RDU1703215

DEVELOPMENT OF SUSTAINABILITY OPTIMIZATION TOOL FOR PNEUMATIC CONNECTOR PRODUCT

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RESEARCH VOT:
RDU1703215

Kolej Kejuruteraan
Universiti Malaysia Pahang

2020

ACKNOWLEDGEMENTS

Firstly, I would like to express my deepest gratitude to Allah s.w.t for giving me this opportunity and time to complete this project despite a lot of challenges that I have to go through along the journey

Special thanks to my grant members who continuously support and contribute ideas in completing this project. At the same time, I would like to thank Universiti Malaysia Pahang (UMP) which provides a grant for me to do the research under RDU1703215.

Lastly, I would like to thank my colleagues in IMAMS Laboratory and other people who involved directly or indirectly for their cooperation for me to complete this project.

DEVELOPMENT OF SUSTAINABILITY OPTIMIZATION TOOL FOR PNEUMATIC CONNECTOR PRODUCT

(Keywords: sustainability, product design, optimization, neural network, pneumatic connector)

Konsep kelestarian diperkenalkan oleh Harlem Brundtland mengandungi tiga kriteria iaitu ekonomi, alam sekitar dan sosial. Walaubagaimana pun, kajian terkini berkenaan indikator yang digunakan semakin menjadi persoalan kerana ianya sukar untuk di ukur dan pengukuran yang digunakan adalah secara tidak langsung. Di dalam perspektif industri pembuatan, kos pembuatan adalah pengukuran kelestarian kewangan sesebuah syarikat yang terdiri daripada enam jenis kos iaitu kos bahan mentah, mata alat pemotongan, cecair penyejuk pemotongan, minyak pelincir, tenaga yang digunakan dan tenaga kerja. Kriteria alam sekitar pula merujuk kepada pengukuran impak kegiatan aktiviti pembuatan kepada alam sekitar seperti impak kitar semula bahan buangan dan tenaga yang digunakan. Kriteria social pula boleh diukur dengan menggunakan pengukuran kesihatan operator. Penilaian ergonomik yang digunakan untuk mengukur impak kesihatan para operator semasa mgangkat beban adalah The Revised NIOSH Weight Lifting Index. Pembangunan perisian bagi projek ini adalah menggukan platform Microsoft Excel. Prijek ini juga menggunakan kaedah neural network dan penyongsangan model neural network bagi tujuan pengoptimuman. Nilai minimum setiap kriteria digunakan bagi mendapatkan satu set pemalar pemotongan yang optimum. Kelajuan pemotongan dan kadar suapan yang optimum adalah 55.25 m/min dan 0.10 mm/rev bagi Aluminum 6061 dan 82.00 m/min dan 0.10 mm/rev dan Brass C3604.

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Sustainability concept was introduced by Harlem Brundtland consists of three criteria's; economics, environmental and social. However, recent research on the indicator used had increasingly called into question where the indicator is difficult to be assessed and the measurement is indirect. In the manufacturing industry perspective, manufacturing costs is the measure of company economic sustainability which consists of six cost assessments which include raw material, tool, coolant, lubricant, energy and manpower. Whilst environmental criterion is a measure of the impact of manufacturing activities on the environment such as chip recycling impact and energy impact. The social criteria can be measured by using the production operator health. The ergonomic assessment used is The Revised NIOSH Weight Lifting Index as the method measures the potential impact of the worker during lifting activities. The development of the software/tool is based on Microsoft Excel platform. The present study also highlights the usage of neural network and inversion of the neural network model assessment for the optimization purpose. Minimum values from each criterion were used to obtain the optimum set of cutting parameters. The optimum cutting speed and feedrate results is 55.25 m/min and 0.10 mm/rev for Aluminum 6061 and 82.00 m/min and 0.10 mm/rev for Brass C3604 material.

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TABLE OF CONTENT

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS

V_b	Flank wear
E_e	Machine power consumption impact
LCI(e)	Electricity emission intensity
PSm	Spindle motor power consumption
PFM	Feed motor power consumption
ΣPP	Feed motor power consumption
C_e	Coolant impact consumption
LCI(cp)	Coolant production emission intensity
LCI(cd)	Coolant disposal emission intensity
Tc	Total coolant amount
LCI(w)	Water distribution emission intensity
Tw	Total water amount
Mt	Machining time
MTTR	Mean time to replenish coolant
LO_e	Lubricant oil impact consumption
MTTD	Mean time to discharge lubricant
Ld	Amount of lubricant discharge
LCI(lp)	Lubricant production emission intensity
LCI(LD)	Lubricant disposal emission intensity
Ch_e	Chip recycling impact
WpV	Workpiece volume
pV	Product volume
d	Material density
LCI(M)	Metal chip recycling emission intensity
RWL	Recommended weight limit
LC	Load constant = 23kg
HM	Horizontal multiplier
VM	Vertical multiplier
DM	Distance multiplier
AM	Asymmetric multiplier
FM	Frequency multiplier
CM	Coupling multiplier

b	The bias term / the neuron's threshold
w	vector
x	Vector
N_h	Number of hidden neuron
N	Number of input
H	The approximation and the gradient
J	Jacobian matrix
W	The connection weight
E_ω	The sum of squared network weights
E_D	The sum of network error
P(A|B)	The posterior probability of A conditional on B
P(B|A)	The prior of B conditional on A
P(B)	The non-zero prior probability of event B
$P(D\|\alpha, \beta, M)$	The likehood function of D for given α, β, M
$P(\alpha, \beta\|M)$	The uniform prior density for the regularization parameters
P(D|M)	The normalization factor
V_c	Cutting speed
a_p	Depth of cut
f_n	Feedrate
K_c	Specific cutting force (N/mm2)
D_c	Material diameter
l_m	Cutting / machined length
n	Spindle speed

LIST OF ABBREVIATIONS

A1	Aluminium machined with cutting parameters option 1
B1	Brass machined with cutting parameters option 1
CNC	Computer Numerical Control
DOSH	Department of Safety and Health
EPA	Environmental Protection Agency
EPEAT	Electronics Product Environmental Assessment Tool
ETT	Energy Tracking Tool
GLM	Generalized Linear Model
GPR	Gaussian Process Regression
HSS	High Speed Steel
ISO	International Organization for Standardization
kg	Kilogram
$kgCO_2$	Kilogram Carbon Dioxide
kW	Kilo Watt
kWh	Kilo Watt Hour
L	Liter
LCA	Life Cycle Assessment
LCE	Life Cycle Costing
MSE	Mean Square Error
NIOSH	National Institute of Occupational Safety and Health
OECD	The Organization for Economic Co-operation and Development
Ra	The arithmetic mean roughness
REBA	Rapid Entire Body Assessment
RULA	Rapid Upper Limb Assessment
RM	Ringgit Malaysia
Rpm	Revolution Per Minute
SEM	Scanning Electron Microscope
SVM	Support Vector Machine
UMP	Universiti Malaysia Pahang

CHAPTER 1

INTRODUCTION

1.1 Problem Statement

Dr. Harlem Brundtland introduced sustainable development concept in the 1980s after realizing the consequence of human needs and activities to the environment (Marksberry & Jawahir, 2008). They added, she defined sustainable development as meeting the needs of the present generations without compromising the ability of future generations to fulfil their own needs.

Since the introduction, sustainable development is increasingly being used by many countries around the world including United Kingdom (UK), United States of America (USA) and Finland as one of the routes for a good and desirable of the society (Holden et al., 2014). At present, three criteria are used in assessing the sustainability concept known as economic, environmental and social criteria. Each of the criteria is assessed using a random indicator as long as the indicator used is relevant to the corresponding case study problem (Slaper & Hall, 2011). For example, in assessing the economic criteria, researchers can use either life cycle costing (LCC) (European Commission (EU), 2018), total manufacturing cost (Haapala, 2012) or even company financial profit or loss (Onat et al., 2014) as their indicators.

For environmental criteria, among the indicators that can be used are product life cycle assessment (LCA) (Jayal et al., 2010) and environmental impact assessment (Narita, 2012) while for social criteria the number of medical certificate leaves, musculoskeletal injury (WorksafeBC, 2008) and ergonomic assessment such as REBA and RULA.

Both policymakers and academic researchers tend to focus on the needs to improve these indicators by assuming that the improved indicators should be better and will be used by others which later could generate a stronger influence on policy and thereby enhance sustainability (Bastianoni et al., 2019; Lehtonen et al., 2016; Li & Mathiyazhagan, 2018).

However, Lehtonen et al., (2016) added, recent research on the indicator used had increasingly called into question where the indicator is difficult to be assessed, and the measurement is indirect. The similar issue raised by Holden et al., (2014), in which they stated that the sustainable development concept had become very comprehensive and sophisticated. They added the concept becomes irrelevant to be used by researchers and policymakers (Holden et al., 2014).

Among the irrelevant indicators being used to measure sustainability is the depletion of environmental resources to pursue economic growth which is similar to living off capital rather than profit (Holden et al., 2014). Additionally, Holden and his colleague highlighted the used of phrases such as weak, very weak, strong and very strong are also tricky to achieve clear justification. They also signified the irrelevant of living standard as one of the sustainable development indicators as this usually being measured in a long term period, not for a short period of time.

Based on these problems stated above, the need to review the sustainable development assessment method primarily for the implementation at the manufacturing process level to reflect directly to the sustainable development is crucial. Also appropriate documented method is highly important.

Therefore in this work, the alternative way is proposed to obtain the sustainability relationship between each criterion. Also, the optimization study is based on the theoretical determination method as well as data generated from experimental work for validation.

1.2 Objective

The objective of the present study is to propose a new sustainability assessment method that can be used specifically at the production floor level. Two main tasks need to be achieved are as follow:

1. To develop a new sustainability assessment model based on Malaysia industry scenario.
2. To demonstrate the new sustainability assessment model focusing on the turning process.
3. Develop a sustainability optimization tool by using computer programming, Microsoft excel or open source platform.
4. To optimize the new sustainability assessment model to obtain the optimised cutting parameters.

1.3 Scope

The limitation of this study includes:

1. The available sustainability assessment method worldwide were identify based on literature survey from previous research papers, technical catalogues and technical articles.
2. The materials involved in the present study is Aluminum 6061 and Brass C3604.
3. The product fabrication process was performed by using Computer Numerical Control (CNC) Turning Machine.
4. The assumptions needed to determine total manufacturing cost, environmental impact, energy usage and ergonomics index were stated in the methodology and results chapter.

1.4 Thesis Arrangement

The content of the thesis consists of five chapters. Chapter One discussed the problem statement, objectives and scopes of the study.

Chapter Two provides an academic review of the sustainability concept, which is implemented at the operational level in an organization. There are three criteria in this concept, namely economic, environmental and social criteria. Each one of these criteria was reviewed intensively. Later, the assessment methods reported by other literature and reviewed by global initiative towards the implementation of sustainability were presented. Lastly, the section reviewed the turning process, multi-criteria decision making (MCDM) methods which the definition, classifications, advantages, disadvantages, its methodology and research survey methods are reviewed in general.

Chapter Three discussed the methodology implemented in the present study. The chapter started with the explanation of project methodology, problem statement, proposed focus questionnaire to obtain feedback from the respondent on the assessment method to assess sustainability, the product chosen for a case study and machining process involved, including the cutting parameters used for fabrication. Later, the design of experiment (DOE) used in this study is reviewed. The case study methodology adopted in this study were divided into two, known as theoretical methodology and experimental methodology. Each of them was described in details in this chapter. Lastly, the optimization by using a machine learning method which was used in this work was also explained.

Chapter Four discussed the results and discussion of findings in the present study. The topics included in the chapter are the raw material grade testing results, the focus questionnaire survey results, the theoretical calculation results where it shows how to calculate the total manufacturing cost in details, the environmental impact the energy consumed during the machining process and the determination of the NIOSH weight lifting index in detailed. Then, the experimental results conducted is also being discussed in detail, coupled with the predicted results. In the predicted results, the explanation of how the predicted results were obtained using a neural network model is discussed in details. Then, the inversed neural network model and the verification of the optimization results being discussed in detailed.

Lastly, Chapter Five discussed the conclusion of the study and the recommendation for future works that can be done to improve this research in the future.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter provides reviews on the sustainability concept, which have been implemented at the managerial level in any organization. There are three criteria reviewed in this concept, economic, environmental and social criteria. Then, the subsequent part reviewed the assessment methods used by other researchers and also global initiative towards the implementation of sustainability. Lastly, the turning process, multi-criteria decision making method and research survey conducted to get feedback from targeted respondent are presented.

2.2 Sustainability

Sustainability concept is introduced by Dr. Harlem Brundtland in the 1980s, after realizing the consequence of industrialization to the environment and human social life. Sustainability concept is defined as activities that meet the needs of the present generation without compromising the ability of future generation to meet their own needs (Marksberry & Jawahir, 2008). Sustainability also refers to the considerations of environmental, economic and social issues in the highlight of cultural, historical, retrospective, perspective and institutional perspective (Mowforth & Munt, 2015; Villeneuve et al., 2017; Wood et al., 2015). In product design view, sustainability requires a system perspective either it is a market, an ecosystem, a social system or the entire world which allows the sustainable design process to address the markets, environment, companies and people (Shedroff, 2009).

According to the report provided by the United Nations (UN), 17 goals are needed to archived to sustain living in the earth where every people can live peacefully (United Nation, 2018). There are:

1. End poverty in all its forms everywhere.
2. End hunger, achieve food security and improved nutrition and promote sustainable agriculture.
3. Ensure healthy lives and promote well-being for all at all ages.
4. Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all.
5. Achieve gender equality and empower all women and girls.
6. Ensure availability and sustainable management of water and sanitation for all.
7. Ensure access to affordable, reliable, sustainable and modern energy for all.
8. Promote sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all.
9. Build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation.
10. Reduce inequality within and among countries.
11. Make cities and human settlements inclusive, safe, resilient and sustainable.
12. Ensure sustainable consumption and production patterns.
13. Take urgent action to combat climate change and its impacts.
14. Conserve and sustainably use the oceans, seas and marine resources for sustainable development.
15. Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss.
16. Promote peaceful and inclusive societies for sustainable development, provide access to justice for all and build effective, accountable and inclusive institutions at all levels.
17. Partnership for the sustainability goals.

For this, the summary of the sustainable development goals provided by United Nation is shown in Figure 2.1.

Figure 2.1 Summary of United Nations sustainable development goals.
Source: United Nation (2018)

Based on the definition given by researchers and organizations, it shows that everyone has their way of defining the sustainability term. For example, Marksberry and Jawahir (2008) noted that the interpretation could lead to anything about sustainability as long as it preserved the ability of future generations to live. Meanwhile, Shedroff (2009) had raised a deeper definition of sustainability term where elaborate it well in terms of product design. As for United Nation (2018), a different perspective is highlighted where they elaborate on the sustainability term very comprehensively in every single aspect of life. All in all, the best way to define sustainability term is by defining it based on the area in which someone is involved. For example, the machining process is in a production line. Hence, the term sustainability in a production line can be described as the ability to perform the machining process of a product for the consumer used without compromising the company financial, environmental and workers health.

2.3 Sustainability Concept: Overview of The Existing Sustainability Assessment Practises

Many indicators can be used to measure sustainability (Slaper & Hall, 2011). The information used to assess the sustainability indicators must be presented in an attractive format according to three groups of people; scientist and professional analysts, policymakers and the public people (Braat, 2012). Besides that, the indicators used must represent the chosen ecosystem, must have a scientific basis, must be quantifiable and the indicators should include a reference or threshold values.

Based on the literature survey, there are 55 assessment tools used by researchers but most of them lacked of holistic approach on sustainability (Moldavska & Welo, 2015). Although there are several assessment tools widely being used, only 17 assessment tools addressed one of two aspects of the sustainability concept. They also stated that only a few of the assessment tools are relevant for manufacturing companies with limited efforts on servicing a sustainability assessment provided account multiple-faceted aspect of sustainability. Similar critics is made by Singh et al., with 41 assessment tools listed which have the same issues (Singh et al., 2012).

Among the indicators used are salary per hour, employment rate, unemployment rate (Hart, 2010), total manufacturing cost (Haapala, 2012) and Growth domestic product (GDP) (Morse, 2018) as economic indicators. Meanwhile, for environmental impact indicators, the assessment method used includes the toxic produced when producing a product, energy impact, waste impact, cutting tool impact (Haapala, 2012), solid waste emission, water and air pollution (Nallusamy et al., 2016). Lastly, for social indicators, the assessment method used is the number of worker expert in doing jobs, social life cycle assessment method (Haapala, 2012), employment rate, poverty rate, worker health and safety (Latif et al., 2017). The summary of the economic, environmental and social criteria indicators used in sustainability assessment are shown in Table 2-1 til Table 2-3 in page 11-12.

Table 2-1 Summary of economic criteria indicator used in the sustainability measurement.

Author(s) / Years	Traditional	Modern	Emphasis
Maureen Hart (2010)	Median income/capita relative to the U.S. average	Number of hours of paid employment at the average wage required to support basic needs	What wage can buy Defines basic needs in terms of sustainable consumption
	Unemployment rate Number of companies Number of jobs	Diversity and vitality of local job base Number and variability in size of companies	The resilience of the job market Ability of the job market to be flexible in times of economic change
	Size of the economy as measured by GNP and GDP	Wages paid in the local economy that is spent in the local economy Dollars spent in the local economy which pays for local labor and local natural resources	Local financial resilience
Haapala and Zhang (2012)	-	Total Manufacturing Cost	-
Simon Bell and Stephen Morse (2018)	-	Gross Domestic Product (GDP)	-

Table 2-2 Summary of environmental criteria indicator used in the sustainability measurement.

Author(s) / Years	Traditional	Modern	Emphasis
Maureen Hart (2010)	Ambient levels of pollution in air and water	Use and generation of toxic materials (both in production and by the end user) Vehicle miles traveled	Measuring activities causing pollution
	Tons of solid waste generated	Percent of products produced which are durable, repairable, or readily recyclable or compostable	Conservative and cyclical use of materials
	Cost of fuel	Total energy used from all sources	Use of resources at a sustainable rate
Haapala and Zhang (2012)	-	Energy Impact, Raw material Impact, Cutting Tool Impact and Coolant Impact	-
United Nation (2018)	-	Water pollution, air pollution and energy consumption	-

Table 2-3 Summary of social criteria indicator used in the sustainability measurement.

Author(s) / Years	Traditional	Modern	Emphasis
Maureen Hart (2010)	SAT and other standardized test scores	Number of students trained for jobs Number of students who go to college and come back to the community	Matching job skills and training to the needs of the local economy
Haapala and Zhang (2012)	-	Social Life Cycle Impact Assessment	-
Latif et al., (2017)		Worker health and safety	-
United Nation (2018)	-	Employment Rate, Unemployment Rate, Poverty Risk	-

Tables 2-1 to 2-3, showed the variables for different indicators used by several researchers to evaluate sustainability. As noted from the table, Maureen Hart (2010) also made a comparison to distinguish between traditional and modern sustainable indicators with justification for each comparison are provided in the evaluation of sustainability.

However, the indicators proposed by Maureen Hart is limited and basically focused only on the worker scope rather than a private company or organizations as a whole. Noted also that, Simon Bell and Stephen Morse (2010) employed the Growth Domestic Product (GDP) as the economics measurement factor. GDP involved higher economy level which usually used by government or ministry level. Hence, for small scale institutions such as private company, GDP measurement seems to be inappropriate as the private entities only focus on the business activity flows such as buy raw material, product conversion through machining process and sell the product for profit gain. Specifically, Haapala and Zhang (2012) approach focused mainly at the production floor level as the costs are included such as raw material, energy, manpower, tool and coolant in their observation. However, lubricant cost is separated in the economic calculation.

Based on the summary in Table 2-2, the reports agreed that any activities that contribute to environmental pollution need to be calculated and included under the environmental impact. Although the aims for environmental assessment is similar, Maureen Hart (2010) stated that the implementation and generation of toxic materials need to be calculated and became a burden in manufacturing companies. For manufacturing companies, the burden to sustain environmental impact is not only cared for by them but also applied to the end-user in terms of responsibilities. Hence, it is not appropriate to include the end-user environmental burden solely to the manufacturer. On the other hand, Haapala and Zhang (2012) suggest a good environmental impact assessment to be applied at the production line but they did not include lubricant impact assessment. The contrary opinion is given by Dahmus and Gwutoski (2004) in which the coolant and lubricant impacts can be neglected since the contribution is too small compared to the number of product being produced. The statement is practical and can be implemented if it involves a product as a case study, but if timing need to be considered; tool, coolant and lubricant impact need to be included in the assessment.

Lastly, for social indicators, there are few reports used education level to evaluate social criteria. Nonetheless, this particular approach is not reliable for social evaluation since there are many educated people who even have a degree but still did not possess any permanent job (Jayasingam et al., 2018). Therefore, employment and unemployment rate can be used to measure sustainability at the government level, but when focuses are at the production floor level, it is unrelated. Hence the most suitable indicators to be used at the production floor level is ergonomics assessment method with the direct impact of social aspect is measured directly.

2.3.1 Economics Criteria

The first criteria in sustainability evaluation are economics criteria. Economics criteria can be described as something analogous to a net financial profit or loss that can be calculated using an uncontroversial formula and used by any business firm (Norman & MacDonald, 2004; Onat et al., 2014). Another method that can be used to evaluate economics criteria is Life Cycle Costing (LCC). It can be defined as a methodology where the cost of a given product/asset is considered throughout its life cycle (European Commission (EU), 2018). Zhang and Haapala (2012) also agreed that economics criteria in sustainability evaluation could be referred to LCC. They also considered LCC as a summation of all costs related to producing a product. This includes the material used, length of equipment life and also the annual time increments during the equipment life taking into consideration the time money value. The costs associated with LCC in fabricating a product is divided into five categories; material cost, tool cost, coolant cost, energy cost and labor cost and can be represented as total manufacturing cost as shown in Equation 2-1.

$$\text{Total Manufacturing Cost} = \text{Material Cost} + \text{Tool Cost} + \text{Coolant Cost} + \text{Energy Cost} + \text{Labor Cost} \tag{2-1}$$

where:

$$\text{Material Cost} = \text{Standard Size Price}\left(\frac{\text{RM}}{\text{Volume}}\right)\times\text{Required Size}\left(\text{Volume}\right) \tag{2-2}$$

$$\text{Tool Cost}=\frac{\text{Tool Contact Time}}{\text{Tool Life}}\times\text{Tool Cost}\left(\frac{\text{RM}}{\text{Point}}\right) \tag{2-3}$$

$$\text{Energy Cost} = \text{Energy used to fabricate a product}\left(\text{kWh}\right)\times\text{Commerical Electrical Tariff}\left(\frac{\text{RM}}{\text{kWh}}\right) \tag{2-4}$$

$$\text{Labor Cost} = \text{Total time to fabricate a product}\left(\text{hour}\right) \times \text{Salary}\left(\frac{\text{RM}}{\text{hour}}\right) \tag{2-5}$$

For coolant used in the machining process, the equations are shown in Equations 2-6 to 2-8 as an example.

$$\text{Make Up Volume} = \frac{\text{Coolant Tank Capacity}\left(\text{L}\right) \times \text{Coolant Loss Rate}}{1 - \text{Coolant Loss Rate}} \tag{2-6}$$

$$\text{Coolant Volume} = \frac{\text{Coolant Tank Capacity}\left(\text{L}\right) + \text{Make Up Volume}\left(\text{L}\right)}{\text{Month Used} \times \text{Actual Output}} \tag{2-7}$$

$$\text{Coolant Cost} = \text{Coolant Volume} \times \text{Coolant Cost Rate} \tag{2-8}$$

If the machining process involves more than one type of cutting tools, each cutting tool cost are considered. Based on the literature survey, there are two common methods used to determine the single point cutting tool life using a turning machine. There are single-pass turning tool life and multi-pass turning tool life method. Here, this study involved a multi-pass turning tool life method. Hence only multi-pass turning tool life method is reviewed.

