Investigation of the Energy Efficient Sustainable Manufacturing Approach and its Implementation Perspectives

A thesis submitted for the degree of Doctor of Philosophy

by

Kanet Katchasuwanmanee

College of Engineering, Design and Physical Sciences

May 2016

Abstract

In the last two decades, energy is becoming one of the main issues in the manufacturing industry as it contributes substantially to production cost, CO_2 emissions, and other destructive environmental impact. Due to rising energy costs, environmental concerns and stringent regulations, manufacturing is increasingly driven towards sustainable manufacturing which needs to address the associated environmental, social and economic aspects simultaneously. One common approach is to achieve sustainability and to implement energy-resource efficient production management systems that enable optimisation of energy consumption and resource utilisation in the production system. However, by reducing energy consumption, the product quality and production cost may be compromised. To remain competitive in the dynamic environment, the energy-efficient management system should not only concern energy consumption but also maintain product quality and production efficiency.

This thesis presents a development of the Energy-smart Production Management (e-ProMan) system which provides a systematic, virtual simulation that integrates manufacturing data relating to thermal effect and correlation analysis between energy flow, work flow and data flow for the heating, ventilation and air conditioning (HVAC) system and production process. First, the e-ProMan system comprises of the multidimensional analysis between energy flow, work flow and data flow. The results showed that the product quality is significantly affected by ambient temperature in CNC precision machining. Product quality appears to be improved at lower temperatures. This research highlights the significance of ambient temperature in sustainable precision machining.

Second, the simulation experiment was modelled at the production process due to it being the main source of energy consumption in manufacturing. An up-hill workload scenario was found to be the most energy and cost-efficient production processes. In other words, energy consumption, CO2 emission and total manufacturing cost could be reduced when workload capacity and operating machine increase incrementally. Moreover, the e-ProMan system was modelled and simulated using the weather forecast and real-time ambient temperature to reduce energy consumption of the HVAC system. The e-ProMan system results in less energy consumption compared to the fuzzy control system. To conclude, the e-ProMan demonstrates energy efficiency at all relevant levels in the manufacturing: machine, process and plant. For the future research, the e-ProMan system needs to be applied and validated in actual manufacturing environments.

Acknowledgements

I would like to express my sincere thanks and gratitude to my principal supervisor, Professor Kai Cheng for the research funding opportunity to study PhD, and my supervisor, Dr Richard Bateman, for their valuable advices, encouragement and all the motivation along the way. Without their assistance and support, this research would not be completed.

Many thanks are extended to Mr Paul Yates for his technical support at the AMEE laboratory, Dr Jennifer Chavanovanich for encouragement and invaluable supports, and also Dr Worapong Sawangsri, Dr Teewara Suwan, Mr Thammarat Somthong, Dr Joe Au, Dr Atanas Ivanov and Dr Timothy Minton who provide valuable great suggestions and discussion for my research from time to time.

I would express my sincere thanks to Brunel University London and the European Commission for providing me with the further study opportunity with a full PhD study sponsorship. I would also like to express my appreciation to my colleagues participating in the EuroEnergest project and their interactive collaboration.

I am deeply indebted to my beloved mother and father for their endless love and moral support throughout my study years in the United Kingdom.

Table of Contents

Page

Page

Page

Page

Page

Abbreviations

CAD	Computer-aided design
CE	Carbon emitted
CES	Carbon emission signature
CFD	Computational fluid dynamics
CI	Confidence Interval
CMM	Coordinate measuring machine
CNC	Computer numerical control.
CoA	Center of area
CO_2	Carbon dioxide
CSM	aCtuatorS Methodology
DAS	Data acquisition system
EC	Energy consumed
EES	Energy-efficient scheduling
EnMS	Energy management system
e-ProMan	Energy-smart Production Management System
F	Degrees of freedom
GHG	Greenhouse gas
GJ	Gigajoule
Gt	Gigatons
HVAC	Heating, ventilation, and air conditioning

ISO	International Organization for Standardization
J	Joule
kWh	Kilowatt hour
LCM	Low carbon manufacturing
NWP	Numerical Weather Prediction
OECD	The Organization for Economic Cooperation and Development
PID	Proportional–integral–derivative
SEC	Specific energy consumption
SISO	Single input single output

Nomenclature

C_L	Labor cost	(£)
C_m	Machine cost	(£)
C_p	Specific heat of air	(kJ/Kg · °C)
C_{pr}	Total cost of a single machining operation	(£)
C_t	Tool cost	(£)
D	Tools diameter	(mm)
$E_{background}$	Energy background	Watt
E_c	Energy consumption of cutting	Watt
E_{load}	Energy load	Watt
$E_{peripherals}$	Indirect energy	Watt
$E_{process}$	Direct energy	Watt
E_{total}	Total energy consumption	kWh
E_t	Total indirect energy consumption	Watt
E_{Tt}	Total energy consumption	Watt
f_z	Feed per tooth	(mm/tooth)
i	Number of workpieces	
k_c	Proportional gain	
K_i	Correction coefficients	
k_r	Specific resistance of cutting	(N/mm^2)

$L(T)$	Length at T	(mm)
m	The number of input linguistic variables.	
n	Total number of workpieces	
N	Number of resource states	
N_s	Spindle Rotational speed (rmp)	(rev/minute)
p	The number of linguistic terms	
P	Power consumption	Watt
P_i	Average power of a system during work operation	Watt
$P_{r,i}(t)$	Power	Watt
Q	Energy consumption of HVAC	kWh
Q_H	Heat transferred from the hot areas	Joule
r	Pearson's coefficient	
r_s	Spearman's coefficient	
R	The total number R of possible rules for a fuzzy system	
R^2	Coefficient of determination	
t_g	Time of production station	(minute)
t_j	Time of idle run	(minute)
T	Temperature	(°C)
T_c	Actual ambient temperature	(°C)
T_h	High temperature	(°C)
$T_h - T_l$	Temperature decline	(°C)

T_H	HVAC temperature to be adjusted	(°C)
T_l	Tool life	(minute)
T_w	Weather forecast in the next hour	(°C)
T_x	Cutting time	(minute)
ΔT	Difference between indoor and outdoor temperatures	(°C)
T_{prod}	Production time	(min)
TR	Sum of the total consumption of the production system	Watt
TW_r	Total energy consumption	kWh
$u(t)$	Output of the control	
V	Volumetric flow rate of air	(m^3/s)
V_b	Flank wear width	(mm)
V_f	Feed speed	(mm/minute)
V_i	Volume of material	(mm^3)
V_x	Cutting speed	(m/minute)
VB_k	Safe limit of flank wear width	(mm)
W_{net}	Useful work produced in a heat engine	Joule
$W_{r,i}$	Energy consumption	Watt
x	The value of the linguistic variable	
x_i	Nominal CAD model value of dimensions	(mm)
$y(t)$	Output of the process	
y_i	Actual measured value of dimensions	(mm)

$y_s(t)$	Desired process output	
z	Number of teeth	
α	Thermal expansion coefficient	
β	Standardised coefficients beta	
η	Efficiency	
η_{device}	Efficiency of a device operating in a process line	
ρ_0	Outside air density	($kg \cdot m^{-3}$)
τ_d	Derivative time	
τ_i	Integral time	

List of Figures

Page

Page

Page

List of Tables

CHAPTER 1

INTRODUCTION

1.1 Background

Over the last decades, energy has played a crucial role in the development of the world with fossil fuels being the main energy sources. While energy is the significant input to the global economic growth, the world's total energy consumption is becoming an increasingly serious issue. As the economy is growing, energy demands also increases with improvements in standards of living. Depicted in Figure 1.1, the International Energy Agency estimated a rise of 7% per annum in the total energy consumption (International Energy Agency Statistics, 2012a /2012b). This would result in a rise of global CO_2 emission from 28 to 41 gigatons (Gt) by 2035. Electricity and heat are regarded as the largest producers of the total CO_2 emissions, thus suggesting immediate actions toward reduction of electricity and heat consumption.

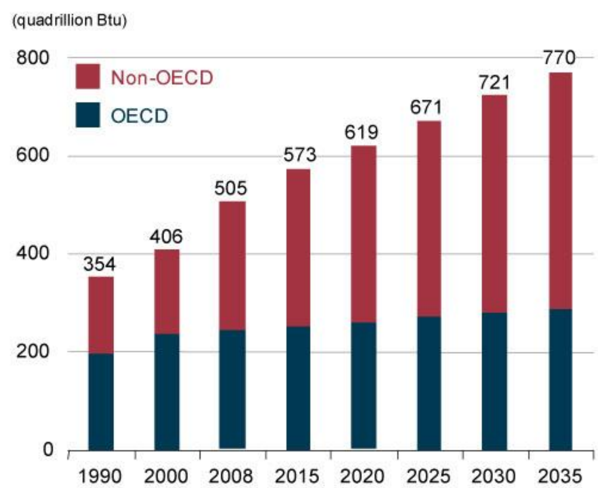


Figure 1.1. The World energy consumption trends
(International Energy Agency Statistics, 2012b)

The new economy has driven the manufacturing industry to operate in a highly competitive environment with growing pressure to reduce the world carbon footprint. Not only has the industry accounted for the largest percentage of the world's total energy consumption, but it is also responsible for the significant proportion of the world CO_2 emissions which has doubled in the last 60 years (Carbon Trust, 2008a/2008b). The extensive world CO_2 emissions have greatly affected the global warming, causing threatening environmental issues such as intensity of hurricanes, spread of diseases in quicker rates, changes in ecosystems and rise in sea levels (Bose, 2010). The destructive environmental impact has introduced economic, technical, social and political challenges in the ways in which energy resources are utilised and managed. Consequently, the current environmental concerns have driven the manufacturing industry towards sustainability, thereby contributing to environment, economy and society (Geretti and Taisch, 2012; Giret et al., 2015).

Research on energy and resource efficiency in manufacturing has expanded in the last decade (Duflou et al., 2012). Attempts have been made to develop a better understanding of sustainable manufacturing in order to respond to more restricted regulations, higher demands for high quality and environmentally friendly products, and scarcity of energy resources (Allwood & Cullen, 2012). Efforts to develop and implement a more effective energy management system in manufacturing have been internationally recognised in various areas including law, standards, technology, benchmarking, energy costs and organisation and operations (Javied et al., 2015). According to the current standards, ISO 50001 energy management system, for sustainable manufacturing, energy-efficient system should be implemented and controlled through a systematic and continuous approach to ensure sustainability and efficiency (ISO, 2016).

Any systems that can accurately predict energy consumption is beneficial to the overall energy management system as it optimises the operation and improves the control systems. More importantly, minimising energy usage through energy and resource efficient management system is not only necessary for environmental development but also essential for gaining competitive advantages and performance outcome. In essence, one way to succeed in the current market is to deliver energy and resource efficient performance through optimisation of manufacturing systems and processes (Rentsch, 2015).

In manufacturing, electrical energy is the main energy used for equipment and machines. Machine tools can generate 70% of the total CO_2 emissions during the use phase (Diaz et al., 2010). For this reason, numerous studies in prior research have developed models to minimise energy usage at this phase (e.g. Kong et al., 2011). Approaches appear to focus on modifying cutting parameters and process and altering peripheral functions. Though these studies provide evidence of energy reduction by altering parameters of machine tools, quality of products produced by these machines is largely unexplored.

Furthermore, manufacturing operation processes collectively consume significant amounts of energy. Accordingly, different models have been introduced to predict and optimise energy consumption during operation processes. As Giret et al. (2015) emphasised production processes are the main elements that contribute to energy efficiency and output quality. Hence, optimisation of manufacturing processes can be advanced to minimise energy consumption and thus CO_2 emission while maintaining the machined product quality. Despite their important roles in sustainability, research on operation process in relation to energy efficiency is still limited. In addition, among the non-production processes, heating, ventilation and air conditioning (HVAC) systems account for more than 50% of the total energy consumption as illustrated in Figure 1.2 (U.S. Energy Information Administration, 2010).

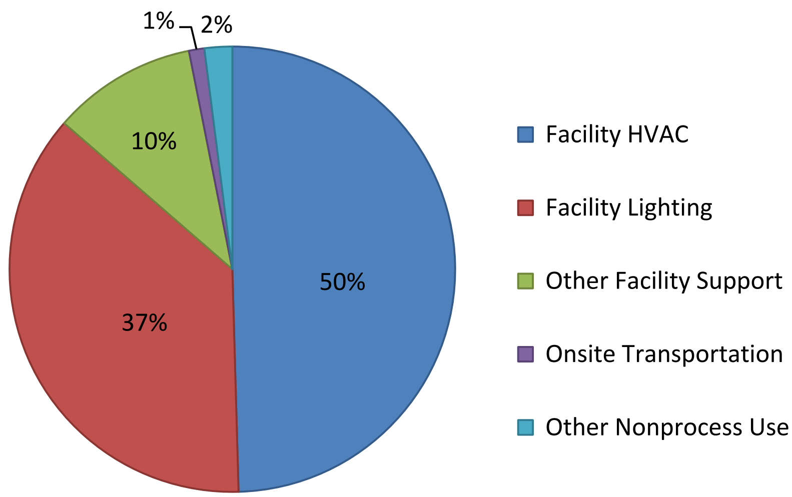


Figure 1.2. Total energy consumption of non-production manufacturing process (U.S. Energy Information Administration, 2010)

In sum, the development of energy efficient system in sustainable manufacturing needs to integrate all applicable levels in the manufacturing plant particularly product, machine, system and process (Giret et al., 2015). An investigation on an individual level would provide a limited scope of knowledge in energy efficiency. Primarily, the production process level is considered the main source of impact on production including cost, energy efficiency and product quality (Trentesaux and Prabhu, 2014). In other words, production process determines the crucial outcome components towards sustainable manufacturing.

To extend the current knowledge and energy efficient management system in sustainable manufacturing, the primary purpose of this thesis is to develop an energy and resource efficient simulation system that models and optimises energy efficiency of the overall manufacturing plant. Specifically, it builds upon past research by considering the weather temperature, ambient shop-floor temperature and temperature at machining in predicting energy consumption of different manufacturing levels.

1.2 Aim and Objectives of the Research

This research project aims to investigate an integrated energy-resource efficient sustainable manufacturing approach and its underlying manufacturing science, which enable quantitative analysis of energy consumption in manufacturing systems so as to render timely in-process decision makings for energy-resource efficient production.

The distinct objectives of this research are:

- To undertake a critical review of the relevant research field and develop the scientific understanding of the state of the art and knowledge gaps in the research area.
- To develop an integrated sustainable manufacturing approach for energy-smart workload management, and the associated predictive control.
- To undertake the correlation analysis on energy consumption, ambient temperature and dimensional accuracy (quality) in sustainable precision machining of aluminium components.
- To develop the in-process virtual simulation for energy-resource efficient manufacturing against the precision manufacturing case study.
- To carry out the experimental trials using the approach and simulations developed, and precision machining scenarios, including HVAC system within the e-ProMan.

1.3 Research Significance and Challenges

In accordance with the key elements of sustainability, the results of this research are expected to have significance and implications that can be applied to solve environmental, economic and social issues. An understanding on correlation relationships between the proposed factors would have an impact on conversation of energy resources while producing manufacturing products that meet a standard quality in an economically efficient way. Manufacturing could adopt the proposed energy-smart production management and apply to the existing energy system in order to reduce energy consumption and CO_2 emission.

For the academic community, the thesis will advance knowledge on energy consumption and energy management system in manufacturing particularly simulation modelling of energy-efficient system. The thesis also provides a more advanced understanding of energy consumption concepts and environment concerns in manufacturing environment. The findings will provide knowledge as the next step for further development of a simulation model for HVAC and production planning considering energy flow, work flow and quality flow.

1.4 Scope of the Dissertation

The thesis is organised into seven chapters. The structure of the subsequent chapters is as follows:

Chapter 2 reviews the concepts and current literature on sustainable manufacturing, energy consumption which includes direct and indirect energy and energy consumption in building and manufacturing, energy efficiency which explores the calculations and levels of analysis, and low carbon manufacturing. ISO 50001 standards are briefly reviewed and are followed by the topic of energy management system in manufacturing. The significance of energy management system, modelling and control systems are described. The chapter concludes with a summary which stresses the current research gaps as shown in the literature.

Chapter 3 presents the Energy-smart Production Management (e-ProMan) system as a simulation modelling of the manufacturing energy management system by first describing the methodology of simulation modelling. Equipment, and measurement and software tools used in the e-ProMan system are explained.

Chapter 4 investigates the research area of precision machining in sustainable manufacturing. It extends the work on the e-ProMan system by focusing on the analytical correlation between energy flow, temperature flow and quality flow to determine the relationships and potentials for the optimal solution for high quality machined product in energy-efficient manufacturing.

Chapter 5 examines the energy and resource-efficient simulation modelling system of production processes in order to model and optimise the machine workload capacity for the energy- and cost-efficient process in manufacturing.

Chapter 6 demonstrates the implementation and results of the simulation examining shop-floor temperature, forecast weather and energy consumption of the HVAC system. It also presents experimental trials in order to integrate the thermal effect, quality of the product, production and workload processes and relationships between the three aforementioned flows to gain a more comprehensive understanding of energy efficiency at machine, process and plant levels in sustainable manufacturing.

Chapter 7 provides the final remarks of the thesis by concluding on the research objectives and knowledge contribution to sustainable manufacturing. Limitations are acknowledged, and directions of future work are recommended.

Figure 1.3 provides an overview of the thesis flow diagram with chapters listed above.

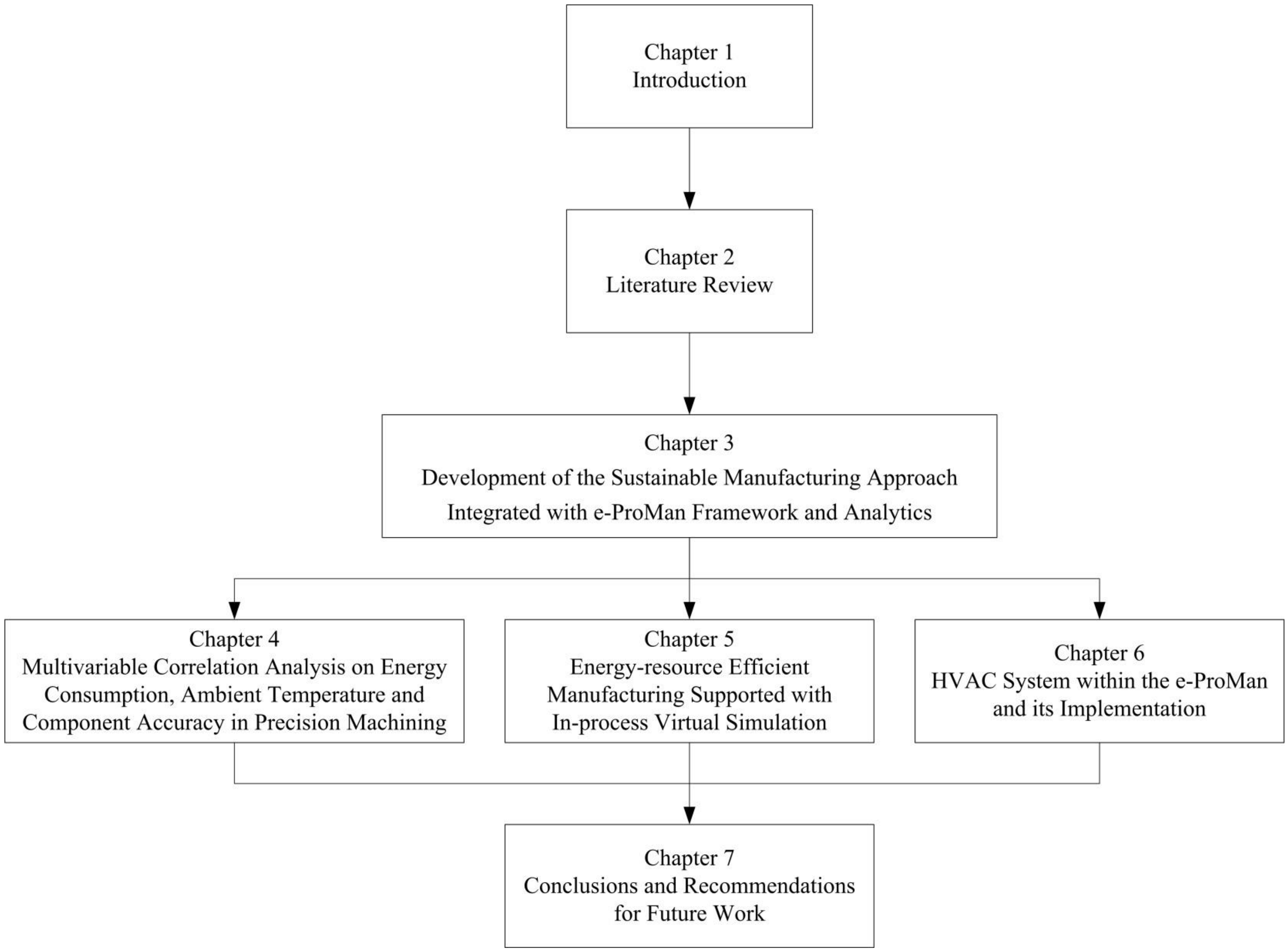


Figure 1.3. Overview of thesis structure

CHAPTER 2

Literature Review

This chapter presents a clear understanding of sustainable manufacturing and low carbon manufacturing concepts, followed by identification and discussions of standards-based environmental, energy consumption and CO_2 emissions and energy management systems in the industrial environment.

2.1 Introduction

For both academics and practitioners, energy consumption and environmental impact has been one of the core topics within manufacturing. Currently, there are various schemes and initiatives that aim to provide useful information about sustainable practices in manufacturing. This research involves the setting, measuring and reporting of reduction targets for climate impacts such as carbon emissions. In particular, it addresses the monitoring and reporting of energy consumption and carbon dioxide emissions and the labelling of these environmental impacts for a more thorough understanding of the levels of global sustainability in manufacturing.

2.2 Sustainable Manufacturing

In principle, sustainable manufacturing involves the study of innovations, environmental concerns, renewable energy, waste elimination and implementations of energy efficiency (Jayal et al., 2010; Carlsson et al., 2008). In order to provide quality standards for human life, manufacturing sectors must be made sustainable throughout the product, process and systems levels by considering their relevant complexity issues (Jayal et al., 2010). Therefore, instead of focusing on an isolated level, efforts towards sustainable manufacturing should be established consistently at these three levels (Jayal et al., 2010).

2.2.1 Sustainable Manufacturing Conception

Currently, there are disparate definitions of sustainable manufacturing. By 1992, over 70 different definitions had already been introduced (Kirkby et al., 1995). For instance, Polunin (1985 cited in WCED, 1987) defined sustainable development as "*a development that meets the needs of the present without compromising the ability of future generations to meet their* *own needs*". More recently, sustainability explained by Lozano (2008) emphasises on the capability to optimise the organisational performance which includes environmental, economic and social viability. According to the widely cited definitions from recent literature, three sustainability criteria suggested are illustrated in Figure 2.1 (Lozano, 2008). The three sustainability criteria collectively formulates that, at a meso level, sustainability is an essential matter that is embedded and implemented throughout all manufacturing stages including business models, processes, systems, and products and services in order to satisfy the established conditions of environmental, economic and social concerns (Garetti and Taisch, 2012).

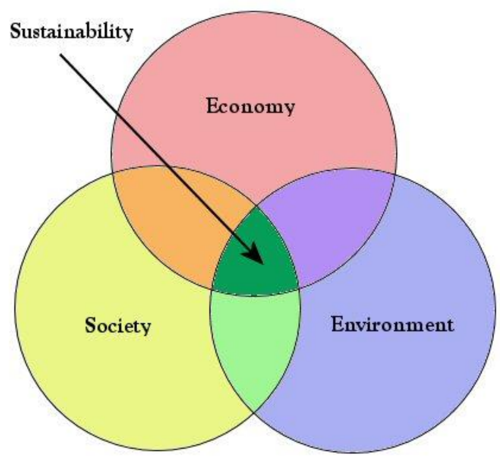


Figure 2.1. Sustainability criteria (Lozano, 2008)

Regarding environmental concerns and challenges, manufacturers need to optimise the use of natural resources, especially non-renewable resources, by efficiently promoting and managing them while minimising any potential adverse impact on the environment. In this connection, the economic criterion demands manufacturers to respond by maintaining new developmental and competitive advantages that can assure wealth and services not only to the industry but also to the broader society. Congruently, challenges of the social concerns involve a quality of life and social development of all individuals within the society which can be improved through wealth and job value creation (Jovane et al., 2008).

2.2.2 Evolution of Sustainable Manufacturing

Currently, researchers have been striving to advance manufacturing operations performance using both qualitative and quantitative criteria. As reported by the U.S. National Council for Advanced Manufacturing, sustainable manufacturing comprises of two main elements which are (1) the sustainable manufacturing applicable to all products accounting for the full life cycles and (2) the manufacturing of sustainable products including manufacturing of energy efficiency, renewable energy, and green building (National Council for Advanced Manufacturing, 2009). From this point of view, integration of sustainable principles, operations, product and services must be performed (Jovane et al., 2008). Therefore, manufacturers must take environmental issues into account alongside the extant manufacturing processes and must also provide advanced development in response to meet the most challenging demands of the society (Byrne and Scholta, 1993).

After a lean manufacturing system was broadly and successfully implemented with the concept of 3R methodology (reduce, reuse, recycle), a development of sustainable manufacturing was then initiated by focusing on the innovation-based 6R methodology to not only reduce, reuse and recycle but also to recover, redesign, and remanufacture the products over the close-loop life-cycle system (Jayal et al., 2010).

Emphasising on the 3R methodology, reduce refers to minimising the use of resources in pre-manufacturing, reducing the use of energy and materials during manufacturing processes, and the reduction of waste throughout the relevant processes (U.S. Environmental Protection Agency, 2008). Reuse involves the reuse of the components of the product or the product itself in order to minimise the usage of new raw materials (U.S. Environmental Protection Agency, 2008). The development of converting used materials or waste into new materials or products is referred to as recycle (U.S. Environmental Protection Agency, 2008). With regard to the additional elements specific to the 6R methodology, recovery concerns the process of organising products for utilisation in the subsequent product life-cycles (U.S. Environmental Protection Agency, 2008). Design for the environment is a development of redesigning products to create sustainable products as redesign products (U.S. Environmental Protection Agency, 2008). Finally, the scope of remanufacturing includes re-processing of the used products in order to restore to their original form or a like-new state with full functions (U.S. Environmental Protection Agency, 2008). Figure 2.2 demonstrates the evolution of sustainable manufacturing concept and the contribution of stakeholder value regarding 6R methodology.

Though there are a variety of perspectives on and definitions of sustainable manufacturing cited by academics and practitioners to develop new advancement in the industry, the majority of studies have similar main concepts to develop manufacturing to be sustainable manufacturing. Achieving sustainability in manufacturing requires not only a single process but the whole manufacturing system. Based on this reasoning, to develop a sustainable methodology for processes, predictive models and optimisation techniques, it is necessary to consider and target energy usage that accounts for the environmental domain of sustainability.

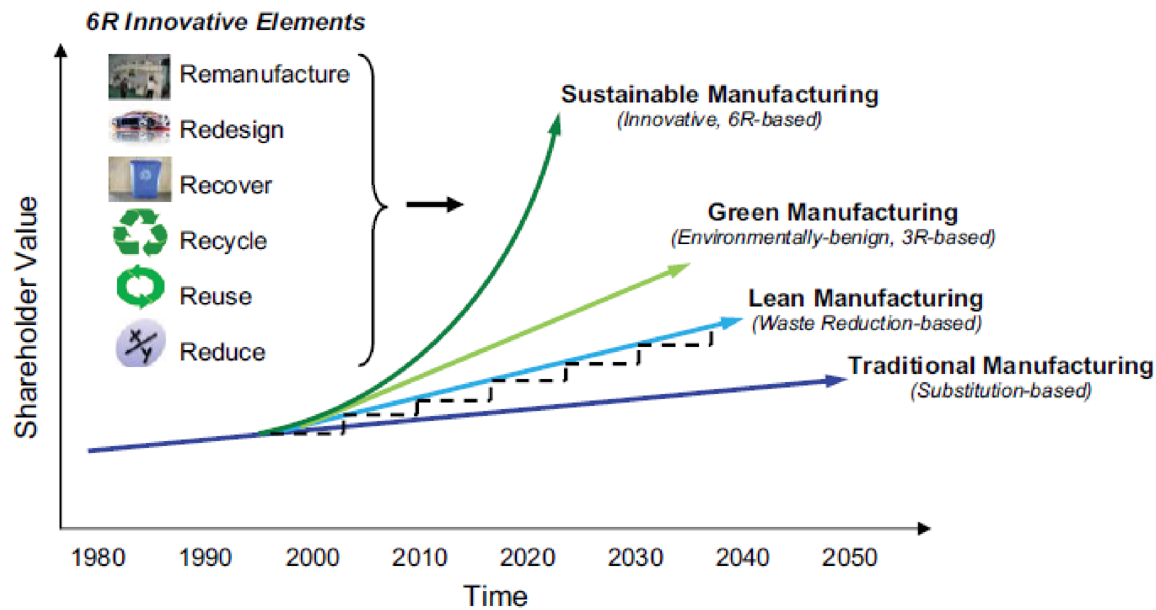


Figure 2.2. The 6R concept in evolution of sustainable manufacturing (U.S. Environmental Protection Agency, 2008).

2.3 Sustainable Precision Machining Concepts and Framework

Fundamentally, sustainability aims to improve the standards of human living while maintaining the resources for future generations (Seliger, 2007). To achieve this, the development of sustainability must consider the interdependency of the economy, society and environment (Giddings et al., 2002). The manufacturing industry has a significant contribution to make across these three dimensions of sustainability (Haapala et al., 2013).

Sustainable manufacturing has been shown to largely rely on technology, and technology - especially machining - has created solutions to effectively preserve energy and meet quality assurance needs (Geretti and Taisch, 2012). For example, various techniques and standards have been implemented to measure the energy consumption of machine tools that take into account economic and environmental aspects of sustainability in manufacturing. Since machine tools contribute to the total energy consumed during the manufacturing processes, standards have been developed to effectively assess energy consumption in order to improve the environmental performance of machine tools along with the machining operations (Nada et al., 2006; Fysikopoulos et al., 2014). Altogether, machining in manufacturing can be improved to minimise energy consumption while preserving the quality of products.

As shown in Figure 2.3, sustainable precision machining is modelled based on an inter-related relationship between product quality, ambient temperature and machining costs. In particular, the high quality of the workpiece indicates the success of product manufacturing performance that corresponds to the economic sustainability. Simultaneously, the amount of energy consumed during the machining process is taken into the modelling framework to address the environmental issues of CO_2 emissions generated during production.

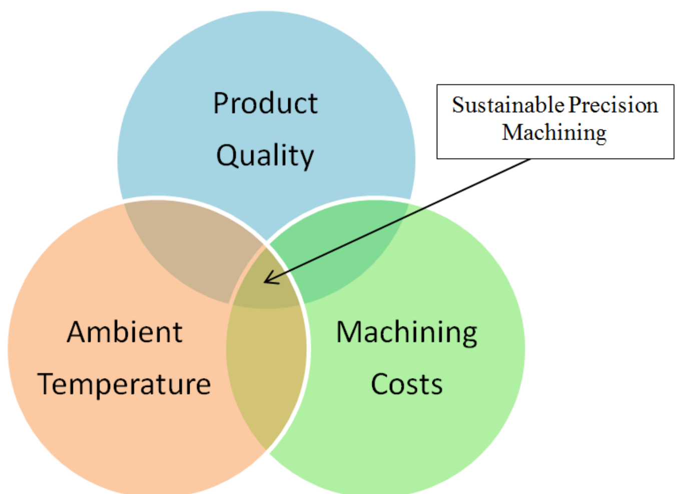


Figure 2.3. Sustainable precision machining framework

2.3.1 Product quality

A variety of factors determine the product quality of CNC precision milling including elements of a workpiece (e.g. strength, hardness, chemical position), tool (e.g. material, geometry, surface integrity), machine tool (e.g. stiffness and state of maintenance) and cutting parameters (e.g. speed, feed and depth of cut) (Grzesik, 2008). These factors have a direct impact on the life of machine tool as they are related to a rate of tool wear. In order to achieve a standard product quality, choosing a proper material, cutting tools and cutting parameters are essential.

2.3.1.1 Cutting Parameters

Cutting parameters substantially affect the product quality, tool wear and tool life of a cutting tool (Juneja, 2003). Since milling tools are generally considered vulnerable and fragile, cutting parameters in the majority of circumstances, follow a conservative approach to determining feed rates and depth of cut. However, to maintain the efficiency of machining, spindle needs to be set at a higher speed to increase volumetric material removal through an increase of the feed rate and cutting speed (Reis et al., 2007). Besides, deflection and chatter of tools should be reduced to preserve their tool life. The cutting parameters need to warrant the functional performance, dimensional accuracy and surface roughness such that machining quality can be attained (Shaw, 2005).

Research experiments have been carried out to optimise cutting parameters. For instance, experimental research conducted by Ghani et al. (2004) was performed on ASIS H13 tool steel to examine the impact of cutting speed, feed rate and depth of cut on the tool life. Among these, the results demonstrated the effects of high feed rate and depth of cut on tool failure due to high cutting forces in the milling operation. A more recent study by Natarajan et al. (2011) proposed an approach to machining parameter optimisation namely response surface methodology. It concluded that low feed rate could improve the surface finish, and moderate cutting speeds and depth of cut could improve the material removal rate.

There are three parameter conditions in the CNC milling machine, which are used for experimentation with including tools diameter, cutting speed and depth of cut (Shaw, 2005 and Juneja, 2003). The cutting speed can be determined the type of material being machined such as aluminium and the cutting tools material which is made from tungsten carbide. Also, the relationship between spindle speed and cutting speed can be calculated by using the equation below. There are two equations to be used in this experiment.

$$V_c = \frac{\pi \times D \times N_s}{1000} \tag{2.1}$$

where N_s is spindle speed (rev/min), V_c is cutting speed (m/min), and D is tools diameter (mm). The other equation is used to calculate feed per rev as shown in Equation (2.2):

$$f_z = \frac{V_f}{N_s \times z} \tag{2.2}$$

where f_z is feed per tooth (mm/tooth), V_f is feed speed (mm/min) and z is number of teeth.

2.3.1.2 Tool Wear

Tool wear is a complex issue that is impacted by a variety of factors including tool material and workpiece material, cutting parameters, machine tool characteristics and cutting fluids (Cheng, 2008). Monitoring of a milling tool is thus fundamental to optimisation of cutting parameters in order to maintain machining quality. Tool wear defines a gradual failure of a cutting tool caused by operation. In machining, this is the key issues as it generally leads to higher production cost and lowers the product quality. There are two common sources of tool wear whereby the first involves inadequate surface finish and the second involves out of tolerance of the work dimension (Cheng, 2008).

In addition, three types of tool wear exist which are established based on the locations in which a gradual wear occurs on a cutting tool: crater, flank and corner wear (Marinoy, 2006). Figure 2.4 demonstrates the specific locations of the three tool wear types.

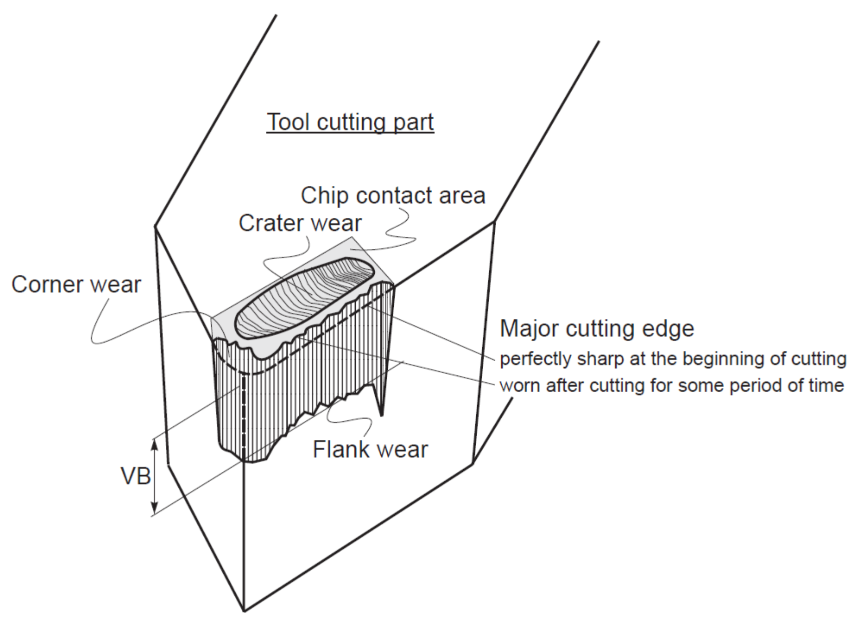


Figure 2.4. Types of wear observed in cutting tools (Marinov, 2006)

First, crater wear is localised on the rake face of the tool caused by the sliding of the chip across the surface mainly due to temperature at the tool-chip and cutting speed (Marinov, 2006). Crater wear disrupts the machining process by increasing the rake angle of the cutting tool leading to an increase a likelihood of cutting. The second type, flank wear, occurs on the relief face of the tool due to friction created by the two surfaces (i.e. machined workpiece and tool flank). The worn area of the tool is also referred as a wear land and is determined by its width labelled as VB. This type of wear also affects cutting forces. Cutting forces can turn into tool failure when greater than the set critical value (i.e. VB > 0.5 mm.). Compared to crater wear, flank wear has greater overall effects on tool cutting as it affects dimensional accuracy, surface finish and process stability. Last, as the name suggests, corner wear takes place at the tool corner. Though corner wear occurs at a segment of the wear land, several researchers consider corner wear as a distinct type of tool wear due to its distinguishing impact on machining precision in relation to dimensions (Cheng, 2008). Particularly, corner wear leads to a dimensional error in machining because it eradicates the cutting tool and therefore gradually increases the dimension of a machined surface. Figure 2.5 depicts the effects of corner wear on the dimensional error of a machined tool.

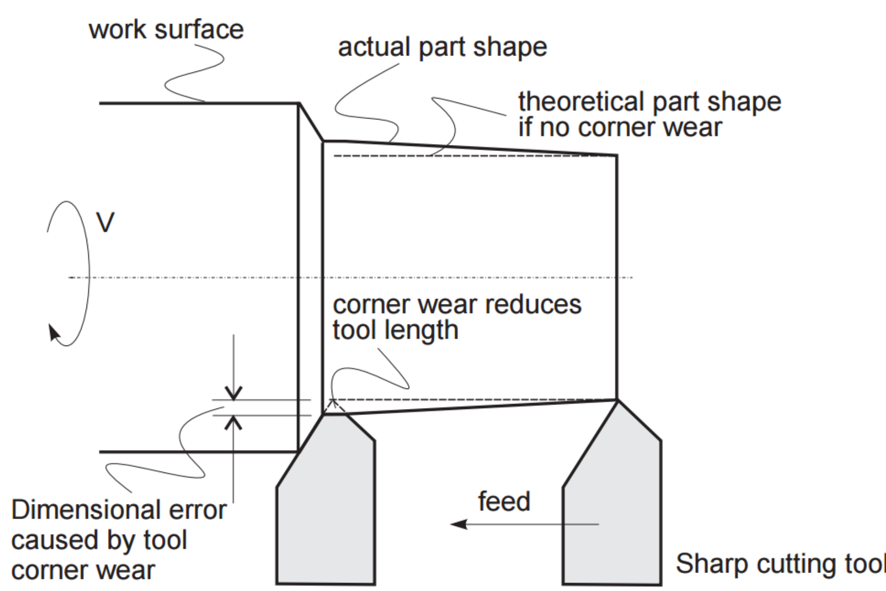


Figure 2.5. The effect of tool corner wear on the dimensional precision (Marinov, 2006)

Figure 2.6 depicts an example of a tungsten carbide milling tool wear that is seriously worn. Whatever the type of tool wear, excessive tool wear in general is detrimental to the tool life and lead to poor surface quality and, more importantly, to accuracy and precision (Jiao and Cheng, 2013).

The process of tool wear is fundamentally dependent on time as the amount of tool wear increases progressively in the process of cutting. When tool wear exceeds a specific limit, tool failure occurs. As mentioned earlier, flank wear is considered as the most critical wear type especially from the process point of view. The width of flank wear land VB is the parameter that needs to be monitored and controlled. For carbide cutting tools, VB_k is a safe limit or an allowable wear land. Tool time, labelled as T_x, is the cutting time for the tool to generate a flake wear land of width VB_k. Figure 2.7 presents a wear curve showing an association between the cutting speed (V_x) the cutting time (T_x) and the width of flank wear land (VB) (Marinov, 2006). This wear curve defines a tool-life criterion of a given wear VB_k.

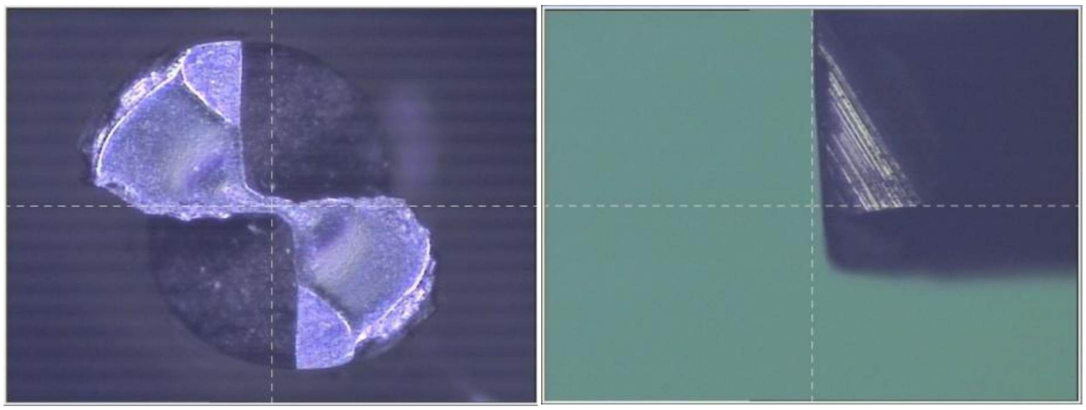


Figure 2.6. Severely worn tungsten carbide milling tool (Jiao and Cheng, 2013)

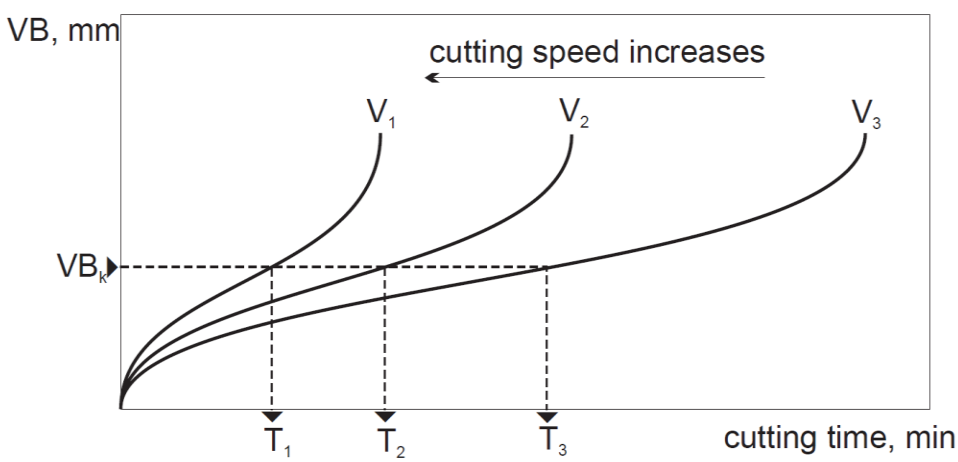


Figure 2.7. Effect of cutting speed on flank wear and tool life of three cutting speeds (Marinov, 2006)

For an end-mill cutter, the ISO 8688-2 (1989) generally recommends a use criterion of 0.3 mm for the VB_k averaged over the teeth for a uniform wear. However, the maximum safe limit can be set at 0.5 mm for a localised wear in cases of wear occurring next to the work cut-face. In line with this standardisation, Davis (1995) specified the maximum safe limit of tungensten carbine material to be 0.5 mm. Sakar (2014) stated the allowable wear land for this same tool to be 0.3 mm. Marinov (2006) suggested that a safe limit for a carbine cutting tool should not exceed 0.4 mm.

To predict the life of tool, Equation (2.3) expressed Taylor's equation of the tool life which can be used to calculate a life of different tool materials before they are repaired (Marinov, 2006).

$$V_c {T_l}^n = C \tag{2.3}$$

V_c is cutting speed (m/min) expressed in m/min. T_l is tool life in minutes. n is exponent for the conditions tested, and C is the constant which varies on tool material. Table 2.1 summarised the values for n and C in the Taylor equation (Sekar, 2014; Shaw, 2005; Juneja, 2003).

Table 2.1. n and C values for Taylor equation for various tool materials

Tool Materials	**Ranges of n values for Taylor Equation**	**Ranges of C values for Taylor Equation (Steel / Non-steel work)**
High-speed steels	0.08-0.2	70 / 120
Cast alloys	0.1-0.15	100 / 150
Carbides	0.2-0.5	500 / 1000
Coated Carbides	0.4-0.6	1000 / 1500
Ceramics	0.5-0.7	2500 / 3000

As indicated by the Equation 2.3, the tool life of an end-milling machine is dependent on various factors including type of workpiece material tool material, tool geometry and cutting conditions. It can be a complicated process to predict the tool life on the account of controllable process parameters, especially in a real workshop setting. Alauddin et al. (1997) demonstrated that the tool life of milling tool can be reduced by an increase in feed, speed and depth of cut. On the contrary, literature also showed that the built-up edge or BUE can occur at the chip interface when machine is at low cutting speed, potentially resulting in a more immediate tool wear (Reis, 2007). Dimensional metrology can be applied to quantify the width of tool flank wear in end-milling process in order to determine the actual tool life.

2.3.1.3 Dimensional Accuracy Measurement

To determine product quality, the present research adopts dimensional metrology which is generally defined as a measurement of product 'dimensions'. The dimensional measurement is used to investigate the dimensional error of product in terms of product quality. Absolute error (e) is the amount of physical error in a measurement period (Baird, 1995).

$$\text{Absolute Error (e)} = y_i - x_i \qquad (2.4)$$

where i is the number of reference points; x_i is the nominal value of dimensions; y_i is the actual measured value of dimensions.

Relative error or Percent error (%error) gives an indication of how good a measurement is relative to the size of the thing being measured. The relation error is used to determine the comparative accuracy of the measurements.

$$\text{Percent Error (\%)} = \left|\frac{Absolute\ Eror}{x_i}\right| \times 100 \qquad (2.5)$$

where y_i is the actual measured value of dimensions.

2.3.2 Ambient Temperature and Environment Control

Cutting temperature is well documented as a critical factor in machining process including its influence on tool wear, surface generation and integrity, cutting force, material properties and machining accuracy (da Silva & Wallbank, 1999; Jiao & Cheng, 2013). Research has highlighted that a small amount of heat generation during cutting can result in a significant expansion of tool material, thus degrading machining accuracy (Moriwaki, 1990). While a bulk of research has shown an effect of thermal deformation on machining errors, evidence of a relationship between ambient temperature and accuracy is rather scarce. However, it is logical to expect that the ambient temperature in the machining process could affect the quality of the product workpiece. Not only does ambient temperature needs to be controlled according to the regulations, but it is also important to reach the highest standard of product quality.

2.3.2.1 Thermal Effects

Typically, most materials expand as the temperature increases (Leach, 2014; Wilson, 1942; Cverna, 2002; Bryan, 1990). The International Standard Organization (ISO 1:2002) sets the standard temperature for gauge block measurements to be at 20°C. Due to thermal expansion, increased temperature causes the gauge blocks to change in size. Thus, it is important to set the temperature to the standard reference condition. The measurement of the gauge block temperature should be performed concurrently with measuring the manual's length to adjust for a change in the length. The correction equation is described by Equation (2.6).

$$L(T) = L(20) \times (1 + \alpha[T - 20]) \quad (2.6)$$

where T is the temperature in °C; $L(T)$ is the length at T; $L(20)$ is the length at 20°C; and α is the thermal expansion coefficient (Leach, 2014). The equation demonstrates that when the coefficient value is large, the temperature measurement needs to be more accurate, and when the temperate deviates from 20°C, the effect of materials' thermal expansion coefficients becomes more significant (Leach, 2014).

2.3.2.2 Temperature Control in Precision Machining

As stated by the UK Workplace Regulations 1992 (Health, Safety and Welfare) (Health and Safety Executive, 2013), *"The temperature of indoor workplaces should be reasonable. The approved code of practice defines a reasonable temperature indoors as being normally at least 16°C unless the work involves severe physical work in which case the temperature should be at least 13°C".* These standards are regulated to assure the quality of machine and well-being of operators at work.

According to an established 'dead band', manufacturing needs to set a cost-saving and stringent requirement on temperature and thermal aspects based on the region of 4 - 5°C between heating and cooling thermostat set points (Carbon Trust, 2011). Ideally, in light-scale factories such as laboratories, the temperatures should range between 16°C and 19°C, whereas the temperature in heavy manufacturing needs to be controlled at a range of 11°C to 14°C (Carbon Trust, 2011).

2.3.3 Machining Operation Costs

By definition, a production cost is the average total cost required to perform a particular machining operation. In manufacturing, the production often comprises of various machining operations using assorted machine tools. Thus, the total product cost includes the production of different components. Equation (2.7) expresses the total cost of a single machining operation C_{pr} which is the sum of the energy cost C_m, tool cost C_t and labour cost C_L (El-Hofy, 2013).

$$C_{pr} = C_m + C_t + C_L \tag{2.7}$$

The machining cost C_m can be calculated by Equation (2.8) which C_e the sum of the power cost consumed by the machine, and C_{sm} is the cost of servicing the machine.

$$C_m = C_e + C_{sm} \tag{2.8}$$

Machining economics are affected by various factors depending on a type of operation such as spindle speed, feed rate and depth of cut (Juneja, 2003).

2.4 Energy Consumption in Manufacturing

Energy is a broad term that is commonly used interchangeably to refer to work, heat and power. For academics and practitioners, energy has a scientifically specific meaning. At the broadest level, energy defines "the capacity of doing work" (Schobert, 2014, pp. 13). As the energy cost accounts for a significant proportion of the total product cost, energy saving is one of the major challenges faced by manufacturers (Mani et al., 2008). Different types of machine tools consume varied amounts of energy (Diaz et al., 2009). Experiments by other researchers have been carried out at a process control level and also at a system level to better determine the environmental impacts of machining (Behrendt et al., 2012; Diaz et al., 2009; Lanz et al., 2010; Newman et al., 2012; Dahmus and Gutowski, 2004). These results can potentially lead to practical methods that effectively minimise adverse impacts on the environment. For example, experiments at the process-level have been conducted to reduce the energy usage in the machining process through improvements in, cutting tools, cutting parameters, tool-workpiece contact mechanics and machining procedure (Behrendt et al., 2012; Diaz et al., 2009; Newman et al., 2012).

2.4.1 Direct and Indirect Energy Consumption

In addition to addressing energy consumption at the two levels, the investigation of this research also considers direct and indirect energy consumption during different production activities of the manufacturing application. These two categories of energy consumption are both required to operate the manufacturing processes and to calculate the total energy consumption (Schlosser et al., 2011). In particular, as the name suggests, direct energy is the sum of energy that directly flow into the machine tool and are consumed by different processes to manufacture a product. On the other hand, the indirect energy defines the energy consumed at the periphery of the machine tool. This category of energy involves the activities that are necessary to maintain the environmental conditions that enable the manufacturing performance within the plant (Seow and Rahimfard, 2011).

Therefore, the total energy consumed E_{total} by a machine tool carrying out to perform a specific process can be expressed by Equation (2.9) where $\mathrm{E}_{process}$ can be regarded as direct energy that largely depends on process parameters and $\mathrm{E}_{peripherals}$ expresses indirect energy where energy background differs depending on the specific machine tool used (Salonitis and Ball, 2013).

$$E_{total} = E_{process} + E_{peripherals} \qquad (2.9)$$

2.4.2 Energy Consumption in Factory Plants

The research in manufacturing literature has investigated energy consumption from two different prospect levels namely plant and process. The plant level concentrates on energy consumption at infrastructure and high-level services that are accountable for controlling and managing the required conditions and surroundings during the production (Seow and Rahimifard, 2011). Heating and cooling, ventilation and lighting are examples of energy activities consumed at the plant level.

This simplistic approach, however, infers several assumptions derived from the multiple sources of factors that might alter the amount of energy consumed during the operations such as data acquisition system (DAS) and energy losses and gains that are accounted for by different power generation techniques. Other circumstances also include seasonal, temperature, climate and relative humidity variations. Consistently, building performance can be affected by these potential variations and fluctuations of maintenance, resulting in data ambiguity. Another plausible cause of data ambiguity involves uncertainties or the estimation of limits of the error that occurs during energy consumption measurement and calculation. Uncertainty differs from measurement error as errors define the extent to which the measured value is deviated from the true value. Uncertainty estimates should address all sources of error that occur at random or systematically.

However, realistically, there are many factors to affect energy usage of a machine, a system or a process as it comprises of different components that may consume energy differently. One common way to calculate the energy consumption of machine is the energy block method which concerns the behaviour of energy consumed by each specific machine (or 'block') during its specific operating state (e.g. standby, processing, and turned off) (Cataldo et al., 2015). An overall energy consumption of machines is computed from energy profiles of each operating state.

Furthermore, a manufacturing process level encompasses a set of processing stages where machining of high production activities typically occurs. The processing stages within some processes may be combined into a single equipment or machine such as a present-day milling machine that consists of different functions (e.g. work handling, tool changes, tool break detection, machine lubrication and chip removal) (Gutowski et al., 2006). Chiefly, these functions are conjoining functions of the main function of the milling tool that can dominantly control the energy requirements at the process level. Other processes exhibit this same behaviour. In general, there is a significant energy requirement to start-up and maintain the equipment in a "ready" position. Once in the "ready" position, there is then an additional requirement which is proportional to the quantity of material being processed.

Energy consumption of a manufacturing process refers to the amount of energy consumed in a production process (Honczarenko and Berliński, 2012). Following the notion of direct and indirect energy, energy consumption in a production system can be summarised by three main parts as shown in Figure 2.8.

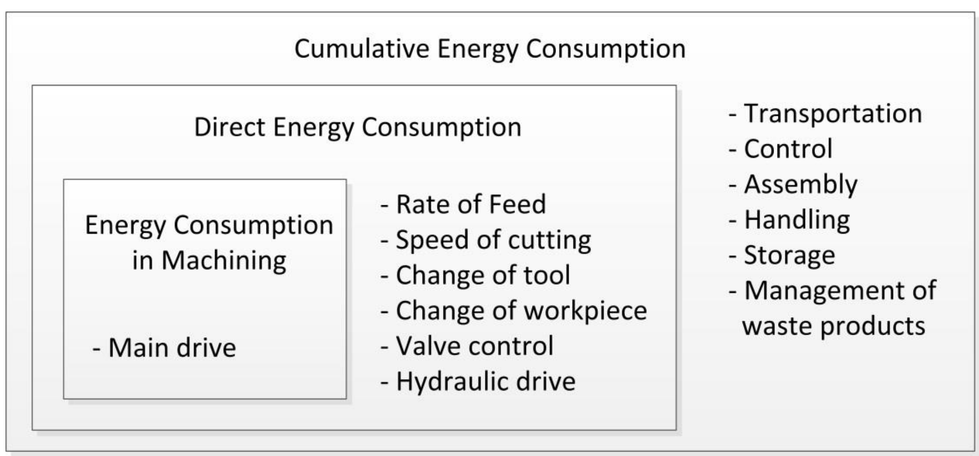


Figure 2.8. Three main parts of energy consumption of manufacturing process (Honczarenko and Berliński, 2012)

Put differently, the direct energy consumption consists of energy consumed directly at machining together with a variety of machining allowances such as rate of feed and change of workpiece. The direct energy consumption is expressed in Equation (2.10) where E_c defines energy consumption of cutting (Watt), k_r defines specific resistance of cutting (N/mm^2), K_i defines correction coefficients and V_i defines volume of material (mm^3) (Honczarenko and Berliński, 2012).

$$E_c = k_r \cdot 10^{-3} \cdot \prod_{i=1}^{n} K_i \cdot V_i \tag{2.10}$$

Adding indirect energy (i.e. energy consumed in auxiliary processes such as transportation and handling), the total indirect energy consumption (E_t) can be calculated by the Equation (2.11) where t_g signifies the time of production station whereas t_j signifies the time of idle run. The average power of a system during work operation is denoted by P_i.

$$E_t = \sum_{i=1}^{n} P_i \cdot (t_g + t_j) \tag{2.11}$$

The total energy consumption (E_{Tt}) can be calculated by Equation (2.12), where E_c defines energy consumption of cutting, and E_t defines the total indirect energy consumption.

$$E_{Tt} = E_c + E_t \tag{2.12}$$

In particular, the energy consumed by the auxiliary processes to maintain the environment of a production process is shown to account for 60 to 90 percent of the total energy consumption (Honczarenko and Berliński, 2012). Using the automotive machine line as an example, Figure 2.9 shows that the actual machining process (i.e. direct energy) requires only about 14.8% of the total energy use or smaller percentages if the machine is operated at lower production rates.

As summarised in Figure 2.10, energy consumption during the production phase at both plant and process viewpoints would provide a more comprehensive understanding and more accurate information on energy consumption in manufacturing.

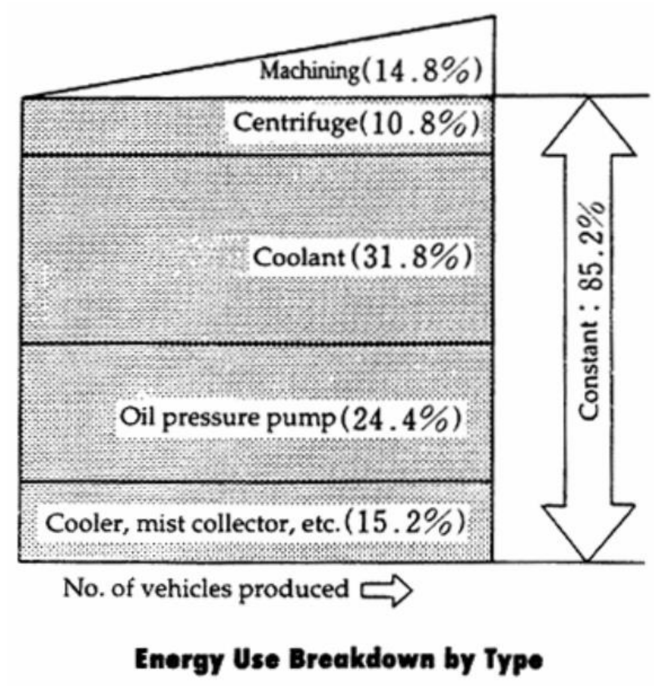


Figure 2.9. Energy at machining and auxiliary processes for an automobile production machining line (Gutowski et al., 2006).

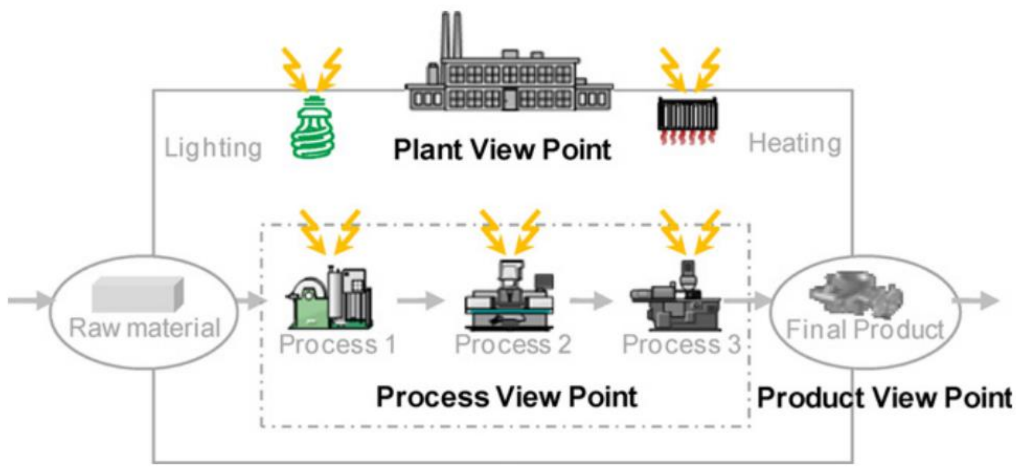


Figure 2.10. Plant, process and product viewpoints to energy flow modelling in manufacturing (Seow et al., 2011).

2.5 Energy Efficiency

Efficiency, or denoted by η, is a measurable term commonly expressed by a ratio of output to input as expressed in Equation (2.13).

$$\eta = \frac{Output}{Input} \tag{2.13}$$

Following this equation, efficiencies thus range from 0 indicating complete inefficiency to 1 indicating a complete efficient process. Since the efficiency ratio is unitless, the calculation can be applied to any parameter (Schobert, 2014).

2.5.1 Energy Efficiency Calculations and Indicators

The term energy efficiency can be operationally defined from the two viewpoints that are, to a certain extent, contrasting but yet related: physical and monetary (Lovins, 2004). From an economic perspective, energy efficiency is viewed from a monetary output / physical input ratio in which monetary units such as money flow are defined as the efficiency parameters. In contrast, engineers define efficiency based on a physical output/ input ratio (Lovins, 2004). Using heat engine as an example, efficiency can be mathematically expressed by Equation (2.14), where T_h indicates high temperature (i.e. difference between the temperature and absolute zero), and $T_h - T_l$ signifies a decline in temperature (Schobert, 2014).

$$\eta = [\ (T_h - T_l)\ /\ T_h\ ] \tag{2.14}$$

In this connection, there is thermodynamic efficiency which is defined by Equation (2.15) where $\mathrm{W_{net}}$ is the useful work produced in a heat engine, and $\mathrm{Q_H}$ is the heat transferred from the hot areas (Turner and Doty, 2007).

$$\eta = \frac{W_{net}}{Q_H} \tag{2.15}$$

Parallel to the above efficiencies, the efficiency of a device operating in a process line can also be calculated using Equation (2.16) (Hordeski, 2004).

$$\eta_{device} = \text{actual energy transfer/ ideal energy transfer} \tag{2.16}$$

Jeswiet and Kara (2008) implied that improving machines and equipment, which can reduce CO_2 emission, are one of the key solutions to minimise the energy consumption. Moreover, Lovins (2004) agreed that energy efficiency has led the manufacturing to become economical and environmental manufacturing. Collectively, energy efficiency significantly contributes to potential economic growth by reducing the cost of manufacturing products and services by means of achieving ‘lower energy costs potentially resulting from reduced amount of energy consumed (Dinçer and Zamfirescu, 2011). In addition, it is also worth noting that while energy efficiency and energy conservation are often used interchangeably, the two terms have distinguishable implications (Herring, 2006). As described above, energy efficiency emphasises on the ratio of energy output and input. On the other hand, the objective of energy conservation is to lower energy consumption often through reducing energy service quality.

2.5.2 Quantitative Analysis on Energy Efficiency

Prior research on energy efficiency in manufacturing has examined energy consumption at various levels, which differs in terms of their assumptions and input. In Duflou et al.’s (2012) review paper, optimisation of energy efficiency covers five analytical levels: device/process, multi-machine system, facility, multi-factory system, and global supply chain. Similarly, Fysikopoulos et al. (2013) identified four hierarchy yet interrelated levels of analysis as process, machine, line and factory respectively. Salonitis and Ball (2013), on the other hand, proposed a more generic approach to energy efficiency analysis, which reflects only at two broad levels: machine tool level and manufacturing system level. Despite differing taxonomy in the literature, this dissertation recognises the importance of distinguishing characteristics between machine and process levels as machine tool level and process level are justified by a different mechanism of energy loss on these two levels (Fysikopoulos et al., 2013). Therefore, the following sections review energy efficiency on the three main levels in manufacturing: machine, process and plant.

2.5.2.1 Energy Efficiency on the Machine

Generally speaking, energy efficiency on a machine level aims to reduce energy consumption of machine tools. Within this level of analysis, one stream of research has focused on measuring energy consumption of machine tools as a means to optimise energy efficiency. Among these studies, Dahmus and Gutowski (2004) examined three main modes of machine tools: off, idle and operating. More recently, Behrendt et al. (2012) extended on the aforementioned modes and studied standby power, component power and machining power of a variety of machine tools mostly medium-sized and large-sized. Generally, energy usage of machines can be reduced by turning off inactive equipment during set-up and by minimising wait times.

Another stream has monitored energy consumption of specific components or conditions of machine tools such as modification of cutting conditions. For example, the study of Mori et al. (2011) showed that energy consumption in milling machines could be reduced by adjusting the cutting conditions to minimise the machining time. However, the cutting conditions need to be within the appropriate range to avoid compromising the quality of the machine components. Similarly, Oda et al. (2012) found that by optimising inclined angle and cutting speed, energy consumption can be reduced.

A review of literature also reveals two approaches to energy efficiency on a machine level. The first approach focuses on estimation energy demand using analytical models, and the second approach focuses on the reduction of energy demand. In line with this, Kianinejad et al. (2015) described Specific Energy Consumption (SEC) as “the energy consumption of machine tool for removing 1 cm^3 of material”. This SEC unit is thus used as an indicator of energy efficiency performance.

2.5.2.2 Energy Efficiency in the Process

Management of energy efficient system at a process level is of particular importance since the transformations of energy occurs during processes. Consumption of machine peripherals and production planning can also be modified by adjusting process parameters, thereby altering the overall energy consumption in manufacturing. Fysikopoulos et al. (2013) highlighted that though the process level consumes relatively less energy, energy efficiency at this level largely contributes to the overall energy efficiency maximisation. There have been various approaches towards process energy efficiency such as optimisation of process parameters, optimisation of process capacity, changing technologies of the production and reducing the unproductive ideal time during operations (Duflou et al., 2012).

To increase energy efficiency, Neugebauer et al. (2011) described that processes in relation to product features and specifications need to be defined such that alternative solutions to a more energy-efficient process can be evaluated. In doing so, process energy demand and consumption of resource can be applied. For instance, grinding consumes a larger amount of energy than turning, thus making grinding a more energy-efficient process.

2.5.2.3 Energy Efficiency in a Manufacturing System

Energy efficiency on a plant level follows a more comprehensive and holistic approach because it involves all relevant production systems including machine components, machine tools, and production lines (Neugebauer et al., 2011). The most challenging element to improve the efficiency of the manufacturing plant is explained by the interrelated relationships of production systems and manufacturing plant services (Müller and Löffler, 2009). In other words, an analysis of energy usage requires information of all energy consumption behaviours (Cataldo et al., 2015). All in all, improvement of energy efficiency depends on the manufacturing processes which includes all interactions between each resource, processes and structures of a plant (Dietmair and Verl, 2009).

Furthermore, Fysikopoulos et al. (2013) described a newly optimised energy-efficient system might show potentials in energy consumption reduction. However, due to different policies and tariffs, the system may not necessarily result in energy cost reduction. In other words, the system can potentially respond efficiently to the environmental concerns but not to economic concerns of sustainability. Therefore, there are great opportunities to advance an understanding of energy efficiency at this level.

2.6 Low Carbon Manufacturing

In the manufacturing industry, electrical energy is the main energy for all machine processes and tools (Jeswiet and Kara, 2008). Jeswiet and Kara (2008) stated that energy usage in the manufacturing procedure was the main cause of the carbon emissions to the environment. The steady rise of carbon dioxide (CO_2) emissions is one of the major factors that cause global warming problem that affects the world population (Bose, 2010) (Köne and Büke, 2010). Since the industrial revolution, the use of fossil fuels has rapidly increased due to the role they play in electricity generation, yielding a significant proportion of greenhouse gases (Köne and Büke, 2010). Currently, low carbon manufacturing systems are not yet fully applied to industrial systems. Nonetheless, alternative sources of energy and renewable energy have been discovered to cope the global warming issue and sustain the manufacturing (Köne and Büke, 2010).

2.6.1 Characterisation of Low Carbon Manufacturing

Tridech and Cheng (2008) explained that the low carbon manufacturing process can represent the quantity of carbon dioxide (CO_2) intensity released at the machine level throughout the plant level. More specifically, there are five components of low carbon manufacturing characteristics that identify the amount of carbon emissions in the process. In order to reach the concept of low carbon manufacturing, these five elements have to be illustrated and achieved as shown in Figure 2.11 (Tridech and Cheng, 2008).

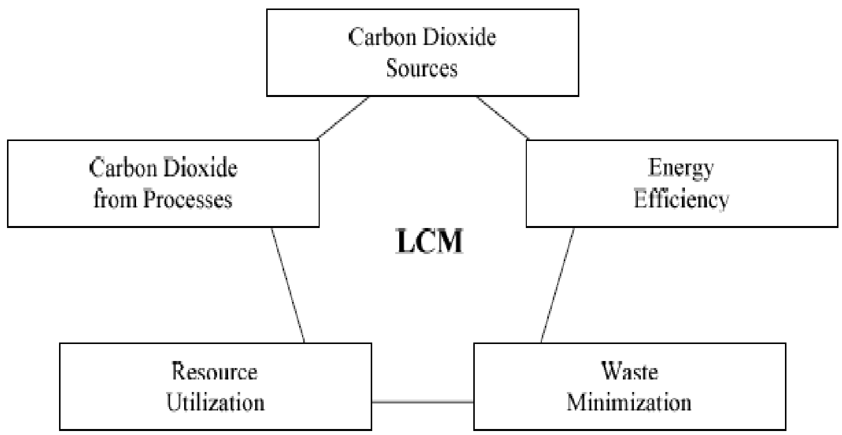


Figure 2.11. Characterisation of low carbon manufacturing (Tridech and Cheng, 2008).

2.6.2 Manufacturing Carbon Footprint

'Carbon footprint' is a term that defines the proportion of greenhouse gas (GHG) emissions caused by activities or entities (Carbon Trust, 2008a). Carbon dioxide (CO_2) mainly causes greenhouse gases in the atmosphere. From the energy point of view, the generating electricity through fossil fuel combustion is a process leading to a large amount of CO_2 emissions (Jeswiet and Kara, 2008). In addition, carbon dioxide from global average energy causes around 60% of the anthropogenic greenhouse gas emissions, globally (Carbon Trust, 2008a).

In every industry, electrical energy is the foremost source for all equipment and machines (Jayal et al., 2010; Carbon Trust, 2008a; Jeswiet and Kara, 2008). Jeswiet and Kara (2008) stated that the primary energy source was an electrical power grid. Carbon emissions are initiated at the point whereby the primary energy is transformed into electricity (Jeswiet and Kara, 2008). Illustrated in Figure 2.12, energy sources as the primary energy are broadly classified into carbon emissions sources including coal, oil and natural gas, and non-carbon emissions sources labelled as ‘green energy’ such as biomass, hydro, nuclear and solar.

