DOCTOR OF PHILOSOPHY

Industry 4.0

intelligent optimisation and control for efficient and sustainable manufacturing

Caires Moreira, Lorena

Award date:
2020

Awarding institution:
Coventry University

Industry 4.0: Intelligent optimisation and control for efficient and sustainable manufacturing

By

Lorena Caires Moreira

June 2019

A thesis submitted in partial fulfilment of the University's requirements for the Degree of Doctor of Philosophy for PhD

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Project Title:

Intelligent Optimisation and Control for Sustainable Machining Processes

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Date of approval:

09 June 2019

Project Reference Number:

P92074

CANDIDATE'S DECLARATION FORM

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ABBREVIATIONS

AISI 4340	American Iron and Steel Institute grade 4340
BS EN24T	British Standard engineering steel treated in *T* condition
CAD	Computer-aided design
CAM	Computer-aided manufacturing
CAPP	Computer-aided process planning
CNC	Computer numerical control
EC	Energy consumption
FFOA	Fruit fly optimisation algorithm
GA	Genetic algorithm
ISO	International Organisation for Standardisation
KEOC	Key efficiency operational criteria
MFOA	Multi-swarm fruit fly optimisation algorithm
MPP	Machining process parameters
MQL	Minimum quantity lubrication
NC code	Numerical control code
PSO	Particle swarm optimisation
PSoE	Power load
SEC	Specific energy consumption
SoE	State of engagement
SoT	State of travelling

NOMENCLATURE

$\boldsymbol{a_e}$	**Cutting width**
a_p	Cutting depth
CH	Chipping wear
D	Cutting tool diameter
f	Feed rate
FL	Flaking wear
MRR	Material removal rate
N	Number of tool teeth
Ra	Average surface roughness
Ra_D	Desired surface roughness
Ra_e	The error between desired and predicted surface roughness
Ra_P	Predicted surface roughness
S	Spindle speed
s_z	Feed per tooth
T	Tool life in time
V	Tool life, in volume of material removed
VB	Flank wear
v_c	Cutting speed
Vr	Volume of material removed

LIST OF PUBLICATIONS

Journal Articles

Moreira, L. C., Li, W., Fitzpatrick, M. E., & Lu, X. (2018). Research on energy consumption and energy efficiency of machine tools : a comprehensive survey. *International Journal of Nanomanufacturing*, 14(2), 140–164. https://doi.org/10.1504/IJNM.2018.091579

Moreira, L. C., Li, W. D., Lu, X., & Fitzpatrick, M. E. (2019). Supervision controller for real-time surface quality assurance in CNC machining using artificial intelligence. *Computers and Industrial Engineering*, 127(December 2018), 158–168. http://doi.org/10.1016/j.cie.2018.12.016

Moreira, L. C., Li, W. D., Lu, X., & Fitzpatrick, M. E. (2019). Energy-Efficient machining process analysis and optimisation based on BS EN24T alloy steel as case studies. *Robotics and Computer-Integrated Manufacturing*, 58(January), 1–12. http://doi.org/10.1016/j.rcim.2019.01.011

Conference Papers

Moreira, Lorena C., Lu, X., Fitzpatrick, M. E., & Li, WD. (2017). Supervision Control for Quality Assurance in Milling Processes. In CIE47 Proceedings, 11-13 October 2017, Lisbon, Portugal (pp. 11–13).

Moreira, Lorena C., Zwiernik, M., Lu, X., Fitzpatrick, M. E., & Li, WD. (2019). Assessment of Energy Efficiency and Productivity of CNC Machining Processes. Proceedings IEEE Measurement and Instrumentation, Mulheim an de Ruhr, Germany.

ABSTRACT

The increasing demand for energy and natural resources, along with global competitiveness and a shift towards mass customisation, represent important factors that have driven the fourth industrial revolution (Industry 4.0). Computer Numerical Control (CNC) machining processes represent one of the most deployed manufacturing processes for parts production worldwide and are well known for its resources and energy-intensive activities. Recently, companies are urgently seeking intelligent approaches to enhance the efficiency and sustainability of machining, to meet the global needs of more sustainability, enhanced competitiveness and, this way, cope with environmental, economic and political factors.

In response to this scenario, this thesis presents two novel approaches of process planning optimisation and real-time supervisory control towards more intelligent, sustainable and efficient manufacturing. The process planning optimisation approach can achieve efficient and sustainable machining by addressing challenging trade-offs of the impacts of machining process parameters and several operational efficiency performance indicators, i.e., energy efficiency, productivity and cutting tool life. To support the trade-offs, an empirical analysis of the cutting tool wear phenomena and cutting tool life, and the influence of machining process parameters on several tool effectiveness indicators (*i.e.*, total cutting time, total cutting length and total volume of material removed) has been carried out. This analysis further supported the investigation of predicting the cutting tool life using power consumption models. Such investigation supported the optimum selection of machining process parameters for the roughing stage. The real-time supervisory control can tackle quality assurance in CNC machining. This system provides in-process support to manual operations of engineers to ensure that the machined parts will meet the challenging precise requirements of surface quality.

To conclude, this thesis contributes towards the development and implementation of more intelligent approaches focusing on both pre and in-process applications to improve the efficiency and sustainability of manufacturing processes. The results from the validation showed that the proposed optimisation approaches effectively supported improved decision-making on input parameters' selection to achieve highly-efficient processes and meet the manufacturing requirements.

DECLARATION

I hereby declare that no portion of the work referred to in the thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institutes of learning.

ACKNOWLEDGEMENTS

Undertaking this PhD has been a truly life-changing experience for me, and it would not have been possible to progress without the support and guidance received from my mom, my dad (*in memory*) and my brothers; my friends, and my ever-supportive supervisory team. I can only thank God for blessing me with such amazing people that have given me the strength, light and motivation to keep up from the beginning to the end of this journey.

I also would like to thank Him for having made everything possible by giving me health, belief, passion and resilience to deliver this thesis.

I would like to gratefully acknowledge Prof. Michael E. Fitzpatrick, my supervisor and Pro-Vice-Chancellor of the Faculty of Engineering, Environment and Computing, for his invaluable encouragement, insights and inspiration throughout my journey.

I would like to express my sincere gratitude to my Director of Studies, Prof. Weidong Li, who has been the constant source of support, guidance and motivation. His careful and kind supervision was essential, and this thesis would not have been possible without him. I also wish to thank my second supervisor Dr Xin Lu for his insightful comments, motivation and pieces of advice.

Another great thank you to the following colleagues at Coventry University for the pleasant working atmosphere, guidance and support which were crucial for this final achievement: Dr Walid Allafi, Ms Susan Lasslett, my PhD colleagues, my Women's Futsal Club teammates and Ana C. for the support on such a steep and stressful final stage to conclude this PhD.

Finally, I wish to acknowledge all my friends and family for their support and encouragement during this journey which have helped me greatly to remain motivated and focused. Thank you!

DEDICATION

This thesis is dedicated to the memory of my lovely father, [Jusenilton Rocha Moreira], who has always trusted and supported my decisions, encouraged and gave me so much love! I also dedicate it to my amazing mother, father and brothers who are vital in my life and to this achievement.

Chapter 1: INTRODUCTION

1.1 INTRODUCTION

According to (Benardos and Vosniakos 2003), there are two main practical problems that engineers face in manufacturing. The first is to determine the values of the process parameters that will yield the desired product quality (meet the technical specifications or manufacturing requirements), and the second is to maximise manufacturing efficiency and sustainability (such as productivity, energy efficiency, and quality) using the available resources.

In the past years, maximising manufacturing efficiency has increasingly become vital in the manufacturing sector not only to maintain business competitiveness but also to meet global requirements such as sustainable development (Jovane *et al.* 2008). These authors have introduced sustainable development as a global strategic vision to meet the economic, social, environmental, and technological challenges currently faced by society and the industrial sector. Moreover, a sustainable society must live within its means and use energy and materials in such a way that will not compromise the living standards and health of future generations. Also, (Smith and Ball 2012) stated that a sustainable society could not be realised without the development of more efficient approaches and technologies, which must, in part, be provided by the manufacturing sector.

Government leaders are increasingly aware of the urgent need to make better use of the world's resources (Geller *et al.* 2006). A series of policies, commitments, and guidelines on reducing lifecycle energy costs and the associated carbon emissions have been launched, which have encouraged and supported efficiency improvements by industrial firms(Park *et al.* 2009). For instance, the Paris Protocol (Rayner and Jordan 2016) signed by many countries such as UK, France, Japan, Germany, and China in December 2015 has established key global environmental targets, which highly depend on the performance of daily activities to be achieved. That is, to meet those goals, more efficient and sustainable manufacturing processes must be achieved to minimise the impacts on major global problems such as climate change (Jovane *et al.* 2008).

Moreover, the manufacturing sector is currently in the spotlight due to its high energy demand. In 2016, the USA Energy Information Administration (Outlook 2016) reported that the industrial sector used more energy than any other sector (approximately 54% of the world's total delivered energy). Furthermore, 66% of such demand was used by manufacturing industries (*e.g.*, food, pulp, and paper, iron and steel, etc.)(Conti *et al.* 2016). Also, in this International Energy Outlook 2016 report, an increase in the worldwide industrial sector energy consumption by an average of 1.2%/year until 2040 is expected. Hence, a reduction in the energy demanded by manufacturing activities is of prime importance.

Since the third industrial revolution, beginning in the 1970s, manufacturing systems have been revolutionised by computer numerical control (CNC) machines, which became predominant in the industrial sector, mainly automotive and aerospace (CNC cookbook, 2015). CNC machining has enabled higher automation, productivity and capabilities to mass production with improved quality of the parts machined. According to (Chandrasekaran *et al.* 2010) machining is one of the four main manufacturing activities, the other three being forming, casting and joining. Furthermore, CNC machines, according to (Liu, Wang, and Liu 2013) are the principal energy-consuming devices in production systems. For this reason, CNC machines and machining processes have been the focus of research communities all over the world. There has been a substantial increase in research related to higher efficiency and energy consumption of CNC machining to make manufacturing activities more sustainable. In addition to, the concept of resources productivity has recently emerged as a sustainable engineering approach to promote the best use of resources to minimise production costs but, at the same time, increase sustainability (Racounter, 2019).

In respect to CNC machining processes, there are critical efficiency operational criteria which must be considered in order to achieve the worldwide target of resources productivity (and sustainability) in manufacturing. Some of the key efficiency operational criteria in CNC machining are energy-efficiency, productivity, cutting tool life, and surface roughness. In the literature, improved process planning has been identified as a critical enabler to higher efficiency and sustainable machining ((Newman *et al.* 2012)(Peng and Xu 2014)(Zhou *et al.* 2016)(Sealy *et al.* 2016) and (Balogun and Mativenga 2013)). During process planning, the operation sequences, machine tools, cutting tools, and machining process parameters are selected, which will significantly affect the output performance of machining.

Traditionally, engineers and machinists have a more direct and more urgent duty to ensure that the systems they work are as resource-efficient as possible. However, as the challenge requires further understanding of the complex relationships between process parameters (such as spindle speed, feed rate, width of cut and depth of cut) and the crucial several efficiency operational criteria, such relationships overwhelm the capabilities of engineers to effectively (or do-right-first-time) select the best process parameters during decision-making in manufacturing planning. As a result, selecting the machining process parameters that will promote the best machining performance represents a significant challenge in CNC machining process planning, even for highly experienced machinists (Avram and Xirouchakis 2011a)(Balogun and Mativenga 2013, Avram and Xirouchakis 2011b).

As manufacturing companies have been under high pressure by economic, environmental, political as well as business competitiveness aspects, Industry and Academia are urgently seeking novel approaches to enhance performance and sustainability of machining. Consequently, novel solutions involving optimisation approaches for CNC machining processes are imperative and urgently required.

Nevertheless, addressing several efficiency criteria at the same time to promote optimal and sustainable process planning and machining control is a primary challenge to achieve resources productivity due to the conflicting responses between key process parameters (*e.g.*, spindle speed, feed rate and cutting depth) and the critical efficiency operational criteria (Yan and Li 2013)(Sushrut S. Pavanaskar 2014)(Wang *et al.* 2015)(Shin, Woo, and Rachuri 2017)(Giret, Trentesaux, and Prabhu 2015)(Camposeco-Negrete, de Dios Calderon Najera, and Miranda-Valenzuela 2016)(Ulsoy and Koren 1993).

Since CNC machining processes are complex in terms of the various machining process parameters, tooling selection, machining strategies, and operations, knowledge gaps still exist. This indicates that the development of effective modelling and optimisation approaches to address the challenges of more efficient and more sustainable machining are urgently demanded (Cuixia, Conghu, and Xi 2017)(Arriaza *et al.* 2017).

Also, the fourth industrial revolution (also referred as Industry 4.0, or Intelligent Manufacturing or Smart Factory) is currently pushing towards the replacement of the traditional ways of decision-making through the development of more intelligent systems which can promote making right-first-time (Davis *et al.* 2012). Moreover, it supports ensuring resources productivity and, consequently, more sustainable manufacturing (Kibira, Morris, and Kumaraguru 2016)(Kusiak 2017)(Lee *et al.* 2013). Moreover, according to (Bleischwitz, Welfens, and Zhang 2017), innovation and technological progress that can trigger using resources more efficiently are still lacking.

Thus, in response to the current scenario, this research work is motivated to address the significant concern of achieving resources productivity (*i.e.*, enhancing the sustainability) in manufacturing activities using CNC machining as case studies. The research gap will be addressed by developing novel optimisation approaches to support decision making and doing-right-first-time for the roughing and finishing stages of CNC machining.

The reasons for tackling the challenge considering the two machining stages are twofold:

- Firstly, the manufacturing requirements and critical efficiency operational criteria differ depending on the machining stage. That is, at the roughing stage, the focus is on high material removal rates which impact significantly on the energy efficiency, productivity and cutting tool life resources, usually constrained by lead time and resources requirements. By contrast, at the finishing stage, the focus is on the surface quality of the machined workpiece, which has to meet the tight tolerances of quality control, usually the only constraint (or requirement).

- Secondly, the type of solution to each stage differs, which impacts on the approach used. That is, at the roughing stage, a process planning (or offline) approach is more suitable due to the multiple objectives' decision-making implications, where engineers will have to be aware before the process. At the finishing stage, an *in-process* approach is more suitable due to the more exceptional capabilities of control which intelligent systems can cooperate with, given the tight tolerances and requirements of quality control. Furthermore, as surface quality can only be physically tested post-process, poor surface quality also impacts on the waste of resources such as time and cutting tools; consequently, an *in-process* solution becomes more attractive to avoid such negative impacts.

1.2 Research Aim and Objectives

The primary aim of this thesis is to enhance the sustainability and efficiency of manufacturing processes by the development of two intelligent approaches for the roughing and finishing stages of CNC machining.

For that, the research design and contributions are based on the empirical approach to build in-depth analysis and knowledge of the relationships between crucial machining process parameters, *e.g.*, spindle speed, feed rate, cutting depth, and the critical efficiency operational criteria, *e.g.*, energy efficiency, productivity, cutting tool life and surface quality. Such knowledge is used to support the development of predictive models and to formulate the intelligent optimisation and control approaches to enhancing the efficiency and sustainability of CNC machining processes. The two novel approaches tackle critical challenges in process planning optimisation for the roughing stage and the quality assurance during the finishing stage of production. By combining the approaches, the approaches promote more intelligent and sustainable manufacturing through more efficient and reliable processes. A framework of the research's aim and contributions are illustrated in Figure 1-1.

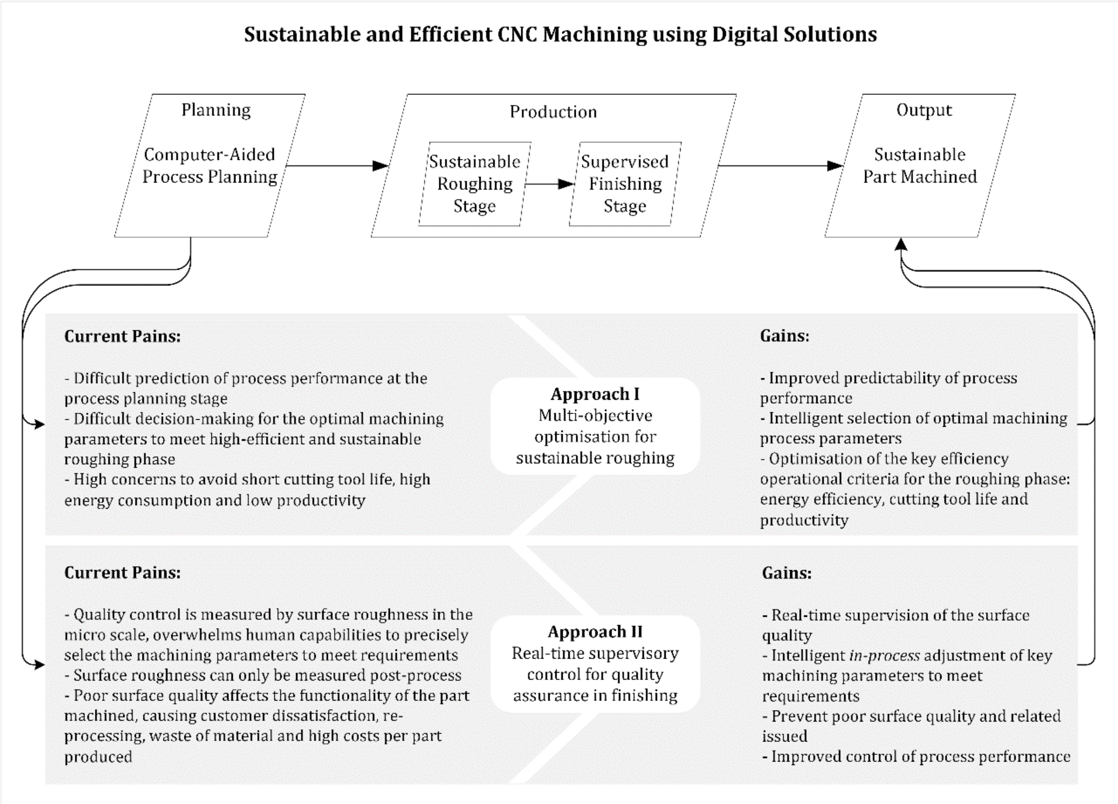


Figure 1-1: Smart workflow of CNC machining processes, which uses predictive models and optimisation algorithms to ensure best output performance and, therefore, resources productivity in manufacturing.

The process planning optimisation (the approach I in Figure 1.1) is a novel efficient and reconfigurable optimisation approach to achieve efficient and sustainable machining by addressing the trade-offs of the impacts of machining process parameters and several operational efficiency performance indicators, i.e., energy efficiency, productivity and cutting tool life. To support such trade-offs decision-making, an empirical analysis of the cutting tool wear phenomena and cutting tool life, and the influence of machining process parameters on several tool effectiveness indicators (*i.e.*, total cutting time, total cutting length and total volume of material removed) has been carried out. This analysis further supported the investigation of predicting the cutting tool life using power consumption models. Such investigation supported the development of the efficient optimisation problem for the optimum selection of machining process parameters for the roughing stage.

The real-time supervisory control (approach II in Figure 1.1) is a novel artificial intelligence supervisory control design has been developed to tackle the quality assurance in CNC machining. This system provides in-process support to manual operations of engineers to ensure that the machined parts will meet the challenging precise requirements of surface quality.

Accordingly, the aim of this research will be achieved through the following objectives:

i. Literature review to understand the relevance of machining process parameters on key efficiency operational criteria (*i.e.*, energy efficiency, productivity, cutting tool life, and surface quality); covering qualitative and quantitative analysis, predictive modelling and multi-objective optimisation approaches, and identifying research gaps;
ii. Design of experiments and experimental tests for data collection, followed by data analysis to identify the significance of each machining process parameters (input factors) on each key efficiency operational criteria and build up in-depth CNC machining knowledge with the use of analysis of variance and main effects analysis;
iii. To develop empirical predictive models for the key efficiency operational criteria as a function of the machining process parameters (spindle speed, feed rate, and cutting width);

iv. To formulate a novel optimisation approach for the roughing stage of machining considering the energy efficiency, productivity and cutting tool life as key efficiency operational criteria to find the best choice of machining process parameters to enhance the productivity of the resources (sustainability) during process planning

v. To formulate a novel optimisation approach for the finishing stage of machining considering the surface quality (surface roughness) as key efficiency operational criteria to adjust the spindle speed and feed rate in real-time to meet the technical requirements for quality control

vi. Test and validate the proposed optimisation approaches using real case CNC machining.

1.3 THESIS OUTLINE

As a result, this research work will present three significant contributions which represent new solutions to tackle the challenge of improving resources productivity and, consequently, the sustainability of CNC machining. The contributions and highlights are also described below and illustrated in Figure 1-2.

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.* 2018).

Chapter 3: Methodology of the study is presented, along with the principal methods used in the research; the experimental details and data collection procedures for each key efficiency operational criteria.

Chapter 4: An in-depth assessment of the cutting tool life and tool wear phenomena is carried out using several tool effectiveness indicators to support decision-making during process planning. Besides, a novel model for the cutting tool life based on power consumption is proposed.

- The tool wear phenomena and cutting tool life assessment based on several tool effectiveness indicators, such as total cutting time and total volume of material removed represent essential knowledge to both industry and academia to achieve more efficient production strategies and promote longer cutting tool life in CNC machining

Chapter 5: A novel model for the energy efficiency analysis is proposed along with a reconfigurable multi-objective optimisation approach for the energy efficiency, productivity and tool life using an improved fruit-fly optimisation algorithm to support decision-making to achieve more efficient and sustainable machining through better selection of the selection of crucial process parameters, *e.g.*, spindle speed, feed rate, cutting width and cutting depth. Part of this chapter is presented in (Moreira *et al.* 2019a).

- The output performance (*i.e.*, KEOC) of machining processes can be predicted and controlled at the early stages of machining (*i.e.*, process planning)

- The approach supports engineers and machinists in selecting the best process parameters that will enhance process resources productivity and sustainability by also accounting for the manufacturing requirements for lead time and cutting tools

Chapter 6: A novel system design for the surface quality assurance in CNC machining is proposed based on supervisory control and neuro-fuzzy models to adjust key process parameters such as spindle speed and feed rate to achieve the requirements of quality control based on the surface roughness. Part of this chapter is presented in (Moreira *et al.* 2019b).

- The system is designed and validated through in simulation environment to enable autonomous control of the surface quality during CNC machining processes to aid engineers and machinists in doing-right-first-time and achieve high-quality machined parts through optimal real-time adjustments of spindle speed and feed rate.

Chapter 7: Conclusions and further work. The research is concluded, the research contributions are highlighted, and future research is outlined.

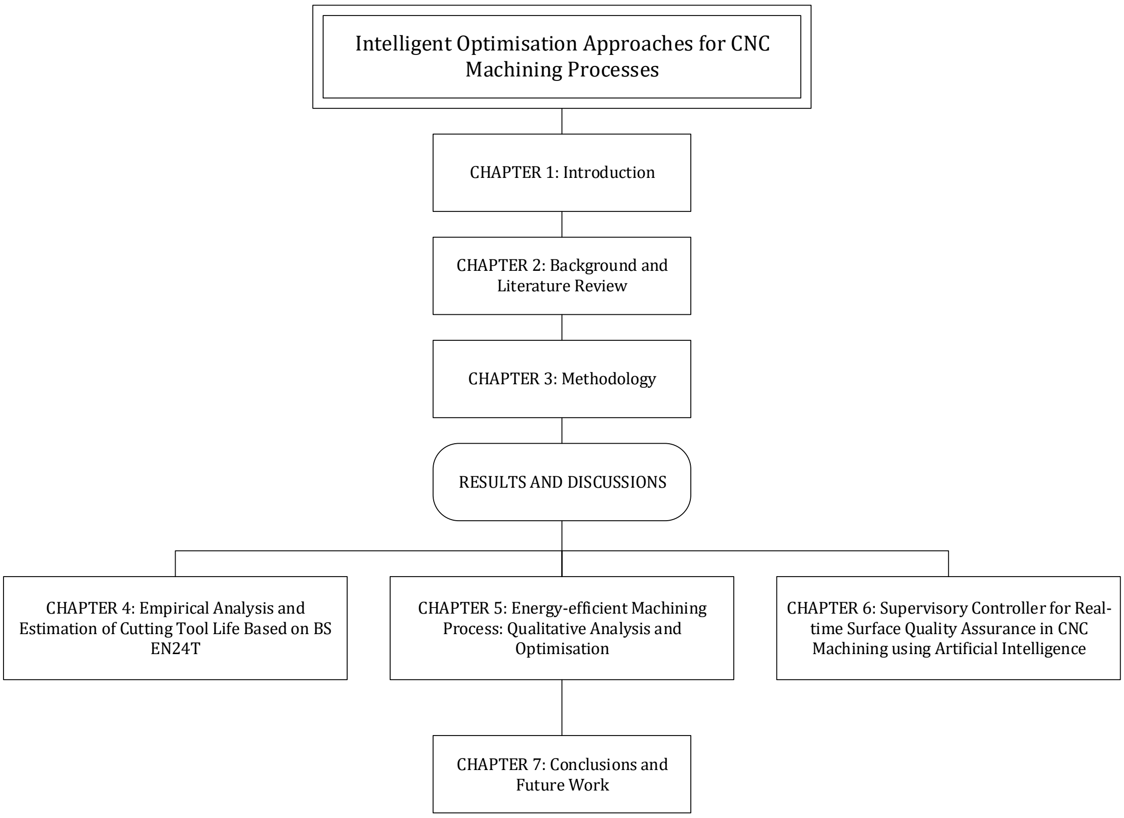


Figure 1-2: Schematic diagram of the logical flow of this thesis chapters.

1.4 BOUNDARIES OF THE STUDY

In this work, resources productivity and sustainability in manufacturing systems are enhanced by, a) at the process planning of roughing stage by implementing the energy consumption, productivity modelling, cutting tool life assessment and optimisation approaches hereby presented; and b) at the finishing stage by implementing surface roughness predictive modelling and the supervisory control system design hereby presented. Furthermore, case studies for the implementation of the modelling methodology and optimisation approach proposed are used to validate the research using hardened steel. CNC machining processes such as milling operations will be used as case studies to validate the research approaches. Regardless of the specific operation and material type, the research contributions proposed can be replicated and extended to different cases and operations in the future.

Chapter 2: BACKGROUND AND LITERATURE REVIEW

2.1 RESEARCH BACKGROUND

2.1.1 THE ROLE OF INTELLIGENT SYSTEMS TO ACHIEVE HIGHLY-EFFICIENT AND SUSTAINABLE MANUFACTURING

As concern with the world's resources use increases due to rise in population and, with that the increasing demand for energy and goods and manufactured products, the need for highly efficient and sustainable manufacturing processes becomes crucial to meet global needs and the sustainable agenda (World population prospects, 2017)(Conti *et al.* 2016).

The World Commission on Environment and Development defined sustainability as the ability to meet the needs of the present without compromising the capacity of future generations to meet their own needs (Nations 1987). In regards to manufacturing systems, sustainability has become an increasingly crucial requirement for manufacturing companies due to several established and emerging aspects such as environmental concerns and governmental targets, scarcity of non-renewable resources, stricter legislation and inflated energy costs, increasing greener consumer behaviour, *e.g.*, preference for environmentally friendly products, and so on (Giret, Trentesaux, and Prabhu 2015). Moreover, as they are responsible for one-third of the total primary energy consumption in the world (Outlook 2016), manufacturing companies have been under increasing pressure to provide more sustainable production systems. From the economic perspective, rises in energy and raw materials price are two important factors that justify the urgent need for intelligent and more energy-efficient processes in manufacturing industries. At the same time, resources such as raw materials for metal machining companies are becoming scarce, which makes imperative the adoption of techniques to reduce waste of material.

Ultimately, to remain competitive on a global manufacturing scale, manufacturing companies need to be aligned with legal and environmental regulations and comply with new customer and market requirements (Jovane *et al.* 2008). Such drivers have pushed the manufacturing sector to improve its competitiveness by employing cutting-edge Information and Communication Technologies (ICTs) in order to secure a new growth engine (IfM 2016). According to (IfM 2019), manufacturing companies face the recurrent challenge to enhance efficiency in their businesses. Further, it is stated in this report that embracing digital technologies to transform their operations will enable the manufacturing sector to operate more effectively and efficiently and, as a result, drive growth and profitability: 94% of UK manufacturers surveyed by the authors agreed with recognising that they must adopt digital technologies to remain competitive.

In recent years, ICTs and related emerging technologies such as Internet of Things (IoT) (Tao *et al.* 2014)(Jing *et al.* 2014), wireless sensor networks (Qiu *et al.* 2006, Qiu and Sha

2007), big data (Chen, Mao, and Liu 2014), cloud computing (Xu 2012, Liu, Wan, and Zhou 2014), embedded system (Wan *et al.* 2010), and mobile Internet (*e.g.*, 5G) (Soliman and Youssef 2003) have been introduced into the manufacturing systems, which has driven the fourth industrial revolution.

The fourth industrial revolution is considered as a new paradigm and represents the collection of cutting-edge technologies that support effective and accurate engineering decision-making in real-time through the introduction of various ICTs and the convergence with the existing manufacturing technologies (Kang *et al.* 2016). These have driven the so-called concept of Intelligent (or Smart) Manufacturing which according to (Kibira, Morris, and Kumaraguru 2016) is defined in part by the introduction of new technologies that are promoting rapid and widespread information flow within the manufacturing system and its control.

Nevertheless, in order to make effective and accurate decision making, ICT systems require manufacturing process knowledge embedded, such as the use of models for predicting the performance of machining and optimising they with the use of algorithms, machine learning or artificial intelligence systems (Chandrasekaran *et al.* 2010).

2.1.2 Demand for Highly-Efficient and Sustainable Machining

According to (Thornton 2010), the manufacturing sector is a source of stronger and more sustainable growth. Also, the energy yearbook published by the U.S. energy information administration pointed out that energy consumption in the industry accounted for approximately 1/3 of the total electricity consumption, where manufacturing was responsible for 90% of the industrial energy consumption, and CNC machines demanded

75% of the manufacturing energy consumption (Outlook 2010)(Zhou *et al.* 2016), as shown in Figure 2-1.

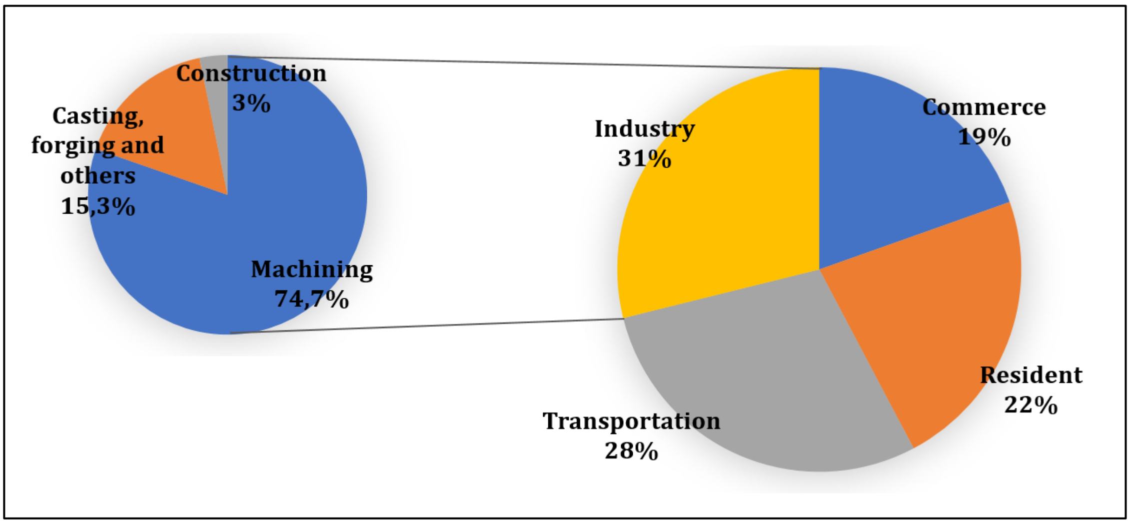


Figure 2-1: Energy demanded by the manufacturing sector (Source: (Outlook 2010)).

Energy consumption is a significant sustainability concern in the machining (or metal cutting) industry (Shin, Woo, and Rachuri 2017). Consequently, the demand for sustainable solutions in CNC machining is increasing (Uhlmann *et al.* 2017).

Production systems can be divided into two primary energy-consuming sources: transportation and transformation of input raw material. As the third industrial revolution, in the early 1970s, landmarked the migration from manual production to automated systems, CNC machines controlled by computer hardware and software became predominant to enhance productivity and quality of machining processes. Also, due to the rise of employment costs and the economic slowdown of most western countries in the same decade, CNC machines become predominant in manufacturing processes, displacing older technologies such as manual machining (CNC cookbook, 2015).

From the era of conventional machine tools to the present era of CNC machines, the prediction of cutting behaviour of processes and optimisation of machining process parameters have been critical areas of research. For this reason, modelling of machining processes has attracted the attention of several researchers as a way to improve CNC machining performance and sustainability (Peng and Xu 2014).

(Chandrasekaran *et al.* 2010) have pointed out in a review that the prediction of surface roughness, cutting force and tool life in machining is a challenging task, but is necessary for proper optimisation of the process. Also, energy consumption and energy efficiency must be considered for prediction due to the high energy demanded by CNC machines.

As computer technology and processing capabilities have evolved, the use of finite element and soft computing methods for modelling and optimisation of machining processes have become increasingly popular and shown significant achievements in improving machining efficiency (Zhang *et al.* 2006, Wang *et al.* 2005, Zarei *et al.* 2009, Deb and Dixit 2008, Dixit and Dixit 2008).

Soft computing approaches, i.e., with the use of digital solutions to physical systems, emerged in the early 1980s and their appearance in manufacturing systems have since increased considerably due to their capabilities of dealing with highly nonlinear, multidimensional and complex engineering problems. Moreover, (Chandrasekaran *et al.* 2010) has defined soft computing as an approach with remarkable ability to model human knowledge and learn in an environment of uncertainty and imprecision. Such an approach has been identified to be a reasonably useful solution to cope with CNC machining processes uncertainties and enhance the effectiveness and accuracy of decision making.

Soft computing tools can be used to predict the critical efficiency operational criteria of machining as well as for the optimisation of the process. Two different uses of soft computing to develop intelligent optimisation of machining processes have been proposed in (Chandrasekaran *et al.* 2010), see Figure 2-2.

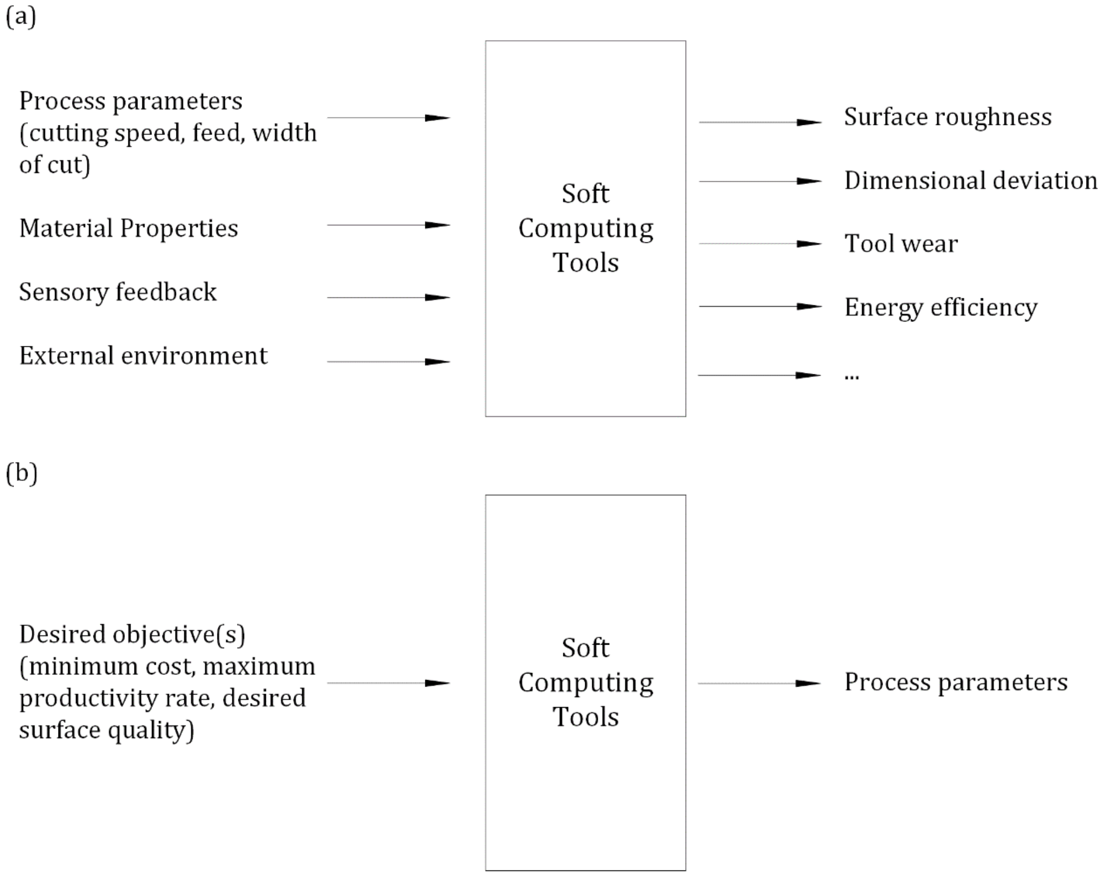


Figure 2-2: Two applications of soft computing in machining: (a) performance prediction and (b) optimisation (Adapted from (Chandrasekaran *et al.* 2010)).