Multi-pass turning is defined as a single point cutting tool that cut the raw material more than one pass using a turning machine (Radovanović, 2018). There are a few methods applied by the researchers to determine the tool life of the single point insert such as using average surface roughness measurement and Scanning Electron Microscope (SEM) image to analyze the tool wear (Ariffin et al., 2018). On the other hand, some researcher used Scanning Electron Microscope (SEM) image to determine the single point cutting tool wear (Ashrafi et al., 2013) and some of them (Kene et al., 2016) used dynamometer, digital microscope and infrared thermometer to determine the tool wear/life.

Kene et al., (2016) also investigate the behaviour of multi-layer coated carbide insert tool wear using sensors in hard turning process. The machine involved is HMT lathe center and the cutting environment used is dry cutting. The cutting parameters reported is the cutting speed of 100 and 150 m/min, the feed rate of 0.15mm/rev and depth of cut of 0.25 mm. The workpiece material used is 55 HRC EN24 hardened steel of diameter 65.00 mm. The cutting tool insert used is multi-layered PVD coated TiAlN nanolayer carbide insert (CNMG120408). Performance measured is cutting temperature, average surface roughness and digital microscope image. It shows that multilayer TiAlN coated carbide insert has shown beneficial economic aspect in terms of tool life, surface roughness and accuracy.

Another reported cutting tool involved in producing the nipple hose connector is drilling cutting tools. There are four types of drilling cutting tools used; namely center drill diameter 3.00 mm, drilling cutting tool diameter 10.00 mm, 13.00 mm and 14.50 mm. A few methods applied by some researchers to determine the drill tool performance such as the total number of holes that can be drilled until the drill bit failed (Nouari et al., 2003). Besides that, the measurement performance used by other researchers to determine the drilling performance is surface roughness, drilling force, cylindricity and image from Scanning Electron Microscope (SEM) (Jadhav et al., 2018); surface finish, force, torque and cylindricity (Ghasemi et al., 2018); and SEM, surface roughness, burr height, average minimum and maximum diameter deviation (Nouari et al., 2003).

Ghasemi et al., (2018) proved the effects of pre-center drill hole and tool material on the thrust force, the surface roughness, the cylindricity in the drilling of Aluminium 7075. They reported the used of CNC Milling Machine, Kistler 5070 Dynamometer and the surface roughness tester, Mahr PS1 for the measurement of cutting force and the drilled surface area of Aluminium 7075 workpiece. The High Speed Steel (HSS) center drill with a diameter of 3.00 mm and three different high speed steel (HSS) drill cutting tool with a diameter of 7.00 mm coated with different coating element are employed. They used HSS-Mo, HSS-Co and HSS-Ti coated drill cutting tools with cutting speed and the feed rate of 25.00 m/min and 0.44 mm/rev, respectively. They observed a build-up edge and tool crack or also known as tool worn in all three drill cutting tools. The tool is worn and cracked at the center of the drill tooltip. They proposed that the drill cutting tool had slipped on the workpiece during the machining process and consequently, generated the angular drill holes which produced higher axial force and surface roughness as compared to pre-center drill holes.

Meanwhile, Jadhav et al., (2018) reported on the CNC Milling Machine and surface roughness tester for the measurement of cutting force and the drilled surface area of Aluminium 6061/Al_2O_{3p} MMC work material using High Speed Steel (HSS) drill with three different cutting speeds of 2200, 2600 and 3000 rpm as well as three different feed rates of 0.05, 0.10 and 0.20 mm/rev. Additionally, Nouari et a.l, (2003) also demonstrated the use of rigid instrumented drilling bench with 14.00 kW power and maximum rotation of 42000 rpm in their work. They used surface roughness tester and cutting force as performance measurement using Aluminium-Copper Alloy AA2024 T351 drill work material with diameter of 6.00 mm of High Speed Steel (HSS) drill for a depth of 25.00 mm using a range of cutting speeds between 24 m/min to 164 m/min and feedrate of 0.04 mm/rev.

Most of the researchers tried to determine the drilling cutting tool performance with the size of a diameter that is less than 7.00 mm as the machining process can be done only for a single pass. However, the usage of the larger diameter of drill cutting tool from the research is less as it is difficult to do a single pass drilling as the drilling tool is easily broken down according to Ghasemi et al., (2018). They highlighted the best machining method for diameter larger than 7.00 mm is through step by step machining process, starting with center drill cutting tool and then drilling the diameter 7.00 mm drilling tool. Nonetheless, the machining process is too long.

Several reports indicated two approaches in determining the tool life of the tool cutter. The first approach involved the used of total contact time with every cutting tool experienced the machining process until its wear or broken down. The method has also had its own drawbacks. Firstly, the total time taken for the machining of the workpiece until the tool wear is observed is varied. Researchers need to repeat the process more than one time in order to make sure that the tool life results are reliable. Secondly, the determination of tool life is based on the number of holes produced until the cutting tool wear. The method is usually applied for the drilling process. Instead of using the drill depth and time parameters as a tool life indicators, the used of holes number produced during the machining could determine the tool life efficiently, but with the condition that the drill depth is equal for all holes.

2.3.2 Environmental Criteria

The second criteria in sustainability evaluation is environmental criteria. For these criteria, the respective company should ensure that the raw material and energy used to give less impact to the environment (Schulz & Flanigan, 2016). The criteria is assessed using life-cycle assessment (LCA) method (Jayal et al., 2010). LCA is an approach used to quantify the overall environmental impact in terms of material and energy consumption during the machining process through the measurement of carbon amount that released into the air. According to Zhang and Haapala (2012), environmental impact assessment for a production line is calculated based on the amount of carbon released into the environment with consideration on the impact of raw materials production, energy consumption of raw material process to the finished product, scrap produced during the manufacturing process and disposal of tools, coolant and lubricant used during the manufacturing process.

In fact, researcher including (Narita, 2012) also conducted environmental impact assessment using the milling machine. The measurement of energy impacts on consumption, coolant, lubricant and chip recycling are based on Equations 2-9 till 2-12.

$$E_e = LCI(e) \times \left(PSm + PFM + \sum PP\right) \tag{2-9}$$

where E_e is referring to machine power consumption impact, *LCI (e)* is the electricity emission intensity, *PSm* is spindle motor power consumption; *PFM* is feed motor power consumption and *ΣPP* is peripheral device power consumption.

$$C_e = \left[\left(LCI(cp)\right) + LCI(cd) \times Tc + LCI(w) \times Tw\right] \times \left[\frac{Mt}{MTTR}\right] \tag{2-10}$$

where C_e is known as coolant impact consumption, *LCI (cp)* is coolant production emission intensity, *LCI (cd)* is coolant disposal emission intensity, *Tc* is the total coolant amount, *LCI (w)* is water distribution emission intensity, *Tw* is the total amount of water being used, *Mt* is machining time and *MTTR* is Mean time to replenish coolant.

$$LO_e = \left[\frac{Mt}{MTTR}\right] \times Ld \times \left(LCI(lp) + LCI(LD)\right) \tag{2-11}$$

where LO_e is referring to lubricant oil impact consumption, *Mt* is moving parts running time, *MTTD* is mean time to discharge lubricant, *Ld* is the amount of lubricant discharged, *LCI (lp)* is lubricant production emission intensity and *LCI (LD)* is lubricant disposal emission intensity.

$$Ch_e = WpV - pV \times d \times LCI(M) \qquad 2\text{-}12$$

where Ch_e is the chip recycling impact, *WpV* is workpiece volume, *pV* is product volume, *d* is material density and *LCI (M)* is the recycling emission of chip metal value.

There are few environmental impact assessment tools developed by private sectors and non-government organizations available in the market such as SIMAPRO, Sofi and Gabi Software (Herrmann & Moltesen, 2015), Eco-it Software (Birch et al., 2010) and sustainability tool in Solidworks software (Dassault System, 2018).

SimaPro software is developed by Pre Sustainability. SimaPro is a tool to collect, analyzed and monitor the sustainability performance of products and services. User can easily model and analyzed complex life cycles in a systematic and transparent way, measure the environmental impact of any products and services across all life cycle stages, identify the hotspots in every aspects in the supply chain, from extraction of raw materials to manufacturing, distribution, use, and disposal (PreConsultant(b), 2018). SimaPro with various integrated databases and impact assessments are used in various LCA applications including Carbon footprint, Water footprint, Product design and eco-design (DfE), Environmental Product Declarations (EPD) and Determination of key performance indicators (KPIs). Most of researchers used SimaPro software for calculating the life cycle of drinking water pipes (Hajibabaei et al., 2018), bamboo boards (Restrepo & Becerra, 2016), ammonia production process (Bicer et al., 2017) and in additive manufacturing versus traditional machining process (Faludi et al., 2015).

Meanwhile, SoFi software is developed by ThinkStep AG, a Germany company for a complex organization to integrate the performance management in their operations and value chain (ThinkStep, 2018). The highly flexible and collaborative platform became a single source for sustainability performance metrics with automated data capture, validation and reporting. SoFi Software able to perform analytics, planning and project management tools as well as industry-leading content libraries for benchmarking and is the best practice for any projects that relate to reducing the impact. The software is also used to access environment, health and safety, carbon management, sustainability reporting, energy management, sustainable supply chain and building portfolio sustainability. Many researchers have used SoFi software in their works that cover areas such as green building (Cays, 2017), assessment of nickel products (Mistry et al., 2016) and detergent product assessment (Schowanek et al., 2018).

Also, GaBi software is developed by a Germany based company named PE International Limited. GaBi Software is a sustainability software with a powerful Life Cycle Assessment engine that supports LCA including Design for Environment, Eco-efficiency, Eco-design, Efficient value chains, Life Cycle Costing (LCC) for Cost reduction; Life Cycle Reporting such as Sustainable Product Marketing, Sustainability Reporting, LCA knowledge sharing; and Life Cycle Working Environment such as Responsible manufacturing. Many industries have used GaBi Software for automotive, building and construction, chemical and petroleum, industrial products, and energy and utility areas (ThinkStep(b), 2019). Among the companies that used the GaBi software to evaluate the sustainability of their products are Audi, BMW, Daimler, Porsche, Renault and Bosch. Besides that, this software also being used in research areas such as sustainable design, Life Cycle Assessment (LCA), product carbon footprint, environmental product declaration (ThinkStep(b), 2019), wastewater treatment (Mahmood, 2016) and product service system (Zhang et al., 2018).

Eco-It software is developed by Pre Sustainability (Pre Consultant(a), 2018). The software requires the user to key in the information of life cycle, production, use and disposal screen manually as the software has no attach/provide any design. The software has a general standard material, energy, transportation, processing and service & infrastructure database options. When involved mass production data and the results presented in carbon emission (kg CO2 or Pt), the software is suitable to be used. Many researchers used Eco-it software for manufacturing ecological concrete (Vieira et al., 2016), solar cooling and heating system (Martinopoulos, 2016), design of the industrial system (Peruzzini & Pellicciari, 2018) and design orientation tools (Vezzoli, 2018).

All in all, it seems that only one tool is capable in evaluating multiple criteria that mimic the sustainability assessment method which is the Sofi Software. Although the Sofi software is efficient in evaluating sustainability, the main problem is the environmental impact technical data used is based on European data and not South East Asia technical data. Other software such as SIMAPRO, Gabi, Eco-it and Solidworks software only capable in assessing environmental impact assessment for a product which not included in the social and economic criteria.

Most of the research on the environmental impact evaluation concerned different application areas and used different environmental impact assessment software. The application areas include supply chain management (Ho et al., 2010), building life cycle (Tam et al., 2018), kitchen utensil (Haapala, 2012), machining process (Duflou et al., 2012; Gbededo & Liyanage, 2018), biodiesel (Herrmann & Moltesen, 2015) and automotive industry (Sakundarini et al., 2012; Stoycheva et al., 2018).

Today, there are many tools developed either for non-profitability organizations or private companies to help the manufacturing industry specifically to evaluate the product in terms of sustainability and environmental impact. The U.S Environmental Protection Agency came out with various specific sustainability evaluation tools to help the industry to evaluate product sustainability (United States Environmental Protection Agency, 2017). The tools are Electronics Product Environmental Assessment Tool (EPEAT), Energy Tracking Tool (ETT), EPA Lean Manufacturing and Environment Toolkit.

Electronics Product Environmental Assessment Tool (EPEAT) is a searchable global registry tool for producing greener electronics products (United States Environmental Protection Agency, 2017). The main target user for the tool is purchasers, manufacturers, resellers and other people who want to find and promote environmentally preferable products. Energy Tracking Tool (ETT) is a tool which provides manufacturers with a simple means to track energy usage, set baselines, establish energy and emissions reduction goals, and evaluate progress towards achieving goals (United States Environmental Protection Agency, 2017). The tool is intended for medium to small sized manufacturing companies which restricted resources and unable to invest for custom data tracking system.

EPA Lean Manufacturing and Environment Toolkits are known as business model and collection of methods that help to eliminate waste while delivering quality products on time (United States Environmental Protection Agency, 2017). Besides that, this tool also targeted to reduce environmental waste while improving product quality, reducing costs, and enhancing customer awareness.

The non-profit organization including Organization for Economic Co-operation and Development (OECD) introduced free Sustainable Manufacturing Toolkit used to evaluate sustainability (OECD, 2011). These toolkits consist of 18 internationally relevant, common and comparable key performance indicators to measure and improve the environmental performance of manufacturing facilities and products. The toolkit aims to provide a practical starting point for businesses around the world to improve the efficiency of their production processes and products, enable the contribution to sustainable development and green growth. The tool of any size and design is also used by non-experts.

There is one organization from Cambridge University that has developed its own sustainability tool. They came out with Cambridge Sustainable Design Toolkit, which designed to provide both the theoretical learning experience and action-based support (Bernhard Dusch, 2018). The toolkit involves a series of individual components, each is developed based on the latest research development. On an academic point of view, the toolkit provides presentations and conceptual frameworks. These help the design practitioner for a better understanding of the true meaning of sustainable design. On a realistic point of view, different card desk support decision making able to perform in the early product development phase. The modular format used in the tool kits also allows adaptation to meet specific project aim or even to be used as a separate individual tool kit components.

2.3.3 Social Criteria

The last criteria in sustainability assessment is social criteria. Social criteria is referring to social dimensions of a community or regional area and include life quality, access to resources, health and education (Esteves et al., 2017; Prenzel & Vanclay, 2014; Slaper & Hall, 2011; Tam et al., 2018). At the production floor level, social criteria is assessed using ergonomics assessment method which consider human safety at the production line and societal benefit (Zhang & Haapala, 2015). According to the Department of Safety and Health (DOSH) Malaysia, manufacturers are responsible for creating safe and healthy working environment taking into consideration the injuries, illumination, noise level and safety protection (Department of Safety and Health Malaysia, 2018).

On the other hand, the manufacturers have social obligation in creating new jobs, providing worker compensation and purchasing insurance. In a much-reduced scope, social criteria at the manufacturing floor is accessed from the ergonomics point of view. Many methods is used to assess social criteria using ergonomics assessment including Musculoskeletal Injury (MSI) Risk Assessment, REBA, RULA and The NIOSH Weight Lifting Index.

2.3.3.1 Musculoskeletal Injury (MSI) Risk Assessment

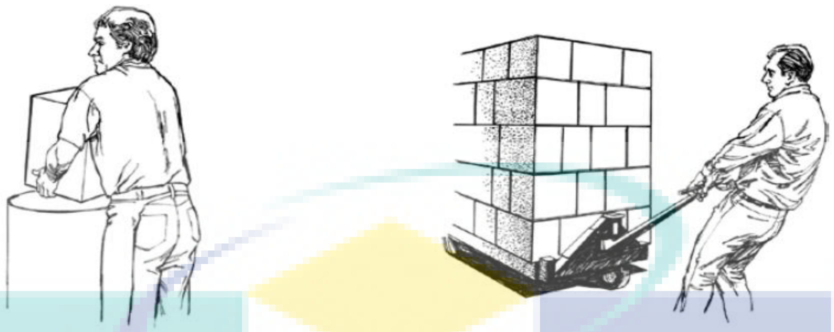
According to the occupational safety lawyer (Hirst, 2018) and WorkSafeBC organization (WorksafeBC, 2008), Musculoskeletal Injury (MSI) is a common type of working injury in all industries that caused from overexertion and repetition motion accidents. MSI signs is observed by looking at particular body parts whether any swelling, redness and difficulty in moving are observed with the symptoms including numbness, pain and tingling are the presence (Mokha et al., 2016; WorksafeBC, 2008). Based on the application, sign and symptoms, MSI is used to measure the ergonomics aspect in the production line. Six jurisdictions need to be followed by employees based on Canadian occupational safety and health legislation. One of them is the prevention of Musculoskeletal Injuries (OSHInsider, 2015).

MSI is an efficient ergonomics measurement method which consists the six detail assessments that are the force required to grip, the force required to lift, lower or carries objects, the force required to pull and push objects, work posture, repetition and local stress. The evaluation scale used the Musculoskeletal Injury (MSI) Risk Assessment rated from 0 to 3, with 0 is referring to not applicable, one is low, two is medium and three is high. The high indicator refers to the actions needed to reduce the potential impact of injury during working.

Meanwhile, the required grip force is referring to the force needed by a worker to grips an object during their work. The examples include gripping and handling a small and slippery tool, a weird shaped object that difficult to hold and holding an awkward shape tool as shown in Figure 2.2

Figure 2.2 Worker hands exert force when gripping a small tool
Source: WorkSafeBC (2008).

Additionally, the force required to lift, lower and carry object is referred to the force needed to lifting, lowering and carrying an object, while force required to pull and push an object is referred to the force needed to pull and push activity as shown in Figure 2.3.



(a) (b)

Figure 2.3 Example of (a) force needed to lift and (b) force needed to pull an object. Source: WorkSafeBC (2008).

In fact, working posture is referring to different body position while doing any work. According to (WorksafeBC, 2008), an awkward position displayed by the worker while doing a job, the muscles, tendons and ligaments worked really hard and consequently stressed out. The body parts involved in the posture working evaluation involved the neck, back, shoulder and wrist and other body parts movement as shown in Figure 2.4.

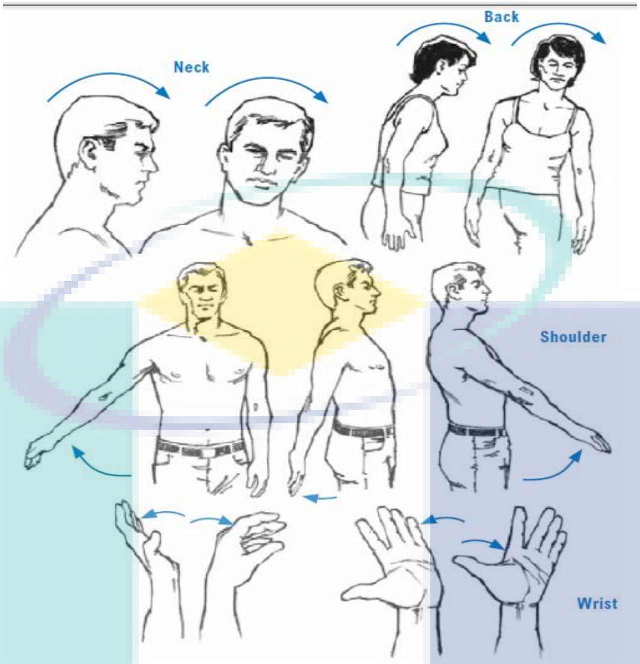


Figure 2.4 Working body posture parts movement for neck, back, shoulder and wrist
Source: WorkSafeBC (2008)

For an operator working at the production line, repetitive work is a must that cycles every day with a little chance of rest or recovery period (WorksafeBC, 2008). This applied to both large and small working muscle as shown in Figure 2.5.

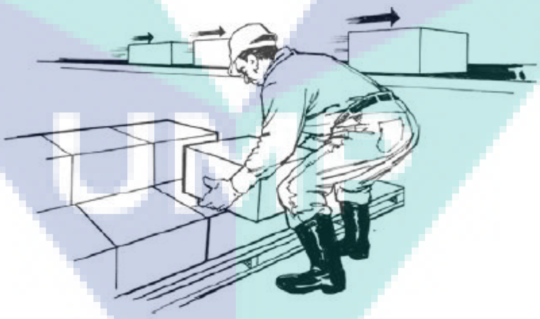


Figure 2.5 Repeatedly lifting heavy box stressed body muscles again and again
Source: WorkSafeBC (2008)

The last assessment in MSI is local contact stress. Local contact stress occurs when a sharp and hard object is in contact with human skin, that results in injuries of nerves and tissues under the skin caused by pressure.

2.3.3.2 Rapid Entire Body Assessment (REBA)

Rapid Entire Body Assessment (REBA) is developed by Higgnet and Mcatamney with the aims to make sure the worker is in a good health condition ergonomically (Higgnet & Mcatamney, 2000). REBA is a survey method developed to investigate the ergonomics problem of a workplace with work-related entire body disorder reported. REBA evaluation method consists of two sections with Section A covers trunk, neck and leg while Section B covers the upper arm, lower arm and wrist. The assessment method results are based on the rating index given by the observer who assesses the operator working performance. In each evaluation regions, the scoring scale for posture and some additional adjustment need to be considered and accounted in the score. Generally, 5 action levels are used in overall results at level 0 with score 1 indicates the risk level is negligible whilst level 1 with score 2 to 3 indicates the low-risk level and level 2 with score 4 to 7 indicates similar low-risk level. Subsequently, level 3 with score 8 to10 indicates the risk level is medium and level 4 with score 11 to 15 indicates that the very high-risk level and action need to be taken immediately. Figure 2.6 shows the summary of Rapid Entire Body Assessment (REBA) developed by ergo-plus.com (ErgoPlus(a), 2018).