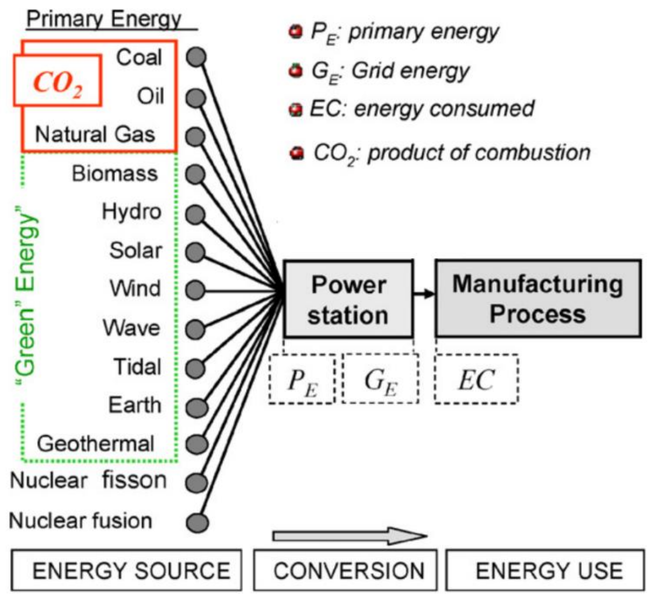


Figure 2.12. Primary energy supplies available (Jeswiet and Kara, 2008).

2.6.3 Quantitative Analysis on Manufacturing Carbon Dioxide Emission

The carbon footprint in manufacturing system can be evaluated using the equation of Carbon Emission Signature (CES) stated by Jeswiet and Kara (2008). In this equation, the carbon emitted CE is calculated by multiplying energy consumed (EC) (GJ) by Carbon Emission Signature (CES) [$\frac{(kg \cdot CO_2)}{Gj}$] as shown in the Equation (2.17) below.

$$\mathrm{CE} = \mathrm{EC} \times \mathrm{CES} \tag{2.17}$$

However, there are one or more primary energy sources for an electrical grid which are coal, natural gas, petroleum, biofuel, hydro, solar, wind, geothermal, earth, wave and tidal. Each of these can be represented with functions: C (coal), NG (natural gas), P (petroleum), B (biofuel), H (hydro), S (solar), W (wind), G (geothermal), E (earth), W (wave) and T (tidal). To calculate the Carbon Emission Signature (CES), the summary of fractions of the primary sources is multiplied by the conversion efficiency (η) for each of the primary energy sources as defined in Equation (2.18) below.

$$\text{CES} = \eta \text{ x } [(112 \times \%\text{C}) + (49 \times \%\text{NG}) + 66 \times \%\text{P}] \quad (2.18)$$

The coefficients of coal (C), natural gas (NG), and petroleum (P) are 112, 66, and 49 respectively, and they are the kilogrammes of carbon emitted per gigajoule of heat releases and are an inevitable fate of combustion in each case. The conversion efficiency (η) = 0.34 is commonly accepted (Carbon Trust, 2008b).

Regarding energy consumption, the amount of CO_2 emissions is computed by the multiple of activity data by CO_2 emissions conversion factor in the unit of kWh and kg carbon dioxide equivalent ($kg \cdot CO_2e$), respectively as summarised in Equation (2.19). The activity data includes the activities of machines or equipment that consumed energy during the period of time (Carbon Trust, 2008a). The CO_2 emissions conversion factors are shown in Figure 2.13. In the UK, the quantity of energy consumption used in units of kWh and CO_2 emissions conversion factor is 0.41205 ($kg \cdot CO_2e \ / \ kWh$) in 2016 (GOV.UK, 2016)

$$\text{Carbon footprint} = \text{Activity data} \times \text{Emission factor} \quad (2.19)$$

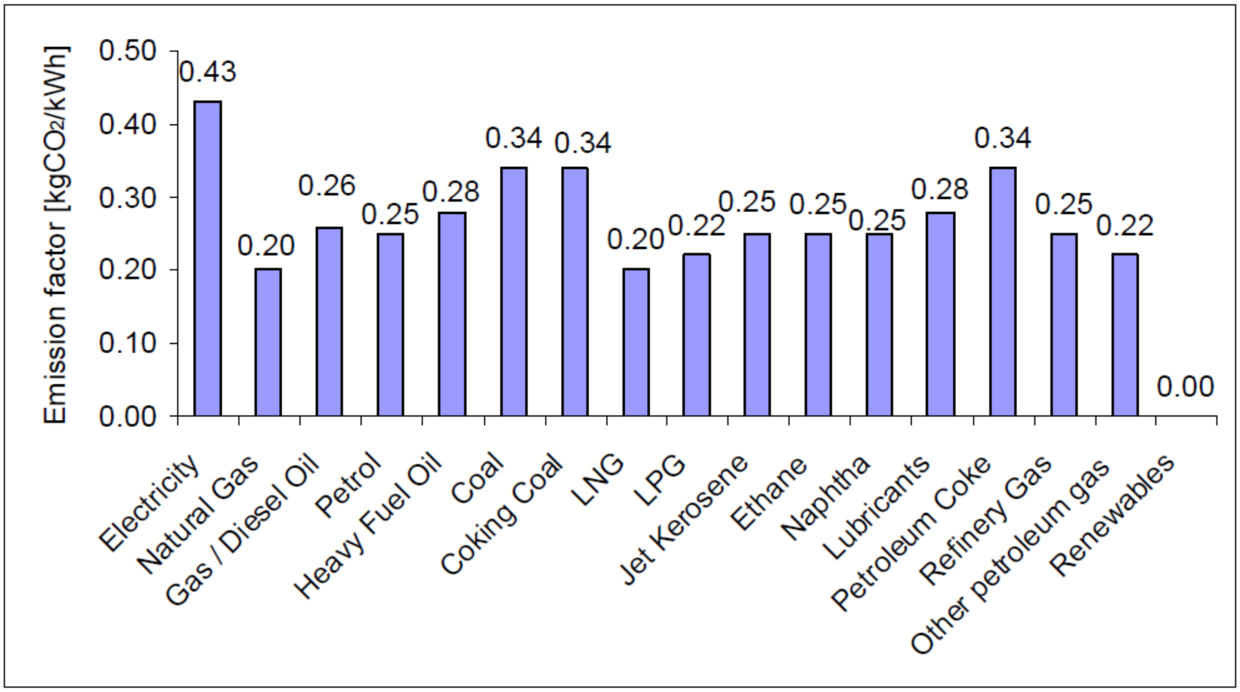


Figure 2.13. The UK carbon emission factor in different types of energy generating sources (Carbon Trust, 2008a).

2.6.4 Impact of Manufacturing Carbon Dioxide Emissions

The major impact of carbon dioxide (CO2) emissions (one of the main greenhouse gases or GHGs) from human activities is evidently the global warming problem (Cook, 2012). The emissions of GHG gradually trap the solar heat in the atmosphere, leading to the greenhouse effect as the solar heat is accumulated from an increased concentration of GHGs (including methane, nitrous oxide and fluorinated gases). Eventually, the accumulated solar heat heightens the atmospheric temperature. Though measurements and predictions have indicated that the rise in temperature due to the global warming is expected to occur every 100 years, both immediate impacts and long-term consequences are seriously threatening.

First, the glaciers and ice caps in most parts of the world have melted at a continually increasing rate, thereby flooding the lowering areas or approximately 100 million individuals in the world who live within 1 metre of the sea water level. On the other hand, there are serious droughts near the equator especially in countries such as India and Africa. The effects of drought harm agriculture which poses severe impacts not only on productivity but also on the supply of fresh water for basic human needs. In addition, several researchers have argued that the rising sea level and sea surface temperatures together with a circulation of heavily moist air could affect intensity, or even frequency, of hurricanes, tornados and tropical storms (Mousavi et al., 2011). Other harmful consequences include an increased acidity of sea water, a quick spread of diseases and a potential extinction of animal populations (Bose, 2010). More importantly, there is evidence to suggest that the climate change as a result of CO2 emissions will be largely irreversible for at least 1,000 years (Solomon et al., 2009). However, according to Bose (2010), "The global warming problem is solvable by the united effort of humanity," thereby suggesting an importance of an effective energy management system implementation that could minimise the CO_2 emissions.

2.7 Resource Efficiency in Sustainable Manufacturing

Generally, resource efficiency describes the efforts to "deliver more with less" resources (ECN, 2013, p. 3). Coupling with concerns for environmental sustainability, energy resource efficiency describes the utilisation of resources in an optimal way by requiring a minimal amount of energy to achieve the established level of product output. An accurate analysis of energy consumption behaviour of relevant machines and systems is, therefore, requisite to an understanding of energy resource efficiency in manufacturing, which involves consumption behaviour of diverse production machines and systems at different operating states (Herrmann and Thiede, 2009; Thiede, 2012). In other words, energy consumption varies with machine operating states that differ from constant (e.g. pumps and control units) and variable rates (e.g. tool positioning) (Gutowski et al., 2006). The utilisation of machines is largely regulated by the shop-floor schedules which thus impact the overall energy consumption of the manufacturing plant. In an attempt to develop a manufacturing system that minimises energy usage, research has focused on two approaches within the production processes: peak power consumption and overall energy consumption (Pach et al., 2014).

2.7.1 Avoiding Peak Power Consumption

As the name suggests, the first approach focuses on avoiding or at least minimising energy consumption at the peak load by using load shifting (Pach et al., 2014). Several studies have utilised this approach as peak load's rate structures have a direct effect on the manufacturing costs. For example, Fang et al. (2011) proposed an advanced modelling using a multi-objective mixed integer linear formulation which modifies the operation speed in order to change the energy consumption behaviour at peak load. Nghiem et al. (2011) created a model which implemented on a hybrid automation and peak power constraint. Other modelling methods include a mixed integer nonlinear programming (Babu and Ashok, 2008) and mixed integer programming (Bruzzone et al., 2012) both aimed to avoid the peak demand through modifying parameters in shop flow. Nonetheless, managing energy efficiency using minimising peak power consumption can be problematic for manufacturing systems with inadequate or restricted peak demands (Pach et al., 2014). Also, it provides information of only one factor among various factors that affect the overall energy consumption behaviour (Menezes et al., 2014). Therefore, this approach is not selected to be the focus of the present energy-efficient system proposed in this thesis.

2.7.2 Reducing the Overall Energy Consumption

To overcome the main limitation of examining peak power consumption, research has also attempted to minimise overall energy consumption of the manufacturing production system (Pach et al., 2014). In doing so, existing methods can be classified into three primary approaches: resource changes, process tuning and optimisation of resource. Figure 2.14 summarises the approaches within manufacturing energy efficiency.

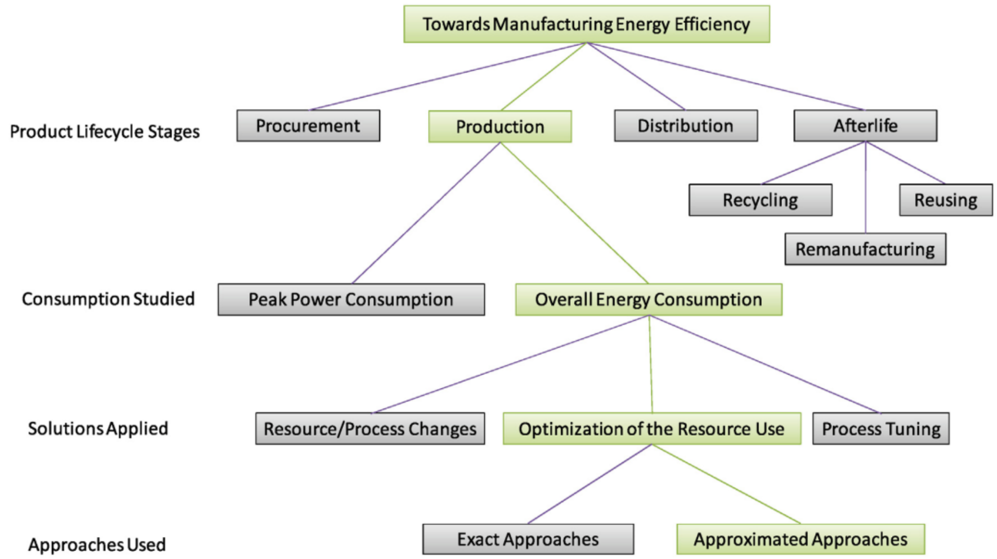


Figure 2.14. A summary of approaches towards energy efficiency in manufacturing (Pach et al., 2014)

2.7.2.1 Resource/ Process Changes

The most straightforward approach to reduce overall energy consumption is to change the resource or production process with the new resource (e.g. machine tool) or process that consumes less energy. Karnouskos et al. (2009) emphasised an overall energy consumption of the manufacturing plant by explaining that energy needs to be monitored and measured real-time. To reduce energy consumed in the plant, machines and processes should auto-manage their operations when no resource is active in operation. Consequently, the operation process and its energy consumption are reduced as a result of auto-managing capacity. However, this approach often involves substantial changes to the existing system which may be costly to the manufacturer (Pach et al., 2014).

2.7.2.2 Process Tuning

Another approach which involves changes to a lesser extent refers to process turning which optimises the existing process based on energy usage and can be less costly compared to changing the overall process (Duflou et al., 2012). Optimisation of process is often performed by modifying process parameters. For example, Mori et al. (2012) enhanced the energy efficiency of milling machine tools by modifying the cutting parameters, synchronising spindle speed and adjusting pecking cycle. In line with this, Bi and Wang (2012) modelled energy consumption of machine tools using their physical behaviours including kinematics and dynamics analysis. Optimising the machine setup, the model could save up to 67% of the total energy consumption during drilling operations. Together, this approach to overall energy consumption reduction often involves modification of process parameters such as spindle speed or feed rate. However, this could lead to reduced quality of the product or shortened resource lifespan, thereby compromising the overall performance of manufacturing (Pach et al., 2014).

2.7.2.3 Optimisation of the Resource Use

To overcome the shortcomings of process changes and process tuning, researchers have optimised the use of resource instead. In other words, the way in which the resource is used is improved or optimised, thereby resulting in reduced energy usage. The changes typically occur in the control system whereas the process itself remains constant (Pach et al., 2014). Research has shown successful outcomes of this approach in which an overall decrease in energy usage is documented.

Moreover, to optimise resource use, two methods have been adopted in research (Pach et al., 2014). The first method referred to as the exact method which focuses on fixed conditions of energy-related variables. An effort to minimise energy consumed in this job-shop environment is, therefore, complicated. Emphasising on the constraint, Vallada et al. (2008) asserted that exact methods are inapplicable for job-shop with complex flow-shop as it consists of a series of numerous operation processes. Hence, exact methods are not suitable for dynamic and frequently altered manufacturing environment (Mařík and McFarlane, 2005).

This limitation has led researchers to utilise the second method- approximated method- more frequently. This method consists of various subcategories such as heuristics and meta-heuristics (Vallada et al., 2008). Approximated methods have been regarded as more effective especially for manufacturing with multiple machines and processes due to its centralised predictive approach which leads to shorter completion times (Lee and Kim, 2008; Shen et al., 2006). For example, Küster et al. (2012) modelled a control system in order to optimise production by using forecast energy prices. This type of optimisation documented the impact of process in managing an energy-efficient system.

With regard to the overall resource use optimisation, more researchers have paid attention to workload of machines and its influence on energy efficiency during a production process such as productive states of machining. An example is a study conducted by Devoldere et al. (2007)

who proposed on machine occupancy. In this study, energy was reduced when a product order was released in the production process. Specifically, the non-production function could save approximately 47% of the milling machine energy consumption. Zhang et al. (2009) attempted to minimise maximal completion and total workload of machines in a flexible job-shop scheduling problem. More recently, Fysikipoulos et al. (2012) considered cost in relation to energy consumption and productive states. This research asserted that though an idle state of a machine reduces energy consumption, it could lower energy efficiency as it does not produce any product. In addition, energy consumption was found to be at the highest at the minimum productive working state, whereas energy was consumed at the lowest when the productive working state was its maximum. The two states accounted for approximately 17% difference in energy consumption and cost. Taken together, literature has provided an empirical evidence that optimisation of resource workload in manufacturing process can minimise energy cost and production cost.

2.8 Machine Loading

A review of literature on machine loading shows that the majority of studies have concerned machine loading problems of flexible manufacturing systems known as FMS (Grieco et al., 2001 and Singh et al., 2015). The major aim of this body of research is to improve, or at least achieve, efficiency in production. This type of production is characterised by a mass production that is automated, high volume and by a job shop production that is low in volume (Groover and Zimmer, 1984). Hence, research has attempted to solve machine loading problems in order to increase productivity, but at the same time flexibility and low volume job shop production are still maintained.

Various solutions have been presented to solve problems of machine loading. For instance, a number of researchers in the early research proposed mathematical programming methods. In the work of Stecke (1983), non-linear 0-1 integer programming was formulated to planning problems of FMS. Other studies in FMS have included the work of Shankar and Srinivasulu (1989) who applied mathematical approach to reduce workload imbalance, the study of Sawik (1990) in which a multi-level integer program was formulated, and the study of Liang and Dutta (1992) who developed a bicriterion mathematical programme to integrally solve problems of part selection and machine loading. In line with this, prior research has also well examined machine loading using multi-criteria objective.

For instance, multiobjective optimisation was demonstrated in the work of Kumar et al. (1990) whereby the min-max approach was used to compromise grouping and machine loading. Mukhopadhyay and Tiwari (1995) took into account machine utilisation and solved loading problem by reducing the maximum difference between machines. Later, Kim and Yano (1997) aimed to simultaneously solve grouping and loading problems. This research demonstrated that balancing workloads across machines while minimising machine groups could decrease makespan in FMS. A heuristic, multi-stage approach was also performed in the study of Nagarjuna et al. (2006) in order to enhance efficiency and maintain flexibility of job shops. With this proposed model, the system unbalance was minimised, and constraints such as machining time and tool slows were met.

In relation to energy consumption, several studies have examined the relationship between energy and machining. Within this body of research, Drake et al. (2006) generally asserted that the amount of energy consumption is great when machine or its component is in an ON or idle state. Twomey (2008) further emphasised that over 10% of the total energy consumption can be saved from turning the machine OFF from the idle state when it is not processing any job. Additionally, Shrouf et al. (2014) described that the total energy consumption changes depending on various factors such as status, transition and duration of each machine and amount of energy consumed at each phase. Among these factors, time of energy usage or production time is one of the most significant factors that amend total energy consumption. One of the machine loading studies concluded that at 90% chiller loading (1,857.30 kW), machine consumed less energy per load than at 50% chiller loading (904.62 kW) which was estimated to be about 2.55kW per 1% chiller loading (Chang et al., 2005). Nonetheless, past research has not well explored machine loading problems that concern energy consumption and product quality simultaneously. Therefore, this needs further investigation of the problem under the real environment scenarios of shop-floor.

2.9 Heating, Ventilation and Air Conditioning (HVAC) Systems

Heating, ventilation and air condition (HVAC) is the main system that consumes energy in the manufacturing system. The operation of HVAC system has a significant effect on the cost of energy consumption (Wang and Ma, 2008). The HVAC system is the world’s energy consuming that uses energy up to 50% of a non-production manufacturing process in the U.S. (U.S. Energy Information Administration, 2010). Moreover, the UK rate of energy consumption is continuously increasing 0.5% per year due to the economic growth that leads to a significant rise in energy usage of the HVAC system (Pérez-Lombard et al., 2008).

Previously, there was an empirical study that demonstrates a similar predictive system operated in building designs of building services (Lück, 2012). Research on energy consumption has extensively focused on both residential and commercial buildings as they account for 20 to 40 percent of the total energy consumption in developed countries (Pérez-Lombard et al., 2008). Generally, energy consumption behaviour of a building can be comprehensively determined by thermodynamics laws that calculate the energy consumption of each component of the building along with other energy information relating to the building and their environments (Zhao and Magoulés, 2012). Accordingly, the energy behaviour includes, for example, weather conditions outside the building, operation, HVAC equipment, utility rate and building construction. In line with this, HVAC systems play the most important role in energy consumption within commercial (agricultural and services) and non-commercial (i.e. residential) buildings in response to a high demand for thermal comfort (Pérez-Lombard et al., 2008). Other main sources of energy consumption include lighting, appliances and water heating. Strategies aimed to reduce energy consumption in buildings have included, for instance, optimisation by means of compactness and shape factor, passive cooling and heating, glazing and shading (Ordóñez and Martínez, 2012).

Typically, the temperatures of inside and outside a building can be different. To maintain an indoor temperature, an HVAC system requires energy to operate and control the temperature in the manufacturing ambient environment. The energy required for the HVAC system in a light factory building represented by Q can be calculated with Equation (2.20).

$$Q = \rho_0 C_p \mathrm{V}(\Delta \mathrm{T}) = \rho_0 C_p \mathrm{V}\,|T_i - T_0| \qquad (2.20)$$

where ρ_0 defines the outside air density, C_p defines the specific heat of air, V defines the volumetric flow rate of air which is also the change in air volume within an hour, T_i is the outside temperature, and T_o is the inside temperature. In general, the value of the specific heat capacity of air is 1 kJ/kg · °C at a normal atmospheric pressure (Cengel, 1998). The value of air density is 1.2754 kg · m^{-3}.

2.9.1 Temperature Variation

The daily temperature within a manufacturing plant, or the ambient thermal environment, is a crucial variable that constantly fluctuates which is potentially due to seasonal temperature variations, solar radiation, increased/decreased heat from machine tools, and other unexpected variations. Temperature variations may be as high as 5°C to 10°C in the morning of the summer days.

Moreover, the effects of ambient temperature fluctuations concern two main areas: regulations and machine performance. First, according to Health, Safety and Welfare Regulations 1992 which states that all workplaces including manufacturing plants must provide comfortable working conditions for employees and non-employees within the premises (Health and Safety Executive, 2013). Specific to thermal comfort in indoor workplaces, a suitable temperature for working conditions is defined as "being normally at least 16°C unless the work involves severe physical work in which case the temperature should be at least 13°C". Consistently, manufacturing plants that involve high thermal effects need to considerably address this matter by complying with the published code of practice to ensure the health and safety of all individuals in the plants. Second, it has been documented that ambient thermal environment affects the accuracy of a machining process and inter-relatedly machine measurement and performance (Black & Kohser, 2008). Consequently, data on ambient temperature within a plant is of a particular importance, especially for the HVAC system performance.

2.9.2 Weather Forecast

Whilst indoor temperatures play a significantly role in manufacturing facilities, indoor temperatures are evidently affected by the outdoor weather. Data on weather forecast can provide useful information to predict the indoor temperatures in the near future. To manage energy system in a more effective way, the system should therefore integrate temperature forecast data as it affects energy efficiency of the tuning process of the temperature controller. Put differently, accurate forecast data can facilitate the operations of the HVAC control system.

As described by Burroughs (2003), future weather or future temperature can be predicted by its intrinsic behaviour of a non-linear system through a non-linear differential equation. This methodological system is the basic element of the Numerical Weather Prediction (NWP) method that is adopted by most forecasting meteorological databases (Zhang & Hanby, 2007).

The NWP employs computer-based systems to simulate short-range weather data by using intelligently adaptive temperature systems to acquire predictive data including hourly temperature weather data (Rodwell & Palmer, 2007)

Mentioned earlier, management of an energy efficient system at an HVAC level is of great importance. Nonetheless, relatively few studies have focused on the HVAC system in manufacturing. Among these is the study of Dababneh et al. (2016) that attempted to reduce peak demand using HVAC workload without affecting production. In particular, 29% of peak demand could be reduced during summer, and 21% peak power could be reduced during winter. Monitoring and optimisation of control systems are not only necessary but also regulated by legislations to ensure comfort in manufacturing. The appropriate temperature in working environment does not only minimise energy consumption, but it can also improve employee's performance. Therefore, the setting point of temperature should be identified. The following sections provide a review of the two types of control systems that are used in HVAC system: PID controller and fuzzy logic controller.

2.9.3 PID Controller

As the name suggests, PID or proportional-integral-derivative controller combines the roles of the three parts: proportional, integral and derivative modes (Sung et al., 2009). The PID system can be considered as conventional or classical system (Dounis and Caraiscos, 2009). The primary objective of PID controllers is to minimise errors of a control system by performing the mathematical operations of the three parts (Kiyak and Gol, 2016). Specifically, the proportional part can be computed with Equation (2.21) (Sung et al., 2009).

$$u_P(\mathrm{t}) = k_c(y_s(\mathrm{t}) - y(\mathrm{t}) \tag{2.21}$$

The Integral control part can be mathematically expressed by Equation (2.22).

$$u_I(\mathrm{t}) = \frac{k_c}{\tau_i}\int_0^t (y_s(t) - y(t))d_t \tag{2.22}$$

The derivative part is expressed by Equation (2.23).

$$u_D(\mathrm{t}) = k_c\tau_d \frac{d(y_s(t) - y(t))}{dt} \tag{2.23}$$

For the three equations, the denotation $y_s(t)$ defines the desired process output, $y(t)$ defines the output of the process, $u(t)$ defines output the of the control. k_c defines the proportional gain, τ_i defines integral time, and τ_d defines derivative time. The parameters should be adjusted accordingly to the process dynamics.

Particularly, the proportional part first creates the controller output by multiplying errors with a specific gain value (Kiyak and Gol, 2016). This improves the accuracy of both static and dynamic response of the controller by means of fast reaction time and reduced errors. The integral part then creates the proportional output with the sum of errors, thereby increasing the static response but reducing the dynamic response time. On the other hand, the derivative part does not affect error recovery when it increases the dynamic response. Together, the PID controller is, therefore, the sum of the three control parts which can be computed with Equation (2.24).

$$\begin{aligned} u(\mathrm{t}) = {} & u_p(t) + u_I(t) + u_D(t) \\ & = k_c\big(y_s(t) - y(t)\big) + \frac{k_c}{\tau_i}\int_0^t (y_s(\tau) - y(\tau))d_\tau \\ & + k_c\tau_d\frac{d(y_s(t) - y(t))}{dt} \end{aligned} \tag{2.24}$$

The three values, k_c, τ_i and τ_d, are regarded as parameters of a tuning procedure which need to be set before operating. Overall, the calculation of the PID controller is simple. According to Sung et al. (2009), PID controllers are widely used in manufacturing due to their simplicity and robustness to uncertainties. PID control system has been extensively applied to HVAC control system in attempt to mininise energy usage. However, conventional PID controllers may not properly analyse nonlinear systems, high-order linear systems, time-delayed linear systems and general complex manufacturing systems that can be expressed with simple mathematical models (Tang et al., 2001). The type of control system, in many situations, is not suitable for optimisation and prediction purposes, but it can be effective in tuning easing and lowering costs (Dounis and Caraiscos, 2009).

2.9.4 Fuzzy Logic Systems

The term ‘fuzzy logic’ was first introduced in the early 1960’s and generally describes the mathematical order which expresses uncertainties. The fuzzy logic control system thus obtains values with logic in an uncertain environment (Kiyak and Gol, 2016). It can examine all states of the system by handling all intermediate values. In building and manufacturing, the fuzzy logic is often applied to the neural networks technology along with algorithms to develop various computer-based intelligent control systems (Dounis et al.,1996).

Several empirical studies have carried out to investigate the energy performance of the various control systems. For instance, Dounis et al. (1996) found that fuzzy controllers are more suitable than the PID controllers or the ON/OFF controllers when controlling for the air quality of ventilated indoor. More recently, Ulpiani et al. (2016) compared the ergonomic performance of the ON/OFF, PID and fuzzy controller for the heating system in a building. The results demonstrated that a more energy efficient (energetic and ergonomic) performance of the fuzzy controller which reduced 30 to 70 percent of energy consumption while constantly maintaining thermal comfort in the building. Similarly, Kiyak and Gol (2016) compared between PID controller and fuzzy logic controller using a solar tracking system and concluded that the fuzzy logic control system could increase 2.39% of energy efficiency.

2.9.4.1 Fuzzy Controllers

Fuzzy controllers are generally used to control fuzzy systems. In traditional control algorithms, a mathematical model is required to control the system. However, numerous physical systems cannot also be modelled mathematically. Nonetheless, if the control strategy can be described qualitatively, fuzzy logic can be used to create a fuzzy controller that reproduces heuristic rules. As shown in Figure 2.15, a fuzzy logical controller consists of three main parts which are fuzzification, implementation of a linguistic control strategy, and defuzzification in a respective order.

The fuzzification is the process of converting crisp inputs (or numerical inputs) into the linguistic terms that are corresponding to the input linguistic variables. A linguistic variable can therefore be fragmented into a set of linguistic terms. For instance, as demonstrated in Figure 2.16, if temperature in a room is set as the linguistic variable, a fuzzy controller may convert the crisp inputs of the thermometer reading on the system with the linguistic terms of “Very Cold”, “Cold”, “Warm”, “Hot” and “Very Hot” that are corresponding to the linguistic variable. However, the value of the temperature can belong to one or more linguistic terms depending on the membership functions that are used to quantify a linguistic term. Membership functions are thus numerical functions used to map crisp input values into the corresponding linguistic term and represent different degree of memberships of linguistic variables. A membership value is continuous and ranges between 0 and 1 where 0 indicates 0% of membership and 1 indicates 100% membership (Chinthamani et al., 2012).

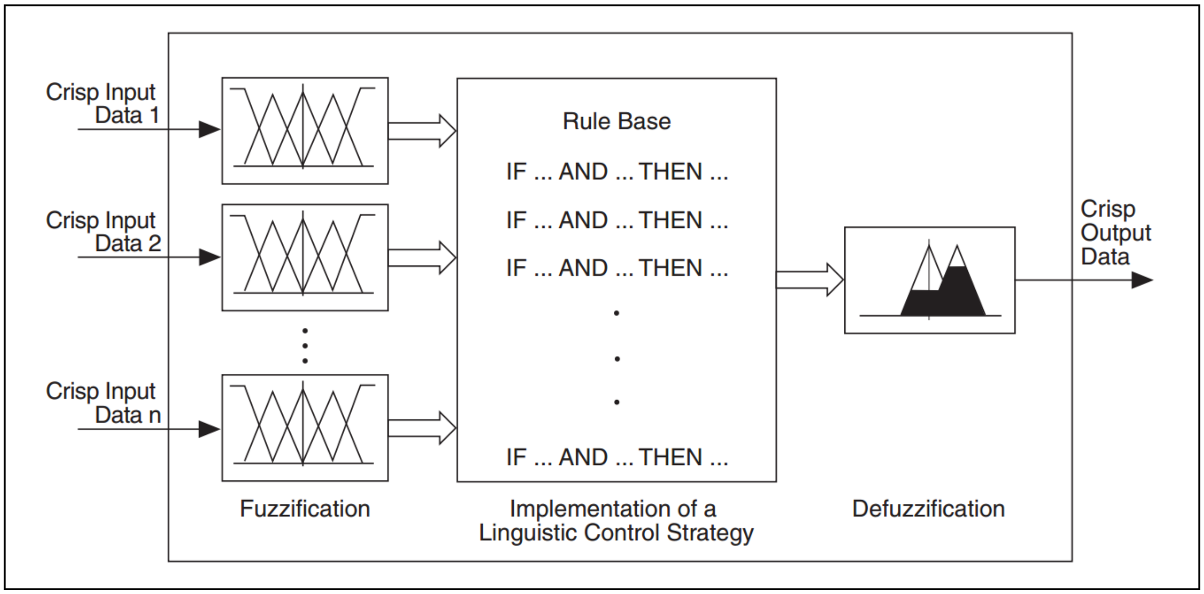


Figure 2.15. Process of a Fuzzy Controller (Bitter et al., 2007)

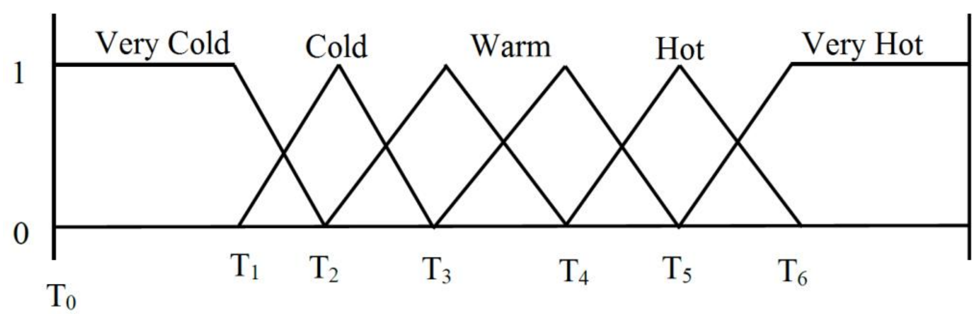


Figure 2.16. An example of temperature crisp input membership function

Rules represent the relationship between the input and output linguistic variables in accordance to their linguistic terms. A rule base is a set-off rule and constructed to control the variable. (Chinthamani et al., 2012). In a fuzzy system, the total number of possible rules denoted as R is described by Equation. (2.25).

$$R = p_1 \times p_2 \times \ldots \times p_n \tag{2.25}$$

where p_n determines the number of linguistic terms for the linguistic variable n. If there are the same number of linguistic terms in an input linguistic variable, Equation (2.26) can be calculated for the total number of possible rules.

$$R = p^m \tag{2.26}$$

where p defines the number of linguistic terms for an input linguistic variable, and m defines the number of input linguistic variables (Chinthamani et al., 2012).

A rule base can be plotted using a matrix representation as a helpful tool to recognise inconsistent and contradictory rules. Cascading fuzzy systems can be used to avoid large rule bases for fuzzy systems with a large number of controller inputs. A rule base is established to control the output variable, and a fuzzy rule is an IF-THEN rule with a premise and a consequence (Isizoh et al., 2012). Table 2.2 and 2.3 provide an example of fuzzy rules for a temperature control system and an example of the matrix representation of the fuzzy rules, respectively.

Table 2.2. An example of fuzzy rules for temperature control system (Chinthamani et al., 2012).

No.	**Fuzzy Rules**
1	IF (temperature is cold OR too-cold AND (target is warm) THEN command is heat
2	IF (temperature is hot OR too-hot) AND (target is warm) THEN command is cool
3	IF (temperature is warm) AND (target is warm) THEN command is no-change

Table 2.3. An example of matrix for the temperature control system (Chinthamani et al., 2012).

Temperature/ Target	Too-cold	Cold	Warm	Hot	Too-hot
Too-cold	No-change	Heat	Heat	Heat	Heat
Cold	Cool	No-change	Heat	Heat	Heat
Warm	Cool	Cool	No-change	Heat	Heat
Hot	Cool	Cool	Cool	No-change	Heat
Too-hot	Cool	Cool	Cool	Cool	No-change

The third part, defuzzification, involves a quantifiable result in which the degrees of membership of output linguistic variables are converted into crisp values that are numerical. This process can be performed with a number of mathematical methods such as the centroid method which is the most common among all available defuzzification methods (Chinthamani et al., 2012). The Centroid method is also known as the center of area (CoA) or center of gravity (CoG) method and is considered as the most useful method because it considers the input and output linguistic terms. According to this method, the fuzzy controller calculates the center of area under the membership functions within the range of the output variables. To calculate the center of this area known as CoA, Equation (2.27) is applied.

$$CoA = \frac{\int_{x_{min}}^{x_{max}} f(x) \cdot x \, dx}{\int_{x_{min}}^{x_{max}} f(x) \, dx} \tag{2.27}$$

where x is the linguistic variable value, and x_{min} and x_{max} are the minimum and maximum values of linguistic variable range.

In a HVAC system, the fuzzy control system is utilised to control the temperature in the environment by regulating a cooling or heating system. The temperature of the room is adjusted based on information of the current room temperature and the target value defined by the system. The fuzzy controller system compares current temperature value to the target value at a given time and then creates a command for cooling or heating. Figure 2.17 illustrates the process of a regular fuzzy logic control system of room temperature.

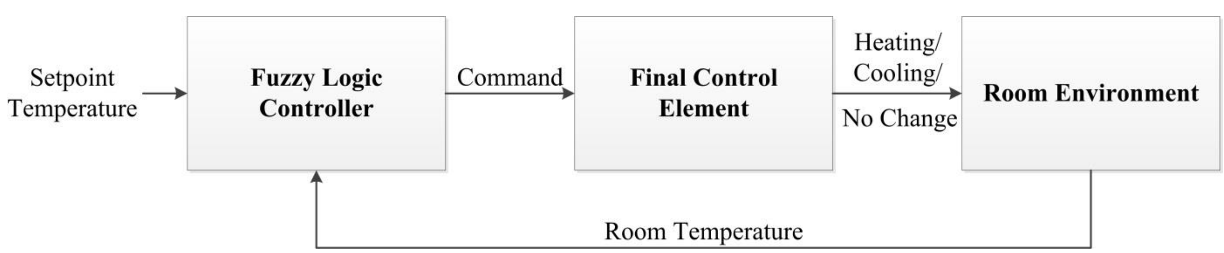


Figure 2.17. A regular fuzzy logic control system of room temperature

2.10 Energy Management System

Despite increasing attention given to advanced developments, there are remarkable opportunities to improve energy performance within the manufacturing industry.

Consequently, a complete energy management system is essential to the establishment of success towards sustained energy-performance (Almaguer, 2012). The challenge within energy management is not related only to the technical elements, but it needs to implement the technical changes to minimise cost effectively but at the same time with minimum disruptions (Turner and Doty, 2007).

2.10.1 Energy Management System Framework

Energy management system refers to the integral sum of various elements that collectively leads to policies, processes and procedures that are established in accordance with the strategic energy objectives. More simple definitions also exist such as a system aimed to monitor expenditures of electricity or fossil fuels (Dinçer and Zamfirescu, 2011). Based on the summary of various definitions in current academic literature, energy management systems consists of an energy-related definition, implementation and controlling through continuously transparent and systematic approach in order to achieve the strategic goals related to sustainability and efficiency (Javied et al., 2015). Moreover, the values of energy management cannot be understated. Evidently, by efficient energy management, immediate and long-term economic return can be attained, thus bringing competitive advantages to manufacturers. Relatedly, well-established management systems can respond to rapid changes in energy technology, and financial-related (e.g. energy price shocks) and environmental concerns (Turner and Doty, 2007).

Despite the varied benefits of energy management system practices to achieve efficiency shown in literature, not all manufacturers have successfully implemented such a system. The common barriers to energy efficiency practices have shown to include, for example, a lack of economic- (e.g. cost reduction) or environmental-related (e.g. concern for environments) motivations, capability (i.e. a lack of resources such as time, technical skills, knowledge, staff and finances), a lack of window of opportunity, a lack of data to evidence positive returns of system adoption or positive returns for the energy saving efforts, and a fear of production disruption (Chai and Yeo, 2012).

The International Organisation for Standardisation or ISO appointed PC242-Energy Management in February 2008 as the project committee to establish a new ISO energy management system (EnMS) standard for energy named ISO 50001 which was released in June 2011. ISO 50001 provides an international framework for all types of organisations including industrial plants and manufacturers of all sizes to effectively use and manage energy and at the same time recognises ways to save money (i.e. economic criterion), to conserve resources and respond to the current climate change. The ISO 50001 framework offers standards and policies for all essential elements which include, but are not limited to, energy management planning for energy use, efficiency, supply and performance, and design and procurement practices for systems and processes related to energy usage (Dörr et al., 2013). The framework of ISO 50001 also covers standards for measurement, documentation and reporting of energy usage and consumption. By demonstrating that the manufacturers have sustainable energy management systems, they are attributable to continual, long-term energy performance improvement. Overall, it aims to offer a systematic framework for organisations to not only establish an energy management system but also to implement, measure, monitor, maintain and improve it (ISO, 2016).

Because manufacturing is largely responsible for a significant proportion of the total world energy consumption and CO_2 emissions that have resulted in high energy prices and ecological damages, it is, therefore, crucial for manufacturers to model, measure and predict energy consumption and efficiency (Park et al., 2009). Energy management systems (EMS) are commonly used to monitor all activities. Technology has played a significant role in the development of energy management systems, and the systems have grown more advanced and sophisticated over the years (Hordeski, 2004). For instance, the earlier systems such as Energy Management and Control Systems (EMCS) utilised computers to optimise energy saving features, equipment operation and initiated the shutdown of machines when they were not in use.

2.10.2 Modelling of Energy Management system

In the last decade, various energy efficient methodological models have been proposed to predict energy consumption for manufacturing systems. In manufacturing, modelling is a practical processing technique that aids a decision-making process in relation to the implementation of effective systems (Johnansson and Grunberg, 2001). The decisions often involve the choice between an analytical (or mathematical) and a simulation modelling approach. Whilst an analytical approach enables a solution to a particular performance measure, simulation modelling may become a more systemically well-suited method in manufacturing handle underlying complex behavioural systems (Blanchard and Fabrycky, 2006).

Because simulation modelling is managed with a computer-based programme, computation of the solution can be performed on any complex manufacturing systems and any sets of assumptions. Rather than finding the optimal values of a prescribed function as in an analytical model, simulation modelling adopts a descriptive model which estimates a set of performance measures that correspond to a set of input data through sample histories (Altiok and Melamed, 2007). More specifically, once the programme creates the models of a specific system, it then proceeds to experiment that is established based on a prescribed set of objectives of the goal. Next, the experiment produces histories, statistics and system behaviour over time.

Importantly, simulation models can effectively explore the alternative system characteristics without actually examining each of the candidate systems, thereby providing great advantages especially for complex manufacturing systems that involve high costs or are difficult to manipulate (Blanchard and Fabrycky, 2006). In manufacturing, a simulation model of an energy system can be adopted to establish 'what-if' scenarios in order to analyse and evaluate energy consumption or other outcomes during different phases of a manufacturing system and processes (Seow et al., 2011).

With the application of an energy simulation model, flows of the manufacturing processes can be easily adjusted and modified. The simulation model can also be expanded to include more variations of products and processes such as lead times, queue times, production lines and batch sizing. For example, using simulation modelling, aCtuatorS Methodology also known as CSM advanced the computation and prediction of the power peaks and energy consumed at the on/off switching of the actuators during the production process (Cataldo et al., 2015). The simulation approach enables modelling of energy efficiency to evaluate energy consumption of various processes in more details and demonstrate energy hotspots in the manufacturing plant (Seow et al., 2011).

Another objective of this methodology concerns the optimisation of a performance measure from an economic perspective by seeking the optimal solution for decisions such as financial risk reduction and a decrease in lead time (Robinson, 1994). Owing to the fact that simulation modeling is a paradigm that establishes a simplified model or representation for evaluating and analysing complex manufacturing systems, this approach, therefore, provides a powerful methodological tool that supports the operations of various manufacturing systems (e.g. production planning, process and control) that are integrally essential to the overall energy management system (Hermandez-Matias et al., 2006; Rossetti, 2010).

2.10.2.1 Process Simulation Software Packages

Computer simulations provide crucial features of a real system for users to test, design and analyse information in a safe and convenient environment (Tavakkoli-Moghaddam and Daneshmand-Mehr, 2005). Several simulation software packages are available in the industry such as ProModel, AnyLogic, Plant Simulation, Lanner and Arena Simulation programme. Most of the simulation programmes provide similar production modelling features and capabilities (Componation et al., 2003.) As modelling appears to be one of the difficult and time-consuming elements of the simulation process, Arena Simulation can provide several advantages over other programmes due to its graphical user-friendly interface and templates (Guneri & Seker, 2008). The modelling can be performed by clicking and dropping the modules into the window. Furthermore, the user-friendly display, the Arena Simulation programme provides important applications for performances in manufacturing production management system (Thierry et al., 2008).

In addition, Kelton et al. (2015) confirmed that the development of Arena is regarded as one of the most successful simulation programmes for analysing complex systems. Figure 2.18 shows an example of Arena Simulation programme model window. Because the simulation software can be used to model both detailed discrete and continuous systems of high-level analysis, complex systems are modelled using pre-packaged SIMAN code modules, blocks and elements (Altiok & Melamed 2007; Banks et al., 2010). Therefore, in this research, Arena Simulation programme (Version 14.5) is adopted as an acquisition and analysis tool in this research.

Similarly, several visual programming tools are available including Python, myOpenLab, PyLab_Works, FlowStone, MatLab and LabVIEW. Among these, Laboratory Virtual Instrument Engineering Workbench (LabVIEW) software is suitable to be used to acquire, display, analyse and present data with a user-interface application (Bitter et al., 2006). Bishop (2007) asserted that the programme provides a series of graphic interface that demonstrates and controls the data acquisition and connects them to a variety of instruments such as

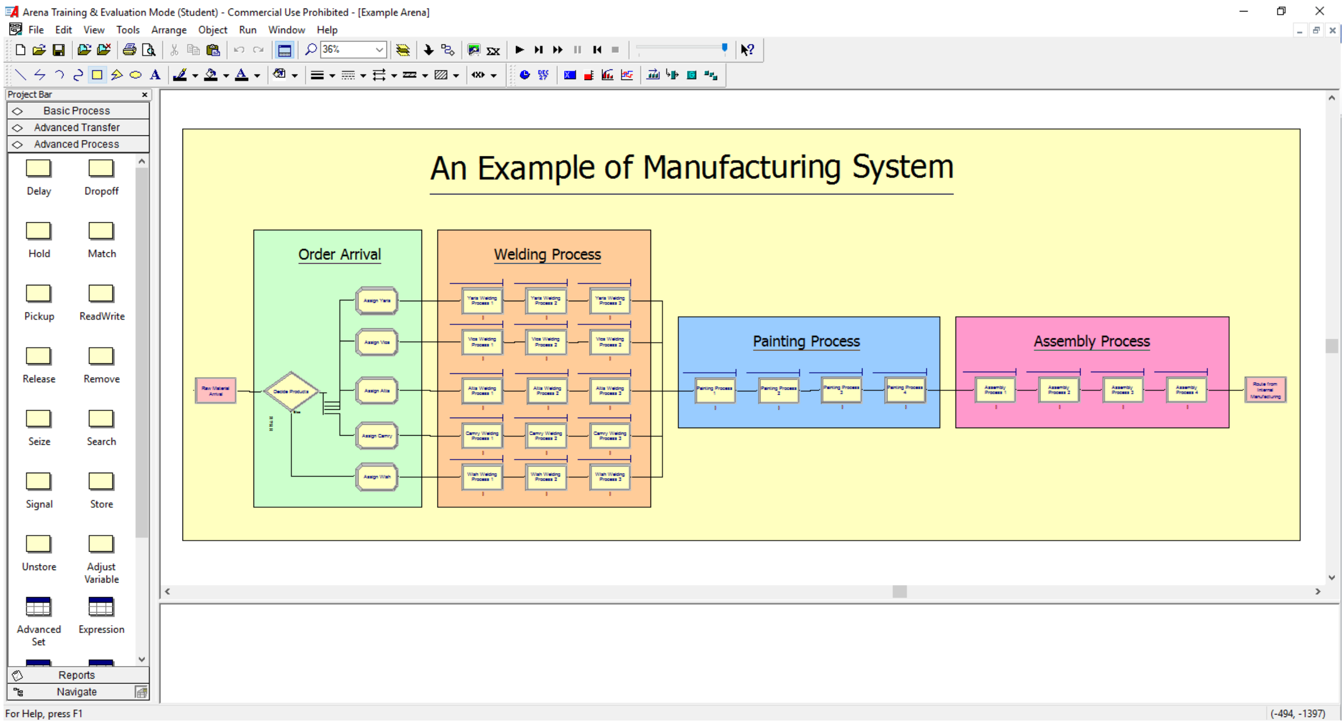


Figure 2.18. Illustration of Arena Simulation programming model window

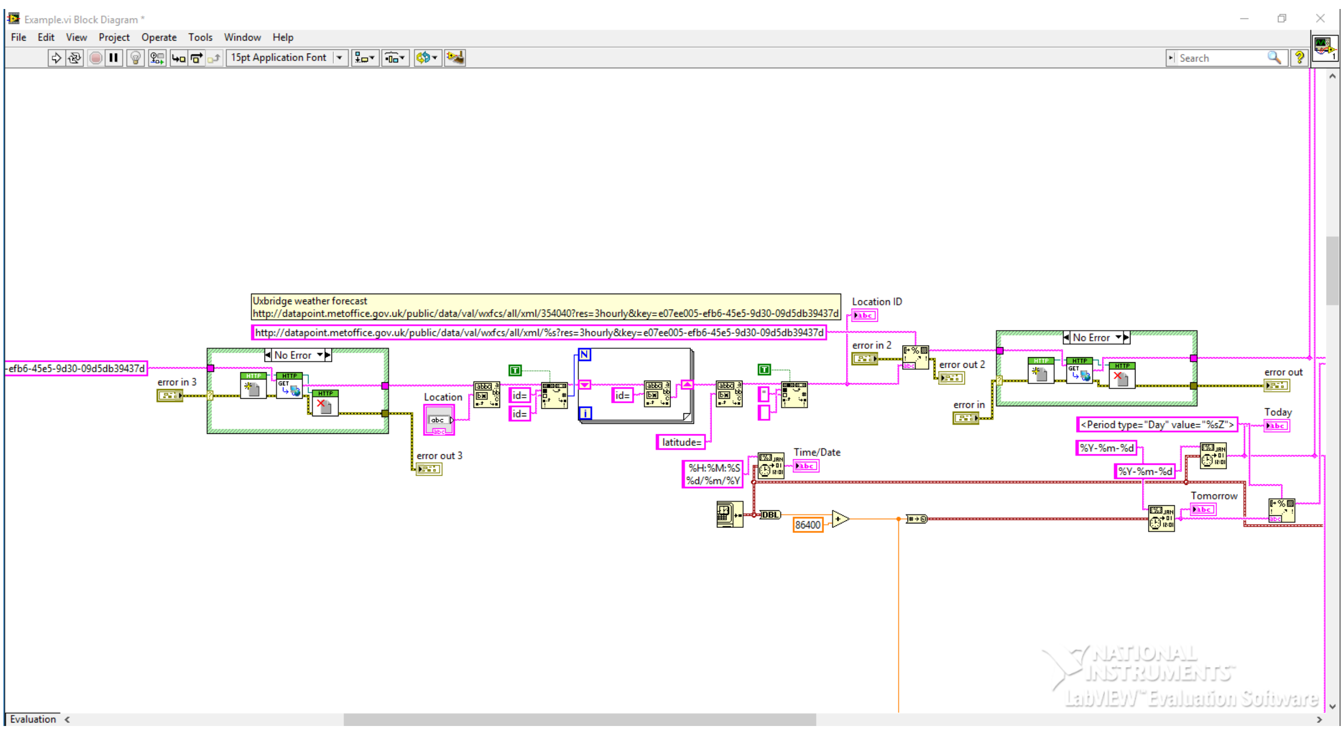


Figure 2.19. Illustration of LabVIEW programming model window

MatLab. In particular, Front Panel window uses the virtual instrument to control and monitor systems whereby each instrument can correspond to Block Diagram. The Block Diagram contains the structure and object that carry data from one instrument to another for programming elements. The connection function allows LabVIEW to improve its performance and overcome its limitations (National Instruments, 2016). LabVIEW programme was developed by the National Instruments to support data acquisition, measurement, analysis and display in laboratory settings (Morris & Langari, 2012). Using built-in signal processing and mathematical functions, the programme can quickly analyse the data both online and offline. Algorithms can also be customised (Bishop, 2007). Figure 2.19 illustrates a LabVIEW application user interface.

2.11 Research Gaps

As discussed in this review of the literature, the current manufacturing industry faces difficult challenges in economic and environmental domains, thereby resulting in increasing demands to develop a more effective energy management system. The implementation of energy management systems has great potential for energy efficient performance which in turn will have an impact on reducing energy consumption and CO_2 emission (European Commission, 2011). While the current literature has shown extensive work in an attempt to improve an energy-efficient system by minimising energy consumption, there is room for improvement due to three major research gaps. To accurately model energy management system, it is important to systematically improve energy efficiency through a methodical, novel approach to the energy consumption of sustainable and low carbon manufacturing at machine, process and shop-floor levels.

Firstly, the existing body of research on sustainable manufacturing has been understudied the relation between product quality and energy efficiency. In other words, a systematic knowledge on how manufacturing environments and energy consumption can collectively enhance product quality is unclear. This is of particular importance to precision manufacturing since accuracy is the primary indicator of machining performance.

Secondly, Geret et al. (2015) recently explained that energy efficiency at the manufacturing plant level needs further investigations in order to provide a more comprehensive development of the energy-efficient management system. Nevertheless, studies on energy efficiency at a manufacturing plant level are highly limited which may be explained by the complexity of methodological analysis. One common strategy to improve efficiency adopted by a number of manufacturing plants is based on the notion that different production rates generate different amount of energy usage.

Finally, the majority of research on energy-efficient HVAC system has focused on buildings. No systematic model has yet been developed for the manufacturing environment which is highly dynamic and complex. Energy-efficient management systems that were developed for buildings are not likely to be suitable for implementation in manufacturing as it comprises of a variety of machines, systems and processes that differ in energy consumption behaviour. Therefore, a systematic model energy management system in manufacturing is necessary to accurately predict energy consumption and control the HVAC system. In industrial environmental conditions, a variety of factors and variables (e.g. plant design, machines, and HVAC system) can certainly affect the total energy consumption and consequently the total carbon emissions.

2.12 Chapter Summary

Considering the recent rises in electricity costs and greater environmental concerns in manufacturing, energy saving has become an essential factor to move closer towards sustainable consumption and production (Katchasuwanmanee, 2015; Mani et al., 2008). The manufacturing industry is responsible for more than 30% of global energy consumption and 40% of CO_2 emissions (Behrendt et al., 2012; Tridech, 2011, Strange, 2008). To address the challenges of climate change and other environmental issues, more energy-efficient and yet high-quality production processes are one potential solution to reduce the total energy consumed in manufacturing. In order to fill the three research gaps identified previously, the following chapters will present a development of an integrated sustainable manufacturing approach energy-smart production management (e-ProMan). The e-ProMan is a simulation modelling which takes into account the systematic relationship between energy flow, work flow and data flow and considers the real-time data from a variety of sources. It is also a HVAC predictive control system and provides decision-making algorithms as an innovative step towards sustainable precision manufacturing. Simulation experiments will also be carried out at machine, process and plant levels in order to extend knowledge on energy-efficient management system in precision manufacturing.

CHAPTER 3

Methodology

The aim of this chapter is to scientifically understand and summarise all methodological choices in the present research which include simulation modelling process and its methodology. It is followed by a summary of statistical analysis of multiple regression and correlation analyses. This chapter also describes the simulation tools and statistical analysis tools used in this research.

3.1 Introduction

Research philosophy is a fundamental element in research as it provides a systematic understanding of how research knowledge is derived and interpreted (Reich and Subrahmanian, 2013). In the last decades, engineering research has increasingly focused on computer-based tools especially simulation modelling (Green et al., 2002). This particular research method and a laboratory experiment follow a scientific, positivist approach in which variables of interest are designed and studied in a laboratory in order to replicate a real-world environment and behaviour of a complex manufacturing system. To fulfil the research objectives, the following sections elaborate on the methodological choices of conducting simulation modelling and quantitative statistical analysis.

3.2 Process Simulation Modelling

Simulation describes a process of generating an environment in order to understand the behaviour of a model in a specific time interval. This environment serves as a medium to connect with the model. Banks (1998) and Son and Wysk (2001) asserted justifications for using simulation modelling as a research method tool. In line with this, Onut et al. (1994) presented simulation modelling by integrating the model into a control system of a shop floor of a Semi-Integrated Manufacturing System or SIMS. In this research, a framework was proposed in which simulation was interfaced with a variety of systems including Material Requirement Planning or MRP system, database management system, host computer, control system and supervisory input system. The results showed that the modelling was able to improve the effectiveness of control and operations in manufacturing. Nonetheless, the data inputted into the model which was collected from the shop floor and relevant systems were not automatically updated. In summary, past studies have provided empirically evidence that show the simulation is a fundamental method in understanding and thus n improving behaviours of manufacturing systems.

3.2.1 Traditional Simulation

In early research, traditional simulation models are used to analyse systems and make decisions on operations and control. They are generally discarded following the implementation of the initial design. A number of researchers have termed traditional simulation models as "throw-away models" which describe models that are used after the plans and designs and are primarily based on historical data (Banks et al., 2010). The limitations of traditional simulation, however, have been acknowledged in research (Komashie et al., 2005, 2008). The disadvantages of this approach are mainly related to time and cost.

First, a manual analysis of input data is typically required in traditional modelling, which involves a large amount of time to complete. In some cases, the required input data may be available in a format that is impractical to use and thus require more time to process. In addition, since traditional simulation largely relies on historical input data, the results generated from the model are not necessarily reliable, especially when the data are no longer valid or relevant. This shortcoming is a crucial issue in manufacturing where its complex systems are highly dynamic. When the data inputted into a model are not obsolete and thus reliable, it is likely that simulation modeling would not accurately predict future events. Hence, the model can become an ineffective tool in understanding the system. Relatedly, since simulation, especially a complex model, can be time consuming, cost of simulating a traditional modelling is recognised as another shortcoming (Chung, 2003). Efforts to collect up-to-date input data can also be costly. Taken these disadvantages into consideration, real-time simulation modelling can enhance a more accurate prediction of future events and potentially reduce cost and time related to data input.

3.2.2 Discrete-Event Simulation (DES) in Real-time Control

To ameliorate the main limitations of traditional simulation, researchers have attempted to develop simulation modeling that is less dependent on time yet can still be integrated into large, complex systems. In manufacturing, the application of discrete-event simulation modeling is real-time which is constrained by timing requirements. Lee et al. (2001) explained that, in order for a real-time system to be simulated efficiently, a model must meet the constraints of time and simulation objectives (Banks, 2001). In this approach to simulation, the environment influences the model after a certain amount of time. After each interval of time, the status of the model is updated and shown according to the accumulation of input data.

Research has well demonstrated the use of discrete-event simulation. For instance, in a study of Vaidyanathan et al. (1998), a discrete event simulation model was developed as a planning tool using a hybrid approach which integrated a planner into the model. Later, Son and Wysk (2001) generated a code for an automatic simulation model to be applied to a real-time control system of a shop floor level. While this model can be applied to a traditional approach, this particular methodological simulation modeling is able to send and receive messages real-time through an Ethernet link and with an application of Rockwell Software Area. The model emphasised the strengths of its implementation and application of predictive simulation in conjunction with real-time data acquisition in dynamic manufacturing. In summary, the review of traditional and discrete-event simulation modeling highlighted the benefits of applying discrete-event simulation modeling to dynamic, complex systems of the current manufacturing industry.

As mentioned in the previous chapter, a number of simulation software packages are available in the industry such as AnyLogic, ProModel, Lanner, Plant Simulation and Arena Simulation programme. However, Guneri and Seker (2008) and Kelton et al. (2015) suggested that the development of Arena is regarded as one of the most successful simulation programmes for analysing complex systems. In addition, LabVIEW programme is suitable to be used as real-time data acquisition (DAQ) compared with other programming tools such as Python, myOpenLab, PyLab_Works, FlowStone, MatLab (Bitter et al., 2006 and Bishop, 2007).

3.2.3 Simulation Modelling Methodology

Arena Simulation programme (version 14.5) was employed to build a simulation model of the manufacturing systems and processes (Kelton et al., 2015). Robinson (1994) proposed four primary steps in simulation modelling methodology: problem analysis, simulating and testing, experimentation and analysis, and implementation. Figure 3.1 identifies the sub-steps in each of the four steps within the modelling process.

3.2.3.1 Problem Analysis

The problem analysis step consists of six sub-steps as follows: identify the problem, set objectives, define experimental factors, determine the conceptual model, collect and analyse data, provide project specification (Thierry et al., 2008). Overall, once the problem is recognised and defined and the objectives are clearly stated, the conceptual model which is a description of the model needs to be developed. The conceptual model should precisely identify the parameters including inputs, outputs and content. Raw data is collected and analysed to improve the accuracy of the simulation model in the subsequent step. However, because data collection could consume extensive time, this sub-step may be carried out simultaneously with the simulating and testing step.

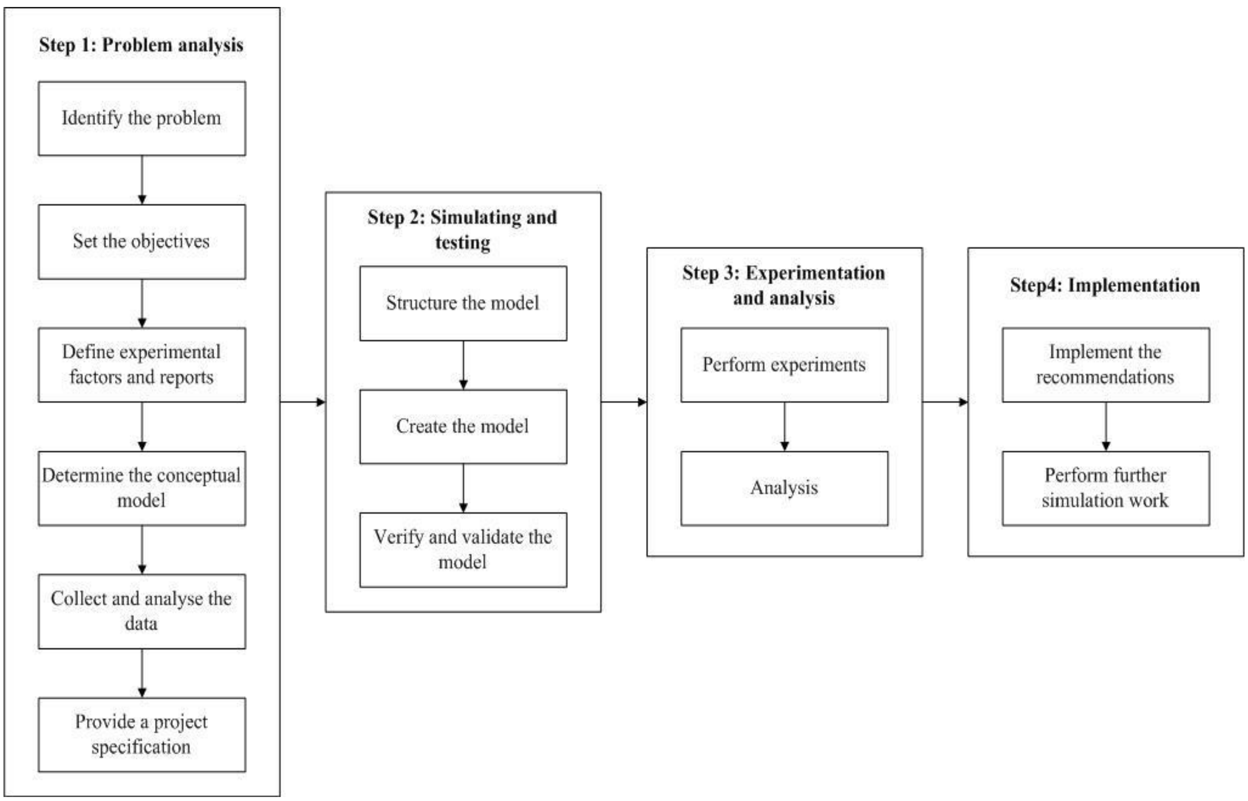


Figure 3.1: Four steps of simulation modelling methodology (Robinson, 1994)

In addition, Thierry et al. (2008) demonstrated the modelling process in relation to the four steps of simulation methodology. The relationship between the modelling process and the four steps are depicted in Figure 3.2.

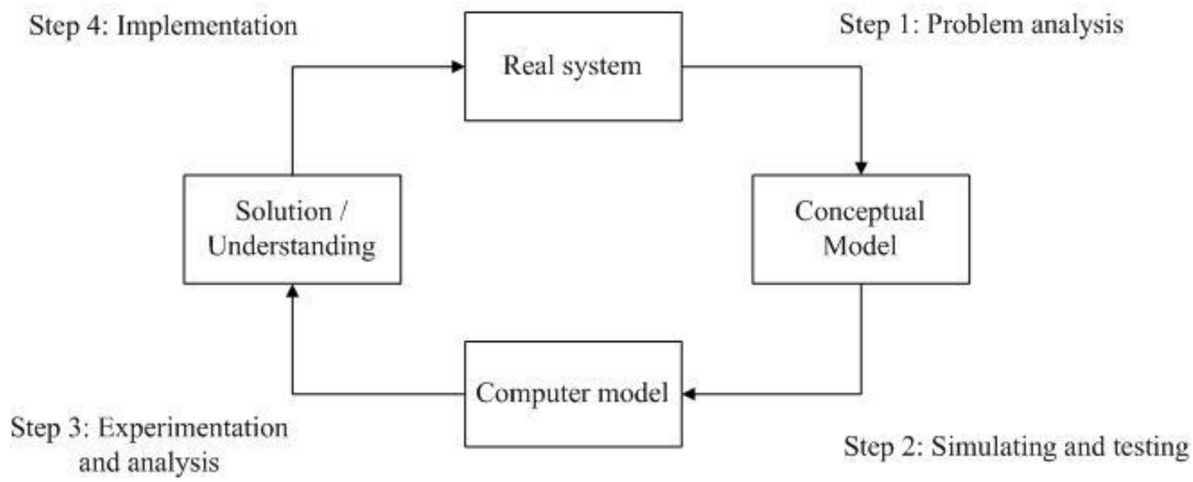


Figure 3.2: Modelling process (Thierry et al., 2008)

3.2.3.2 Simulating and Testing

Mainly, this step involves the computer model which is defined as the simulation model that is implemented on a computer and consists of three sub-steps: (1) structure, (2) create, and (3) verify and validate the model (Robinson, 1994, 2014). The computer model is first structured to test the components, reliability and logic. In this second sub-step, the computer model is created with the simulation software tool (i.e. Arena Simulation programme in this research) based on the structural model and acquired data. Last, the model is verified according to the logical rules and validated in order to further enhance accuracy and reliability of the output model and to ensure that it meets the objectives identified in the first step (Ingemansson and Bolmsjo, 2004; Robinson, 1994).

3.2.3.3 Experimentation and Analysis

This third step involves an experiment and analysis to gain improvements or understanding of the 'real world' situations or problems (Robinson, 2014). This step refers to the 'what-if' analysis process which modifies the model's inputs, run the model, observe and analyse the results, and then modify changes to the inputs again, if necessary, to improve the robustness of the solution and more importantly to achieve the objectives. Robinson (1994) also refers the 'what-if' analysis process to interactive experimentation.

3.2.3.4 Implementation

Implementation is carried out for three main purposes: to implement the findings from the simulation to improve the 'real world' problem, to implement the model, and to gain understand for learning purposes (Robinson, 2014). In this step, recommendations can also be implemented with the results for improvements and future work.

3.3 Statistical Analysis

Statistical analysis is a systematic approach in which data are analysed in order provide answers to the research question (Morris, 2010). In an experimental case study, data are typically derived from the process of data acquisition such as measurement. As a result, a set of data includes a number of independent and dependent variables. In the present dissertation, the relationship between the variables of interest, namely energy consumption, product quality and temperature, is analysed by a mathematical method called regression model. The strength of the relationship is identified with a correlation index called correlation analysis (Montgomery, 2013).

A variety of statistical software packages are available such as SPSS, SAS, R, Stata, SYSTAT, JMP and MINITAB. Coakes and Steed (2001) stated that SPSS can efficiently analyse large sets of data. Levesque (2005) claimed that SPSS is a powerful tool which comprises of various function such as acquiring, merging, and transforming data. It also provides user friendly graphical interface (Levesque, 2005). Hence, statistical analysis was investigated with the statistical analysis software package SPSS version 20 in this dissertation. In addition, Hilbe (2003) suggested that SigmaPlot is a tool for users to create complex two- and three-dimensional graphs. Thus, SigmaPlot programming is used to illustrate the 3D correlation analysis.

3.3.1 Multiple Regression Analysis

Regression analysis is a mathematical process for constructing a model which describes the relationship between dependent and independent variables that are continuous (Seber and Lee, 2003). The model is then fitted in order to acquire the estimator from the unknown parameter values often with a least squares method. This method aims to produce fitted line that is the closest to the data points (Draper and Smith, 1998). Thus, distances between each of the collected data points and the fitted line are minimised. In addition, various regression models are available to analyse the data to predict the value of the dependent variable from the value of the independent variable. In the simplest form, simple regression model explains a relationship between one independent and one dependent variable. However, when multiple independent variables are involved, conducting several simple regression model tests separately can result in an increase in type I error. Hence, multiple linear regression analysis is more appropriate when there are two or more independent variables.

Multiple linear regressions are extended from the least squares regression to the equation of one 2D plane which is expressed in Equation (3.1) (Draper and Smith, 2014).

$$z = ax + by + c \tag{3.1}$$

The equation minimises the vertical distances between the x_i, y_i, z_i points and the plane. In doing so, the values of a, b, and c need to be solved in Equation (3.2).

$$G(a, b, c) = \sum (z_i - ax_i - by_i - c)^2 \tag{3.2}$$

Assuming the linearity exists and there is:

$$\frac{\partial G}{\partial a} = 0, \frac{\partial G}{\partial b} = 0, \frac{\partial G}{\partial c} = 0 \tag{3.3}$$

The matrix equation for a, b, and c can then be established as:

$$\begin{bmatrix} \sum x_i^2 & \sum x_i y_i & \sum x_i \\ \sum x_i y_i & \sum y_i^2 & \sum y_i \\ \sum x_i & \sum y_i & n \end{bmatrix} \begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} \sum x_i y_i \\ \sum y_i z_i \\ \sum z_i \end{bmatrix} \tag{3.4}$$

The solution for a, b, and c can be found when the matrix on the left is invertible, i.e. the determinant being not equal to zero.

3.3.2 Correlation Analysis

In order to investigate the correlation between two variables, the use of different indices needs to be selected. There are three main types of correlation coefficients which are Pearson's coefficient (r), Spearman's coefficient (r_s), and Kendall's coefficient (τ) (Hauke and

Kossowski, 2011). Pearson's correlation coefficient is a widely used statistical measure which defines the strength of a linear relationship between two continuous variables and varies from + 1 through 0 to – 1 (Hauke and Kossowski, 2011). It is denoted by *r*.

Figure 3.3 depicts examples of graphical representations of correlation and Pearson (r) correlation data. As depicted in Figure 3.3, the positive values denote a positive linear correlation whereas negative values denote a negative linear correlation. A value of 0 denotes no linear correlation. Benesty et al., 2009 suggested that the absolute values of *r* ranging from 0 to 0.19 are described as "very weak", the values between 0.20 and 0.39 are "weak", the values between 0.40 and 0.59 are "moderate", the values between 0.60 and 0.79 are "strong", and the values between 0.80 and 1.0 are "very strong".

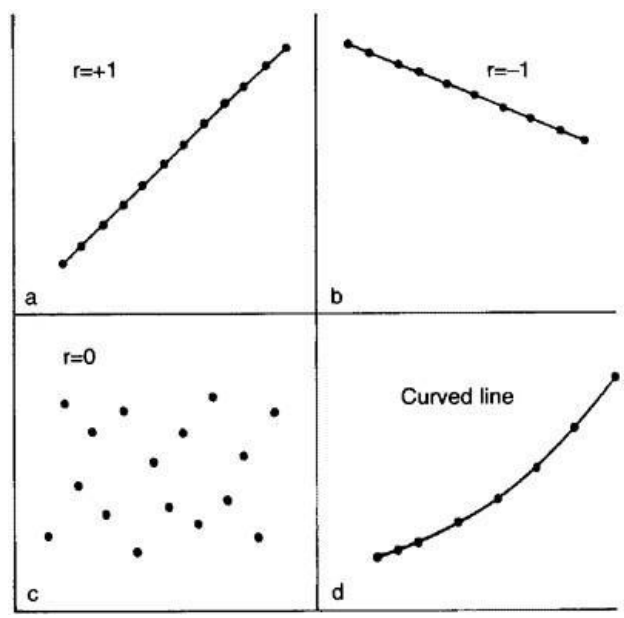


Figure 3.3: Graphical correlation coefficient (Draper and Smith, 2014)

In multiple regression analysis, correlation coefficient (*r*) alone is not sufficient to explain a multi-linear relationship because there are multiple variables involved. Draper and Smith (2014) described that R^2 (coefficient of determination) takes into account correlation of the multiple pairs in the multiple linear regression model.