In this research, the design (a) in Figure 2-2 will be adapted to develop the optimisation approach for process planning (or offline) applications focused on the roughing phase of machining. In this approach, predictive models are used to estimate the critical efficiency operational criteria energy efficiency, productivity and cutting tool life, which will be used to find the best choice of machining process parameters (MPP) (*i.e.*, spindle speed, feed rate, and engagement depth) based on several manufacturing requirements. The design (b) in Figure 2-2 will be adapted to develop the optimisation approach for real-time applications focused on the finishing phase of machining. In this approach, predictive models are used to estimate the KEOC surface quality in order to promote the optimal adjustment of spindle speed and feed rate parameters. As a result, the two optimisation approaches will be combined to promote intelligent optimisation of CNC machining to promote resource productivity and enhance the sustainability of manufacturing.

2.1.3 MACHINING PROCESS PLANNING AND MILLING OPERATIONS

In CNC machining, milling is the second most common operation for metal cutting (Benardos and Vosniakos 2002). Milling operations are used for producing flat or curved surfaces and prismatic shapes and are widely used in producing parts for the automotive and aerospace sectors.

Milling is a multipoint cutting tool process in which the cutting tool rotates at a given speed (*i.e.*, the spindle speed) and moves in Z-axes direction while the feed table moves (*i.e.*, feed rate) past the cutter in different directions (X, Y directions)(CNC cookbook, 2015), shown in Figure 2-3. The feeds (f), speeds (S) and directions – or cutting tool positioning, defined by the cutting width (or radial depth of cut, a_e) and cutting depth (or axial depth of cut, a_p) – are called machining process parameters (MPP) and are defined during the process planning by engineers and machinists.

During the machining process, as the cutter rotates, each cutter tooth (or flute) removes a small amount of material from the advancing work for each spindle revolution. This way, the unwanted metal is removed to obtain the final shape desired.

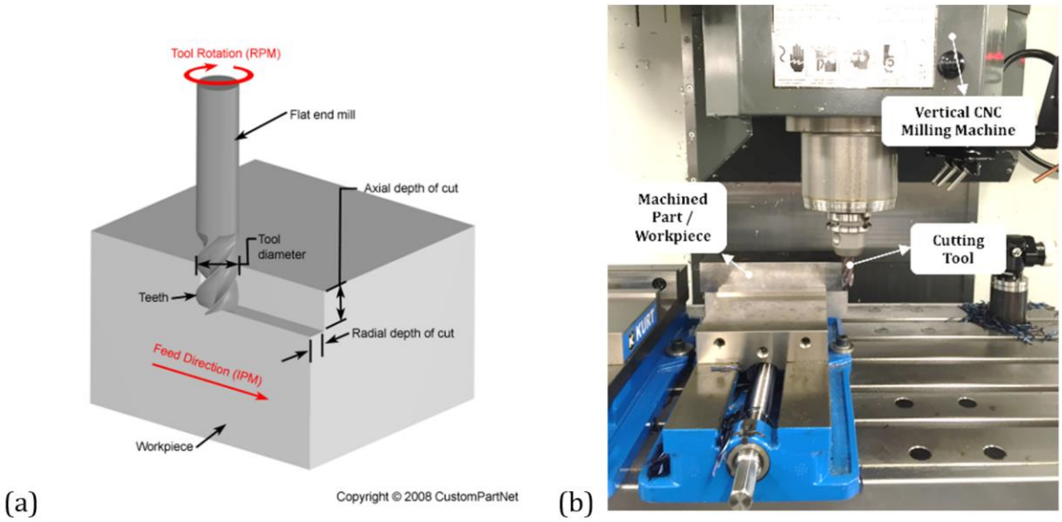


Figure 2-3: (a) Illustration of milling operation and the machining process parameters (Source: Custompartnet), (b) Milling operations set up on a CNC machine.

Research in machine technology, machining processes strategies and product designs have been conducted in recent years (Braungart, McDonough, and Bollinger 2007)(Sheng and Kok-Soo 2010)(Strano, Monno, and Rossi 2013)(Avram and Xirouchakis 2011)(Jia *et al.* 2016, Lv *et al.* 2016). Nevertheless, the requirements that machining processes have to meet change according to new environmental, economic and energy efficiency aspects. Such requirements make the need for continuous improvements of machining equipment, process planning and machining strategies towards sustainability to be imperative. A correct selection of MPP is crucial to promote higher efficiency and sustainable machining (Newman *et al.* 2012, Rajemi 2010, Lasemi, Xue, and Gu 2010).

Also, when selecting the MPP during process planning, the manufacturing requirements such as lead time and limitation of resources (*e.g.*, cutting tools availability) must be considered. Moreover, such requirements and the best key efficiency operational criteria will vary depending on the characteristic of the process, *i.e.*, roughing or finishing stages of production. Accordingly, the best choice of machining process parameters will depend on the stage of production and those manufacturing requirements. Such dependency is well-known as complicated and overwhelming to engineers trying to make correct decisions to achieve high-efficient and sustainable milling (Zhou, Liu, and Cai 2015).

For this reason, in this research, the spindle speed (and cutting speed), feed rate (and feed per tooth) and engagement depth (cutting width and cutting depth) will be the core input variables for investigation of their effects on the KEOC energy consumption, surface finish, productivity and tool wear. The investigation will involve qualitative analysis, predictive modelling and the development of intelligent optimisation approaches.

The following sections will highlight the current research scenario of investigations on the crucial efficiency operational criteria.

2.2 LITERATURE REVIEW

2.2.1 TOWARDS INTELLIGENT CNC MACHINING PROCESSES: MODELLING AND OPTIMISATION APPROACHES

In the current manufacturing environment, many large industries use highly automated and computer numerically controlled machines as their strategy to adapt to the ever-changing competitive market requirements (Venkata Rao, Murthy, and Mohan Rao 2014). 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. Besides, the manufacturing industry is continuously moving towards more customised products, driving the need for manufacturing systems to produce different parts with minimum effort required for re-planning, re-programming, and re-optimising the process parameters (Bosetti, Leonesio, and Parenti 2013).

In the case of CNC machining, this means that the procedures required to start the machining of a new part – which are costly, time-consuming, and demand the expertise of machinists and technicians – will have to be gradually automated, by enabling the CNC machine controller(s) to autonomously perform some of the operations more accurately, in a shorter time and without the need for human resources. According to (Hu *et al.* 2016), machining processes efficiency and quality of machined parts can be improved by monitoring, analysing, and diagnosing the process of product manufacturing.

Furthermore, (Newman *et al.* 2012) states that the success of manufacturing processes depends on the selection of the optimal machining process parameters (MPP). This is because the selection of MPP has a significant impact on the energy consumed, quality of the machined part, shop floor productivity and production costs in CNC machining. Despite its essential role in the output of manufacturing processes, the selection of MPP is still made based on machinists' experiences and machining handbooks.

Consequently, considering the significance of such step together to the economic, legal, political and environmental aspects which the manufacturing sector must cope with, many researchers have been addressing this problem in order to provide more intelligent and sustainable solutions to improve decision-making and selection of MPP in CNC machining.

(Shunmugam, Reddy, and Narendran 2000, Venkata Rao, Murthy, and Mohan Rao 2014) highlighted 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 valid optimisation criteria, as well as knowledge of mathematical and numerical modelling and optimisation techniques. (Shea *et al.* 2010) have proposed different approaches for enhancing the level of automation of CNC machining processes by considering CAPP/CAM techniques (Davim 2015), and autonomous toolpath design (Ahn *et al.* 2001) (Bosetti, Leonesio, and Parenti 2013). However, these works do not consider the step of choosing an optimal set of machining process parameters, given a previous definition of machine tool, workpiece material, cutting tools, fixtures, and sequence of toolpaths.

In this thesis, the focus is to employ modelling and optimisation algorithms to develop an intelligent optimisation system to select the best choice of MPP that generates the most sustainable performance for the roughing stage, and best quality performance for the finishing stage of CNC machining. Multiple critical efficiency operational criteria are considered for the optimisation, as follows: energy efficiency, cutting tool life, and productivity for the optimisation approach at the roughing stage; and the surface quality (or surface roughness) for the optimisation approach at the finishing stage of CNC machining processes. Thus, in the next section, a comprehensive survey of the research approaches on modelling of energy consumption, cutting tool life and surface quality (as a function of surface roughness) of CNC machining processes will be provided.

2.2.2 Approaches to Assessing and Modelling Energy Consumption

The energy distribution within machining processes depends on the characteristics of the process (roughing or finishing) as well as the machine components. (Zhou *et al.* 2016) summarised the types of energy consumption for machine tools into five different components: composition, operation status, energy attribute main energy consumption components and functional movement (in Figure 2-4). Such definitions are essential for the development of energy consumption models and energy efficiency evaluation of machine tools, which, according to (Zhou *et al.* 2016), are prerequisites for energy savings in manufacturing.

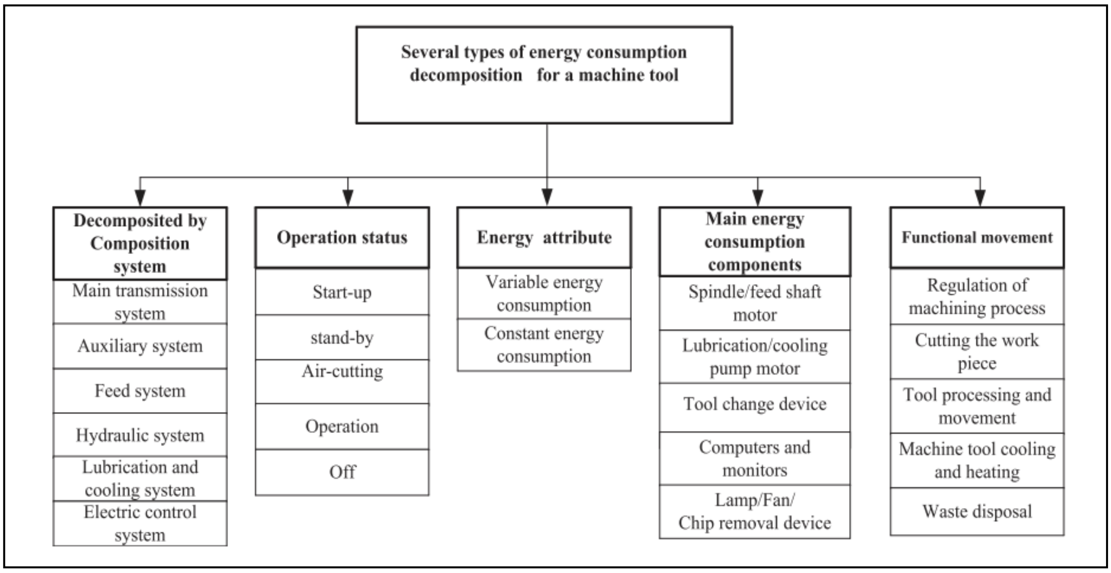


Figure 2-4: Different ways of decomposing energy consumption for CNC machines (Source: (Zhou et al. 2016)).

According to (Lv *et al.* 2016), accurate characterisation of the energy consumed by machining processes is a starting point to improve manufacturing energy efficiency and reduce the associated environmental impact. Therefore, it is of utmost importance to comprehend how energy consumption in machining processes has been addressed in order to enhance the energy efficiency in production systems.

Moreover, necessary action was taken by the International Organization for Standardization (ISO) to develop the standard *Environmental evaluation of machine tools* (ISO 14955-1 2010). 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. Table 2-1 provides some approaches that have been developed in recent years and related research work.

Table 2-1: Research topics on energy consumption of machining.

Research topic	Related work
Eco-design of machine equipment/product.	(Braungart, McDonough, and Bollinger 2007) (Sheng and Kok-Soo 2010)(Strano, Monno, and Rossi 2013)
Analysis of machining parameter/machining configuration.	(Newman *et al.* 2012, RAJEMI 2010, Qiu *et al.* 2006)(Park and Kim 1998, Bhushan, Kumar, and Das 2010, Jeon, Lee, and Wang 2019, Rizvi 2018)
Machining operation sequence/tool path optimisation.	(Abu Qudeiri, Yamamoto, and Ramli 2007, Ehmann *et al.* 1997)(Edem 2016, Balogun *et al.* 2013)
Machining behaviour/motion evaluation.	(Avram and Xirouchakis 2011, Seker, Kurt, and Ciftci 2004)
Machining monitoring.	(Liu, Wang, and Liu 2013, Simeone, Segreto, and Teti 2013, Segreto, Simeone, and Teti 2013, Behrendt, Zein, and Min 2012)
Multi-objective optimisation of machining parameters.	(Arriaza *et al.* 2017, Yan and Li 2013)(Nouari *et al.* 2003, Zhang, Owodunni, and Gao 2015)
Cloud manufacturing.	(Liu, Wan, and Zhou 2014, Tao *et al.* 2014)(Xu 2012)

An exponential growth in research publications in the last two decades, published in (Moreira *et al.* 2018), which clearly shows the academic and practitioners' strong interests on this topic (see Figure 2-5).

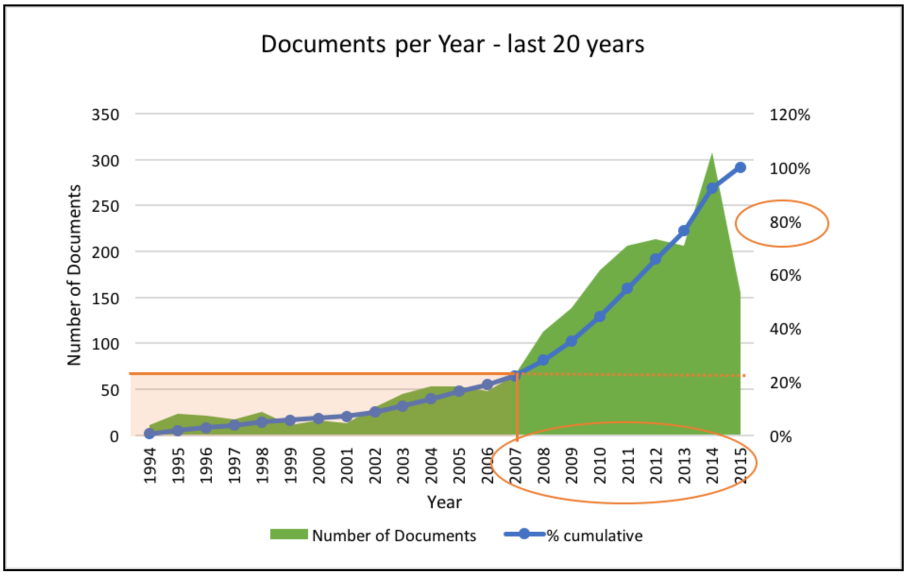


Figure 2-5: Research publications related to the energy of CNC machining.

The electricity demanded by the servomotors of CNC machines on a factory shop floor produces energy consumption data that, when well-processed, are a valuable information source. Based on the data, energy consumption (EC) predictive models can be developed to enhance the sustainability of machining. Energy consumption models can be used to assess and improve the overall efficiency of shop floors, aid production engineers in scheduling optimisation, and support machining systems to be self-controlled and self-optimised through embedded optimal control algorithms. Nevertheless, energy consumption has not often been considered in manufacturing strategies during the planning stage. However, this issue is becoming more prevalent and is a topic of concern in the board room in the last five years (O'Driscoll and O'Donnell 2013). By integrating energy consumption criteria into a process planning and operating structure, a reduction in process energy demand is expected. Thus, energy modelling of a machine tool for energy consumption prediction is of prime importance.

To develop effective energy consumption models, research work must be carried out for both qualitative and quantitative understanding. Accordingly, several energy consumption models for both the entire machine tool and for the specific energy consumption of cutting processes have been developed. The related work is summarised in Table 2-2.

Table 2-2: Energy models for machining processes.

Author	Type*	Machining Model
(Wang 2013)	DE	$E(M_i) = E(M_i)_{idle} + E(M_i)_{.working} + E(M_i)_{.toolchange} + E(M_i)_{.set-up}$
(Nee *et al.* 2013)	DE	$E = \sum_{i=1}^{n} Estatei = \sum_{i=1}^{n}\sum_{j=1}^{m} E_{state_i, component_j} = \sum_{i=1}^{n}\sum_{j=1}^{m} P_{state_i component_j} \cdot t_i$
(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.
(Newman *et al.* 2012)	SE	$e = \frac{P}{f.h.D}$ Where P is the power demanded; f and h are feed rate and dep9th of cut, respectively; and D is the total volume removed.
(He *et al.* 2011)	DE	$E_{total} = E_{spindle} + E_{feed} + E_{tool} + E_{cool} + E_{fix}$ This can be expanded to: $E_{total} = \int_{t_{me}}^{t_{ms}} P_m dt + \int_{t_{ce}}^{t_{cs}} P_c\, dt + \sum_{i=1}^{m} \int_{t_{fs}}^{t_{fe}} P_i dt + P_{tool} t_{tool} + P_{cool}(t_{coe} - t_{cos}) + (P_{servo} + P_{fan})(t_e - t_s)$
(Avram and Xirouchakis 2011)	SE	$E_{DE} = E_{aY} + E_{SY} + E_{dY} + E_{run} + E_{cut}$ This can be expanded to: $E_{DE} = \int_{t'_0}^{t'_1} P_{aY} dt + \int_{t'_1}^{t'_2} P_{SY} dt + \int_{t'_2}^{t'_3} P_{dY} dt + \int_{t'_0}^{t'_3} P_{run} dt + \int_{t'_1}^{t'_2} P_c dt$
(Mori *et al.* 2011)	SE	$\eta = -10 \log \frac{\sum_{i-1}^{n} y_i^2}{n}$ Where y_i (Wh/cc) is the power consumption per material removal unit, and n is the number of experiments per condition.
(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.

	SE	$E_{cut} = K_{cut} \cdot w \cdot b \cdot z^p \cdot v_f^{1-p} \cdot n^p$	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.
(Diaz, Redelsheimer, and Dornfeld 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.
	SE	$e_{cut} = k * \frac{1}{MRR} + b$	Where k is the machines constant, MRR is the material removal rate, and b represents the steady-state specific energy.
(Li and Kara 2011)	SE	$SEC = C_0 + \frac{C_1}{MRR}$	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.
(Draganescu, Gheorghe, and Doicin 2003)	SE	$E_{cs} = \frac{P_c}{60\eta Z}$	Where P_c is the necessary cutting power at the main spindle (kW), Z the material removal rate (cm^3/min) and E_{cs} the specific consumed energy (kWh/cm^3).
(Li, Yan, and Xing 2013)	SE	$SEC = k_0 + k_1 \cdot n/MRR + k_2/MRR$	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 rounds/second.

**DE: Direct Energy, refers to models considering the entire machine tool system; SE: Specific Energy, refers to models considering the machining cutting process specifically.*

The models in Table 2-2 have been developed based on selected applications (future use) to meet the research purpose, such as specific prediction of performance or optimisation problem formulation which must account for the independent variables used in the model. For example, some models consider the entire energy consumption of the machine tool (such as the models categorised as direct energy, DE), while others only account for the energy consumed during the cutting process (such as the models categorised as specific energy, SE). Moreover, models that include MRR as independent variable usually are used for analysis related to productivity.

Also, it can be observed the use of different terminology for the same meaning of the type of energy consumption. Based on this literature review, a matrix with similarities in terminology has been developed, to support researchers in better understanding the energy consumption models published (see Figure 2-6).

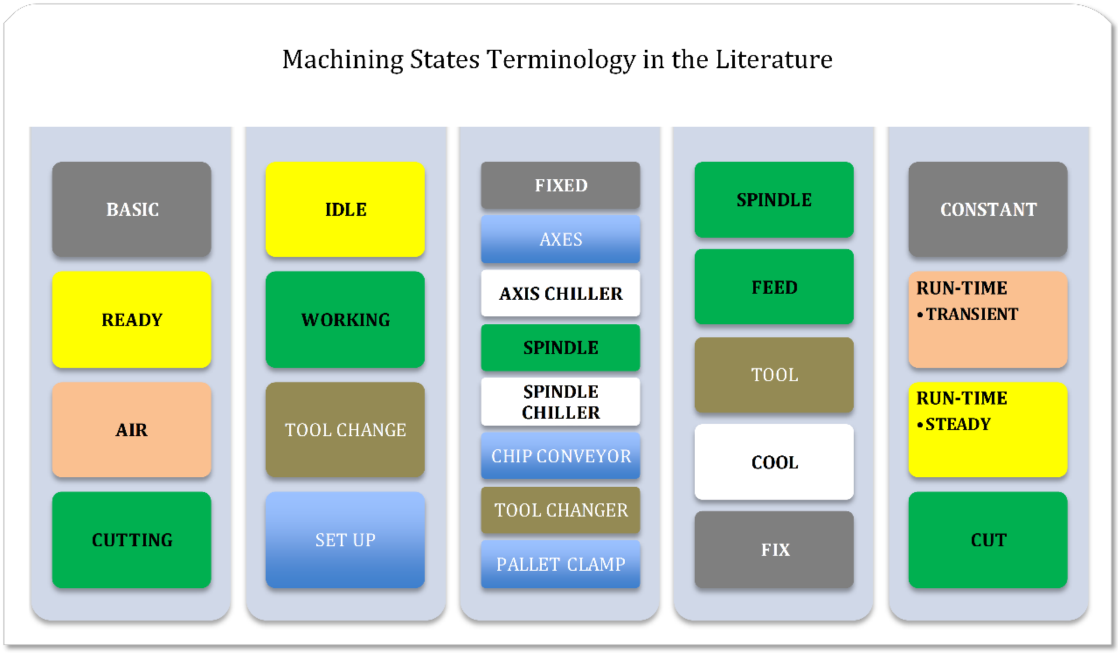


Figure 2-6: Similarities in machining states terminology.

Recently, methods such as analysis of variance (ANOVA), Response Surface Methodology (RSM), Taguchi signal-to-noise ratio, and Artificial Neural Networks (ANN) have been employed to analyse the relationships between cutting parameters and energy consumption, and establish energy predictive models (Camposeco-Negrete, de Dios Calderon Najera, and Miranda-Valenzuela 2016, Draganescu, Gheorghe, and Doicin 2003, Li and Kara 2011, Diaz, Redelsheimer, and Dornfeld 2011, Nancy Diaz1, Elena Redelsheimer1 2011, Newman *et al.* 2012, Peng and Xu 2014).

(Camposeco-Negrete, de Dios Calderon Najera, and Miranda-Valenzuela 2016) carried out an experimental investigation on different machine tools using non-linear regression. The results show that the motion of the CNC machine tool is the primary source of energy consumption.

Many other researchers have used several approaches and techniques for understanding the energy consumption of CNC machining processes. A common way of energy and productivity assessment is through the Material Removal Rate (*MRR*) (Mori *et al.* 2011, Draganescu, Gheorghe, and Doicin 2003). That is because the *MRR* is estimated based on crucial cutting parameters: spindle speed (S), feed rate (f), depth of cut (a_e) and width of cut (a_p). Although this approach simplifies the modelling process, since it comprises two coefficients to be estimated and only one input is necessary, the *MRR*, by doing this, assumes that all cutting parameters have the same effect on the energy consumption. (Sealy *et al.* 2016) observed low predictive accuracy of such models when employed in estimating the net specific energy, or specific energy consumption for the state of engagement (SEC_{SoE}), which represents the amount of energy required to remove a unit volume of material during actual cutting (or state of engagement): the energy required to maintain the CNC machine ON (known as basic and idling energy), and the energy consumed during air cutting (also known as travelling energy) are not considered. This way, this indicator is mainly influenced by the cutting parameters, workpiece material, and tooling.

To date, there has been little research focused on the net specific energy (Lv *et al.* 2016). Further, no effort has been made towards the implementation of machining net power and machining time estimation models to obtain optimum cutting parameters which can maximise the energy efficiency of milling operations. Other factors involved in the machining process, such as tool wear, mode of milling, types of cutter tool holder and workpiece holding systems, are still lacking analysis regarding their impact on energy consumption, so should be involved in the empirical modelling to develop more robust predictive models.

Based on that, this thesis develops a useful energy consumption model considering the machining cutting variables of spindle speed, feed rate, engagement depth (*i.e.*, the cutting depth and cutting width. Also, the machining net power (power load) is introduced to assess the cutting tool life.

2.2.3 Approaches to Assessing and Modelling the Cutting Tool Wear and Tool Life

In CNC machining processes, the cutting tools profoundly affect the production performance such as productivity, quality of the machined part and power consumption (*Machining: Fundamentals and Recent Advances* 2008). The health state of a cutting tool is defined by the amount of tool wear identified, since tool wear leads to tool failure. According to many authors, the failure of cutting tools occurs as premature tool failure (in this work called abrupt failure) and progressive tool wear (in this work called gradual failure). Generally, the wear of cutting tools depends upon the tool material, workpiece material, cutting fluids, machine tool and fixturing and machining process parameters (cutting speed, feed rate, cutting width and cutting depth).

Flank and crater wear are the most critical measured forms of cutting tool wear, where flank wear is most commonly used to wear monitoring and prediction models. Tool wear curves show the relationship between the amount of flank wear (in mm) and the cutting time (CT) or overall length of the cutting path (L). Figure 2-7 shows the cutting tool wear profile.

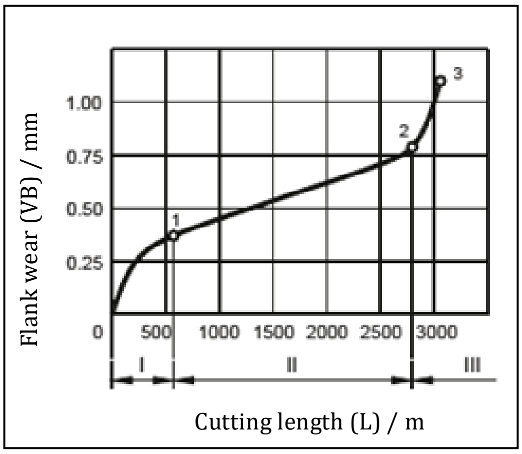


Figure 2-7: Progression of cutting tool wear for increasing cutting length.

Region I in Figure 2-7 represents the initial wear region. The considerably high wear rate (*i.e.*, the increase of tool wear per unit CT or L) in this region is explained by accelerated wear of the tool layers damaged during manufacturing. Region II is considered as steady-state wear, which represents the typical operating region for the cutting tool. The region III is known as the accelerated wear region, accompanied by high cutting forces, temperatures, and severe tool vibrations, also leading to tool failure.

Typically, the value of flank wear (VB) that will define tool failure is selected from the range 0.15-1.00 mm depending on the type of machining operation, the condition of the machine tool and the quality requirements of the operation. This value is called maximum flank wear (VB_{max}) and is often called the criterion of tool life. When a cutting tool presents flank wear beyond the life criterion (*i.e.*, established VB_{max}), it has to be replaced to avoid poor machining performance.

Tool life is essential in machining since considerable time and resources are lost whenever a tool is replaced and reset. The short life of cutting tools represents one of the significant concerns in manufacturing companies due to the cost and environmental aspects. Also, the worn tools will require reprocessing for re-use or become waste which then becomes a harm to the environment.

Furthermore, cutting tool life is even more critical when machining hardened steel because the wear progresses fast and, therefore, decreases the tool life rapidly, regardless of the tool material used (Machado and Diniz 2017). The authors' further state that this is due to the high cutting forces and heat generated, which cause rapid tool wear and short tool life. Besides, such materials typically present low thermal conductivity, so resulting in higher temperatures closer to the cutting edge, causing strong adhesion between the tool and workpiece material (Zoya and Krishnamurthy 2000).

Consequently, over the years numerous research efforts have been made to improve the cutting tool life by investigating tool wear phenomena and related issues to assist in choosing suitable machining conditions (Su *et al.* 2012). According to (Zhu, Zhang, and Ding 2013), the resulting cutting heat coupled with the work hardening leads to a series of problems, such as excessive tool wear, short tool life, low productivity, and large amount of power consumption etc., in which the excessive tool wear has become one of the main bottlenecks that constraint the machinability of difficult-to-machine materials.

The nature of tool wear is as yet unclear despite numerous investigations, and this is due to the complex physical, chemical, and thermomechanical phenomena that occur during the material removal process (Astakhov 2004, *Machining: Fundamentals and Recent Advances* 2008). Some of the mechanisms of wear have been defined as adhesion, abrasion, diffusion, and oxidation (*Machining: Fundamentals and Recent Advances* 2008), and act simultaneously with the predominant influence of one or more. Promoting a longer cutting tool life has been a significant challenge in Industry at any particular time. According to

(Park and Ulsoy 2012) estimating flank wear is of great concern since the amount of flank wear is often used in estimating the tool life. The wear phenomena (*e.g.*, flank wear) will progress gradually or abruptly and cause the end of tool life (or tool failure). Such progression will highly depend on the cutting conditions (such as choice of MPP), whose relationships are known to be complex and, for this reason, tool wear assessment and tool life prediction remain significant challenges in the industry (Astakhov 2004, Halim, Ascroft, and Barnes 2017, Tai *et al.* 2014, Li *et al.* 2014).

In Industry and Academia, the cutting tools are mainly assessed based on the total cutting time as a life indicator. That is, the amount of time that a cutting tool can be used before the progression of flank wear reaches its limit (or life criterion). One of the reasons for using such an indicator is because cutting time can be easily trackable through the CNC machine control unit. Also, process conditions are chosen to give maximum productivity, often resulting in tool life being measured in minutes (Astakhov 2007). However, other indicators (in this work called tool effectiveness indicators), such as total cutting length and total volume of material removed per tool, have not been well investigated yet, leaving gaps of research to support improved machining strategies.

In recent decades, many researchers have employed an empirical approach to investigate wear phenomena and cutting tool life. In (Machado and Diniz 2017) the wear mechanisms have been investigated for different types of tool inserts' material applied in turning and milling operations focusing on building knowledge to support the development of improved cutting tools, using different workpiece material including BS EN24T (AISI 4340), the material used in this thesis. However, the effects of machining process parameters on tool life have not been considered in the investigation.

(Nouari *et al.* 2003) investigated improved machining strategies by considering tool geometry and cutting conditions to enhance cutting tool life for drilling of aluminium alloys under dry conditions. It was observed that diamond as a tool coating material would improve cutting life, and high cutting speed and low feed rate will provide better dimensional accuracy and surface quality, while the influence of MPP on the cutting tool life was not studied.

In (Gowd *et al.* 2014), the effects of MPP spindle speed, feed rate and depth of cut have been studied on the tool wear in turning operations in AISI S2 workpiece material. (El-Kady *et al.* 2015) investigated the effects of MPP cutting speed, feed rate and depth of cut on the cutting forces, surface roughness and tool wear using two different nanocomposite materials in turning operations under dry conditions. It revealed that tool flank wear increased by increasing the cutting speed. However, the investigations did not consider milling operations. (Li, Zeng, and Chen 2006) conducted an experimental study of the tool wear propagation and cutting force variations in the end milling of Inconel 718 with coated carbide inserts. The results showed that significant flank wear was the predominant failure mode affecting the tool life. In (Bhushan, Kumar, and Das 2010) the effects of MPP cutting speed, feed rate and depth of cut on the tool flank wear were investigated for different cutting tool inserts using Al alloy reinforced with Silicon Carbide (SiC) particulates as workpiece material. The results revealed that the flank wear increased by a factor of 2.4 and 1.3 for the carbide and PCD inserts, respectively, with an increase in cutting speed from 180 to 240 mm/min. In this direction, according to (Zhu, Zhang, and Ding 2013), reducing tool wear and prolonging tool life are crucial aspects to achieve maximum efficiency in manufacturing.

Investigations on the relationships of MPP (such as cutting speed, feed rate and cutting depth) on the cutting tool life are vital to develop understanding and knowledge to improve CNC machining strategies and, this way, achieve longer tool life. Recent studies have only considered the tool life in terms of cutting tool time, while the effects of machining process parameters on tool life indicators such as the total volume of material removed per tool have not been investigated yet. Such investigations will promote in-depth understanding and knowledge to improve decision making in process planning. Further, it will support achieving resources productivity, that is, minimise the cost of production and promote sustainability. Therefore, the relationship between several machining process parameters and three tool effectiveness indicators will be addressed in this thesis.

Therefore, cutting tool wear and life prediction (in the field of tool condition monitoring) play a crucial role in finding improved machining strategies to enable effective production. Moreover, an accurate prediction of tool life can not only improve the efficiency in the usage of the tool to achieve the reduced cost but also can avoid the workpiece scrapping phenomenon caused by tool damage in the material removal process. Therefore, the tool life prediction is an essential part of the cutting process, where high-speed cutting tool failure and tool life have been the attention of several researchers, whose main goals are:

- Improving the design of cutting tools geometries and coating materials
- Determination of optimum cutting conditions

In the field of tool condition and monitoring two main research streams have been identified: using direct measurements such as touch probe, optical sensors and computer vision (Wang *et al.* 2007, Kurada and Bradley 1997); and indirect measurements such as cutting force (Bandyopadhyay *et al.* 1986, Elbestawi, Papazafiriou, and Du 1991, Martinho, Silva, and Baptista 2008, Sarhan *et al.* 2001), acoustic emission (Mathew, Pai, and Rocha

2008), vibration (Orhan *et al.* 2007), power (Shao, Wang, and Zhao 2004). The direct measurements have the advantage of providing high accuracy; however, they cannot provide real-time (or continuous) data; while the advantages of the indirect measurements are that they can provide real-time estimations of the cutting tool conditions, this way, allowing online monitoring and further enabling in-process control. Table 2-3 summarises some related research works and the details related to cutting tool life predictive models.

Table 2-3: Research work on tool life modelling.

Reference	Factors (inputs)	Output	Methods
(Taylor 1908)	v_c, f and a_p	Tool life (in min)	Regression
(Park and Ulsoy 2012)	v_c, f, a_p	Cutting force, flank wear	Empirical approach; use of state space and least squares algorithm for parameter estimation.
(Kaye et al. 1995)	v_c, f, a_p and material hardness	Flank wear	RSM
(Mandal, Doloi, and Mondal 2011)	v_c, f, a_p	Flank wear	RSM
(Palanisamy, Rajendran, and Shanmugasundaram 2008)	v_c, f, a_p	Flank wear	Regression and ANN
(Kaya, Oysu, and Ertunc 2011)	Cutting force (F) and torque (T), cutting time (t), v_c, f and a_p	Flank wear	ANN
(Arsecularatne 2003)	Cutting tool temperature	Cutting force	-
(Huang and Dawson 2005)	Ratios of friction, cut and F	Flank wear	-

As shown in Table 2-3, the rational choice of combinations of cutting parameters is essential for reducing tool wear to prolong tool life (Zhu, Zhang, and Ding 2013). Also, cutting force signals have been widely employed as inputs for the cutting tool life prediction to improve machining efficiency. However, to acquire cutting force signals, it is required to have an in-situ dynamometer in each CNC machine, but such equipment is very costly. Moreover, considering the costs involved (such as cutting tools, workpiece material, time for experimental set up and data collection procedures) in obtaining the empirical relations between inputs (*e.g.*, cutting force) and output (*e.g.*, flank wear and tool life), a more fundamental approach that can reduce the experiments will be of great value (Arsecularatne 2003).