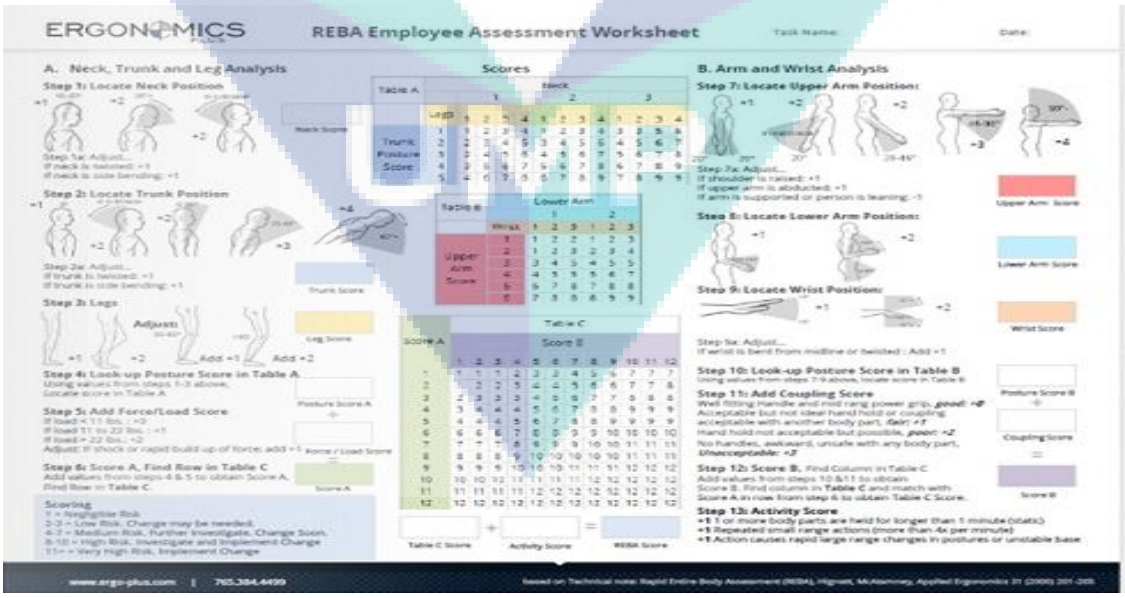


Figure 2.6 Summary of Rapid Entire Body Assessment (REBA). Source: ErgoPlus (a) (2018)

2.3.3.3 Rapid Upper Limb Assessment (RULA)

Rapid upper limb assessment (RULA) is referring to the indexed rating survey method developed for the ergonomics investigations of the workplace with work-related upper limb disorder reported (McAtamney & Corlett, 1993). Similar to REBA assessment method, two sections in the RULA evaluation method. The first one is Section A consists of the upper arm, lower arm, wrist and wrist twist, while the second section is Section B consists of neck, trunk and leg. In total, 14 steps requires answers from the evaluator to obtain the RULA final score. 4 actions level employed in RULA overall results in which level 1 with score one to two indicates the acceptable posture if it is not maintained or repeated for a long period of time while level 2 with score three to four indicates requires further investigation and changes. Next, level 3 with score five to six indicates investigation and changes are required soon and finally level 4 with score seven indicates investigation and changes are needed immediately. Figure 2.7 shows the summary of RULA developed by ergo-plus.com (ErgoPlus(b), 2018).

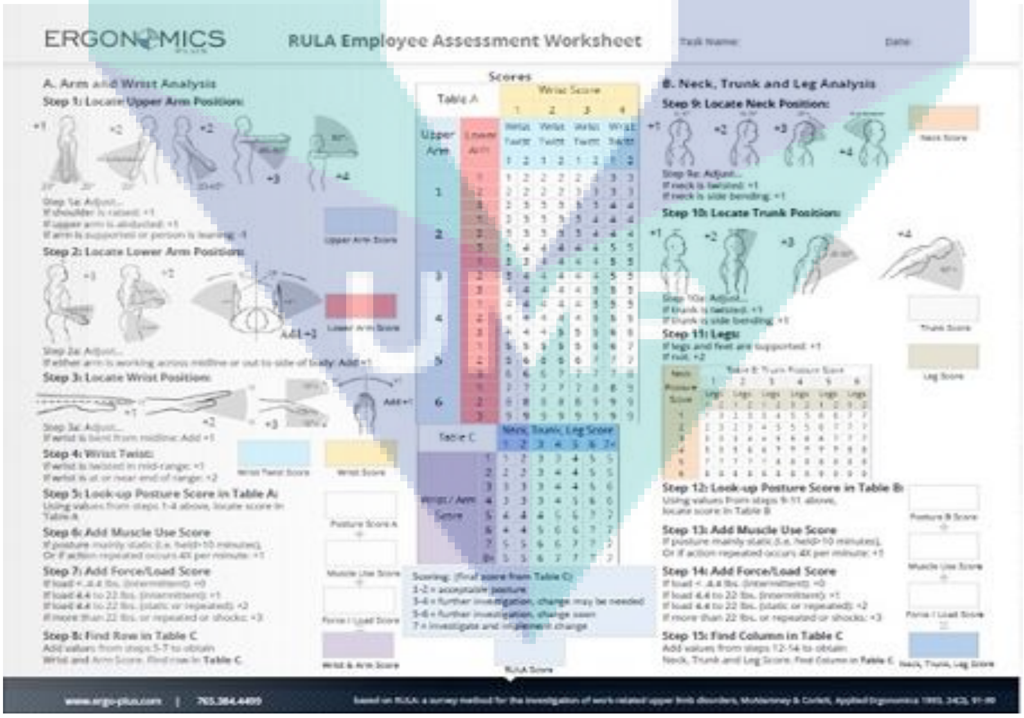


Figure 2.7 Summary of Rapid upper limb assessment (RULA). Source: ErgoPlus(b) (2018).

2.3.3.4 The Revised NIOSH Weight Lifting Index

Manual lifting tasks are identified as one of the significant contributors to the injury in most of the industry sector (Department of Safety and Health Malaysia, 2018). The main contribution of the problem is the lack of weight lifting awareness among the workers in the workplace. This type of injury affects both employer and employee as it happened. For the employee, suffering the injury is inevitable. In some cases, the employee is hospitalized if the critical injury occurred. For the employer, the treatment cost cover is a must and at the same time, more money is spent to find another worker to cover the injured employee. The revised NIOSH weight lifting index is introduced in 1993 to identify the hazardous of lifting activity and efforts to minimize them (Waters et al., 1993). The equation used in the evaluation is shown in Equations 2-13 and 2-14.

$$\text{Lifting Index}\left(\text{LI}\right)=\frac{\text{Load Weight}}{\text{Recommended Weight Limit}}=\frac{\text{L}}{\text{RWL}} \qquad \text{2-13}$$

$$\text{RWL}=\text{LC}\times\text{HM}\times\text{VM}\times\text{DM}\times\text{AM}\times\text{FM}\times\text{CM} \qquad \text{2-14}$$

where LC is load constant = 23kg, HM is Horizontal Multiplier, VM is Vertical Multiplier, DM is Distance Multiplier, AM is Asymmetric Multiplier, FM is Frequency Multiplier, and CM is Coupling Multiplier.

HM stands for horizontal multiplier with the measured horizontal distance between the point of projection and mid-point between inner ankle bones is calculated as shown in Figure 2.8. The equation used is 25/H, with the H distance measured in a metric unit. The summary of the horizontal multiplier (HM) is shown in Table 2-4.

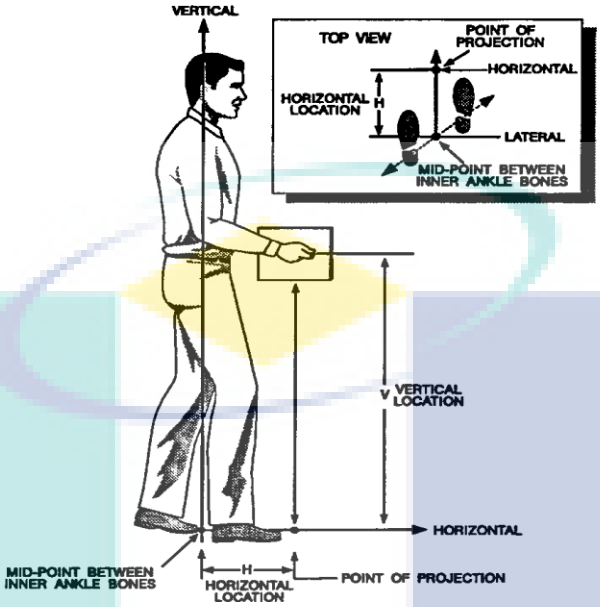


Figure 2.8 Graphical presentation of horizontal and vertical location. Source: Waters et al., (1993).

Table 2-4 The summary of horizontal multiplier (HM) values.

H (cm)	HM
≤ 25	1.00
28	0.89
30	0.83
32	0.78
34	0.74
36	0.69
38	0.66
40	0.63
42	0.60
44	0.57
46	0.54
48	0.52
50	0.50
52	0.48
54	0.46
56	0.45
58	0.43
60	0.42
63	0.40
> 63	0.00

Source: Waters et al., (1993).

The vertical multiplier (VM) is a distance of the hands above the floor measurement as shown in Figure 2.8. The equation proposed in this measurement is $1-(0.003\ |v-75|)$ and for distance multiplier, the equation used is $0.82 + (4.5/D)$ with D is referring to the absolute value of the difference between vertical heights at the destination or origin of the lift (Waters et al., 1994). The summary of the vertical multiplier (VM) and distance multiplier (DM) are shown in Table 2-5 and Table 2-6.

Table 2-5 The summary of vertical multiplier (VM) values.

V (cm)	VM
0	0.78
10	0.81
20	0.84
30	0.87
40	0.90
50	0.93
60	0.96
70	0.99
80	0.99
90	0.96
100	0.93
110	0.90
120	0.87
130	0.84
140	0.81
150	0.78
160	0.75
170	0.72
175	0.70
> 175	0.00

Source: Waters et al., (1993)

Table 2-6 The summary of distance multiplier (DM) values.

D (cm)	DM
≤ 25	1.00
40	0.93
55	0.90
70	0.88
85	0.87
100	0.87
115	0.86
130	0.86
145	0.85
160	0.85
175	0.85
>175	0.00

Source: Waters et al., (1993)

Erlinda and colleagues came out with vertical multiplier (VM) measurement for South-East Asia people specifically for Indonesian people (Muslim et al., 2013).

According to Muslim (2013), the Revised NIOSH Weight Lifting Index is tested to American and European people whereas for Asian country especially South East Asia people no evidence it is reported. They analyzed the vertical multiplier for a male industrial worker in Indonesia through the assessment of biomechanics, physiology and psychophysical tests. The results proved that the vertical multiplier equation for South-East Asia people is different from the published revised NIOSH weight lifting index equation. The multiplier equation results for Indonesian male worker is reported as VM = 1-0.0310083 (68-V) and VM = 1-0.00708215 (68-V).

The asymmetric multiplier (AM) measures how far an object is displaced from the front of the worker body at the beginning or end of the lift in degree as shown in Figure 2.9. According to Waters et al., (1993), the asymmetric angle is defined by the location of the load relative to the worker mid-sagittal plane, as described by a neutral body posture rather than the position of feet or the extent of body twist. The equation used is 1 – (0.0032A) for metric measurement. The neutral body position is referring to a body position where the hands are placed directly in front of the body and exists a minimal twisting movement on leg torso or shoulder. The summary of the asymmetric multiplier (AM) is shown in Table 2-7.

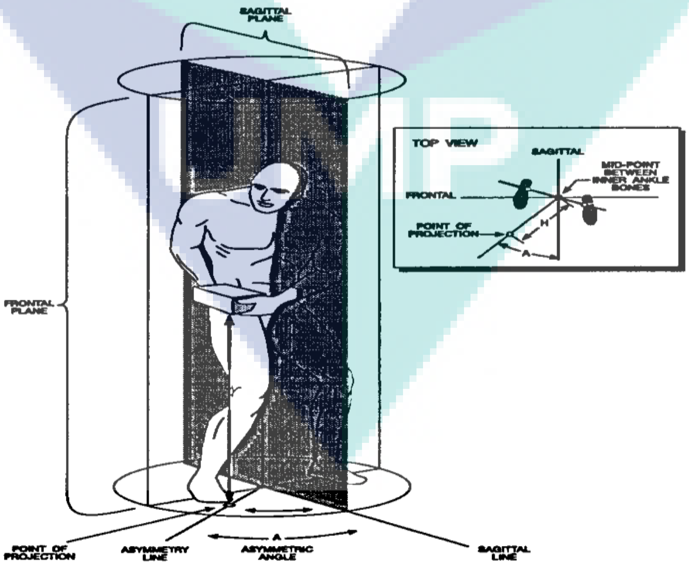


Figure 2.9 Graphical presentation of asymmetric angle.
Source: Waters et al., (1993)

Table 2-7 The summary of the asymmetric multiplier (AM) values.

A (Degree)	AM
0	1.00
15	0.95
30	0.90
45	0.86
60	0.81
75	0.76
90	0.71
105	0.66
120	0.62
135	0.57
>135	0.00

Source: Waters et al., (1993)

Next, the frequency multiplier (FM) is defined as the average number of lifts per minute and over the time taken is more than 15 minutes. The summary of the frequency multiplier are shown in Table 2-8.

Table 2-8 The summary of frequency multiplier (FM) values.

Lifting Frequency (F)	≤ 1 Hour V<76.2cm	≤ 1 Hour V≥76.2cm	Work > 1 but ≤ 2 Hours V<76.2cm	Duration > 1 but ≤ 2 Hours V≥76.2cm	> 2 but ≤ 8 Hours V<76.2cm	> 2 but ≤ 8 Hours V≥76.2cm
≤ 0.2	1	1	0.95	0.95	0.85	0.85
0.5	0.97	0.97	0.92	0.92	0.81	0.81
1	0.94	0.94	0.88	0.88	0.75	0.75
2	0.91	0.91	0.84	0.84	0.65	0.65
3	0.88	0.88	0.79	0.79	0.55	0.55
4	0.84	0.84	0.72	0.72	0.45	0.45
5	0.80	0.80	0.60	0.60	0.35	0.35
6	0.75	0.75	0.50	0.50	0.27	0.27
7	0.70	0.70	0.42	0.42	0.22	0.22
8	0.60	0.60	0.35	0.35	0.18	0.18
9	0.52	0.52	0.30	0.30	0.00	0.00

Source: Waters et al., (1993)

The coupling multiplier (CM) is referring to the quality of the hand to hold, grip and cut-off the object. The measurement basically based on the coupling quality either good, fair or poor. The summary of the coupling classifications and coupling multiplier are shown in Table 2-9 and Table 2-10.

Table 2-9 The summary of hand to object coupling classifications.

Good	Fair	Poor
For Optimal design containers with optimal handle design, an excellent hand to object coupling would be defined as handles or hand-hold cut-outs of optimal design which allows being handled easily	For optimal container design, a fair hand to object coupling would be described as handles or hand hold cut-outs of less than optimal design but still capable of lifting the object	For container less than the optimal design or loose part or irregular objects that are bulky, hard to handle or have sharp edges
For loose parts or irregular objects which are not usually containerized, a good hand to object coupling would be defined as a comfortable grip in which the hand can easily wrap around the object	For optimal design containers with no handles or hand-hold cut-outs or for loose parts or irregular objects, a coupling is defined as a grip in which the hand can be flexed about 90 degree	Lifting non-rigid bags (example: bags that sag in the middle)

Source: Waters et al., (1993)

Table 2-10 The summary of coupling multiplier values.

Coupling Type	Coupling V<75cm	Multiplier V≥75cm
Good	1.00	1.00
Fair	0.95	1.00
Poor	0.90	0.90

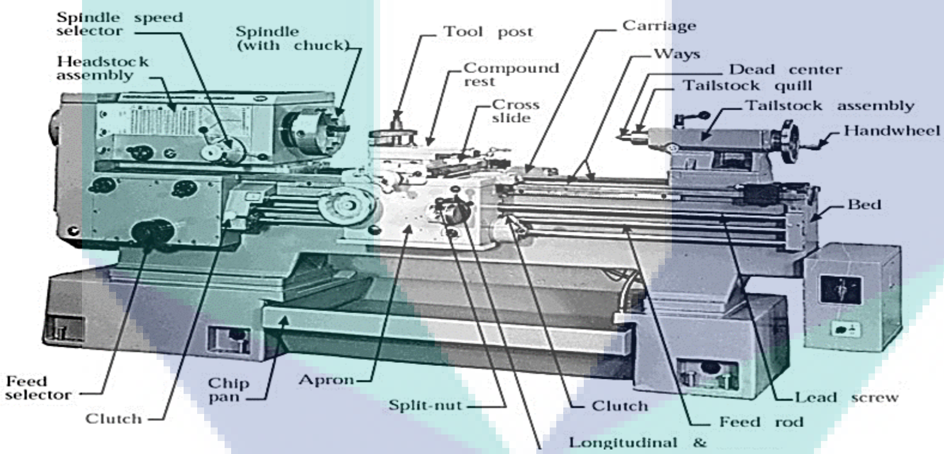
Source: Waters et al., (1993)

Overall, each of the ergonomic assessment reviewed proved to possess its advantages and disadvantages. For instance, Musculoskeletal Injury (MSI) Risk assessment is a comprehensive assessment method to assess the musculoskeletal injury. However, the drawback of the method is that the scale number used in the evaluation and each scale represent different things. Similar situation is observed in REBA and RULA assessment methods.

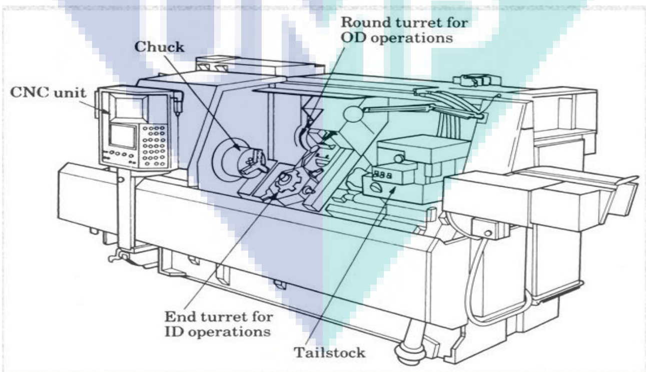
Different situation occurred for The Revised NIOSH Weight Lifting Index. Here, Waters et al., (1993) used scaling method to measure seven multiplier values with the uniqueness of the method focusing on the real weight of the workpiece and at the same time pallet weight is included to make the index determination more accurate. This element is crucial as it allows researchers to create a linkage between environmental and economic criteria.

2.4 Turning Process

Turning process is one of the most basic machining processes with the part is continuously rotated during machining process (Kalpakjian & Schmid, 2014; Vijayaraghavan et al., 2016). The typical workpiece shape used in the turning process either cylindrical, cubical or hexagonal symmetry material, where it is turned using a single-point cutting tool with a high cutting speed (Kim et al., 2015). The turning processes is run using a conventional lathe machine or computer numerical control (CNC) lathe machine as shown in Figure 2.10.



(a)



(b)

Figure 2.10 Types of Lathe machine; (a) Conventional (b) CNC Turning Machine. Source: Kalpakjian and Schmid (2014).

The machining processes that are performed using a lathe machine include turning, facing, cutting with form tools, boring, drilling, and threading. Turning is known as a process to produce straight, grooved or conical workpiece such as straight and conical shafts, and pins. The process involved are straight turning, taper turning, grooving and profiling. While facing is referring to a process performed to produce a flat surface and at the same time to remove any rust at the surface of the workpiece. Next, cutting with form tools are used to produce various axisymmetric shapes for aesthetic purpose. Boring is a process enlarging the hole or cylindrical cavity either by producing internal groove or for a special purpose function. Drilling is a process of making various size of holes and lastly, threading is known for a process to produce screw thread either internally or externally. All the machining processes example is shown in Figure 2.11.

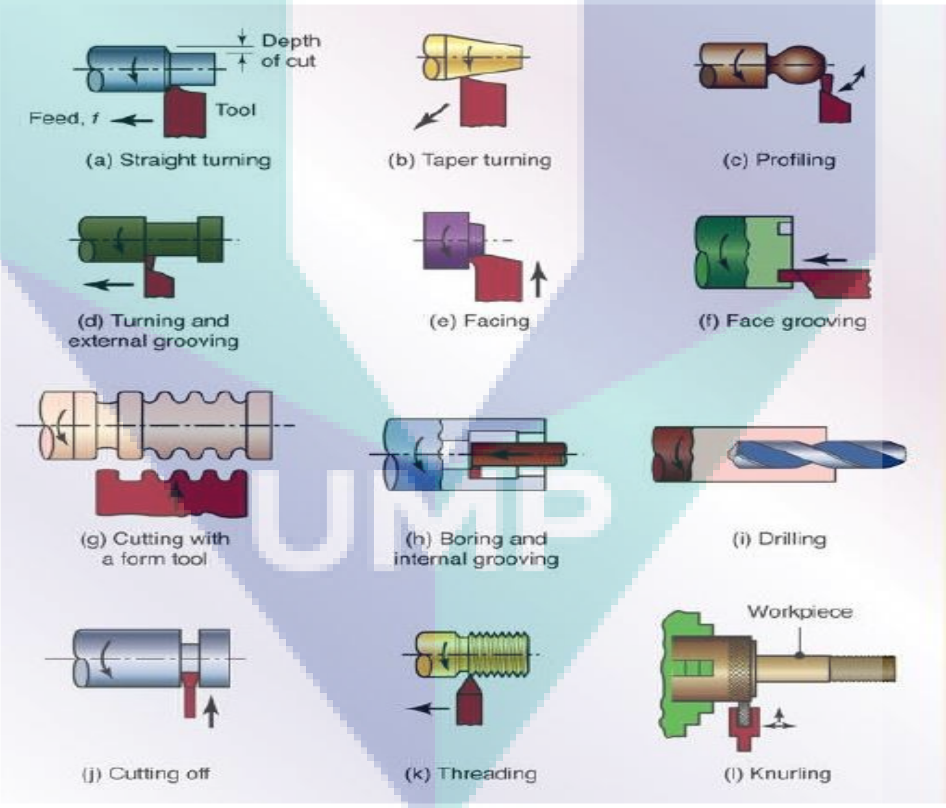


Figure 2.11 Various machining process can be done by using a lathe machine.
Source: Kalpakjian and Schmid (2014).

