rate (*f*) [mm/min]	Depth of cut(a_p) [mm]	Width of cut (a_e) [mm]	Cutting Energy CE [kJ]
1	1000	200	0.2	5	555.802
2	1000	200	0.3	10	204.929
3	1000	200	0.4	15	108.519
4	1000	250	0.2	5	446.109
5	1000	250	0.3	10	166.05
6	1000	250	0.4	15	89.823
7	1000	300	0.2	5	381.832
8	1000	300	0.3	10	142.976
9	1000	300	0.4	15	73.988
10	1500	200	0.2	10	357.042
11	1500	200	0.3	15	162.727
12	1500	200	0.4	5	319.031
13	1500	250	0.2	10	289.604
14	1500	250	0.3	15	133.648
15	1500	250	0.4	5	258.476
16	1500	300	0.2	10	233.559
17	1500	300	0.3	15	112.551
18	1500	300	0.4	5	213.109
19	2000	200	0.2	15	264.303
20	2000	200	0.3	5	445.797
21	2000	200	0.4	10	185.62
22	2000	250	0.2	15	213.939
23	2000	250	0.3	5	358.579
24	2000	250	0.4	10	151.343
25	2000	300	0.2	15	180.886
26	2000	300	0.3	5	306.85
27	2000	300	0.4	10	128.147