On the other hand, power consumption signals have been shown to present a strong correlation with cutting force and (Drouillet *et al.* 2016) has developed a cutting tool life condition monitoring using power signals and reported good results. To date, using power consumption signals as input to the cutting tool life prediction has not been well investigated, which leaves gaps in research to produce more accessible (and affordable) alternatives to tool condition monitoring, especially to small and medium enterprises (SMEs), since such equipment are considerably cheaper compared to cutting force systems. For this reason, in this paper, a correlation study involving cutting tool life and the power consumption is carried out. Such analysis supports the development of a semi-empirical predictive model for the cutting tool life based on power consumption.

2.2.4 Approaches to Assessing and Modelling the Surface Quality

The surface quality of a machined part is one of the essential product quality characteristics and in most cases a technical requirement for mechanical products (Lu

2008). Surface quality is commonly referred to as to through surface roughness, defined as the deviation from the normal surface.

In industry, there are various simple surface roughness amplitude parameters such as root-mean-square roughness (Rq), maximum peak-to-valley roughness (R_{max}) and the roughness average (*Ra*). The latter is the most common parameter used in practical applications and, therefore, will be used in this research. The average roughness (*Ra*) is the area between the roughness and the line describing its mean value (see Equation (2-1) and Figure 2-8). *Ra* can be obtained by calculating the integral of the absolute value of the roughness profile height over the evaluation length, as shown below:

$$Ra = \frac{1}{L}\int_0^L |Y(x)|dx \tag{2-1}$$

Recently, several researchers have conducted investigations on new approaches for CNC machining control in achieving a better surface quality of machined workpieces (Ezugwu *et al.* 2005, Mia *et al.* 2018, Pimenov, Bustillo, and Mikolajczyk 2017, Simunovic *et al.* 2016)(Yang and Chen 2001). Some prediction models based on empirical approaches have been developed to analyse the relationships between machining process parameters and the surface roughness.

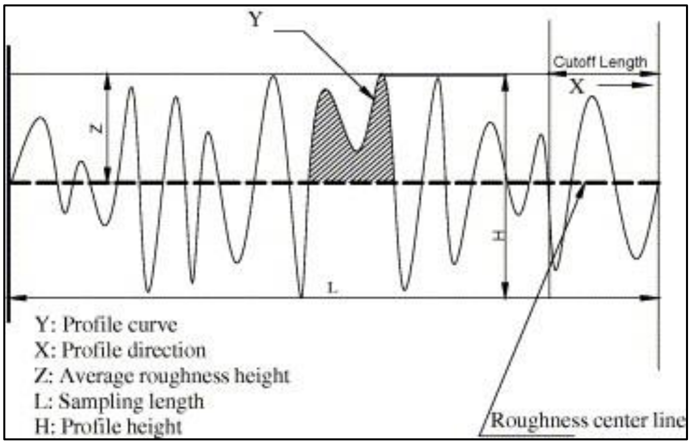


Figure 2-8: Representation of a surface roughness profile, where the dotted line represents the average surface roughness (Ra) (Source: (Yang and Chen 2001)).

Empirical findings have been identified for further development of optimised control, and the majority of them have been built based on Artificial Intelligence (AI) algorithms (Abidin *et al.* 2012). For instance, based on empirical approaches and AI, a prediction model for surface roughness has been developed (Abidin *et al.* 2012). This research is aimed to provide optimised machining conditions by minimising cutting forces to improve surface roughness. Combined neural-fuzzy approaches have been developed in (Chen *et al.* 2015) and (Abidin *et al.* 2012), which have been validated through turning case studies. The authors have stated and justified that the methods are ideally suited for surface roughness prediction owing to open model structures, which can incorporate human expertise and process uncertainties. By using neural networks and the harmony search algorithm, an approach has been presented by defining optimum machining parameters in order to achieve minimum surface roughness (Chen *et al.* 2015).

A neural-networks based research on predicting surface roughness of machined workpieces after face milling at various cutting speeds, feeds, and depths have been presented in (Volpe Lovato *et al.* 2018). A genetically optimised neural network system has been proposed for the prediction of constrained optimal machining conditions in minimising surface roughness (Abidin *et al.* 2012). In summary, these approaches can assist engineers in selecting machining parameters to minimise the surface roughness during process planning. However, research of real-time control of machining parameters to improve surface roughness based on manufacturing requirements still lacks investigation.

To support real-time monitoring during machining execution, an investigation based on digital images for predicting surface roughness has been presented in (Chen *et al.* 2015). In the approach, an adaptive neuro-fuzzy inference system has been developed by considering spindle speed, feed per tooth, and cutting depth. Furthermore, this work is presented as an investigative study for developing a real-time monitoring system for machining processes. However, in the research, real-time correction of machining parameters to ensure surface roughness has not been considered yet. An evolutionary neuro-fuzzy system has been proposed in (Volpe Lovato *et al.* 2018), through which optimal machining parameters for controlling surface roughness during real-time execution have been identified. Also, the use of image processing to assess the quality of free-form profiles for quality control after machining processes has been proposed in (Abidin *et al.* 2012) and (Chen *et al.* 2015). Although these reviewed approaches have offered good results for monitoring surface quality, real-time control on surface quality is still required.

Approaches to real-time monitoring and control in CNC machining have become more evident in recent years. Online optimisation through adaptive control can provide significant advances in improving manufacturing efficiency, surface quality and tool-life saving (Volpe Lovato *et al.* 2018). Furthermore, this work highlights that Adaptive Control (AC) has been introduced as an effective method of optimising machining parameters online. In recent years, the implementation of fuzzy logic models for predicting and controlling surface roughness has raised as this technique gains popularity from its abilities to model process uncertainties (Abidin *et al.* 2012). Moreover, Fuzzy Logic Controllers (FLC) have been increasingly applied owing to their strong capabilities in processing linear and highly non-linear systems (Chen *et al.* 2015). An FLC uses a flexible set of if-then rules, dealing with process complexity by creating heuristics to be aligned with human knowledge and experiences more closely (Volpe Lovato *et al.* 2018)(Abidin *et al.* 2012). FLC has been proved to be superior to conventional non-fuzzy controllers. Some critical contributions of fuzzy systems for modelling and control have been highlighted in (Chen *et al.* 2015). In summary, these research works have been great incentives for using neuro-fuzzy and FLC for assisting in improving the surface quality problem during real-time machining execution.

2.2.5 Optimisation Approaches for CNC Machining

The use of optimisation algorithms is a crucial step towards increasing machining efficiency, cost reduction, and manufacturing sustainability. Significant efforts have been made by the research community to address complex manufacturing scenarios, involving environmental, legal, economic and quality requirements.

Process planning (or off-Line) multi-objective optimisation represents a real-time property category called off-line machining process control. That is, machining process information is acquired and saved during or at a particular stage of the machining process (*i.e.*, data collection). Then the collected data is saved and analysed externally by, for example, machining process controllers, which then adjust (or find the optimum) machining process parameters during process planning for later implementation into the next machining processes.

Additionally, according to (Volpe Lovato *et al.* 2018), the essential steps to develop optimisation approaches are:

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

Table 2-4 shows related work to single and multi-objective approaches to improve the decision making of CNC machining process parameters. The table also summarises the optimisation methods and objectives that have been used in recent years.

Table 2-4: Related work on the use of optimisation methods for machining processes.

Related Work	Methods	Objectives	Cutting parameters
(Wang *et al.* 2015)	Pattern search (PS), Genetic algorithm (GA) and Simulated annealing (SA)	Energy consumption and Productivity	Cutting speed (v_c), a_p and a_e
(Sonomez *et al.* 1999)	Dynamic programming and Geometric programming	Production rate	v_c and feed per tooth (s_z)
(Ozcelik, Oktem, and Kurtaran 2005)	GA	Surface roughness	v_c, f, a_p and a_e
(Sreeram *et al.* 2006)	GA	Tool life	a_p
(Li *et al.* 2014)	GA	SEC and machining time	S, f, a_p and a_e
(Nee *et al.* 2013, Baskar *et al.* 2006)	GA, Hill climbing algorithm and Memetic algorithm	Maximum profit	S and f

As shown in Table 2-4, genetic algorithms are amongst the most popular algorithms for solving machining optimisation problems. Also, a considerable number of optimisation objectives have been considered. However, an efficient and reconfigurable optimisation strategy, especially considering both the specific energy and the manufacturing requirements for cutting tool life and productivity, has not yet been accomplished. The trade-offs involved between these criteria are the core motivations of this work.

Also, recently, newer algorithms have been developed to cope with emerging engineering problems as well as the newer requirements of Industry 4.0, such as accuracy of decision-making systems and computational time and ease of applicability. In this work, a new improved nature-inspired optimisation algorithm will be introduced based on the Fruit Fly Optimisation Algorithm (FFOA).

FFOA has been successfully applied to several optimisation problems such as autonomous surface vessels' control (Chen *et al.* 2015), data mining (Volpe Lovato *et al.* 2018) and traffic flow control (Volpe Lovato *et al.* 2018). However, its ability to solve trade-offs of machining parameters has not yet been thoroughly investigated. In this research work, an improved version of the FFOA will be proposed to cope with the problem formulated of intelligent optimisation of machining processes.

Chapter 3: METHODOLOGY – EXPERIMENTAL APPROACH AND IMPLEMENTATION

3.1 INTRODUCTION

CNC machining key performance criteria include energy efficiency, productivity, surface quality, and cutting tool life. Modelling those performance criteria is necessary to develop intelligent systems and implement sustainable optimisation of processes and parameters. This is required for developing recommendations and support more intelligent decisions for energy and resources demand management.

To develop such systems, the experimental research approach has been adopted and carried out where milling operations were performed, and the performance criteria of the operations were measured accordingly. The information obtained from the measured data formed the basis of the analysis, modelling and optimisation processes of this study.

This chapter presents the details of the research methods, experiments and data collection procedures. The methodology adopted has been designed based on the two intelligent systems (or approaches) proposed: i) the multi-objective optimisation approach for the roughing stage of machining, and ii) the surface quality assurance approach for the finishing stage of machining. For the development of both approaches, quantitative analysis, modelling and optimisation problem formulation have been developed.

Figure 3-1 shows a detailed flowchart of the methodology of this study, considering the critical research outcomes.

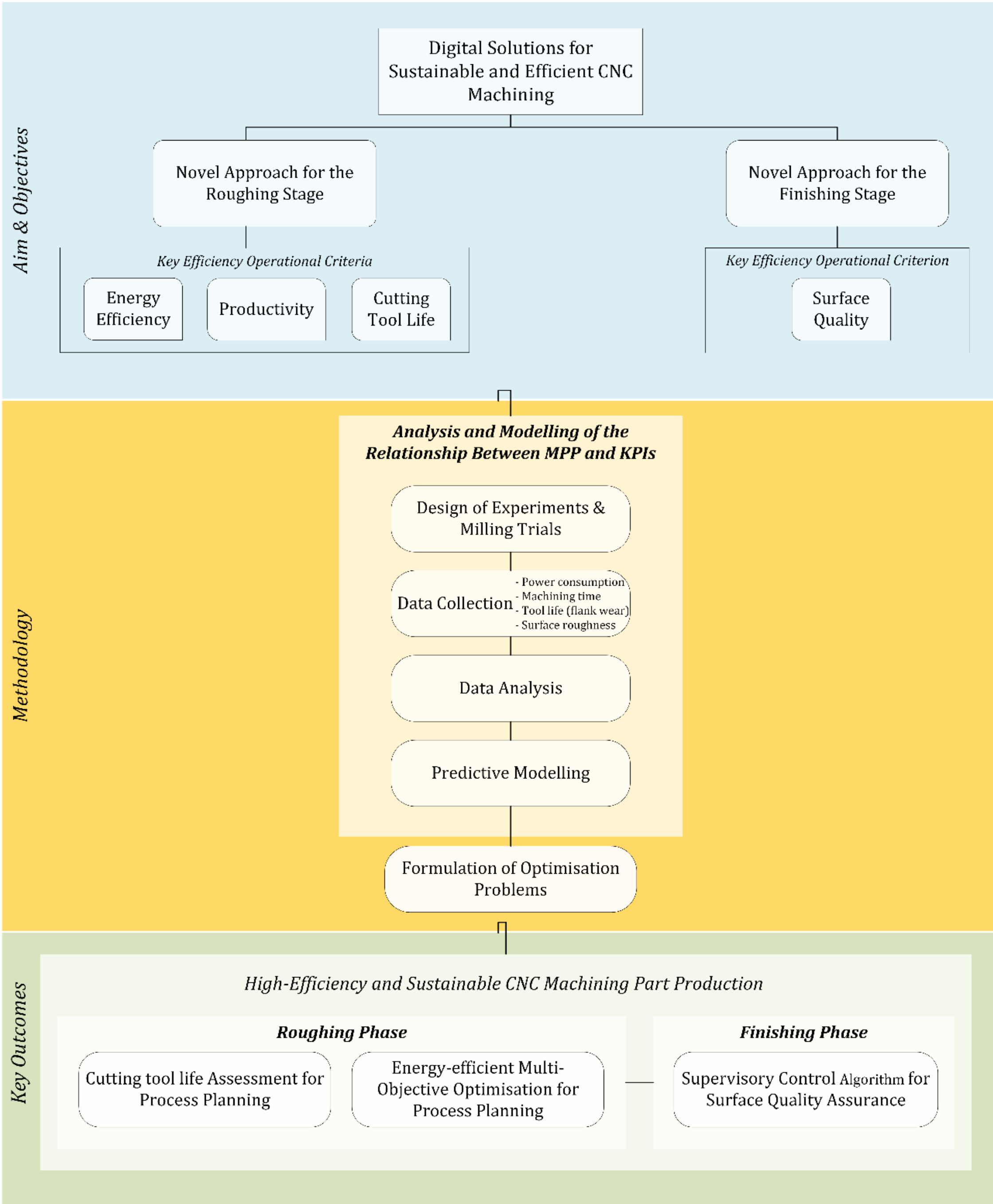


Figure 3-1: Schematic of research methodology.

3.2 EXPERIMENTAL RESEARCH APPROACH

The empirical (or experimental) approach is commonly adopted for tackling engineering issues (Saeema 2007). In this work, the empirical approach will follow the framework presented in Figure 3-2.

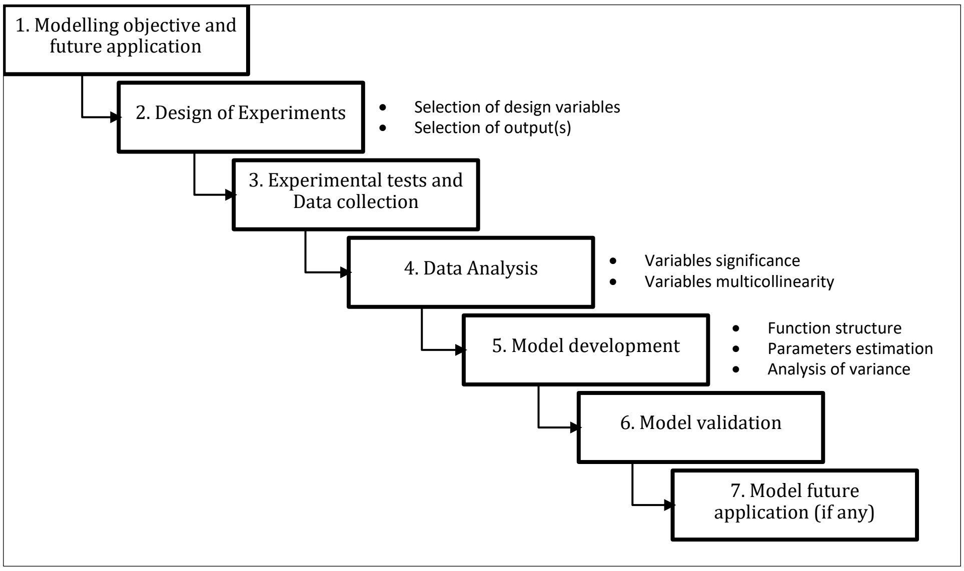


Figure 3-2: Empirical modelling process (Source: (Moreira 2016)).

Several methods and techniques will be used at each step of the empirical modelling framework. The selection of the methods will highly depend on the modelling objectives. Some methods found in the literature are shown in Table 3-1.

Table 3-1: 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) and (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), (Bhattacharya *et al.* 2009), (Nalbant *et al.* 2007) and (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) and (Calvanese *et al.* 2013)
Model analysis	ANOVA, Sensitivity analysis	(Winter *et al.* 2013) and (Lee *et al.* 1998)

As shown in Table 3-1, the empirical approach has been widely employed for modelling machining process performance criteria and has been proved to deliver accurate models. A key advantage of using such an approach is the reliability of the knowledge construction process, which is based on evidence collected from actual experiments (*i.e.*, measured data). Also, data collection is essential for predictive modelling processes. This way, the experimental approach is suitable for the objectives and primary goal of this research. Consequently, it will be employed to develop the knowledge and data collection to model the relationship between crucial machining process parameters (such as spindle speed, feed rate, cutting width and cutting depth) and key efficiency operational criteria (such as energy efficiency, productivity, cutting tool life, and surface quality). The future application of the models will be the intelligent systems for the roughing and finishing stages of machining.

The selected methods used for the design of experiments, analysis, modelling and optimisation process will be further described in the following sections.

3.3 Research Methods and Experiments

In this section, the methods used to achieve the aim of this research are presented. Figure 3-3 shows a summary of the methods.

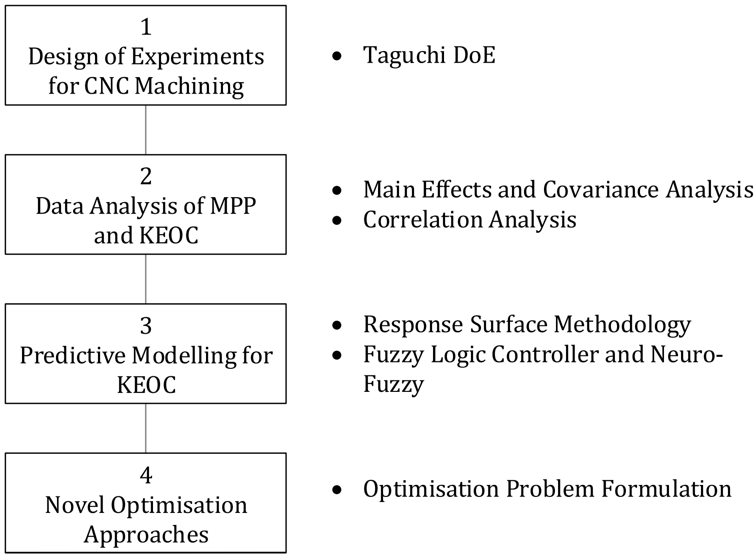


Figure 3-3: Research methodology steps and methods.

As shown in Figure 3-3, the empirical approach was employed onto a structured set of steps to design and collect the data used to draw the observations and understanding of the modelling and optimisation processes.

Also, a series of statistical methods are employed throughout the methodology, from designing the experiments to analysing the models' performance. Key aims of the statistical analysis, according to (Shevlyakov 2016), are given as follows:

- To provide a compact representation of data
- To estimate the model parameters
- To allow prediction

The methods used will be explained in more details in the following sections.

3.3.1 Design of Experiments using Taguchi DoE

Design of experiments (DoE) (or experimental planning) is the key to a successful empirical study (Gacula 2008). DoE is a statistical technique that provides a structured approach to data design and collection, by considering the trade-offs between the number of resources required for experimental trials and the statistical requirements for the data analysis. Moreover, good experimental planning results in the reduction of experimentation costs, ease of interpretation of results, and the collection of good data to result in a useful and meaningful outcome (Seltmann 2012).

The design of experiments of this research was performed using the Taguchi method, which optimised the number of resources required (such as tooling, workpiece material and time) and, at the same time, guaranteed the reliability of the observations through the experimental trials. The objective of the experimental trials is to investigate the effects of crucial machining process parameters (*i.e.*, spindle speed, feed rate, cutting width and cutting depth) on the key efficiency operational criteria (*i.e.*, energy efficiency, productivity, cutting tool life, and surface quality) of machining. For that, five levels of the selected machining process parameters are defined for investigation. This number of levels provides sufficient coverage of the machining process parameters ranges while meeting the statistical data analysis requirements.

The number of factors and levels impacts on the total number of experimental trials and, consequently, on the resources required. Several resources are required for running the CNC machining experimental trials such as BS EN24T (or AISI 4340) steel alloy workpiece materials, lubricant, including cutting tools, metrology equipment, machinists, engineers and experts' time for the data collection procedures for each key efficiency operational criteria. Consequently, optimising the number of experimental trials is of paramount importance.

Taguchi DoE was crucial to maximise the use of resources required for the data collection process of this research. Furthermore, it ensured all factors are evenly present and, this way, guaranteeing that satisfactory data is collected.

There are two sets of experimental trials that Taguchi DoE was mainly employed to design the experimental trials for data collection: i) experimental design for the data collection of cutting tool wear and tool life, presented in Chapter 4, where Taguchi L25 array was used (please see appendix A); and, ii) experimental design for the energy consumption and surface quality data collection, presented in Chapters 5 and 6, respectively, where Taguchi L24 was used (please see appendix B).

The Taguchi arrays provide the number of levels that covers well the range for each input machining process parameters and supports the reliable observation of the relationship between inputs and output factors.

3.3.2 Experimental Design, Setup, and Data Collection Procedures

This section presents the experimental setup and data collection procedures for the milling experimental trials. Experimental trials were performed using a vertical milling CNC machine where the experimental design was used to set the trials for the data collection on the process performance considering the key efficiency operational criteria. A summary of the key efficiency operational criteria and measurement procedures are as follows:

- for the energy efficiency and productivity, the power consumption of the cutting process of each trial was monitored in the time domain using a sensors network system;

- for the cutting tool life, a digital microscope was used to capture the cutting tool wear and the end of the useful life of the cutting tools of each trial;
- for the surface quality, a surface profilometer equipment was used to test the average roughness of the surface of the machined workpiece of each trial.

For the above, experimental planning, sensor systems, and metrology equipment are used to acquire the data for analysis, modelling and optimisation purposes.

The details of the experimental setup, including CNC machine, workpiece material, cutting conditions and tooling are provided in Section 3.3.3. The details of the design of experiments for the machining process parameters of each milling trial will be presented in Section 3.3.4. Section 3.3.5, followed by the data collection procedures for each of the critical efficiency operational criteria, will be provided in detail.

3.3.3 EXPERIMENTAL SET-UP

The experimental trials were carried out on a 3-axis vertical milling machine, which comprises a 30HP (22.4 kW) 415 V vector drive, with a maximum spindle speed of 8100 rpm. The relevant CNC machine and set-up are shown in Figure 3-4.

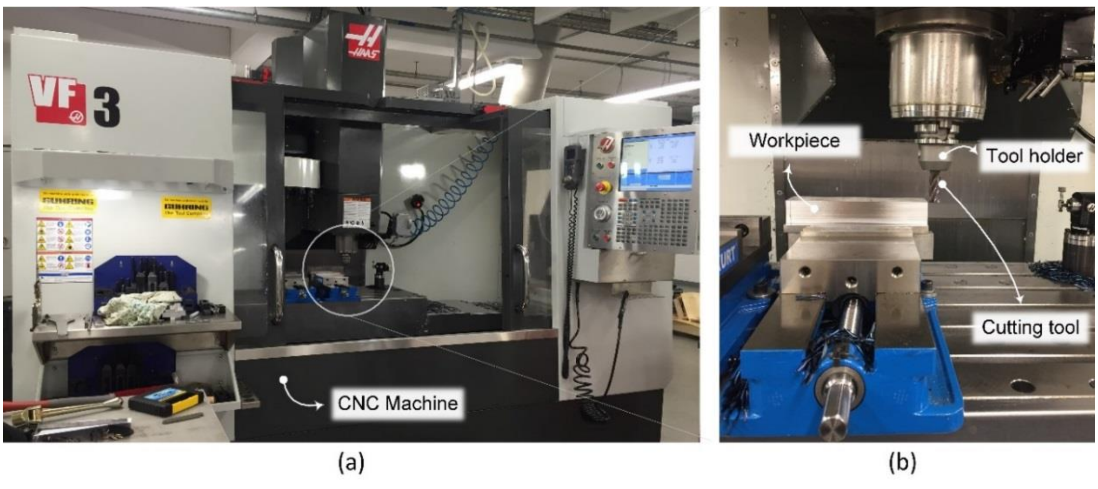


Figure 3-4: (a) Haas VF-3 vertical milling machine, (b) machined workpiece and cutting tool.

Machining hardened steel parts have become more prevalent in manufacturing processes, particularly in the mould and die industries and subsequently in making automotive and aerospace components (Hafiz 2008). In this research, the workpiece material is the hardened steel BS EN24T (AISI 4340), a high-strength steel alloy (HB 250-300). The grade is a nickel-chromium-molybdenum combination, offering high tensile steel strength, with good ductility and wear resistance characteristics. The composition and properties are shown in Table 3-2.

There are two reasons for selecting this material: 1) the material is widely used for several engineering applications in automotive and aerospace industry such as gear shafts, propellers, and so on (Steel Express 2018); 2) BS EN24T alloy steel is a hard material, and the energy consumption for machining hard materials is higher than that of soft materials owing to the greater torque (therefore, power) required to remove a unit of volume of material out of the workpiece stock (Sealy et al. 2016).

The cutter tool used is a solid tungsten carbide (shown in Table 3-3), held by a side-lock tool holder. The machining processes were carried out in up milling mode (*i.e.*, the cutting tool rotates clockwise, and the feed table travels from left to right, this is the commonly used model used for rough cutting operations), under minimum quantity lubrication (MQL) conditions.

According to (Tai *et al.* 2014), the elimination of lubricant coolant systems creates significant saving from energy and equipment reduction of the waste stream and shop floor space, cleaner and healthier work environment and supports the achievement of more sustainable machining.

Table 3-2: The material properties of the machined workpiece.

Material type: BS EN24T alloy steel (AISI 4340)

Composition: C 0.36-0.44 / Si 0.10-0.35 / Mn 0.45-0.70 / S<0.040 / P<0.035 / Cr 1.00-1.40 / Mo 0.20-0.35 / Ni 1.30-1.70		
Property	Value	Unit
Density	7850	kg/m^3
Young's modulus	210	GPa
Hardness - Brinell	248-302	HB

The part selected is a jaw-type geometry for which the CNC machining process requires side milling operations on both sides (Figure 3-5). Side milling is a typical CNC machining operation. Consequently, the experimental results can apply to a wide range of machining processes, for either roughing or finishing stages. The toolpath strategy is a unidirectional route with the cutting tool always engaged onto the workpiece, as shown in Figure 3-5.

Table 3-3: Cutting tool specifications.

Tool property	Specifications
Tool ID	End mill
Tool diameter (D)	16 mm
No. of teeth	4
Feed per tooth (s_z)	0.025 – 0.1 mm/tooth
Cutting speed (v_c)	150 – 250 mm/min
Corner radius	0.16 mm
Cutter material	Solid tungsten carbide

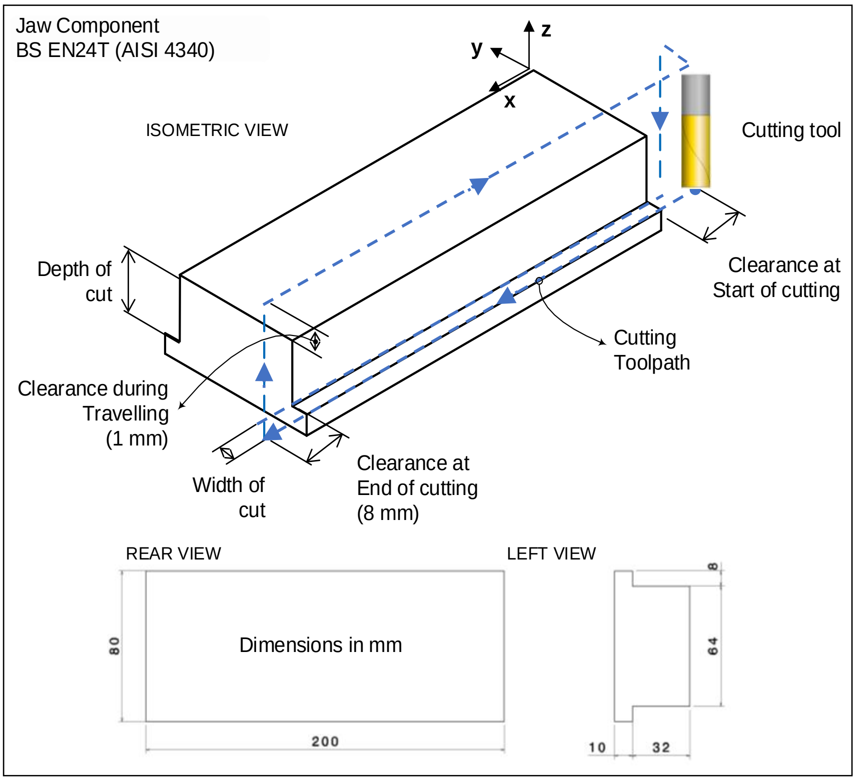


Figure 3-5: CAD design of the machined metal component and dimensions with side milling operations.

For the toolpath, a safe clearance distance of 8 mm is set in the X direction for the cutting tool on the start and end of the machining process, and 1 mm clearance in Z. That is, the cutting tool travels 8 mm with the supplied feed rate before and after engaging onto the workpiece.

The jaw-part is CNC machined under several computer-aided process planning (CAPP) configurations of spindle speed, cutting width and cutting depth and feed rate, as provided on the design of experiments, presented in the following section.

3.3.4 Design of Experiments of Milling Trials

Taguchi DoE experimental trials were designed considering several levels of the MPP to investigate the relationships between machining process parameters and key efficiency operational criteria energy efficiency, productivity, cutting tool life, and surface quality, for the roughing and finishing stages of milling. Furthermore, five levels of MPPs spindle speed, cutting speed, feed rate, feed per tooth, cutting width and cutting depth are selected to analyse the significance and the interaction effects for the roughing stage of milling.

To select the levels of the machining process parameters, firstly, the highest and lowest levels of cutting speed (v_c) and feed per tooth (s_z) were defined heuristically based on the machinists' knowledge. After that, the intermediate levels middle-low (M-L), middle (M) and middle-high (M-H) were calculated through Equations (3-1) to (3-4):

$$I_{v_c} = \left(v_{c_{Hi}} - v_{c_{Lo}}\right)/(n_{level} - 1) \tag{3-1}$$

$$v_{c_i} = v_{c_{i-1}} + I_{v_c} \tag{3-2}$$

$$I_{s_z} = \left(s_{z_{Hi}} - s_{z_{Lo}}\right)/(n_{level} - 1) \tag{3-3}$$

$$s_{z_i} = s_{z_{i-1}} + I_{s_z} \tag{3-4}$$

where I is the interval between each level of v_c and s_z; i stands for the intermediate levels; n_{level} is the number of levels desired, where $n_{level} = 5$.

Then, the calculated values of vc and sz for the five levels and the cutting tool diameter (D) were further used to calculate the spindle speed (S), feed rate (f) and width of cut (a_e) using the following Equations (3-5) to (3-7):

$$S_i = v_{c_i} \cdot 1000/\pi \cdot D \tag{3-5}$$

$$f_i = N \cdot s_{z_i} \cdot S_i \tag{3-6}$$

$$a_{e_i} = a_{e_f}/n_{pass_i} \tag{3-7}$$

where D is the diameter of the cutting tool; N is the number of tool teeth; i stands for the different levels (such as Lo, M-L and Hi); a_{e_f} is the final width from the part design; n_{pass_i} is the *i-th* number of cutting passes, which must be an integer for the CNC code. The highest a_e value is 4 mm, which has been tested by pre-experimental trials considering the machining holding and fixtures capabilities.

Table 3-4 shows the levels of the cutting parameters obtained according to the above Equations.

Table 3-4: Machining process parameters used in the DoE, where D = 16 and N = 4.

Levels	v_c / mm min^{-1}	s_z / mm tooth^{-1}	S / rpm	f / mm min^{-1}	a_e / mm
1. Lo	150.0	0.025	3000	300	1.60
2. M-L	184.5	0.059	3670	870	2.00
3. Re	200.0	0.070	4000	1115	4.00
4. M-H	218.7	0.082	4350	1430	2.67
5. Hi	250.0	0.100	5000	2000	4.00

The machining process parameters shown in Table 3-4 are used to calculate the material removal rate (MRR) with the use of Equation (3-8). MRR is a significant evaluation parameter for both energy efficiency and productivity criteria (Sealy *et al.* 2016). Thus, this parameter is included in several levels in the experimental design. To calculate the levels, the minimum and maximum calculated values of MRR using the designed MPP are used to define the lowest (Lo) and Highest (Hi) productivity levels. Then, the intermediate levels are defined heuristically considering the distribution of MRR values within the range.

$$MRR = f \cdot a_e \cdot a_p = (v_c \cdot 1000 \cdot N \cdot s_z / \pi \cdot D) \cdot a_e \cdot a_p \tag{3-8}$$

where a_p is the depth of the cut (in this research, it was chosen as 32 mm, which corresponds to the full depth of the geometry of the part); and MRR is the material removal rate in cm^3/min.

The levels of *MRR* are used for data analysis and optimisation purposes. The machining process parameters shown in Table 3-4 are used as input for the CAPP of the milling trials, while the critical efficiency operational criteria (or output factors) are measured accordingly based on the measurement procedures during or after the trials.

The data collection details for each of the key efficiency operational criteria are provided in the following section.

3.3.5 Data Collection Equipment and Procedures for the Performance of Milling Trials

According to (Oshima 1988), measuring performance is fundamental to assuring performance. That is, data collection through measurements of the process responses (or output factors) is of paramount importance to build up the understanding on the relationships between input and output factors, to form the predictive models.

Moreover, these will be essential to develop the optimisation approaches for the CNC machining roughing and finishing stages of this research. Therefore, the output factors (or critical efficiency operational criteria) will be measured for each experimental trial carried. The key efficiency operational criteria are energy efficiency, productivity, cutting tool life and surface quality, which specifics and measurement procedures are provided as follows.

1. **Power, Energy consumption and Energy Efficiency Measurement Procedures**

Energy consumption and energy efficiency have increasingly become a critical efficiency operational criterion of CNC machining processes due to costs, environmental and political aspects (Bai and Wang 2006). According to (Larsen 1980), measuring the energy consumption of such processes is a crucial step to achieve more energy-efficient CNC machining.

In this research, a sensor network system is used to monitor the power consumption of the milling trials. To obtain the power consumption, a Hall-effect current sensor system is clamped on the power source for feed axis and spindle servo motors, and the general power servo of the CNC machine. The power readings are stored in the SQL database, which is accessed for the data analysis at the end of each trial. The sensors system was calibrated before running the trials, and the sampling of sensor readings was set to 10 Hz. Such sampling frequency is sufficient for the application; that is, coping with the dynamics of the system and acquiring appropriate power consumption profiles and at the same time does not use substantial system memory space. Further system specifications are provided in (Zadeh 1965).

The power consumption readings of all experimental trials are treated using MATLAB/Simulink software. The power data (P) is then converted to energy consumption (EC) and energy efficiency (SEC) using Equations (3-9) and (3-10), respectively, which considers the machining time (t) of each trial. The data was also used to determine the CNC machining time, used for the productivity criterion.

The energy consumption is analysed under two distinct machining states:

- State of engagement (SoE) represents the process of material removal (actual cutting)
- State of non-engagement travelling (SoT) represents non-cutting movements (air cutting).