Generally, three cutting parameters involved in turning process using a lathe machine. The parameters include cutting speed, feedrate and depth of cut. Cutting speed is referring to the speed at which the workpiece moves in the rotational direction and measured in meter per minute (m/min). Feedrate is expressed as a distance in which the tool travels in one revolution of the part. Depth of cut is the distance that the cutting tool moves into the workpiece for cutting purpose. Besides that, machining time and power used during the turning process are also important since they are related to sustainability measurement. Machining time (*t*) for a workpiece of *l* length is calculated by noting that the tool travels at a feedrate of fN. The power used during the turning process is calculated using torque and ω where torque = $F_c D_{avg}/2$ and ω = 2πN. The cutting speed, machining time and power used during the turning process formulas is further manipulated using Equations 2-15 to 2-17 where *D* represents workpiece diameter and *N* represent the rotational speed of the workpiece.

$$\text{Cutting Speed}\left(V\right)=\pi DN \tag{2-15}$$

$$\text{Machining Time}\left(t\right)=\frac{1}{fN} \tag{2-16}$$

$$\text{Power Used}\left(P\right)=\text{Torque}\times\omega \tag{2-17}$$

2.5 Multi-Criteria Decision Making (MCDM) Method

Multi-criteria decision making (MCDM) method is a procedure that combines the performance of decision alternatives across several contradicting either qualitative or quantitative criteria and results in a compromise solution (Kolios et al., 2016). MCDM can be divided into two groups, known as Multiple Attribute Decision Making (MADM) and Multiple Objective Decision Making (MODM) (Penadés-Plà et al., 2016).

MADM is a priori process used to evaluate discrete variables (Penadés-Plà et al., 2016). The basic principles of this process are to convert multi-objective optimisation problems to the single-objective optimisation problem by combining several different objective functions as a single objective function (Zhang et al., 2015). Here, expert take part in the initial stage of the process where they give a weight for each criterion or assessing any attribute of the bridge. The final results in this method are the best solution or a solution ranking. Weighted Sum Method (WSM), Analytical Hierarchy Process (AHP), Preference Ranking Organisation Method (PROMETHE) and Multi Attribute Utiliti Theory (MAUT) are among the example of posteriori process (Kumar et al., 2017).

According to Kumar et al., (2017), weighted sum method uses a simple computation method and suitable for single dimension problem; but the weaknesses are it's only using a basic estimation process of one's penchant function, and it fails to integrate multiple preferences. For the analytical hierarchy process, this method is adaptable; it doesn't involve complex mathematic calculation and based on a hierarchical structure where each criterion can be better focused and transparent. The disadvantages of using this method are its interdependency between objectives and alternative solution which will lead to poor results. Besides that, the involvement of more decision-maker can make the case study more complex when assigning weight and lastly, the data collected is based on experience people.

Kumar et al., (2017) added, PROMETHE also have advantages and disadvantages. Its advantages are this method involves group level decision, it deals with qualitative and quantitative information and it incorporates uncertainty and fuzzy information. It also has disadvantages such as it doesn't structure the objective properly, it depends on the decision maker to assign weight and this method is complicated and users are limited to experts. Lastly, Kumar et al., (2017) explain the advantages of MAUT are its simultaneous compute preference order for all alternatives; it dynamically updates value changes due to any impact and its account for any difference in any criteria. The disadvantages are it needs precise input from decision-maker and the outcome of the decision criteria is uncertain.

MODM, on the other hand, is a posteriori process which allows for the obtainment of a continuous set of solution regarding two or more criteria called Pareto front (Penadés-Plà et al., 2016). These solutions are characterized by consideration each of the criteria is equally good. The expert also takes part in the end stage of the process to choose the final solution to be implemented. Genetic Algorithm (GA), Particle Swam Optimisation (PSO) and Artificial Neural Network (ANN) are among the example of posteriori process. The genetic algorithm also has its pros and cons (Beg & Islam, 2016). For example, this method is flexible and widely acceptable optimisation process. Besides that, it tends to avoid local minima and find a global solution in the whole problem space. This method also can optimise a lot of parallel measures simultaneously. The cons of this method is time consuming to produce the optimise result since it search the whole problem space; hence, it requires expensive investment in terms of memory and computation.

Particle swarm optimisation algorithm also has its advantages and disadvantages (Li et al., 2014). The advantages of the algorithm are its fast computing speed and parallel processing while its disadvantages are that it is easy to fall into a local minimum in high-dimensional space and has a low convergence rate in the iterative process. The artificial neural network offers several advantages and disadvantages including it require less formal statistical training; it can implicitly detect the complex nonlinear relationship between dependent and independent variables, the ability to detect all the possible interactions between predictor variables and the ability of multiple training algorithms (Tu, 1996). He added the disadvantages include its "black box" nature, greater computational burden, proneness to overfitting and empirical nature of model development.

Another aspect to be considered in using the multi-criteria decision making method is the application of Principle Component Analysis (PCA) concept method in MCDM (Ioele et al., 2011). PCA is widely used to reduce the number of variables used in the data matrix (Ioele et al., 2011). Ioele et al., (2011) added, the use of PCA combined with MCDM method usually improves the training speed, enhance the robustness of the model and reduces the calibration errors. On the other hand, there are a few disadvantages of this method such as the simplest invariance when using PCA method could not be captured unless the training data explicitly provide this information (Karamizadeh et al., 2013).

Since this study adopted the artificial neural network model because of its advantages listed in the above paragraph, only this algorithm will be reviewed. At the same time, to obtain the optimal results, the inversed artificial neural network will be used and been reviewed.

2.5.1 Artificial Neural Network (ANN) Model

Artificial neural network or also known as a neural network is a mathematical model that tries to simulate the functionality of the biological nervous system (Mohamed, 2017). The nerve system consists of a group of interconnected neurons and process information by using a connectionist approach to computation (El-Bhrawy, 2016). The neural network is an adaptive system that changes its structure based on the information given in terms of data either based on internal or external information that flows in the network during the learning phase (Mohamed, 2017). Neural network model can be used to model either linear or non-linear statistical data problems. Besides that, it also can be used to model the complex relationship model between inputs and outputs or vice versa to find patterns in the data set (El-Bhrawy, 2016). He added that neural network is an interconnected group of nodes, akin to a vast network of neurons in the human brain. Figure 2.12 shows the interconnection of the human brain and the similarity of neural network.

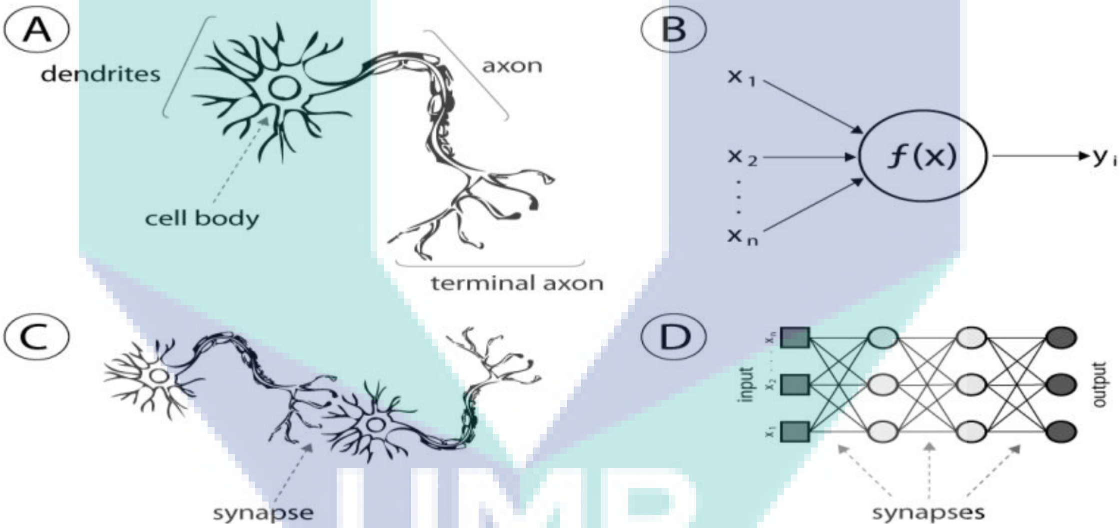


Figure 2.12 Interconnection of the human brain and the similarity of the neural network; (A) Human neuron, (B) Neuron or hidden unity, (C) Biological synapse, (D) Neural network synapse.
Source: El-Bhrawy (2016).

In the neural network, there are three basic rules in developing the mathematical model which known as multiplication, summation and activation (Mohamed, 2017). Each inputs value in the neural network will be multiplied with a specific weight. This weighted inputs will be added with a bias term and both weighted will be transformed by an activation function to compute the output. According to Mohamed (2017), the weight that associated with each input provides the strength of the synapse. The higher the strength of synapse value means, the stronger the input. The weight can be either positive or negative value where, if the weight is positive, $(w_i > 0)$ which indicate that it have an extraordinary connection; while if the weight is negative, $(w_i < 0)$ it inhibits the neuron activity.

The fundamental processing element in a neural network is called perception. It has inputs of x_i that may come from the external input environment or it may be the outcome of other perceptron (Mohamed, 2017). He added, that the output of this perceptron can be derived as follows:

$$y=\sum_{i=1}^{N} w_i x_i + b \qquad \text{2-18}$$

where b represent the bias term or known as the neuron's threshold. The neuron's threshold also can be considered as an additional input where it is always unity and its weight is equal to *b*. The perceptron output can be written as a dot product:

$$y=w^T x \qquad \text{2-19}$$

where *w* and *x* are the two vectors. In neural network, the activation function defines the neuron properties any activation function $\emptyset(.)$ moreover, the output can be expressed as:

$$y=\phi\left(\sum_{i=1}^{N} w_i x_i + b\right) \qquad \text{2-20}$$

The determination $\emptyset$ of the neuron is mainly depended upon the nature of the corresponded case study that needs to be solved. The $\emptyset$ act as a transformation entity that allows the neuron output to takes a value between the specified range such as [0,1] or [1, -1] which relies on the chosen function (Mohamed, 2017). The most popular activation function is the threshold function, which has only two possible outcomes; either 0 or 1. If the total input is less than a specific threshold, it is 0 while if the total input is greater or equal to that of a specific threshold, the value is 1 and can be written as:

$$y=\begin{cases} 1, \text{If } w^T x \geq 0 \\ 0, \text{If } w^T x \leq 0 \end{cases} \qquad \text{2-21}$$

For non-linear function, the sigmoid function is used (Mohamed, 2017). The sigmoid function acts as a rigid function that balance between the linear and non-linear case with the graph created is in the S shape. The sigmoid function can be written as:

$$y = \text{sigmoid}\left(w^T x\right) = \frac{1}{1 + \exp(-w^T x)} \quad \text{2-22}$$

Which the sigmoid function takes a value between 0 to 1, in some instances but in some cases, interval [-1, 1] can be used. In the latter case, the threshold can be defined as:

$$y = \begin{cases} 1, \text{If } w^T x > b \\ 0, \text{If } w^T x = b \\ -1, \text{If } w^T x < b \end{cases} \quad \text{2-23}$$

The overall neural network mathematical function framework is summarized as in Figure 2.13.

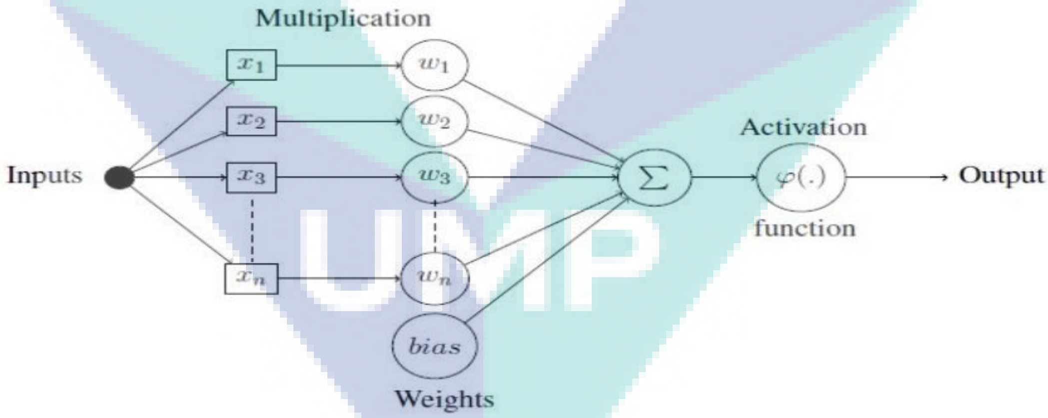


Figure 2.13 Neural network mathematical function framework.
Source: Mohamed (2017)

2.5.1.1 Number of Hidden Neuron

One of the major problem usually faced by researchers who used neural network technique in their research is to determine the right number of hidden neurons to be used so that their developed mathematical model will not be underfitting or overfitting (Panchal & Panchal, 2014; Sheela & Deepa, 2013). Sheela and Deepa (2013) added a few methods proposed to determine the correct number of hidden neurons. However, most of the methods are based on trial on the rule. In their paper, Sheela and Deepa (2013) present their proposed method on how to determine the number of hidden neuron.

Besides that, a few other methods are reviewed to determine the number of hidden neuron from other researchers starts from the year 1995 to 2013. According to Sheela and Deepa (2013), the methods are from Li et al. (Equation 2.25), Tamura and Tateishi (Equation 2.26), Fujita (Equation 2.27), Zhang et al. (Equation 2.28), Jinchuan and Xinzhe (Equation 2.29), Xu and Chen (Equation 2.30), Shibata and Ikeda (Equation 2.31), and Hunter et al., (Equation 2.32). The equation proposed by Sheela and Deepa (2013) is shown in Equation (2.24) and the rest of the researchers are as follows:

$$N_h = \frac{4n^2+3}{n^2-8} \tag{2-24}$$

$$N_h = \frac{\left(\sqrt{1+8n}-1\right)}{2} \tag{2-25}$$

$$N_h = N-1 \tag{2-26}$$

$$N_h = \frac{K\log\|P_c Z\|}{\log S} \tag{2-27}$$

$$N_h = \frac{2^n}{n+1} \tag{2-28}$$

$$N_h = \frac{\left(N_m+\sqrt{N_p}\right)}{n+1} \tag{2-29}$$

$$N_h = c_f\left(N/d\log N\right)^{0.5} \tag{2-30}$$

$$N_h = \sqrt{N_i N_0} \tag{2-31}$$

$$N_h = 2^n-1 \tag{2-32}$$

Baghirli (2015) used three learning algorithms to train the collected to obtain the mathematical model in Matlab Software. These algorithms are Lavenberg-Marquardt backpropagation, Scaled Conjugate Gradient and Bayesian Regularization.

The Lavenberg-Marquardt backpropagation algorithm is developed by Kenneth Lavenberg and Donald Marquardt, provided that the numerical solution could minimize a non-linear function problem (Batra, 2014). The algorithm is suitable to be applied to small and medium-size problems where it can process quickly and has a stable convergence. Batra (2014) added Lavenberg-Marquardt algorithm introduces an approximation to Hessian matrix where it ensures that the approximation of Hessian matrix JTJ is invertible.

Baghirli (2015) and Batra (2014),used the approximation and the gradient is computed as:

$$H = JtJ + ul \qquad 2\text{-}33$$

where *J* represents a Jacobian matrix composed of the first order derivatives of the network errors for the weight and bias. The obtained matrix used standard backpropagation technique shows less complexities than the Hessian matrix for the computing process (Baghirli, 2015). The constant, u is known as the combination coefficient with only positive value and the l is the identity matrix. Baghirli (2015) updated the rule of Lavenberg-Marquardt algorithm to become:

$$W_{k+1} = W_k - (J_k{}^t J_k + ul)\, J_k e_k \qquad 2\text{-}34$$

where W represents the connection weight. The searching activity is performed along the conjugate direction where it can produce a faster convergence than the steepest descent direction and at the same time preserving the minimization error achieved in all previous steps (Baghirli, 2015).

Baghirli also indicated that the conjugate gradient algorithm adjusted the step size in each iteration with the determination of step size is based on the search made along the conjugate gradient direction that directly minimizes the function performance along the line. Conjugate gradient algorithm performed relies upon the steepest descent direction at the first iteration, as shown in Equation 2.35 (Baghirli, 2015). The conjugate gradient which typically used with line search technique could prevents the Hessian matrix calculation from determining the optimal distance which move along the current search direction, as shown in Equation 2.36 (Baghirli, 2015). The determination of the next search direction must be conjugate with the previous search direction, as shown in Equation 2.37.

$$P_o = -g_o \tag{2-35}$$

$$X_{k+1} = X_k + \alpha_k g_k \tag{2-36}$$

$$P_k = -g_k + \beta_k P_{k+1} \tag{2-37}$$

where:

$$\beta_k = \frac{\left(\left|g_{k+1}\right|^2 - g_{k+1}{}^T g_k\right)}{g_k{}^T g_k} \tag{2-38}$$

$$P_{k+1} = -g_{k+1} + \beta_k P_k \tag{2-39}$$

Baghirli (2015) added another method used to estimate the step size by combining the model trust region approach obtained from the Lavenberg-Marquardt algorithm with the conjugate gradient approach which also known as the scaled conjugate gradient. The scaled conjugate gradient algorithm equation is shown in Equation 2.37 where E is the total error function, E' is the gradient of E, α_k and σ_k scaling factors are introduce to approximate the Hessian matrix and initialized at the beginning of the algorithm when $0<\alpha_k<10^{-6}$ and $0<\sigma_k<10^{-4}$.

$$S_k = \frac{E'(w_k + \sigma_k P_k) - E'(w_k)}{\sigma_k} + \lambda_k P_k \tag{2-40}$$

Bayesian regularization algorithm updates the weight and bias values according to Lavenberg-Marquardt optimization (Baghirli, 2015). The algorithm minimizes a combination of squared errors and weights and determines the correct combination to produce a generalized network. Bayesian regularization introduce F (ω) or also known as network weight into the objective training function as shown in Equation 2-41.

$$F(\omega) = \alpha E_{\omega} + \beta E_{D} \qquad 2\text{-}41$$

where E_{ω} is the sum of squared network weights, E_D is the sum of network error and α and β is the objective function parameters. In this method, the network weights are viewed as random variables; and the network weight distribution and training set are considered as Gaussian distribution (Baghirli, 2015). The α and β were defined by using the Bayes' Theorem, where it relates two variables, A and B based on their prior or posterior probabilities such as in Equation 2-42.

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \qquad 2\text{-}42$$

where $P(A|B)$ is the posterior probability of A conditional on B, $P(B|A)$ is the prior of B conditional on A, $P(B)$ is the non-zero prior probability of event B which also known as normalizing constant. To find the optimum weight space, the Equation 2-41 should minimized, which equivalent to maximizing the posterior probability function as, given in Equation 2-43.

$$P(\alpha,\beta|D,M) = \frac{P(D|\alpha,\beta,M)P(\alpha,\beta|M)}{P(D|M)} \qquad 2\text{-}43$$

where α and β are the factors that need to be optimised, D is the weight distribution, M is the particular neural network architecture, $P(D|M)$ is the normalization factor, $P(\alpha,\beta|M)$ is the uniform prior density for the regularization parameters and $P(D|\alpha,\beta,M)$ is the likehood function of D for given α,β,M. According to Baghirli (2015), maximizing the posterior function $P(\alpha,\beta|D,M)$ is equivalent of maximizing the likehood function $P(D|\alpha,\beta,M)$.

When completing this process, the optimum values of α and β for a specific given space are found. Next, the algorithm moves to Lavenberg-Marquardt phase where the Hessian matrix calculation takes place and update the weight space in order to minimize the objective function (Baghirli, 2015). He added, if the convergence is not met, the algorithm will estimate new values for α and β and the whole procedure will be repeated until the convergence is reached.

The neural network machine learning model have been used in various research areas, but none of them are specifically employed at the production line level. Some of the reported works reviewed the sustainability of machining processes using triple bottom line methodology (Álvarez et al., 2017). While others reported the used of neural network model to covers areas such as in accounting, finance, marketing and human resources (El-Bhrawy, 2016); wind energy system (Ata, 2015) and engine performance (Noor et al., 2015). However, some of the works aso included the estimation of the manufacturing cost of jet engine components (Loyer et al., 2016) and pharmaceutical (Lavecchia, 2015) apart from broad areas of manufacturing such as sustainable product manufacturing (Wuest et al., 2016); surface roughness prediction (Beatrice et al., 2014; Mia et al., 2017), drilling operation (Kannan et al., 2014) and milling operation (Khorasani & Yazdi, 2017).

2.5.2 Artificial Neural Network Inverse (ANNi)

Artificial neural network inverse (ANNi) methodology is used particularly for weights and bias obtained from an artificial neural network (ANN) model for optimization of input variables (Conde-Gutiérrez et al., 2018). Generally, the ANN performs a learning process from inputs data to simulate the output results. On the other hand, the ANNi model proposed an assessment method where the proposed simulated output value can be extrapolated to search the optimal input variables.

The application of ANNi model has been progressing very well and has attracted researchers from an engineering background to estimate the optimization of the operating conditions for steam turbine (Hamzaoui et al., 2015; Márquez-Nolasco et al., 2018), solar radiation collector (Reyes-Télleza et al., 2016), heat transformer (Conde-Gutiérrez et al., 2018), food industry (Hernández, 2009), compressor performance (Cortés et al., 2009) and polygeneration (Hernández et al., 2013).

Hamzaoui et al., (2015) perform research on the operating conditions of the steam turbine blade. They developed an integrated approach using the inverse artificial neural network (ANNi) coupled with the Nelder Mead optimization method to estimate the required resonance stress when a turbine blade at the end of its useful life. The results show that a combination of ANNi and Nelder Mead optimization method capable to predict the resonance stress of the turbine blade at the end of its useful life.

Conde-Gutiérrez et al., (2018) perform research on parabolic trough collectors (PTC) to concentrate the solar radiation and in turn transferred heat along a tube. The PTC used the copper tube to heat water for residential use. ANN model is developed to predict the hot-water outlet temperature, and its inverse (ANNi) is used to optimize the system's performance. The best fitting training data is acquired with the architecture of 9-9-1 considering a hyperbolic tangent sigmoid transfer-function in the hidden layer and a linear transfer function in the output. It is observed that the predicted and experimental data fulfil a satisfactory agreement ($R2 > 0.9854$, $RMSE > 0.8055$ and $MAE \sim 0.0586$). From this ANN model, a strategy is applied for optimizing the feeding tank temperature to increase the water outlet temperature of the PTC, using inverse artificial neural networks (ANNi) and solved by the method of genetic algorithms (GAs). These results showed that the highest outlet temperature reached by the PTC was 49°C.