R^2 explains how well the least squares line fits the collected data where the large value defines a closer fit between the line and the data (Seber and Lee, 2012). It also defines the amount of variability of the dependent variable that is explained by the independent variables. Therefore, the R^2 is a useful measurement to estimate the strength of the association between the variables in the model (Seber and Lee, 2012). In Figure 3.4, the graphs demonstrate the value of the response variable variation that is explained by a linear model showing three simulated data of X and Y values. The values can be multiplied by 100 to give a percentage.

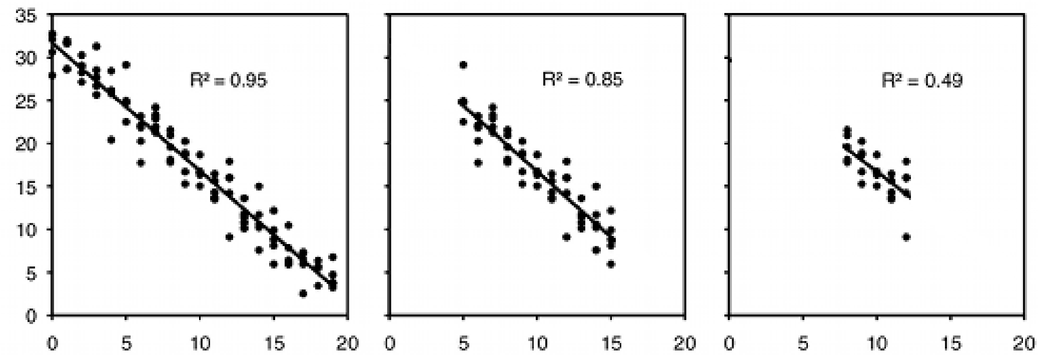


Figure 3.4: Examples of determination correlation (R^2) data (Seber and Lee, 2012)

Furthermore, significance level (or *α*) is adopted to describe the statistical significance of a regression model (Cohen, 1988). Specifically, the p value which defines the probability of rejecting the model as significant when it is in fact statistically significant (Cohen, 1988). Typically, a significance level is set at 0.05 in engineering and management fields (Cohen, 1988. In other words, the model and independent variables are stated to be statistical significant in predicting values of the dependent variable when the *p* value is less than 0.05 (Cohen, 1988 and Anderson, 1984).

3.4 Chapter Summary

Research method is fundamental as it provides a systematic plan in how research is carried out. The present chapter describes the concept and provides the rational justification for conducting a simulation modelling method. In the following chapter, a simulation model of the proposed Energy-smart Production Management System (e-ProMan) is introduced and elaborated in more details. Statistical analysis is also described in this chapter.

CHAPTER 4

Development of the Sustainable Manufacturing Approach Integrated with e-ProMan Framework and Analytics

The primary objective of the present chapter is to develop a scientific and methodology based approach for sustainable manufacturing by using modelling simulation and energy efficiency management system. The process and steps of the simulation are elaborated. More importantly, the chapter presents the Energy-smart Production Management (e-ProMan) system as an advanced simulation platform for modelling and management of energy use in a manufacturing system. The chapter also describes the measurement tools and software programmes and their implementation in this energy management system.

4.1 Introduction

In manufacturing, energy management systems employ an empirical methodology that systematically consists of monitoring, analysing and optimising as proposed in Figure 4.1 (Costa et al., 2013). At a simple level of analysis, the monitor function is carried out to understand what, when and where energy is consumed. The analyse function is to achieve better utility rates by utilising resources or changing behaviour. Finally, the optimise function aims to improve equipment performance by reducing energy usage. When necessary, the process continually repeats in order to find the optimum solution.

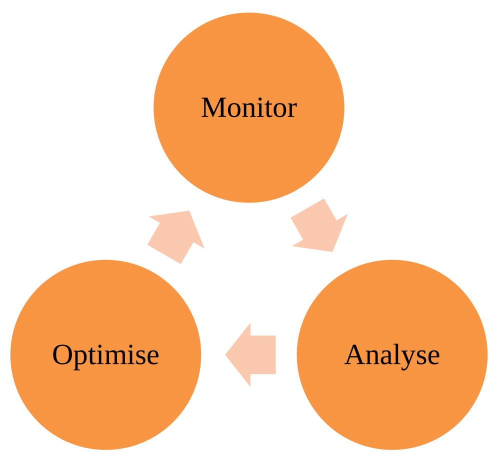


Figure 4.1: Energy management cycle

In the current manufacturing environment where processes are highly complex, numerical or mathematical methods alone may be impractical to monitor, analyse and optimise the overall behaviour of energy consumption at different levels of analysis (Altiok & Melamed, 2007). Simulation methods, however, enable the energy management system to identify and evaluate the flows of information in the manufacturing processes and plant. Specifically, these methods provide more advantages over other methods as simulations examine the existing model and then propose the implemented system according to the 'what-if' analysis, thereby resulting in an optimal solution to modelling for manufacturing applications (Banks et al., 2010). Robinson (2014) also highlighted other advantages of simulation over experimentation including less cost and time and unavailability of a real system for experimentation. Accordingly, the present research employs simulation modelling as the main methodology to monitor, analyse and optimise the energy management system in manufacturing.

4.2 Development of the the e-ProMan System

Considering the significance of correlational and analytical analysis in real-time decision making in relation to energy efficiency, the present research develops and proposes a simulation model of energy consumption or energy-smart production management system (e-ProMan) (Katchasuwanmanee et al., 2015). As shown in Figure 4.2, the e-ProMan presents user-friendly factory displays demonstrated with 3D CAD models. It is a predictive modelling and simulation system which performs by (1) acquiring the inputs from the historical and real-time data, (2) evaluating on the three-dimensional correlation between energy flow, work flow and data flow and (3) providing real-time decision making in the most accurate way as possible.

More specifically, the manufacturing data in this proposed energy-efficient management system consist of four real-time data types: weather forecast, shop-floor ambient temperature, production processes and workload (both real-time and historical), and energy consumption of machines (i.e. HVAC system and CNC milling machines). The manufacturing data are gathered using two analysis and implementation tools: Arena Simulation programme and LabVIEW. Accordingly, the e-ProMan system is used to analyse in order to gain results of the multidimensional relationships between energy flow, work flow and data flow in the manufacturing. The results of the correlational analysis will advance the development of a control system and optimisation concerning the minimisation of energy usage and CO_2 emissions in manufacturing.

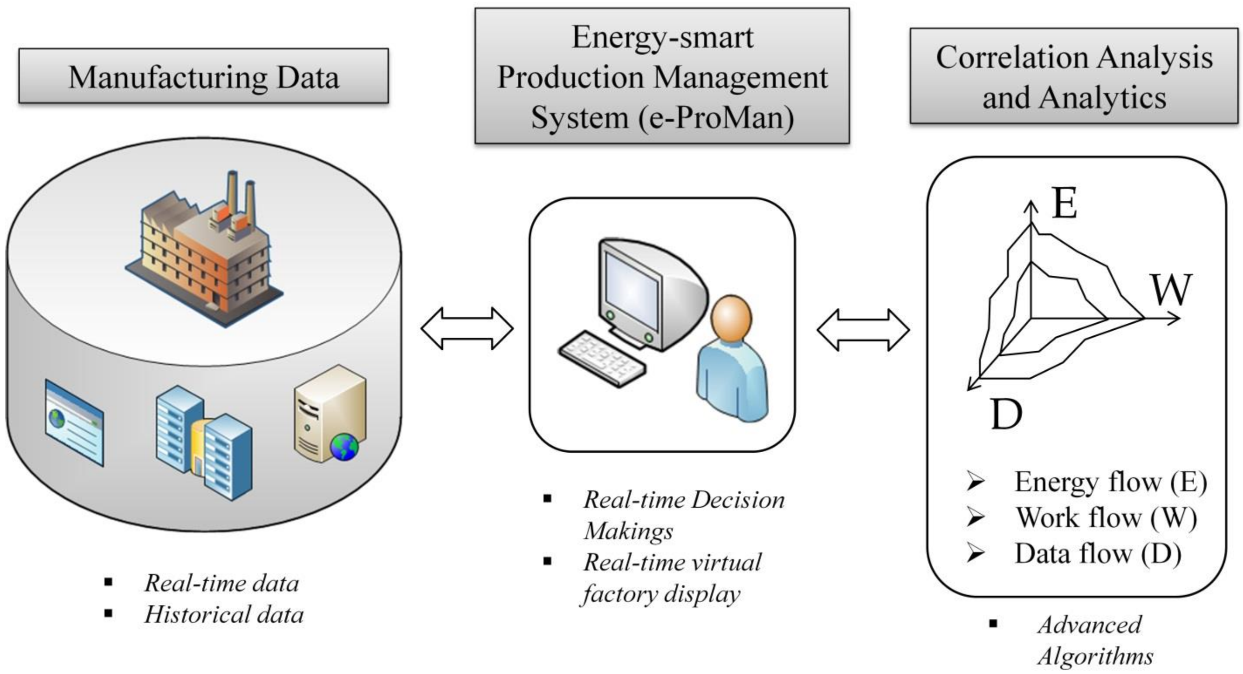


Figure 4.2. Architecture of the energy-smart production management system (e-ProMan)

4.2.1 Measurement Instruments

To acquire manufacturing data, three main performance measurement tools are used within the e-ProMan system: thermal camera, temperature sensors and power logger. Briefly, a thermal camera is installed and used to measure the temperature at a surrounding area of the operating machine. The ambient temperature of the manufacturing plant and outside temperature are measured with temperature sensors. Power logger is employed to measure the actual energy consumption of the operating machine.

Theoretical analysis on temperature flows is carried out against the experimental data by CFD in the experimental models to identify temperature distribution and air movement predications. Last, the acquired data is put into Arena Simulation programme via LabVIEW in order to evaluate and calculate the sum of energy consumption and CO_2 emissions throughout the manufacturing process. Figure 4.3 summarises the flow and sequence of the methodological measurement tools within the present energy management system.

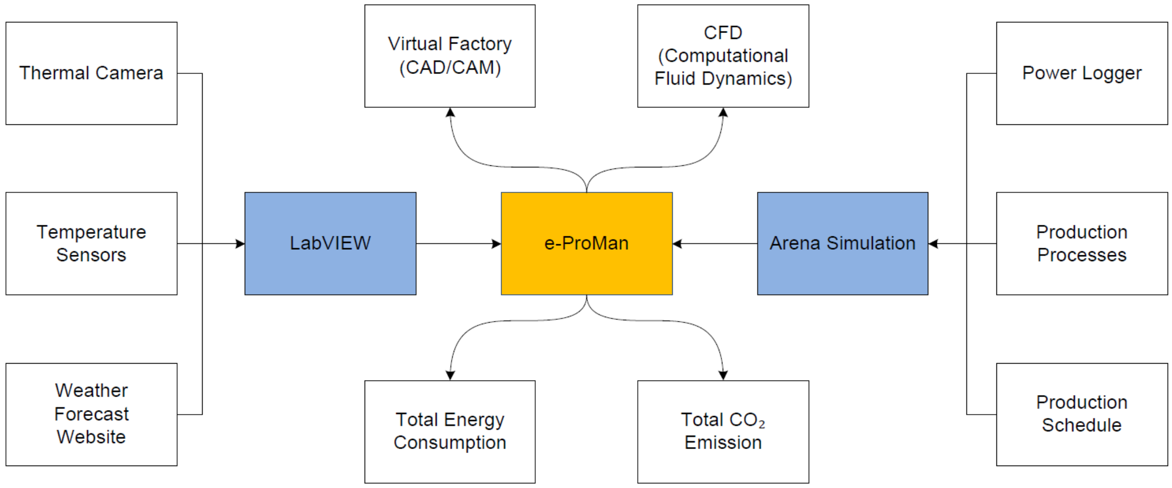


Figure 4.3: The flows of methodological tools in e-ProMan system

4.2.1.1 Thermal Camera

A thermal camera OPTRIS PI 160TAK is installed and used to gather real-time data of the surrounding area of operating machine and workpieces as shown in Figure 4.4. This device is an infrared and non-contact temperature tool that enables both point and area measurements at a specific area or at the machine. This thermal camera can virtually capture and display temperatures within a range between -20 and 900 degrees Celsius, and it can detect wavelengths in the spectral range of 7.5 to 13 µm with a speed of 120 Hz. An example of the thermal display is presented on the right side of Figure 4.4.

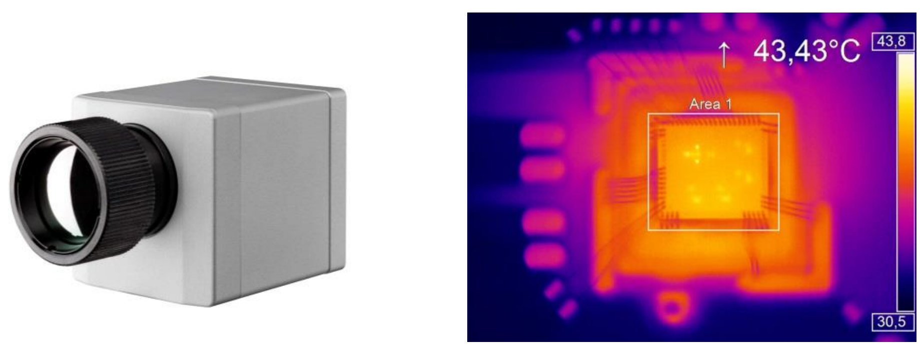


Figure 4.4: Thermal camera optris PI 160TAK (left) and thermal camera display (right) (Optris, 2016)

4.2.1.2 Temperature Sensor

The AREXX temperature logger is a real-time dynamic system to measure and log temperature data connecting with computers (Arexx Engineering, 2013). The temperature logger consists of two equipment components which are temperature sensor and USB base station (Arexx Engineering, 2013). Both of them are connected to each other using wireless links and are then linked to the computer as presented in Figure 4.5.

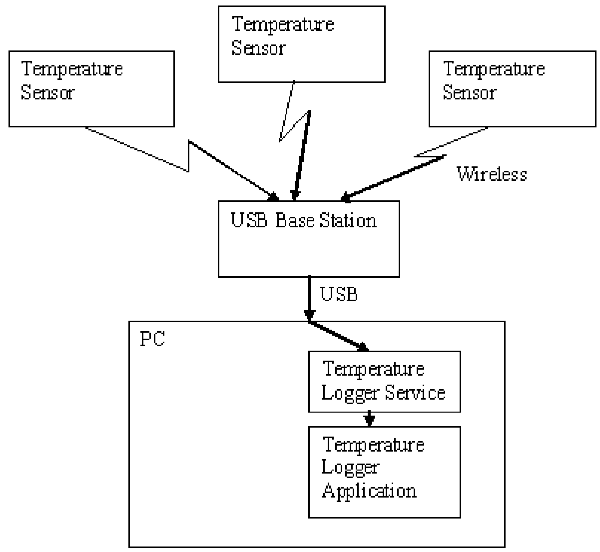


Figure 4.5: Temperature logger process chart (Arexx Engineering, 2013)

Specifically, the temperature sensors, as shown in Figure 4.6, acquire all temperature values while the software is running in the background mode. The left side of Figure 4.6 shows the temperature sensor that is used to measure the ambient temperature of the shop-floor, whereas the sensor on the right side of the figure is used to measure the outside temperature. According to Arexx Engineering (2013), the sensors are designed to measure temperatures in a wide range between -30 and +80 degrees Celsius and capture temperature every second. As shown in Figure 4.7, the USB base station can synchronously receive data from a maximum of 50 wireless temperature sensors.

Figure 4.6: Inside temperature sensor (left) and outside temperature sensor (right) (Arexx Engineering, 2013)

Figure 4.7: USB base station (Arexx Engineering, 2013)

Figure 4.8 displays the temperature logger measurement software illustrating time and date graphically. The device is connected to its online website via lan-line cable; thus, the temperature data can be accessed real-time and only available for client network. This software can track the data over several years and continually save the data as long as the linked computer is running (Arexx Engineering, 2013).

4.2.1.3 Power Logger

Fluke's literature (2013) stated that "The Fluke 1735 Power Logger is the ideal electrician or technician's power meter for conducting energy studies and basic power quality logging". In the e-ProMan system, power logger is selected and utilised to acquire energy consumption of a machine in a manufacturing environment on cutting trial with different machining conditions. As displayed in Figure 4.9 and Figure 4.10, the power logger is attached to the three phase electrical cable using the three-phase clamps (I1A/10A PQ3, 3-PHASE 1A/10A MINI CURRENT CLAMP SET FOR PQ). The measured data related to energy consumption are then linked to the LabVIEW programme and to the Arena simulation programme to create user interface display in a user-friendly manner. Figure 4.11 presents the graph results of the voltage average and current average displayed in the LabVIEW programme.

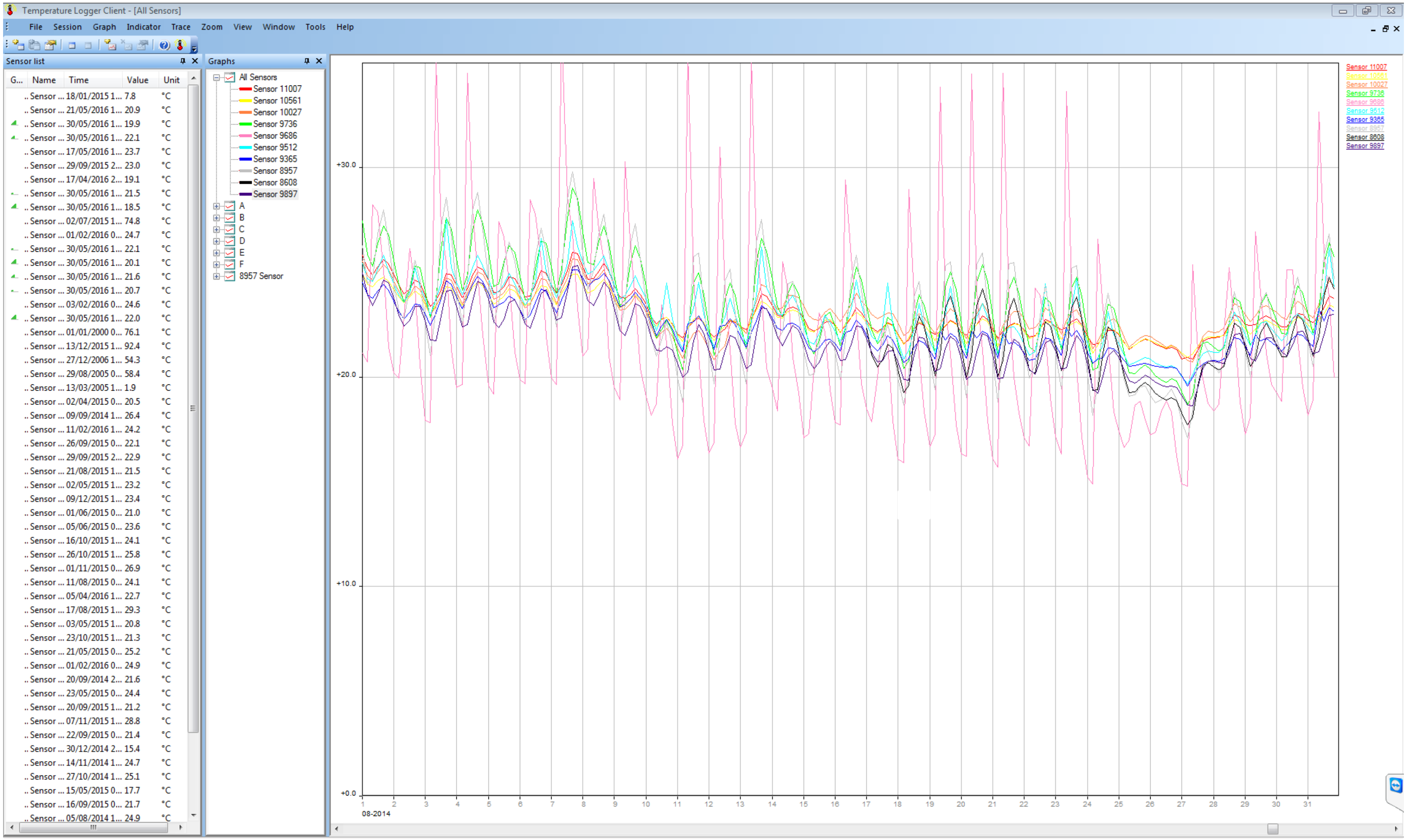


Figure 4.8: Multi-temperature logger experiment user interfac

4.2.2 Manufacturing Real-Time Data

At this research stage, the manufacturing data of the e-ProMan system include three real-time data sources: weather forecast, shop-floor ambient temperature and energy consumption of a HVAC system.

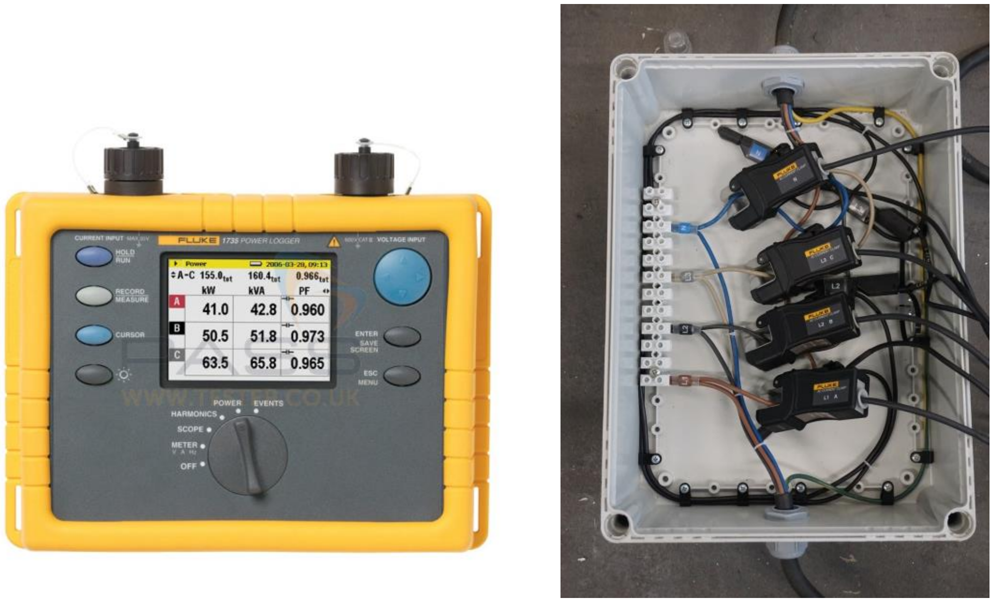


Figure 4.9: The power logger connected to the three-phase clamps (Fluke, 2013)

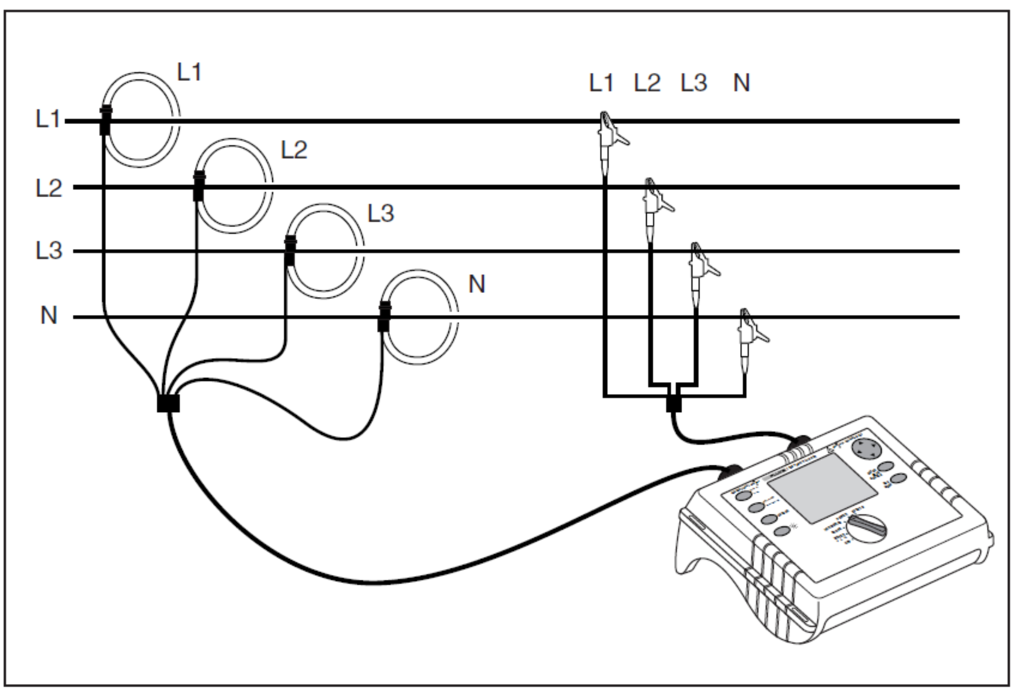


Figure 4.10. Measurement of three phase motor (Fluke, 2013)

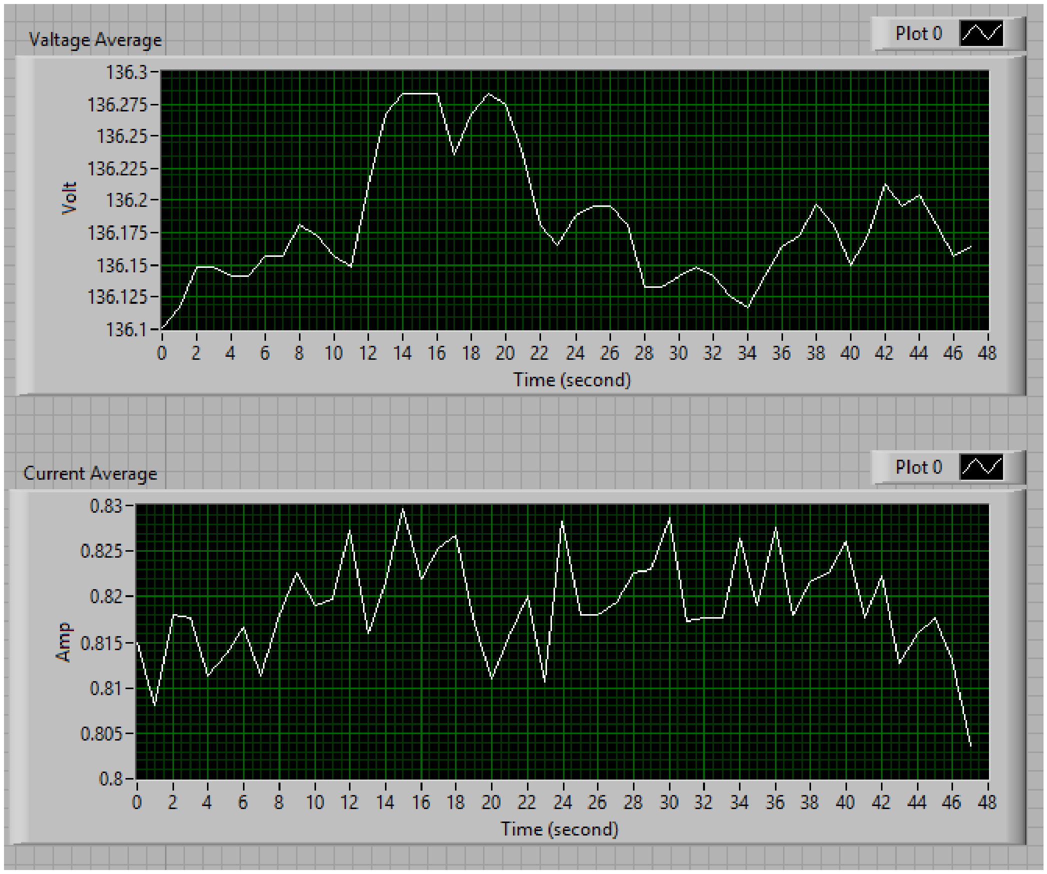


Figure 4.11: An example of voltage and current display results in LabVIEW

4.2.2.1 Weather Forecast Data

Various commercial weather forecast websites that provide real-time weather predictive data are freely available such as Weather Channel, Metcheck, BBC Weather and Met Office. The e-ProMan system particularly selects Met Office, one of the UK's well-recognised meteorological websites, because it adopts the Numerical Weather Prediction (NWP) model. The NWP model employs a computer-based simulation and is regarded as the most reliable predictive system (Rodwell & Palmer, 2007). Figure 4.12. presents an example of the weather forecast data on the Met Office website page. The e-ProMan system retrieves real-time next-hour weather forecast data from the Met Office database which are directly linked to and displayed on the LabVIEW as demonstrated in Figure 4.13. The three main displays provide weather data on temperature, wind and humidity.

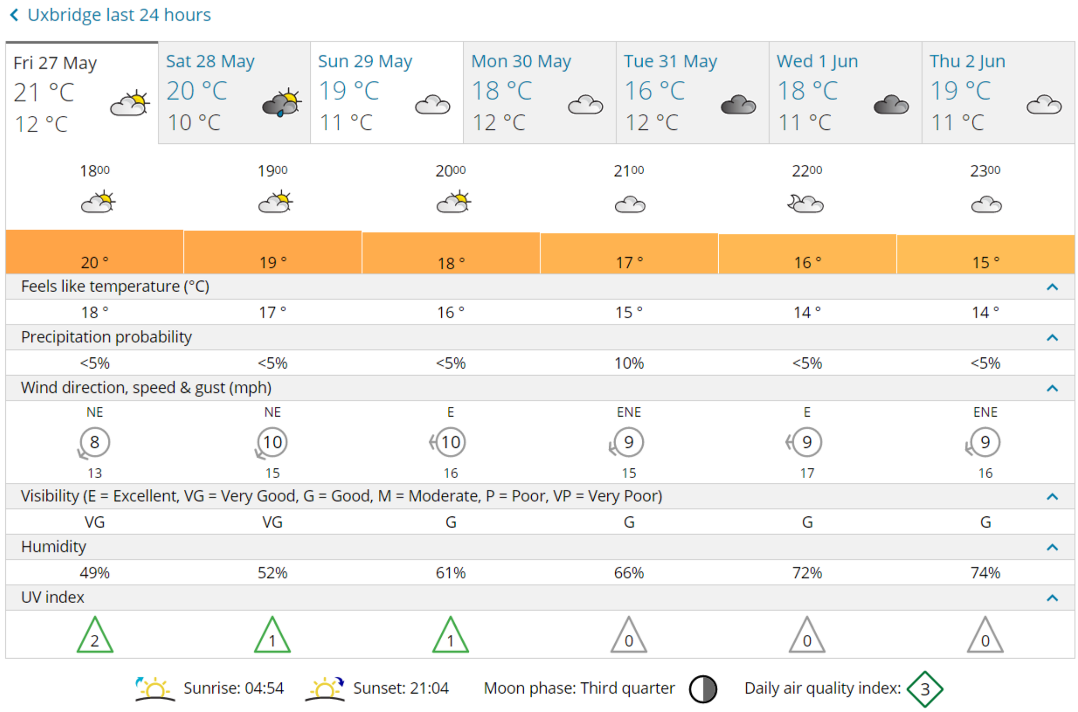


Figure 4.12. Met Office weather forecast data (Met Office, 2016)

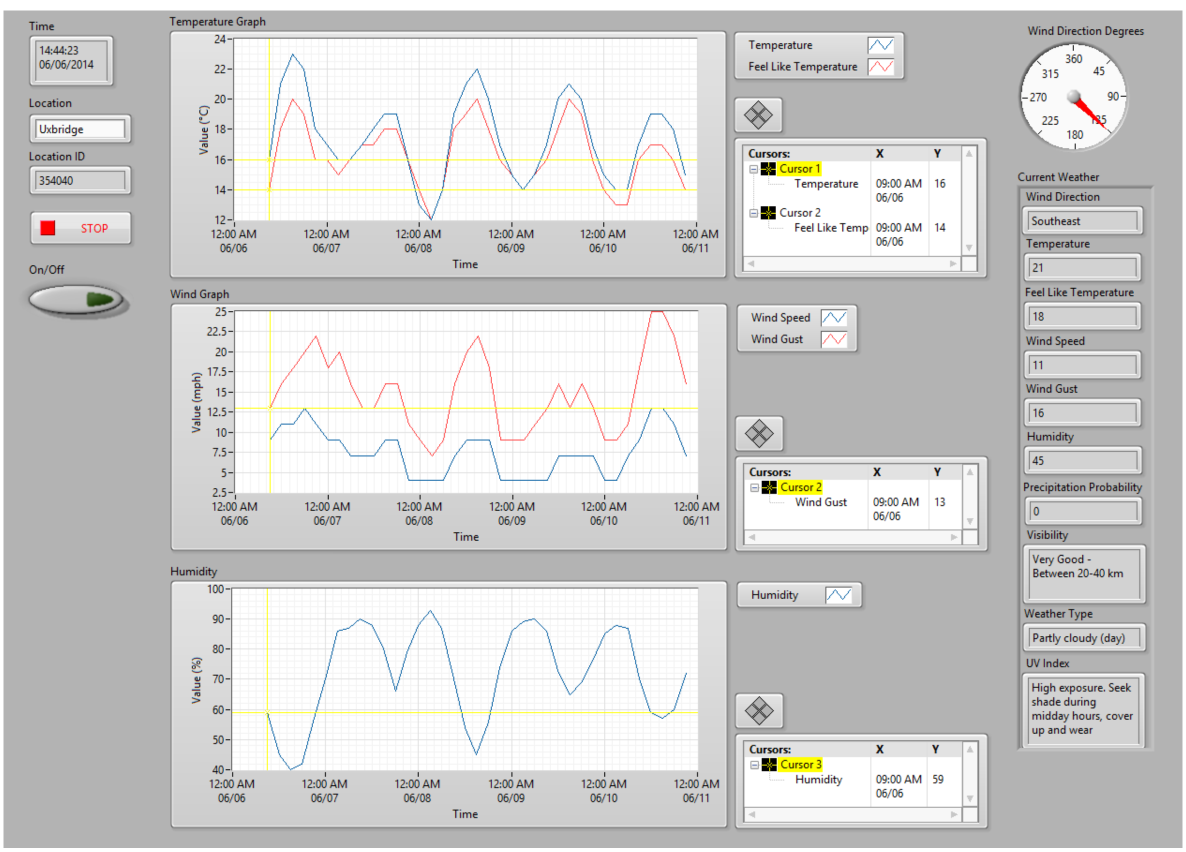


Figure 4.13. Predictive weather forecast data in LabVIEW

4.2.2.2 Shop-floor Temperature Data

Data of shop-floor temperature are collected from the ambient temperature of the Advanced Manufacturing and Enterprise Engineering (AMEE) Laboratory at Brunel University London as shown in Figure 4.13.

Figure 4.14. AMEE laboratory at Brunel University London

A total of 10 temperature sensors are equipped across the shop-floor. The laboratory layout is designed and modelled with the CAD (computer-aided drafting) system tool. Figure 4.15 presents the two-dimensional (2D) CAD model of the shop-floor which illustrates the locations of the equipped temperature sensors (yellow dots). Figure 4.16 depicts the three-dimensional (3D) CAD model illustrating the measuring positions of the ten temperature sensors located on each side of the shop-floor.

As shown in Figure 4.17, the real-time shop-floor temperature data are first linked to BS-1000 LAN base station, then connected and displayed on the web browser via a script based web service. The 3D CAD model is then synchronised to the LabVIEW which established the distribution of thermal environment in the colour-coded by demonstrating and comparing temperatures between each point in the manufacturing environments as shown in Figure 4.18.

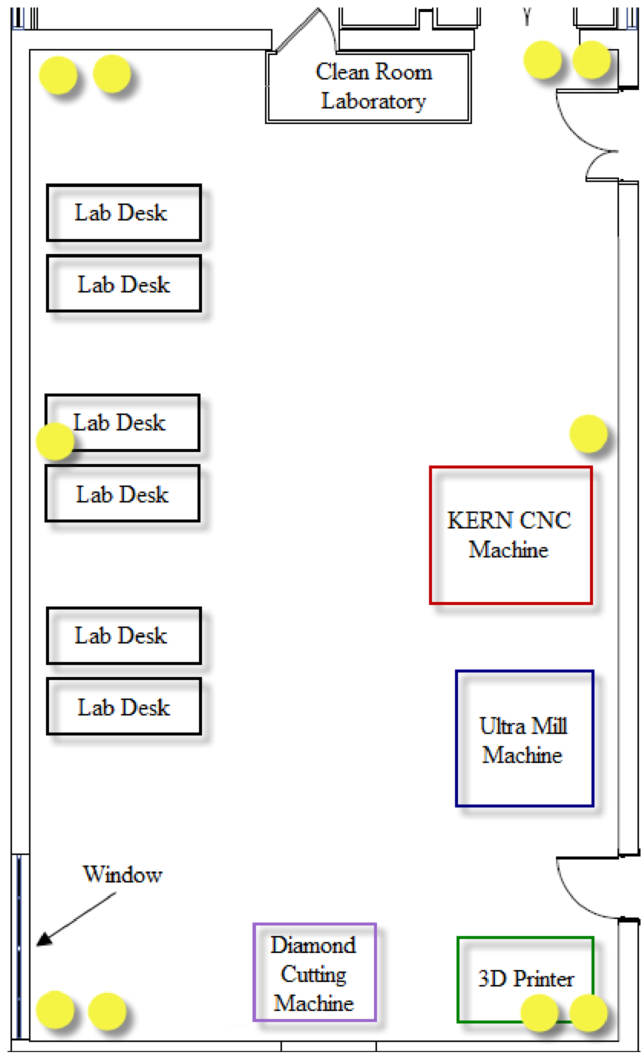


Figure 4.15. Brunel AMEE Laboratory Layout in CAD

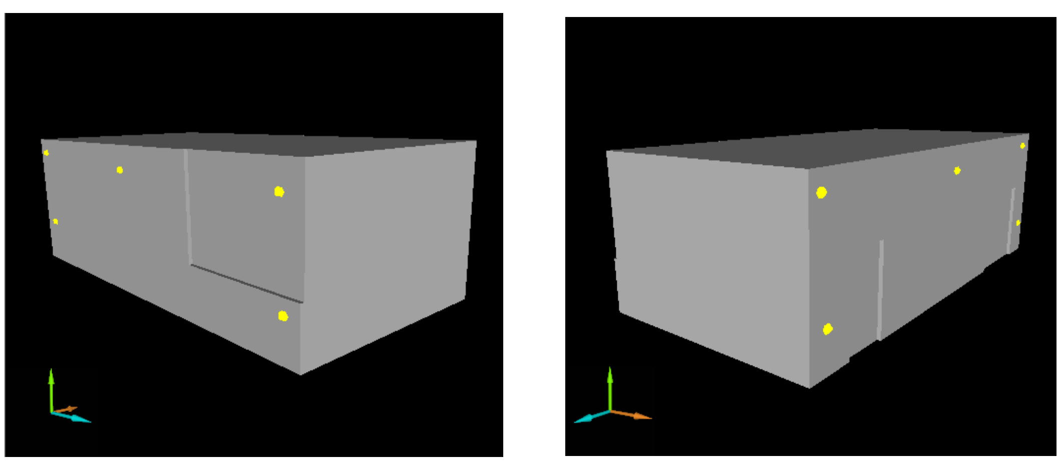
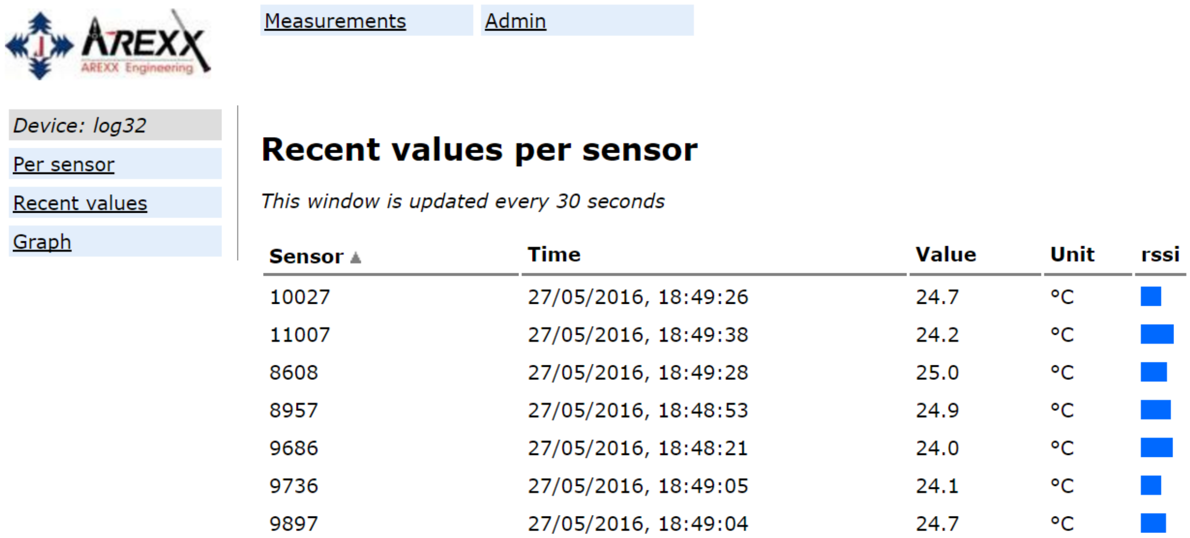


Figure 4.16. Outside view (left) and inside view (right) of Temperature Sensors Measuring Positions in the AMEE Laboratory



Measurements Admin

Device: log32

Per sensor

Recent values

Graph

Recent values per sensor

This window is updated every 30 seconds

Sensor ▲	Time	Value	Unit	rssi
10027	27/05/2016, 18:49:26	24.7	°C	
11007	27/05/2016, 18:49:38	24.2	°C	
8608	27/05/2016, 18:49:28	25.0	°C	
8957	27/05/2016, 18:48:53	24.9	°C	
9686	27/05/2016, 18:48:21	24.0	°C	
9736	27/05/2016, 18:49:05	24.1	°C	
9897	27/05/2016, 18:49:04	24.7	°C	

Figure 4.17. Real-time temperature sensor data acquisition

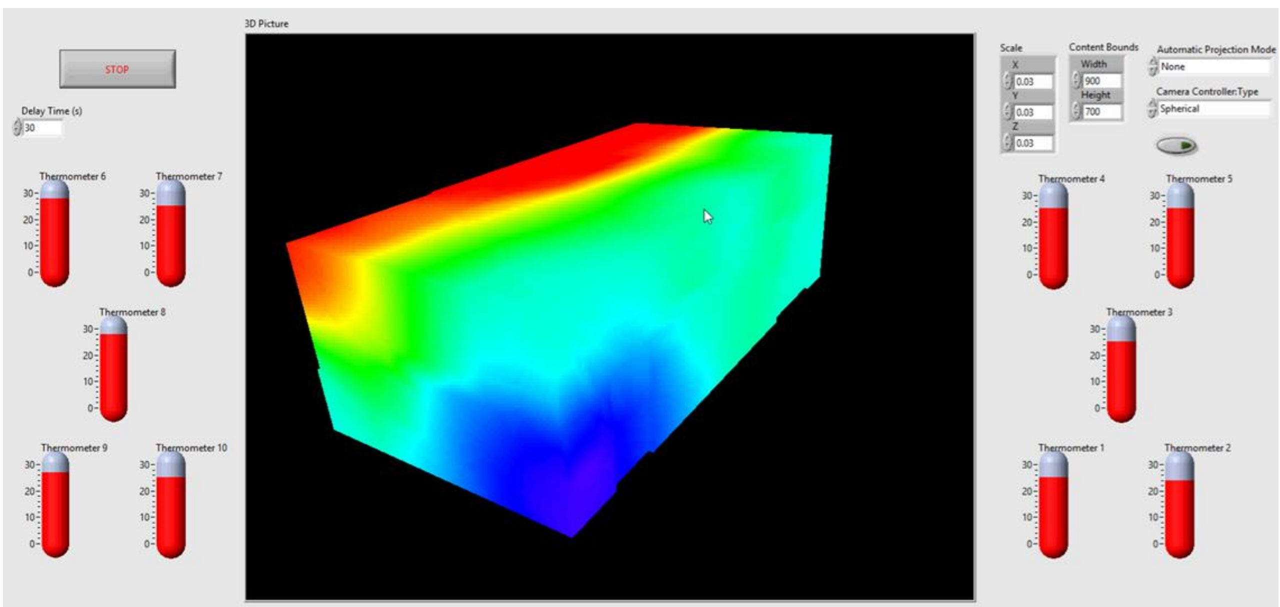


Figure 4.18. Real-time 3D sensor mapping

4.2.2.3 HVAC System Data

As described in Chapter 2, the Health, Safety and Welfare Regulations 1992 state that the temperatures in laboratories should be in the range between 16 and 19 C (Health and Safety Executive, 2013). Thus, the ideal temperature defined by the range of these regulations is demonstrated in LabVIEW 3D sensor mapping shown in Figure 4.19. Typically, HVAC systems are operated to adjust and maintain temperatures in buildings and also in manufacturing plants using the simple logic of the difference between indoor and outdoor temperatures (ΔT). This research implements an integrated HVAC system together with the ambient shop-floor temperature data and weather forecast data. Figure 4.20. illustrates the user interface of HVAC system of the e-ProMan application system.

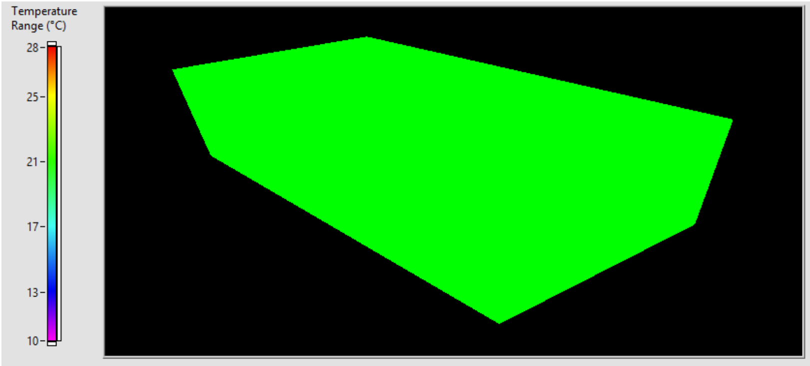


Figure 4.19. Ideal temperature

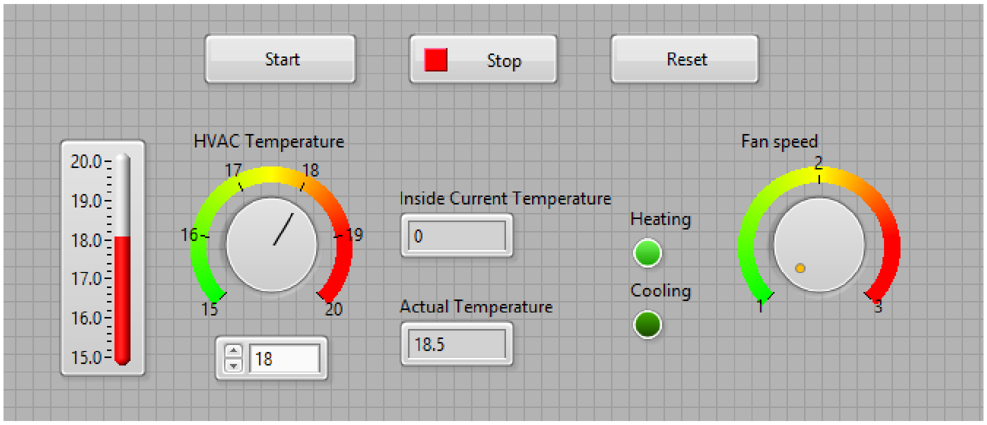


Figure 4.20. HVAC system controller

4.2.2.4 Production Manufacturing Data

The capabilities of Arena enable the production management system to monitor and analyse the system to gain improvements in various areas such as energy consumption and resources. Moreover, simulation in Arena can model a variety of systems such as manufacturing plant with a set of various machines, processes, people and devices as shown in Figure 4.21. The implementation of Arena combines graphic and textual paradigms and presents a module-based simulation that can model any 'what-if' scenario that involves the flow of activities through a set of processes using the SIMAN simulation language (Altiok & Melamed, 2007).

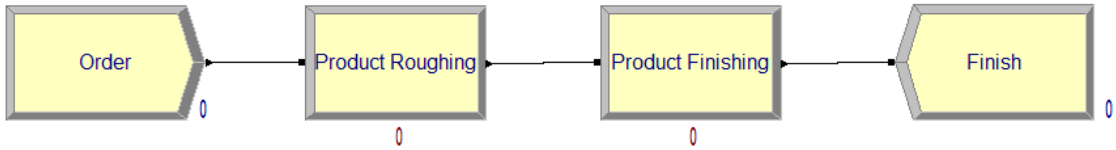


Figure 4.21. A simulation of milling production in Arena Simulation programme

The other software programme employed in the present energy management system is the LabVIEW programme. In this research, LabVIEW is primarily used as a data acquisition system to continuously link the raw data gathered from the three measurement tools (i.e. thermal camera, temperature sensors and power logger) to the Area Simulation programme in a real-time manner. The analysis of the simulation model is also performed with LabVIEW including multi correlation analysis, HVAC fuzzy system and e-ProMan system. Last, LabVIEW is employed to display and model the simulation model of the energy management system including user friendly display.

4.3 Chapter Summary

The present chapter presents a prototype of the Energy-smart Production Management (e-ProMan) system that is systematically developed from a computer-based simulation modelling and describes the measurement tools and software programmes within the system. The simulation method provides a valuable tool to monitor, analyse and optimise the effectiveness of a complex energy management system without having to conduct actual 'real-world' situations. The e-ProMan acquires the data from various sources including real-time temperature data in order to present a virtual friendly display and provide decision making. By obtaining both types of data, the e-ProMan is proposed to control and adjust the shop-floor temperature environments, calculate energy consumption and thus CO_2 emission to achieve sustainable manufacturing.

CHAPTER 5

Multivariable Correlation Analysis on Energy Consumption, Ambient Temperature and Component Accuracy in Precision Machining

This chapter presents an experiment-oriented correlation analysis approach to investigate the intrinsic relationships between the machining accuracy, ambient temperature and total energy consumption including HVAC system and machining energy consumption in CNC precision milling, which aims to establish a scientific understanding of a sustainable precision machining system on a quantitative analysis basis. The CNC milling experiments were conducted on 40 aluminium workpieces, which was used to quantify quality error percentages at various ‘shop-floor’ temperature conditions ranging between 23°C and 27°C. A total of 14 dimensions were measured at reference points on each workpiece plate, giving a total of 560 data measurements.

5.1 Introduction

Quality improvement in manufacturing is the key indicator of performance that has a crucial impact on competitiveness (Nada et al., 2006). One approach to improving the product quality is to leverage the accuracy of the machining processes involved. Specifically, geometrical and dimensional accuracy significantly characterises manufactured parts with thermal deformation being of particular importance as it leads to machining errors (Archenti, 2014). Therefore, much recent research in manufacturing has paid great attention to the effect of temperature variation on machining precision to continuously assure and achieve a high quality of components and products (Shin et al., 1991; Katchasuwanmanee et al., 2015; Shu et al., 2013). Current literature on machining accuracy due to temperature has addressed methodological advancement on the machine tools and material properties, cutting tool material and condition, and machining parameters (Cheng, 2008).

A correlational analysis on machining quality, energy consumption and temperature variations is presented in the context of sustainable precision machining. The investigation aims to determine the accuracy performance of a three-axis CNC milling machine while taking into account the environmental temperature variations and energy usage throughout the machining process. A parametric compensation method is employed to compute the quality errors of aluminium milling produced by the temperature variable conditions. By adopting a multidimensional analytical approach, the experimental and analytical results could provide a holistic framework for the scientific understanding of sustainable precision machining, which addresses the needs for high precision sustainable machining for high-value manufacturing purposes.

5.2 Multivariable Correlation Analysis for Sustainable Precision Machining

5.2.1 Machining Quality Linking to Component Dimensional Accuracy

In response to a growing demand for advanced standards of machining accuracy, various approaches to characterise machine tools have been developed (Shin et al., 1991). Accuracy of machined parts depends on a variety of elements including machine tool accuracy, cutting tool materials, the material properties of the workpiece, environmental temperature change and machining parameters such as feed rate, cutting speed and depth of cut (Shin et al., 1991; Chen et al., 2013; Schwenke et al., 2008). Both static and dynamic characteristics of machining should be accurately analysed, and errors should be adjusted accordingly to assure the quality of products.

When manufacturing environment is well regulated, a machine has the potential to position itself within micrometres (Shin, 1991). Nonetheless, the environmental condition during the machining process is not necessary ideal where, for instance, the temperature of the surrounding air can fluctuate. The majority of machines in production, therefore, may not operate under the optimal condition. Variations of the temperature could cause thermal distortion of a workpiece.

In this research, quality of machining is defined by the machining error which is the distance between the nominal CAD model and the actual measured point after machining. Following the relative error or percent error (%error) of Equation (2.5) in Chapter 2, the formula for the quality error is specifically applied to measure the machining error and calculated as shown in Equation (5.1).

$$\text{Quality Error (\%)} = \frac{\sum_{i=1}^{n}\left(\left|\frac{y_i - x_i}{x_i}\right| \times 100\right)}{n} \tag{5.1}$$

where i is the number of reference points; x_i is the nominal CAD model value of dimensions; y_i is the actual measured value of dimensions; and n is the total number of measurement points.

Taking into account the numerous possibilities of cutting conditions, the performance of a machine tool cannot be assessed directly based on machining experiments, yet the experiments can generate practical results that are potentially useful to model correlations between the errors of volumetric accuracy and the actual cutting (Shin, 1991).

5.2.2 Temperature Variations in Manufacturing

As illustrated in Figure 5.1, in a precision machining system the energy sources (e.g. cutting heat and thermal sources) at machine tools and the temperature variations in the local work environment have integral effects on the respective thermal expansions on the machine tool and workpiece and consequently on the accuracy of the component and the environmental impact from the machining (Shu et al., 2013; Cheng, 2008; Chen et al., 2013). Accordingly, the relationships between thermal deformations and outcomes namely machining accuracy, energy consumption and productivity rates are collectively inter-related. As thermal deformation and outputs are substantially affected by heat from various sources, it is essential to consider the variations of temperature in the manufacturing environment.

The properties of a workpiece material identify thermal deformation (Kruth et al., 2000; Shaw, 2005). As described by Equation (2.6), a large coefficient of thermal expansion results in a relatively larger deformation (Leach, 2014; Wilson, 1942; Cverna, 2002). From previous research, the aluminium material has a high value of thermal expansion coefficient, so significant differences in deformations can be expected to result from the range of temperature values (Ho and Taylor, 1998). For this reason, an aluminium material (AW 6082-T6) was chosen to be machined in this research experiment in order to exhibit easily detectable deformations.

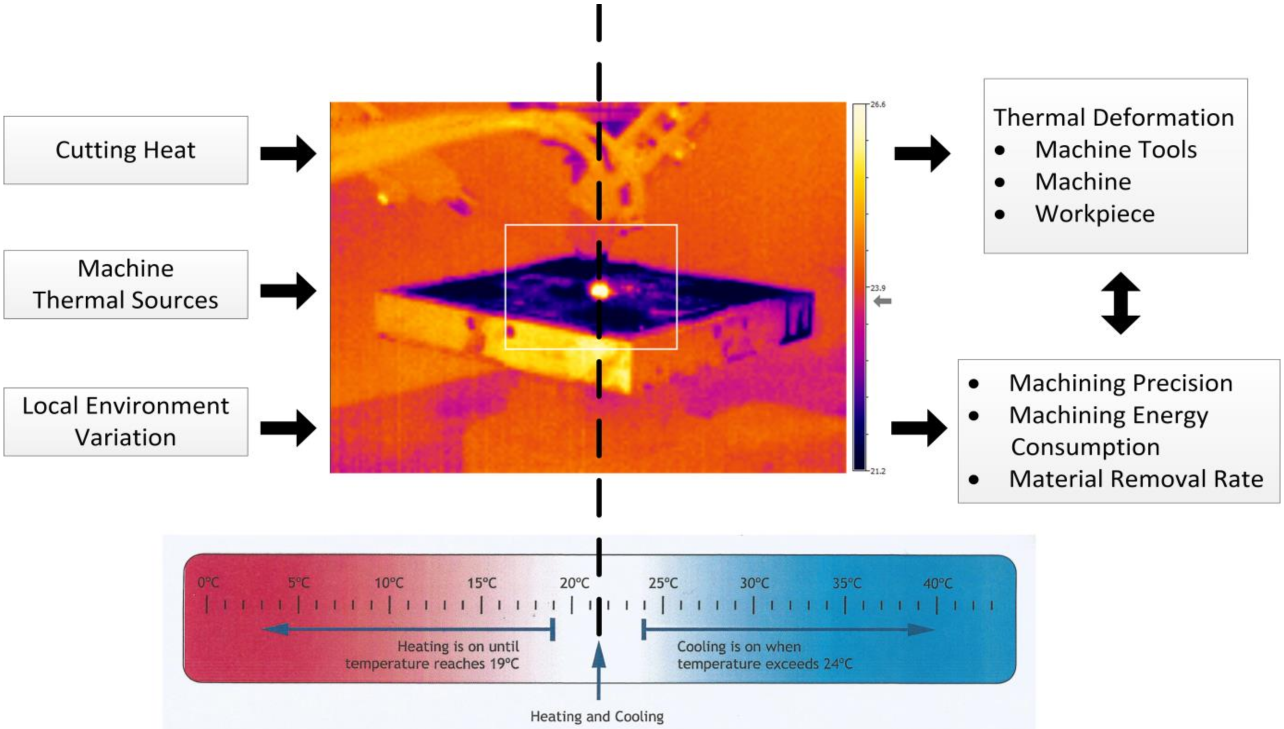


Figure 5.1. Thermal / temperature envelope and the associated interrelationships within the machining system

5.2.3 Energy Consumption in Precision Machining

The majority of past studies have focused on the process parameters and their impact on energy consumption in a manufacturing process. The end-milling process is primarily chosen due to its common use in the industry (Diaz et al., 2009). The energy demand of a machine tool comprises a constant and variable component. The constant part functions independently of the process parameters and is allocated to different parts of the machine tool such as computer, lighting and lubricants (Dahmus and Gutowski, 2004). On the other hand, the variable part functions dependently of the process parameter and is allocated to the drives or spindles of the axes. In this experiment, parameters of the machining process were set under the same conditions with vary of ambient temperatures that were speculated to affect machining energy consumption. The following sections describe the effect of the ambient temperature on energy consumption. The correlation between energy usage and quality is also presented.

5.3 Experimental Case Study

This research was conducted in the Brunel University London Advanced Manufacturing Laboratory and covered the data collection tests for the entire machine work area. Forty cutting test with aluminium (AW 6082-T6) were performed on the CNC machine at different periods of time during the days in order to obtain different temperatures in the local environment of the laboratory. Data acquisition was obtained specifically at 9.00am, 11.00am, 2.00pm and 4.00pm over the ten days period.

5.3.1 Experimental Setup

The milling trials were carried out on a high precision CNC milling machine (KERN 5 Axis HSPC 2216), the machining experiments are shown in Figure 5.2 (a). As illustrated in Figure 5.2 (c), a batch of 40 purposely designed aluminium components (AW 6082-T6) were machined with a dimension of 100mm X 100mm X 10mm in order to highlight the dimensional accuracy of machining side during the milling process. After the CAD model was performed to design the aluminium workpieces as shown in Figure 5.3 (a), tool paths simulation using Powermill was carried out so as to obtain the best CNC milling tool path as depicted in Figure 5.3 (b). The milling machine was operated approximately 35 minutes for machining each workpiece with Spray-nozzle coolant (SD18) as illustrated in Figure 5.2 (f). The SD18 Spray-nozzle lubrication system was set at a viscosity of 100 kPa (1 bar) at 20°C.

Tungsten-carbide mill tool was used for end-mill machining in this experiment as it is more cost-effective, has better wear resistance and offers higher toughness compared with other available tools (Sekar, 2014). According to speed and feed recommendations of SGS Tool (2016), the spindle speed was set at 12,000 rev/min with a cutting speed of 226 m/min. According to Taylor's equation of the tool life (Sekar, 2014; Shaw, 2005; Juneja, 2003) and the setup parameters in this experiment, the approximated tool life was calculated by using Equation (2.3) in Chapter 2. From Table 2.1, Sekar (2014) suggested n value is 0.2 for uncoated carbide tool and C value for non-steel work is 1000 as calculated follow;

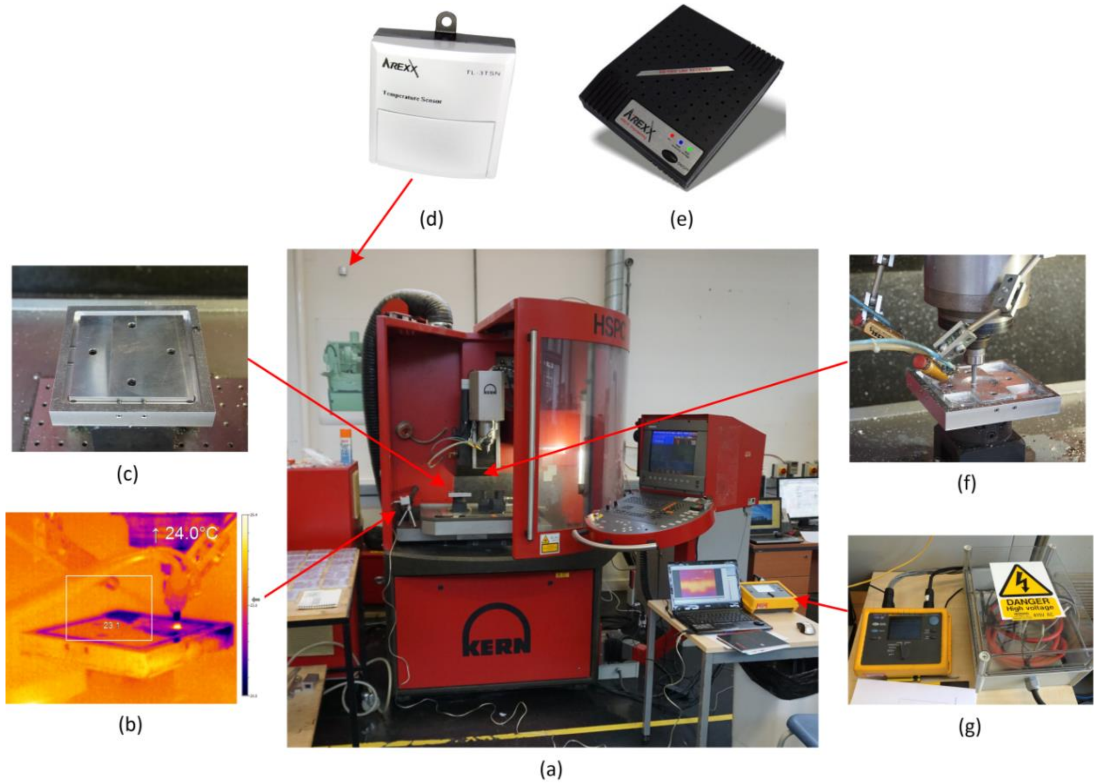


Figure 5.2. Precision milling experimental process: (a) Kern CNC milling machine, (b) thermal camera user interface, (c) aluminium block experimental setup, (d) temperature sensor, (e) LAN based receiver, (f) aluminium machining, and (g) power logger

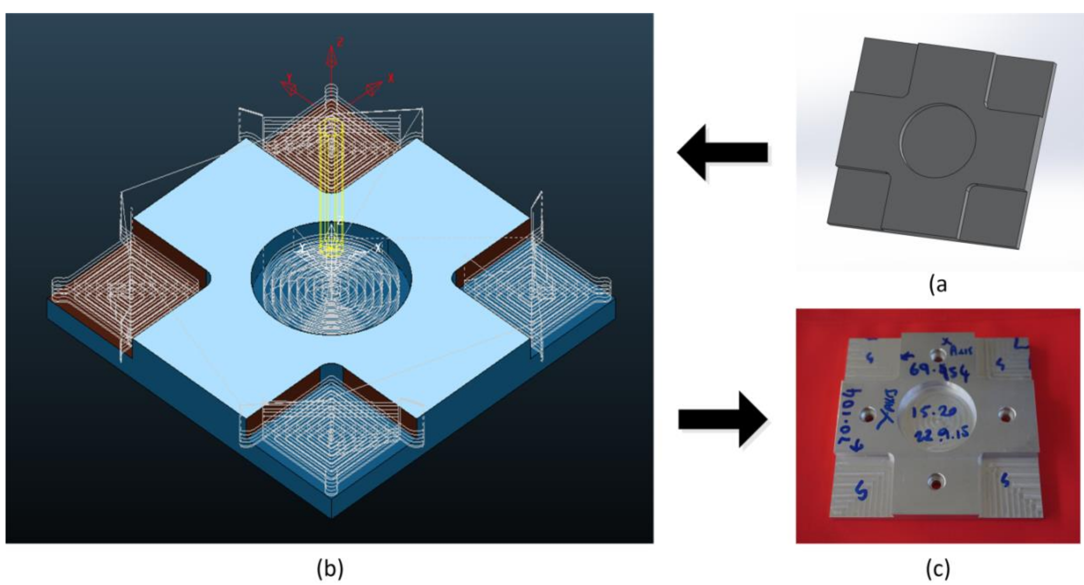


Figure 5.3. Design and manufacturing procedures for the experimental workpiece: (a) design and simulation, (b) tool path generation, and (c) machined sample workpiece

$$V_c {T_l}^n = C$$

$$226.29 \times {T_l}^{0.2} = 1000$$

$${T_l}^{0.2} = \frac{1000}{226.29} = 4.425$$

$$(0.2)\ \log T_l = \log 4.425$$

$$\log T_l = 3.229$$

$$T_l = 1{,}696.125\ minutes$$

As a result, the approximated tool life was 1,696 minutes. Hence, one tungsten-carbine mill tool could be cut up into 48 workpieces in this experiment. However, two different sets of milling tools were used for roughing and finishing in order to acquire better quality. Table 5.1 lists a summary of the machining conditions and the associated experimental setup.

5.3.2 Energy Consumption Measurement

For energy consumption measurement hardware, a 'Power logger' (FLUK 1735) was chosen as it provides high precision measurement level (Noureddine et al., 2013). As shown in Figure 5.2 (g), the Fluke 1735 power logger was used to individually measure all three phases of the power supplied to provide total energy consumption of the process by using a 3-phase clamper (I1A/10A PQ3, 3-PHASE 1A/10A MINI CURRENT CLAMP SET FOR PQ). After a connection was established, the results were automatically downloaded to the computer.

5.3.3 Temperature Monitoring in the Machining Process

An experimental setup was performed to efficiently monitor the thermal distortion. Thus, temperature monitoring needed to be recorded during the CNC machining of the aluminium workpiece. There is no precise temperature control in this Brunel laboratory, so the experiments were run at different time periods and at different weather conditions in order to obtain the required variations in ambient temperature. The ambient temperature variation of the workshop was recorded by using a set of temperature sensors (AREXX TL-3TSN Multi-logger) as presented in Figure 5.2(d). The three temperature sensors were placed around the CNC machine with the distance of 1 metre away from the CNC machine to monitor the ambient temperature variation in the machining process with the sensors broadcasting a new measurement every 45 (+/- 15) seconds. In Figure 5.2(e), the real-time results were automatically transferred to LAN based receiver (AREXX BS-1000) to be analysed. In Figure 5.2 (b), the temperature measurements were validated by using thermal images from the thermal camera (OPTRIS PI 160TAK). The tests focused on the ambient temperature variations between the range of 23°C and 27°C during the machining process.

Table 5.1 Elements of experiment set-up for machining the designed workpiece

Elements of Experiment Set-up	**Descriptions**
Machine	Kern CNC milling machine
Process	End Mill
Material	Aluminium Alloy (6082-T6)
Block size (workpiece)	100mm x 100mm x 10mm
Cutting tool	6 mm tungsten carbide
Number of teeth	2
Depth of cut (Roughing)	1 mm (5 times)
Depth of cut (Finishing)	0.1 mm
Feed speed (V_f)	600 mm/min
Spindle rotational speed (N_s)	12,000 rev/min
Cutting speed (V_c)	226.29 m/min
Feed per tooth (f_z)	0.025 mm/tooth
Duration (Roughing)	30 mins
Duration (Finishing)	5 mins
Coolant system	Mist
Combining with air pressure	100 kPa at 20°C

5.3.4 Components Accuracy Measurement

Following the completion of the machining experiments, the measurements of machining error were taken by using a Coordinate Measuring Machine (CMM) – MITUTOYO FN503. CMMs are precision machines that produce three-dimensional Cartesian coordinate space measurements with the resolution of 1 μm (Black & Kohser, 2008). The MITUTOYO FN 503 CMM was located in a temperature controlled laboratory because the temperature in the environment is one of the main influences on CMM accuracy (Leach, 2014). Specifically, the common establishment of the standard measuring temperature is set at 20°C (Black & Kohser, 2008). This standard is greater importance when the measurements accuracies are greater than

0.0025 mm. Because this experiment is based on the precision measuring purposes, the temperature of the laboratory in which the CMM was located and controlled at 20°C.

Probing was done on the fixture of the workpiece with the machining error being indicated by the difference in the probe deflections between the reference points. In this research, there were 14 different dimensions of machining error measurement including 9 lengths and 5 depths errors that were performed related to reference points as described in Figure 5.4 (a). The results of three-time measurements were averaged and summarized. After programming the CMM code shown in Figure 5.4 (b), the entire experimental process was automated by generating an NC program on a CAD system and operating the measurement process on the 40 aluminium workpieces as depicted in Figure 5.4 (c). After this, simplified test sheets were provided for investigation and analysis.