Also, the power load ($\bar{P}_{SoE}$), which is the average of the power during the SoE, is introduced to assess the energy consumption performance during a machining process. Similarly, $\bar{P}_{SoT}$

is the average of the power during the SoT. EC_{SoE} and EC_{SoT} stand for the total energy consumption during the SoE and SoT, respectively. Also, the specific energy consumption (SEC) during the SoE is used to indicate the machining process's energy efficiency when removing materials. The relevant computations are in the following Equations (3-9) to (3-10).

$$EC_i = \int_0^{t_i} Pdt \quad (3\text{-}9)$$

$$SEC_i = \int_0^{t_i} Pdt\,/V \quad (3\text{-}10)$$

$$\bar{P}_{SoE} = \int_{t_1}^{t_{SoE}} P_{SoE}dt/\sum_{n_{pass_1}}^{n_{pass_n}} t_{SoE} \quad (3\text{-}11)$$

$$EC_{SoE} = \int_{t_1}^{t_{SoE}} P_{SoE}dt \quad (3\text{-}12)$$

$$\bar{P}_{SoT} = \int_{t_1}^{t_{SoT}} P_{SoT}dt/t_{SoT} \quad (3\text{-}13)$$

$$EC_{SoT} = \int_{t_1}^{t_{SoT}} P_{SoT}dt \quad (3\text{-}14)$$

where EC, P and t stand for energy consumption, power and machining time, respectively, of each i^{th} trial. V is the volume removed during machining, t_{SoE} is the machining time during the SoE for each cutting pass n.

The final data are analysed using statistical methods, main effects and covariance analysis. The outcomes of the analysis represent an in-depth investigation of the relationships between spindle speed, feed rate, cutting width and cutting depth on the power load, energy efficiency and productivity.

2. Cutting Tool Wear and Tool Life Measurement Procedures

Cutting tools represent a significant cost in CNC machining processes (Benkedjouh *et al.* 2015). Extending the life of cutting tools is urgently demanded due to cost and sustainability aspects (Oshima 1988). Furthermore, machining process parameters play a significant effect on cutting tool life; consequently, a correct selection of MPP can increase the life of cutting tools (Bai and Wang 2006). Therefore, in this research, cutting tool life measurements are carried out for several experimental trials. For that, the tool wear width of the cutting tools is assessed throughout the cutting processes of each milling trial.

In more details, the cutting process to produce the jaw-part design was replicated for a large quantity of material removal using side milling operations until the cutting tools reached the end of life, for each experimental trial. It is important to note that for each trial, a new (or sharp) cutting tool was used. The conditions of each cutting tool were assessed using a microscope before each cutting process. The machining process characteristics are illustrated in Figure 3-6.

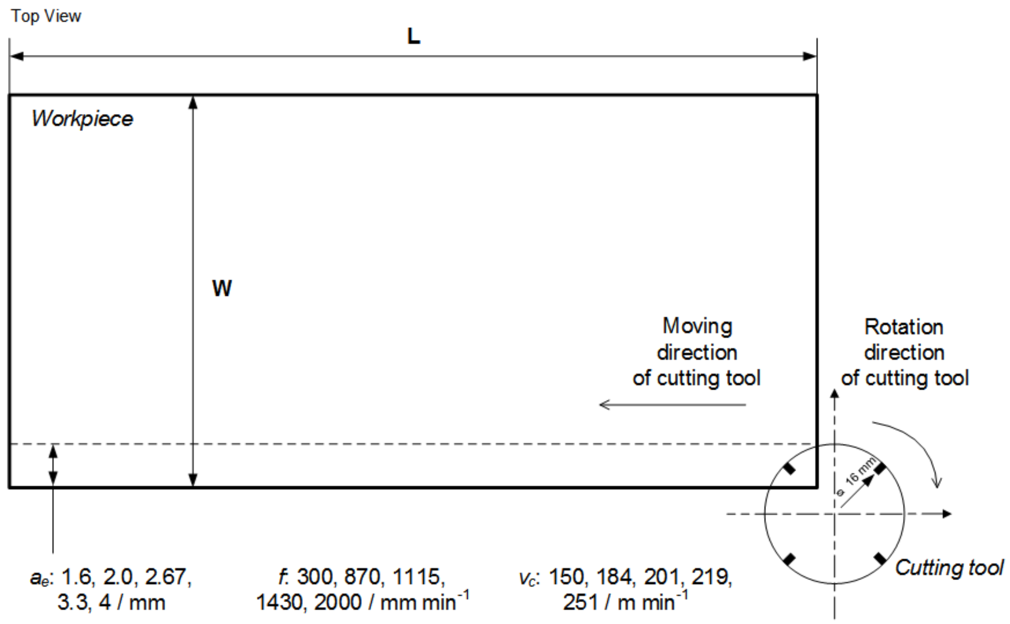


Figure 3-6: Illustration of the side milling operations.

During the trials, the machining process is stopped at several cutting lengths (such as 10 meters from the beginning, considering the increase of tool wear is higher at the start of life, and then at every 20 meters of cutting length). Then, at each cutting length interval, the cutting tool is taken to the metrology lab, and the wear width condition is assessed using a KEYENCE VHX-5000 digital microscope. The values of wear width are then measured and recorded in MS Excel 2016. Such measurement process occurs until the wear width of the cutting tools reached the criterion of total tool life, which in this research is maximum flank wear (VB_{max}) equal to 0.4 mm – which is the recommended cutting tool life criterion in CNC machining for roughing processes.

Such tool life criteria and measurement procedures of the tool wear width follows the standards presented in (ISO 8688-2). ISO 8688-2 has been developed on the initiative of the International Institution for Production Engineering Research (CIRP) and applies to end milling operations, which represent a significant manufacturing activity. This ISO specifies recommended procedures for tool-life testing for end milling operations.

Based on that, experimental analysis of several deterioration phenomena (such as flank wear, chipping, and flaking) is taken at the several steps of the machining process using digital optical images. So, once the measured wear width is more significant than 0.4 mm, the cutting tool reaches the end of its useful life.

The cutting tool reached the end of its useful life in two types of failure: gradual and catastrophic. Therefore, the deterioration phenomena and end of useful life assessment are classified accordingly, see details in Table 3-5.

A gradual failure stands for the progressive increase of wear width during the machining process; while catastrophic wear stands for the sudden end of useful life due loss of tool fragments when the measured wear width is higher than the tool life criteria. The measurements of wear width are taken in three regions of the cutting tool: cutting tooltip, lower cutting edge and upper cutting edge (illustrated in Figure 3-7(a)), as recommended by the ISO 8688-2.

Table 3-5: Deterioration phenomena for the cutting tool.

Failure type	**Deterioration phenomena**	**End of useful life criteria (VB_{max})**
Gradual	Flank wear (VB) VB1 uniform flank wear VB2 non-uniform flank wear VB3 localised flank wear	$VB_{max} \geq 0.4$ mm
Catastrophic	Chipping (CH) or Flaking (FL) CH1 uniform chipping CH2 non-uniform chipping	CH_{max} or $FL_{max} \geq 0.4$ mm

It is important to note that the cutting tool life assessment is carried at each position independently. More details on how the measurements of flank wear were taken can be seen in Figure 3-7(b). The tool deterioration phenomena and the measured wear width at each cutting length and each region were recorded for each experimental trial.

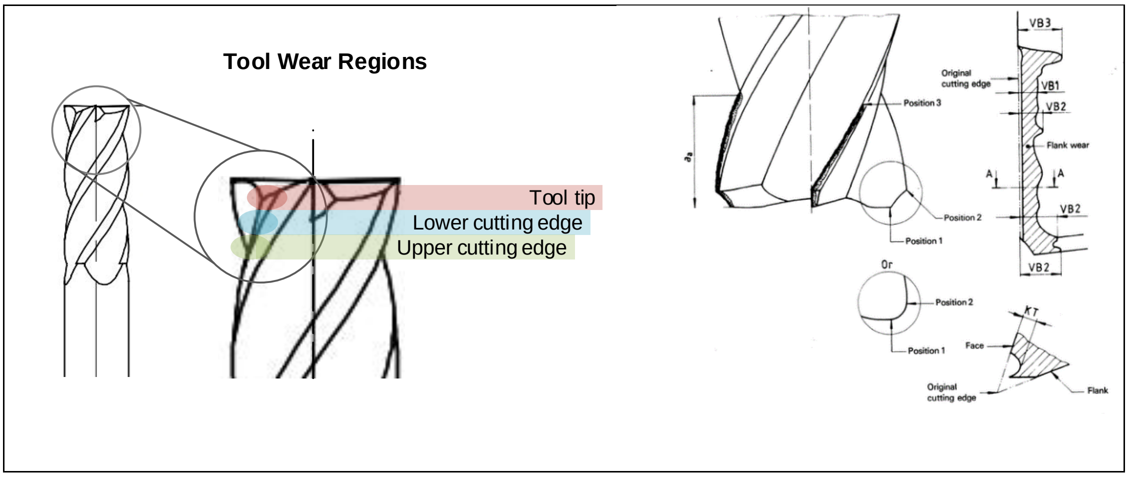


Figure 3-7: (a) Positions of tool deterioration. (b) Wear on end mill cutters (Source: ISO-8688).

The data collected on tool wear width and cutting tool life are analysed using statistical method main effects analysis which investigates the relationships between cutting speed, feed per tooth and width of cut on the cutting tool life. Besides, the knowledge acquired from such analysis is further employed to carry out a correlational analysis between the cutting tool life (such as cutting length, cutting time and volume of material removed) and the power consumption.

3. Surface Roughness Measurement Procedures

Surface quality (or surface finish measured by the surface roughness) represents one of the main problems that engineers face in CNC machining. Two of the reasons include the significant impacts of the surface roughness on the technical requirements and the functionality of the part (De Caluwe 1997). Also, the increase of consumer needs for quality metal cutting of products with more precise tolerances and better product surface roughness has driven the industry to continuously improve quality control of machining processes (Zadeh 1965). Moreover, poor surface roughness profile impacts negatively on production lead time, costs and environment.

The roughness profile is the basis for evaluation of the surface profile parameters (Oshima *et al.* 1988). The global evaluation of the surface roughness on a profile used for quality purposes in CNC milling operations is the arithmetic mean deviation (or average surface roughness) of the assessed profile (*Ra*). Consequently, this parameter is considered for the surface roughness and, thus, the quality criterion in this research work.

Metrology equipment Mitutoyo FormTracer 3100 was selected to measure the surface roughness (*Ra*) of the machined workpieces from the experimental trials. This equipment is comprised of a stylus profilometer for taking the measurements. Then, the measured *Ra* profile was recorded and extracted for data analysis. *Ra* can be obtained by calculating the integral of the absolute value of the roughness profile height over the evaluation length, as shown below:

$$Ra = \frac{1}{L}\int_0^L |Y(x)|dx \tag{3-15}$$

The set-up of the experiments and data collection are presented in Figure 3-8.

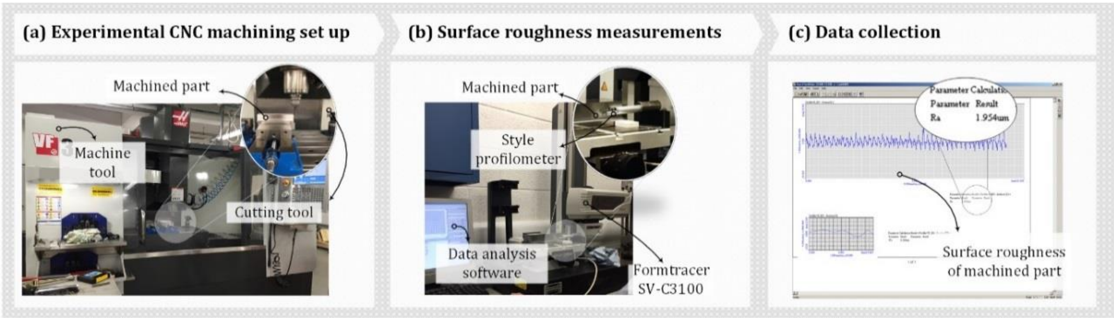


Figure 3-8: Experimental set up for the surface roughness measurements of machined parts.

The data collected from all experimental trials are analysed using statistical method main effects analysis to evaluate the significance of input factors spindle speed and feed rate, which are critical in-process adjustable machining process parameters, on the surface roughness. The results are further implemented to develop a predictive model for this key efficiency operational criteria.

3.4 Data Analysis Using Main Effects and Covariance Analysis

The data analysis is a crucial step to define the significance of relationships between input and output factors, which is of paramount importance to build essential machining knowledge to aid engineers and machinists in decision making. In addition, such knowledge will be further used to help to select the most suitable model structure for the development of the predictive models. This latter is essential due to the requirements of the models' future applications such as the trade-offs between model complexity and computational time.

Main effects and covariance analysis are statistical methods commonly used to analyse the variance of responses (or output factors) given specific changes in the input factors (Bai and Wang 2006). Such methods are used to assess the statistical significance of the relationships between the input and output factors. In this research, the main effects and covariance analysis will be used to investigate the relationships between the several machining process parameters and the key efficiency operational criteria.

Furthermore, main effects analysis, also known as one-way analysis of variance (ANOVA), allows the investigation of the magnitude of change on the outputs based on the mean value due to the changes on the input factors. A significant main effect occurs when several levels of specific input factors cause a considerable deviation of the response from its mean value (Larsen 1980). Covariance analysis, also known as two-way ANOVA, allows the investigation of the multicollinearity between two inputs and a specific output factor. A significant covariance occurs when multiple factors are correlated not just to the output factor, but also to each other.

Such results lead to essential knowledge for improving CNC machining performance based on the quantitative analysis and are further used to support the development of the predictive models for the key efficiency operational criteria as a function of the machining process parameters. That is, the relationships between these will be identified; therefore, such findings support the selection of the appropriate modelling structure and methods.

3.4.1 Predictive Modelling Methods

Predictive modelling is used to establish the relationships between given input factors and the desired output factors. For that, classical mathematical or artificial intelligence (AI) techniques can be employed to establish such relationships. The key outcome is a predictive model of the output factor as a function of the input factors, commonly applied to improve decision-making processes, especially for engineering applications (De Caluwe 1997).

In this work, predictive models are developed and used to support decision-making CNC machining planning. Furthermore, such models are employed to test and validate the proposed optimisation solutions for the roughing and finishing stages of machining.

Consequently, several modelling techniques, such as classical mathematical and AI, are tested to form the models. The model's inputs (or predictors) stand for the MPP (*i.e.*, spindle speed, feed rate, cutting width and cutting depth), while the outputs (or predictands) are the key efficiency operational criteria: energy efficiency, productivity, cutting tool life, and surface roughness.

The decision upon the method used was made based on the relationships between machining process parameters and key efficiency operational criteria, identified using main effects analysis. Since such relationships will have their requirements and specifications of future applications (such as process planning or real-time systems). The methods used for the modelling processes are briefly explained in the following sections.

3.4.2 MODELLING USING RESPONSE SURFACE METHODOLOGY

Response surface methodology (RSM) is an extensively used technique for modelling and optimisation problems in engineering (Tengeleng and Armand 2014). It is a collection of statistical and mathematical methods that describe response(s) (or output factors) as a function of input factors. In manufacturing, RSM is used to model and optimise processes from data collected through experimental tests (Zadeh 1965).

In this methodology, it is assumed that the input factors are continuous and controllable by experiments with minor errors. An RSM quadratic model is a second-order regression model and is given as:

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum_{i=1}^{k-1} \sum_{j>1}^{k} \beta_{ij} x_i x_j \qquad (3\text{-}16)$$

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.

In RSM, there are three other types of model structure: linear, interaction and pure quadratic. The selection of the model structure depends upon the order and significance of the relationships between input and output factors, which can be revealed through the main effects and correlation analysis.

Also, the statistical significance can be tested using the p-value of each model term. The number of terms impact on the complexity of the model and may have a significant impact on the computational time when implementing that model, for example, at optimisation applications (Mamdani 1974).

Moreover, in the RSM model, shown in Equation (3-16), the β coefficients are estimated using experimental data and the standard linear least squares method (LSM)

3.4.3 Modelling Using Fuzzy Logic

Initially outlined by and further developed by (Mamdani and Assilian 1975) in the early 1970s, fuzzy logic (FL) models' applications exhibited their first industrial and commercial growth in Japan in the 1980s. Since then, Japanese companies have adopted such methods for several applications such as automobile automatic transmission, thermal control, washing machines, and so on (Bai and Wang 2006). Moreover, US and European companies have widely deployed a fuzzy logic model and controllers for several applications (Larsen 1980).

One of the critical strengths of FL is its ability to handle uncertainties between predictors and response variables (De Caluwe 1997). That is, unlike a classical control strategy, which is a point-to-point control, fuzzy logic control is a range-to-point or range-to-range control. Furthermore, FL models are knowledge-based models usually derived from a knowledge acquisition process (such as observations, tacit knowledge, and experimental data).

There are two types of FL models: Mamdani (Mamdani 1975) and Sugeno (Sugeno 1985). Both types consist of the same four core parts: the fuzzification interface, the fuzzy inference engine, the fuzzy rule base and the defuzzification interface (as shown in Figure 3-9).

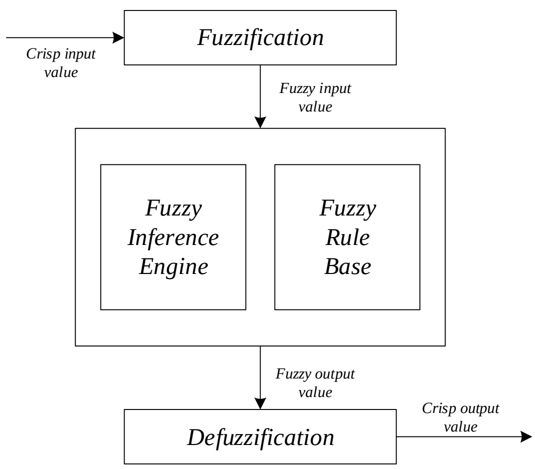


Figure 3-9: Fuzzy Logic Controller schematic.

The fuzzification interface converts classical data (or crisp input) into fuzzy data with the use of membership functions (fuzzy sets). The membership functions can have different shapes such as triangular, rectangular and trapezoidal. The selection of the best shape configuration depends on the relationship being modelled. In practical terms, several configurations of membership functions shapes of input and output factors are tested, and the predictive accuracy of the final model is assessed using the mean squared error (MSE)(Tengeleng and Armand 2014). Therefore, the minimum achieved MSE represents the best shape configuration.

The fuzzy inference process combines the membership functions with the fuzzy rules to depict the fuzzy output. The fuzzy rules have the following form:

IF (a set of conditions are satisfied) THEN (a set of consequences can be inferred)

Since the antecedents and the consequents of the IF-THEN rules are associated with fuzzy concepts (linguistic terms), they are also called fuzzy conditional statements. The fuzzy sets should give the inputs for the fuzzy rule-based systems, and therefore, the crisp inputs will have to be fuzzified. Also, the output of a fuzzy system is always a fuzzy set, and therefore, the fuzzy value will have to be defuzzified. Finally, the defuzzification interface converts the fuzzy output into a crisp output (Bai and Wang 2006). The difference between Mamdani and Sugeno is seen at the defuzzification interface, wherein a Mamdani FL model the crisp output value is calculated through output membership functions. Whereas in the Sugeno FL model, the crisp output value is calculated through output mathematical equations (Bai and Wang 2006).

In this work, FL is used to develop the models in the control loop for the adjustments of spindle speed and feed rate, which are an essential part of the supervisory control system for the finishing phase of machining. Such a system is designed to promote autonomous control of the surface quality during the cutting process.

3.4.4 MODELLING USING ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

The combination of Artificial Neural Networks (ANN) and Fuzzy Inference Systems (FIS) have been attracting the interest of researchers in various scientific and engineering fields due to the increasing demand for adaptive intelligent systems to develop solutions for real-world problems (Abraham 2001).

Adaptive neuro-fuzzy inference system (ANFIS) or neuro-fuzzy is a modelling technique where artificial neural networks (ANN) and FL are combined to form predictive models. In this technique, ANN algorithms are employed to define the membership functions, fuzzy rules and output equations using experimental data. The critical advantage of neuro-fuzzy models lies in the minimisation of human error during the modelling process, given the nonlinearities between input and output factors. This advantage, aligned with the learning capabilities of the technique, defines the selection of this method for the development of the surface roughness predictive model – presented later in Chapter 6.

Therefore, the neuro-fuzzy model represents a Sugeno type of FL model. The Sugeno method is computationally effective and works well with optimisation and adaptive techniques, which makes it suitable for the application. More information on this type of fuzzy logic model can be found in (Sugeno and Michio 1985). The general architecture of the two-input single-output neuro-fuzzy model is shown in Figure 3-10.

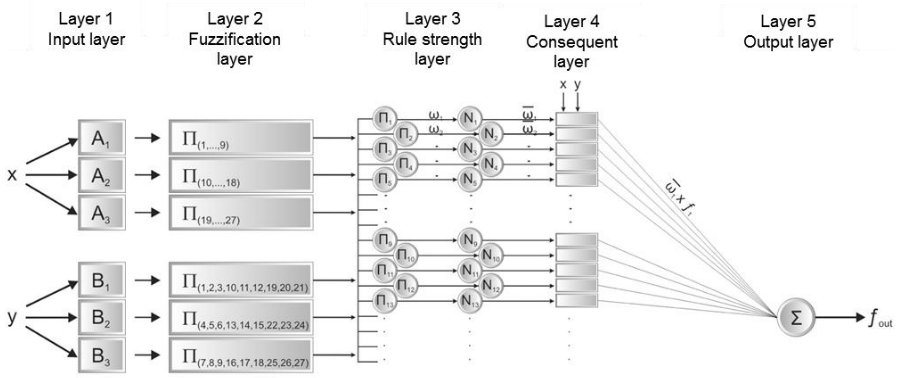


Figure 3-10: General architecture of the ANFIS model.

This method is a programmed procedure for defining all the FIS coefficients (also called parameters) by using experimental data for training the FIS. The FIS defines the model's engine, which is comprised of the fuzzification layer, rule strength layer, consequent layer, and the output layer. Also, the layers of the neuro-fuzzy model consist of several nodes described by node functions, such as layers 1 and 2 include adaptive nodes, and the node functions can be described as shown below: $Q_{1,i} = \mu A_j(x) \begin{cases} j = 1, f_{ori} = 1, \cdots, 9 \\ j = 2, f_{ori} = 10, \cdots, 18 \\ \vdots \end{cases}$

(3-17)

$$Q_{1,i} = \mu B_j(x) \begin{cases} j = 1, f_{ori} = 1,2,3,10,11,12,19,20,21 \\ j = 2, f_{ori} = 4,5,6,13,14,15,22,23,24 \\ \vdots \end{cases}$$

where x and y are nodes input; A_j and B_j are linguistic labels, and μA_j and μB_j are membership functions. Membership functions define the degree of significance in which an input variable satisfies the defined rule premise. The fuzzy rules are written, as shown in Equation (3-22), as shown below:

$$\begin{array}{l} Rule1: IF\ x\ is\ A_1\ and\ is\ B_1\ then\ z\ is\ f_1(x,y) \\ Rule2: IF\ x\ is\ A_1\ and\ is\ B_2\ then\ z\ is\ f_2(x,y) \\ \vdots \end{array} \qquad (3\text{-}18)$$

$Rule\ n$

In the present case, the triangular input membership functions are applied, which generally form is shown in Figure 3-11.

$$\mu_A(x) = \begin{cases} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a < x < b \\ 1, & x = b \\ \dfrac{c-x}{c-b}, & b < x < c \\ 0, & x \ge c \end{cases}$$

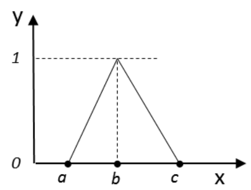


Figure 3-11: Triangular membership functions crisp to fuzzy conversion equations.

Moreover, the defuzzification process is done by using the weighted method to obtain the crisp output, which formula is shown in Equation (3-23).

$$FinalOutput = \sum_{i=1}^{N} w_i f_i / \sum_{i=1}^{N} w_i \qquad (3\text{-}19)$$

where w and f represent the weight for the i^{th} output function, respectively.

Thus, the data collected from the experimental trials will be used to train the neuro-fuzzy model using backpropagation and the least squares algorithms, to obtain the predictive model for the surface roughness as a function of the spindle speed and feed rate.

3.4.5 Intelligent Approaches to CNC Machining

The two systems to enhance CNC machining sustainability developed in this research are within the areas of optimisation. Since optimisation algorithms have been increasingly applied to engineering problems to improve performance, reduce costs and improve processes quality. A wide range of optimisation algorithms is available, which the nature-inspired algorithms have been proven to provide an excellent performance such as genetic algorithms (Yang 2014). Nevertheless, as new problems and manufacturing requirements change over time, the algorithms must continue evolving to cope with such changes.

Also, novel strategies to multi-objective optimisation in manufacturing are urgently in demand to effectively improve production and the use of resources.

3.4.6 Fruit Fly Optimisation Algorithm

FFOA is a novel nature-inspired optimisation algorithm which is inspired by the behaviour of fruit flies (Xing and Gao 2014a). This algorithm has been recently developed by (Pan 2012), inspired by the foraging behaviour of the fruit flies, based on their sensing and perception characteristics to find food, especially in osphresis and vision (Xing and Gao 2014b). Recently, this algorithm has been used for solving optimisation problems by mimicking the highly-advanced sense of smell of insects to detect food locations. This modern algorithm has presented an outstanding performance on solving optimisation problems, especially in business and finance areas which require highly reliable predictions (Pan 2012). The basic principles of fruit flies' food search are as follows:

i. Fruit fly will smell the food source by osphresis organ and fly towards that location
ii. After getting close to the food location (when the smell concentration is higher), the sensitive vision is also used for finding food and other fruit flies' flocking location
iii. It then flies towards such location.

Therefore, the optimisation algorithm will follow the procedures of such behaviour. Further details of the optimisation algorithm steps are presented in (Xing and Gao 2014a). Additionally, the core advantages of FFOA are a simple computational process, ease of understanding and easy implementation with satisfactory performance. In this research, an improved version of the FFOA will be proposed to cope with the problem formulated of intelligent optimisation of machining processes.

The improved algorithm of the FFOA, called iMFOA, will be further discussed in Chapter 5. Moreover, such an algorithm will be used to find the optimal cutting conditions for the multi-objective optimisation problem of energy efficiency, productivity and cutting tool life. The results will be further compared to the results obtained using the genetic algorithms, a widely used algorithm to solve engineering problems. More details on the genetic algorithms can be found in (Yang 2014).

Chapter 4: Empirical Analysis and Estimation of Cutting Tool Life Based on BS EN24T Alloy Steel

4.1 Introduction

In CNC machining processes, production costs and quality are significantly affected by cutting tool life (Liew and Ding 2008, Jantunen 2002). According to (Malekian, Park, and Jun 2009), cutting tool failures (*i.e.*, wear and breakage) represent approximately 20% of the downtime of a CNC machine. Furthermore, these authors discovered that the cost of cutting tools and their replacement account from 3% to 12% of total production costs. Meanwhile, cutting tool wear presents a direct impact on the quality of surface finish, dimensional precision and ultimately cost of the finished product.

In order to achieve the maximum potential of production efficiency, an important aspect is to reduce tool wear and prolong tool life (Zhu, Zhang, and Ding 2013). Therefore, the prediction of tool failures and enhancing cutting tool life are crucial to improve resources productivity in manufacturing, *i.e.*, reduce cost, improve quality, enhance sustainability and increase productivity.

Cutting tool life is determined by tool wear, which is defined as the progressive loss during material removal from a machining surface (Kalpakjian 2001). Tool wear occurs due to the contact between the chip and the machining surface of a workpiece (Machado and Diniz 2017). In machining, the tool wear will have a maximum value which defines the cutting tool life, such as maximum flank wear (VB) (ISO 8688-2 1989). This criterion of tool life is essential to indicate when a tool is severely worn for replacement, to avoid a poor accuracy and surface finish of the workpiece being machined (Benkedjouh *et al.* 2015).

The nature of cutting tool wear is complicated, and further research is still necessary for spite of numerous investigations (Astakhov 2004). Tool wear is affected by various factors, such as type of material, cooling and lubrication conditions, machining process parameters (MPP) including cutting speed (v_c), cutting depth (a_p) and feed per tooth (s_z) (Sağlam and Kaçar 2003, Senthil Kumar, Raja Durai, and Sornakumar 2006).

Amongst the factors, MPP has been identified as a significant factor affecting tool wear (Bhushan, Kumar, and Das 2010, Gowd *et al.* 2014, Liew and Ding 2008). However, it is challenging for machinists/engineers to heuristically find the best selection of MPP solely based on their experience and tooling handbooks. The relationship between tool wear progression and MPP is complicated, which overwhelms operators' capabilities. It is crucial to carry out research to identify suitable MPP in order to promote longer cutting tool life and also meet other production requirements such as productivity or surface quality.

The empirical analysis which investigates those relationships, as well as predictive modelling for the cutting tool life, are two binding resources to support machinists' decision-making during process planning. Furthermore, when machining hardened steel, the wear is even more critical because the wear progresses fast and, therefore, decreases the tool life rapidly (Machado and Diniz 2017). The authors further stated that this is due to the high cutting forces and heat generated, which cause rapid tool wear and short tool life. In addition to, such materials usually present low thermal conductivity, this way, resulting in higher temperatures closer to the cutting edge, causing strong adhesion between the tool and workpiece material (Zoya and Krishnamurthy 2000).

In process planning of CNC machining for hard materials, there are two main challenges to achieve more sustainable processes (Tao and Xun 2012, Li *et al.* 2014, Tai *et al.* 2014):

(1) There are various machining conditions and configurations (*e.g.*, material type, tooling, cooling conditions), and machining operations (*e.g.*, turning, milling). For this reason, empirical studies are needed to cover such a wide range of machining conditions and, this way, construct the knowledge of discovering their relationship with the cutting tool life.

(2) It is an expensive and time-consuming process to establish predictive models for cutting tool life, due to the number of resources and procedures required. For this reason, studies on the development of more effective ways to predict the cutting tool life are of paramount importance.

Hence, in this research, the challenges above are thereby addressed by the following work:

(1) An empirical analysis is carried out to provide an in-depth investigation of the relationships between MPP (including cutting speed, feed per tooth and cutting depth) and the cutting tool life in milling of the BS EN24T hardened steel. For that, several experimental trials are designed using the Taguchi L25 array for data

collection, where the deterioration phenomena (such as flank wear, chipping and flaking) of the worn cutting tools are investigated throughout the process using optical images. The collected data is analysed based on three different Tool Effectiveness (TE) indicators: total cutting time, total cutting length and total material removed. Then, the main effects analysis is used to identify the significance of MPP on each tool life indicator. The results are then discussed, and essential machining knowledge is built to support better decision making and promote improved machining strategies to prolong the cutting tool life.

(2) The empirical results are used to do a correlation analysis between the cutting tool life and the mean power consumption during the state of engagement. This analysis is further used to investigate the feasibility of using power consumption as a mediator to predict the cutting tool life. Such analysis is used to support the development of a novel predictive model for the cutting tool life based on power consumption models.

4.2 ANALYSIS OF TOOL EFFECTIVENESS INDICATORS AND MACHINING PROCESS PARAMETERS

According to (Astakhov 2004), the proper assessment of tool wear requires some quantitative characteristics, which will be referred to as tool effectiveness indicators (tool life) in this work. The most common tool effectiveness used in the industry are:

(1) the time during which the tool works continuously called total cutting time *(T_{max})*;

(2) the length of the tool path called total cutting length (L_{max});

(3) the amount of volume of removed material which the tool removes called total volume of material removed (V_{max}).

The value of the tool life will depend on the tool life criterion, which is typically defined as the maximum tool wear value (such as maximum flank wear, VB_{max}). In particular, among the tool life indicators, the total volume of removed material has a great potential to enhance the performance of roughing machining, as it can be easily aligned with the material removal rate (MRR), an essential measure of productivity.

In this research, investigations on the effects of MPP on the tool life indicators (*i.e.*, T_{max}, in min; L_{max}, in m; and, V_{max}, in cm^3) will be carried out to support machinists and engineers on the appropriate selection of tool life. This process will be aligned with the optimal selection of machining process parameters, to enhance the life of cutting tools and, consequently, minimise the impacts of tool failure on cost, quality, and productivity.

The design of experiments, experimental setup and measurement procedures presented in Chapter 3, Section 3.3, were performed to run the 25 experimental trials where tool wear data was collected for the determination of cutting tool life. This data is further used to calculate the tool effectiveness indicators.

To calculate the tool effectiveness, the value of flank wear width (VB) (please refer to Chapter 3 Section 3.3.5 for the measurement procedures details), of each trial, was recorded for several cutting lengths (L) until the measured wear width was greater than 0.4 mm, when the cutting tool failure was identified (ISO 8688-2 1989). At the point, the experimental trial finishes and the values of the final cutting length (L_f) and final wear width (VB_f) were recorded. However, since the value of L_f will usually be beyond the tool wear criterion (VB_{max} = 0.4 mm), the curve fitting technique is used here to develop regression models in order to identify the tool life (*e.g.*, L_{max}) for the given VB_{max} for each experimental trial. Figure 4-1 shows the example of one experimental trial where the several values of tool wear were measured (in Y-axis) along the cutting process for several cutting lengths (in X-axis). It can be noted that the moment where the failure is experimentally observed will be used to define L_f. However, as this point has to be avoided to prevent the tool failure, the point of interest (when VB = 0.4 mm) will be located between the failure point and the last measured cutting length (highlighted by the circle in Figure 4-1).

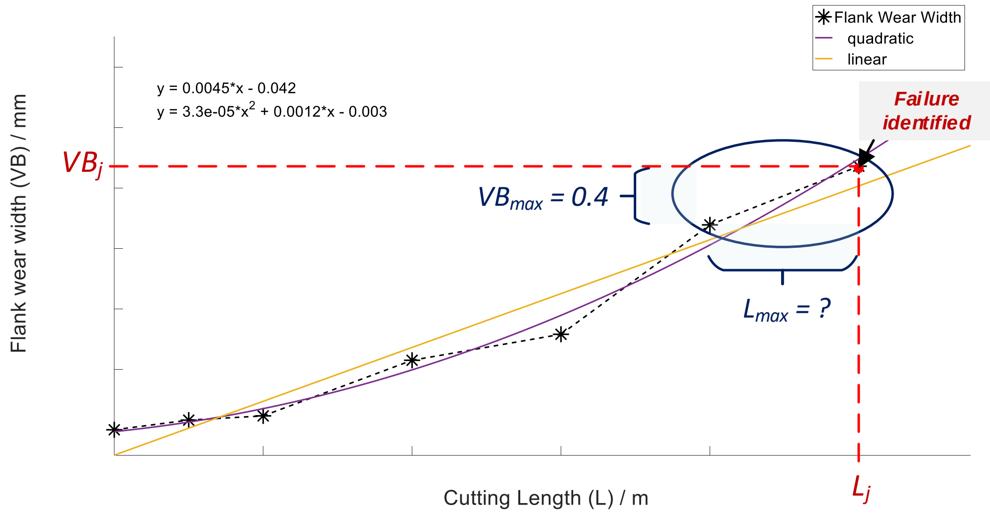


Figure 4-1: Flank wear measurements for several cutting lengths and curve fitting using first and second order.

For the curve fitting, several model structures (such as first, second and third-order models) were tested to fit the data. The least square algorithm (presented in Chapter 3) was used to estimate the models' coefficients, and root mean squared error (RMSE) was employed to assess the models' predictive accuracy. The test showed that the third-order models are not suitable to represent the data due to the high residuals observed (*i.e.*, the error between predicted and actual responses); therefore, poor predictive accuracy. While the first and second-order models represented good fit the trials based on the good predictive accuracy observed for the trials. The models' structure for the first and second-order models are given in Equations (4-1) and (4-2).

$$VB_i = aL_i + b + \varepsilon \tag{4-1}$$

$$VB_i = aL_i^2 + bL_i + c + \varepsilon \tag{4-2}$$

where y and x stand for the VB and L of the i^{th} experimental trial, respectively; and a, b and c are the coefficients of the model.