Hernández (2009) applied ANNi to optimize the operating conditions on heat and mass transfer during foodstuffs drying. To demonstrate the ANNi method, two separate feedforward networks (ANN) with one hidden layer reported by Hernández et al., (2004) were used. The application of food drying is at the drying process of cassava and mango. Innovative Food Science and Emerging Technologies, 5, 56–64, are used to obtain temperature and moisture kinetics simulations during the drying process. The parameters take into account is air temperature, air velocity, shrinkage as a function of moisture content, time and air humidity as well-known input parameters. Levenberg–Marquardt learning algorithm, hyperbolic tangent sigmoid transfer-function, linear transfer-function and three neurons in the hidden layer are considered in both models. Results of the ANNi showed a good agreement with the experimental and simulated data ð error<0:001%Þ. Then ANNi could be applied to determine the optimal parameters during mango and cassava drying with elapsed time minor to 0.3 seconds.

According to Hernández (2009), one of the ways to optimize the parameters related to compressor performance is by using ANN and the Nelder–Mead simplex optimization method. It inverts the ANN to find the optimum parameter value under given conditions. Firstly, the ANN model was developed to predict the compressor pressure ratio, isentropic compressor efficiency, corrected speed, and finally corrected the air mass flow rate. Input variables for this ANN include the ambient pressure, ambient temperature, wet bulb temperature, cooler temperature drop, filter pressure drop, outlet compressor temperature, outlet com-pressor pressure, gas turbine net power, exhaust gas temperature, and finally fuel flow mass rate. Feed-forward with one hidden layer, a Levenberg–Marquardt learning algorithm, a hyperbolic tangent sigmoid transfer function and a linear transfer function was used. The best fitting with the training database was obtained with 12 hidden neurons. For the validation, simulation and experimental database were in good agreement ð R2>0:99Þ. Thus, the obtained ANN model can be used to predict the operating conditions when input parameters are well-known. The ANNi result shows a good agreement with experimental and target data (error <0.1%), where the cooler temperature is found for a required efficiency. Therefore, the proposed methodology of ANNi can be applied to optimize the performance of the compressor with an elapsed time minor to 0.5 seconds.

2.6 Research Survey

Selection of criteria that should be used need to be done during the research work and reasons for each selection needs to be clarified for a better understanding. Practically, the survey research method remains as more than art as compared to the science to gather needed data (Nardi, 2018). Research survey is defined as the collection of information from a sample of peoples/respondents through their responses to question (Ponto, 2015). There are many different ways of gathering data depending on the types of questions given, the scope/field of study, the financial assistance and time limitations with the number of other parameters detailed that needed (Nardi, 2018). Ponto (2015) added that research survey is used in a form of either quantitative (such as using a questionnaire with numerical rated items) or qualitative (such as using open-ended questions) strategies or both to perform the data collection. There are 5 methods stated by Nardi (2018) known as quantitative surveys, interviews (phone and face to face), focus group interviews, experiments and qualitative (observation and field). The advantages and disadvantages of each method are summarised Table 2-11.

Table 2-11 Summary on the comparison points for data collection methods.

Method	Advantages	Disadvantages
Quantitative: Surveys	Less costly to reach larger samples	Self-report requires reading ability in the language (age, eyesight limitations, education)
	Standardised questions	
	Ideal for asking about opinions and attitudes	The possible gap between what people report they do and what they actually do
	Less labour-intensive to collect data or train researchers	Return rate can be low for mailed and computer-based surveys, thus limiting generalizability
	Can guarantee anonymity	Closed-ended questions can be restrictive and culturally sensitive or dependent
	Suitable for probability sampling and more accurate generalizability	Difficult to explain the meaning of items and probe answers
	Easier to code closed-ended items	Depend on asking about recollected behaviour
	Respondents can answer at own pace	More difficult to code open-ended responses
	Better for sensitive and personal topics	Can't guarantee respondent answering it was the person intended to answer it
	Easier to replicate a study	Requires skill in questionnaire design
	Can address multiple topics in one survey	Long and complicated surveys can be tiring to complete and lead to errors
	Ideal for computer-based and online surveys	Easy to overlook, skip around, and misunderstand questions
	Easier to compare with other studies using similar questions	More difficult to generate reliability and validity for one-time-use questionnaires

Table 2-11 Continued

Method	Advantages	Disadvantages
Interviews: Structured face-to-face or telephone	Standardised questions for structured interviews	Limited to smaller samples
	Can explore and probe for additional information	Face-to-face interviews can be time consuming
	Can clarify the meaning of questions	Training required for interviewers
	Telephone interviews are less costly and can reach larger samples	More difficult to code open-ended responses and unstructured interviews
	Less likely to have skipped or missed questions	Interviewer characteristics (race, sex, age) and style could bias responses
	Unanticipated answers can occur, thus leading to new, unexpected findings	Some respondents reluctant to give information over the telephone
		Not as ideal for collecting sensitive or personal information
		More difficult to replicate
		Face-to-face interviews are not anonymous
		Telephone surveys are not ideal for complicated closed-ended items or choices
		Face-to-face interviews may require payment for participants
Interviews: Focus groups	Ideal for exploratory research	Not as ideal for collecting sensitive or personal information in some cultures
	Better for insights about complex issues and topics	A few people can dominate the discussions
	Suitable for studying opinions and attitudes	Responses easily affected by what others say
	Group interaction generates new ideas as respondents build on others' comments	Minority views often not disclosed
	Can probe for additional information	Not as suitable for studying the behavior
	Best for small groups (six to 12 range)	Time intensive to run
		Requires expert skills in leading groups
		Small sample sizes in one geographic area
		May require payment for participants

Table 2-11 Continued

Method	Advantages	Disadvantages
Experiments	Ideal for studying cause-and-effect explanations Better control of variables Easier to replicate Suitable for collecting quantitative data and doing statistical analyses Better for achieving internal and external validity Good for A/B marketing designs	Ideal for smaller samples but limited generalizability Experimental laboratory situations are artificial Narrow range of behavior is measured Respondents may act in a way because they know they are being studied (demand characteristics of experiments) Can take much time to run experiments Equipment costs May require payment for participants Ethical concerns about informed consent and harm
Qualitative: Observations and field methods	Ideal for studying behaviour in actual sites Unanticipated and unexpected findings can be collected Not limited to structured items on a survey Allows for respondents' views and perspectives Behaviour and situational factors observed in context and real-time Nonverbal data can be observed and analyzed Ideal for studying interactions among people Content analysis can be performed on documents and other written or visual records and artefacts	Limited to smaller samples Time consuming More difficult to code observations and responses Reliability of coding of observations or other content analyses needs to be established Observer bias can affect what is being observed and how Respondents' behaviour can be affected by being observed More difficult to assess opinions and attitudes Field notes take more time to write and analyze More difficult to replicate Ethical concerns about informed consent, the role of the participant-observer, and potential harm Not ideal for some quantitative statistical analyses

Based on Table 2-11, it can be concluded that a focus group interview has a good advantage to be implemented to assess sustainability assessment method. This is because the ideality for research exploration is better in terms of the insights of the complex issues and topics, and suitable for studying opinions and attitudes. Besides that, focus groups elicit a range of ideas, attitudes, experience and opinion given by a sample of respondents on a defined topic (Horhota et al., 2014). Horhota et al., (2014) reported that by implementing this method, researchers more inclined to receive more information from the respondents since they are encouraged to elaborate in-depth on issues by the moderator which can be done either by face to face interviews or by a phone call.

Unlike other interview methods, the questions provided to the respondent need to be outlined, selected and organized carefully (Garrison et al., 1999). There are three things need to be considered in developing the questionnaire. The first consideration is the sequencing of question need to be from general to specific. Secondly, the question should be open-ended questions instead of dichotomous. Thirdly, should focus on the respondent personal experience. Garrison et al., 1999 elaborate in details that each questionnaire the best to include the opening question where everyone answers the question as an icebreaker to start the interview session, introductory question where the respondent was introduced to the topic of discussion, transition question where it acts as a shift conversation into the key question and the ending question to bring closure to the discussion.

For example, among the suitable question can be asked regarding sustainability in urban planning are (a) why environmental sustainability is assessed in urban planning? (b) how does environmental assessment steer decision making in urban planning? (c) what is the role of urban planning in environmental sustainability? (d) how is the power of urban planners to promote environmental sustainability limited? and (e) how is urban density considered in terms of environmentally sustainable land use? (Säynäjoki et al., 2014). According to Säynäjoki et al., (2014), question a, b, and c is a direct question which can be used as a transition question and question d and e is a key question to the power of urban planning topic.

Based on the literature survey conducted, there are researchers that conduct research in the sustainability research area but the assessment method used are too broad and sometimes misleading because it is not directly related to the case study presented. The idea is that the proposed assessment method should also act as a universal assessment method which can be used by everyone. However, in reality, it is complicated to be implemented since the problems are different and the assessment method suitable to be used is also different. When focusing at the machining process level, the best assessment method that can be used is the methods related to the machining process such as total manufacturing cost to produce a product; their environmental impact while machining and impact to the operator who conduct the machining process.

In order to make sure the assessment method propose is realible, survey methods are reviewed to identify the most suitable method to be implemented. The respondent for the survey is varied depanding on the specific case study. For manufacturing industry, the respondent is the best to comes from the manufacturing industry background.

Different researchers used different optimization methods to optimised the cutting parameters. Some researchers used artificial neural network, inversed artificial neural network model, genetic algorithm, PROMETHEE, analytic hierarchy process (AHP), Fuzzy AHP or even hybrid algorithm to perform the optimisation process based on the data obtained. Each optimization method have their own advantages and disadvantages which have been identified.

2.7 Software / Tool Development

Commonly, software development is known as the various programs used to operate computers, analyze data, or running devices. Software can be divided into two categories known as system software (includes operating systems and any program that supports application software) and application software. For instances, Windows 7, 8, and 10, antivirus, Linux, and Mac OS are examples of system software; while Microsoft Office, Adobe Photoshop, Google Chrome and Picasa is the example for application software. In this context, the software is a tool that is used to help and ease the users in interpreting and simulating data by using a program. Database software is designed to create databases which are used to store information, backup and recovery data, data presentation and security management, and also extract the information contained within them. The example of the available database software programs in the market are Microsoft Excel, QuickBase, Google Sheets, AppleWorks, Javelin, and Microsoft SQL Server. Every software has its pros and cons. Based on the software mentioned, three well-known database software which are Microsoft Excel, Google Sheets, and Microsoft SQL Server are selected and compared based on their advantages and disadvantages which are tabulated in Table 2-12 and Table 2-13.

Table 2-12 Advantages of database software (Microsoft Excel, Google Sheet and Microsoft SQL Server).

Microsoft Excel	**Google Form**	**Microsoft SQL Server**
Advanced functionality	Free	Easy administration
Unlimited storage	Easy to use	Easy to be used and develop
More customizable	Built-in revision history	Reliable and stable
More formulas and functions	Better visibility	Reasonable cost
No need the Internet	Have some add-ons	-

Table 2-13 Disadvantages of database software (Microsoft Excel, Google Sheet and Microsoft SQL Server).

Microsoft Excel	**Google Form**	**Microsoft SQL Server**
Advanced functionality	Free	Easy administration
Unlimited storage	Easy to use	Easy to be used and develop
More customizable	Built-in revision history	Reliable and stable
More formulas and functions	Better visibility	Reasonable cost
No need the Internet	Have some add-ons	-

Based on Table 2-12 and Table 2-13, Microsoft Excel has the most probability to be used as it has advanced functionality and has more options for data visualization. Furthermore, compared to other software, usually Microsoft Excel is automatically installed in a new computer or laptop together with the license. So, the price of the software is excluded and also all people can use Microsoft Excel without the need to connect to the Internet or download and install other software.

CHAPTER 3

METHODOLOGY

3.1 Introduction

This chapter discussed the methodology involves in the present study. The chapter started with the explanation of project methodology, development of a questionnaire to select the suitable assessment methods for each criterion, choice of product for a case study and machining process involved, including the fabrication cutting parameters. Later, the present design of experiment (DOE) is reviewed. The case study methodology adopted in the present study were divided into two - theoretical and experimental methods. Each of them was described in details in the present chapter. Lastly, the optimization by using a machine learning method which was used in this work was also explained.

3.2 Project Methodology Summary

The summary of the general framework model to complete this project are shown in Figure 3.1. This project starts with identifying a problem statement and performing literature survey to have a better understanding of the sustainability concept. Next, a literature survey of sustainability criteria and its assessment methods that can be used were reviewed. At the same time, a survey questionnaire was developed to get feedback on a suitable assessment method to be used.

Then, a product was selected as a case study to show how the proposed method works and the assessment method being used were finalized. After that, theoretical data were calculated and a series of experiment was conducted for data collection. The collected data were analysed by using a comparison method between theoretical and experimental data and then neural network and inversed neural network evaluation was done to obtain the optimum cutting parameters. If the results obtained is good, the optimised cutting parameters result will be tested with the theoretical and experimental method to obtain the results for validation and verification purpose. Lastly, based on the results obtained, discussion of the finding is done and ending with the conclusion of the project. The detailed process flow chart is shown in Figure 3.2. The detail explanation was discussed in the next sections (Sections 3.3 until 3.8).

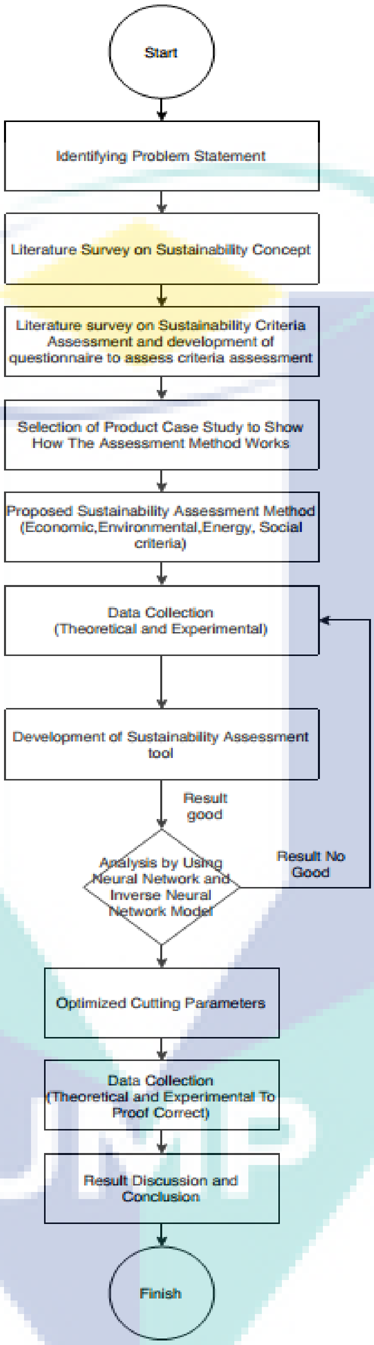


Figure 3.1 General framework used to complete this study.

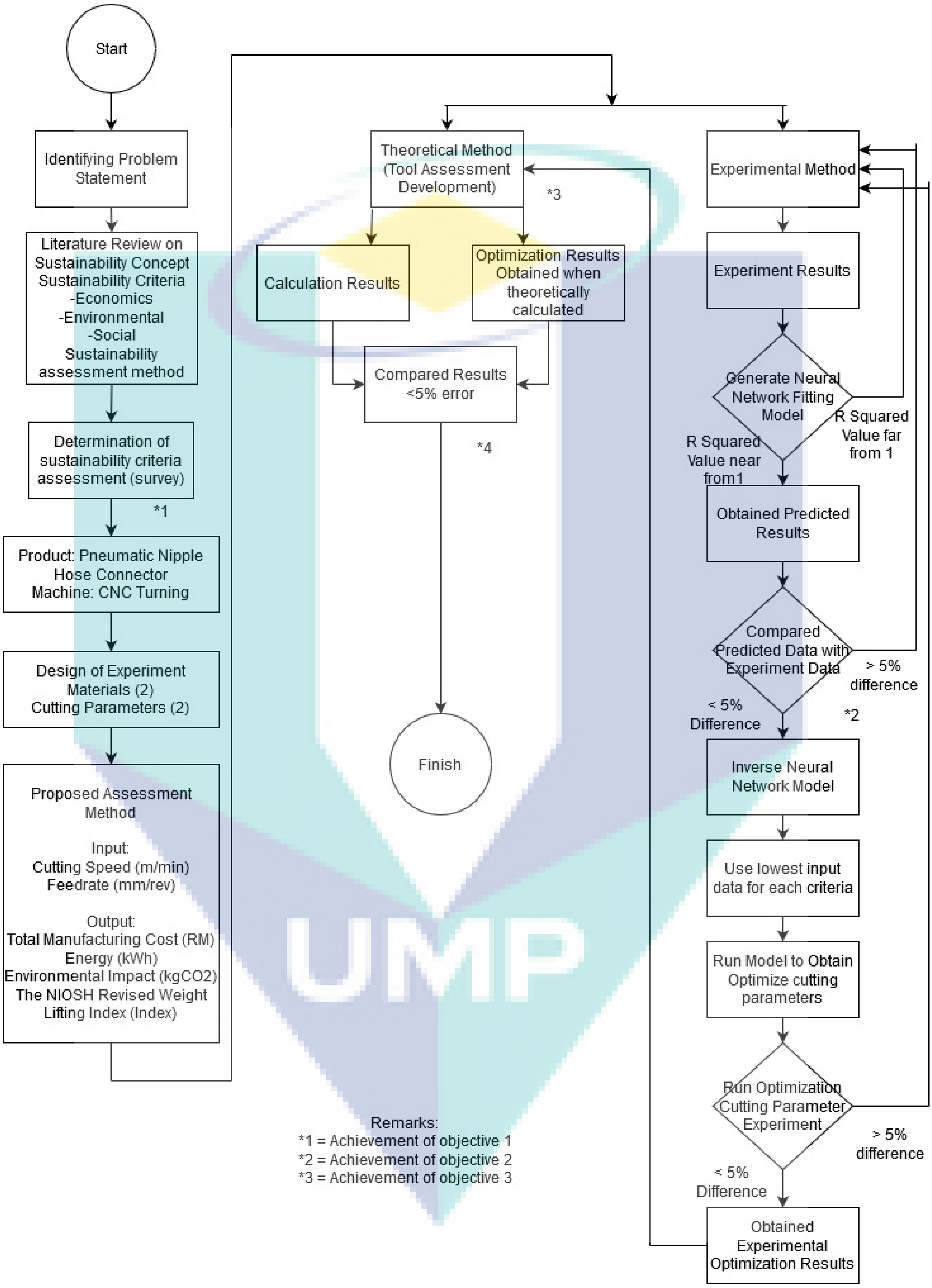


Figure 3.2 Summary of detail process flow taken to complete the project.

3.3 Problem Statement Formulation

The work started with the identification of the problem statement through literature survey to tackle the gaps and the current sustainability situations. To date, researchers spent most of their time, money and effort to propose one suitable method that can evaluate and optimize sustainability. Each of them tries to evaluate sustainability by using different assessment methods until the current methods used becomes unreasonable and difficult to evaluate either by using theoretical or even experimental approaches. One of the difficult part to evaluate is the energy consumption due to the generation of dynamic current flow from a power source to the machine.

The current project is proposed as an impact from the literature findings that most of the researchers tend to use different indicators to evaluate sustainability where some of the indicators are not suitable to be used. Besides that, most of the researchers tend to optimized cutting parameters with single criteria such as manufacturing costs, product quality (surface roughness), energy consumed during the machining process and environmental impact with most of the reported methods are considered as a two-dimensional evaluation method.

Besides, few researchers details the impact aspects involved manufacturing cost, energy usage, environmental and ergonomics of the worker at the production floor. However, none of them used Malaysia technical data in their reported study. Hence, the present study looked in detail the aspect used in the sustainability concept with additional energy as another criterion due to the urgency needs to save energy during the machining process highlighted by engineers and executives during discussions.

3.4 Questionnaire Survey to Proposed Assessment Method for Each Criterion

The proposed assessment method used in the present work is based on the feedback from the selected expert, which involved in giving feedback of the survey. The survey questionnaire development is based on Garrison et al., (1999) and Nardi (2018) recommendations which consist of eight questions that cover from personal age, qualification level, working experience and a list of sustainability assessment criteria to be selected and proposed the new assessment method with reason. There are three criteria evaluated in sustainability, namely, economics, environmental impact and social impact criteria. Based on the literature survey, six, eight and five assessment methods listed for economic, environmental and social criterion, respectively.

The assessment methods listed under economic criteria includes salary and costs of raw material, cutting tool, coolant, lubricant and energy. Under environmental criteria, the assessment methods listed are pollution of water, air, land and impacts of energy, cutting tool, coolant, lubricant and chip recycling. Lastly, the assessment methods listed for social criteria are numbers of medical certificates, worker salary, NIOSH revised weight lifting index, REBA and RULA. The summary of the developed questionnaire is shown in Appendix A.

3.5 Product Case Study: Pneumatic Nipple Hose Connector

The product used is pneumatic nipple hose connector as shown in Figure 3.3. The product is selected because it involved more than one machining process and more than one cutting tool. One machining process using one cutting tool is a straight forward measurement, while the usage of more than one machining process and cutting tool required a detailed understanding especially in the theoretical part where at some stage there is energy consumption but no cutting process involved. Besides that, based on the reported high demand from the customer since it has been used in many industries to connect high compressed air hose for multi-purpose usage.

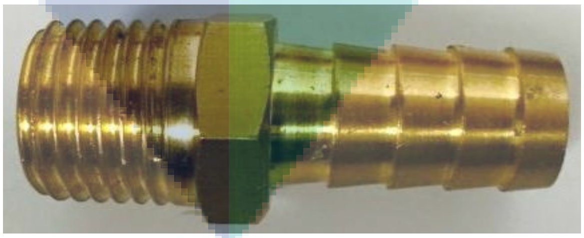


Figure 3.3 Pneumatic nipple hose connector.