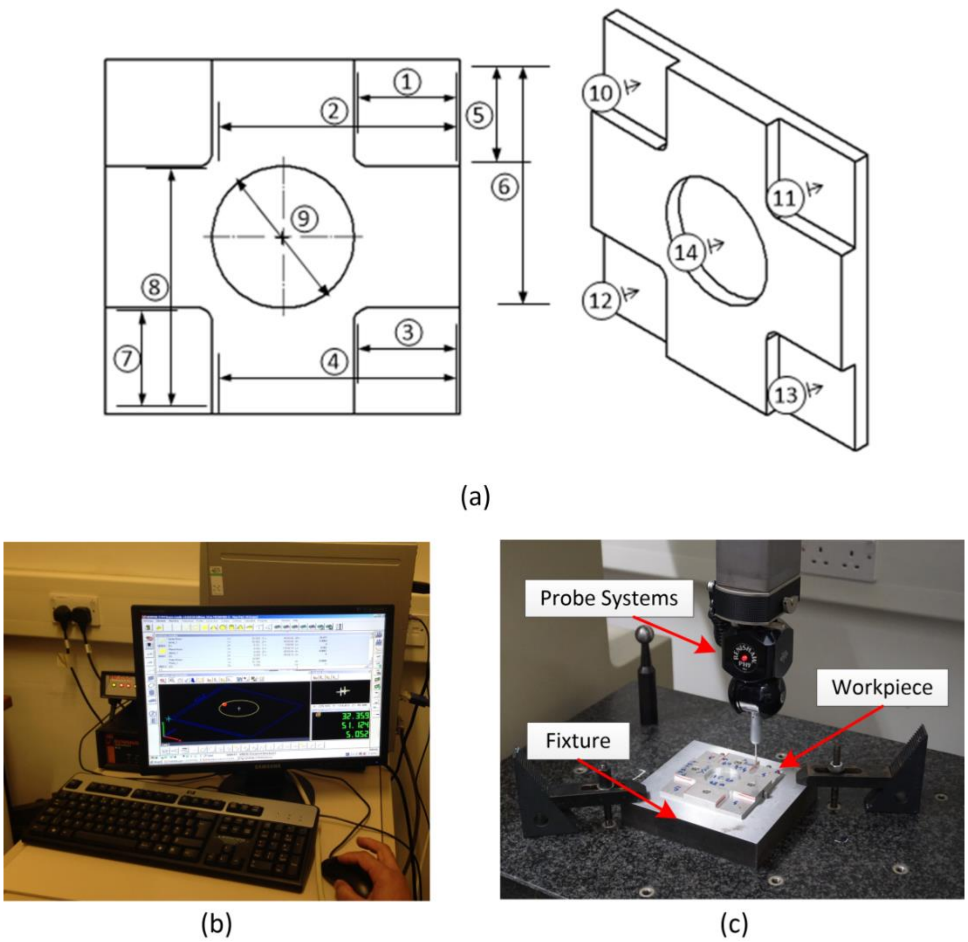


Figure 5.4. Metrology measurement and assessment on the workpiece at a CMM:
(a) Workpiece designed and its methodology measurement strategies,
(b) CMM program coding, and (c) CMM measurement in process

5.3.5 Tool Wear Measurement

Prior to each cutting trial, two types of tool wear measurements were continuously monitored which were tool length and cutting edge radius. The online and offline tool length and its variation were measured using the Blum laser control system and TESA-200 Optical microscope as demonstrated in Figure 5.5 (a) and Figure 5.5 (b), respectively. The tool length was measured both before and after machining to investigate the tool wear. In Figure 5.5 (c), the used tools were observed and measured the tool wear in terms of cutting edge radius using JEOL JCM-6000 Scanning Electron Microscopes (SEM) and MatLab programme.

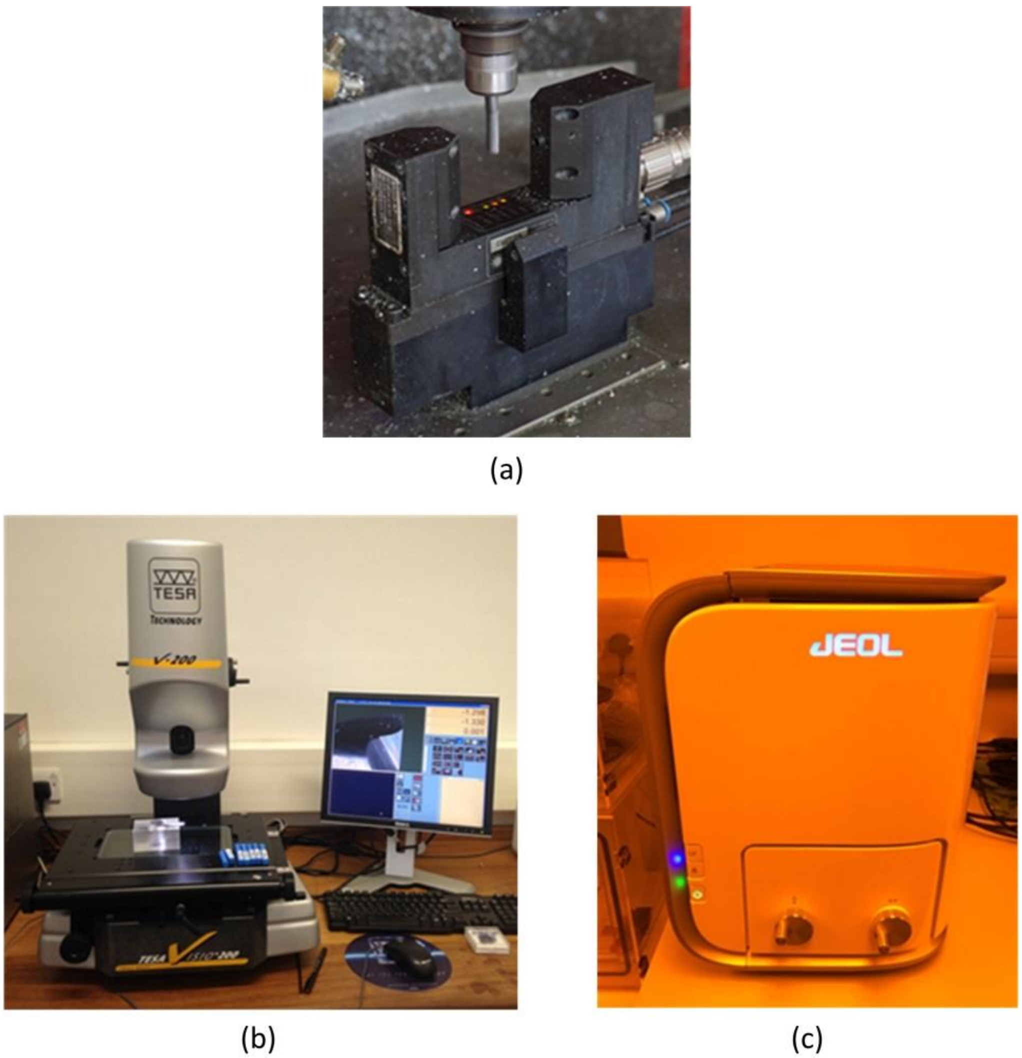


Figure 5.5. Tool wear measurement: (a) Blum laser control system, (b) TESA-200 Optical microscope, and (c) JEOL JCM-6000 Scanning Electron Microscopes (SEM)

Figure 5.6 illustrates a 3D schematic diagram of end milling tool wear from ISO 8688-2 (1989) describing the main wear patterns and localisation. ISO 8688-2 (1989) explained that wear land A-A which is normally of constant width and extends over those portions of the tool flanks adjoining the entire length of the active cutting edge. Hence, Uniform flank wear (VB1) is considered to be measured as a flank wear for this experiment which means the wear along the axial depth of cut.

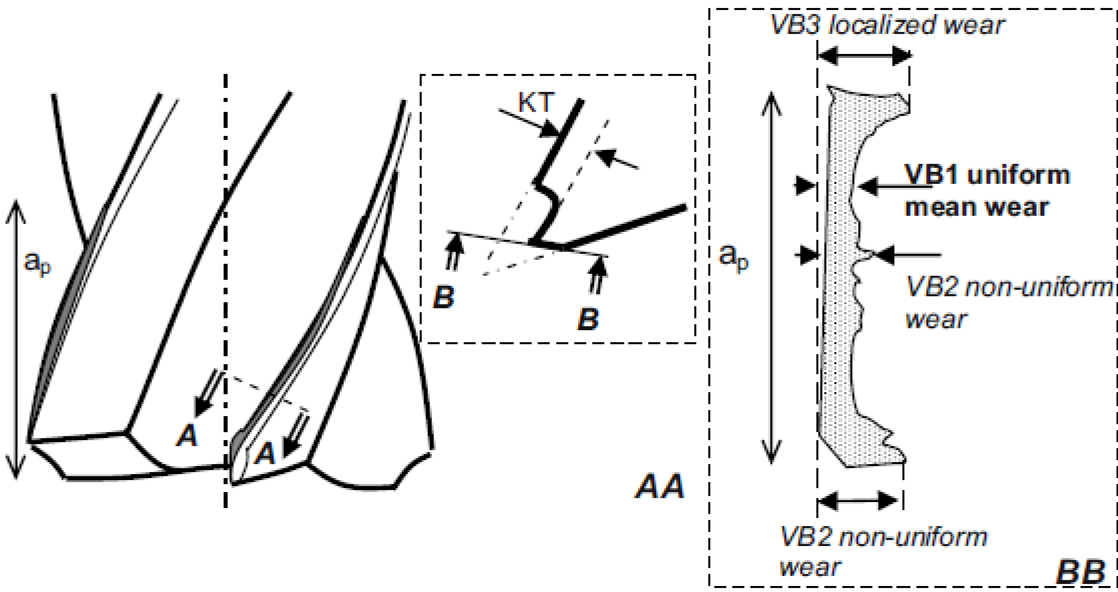


Figure 5.6. 3D schematic end milling tool wear

5.4 Results and Discussion

According to ISO Standard 8688-2: 1989, the tool wear measurement is used to identify the width of a flank wear land which could lead to tool failure. The results of tool wear measurement were 114 μm and 58 μm for roughing and finishing tools (Appendix M). The ISO 8688-2 (1989) stated that the maximum safe limit of tungsten carbide material should not exceed 300 μm for an end-mill cutter. Thus, the tools used in this experiment were at an acceptable condition to continue machining and were unworn.

Figure 5.7 shows a comparison of the geometry and morphology between the condition of the new tool before machining and the condition after machined 40 workpieces (1400 minutes) of the roughing and finishing tools as shown in Figure 5.7 (a) and (c). In Figure 5.7 (b) and (d), the cutting edge of the used roughing and finishing tools are relatively worn.

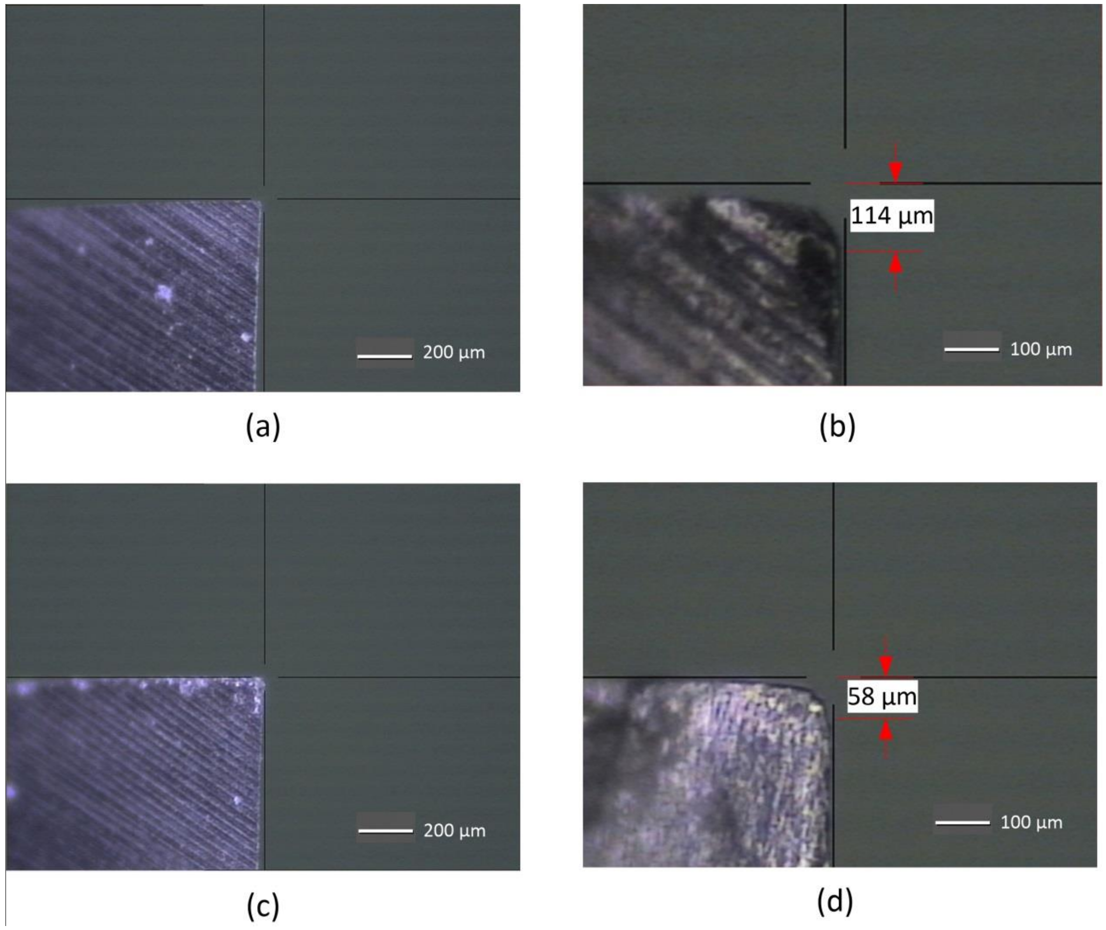


Figure 5.7. Tool wear cutting edge before and after machining: (a) Roughing tool before machining, (b) Roughing tool after machining, (c) Finishing tool before machining, and (d) Finishing tool after machining

Due to the manufacturing limitation and material properties, the cutting edge radius of tungsten carbide milling tool is normally about 3-5 μm (Malekian et al., 2009). The cutting edge radius of the two milling tools is shown in Figure 5.8. The cutting radius was investigated by using SEM. The cutting edge radius of roughing and finishing tools increased from 4.5332 μm to 20.833 μm and from 4.3844 μm to 12.8108 μm, respectively. These final cutting edge radius values did not exceed the tool life criteria value of 60 μm (ISO 8688-2, 1989). Hence, the milling tools were not worn yet.

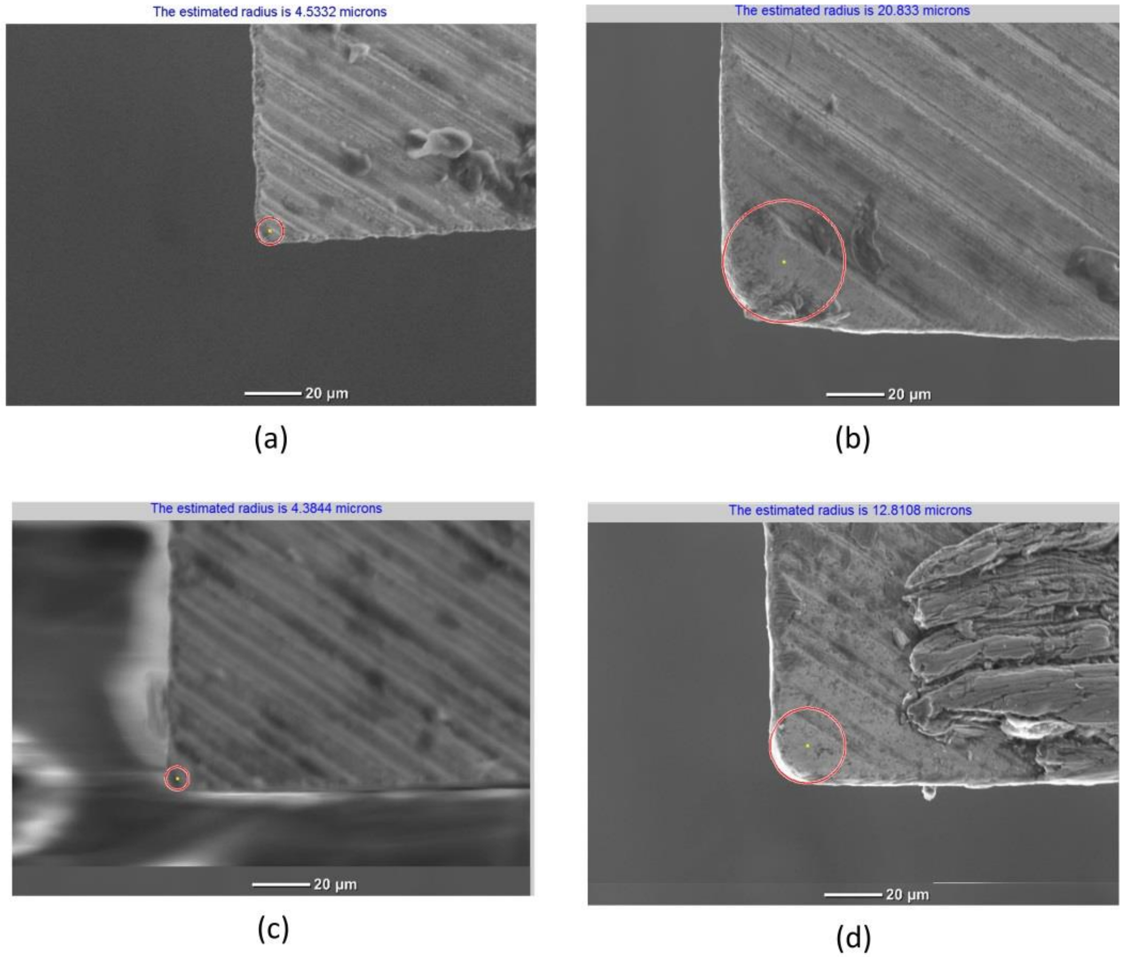


Figure 5.8. Cutting edge radius of tungsten carbide tools before and after machining: (a) Roughing tool before machining, (b) Roughing tool after machining, (c) Finishing tool before machining, and (d) Finishing tool after machining

With regard to the economic aspect of sustainable precision machining, the total machining costs were analysed. Following Equations (2.7) and (2.8) described in Chapter 2, the total cost of a single machining operation comprises of material cost, tool cost, machine maintenance cost, labour cost and the sum of the energy cost. The total machining cost to produce 40 aluminium workpieces in this experiment based on the operating time of 1,400 minutes was 532.09 pounds as follow;

$$\begin{aligned} \mathit{Total\ Cost\ of\ a\ Single\ Machining\ Operation} \\ = \mathit{Power\ Cost} + \mathit{Machine\ Maintenance\ Cost} + \mathit{Tool\ Cost} \\ + \mathit{Labour\ Cost} \end{aligned}$$

$$= (Electricity\ Cost\ \times Total\ Energy\ Consumption) + (Maintenance\ Cost\ per\ day \times Number\ of\ Operating\ Days) + (Material\ Cost + \ Tool\ Cost) + (Technician\ Cost\ per\ day\ \times working\ days)$$

$$= (£0.16\ \times 435.25) + (£12.525\ \times 10) + (£2.70\ \times 40) + (£18.45\ \times 2) + (£19.23\ \times 10)$$

$$= £69.64 + \ £125.25 + £108 + \ £36.90 + \ £192.30$$

$$Total\ Operation\ Cost\ = £532.09$$

In addition, applying Equation (2.19) to the calculation, the total CO_2 emitted during this machining process was calculated to be 179.345 $\text{kg} \cdot \text{CO}_2\text{e}$ as follow;

$$\text{Carbon footprint} = \ \text{Activity data} \times \ \text{CO2 emissions conversion factor}$$

$$= 435.25\ \times 0.41205$$

$$= \ 179.345\ \ \text{kg} \cdot \text{CO}_2\text{e}$$

The results of ambient temperature, quality error and total energy consumption including HVAC system and machining of the 40 machined aluminium workpieces are summarised as shown in Appendix K. The workpiece dimensional error of 14 CMM measurements was calculated by using the Equation 5.1. For example, workpiece number 23 machining on 12nd October 2016 at 11.19am at ambient temperature 25.8°C. The workpiece quality error is calculated as follow;

$$\text{Workpiece Quality Error (\%)} = \frac{\sum_{i=1}^{14} \left(\left| \frac{y_i - x_i}{x_i} \right| \times 100 \right)}{14}$$

$$= \frac{\left(\left| \frac{30.016 - 30}{30} \right| \times 100 \right) + \left(\left| \frac{70.024 - 70}{70} \right| \times 100 \right) + \left(\left| \frac{30.015 - 30}{30} \right| \times 100 \right) +}{20}$$

$$\frac{\left(\left| \frac{69.925 - 70}{70} \right| \times 100 \right) + \left(\left| \frac{30.017 - 30}{30} \right| \times 100 \right) + \left(\left| \frac{70.034 - 70}{70} \right| \times 100 \right) +}{20}$$

$$\frac{\left(\left|\frac{29.907-30}{30}\right|\times 100\right)+\left(\left|\frac{69.916-70}{70}\right|\times 100\right)+\left(\left|\frac{5.011_i-5}{5}\right|\times 100\right)+}{20}$$

$$\frac{\left(\left|\frac{5-5}{5}\right|\times 100\right)+\left(\left|\frac{5.03-5}{5}\right|\times 100\right)+\left(\left|\frac{5.042-5}{5}\right|\times 100\right)+}{20}$$

$$\frac{\left(\left|\frac{5.021-5}{5}\right|\times 100\right)+\left(\left|\frac{39.984-40}{40}\right|\times 100\right)+}{20}$$

$$\text{Workpiece Quality Error (\%)} = 0.2072$$

After running the Chi-square test in the "Input Analyser programme", the results show that the corresponding *p*-value of temperature was less than 0.005 for normal distribution expression as shown in Appendix L. Hence, the number of tests was reliable. Furthermore, the skewness values of ambient temperature, total energy consumption and quality error were -0.49, 0.552 and -0.136, respectively which are less than +/- 1. These results suggest no issue of an outlier (Field, 2013).

A linear regression analysis was performed with the statistical analysis software package SPSS version 20. First, the results testing ambient temperature as a predictor indicated that ambient temperature explained 85.2% of the variance in quality error, $R^2 = 0.852$, $F(1,18) = 103.345$, $p < 0.001$. It significantly predicted quality error in a positive direction, $\beta = 0.923$, $p < 0.001$. A correlation chart of ambient temperature and dimensional error (quality) generated from milling aluminium blocks is demonstrated in Figure 5.9. Within the temperature range between 23°C and 27°C, the percentage of machining error increased while the environment temperature rose. These results suggest that the quality of the workpiece decreases at higher ambient temperatures. This could be explained by the thermal expansion as the ambient temperature affects the geometry of aluminium workpiece. Consequently, the quality of the product is degraded when the temperature increases. The regression model of dimensional error and ambient temperature is described by Equation (5.6).

$$y = 0.02x - 0.322 \tag{5.6}$$

where x is ambient temperature; and y is dimensional error.

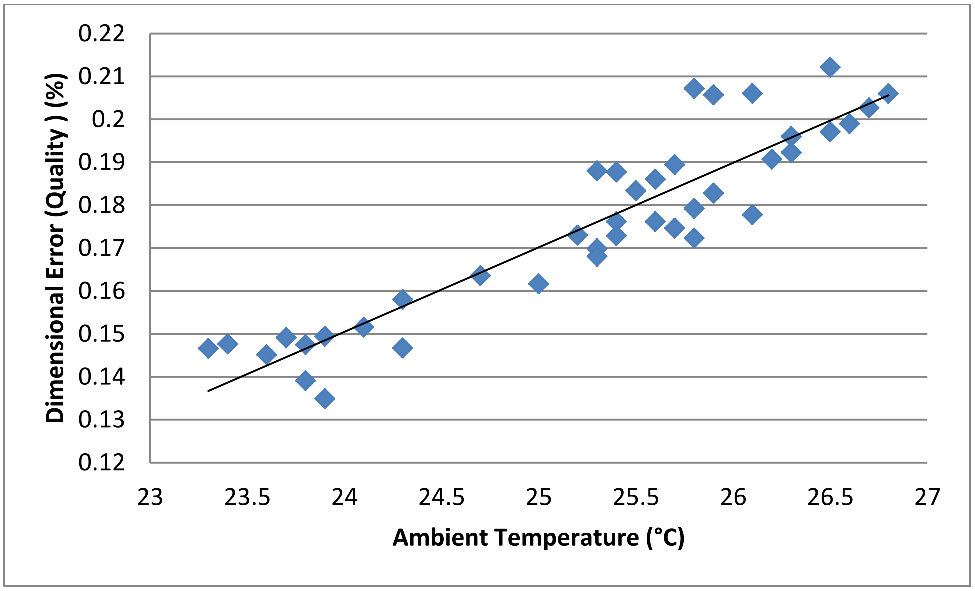


Figure 5.9. Ambient temperature versus dimensional error (quality)

In contrast, a negative correlation was found between ambient temperature and total energy consumption, plotted in Figure 5.10. The results of the regression indicated that temperature as a predictor explained 85.1% of the variance in total energy consumption, $R^2 = 0.851$, $F(1, 18) = 103.071$, $p < 0.001$. Ambient temperature significantly predicted total energy consumption, $\beta = -0.923$, p < 0.001. At 26.3°C, the CNC milling machine consumed approximately 10.57 kWh to finish the workpiece which was at the lowest power usage. Moreover, operating the CNC machine used the largest amount energy which was about 11.32 kWh at around 23.3°C. Therefore, less energy was consumed at higher ambient temperatures. The regression model of total energy consumption and ambient temperature is described by Equation (5.7).

$$y = -0.18x + 15.427 \tag{5.7}$$

where x is ambient temperature; and y is total energy consumption.

The results of regression testing total energy consumption as a predictor indicated total energy consumption explained 80.2% of the variance in quality error, $R^2 = 0.802$, $F(1, 18) = 73.139$, $p < 0.001$. Total energy consumption negatively and significantly predicted quality error, $\beta = -0.896$, $p < 0.001$, as illustrated in Figure 5.11. These findings suggest a better quality of workpiece was provided by a higher machining energy consumed.

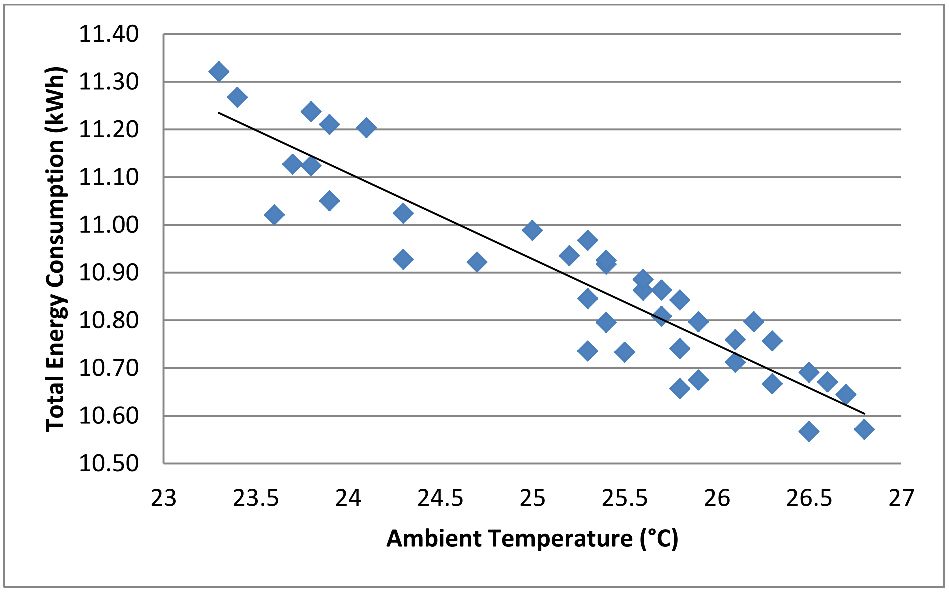


Figure 5.10. Ambient temperature versus total energy consumption

The results of the multiple linear regression indicated the two predictors- ambient temperature and total energy consumption- explained 86% of the variance in quality error, $R^2 = 0.86$, $F(2, 37) = 113.722$, $p < 0.001$. Specifically, ambient temperature significantly uniquely predicted quality error, $\beta = 0.656$, $p < 0.01$, 95% CI [0.007, 0.21]. In contrast, total energy consumption did not significantly predict quality error, $\beta = -0.286$, $p < 0.087$, 95% CI [-0.68, 0.05]. Figure 5.12 and 5.13 demonstrate the 3D correlation between the three factors using the simulating Matlab and SigmaPlot program. From Equation (3.4), the three dimensional correlation of % quality error, total energy consumption and ambient temperature is described by Equation (5.8).

$$z = 0.014x - 0.031y + 0.164 \quad (5.8)$$

where z is quality error; x is ambient temperature; and y is total energy consumption.

The overall results of this experiment indicate that the ambient temperature should be controlled accordingly to achieve product quality standards and also to reduce the energy usage. Whilst this thesis can identify significant factors that can improve accuracy, examining all parameters to predict machining error better is a complex task considering the variability of parameters that cannot be defined.

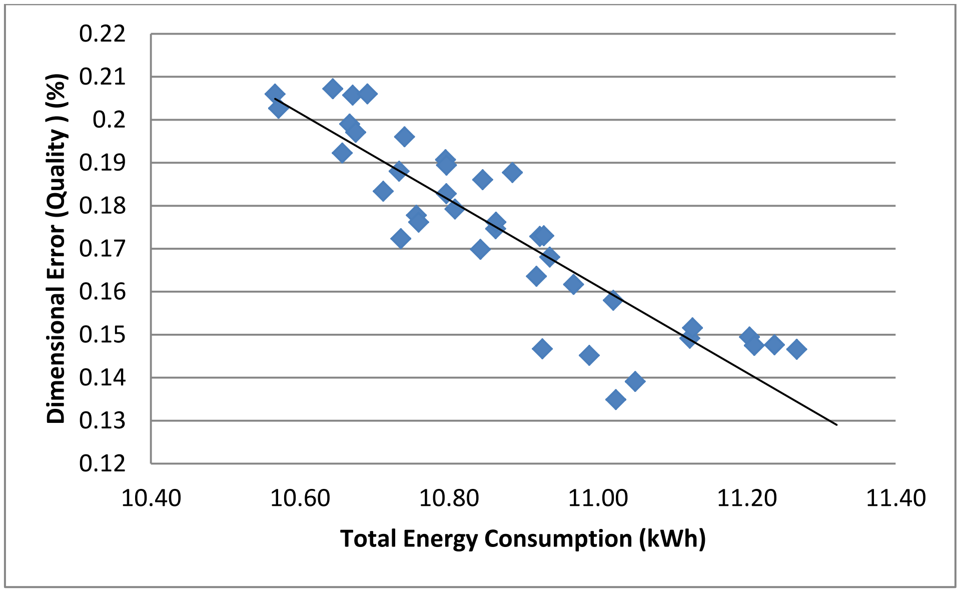


Figure 5.11. Total energy consumption versus dimensional error (quality)

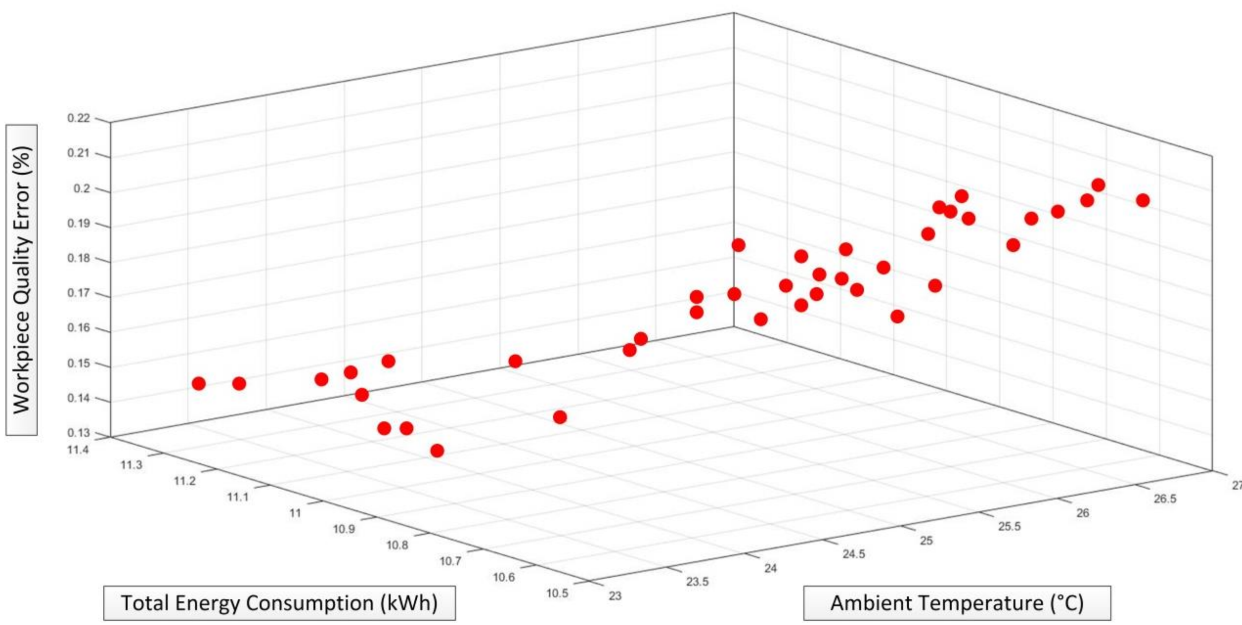


Figure 5.12. 3D correlation analysis in Matlab programming

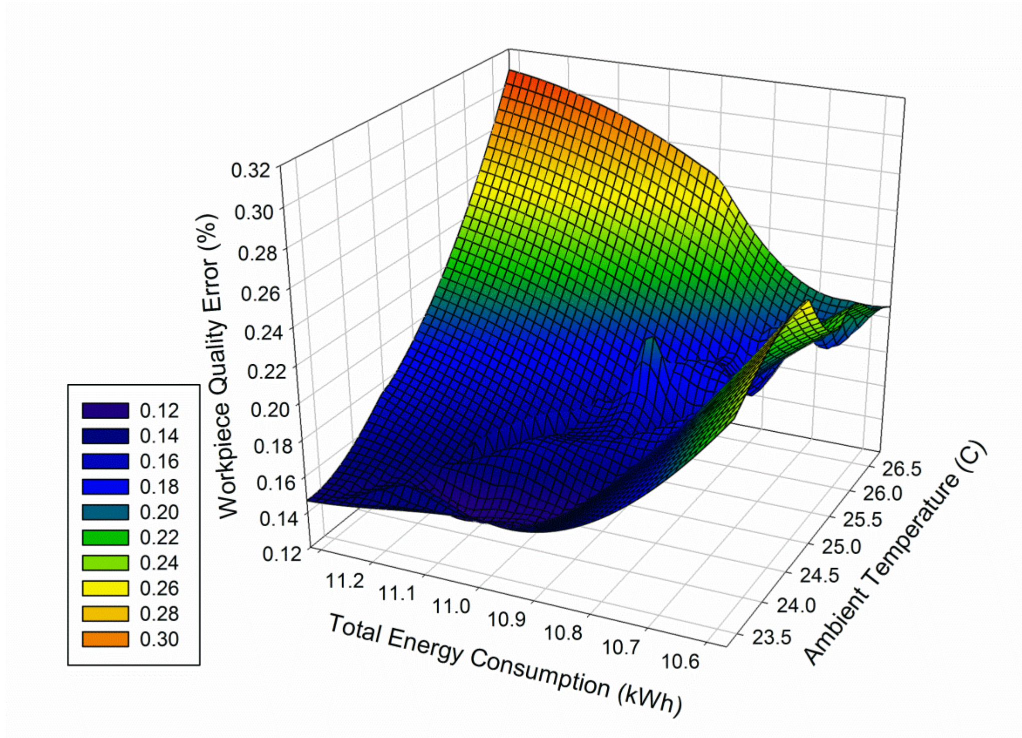


Figure 5.13. 3D correlation analysis in SigmaPlot programming

5.5 Chapter Summary

This chapter presents an approach to a correlation analysis on machining accuracy, total energy consumption including HVAC system and machining energy consumption, and ambient temperature variations in sustainable precision machining. The research integrally takes account of total energy consumption during the machining process and the effect of temperature variation on machining quality in a quantitative analysis. Measured surrounding temperature and total energy consumption data were used as a collective indicator for machining quality levels. Quality error percentage was defined by the difference in value between the nominal CAD model and the actual measured point after machining in the temperature range between 23°C and 27°C.

The correlational analysis on the experimental cutting trials results indicates that in precision machining, the environmental temperature influences the machining error which increases with the rise of surrounding temperature, but in contrast, the total energy consumption of the CNC milling machine falls. Thus, the temperature variations in precision machining processes need to be controllable according to the component quality specifications in order to obtain the required quality standard while minimising the total energy consumption throughout the process. The correlation analysis results show that a rise in surrounding temperature is associated with increasing quality error of machining and lower total energy consumption during machining.

These findings are consistent with past studies on cutting temperature which were explained by the thermal expansion that high-temperature values could deform machined workpiece properties (Leach, 2014; Wilson, 1942; Cverna, 2002; Bryan, 1990). Besides cutting temperature, the present experiment highlights that ambient temperature is another element of temperature that has an impact on precision machining. The contribution of this work represents some first steps to scientifically understand the intrinsic relationships between machining accuracy, ambient temperature and total energy consumption in CNC precision milling and thus to establish a more sustainable precision machining system.

CHAPTER 6

Energy-resource Efficient Manufacturing Supported with In-process Virtual Simulation

Building upon the current literature on energy-efficient production and processes, the purpose of the research in this chapter is to model the optimisation of the production workload at a manufacturing process level by empirically investigating on minimisation of energy consumption of CNC machines. Additionally, an innovative simulation approach to energy-resource efficient management system in manufacturing is presented as a virtual simulation using a simulation modelling method that monitors and produces user-friendly displays in real-time in order to construct a systematic decision-making based on analytical and correlational relationships. The results are described in relation to energy efficiency in sustainable precision manufacturing.

6.1 Introduction

Production processes are important activities in manufacturing which involve utilisation of resources and time span of the production operations (Nejad et al., 2011). The implications of these activities become remarkably important as manufacturers are now operating in highly dynamic and highly complex environments. Planning and optimisation of a production process need to be systematically simulated in order to manufacture machined products in a sustainable- yet precise- way, thereby gaining competitive advantages and leading to enhanced productivity (Phanden et al., 2013). In line with this, the production process is to allocate the operations on machines while maintaining the established parameters of the production process. Therefore, production operations are interrelatedly bound together by the same resources and should be thus comprehensively modelled and optimised.

Most studies on machining have highlighted on optimisation cutting parameters in order to minimise processing time. Increasing certain parameters such as cutting speed and feed rate could reduce processing time. However, they may incur higher costs resulting from tool wear and tool failure, suggesting that a decision on optimisation of resources should not overlook the total manufacturing cost (Kayan and Akturk, 2005). While cutting parameters appear to be one of the main areas under investigating, more researchers have examined on workload optimisation in CNC machining (Hoeck, 2008).

Despite the importance of gaining competitive advantages through optimised processes and reduced operating cost, manufacturing cannot fail to consider its roles towards sustainability. Evidently, efforts to improve on sustainable manufacturing systems need to be integrated at all applicable levels including production processes (Giret et al., 2015). Zhang et al. (2015) presented a model which takes into account processing time, workload and CO_2 emission. While the model of this study provided a contribution to sustainable manufacturing, it neglects the element of cost. In response to the gap of research knowledge and escalating demand for sustainability, research embedded in this chapter attempts to put forward the development of a simulation modelling of an energy-resource efficient system that examines the impact of workload on energy consumption of the machining system and total production costs.

6.2 Resource Efficiency based on Energy Demand

Manufacturing processes are energy demanding and are thus the main sources of energy consumption (Giret et al., 2015). A set of production processes composes a larger production system which also consists of various machines that serve different levels. For this reason, the production process should be managed and controlled in accordance with the collective functions of the production system that comprises of differing technical machines. Machines generate energy consumption and energy load profiles that are accumulated throughout the production process. To avoid energy wasted, inactive resources especially machines need to turn off the energy supply operation during the time slot that involves no production (Pach et al., 2014). Conversely, the power supply should be turned on by the resource when the production line starts. These assumptions emphasise on the notion that resources require information about production in consideration to produce energy consumption behaviour in a steady and persistent way.

This research develops the modelling system which simply defines energy efficiency by the total energy consumption and defines effectiveness with each resource in different conditions. To calculate the total energy consumption of the production system, three formulas are applied to the modelling in a hierarchical order (Pach et al., 2014). In the first order, energy consumption of a resource, denoted by *r*, in its specific operating state e.g. idle, operating and shutdown, denoted by i, is expressed by Equation (6.1) where energy consumption is defined by $W_{r,i}$, production time is defined by T_{prod}, and power is defined by $P_{r,i}(t)$.

$$W_{r,i} = \int_0^{T_{prod}} P_{r,i}(t)dt \tag{6.1}$$

Using the same symbols, the total energy consumption of a resource comprises of energy consumption in all resource states and can be computed with Equation (6.2) where TW_r defines the total energy consumption and N defines the number of resource states.

$$TW_r = \sum_{i=1}^{N} W_{r,i} \tag{6.2}$$

In the last hierarchical order, the total energy consumption of the production system is equal to the sum of energy consumption of accumulated resources and is mathematically computed with Equation (6.3) where TR defines the total energy consumption of the production system, and R defines the number of resources in the system.

$$TR = \sum_{r=1}^{R} TW_r \tag{6.3}$$

Moreover, production workload is the key element that determines the efficiency of production in the production processes. Thus, different workload parameters lead to changes in energy efficiency and gradually to changes in emissions. To develop sustainable production plan, it is necessary for the modelling to involve a methodological approach that incorporates the optimisation of both input and output means to optimising workload.

6.3 Virtual Simulation of Energy-resource Efficiency

In this experiment, the method of simulation modelling is built upon the Energy-smart Production Management (e-ProMan) system that was developed and implemented in Chapter 3. To extend on the previous knowledge, the current development of the virtual simulation of the energy-resource efficient system takes into account the roles of the production system at the process level which examines energy and resource efficient performance of the manufacturing. Also, the presented simulation modelling at this stage provides the comprehensively interrelated relationships with the real-time dynamics of the variously equipped machine tools in order to efficiently optimise the design and control systems of the production processes.

In addition, the framework of this virtual simulation of the energy-resource efficient system in this research stage does not intend to provide a systematic examination of a specific machine or an individual manufacturing system of a process analysis level. Rather, the objective of this research stage is to intrinsically acknowledge various functions with respect to energy consumption determined by an evaluation of both input and output flows related to energy. To better model an energy-efficient system, the systematic approach employed in this system follows a hierarchical structure of simulation which considers four different levels as suggested by Herrmann and Thiede (2009). The four levels are input, logic, user and evaluation of simulation.

Furthermore, the application of this virtual simulation comprises a variety of adjustable process modules that improve applicability as they minimise knowledge modelling and modelling efforts. Particularly, process modules can be altered within the appropriate parameters through accessible data. Ultimately, they facilitate the virtual simulation to establish the fundamental performance of production processes within the manufacturing plant. Thereby, detail level can be modified in accordance to the objectives of analysis. When the background data are involved, augmentation of minor processes into individual process modules may be required such that the information on energy consumption can be obtained from each of the process modules.

More specifically, the methodological implementation of the current virtual simulation experiment employs a three-step systematic approach partially adopted from Herrmann and Thiede (2009) as follows.

Step 1: Production Processes

Firstly, the main objective is to acquire a more thorough understanding of the mechanical and organisational characteristics that are crucially relevant to the production processes under the scope of simulation modelling. The information and data relating to manufacturing machines, systems, flows and management, especially relevant to energy consumption and efficiency, needs to be obtained and understood.

Step 2: Production Energy Analysis

Next, the focus lies within the analysis aspect of energy which includes input flow and output flows of all necessary production machine tools and systems. By deeply analysing all energy flows, more accurate data on energy consumption can be obtained. Thus, it is crucial to analyse the complete production process model that are fundamental to the direct production processes. It may be useful to review documents or regulations to attain an overview of energy consumption in the manufacturing plant. Nonetheless, since the values of energy consumption stated in most media documentations appear to be higher than the actual energy usage, the analysis can potentially benefit from the actual measurements of energy consumption, especially for the major production processes (Herrmann and Thiede, 2009).

Step 3: Integrated Simulation of Production Processes

Last, this step is regarded as an essential step as it provides the final simulation modelling that integrates the manufacturing of production processes with analytical, interdependent relationship between the energy and work flows. Put differently, elements of the integral production processes are combined with measured data of various machine tools in order to simulate the outcomes of energy-efficient measures. The modelling of the virtual simulation in a manufacturing plant level is fundamental to this experiment as it would aid the problem dynamics for the complete manufacturing system.

6.4 Simulation of CNC Milling Production Processes

According to Cheng and Bateman (2008), virtual modelling application as proposed in this research is a development of an energy-resource efficient system based on in-process analysis that supports real-time manufacturing decision-makings through advanced use of ICT techniques. The optimisation concept of this experiment is shown in Figure 6.1 which begins with production process data including machine profiles and machine conditions followed by a simulation of workload scenarios assumptions and ends with an investigation of the optimisation model by applying the optimum scenario into the simulation process.

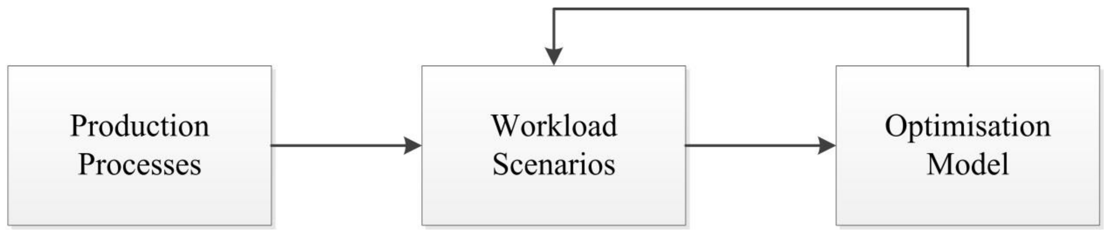


Figure 6.1. Optimisation concept for energy-resource efficient machining

The simulation of the energy-resource efficient system presented in this chapter was conducted in the experimental set up at the Advanced Manufacturing and Enterprise Engineering (AMEE) Laboratory at Brunel University London. In general, this simulation was performed by gathering the input of energy consumption of CNC milling process using energy measurement tool (Power logger- Fluke 1735) to measure the energy consumed at the CNC milling machine as shown in Chapter 5 (Appendix K). The experiment was carried out at various 'shop-floor' temperature conditions ranging between 23°C and 27°C. This production process used 'first in first out concept' throughout the production line.

6.4.1 Simulation Scenarios

In total, the simulated model consisted of four CNC milling production machines using three machine operating statuses (i.e. operating, idle and shutdown) during 700 minutes period in order to finish the cutting process of the total 40 aluminium workpieces as identical to the experiment set up in Chapter 5. Figure 6.2 illustrates the simulation modelling of the CNC production process (Appendix R). The simulation modelling started with 'Product Input' and 'Assign Product Specification' modules to classify the beginning product including time arrival, energy consumption and CO_2 emission. Then, 'Decide Resource CNC Milling' was used to feed the aluminium workpieces into the CNC milling process which in this case, an aluminium workpiece would be allocated to the first available CNC milling machine resource. The 'Process CNC Milling' module consisted of roughing and finishing processes, and the operation time was about 35 minutes including 30 minutes of roughing and 5 minutes of finishing. After running the Chi-square test in the "Input Analyser programme", the distribution of CNC milling operation was 'NORM(2.1e+003, 15.8)', and the results showed that the corresponding *p*-value of operating time was less than 0.05 for normal distribution expression as shown in Appendix O. The final section consisted of 'Record' and 'Dispose' modules which used to acquire and record the energy consumption, CO_2 emission and production costs including each process and the total production process. As shown in the horizontal lines, the simulation was based on the four CNC milling machines. For example, ‘Process CNC Machine 1’ was for process 1.

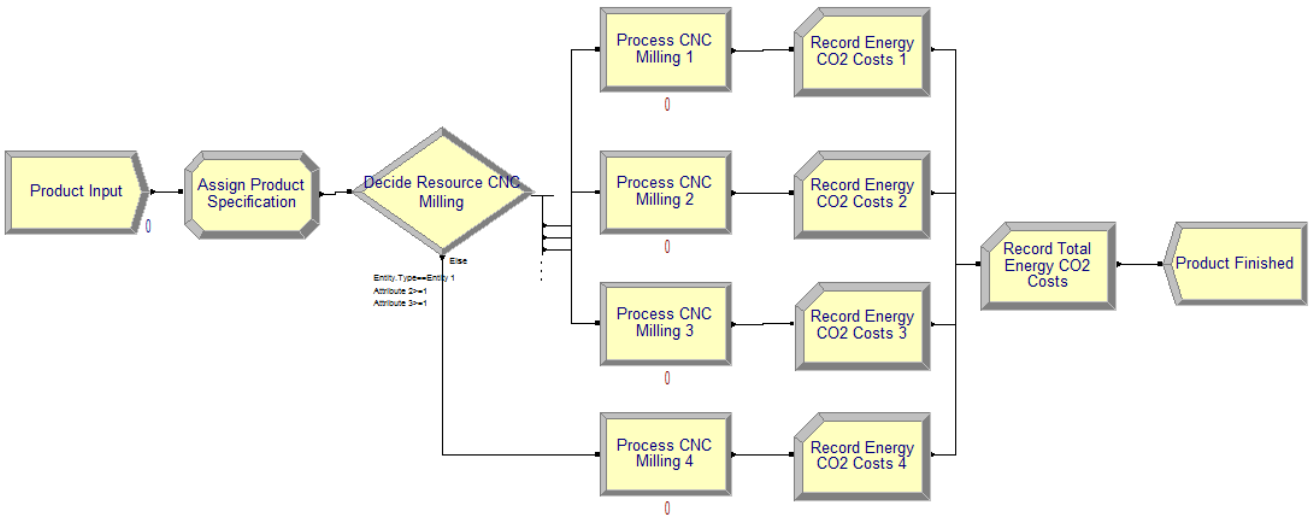


Figure 6.2. Arena Simulation modelling in CNC milling production process

In addition, three scenarios were proposed for the simulation of machine capacity workload. Time and workload capacity of the three scenarios are depicted in Figure 6.3. The workload scenarios were labelled as (a) up-hill, (b) down-hill and (c) balanced scenario. Operating time was constant across the three scenarios which is 700 minutes. The three workload scenarios were simulated in order to determine the scenario with the lowest and highest energy consumed.

First, the up-hill scenario started operating with one CNC milling machine. After 175 minutes, the second CNC milling then started machining together with the first machine. Applying the same pattern, the workload increased to 75% as the three CNC machines were operating together at 350 minutes. At 525 minutes, all four machines were working at the same time. In contrast, the down-hill scenario started with full-load machining or workload capacity of 100% until 175 minutes. After, the number of operating machines reduced to three CNC machines. At 350 minutes, another CNC machine was shut down. Between the minutes of 525 and 700 minute, only one CNC machine was operating. Finally, the third scenario or balanced scenario was to demonstrate the use of the average workload of all four CNC machines to complete the total assigned aluminium workpieces within the given time frame.

Every KERN CNC machine needs to warm-up at least 15 minutes to perform efficient performance (Rainfordprecision, 2016).

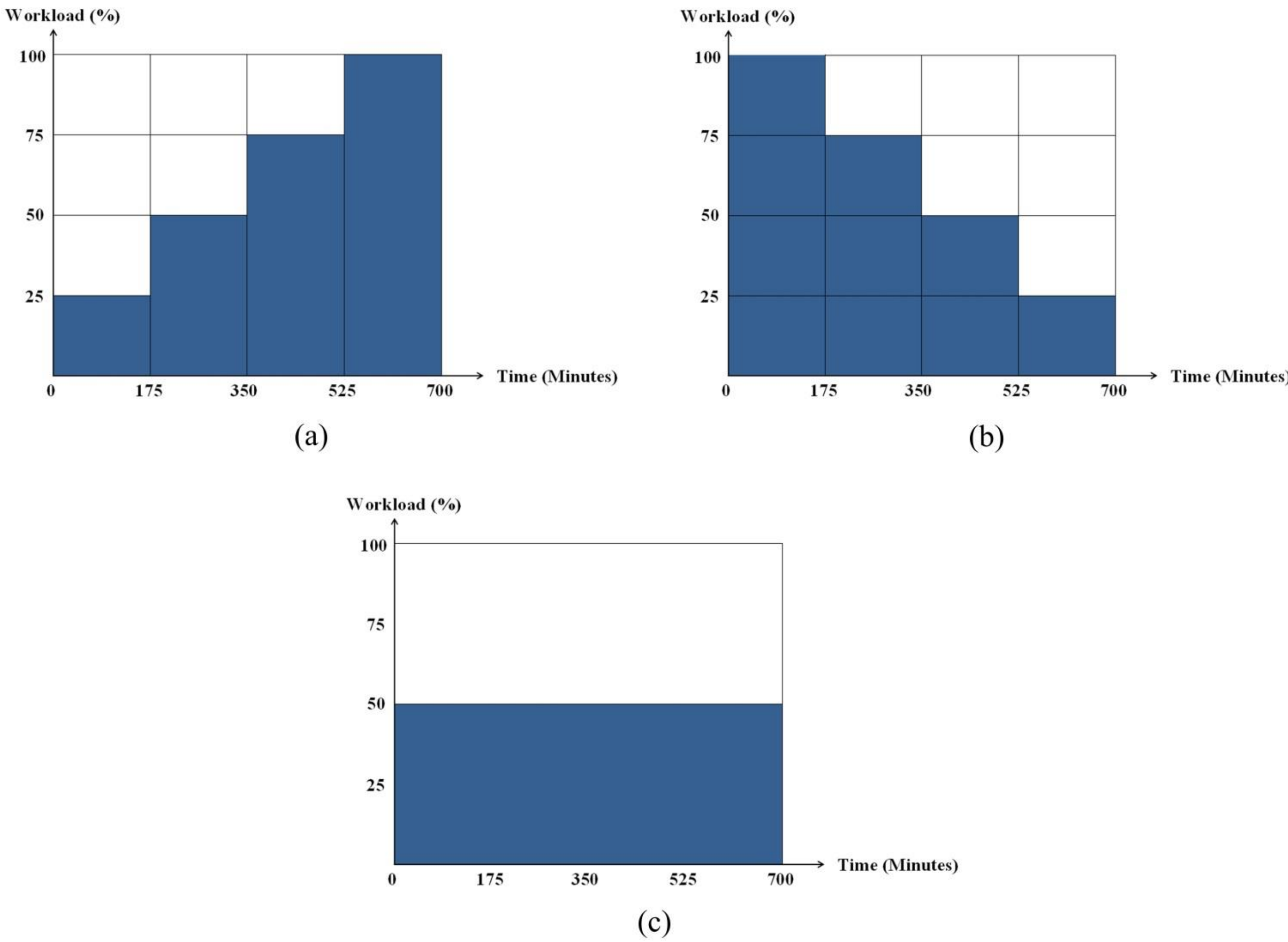


Figure 6.3. Three scenarios of machine capacity workload; (a) up-hill scenario, (b) down-hill scenario, and (c) balanced scenario

6.5 Results and Discussion

In order to monitor the resources, particularly machines, of the virtual simulation model, the top right panel of the LabVIEW shown in Figure 6.4 displays the simulation of the CNC milling production processes in the manufacturing. The simulation modelled the CNC milling production system in Arena Simulation programme with various workload scenarios at the replication of 20 times. The significant level for the confidence level was greater than 0.95. The simulation of the processes, however, was created in the Arena Simulation programme which then linked back to the LabVIEW. In Figure 6.4, the virtual display was performed by

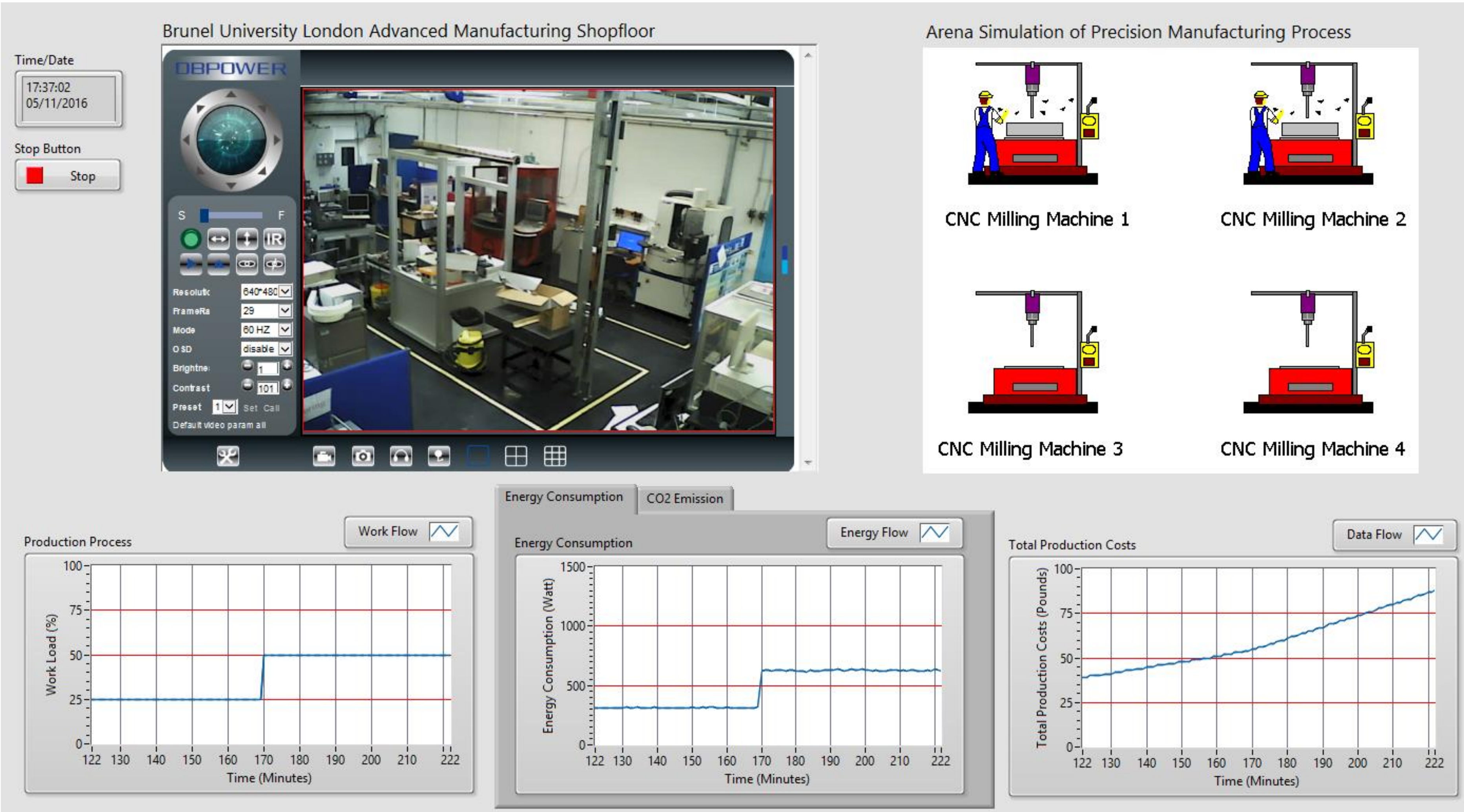


Figure 6.4. Virtual simulation on the energy-resource efficient system

the LabVIEW programme which comprises of five different components: shop-floor monitoring, simulation of the production process, CO_2 emission, energy consumption and resource workload in a clockwise order.

From Figure 6.3, the total energy consumption of up-hill, down-hill and balanced scenarios were calculated by using Equation (5.1), (5.2) and (5.3) as shown below;

$$\begin{aligned} &Total\ Energy\ Consumption\ of\ the\ Production\ System \\ &\qquad = Total\ Energy\ Consumption\ of\, CNC_1 \\ &\qquad + Total\ Energy\ Consumption\ of\, CNC_2 \\ &\qquad + Total\ Energy\ Consumption\ of\, CNC_3 \\ &\qquad + Total\ Energy\ Consumption\ of\, CNC_4 \end{aligned}$$

$$\begin{aligned} &Total\ Energy\ Consumption\ of\, CNC_x \\ &\qquad = \left(\int_0^{T_{prod}} P_{warm-up}(t)dt\right) + \left(\int_0^{T_{prod}} P_{operate}(t)dt\right) \\ &\qquad + \left(\int_0^{T_{prod}} P_{shutdown}(t)dt\right) \end{aligned}$$

$$\begin{aligned} &Total\ Energy\ Consumption\ of\ the\ Production\ System\ (Up - hill\ scenarios) \\ &\qquad = \left(\left(\int_{-30}^{0} 212.2(t)dt\right) + \left(\int_0^{700} 254.07(t)dt\right) + \left(\int_0^{0} (0)(t)dt\right)\right) \\ &\qquad + \left(\left(\int_{145}^{175} 212.2(t)dt\right) + \left(\int_{175}^{700} 254.07(t)dt\right) \right.\\ &\qquad \left. + \left(\int_0^{145} (0)(t)dt\right)\right) \\ &\qquad + \left(\left(\int_{320}^{350} 212.2(t)dt\right) + \left(\int_{350}^{700} 254.07(t)dt\right) \right.\\ &\qquad \left. + \left(\int_0^{320} (0)(t)dt\right)\right) \\ &\qquad + \left(\left(\int_{465}^{495} 212.2(t)dt\right) + \left(\int_{525}^{700} 254.07(t)dt\right) \right.\\ &\qquad \left. + \left(\int_0^{465} (0)(t)dt\right)\right) \\ &\qquad = 458.35\ kWh \end{aligned}$$

$$Total\ Energy\ Consumption\ of\ the\ Production\ System\ (Down-hill\ scenarios)$$

$$
\begin{aligned}
&= \left(\left(\left(\int_{-30}^{0} 212.2(t)dt\right) + \left(\int_{0}^{700} 254.07(t)dt\right)\right.\right. \\
&\quad \left.+ \left(\int_{0}^{0} (0)(t)dt\right)\right) \\
&\quad + \left(\left(\int_{-30}^{0} 212.2(t)dt\right) + \left(\int_{0}^{525} 254.07(t)dt\right)\right. \\
&\quad \left.+ \left(\int_{525}^{700} (0)(t)dt\right)\right) \\
&\quad + \left(\left(\int_{-30}^{0} 212.2(t)dt\right) + \left(\int_{0}^{350} 254.07(t)dt\right)\right. \\
&\quad \left.+ \left(\int_{350}^{700} (0)(t)dt\right)\right) \\
&\quad + \left(\left(\int_{-30}^{0} 212.2(t)dt\right) + \left(\int_{0}^{175} 254.07(t)dt\right)\right. \\
&\quad \left.\left.+ \left(\int_{175}^{700} (0)(t)dt\right)\right)\right) \\
&= 459.47\ kWh
\end{aligned}
$$

$$Total\ Energy\ Consumption\ of\ the\ Production\ System\ (Balanced\ scenarios)$$

$$
\begin{aligned}
&= \left(\left(\left(\int_{-30}^{0} 212.2(t)dt\right) + \left(\int_{0}^{700} 254.07(t)dt\right) + \left(\int_{0}^{0} (0)(t)dt\right)\right)\right. \\
&\quad + \left(\left(\int_{145}^{175} 212.2(t)dt\right) + \left(\int_{175}^{700} 254.07(t)dt\right)\right. \\
&\quad \left.+ \left(\int_{0}^{145} (0)(t)dt\right)\right) \\
&\quad + \left(\left(\int_{320}^{350} 212.2(t)dt\right) + \left(\int_{350}^{700} 254.07(t)dt\right)\right. \\
&\quad \left.+ \left(\int_{0}^{320} (0)(t)dt\right)\right)
\end{aligned}
$$

$$+\left(\left(\int_{465}^{495} 212.2(t)dt\right) + \left(\int_{525}^{700} 254.07(t)dt\right)\right.$$
$$\left.+\left(\int_{0}^{465} (0)(t)dt\right)\right)$$
$$= 450.99\ kWh$$

Total energy consumption of the three workload scenarios was first analysed. According to Figure 6.5, the up-hill and down-hill scenarios were found to consume similar amount of energy at 458.35 and 459.47 kWh, respectively. Based on these results, different workloads of a production process consumed a different amount of energy while producing the same level of productivity. In the up-hill scenario, the production process operated throughout 700 minutes period which started at the lowest machine capacity. The capacity is increased incrementally over the period of time. This scenario was found to be the most energy-resource efficient workload process. On the other hand, in the down-hill scenario, the production process operated by increasing the capacity over the period of time which consumed the highest energy. Importantly, the balanced workload scenario, which operated with an half of workload throughout the process, consumed the least amount of energy at approximately 450.99 kWh.

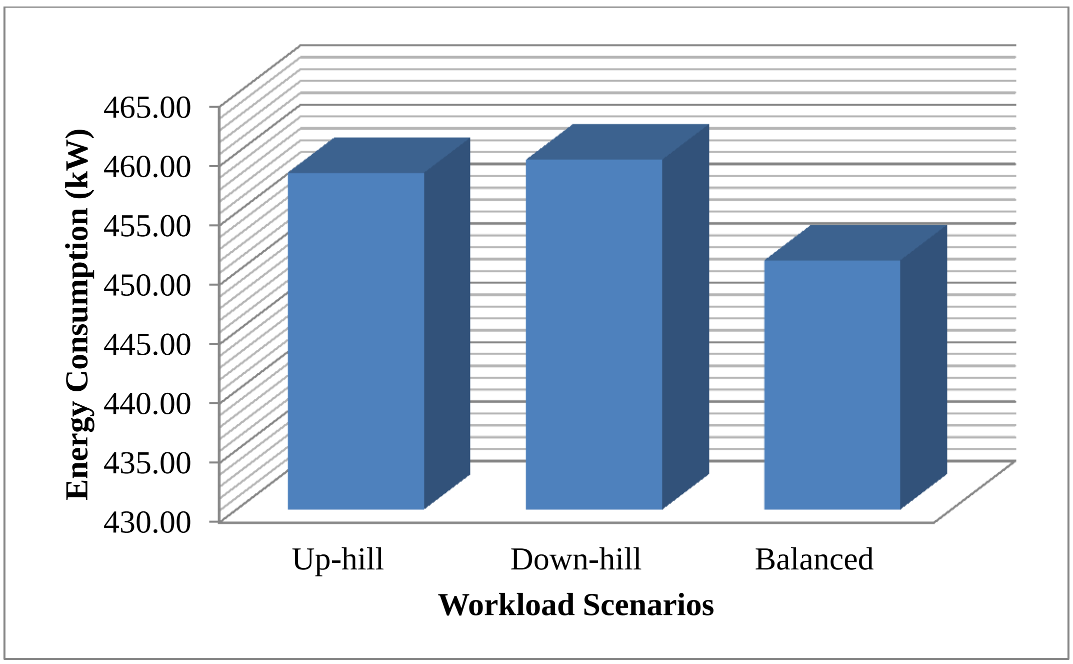


Figure 6.5. Total energy consumption at the three workload scenarios

Among the three scenarios, the balanced workload scenario was the most energy-resource efficient scenario. As Chang et al (2005) suggested that the higher machine workload, the higher energy usage. Hence, the results of the experiment confirmed the balanced workload which is 50% of machine workload over the period of time gives the lowest energy consumption compared with up-hill and down-hill scenarios.

The total machining cost to produce 40 aluminium workpieces in this experiment based on three workload scenarios are summarised in Table 6.1. In addition, applying Equation (2.19) to the calculation, the total CO2 emitted during the machining process are also summarised in Table 6.1. Overall, the findings indicate that by reducing the energy consumption, the balanced scenario also yields the lowest total production costs at £534.61, followed by balanced and down-hill workload production, respectively as calculated in following;

$$\begin{aligned}\mathit{Total\ Cost\ of\ the\ Machining\ Operation} &= \mathit{Power\ Cost} + \mathit{Machine\ Maintenance\ Cost} + \mathit{Tool\ Cost} \\ &\quad + \mathit{Labour\ Cost}\end{aligned}$$

$$\begin{aligned}&= (\mathit{Electricity\ Cost} \times \mathit{Total\ Energy\ Consumption}) \\ &\quad + (\mathit{Maintenance\ Cost\ per\ day} \\ &\quad \times \mathit{Number\ of\ Operating\ Days}) \\ &\quad + (\mathit{Material\ Cost} + \mathit{Tool\ Cost}) \\ &\quad + (\mathit{Technician\ Cost\ per\ day} \times \mathit{working\ days})\end{aligned}$$

$$\begin{aligned}&= (£0.16 \times 450.99) + (£12.525 \times 10) + (£2.70 \times 40) + (£18.45 \times 2) \\ &\quad + (£19.23 \times 10)\end{aligned}$$

$$= £72.16 + £125.25 + £108 + £36.90 + £192.30$$

$$\mathit{Total\ Operation\ Cost} = £534.61$$

In addition, applying Equation (2.19) to the calculation, the total CO_2 emitted of the balanced scenario was calculated to be 179.345 $kg \cdot CO_2e$ as follow;

$$\text{Carbon footprint} = \text{Activity data} \times \text{CO2 emissions conversion factor}$$

$$= 450.99 \times 0.41205$$

$$= 185.83 \ \text{kg} \cdot CO_2e$$

Table 6.1 Total production costs and CO_2 emission of the three workload scenarios

Workload Scenarios	Total Production Costs (Pounds)	CO_2 Emission (kg)
Up-hill	535.79	188.86
Down-hill	535.97	189.32
Balanced	534.61	185.83

6.6 Chapter Summary

To respond to environmental concerns and higher energy costs, manufacturing industry has put great efforts into sustainability. Since production processes are responsible for high energy consumption, optimising an energy-efficient system at this manufacturing level is of an important concern for both academic and practitioners. At the same time, energy costs and high competition have driven manufacturers to pay closer attention to economic output especially productivity and production costs. This chapter developed an energy-resource efficient simulation system which collectively considered energy consumption and machine workload in a production process of CNC machining. The findings demonstrated the implication of using a balanced production in which the workload capacity and number of operating machines are at 50% workload throughout the process. This scenario of a production process was shown to reduce energy consumption, total production costs and CO_2 emissions the three elements that are essential to sustainable manufacturing.

CHAPTER 7

HVAC System within the e-ProMan and its Implementation

This chapter presents three experimental trials that examined simulation of energy efficiency at the manufacturing levels of heating, ventilation and air conditioning (HVAC) system considering weather forecast. The experiment trials were carried out with the Energy-smart Production Management (e-ProMan) system to provide a more integrated and comprehensive analysis of manufacturing data, machine accuracy and correlational analysis of the three flows (i.e. energy, data and work) based on the proposed e-ProMan system presented in Chapter 3. The objective was also to demonstrate an implementation of the e-ProMan system in a manufacturing level. Results and discussions of each experimental trial are provided.

7.1 Introduction

In order to efficiently reduce energy in manufacturing, the overall energy consumption which consists of energy usage at different machines, processes and systems need to be investigated and reduced. As described in the current research gaps (Section 2.9), research on HVAC system in manufacturing buildings that considers energy consumption at a manufacturing level is limited. To contribute to the limited knowledge, the experimental trials will demonstrate the e-ProMan implementation and its applications on minimisation of energy consumption and thus carbon mission. In order to validate the performance of the e-ProMan, its predictive HVAC system is simulated and compared to the fuzzy logic system which is shown to be the most accurate control system (Dounis et al., 1996; Ulpiani et al., 2016). In addition, the final implementation of the e-ProMan is illustrated through a simulation modelling that integrates predictive and real-time data and the correlational relationship between energy consumption, product quality and ambient temperature on the HVAC system and production processes. Taken together, the e-ProMan takes into account energy consumption at different levels namely machine, shop-floor and production process.