After that, the models were used to calculate L_{max} by using the value of VB = 0.4 mm. After that, the values of L_{max} were converted to the other tool effectiveness using the MPP and MRR of each trial (Equations (4-3) to (4-5)). As shown in Equation (4-4), T_{max} is calculated by dividing L_{max} by the feed rate, while V_{max} is calculated by multiplying T_{max} by MRR, as shown in (4-5).

$$MRR = f \cdot a_p \cdot a_e \tag{4-3}$$

$$T_{max} = L_{max}/f \tag{4-4}$$

$$V_{max} = T_{max} \cdot MRR \tag{4-5}$$

where f, a_p, a_e stand for feed rate, cutting depth and cutting width, respectively.

The resulting L_{max}, V_{max} and T_{max}, for each trial will be used to evaluate the impacts of the cutting parameters (*i.e.*, cutting speed, feed rate, and engagement) on the tool life. Such an assessment is essential to:

- Identify improved strategies and recommendations for machining processes
- Guide the correct selection of the tool effectiveness indicator

Also, the tool life indicators are ranked based on a priority order of cutting tool life for the roughing stage of machining. That is, the most desired performance will refer to the highest amount of volume of material that a cutting tool can remove during its useful life. The tool life indicators will be ranked considering its association with such desired performance, as follows: first priority V_{max}, second priority L_{max} and third priority T_{max}.

4.3 Analysis of Tool Effectiveness and Machining process Parameters on Tool Wear

The images and wear width data collected through the experimental trials, and measurement procedures (presented in Chapter 3) are used to study the tool wear progression and cutting tool life. The worn cutting tools were assessed based on the definitions of three wear phenomena according to the (ISO 8688-2 1989), as follows:

- Flank Wear (VB) represents a loss of tool material from the tool flanks during cutting, which results in the progressive development of a wear land. Furthermore, VB has the following three types:
  - Uniform flank wear (VB_1): wear land which is usually of constant width and extends over those portions of the tool flanks adjoining the entire length of the active cutting edge;
  - Non-uniform flank wear (VB_2): wear land which has an irregular width and for which the profile generated by the intersection of the wear and the original flank varies at each position of measurement;
  - Localised flank wear (VB_3): an exaggerated and localised form of flank wear, which is developed at a specific part of the flank.

- Flaking (FL) loss of tool fragments in the form of flakes from the tool surfaces.

- Chipping (CH) represents an edge deterioration where parts of the edge in a cutter break away. Furthermore, CH has the following types:
- Uniform chipping (CH_1): loss of tool fragments of approximately equal size along the cutting edges.
- Non-uniform chipping (CH_2): occurs mostly in connection with cracks at a small number of positions.
- Localised chipping (CH_3): occurs consistently at a particular position along the active cutting edge.

Experimental results in this research revealed that the above three wear phenomena affect the end of useful lives of cutting tools. Among them, flank wear was the most predominant phenomenon (80% of all the trials), followed by chipping (12%) and flaking (8%). The wear phenomena of worn cutting tools, identified through the experimental trials, are shown in Figure 4-2.

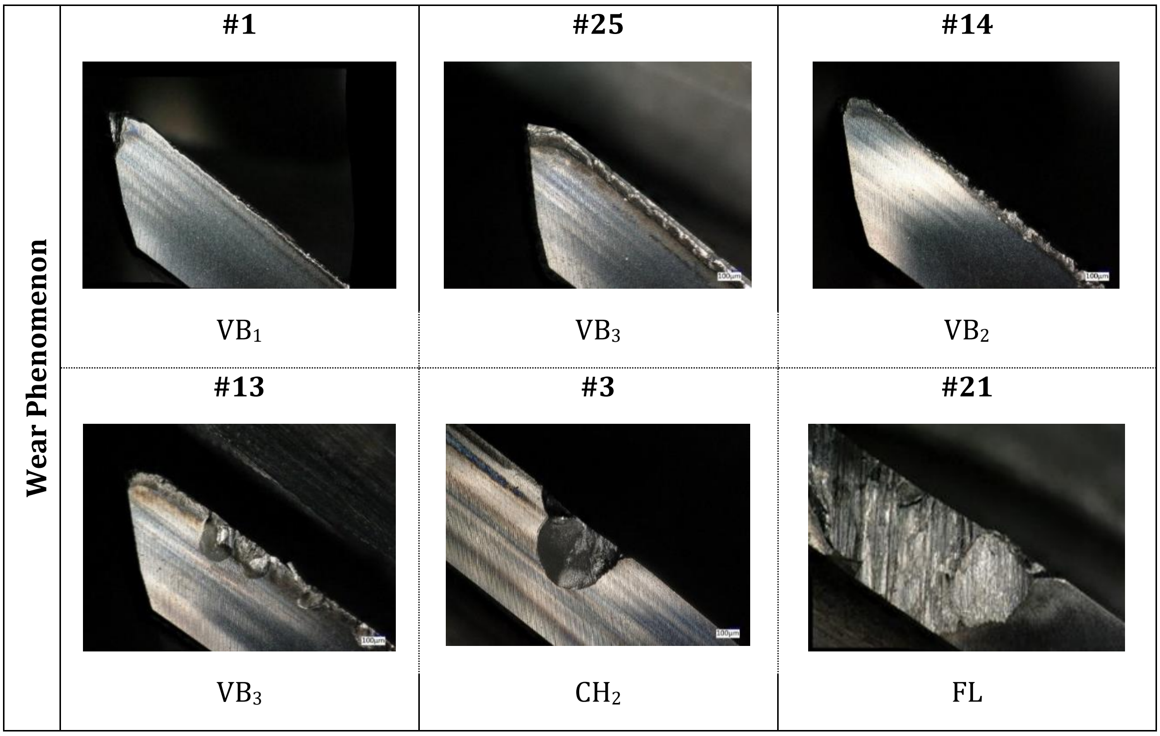


Figure 4-2: Positioning of tool deterioration phenomena.

Also, it was noticed that when deterioration starts with uniform flank wear (VB_1), the wear will tend to progress towards non-uniform (VB_2) and localised flank wear (VB_3). Then, it could lead to catastrophic failure led by non-uniform chipping (CH_2) and flaking (FL). For instance, the deterioration of Experimental trial 21 began with VB_1 = 0.021 mm at the tooltip after 10 meters of cut. At 20 meters of cut, the wear width progressed to VB_2 = 0.055 mm at the lower cutting edge. After that, the cutting tool reached the end of life abruptly at cutting length 40 m due to FL = 0.717 mm, which was observed at the upper cutting edge of the tool (shown in Figure 4-3).

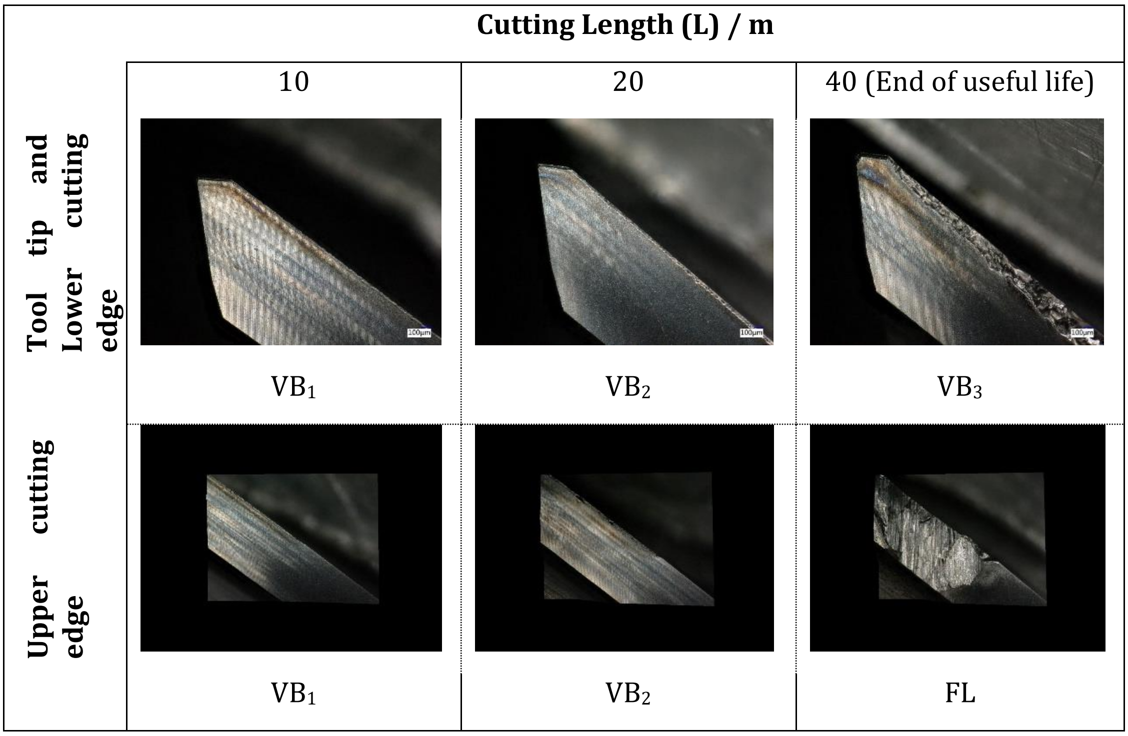


Figure 4-3: Deterioration of cutting tool based on MPP of experimental trial #21.

Therefore, each experimental trial was carefully assessed at each cutting length (L) until the worn tool reached its end of useful life. After such assessment, the trials in which worn cutting tools presented catastrophic failure (*i.e.*, due to chipping or flaking) were separated from the gradual failure (*i.e.*, due to flank wear). This is recommended by the ISO 8688, to ensure that the assessment of the impacts of factors (such as the MPP) will be based on each specified wear phenomenon.

The data set which presented catastrophic failure comprises of Experimental trials 5, 9, 10, 12 and 21, which details are presented in Table 4-1.

Table 4-1: Details of catastrophic failure of worn cutting tools.

Experimental trial #	**Machining cutting parameters**				**Deterioration phenomena**
	Cutting speed (mm/min-1) | Level	Feed rate (mm/min-1) | Level	Cutting width (mm) | Level	MRR (cm3/min-1) | Level	
5	151 | Lo	2000 | Hi	4 (25% of D) | Hi	64 | Hi	Non-uniform chipping (CH2)
9	185 | M-Lo	1430 | M-Hi	4 (25% of D) | Hi	37 | M	Non-uniform chipping (CH2)
10	185 | M-Lo	2000 | Hi	1.6 (10% of D) | Lo	20 | M-Lo	Non-uniform chipping (CH2)
12	200 | Rec	870 | M-Lo	3.3 (20% of D) | M-Hi	17 | M-Lo	Flaking (FL)
21	250 | Hi	300 | Lo	3.3 (20% of D) | M-Hi	6 | Lo	Flaking (FL)

The results presented in Table 4-1 show that the combination of low and high levels of machining cutting parameters will lead to catastrophic wear, which causes short tool life and severe damages to the machined parts. Meanwhile, catastrophic failure occurrence is difficult to be predicted (M.A. Lajis, A.N. Mustafizul Karim and Amin, A.M.K. Hafiz 2008, Zhu, Zhang, and Ding 2013). The experimental results for the tool life of the catastrophic failure data set are presented in Figure 4-4.

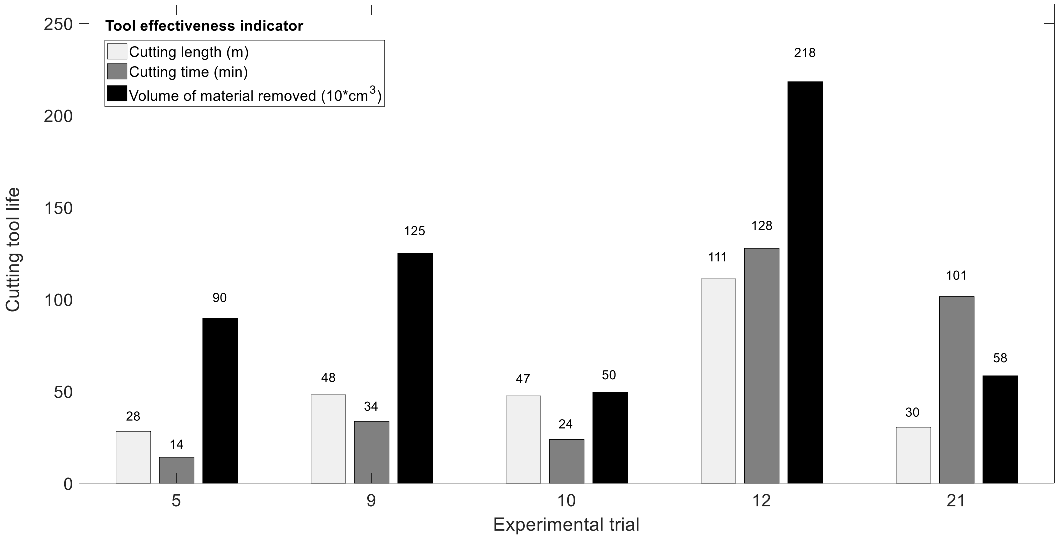


Figure 4-4: Results for the tool effectiveness of the experimental trials with catastrophic failure occurrence.

Figure 4-4 shows that the choice of tool life indicator impacts on the selection of the optimal machining process parameters. For instance, such observation is evident when comparing the cutting tool life of trials 10 and 21. In trial 10 T_{max} = 24 min while in trial 21 T_{max} = 101. Therefore, based on T_{max}, the tool life and MPP in trial 21 are more effective than those of trial 10. However, if L_{max} is selected as TE, then in trial 10 L_{max} =47 m, while in trial 21 L_{max} = 30 m. Thus, trial 10 presents better effectiveness in the tool life and MPP. For this reason, the effects of each MPP (cutting speed, feed rate, and cutting width) on each tool life (total cutting time, cutting length and volume of material removed) will be investigated in order to select the maximum cutting tool life.

4.4 Analysis of Machining Process Parameters Influences on Tool Effectiveness Indicators

In this section, the effects of MPP (*i.e.*, cutting speed, feed rate and cutting depth) on TE: total cutting length L_{max}, total cutting time T_{max} and total volume of material removed V_{max}, will be investigated. The main focuses of this investigation are: (1) to identify the optimal selection of MPP condition for each TE; (2) to identify the significance of the effect of each machining process parameters on each tool life using main effects analysis; (3) to identify optimal strategies (or rules) to support engineers on the selection of the most appropriate tool life indicator based on the selection of MPP, so as to achieve best machining performance.

Furthermore, the overall CNC machining performance, such as productivity (described by the material removal rate), will also be considered during the discussions for the impacts of machining process parameters. The alignment between MPP planning and productivity is crucial for the correct selection of the tool life due to the manufacturing requirements (Liew and Ding 2008). As a result, the findings discussed below will support a more accurate decision-making process during MPP planning. The knowledge shall be used for either process planning phase (offline approaches) and the development of smart systems (online approaches).

The results of the cutting tool life for the three tool life of the gradual wear data set are displayed in Figure 4-5. Similarly, to the catastrophic wear data set in the previous section, the results shown in Figure 4-5 indicate that there are conflicts between tool life and MPP selection. That is, the selection of machining process parameters may present the better effectiveness based on one the tool life (*e.g.*, T_{max}), but it is worse for another tool life indicator (*e.g.*, V_{max}). For example, trial 16 (MPP: v_c = 219 mm/min, f = 300 mm/min, a_e = 3.3 mm) presented better total cutting tool life (T_{max} = 113 min) than trial 17 (MPP: v_c = 219 mm/min, f = 870 mm/min, a_e = 4 mm), but trial presented better tool life based on the total volume of material removed (V_{max} = 1233), also illustrated in Figure 4-5.

Thus, the optimal choice of MPP (*i.e.*, v_c, f, a_e) that will promote the best cutting tool life will highly depend on the selection of the most appropriate TE. Hence, further investigations will be carried out to identify optimal strategies (or rules) to support engineers on the selection of the TE, to lead to the most optimum selection of MPP and, consequently, best machining performance (most extended cutting tool life with considering the manufacturing constraints).

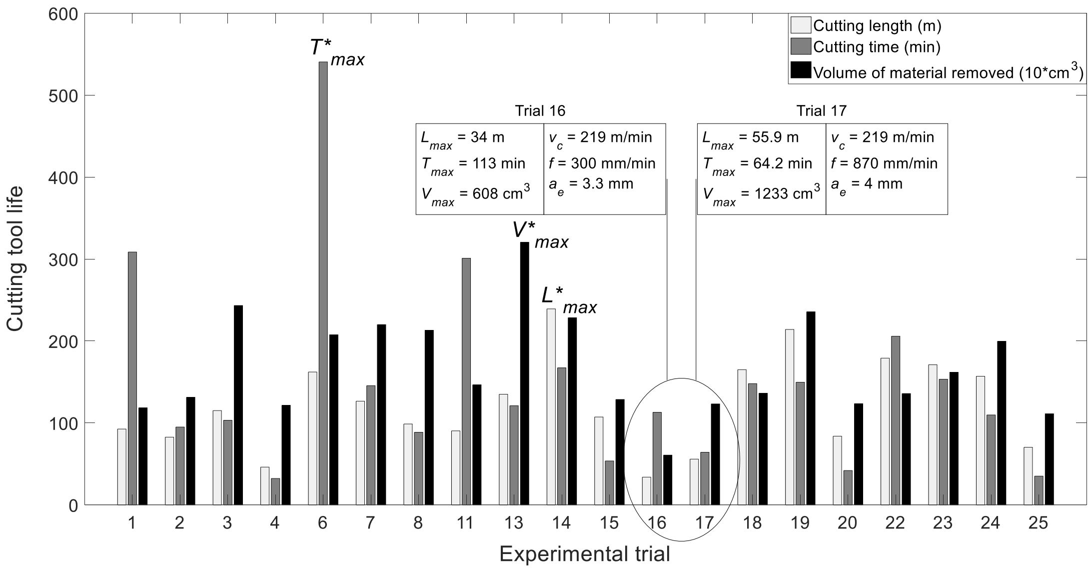


Figure 4-5: Results for the tool effectiveness of the experimental trials with gradual failure occurrence.

The longest cutting tool life for the tool life indicators L_{max}, T_{max} and V_{max} were trials 14, 6 and 13, respectively, which details are given in Table 4-2.

Table 4-2: Experimental trials that presented optimum cutting tool life for each TE.

Tool Life Indicator	**Best Trial #**	**Tool life**	**Machining cutting parameters**				**Deterioration phenomena**
			Cutting speed (mm/min^{-1}) | Level	Feed rate (mm/min^{-1}) | Level	Cutting width (mm) | Level	MRR (cm^3/min^{-1}) | Level	
L_{max}	14	239 m	200 | Rec	1430 | M-Hi	1.6 (10% of D) | Lo	14 | M-Lo	Flank wear (VB_2)
T_{max}	6	540 min	185 | M-Lo	300 | Lo	2 (12.5% of D) | M-Lo	4 | Lo	Flank wear (VB_3)
V_{max}	13	3206 cm^3	200 | Rec	1115 | Rec	4 (25% of D) | Lo	27 | M	Flank wear (VB_2)

Also, the experimental results revealed that despite the choice of TE, the selection of MPP plays a significant effect on the cutting tool life. Since the priority for the tool life in this research is Vmax, due to its close relationship with the productivity (and material removal rate), several recommendations focusing on such tool life will be provided below. The recommendations will support high performance for applications in process planning for the roughing stage. Such a stage is more crucial to cutting tool life due to the high material removal rates involved during cutting

4.5 MAIN EFFECTS OF MACHINING PROCESS PARAMETERS ON TOOL LIFE

According to (Roy 2010), the knowledge of the contribution of individual factors is a key to deciding the nature of the control to be established on a production process. Hence, the primary effect analysis will be used to identify the significance of each machining cutting parameter on each of the tool life indicators. Figure 4-6, Figure 4-7 and Figure 4-8 show the main effect plots based on the experimental results collected for L_{max}, T_{max} and V_{max}, respectively. Minitab v17 software was used to conduct the analysis.

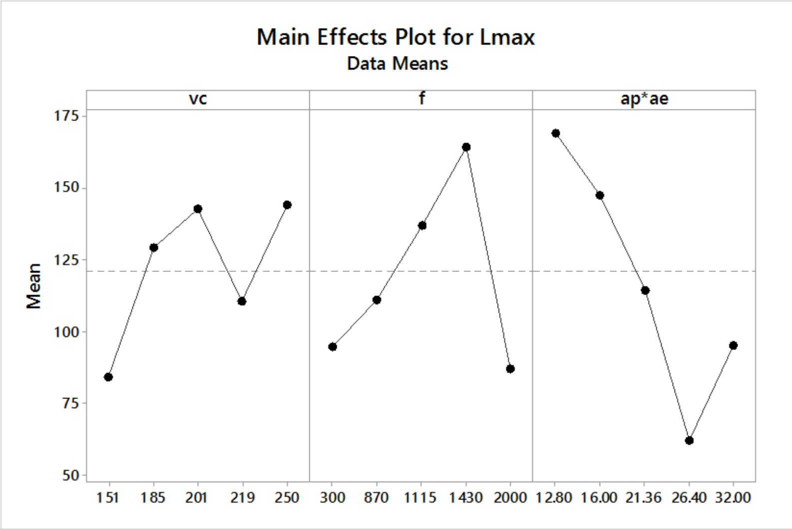


Figure 4-6: Main effects of machining process parameters cutting speed, feed rate, and cutting depth on cutting tool life based on total cutting length in meters.

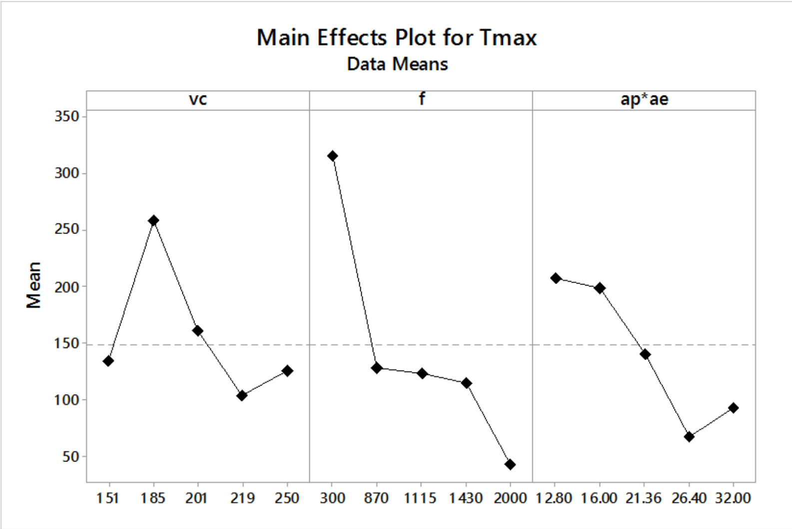


Figure 4-7: Main effects of machining process parameters cutting speed, feed rate, and cutting depth on cutting tool life based on total cutting time in minutes.

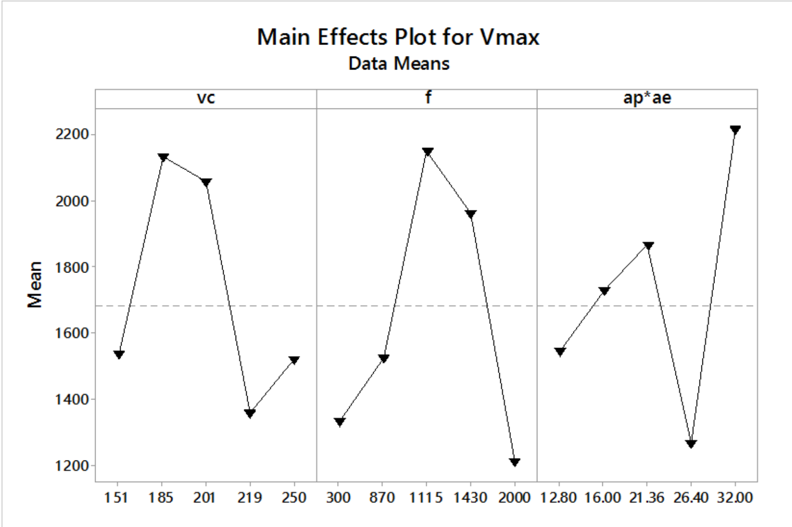


Figure 4-8: Main effects of machining process parameters cutting speed, feed rate, and cutting depth on cutting tool life based on the total volume of material removed in cubic centimetres.

Nonlinear effects of machining process parameters on the several tool life indicators have been identified based on the main effect plots shown in Figure 4-6, Figure 4-7 and Figure 4-8. Furthermore, it shows that machining cutting parameters will present different main effect directions, depending on the tool life indicator selected. For instance, the main effects of feed rate on total cutting length (L_{max}) and total cutting time (T_{max}) diverged from Lo to M-Hi levels, where L_{max} is better with the increase in *f*, but T_{max} will be negatively affected.

Also, the impacts of each machining cutting parameter on the tool life indicators, obtained from the above principal effect analysis, are shown in Table 4-3.

Table 4-3: Main effects of MPP on tool effectiveness.

Parameter	L_{max}	T_{max}	V_{max}
v_c	2 (0.00462)	2 (0.00091)	2 (-0.0023)
f	3 (0.000063)	3 (-0.000583)	3 (0.000092)
a_p*a_e	1 (-0.05414)	1 (-0.02906)	1 (0.00629)

From Table 4-3, it can see that a_p*a_e is observed as the most significant MPP for L_{max} and V_{max}, followed by v_c and *f; f* has the highest significance on T_{max}. Furthermore, it shows the conflicting relationships between the tool life indicators and MPP combinations; this way, emphasising how crucial the selected tool life indicator affects the choice of the optimal MPP.

. Thus, the recommendations on selecting appropriate cutting parameters to improve the tool effectiveness in CNC machining of BS EN24T (AISI 4340), when considering high material removal rates (*i.e.*, high productivity), based on the experimental results are:

- Selecting the width of cut (a_e):
    - High a_e (*i.e.*, 4 mm or 25% of tool diameter D) is best combined with Middle level of v_c (*i.e.*, 200 m/min) and Middle level of s_z (*i.e.*, 0.069 mm/tooth), which correspond to the recommended values from the tooling handbook. Such cutting parameters generated the highest tool effectiveness, Vr = 3,205.9 cm^3/tool, and gradual flank wear progression (VB) until it reached the end of life, validated in trial 13.
    - However, High a_e must not be combined with Low or High v_c (*i.e.*, below 150 above or 250 m/min) along with Low or High s_z (*i.e.*, below 0.015 or above 0.125 mm/tooth). Such cutting parameters promoted the worst tool effectiveness, Vr = 897.4, 495.1 and 583.8 cm^3/tool, validated in Trials 5, 10 and 21, respectively, due to catastrophic failure chipping and flaking wear phenomena.
- Selecting the feed per tooth (s_z):
    - High s_z (*i.e.*, above 0.125 mm/tooth or 178% of s_z recommended) is best combined with Middle v_c (*i.e.*, 200 m/min) and M-Low a_e (*i.e.*, 2 mm). Such cutting parameters promoted the best tool effectiveness amongst the trials using Hi cutting feed, with V = 1305 cm^3/tool and flank wear progression (VB), validated in Trial 15.
    - However, in general, a Hi s_z is not recommended since it will lead to poor tool effectiveness compared to the other levels of s_z; for instance, the tool life would be twice better if the level M-Hi s_z (*i.e.*, 0.089 mm/tooth) was selected instead of Hi, along with M or M-Hi v_c and M-Lo a_e, as validated through trials 14 and 19, which results were Vr = 2285 and 2356 cm^3/tool, respectively. Also, High s_z must not be combined with M-Low v_c (*i.e.*, equal or below 185 m/min) and Low or Hi a_e (*i.e.*, below 1.6 mm or above 4 mm). Such cutting parameters promoted the worst

tool effectiveness, Vr = 897.4 and 495.1 cm^3/tool, validated in trials 5 and 10, due to chipping wear phenomenon (CH_2).

- Selecting the cutting speed (v_c):
  - High v_c (*i.e.*, above 250 m/min or 125% of v_c recommended) is best combined with Middle s_z (*i.e.*, 0.071 mm/tooth) and Middle a_e (*i.e.*, 2 mm). Such cutting parameters promoted the best tool effectiveness amongst the trials using Hi cutting speed, with V = 1997 cm^3/tool, validated in trial 24, and flank wear width progression (VB).
  - However, High v_c must not be combined with Low s_z (*i.e.*, below 0.015 mm/tooth) and High a_e (*i.e.*, above 4 mm or 25% of D). Such cutting parameters promoted the worst tool effectiveness, V = 584 cm^3/tool, validated in trial 21, due to flaking wear phenomenon (FL).

Based on the results, the best combination of machining cutting parameters will depend on the tool life indicator selected. Such finding emphasises the importance of selecting the correct indicator for tool effectiveness during the process planning for the most appropriate choice of MPP. Consequently, an investigation on the impacts of each machining cutting parameter on each tool life is of paramount importance.

4.6 Correlational Analysis Between Tool Effectiveness and the Power Load

This section aims to provide a correlation analysis between the tool effectiveness indicators and the energy consumption of machined parts. Such analysis involves the feasibility of developing a new predictive model for the cutting tool life based on the power load (average power during engagement) to improve the sustainability of process planning. A schematic of the goal of the section is provided in Figure 4-9.

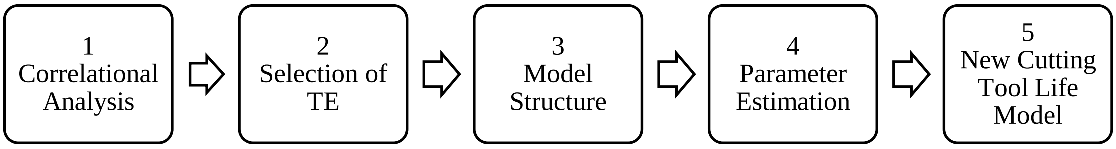


Figure 4-9: Schematic of the correlational analysis to develop cutting tool life model based on mean power consumption.

Firstly, it is important to explain the concept of the power load (P_{SoE}). The power load has been introduced in Chapter 5 as a response to the average power consumption during the state of engagement of side milled machined parts and can be seen in Equation (4-6). Furthermore, it has been theoretically studied as a mediator for the cutting tool life assessment, supported by the physical principles of power, force, and cutting speed.

$$\bar{P}_{SoE} = \int_{t_1}^{t_{SoE}} P_{SoE}\,dt \Big/ \sum_{n_{pass_1}}^{n_{pass_n}} t_{SoE} \tag{4-6}$$

where P_{SoE} and t_{SoE} stand for the power load and cutting time during the state of engagement, respectively, for cutting pass n.

It is also important to note that a validation of the correlation between the power load and the cutting tool life supports overcoming research barriers in CNC machining optimisation such as:

- Cutting tool life assessment for the development of predictive models are very costly, which makes it challenging to cover the broad machining conditions provided the various workpiece materials type, cutting tools and cutting conditions.
- Real-time prediction of cutting tool life is urgently demanded; therefore, investigations on feasible solutions using affordable technologies (such as energy monitoring systems) for online applications are of paramount importance.

In addition to that, the energy assessment and development of predictive models are less costly and have received increased attention due to environmental awareness in the industry sector. Therefore, using power consumption to predict cutting tool life will allow the use of existent real-time power monitoring systems to support smart systems (*e.g.*, cloud platforms) making cutting tool life predictions.

The experimental results for each tool life indicator will be analysed against the power load estimated during the trials. Then, in order to develop the correlational analysis, the values of P_{SoE} and tool life (*i.e.*, L_{max}, T_{max} and V_{max}) were normalised using Equation (4-7) and (4-8).

$$\bar{P}_{SoE} = \beta_0 + \beta_1 \cdot S + \beta_2 \cdot f + \beta_3 \cdot a_e a_p + \beta_{11} \cdot S^2 + \beta_{22} \cdot f^2 + \beta_{12} S \cdot f \tag{4-7}$$

$$y_{norm_i} = (y_i - \min(y_i))/(\max(y_i) - \min(y_i)) \tag{4-8}$$

where $\beta_{0,1,2,3,\,11,12,22}$ are the model coefficients, provided in Table 4-4; y_{norm} is the normalised result of each response, *i.e.*, L_{max}, T_{max}, V_{max} and P_{SoE} of experimental trial *i*.

Table 4-4: Power load model coefficients.

Coefficient	Value	Significance (P value: α < 0.05) *
β_0	−16.1700	0.000
β_1	0.00577	0.036
β_2	0.01225	0.000
β_3	0.1751	0.000
β_{11}	−1e-6	0.001
β_{22}	−2e-6	0.000
β_{12}	2e-6	0.005

** Interval of confidence is 95%, i.e., α=0.05.*

The normalised results of L_{max}, T_{max}, V_{max} have been plotted against P_{SoE}, which has been sorted in a descendant order to facilitate visualising the existence of correlation (see in Figure 4-10).

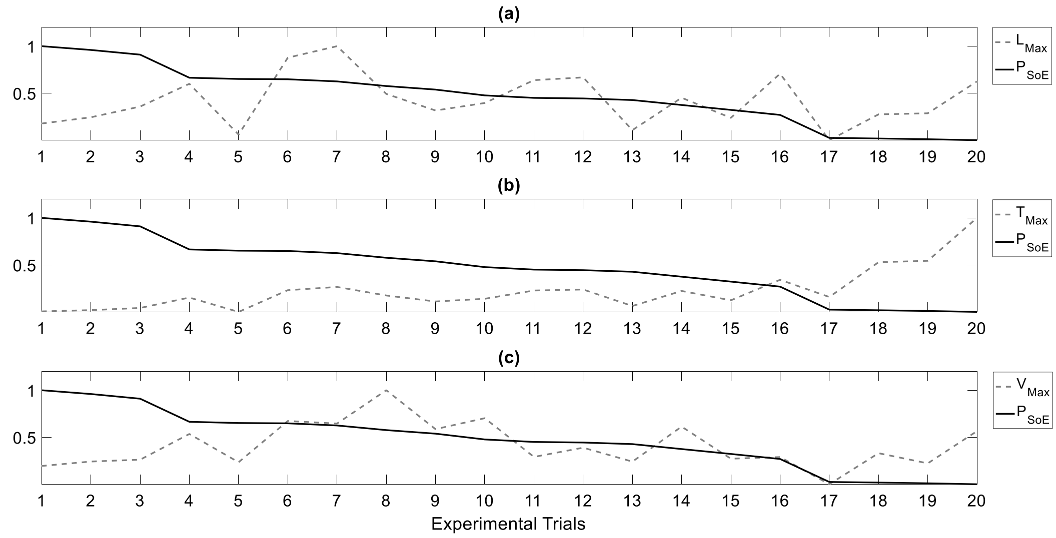


Figure 4-10: Plots of normalised cutting tool life L_{max}, T_{max} and V_{max} *versus* the normalised mean power during the engagement (P_{SoE}) of experimental trials. A strong correlation is observed in the graph (b), between the T_{max} and P_{SoE}.

From Figure 4-10(b) it can be seen that T_{max} presents a negative correlation with P_{SoE}, *i.e.*, the cutting tool life will decrease as P_{SoE} increases; while based on Figure 4-10(a) and (c), L_{max} and V_{max} do not present a correlation with P_{SoE}. The correlation between the tool life and P_{SoE} were quantified using Pearson correlation method using Minitab 2017 software. The results are presented in Table 4-5.

Table 4-5: Quantified correlation between power load and tool effectiveness indicators.

Variables	Correlation coefficient (r_s)	P-value
P_{SoE} vs L_{max}	0.055	0.819
P_{SoE} vs T_{max}	-0.718	0.000
P_{SoE} vs V_{max}	0.114	0.632

The results in Table 4-5 validated the existence of a strong correlation between P_{SoE} and T_{max}, furthermore, represented by a negative linear relationship. The results further support the theoretical approach of employing the power load as a mediator for predictions of the cutting tool life. It is important to note that such mediation should only be done using T_{max} as TE, while L_{max} and V_{max} should not be adopted due to its weak correlations with the P_{SoE}.