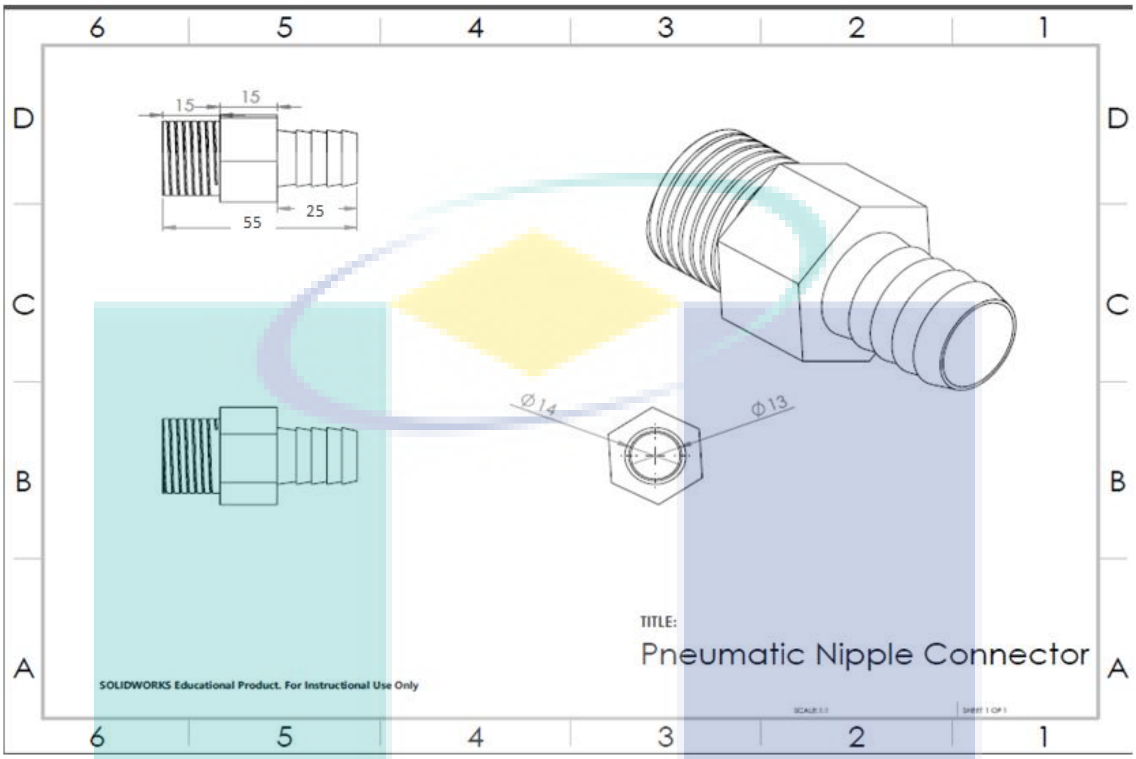
Based on the catalogue provided by suppliers, there is two common material used to produce the pneumatic nipple hose connector, that is, Aluminium 6061 and Brass

C3604. Since the pneumatic connector is in hexagonal symmetry, to simplify the manufacturing process, both materials were ordered in the hexagonal shape.

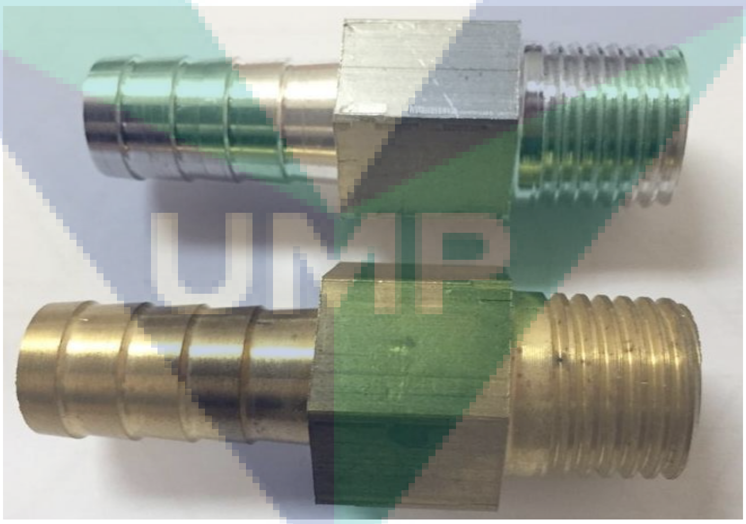
Upon receiving the product from the supplier, the sample was first sent to the foundry laboratory to confirm their material composition. The material grades inspection was done using Oxford Spectrometer machine as shown in Figure 3.4, which is located at the Foundry Laboratory, Faculty of Mechanical Engineering, Universiti Malaysia Pahang (UMP).

Figure 3.4 Spectrometer used to determine the material grade.

The pneumatic nipple hose connector is redesigned, particularly around the hexagonal part since the CNC Turning Machine used has the limitation for holding the thin part. Therefore, the hexagonal part was clamped and the alteration of the thickness from 5.00 mm to 15.00 mm is carried out. This is to ensure that the sample can be clamped in the CNC Turning Machine during the subsequent process. The new pneumatic nipple hose connector design is shown in Figure 3.5. The new pneumatic nipple connector design is divided into two parts, the hose and the screw.



(a) Redesign pneumatic nipple hose connector.



(b) Fabricated pneumatic nipple hose connector.

Figure 3.5 New design of pneumatic nipple hose connector (a) Redesign (b) Fabricated

3.6 Machining Process and Cutting Parameters

The pneumatic nipple hose connectors are fabricated using Okuma LB15 CNC Turning Machine as shown in Figure 3.6 at the CNC Machining Laboratory, Faculty of Engineering, Universiti Malaya. The machine is an old CNC Turning machine which is bought in the early 1990s where some of the spare part components already changed for different brand compared to the original one. The controller used also changed for different brand, which is different from the original one.

Figure 3.6 Okuma LB15-II CNC Turning Machine

In the present study, it is expected different sets of cutting parameters usage affect the sustainability assessment in terms of economic criteria. This is because based on Equation 2.3 and 2.4 cutting parameters will directly affect the energy and tool cost. Meanwhile, the workpiece material length gives a direct impact on the environmental and social criteria under chip recycling impact assessment and the Revised NIOSH Weight Lifting Index assessment.

The cutting parameters used to fabricate the pneumatic connector were proposed based on manufacturing process and technology book (Kalpakjian & Schmid, 2014) recommendation and also the consideration of Okuma LB 15-II CNC Turning machine cutting parameters limitation used in this study. Types of machining process involved include rough cutting, fine cutting, thread cutting, center drill process and drilling process. The overall set of cutting parameters used are shown in Table 3-1.

Table 3-1 The set of cutting parameters used for rough and fine cutting using CNC Turning machine.

Cutting Parameters Option	Description
1	Cutting Speed: 42m/min; Feedrate: 0.1mm/rev; Depth of Cut: 0.50, 0.25mm
2	Cutting Speed: 42m/min; Feedrate: 0.2 mm/rev; Depth of Cut: 0.50, 0.25mm
3	Cutting Speed: 83m/min; Feedrate: 0.1mm/rev; Depth of Cut: 0.5, 0.25mm
4	Cutting Speed: 83m/min; Feedrate: 0.2 mm/rev; Depth of Cut: 0.50, 0.25mm

The cutting tool used in the fabrication process is coated by carbide coded as TNMG160404 for roughing and fine cutting process. For the stepping part, VCMT160404 coated carbide insert is used. The threading process is carried out using 16ERG60 cutting tool as shown in Figure 3.7.

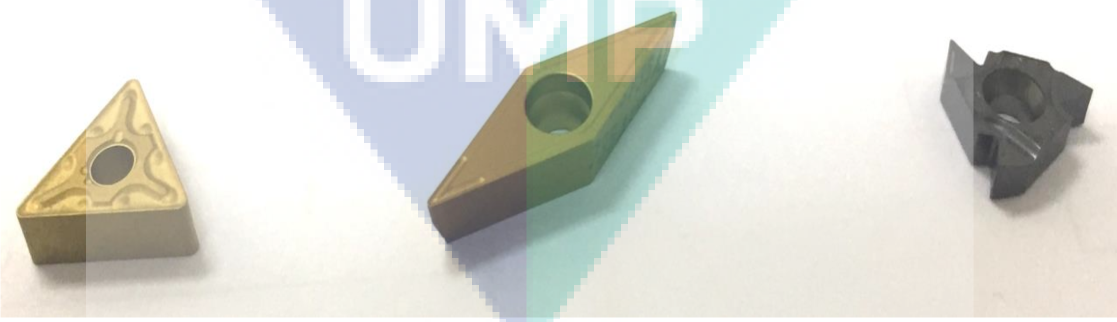


Figure 3.7 From the left TNMG160408, VCMT160404 and 16ERG60 insert used in the turning and threading process.

The machining process started with hose part machining using TMNG160408 insert for roughing and VCMT160404 insert for stepping based on the cutting parameters shown in Table 3-1. It is noted that the work material diameter is reduced from 27.00 mm to 17.00 mm. Then, the work material is turned to the other side for the threaded cutting part to have a diameter range from 27.00 mm to 21.00 mm using TNMG160408 insert.

In the following step, the thread cutting process took place. Before the thread machining process conducted, the thread sample was measured using thread gauge and the results indicated a value of 14G 7/16 inch type with 60° thread angle. Based on the metrics thread data chart, there were 14 threads available in one-inch material, the pitch is 1.814 mm and the thread height is 1.162 mm. The major diameter is 11.113 mm, the pitch diameter is 9.951 mm, and the minor diameter male thread is 8.789 mm. The machining process of the thread is done using the 16ERG60 insert as shown in Figure 3.7 with the cutting speed of 26 m/min, the feed rate of 0.1 mm/rev and the depth is 0.0612 mm for 19 times to obtain the 1.162 mm thread depth.

Next, the drilling process is carried out starting with marking a center point by using center drill tool with a cutting speed of 9.426 m/min or 1000 rpm, the feed rate of 0.1 mm/rev, the center drill diameter is 3.00 mm and depth of cut of 1.00 mm for three times. Then, drilling process took place starting with diameter 10.00 mm drill tool by using cutting speed of 30.00 m/min, the feed rate of 0.1 mm/rev and depth of cut of 1.00 mm until the hole is drill through.

After that, the first boring process takes place by using diameter 13.00 mm drill tool with the boring depth of through hole. Lastly, the other boring process is performed by using 14.50 mm diameter drilling tool with a drill depth of 21.00 mm. The cutting speed used for the boring process is 30.00 m/min for cutting speed, a feed rate of 0.10 mm/rev and depth of cut of 1.00 mm until the desired depth of cut achieved.

3.7 Sustainability Criteria Assessment Method

There are four assessment methods used for product sustainability evaluation criteria in the present study. All the assessment methods used in the present study is based on the disadvantages identified in the literature survey (Sub-topic 2.3) and also from the feedbacks from respondent highlighted in sub-topic 3.4. There are total manufacturing cost for economics criteria, environmental impact assessment for environmental criteria, the NIOSH Revised Weight lifting Index for social criteria and additional energy consumption assessment method as a new independent criterion to overcome the disadvantage of using the PCA concept method listed by Karamizadeh et al., (2013). At the same time, he assessment method is included in the study as it is crucial to monitor the consumption energy used because the amount of energy used to fabricate is vast and the energy cost keeps on increasing from time to time based on the feedback from engineers and executives.

Therefore, sustainability assessment method used is divided into two sections, known as theoretical and experimental methodology sections. The theoretical section discussed in detail how the evaluation assessments were done theoretically and the experimental section discussed how the evaluations were performed through experiments.

3.7.1 Theoretical Methodology

3.7.1.1 Total Manufacturing Cost – Economic Criteria

The assessment method used for economic criteria is based on the total manufacturing cost proposed by Zhang & Haapala (2015) with some modifications. They did not include the lubricant cost in the manufacturing cost calculation due to the high amount of product produced as compared to the amount of lubricant used. Therefore, it is neglected. In the present study, the lubrication cost is taking into consideration because the amount of lubricant used in the CNC Turning machine is enormous (around 40 Liters) (Okuma Machinery Works Ltd, 1987) and the total manufacturing cost is calculated using Equation 3-1 as shown below.

$$\text{Total Manufacturing Cost} = \text{Raw Material Cost} + \text{Tool Cost} + \text{Coolant Cost} + \text{Lubricant Cost} + \text{Energy Cost} + \text{Labor Cost} \tag{3-1}$$

Equations 3-2 to 3-4 are used to determine the raw material cost for cylindrical hexagon shape. Noted that the value of 6 represents the 6 triangles of a hexagon shape.

$$\text{Volume} = \frac{\text{Base} \times \text{Tall}}{2} \times 6 \times \text{Raw Material Length (height)} \quad 3\text{-}2$$

$$\text{Mass} = \text{Volume} \times \text{Material Density} \quad 3\text{-}3$$

$$\text{Raw Material Cost} = \text{Raw Material Mass (gram)} \times \text{Raw Material Price} \left(\frac{\text{RM}}{\text{gram}}\right) \quad 3\text{-}4$$

Based on the hexagon volume formula, the base and tall values are assumed to be fixed where the base is 1.40 cm and tall is 0.95 cm for Aluminium 6061 work material while the base and tall measurement for Brass C3604 is 1.50 cm and 1.25 cm, respectively. The density of Aluminium 6061 is 2.70 g/cm^3 (ASM Aerospace Specification Metals Inc., 2018) while for brass is 8.43 g/cm^3 which taken from (Yamashin Steel Company Inc., 2016). The standard price for one meter Aluminium 6061 is RM 67.21 and Brass C3604 is RM 272.00 bought from the supplier before experimenting.

The tool cost is calculated using Equation 2-3, where the tool cost is a product of tool contact time divided by tool life and multiply with the tool cost. In the present study, the tool contact time is a time needed to cut work material from the starting machining point to the ending of the cutting point. The tool life determination for straight turning and profile turning process is based on three groups of researchers (Ariffin et al., 2018; Li et al., 2017; Nouari et al., 2003).

Li et al., (2017) adopted a multi-pass turning process where they measured the energy consumed after three, four and five passes during machining using a milling machine. The concept is applied in the present study to monitor the surface roughness and holes diameter results because the machining process will take a long time to be completed.

The machine involved in the tool wear study is the CNC turning machine and the Aluminium 6061 and Brass C3604 with the diameters of 27.5 mm for aluminum 6061 and 29.00 mm for Brass C3604 are used as the materials. Each of the work material is cut into 250 mm length with the machining length of 230 mm. There are three types of insert involved with four different machining process in the present study. TNMG160408 insert is used for rough and finish cuttings, VCMT160404 insert is used for profile cutting and 16ERG60 insert is used for thread cutting operation.

The cutting speeds used for TNMG160404 insert are 42.00 and 83.00 m/min, the feed rate of 0.1 and 0.2 mm/rev and depth of cut of 0.50 mm and 0.25 mm. For VCMT160404 insert, the cutting speeds used are 42.00 and 83.00 m/min for cutting speed, the feed rate of 0.1 and 0.2 mm/rev and depth of cut of 0.25 mm such as shown in Table 3.1. Lastly, for 16ERG60 insert, the cutting speeds used are 26.00 m/min for cutting speed, the feed rate of 0.1 mm/rev and depth of cut of 0.10 mm.

The cutting performance measurement used to determine the insert tool life for the present study includes cutting area surface roughness for straight and contour cutting process, while the cutting tool image before and after performing machining process is adopted for thread cutting process. The method is employed to determine the tool life as cutting area surface roughness relates to the quality of the product surface. Additionally, the thread cutting process is not suitable to measure the area of surface roughness due to the thread contour shape produced is difficult to measure. However, using the cutting tool image before and after the machining process, the ability to identify the tool wear was a success. The experiment stopped once it fulfills either one of these two conditions. The first condition is for Aluminium 6061 with the surface roughness produce is more than 8.400 µm for the rough cutting process and 1.600 µm based on the measured finished product. The second condition is when the cutting tool failure due to the tool breakdown during the machining process.

For Brass C3604, the first condition of product surface roughness is more than 7.00 µm for the rough cutting process and 1.200 µm based on the measured finished product surface roughness. The value of rough cutting surface roughness is adopted from (Islam et al., 2017) for Aluminium 6061 and Brass C3604 the surface roughness value is adopted from (El-Hossainy, 2010). The second condition is when the cutting tool failure occurred due to the tool breakdown during the machining process.

The selection of the first condition is based on the previous works mainly for the rough cutting process and for product surface finish, the product surface roughness is measured to ensure the quality of the product was maintained at the same level as sold in the market. For thread cutting insert, it is difficult to measure the surface roughness of the thread area. Hence, the stopping conditions is only based on the cutting tool image after the machining process. The surface roughness is measured using Mahr surface tester, as shown in Figure 3.8 and the after cutting tool image is captured using a digital camera.

Figure 3.8 Mahr MarSurf PS1 surface roughness tester.

To determine the tool life of drilling cutting tool, Equation 3-5 is adopted (Ghasemi et al., 2018; Jadhav et al., 2018; Nouari et al., 2003).

$$\text{Drilling Tool Cost (/Product)} = \left(\frac{1}{\text{Total Number of Holes Produce Until Tool Wear}} \right) \times \text{Drill Tool Cost (RM)} \quad 3\text{-}5$$

The machine used to determine the drilling cutting tool life is the CNC RoboDrill machine and the workpiece are Aluminium 6061 and Brass C3604 with similar dimensions of 200 mm x 200 mm x 55 mm for both. The largest diameter for hole drill has a value of 14.50 mm. Theoretically, a 14.50 mm hole diameter can be obtained by using 14.50 drill cutting tool diameter. Practically, the step drilling process is implemented to increase the productivity and drilling cutting tool life and at the same time to reduce the cutting force and torque produced during the machining process. Step drilling procedure is applied with more than one drilling cutting tool involved in the machining process to obtain the 14.50 mm hole diameter.

The drilling process started with drilling the center of the workpiece using a 3.00 mm diameter of center drilling cutting tool. The cutting speed used is 9.426 m/min, with the feed rate of 0.1 mm/rev and the depth of cut of 1.00 mm each for three times using a peck drill method, to obtain the total depth of 3.00 mm. Next, the drilling process started using 10.00 mm diameter size of drill cutting tool followed by 13.00 mm in and 14.50 mm diameters drills cutting tool. The cutting parameters used here are 30.00 m/min for cutting speed, feed rate of 0.1 mm/rev and the depth of cut of 1.00 mm each until the drill through hole is achieved for drilling tool diameter 10.00 mm and 13.00 mm while for a diameter of 14.50 mm, the drilling tool depth is 21.00 mm.

The cutting performance measurement used to determine the tool life in the drilling process is based on the number of holes produced from the drilling process. On the other hand, the experimental observation is used to determine the stopping criteria for the drill cutting tool where the experiment is stopped once it has fulfilled either one of these following two conditions. The first condition is when the produced hole diameter size is more than 0.05 mm and the second condition is when the drill cutting tool started to fail during the machining process. Principally, the selection of the first condition is taken based on the product tolerance requirement given by the supplier based on the catalog where the maximum hole diameter value is 0.05 mm. The hole diameter measurement took based on the method adopted from Firouzdor and friends (Firouzdor et al., 2008) where the surface roughness of drilled hole is measured for the consecutive of first, fifth, tenth holes and continued after the tenth holes onwards for all the drilling cutting tool failures.

Further on this, both coolant and lubricant costs were then determined using Equations 2-6 to 2-8, as stated in Chapter Two. The capacity for coolant and lubricant tanks is 150 and 40 liters, respectively based on the supplied machine catalogue (Okuma Machinery Works Ltd, 1987). Practically, the coolant and lubricant need to be changed for every six and three months, respectively and both coolant and lubricant loss rate is 15% as claimed by Zhang & Haapala (2015). The assumption of total output used to determine the cost of coolant is 31, 680 units for six months of usage before it needs to be changed. For a month, it is assumed that the working days are to be 22 days and that in a day, two shifts involved which gives an average of one shift output to be 120 units. The assumption of total output used to determine the lubricant cost is 15, 840 units with the lubricant are used for three months before it changed. Both the coolant and lubricant costs used in the present study are based on UMP Inventory database in which the coolant price is stated as RM 44.24 / liter and RM 25.0209 / liter for lubricant.

The calculation of energy cost is adopted from Zhang & Haapala (2015) as shown in Equation 2-4. The assumption of industrial electricity rate in the present study is plateau with a value of RM 0.38 per kWh (Tenaga Nasional Berhad TNB, 2017). The labor cost also calculated based on the average daily output, as shown in Equation 3-6, which exclude the usage of machining time, as shown in Equation 2-7.

$$\text{Labor Cost (/Product)} = \left(\frac{\text{Salary}}{\text{Working days (/Month)} \times \text{Average Daily Output}} \right) \qquad 3\text{-}6$$

The reason for this is the machining time used to machine the pneumatic connector is excluded and not considered as part of the labor cost calculation as the worker's responsibility is multi-task. During the machining process, the worker not only controls one single machine, but he/she needs to handle more than one machine that produces different types of products at the same time. Apart from that, he/she also needs to record the number of waste products produced and at the same time, the quality check of the product simultaneously run before proceeding to the next workstation. Hence, the labor cost is based on the average monthly output, which explicitly excluded the machining time. The assumption made in the present study for operator salary is RM 2,500 per month and the total working days is 22 days per month. At the moment, Malaysia basic salary is RM1200 per month for basic skill worker (Ahmat et al., 2019; Hwa et al., 2019). Handling a CNC Turning machine requires high skilled worker who's able to handle and troubleshooting the machine when it is broken down. Hence the salary is assumed to be at RM2500.

3.7.1.2 Environmental Impact Assessment – Environmental Criteria

The second criteria evaluated in the present study is environmental criteria. The assessment of environmental criteria in production line mainly consists of impacts of the cutting tool, chip recycling, energy usage, disposal of coolant and lubrication (Narita, 2012). Here, both the chip re-cycling and energy impacts used are based on (Dahmus & Gutowski, 2004), in which the total number of product produced using a similar cutting tool is relatively high as compared to the weight of the cutting tool itself. Hence it can be neglected. A similar justification is used for exemption of coolant and lubricant in the present study.

Therefore, the detail explanations of the assumption highlighted beforehand are as follows. For coolant and lubricant usages, they are changed only when maintenance is done periodically starting from the third month until the sixth month in which within the period gap thousands of products are produced. Thus, both the coolant and lubricant impacts on environmental evaluation are neglected. The impact on chip recycling is assessed based on Narita (2012) method in which the consideration on the amount of carbon weight released into the air by the scrap material produced from the machining process is crucial as shown in Equation 2-12. The chip re-cycling constant value used for Aluminium 6061 is 8.19 $kgCO_2$ and for Brass C3604 is 2.42 $kgCO_2$ (Hammond & Jones, 2008).

Although Narita (2012) already published the guidance on how to measure the theoretical energy consumed during machining process in Equation 2-9, it is not preferable to use the equation in the present study since it is difficult to turn off all the related sensors attached at the back of the CNC Turning machine door. Besides that, the space area to attach all power harmonic analyzer clamps to the motor is limited and some of the wires need to be changed for a longer wire in order to suit the clamp. This gives effect to the machine function. Hence, the determination of theoretical energy impacts used in the present study were calculated based on the adopted theoretical calculation method (Sandvik Coromant, 2017) as shown in Equation 3-7 till 3-11 specifically for turning process, drilling process, boring process of drilling cutting tool, total energy consumed during machining process and their impact to the environment, respectively.

$$P_{c\_turn} = \left(\frac{V_c \times a_p \times f_n \times K_c}{60000}\right) \tag{3-7}$$

$$P_{c\_drill} = \left(\frac{V_c \times D_p \times f_n \times K_c}{60000}\right) \tag{3-8}$$

$$P_{c\_boring} = \left(\frac{V_c \times a_p \times f_n \times K_c}{60000}\right) \times \left(1 - \frac{a_p}{D_c}\right) \tag{3-9}$$

$$\sum P_{c\_total} = \sum P_{c\_Turn} + \sum P_{c\_drill} + \sum P_{c\_boring} \tag{3-10}$$

$$E_e = \sum P_{c\_total} \times 0.7470\, kgCO_2 \tag{3-11}$$

where P_{c_turn} is referring to the required power for the turning process, P_{c_drill} is the power required to perform drilling, P_{c_boring} is the power required to perform boring, ΣP_{c_total} is the total energy used to fabricate the pneumatic connector, E_e is the calculated energy impact to the environment ($kgCO_2$) with the constant value of carbon footprint is 0.747 $kgCO_2$ adopted from Lojuntin (2015), V_c is cutting speed (m/min), a_p is depth of cut (mm), f_n is federate (mm/min), K_c is Specific cutting force (N/mm^2) and Dc is drill diameter.