7.2 Model and Architecture of HVAC System within the e-ProMan

HVAC is the system that is used to control a comfortable level of the ambient environment in a building. Due to the temperature-controlling function, an HVAC system consumes a significant amount of energy in order to maintain the set point temperature in manufacturing facilities. The e-ProMan system operates by controlling the temperatures of the laboratory shop-floor in the simulation modelling in accordance to the ideal comfort temperatures in light factories (including laboratories) which are stated to range between 16°C and 19°C (Health, Safety and Welfare Regulations, 1992). According to this established HVAC guidelines (Carbon Trust, 2011), the heating system would automatically turn on when the shop-floor temperature drops below 16°C, whereas the air conditioning system would operate when the temperature rises above 19°C. Consequently, the simulation of the e-ProMan HVAC controller operates by comparing the real-time shop-floor temperature to the ideal comfort temperature and also by integrating weather forecast temperature data to improve the decision of adjusting temperature in HVAC system that can lead to enhance the manufacturing energy management system. The e-ProMan HVAC system uses a fuzzy logic algorithm in LabVIEW programme which includes the HVAC optimum setpoint to reduce the energy consumption and thus CO_2 emission. Figure 7.1 illustrates the overview of the e-ProMan HVAC system.

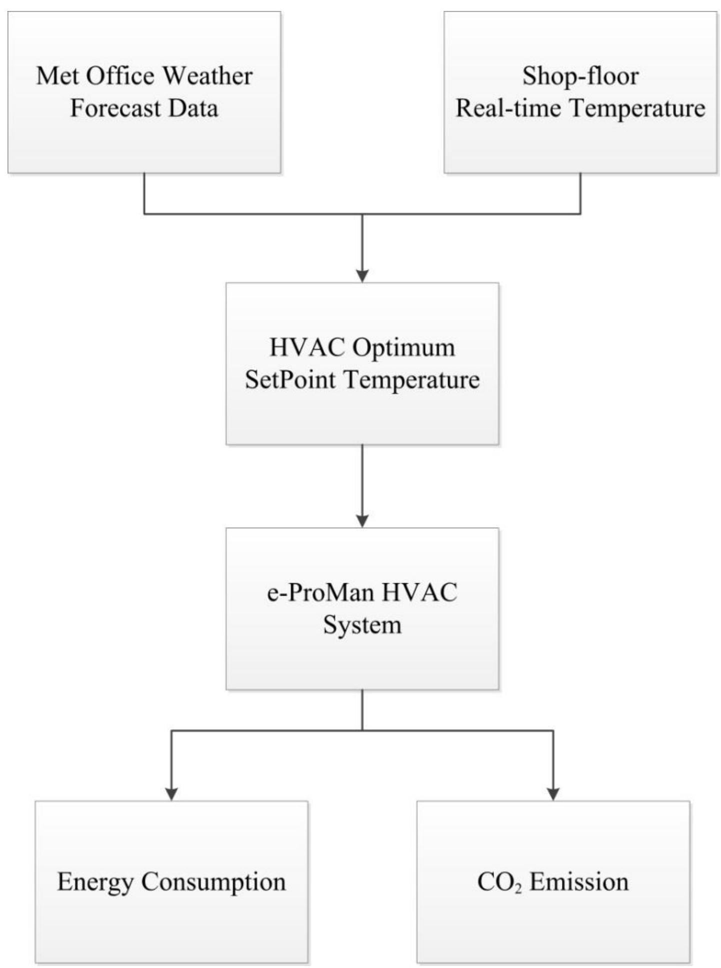


Figure 7.1. Overview of the e-ProMan HVAC system

In the present e-ProMan HVAC system, the simulation controller adjusts the HVAC system based on the value of temperature derived from Equation (7.1). This research proposes eight equations which are applied into a regular fuzzy HVAC system in order to investigate the HVAC optimum setpoint temperature equation for the e-ProMan HVAC system in terms of the total energy consumption. The eight equations and total energy consumption derived from each equation are summarised in Table 7.1, and the statistical test of the eight equations are shown in Appendix S. According to these results, the second equation is considered the most energy efficient for the HVAC system as it consumed 1,968.50 kWh during the experimental period in the summer.

Table 7.1. Total energy consumption after applied e-ProMan HVAC setpoint temperature equations

No.	e-ProMan HVAC Setpoint Temperature Equations	Total Energy Consumption (kWh)
1	$T_e = T_H + (T_w - T_c)$	2,285.60
2	$T_e = T_H + (\frac{T_w - T_c}{2})$	1,968.50
3	$T_e = T_H + (\frac{T_w - T_c}{3})$	2,070.45
4	$T_e = T_H + (\frac{T_w - T_c}{4})$	2124.00
5	$T_e = T_H + (\frac{T_w - T_c}{5})$	2,197.20
6	$T_e = T_H + (\frac{T_w - T_c}{6})$	2,231.25
7	$T_e = T_H \pm \sqrt{\lvert T_w - T_c \rvert}$	1,982.20
8	$T_e = T_H \pm \sqrt[3]{\lvert T_w - T_c \rvert}$	2,013.80

where T_e is the e-ProMan HVAC setpoint temperature, T_H is the HVAC setpoint temperature to be adjusted, T_c is current outside temperature, and T_w is a value of weather forecast temperature in the next hour.

$$T_e = T_H + (\frac{T_w - T_c}{2}) \quad (7.1)$$

The simulation controller operates every one hour in advance by considering (1) the current outside temperature T_c measured by the temperature sensor and (2) the weather temperature in the next hour T_w obtained from predictive weather forecast database in order to reduce energy usage consumed by the operation of the HVAC system. For example, if the real-time weather forecast database predicts a 5°C rise in weather temperature in the next hour, the e-ProMan HVAC setpoint temperature of the controller system in the simulation is adjusted accordingly.

In Figure 7.2, the Single Input Single Output (SISO) in the LabVIEW programme is designed and implemented using fuzzy controller which is a method of rule-based decision making using for process control. The fuzzy controller uses identified rules to control a fuzzy system based on the current values of input variable which is the difference between the current ambient temperature and the ideal ambient temperature. Triangular forms of membership function and a collection of logic rules in the form of If-Then statements are set and illustrated in Figure 7.3 and Figure 7.4, respectively. Then, the parameters adjust themselves to the algorithm as stated by Equation (2.27) in Chapter 2. The center of area (CoA) method of defuzzification is performed, and the HVAC setpoint temperature output is thus attained. The value of HVAC setpoint temperature is converted into the e-ProMan HVAC setpoint temperature using Equation (7.1).

After that, the HVAC algorithm system is operated consequently by using the e-ProMan HVAC setpoint temperature as shown in Figure 7.5. The heater and cooler were operated when the ambient temperature was not within the expected temperature range.

7.3 Forecastive Control on the e-ProMan HVAC System

The present research was conducted at the Advanced Manufacturing and Enterprise Engineering (AMEE) Laboratory at Brunel University London. The laboratory has a floor area of 180 m^2 with 5 metres ceiling. In particular, it was carried out at two different seasonal periods (summer and winter) in order to capture the high variability of weather. The summer experiment was monitored between 1st and 31st August 2014 which is considered as having the most fluctuation in temperatures compared with other periods. The winter experiment was between 1st and 31st January 2015.

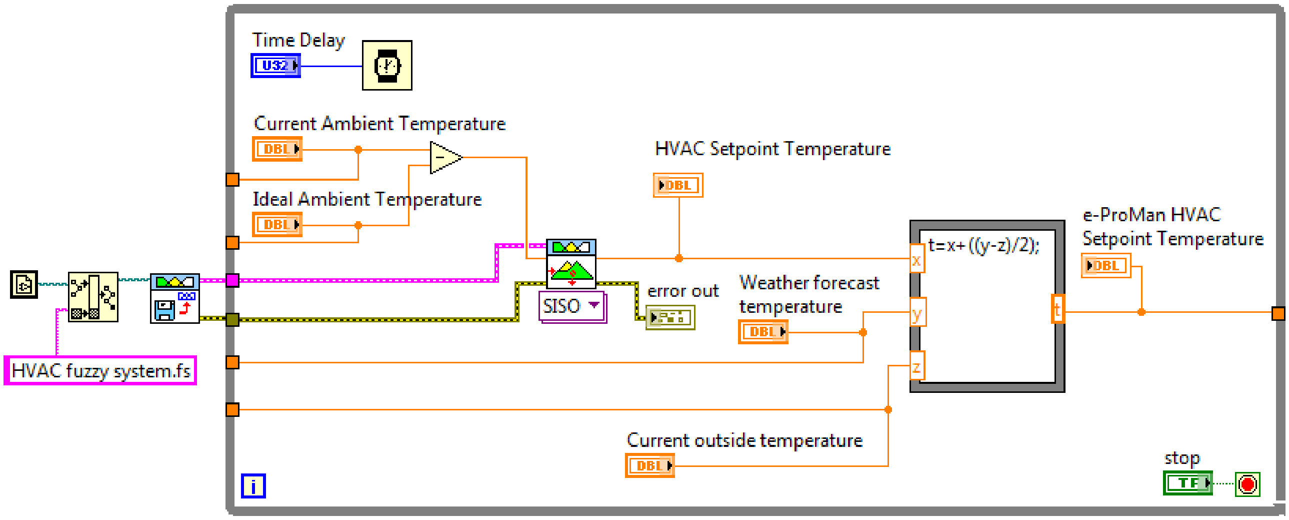


Figure 7.2. e-ProMan HVAC system fuzzy logic controller

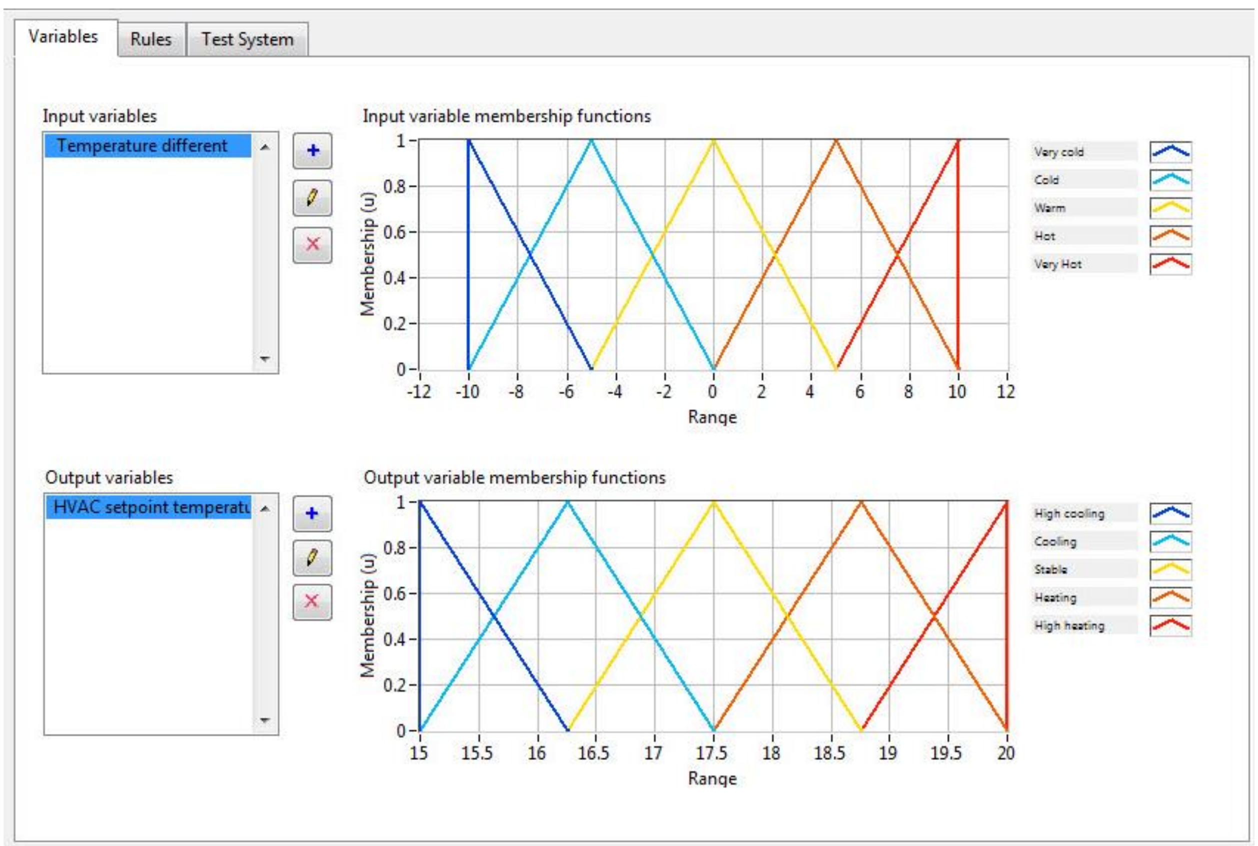


Figure 7.3. HVAC system triangular form of membership function

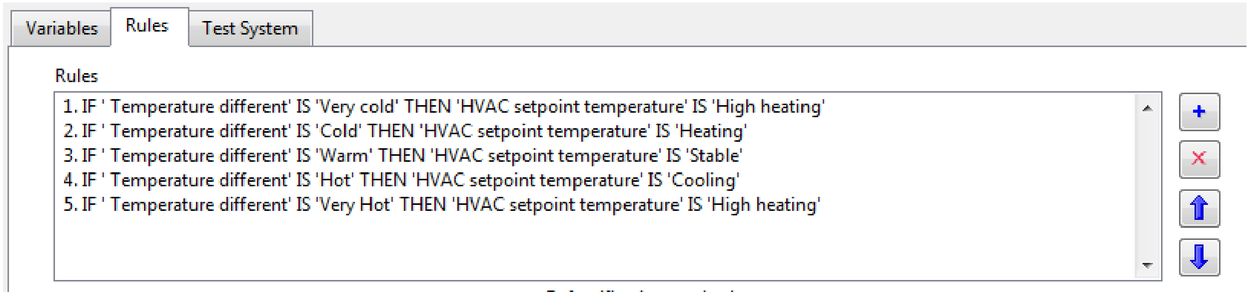


Figure 7.4. HVAC system fuzzy logic rules

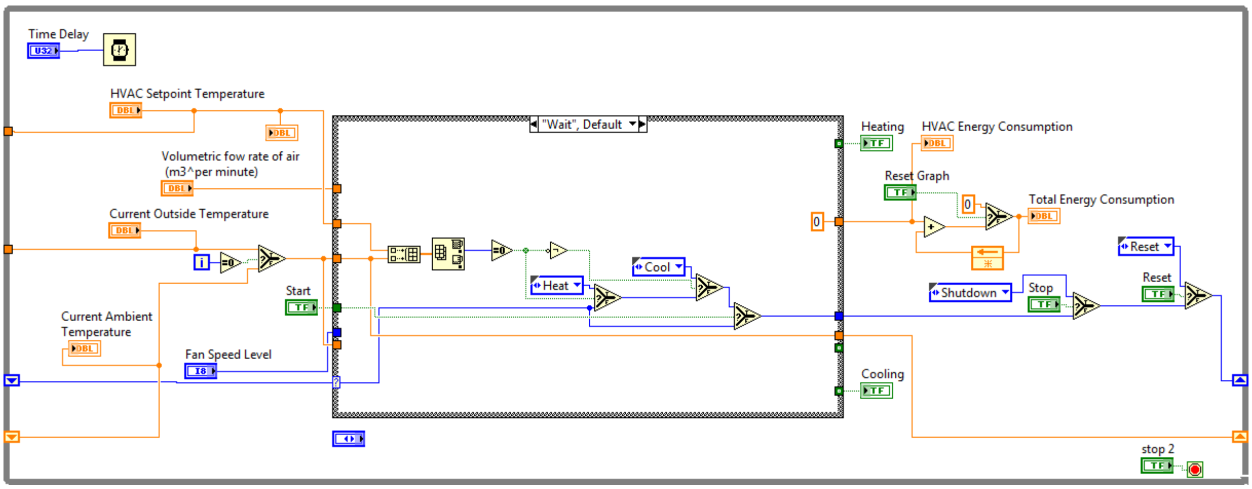


Figure 7.5. HVAC system algorithm

As shown in Figure 7.6, the LabVIEW programme was run to display the e-ProMan system by obtaining the real-time data (i.e. weather forecast, shop-floor temperature and energy usage of the HVAC system) and by demonstrating the feasibility of the predictive control of the HVAC system in the manufacturing system. As displayed on the top right side of the Figure 7.6, the HVAC predictive control of the e-ProMan system comprehensively and virtually displays the real-time 3D colour-correlated thermography of the CAD model temperature measuring shop-floor. The main HVAC controller is shown in the bottom left side of the system, and the real-time shop-floor temperature and real-time weather forecast data are displayed in the middle and on the bottom right side of the panel system respectively. The shop-floor temperature data displayed on the e-ProMan system is the average temperature values obtained from the ten temperature sensors.

In addition, with regard to energy consumption, the e-ProMan system considers two assumptions. First, a central air condition typically consumes approximately 3,000 to 5,000

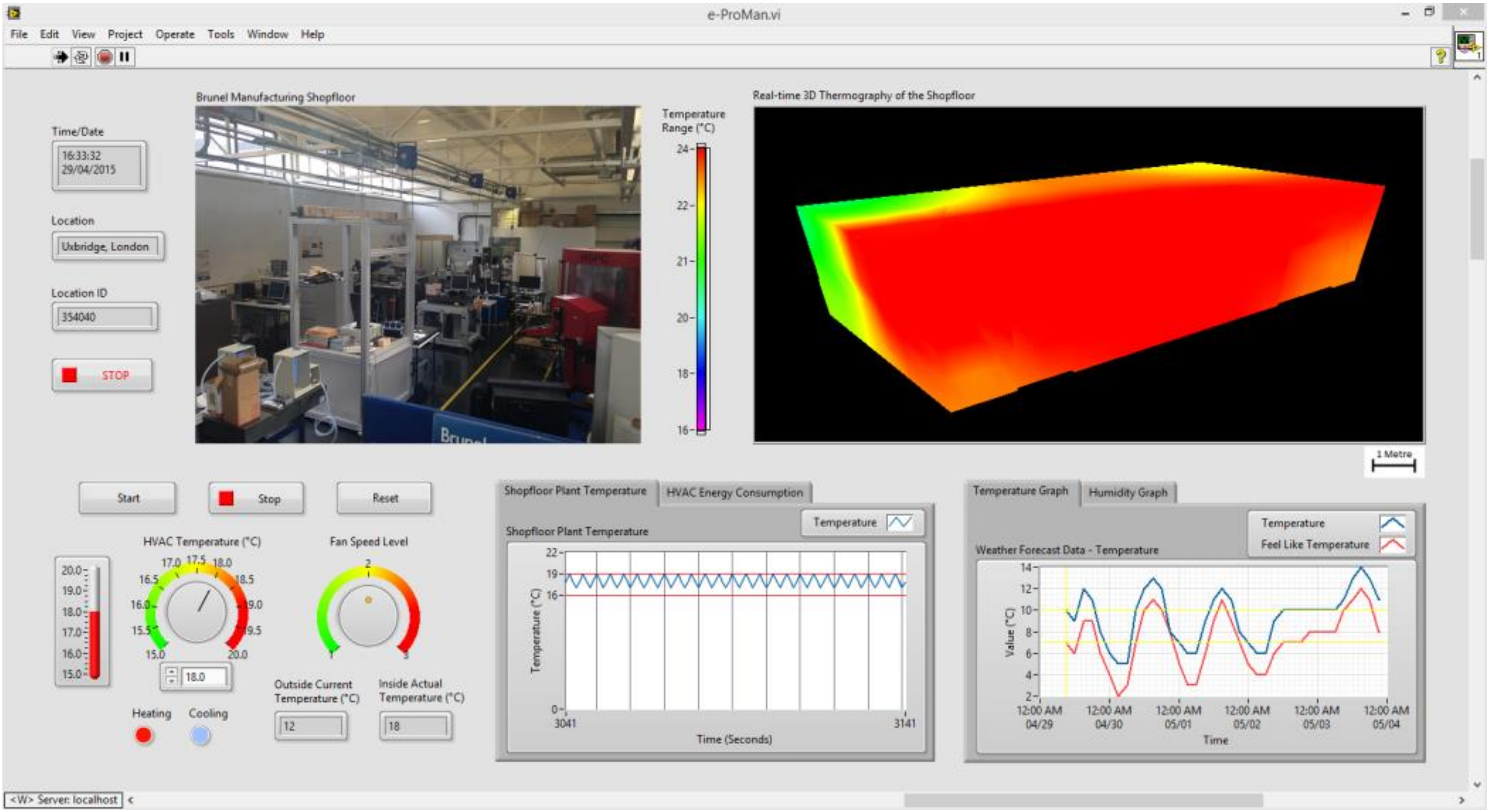


Figure 7.6. Forecastive control on the e-ProMan HVAC system

Watts/hour and operates between three and seven months a year during summer depending on the current weather at the time. Second, a water heater consumes approximately 3,000 to 4,000 Watts/hour during winter (Carbon Trust, 2011).

To evaluate the energy usage of the HVAC system, the analysis first considered the overall temperatures of the shop-floor during the two experiments. Figure 7.7 summarised the average temperatures displayed in a two-hour time interval during the summer (August 2014) and winter (January 2015) periods. The average shop-floor temperatures of each experiment were calculated using the average of the temperatures acquired from the total of 31 days in which each of the experiments was conducted. From these results, the temperatures in summer fluctuated sharply between 6.00 am and 11.00 am where the average temperature dropped to the lowest at approximately 17°C at 5.00 am and then reached the highest at 29°C at 10.00 am. On the other hand, the average shop-floor temperatures slightly fluctuated in the winter experiment. The temperatures between midnight and 9.00 am remained mostly stable within the range of 12°C. The lowest temperature was at 12°C at 2.00 am, and the highest temperature was at approximately 15°C at 11.00 am. Based on these results, the air conditioning system would operate more frequently in the morning during the summer period, whereas the heating system would operate most of the time during the winter period.

The second part of the analysis evaluated a reduction in energy consumption of the HVAC system by comparing between the two simulation systems: ON/OFF system and e-ProMan system. The ON/OFF system was regarded as a basic of HVAC system, whereas the e-ProMan system was proposed as an advanced modelling of HVAC system concerning real-time and predictive temperature data. As illustrated in Figure 7.8, total energy consumption in the two systems was generally higher in winter than in the summer. Importantly, the results of the simulation further showed a larger amount of total energy consumption in the ON/OFF system for both summer and winter when compared to the total energy consumption in the e-ProMan system.

Table 7.2 provides more detailed results of HVAC energy consumption of the two systems during the two seasonal periods. In August 2014 during the summer period, the proposed e-ProMan simulation system consumed 1,968.50 kWh which was reduced from 2,317.50 kWh of energy consumed in the ON/OFF system, resulting in 15% of energy saving. Approximately 143.81 kg CO_2 emission was thus reduced. The same pattern was also shown for the winter experiment. The total of 2,628 kWh energy consumption in the ON/OFF system was reduced by 10.69%, and CO_2 emission was reduced by about 115.79 kg compared to the total of 2,347 kWh energy consumption in the e-ProMan system. Together, the energy consumption was reduced in both experiments.

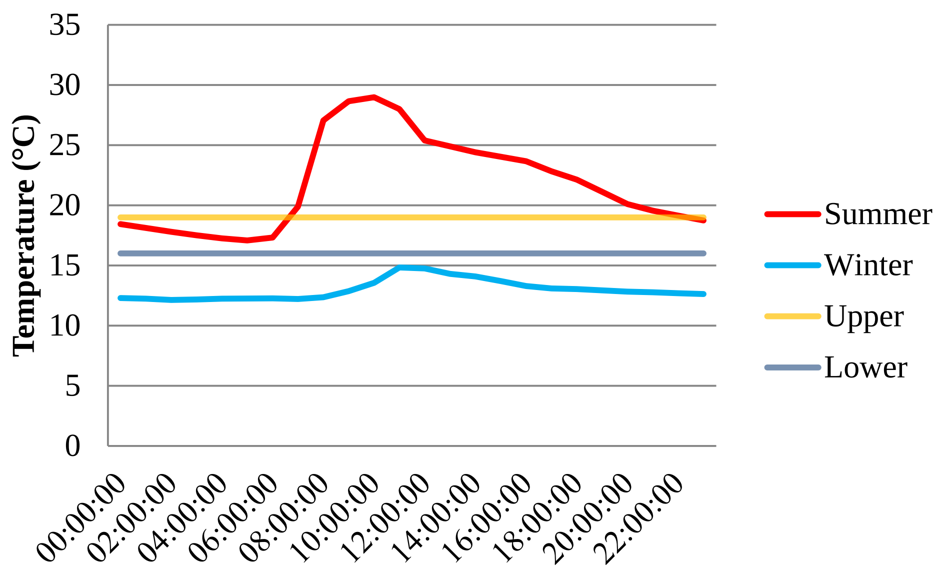


Figure 7.7. An average of Brunel laboratory shop-floor temperature in summer and winter

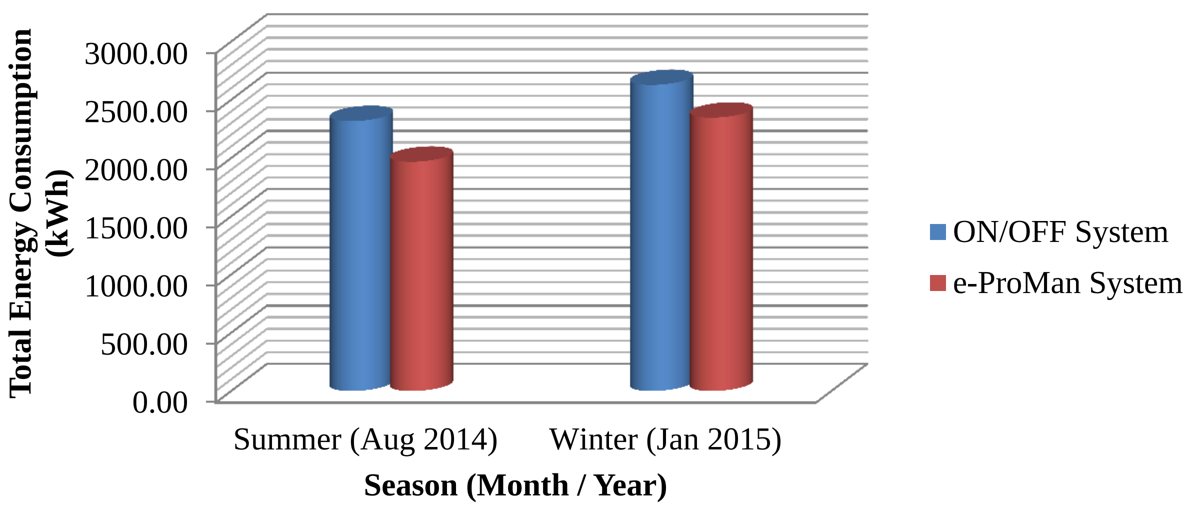


Figure 7.8. Results of the total HVAC energy consumption

Table 7.2 Results of HVAC energy consumption in ON/OFF and e-ProMan systems

	Summer (Aug 2014)	**Winter (Jan 2015)**
ON/OFF System (kWh)	2,317.50	2,628.00
e-ProMan System (kWh)	1,968.50	2,347.00
Energy Saving (%)	15.06	10.69

The findings suggest that both real-time temperature and weather forecastive data are necessary for the HVAC control system as they enable the e-ProMan system to adjust the temperatures accordingly to the ideal comfort temperatures stated by the regulations. Moreover, the predictive data of weather enabled the control system to adjust the HVAC operating status according to the ideal temperature range, thereby reducing the energy usage at the HVA system. Compared to the conventional ON/OFF system, the e-ProMan system was found to save 15% of energy in summer and 10% in winter.

The predicted weather helped the HVAC system reducing more energy in the summer than in the winter by minimising the ambient temperature fluctuation. In the winter, the heating system was working all the time; on the other hand, in the summer, the HVAC system was occasionally turned off. Therefore, the effectiveness of the e-ProMan system was found to be more pronounced during the summer period which is characterised by large weather temperature variations especially in the morning hours. Similar results were also observed in the work of Dababneh et al. (2016) which modelled an energy demand response of the HVAC system in summer and winter. In this research, a greater energy demand reduction was found in summer compared to winter. Taken together, the virtual, user-friendly simulation of the e-ProMan system shows promising results for energy consumption system and thus for energy efficiency in manufacturing.

7.4 HVAC Experimental Trials on the Shop-floor

In this simulation experiment, the e-ProMan HVAC system was tested in the AMEE laboratory which gathered real-time ambient data of the laboratory shop-floor, weather forecast data and machining energy consumption data. The experiment was conducted at a CNC machine which operated over the 4-hour period (1.00 pm-5.00 pm) on 14th October 2015 when the outside temperatures of the laboratory were between 13°C and 18°C. The inside temperatures of the laboratory were between 20.4°C and 27.8°C. Figure 7.9 shows a comparison between inside and outside temperatures during the period in which the experiment was conducted. The temperature both inside and outside were increased over the period on time.

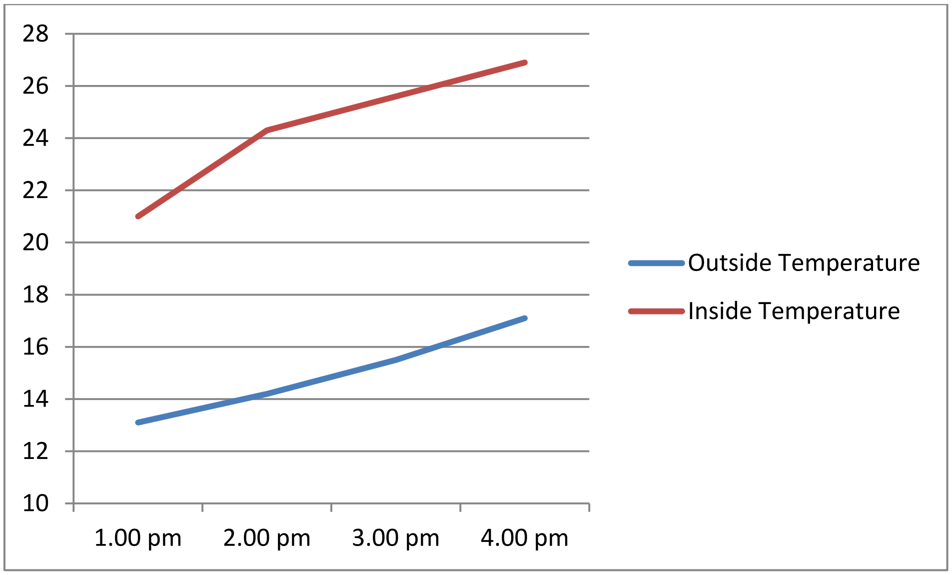


Figure 7.9. Temperature outside and inside the laboratory during HVAC system experiment

The 3D thermal distributions of the shop-floor plan between 1.00 pm and 4.00 pm are illustrated in Figure 7.10. Evidently, the shop-floor temperatures increased significantly during the afternoon hours as the red areas of the thermography expanded and covered most of the shop-floor areas.

The second part of the simulation compared energy efficiency between the fuzzy logic controller and HVAC controller in the e-ProMan system. Figure 7.11 summarised the amount of the energy consumed in the simulating fuzzy logic system and the HVAC e-ProMan system. The results showed that the HVAC controller in the e-ProMan system consumed less energy than the fuzzy logic controller. The e-ProMan system saved energy by more than 0.53 kWh or 3.57%, thus reducing the CO_2 emission by approximately 0.21 kilogrammes during the experiment as illustrated in Figure 7.12.

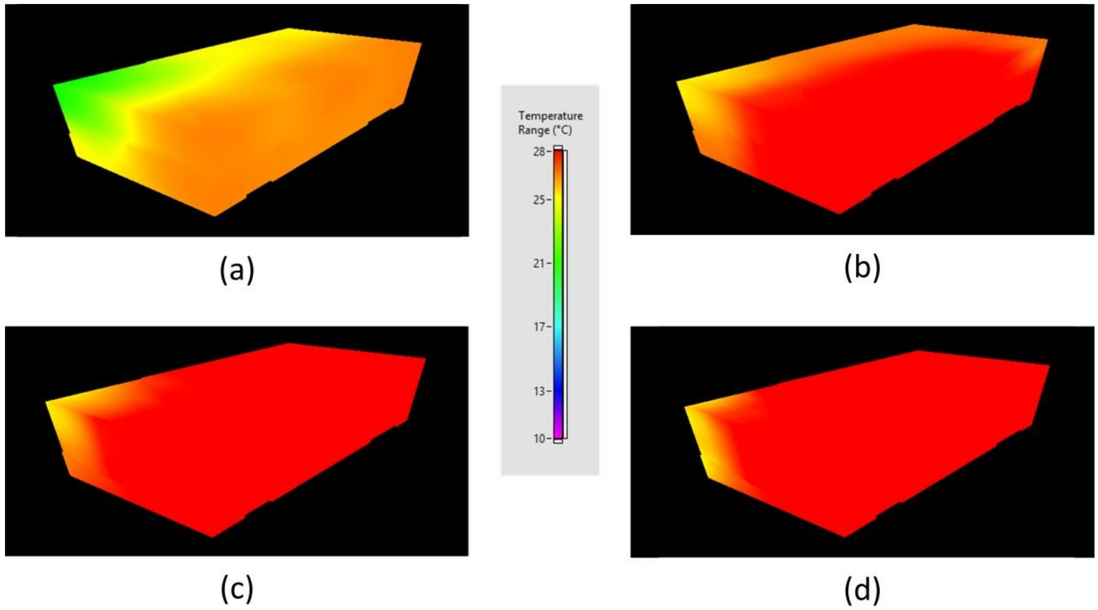


Figure 7.10. Shop-floor thermal distributions at (a) 1.00 pm, (b) 2.00 pm, (c) 3.00 pm and (d) 4.00 pm

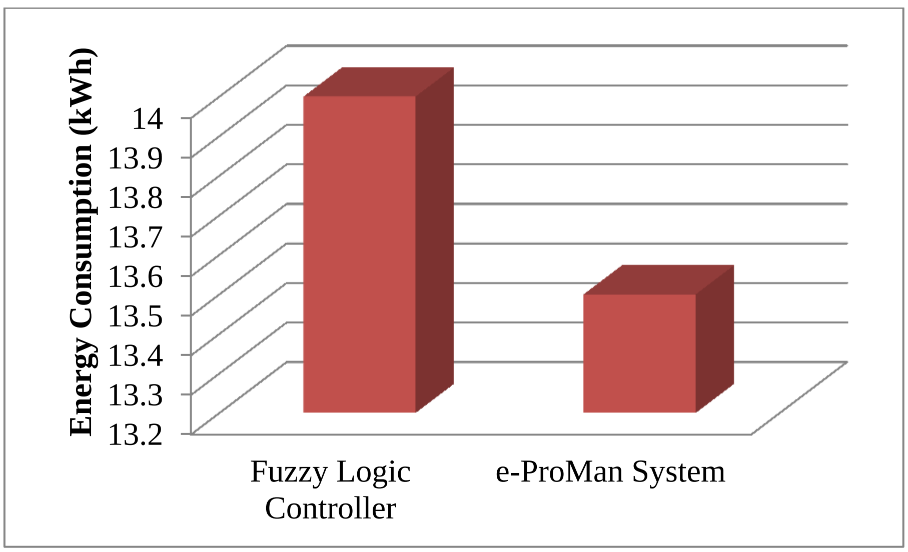


Figure 7.11. The comparison of energy consumption between fuzzy logic controller and e-ProMan system

In other words, if the CNC milling machine operates every day on an 8-hour shift excluding weekends, the e-ProMan system would save approximately 275.6 kWh and reduce carbon emissions by 115.89 kg per annum for the HVAC system in the manufacturing shop-floor. Consistent with the previous HVAC experiment, the predictive control system of the e-ProMan which considers real-time weather forecast data confirms its implication on energy efficiency especially when there is a large variation in temperature such as in the afternoon period and in the summer season.

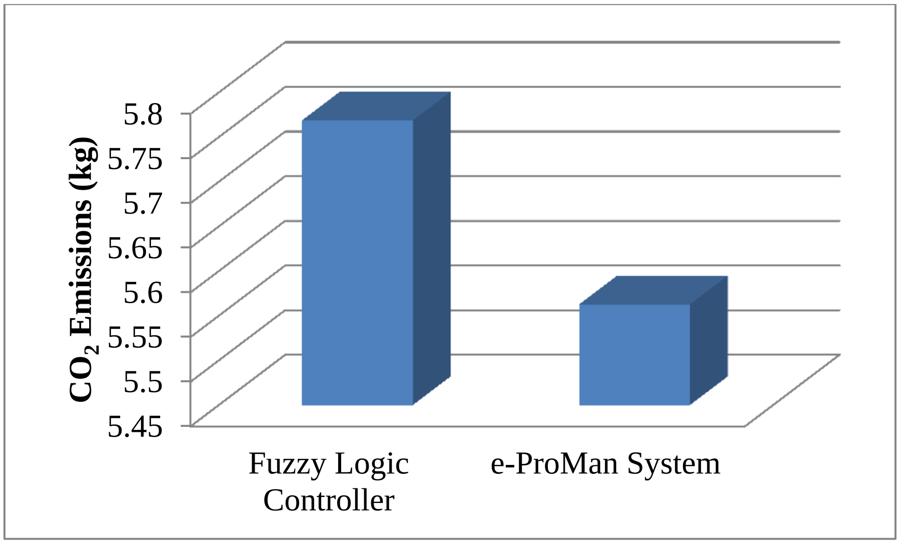


Figure 7.12. The comparison of CO_2 emission between fuzzy logic controller and e-ProMan system

7.5 Experimental Trials on Virtual Production System Modelling Working with Internet

In this last experimental trial, the main objective was to provide an implementation of the e-ProMan virtual production web-based system. This system offers a real-time monitoring publishing on the web server in order to observe and control the manufacturing system.

As displayed in Figure 7.13, the virtual production system consists of 9 elements which are 3D shop-floor thermal distribution (top left panel), real-time web camera, simulation of production process, dimensional error (quality), e-ProMan HVAC system, total energy consumption, weather forecast and shop-floor ambient temperature in a clockwise order.

According to the results of production workload in Chapter 6, the most energy-efficient scenario of schedule (i.e. up-hill scenario) was applied as a case study in the e-ProMan system using four CNC milling machines to finish the cutting process of the total 40 aluminium workpieces. The e-ProMan HVAC system was added into the case study to control the shop-floor temperatures. Moreover, the regression line equations (Equation 5.6), which resulted from the correlational analysis presented in Chapter 5, were applied to this simulation model

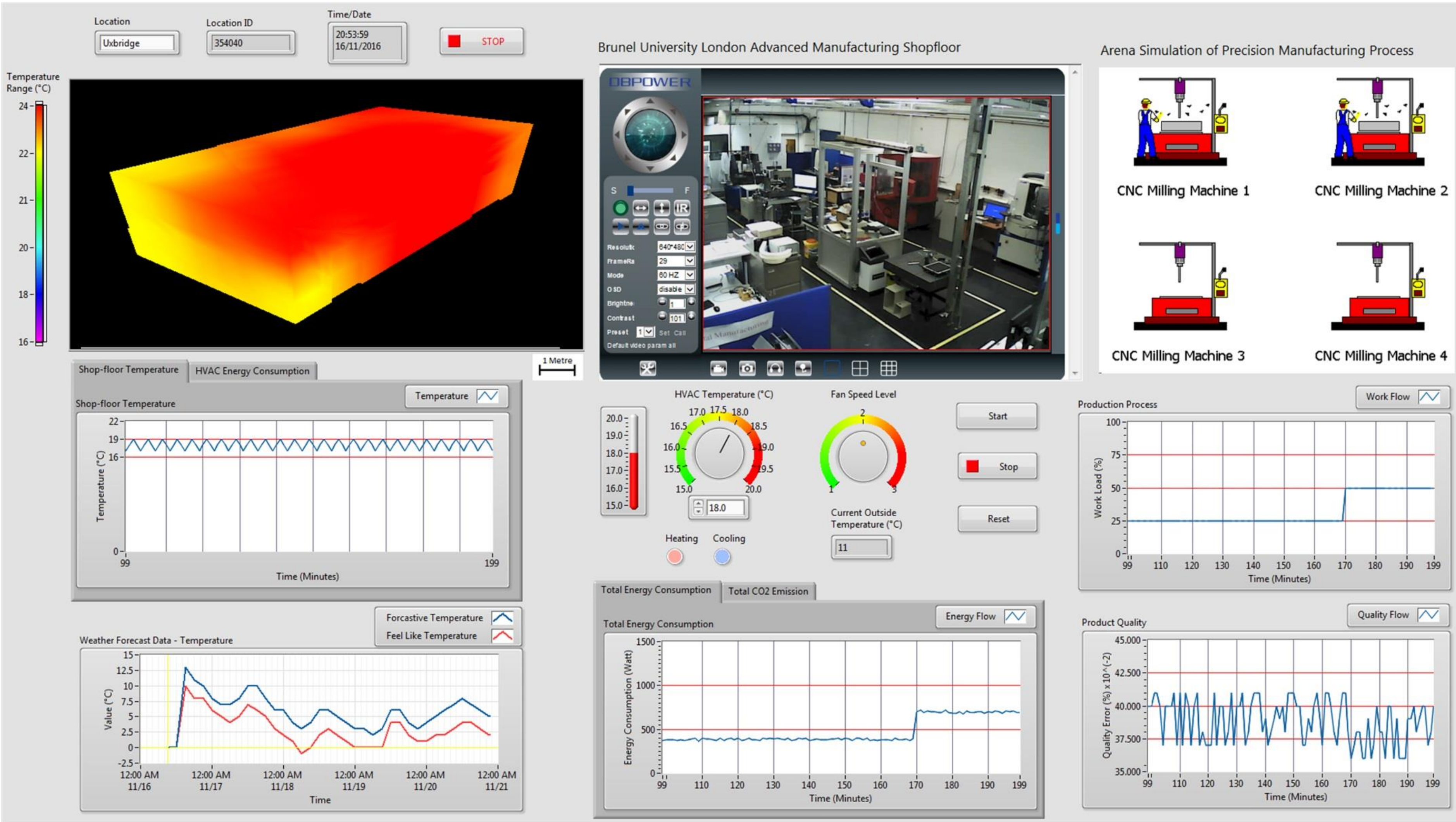


Figure 7.13. Web-based virtual production system modelling and analysis

in order to display the results of the three-dimensional correlation of energy consumption, ambient temperature and product quality.

After running the virtual production modelling system, the simulation provided the results of energy usage of the e-ProMan HVAC system, production processes, total energy consumption and also CO_2 emission as summarised in Table 7.3. With the e-ProMan HVAC controllers together with the production processes based on an up-hill scheduling scenario consumed approximately 467.7 kW which contributed to approximately 192.71 kilogrammes of CO_2 emission.

Table 7.3 Overall results of the virtual production modelling system

	Energy Consumption (kWh)	**CO_2 Emission (kg)**
HVAC system	45.51	18.75
4 Precision Milling Machines	422.19	173.96
Total	467.7	192.71

7.6 Chapter Summary

This chapter aimed to provide experimental testing of the simulation modelling of the Energy-smart Production Management (e-ProMan) system. This energy management system established an innovative method to demonstrate and analyse the real-time web-based manufacturing data including work flow, energy flow and data flow. The development of the e-ProMan system provides a preliminary model of the manufacturing data-based simulation on the energy efficiency of the HVAC system level in the manufacturing. In particular, the e-ProMan system inputs real-time manufacturing data of weather forecast, outside and ambient shop-floor temperatures, and energy consumption of the HVAC system. By simulating and analysing the model, a reduction of energy consumption was supported by the implementation of the e-ProMan system. Moreover, an experiment trial illustrated the energy-efficient performance of the e-ProMan system as a result of its predictive HVAC control system, workload optimisation in a production process and the quantitative three-dimensional correlation between energy flow, work flow and data flow.

CHAPTER 8

Conclusions and Recommendations for Future Work

8.1 Conclusions

The research conclusions can be drawn as follows:

(1) A simulation-based methodology which models thermal and energy management for real-time decision makings in energy-efficient manufacturing. To achieve the established research objective, the Energy-smart Production Management (e-ProMan) system was developed. The e-ProMan system was proposed as a virtual, user-friendly simulation-based system that provides real-time decision makings from modelling weather forecast, shop-floor outside temperature and ambient temperature data and from a quantitative three-dimensional correlation analysis of energy flow, work flow and data flow. In order to evaluate the effectiveness of the e-ProMan system performance at different levels, the conclusions are summarised as follows.

(2) The dimensional accuracy in precision machining was investigated by integrating precision machining with energy efficiency in sustainable manufacturing. In response to an increasing demand for higher standards of products, machining accuracy is crucial but often consumes more energy. Built upon the previous experiment which demonstrated the important role of thermal effect in energy consumption of manufacturing machines and systems, an experiment was conducted to provide a correlational analysis of energy consumption, dimensional error quality of workpiece and ambient temperature. The experiment performed machining accuracy trials on milling workpieces and employed a three-dimensional correlational analysis. The findings suggest that at high ambient temperatures, quality errors appear to increase, but less energy is consumed. More important, product quality is found to be significantly affected by temperatures in which higher product quality occurs at low temperatures. This experiment highlights that the temperature variations at the ambient shop-floor can have an effect on quality error, thereby emphasising the need to control the temperatures according to maintain the standard quality of machined products. The correlational analysis expands the knowledge on thermal expansion and illustrates its implications for the e-ProMan system.

(3) The production process is the main sources of energy consumption in manufacturing. Therefore, workload optimisation at this level can significantly contribute not only to the overall energy efficiency of the plant, but also the total cost of production. The simulation

experiment was performed to examine energy consumption of a machining production process by simulating different scenarios of workload. First, up-hill scenario workload is found to consume less amount of energy. In this scenario, workload starts at its minimum capacity then increases incrementally throughout the planned hours. The up-hill scenario is also empirically shown to reduce total production cost and CO_2 emission.

(4) The e-ProMan system models the predictive HVAC system which controls the shop-floor temperature to the thermal comfort range during Summer and Winter seasons. The simulation experiment provides evidence to support the energy-efficient performance of the e-ProMan system in which 15% of energy consumed by the HVAC system can be saved in the Summer and 10% of energy can be saved in the Winter. Because of the larger temperature variations in the Summer, the energy-efficient performance of the e-ProMan system is more pronounced in the Summer. This work emphasises the importance of predictive control system which considers weather forecast and shop-floor temperature in the real-time decision makings.

In conclusion, as highlighted throughout the dissertation, a systematic approach is essential in a simulation modelling development of an energy-efficient application in manufacturing. To successfully optimise energy consumption while maintaining high quality product, the energy-efficient management system should be implemented in order to continuously increase energy efficiency and achieve sustainability. The Energy-smart Production Management (e-ProMan) system is shown to be an applicable system that increases energy efficiency for different levels of manufacturing plants.

The contributions to knowledge in light of the research are summarised below;

- The multiple correlation analysis of ambient temperature, energy consumption and dimensional error quality of workpiece was investigated in sustainable precision machining
- The e-ProMan system was developed at different levels by integrating the different components that are found to be important within the energy-efficient management system namely thermal effects (i.e. weather forecast and real-time ambient temperature and temperature at machining), workload of production process, and correlational analysis of work flow, energy flow and data flow.

8.2 Recommendations for Future Work

Despite the benefits gained from the simulation system, this research has several limitations which can be further studied in the future investigations. With regard to methodological issues, the following areas are recommended for future work.

1) Despite the advantages of simulation, the results from the simulation experiments were based on ‘what-if’ scenarios. Real data obtained from actual experimentation (i.e. energy consumption in a production process) would enhance the reliability of the results and thus validate the energy-efficient simulation system. The e-ProMan system should further be implemented in the real manufacturing settings- potentially of different machines, products and in order to verify its performance.
2) The concept of big data manufacturing should be integrated into the e-ProMan system in order to provide remarkably useful information that enables manufacturers to better learn, understand and evaluate the current situations in the manufacturing plant. Such information is essential to productivity, and to modelling and improvement of an energy-efficient system including difference type of machines and operation processes.

References

Alauddin, M., El Baradie, M. A. and Hashmi, M. S. J. (1997) 'Prediction of tool life in end milling by response surface methodology', *Journal of Materials Processing Technology*, 71(3), pp. 456-465.

Altiok, T. and Melamed, B. (2007) *Simulation Modeling and Analysis with Arena*. Academic press.

Allwood, J. M. and Cullen, J. M. (2012) *Sustainable materials: With both eyes open*. Cambridge: UIT Cambridge.

Almaguer, J. A. (2012) *Fundamentals of Materials for Energy and Environmental Sustainability*. Cambridge University Press, the United States of America. (Chapter 38).

Altintas, Y. (1992) 'Prediction of cutting forces and tool breakage in milling from feed drive current measurements', *Journal of Engineering for Industry*, 114(4), pp. 386-392.

Anderson, T.W. (1984) *Multivariate statistical analysis*. Pearson Education International, New York, NY

Arexx Engineering (2013) *Wireless Usb Temperature Logging System*. Available: http://www.arexx.com/arexx.php?cmd=goto&cparam=p_templogger_bs500 (Accessed 19th April 2013).

Babu, C. A. and Ashok, S. (2008) 'Peak load management in electrolytic process industries', *IEEE Transactions on Power Systems*, 23, pp. 399-405.

Baird, D.C. (1962) *Experimentation: an introduction to measurement theory and experiment design*. 3rd edn. Englewood Cliffs, NJ: Prentice Hall.

Bal Seal Engineering, (2004) Coefficient of thermal expansion for various materials at different temperatures. Available at: http://www.balseal.com/sites/default/files/tr18_020707131421.pdf (Accessed 5 September 2016).

Banks, J. (1998) *Handbook of simulation: principles, methodology, advances, applications, and practice‖,* Wiley, New York, USA.

Banks, J., Carson, J. S., Nelson, B. L. and Nicol, D. M. (2010) *Discrete-event System Simulation*. 5th edn. Upper Saddle River, NJ: Pearson Education.

Behrendt, T., Zein, A. and Min, S. (2012) 'Development of an energy consumption monitoring procedure for machine tools', *CIRP Annals -Manufacturing Technology*, 61(1), pp. 43–46.

Benesty, J., Chen, J., Huang, Y. and Cohen, I. (2009) Pearson correlation coefficient. *In Noise reduction in speech processing* (pp. 1-4). Springer Berlin Heidelberg.

Bi, Z. M. and Wang, L. (2012) 'Optimization of machining processes from the perspective of energy consumption: A case study', *Journal of Manufacturing Systems*, 31, pp. 420-428.

Bishop, R. H (2007) *LabVIEW 8 Student Edition*. 4th edn. New York, NY: Pearson Prentice Hall.

Bisu, C. F., Zapciu, M., Cahuc, O., Gérard, A. and Anica, M., (2012) 'Envelope dynamic analysis: a new approach for milling process monitoring', *The International Journal of Advanced Manufacturing Technology*, 62(5-8), pp. 471-486.

Bitter, R., Mohiuddin, T. and Nawrocki, M. (2006) *LabVIEW: Advanced programming techniques*. Boca Raton, FL: CRC Press.

Black, J. T. and Kohser, R. A. (2008) *Materials and Processes in Manufacturing.* 10th edn. Chichester: John Wiley & Sons.

Blanchard, B. S. and Fabrycky, W. J. (2006) *Systems Engineering and Analysis*. 4th edn. New Jersey, NJ: Pearson Prentice Hall.

Bose, B. K. (2010) 'Global warming: Energy, environmental pollution, and the impact of power electronics', *Industrial Electronics Magazine, IEEE*, 4(1), pp. 6-17.

Bruzzone, A. A. G., Anghinolfi, D. , Paolucci, M. and Tonelli, F. (2012) 'Energy-aware scheduling for improving manufacturing process sustainability: A mathematical model for flexible flow shops', *CIRP Annals-Manufacturing Technology*, 61, pp. 459-462.

Bughin, J., Chui, M. and Manyika, J. (2010) 'Clouds, big data, and smart assets: Ten tech-enabled business trends to watch', *McKinsey Quarterly*, 56(1), pp.75-86.

Burroughs, W. (2003). *Weather Cycles*. 1st edn. Cambridge: Cambridge University Press.

Byrne, G. and Scholta, E. (1993). 'Environmentally clean machining processes—a strategic approach', *CIRP Annals-Manufacturing Technology*, 42(1), pp. 471-474.

Carbon Trust (2008a) *Guide to PAS 2050: How to Assess the Carbon Footprint of Goods and Services*. London: British Standards Institution.

Carbon Trust (2008b) *PAS 2050: 2008, Specification for the Assessment of the Life Cycle Greenhouse Gas Emissions of Goods and Services,* London: British Standards Institution.

Carbon Trust (2011) Heating, Ventilation and Air Conditioning (HVAC), London: British Standards Institution.

Carlsson, A., Hjelm, S., Holmgren, B., Malmsköld, L., Granström, M., Svenningstorp, J. and Wik, A. (eds) (2008) *Sustainable Manufacturing Systems Capable of Producing Innovative Environmentally Friendly and Safe Products*. 3rd edn. Swedish Automotive Manufacturing Group.

Cataldo, A., Scattolini, R. and Tolio, T. (2015) 'An energy consumption evaluation methodology for a manufacturing plant', *CIRP Journal of Manufacturing Science and Technology*, 11, pp. 53-61.

Çengel, Y. (1998). *Heat transfer*. 1st ed. Boston, Mass.: WBC McGraw-Hill.

Chai, K. H. and Yeo, C. (2012) 'Overcoming energy efficiency barriers through systems approach: A conceptual framework', *Energy Policy*, 46, pp. 460-472.

Chang, Y.C., Lin, J.K. and Chuang, M.H. (2005) 'Optimal chiller loading by genetic algorithm for reducing energy consumption'. *Energy and Buildings*, 37(2), pp.147-155.

Cheng, K. (ed.) (2008) *Machining dynamics: fundamentals, applications and practices*. London: Springer Science & Business Media.

Cheng, K. and Bateman, R. J. (2008) 'E-Manufacturing: characteristics, applications and potentials', *Progress in Natural Science*, 18, pp. 1323–1328.

Chinthamani, B., Mol, M.P.R., Kamini, K.P. and Sughashini, K.R., (2012). 'Fuzzy based control using LabVIEW for MISO temperature process'. *International Journal of Research in Engineering and Technology*. 1(2), pp.108-114.

Coakes, S.J. and Steed, L.G. (2001) *SPSS: analysis without anguish: version 10.0 for Windows*. John Wiley and Sons, Australia.

Cohen, J. (1988) *Statistical power analysis for the behavioral sciences Lawrence Earlbaum Associates*. Hillsdale, NJ.

Componation, P. J., Gholston, S. E., Hyatt, L. A. and Simmons, B. B. (2003) 'Benefits of modeling and simulation in implementing a shared component build strategy', *Systems engineering*, 6(2), pp. 63-75.

Cook, P. J. (2012) 'Clean energy, climate and carbon', *Carbon Management*, 3(3), pp. 259-263.

Costa, A., Keane, M. M., Torrens, J. I. and Corry, E. (2013) ‘Building operation and energy performance: Monitoring, analysis and optimization toolkit’, *Applied Energy*, 101, pp. 310-316.

Dababneh, F., Atanasov, M., Sun, Z. and Li, L. (2015) ‘Simulation-based electricity demand response for combined manufacturing and HVAC system towards sustainability’, *ASME 2015 International Manufacturing Science and Engineering Conference Volume 2*, North Carolina, USA., June 8–12, 2015, pp. 1-7.

Dahmus, J. and Gutowski, T. (2004) ‘An Environmental Analysis of Machining’, *Proceedings of the 2004 ASME IMECE*, November 13-19, 2004, Anaheim, CA.

da Silva, M. B. and Wallbank, J. (1999) ‘Cutting temperature: prediction and measurement methods—a review’, *Journal of materials processing technology*, 88(1), pp. 195-202.

Draper, N.R. and Smith, H. (2014) *Applied regression analysis*. John Wiley & Sons.

Davis, J. R. (ed.) (1995) *ASM specialty handbook: tool materials*. Materials Park, OH: ASM international.

Devoldere, T., Dewulf, W., Deprez, W., Willems, B., Duflou, J. R. (2007) ‘Improvement potential for energy consumption in discrete part production machines’, In: *Proceedings of the 14th CIRP Conference on Life Cycle Engineering*, Tokyo, Japan

Diaz, N., Helu, M., Jarvis, A., Tönissen, S., Dornfeld, D. and Schlosser, R., (2009) ‘Strategies for minimum energy operation for precision machining’, *Laboratory for Manufacturing and Sustainability*. Available at: http://escholarship.org/uc/item/794866g5# (Accessed 1 September 2016).

Diaz, N., Helu, M., Jayanathan, S., Chen, Y., Horvath, A. and Dornfeld, D. (2010) ‘Environmental analysis of milling machine tool use in various manufacturing environments’, *IEEE International Symposium on Sustainable Systems and Technology*, pp. 1-6.

Dietmair, A. and Verl, A. (2009) ‘A generic energy consumption model for decision making and energy efficiency optimisation in manufacturing’, *International Journal of Sustainable Engineering,* 2(2), pp. 123-133.

Dinçer, I. and Zamfirescu, C. (2011) *Sustainable Energy Systems and Applications.* New York, NY: Springer.

Dörr, M., Wahren, S. and Bauernhansl, T. (2013) ‘Methodology for energy efficiency on process level’, *Procedia CIRP,* 7, pp. 652-657.

Dounis, A. I., Bruant, M., Santamouris, M., Guarracino, G. and Michel, P. (1996) ‘Comparison of conventional and fuzzy control of indoor air quality in buildings’, *Journal of Intelligent and Fuzzy Systems,* 4(2), pp. 131-140.

Dounis, A. I. and Caraiscos, C. (2009) ‘Advanced control systems engineering for energy and comfort management in building environment- A review’, *Renewable and Sustainable Energy Reviews,* 13, pp. 1246-1261.

Drake, R., Yildirim, M.B., Twomey, J.M., Whitman, L.E., Ahmad, J.S. and Lodhia, P. (2006) Data collection framework on energy consumption in manufacturing.

Draper, N.R. and Smith, H. (2014) *Applied regression analysis.* John Wiley & Sons.

Duflou, J. R., Sutherland, J. W., Dornfeld, D., Hermann, C., Jeswiet, J., Kara, S., Hauschild, M., Kellens, K. (2012) ‘Towards energy and resource efficient manufacturing: A processes and systems approach’, *CIRP Annal—Manufacturing Technology*, 61, pp. 587-609.

ECN (2013) *Resource efficiency: What does it mean and why is it relevant?* Available at: https://www.ecn.nl/docs/library/report/2013/o13004.pdf (Accessed 16th April 2016).

El-Hofy, H. A. G. (2013) *Fundamentals of machining processes: conventional and nonconventional processes*. Boca Raton, FL: CRC press.

European Commission (2016) *What can big data do for you?*. Available at: https://ec.europa.eu/digital-single-market/en/what-big-data-can-do-you (Accessed 16th April 2016).

Fang, K., Uhan, N., Zhao, F., Sutherland, J. W. (2011) 'A new approach to scheduling in manufacturing for power consumption and carbon footprint reduction', *Journal of Manufacturing Systems*, 30, pp. 234-240.

Field, A.P. (2013) *Discovering statistics using IBM SPSS statistics: and sex and drugs and rock'n'roll*, 4^{th} edn. London: SAGE Publications.

Fluke (2013) *Fluke 1735 three-phase power logger*. Available at: http://www.fluke.com /fluke/uken/power-quality-tools/logging-power-meters/fluke-1735.htm?pid=56028 (Accessed 10 April 2015).

Fysikopoulos, A., Alexios, P., Georgios, P., Panagiotis, S. and George. C. (2013) 'Energy efficiency of manufacturing processes: a critical review', *Procedia CIRP*, 7, pp. 628-633.

Fysikopoulos, A., Anagnostakis, D., Salonitis, K. and Chryssolouris, G. (2012) 'An empirical study of the energy consumption in automotive assembly', *Procedia CIRP*, 3, pp. 477-482.

Gahm, C., Denz, F., Dirr, M. and Tuma, A. (2016) 'Energy-efficient scheduling in manufacturing companies: A review and research framework', *European Journal of Operational Research*, 248, pp. 744-757.

Garetti, M. and Taisch, M., (2012) 'Sustainable manufacturing: trends and research challenges', *Production Planning & Control*, 23(2-3), pp.83-104.

Ghadi, Y. Y., Rasul, M. G. and Khan, M. M. K. (2016) 'Design and development of advanced fuzzy logic controllers in smart buildings for institutional buildings in subtropical Queensland', *Renewable and Sustainable Energy Reviews*, 54, pp. 738-744.

Ghani, J. A., Choudhury, I. A. and Hassan, H. H. (2004) 'Application of Taguchi method in the optimization of end milling parameters', *Journal of Materials Processing Technology*, 145(1), pp.84-92.

Giret, A., Trentesaux, D. and Prabhu, V. (2015) 'Sustainability in manufacturing operations scheduling: A state of the art review', *Journal of Manufacturing Systems,* 37, pp. 126-140.

GOV (2016a) *Greenhouse gas reporting –conversion factors.* Available at: https://www.gov.uk/government/publications/greenhouse-gas-reporting-conversion-factors-2016 (Accessed 5th September 2016).

GOV (2016b) *Quarterly energy prices.* Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/555982/QEP_Q216.pdf (Accessed 5th September 2016).

GOV (2016c) *Sponsorship: Codes of practice for skilled workers.* Available at: https://www.gov.uk/government/publications/sponsorship-codes-of-practice-for-skilled-workers (Accessed 10th September 2016).

Green, G., Kennedy, P. and McGown, A. (2002) 'Management of multi-method engineering design research: a case study'. *Journal of Engineering and Technology Management*, 19(2), pp.131-140.

Grieco, A., Semeraro, Q. and Tolio, T. (2001) 'A review of different approaches to the FMS loading problem'. *International Journal of Flexible Manufacturing Systems*, 13(4), pp.361-384.

Groover, M. and Zimmers, E.W.J.R. (1983) *CAD/CAM: computer-aided design and manufacturing*. Pearson Education.

Grzesik, W. (2008) *Advanced machining processes of metallic materials: theory, modelling and applications*. Oxford: Elsevier.

Guneri, A. F. and Seker, S. (2008) ‘The use of Arena simulation programming for decision making in a workshop study’, *Computer Applications in Engineering Education*, 16(1), pp. 1-11.

Gutowski, T., Dahmus, J. and Thiriez, A. (2006) ‘Electrical energy requirements for manufacturing processes’, *13th CIRP International Conference on Life Cycle Engineering,* 31, pp. 623-638.

Hauke, J. and Kossowski, T. (2011) ‘Comparison of values of Pearson’s and Spearman’s correlation coefficient on the same sets of data’. *Quaestiones Geographicae,* 2(30), pp. 87-93.

Health and Safety Executive (2013) *Workplace health, safety and welfare: Workplace (Health, Safety and Welfare) Regulations 1992*. Available at: http://www.hse.gov.uk/pUbns/priced/l24.pdf (Accessed 16th April 2016).

Helal, S., Swigger, K. and Vetter R. (2013). Computer: big data. IEEE Computer Soc, 46, pp.23-53.

Herring, H. (2006) ‘Energy efficiency- A critical review’, *Energy,* 31(1), pp. 10-20.

Herrmann, C., and Thiede, S. (2009) ‘Process chain simulation to foster energy efficiency in manufacturing’, *CIRP- Journal of Manufacturing Science and Technology,* 1, pp. 221-229.

Hilbe, J.M. (2003) ‘A review of current SPSS products: SPSS 12, SigmaPlot 8.02, SigmaStat 3.0, Part 1’. The American Statistician, 57(4), pp.310-315.

Ho, C.Y. and Taylor, R.E. (1998). *Thermal expansion of solids*: *Vol. 4*. Hertfordshire: ASM international.

Hoeck, M. (2008) ‘A workload control procedure for an FMC integrated in a job shop’, *International Journal of Computer Integrated Manufacturing*, 21(6), pp. 666-675.

Honczarenko, J. and Berliński, A. (2012) ‘Energy consumption modeling of processes in the automated manufacturing systems’, *Management and Production Engineering Review*, 3(1), pp. 92-96.

Hordeski, M. F. (2004) *Dictionary of Energy Efficiency Technologies*. 1st edn. Vancouver: Fairmont Press.

Hsieh, W. H., Lu, M. C. and Chiou, S. J., (2012) ‘Application of backpropagation neural network for spindle vibration-based tool wear monitoring in micro-milling’, *The International Journal of Advanced Manufacturing Technology*, 61(1-4), pp. 53-61.

Ingemansson, A. and Bolmsjö, G. S. (2004) ‘Improved efficiency with production disturbance reduction in manufacturing systems based on discrete-event simulation’, *Journal of Manufacturing Technology Management*, 15(3), pp. 267-279.

International Energy Agency Statistics (2012a) *CO2 Emissions from Fuel Combustion Highlights*. 2012 edn. IEA, France.

International Energy Agency Statistics (2012b) *Key World Energy Statistics*. 2012 edn. IEA, France.

Isizoh, A.N., Okide, S.O., Anazia, A.E.A.E. and Ogu, C.D., 2012. ‘Temperature control system using fuzzy logic technique’. *International Journal of Advanced Research in Artificial Intelligence*, 1(1), pp.27-31.

ISO 8688-2 (1989) Tool life testing in milling – Part 2: End milling.

ISO (2016) *ISO 50001 - Energy management – ISO*. Available: http://www.iso.org/iso/ home/ standards/management-standards/iso50001.htm (Accessed 19th April 2016).

Javied, T., Rackow, T. and Franke, J. (2015) ‘Implementing energy management system to increase energy efficiency in manufacturing companies’, *Procedia CIRP*, 26, pp.156-161.

Jayal, A. D., Badurdeen, F., Dillon Jr., O.W. and Jawahir, I. S. (2010) 'Sustainable manufacturing: Modeling and optimization challenges at the product, process and system levels', *CIRP Journal of Manufacturing Science and Technology*, 2(3), pp. 144-152.

Jeswiet, J. and Kara, S. (2008) 'Carbon emissions and CES™ in manufacturing', *CIRP Annals-Manufacturing Technology*, 57(1), pp. 17-20.

Jiao, F. and Cheng, K. (2013) 'An experimental investigation on micro-milling of polymethyl methacrylate components with nanometric surface roughness', *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, DOI: 10.1177/0954405413507251

Johansson, B. and Grunberg, T. (2001) 'An enhanced methodology for reducing time consumption in discrete event simulation project', *Proceedings of the 13th European Simulation*, 13(1), pp. 61-64.

Jovane, F., Yoshikawa, H., Alting, L., Boër, C., Westkamper, E., Williams, D., Tseng, M., Seliger, G. and Paci, A. (2008) 'The incoming global technological and industrial revolution towards competitive sustainable manufacturing', *CIRP Annals-Manufacturing Technology*, 57(2), pp. 641-659.

Juneja, B. L. (2003) *Fundamentals of metal cutting and machine tools*. New Delhi: New Age International.

Karnouskos, S., Columbo, A. W., Lastra, J. L. M., Popescu, C. (2009) 'Towards the energy efficient future energy', *7th IEEE International Conference on Industrial Informatics INDIN*, pp. 367-371.

Katchasuwanmanee, K., Bateman, R., and Cheng, K., 2015, 'Development of the Energy-Smart Production Management System (e-ProMan): A Big Data Driven Approach, Analysis and Optimization', *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, pp. 1-7. DOI: 10.1177/0954405415586711.

Kayan, R. K. and Akturk, M. S. (2005) ‘A new bounding mechanism for the CNC machine scheduling problems with controllable processing times’, *European Journal of Operational Research*, 167(3), pp. 624-643.

Kelton, W. D., Sadowski, R. and Zupick, N. B. (2015) Simulation with Arena. 6th edn. New York, NY: McGraw Hill.

Kianinejad, K., Uhlmann, E. and Peukert, B. (2015) ‘Investigation into energy efficiency of outdated cutting machine tools and identification of improvement potentials to promote sustainability’, *Procedia CIRP 26*, pp. 533-538.

Kim, Y.D. and Yano, C.A. (1997) A new branch and bound algorithm for loading problems in flexible manufacturing systems. *International Journal of Flexible Manufacturing Systems*, 6(4), pp.361-381.

Kirkby, J., O’Keefe, P. and Timberlake, L. (1995) ‘Sustainable development: An introduction’, in Kirby, J. et al. (eds.) *The earthscan reader in sustainable development*. London: Earthscan, pp. 1-14.

Kiyak, E. and Gol, G. (2016) ‘A comparison of fuzzy logic and PID controller for a single-axis solar tracking system’, *Renewables: Wind, Water, and Solar,* 3(7), pp. 1-14.

Komashie, A. & Mousavi, A. 2005, ‘Modeling emergency departments using discrete event simulation techniques’, *Proceedings - Winter Simulation Conference*, pp. 2681-2685.

Köne, A.Ç. and Büke, T. (2010) ‘Forecasting of CO_2 emissions from fuel combustion using trend analysis’, *Renewable and Sustainable Energy Reviews*, 14(9), pp. 2906-2915.

Kong, D., Choi, S., Yasui, Y., Pavanaskar, S., Dornfeld, D., Wright, P. (2011) ‘Software-based tool path evaluation for environmental sustainability’, *Journal of Manufacturing Systems*, 30(4), pp. 241-247.

Kumar, P., Singh, N. and Tiwari, N.K. (1990) Multicriteria analysis of the loading problem in flexible manufacturing system using Max-Min approach. *International Journal of Production Research*, 2(2), pp.13-23.

Küster, T., Lützenberger, M., Freund, D., Albayrak, S. (2012) 'Distributed optimization of energy costs in manufacturing using multi-agent system technology', *Proceedings of the 2nd international conference on smart grids green communications and IT energy-aware technologies*, Maho Beach, St. Maarten, pp. 53-59.

Larsen, N. E. and Alting, L. (1992) 'Dynamic planning enriches concurrent process and production planning', *International Journal of Production Research*, 30(8), pp. 1861–1876.

Leach, R. (2014) *Fundamental Principles of Engineering Nanometrology*. Elsevier, Philadelphia, PA.

Lee, J. H. and Kim, C. O. (2008) 'Multi-agent systems applications in manufacturing systems and supply chain management: A review paper', *International Journal of Production Research*, 46, pp. 233-265.

Levesque, R. (2005) *SPSS programming and data management: A guide for SPSS and SAS users*. Spss.

Liang, M. and Dutta, S.P. (1992). 'Combined part selection, load sharing and machine loading problem in hybrid manufacturing systems'. *The International Journal of Production Research*, 30(10), pp.2335-2349.

Lovins, A. B. (2004) 'Energy efficiency, taxonomic overview', *Encyclopaedia of Energy*, 2(283-402), pp. 6.

Lozano, R. (2008) 'Envisioning sustainability three-dimensionally', *Journal of Cleaner Production*, 16(17), pp. 1838-1846.

Lück, K. (2012) ‘Energy Efficient Building Services for Tempering Performance-oriented Interior Spaces – A Literature Review’, *Journal of Cleaner Production*, 22(1), pp. 1-10.