In order to validate such an approach, a predictive model for the T_{max} based on P_{SoE} will be developed and tested accordingly.

4.7 Modelling and Validation of Tool Life based on Power Consumption

In the literature, several models for the cutting tool life in terms of cutting time can be found. Taylor Equation (Taylor 1908) (see in Equation (5-9)) is amongst the most common models adopted for tool life predictions, which correlates the cutting tool as a function of cutting speed and material and tooling properties. At the same time, cutting speed is used in the physical principles of linear cutting as an independent variable to describe the power consumption along with force.

Therefore, in this work, Equations (4-9) and (4-10) will be combined which resulting model correlates the T_{max} and P_{SoE}, as presented in Equation (4-11). Such a model will be adopted for the modelling process to test and validate the proposed correlation.

$$v_c \cdot T^n = C \tag{4-9}$$

$$P_{SoE}(\beta, MPP) = v_c \cdot F \tag{4-10}$$

$$T^n = C \cdot F / P_{SoE}(\beta, MPP) \tag{4-11}$$

where v_c is the cutting speed, T is the cutting tool life in minutes; n and C are the coefficients for tool geometry and workpiece material properties, respectively; P_{SoE} is the power consumption during the state of engagement, which is a function of the coefficients β and the input MPP (*i.e.*, S, f and $a_p * a_e$), and F is the cutting force acting at the cutting tool.

In Equation (4-11), the F factor, which varies with the choice of MPP, plays a significant effect on the cutting tool life (M.A. Lajis, A.N. Mustafizul Karim and Amin, A.M.K. Hafiz 2008) (Caldeirani Filho and Diniz 2002). Consequently, the coefficients of the P_{SoE} model, *i.e.*, β, need to be adjusted to reflect the effects of such a factor. The solution is then to estimate the new coefficient α using the experimental results based on the data collected, this way, obtaining the adjusted P_{SoE} model. Such a model will then be used on the final equation that correlates tool life and power load, Equation (4-12).

$$T^n = C / P_{SoE_{adj}}(\alpha, MPP) \tag{4-12}$$

Equation (4-12) will be solved using the experimental results to obtain the new coefficients α for the $P_{SoE_{adj}}$ model. For that nonlinear regression using least squares method will be employed for using MATLAB/Simulink 2017b. Additionally, coefficients n and C were obtained from the literature based on the properties of tooling and workpiece material, where n = 0.6 and C = 250. Also, beta coefficients from the P_{SoE} model were used as initial values for the initialisation of the coefficient estimation process.

The alpha coefficients estimated are presented in Table 4-6, in addition to, these were divided by beta coefficients to calculate the adjusting factors. Such factors were calculated for the several power model terms and will support the adjustment of other power models without the need for tool wear experiments. That is, the factors are employed to adjust power models to enhance the accuracy of tool life predictions.

Table 4-6: Results of coefficient estimates.

i	Constant	S	f	$a_p a_e$	S^2	f^2	S•f
α_i	55.64	-0.031	0.02	0.44	4.24	2.61	-4.32
β_i	-16.17	0.006	0.01	0.18	1e-05	2e-05	2e-05
Adjusting factor	3.44	5.45	1.68	2.49	0.42	0.13	0.22

The new model for cutting tool life prediction based on the adjusted power load presented a coefficient of determination *R-sq* = 0.92, this way, validating the excellent performance of employing P_{SoE} to estimate the tool life for the T_{max}.

4.8 CONCLUSIONS

In this chapter, cutting tool wear progression and cutting tool life were investigated using the empirical approach. For that, 25 experimental trials were carried out for data collection on side milling CNC machining operations using hardened steel BS EN24T (AISI 4340).

The tool wear assessment revealed that flank wear was the most predominant deterioration phenomenon that defined the maximum life of the cutting tools, representing 80% of the experimental trials, followed by chipping (12%) and flaking (8%). Further, the wear of the cutting tools initialised with uniform flank wear (VB_1) and reached the failure gradually due to non-uniform flank wear (VB_2) or localised flank wear (VB_3). After that, 20% of the cutting tools reached the failure catastrophically due to non-uniform chipping (CH_2) or flaking (FL). Based on the experimental trials, low and high levels of machining process parameters (MPP) cutting speed (v_c), feed rate (f) and cutting width (a_e) together must be avoided to prevent catastrophic (or catastrophic) failure of the cutting tool.

Also, the results pointed out that the best selection of machining process parameters that will enhance the cutting tool life highly depends on the cutting tool life indicator (*i.e.*, total time, cutting length or volume of material removed). Furthermore, the empirical analysis revealed that:

- To achieve long cutting tool life in terms of cutting time (in min), the best selection of MPP is a middle-low level of cutting speed, low level of feed rate and middle-low level of cutting width;
- To achieve long cutting tool life in terms of cutting length (in m), the best selection of MPP is the tooling handbook recommended level of cutting speed, middle-high level of feed rate and middle-low level of cutting width;
- To achieve long cutting tool life in terms of volume of material removed (in cm^3), the best selection MPP are: the tooling handbook recommended levels of cutting speed and feed rate, and the middle level of cutting width.

Then, the effects of each machining process parameters (*i.e.*, cutting speed, feed rate, and cutting width) on the tool life (*i.e.*, T_{max}, L_{max} and V_{max}) were further investigated using main effects' analysis. The key outcomes are several recommendations on selecting appropriate cutting parameters to improve the in CNC machining of BS EN24T (AISI 4340), when considering high material removal rates (*i.e.*, high productivity) have been provided based on the experimental results, in Section 4.5. The recommendations are to support engineers and machinists in enhancing machining performance, *i.e.*, improving cutting tool life for high productivity process planning.

Also, the empirical analysis of tool wear and tool life assessment were used to study the correlation between the cutting tool life and the power consumption of the machining trials to develop a novel predictive model. The results of the correlational study showed that total cutting time presented a strong correlation with the mean power consumption, while total cutting length and volume of material removed did not present a strong correlation. Consequently, a novel cutting tool life model was developed using the power consumption as a mediator to predict the total cutting time using machining process parameters as input variables. This model was tested, and the validation results presented satisfactory predictive accuracy, R-sq adjusted equal to 0.92.

The novel model is a significant step to validate the use of power consumption models to mediate the prediction of cutting tool life in machining operations. Such a finding has a significant impact on cutting tool life prediction approaches. The traditional approach to develop empirical models for cutting tool life requires several experimental trials which are expensive and time-consuming, while the power consumption measurements would be a more cost-effective way.

Chapter 5: Energy-Efficient Machining Process: Quantitative Analysis and Optimisation

5.1 Introduction

It is vital to develop effective and innovative manufacturing strategies to meet the targets of energy savings for global sustainable societies. To develop innovative process planning strategies for machining, it is crucial to develop effective energy consumption modelling and optimisation methodologies. Energy information from machining processes is the key to assist in process planning or lifecycle analysis and improve CNC machining energy efficiency (Arriaza *et al.* 2017, Yingjie 2014).

As CNC machining processes are complex in terms of the various cutting parameters, machining strategies, and operations, the decision-making for process planning overwhelms human capabilities. It is essential to develop an effective optimisation solution by creating knowledge-embedded soft computing methods, to assist humans in planning more efficient processes. To date, some energy consumption optimisation approaches for process planning for CNC machining have been developed (Tao and Xun 2012, O'Driscoll and O'Donnell 2013). To address the current research gaps, this chapter presents qualitative analysis and optimisation considering key machining parameters for CNC processes to achieve energy-efficient processes.

In this chapter, an experimental investigation on the relationship between crucial machining parameters and energy consumption has been conducted. This facilitates machining process planners to choose suitable production strategies to minimise energy consumption during machining. A multi-objective optimisation model has been formulated, considering the energy efficiency, productivity and cutting tool life to fine-tune machining parameters. An improved multi-swarm fruit fly optimisation algorithm (iMFOA) has been developed for solving the optimisation problem. Case studies and algorithm benchmarking have been conducted to validate the effectiveness of the algorithm.

5.2 EXPERIMENTAL DETAILS AND RESULTS

Taguchi fractional factorial was used to define the design of experiments, and several experiments were carried out based on the orthogonal principle using the machining process parameters shown in Table 5-1 – calculated as provided in Chapter 3. Material Removal Rate (*MRR*) is a significant evaluation factor on energy consumption and productivity (Diaz, Redelsheimer, and Dornfeld 2011, Kara and Li 2011, Nee *et al.* 2013).

Thus, to evaluate the results considering this factor, the *MRR* of each trial was calculated using the machining process parameters in Table 5-1 and Equation (5-1):

$$MRR = f \cdot a_e \cdot a_p = (v_c \cdot 1000 \cdot N \cdot s_z / \pi \cdot D) \cdot a_e \cdot a_p \tag{5-1}$$

where a_p is the depth of the cut (in this research, it was chosen as 32 mm, the full depth of the designed part); and *MRR* is the material removal rate in cm^3/min.

The levels of spindle speed (S), feed rate (f) and width of cut (a_e) are obtained based on the defined levels of v_c and s_z, the tool diameter (D) and number of tool teeth (N) using the Equations (3-5) to (3-7), provided in Section 3.3.4.

Table 5-1: Machining process parameters of experimental trials.

Levels	v_c / mm min^{-1}	D / mm	N / tooth	s_z / mm $tooth^{-1}$	S / rpm	f / mm min^{-1}	a_e / mm
1. Re	200.0	16	4	0.070	4000	1115	4.00
2. Lo	150.0	16	4	0.025	3000	300	1.60
3. M-L	184.5	16	4	0.059	3670	870	2.00
4. M-H	218.7	16	4	0.082	4350	1430	2.67
5. Hi	250.0	16	4	0.100	5000	2000	4.00

To correlate the *MRR* as an indicator for the productivity and to facilitate decision-making, the minimum and maximum calculated values of *MRR* have been used to define the lowest (Lo) and Highest (Hi) productivity levels. The intermediate levels were defined heuristically considering the distribution of *MRR* values within the range. Table 5-2 shows the experimental design, including the machining process parameters and productivity levels.

The experimental trials were replicated twice; the results between trials showed variations lower than 3%, therefore, presenting satisfactory replicability. During the experimental trials, the power data monitored as a function of time shows that different sets of machining parameters generated different power profiles. Figure 5-1 shows the power profiles of the milling trials, which demonstrate the impacts of machining parameters sets on machining time and power loads.

Table 5-2: Experimental design based on Taguchi DoE.

Trial	S / rpm	f / mm min^{-1}	a_e / mm	a_p / mm	MRR / mm^3 min^{-1}
1	3000	1115	4.00	32	142720
2	3670	1115	4.00	32	142720
3	4350	1115	4.00	32	142720
4	5000	1115	4.00	32	142720
5	4000	300	4.00	32	38400
6	4000	870	4.00	32	111360
7	4000	1430	4.00	32	183040
8	4000	2000	4.00	32	256000
9	3000	870	4.00	32	111360
10	3000	1430	4.00	32	183040
11	3000	2000	4.00	32	256000
12	3670	870	4.00	32	111360
13	3670	1430	4.00	32	183040
14	3670	2000	4.00	32	256000
15	4350	870	4.00	32	111360
16	4350	1430	4.00	32	183040
17	4350	2000	4.00	32	256000
18	5000	870	4.00	32	111360
19	5000	1430	4.00	32	183040
20	5000	2000	4.00	32	256000
21	4000	1115	1.60	32	57088
22	4000	1115	2.00	32	71360
23	4000	1115	2.67	32	95266
24	4000	1115	4.00	32	142720

The data collected for power consumption and time of all experimental trials were treated using data analysis software. The values of the power load (P_{SoE}) have been correlated to the cutting tool's life based on the physical principles and machining parameters influences (see Equation (5-2). Based on the literature, it is well-known that high cutting speeds and high cutting forces will decrease the tool life, therefore, by employing $\bar{P}_{SoE}$ as a mediator based on Equation (5-2), high values of power load will imply short tool life. Accordingly, the values of the power load were normalised and used to define the several degrees of tool life.

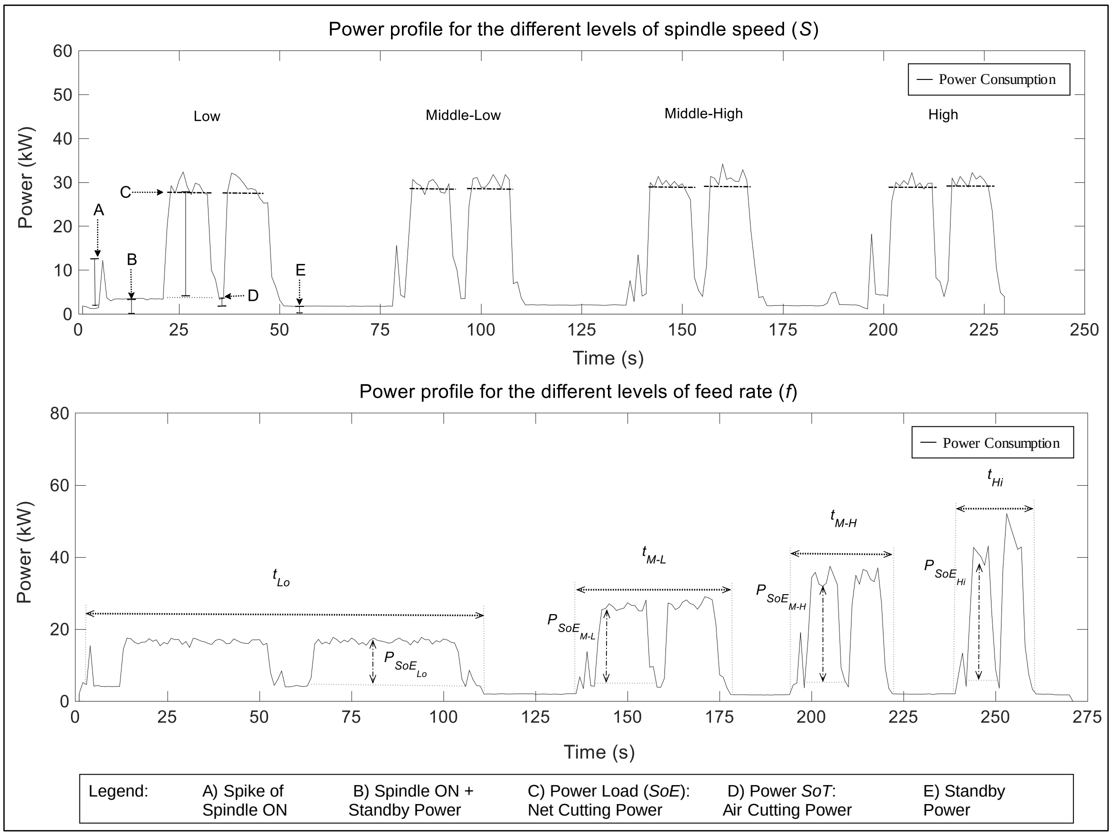


Figure 5-1: Power profile of machining experiments on BS EN24T Alloy workpiece (a) Spindle speed analysis: power load in 'C' is not significantly affected from Low to High levels of S (b) Feed rate analysis: power load increases, while machining time t decreases, from Low to High levels of f.

The results are summarised in Table 5-3.

$$P_{SoE} = F \cdot v_c \tag{5-2}$$

where F and v_c represent the combined axial and radial cutting forces and the cutting speed, respectively.

Table 5-3: Experimental results for milling on BS EN24T alloy steel.

Trial	EC / kJ		% SoT	t / s		$\bar{P}_{SoE}$ / kW	Cutting Tool Life Level	SEC_{SoE} / kJ cm^{-3}	Energy Efficiency Level
	SoE	SoT		SoE	SoT				
1	580	92	14	20	10	29	M	11	M-H
2	595	94	14	20	10	30	M	12	M-H
3	608	97	14	20	10	30	M	12	M-H
4	603	100	14	20	10	30	M	12	M-H
5	1297	128	9	78	21	17	Hi	25	Lo
6	694	94	12	26	11	27	M-H	14	M-H
7	544	79	13	16	8	34	M-Lo	11	M-H
8	497	63	11	12	6	41	Lo	10	Hi
9	1519	185	21	80	23	19	Hi	20	M-L
10	1222	146	19	63	17	21	M-H	16	M
11	1199	103	8	48	13	25	M-H	16	M
12	1011	61	6	32	9	32	M-L	13	M-H
13	1066	86	7	40	10	27	M-H	14	M-H
14	878	88	9	24	8	37	M-Lo	11	M-H
15	650	143	18	16	9	41	Lo	8	Hi
16	1105	97	8	40	10	28	M-H	14	M
17	828	107	11	24	8	35	M-L	11	M-H
18	675	142	17	16	9	42	Lo	9	Hi
19	1118	97	8	40	10	28	M-H	15	M
20	848	106	11	24	8	35	M-L	11	M-H
21	686	146	18	16	9	43	Lo	9	Hi
22	1158	107	8	40	10	29	M	15	M-H
23	902	113	11	24	8	38	Lo	12	M-H
24	688	159	19	16	9	43	Lo	9	Hi

5.3 EXPERIMENTAL RESULTS AND ANALYSIS

Qualitative analysis is an efficient means for obtaining knowledge from a complex environment, and thus this method is used in this section to understand the relationships of crucial cutting parameters in machining processes and the energy consumption to produce BS EN24T (AISI 4340) parts.

The analysis of the significance of the critical parameters on the energy consumption reveals the order of relationships between each input and this response and supports the selection of the correct mathematical model for the optimisation. Also, this section will contribute, mainly, as follows:

- Machining strategies for the selected workpiece material, BS EN24T (AISI 4340), where the assessment of cutting parameters on key performance criteria when machining such a material, widely used in the industry, will support machinists and engineers in improving manufacturing processes.
- The introduction of power load as a critical evaluation criterion and the validation of its significance when considering the effects of cutting parameters through the qualitative analysis.

The results of $\bar{P}_{SoE}$ and SEC in Table 5-3 reveal that the machining performance (analysed through the power, energy and time) is significantly affected by the selection of machining parameters and key trade-offs have been identified. For instance, Trial 24 requires the highest power load, 43 kW, while Trial 5 presents the lowest, 16.53 kW. Nevertheless, the energy efficiency of Trial 24 (SEC=9 kJ/cm^3) is better than that of Trial 5 (SEC=25 kJ/cm^3), that is due to the higher machining time spent for Trial 5.

Furthermore, there are two main observations based on the results for the energy consumed during the state of engagement (SoE) and the state of travelling (SoT):

- The energy required during the SoT is between 6% to 21% of the overall EC (EC_{SoE} + EC_{SoT}) for all trials. The results reveal that the amount of energy consumed during the SoE is the most significant over the SoT. Moreover, SoE varies from 79% to 94% of the overall energy consumed. Consequently, the investigation finds that the machining parameters play an even more critical role in the energy efficiency of the production.
- Based on the energy results for SoT, it is observed that the amount of energy varies significantly between the experimental trials. This was caused by the different safe clearance distance set in the numerical control code (NC code), in which the cutting tool moves with the supplied feed rate and spindle speed (*i.e.*, the experimental values) to approach the workpiece. These observations are machine-dependent

(*e.g.*, vector drive horsepower and drive technology). Moreover, are out of the scope of this research work, but will be considered for future work.

The effects of machining parameters, spindle speed (S), feed rate (f) and width of cut (a_e) on the power, energy and time required during SoE are investigated as follows.

5.3.1 SPINDLE SPEED EFFECTS

The main effects of spindle speed on the power load and energy are analysed. The results of the experiments are presented in Figure 5-2.

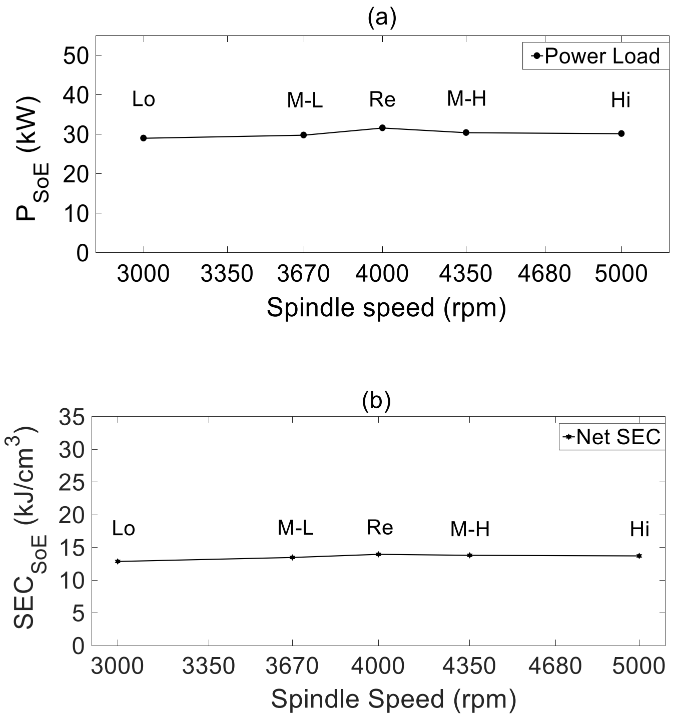


Figure 5-2: Experimental results on BS EN24T alloy (a) Relationship between S and (P_{SoE}), mean power oscillation is ± 5% (b) Relationship between S and SEC.

The main results from the experimental trials show that:

- Changes in the *spindle speed* do not generate substantial effects on $\bar{P}_{SoE}$, as shown in Figure 5-2(b). S does not affect the machining time as previously known.

- During the travelling time, more energy is wasted at higher levels of spindle speed, since the spindle motor requires more power at higher speeds. Furthermore, the results revealed an increase in energy demand of approximately 3% during the SoT caused by the increase in approximately 20% in the spindle speed.
- The power load $\bar{P}_{SoE}$ increases slightly from the lowest level of S until the recommended level of S. Then, beyond the recommended level, a slight drop of $\bar{P}_{SoE}$ is identified (as shown in Figure 5-2(a)). This way, the middle-high level of S represents the maximum point at which by increasing S the amount of material removed per cutting tool revolution has a positive effect on the energy consumption, considered that all other machining process parameters are kept unchanged. This reveals that the cutting load per unit time is smaller. Therefore, high levels of S promote a slight decrease in the power load.
- S does not have substantial effects on energy efficiency, as shown in Figure 5-2 (b).

The results show that a selection of low or high levels of S is more appropriate to achieve energy efficiency in machining processes. The low level due to the savings on the state of travelling, and the high level due to the savings due to the smaller cutting load per unit time. However, it is essential to notice that high cutting speeds are known to decrease the cutting tool life (Caldeirani Filho and Diniz 2002).

5.3.2 Feed Rate Effects

Feed rate (f) is one of the significant factors that determine the material removal rate (MRR) and, hence, productivity, as shown in Equation (5-1). That is, an increase in f while maintaining other parameters unchanged will lead to a greater MRR. Figure 5-3 shows the results of the experimental trials for the feed rate analysis.

The main findings of this experimental investigation are:

- Substantial effects of the f on the power load and machining time t_{SoE} are observed. Through the standard deviations of the power load ($\sigma_{f_{P_{SoE}}} = 8$, and mean $\bar{x}_{f_{P_{SoE}}} =$ 30 kW), and machining time ($\sigma_{f_t} = 25$, and mean $\bar{x}_{f_t} = 33$ s), these values show that f generates a more significant impact on the machining time compared to the power load, approximately three times. This could be a conflict when considering a sustainable process, since the increase in the feed rate would increase the productivity rate but, at the same time, increase the power load.
- Increasing the feed rate reduces the machining time, as shown in Figure 5-3(a). The machining time is reduced by approximately 85% at the maximum level of feed rate when compared to the lowest level of f.
- Increasing the feed rate increases the machining power load, as shown in Figure 5-3(b). The power load at the high level of f is approximately three times greater than at the low level.
- A high level of f promotes better energy efficiency owing to savings in machining time. The process at the low level required 2.6 times more specific energy (kJ/cm^3) compared to the high level, shown in Figure 5-3(c). However, the drawback is that it produces higher cutting forces and higher temperatures at the cutting tool, consequently, shortening the tool life.

The results suggest that the selection of Middle-low or Middle-high feed rate levels are more appropriate to make a balance between energy, time and cutting tool life.

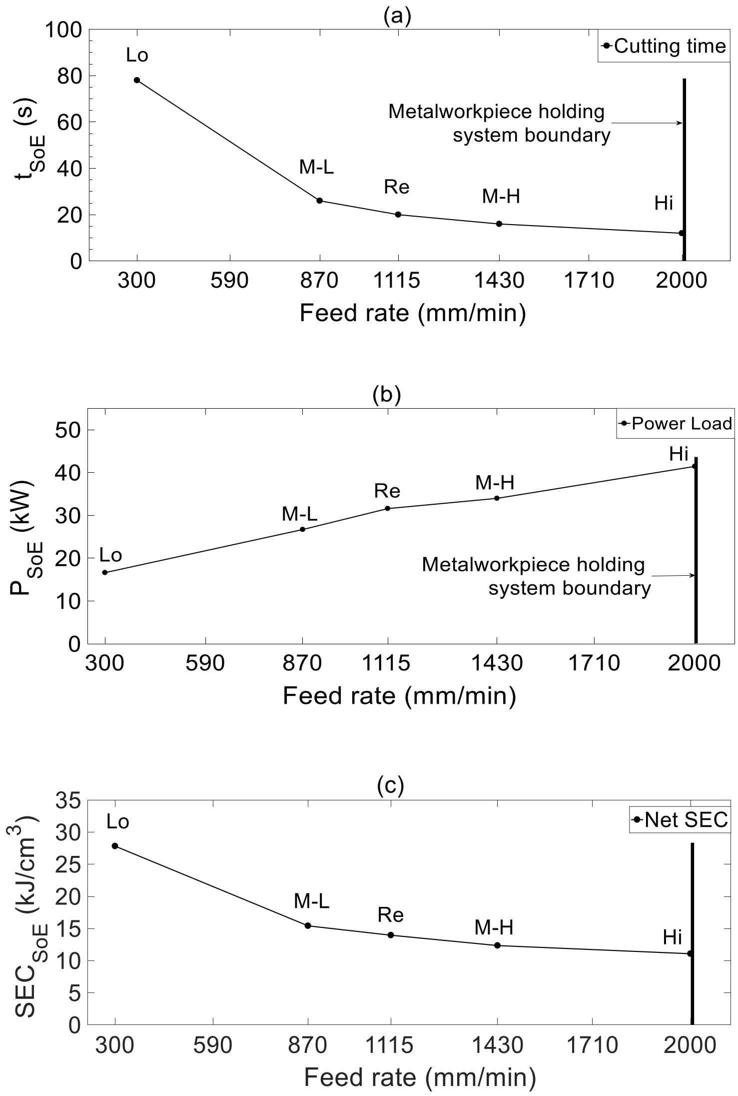


Figure 5-3: Experimental results on BS EN24T alloy (a) Relationship between t_{SoE} and f (b) Relationship between f and P_{SoE}, mean power oscillation is ± 5% (c) Relationship between SEC and f.

5.3.3 CUTTING WIDTH EFFECTS

Width of cut influences material removal rate in a machining process, as shown in Equation (4-1). The experimental results of a_e on machining processes are presented in Figure 5-4.

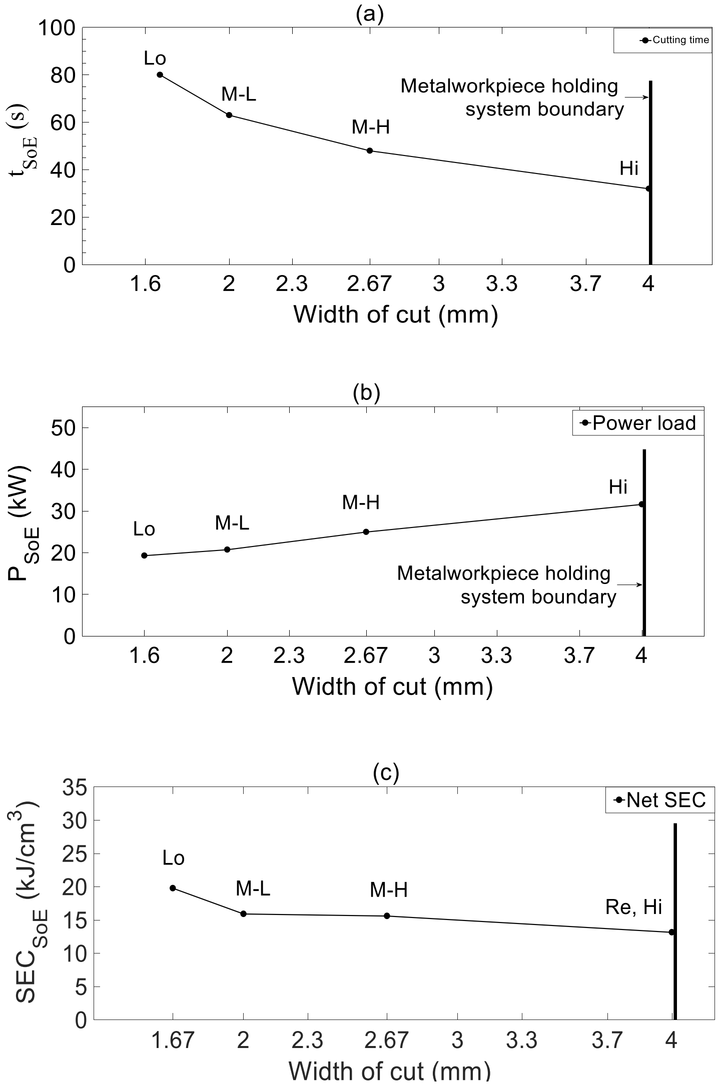


Figure 5-4: Experimental results on BS EN24T alloy (a) Relationship between t_{SoE} and a_e (b) Relationship between a_e and P_{SoE}, mean power oscillation is ± 5% (c) Relationship between SEC and a_e.

Significant effects of a_e on the power load, machining time and energy efficiency are revealed. A summary of the observations is provided below:

- To clarify the significant effects of a_e on the power load and machining time, the standard deviations and means are provided as follows. For the power load $\sigma_{ae_{P_{SoE}}} = 7$, and mean $\bar{x}_{ae_{P_{SoE}}} = 24$ kW. For the machining time, $\sigma_{a_{e_t}} = 24$, and mean $\bar{x}_{a_{e_t}} = 56$ s. These values show that changes in the cutting width will have a more significant effect on the machining time than on the power load, which supports positively a trade-off when considering productivity and cutting tool life.

- Increasing the cutting width will decrease significantly in machining time, as shown in Figure 5-4(a). The machining time at the Hi level was 60% shorter compared to the time at the Lo level.
- Increasing the cutting width will also increase the radial contact between the cutter tool and the workpiece. It causes high stress and power load during the material removal process. Consequently, it increases the workload at the tooltip, which can be seen through the power load response shown in Figure 5-4(b). The results reveal that the power load at Hi level (4 mm) is 38% greater than at the Lo level (1.67 mm), and a nonlinear relationship describes it.
- A High width of cut will give a more energy-efficient process owing to the reductions in machining time. However, the drawback is the high power load, which means greater cutting forces and chip load on the cutter tool, consequently, shortening the tool life. For instance, at Hi level of a_e, the operation was 33% more energy-efficient compared to the Lo level shown in Figure 5-4(c).

The results suggest that the selection of Middle-low or Middle-high levels are more appropriate when considering energy, time and tool life for a sustainable process.

Nevertheless, the trade-offs revealed by the qualitative analysis emphasise that the selection criteria of optimal cutting parameters should also consider production constraints such as lead time or cutting tool availability; otherwise, the process is not productive, energy-efficient, nor improves the cutting tool life. This observation is considered further in the optimisation problem.

5.4 OPTIMISATION OF ENERGY CONSUMPTION

In this section, an optimisation problem is presented considering the experimental results collected. Also, the fitness functions for the optimisation, *i.e.*, energy efficiency, cutting tool life and productivity are defined.

5.4.1 OPTIMISATION MODELLING

The energy required during the state of engagement (SoE) for the milling on BS EN24T alloy (AISI 4340) accounted for 79% to 94% of the overall energy consumption. Therefore, significant energy saving in machining processes is possible if the energy during SoE (EC_{SoE}) could be minimised. The following formulas represent EC_{SoE} and the related parameters:

$$t_{SoE} = V/MRR \tag{5-3}$$

$$EC_{SoE} = \bar{P}_{SoE} \cdot t_{SoE} = \bar{P}_{SoE} \cdot V/MRR \tag{5-4}$$

$$\bar{P}_{SoE} = f_1(S, f, a_e \cdot a_p) \tag{5-5}$$

$$MRR = f_2(f, a_e \cdot a_p) = f \cdot a_e \cdot a_p \tag{5-6}$$

where P_{SoE} is the average power used during SoE, V is the removed volume of material, MRR is the material removal rate, S, f, $\mathrm{a_e}$, a_p are the cutting parameters spindle speed, feed rate, cutting width and cutting depth, respectively.

In order to establish the function of $\bar{P}_{SoE}$, a Responsive Surface Regression Model was developed. The model structure is presented below:

$$\bar{P}_{SoE} = \beta_0 + \beta_1 \cdot S + \beta_2 \cdot f + \beta_3 \cdot a_e a_p + \beta_{11} \cdot S^2 + \beta_{22} \cdot f^2 + \beta_{12} S \cdot f \tag{5-7}$$

where $\beta_{0,1,2,11,12,22}$ are coefficients to be determined.

The experimental results were used to calculate the coefficients of the P_{SoE} regression model. The output data was filtered using a single exponential smoothing technique. This is an additional step before the coefficient estimation process to reduce the random fluctuations in the time series for the collected data, thus providing a more accurate pattern of the power load of each experimental trial. By taking this step, the accuracy of the final predictive model is increased by 3%. Subsequently, non-linear regression and the least squares methods are employed to estimate the model's coefficients. The estimated coefficients are given in Table 5-4. The accuracy of the smoothed model is R^2-adjusted equal to 0.94, which shows the achievement of satisfactory predictive accuracy.

Table 5-4: Power load model coefficients.

Coefficient	Value	Significance (P value: $\alpha < 0.05$) *
β_0	−16.1700	0.000
β_1	0.00577	0.036
β_2	0.01225	0.000
β_3	0.1751	0.000
β_{11}	−1e-6	0.001
β_{22}	−2e-6	0.000
β_{12}	2e-6	0.005

* Interval of confidence is 95%, *i.e.*, α=0.05.

This model was validated using experimental validation data. The results of the estimated $\bar{P}_{SoE}$ presents a predictive accuracy R^2 of 0.98, which shows excellent performance.

From Equation (5-8), it can be observed that to minimise EC_{SoE}, $\bar{P}_{SoE}$ should be minimised and *MRR* should be increased. Based on this, an optimisation objective (fitness function) to minimise SEC_{SoE} has been formulated, and the indicator for energy efficiency, is set up below:

$$\begin{cases} Minimise\ SEC_{SoE} = V * (\rho_1 \cdot \bar{P}_{SoE} + \rho_2 \cdot 1/MRR) \\ \text{Subject to:} \\ 3000 \leq S \leq 5000 \\ 300 \leq f \leq 2000 \\ 51.2 \leq a_e a_p \leq 128 \end{cases} \tag{5-8}$$

where x_1, x_2 and x_3 are spindle speed, feed rate and cutting depth, respectively; and, ρ_1 and ρ_2 are weightings, where $\rho_1 + \rho_2 = 1$, and V is the volume of material removed.

$\bar{P}_{SoE}$ is also related to the cutting tool's life. Increases in $\bar{P}_{SoE}$ will generate increases in cutting forces and temperature on the cutting tool so that the life of the tool will be reduced. MRR represents the process' productivity. Regarding the setting of the two weights, a strategy has been designed heuristically based on the relevance of the power load and material removal rate to the cutting tool life and productivity, respectively. Besides, machinists experts were contacted to assist in defining the weights based on their experience and tooling handbook. The results of the strategy for the settings are presented in Table 5-5.

Table 5-5: Weighting strategy for optimisation algorithm based on the manufacturing requirements.