Based on the specific cutting force figure proposed by Sandvik Coromant (Sandvik Coromant, 2017), for Aluminium 6061 and Brass C3604 technical data, the percentage of Si is less than 1 % with the Aluminium 6061 material hardness is 95HB. Hence as indicated in Figure 3.9 the specific cutting force is 650 N/mm^2 for Aluminium 6061, while for Brass C3604, the value is 550 N/mm^2 with the Plumbum percentage is more than 1% and the material hardness is 110HB.

MC code	Material group		Material sub-group		Manufacturing process		Heat treatment		nom	Specific cutting force, k_{c1} (N/mm^2)	m_c
N1.1.Z.UT	1	aluminium based alloys	1	commerically pure	Z	cast	UT	untreated	30 HB	350	0.25
N1.2.Z.UT	1		2	AlSi alloys, Si ≤1%	Z		UT		60 HB	400	0.25
N1.2.Z.AG	1		2		Z		AG	aged	100 HB	650	0.25
N1.2.S.UT	1		2		S	sintered	UT	untreated	75 HB	410	0.25
N1.2.C.NS	1		2		C		NS	not specified	80 HB	410	0.25
N1.3.C.UT	1		3	AlSi cast alloys, Si ≤1% and <13%	C	cast	UT	untreated	75 HB	600	0.25
N1.3.C.AG	1		3		C		AG	aged	90 HB	700	0.25
N1.4.C.NS	1		4	AlSi cast alloys, Si ≥13%	C		NS	not specified	130 HB	700	0.25
N2.0.C.UT	2	magnesium based alloys	0	main group	C	cast	UT	untreated	70 HB		
N3.1.U.UT	3	copper based alloys	1	non-leaded copper alloys (incl. electrolytic copper)	U	not specified	UT	untreated	100 HB	1350	0.25
N3.2C.UT	3		2	leaded brass & bronzes (Pb ≤1%)	C	cast	UT		90 HB	550	0.25
N3.3.S.UT	3		2		S	sintered	UT		35 HB		
N3.3.U.UT	3		3	free cutting copper based alloys (Pb >1%)	U	not specified	UT		110 HB	550	0.25
N3.4.C.UT	3		4	high strength bronzes (>225HB)	C	cast	UT		300 HB		
N4.0.C.UT	4	zinc based alloys	0	main group	C	cast	UT	untreated	70 HB		

Figure 3.9 Specific cutting force, Kc values for Aluminium 6061 and Brass C3604. Source: Sandvik Coromant (2017).

As the machining process took place, there was a time where the cutting tool moves back to the starting point. Theoretically, there is no energy consumed if there is no machining process occurs; however, the energy used for that particular movement was counted. Hence, the power consumed during the backward movement was also included. There were four types of motor consumed energy during idle machining process known as spindle motor, coolant pump motor, lubricant pump motor and z-axis drive motor. Based on the catalogue provided by the supplier (Okuma Machinery Works Ltd, 1987); the power rating is 8.33 watt per second for spindle motor energy, 0.42 watt each per second for x-axis drive motor and hydraulic pump motor, 0.694 watts per second for lubricant pump motor and 0.667 watts for the z-axis drive motor. The moving time recorded from the observation during the turning process is 1 second which described the tool movement from the starting point towards new workpiece point and another 1 second back from its cutting endpoint to its starting point.

3.7.1.3 The Revised NIOSH Weight Lifting Index – Social Criteria

The third criterion is the social criteria. In the present study, the quality life of the production line operator is considered as one of the assessment methods. The quality life of production line operator is measured based on the ergonomic assessment method as it reflects the immediate impact on the labor factor in production floor level (Zahari Taha & Salaam, 2016).

The decision to use only this particular method to access the ergonomic factors is based on the fact that the dangerous work done related to the ergonomic in the present study involved lifting the heavy workpiece in a pallet. The assessment method adopted is based on the NIOSH Revised Lifting Equation with some modification as proposed by Muslim et al., (2013), which is modified based on South East Asia male anthropometric data. At the end of the experiment, only The NIOSH Revised Lifting Equation is used due to the weight data counted in the calculation of material cost that linked indirectly to The NIOSH Revised Lifting Equation. There is no relationship between any data used with Musculoskeletal Injury (MSI) assessment method, REBA and RULA methods since all of these three assessment methods employed only scaling type method. Hence, Musculoskeletal Injury (MSI), REBA and RULA assessments were not engaged since there is a need to link the data across the used criteria.

The assumption made in this study is that one empty pallet weighed 1.00 kg consists of 24 pieces of raw material which are assumed to have the same weight of workpiece with the pallet need to be lifted from the floor and walked about 5.00 meters and placed it in a rack as shown in Figure 3.10. The evaluation method is based on Equations 2-13 and 2-14, as stated in Chapter Two.

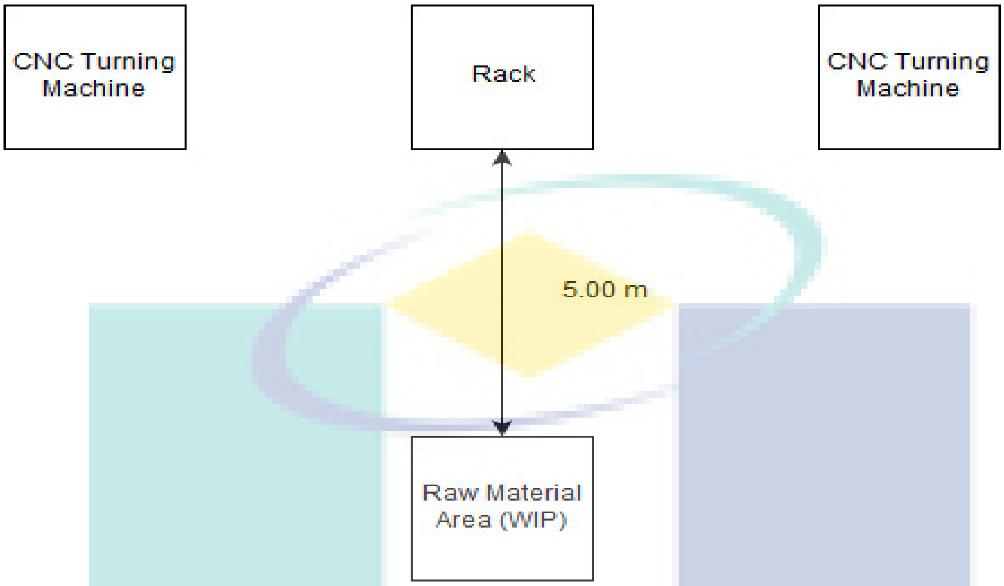


Figure 3.10 Production floor layout arrangement.

3.7.1.4 Energy Criteria – The New Criteria Introduced

The last criteria introduced in the present study is the energy criteria. It is introduced because of the data nature used in the current study. As we know, in economic criteria, the amount of energy was used to determine the energy cost while in environmental criteria it was used to determine the environmental impact. In the current study, the data used to generate the neural network model is based on the total manufacturing cost data and total environmental impact data; not every single detail assessment data. When this method is implemented and optimised, it will not necessarily be optimised the energy data; hence to make sure the energy data specifically optimised, these criteria were introduced.

In the present context, energy criteria are referring to the amount of energy used during the machining process. This criterion is highlighted in the present work due to the high level of energy used to fabricate a product. The aim for the criteria is to monitor and perhaps to reduce the amount of energy used during the fabrication process to protect the environment pollution in the future as stated by one of the respondents in the feedback survey. There are seven machining processes involved in fabricating the pneumatic nipple hose connector. These include rough cutting, fine cutting, profile cutting, thread cutting, center drill, drill and boring process. These data are extracted from the environmental integrity criteria using Equations 3-7 to 3-10. In the present study, energy consumed during the idle state of machine idle is also considered to ensure a much more precise energy calculation. Besides that, the efficiency of the machine is also included, as suggested by Sandvik Coromant (2017).

3.7.2 Experimental Methodology

The second method adopted in the present study is an experimental methodology. Here, a series of the experiment has been conducted to collect the data for validation purpose where the results obtained were compared with the theoretical output. The assessment method used to evaluate all of the four criteria is different from the theoretical approach. For example, the equation of total manufacturing cost used in this part is similar with theoretical methodology as expressed in Equation 3-1 but with the consideration of the method in calculating the raw material cost and energy cost is different.

In the experimental method, the raw material cost is calculated based on Equation 3-4, and the weight is weighted using a digital weight scale and not based on theoretical calculation determination, as shown in Figure 3.11. Practically, when the long straight hexagon bar is cut into small pieces, each of the parts became different although they possess a similar length size. These are due to the vibration occurs during the cutting process and the current condition of the band saw machine chain used to cut the raw material would give impact to the raw material in terms of their weight.

Figure 3.11 AND Digital weight scale used to weight the raw material.

Energy cost calculation used in the experiment is based on the energy used during the machining process multiply with the electrical tariff (RM/kWh) as expressed in Equation 2-4.

The second criterion evaluated in the present study is environmental impact criteria. In this criteria, there are two different approaches used. The first one is the assessment of chip recycling impact based on the weighted of the raw material and the finished product is weighted using a digital weight scale to obtain the total amount of material removed during the machining process. The second approaches are energy impact, which assessed using Fluke 437-II power harmonic analyzer as further explained in the following paragraph.

The third criteria are social criteria. The assessment method used in this part is similar to the experimental method, but with the differences in raw material weight and the finished product weight. The digital weight scale is used to measure the weight rather than to determine the weight using theoretical calculation, which could be complicated as it involved product volume and density data.

Lastly, the fourth criterion is energy criteria. This criterion was assessed based on the measured used energy during machining process using Fluke 437-II power harmonic analyzer, as shown in Figure 3.12. The OKUMA LB 15 CNC Turning Machine is a three-phase electrical machine, three life wire and one earth wire that need to be clamp in device measurement. The back door of the CNC turning machine need open so that the measuring device would be attached at the main power supply that directly entered into the machine, as shown in Figure 3.13 and Figure 3.14. The Fluke 437-II equipment setting need to be changed to energy setting and the clamp device used need to be selected in the device lists. The energy data in kilowatt-hour (kWh) need to be collected in the present as the reading is display directly on the digital display screen after the machining process finished.

Figure 3.12 A set of Fluke 437-II Power harmonic analyzer.

Figure 3.13 Fluke 437-II Power Harmonic Analyzer cable setup for three-phase connections.

Figure 3.14 Fluke 437-II Power Harmonic Analyzer cable setup for neutral and ground connections.

3.8 Optimization by Using Machine Learning Method

All of the four criteria data are determined both via theoretical and a series of experimental work. Here, the next accomplishment is the comparison of both data in order to validate the validity range. The most critical criteria in the present study are the energy criteria to obtain the energy consumption is different from another criterion. The maximum range of percentage difference for energy criteria used is 12 % adopted from Navani (Navani et al., 2012). For simplification, the maximum range for the other three criteria is similar; that is, 12 %. If the percentage difference is below than 12%, the correction is done using machine learning optimization based on neural network fitting. If the problem persists such that more than 12% error, the experiment is re-done.

In performing optimization using neural network fitting, the inputs used are cutting speed and feed rate while the output is all the four criteria assessments known as total manufacturing cost, environmental impact assessment, energy consumed during the machining process and the revised NIOSH weight lifting index. The method used for optimization is adopted from Hernandez (Cortés et al., 2009), where the standard neural network fitting and inversed neural network fitting process are used to obtain the optimized cutting parameter. The main reason for choosing neural network fitting is because the characteristic of the energy data collected is in a dynamic state where there is a sign of energy fluctuation between the experiments that have been conducted although by using the same cutting parameter for three times, based on the conducted experiments.

The optimization process starts with a standard neural network fitting using experimental data. Matlab software is used to perform the fitting process. At the first place, the input and output targets need to be specified. In this case, the inputs are cutting speed and feed rate. Raw material length is not included in the output because all of the raw material sample lengths are the same which have been specifying at the beginning of the experiment. The outputs are total manufacturing cost, environmental impact, energy used to fabricate a product and the NIOSH revised weight lifting index. The samples are arranged in a matrix row.

The next step is to specify the number of hidden neuron. According to Sheela & Deepa (2013), it is crucial to set the correct number of hidden neuron in neural network fitting as it will be either underfitting or overfitting if it is set wrongly. They explained that the stability of the neural network is estimated by error. If the error is minimal, it shows that the model is in a good condition (stable) while if the error is high; it shows that the stability is not in a good condition (worst). Sheela & Deepa (2013) used Equation 2-24 to determine the number of hidden neurons which also being used in this study. The main reason for the selection of the equation proposed by Sheela & Deepa (2013) is due to their series of intensive experiments in the related before it was published. The training algorithm used in this study is Lavenberg – Marquardt algorithm because this algorithm works faster when it trains small and moderate size neural network data (Mia & Dhar, 2016). When running the neural network fitting to generate the neural network model, the results of R^2 and MSE usually indicates the quality of the model (Mathworks, 2017). The nearer the value of R^2 to 1.00, the accurate the model, and the lower the MSE value, the accurate the model (Kaytez et al., 2015).

Next, the neural network model obtained will be tested with the experimental input data to obtained the predicted value. If the percentage error between the experimental results data and the predicted data is less than 5% (Kant & Sangwan, 2015), the determination of the inversed neural network model will be done. If the error is more than 5%, the experimental work needs to be done again to make sure that the error obtained is less than 5%.

In the inversed neural network model, the input and output data is switched. Here, the input is total manufacturing cost, environmental impact assessment; energy consumed during the machining process and the NIOSH revised weight lifting index; while the output is cutting speed and feed rate. The samples are arranged in a matrix row same as in the standard neural network model method. The next step is to specify the number of the hidden neuron and again, Equation 2-24 has been adopted to determine the number of the hidden neuron. The training algorithm used in this study is Lavenberg – Marquardt; the same method adopted from the standard neural network fitting. Again, the results of R^2 and MSE were used as an indication to justify the quality of the model generated.

The next step is to identify the lowest value for each criterion based on the neural network predicted results for all four criteria. This values will be used in the inversed neural network model as input data to obtain the optimum cutting parameters that compromised all the four criteria assessment. The main reason to use the lowest value for each criteria is because the objective of the present study is to minimize all the criteria. Based on the optimum cutting parameters proposed by the inversed neural network model, an experiment is conducted again to verified and validate the results.

At the same time, the purposed cutting parameters are tested in the theoretical model to verify and validate for the second time. The optimized cutting parameter results tested in the theoretical model is compared with the experimental verification and validation data to prove that this method can be used to find an optimum cutting parameter. If the percentage difference is less than 5%, the method is proof good and can be accepted, but if the percentage difference is more than 5%, it will be rejected and the neural network inversed neural network model will be rechecked and run again. The methodology taken in this study is applied to the both Aluminium 6061 and Brass C3604 separately.

The present study adopt the sustainability assesment method from a few researchers. The economic assessment method is based on Zhang & Haapala (2015) with some modifications such as the additional lubricant cost included in the assessment method. Besides that, the determination of labor cost is based on the average monthly out put and did not based on the machining time cost because the operator work is multi-tasking.

Environmental impact assessment consists of energy impact, chip recycling impact, cutting tool impact, coolant and lubricant impact. Based on Dahmus & Gutowski (2004), the number of product produced is higher if compared to the amount of coolant, lubricant and cutting tool used in the machining process. Hence the amout of carbon produce in these three items can be neglected.

The reason to use the revised NIOSH Weight Lifting Index in measuring the social impact assessment is due to the ergonomic-based problem of the system and the prompt monitoring and improvement are needed to reduce the impact to the worker.

While the use of energy criteria is because the implementation of principal component analysis (PCA) in the whole of optimization data. According to Karamizadeh et al., (2013), invariance could not be captured if only PCA concept method is used.

Hence, to improve the optimization calculation, energy criteria which are the additional criteria are introduced. Apart from the contribution to the economic and environemental impact assessment results, energy criteria possess a huge effect on the environmental impact.

Artificial neural network (ANN) model and inversed artificial neural network (ANNi) model are selected to perform the optimization calculation of the preliminary data obtained from both the theoretical and experimental data collection. These data is the kick start to perform optimisation process, hence ANN and ANNi is selected.

3.9 Software / Tool Development: Visual Basic for Application (VBA)

Visual Basic for Applications (VBA) was released in 1987, regarded as the third generation event-driven programming language. Being the first visual development tool for Microsoft, VBA is considered as one of the most powerful programming languages as it allows programmers to create software interface and also codes in an easy to use graphical environment. When compared to other computer programming languages such as C programming, C++ and Java, VBA is easier to understand and learn, and also simple to develop. By creating a Macro, the programmer can visualize a message box for users to add and edit data to necessary sheets for data validation as shown in Figure 3.15.

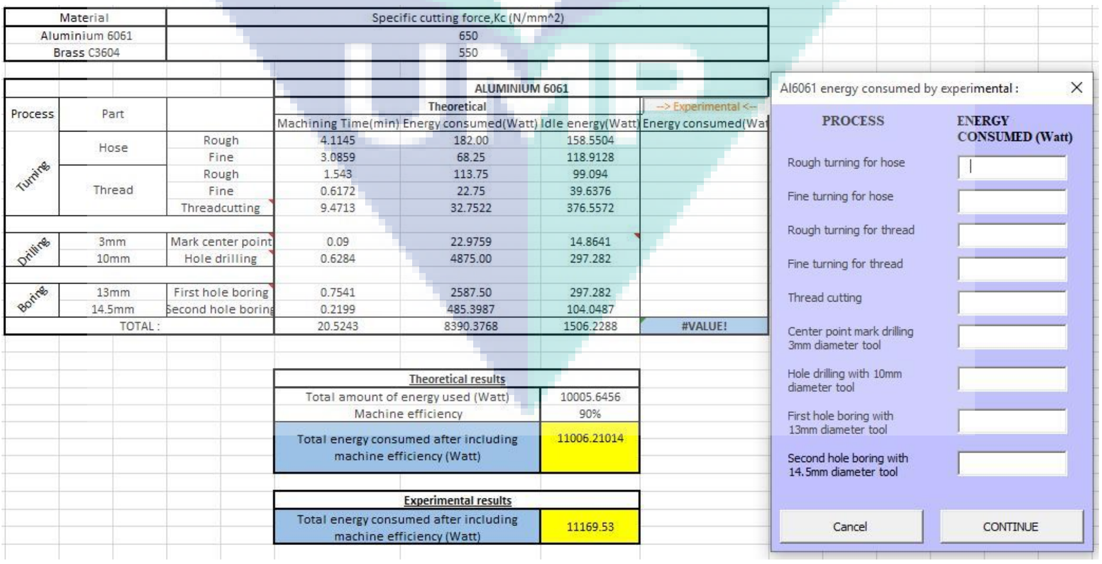


Figure 3.15 Message box by VBA

After inserting button control in Developer Tab in Microsoft Excel, programmer can press Alt+F11 to open Visual Basic Application Editor (VBA Editor). Later, the button contol is assigned to the wanted macro from the “Macro Name” list to run the VBA macros in Excel. Figure 3.16 shows the VBA Editor’s interface.

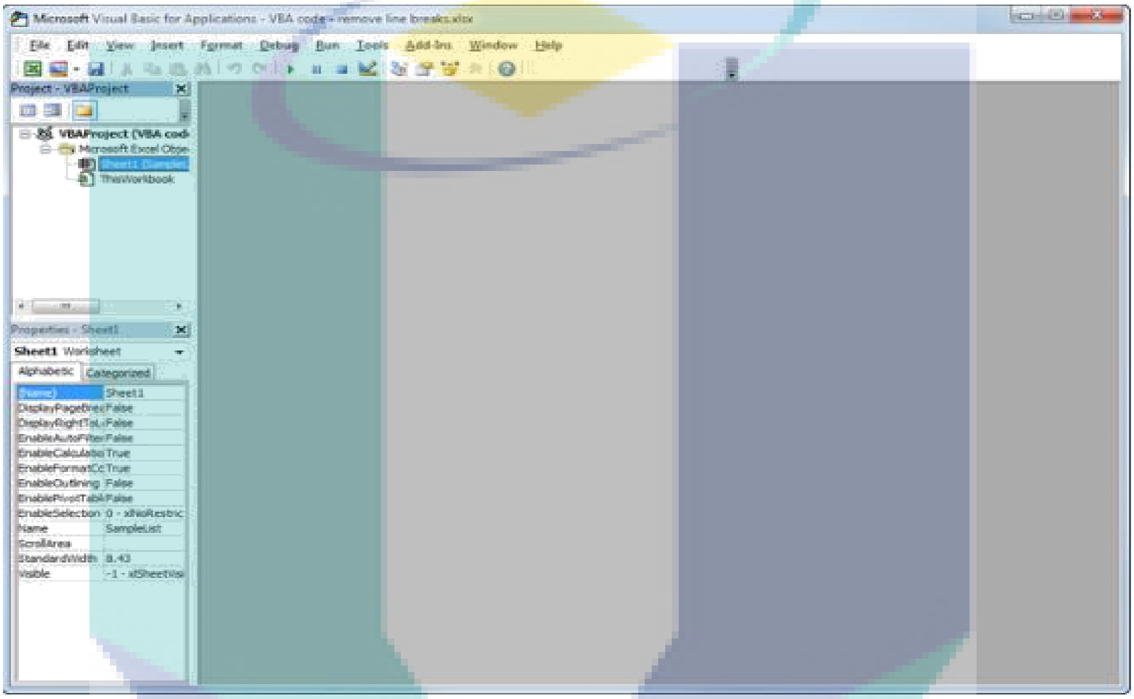


Figure 3.16 Visual Basic Editor in Microsoft Excel.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Introduction

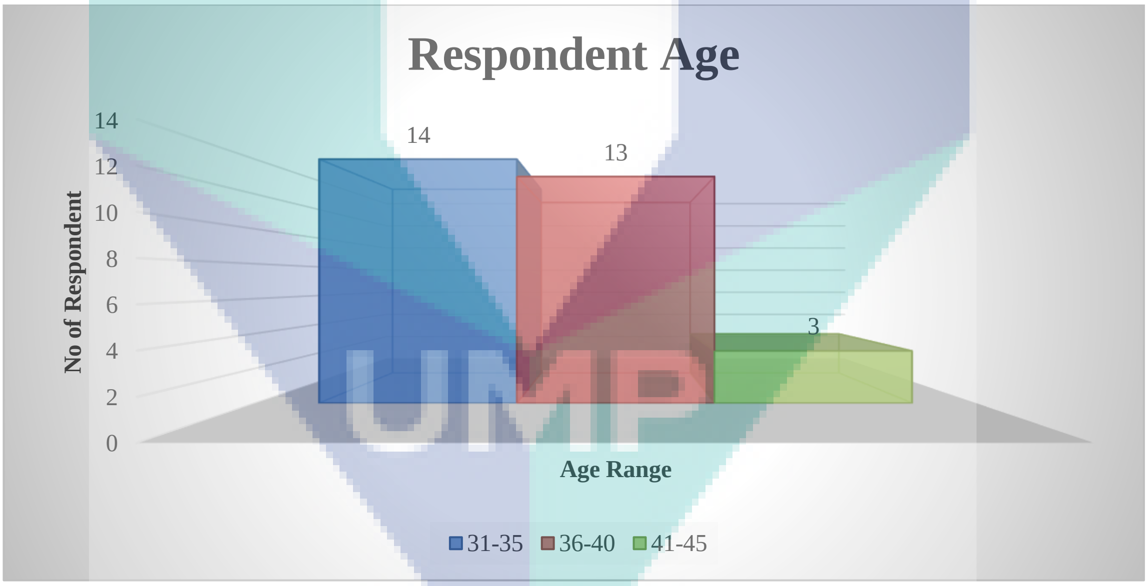
This chapter discussed the results and discussion of the present study. The topics covered in this section are the focus questionnaire survey results, raw material grade testing results, the theoretical calculation results (details calculation on the total manufacturing cost, the environmental impact and the energy consumed during the machining process) and the details on determination of the NIOSH weight lifting index. Later on, the experimental along with predicted results obtained are discussed. For predicted results, the details explanation on how the results obtained using a neural network model is discussed further. At the same time, the inversed neural network model and the verification of the optimization results are included in the discussion.