Malekian, M., Park, S.S. and Jun, M.B. (2009) ‘Tool wear monitoring of micro-milling operations’, *Journal of Materials Processing Technology*, 209(10), pp. 4903-4914.

Mařík, V. and McFarlane, D. (2005) ‘Industrial adoption of agent-based technologies’, *IEEE Intelligent Systems*, 1, pp. 27-35.

Marinov, V. (2006) Manufacturing technology. *Cutting Temperature*, p. *74*.

Mati, Y. and Xie, X. (2003) ‘A polynomial algorithm for a two-job shop scheduling problem with routing flexibility’, *IEEE International Conference on Robotics and Automation*, 1, pp 157-162.

May, G., Taisch, M. and Kelly, D. (2013) ‘Enhanced energy management in manufacturing through systems integration’, *Industrial Electronics Society, IECON 2013 - 39th Annual Conference of the IEEE*, 10-13 Nov. 2013, pp. 7525-7530.

Menezes, A. C., Crippes, A., Buswell, R. A., Wright, J. and Bouchlaghem, D. (2014) ‘Estimating the energy consumption and power demand of small power equipment in office buildings’, *Energy and Buildings*, 75, pp. 199-209.

Met Office (2016) Uxbridge Weather Forecast [Online] Available at: http://www.metoffice.gov.uk/public/weather/forecast/gcptm05c7 [Accessed 27th May 2016]

Montgomery, D.C. (2013) *Design and analysis of experiments*. John Wiley & Sons.

Mori, M., Fujishima, M., Inamasu, Y., Oda, Y. (2011) ‘A study on energy efficiency improvement for machine tools’, *CIRP Annals-Manufacturing Technology*, 60, pp. 145-148.

Morris, M. (2010) *Design of experiments: An introduction based on linear models*. CRC Press.

Morris, A. S. and Langari, R. (2013) *Measuring and Instrumentation: Theory and application*. Cambridge: Academic Press.

Mousavi, M. E., Irish, J. L., Frey, A. E., Olivera, F. and Edge, B. L. (2011). 'Global warming and hurricanes: the potential impact of hurricane intensification and sea level rise on coastal flooding', *Climatic Change*, 104(3-4), pp.575-597.

MSC Industrial Supply Co. (2016) *SGS carbide tool: 40341*. Available at: https://www.mscdirect.co.uk/JHSGS-40341D/SEARCH:KEYWORD/product.html (Accessed 10th September 2016).

Mukhopadhyay, S.K. and Tiwari, M.K. (1995) 'Solving machine loading problems of FMS using conjoint measurement'. *In Proceedings of 13th International Conference on Production Research*, (pp. 74-76).

Müller, E. and Löffler, T. (2009) **'**Improving energy efficiency in manufacturing plants – Case studies and guidelines', *16th CIRP International Conference on Life Cycle Engineering (LCE 2009)*, Cairo, Egypt, 03–06 May (2009).

Nagarjuna, N., Mahesh, O. and Rajagopal, K. (2006) 'A heuristic based on multi-stage programming approach for machine-loading problem in a flexible manufacturing system'. *Journal of Robotics and Computer-Integrated Manufacturing*, 22(4), pp.342-352.

Natarajan, U., Periyanan, P. R. and Yang, S. H. (2011) 'Multiple-response optimization for micro-endmilling process using response surface methodology', *The International Journal of Advanced Manufacturing Technology*, 56(1-4), pp. 177-185.

National Council for Advanced Manufacturing (2009) *Sustainable manufacturing*. Available at: http://nacfam02.dev.web.sba.com/PolicyInitiatives/SustainableManufacturing/tabid/64/Default.aspx (Accessed 26th April 2013).

National Instruments (2016) *NI LabVIEW - Improving the Productivity of Engineers and Scientists - National Instruments*. Available at: http://www.ni.com/labview/ (Accessed 22 July 2016).

Nejad, H. T. N., Sugimura, N. and Iwamura, K. (2011) 'Agent-based dynamic integrated process planning and scheduling in flexible manufacturing systems', *International Journal of Production Research*, 49(5), pp. 1373–1389.

Neugebauer, R., Wabner, M., Rentzsch, H. and Ihlenfeldt, S. (2011) 'Structure principles of energy efficient machine tools', *CIRP Journal of Manufacturing Science and Technology,* 4, pp. 136-147.

Nghiem, T., Behl, M., Pappas, G. J., Mangharam, R. (2011) 'Green scheduling: Scheduling of control systems for peak power reduction', *Green computing conference and workshops (IGCC) 2011 International*, pp. 1-8.

Noureddine, A., Rouvoy, R., Seinturier, L. (2013) 'A review of energy measurement approaches', *ACM SIGOPS Operating Systems Review*, 47, pp. 42-49.

Oda, J., Akimoto, K., Tomoda, T., Nagashima, M., Wada, K. and Sano, F. (2012) 'International comparison of energy efficiency in power, steel, and cement industries', *Energy Policy,* 44, pp. 118-129.

Opris (2016). Press Pictures Gallery Sample [Online]. Available: http://www.optris.com/press-pictures-gallery-applications. [Accessed 12th March 2016]

Onut, S., Gunay, F.G., Demirel, T. & Erdem, H.I. 1994, 'Using simulation for shop floor control', *Yugoslav Journal of Operations Research,* 4(2), pp. 195-203.

Pacheco, R., Ordóñez, R. P. and Martínez, G. (2012) 'Energy efficient design of building: A review', *Renewable and Sustainable Energy Reviews,* 16, pp. 3559-3573.

Pach, C., Berger, T., Sallez, Y., Bonte, T., Adam, E. and Trentesaux, D. (2014) 'Reactive and energy-aware scheduling of flexible manufacturing systems using potential fields', *Computers in Industry*, 65, pp. 434-448.

Park, C. W., Kwon, K. S., Kim, W. B., Min, B. K., Park, S. J., Sung, I. H., Yoon, Y. S., Lee, K. S., Lee, J. H. and Seok, J. (2009) 'Energy consumption reduction technology in manufacturing—A selective review of policies, standards, and research', *International Journal of Precision Engineering and Manufacturing*,10(5), pp.151-173.

Pérez-Lombard, L., Ortiz, J. and Pout, C. (2008) 'A review on buildings energy consumption information', *Energy and Building,* 40, pp. 394-398.

Phanden, R. K., Jain, A. and Verma, R. (2013) 'An approach for integration of process planning and scheduling', *International Journal of Computer Integrated Manufacturing*, 26(4), pp. 284-302.

Polunin, N. (1985) 'World Commission on Environment & Development', *Environmental Conservation*, 12(1), pp. 78-79.

Reich, Y. and Subrahmanian (2013). 'Philosophy of design, science of design, engineering of design: What is your choice?', *Research in Engineering Design*, 24, pp. 321-323.

Reis, L. L., Silva Júnior, W. M. D. and Machado, Á. R. (2007) 'Effect of cutting speed and cutting fluid on the BUE geometry of a SAE 12L14 free machining steel', *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, 29(2), pp. 196-201.

Rentsch, R., Heinzel, C., Brinksmeier, E. (2015) 'Artificial intelligence for an energy and resource efficient manufacturing chain design and operation', *Procedia CIRP*, 33, pp. 139-144.

Robinson, S. (1994) *Successful Simulation: Practical approach to simulation projects*. London: McGraw-Hill.

Robinson, S. (2014) *Simulation: The Practice of Model Development and Use*. 2nd edn. Basingstoke: Palgrave Macmillan.

Rodwell, M.J. and Palmer, T.N. (2007). Using numerical weather prediction to assess climate models. *Quarterly Journal of the Royal Meteorological Society*, *133*(622), pp.129-146.

Rossetti, M. D. (2010) *Simulation Modelling and Arena*. 1st edn. ISTE Ltd and John Wiley & Sons.

Salonitis, K. (2015) 'Energy efficiency assessment of grinding strategy', *International Journal of Energy Sector Management,* 9(1), pp. 20-37.

Salonitis, K. and Ball, P. (2013) 'Energy efficient manufacturing from machine tools to manufacturing systems', *Procedia CIRP,* 7, pp. 634-639.

Sawik, T. (1998) A lexicographic approach to bi-objective loading of a flexible assembly system. *European Journal of Operational Research*, 107(3), pp.656-668.

Schlosser, R., Klocke, F., Döbbeler, B., Riemer, B., Hameyer, K., Herold, T., Zimmermann, W., Nuding, O., Schindler, B.A. and Niemczyk, M.n. (2011). 'Assessment of energy and resource consumption of processes and process chains within the automotive sector', *Glocalized Solutions for Sustainability in Manufacturing*, pp. 45-50.

Schobert, H. H. (2002) *Energy and Society: An introduction*. Boca Raton, FL: CRC Press.

Seber, G.A. and Lee, A.J. (2012) *Linear regression analysis (Vol. 936).* John Wiley & Sons.

Sekar, K.V (ed.) (2014) *Manufacturing engineering and technology*. Englewood, NJ: Prentice Hall.

Seow, Y. and Rahimifard, S. (2011) 'A framework for modelling energy consumption within manufacturing systems' *CIRP Journal of Manufacturing Science and Technology*, 4(3), pp.258-264.

SGS Tool (2016) *Speed & feed recommendations*. Available: http://www.sgstool.com/PDF-speedfeeds/SGS-Speeds-Feeds-GP.pdf (Accessed 19th July 2016).

Shanker, K. and Srinivasulu, A. (1989) Some solution methodologies for loading problems in a flexible manufacturing system. *International Journal of Production Research*, 27(6), pp.1019-1034.

Shaw, M.C. (2005) *Metal cutting principles: Vol. 2*. Oxford: Oxford university press.

Shen, W., Hao, Q., Yoon, H. J., Norrie, D. H. (2006) ‘Applications of agent-based systems in intelligent manufacturing: An updated review’, *Advanced Engineering Informatics*, 20, pp. 415-431.

Shrouf, F., Ordieres-Meré, J., García-Sánchez, A. and Ortega-Mier, M. (2014) Optimizing the production scheduling of a single machine to minimize total energy consumption costs. *Journal of Cleaner Production*, 67, pp.197-207.

Singh, R., Singh, R. and Khan, B.K. (2015) A Critical review of machine loading problem in flexible manufacturing system. *World Journal of Engineering and Technology*, 3(04), pp. 271-290.

Solomon, S., Plattner, G. K., Knutti, R. and Friedlingstein, P. (2009) ‘Irreversible climate change due to carbon dioxide emissions’, *Proceedings of the national academy of sciences*, pp.pnas-0812721106.

Son, Y.J. & Wysk, R.A. 2001, ‘Automatic simulation model generation for simulation-based, real-time shop floor control’, *Computers in Industry,* 40(3), pp. 291-308.

Soyguder, S., Karakose, M. and Alli, H. (2009) ‘Design and simulation of self-tuning PID-type fuzzy adaptive control for an expert HVAC system’, *Expert Systems with Applications*, 36(3), pp.4566-4573.

Stecke, K.E. (1983) Formulation and solution of nonlinear integer production planning problems for flexible manufacturing systems. *Management Science*, 29(3), pp.273-288.

Sumicarbide (2016) *Technical guidance tool failure & tool life*. Available: http://www.sumicarbide.com/pdf/turn/tb_toolfailure.pdf (Accessed 19th July 2016).

Sung, S. W., Lee, J. and Lee, I. (2009) *Process Identification and PID Control.* Hoboken, NJ: John Wiley & Sons.

Tang, K. S., Man, K. F., Chen, G. and Kwon, S. (2001) 'An optimal fuzzy PID controller', *IEEE Transactions on Industrial Electronics,* 48(4), pp. 757-765.

Tansel, I. *et al.* (1998) 'Micro-end-milling—III. Wear estimation and tool breakage detection using acoustic emission signals', *International Journal of Machine Tools and Manufacture,* 38(12), pp. 1449-1466.

Tavakkoli-Moghaddam, R. and Daneshmand-Mehr, M. (2005) 'A computer simulation model for job shop scheduling problems minimizing makespan', *Computers & Industrial Engineering,* 48(4), pp. 811-823.

Tridech, S. and Cheng, K. (2008) 'Low carbon manufacturing: characterisation, theoretical models and implementation', *Proceeding of the 6th International Conference on Manufacturing Research (ICMR08)*. 9-11 September, pp.403-412.

Thiede, S. (2012) *Energy efficiency in manufacturing systems*. Springer, Heidelberg.

Thierry, C., Thomas, A. and Bel, G. (2008) *Simulation for Supply Chain Management*. 1st edn. Chichester: John Wiley & Sons.

Trentesaux, D. and Prabhu, V. (2014) 'Sustainability in manufacturing operations scheduling: stakes, approaches and trends', in Grabot, B., Vallespir, B., Gomes, S., Bouras, A., Kiritsis, D., (eds.) Advances in Production Management Systems: Innovative and Knowledge-Based Production Management in a Global-Local World. Springer, Heidelberg, pp. 106–113.

Turner, W. C. and Doty, S. (2007) *Energy Management Handbook*. Vancouver: The Fairmont Press.

Twomey, J., Yildirim, M.B., Whitman, L., Liao, H. and Ahmad, J. (2008) *Energy profiles of manufacturing equipment for reducing consumption in a production setting*. Wichita State University. Wichita, KS.

Ulpiani, G., Borgognoni, M., Romagnoli, A. and Di Perna, C. (2016) 'Comparing the performance of on/off, PID and fuzzy controllers applied to the heating system of an energy-efficient building', *Energy and Building*, 116, pp. 1-17.

U.S. Environmental Protection Agency (2008). Municipal Solid Waste (MSW) –Reduce, reuse, and recycle. Available: http://www.epa.gov/msw/reduce.htm (Accessed 20th April 2013).

Vallada, E., Ruiz, R., Minella, G. (2008) 'Minimising total tardiness in the m-machine flowshop problem: A review and evaluation of heuristics and metaheuristics', *Computers & Operations Research*, 35, pp. 1350-1373.

Wamba, S. F., Akter, S., Edwards, A., Chopin, G. and Gnanzou, D. (2015) 'How 'big data' can make big impact: Findings from a systematic review a longitudinal case study', *International Journal Production Economics*. 165, pp. 234-246.

Wang, L. and Alexander, C. A. (2015) 'Big data in design and manufacturing engineering', American Journal of Engineering and Applied Sciences. 8(2), pp. 223-232.

Wang, S. and Ma, Z. (2008) 'Supervisory and optimal control of building HVAC systems: A review', *HVAC&R Research*, 14(1), pp. 3-32.

Waurzyniak, P. (2015) 'Why manufacturing needs real-time data collection', *Manufacturing Engineering*. 155(4), pp. 53-61.

WCED (1987) *Our Common Future*. Oxford: Oxford University Press.

Youn, J. W., Yang, M. Y. and Park, H. Y. (1994) 'Detection of cutting tool fracture by dual signal measurements' *International Journal of Machine Tools and Manufacture*, 34(4), pp. 507-525.

Zhang, C., Gu, P. and Jiang, P. (2015) 'Low-carbon scheduling and estimating for a flexible job shop based on carbon footprint and carbon efficiency of multi-job processing', *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, 229(2), pp. 328-342.

Zhang, G., Shao, X., Li, P. and Gao, L. (2009) 'An effective hybrid particle swarm optimization algorithm for multi-objective flexible job-shop scheduling problem', *Computers & Industrial Engineering*, 56(4), pp. 1309-1318.

Zhang, Y., Liu, S., Si, S., and Yang, H. (2015) 'Production system performance prediction model based on manufacturing big data', *Proceedings of 2015 IEEE 12th International Conference on Networking, Sensing and Control Howard Civil Service* , International House, Taipei, Taiwan, April 9-11, 2015 pp. 277-280.

Zhang, Y. and Hanby, V. (2007). 'Short-term prediction of weather parameters using online weather forecasts', *Proceedings: Building Simulation*, pp. 1411-1416.

Zhao, H. and Magoulés, F. (2012) 'A review of the prediction of building energy consumption', *Renewable and Sustainable Energy Reviews,* 16, pp. 3586-3592.

Zhou, J. H., Pang, C. K., Zhong, Z. W. and Lewis, F. L. (2011) 'Tool wear monitoring using acoustic emissions by dominant-feature identification', *IEEE Transactions on instrumentation and measurement*, 60(2), pp. 547-559.

Zhu, K., Mei, T. and Ye, D. (2015) 'Online condition monitoring in micromilling: a force waveform shape analysis approach', *IEEE Transactions on Industrial Electronics*, 62(6), pp. 3806-3813.

APPENDICES

Appendix A: List of Publications Resulting from the Research

Journals

- Katchasuwanmanee, K., Bateman, R., and Cheng, K., 2015, "Development of the Energy-Smart Production Management System (e-ProMan): A Big Data Driven Approach, Analysis and Optimization", *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, 230(5) pp. 972-978. DOI: 10.1177/0954405415586711. SAGE.
- Katchasuwanmanee, K., Cheng, K, and Bateman, R., 2016, "Investigation on Simulation based Energy-Resource Efficient Manufacturing Integrated with In-Process Virtual Management", *Chinese Journal of Mechanical Engineering – Special Issue on Future Digital Design and Manufacturing Technologies for Manufacturing Innovation: Embracing Industry 4.0 and Beyond*, 29(6) pp.1083-1089. DOI: 10.3901/CJME.2016.0714.080. Springer.
- Katchasuwanmanee, K., Bateman, R., and Cheng, K., 2016, "An Integrated Approach to Energy Efficiency in Automotive Manufacturing Systems: Quantitative Analysis and Optimisation", *Production and Manufacturing Research.* Taylor & Francis (Accepted).
- Katchasuwanmanee, K., Bateman, R., and Cheng, K., 2016, "An Investigation into Correlation Analysis of Machining Quality, Energy Consumption and Temperature Variations for Sustainable Precision Machining", Journal of Manufacturing Science and Engineering – Special Issue on: Sustainable Manufacturing. ASME. (Under review).

Conferences

- The 37th International Matador Conference, Manufacturing Automation and Systems Technology Applications Design Organisation and Management Research on 25th – 27th July 2012. Title: Complexity in Manufacturing Supply Chain Applied to Automotive Industry: Modelling, Analysis and a Case Study, Manchester, UK.
- The 13th International Conference on Manufacturing Research on 8th – 10th July 2015, Title: An Integrated Approach to Energy Efficiency in Automotive Manufacturing Systems: Quantitative Analysis and Optimisation, Bath, UK.
- International conference of Digital Design and Manufacturing Technologies on 12th – 13th April 2016. Title: Investigation on Simulation on Simulation based Energy-Resource Efficient Manufacturing Integrated with In-Process Virtual Management, Newcastle, UK.

Appendix B: List of ISO Standards Associated with EuroEnergest Project

Table B1 List of standards associated with EuroEnergest and the automotive industry

Standards	Description	Current status
ISO 9001:2008	Quality Management System	Current
ISO 16001:2008	Hazard Detection Systems (HDS) and Visual Aids (VA) Test Method and Performance	Current
ISO 14001:2004	Environmental Management Systems	Current
ISO 14020:2001	Environmental labels and declarations – General principles	Current
ISO 14021:2001+A1:2011	Environmental Labels and Declarations	Current
ISO 14025:2010	Environmental labels and declarations – Type III environmental declarations – Principles and procedures	Current
ISO 14044:2006	Environmental Managements – Life cycle assessment – Requirements and Guidelines	Current
ISO/TR 14062:2002	Environmental Management	Current
DIN EN 16001	Energy Management Systems in Practice	Replaced with ISO 50001
ISO 50001:2011	Energy Management Systems	Current
ISO 15011-2:2009	Health and Safety in Welding and Allied Processes	Current
ISO 10263-4:2009	HVAC test method and performance	Current
ISO/EN 15316:2012	Heating systems in buildings	Current
ISO/EN 14825:2012	Air Conditioners	Current

Appendix C: Coefficients of Thermal Expansion for Various Materials

Table C1 Coefficients of thermal expansion for steel (Bal Seal Engineering, 2004)

Steel (α)	
	(0° to 93°C)
303 SS	(17.3×10^{-6})
304 SS	(15.8×10^{-6})
347 SS	(16.7×10^{-6})
410 SS	(9.9×10^{-6})
416 SS	(9.9×10^{-6})
15-5 PH SS	(10.8×10^{-6})
17-4 PH SS	(10.8×10^{-6})
17-7 PH SS	(15.3×10^{-6})
A286 SS	(16.6×10^{-6})
4140 High Alloy Steel	(22.9×10^{-6})
4340 High Alloy Steel	(22.3×10^{-6})
H13 Tool Steel	(20.7×10^{-6})
H11 Tool Steel	(20.7×10^{-6})
Tungsten Carbide K801	(4.9×10^{-6})
Vasco T-250	(10.1×10^{-6})

Table C2 Coefficients of thermal expansion for aluminium (Bal Seal Engineering, 2004)

Aluminium (α)	
	(20° to 100°C)
356	(21.4×10^{-6})
2014	(22.5×10^{-6})
2024	(22.7×10^{-6})
6061	(23.4×10^{-6})
6082-T6	(24×10^{-6})
7075	(23.2×10^{-6})

Table C3 Coefficients of thermal expansion for other alloys (Bal Seal Engineering, 2004)

Other Alloys (α)	
Titanium 6AL-4V	(8.6×10^{-6})
Brass	(20.3×10^{-6})
Copper	(16.65×10^{-6})
Iron	(11.8×10^{-6})
Platinum	(8.8×10^{-6})
Gold	(14.2×10^{-6})
Silver	(18.9×10^{-6})

Appendix D: Experimental Equipment Specifications

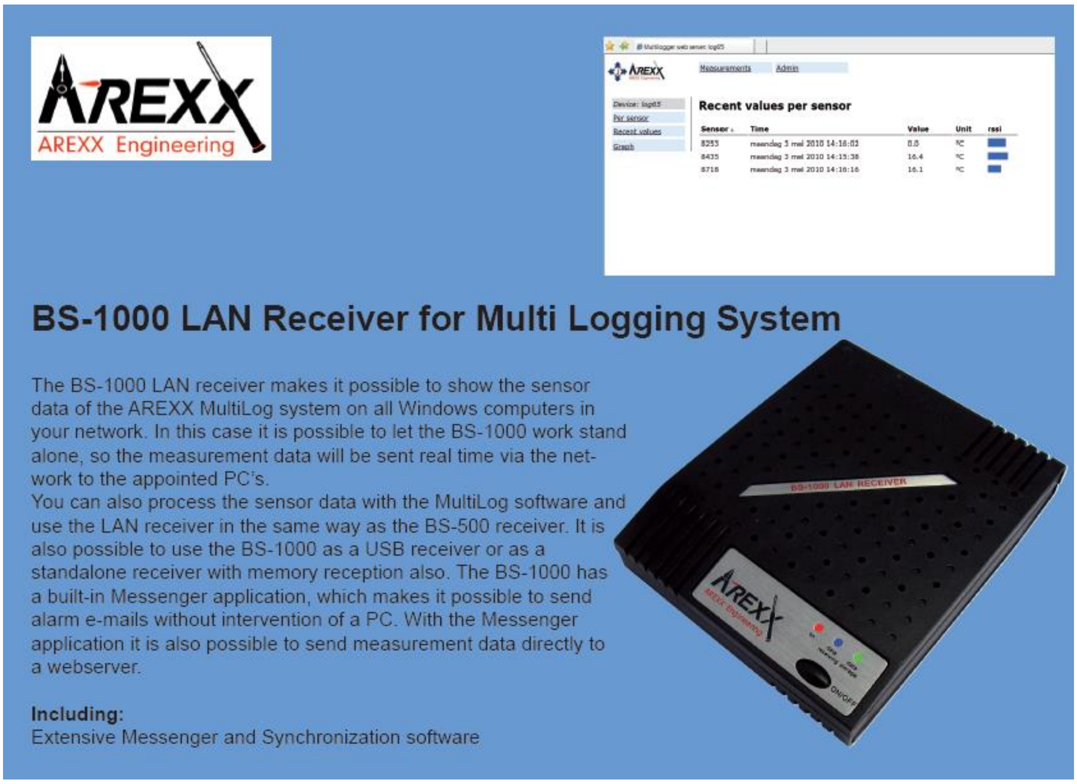
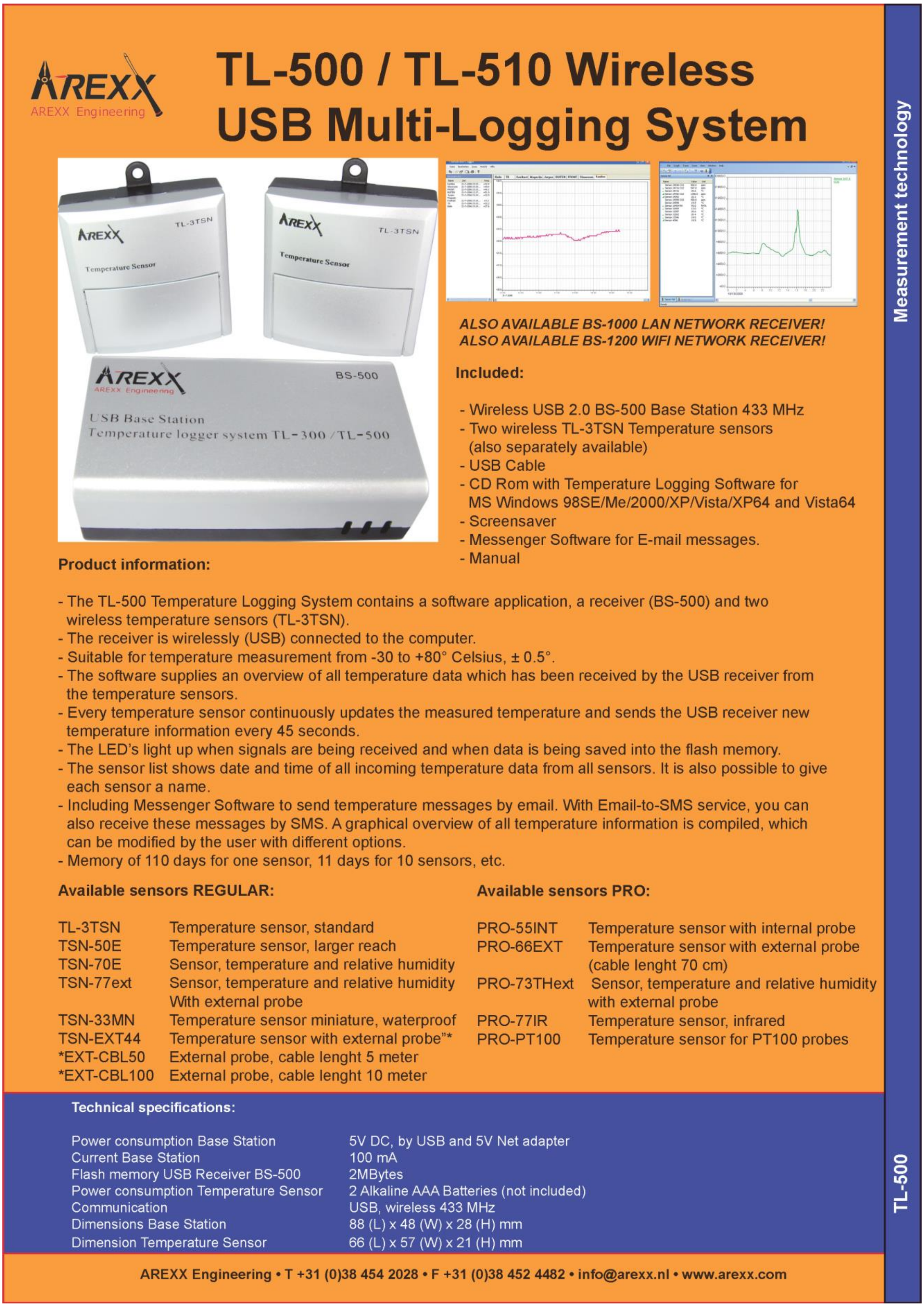


Figure D1. BS-1000 lan receiver for multi logging system

Table D2: BS1000 Device Logging Codes

Rule	Device	Code	Description
Startup	0	0	startup device
Access	0	code	open new session code: 0 = success, 1 = failed
Access	0	2	log in failed
Time	0	0	time set by network time server
Time	0	1	time query timed out
Time	0	2	time server not resolved
Time	1	0	time set by usb
Startup	1	0	reset device to default settings
DHCP	0	0	dhcp configured
rulenb	device	0	rule executed with beep
rulenb	device	1	rule http address unresolved
rulenb	device	2	rule http request timeout
rulenb	device	3	rule hhtp request parse error
rulenb	device	4	rule hhtp request cannot connect
rulenb	device	5	rule hhtp request timeout
rulenb	device	6	rule hhtp request timeout
rulenb	device	7	rule hhtp request timeout
rulenb	device	8	rule hhtp request closed unexpected
rulenb	device	21	rule condition parse error
rulenb	device	22	rule condition parse error
rulenb	device	code	smtp server or http server result code for rule
rulenb	device	1	no mail server address
rulenb	device	2	cannot connect to mailserver



AREXX Engineering

TL-500 / TL-510 Wireless USB Multi-Logging System

Measurement technology

ALSO AVAILABLE BS-1000 LAN NETWORK RECEIVER!
ALSO AVAILABLE BS-1200 WIFI NETWORK RECEIVER!

Included:

- Wireless USB 2.0 BS-500 Base Station 433 MHz
- Two wireless TL-3TSN Temperature sensors (also separately available)
- USB Cable
- CD Rom with Temperature Logging Software for MS Windows 98SE/Me/2000/XP/Vista/XP64 and Vista64
- Screensaver
- Messenger Software for E-mail messages.
- Manual

Product information:

- The TL-500 Temperature Logging System contains a software application, a receiver (BS-500) and two wireless temperature sensors (TL-3TSN).
- The receiver is wirelessly (USB) connected to the computer.
- Suitable for temperature measurement from -30 to +80° Celsius, ± 0.5°.
- The software supplies an overview of all temperature data which has been received by the USB receiver from the temperature sensors.
- Every temperature sensor continuously updates the measured temperature and sends the USB receiver new temperature information every 45 seconds.
- The LED's light up when signals are being received and when data is being saved into the flash memory.
- The sensor list shows date and time of all incoming temperature data from all sensors. It is also possible to give each sensor a name.
- Including Messenger Software to send temperature messages by email. With Email-to-SMS service, you can also receive these messages by SMS. A graphical overview of all temperature information is compiled, which can be modified by the user with different options.
- Memory of 110 days for one sensor, 11 days for 10 sensors, etc.

Available sensors REGULAR:

TL-3TSN	Temperature sensor, standard
TSN-50E	Temperature sensor, larger reach
TSN-70E	Sensor, temperature and relative humidity
TSN-77ext	Sensor, temperature and relative humidity With external probe
TSN-33MN	Temperature sensor miniature, waterproof
TSN-EXT44	Temperature sensor with external probe"*
*EXT-CBL50	External probe, cable lenght 5 meter
*EXT-CBL100	External probe, cable lenght 10 meter

Available sensors PRO:

PRO-55INT	Temperature sensor with internal probe
PRO-66EXT	Temperature sensor with external probe (cable lenght 70 cm)
PRO-73THext	Sensor, temperature and relative humidity with external probe
PRO-77IR	Temperature sensor, infrared
PRO-PT100	Temperature sensor for PT100 probes

Technical specifications:

Power consumption Base Station	5V DC, by USB and 5V Net adapter
Current Base Station	100 mA
Flash memory USB Receiver BS-500	2MBytes
Power consumption Temperature Sensor	2 Alkaline AAA Batteries (not included)
Communication	USB, wireless 433 MHz
Dimensions Base Station	88 (L) x 48 (W) x 28 (H) mm
Dimension Temperature Sensor	66 (L) x 57 (W) x 21 (H) mm

TL-500

AREXX Engineering • T +31 (0)38 454 2028 • F +31 (0)38 452 4482 • info@arexx.nl • www.arexx.com

Figure D3. TL-500 / TL-510 wireless USB multi-logging system

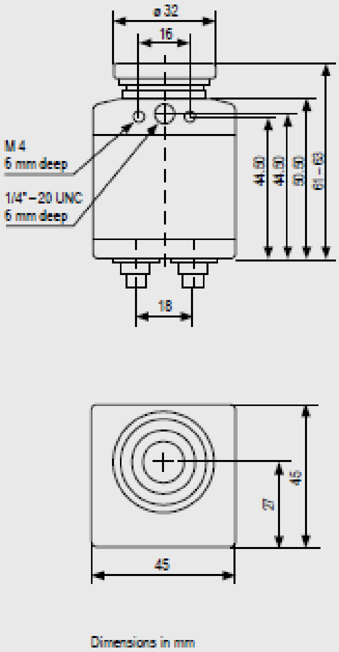
optris® PI 160

INFRARED CAMERA
WITH 120 Hz FRAME RATE

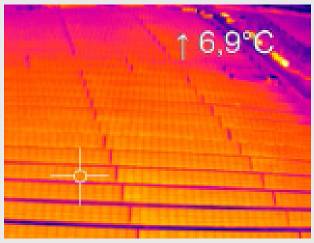
innovative infrared technology

Small camera ideal for OEM use

- Outstanding value for money
- Very good thermal sensitivity from 80 mK
- Thermal image in real time with up to 120 Hz
- Thermal analysis kit including 3 lenses (optional)
- Detector with 160 x 120 pixels
- Compact design (dimensions: 45 x 45 x 62 mm)
- Includes license-free analysis software and full SDK



Surface measurements in industrial application



The optris® PI 160 infrared camera is always used when temperature monitoring of surfaces is required and the single point measurement of pyrometers is no longer sufficient.

Nowadays surface measurements are essential in the automotive field, in plastic applications and in the solar industry.

Suitable lenses for every measurement distance

Same measurement field size at different measurement distances:

- Wide-angle lens:
  0.27 m measurement distance
- Standard lens:
  0.6 m measurement distance
- Telephoto lens:
  2.13 m measurement distance

Hand as measurement object:
measurement field size 240 mm x 180 mm
pixel size 1.5 mm

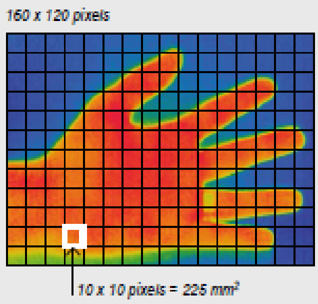
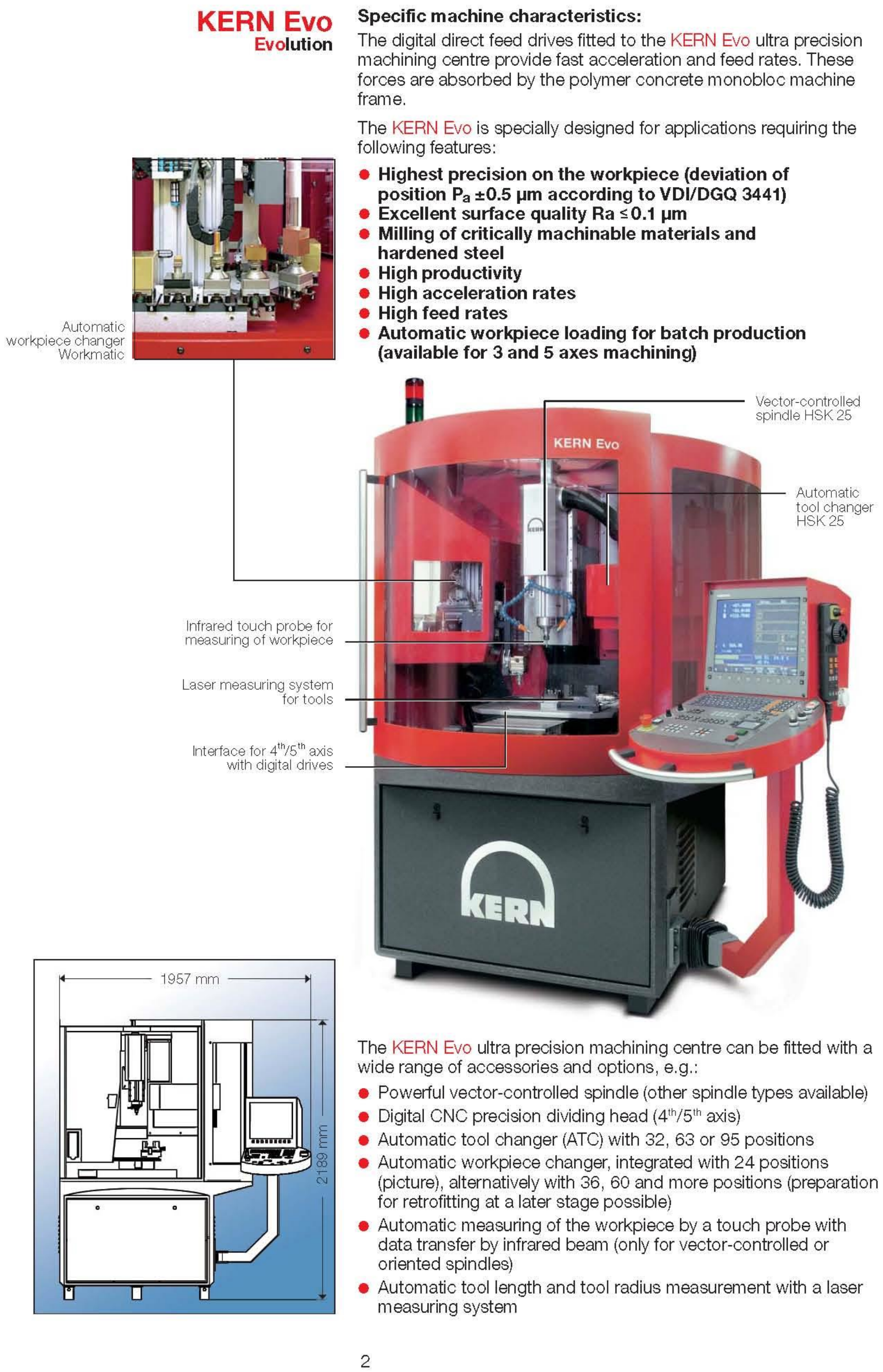


Figure D4. Specifications of Thermal Camera



KERN Evo
Evolution

Specific machine characteristics:

The digital direct feed drives fitted to the KERN Evo ultra precision machining centre provide fast acceleration and feed rates. These forces are absorbed by the polymer concrete monobloc machine frame.

The KERN Evo is specially designed for applications requiring the following features:

- **Highest precision on the workpiece (deviation of position P_a ±0.5 µm according to VDI/DGQ 3441)**
- **Excellent surface quality Ra ≤ 0.1 µm**
- **Milling of critically machinable materials and hardened steel**
- **High productivity**
- **High acceleration rates**
- **High feed rates**
- **Automatic workpiece loading for batch production (available for 3 and 5 axes machining)**

The KERN Evo ultra precision machining centre can be fitted with a wide range of accessories and options, e.g.:

- Powerful vector-controlled spindle (other spindle types available)
- Digital CNC precision dividing head (4th/5th axis)
- Automatic tool changer (ATC) with 32, 63 or 95 positions
- Automatic workpiece changer, integrated with 24 positions (picture), alternatively with 36, 60 and more positions (preparation for retrofitting at a later stage possible)
- Automatic measuring of the workpiece by a touch probe with data transfer by infrared beam (only for vector-controlled or oriented spindles)
- Automatic tool length and tool radius measurement with a laser measuring system

2

Figure D5. Specifications of KERN CNC machine

SD18 Spray Nozzle

The classic precision coaxial spray head

Spray air adjustable directly at spray head

Finely adjustable fluid quantity

Technical data

Connectors:		
Oil		+
Guide air	Coupled	
Spray air		
Flat spray air		-
Sealing materials:	Viton (FPM)	
Spray angle:	α=15°	
Spray pattern:		

Fluid volume at 1 bar:	
Viscosity of 1 at 20°C [mm2/s]	0 – 6400 ml/h
Viscosity of 100 at 40°C [mm2/s]	0 – 580 ml/h
Viscosity of 400 at 40°C [mm2/s]	0 – 115 ml/h

Basic nozzle settings

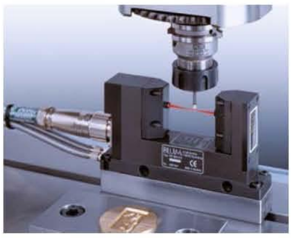
Parameter		Basic settings	
Viscosity at 40°C [mm2/s]	< 60	60 – 200	200 – 600
Guide air [bar]	2.7	2.7	2.7
Oil pressure [bar]	< 0.5	0.5 – 1.0	> 1.0
Spray air [bar]	0.5	0.7	1.0
Flat spray air (if available) [bar]	0.8	1.0	1.5 – 2.0
Guide air pistons [bar]	3.0 – 5.0	3.0 – 5.0	3.0 – 5.0

Figure D6. Specifications of Coolant (SD18 Spray Nozzle)

LaserControl Nano NT | Non-contact tool setting system for machine tools

Compact, highly precise support system for tool setting and monitioring in micromachining applications

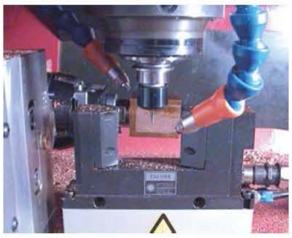
- High-end system for measurement of smallest tools (from ∅ 5 µm)
- Perfect for small and highly precise machines
- Measurement at nominal spindle speed
- Highest absolute accuracy due to focused laser beam
- Process reliability due to patented NT-Electronics
- Pre-aligned laser for easy mounting
- Programmable by integrated microprocessor



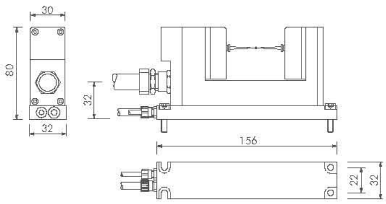
Nano NT – perfect for micro-tools

Your benefit:

- Best measuring accuracy
- Increased productivity and production quality
- No subsequent damage due to tool breakage
- Reduced set-up time and unmanned operation
- Reduced scrap rate



Compact design



NT-H and NT-H 3D versions also available

Technical data

Laser safety classification	Class 2 acc. to IEC60825-1, 21 CFR 1040.10
Laser type	Visible red light laser | 630 ... 700 nm | <1 mW
Protection class	IP68
Power supply	24 V DC/160 mA
Inputs/Outputs	24 V DC | 0 ... 5 V DC analogue output *
Repeatability	0.1 µm 2σ **
Minimum tool diameter	Default: 15 µm **
	Option BL105: 5 µm **
Test speed (spindle)	Up to 200.000 rpm

* Option
** Depending on installation situation, stability of fixation, distance and measuring mode

100 % reliable due to Blum-protection system

Version 04|15, Subject to technical change without notice

BLUM
focus on productivity

Blum worldwide Service & Support
More than 40 subsidiaries and service offices.
www.blum-novotest.com

Blum-Novotest Ltd.
Unit 15 Granary Wharf Business Park
Wetmore Road, Burton upon Trent
Staffordshire , DE14 1DU
United Kingdom
Phone: +44 1283 569691
Fax: +44 1283 563687
info@blum-novotest.co.uk

Blum-Novotest, Inc.
4144 Olympic Boulevard
Erlanger, KY 41018
USA
Phone: +1 (859) 344 6789
Fax: +1 (859) 344 6799
solutions@blum-novotest.us

Blum-Novotest GmbH | Kaufstrasse 14 | 88287 Gruenkraut | Germany | +49 751 6008-0 | vk@blum-novotest.com

Production Metrology Made in Germany

Figure D7. Specifications of BLUM laser control

Mitutoyo FN503

Stock#: XSX6390

Make: Mitutoyo

Model: FN503

Year:

DCC: DCC

X Travel: 20.00"

Y Travel: 16.00"

Z Travel: 12.00"

Overall Height: 91"

Controller: UCC2

Software: OpenDMIS

Software Version: V2.8

Probe Head: PH20

Touch Probe: TP20

Figure D8. Specifications of Coordinate Measuring Machine (CMM) – MITUTOYO FN503

TESA TECHNOLOGY

TESA-REFLEX®

ZELO STABILNA IN TOGA MEHANSKA KONSTRUKCIJA

Stabilna jeklena konstrukcija v kombinaciji z granitnimi mizami in optičnimi merilnimi sistemi zagotavlja oprema optimalne merilne pogoje za kvalitetna merjenja v vseh pogojih uporabe in nam omogoča varne in zanesljive meritve.

VARIOUS LIGHT ILLUMINATIONS FOR PRECISE MEASUREMENT OPERATIONS

Vsi TESA-VISIO stroji so opremljeni z LED osvetlitvenim sistemom,kin am omogoča dolgo življensko dobo in hladno osvetlitev,ki tako ne vpliva na meritve. Prav tako nam omogoča preko diaskopske osvetlitve (od zgoraj-skozi zoom) meritve slepih izvrtin.

GL verzija strojev nam omogoča skozi konstrukcijo "ringlight" osvetlitev pod različnimi koti osvetlitev in sicer (od 90° do 45°).

TESA-REFLEX VISTA

Posebej razvit program za vsako TESA VISIO opremo, ki omogoča merilcu skozi merilni process,da lahko hitro in enostavno določi in izmeri geometrijo merjenca. Z uporabo funkcije "compar"-(primerjaj),pa lahko delamo tudi direktno primerjavo med dejanskim in CAD modelom.

TESA-REFLEX VISION

Ta programski paket je narejen posebej za TESA-VISIO 300 GL DCC – motorni pomik in nam omogoča zelo enostavno in hitro uporabo te CNC opreme.

TESA-REFLEX Vision omogoča avtomatske meritve vseh geometrijskih oblik,vodi merilca po merjencu in mu omogoča meritve in primerjavo vseh dimenzij. Vse te lastnosti odlikujejo to opremo z veliko učunkovitostjo in uporabnostjo.

Njena prednost pa je še posebej v zelo enostavni priučitvi dela na njej, saj potrebujemo za šolanje programa TESA – REFLEX samo nekaj ur treninga.

TEHNIČNI PODATKI

Kataloška številka	06830401	06830428	06830601	06830634
TESA-VISIO 200 GL	•	•		
TESA-VISIO 300 GL			•	•
Merilni obseg, X/Y/Z (mm)	200x100x150	200x100x150	300x200x150	300x200x150
Pomik	ročni	ročni	ročni	motorni
TESA-REFLEX Vista software	•	•	•	
TESA-REFLEX Vision software				•
Natančnost (m ≤5 kg)				
$MPE_{X,Y}$ (E_X, E_Y) (µm) (L in mm)	2 + 10L/1000	2 + 10L/1000	2 + 4L/1000	1,6 + 4L/1000
MPE_{XY} (E_{XY}) (µm) (L in mm)	2,9 + 10L/1000	2,9 + 10L/1000	2,5 + 4L/1000	2 + 4L/1000
MPE_Z (E_Z) (µm) (L in mm)*	2,9 + 10L/1000	2,9 + 10L/1000	2,9 + 5L/1000	2,9 + 5L/1000
Camera and optics				
CCD colour camera	•	•	•	•
Indexable manual Zoom, 6,5x	•			
Motorised zoom, 6,5x		•	•	•
Motorised zoom, 12x			Opcijsko	Opcijsko
Diascopic illumination, green	•	•	•	•
Parallel diascopic illumination	Opcijsko	Opcijsko	Opcijsko	Opcijsko
Coaxial light	•	•	•	•
Segmented white ringlight (4 x 90°)	•	•		
Segmented white ringlight (4 x 90° + 8 x 45°)			•	•
Laser pointer	•	•	•	•

*Mechanical accuracy

WHEN YOU NEED TO BE SURE

TESA TECHNOLOGY

Figure D9. Specification of optical microscope (TESA 200)

Specifications

Magnification	Secondary electron image: ×10 to ×60,000 Backscattered electron image: ×10 to ×30,000 (when image size is 128 mm × 96 mm)
Imaging mode	Secondary electron image, backscattered electron image
Accelerating voltage	Secondary electron image; 5 kV, 10 kV, 15 kV (3 stages) Backscattered electron image; 10 kV, 15 kV (2 stages)
Electron gun	Small gun with cartridge filament integratinng wehnelt
Bias current	Auto bias (linked to accelerating voltage and filament current)
Condenser lens	Two stage electromagnetic zoom condenser lens
Objective lens	Electromagnetic lens
Auto magnification correction	Magnification corrected with reference to sample height (7 mm, WD56 to 53 mm, WD10)
Preset magnification	6 levels, user programmable
Specimen stage	Manual control for X and Y: X: 35 mm, Y: 35 mm
Maximum sample size	70 mm diameter × 50 mm height
Specimen exchange	Draw-out mechanism
Image memory	One, 1,280 × 960 × 16 bits
Pixels	640 × 480, 1,280 × 960
Image processing	Pixel accumulation Image accumulation (recursible)
Automated functions	Filament, alignment, focus, stigmator, exposure
Metrology	Distance between 2 points, angles
File format	BMP, TIFF, JPEG
Computer	PC (desktop PC), OS Windows®7
Monitor	23 inch wide LCD monitor (touch panel)
Evacuation system	Fully automatic, TMP: 1, RP: 1

Optional accessories

- ◆ Tilt rotation motorized holder
  Tilt: -15° to +45°; rotation: 360°
- ◆ EDS

Installation requirements

Power supply	Voltage: Single phase AC 100 V (120 V, 220 V, 240 V) 50/60 Hz, 700 VA (AC 100 V), 840 VA (AC 120 V), 880 VA (AC 220 V), 960 VA (AC 240 V), Fluctuation ±10% or less, with grounding
Installation Room	
Room temperature	15 to 30°C
Humidity	60% or less
Operation table	Sturdy table with a loading capacity of 100 kg or more
Weight	Main console: approximately 50 kg RP: approximately 9 kg Power supply box: approximately 10 kg
Base unit dimensions	(Width) (Depth) (Height) 325 mm × 490 mm × 430 mm

※ Specifications subject to change without notice.
※ The official name of Windows7 is Microsoft(R), Windows(R), Operating System.
※ Windows is a registered trademark of Microsoft Corp. in the U.S.
※ Other trademarks referenced in this catalog and marked with* are the property of our allied companies.

System composition

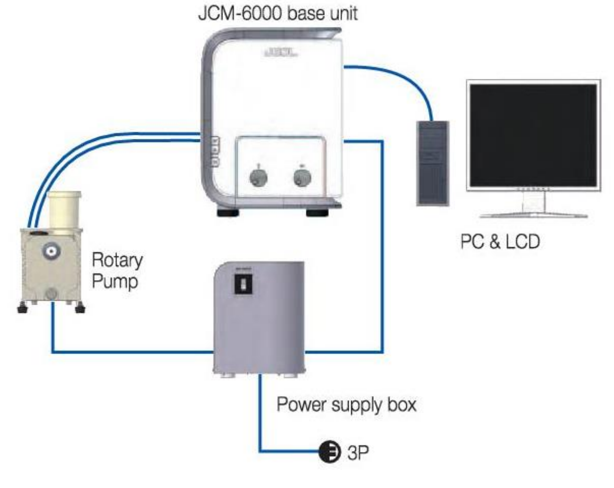


Figure D10. Specifications of JEOL JCM-6000 Scanning Electron Microscopes (SEM)

Appendix E: Specifications of Aluminium Alloy 6082-T6

Aluminium Alloy
6082 - T6~T651 Plate

aalco®

SPECIFICATIONS

Commercial	6082
EN	6082

Aluminium alloy 6082 is a medium strength alloy with excellent corrosion resistance. It has the highest strength of the 6000 series alloys. Alloy 6082 is known as a structural alloy. In plate form, 6082 is the alloy most commonly used for machining. As a relatively new alloy, the higher strength of 6082 has seen it replace 6061 in many applications. The addition of a large amount of manganese controls the grain structure which in turn results in a stronger alloy. It is difficult to produce thin walled, complicated extrusion shapes in alloy 6082. The extruded surface finish is not as smooth as other similar strength alloys in the 6000 series.
In the T6 and T651 temper, alloy 6082 machines well and produces tight coils of swarf when chip breakers are used.

Applications
6082 is typically used in:
~ Highly stressed applications
~ Trusses
~ Bridges
~ Cranes
~ Transport applications
~ Ore skips
~ Beer barrels
~ Milk churns

CHEMICAL COMPOSITION

BS EN 573-3:2009
Alloy 6082

Element	% Present
Silicon (Si)	0.70 - 1.30
Magnesium (Mg)	0.60 - 1.20
Manganese (Mn)	0.40 - 1.00
Iron (Fe)	0.0 - 0.50
Chromium (Cr)	0.0 - 0.25
Zinc (Zn)	0.0 - 0.20
Others (Total)	0.0 - 0.15
Titanium (Ti)	0.0 - 0.10
Copper (Cu)	0.0 - 0.10
Other (Each)	0.0 - 0.05
Aluminium (Al)	Balance

ALLOY DESIGNATIONS

Aluminium alloy 6082 also corresponds to the following standard designations and specifications **but may not be a direct equivalent:**
AA6082
HE30
DIN 3.2315
EN AW-6082
ISO: Al Si1MgMn
A96082

TEMPER TYPES

The most common tempers for 6082 aluminium are:

- T6 - Solution heat treated and artificially aged
- O - Soft
- T4 - Solution heat treated and naturaly aged to a substantially stable condition
- T651 - Solution heat treated, stress relieved by stretching then artificially aged

SUPPLIED FORMS

Alloy 6082 T6 & T651 is typically supplied as Plate and Shate.

- Plate
- Sheet

GENERIC PHYSICAL PROPERTIES

Property	Value
Density	2.70 g/cm³
Melting Point	555 °C
Thermal Expansion	24 $\times 10^{-6}$ /K
Modulus of Elasticity	70 GPa
Thermal Conductivity	180 W/m.K
Electrical Resistivity	0.038 $\times 10^{-6}$ Ω .m

[1 OF 2] CONTINUED

Figure E1. Specifications of Aluminium Alloy 6082-T6

Aluminium Alloy
6082 - T6~T651 Plate

aalco®

MECHANICAL PROPERTIES

BS EN 485-2:2008 *Plate* *6.00m to 12.5mm*	
Property	Value
Proof Stress	255 Min MPa
Tensile Strength	300 Min MPa
Elongation A50 mm	9 Min %
Hardness Brinell	91 HB

Properties above are for material in the T6 and T651 condition

BS EN 485-2:2008 *Plate* *12.5mm to 100.00mm*	
Property	Value
Proof Stress	240 Min MPa
Tensile Strength	295 Min MPa
Hardness Brinell	89 HB

Properties above are for material in the T6 and T651 condition

BS EN 485-2:2008 *Plate* *100.00mm to 150.00mm*	
Property	Value
Proof Stress	240 Min MPa
Tensile Strength	275 Min MPa
Hardness Brinell	84 HB
Elongation A	6 Min %

Properties above are for material in the T6 and T651 condition

WELDABILITY

6082 has very good weldability but strength is lowered in the weld zone. When welded to itself, alloy 4043 wire is recommended. If welding 6082 to 7005, then the wire used should be alloy 5356.

Weldability – Gas: Good
Weldability – Arc: Good
Weldability – Resistance: Good
Brazability: Good
Solderability: Good

FABRICATION

Workability - Cold: Good
Machinability: Good

CONTACT

Address:	Please make contact directly with your local service centre, which can be found via the Locations page of our web site
Web:	www.aalco.co.uk

REVISION HISTORY

Datasheet Updated	11 January 2016

DISCLAIMER

This Data is indicative only and as such is not to be relied upon in place of the full specification. In particular, mechanical property requirements vary widely with temper, product and product dimensions. All information is based on our present knowledge and is given in good faith. No liability will be accepted by the Company in respect of any action taken by any third party in reliance thereon.

Please note that the 'Datasheet Update' date shown above is no guarantee of accuracy or whether the datasheet is up to date.

The information provided in this datasheet has been drawn from various recognised sources, including EN Standards, recognised industry references (printed & online) and manufacturers' data. No guarantee is given that the information is from the latest issue of those sources or about the accuracy of those sources.

Material supplied by the Company may vary significantly from this data, but will conform to all relevant and applicable standards.

As the products detailed may be used for a wide variety of purposes and as the Company has no control over their use; the Company specifically excludes all conditions or warranties expressed or implied by statute or otherwise as to dimensions, properties and/or fitness for any particular purpose, whether expressed or implied.

Advice given by the Company to any third party is given for that party's assistance only and without liability on the part of the Company. All transactions are subject to the Company's current Conditions of Sale. The extent of the Company's liabilities to any customer is clearly set out in those Conditions; a copy of which is available on request.

[2 OF 2]

Figure E2. Mechanical properties of Aluminium Alloy 6082-T6

Appendix F: Specifications of Cutting Tool

2 Flute End Mills

End Mills for General Purpose Use

Tool Details | Speeds & Feeds | Icons Legend

SGS General Purpose End Mills are manufactured to the highest standards on state of the art CNC equipment. Held to the same standard as High Performance product, the SGS General Purpose End Mill delivers consistent dependable performance beyond a typical General Purpose End Mill.

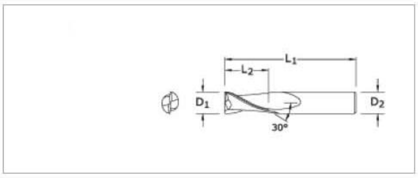
Features & Benefits:

- Lab inspected and certified raw material
- Precision CNC ground to industry leading specifications
- Consistent quality and predictable performance

2 Flute Square End General Purpose End Mill-Metric

Tolerances (mm)

D1	D2
+0,000/-0,05	h6



Cutting Diameter (D_1) mm	Length of Cut (L_2) mm	Overall Length (L_1) mm	Shank Diameter (D_2) mm	Uncoated EDP No.	Ti-NAMITE (TiN) EDP No.	Ti-NAMITE-A (AlTiN) EDP No.	Ti-NAMITE-C (TiCN) EDP No.
1,0	4,0	38,0	3,0	40305	48628	48671	48650
1,5	4,5	38,0	3,0	40309	48629	48672	48651
2,0	6,3	38,0	3,0	40313	48630	48673	48652
2,5	9,5	38,0	3,0	40317	48631	48674	48653
3,0	12,0	38,0	3,0	40321	48632	48675	48654
3,5	12,0	50,0	4,0	40325	48633	48676	48655
4,0	14,0	50,0	4,0	40329	48634	48677	48656
4,5	16,0	50,0	6,0	40333	48635	48678	48657
5,0	16,0	50,0	6,0	40337	48636	48679	48658
6,0	19,0	50,0	6,0	40341	48637	48680	48659
7,0	19,0	63,0	8,0	40345	48638	48681	48660
8,0	20,0	63,0	8,0	40349	48639	48682	48661
9,0	22,0	75,0	10,0	40353	48640	48683	48662
10,0	22,0	75,0	10,0	40357	48641	48684	48663
11,0	25,0	75,0	12,0	40361	48642	48685	48664
12,0	25,0	75,0	12,0	40365	48643	48686	48665
14,0	32,0	89,0	14,0	40369	48644	48687	48666
16,0	32,0	89,0	16,0	40373	48645	48688	48667
18,0	38,0	100,0	18,0	40377	48646	48689	48668
20,0	38,0	100,0	20,0	40381	48647	48690	48669
25,0	38,0	100,0	25,0	40385	48648	48691	48670

Figure F1. 2 Flutes end mill tungsten carbide tool

Appendix G: Aluminium Workpiece Drawing

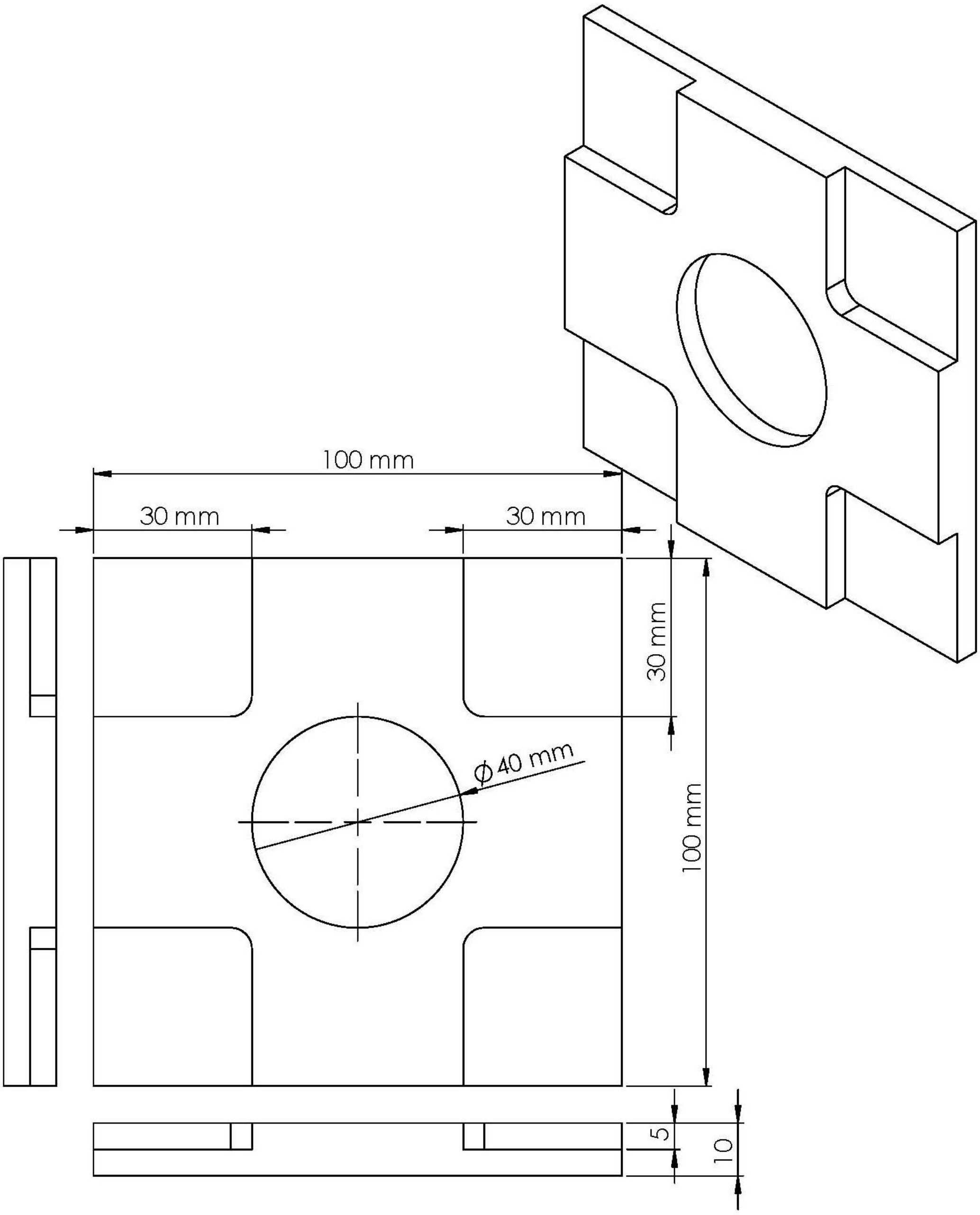


Figure G1. Aluminium Workpiece Drawing

Appendix H: Temperature Control Range in Different Sectors

Sector	Building/room type	Temperature (ºC)
Offices/service companies	Computer rooms	19-21
	Banks, building societies, post offices	19-21
	Offices	21-23
Hospitality	Restaurants/dining rooms	22-24
	Bars	20-22
	Hotels	19-21
Schools/further and higher education	Educational buildings	19-21
Industrial/factories	Heavy work	11-14
	Light work	16-19
	Sedentary work	19-21
Hospitals and healthcare	Bedheads/wards	22-24
	Circulation spaces/wards	19-24
	Consulting/treatment rooms	22-24
	Nurses' stations	19-22
	Operating theatres	17-19
Public buildings	General building areas	19-21
	Law courts	19-21
	Libraries	19-21
	Exhibition halls	19-21
	Laundries	16-19
	Churches	19-21
	Museums and art galleries	19-21
	Prisons	19-21
Retail	Retail buildings	19-24
Sports and leisure	Changing rooms	20-25
	Sports halls	15
	Pool halls	28-30*

Figure H1. Temperature control range in different sectors (Carbon Trust, 2011)

Appendix I: Cutting Speed and Feed Recommendations

Speed & Feed Recommendations

Group	Series 1M, 3M, 5M, 14M, 15M, 16M, 17M, 59M Metric	Hardness BRINELL	Operation	Flutes	Ae x D_1	Ap x D_1	Vc (m/min)		Diameter (D_1) (mm) 0.4	0.75	1.5	3	6	10	12	20	25
S	**SUPER ALLOYS (NICKEL, COBALT, IRON BASE) Inconel 601, 617, 625, 718, Incoly 800, Monel 400,Rene, Waspalloy**	≤ 300	Profile				20	RPM	15753	8402	4201	2100	1050	630	525	315	252
								Fz	0.0005	0.0007	0.0014	0.004	0.010	0.021	0.024	0.032	0.035
				2	≤ 0.50	≤ 1.5	(16-24)	Feed (mm/min)	16	12	12	17	21	26	25	20	18
				3	≤ 0.25	≤ 1.5			24	18	18	25	32	40	38	30	26
				4	≤ 0.25	≤ 1.5			32	24	24	34	42	53	50	40	35
			Slot				14	RPM	10906	5816	2908	1454	727	436	364	218	174
								Fz	0.0005	0.0007	0.0014	0.004	0.010	0.021	0.024	0.032	0.035
				2	1	≤ 1	(11-16)	Feed (mm/min)	11	8	8	12	15	18	17	14	12
				3	1	≤ 0.5			16	12	12	17	22	27	26	21	18
				4	1	≤ 0.4			22	16	16	23	29	37	35	28	24
S	**TITANIUM ALLOYS Ti6Al4V, Ti6Al2Sn4Zr2Mo, Ti4Al4Mo2Sn0.5Si, Ti10Al2Fe3Al, Ti5Al53Mo3Cr, Ti7Al4Mo, Ti3Al8V6Cr4Zr4Mo, Ti6Al6V6Sn, Ti152 Cr3Sn3Al**	≤ 350	Profile				55	RPM	43624	23266	11633	5816	2908	1745	1454	872	698
								Fz	0.0005	0.0010	0.0019	0.004	0.012	0.024	0.029	0.037	0.042
				2	≤ 0.50	≤ 1.5	(44-66)	Feed (mm/min)	44	47	44	47	70	84	84	65	59
				3	≤ 0.25	≤ 1.5			65	70	66	70	105	126	127	97	88
				4	≤ 0.25	≤ 1.5			87	93	88	93	140	168	169	129	117
			Slot				40	RPM	31506	16803	8402	4201	2100	1260	1050	630	504
								Fz	0.0005	0.0010	0.0019	0.004	0.012	0.024	0.029	0.037	0.042
				2	1	≤ 1	(32-48)	Feed (mm/min)	32	34	32	34	50	60	61	47	42
				3	1	≤ 0.5			47	50	48	50	76	91	91	70	64
				4	1	≤ 0.4			63	67	64	67	101	121	122	93	85
N	**ALUMINUM ALLOYS 2017, 2024, 356, 6061, 7075**	≤ 150	Profile				268	RPM	213272	113745	56872	28436	14218	8531	7109	4265	3412
								Fz	0.0015	0.0032	0.0060	0.014	0.038	0.080	0.096	0.128	0.140
				2	≤ 0.50	≤ 1.5	(215-322)	Feed (mm/min)	640	728	682	796	1081	1365	1365	1092	955
				3	≤ 0.25	≤ 1.5			960	1092	1024	1194	1621	2047	2047	1638	1433
			Slot				195	RPM	155107	82724	41362	20681	10340	6204	5170	3102	2482
								Fz	0.0015	0.0032	0.0060	0.014	0.038	0.080	0.096	0.128	0.140
				2	1	≤ 1	(156-234)	Feed (mm/min)	465	529	496	579	786	993	993	794	695
				3	1	≤ 0.5			698	794	745	869	1179	1489	1489	1191	1042
N	**COPPER ALLOYS Alum Bronze, C110, Muntz Brass**	≤ 140	Profile				148	RPM	117542	62689	31344	15672	7836	4702	3918	2351	1881
								Fz	0.0008	0.0015	0.0031	0.007	0.019	0.040	0.048	0.064	0.070
				2	≤ 0.50	≤ 1.5	(118-177)	Feed (mm/min)	188	188	194	219	298	376	376	301	263
				3	≤ 0.25	≤ 1.5			282	282	292	329	447	564	564	451	395
				4	≤ 0.25	≤ 1.5			376	376	389	439	596	752	752	602	527
			Slot					RPM	84824	45239	22620	11310	5655	3393	2827	1696	1357
								Fz	0.0008	0.0015	0.0031	0.007	0.019	0.040	0.048	0.064	0.070
				2	1	≤ 1		Feed (mm/min)	136	136	140	158	215	271	271	217	190
				3	1	≤ 0.5			204	204	210	238	322	407	407	326	285
				4	1	≤ 0.4			271	271	280	317	430	543	543	434	380
	PLASTICS Polycarbonate, PVC, Polypropylene		Profile				268	RPM	213272	113745	56872	28436	14218	8531	7109	4265	3412
								Fz	0.0015	0.0032	0.0060	0.014	0.038	0.080	0.096	0.128	0.140
				2	≤ 0.50	≤ 1.5	(215-322)	Feed (mm/min)	640	728	682	796	1081	1365	1365	1092	955
				3	≤ 0.25	≤ 1.5			960	1092	1024	1194	1621	2047	2047	1638	1433
				4	≤ 0.25	≤ 1.5			1280	1456	1365	1592	2161	2730	2730	2184	1911
			Slot				195	RPM	155107	82724	41362	20681	10340	6204	5170	3102	2482
								Fz	0.0015	0.0032	0.0060	0.014	0.038	0.080	0.096	0.128	0.140
				2	1	≤ 1	(156-234)	Feed (mm/min)	465	529	496	579	786	993	993	794	695
				3	1	≤ 0.5			698	794	745	869	1179	1489	1489	1191	1042
				4	1	≤ 0.4			931	1059	993	1158	1572	1985	1985	1588	1390
	GRAPHITE		Profile				201	RPM	159954	85309	42654	21327	10664	6398	5332	3199	2559
								Fz	0.0015	0.0032	0.0060	0.014	0.038	0.080	0.096	0.128	0.140
				2	≤ 0.50	≤ 1.5	(161-241)	Feed (mm/min)	480	546	512	597	810	1024	1024	819	717
				3	≤ 0.25	≤ 1.5			720	819	768	896	1216	1536	1536	1228	1075
				4	≤ 0.25	≤ 1.5			960	1092	1024	1194	1621	2047	2047	1638	1433
			Slot				146	RPM	116330	62043	31021	15511	7755	4653	3878	2327	1861
								Fz	0.0015	0.0032	0.0060	0.014	0.038	0.080	0.096	0.128	0.140
				2	1	≤ 1	(117-176)	Feed (mm/min)	349	397	372	434	589	745	745	596	521
				3	1	≤ 0.5			523	596	558	651	884	1117	1117	893	782
				4	1	≤ 0.4			698	794	745	869	1179	1489	1489	1191	1042

Figure I1. Cutting Speed and feed recommendations (SGS Tool, 2016)