Description	Weighting Selection*
Cutting tools are the major constraint.	$0.8 \leq \rho_1 \leq 0.9$
Cutting tools are more constrained than lead time.	$0.5 < \rho_1 < 0.8$
Both resources are constrained.	$\rho_1 = \rho_2 = 0.5$
Lead time is more constrained than cutting tools.	$0.5 < \rho_2 < 0.8$
Lead time is the major constraint.	$0.8 \leq \rho_2 \leq 0.9$

*Weights law: $\rho_1 + \rho_2 = 1$

The appropriate strategy is chosen by the engineer or process planner based on the immediate availability of the resources, cutting tools, and lead time – or which has the greatest immediate priority. After that, the appropriate weights, ρ_1 and ρ_2, are selected from the weighting strategy table and included into with the objective. This way, the objective function within the optimisation process is reconfigured to align the machining process parameters with the factory's immediate requirements. As a result, the optimal solution achieved by the optimisation process for the machining operation is also the best solution for the factory.

5.4.2 Optimisation Algorithm: Improved Multi-swarm Fruit-fly Optimisation Algorithm

An improved optimisation algorithm, based on the recent fruit fly optimisation algorithm (FFOA), was initially considered to solve the optimisation problem formulated. FFOA is a nature-inspired algorithm for solving optimisation problems by mimicking the highly-advanced sense of smell of insects to detect food locations (Xing and Gao 2014, Chen *et al.* 2013) However, its ability to solve trade-offs of machining parameters has not yet been thoroughly investigated.

To address this gap, a multi-swarm fruit fly optimisation algorithm (MFOA) developed by (Pan 2012, Yuan *et al.* 2014) was improved to cope with the machining optimisation. The optimisation problem formulated (in Equation (5-8) comprises three input variables (*i.e.*, machining parameters v_c, s_z and $a_e a_p$) which are constrained by the safe boundaries. However, the MFOA algorithm is designed to solve problems with two non-constrained input variables. Consequently, further improvements were made to the original MFOA algorithm. Significant changes to achieve improved MFOA (iMFOA) can be found below:

- A third axis is included to specify the fruit fly coordinates (*i.e.*, positions), so the algorithm can cope with the three input variables.

- A penalty function is included to constrain the power load fitness function, which cannot be above a certain level to guarantee energy sustainability.

Figure 5-5 shows the algorithm schematic and illustration of the iMFOA.

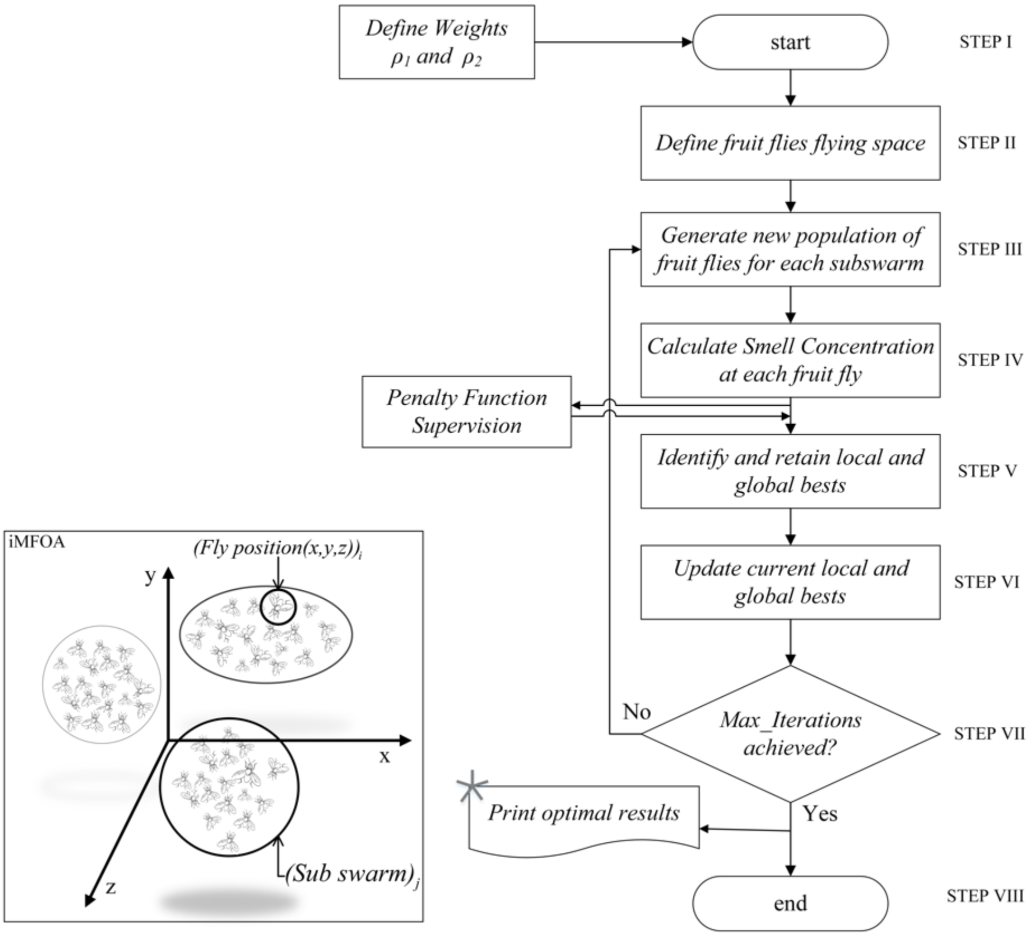


Figure 5-5: Flowchart of the improved MFOA (iMFOA) algorithm.

Firstly, an engineer or process planner defines the production weights (*i.e.*, ρ_1 and ρ_2), to align the optimisation engine with the immediate production priorities (cutting tool life and lead time), so the algorithm can be initialised (STEP I). Then, based on the process' safe boundaries (calculated in STEP II) the fruit flies' populations (*i.e.*, sub swarms) are generated in STEP III. Each fruit fly position, *i.e.*, $(x, y, z)_i$, represents a combination of the cutting parameters S, f and $a_p \cdot a_e$. This process can be represented as follows:

$$X_{new}(i,j) = x_{initial}(i,j) + randi(boundaries_{SpindleSpeed}) \quad (5\text{-}9)$$

$$Y_{new}(i,j) = y_{initial}(i,j) + randi(boundaries_{FeedRate}) \quad (5\text{-}10)$$

$$Z_{new}(i,j) = z_{initial}(i,j) + randi(boundaries_{EngagementDepth}) \quad (5\text{-}11)$$

where X, Y and Z_{new} are the fruit flies' positions of the new populations; i is the fruit fly, and j is the sub swarm; x, y and $z_{initial}$ are the initial positions which are set to be zero at the start; *randi* is a computational function to select the respective values within the cutting parameters minimum and maximum boundaries.

To calculate the smell concentration (fitness) of each fruit fly, in STEP IV, the new populations for fruit flies are called into each of the fitness functions, *i.e.*, *SEC*, $\bar{P}_{SoE}$ and *MRR*. In the optimisation problem, these fitness functions are combined to save computational time as follows:

$$Smell_{SEC}(i,j) = \rho_i \cdot \bar{P}_{SoE}(i,j) + \rho_2 \cdot 1/MRR(i,j) \quad (5\text{-}12)$$

The output values of $\bar{P}_{SoE}$ and smell concentration are evaluated by a penalty function which judges the energy efficiency and cutting tool life based on the knowledge embedded into the system. If the power load is above the thresholds defined empirically, it reduces the smell concentration considerably. This supervisory loop ensures that inefficient cutting conditions are not identified as local or global best, in STEP V and, consequently, not retained in STEP VI.

Fruit flies (i) with the highest smell concentration within a sub swarm (j) are identified as local bests, while the fruit fly represents the global best with highest smell concentration among all sub swarms. Further, the local bests are used to substitute the initial positions and generate the new populations for the next iteration. This process occurs recursively until the maximum number of iterations is reached, so the global best fruit fly, which holds the optimal cutting parameters and smells concentration path, is achieved.

5.5 CASE STUDY FOR VALIDATION OF THE OPTIMISATION APPROACH

A case study, including three real-case manufacturing scenarios, is presented in this section. This way, the proposed optimisation problem, and iMFOA algorithm can be assessed. This will be done by evaluating the optimisation outputs considering some essential rules to achieve sustainable machining. The details of the manufacturing scenarios are given in Table 5-6.

Table 5-6: Manufacturing scenarios for the optimisation problem.

Real-case scenarios of immediate factory requirements	Immediate Production Priority
a) The production batch requires highly expensive cutting tools; however, the lead time is also a priority since there is a fine for not meeting the deadline.	If both resources are a priority, then the same weight is given to both resources: $\rho_1 = \rho_2 = 0.5$
b) The deadline for delivering the production order has been extended; the manager asks to reconfigure the machining operations to prolong cutting tool life.	If prolonging cutting tools' life is the priority, then higher weight is given to tool life: $\rho_1 = 0.8$, $\rho_2 = 0.2$
c) The deadline for delivering the production order has been shortened; the manager asks to reconfigure the machining operations to boost productivity.	If shortening lead time is the priority, then higher weight is given to productivity: $\rho_1 = 0.2$, $\rho_2 = 0.8$

Specific energy consumption (SEC), power load (P_{SoE}) and material removal rate (MRR) are used as key efficiency operational criteria for the energy efficiency, cutting tool life and productivity, respectively. Furthermore, the optimal performances are analysed considering the rules for sustainable machining, as below:

- The smaller the *SEC,* the better the energy efficiency.
- The higher the *MRR,* the better the productivity.
- The smaller the P_{SoE}, the better the cutting tool life.

Accordingly, the optimisation results for each manufacturing scenario will be discussed based on the above rules. This further supports the selection of the best result amongst the three optimisation algorithms employed for benchmarking analysis: GA (Yang 2014), FFOA (Xing and Gao 2014) and the iMFOA.

The details for the algorithm initialisation are: the production constraints' weights are defined heuristically based on each scenario characteristics. Then, the initial set up for the algorithm engine is defined as the number of subswarms equal to 10, size of the population of fruit flies per subswarm equal to 25, and the maximum number of iterations equal to 1000.

The optimisation algorithm was run under the initial set-up. Figure 5-6 shows the smell concentration path containing the globally best values during the convergence to the optimal solution from the iMFOA algorithm. This figure shows that there have not been significant improvements in the smell concentration beyond 375 iterations. That is, the globally best values of the machining process parameters at 375 iterations, found by the algorithm, are close enough to the best MPP. Further, as the computation time is a critical factor to indicate the system performance of an optimisation process, 400 iterations have, therefore, been selected in this work as the best trade-off between computation time and output performance.

Table 5-7 shows the optimisation results, *i.e.*, optimal cutting parameters and estimated SEC, MRR and P_{SoE}, obtained from the algorithms used to solve the three manufacturing scenarios.

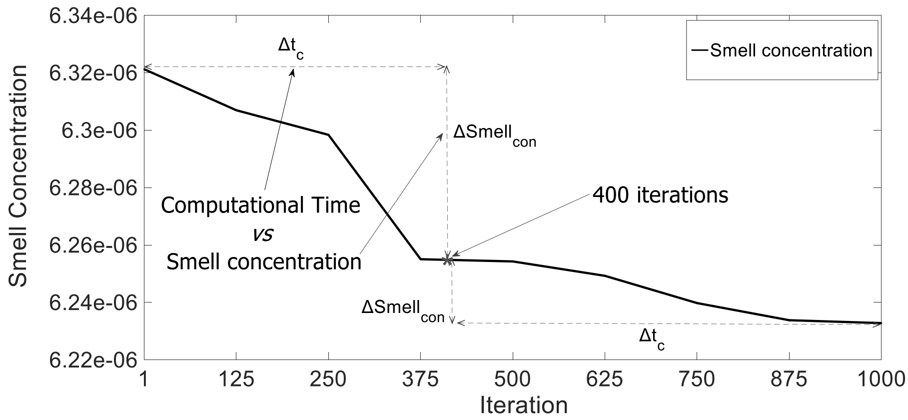


Figure 5-6: Smell concentration path during optimisation using the iMFOA algorithm.

Table 5-7: Optimisation results and calculated key efficiency operational criteria.

Scenario Constraint		Optimisation Algorithm	Optimal Cutting Parameters			Key Sustainable Indicators		
			Cutting Speed / mm min^{-1}	Feed per tooth / mm tooth^{-1}	Engagement depth / mm	SEC / kJ cm^{-3}	MRR / cm^{3} min^{-1}	Power Load / kW
a)	Lead time and Cutting tools	iMFOA	250.3	0.0336	80.10	17.6*	53.7	15.8
		FFOA	167.8	0.0444	103.30	20.1	61.3	20.6
		GA	250.4	0.0338	77.59	17.7	52.2	15.4
b)	Cutting tools	iMFOA	151.1	0.0188	55.00	15.8	20.6	5.4*
		FFOA	175.2	0.0259	58.80	24.8	21.2	8.8
		GA	237.8	0.0212	52.00	17.9	20.9	6.3
c)	Lead time	iMFOA	250.2	0.1236	105.70	12.7	157.2*	33.4
		FFOA	152.5	0.0611	90.60	18.3	67.1	20.5
		GA	163.4	0.1096	107.12	13.1	152.8	33.5

**Optimal value based on rules and manufacturing requirements.*

The results from the optimisation process highlighted in Table 5-7 are summarised below:

- From case *a),* since both technical requirements lead time and cutting tools are constrained, the best solution will be decided considering the most energy-efficient process. That is, the set of machining parameters that provides the lowest specific energy consumption represents the optimal solution for this scenario. From Table 5-7, the results of the iMFOA algorithm provide the most energy-efficient process, indicating this is the optimal solution. Although the genetic algorithm achieved similar performance, when comparing iMFOA with FFOA, the iMFOA provides approximately 12% more energy savings per cm^3 of material removed.

- From case *b),* cutting tools are the production constraint, and as stated previously, the lifetime of the cutting tools is proportionally correlated with the power load. Consequently, the best solution will be decided considering the lowest power load value. From, the iMFOA can predict conditions that have 13% lower power load in comparison with the popular GA algorithm, or 38% improvement compared to the FFOA algorithm.
- From case *c),* the lead time is the production constraint. The best solution will be decided considering the highest material removal rate value. From Table 5-7, *MRR* obtained from the results obtained by iMFOA presents 3% better productivity rate compared to GA; and 2.3 times better productivity rate while still being more energy-efficient (5.6 fewer kJ per cm^3 of material removed) compared to FFOA.

The results from the iMFOA algorithm showed better performance, especially when compared to the FFOA algorithm. This validates the improvements made to the previous MFOA and the advantages of using this swarm algorithm in machining optimisation. Also, in this case, iMFOA presented a slightly better performance than GA. In this case, iMFOA was able to find a better solution with the same search space and the number of iterations.

This case study uses real-case manufacturing requirements to validate the optimisation approach proposed in this research. Furthermore, it proves that the weighting strategy is an easy and effective method to align the manufacturing requirements, this way, bridging the gaps between ideal academic solutions and best solutions for the industry sector.

5.6 Conclusions

To achieve energy-efficient CNC machining processes, it is essential to develop an effective analysis and optimisation approaches to evaluate the impact of machining parameters on energy consumption and identify optimal parameters. In this work, via experiments and qualitative analysis, key machining parameters affecting energy efficiency have been analysed in detail. The findings facilitate machining process planners in choosing suitable machining parameters to minimise energy consumption during machining. Based on the analysis, an improved multi-swarm fruit fly optimisation algorithm has been developed to optimise machining parameters. Case studies and benchmarking have been conducted to test the algorithm. The main conclusions are:

1) The feed per tooth has the most significant effect on the machining time, specific energy and power load. For energy-efficient CNC machining, high feed rates are suggested due to the savings in machining time (and lead time); however, if cutting tools limit production, the optimal machining conditions should be reconfigured to low levels of feed per tooth and cutting speed, while the tooling handbook should recommend the engagement depth.

2) The developed optimisation approach is a useful tool to fine-tune the critical machining parameters to guarantee energy efficiency during machining processes and meet the requirements for shorter lead time and longer cutting tool life. The improved multi-swarm fruit fly optimisation algorithm provided better performance compared to a traditional fruit fly optimisation algorithm and the commonly used genetic algorithm.

Chapter 6: SUPERVISORY CONTROLLER FOR REAL-TIME SURFACE QUALITY ASSURANCE IN CNC MACHINING WITH THE USE OF ARTIFICIAL INTELLIGENCE

6.1 INTRODUCTION

For Computer Numerical Control (CNC) machining, the surface quality of machined parts is an important criterion to evaluate the performance of production processes. Poor surface quality generates high waste and mal-functionality of products, as well as customer dissatisfaction (Benardos and Vosniakos 2003). Surface quality (measured by the surface roughness, *Ra*) is difficult to predict solely based on machinists' experiences, as machining process parameters (*e.g.*, feed rate, spindle speed) generate complex effects on such criteria (Lu 2008). Consequently, it is challenging to select the correct machining parameters that will precisely achieve the desired surface roughness when machining a part. Nevertheless, a majority of companies have been still using machinists' experiences to control the surface quality of machined parts, which can lead to low efficiency in decision making and poor surface quality in machining control. Hence, new optimisation and control approaches, which can efficiently guide machining processes to meet the technical requirements of surface roughness are urgently required.

To further improve real-time control on surface quality, in this work, a novel systematic approach using a fuzzy logic based supervision controller has been developed. Based on intelligent real-time control of machining parameters (feed rate and spindle speed), it is aimed to support process planning decision making as well as manual adjustments made by the operations to ensure the surface quality requirements are achieved. In this approach, neuro-fuzzy, FLC and classical control theory are integrated to develop the novel supervision controller.

A neuro-fuzzy prediction model is used to estimate the surface roughness based on real-time input of machining parameters monitored via smart sensors mounted on CNC machines. In order to provide a training set for the prediction model, and the relationships between feed rate and spindle speed with surface roughness are investigated through Taguchi design of experiments and empirical analysis. During machining processes, real-time feed rates and spindle speeds are used as input to analyse surface roughness. The new surface quality control is innovatively designed by employing the knowledge gained from experiments, and fuzzy logic controllers were innovatively combined with proportional-integral sub-controllers, to enhance the performance of the proposed system. A milling case study based on milling processes for the BS EN24T steel alloy has been used to validate the system performance through a simulation environment. Through the case study, it is demonstrated that the approach is adequate to support high-quality machining processes, which is evidenced by the significant improvements promoted by the controller when correcting the planned parameters by machinists to achieve several technical requirements for the surface quality.

6.2 BACKGROUND AND SYSTEM DESIGN

Conventionally, process planning for CNC machine tools depends on a machinist's knowledge and experience for selecting machining parameters (*e.g.*, feed rate and spindle speed). To prevent poor surface quality, the most common strategy is to select conservative machining parameters. However, this strategy is unable to achieve desired surface quality and high metal removal rate (Lu 2008). The research idea in this chapter is to develop a multi-variable intelligent supervisory controller, which will enable surface quality assurance during CNC machining. The proposed idea is illustrated in **Error! Reference source not found.**.

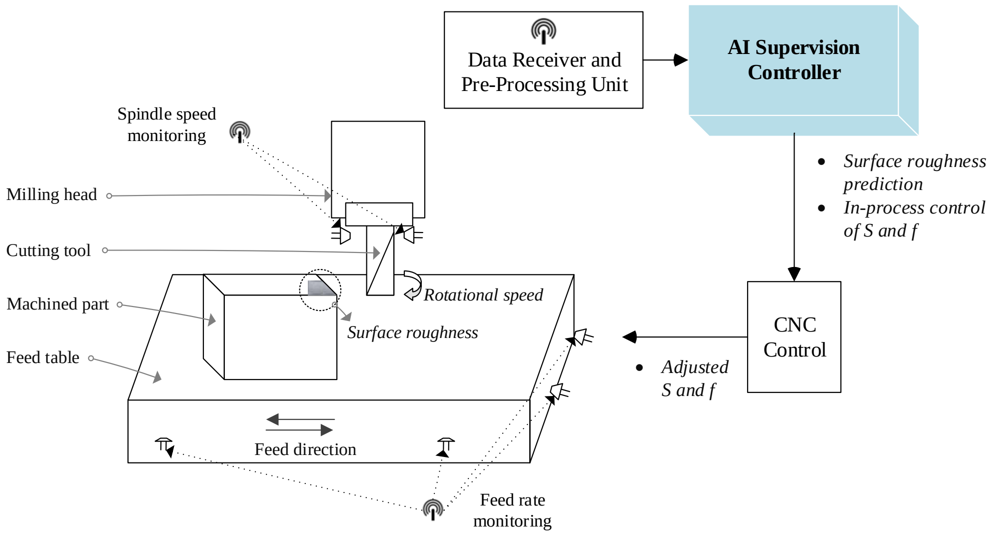


Figure 6-1: CNC machining enabled by the supervisory controller for surface quality assurance.

Smart sensors are mounted in the CNC machine to acquire real-time data of machining parameters (*e.g.*, feed rate and spindle speed). These will be pre-processed in a data processor and used as inputs to the supervisory controller. This controller comprises a surface roughness predictor based on the acquired inputs so that the quality of the workpiece will be assessed in real-time by comparing the predicted and the desired surface roughness (*i.e.*, technical requirements).

The results from the surface roughness comparison will be used to trigger the commands of the controller for adjusting the feed rate and spindle speed. Such commands are defined by fuzzy-rule-based proportional-integral loops for the control adjustment, which will be designed to correct those machining parameters until the technical requirements and tolerances of quality control are met. Thus, the goal of the quality control approach presented in this work is to assist the operation and ensure the technical requirements are achieved. That is, it supports machinists in doing-right-first-time, and avoiding all the drawbacks above of poor surface quality during execution.

Neuro-fuzzy and FLC are the selected methods for designing the supervisory controller in this research. The controller will be tested and validated using a case study involving side milling on BS EN24T under the MATLAB/Simulink simulation environment.

The methodology for the development of the supervisory controller for the surface quality assurance is shown in Figure 6-2.

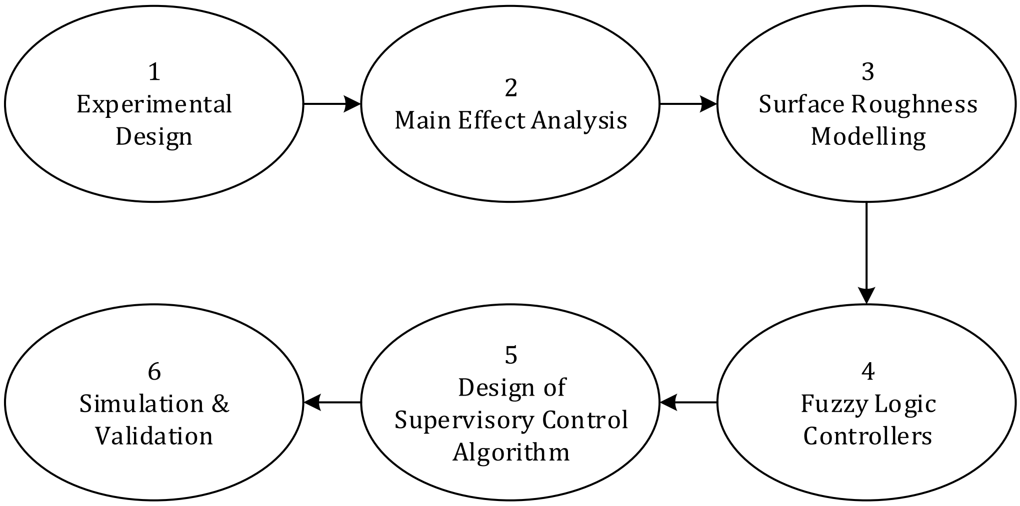


Figure 6-2: Procedures for the supervisory controller design.

This section presents the development of a systematic methodology to achieve the aim of this Chapter. The control design procedure is divided into four steps, described as follows:

I. Experimental design and analysis of machining parameters' effects on the surface roughness: experimental data are collected to support building knowledge on the effects of machining parameters (*i.e.*, feed rate and spindle speed) on the surface roughness. For that, surface roughness measurements are taken by using a surface quality testing equipment. Taguchi design of experiments (DoE) is performed by including different levels of feed rates and spindle speeds, to carry experimental trials of CNC machining of producing machined workpieces.

II. Surface roughness modelling and fuzzy logic controllers: the data collected is used to train a neuro-fuzzy model of the surface roughness as a function of machining process parameters. The feed rate and spindle speed represent the model input while the output generates the surface roughness. This stage is to develop a quantitative model to predict the surface roughness in real-time.

III. Design of supervisory control algorithm: the surface roughness prediction model and fuzzy logic controllers are employed to build the decision-making system which triggers a closed-loop control algorithm. The supervision controller is comprised of two fuzzy-rule-based and two Proportional Integral (PI) sub-controllers. The two fuzzy rule-based sub-controllers will determine the feed rate and spindle speed scaling factors based on the error, and the cascaded PI sub-controllers will use the scaling factors to correct the feed rate or spindle speed.

IV. Simulation and validation: The supervisory controller design is implemented in a simulation environment using MATLAB/Simulink and tested using a milling case study. Testing the system in a simulation environment will evaluate the effectiveness of the prediction and control subsystems, as well as provide traceability of the surface roughness profile based on the adjustments of feed rate and spindle speed. Such a profile represents a binding outcome for the learning process in research and development and will help to identify opportunities for improvements in the controller design. Moreover, the simulation assessment is one crucial step before constructing and implementing the physical system in the future. A comparison between traditional process planning and the supervision controller results will be carried out. In the former, the feed rate and spindle speeds were heuristically defined by experienced machinists to achieve several technical requirements of surface roughness. Each scenario will be run three times, and each simulation run was set to 2000 s, based on pre-tests, which showed that this value would be more than enough for the controller to operate and find the optimal cutting conditions. Consequently, the surface roughness profile will be generated and analysed, so as the abilities of the controller design in correcting the machining parameters to achieve the technical requirements.

6.3 Experimental Details and Results

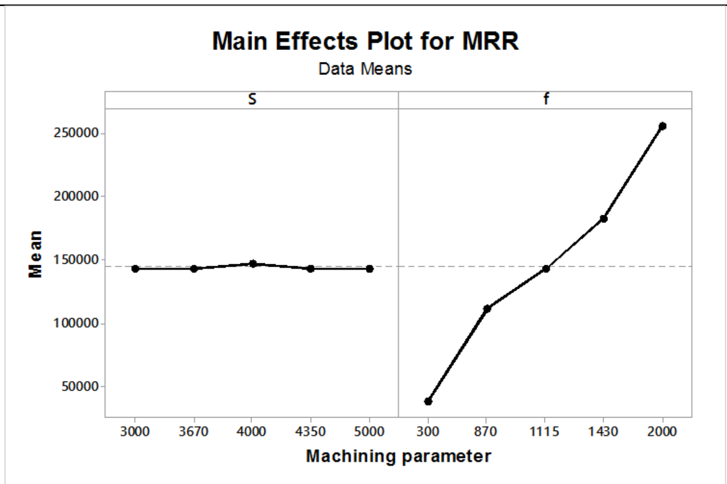
The experimental details and results of the data acquired will be used for the knowledge construction and are hereby presented.

The results obtained from the CNC machining trials and measurements of the surface roughness are presented in Table 6-1. Main effects analysis were carried out to quantify the effects of inputs feed rate (f) and spindle speed (S) on the outputs MRR and surface roughness. This will provide the essential knowledge required to develop a deep understanding of their relationships, essential to the development of the controller architecture. The main effects plots obtained from the experimental results are presented in Figure 6-3.

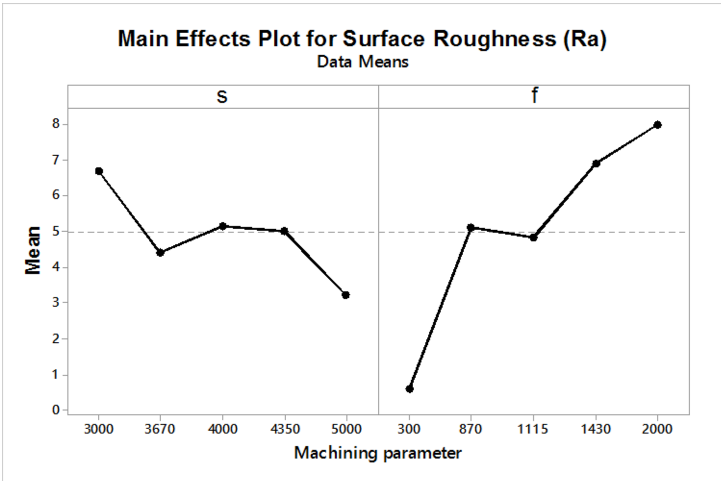
Table 6-1: Experimental results for the surface roughness measurements.

Trial	*Spindle Speed (S) / rpm*	*Feed Rate (f) / mm min^{-1}*	*Material Removal Rate (MRR) / mm^3 min^{-1}*	*Surface Roughness (Ra) / µm*
1	3000	1115	142720	6.7
2	3670	1115	142720	4.4
3	4350	1115	142720	5
4	5000	1115	142720	3.2
5	4000	300	38400	0.7

6	4000	870	111360	5.1
7	4000	1430	183040	6.9
8	4000	2000	256000	8



(a)



(b)

Figure 6-3: The main effects of S and f on MRR and surface roughness, (a) S (rpm) and f (mm/min) vs MRR (cm^3/min), (b) S and f vs surface roughness (Ra).

The results from the experimental results and main effect plots (Figure 6-3) are summarised as follows:

- By changing the levels of spindle speed (*S*), variations of up to 3.5 µm were observed on the surface roughness. By changing the levels of feed rates (*f*), variations of up to 7.4 µm were observed on the surface roughness. These values will be used to define the fuzzy logic models and control strategies for multiple-variable control in the controller design, in Figure 6-3.

- Spindle speed and feed rate have significant effects on the surface roughness, and only the feed rate has a significant effect on material removal rate. These have been evidenced by the plots of spindle speed and feed rate for *MRR* and surface roughness, respectively, shown in Figure 6-3.
- Feed rate presents more significant effects on the surface roughness compared to the spindle speed, as revealed by the steeper curve of the *f* plot, in Figure 6-3.
- Higher spindle speeds could improve the surface quality, but these are nonlinearly correlated, as shown in Figure 6-4(a). Significant changes in *Ra* were observed from 3000 to 3670 rpm, and from 4350 to 5000 rpm, while a lower impact on *Ra* was observed from 3670 to 4350 rpm.
- Lower feed rates will tend to improve the surface quality, but these are nonlinearly correlated, *i.e.*, the response acts differently for the changes in *f*, as shown in Figure 6-4(b). Furthermore, significant changes in *Ra* were observed from 300 to 670 mm/min, and from 1430 to 2000 mm/min, while a smaller impact was observed from 670 to 1430 levels.

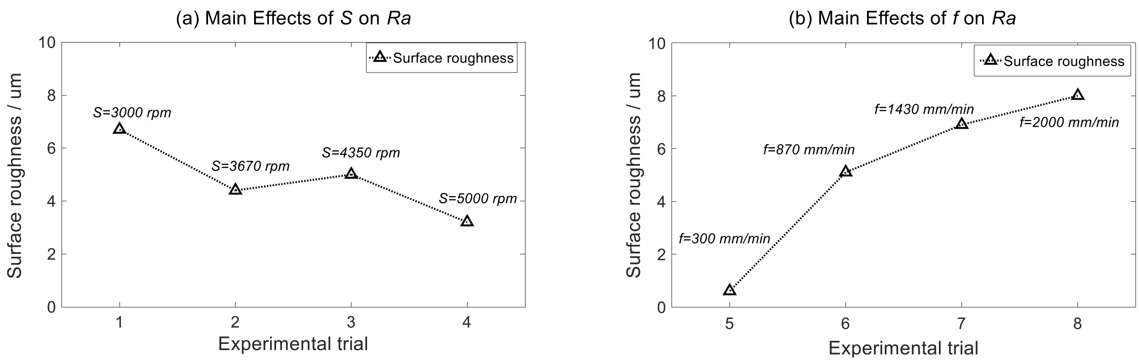


Figure 6-4: Surface roughness as a function of Spindle speed and Feed rate for machining BS EN24T (AISI 4340), (a) S vs surface roughness, for f = 1115 mm/min, (b) f vs surface roughness, for S = 4000 rpm.

The significant impacts of spindle speed and feed rate on the surface roughness validate the selection of these machining parameters to be the controllable variables of the supervision controller. Consequently, the selection of such variables is also advantageous to refine the manual adjustments on those, performed by machinists, and meet the quality requirements precisely.

6.4 Supervisory Controller: Prediction Model, Control Design and Schematic

In this section, the control strategies of the supervision controller are described in detail. The supervision controller is a closed-loop system, consisting of a surface roughness prediction model, a multi-variable supervisor controller, and unit feedback (in Figure 6-5).

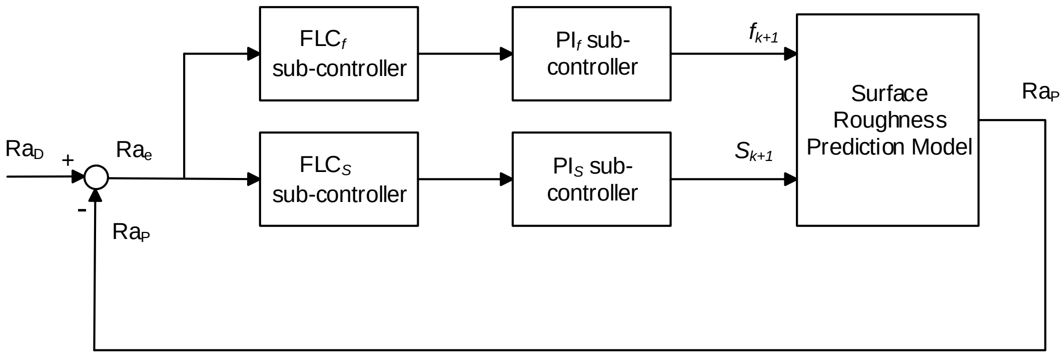


Figure 6-5: Block diagram of the supervision controller, where the subscripts f, S, D, and P refer to feed rate, spindle speed, desired and predicted, respectively.

The supervision controller for surface quality assurance will require a surface roughness prediction model, as shown in Figure 6-5. Such a model will monitor the conditions of CNC machining processes and provide the measurements in real-time for the controller system. The prediction model is based on the readings of the feed rate (*f*) and spindle speed (*S*). *f* and *S* are then adjusted in-process to achieve the required surface roughness. Coping with multiple machining parameters in real-time control is more challenging due to the trade-offs between manufacturing requirements such as the surface quality and productivity (*i.e.*, given by MRR), and the nonlinearity between the inputs and the surface roughness (Lu 2008). Thus, the prediction model has been developed using the Adaptive Neuro-fuzzy Inference System (ANFIS) (also called neuro-fuzzy) modelling method. The general architecture of a two-input single-output neuro-fuzzy model is shown in Chapter 3, Figure 3-10.

The neuro-fuzzy model is a Sugeno type of fuzzy logic model. The Sugeno method is computationally effective and works well with optimisation and adaptive techniques, which makes it suitable for this application. More information on this type of fuzzy logic model can be found in (Sugeno and Michio 1985). The model's engine is defined by the fuzzy inference system (FIS), which is comprised of the input membership functions, the fuzzy rules, and the output equations. This method is a programmed procedure for defining all the FIS coefficients (also called parameters) by using experimental data for training the FIS.

Thus, the data collected through the experimental trials will be used to train the neuro-fuzzy model using backpropagation and the least squares algorithms to obtain the FIS of the model – the further details of calculations are presented in Chapter 3, Section 3.4.5. This way, the predictive model to estimate the surface roughness as a function of the machining parameters (*i.e.*, feed rate and spindle speed) will be formed. The input ranges of spindle speed and feed rate are defined considering the safe cutting zone of machining. The cutting zones were defined in the DoE, where for the spindle speed the range is between 3000 and 5000 rpm, and for the feed rate, the range is between 300 and 2000 mm/min, respectively.