Appendix J: Fluke Power Logger Display

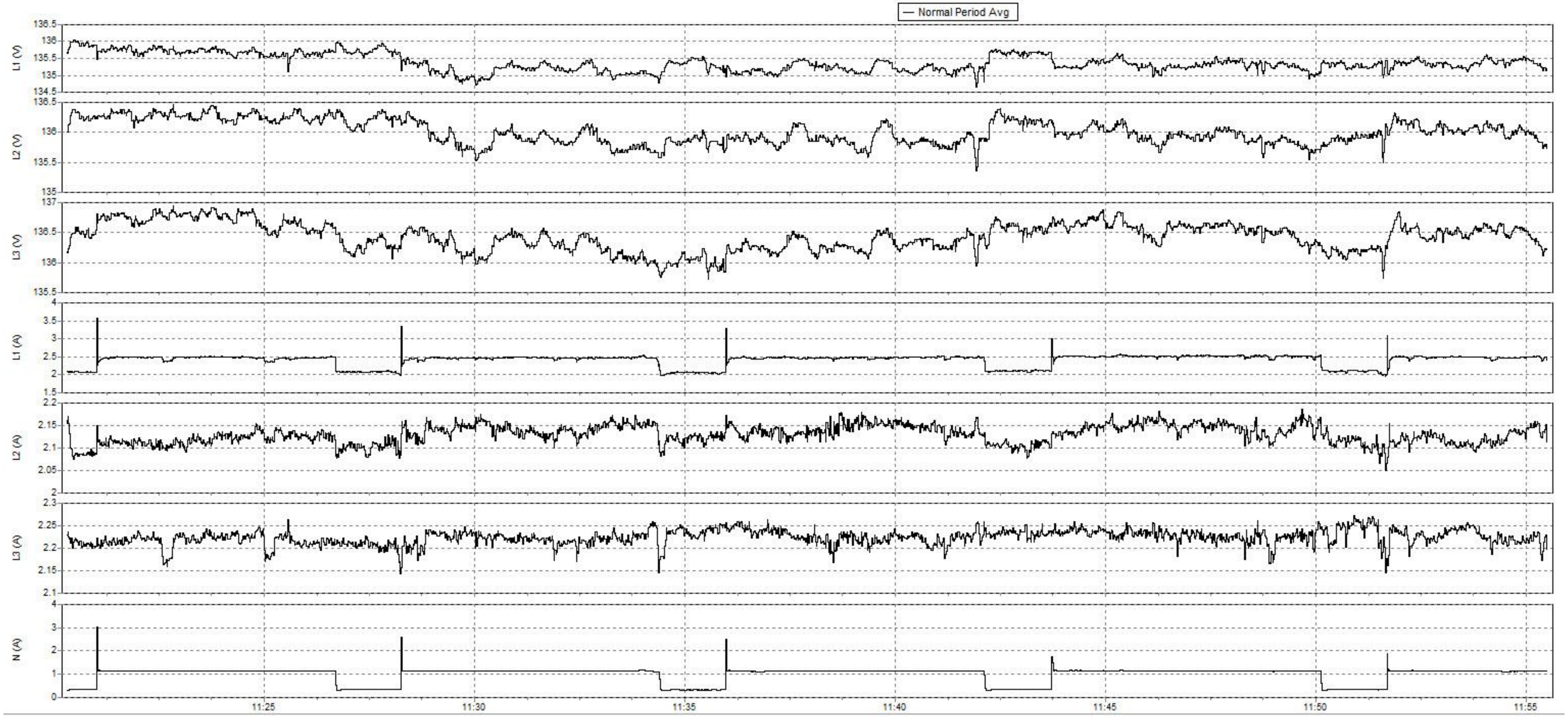


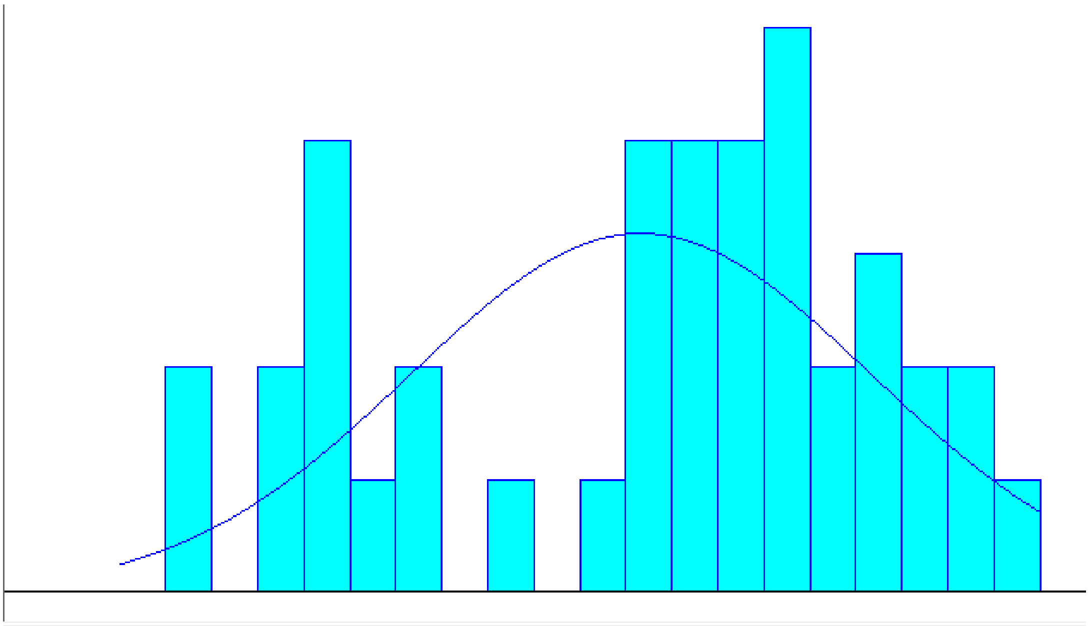
Figure J1. Fluke power log displaying three phrases of voltages and currents results

Appendix K: Three Dimensional Correlations Experimental Results

Table K1 Three Dimensional Correlation Analysis Results

Day	Workpiece No.	Ambient Temperature (°C)	Total Energy Consumption (kWh)	Quality Error (%)
1	1	23.6	11.02	0.1452
	2	25.3	10.85	0.1698
	3	26.1	10.760	0.1778
	4	25.5	10.73	0.1834
2	5	23.7	11.13	0.1491
	6	24.3	10.93	0.1467
	7	26.2	10.797	0.1907
	8	25.2	10.94	0.1730
3	9	23.9	11.05	0.1349
	10	24.7	10.92	0.1636
	11	26.5	10.691	0.1971
	12	25.9	10.797	0.1828
4	13	23.3	11.32	0.1466
	14	25.7	10.863	0.1746
	15	26.3	10.757	0.1960
	16	26.6	10.671	0.1990
5	17	23.8	11.24	0.1475
	18	25	10.99	0.1617
	19	25.6	10.86	0.1860
	20	25.8	10.74	0.1723
6	21	23.4	11.27	0.1476
	22	26.5	10.57	0.2122
	23	25.8	10.66	0.2072
	24	25.7	10.81	0.1894
7	25	23.8	11.12	0.1391
	26	25.4	10.80	0.1762
	27	26.3	10.67	0.1923
	28	25.4	10.92	0.1877
8	29	23.9	11.21	0.1494
	30	25.8	10.842	0.1792
	31	26.1	10.71	0.2060
	32	26.8	10.571	0.2060
9	33	24.1	11.20	0.1516
	34	25.3	10.74	0.1880
	35	25.3	10.97	0.1681
	36	25.9	10.67	0.2057
10	37	24.3	11.02	0.1580
	38	25.6	10.89	0.1762
	39	25.4	10.93	0.1729
	40	26.7	10.644	0.2027

Appendix L: Statistical Results



```
        Distribution Summary

Distribution:   Normal
Expression:     NORM(25.3, 1)
Square Error:   0.028002

Chi Square Test
  Number of intervals   = 6
  Degrees of freedom    = 3
  Test Statistic        = 13.1
  Corresponding p-value < 0.005

Kolmogorov-Smirnov Test
  Test Statistic        = 0.164
  Corresponding p-value > 0.15

        Data Summary

Number of Data Points   = 40
Min Data Value          = 23.3
Max Data Value          = 26.8
Sample Mean             = 25.3
Sample Std Dev          = 1.02

        Histogram Summary

Histogram Range         = 23 to 27
```

Figure L1. Chi-Square Test of ambient temperature data

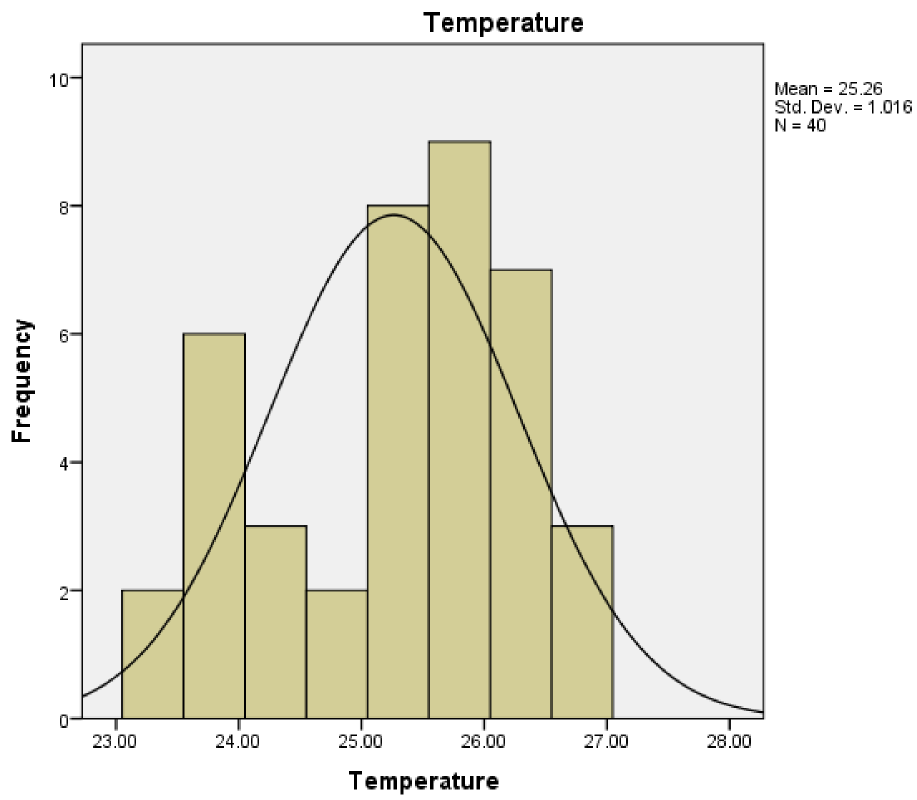


Figure L2. Ambient temperature data histogram

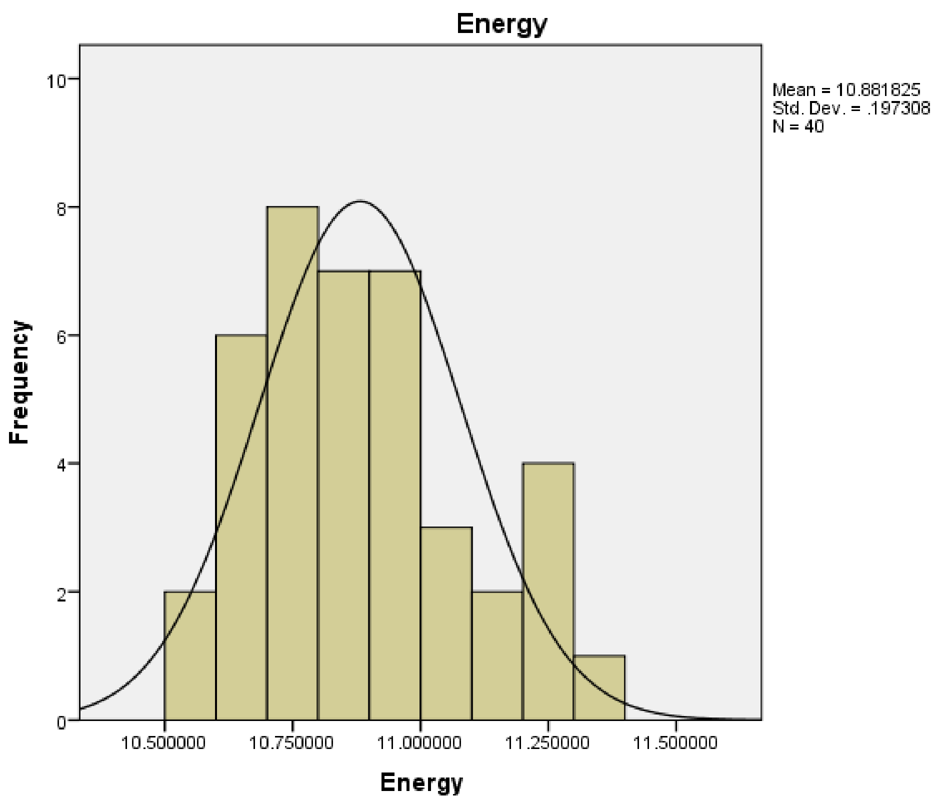


Figure L3. Total energy consumption data histogram

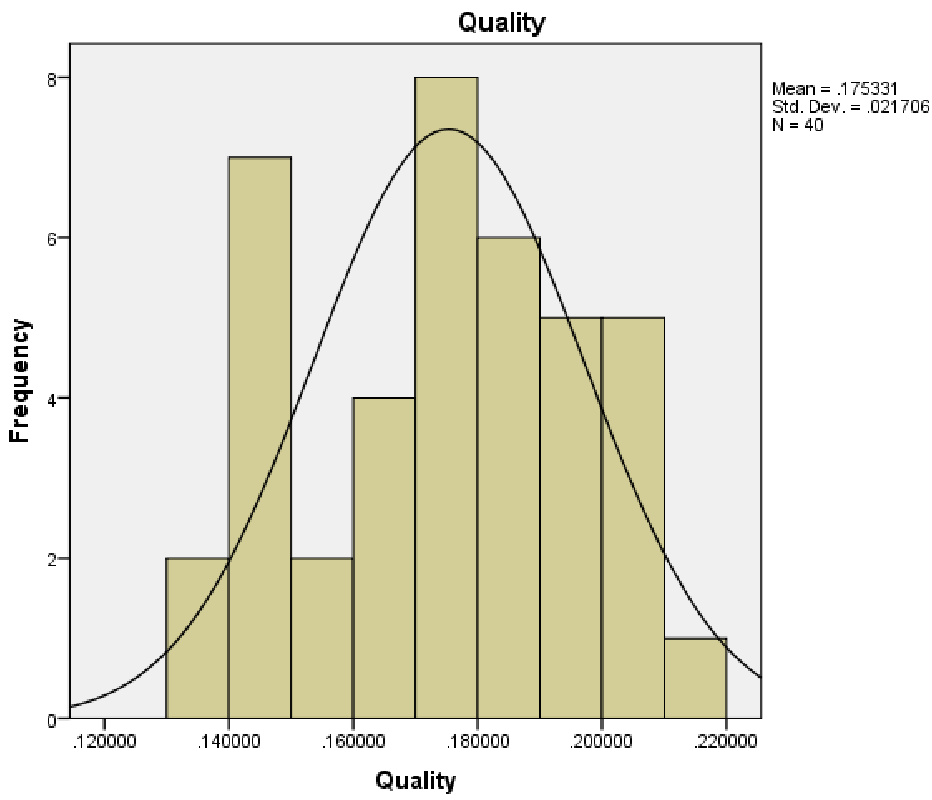


Figure L4. Workpiece quality error data histogram

Table L1. Skewness results

		Ambient Temperature	Total Energy Consumption	Quality
N	Valid	40	40	40
	Missing	0	0	0
Skewness		-.490	.552	-.136
Std. Error of Skewness		.374	.374	.374
Kurtosis		-.922	-.458	-1.066
Std. Error of Kurtosis		.733	.733	.733

Table L2. SPSS regression analysis ambient temperature predicting workpiece quality error results

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.921[a]	.849	.845	.008555524

a. Predictors: (Constant), Ambient Temperature

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.016	1	.016	213.063	.000[b]
	Residual	.003	38	.000		
	Total	.018	39			

a. Dependent Variable: Workpiece Quality Error

b. Predictors: (Constant), Ambient Temperature

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.322	.034		-9.444	.000
	Ambient Temperature	.020	.001	.921	14.597	.000

a. Dependent Variable: Workpiece Quality Error

Table L3. SPSS regression analysis ambient temperature

Predicting total energy consumption results

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.926[a]	.858	.854	.075364471

a. Predictors: (Constant), Ambient Temperature

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.302	1	1.302	229.313	.000[b]
	Residual	.216	38	.006		
	Total	1.518	39			

a. Dependent Variable: Total Energy Consumption

b. Predictors: (Constant), Ambient Temperature

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	15.427	.300		51.356	.000
	Ambient Temperature	-.180	.012	-.926	-15.143	.000

a. Dependent Variable: Total Energy Consumption

Table L4. SPSS regression analysis total energy consumption predicting workpiece quality error results

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.894[a]	.799	.794	.009854011

a. Predictors: (Constant), Energy Consumption

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.015	1	.015	151.256	.000[b]
	Residual	.004	38	.000		
	Total	.018	39			

a. Dependent Variable: Quality Error
b. Predictors: (Constant), Energy Consumption

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.246	.087		14.311	.000
	Total Energy Consumption	-.098	.008	-.894	-12.299	.000

a. Dependent Variable: Workpiece Quality Error

Table L5. SPSS multiple regression analysis predicting workpiece quality error results

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.928[a]	.860	.853	.008328971

a. Predictors: (Constant), Energy Consumption, Ambient Temperature

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.016	2	.008	113.953	.000[b]
	Residual	.003	37	.000		
	Total	.018	39			

a. Dependent Variable: Quality Error

b. Predictors: (Constant), Energy Consumption, Ambient Temperature

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	.165	.279		.591	.588	-.400	.729
	Ambient Temperature	.014	.003	.656	4.024	.000	.007	.021
	Total Energy Consumption	-.032	.018	-.287	-1.759	.087	-.068	.005

a. Dependent Variable: Workpiece Quality Error

Appendix M: Tool Wear Measurement Results

Table M1 Magnitude of roughing tool wear results from Blum laser system

Workpiece No.	Machining Time (minutes)	Tool Wear (µm)
1	30	9
2	60	15
3	90	19
4	120	25
5	150	30
6	180	33
7	210	37
8	240	39
9	270	42
10	300	46
11	330	49
12	360	53
13	390	56
14	420	58
15	450	60
16	480	61
17	510	63
18	540	66
19	570	68
20	600	71
21	630	73
22	660	75
23	690	76
24	720	78
25	750	79
26	780	81
27	810	84
28	840	86
29	870	88
30	900	91
31	930	93
32	960	96
33	990	98
34	1020	101
35	1050	103
36	1080	105
37	1110	108
38	1140	111
39	1170	112
40	1200	114
Total		114

Table M2 Magnitude of finishing tool wear results from Blum laser system

Workpiece No.	**Machining Time (minutes)**	**Tool Wear (µm)**
1	5	4
2	10	6
3	15	8
4	20	9
5	25	11
6	30	12
7	35	13
8	40	15
9	45	16
10	50	18
11	55	19
12	60	21
13	65	23
14	70	24
15	75	25
16	80	26
17	85	27
18	90	28
19	95	30
20	100	31
21	105	33
22	110	34
23	115	36
24	120	37
25	125	39
26	130	40
27	135	41
28	140	43
29	145	45
30	150	46
31	155	47
32	160	48
33	165	49
34	170	51
35	175	52
36	180	53
37	185	55
38	190	56
39	195	57
40	200	58
Total		58

Table M3 Cutting edge results of roughing tool from SEM

Machining Time (minutes)	**Tool Cutting Edge Radius (µm)**
0	4.5332
120	7.6343
240	8.9646
360	9.4382
480	10.1692
600	11.9811
720	13.4812
840	14.6927
960	15.9731
1080	18.8214
1200	20.8330

Table M4 Cutting edge results of finishing tool from SEM

Machining Time (minutes)	**Tool Cutting Edge Radius (µm)**
0	4.3844
20	4.8228
40	5.2087
60	5.5889
80	6.3713
100	6.4988
120	7.2136
140	8.3678
160	9.6230
180	10.7778
200	12.8108

Appendix N: Economic Data

Table N1 Operating CNC Costs

Lists	Details	Costs	Units
Energy	Electricity (current)	£0.16[1]	Pounds/kWh
Maintenance	Kern CNC	£3,256.50[2]	Pounds/year
Material	Aluminium workpiece	£2.70[3]	Pounds/workpiece
Machine Tool	Tungsten Carbine Tool	£18.45[3]	Pounds
Labour	Technician	£19.23[4]	Pounds/hour

[1] GOV (2016) Quarterly energy prices

[2] Rainford Precision Machines Limited and Brunel University London purchase orders

[3] MSC Industrial Supply Co. (2016)

[4] Human Resource Departments: Brunel University London

$$Total\ Maintenance\ Costs\ per\ year = \frac{Total\ Service\ Costs + Spare\ Parts\ Costs}{Number\ of\ Years}$$

$$= \frac{(Pump\ Spare\ Part + Service\ Cost) + (Drive\ XYZ\ Spare\ Part + Service\ Cost)}{Number\ of\ Years}$$

$$= \frac{(£8,120\ \times\ 2) + £1,374 + £1,925}{6}$$

$$= \frac{£19,539}{6}$$

$$= £3,256.5\ per\ year$$

$$= £62.625\ per\ week$$

$$= £12.525\ per\ day\ (working\ day)$$

*Brunel University bought the KERN CNC machine since 2001

$$Labour\ Costs = Average\ Technician\ Salary\ per\ annum$$

$$= £40{,}000\ per\ year$$

$$= \frac{£40{,}000}{52}\ per\ week$$

$$= £769.23\ per\ week$$

$$= \frac{£769.23}{40}\ per\ hour$$

$$= £19.23\ per\ hour$$

Rainford Precision Machines Limited
Pasture Lane Business Centre
Rainford
St Helens
Merseyside
WA11 8PU
VAT Reg No: 643 8363 24

Telephone 01744 889726
Fax 01744 885201

Quotation	Page 1

Brunel University
Finance Department
Kingston Lane
Uxbridge
Middlesex
UB8 3PH

Order No.	14743
Invoice/Tax Date	20/02/2017
Cust. Order No.	Ref: Paul Yates
Account No.	BR4493

Qty Ordered	Product Code	Product Description	Unit Price	Net Price
0.00	M	ESTIMATED Service Costs re on site visit for KERN HSPC Serial No 392 NB - This does not include spare parts.	£0.00	£0.00
1.00	200000128	Check up of all axis X, Y and Z by a KGM	£0.00	£0.00
20.00	BLCS-0001	Working Time External (per hour)	£0.00	£0.00
12.00	BLCS-1001	Travelling Time (per hour)	£0.00	£0.00
1.00	200000095	Rental Car	£0.00	£0.00
1.00	200000015	Flight Costs	£0.00	£0.00
1.00	200000016	Airport Transfer	£0.00	£0.00
4.00	200000017	Overnight Accommodation	£0.00	£0.00
5.00	200000019	Expenses	£0.00	£0.00
1.00	200000020	Service Preparation Costs I	£0.00	£0.00
1.00	9999	ESTIMATED Total Service Cost re on site visit for KERN HSPC Serial No 392. This does not include any required spare parts.	£8,120.00	£8,120.00

NB The service offer is based on necessary service due to normal wear and tear and according to requirement. Any additions or extras required due to extended maintenance will be added to your account. The machine will not be refurbished. The offer is just a suggestion. When the machine is being serviced spare parts will be exchanged according to requirement and invoiced to our actual assembly and start-up costs.

Figure N1. Estimated KERN CNC machine total service costs

Official Purchase Order (305/44689)

Brunel University London

RAINFORD PRECISION MACHINES

Transmitted By email to sales@rainfordprecision.com

Order No 305/44689
Order Date 02/10/2013 3:47PM
Requested By Paul Yates
School of Engineering and Design
Paul.Yates@brunel.ac.uk

paul yates pump for kern 02/10/2013 2:13PM

Order Description paul yates pump for kern 02/10/2013 2:13PM

Comments

please ensure that Attention of Paul Yates is on the delivery address .

please ensure that Attention of Paul Yates is on the delivery address .

Please supply the following goods or services

No	Item Code / Job	Product / Service Description	Unit Price	Qty	VAT	Total
1		Pump for Kern Machine	£1045.00 / Each	1	£209.00	**£1045.00**
2		Packing, Tansport , Insurance appox cost	£100.00 / Each	1	£20.00	**£100.00**
				Total (excl.VAT)		**£1145.00**
				VAT		**£229.00**
				Total (incl.VAT)		**£1374.00**

Delivery Address: Distribution Centre / Paul Yates

Ship to:

Distribution Centre
Brunel University
Kingston Lane
Uxbridge UB8 3PH
Middlesex
UK

Mark For:

Name Paul Yates
Room Workshop
Building Joesph lowe
Delivery Date 07/10/2013
Tel No 01895266598
Email paul.yates@brunel.ac.uk

Payment Method: To Be Invoiced - Finance Dept (Payments)

Brunel University
Kingston Lane
Uxbridge
UB8 3PH

Payment Type To Be Invoiced
Name on Invoice Finance Dept (Payments)
Cheque with Order No

Important Instructions to Suppliers/Vendors:

Invoicing to Brunel University other than by POST:

Suppliers where possible should log into Brunel's Supplier Portal to register their invoices. For Portal logging in queries please contact procurement@brunel.ac.uk in the first instance

Terms and Conditions:

University's standard conditions of contract can be obtained from the Procurement Department at procurement@brunel.ac.uk

Page 1 of 1

Figure N2. Replacement KERN CNC pump costs

Rainford Precision Machines Limited
Pasture Lane Business Centre
Rainford
St Helens
Merseyside

VAT Reg No: 643 8363 24
Tel No: 01744 889726
Fax No: 01744 885201

Quotation Page 1

Brunel University
Finance Department
Kingston Lane
Uxbridge
Middlesex
UB8 3PH

Order No.	6884
Invoice/Tax Date	29/05/2012
Cust. Order No.	Ref: Paul Yates
Account No.	BR4493

Qty	Product Code	Product Description	**Unit Price**	**Net Price**
0.00	M	Spare Parts for KERN HSPC Serial Number 392	£0.00	£0.00
1.00	110420001	Drive XYZ, digital	£1,925.00	£1,925.00
1.00	9997	Packing, transport and insurance to be charged extra at cost	£0.00	£0.00

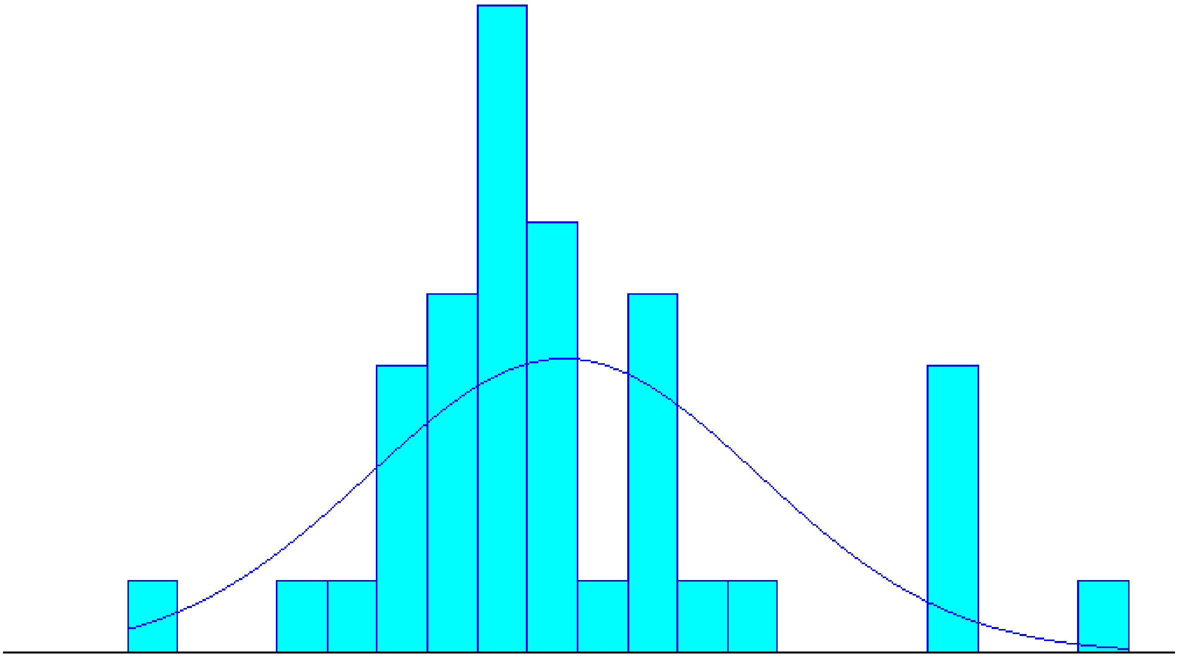
Delivery Address
Brunel University
Central Stores
Kingston Lane
Uxbridge
Middlesex
UB8 3PH

Figure N3. Replacement KERN CNC drive XYZ costs

Appendix O: CNC Milling Production Data

Table O1 CNC milling machine operating time for aluminium cutting

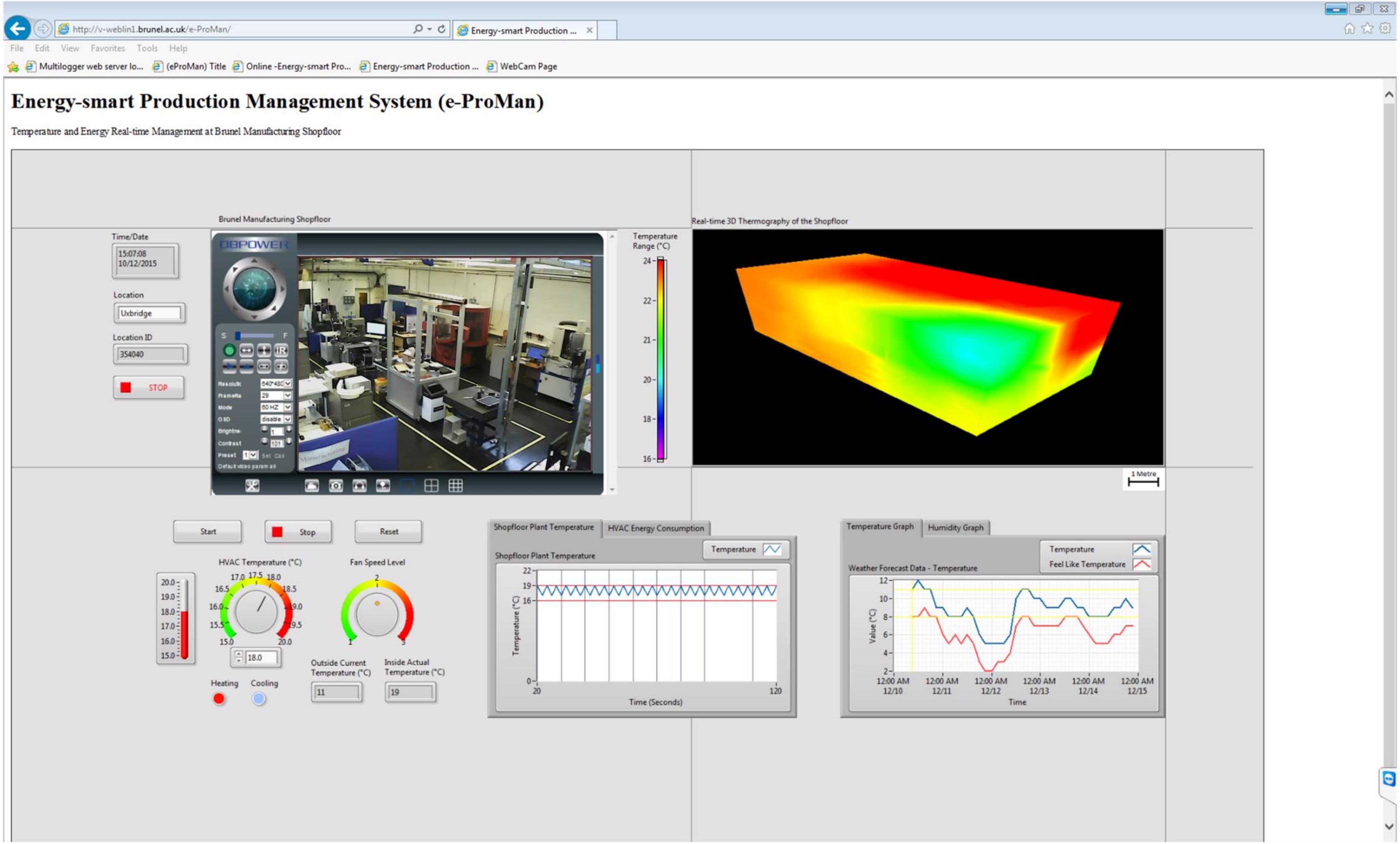
	Operation Time	
	Minutes	Seconds
1	34.93	2096
2	35.35	2121
3	34.64	2079
4	34.64	2079
5	34.99	2099
6	34.64	2078
7	34.99	2099
8	34.64	2078
9	35.68	2141
10	34.60	2076
11	34.95	2097
12	34.60	2076
13	35.29	2118
14	34.59	2075
15	34.93	2096
16	35.63	2138
17	34.92	2095
18	35.27	2116
19	34.92	2095
20	35.61	2137
21	34.90	2094
22	35.60	2136
23	34.53	2072
24	34.88	2093
25	35.23	2114
26	34.87	2092
27	35.57	2134
28	34.50	2070
29	34.85	2091
30	35.20	2112
31	34.49	2070
32	34.67	2080
33	35.01	2101
34	35.08	2105
35	35.22	2113
36	35.19	2111
37	34.80	2088
38	34.81	2089
39	34.82	2089
40	35.17	2110



```
        Distribution Summary

Distribution:   Normal
Expression:     NORM(2.1e+003, 15.8)
Square Error:   0.047624

Chi Square Test
  Number of intervals   = 6
  Degrees of freedom    = 3
  Test Statistic        = 12.5
  Corresponding p-value = 0.00605

        Data Summary

Number of Data Points   = 40
Min Data Value          = 2.07e+003
Max Data Value          = 2.15e+003
Sample Mean             = 2.1e+003
Sample Std Dev          = 16

        Histogram Summary

Histogram Range         = 2.07e+003 to 2.15e+003
```

Figure O1. Chi-Square Test of CNC milling operating time for cutting aluminium workpiece data

Appendix P: e-ProMan Web-based User Interface


http://v-weblin1.brunel.ac.uk/e-ProMan/
Energy-smart Production ...
File Edit View Favorites Tools Help
Multilogger web server lo... (eProMan) Title Online -Energy-smart Pro... Energy-smart Production ... WebCam Page
Energy-smart Production Management System (e-ProMan)
Temperature and Energy Real-time Management at Brunel Manufacturing Shopfloor
Brunel Manufacturing Shopfloor
Real-time 3D Thermography of the Shopfloor
Time/Date
15:07:08
10/12/2015
Location
Uxbridge
Location ID
354040
STOP
Temperature Range (°C)
24
22
21
20
18
16
1 Metre
Start
Stop
Reset
HVAC Temperature (°C)
Fan Speed Level
18.0
Heating
Cooling
Outside Current Temperature (°C)
11
Inside Actual Temperature (°C)
19
Shopfloor Plant Temperature
HVAC Energy Consumption
Temperature
Time (Seconds)
Temperature Graph
Humidity Graph
Weather Forecast Data - Temperature
Feel Like Temperature
Value (°C)
12:00 AM 12/10
12:00 AM 12/11
12:00 AM 12/12
12:00 AM 12/13
12:00 AM 12/14
12:00 AM 12/15
Time

Appendix Q:

Parts of LabVIEW Programming

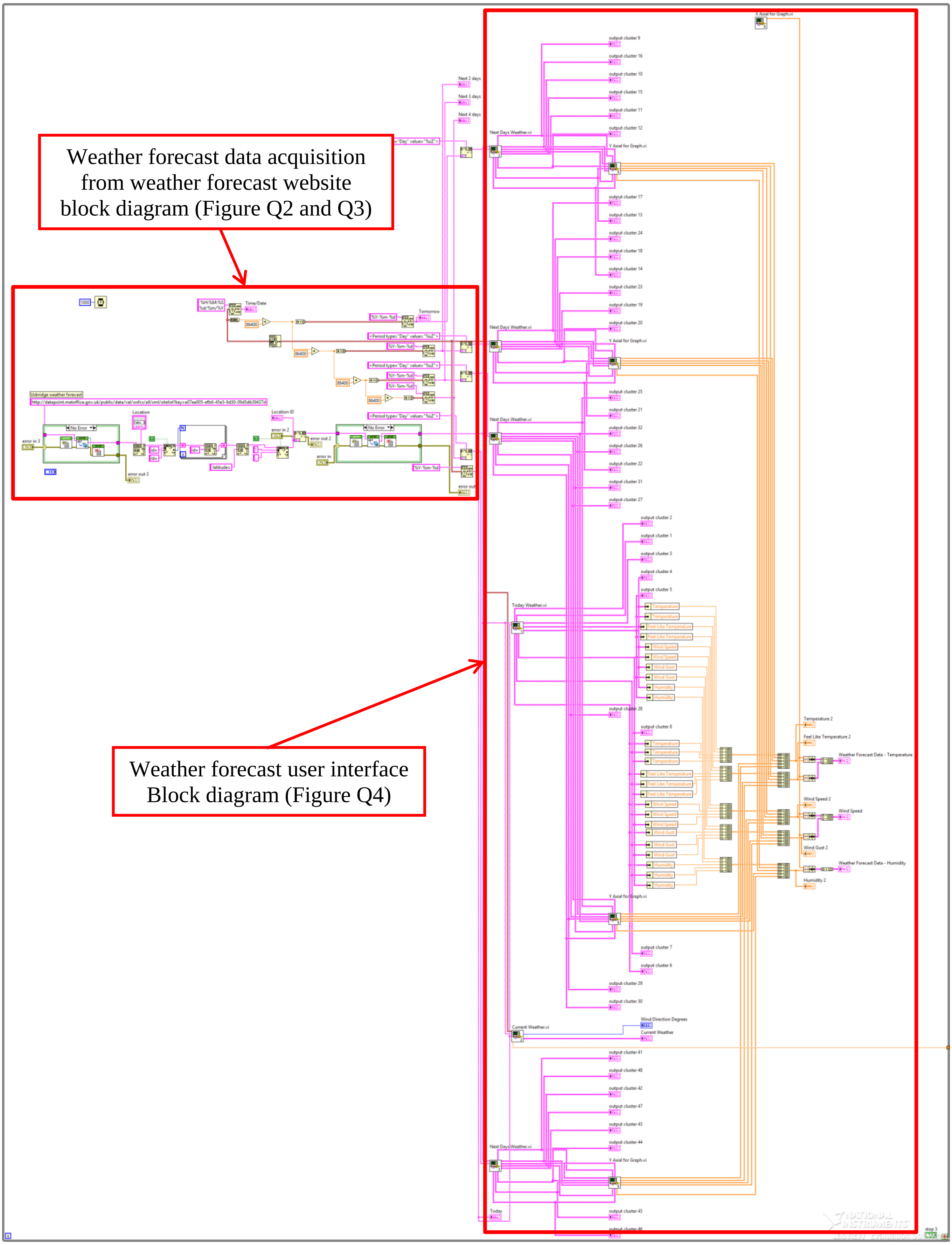


Figure Q1. Block diagram for weather forecast overview of data acquisition

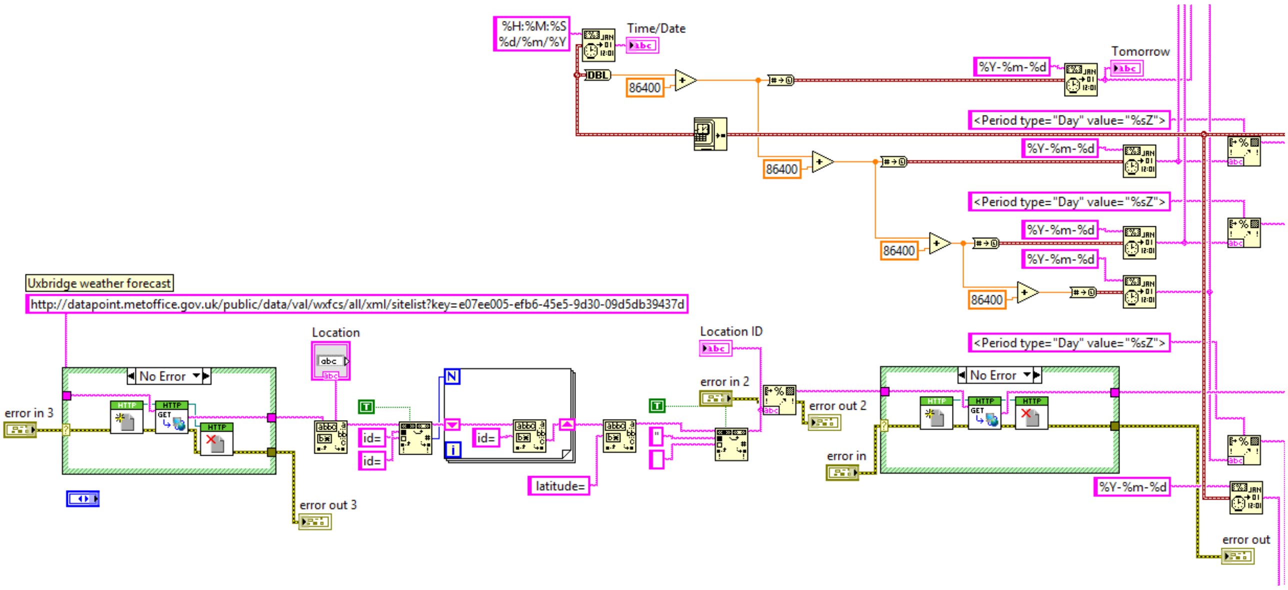


Figure Q2. Block diagram for weather forecast data acquisition from weather forecast website

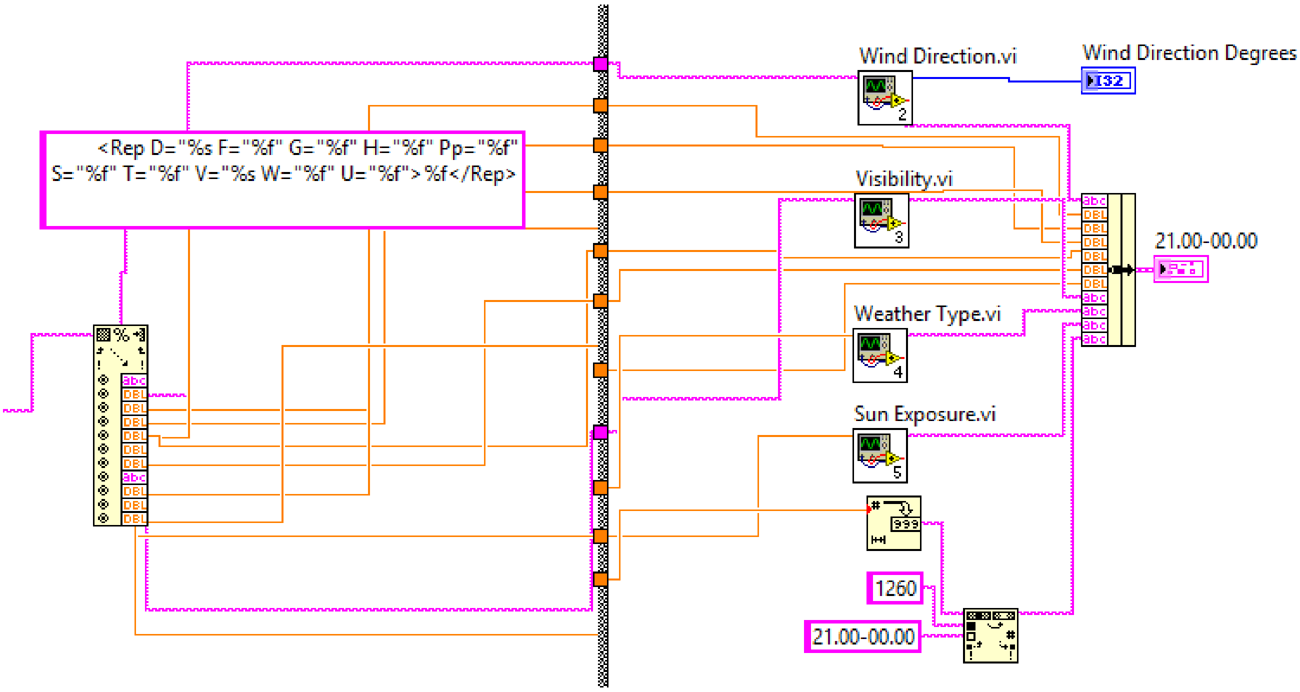


Figure Q3. Block diagram for weather forecast user interface

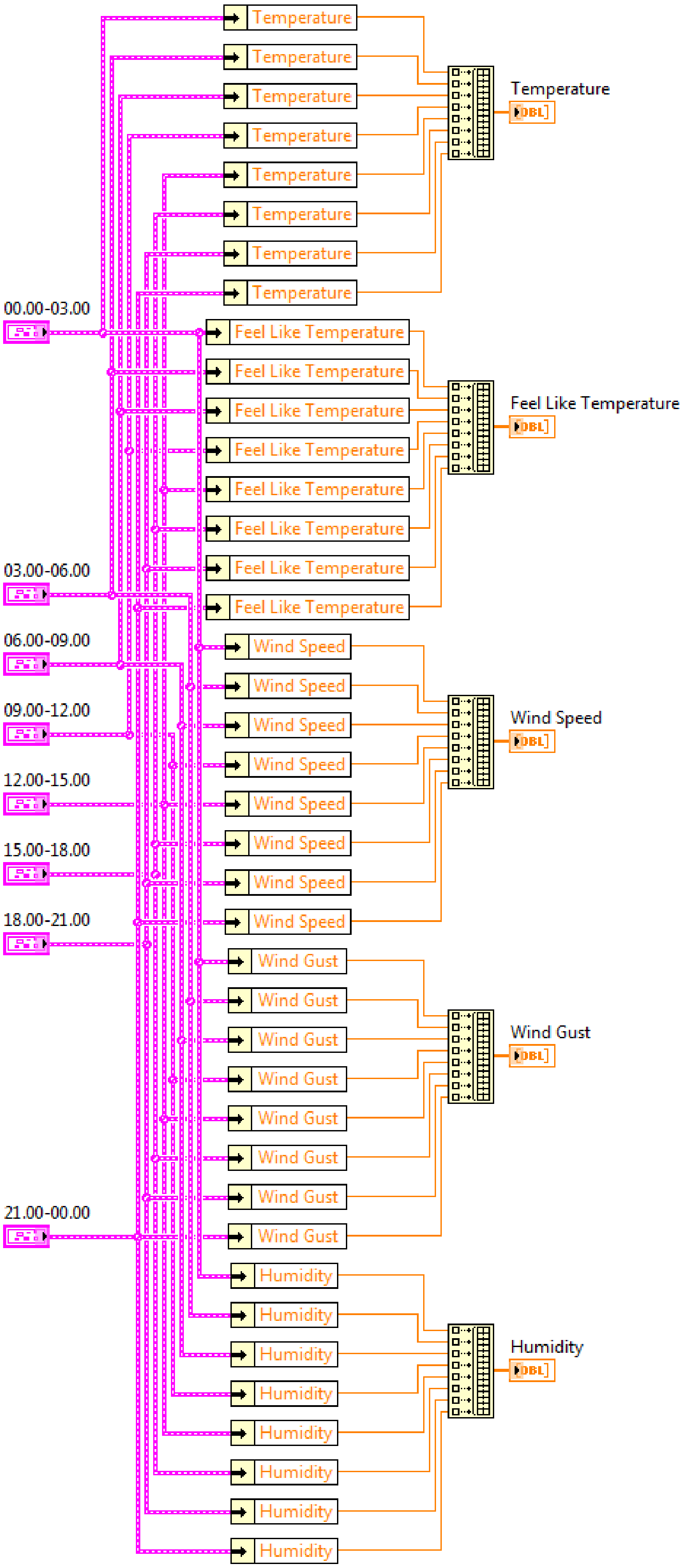


Figure Q4. Block diagram for weather forecast 3-hours interval display

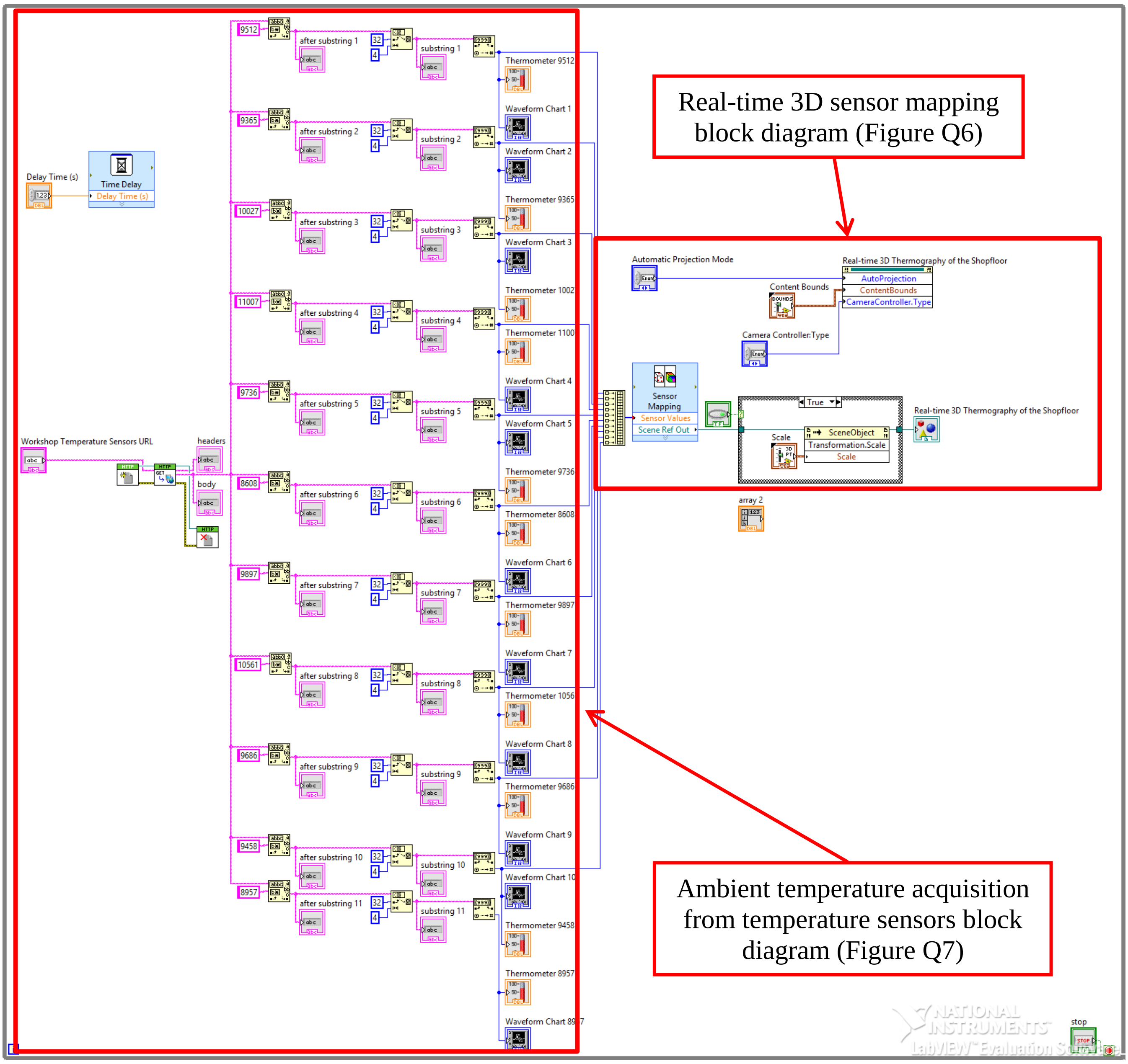


Figure Q5. Block diagram for overview of laboratory ambient temperature data acquisition

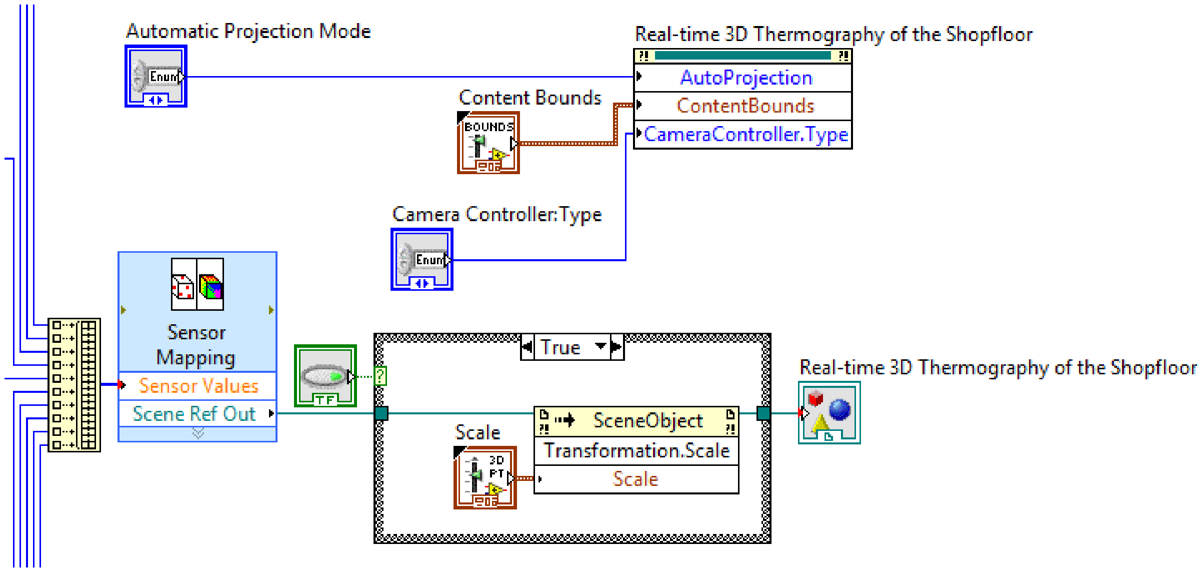


Figure Q6. Block diagram for real-time 3D sensor mapping

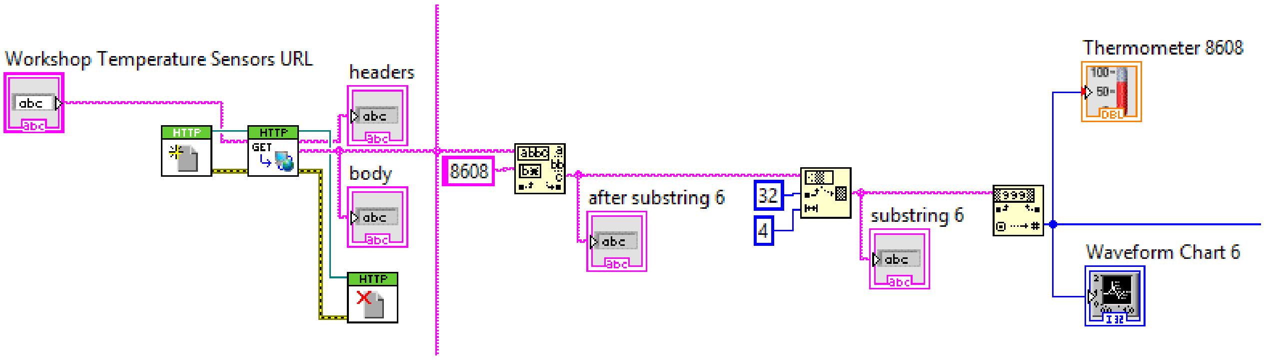


Figure Q7. Block diagram for ambient temperature acquisition from temperature sensors

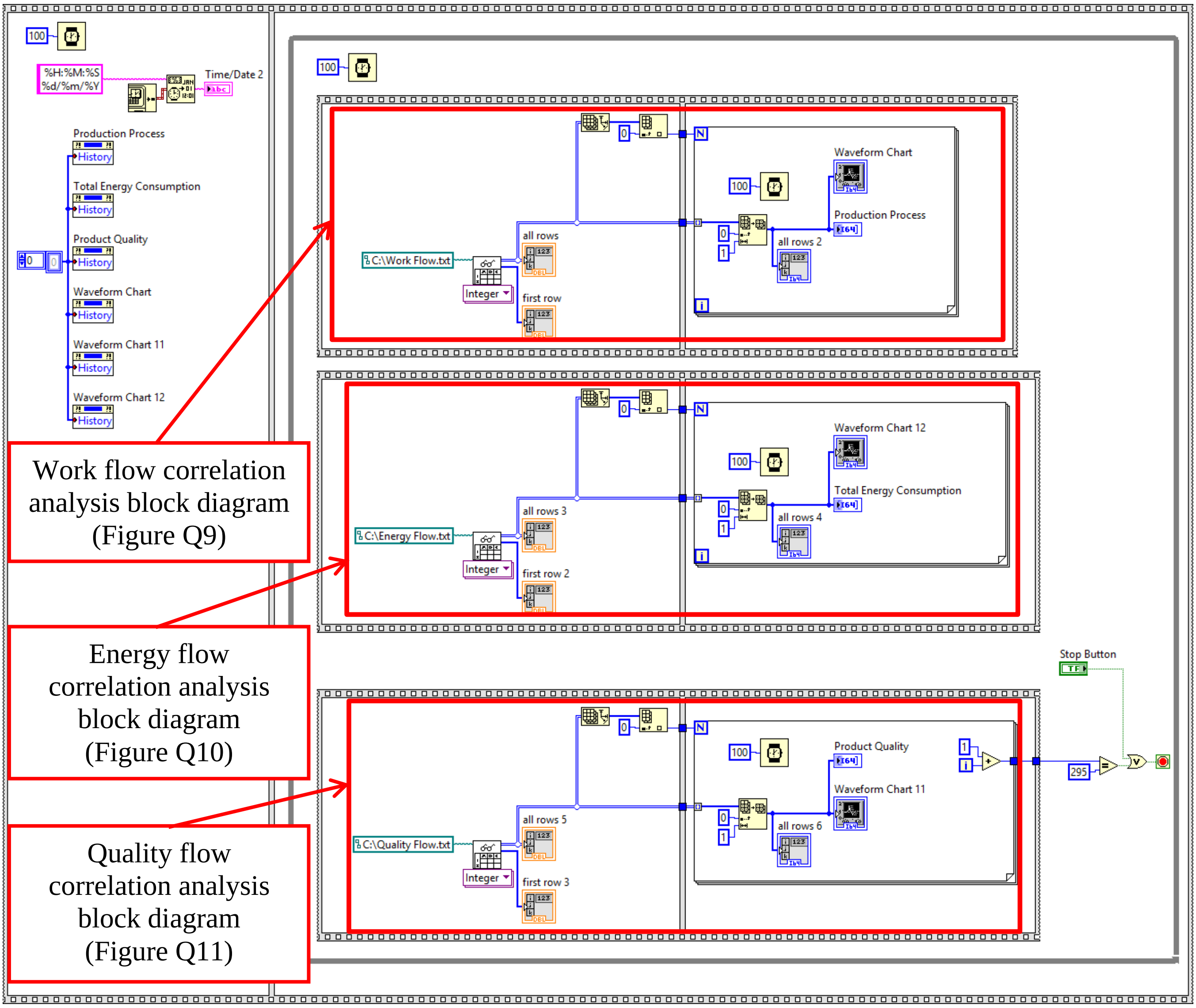


Figure Q8. Block diagram for three dimensional correlation analysis of work flow, energy flow and quality flow