Several attempts of fuzzy sets (*i.e.*, number and shape of the membership functions) were made to achieve the model with the maximum predictive accuracy. As a result, the best model is represented by the inputs modelled by six triangular-shaped membership functions and 36 inference rules. The fuzzy sets are illustrated in Figure 6-6. The final mean squared error of the prediction model based on the validation data is 0.1 µm, which provides a minimum predictive accuracy of 83.3%.

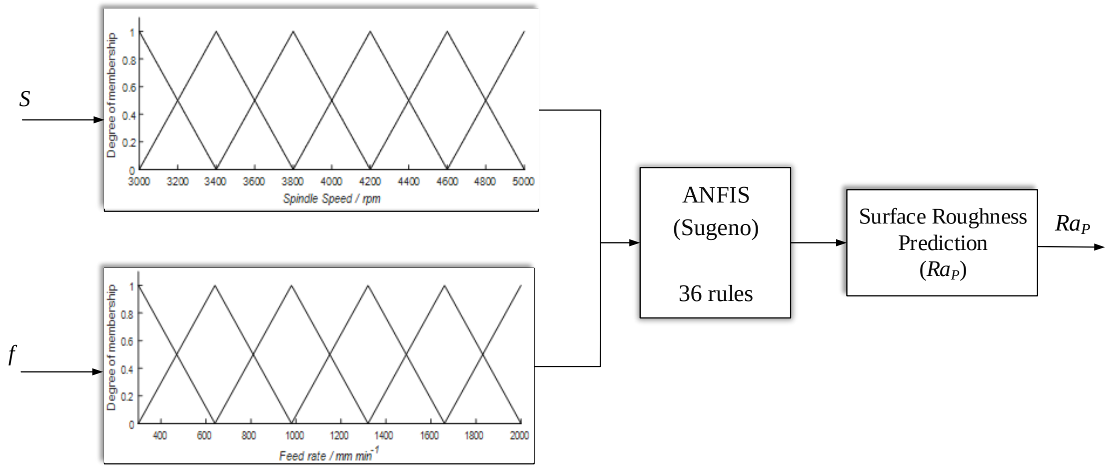


Figure 6-6: Neuro-fuzzy surface roughness predictive model based on Spindle Speed and Feed rate.

Accordingly, the prediction model will provide the predicted surface roughness (Ra_P) based on the machining parameters, feed rate and spindle speed. The Ra_P values will be used to assess the quality of the current machining conditions based on the technical requirements or the desired surface roughness (Ra_D). The next step will be the control strategies using the multi-variable fuzzy logic controllers.

6.5 Controller Design and Strategies

As shown in Figure 6-6, the supervision controller has two sub-controllers, called Fuzzy Logic Controllers (FLC), and classical proportional-integral sub-controllers (PI) for the feed rate and spindle speed adjustments. Therefore, it is necessary to develop the sub-controllers for feed rate (FLC_f) and spindle speed (FLC_S) which are cascaded by the PI loop, to promote the multi-variable control.

FLC_f and FLC_S are rule-based models that output the scaling factors to augment the PI control of feed rate and spindle speed, respectively. The FLC_f and FLC_S have been developed using the Mamdani fuzzy logic method (Mamdani and Assilian 1975). In this method, the fuzzy implication is modelled by Mamdani's minimum operator. The conjunction operator is *min*, the t-norm from the compositional rule is a *min,* and for the aggregation of the rules, the *max* operator is used. A more comprehensive explanation of this method can be found in (Dadios Elmer 2012). The fuzzy sets and inference rules of the FLC_f and FLC_S were defined heuristically based on the findings of the experimental results and CNC machining process knowledge gained through the experimental analysis in Section 6.3, respectively. The design procedure of the FLC_f and FLC_S depends on the value of the surface roughness error (Ra_e), *i.e.*, the difference between the desired and the predicted surface roughness, as shown in Equation (6-1).

$$Ra_e = Ra_D - Ra_P \qquad (6\text{-}1)$$

where Ra_e, Ra_D, Ra_P are the error, desired and predicted surface roughness, in μm.

This multi-variable decoupling is needed so the control loop of *f* will only be triggered by surface roughness errors that are above a certain threshold, this way reducing the negative impact of parameters control on the process productivity (measured by the material removal rate, *MRR*). Such a threshold will be defined considering the maximum change that *S* can promote to minimise Ra_e, which will be defined considered the data analysis in Section 6.3. The data analysis revealed that changes up to 3.5 μm could be achieved by correcting only the spindle speed. Thus, a threshold of two-thirds of this value is selected for the activation of *f* corrections, provided the high significance of this parameter on the *Ra* and MRR.

The range of Ra_e was defined considering the minimum and maximum values of surface roughness from the measured results shown in Table 6-1. This further supports defining the membership functions, responsible for transforming the crisp input into the fuzzy input. The output of FLC_S and FLC_f are the scaling factors λ_s and λ_f, respectively, which crisp values are obtained using the centroid defuzzification method (Equation (6-2)). The decision of the number and shape of the output membership functions lies on the significance of each machining parameter on the surface roughness.

$$FinalOutput = \int_z \mu(z) z dz \Big/ \int_z \mu(z) dz \tag{6-2}$$

As a result, the structure of the FLC_S is determined by six triangular input MFs, six triangular output MFs, and six IF-THEN inference rules (as presented in Figure 6-7). Besides, the structure of the FLC_f is determined by six triangular input MFs, six trapezoidal output MFs, and six IF-THEN inference rules (as presented in Figure 6-8).

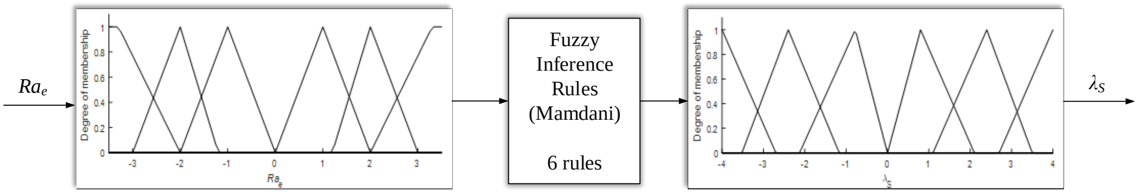


Figure 6-7: Fuzzy logic model for the spindle speed scaling factor (FLC_S).

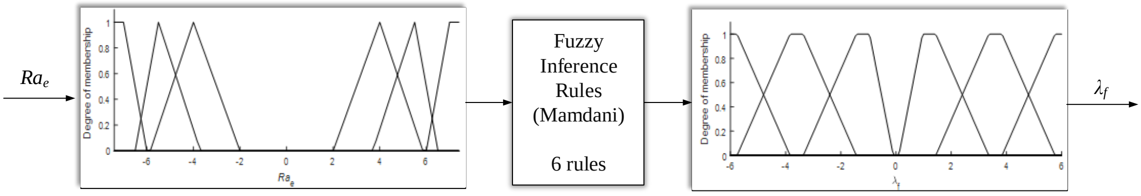


Figure 6-8: Mamdani fuzzy logic model for the feed rate scaling factor (FLC$_f$).

Furthermore, the fuzzy inference rules for the FLC$_S$ can be described as if the surface roughness error (Ra_e) is negative (*e.g.*, between −3.5 and 0), it means that the predicted surface roughness (Ra_P) is higher than the desired (Ra_D) (based on Equation (6-1)). Consequently, in order to minimise Ra_e, *i.e.*, to obtain Ra_P equal the Ra_D, the spindle speed should be increased, according to the relationship between S and Ra, revealed by the empirical analysis.

For the FLC$_f$, the range of input to activate the control action follows the multi-variable control strategy defined previously, where the feed rate control should be only triggered when Ra_e *is* higher than 2 μm or smaller than −2 μm. This can be seen in the input model of Figure 6-8 (left side). Also, if Ra_e is negative (*i.e.*, between −7.4 and −2), the fuzzy rules have been defined to decrease the feed rate, according to the relationship between f and Ra, revealed by the empirical analysis.

A correction combination of fuzzy sets and fuzzy rules should address the nonlinearities between S and f with the Ra. Moreover, the significances of spindle speed and feed rate on the surface roughness have been considered in the design of both FLC input membership functions. That is, due to the feed rate effects on the productivity, values of Ra_e between −2 μm and 0, and 0 and 2 μm, will not activate control commands on this parameter and will trigger the correction of spindle speed only. In this case, the fuzzy logic open model structure played a crucial role in addressing the multi-variable control strategy and supported making a balanced trade-off between surface roughness and productivity rate on this challenging problem.

Thus, the controller system covers the entire safe cutting zones of S and f to promote the supervision and correction of these machining parameters. As a result, the final surface quality of the machined workpiece will be as desired by the process engineers.

6.6 Schematic and Functioning of the Supervisory Controller

The schematic of the supervision controller, targeting to ensure the required surface quality of machined workpiece is met, is presented in Figure 6-9. It is designed to supervise and proposed the most appropriate feed rate and spindle speed to achieve the desired quality technical requirements.

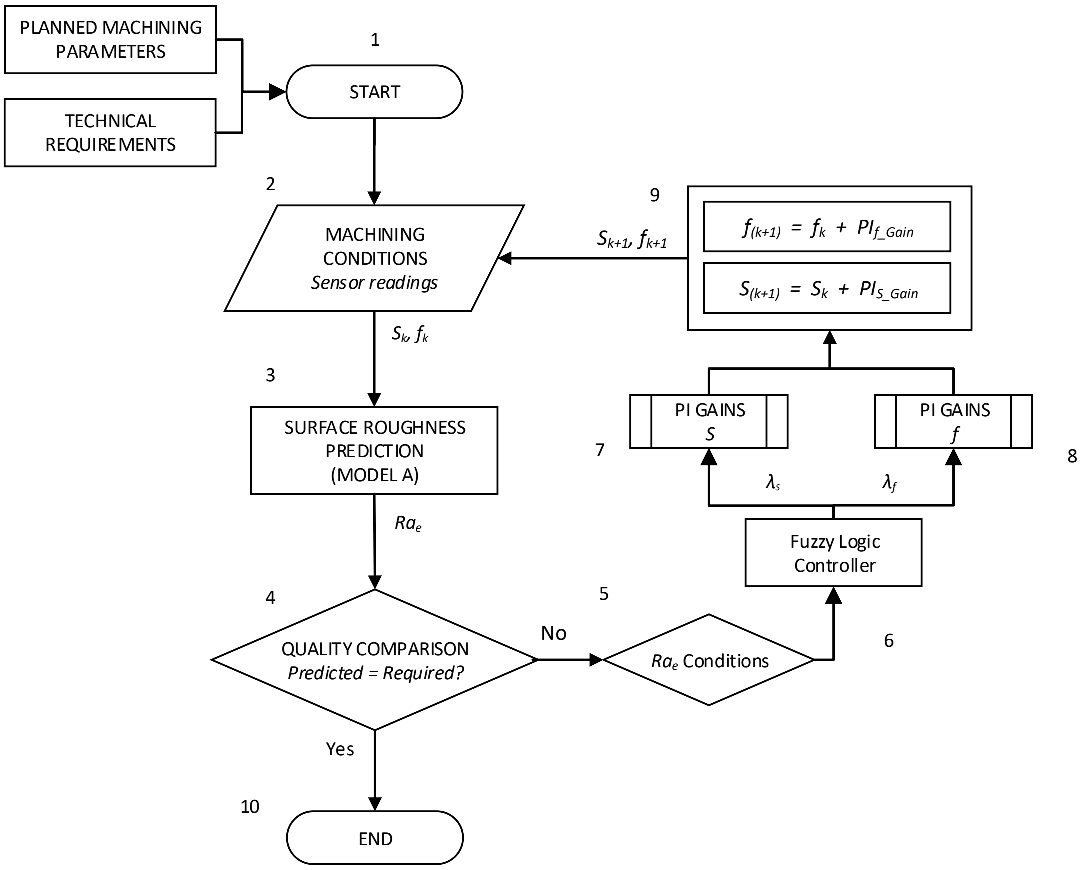


Figure 6-9: Supervisory controller schematic for the surface quality assurance in milling.

The following steps can describe the supervision controller functioning:

- Step 1: the engineer provides the initial set up using the planned machining parameters and the technical requirements for the surface roughness for the controller initialisation
- Step 2: CNC machining will start and the readings from the smart sensors employed in the CNC machine for monitoring the feed rate and spindle speed at time sample k will be used in the decision system in Step 4.
- Step 3: the neuro-fuzzy prediction model will use the sensor signals to estimate the surface roughness in real-time.

- Step 4: the predicted surface roughness (Ra_P) at time k will be compared to the desired surface roughness (Ra_D), *i.e.*, the technical requirements, and the surface roughness error (Ra_e) will be calculated using Equation 6, this way, assessing if the surface quality meets the requirements.
- Step 5: if Ra_e indicates that the technical requirements will not be achieved, *i.e.*, Ra_e is higher than the tolerance of quality control (± 5% of Ra_D), then Ra_e will be used to trigger the multiple-variable control loop to adjust the f and S. Otherwise, the values of f and S are kept the same and no command control is activated.
- Step 6: the value of Ra_e is used to activate the adjustment of f and S. Accordingly, the fuzzy logic controllers for f and S receive the value Ra_e and calculate the scaling factors λ_f and λ_S, respectively, to provide the appropriate proportional and integral gains to correct these machining parameters. The experimental results will be used to define the FLC models, employed to augment the S and f gains.
- Steps 7 and 8: comprise the proportional and integral gains that will augment the factors λ_f and λ_S to correctly adjust f and S, respectively. Such design self-tunes the controller performance based on the previous Ra_e, at time $k-1$. Furthermore, in Step 7, the FLC_S will be activated for Ra_e values smaller than 3.5 μm or greater than −3.5 μm. This strategy will force the activation of FLC_f only (Step 8) in order to achieve Ra_e smaller this threshold (since Ra is more sensitive to f than to S). Also, it will avoid the drawbacks of correlation effects caused by the changes in S and f at the same time. Consequently, when the Ra_e is smaller than the set threshold, S only should able to deal with the error minimisation. Therefore, the FLC_f is only activated for Ra_e values greater than 2 μm or smaller than −2 μm. This way, the impact on the material removal rate is also minimised, since such Ra_e can be dealt with by correcting the S only – which will not affect the MRR.

- Step 9: the corrected values of f and S, *i.e.*, $f_{(k+1)}$ and $S_{(k+1)}$ will be calculated using Equations (6-3) and (6-4), respectively, and will be provided to the CNC machine control.

$$f_{(k+1)} = f_{(k)} + PI_{f_{(k)}} \tag{6-3}$$

$$S_{(k+1)} = S_{(k)} + PI_{S_{(k)}} \tag{6-4}$$

  where S_k and PI_s are the spindle speed, the proportional, and the integral augmented gains for the spindle speed, at time k, respectively; and f_k and PI_f are the feed rate, the proportional, and the integral augmented gains for the feed rate, at time k, respectively. After that, the next supervised loop starts based on the corrected machining conditions, and the loop restarts in Step 3.

- Step 10: the control commands are terminated when the Ra_e is zero or within the tolerance of quality control.

6.7 Case Study: Side Milling on BS EN24T Steel Alloy

In this section, a case study of milling operations is presented to validate the approach for surface quality assurance. The experimental data discussed earlier have been used to develop the surface roughness prediction model and the fuzzy logic controllers for the feed rate and spindle speed. Also, several technical requirements will be used to compare the performance between a traditional machining process (*i.e.*, based on the expertise of machinists for defining the f and S values heuristically) and the supervised machining process (*i.e.*, based on the supervision and multivariable control of the supervisory controller).

The prediction model, the controllers and the schematic provided in Figure 6-9, have been implemented to develop the simulation model of the supervisory controller for the quality assurance in a MATLAB/Simulink environment. The flow of the supervisory controller is presented in Figure 6-10.

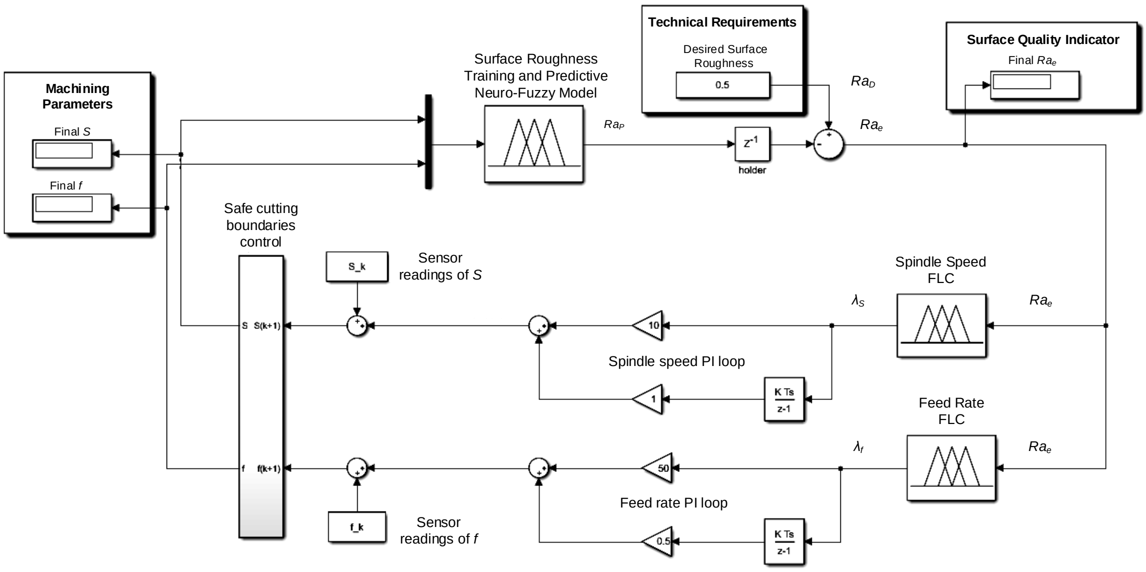


Figure 6-10: AI supervision controller for quality assurance in milling.

To evaluate the capabilities and robustness of the multiple-variable control design and strategies, several application scenarios have been defined by considering different technical requirements for surface roughness.

The scenarios have been presented to two experienced machinists, who have been asked to define the initial conditions of feed rate and spindle speed. Six values of technical requirements for the surface roughness of the machined parts have been selected, ranging from 0.5 µm to 7 µm. Also, two initial conditions for each of the machining parameters have been selected by considering their extreme values, *i.e.*, their minimum and maximum values based on the safe machining boundaries. Since the machining parameters have conflicting effects on the surface roughness, the test should exhaust the abilities of the controller in selecting the appropriate machining parameters to achieve the technical requirements. The results of the tests are presented in Table 6-2 and Figure 6-11.

Table 6-2: Results from performance tests on multivariable AI supervisory controller.

Technical Requirement (Ra_D) / µm		Planned Parameters (Machinists' decision)				Adjusted Parameters (AI Supervisory Controller Adjustments)			
		S / rpm	f / mm min^{-1}	Absolute Error (Ra_e) / µm	Ra_e / %	Adjusted S / rpm	Adjusted f / mm min^{-1}	Absolute Error (Ra_e) / µm	Ra_e / %
a	0.5	5000	300	0.1	20	4128	300	0.002	0.43
b	1	5000	600	0.99	98.7	5000	600	0.99	98.7
c	3	4000	1200	3.6	118.8	4969	1053	0.12	4
d	4.5	3500	1680	0.88	19.6	4818	1579	0.001	0.02
e	6	3000	1800	2	33.6	4177	1801	0.095	1.6
f	7	3000	2000	2.9	40.7	4172	1947	0.006	0.1

The results achieved by the AI supervision controller in all tests, except for Test (b), have shown that the proposed approach can make significant improvements through the adjustment of *S* and *f*. For instance, in Test (c), the controller has corrected the machinist's pre-planned *f* and *S*, such that improvement the Ra_e was reduced from 3.6 µm to 0.12 µm, which corresponds to 0.02% of the technical requirement; this way, guaranteeing that the final quality is within the tolerance of quality control (± 5% of Ra_D). Furthermore, the best machining parameters revealed are f = 1053 mm/min and S = 4969 rpm.

In Test (b), when the technical requirement is 1 µm and the chosen values of feed rate and spindle speed are 5000 rpm and 600 mm/min, respectively, the controller could not refine the process conditions, and the error is not minimised. The reason is that the condition established in the system design for the feed rate control loop, *i.e.*, control commands, will only be activated for Ra_e > 2 μm. As shown in Figure 6-11(b), the value of Ra_e is always smaller than 2 μm. As thus, the feed rate controller has not been activated. Since the spindle speed has been already in its best condition, further improvements on the surface roughness could not be promoted. One way of overcoming this limitation is by reducing the threshold for feed control. Another way is to include an extra loop for the feed rate control which would take action in case the Ra_e is higher than the tolerance, and the spindle is at its maximum speed. This will be the future research for improvement.

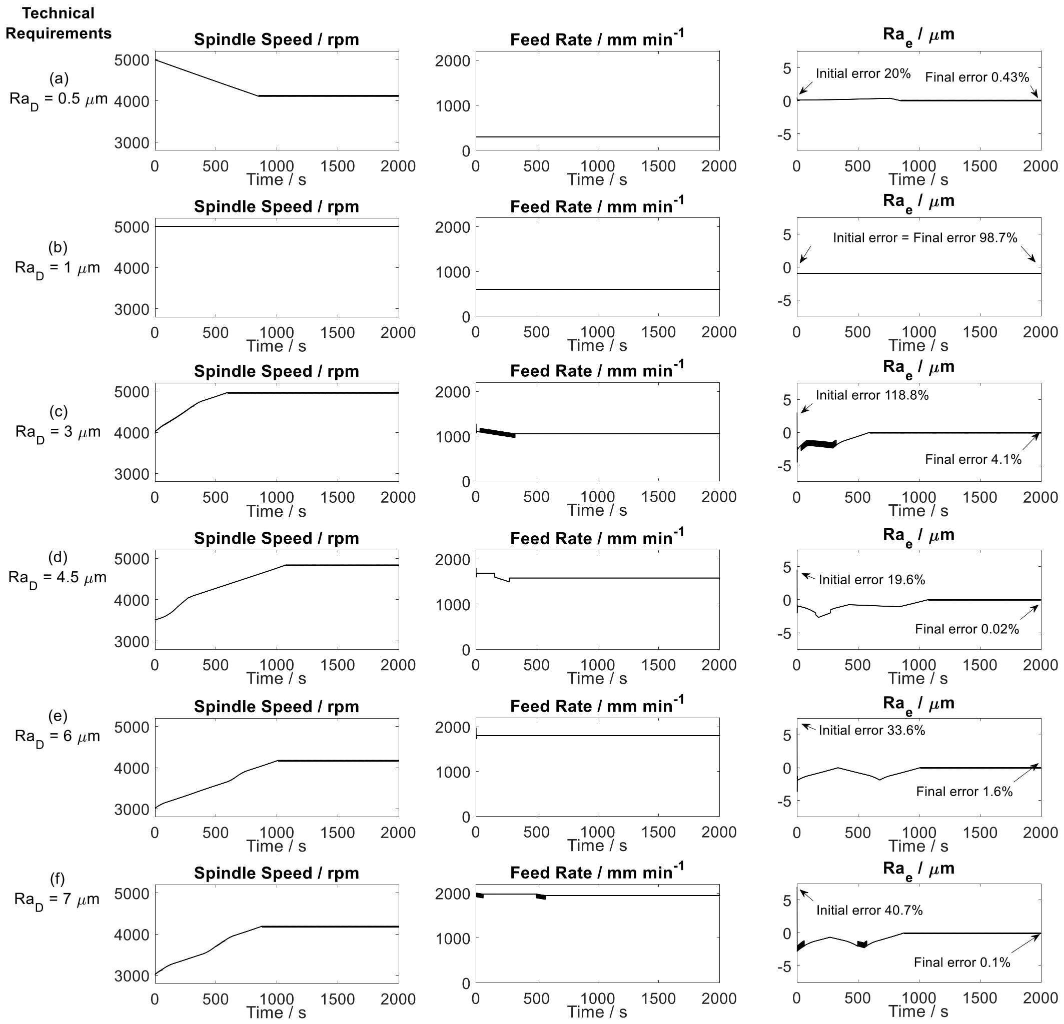


Figure 6-11: Correction of spindle speed and feed rate to achieve technical requirements.

The overall results from the performance test, presented in Table 6-2, show that the supervision controller can improve the quality of the machined part significantly through correct adjustments of S and f. Hence, the results achieved by the supervisory controller show that this is a useful tool for supporting high-quality CNC machining processes.

Also, a vital advantage of the multi-variable AI supervision controller is that it can cover a wide range of technical requirements by providing accurate control of f and S accordingly. This way, the system supports avoiding the waste of time and money by considering the manufacturing specification.

6.8 CONCLUSIONS

In many mechanical applications, a high surface roughness value is often undesirable, but a low surface roughness can be time-consuming and costly to achieve. This chapter presents a novel supervisory control approach to ensure the desired surface quality is achieved in Computer Numerical Controlled (CNC) machining processes and ensure optimal process performance. For that, the development of an artificial intelligent (AI) supervisory controller design and strategies have been presented in detail. The proposed AI supervisory controller is designed to ensure that the technical requirements for the surface quality will be achieved through in-process optimal adjustments of the key machining parameters of feed rate and spindle speed. The system is comprised of a neuro-fuzzy surface roughness predictive model and fuzzy-rule-based proportional-integral controllers, which are innovatively combined for monitoring and closing the loop to adjust the machining parameters, respectively.

The simulation results from the case study using side milling operations on BS EN24T (AISI 4340) steel alloy show that the proposed system is effective in adjusting the CNC machining parameters (*i.e.*, feed rate and spindle speed) for high-quality machining processes. Furthermore, the system has been analysed through several scenarios, where comparisons with the traditional process planning (where machinists heuristically select the machining parameters) and the supervisory controller were carried out. The results show that the system significantly improved the quality of the machining process compared to the initial conditions given by the experienced machinists. In one of the scenarios, the system minimised the surface roughness error from 3.6 μm to 0.12 μm. This guaranteed that the surface quality was within the tolerances of quality control by a margin between 0.02% and 4%.

Furthermore, the results show research innovations clearly by disclosing that:

- a vital advantage of the multi-variable AI supervisor controller is its ability to effectively adjust feed rate and spindle speed during real-time machining processes;
- the system can be easily adaptable and reconfigured to other machining operations (*e.g.*, turning) by adopting predictive models from the literature and following the proposed design procedures of this work to develop the supervisory control strategies of the new system.

To conclude, the proposed approach overcomes the limitations of the current solutions in the literature and represents a significant step towards smart manufacturing and autonomous machining. Also, it has shown to be an effective tool to enable autonomous surface quality assurance in CNC machining.

Chapter 7: CONCLUSIONS AND FUTURE WORK

7.1 OVERALL CONCLUSIONS

Manufacturing processes such as CNC machining are in the spotlight for the high energy they consume, and their low overall efficiency, due to costs, legislation and environmental concerns. In this research, novel intelligent optimisation and control approaches (digital solutions) have been developed to promote more intelligent CNC machining and have been successfully proven to achieve more efficient and sustainable manufacturing.

By splitting the challenge for more efficient and sustainable machining into two stages (roughing and finishing), the overall gain in the machining process workflow was augmented by the gains achieved at each stage. This is because after analysing the machining workflow, it was observed that each stage has its process particularities (such as planning, manufacturing requirements) and their key efficiency operational criteria. This way requires a more focused solution to address the current challenge identified in the industry (as explained in Figure 1.1).

Consequently, a combination of the proposed approaches I and II, *i.e.*, multi-objective optimisation for sustainable roughing and real-time supervisory control for quality assurance in finishing, respectively, were essential to achieve the aim of this research effectively: production of more sustainable outputs (or parts machined) through high-efficient and reliable production processes.

Furthermore, the findings of this research validate the use of digital solutions to promote optimal decision-making at the early stages (process planning) and *in-process* of machining. Also, such solutions (through approaches I and II) enhanced the reconfigurability of production processes and promoted greater alignment between optimal input parameters (machining process parameters) and the immediate requirements of manufacturing (such as cutting tools availability and lead time) yet achieving more sustainable processes.

Using the empirical methodology was crucial to address the critical trade-offs between machining process parameters and the key efficiency operational criteria. Besides, essential machining knowledge was developed based on an in-depth data analysis of the relationships between spindle speed, feed rate and cutting depth and the energy efficiency, productivity, cutting tool life, and surface quality.

The knowledge and data acquired were vital to achieve accurate and fit for purpose intelligent optimisation approaches. The experimental data set for the cutting tool life were determinant to cope with the challenges of multi-objective optimisation using machining process parameters and key efficiency operational criteria. Furthermore, the findings reveal a strong correlation between power consumption and the cutting tool life. By revealing this correlation, a novel efficient, reconfigurable and multi-objective optimisation problem could be formulated accounting for the energy efficiency, cutting tool life and productivity, and the development of machining strategies considering the immediate manufacturing requirements for cutting tools availability and lead time. The results from several testing and validation scenarios showed that the developed optimisation approach is an effective tool to fine-tune the critical machining parameters to guarantee energy efficiency during machining processes and meet the requirements for shorter lead time and longer cutting tool life. The improved multi-swarm fruit fly optimisation algorithm provided better performance compared to a traditional fruit fly optimisation algorithm and the commonly used genetic algorithm. The conclusions of this research work have been summarised into contributions to knowledge, a summary of optimisation approaches and validation results and, finally, recommendations for future work.

7.1.1 CONTRIBUTION TO KNOWLEDGE

The critical experimental findings from the analysis of the effects of machining process parameters and the energy efficiency, presented in Chapter 5, revealed that:

- For side milling, 79% to 94% of the overall energy consumed during the process was used during the state of engagement (the actual cutting). Consequently, the results revealed that the machining process parameters play a highly critical role in the energy efficiency of the production for such milling operations.
- A useful energy efficiency model has been developed based on the concept of the power load, which represents the average amount of energy consumed during the state of engagement. The model unleashes an effective way to address the challenging trade-offs of multi-objective optimisation involving three key efficiency operational criteria: energy-efficiency, productivity and cutting tool life.

- Changes in the levels of spindle speed do not have substantial effects on energy efficiency, power load or machining time. However, during the state of travelling, more energy is wasted at higher levels of spindle speed, since the spindle motor requires more power at higher speeds. An increase in energy demand by 3% during the state of travelling was caused for every 20% increase in the spindle speed.
- The feed rate has the most significant effect on the machining time, energy efficiency and power load. A high level of feed rate (2000 mm/min) promotes better energy efficiency owing to savings in machining time: a consumption of approximately 70% less energy per cm^3 of material removed compared to a low level (300 mm/min) was observed. However, the drawback is that a higher feed rate will increase the cutting forces and temperatures at the cutting tools tip, consequently shortening their tool life. The experiments revealed that the life of cutting tools using low levels of feed rate achieved a life of 540 min, compared to 14 min when using the highest feed rate.
- The cutting width has significant effects on energy efficiency, machining time and power load. A high cutting width will promote a more energy-efficient process owing to savings in machining time. However, the drawback is the higher power load, which means greater cutting forces and chip load on the cutter tool, consequently shortening the tool life. For instance, at a high level of the cutting width (4 mm), the operation was 33% more energy-efficient compared to a lower level (1.67 mm).
- Besides, the empirical analysis of tool wear and tool life were used to study the correlation between the cutting tool life and the power consumption of the machining trials to develop a novel predictive model. The results of the correlational analysis showed that the tool life indicator total cutting time

presented a strong correlation with the mean power consumption, while the total cutting length and total volume of removed material indicators did not present a strong correlation. Therefore, a novel cutting tool life model was developed considering the prediction of the total cutting time based on the mean power consumption, and machining process parameters as input variables. This model was tested and validated; the validation results presented satisfactory predictive accuracy, R-sq adjusted equal to 0.92.

7.1.2 Summary of Intelligent Optimisation Approaches and Validation Results

The multi-objective optimisation approach for the roughing stage of CNC machining has successfully addressed the challenging trade-offs between machining process parameters and the key efficiency operational criteria (energy efficiency, cutting tool life, and productivity). To address such challenges, a novel strategy that takes into account the manufacturing requirements for lead time and cutting tools availability was combined with the optimisation problem formulated to improve the effectiveness of the decision-making. That is, the results obtained from the optimisation approach are also aligned with the current constraints in the manufacturing resources.

A novel improved multi-swarm fruit-fly optimisation algorithm was used to obtain the optimal results. The optimisation algorithm and strategies were validated using several manufacturing scenarios. The results from the validation study showed that:

- For energy-efficient CNC machining, high feed rates are suggested due to the savings in machining time (and lead time constraints); however, if cutting tools limit production, the optimal machining conditions should be reconfigured to low levels of feed per tooth and cutting speed, while the cutting depth should be as recommended by the tooling handbook.
- The weighting strategy to align the optimal solution with the manufacturing requirements for lead time and cutting tools availability enabled a more realistic optimisation approach for industrial applications. The validation results from the manufacturing scenarios showed that the optimal machining process parameters obtained through the optimisation algorithm helped in meeting such requirements.
- The developed optimisation approach is a useful tool to fine-tune the critical machining parameters to guarantee energy efficiency during machining processes and meet the requirements for shorter lead time and longer cutting tool life.
- The improved multi-swarm fruit fly optimisation algorithm provided better performance compared to a traditional fruit fly optimisation algorithm and the commonly used genetic algorithm.

The cutting tool wear assessment and the correlational study results between the tool life and the power consumption validated the existence of a high correlation between the tool life and power consumption. Moreover, such results revealed that the power load represents a suitable means to address cutting tool life improvements. Based on the results, the novel model of the cutting tool life based on power consumption and machining process parameters presented satisfactory performance (coefficient of determination = 0.92).

The optimisation approach for the control of surface quality during the finishing stage of CNC machining has successfully addressed the challenging adjustments of spindle speed and feed rate to accurately achieve the desired surface roughness. As a result, by considering the manufacturing requirements (or desired surface roughness), the approach supports reducing re-work processing and generation of waste due to low-quality parts. Also, the decision-making process using a neuro-fuzzy predictive model for the prediction of the surface roughness and fuzzy logic controllers for the fine adjustments of the spindle speed and feed rate successfully achieved the core goal of the system.

In summary, the validation results for the intelligent optimisation approaches proposed in this research ensured the achievement of more efficient and sustainable machining processes with the use of soft computing. This further ensures that the primary aim of this thesis has been successfully achieved. Nevertheless, there are recommendations for future work in order to enhance the applicability and impact of the proposed optimisation approaches.

7.1.3 RECOMMENDATIONS FOR FUTURE WORK

The recommendations for future work include as follows:

- To expand the multi-objective optimisation approach to facilitate energy-efficient CNC machining for other types of operations such as turning, boring, and electro-discharge machining. Also, including other requirements to use this approach for online decision and optimisation.
- To validate the cutting tool life model as a function of power models for different material types. An implementation of the model for real-time applications on the prediction of cutting tool life should also be studied.

- To consider dynamics factors of CNC machining such as cutting tool vibration into the model and control loop of the surface quality assurance controller to achieve higher decision-making accuracy.

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APPENDIX A

Trial Number	**Factor**		
	Cutting Speed (v_c)	Feed Rate (f)	Cutting Width (a_e)
1	1	1	1
2	1	2	2
3	1	3	3
4	1	4	4
5	1	5	5
6	2	1	2
7	2	2	3
8	2	3	4
9	2	4	5
10	2	5	1
11	3	1	3
12	3	2	4
13	3	3	5
14	3	4	1
15	3	5	2
16	4	1	4
17	4	2	5
18	4	3	1
19	4	4	2
20	4	5	3
21	5	1	5
22	5	2	1
23	5	3	2
24	5	4	3
25	5	5	4

APPENDIX B

Trial Number	Factor		
	Cutting Speed (v_c)	Feed Rate (f)	Cutting Width (a_e)
1	1	3	4
2	2	3	4
3	4	3	4
4	5	3	4
5	3	1	4
6	3	2	4
7	3	4	4
8	3	5	4
9	1	2	4
10	1	4	4
11	1	5	4
12	2	2	4
13	2	4	4
14	2	5	4
15	4	2	4
16	4	4	4
17	4	5	4
18	5	2	4
19	5	4	4
20	5	5	4
21	3	3	1
22	3	3	2
23	3	3	3
24	3	3	4

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