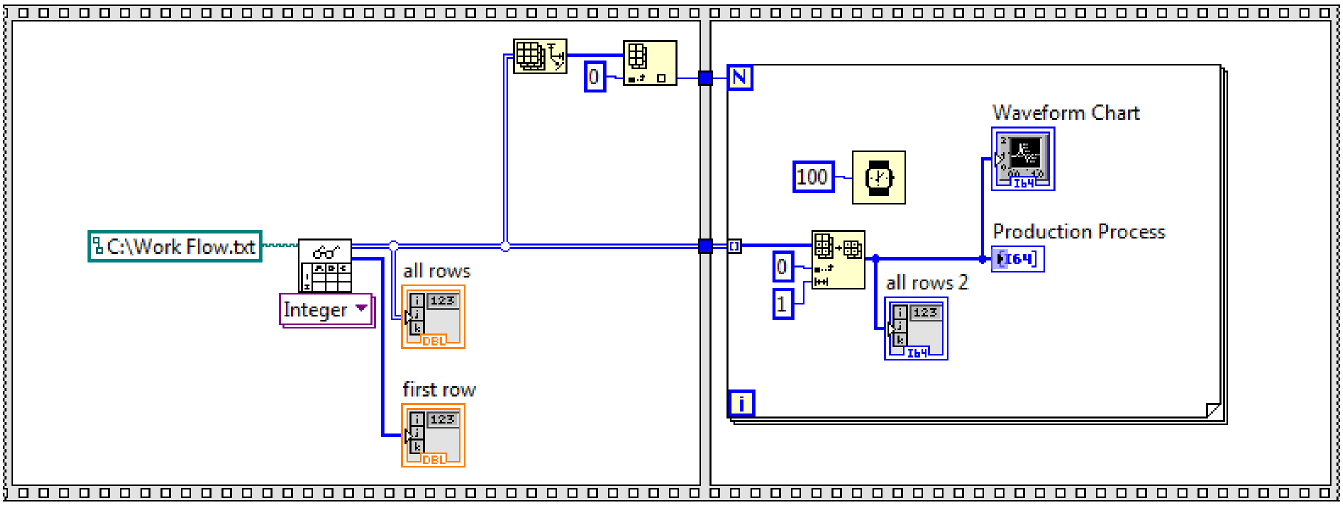


Figure Q9. Block diagram for work flow correlation analysis

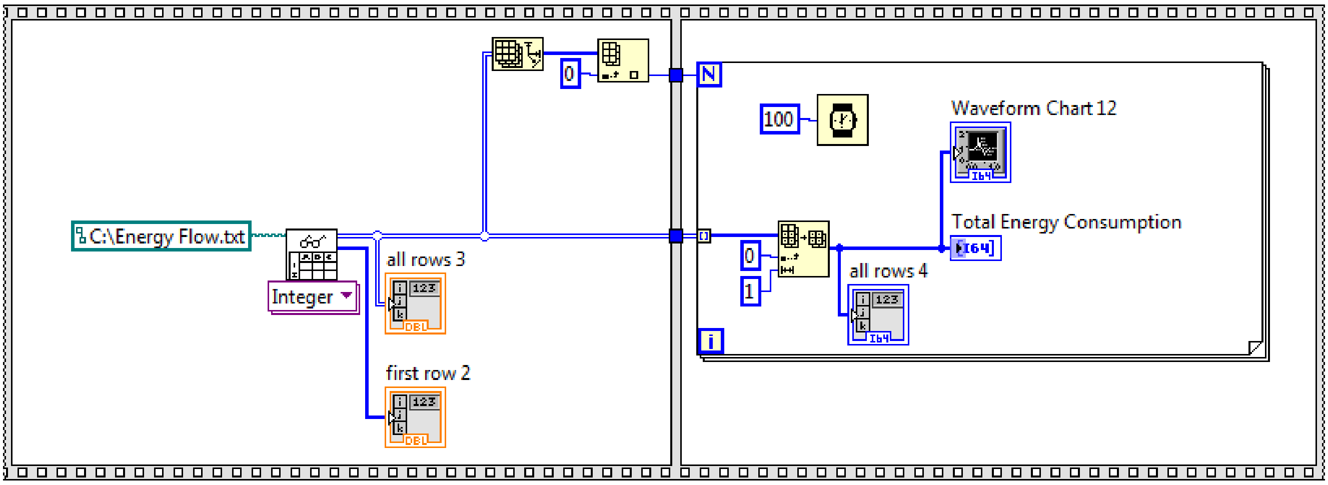


Figure Q10. Block diagram for energy flow correlation analysis

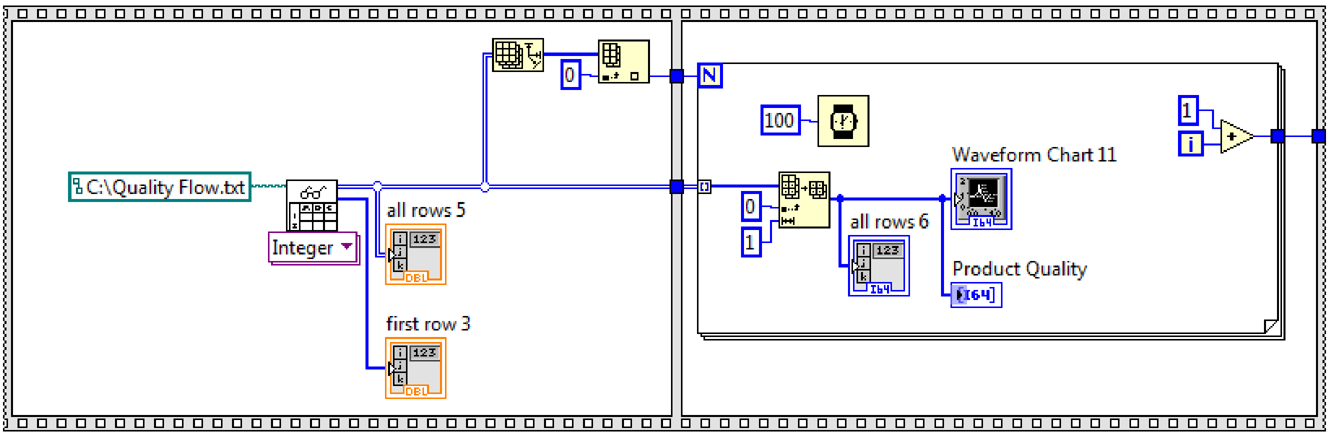


Figure Q11. Block diagram for quality flow correlation analysis

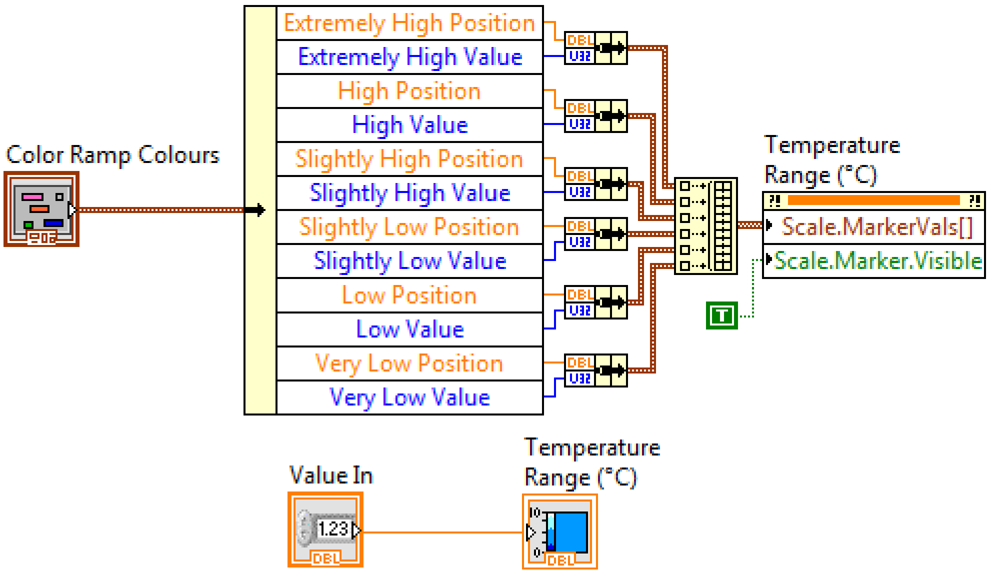


Figure Q12. Block diagram for 3D temperature range

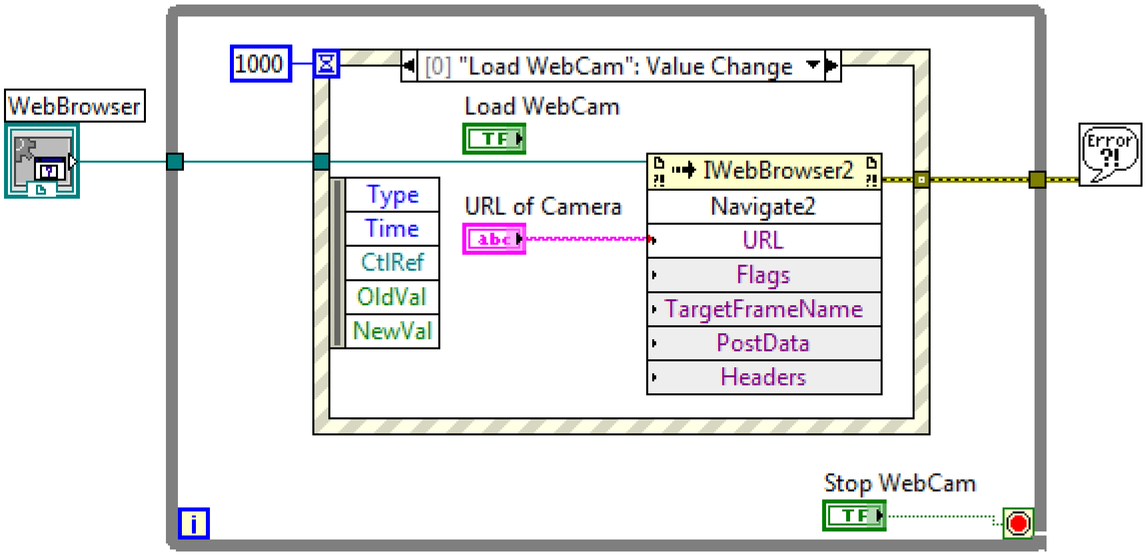


Figure Q13. Block diagram for virtual manufacturing display

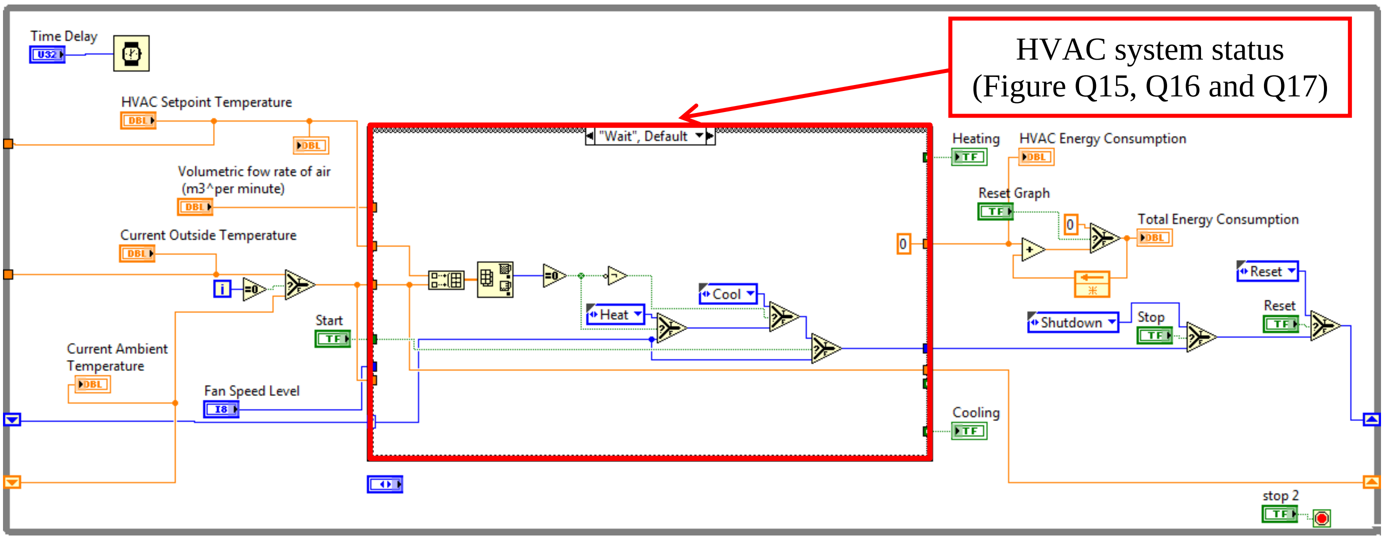


Figure Q14. Block diagram for HVAC system algorithm overview

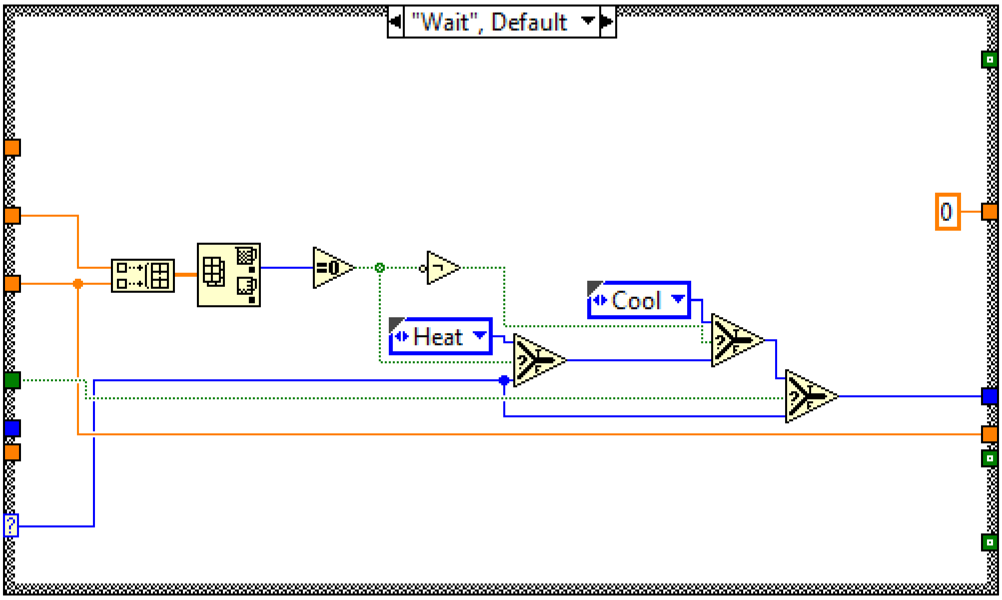


Figure Q15. Block diagram for HVAC algorithm of checking condition

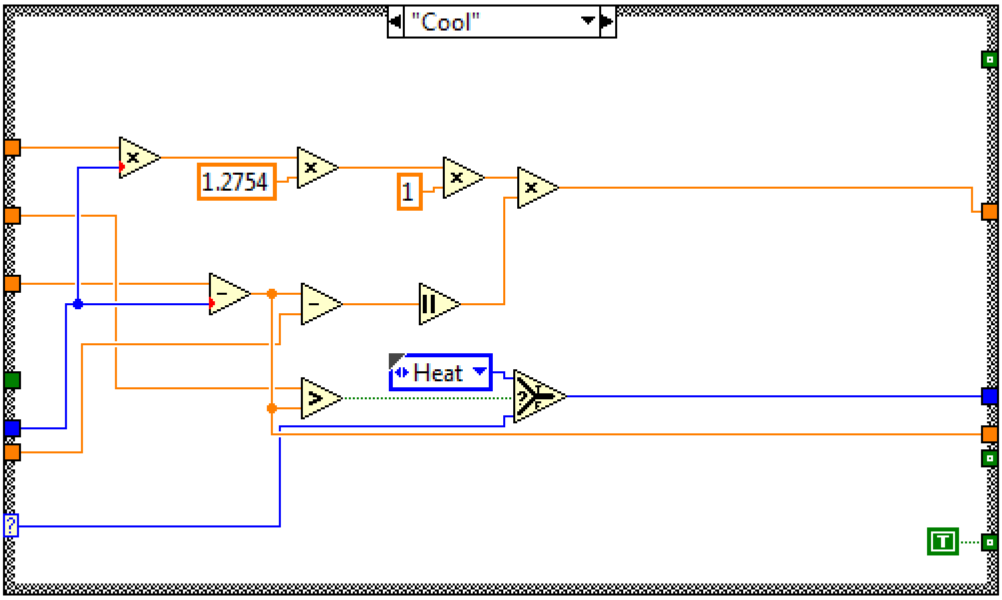


Figure Q16. Block diagram for HVAC algorithm of air conditioning

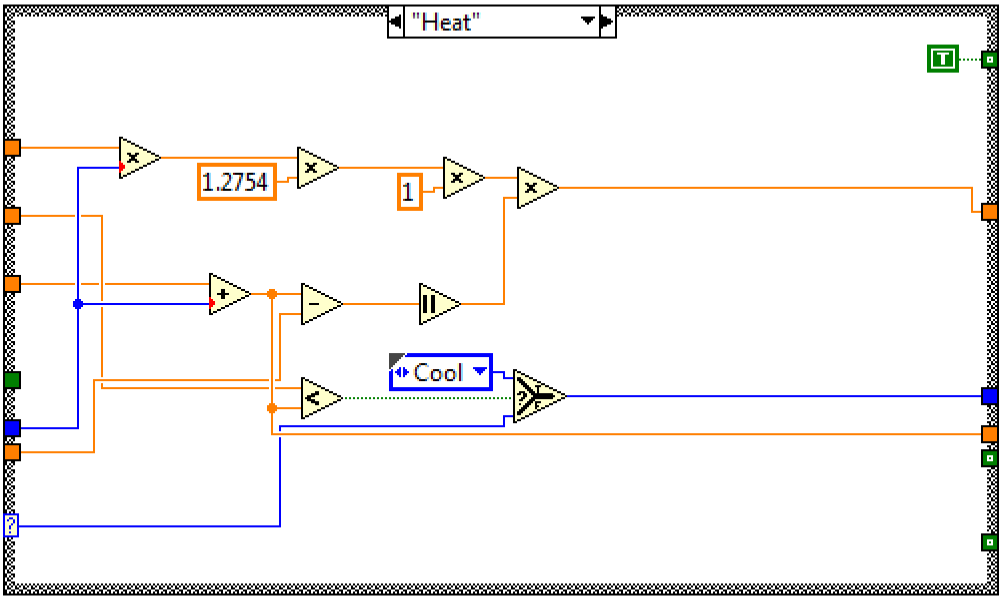


Figure Q17. Block diagram for HVAC algorithm of heating

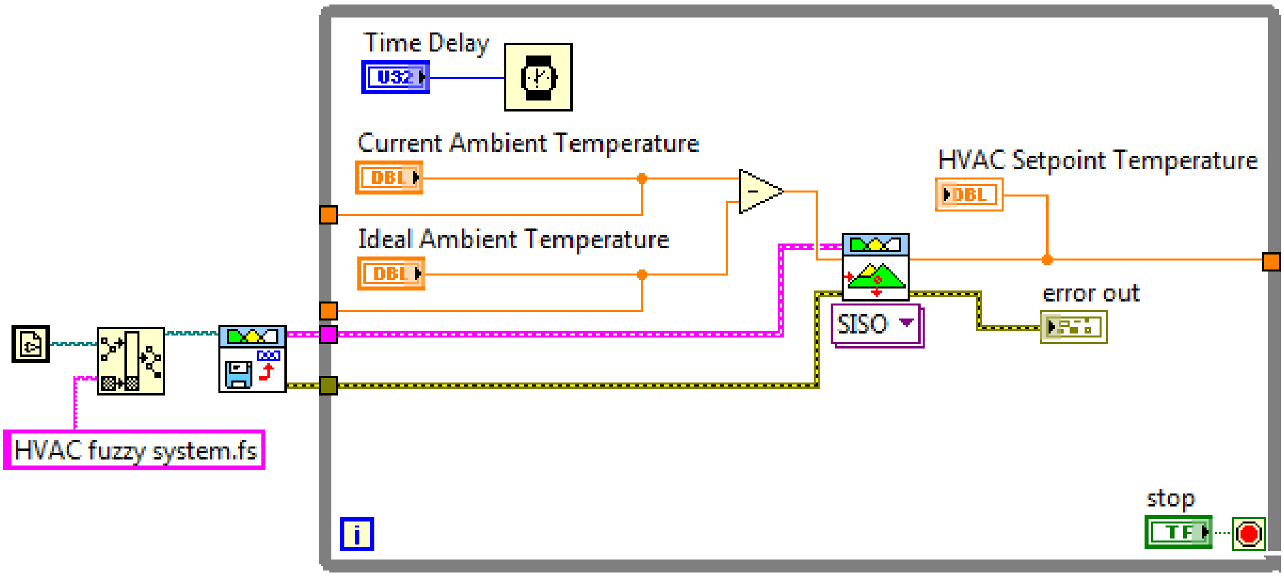


Figure Q18. Block diagram for regular HVAC system fuzzy logic controller

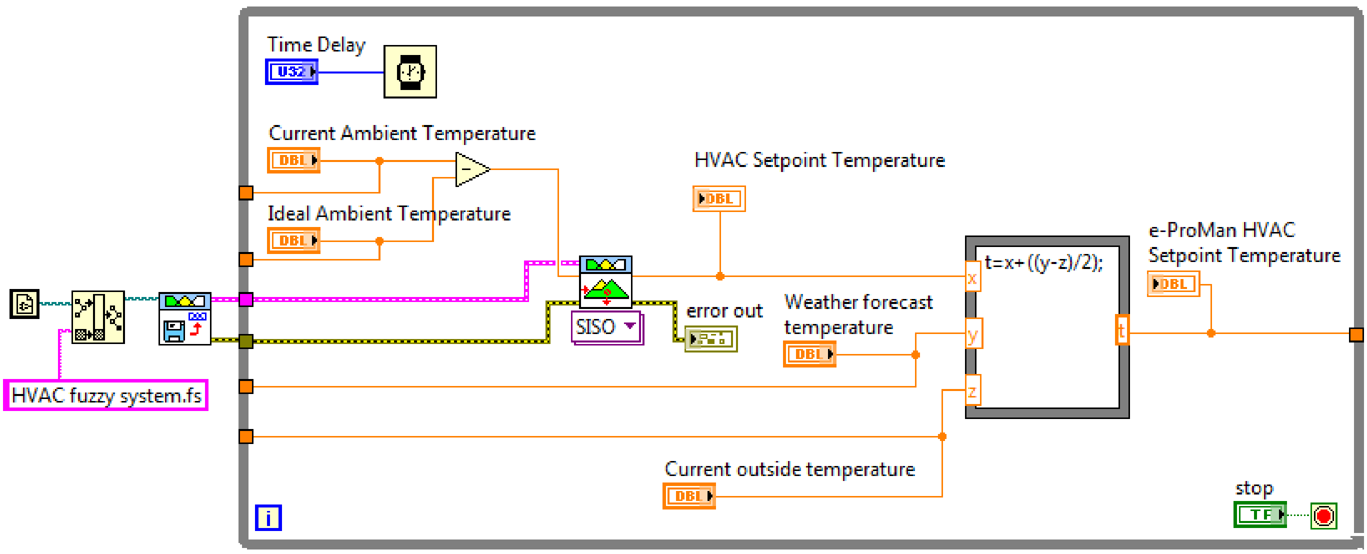


Figure Q19. Block diagram for e-ProMan HVAC system fuzzy logic controller

```xml
<SiteRep>
  <Wx>
    <Param name="F" units="C">Feels Like Temperature</Param>
    <Param name="G" units="mph">Wind Gust</Param>
    <Param name="H" units="%">Screen Relative Humidity</Param>
    <Param name="T" units="C">Temperature</Param>
    <Param name="V" units="">Visibility</Param>
    <Param name="D" units="compass">Wind Direction</Param>
    <Param name="S" units="mph">Wind Speed</Param>
    <Param name="U" units="">Max UV Index</Param>
    <Param name="W" units="">Weather Type</Param>
    <Param name="Pp" units="%">Precipitation Probability</Param>
  </Wx>
  <DV dataDate="2016-11-15T06:00:00Z" type="Forecast">
    <Location i="354040" lat="51.5481" lon="-0.4781" name="UXBRIDGE" country="ENGLAND"
    continent="EUROPE" elevation="42.0">
      <Period type="Day" value="2016-11-15Z">
        <Rep D="WSW" F="11" G="16" H="94" Pp="10" S="7" T="12" V="MO" W="8" U="0">180</Rep>
        <Rep D="WSW" F="11" G="20" H="93" Pp="9" S="9" T="13" V="MO" W="8" U="0">360</Rep>
        <Rep D="W" F="12" G="16" H="95" Pp="5" S="7" T="13" V="MO" W="7" U="1">540</Rep>
        <Rep D="W" F="13" G="16" H="91" Pp="6" S="9" T="14" V="GO" W="7" U="1">720</Rep>
        <Rep D="W" F="13" G="13" H="93" Pp="12" S="7" T="14" V="MO" W="8" U="1">900</Rep>
        <Rep D="WSW" F="12" G="13" H="95" Pp="11" S="7" T="13" V="MO" W="8" U="0">1080</Rep>
        <Rep D="WSW" F="11" G="16" H="96" Pp="12" S="7" T="13" V="MO" W="8" U="0">1260</Rep>
      </Period>
      <Period type="Day" value="2016-11-16Z">
        <Rep D="WSW" F="11" G="18" H="96" Pp="44" S="9" T="13" V="GO" W="8" U="0">0</Rep>
        <Rep D="SW" F="10" G="22" H="95" Pp="21" S="11" T="12" V="GO" W="8" U="0">180</Rep>
        <Rep D="WSW" F="10" G="25" H="93" Pp="53" S="11" T="12" V="GO" W="12" U="0">360</Rep>
        <Rep D="WSW" F="10" G="25" H="87" Pp="28" S="13" T="12" V="GO" W="10" U="1">540</Rep>
        <Rep D="WSW" F="10" G="27" H="75" Pp="5" S="13" T="13" V="VG" W="7" U="1">720</Rep>
        <Rep D="WSW" F="10" G="25" H="78" Pp="11" S="11" T="12" V="VG" W="7" U="1">900</Rep>
        <Rep D="W" F="9" G="20" H="83" Pp="13" S="9" T="11" V="GO" W="7" U="0">1080</Rep>
        <Rep D="WSW" F="7" G="18" H="81" Pp="12" S="9" T="9" V="VG" W="7" U="0">1260</Rep>
      </Period>
      <Period type="Day" value="2016-11-17Z">
        <Rep D="WSW" F="6" G="16" H="84" Pp="6" S="9" T="8" V="VG" W="7" U="0">0</Rep>
        <Rep D="SW" F="5" G="18" H="87" Pp="7" S="9" T="7" V="VG" W="7" U="0">180</Rep>
        <Rep D="SW" F="5" G="18" H="85" Pp="9" S="9" T="7" V="VG" W="7" U="0">360</Rep>
        <Rep D="SW" F="5" G="22" H="83" Pp="10" S="11" T="8" V="VG" W="7" U="1">540</Rep>
        <Rep D="SW" F="7" G="31" H="77" Pp="15" S="16" T="10" V="GO" W="3" U="1">720</Rep>
        <Rep D="SW" F="7" G="31" H="81" Pp="47" S="16" T="10" V="GO" W="10" U="1">900</Rep>
        <Rep D="WSW" F="5" G="25" H="82" Pp="39" S="13" T="8" V="VG" W="9" U="0">1080</Rep>
        <Rep D="SW" F="3" G="22" H="82" Pp="9" S="11" T="7" V="VG" W="2" U="0">1260</Rep>
      </Period>
      <Period type="Day" value="2016-11-18Z">
        <Rep D="SW" F="2" G="22" H="81" Pp="5" S="11" T="6" V="VG" W="7" U="0">0</Rep>
        <Rep D="SW" F="1" G="20" H="84" Pp="1" S="9" T="5" V="VG" W="2" U="0">180</Rep>
        <Rep D="SW" F="0" G="18" H="84" Pp="1" S="9" T="4" V="VG" W="0" U="0">360</Rep>
        <Rep D="SW" F="1" G="18" H="82" Pp="2" S="9" T="4" V="VG" W="1" U="1">540</Rep>
        <Rep D="WSW" F="4" G="25" H="67" Pp="3" S="11" T="7" V="VG" W="3" U="1">720</Rep>
        <Rep D="WSW" F="4" G="20" H="68" Pp="12" S="11" T="7" V="VG" W="7" U="1">900</Rep>
        <Rep D="SW" F="2" G="16" H="81" Pp="5" S="9" T="5" V="VG" W="7" U="0">1080</Rep>
        <Rep D="SW" F="1" G="16" H="86" Pp="2" S="7" T="4" V="VG" W="2" U="0">1260</Rep>
      </Period>
      <Period type="Day" value="2016-11-19Z">
        <Rep D="SW" F="0" G="13" H="88" Pp="4" S="7" T="3" V="VG" W="7" U="0">0</Rep>
        <Rep D="SW" F="0" G="13" H="89" Pp="5" S="7" T="3" V="VG" W="7" U="0">180</Rep>
        <Rep D="SW" F="-1" G="13" H="90" Pp="3" S="7" T="2" V="VG" W="2" U="0">360</Rep>
        <Rep D="SW" F="0" G="13" H="88" Pp="1" S="7" T="3" V="VG" W="1" U="1">540</Rep>
        <Rep D="SW" F="4" G="18" H="75" Pp="3" S="9" T="7" V="VG" W="3" U="1">720</Rep>
        <Rep D="SW" F="5" G="16" H="74" Pp="10" S="7" T="7" V="VG" W="7" U="1">900</Rep>
        <Rep D="SSW" F="3" G="13" H="86" Pp="7" S="7" T="5" V="GO" W="7" U="0">1080</Rep>
        <Rep D="S" F="2" G="16" H="88" Pp="14" S="9" T="5" V="GO" W="7" U="0">1260</Rep>
      </Period>
```


Figure Q20. Weather forecast Met Office weather data acquisition

```
<Location elevation="177.0" id="99081" latitude="50.767" longitude="-3.9" name="North Wyke"
region="sw" unitaryAuthArea="Devon"/>
<Location elevation="43.0" id="99086" latitude="54.667" longitude="-5.75" name="Helens Bay"
region="ni" unitaryAuthArea="County Down"/>
<Location elevation="178.0" id="99093" latitude="52.99" longitude="-2.27" name="Keele"
region="wm" unitaryAuthArea="Staffordshire"/>
<Location elevation="99.0" id="3520" latitude="52.242" longitude="-2.885" name="Shobdon Saws"
region="wm" unitaryAuthArea="Herefordshire"/>
<Location elevation="75.0" id="3522" latitude="52.083" longitude="-2.8" name="Hereford"
region="wm" unitaryAuthArea="Herefordshire"/>
<Location elevation="96.0" id="3535" latitude="52.48" longitude="-1.689" name="Coleshill"
region="wm" unitaryAuthArea="Warwickshire"/>
<Location elevation="85.0" id="3560" latitude="52.225" longitude="-0.464" name="Bedford"
region="ee" unitaryAuthArea="Bedford"/>
<Location elevation="3.0" id="3605" latitude="51.713" longitude="-4.368" name="Pembrey Sands
Samos" region="wl" unitaryAuthArea="Carmarthenshire"/>
<Location elevation="210.0" id="3647" latitude="51.86" longitude="-1.692" name="Little
Rissington (Esaws)" region="sw" unitaryAuthArea="Gloucestershire"/>
<Location elevation="204.0" id="3660" latitude="51.68" longitude="-0.802" name="High Wycombe"
region="se" unitaryAuthArea="Buckinghamshire"/>
<Location elevation="113.0" id="3670" latitude="51.6169" longitude="-0.4" name="Northwood"
region="ee" unitaryAuthArea="Hertfordshire"/>
<Location elevation="87.0" id="3684" latitude="51.896" longitude="0.453" name="Andrewsfield"
region="ee" unitaryAuthArea="Essex"/>
<Location elevation="49.0" id="3716" latitude="51.405" longitude="-3.44" name="St-Athan"
region="wl" unitaryAuthArea="Vale of Glamorgan"/>
<Location elevation="145.0" id="3740" latitude="51.5031" longitude="-1.9924" name="Lyneham"
region="sw" unitaryAuthArea="Wiltshire"/>
<Location elevation="72.0" id="3768" latitude="51.279" longitude="-0.772" name="Farnborough"
region="se" unitaryAuthArea="Hampshire"/>
<Location elevation="113.0" id="3153" latitude="54.803" longitude="-4.008" name="Dundrennan"
region="dg" unitaryAuthArea="Dumfries and Galloway"/>
<Location elevation="245.0" id="3155" latitude="55.627" longitude="-3.735" name="Drumalbin"
region="st" unitaryAuthArea="South Lanarkshire"/>
<Location elevation="242.0" id="3162" latitude="55.311" longitude="-3.206" name="Eskdalemuir"
region="dg" unitaryAuthArea="Dumfries and Galloway"/>
<Location elevation="57.0" id="3166" latitude="55.928" longitude="-3.343"
name="Edinburgh/Gogarbank" region="dg" unitaryAuthArea="Edinburgh"/>
<Location elevation="227.0" id="3226" latitude="54.572" longitude="-2.413" name="Warcop"
region="nw" unitaryAuthArea="Cumbria"/>
<Location elevation="211.0" id="3230" latitude="55.285" longitude="-2.279" name="Redesdale Camp
(Samos)" nationalPark="Northumberland National Park" region="ne"
unitaryAuthArea="Northumberland"/>
<Location elevation="146.0" id="3238" latitude="55.02" longitude="-1.88" name="Albemarle"
region="ne" unitaryAuthArea="Northumberland"/>
<Location elevation="32.0" id="3257" latitude="54.296" longitude="-1.53" name="Leeming"
region="yh" unitaryAuthArea="North Yorkshire"/>
<Location elevation="33.0" id="3261" latitude="54.134" longitude="-1.414" name="Dishforth
Airfield" region="yh" unitaryAuthArea="North Yorkshire"/>
<Location elevation="14.0" id="3266" latitude="54.045" longitude="-1.25" name="Linton On Ouse"
region="yh" unitaryAuthArea="North Yorkshire"/>
<Location elevation="9.0" id="3407" latitude="52.802" longitude="-4.124" name="Llanbedr"
nationalPark="Snowdonia National Park" region="wl" unitaryAuthArea="Gwynedd"/>
<Location elevation="138.0" id="3453" latitude="52.727" longitude="-0.654" name="Cottesmore"
region="em" unitaryAuthArea="Rutland"/>
<Location elevation="73.0" id="3462" latitude="52.6111" longitude="-0.459" name="Wittering"
region="ee" unitaryAuthArea="Peterborough"/>
<Location elevation="21.0" id="3482" latitude="52.651" longitude="0.569" name="Marham"
region="ee" unitaryAuthArea="Norfolk"/>
<Location elevation="42.0" id="300689" latitude="55.8062" longitude="-4.57112" name="Howwood"
region="st" unitaryAuthArea="Renfrewshire"/>
<Location elevation="19.0" id="310012" latitude="53.4113" longitude="-2.9887" name="Liverpool"
region="nw" unitaryAuthArea="Merseyside"/>
<Location elevation="4.0" id="310153" latitude="50.4614" longitude="-3.5241" name="Torquay"
region="sw" unitaryAuthArea="Torbay"/>
<Location elevation="22.0" id="310191" latitude="50.7623" longitude="-1.2991" name="Cowes"
region="se" unitaryAuthArea="Isle of Wight"/>
<Location elevation="28.0" id="310202" latitude="51.2047" longitude="-4.1256" name="Ilfracombe"
region="sw" unitaryAuthArea="Devon"/>
```


Figure Q21. Weather forecast Met Office location data acquisition

Appendix R:

Parts of Arena Simulation Programming

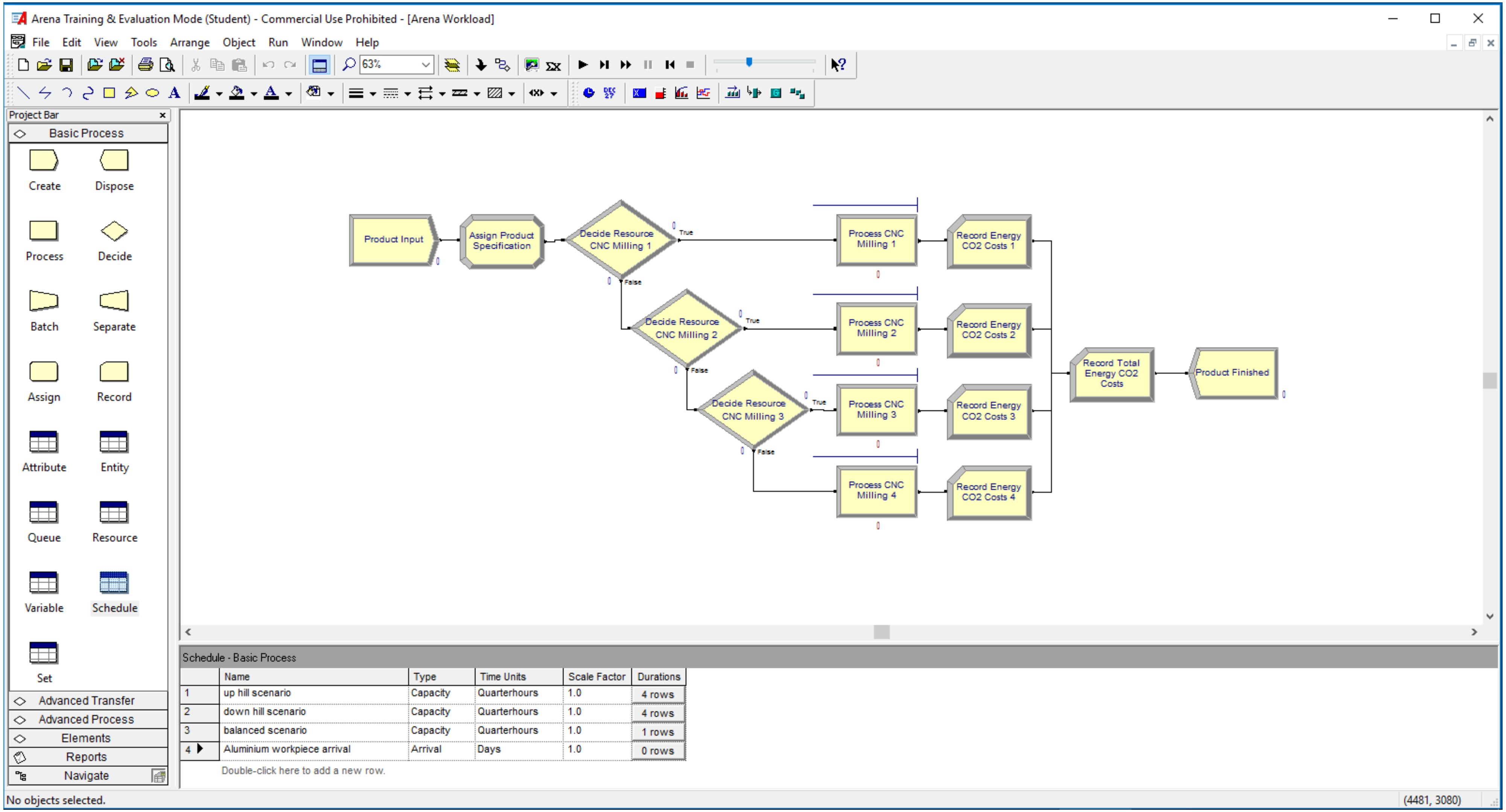


Figure R1. Arena simulation programming for overall four CNC milling machines process

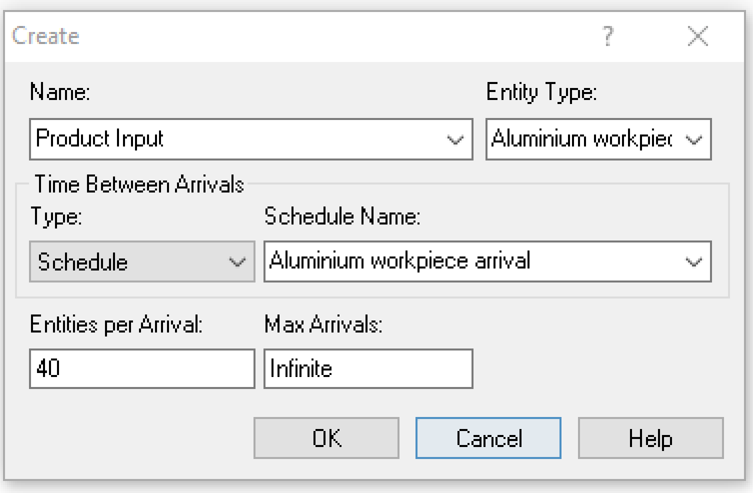


Figure R2. ‘Create Module’ for aluminium workpiece arrival

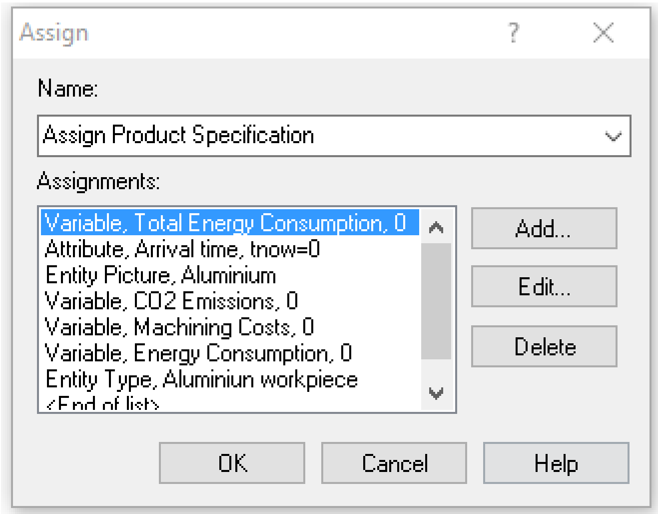


Figure R3. ‘Assign Module’ for product specification

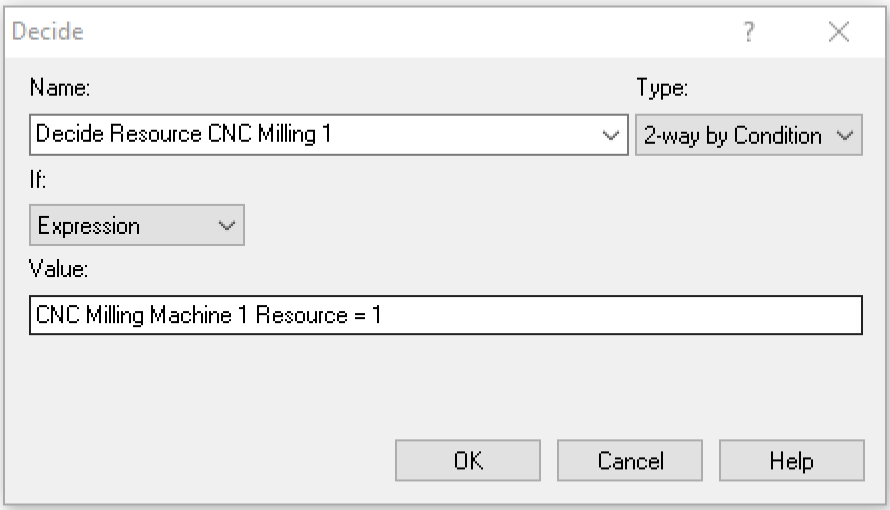


Figure R4. ‘Decide Module’ for checking availability of CNC milling machine resource 1

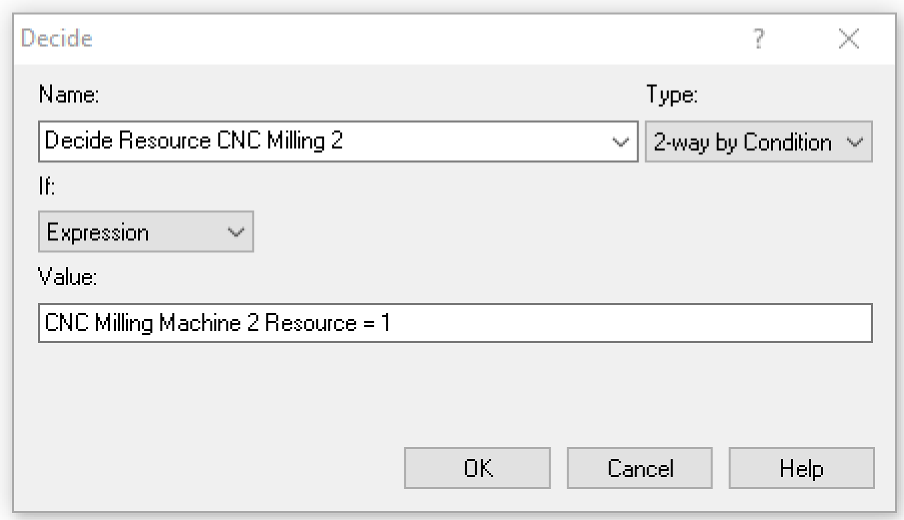


Figure R5. ‘Decide Module’ for checking availability of CNC milling machine resource 2

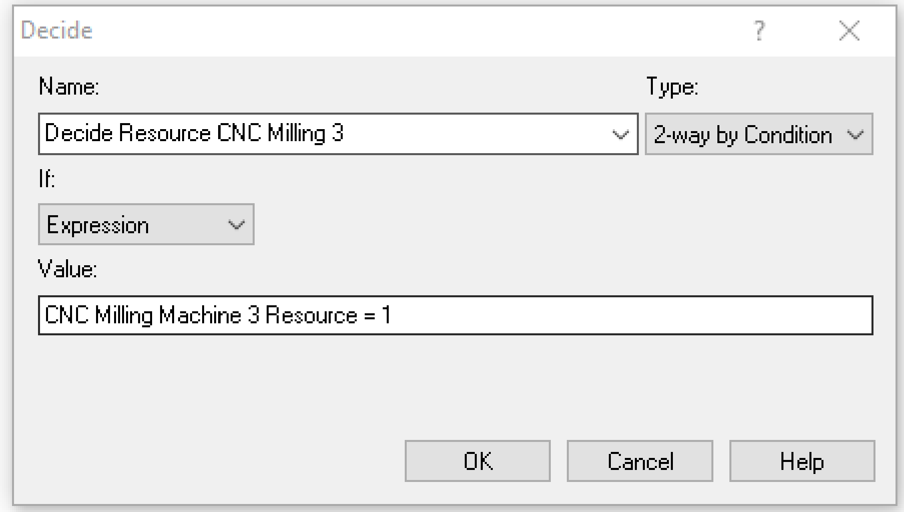


Figure R6. ‘Decide Module’ for checking availability of CNC milling machine resource 3

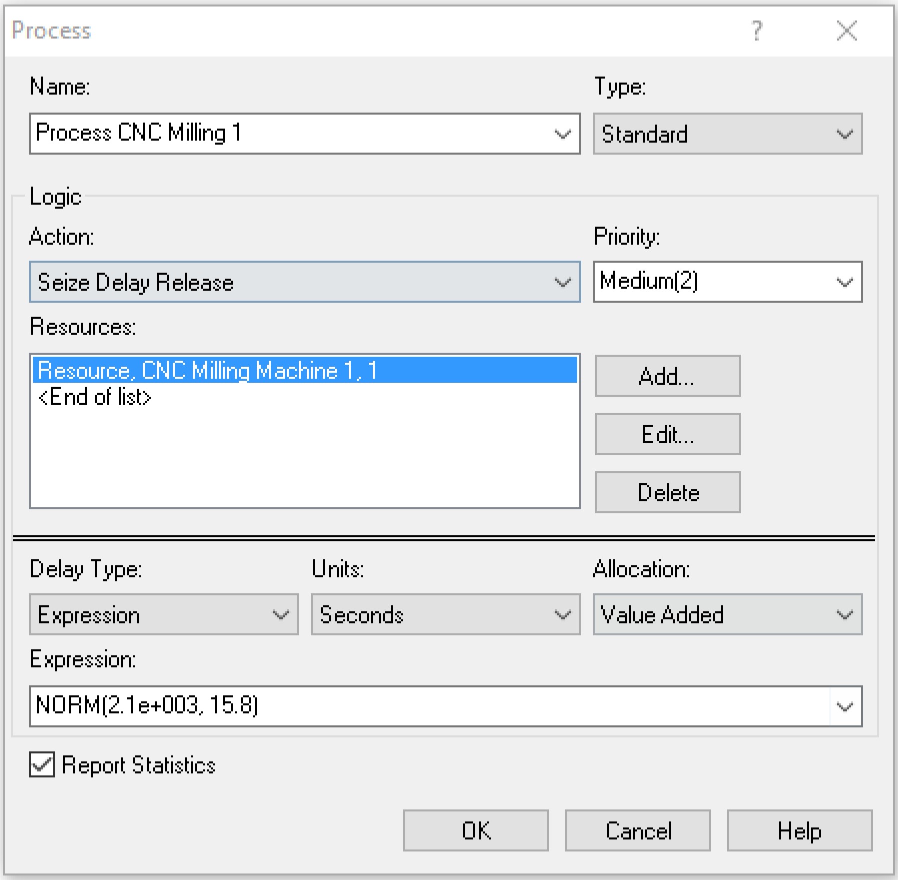


Figure R7. ‘Process Module’ for process CNC milling 1

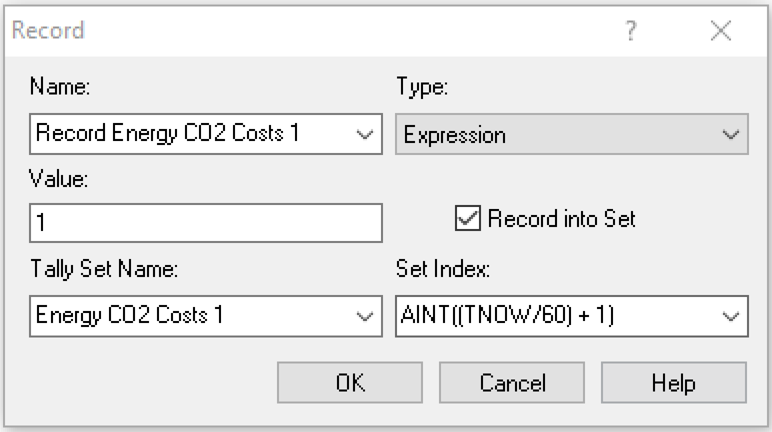


Figure R8. ‘Record Module’ for energy consumption, CO_2 emission and production costs

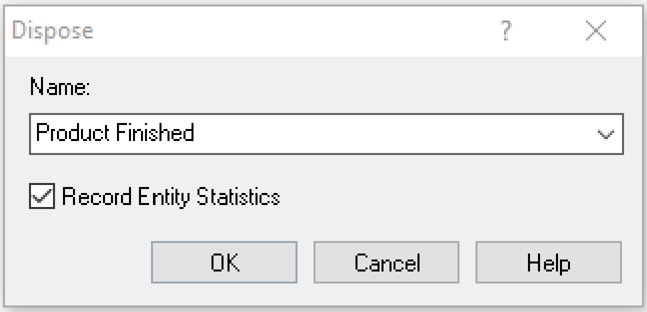


Figure R9. ‘Dispose Module’ for product finished

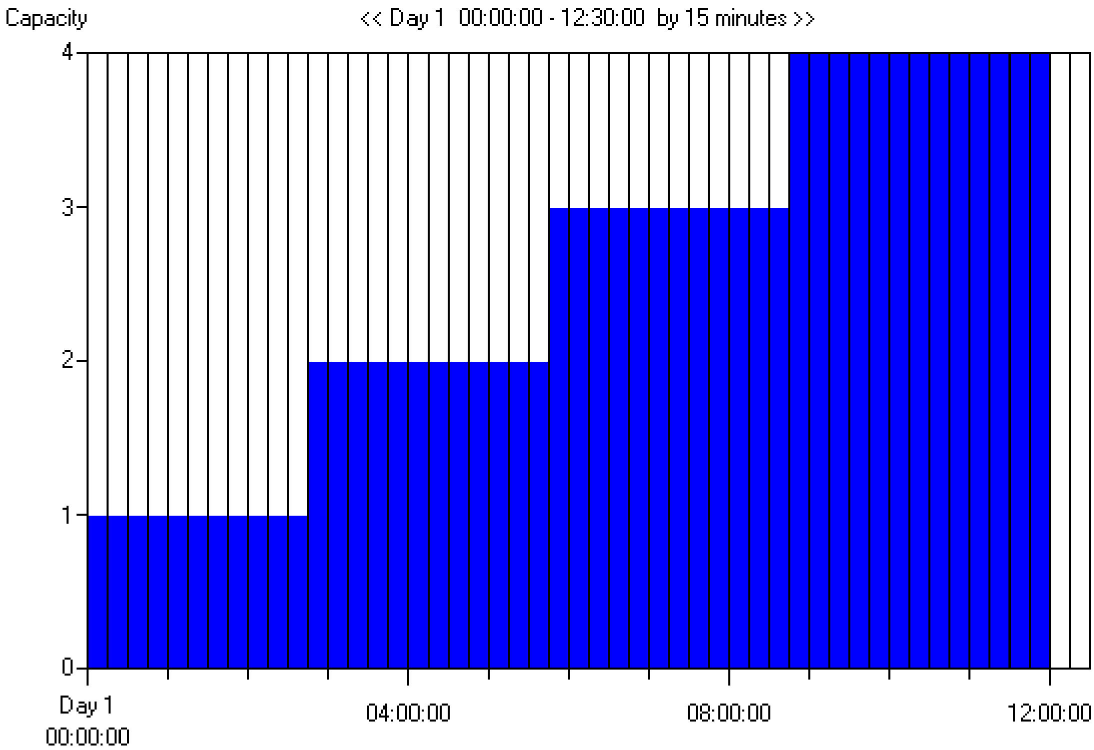


Figure R10. ‘Up-hill scenario’ schedule for CNC milling machine resources

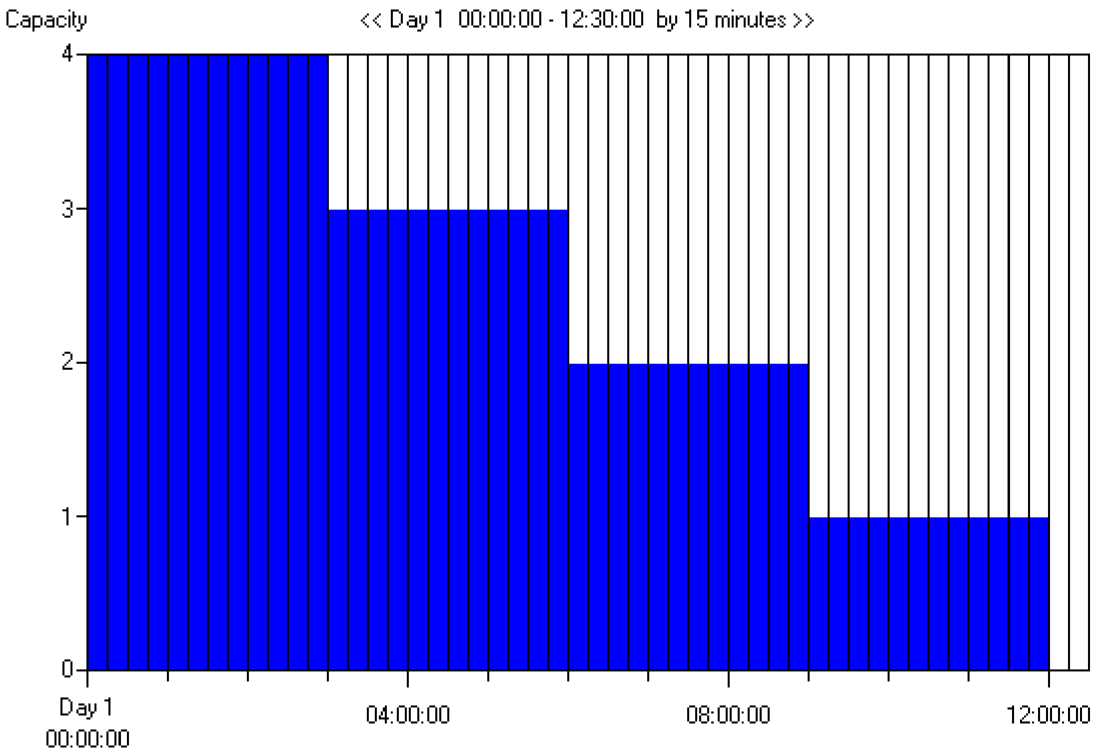


Figure R11. ‘Down-hill scenario’ schedule for CNC milling machine resources

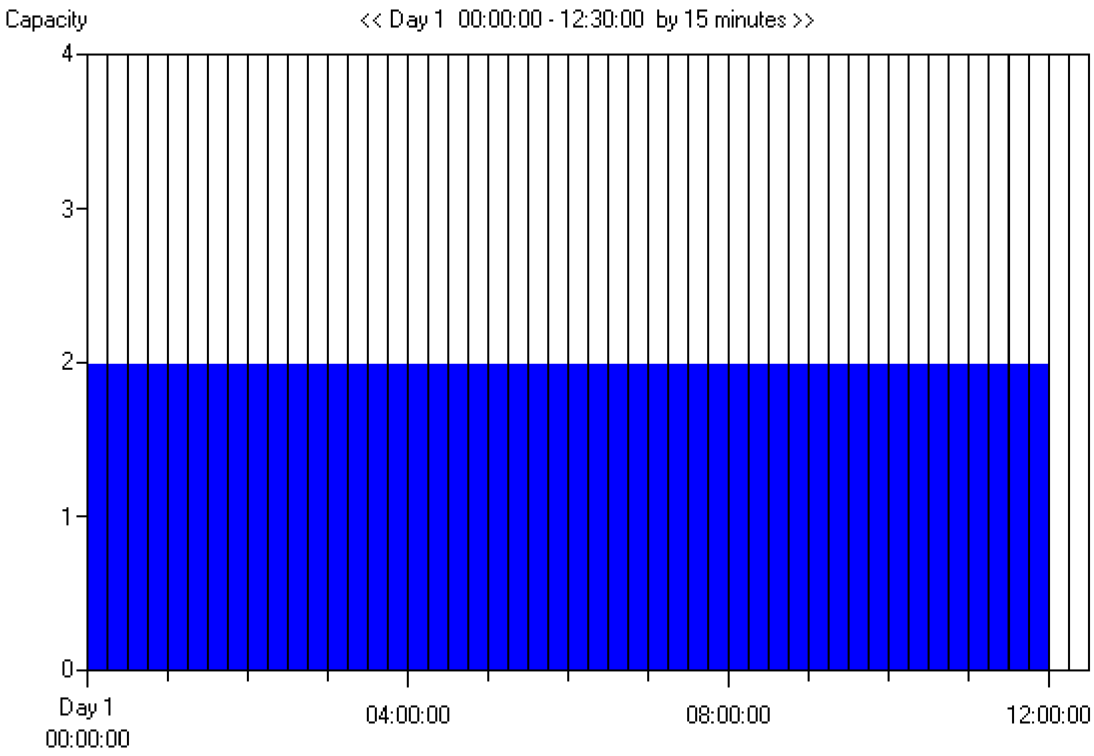
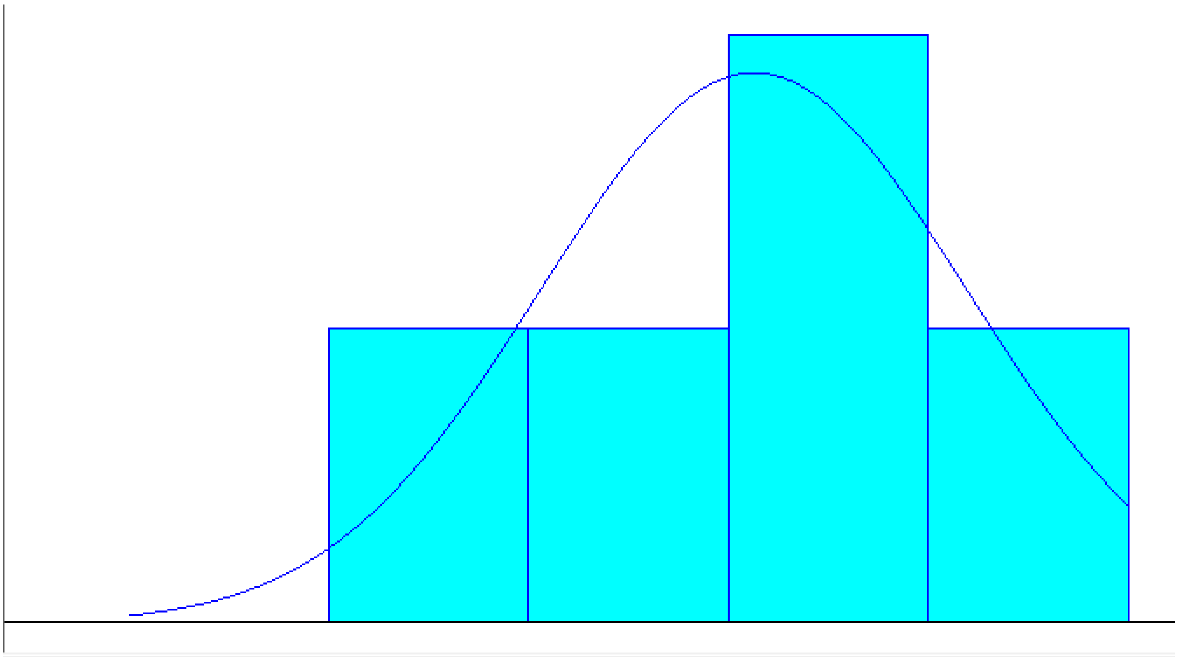


Figure R12. ‘Balanced scenario’ schedule for CNC milling machine resources

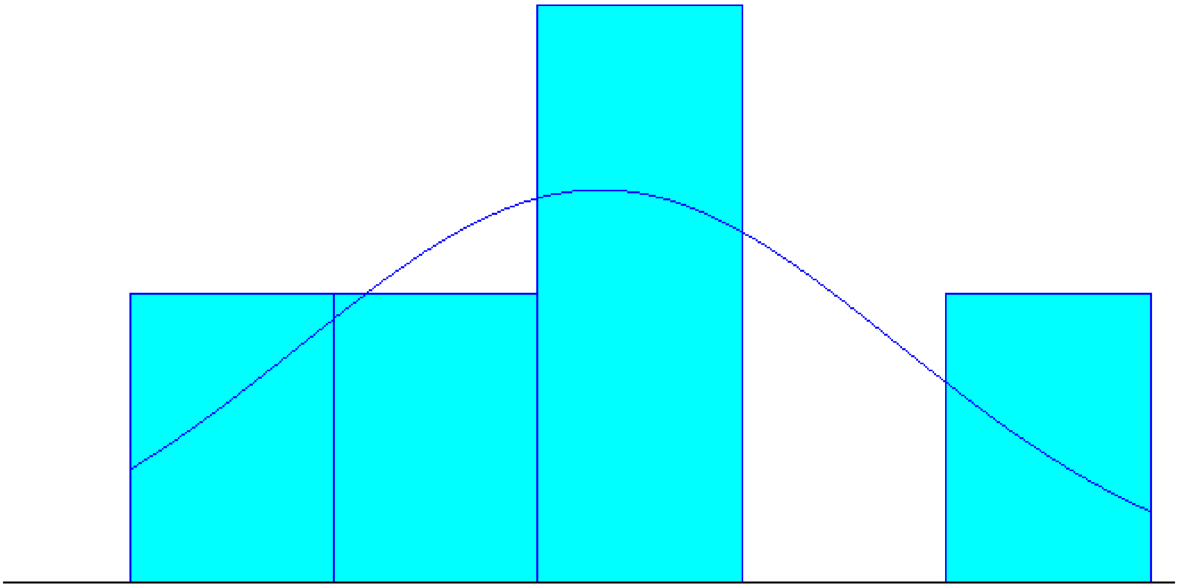
Appendix S:

Statistical test of e-ProMan HVAC setpoint temperature equations



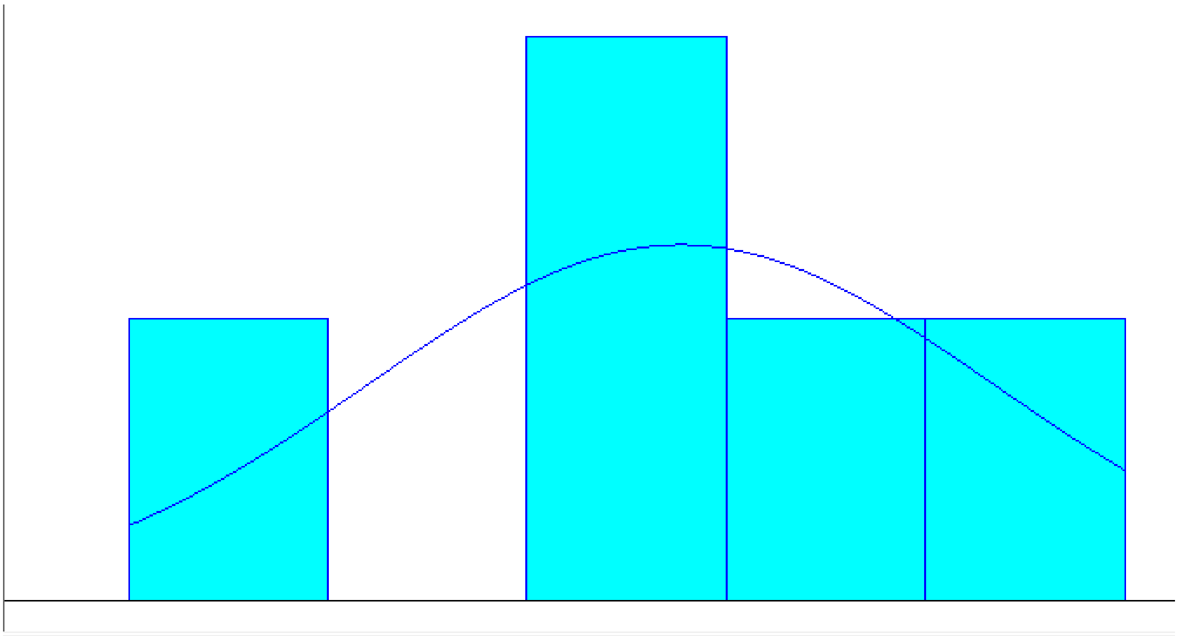
```
        Distribution Summary

Distribution:   Normal
Expression:     NORM(2.29e+003, 3.41)
Square Error:   0.022727


Kolmogorov-Smirnov Test
  Test Statistic         = 0.198
  Corresponding p-value > 0.15

        Data Summary

Number of Data Points   = 5
Min Data Value          = 2.28e+003
Max Data Value          = 2.29e+003
Sample Mean             = 2.29e+003
Sample Std Dev          = 3.81

        Histogram Summary

Histogram Range         = 2.27e+003 to 2.29e+003
Number of Intervals     = 5
```

Figure S1. Statistical test of e-ProMan HVAC setpoint temperature equation No.1



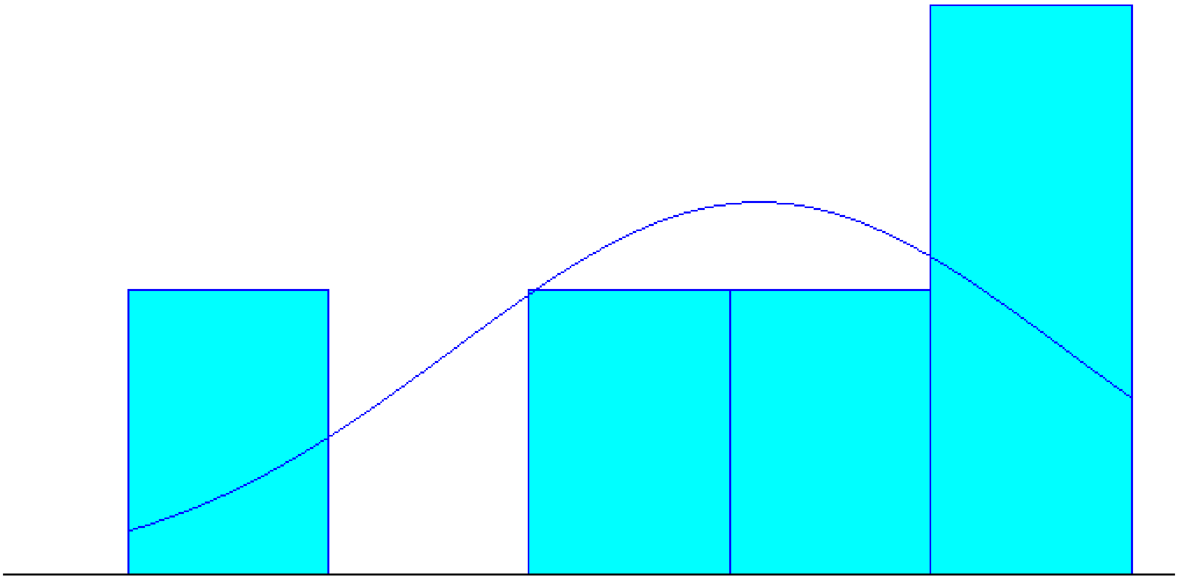
```
        Distribution Summary

Distribution:   Normal
Expression:     NORM(1.97e+003, 2.05)
Square Error:   0.073752


Kolmogorov-Smirnov Test
  Test Statistic        = 0.186
  Corresponding p-value > 0.15

        Data Summary

Number of Data Points   = 5
Min Data Value          = 1.97e+003
Max Data Value          = 1.97e+003
Sample Mean             = 1.97e+003
Sample Std Dev          = 2.29

        Histogram Summary

Histogram Range         = 1.97e+003 to 1.97e+003
Number of Intervals     = 5
```

Figure S2. Statistical test of e-ProMan HVAC setpoint temperature equation No.2



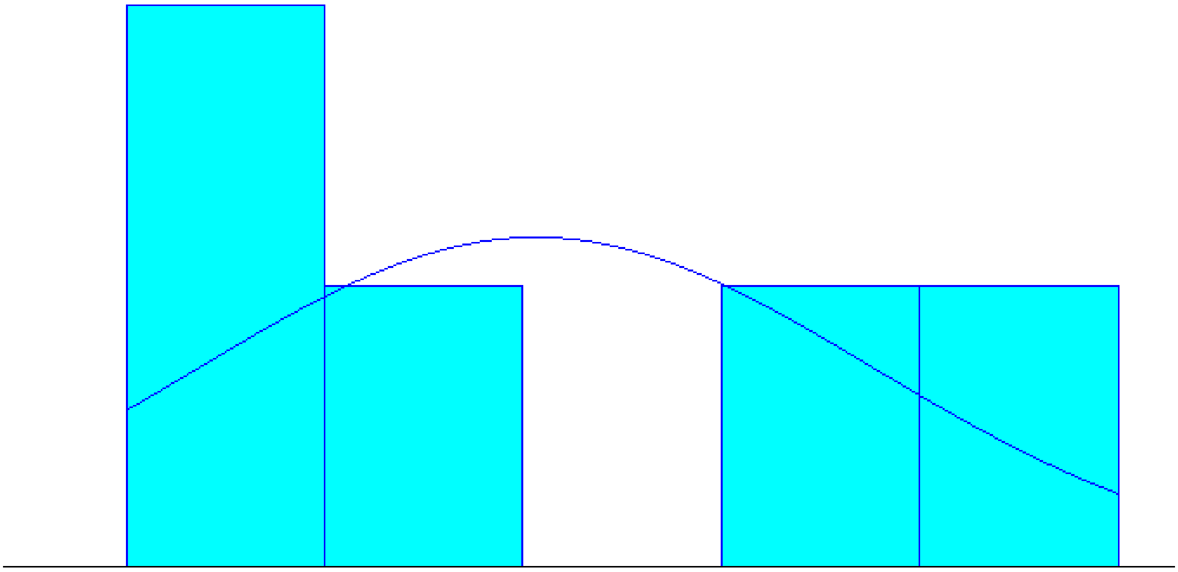
```
        Distribution Summary

Distribution:   Normal
Expression:     NORM(2.07e+003, 5.04)
Square Error:   0.073114


Kolmogorov-Smirnov Test
  Test Statistic        = 0.256
  Corresponding p-value > 0.15

        Data Summary

Number of Data Points   = 5
Min Data Value          = 2.06e+003
Max Data Value          = 2.08e+003
Sample Mean             = 2.07e+003
Sample Std Dev          = 5.64

        Histogram Summary

Histogram Range         = 2.06e+003 to 2.08e+003
Number of Intervals     = 5
```

Figure S3. Statistical test of e-ProMan HVAC setpoint temperature equation No.3



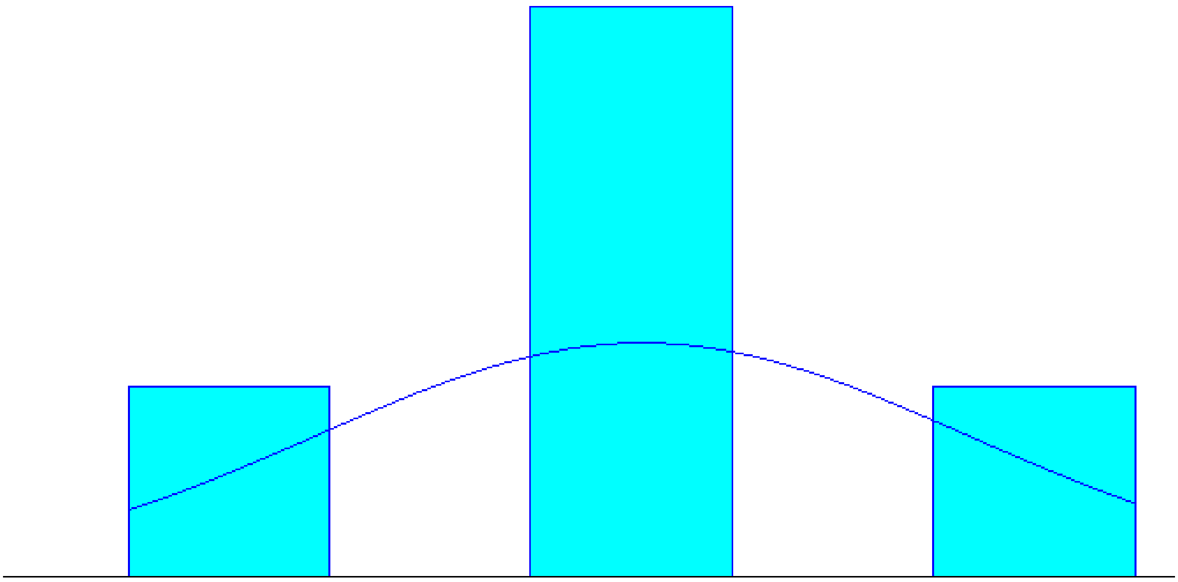
```
        Distribution Summary

Distribution:   Normal
Expression:     NORM(2.12e+003, 2.13)
Square Error:   0.095418


Kolmogorov-Smirnov Test
  Test Statistic         = 0.225
  Corresponding p-value > 0.15

        Data Summary

Number of Data Points    = 5
Min Data Value           = 2.12e+003
Max Data Value           = 2.13e+003
Sample Mean              = 2.12e+003
Sample Std Dev           = 2.38

        Histogram Summary

Histogram Range          = 2.12e+003 to 2.13e+003
Number of Intervals      = 5
```

Figure S4. Statistical test of e-ProMan HVAC setpoint temperature equation No.4



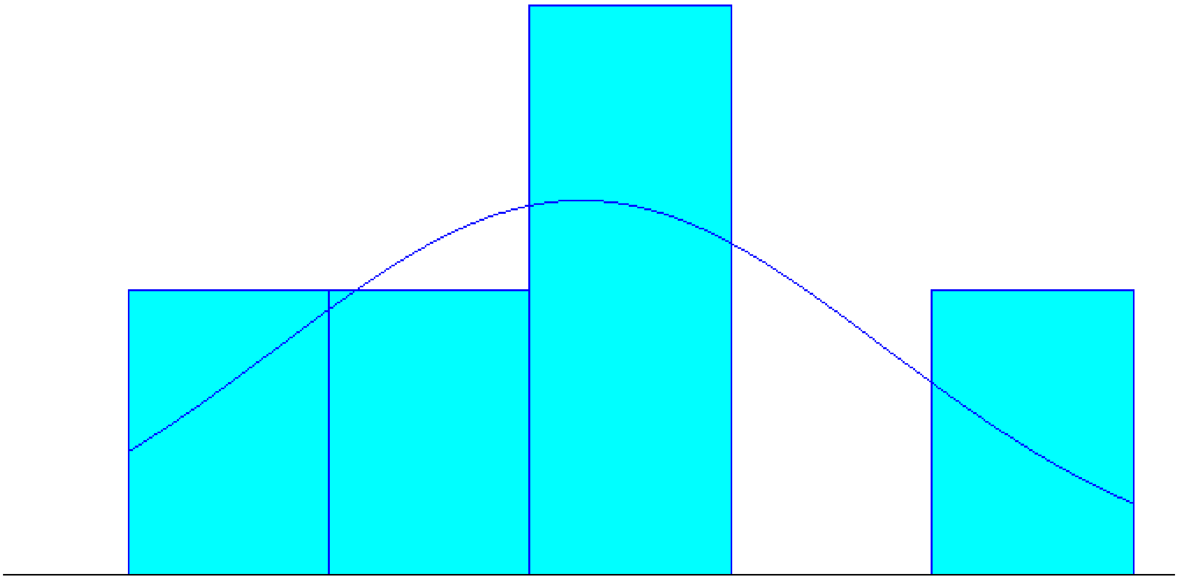
```
        Distribution Summary

Distribution:   Normal
Expression:     NORM(2.2e+003, 2.71)
Square Error:   0.126135


Kolmogorov-Smirnov Test
  Test Statistic         = 0.258
  Corresponding p-value > 0.15

        Data Summary

Number of Data Points    = 5
Min Data Value           = 2.19e+003
Max Data Value           = 2.2e+003
Sample Mean              = 2.2e+003
Sample Std Dev           = 3.03

        Histogram Summary

Histogram Range          = 2.19e+003 to 2.2e+003
Number of Intervals      = 5
```

Figure S5. Statistical test of e-ProMan HVAC setpoint temperature equation No.5



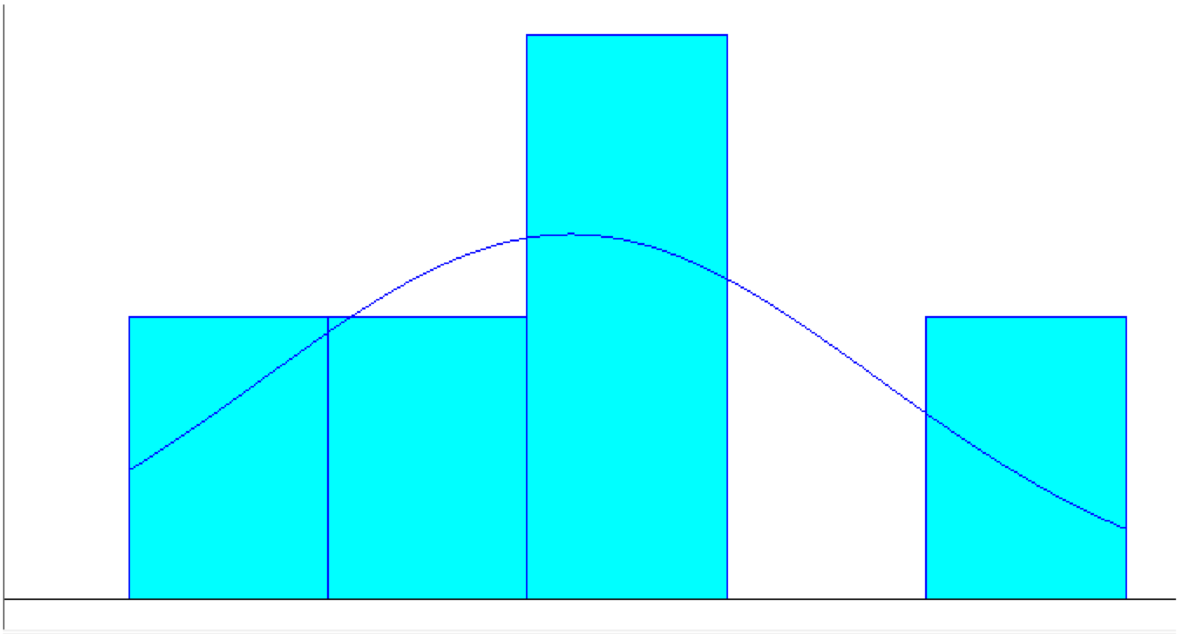
```
        Distribution Summary

Distribution:   Normal
Expression:     NORM(2.23e+003, 3.23)
Square Error:   0.223224


Kolmogorov-Smirnov Test
  Test Statistic          = 0.215
  Corresponding p-value > 0.15

        Data Summary

Number of Data Points   = 5
Min Data Value          = 2.23e+003
Max Data Value          = 2.24e+003
Sample Mean             = 2.23e+003
Sample Std Dev          = 3.61

        Histogram Summary

Histogram Range         = 2.23e+003 to 2.24e+003
Number of Intervals     = 5
```

Figure S6. Statistical test of e-ProMan HVAC setpoint temperature equation No.6



```
        Distribution Summary

Distribution:   Normal
Expression:     NORM(1.98e+003, 2.03)
Square Error:   0.072900


Kolmogorov-Smirnov Test
  Test Statistic        = 0.2
  Corresponding p-value > 0.15

        Data Summary

Number of Data Points   = 5
Min Data Value          = 1.98e+003
Max Data Value          = 1.99e+003
Sample Mean             = 1.98e+003
Sample Std Dev          = 2.27

        Histogram Summary

Histogram Range         = 1.98e+003 to 1.99e+003
Number of Intervals     = 5
```

Figure S7. Statistical test of e-ProMan HVAC setpoint temperature equation No.7



```
        Distribution Summary

Distribution:   Normal
Expression:     NORM(2.01e+003, 2.46)
Square Error:   0.072461


Kolmogorov-Smirnov Test
  Test Statistic         = 0.301
  Corresponding p-value > 0.15

        Data Summary

Number of Data Points    = 5
Min Data Value           = 2.01e+003
Max Data Value           = 2.02e+003
Sample Mean              = 2.01e+003
Sample Std Dev           = 2.75

        Histogram Summary

Histogram Range          = 2.01e+003 to 2.02e+003
Number of Intervals      = 5
```

Figure S8. Statistical test of e-ProMan HVAC setpoint temperature equation No.8