4.2 Survey Questionnaire Results

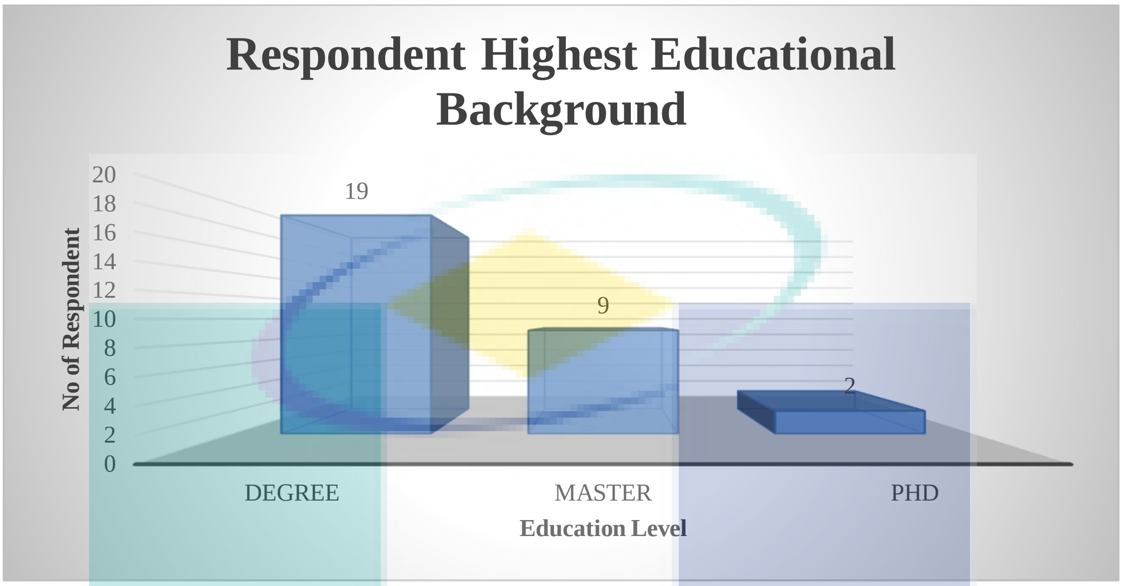
The proposed assessment method used in the present work is based on the feedback from the questionnaire survey given to the respondent to answer it. In the questionnaire; age, highest education background, working position and working experience is also asked. There is 30 respondent selected to involve in this survey and they were selected randomly based on the requirement that the respondent must be a working people or further study in PhD. Most of them aged around 30-45 years old with degree holder as the average highest education background. When looking at the working position, the majority work as an engineer with an average working experience of 12 years old. There are three criteria evaluated in sustainability, namely, economics, environmental impact and social impact criteria. Based on the literature survey, six, eight and five assessment methods listed for economic, environmental and social criterion, respectively.

The assessment methods listed under economic criteria includes salary and costs of raw material, cutting tool, coolant, lubricant and energy. Under environmental criteria, the assessment methods listed are pollution of water, air, land and impacts of energy, cutting tool, coolant, lubricant and chip recycling. Lastly, the assessment methods listed for social criteria are numbers of medical certificates, worker salary, NIOSH revised weight lifting index, REBA and RULA.

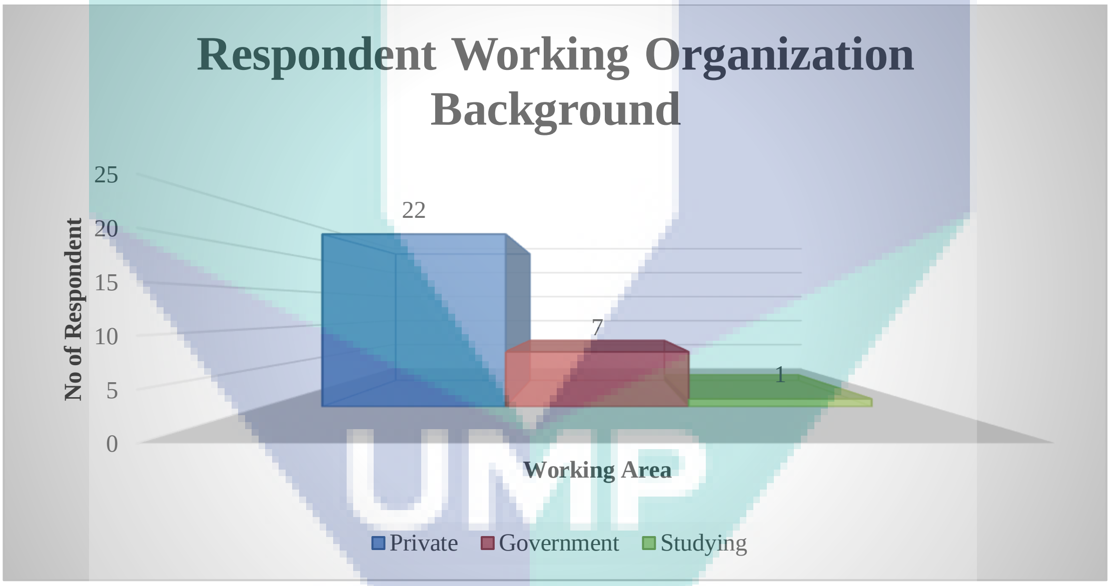
Respondent is asked to select the assessment method that they feel essential for the production line level and suggestions are welcomed if they have others assessment method that possible to be used. The output response of the feedback is shown in Figure 4.1 until Figure 4.3.



(a) Respondent Age



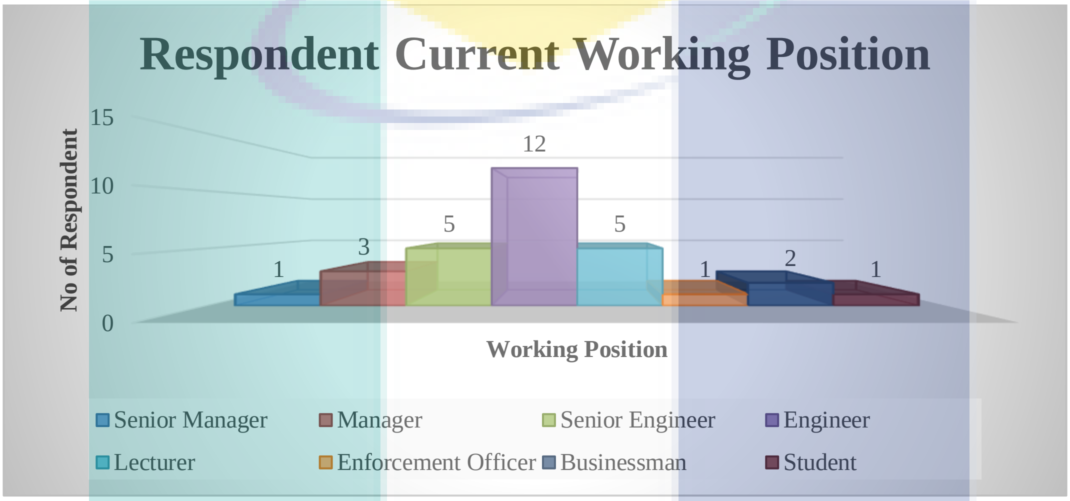
(b) Respondent Highest Educational Background



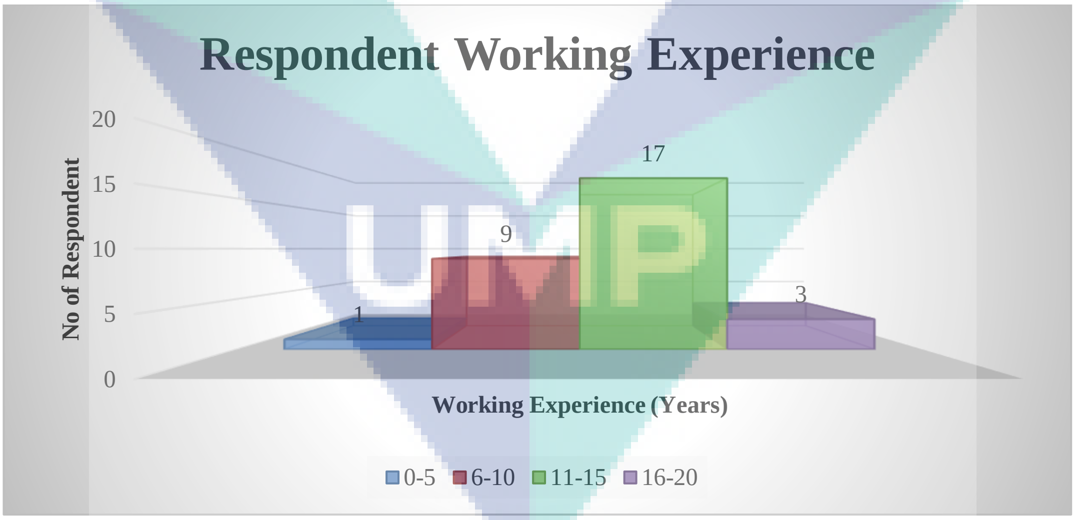
(c) Respondent Working Organization Background

Figure 4.1 Respondent feedback on age, highest education background and working organisation.

Figure 4.1 shows the respondents' feedback based upon their age, highest education background and their working organisation. Figure 4.1 (a) indicated that the respondent age range is between 31 to 45, 36 to 40 and 41 to 45 years old with 14, 13 peoples and 3 peoples. On the other hand, Figure 4.1 (b) shows respondent highest education background. From the survey, there are 19 people with a degree qualification, followed by a master degree with 9 peoples and PhD degree with 2 people. Lastly, figure 4.1 (c) shows the working organisation of the respondent. Out of 30 respondent, 22 peoples working in private company while 7 people working with government and one person still furthering study.



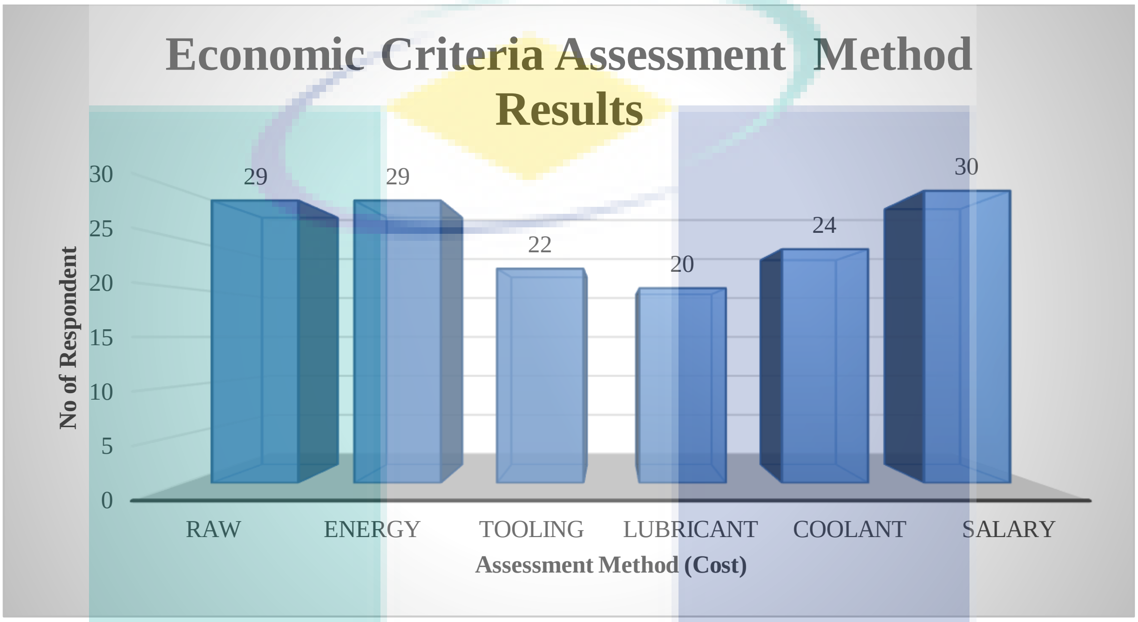
(a) Respondent working positions



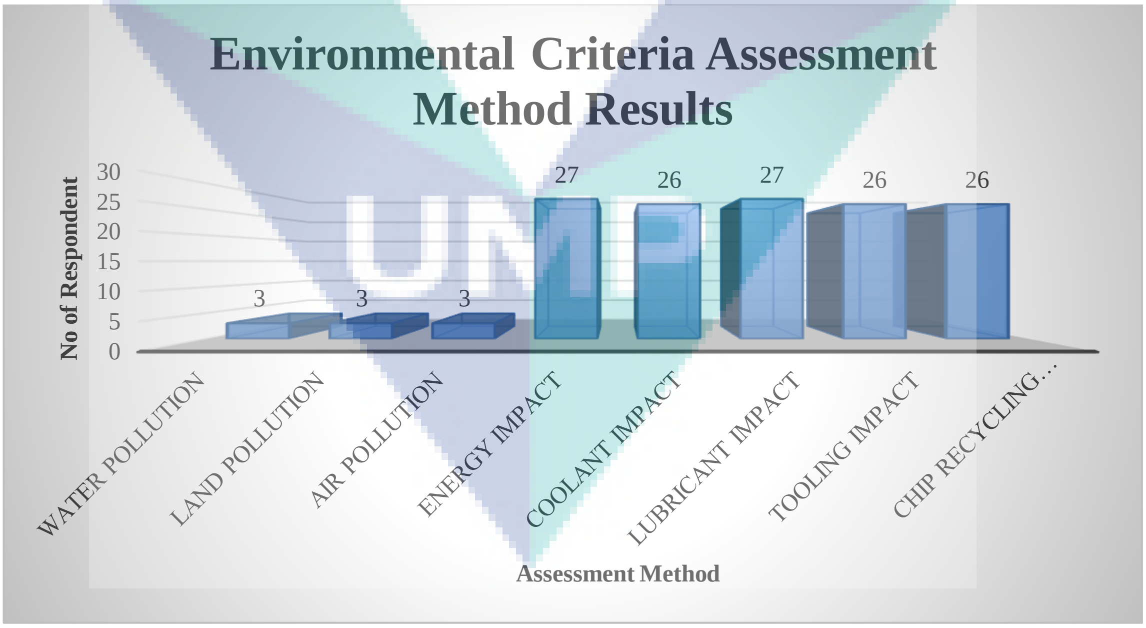
(b) Respondent working experience

Figure 4.2 Respondent feedback on their (a) working position and (b) working experience.

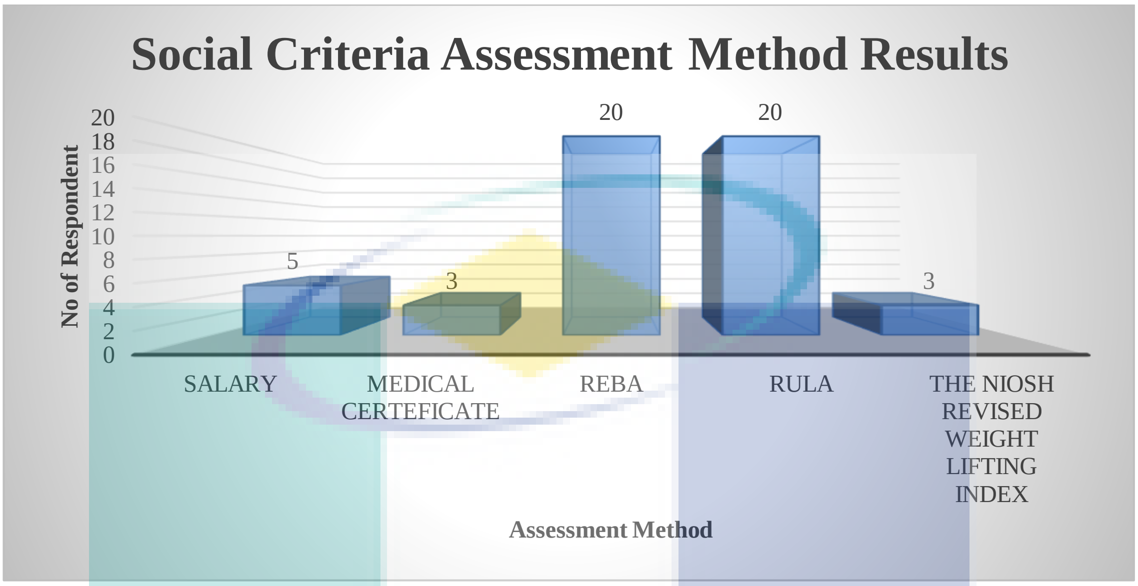
Figure 4.2 shows the respondent feedback on their working positions and working experience. With the majority of the respondent have working experience for more than nine years and their working positions ranging from engineer till senior manager. Thus, it can be concluded that most of the respondents have good working experience in making decisions.



(a) Economic criteria assessment method results



(b) Environmental criteria assessment method results



(c) Social criteria assessment method results

Figure 4.3 Respondent feedback on (a) economic, (b) environmental and (c) social criteria assessment methods.

Figure 4.3 shows the respondent feedback on economic, environmental and social criteria assessment methods. For economic criteria, the majority of the respondent vote for RAW (Raw Material) cost, energy cost and salary as an assessment for economic criteria assessment which scored 29, 29 and 30 respondents. Meanwhile, only 22, 20 and 24 respondents selected tooling, lubricant and coolant cost to be included in the economic cost. One suggestion from one of the respondent to used all the assessment method as an assessment method for economic criteria and named it as total manufacturing cost. Based on the survey results, all assessment methods will be included under economic criteria since it reflects the overall manufacturing cost.

For environmental criteria assessment method, majority of the respondent vote for energy, coolant, lubricant, tooling and chip recycling impact as the assessment methods with the score of 27, 26, 27, 26 and 26 respondents. Only three people each vote for water, land and air pollution as the assessment methods for environmental impact assessment. Based on the survey results, energy, coolant, lubricant and chip recycling impact will be included under the environmental criteria assessment methods. On the other hand, there is one opinion by researchers who argue that coolant, lubricant and tooling impact being included in the assessment since the number of product produced is too high compared to the amount of coolant, lubricant and tooling being used (Dahmus & Gutowski, 2004).

Finally, for environmental criteria assessment methods, the majority of the respondents choose REBA and RULA methods to be included in the assessment. The rest, only five respondents choose salary, three people choose medical certificate (mc) and The NIOSH Revised Weight Lifting Index. One comment stated that the assessment mainly depends on the situation, although he/she already selected one of the assessment methods. If developing a system or framework used to proposed the study, one should select the assessment method that produces/used data that also used other criteria or input data which needed. Based on the results and comment from the respondent, The Revised NIOSH Weight Lifting Index is selected to be used under the social criteria assessment method since some of the data required calculation from other criteria.

4.3 Raw Material Testing Results

The materials grade identification for raw Aluminum 6061 and Brass C3604 are carried out in the first place. The identification process is conducted in the Foundry Laboratory, Faculty of Mechanical Engineering, Universiti Malaysia Pahang using Oxford spectrometer. The identification process started by cutting each of the materials into the size of 20.00 mm in thickness with a hand saw. Then, both of the materials are ground to obtained flat surfaces prior to the identification process. The flat surface is important to prevent the possibilities of losing electron into the air after being contacted to the surface of the materials. Here, several areas involved in the test. We have decided to shoot electron to three different points for both brass and aluminum materials (as shown in Figure 4.4). The summaries for Brass C3604 and Aluminium 6061 used are tabulated in Table 4-1 and Table 4-2, respectively which consists of the percentage of materials composition based reference (ASM Aerospace Specification Metals Inc., 2018; Daechang Co. Ltd, 2018) and test values.

(a) (b)

Figure 4.4 (a) Brass C3604 Material (b) Aluminum 6061 testing sample.

Table 4-1 Summary on the composition of Brass C3604 based on the percentage obtained from reference and test.

Material	Tested (%)	Reference (%)
Copper (Cu)	58.5	57.0-61.0
Plumbum (Pb)	3.37	1.80-3.70
Ferrum (Fe)	0.319	Max 0.5
Tin (Sn)	0.466	Max 0.5
Zinc (Zn)	35.8	34.3-41.2

Source: Daechang Co. (2018)

Table 4-2 Summary on the composition of Aluminium 6061 based on the percentage obtained from reference and test.

Material	Tested (%)	Reference (%)
Aluminum (Al)	96.8	95.8-96.8
Chromium (Cr)	0.0855	0.04-0.35
Copper (Cu)	0.271	0.15-0.40
Ferrum (Fe)	0.205	Max 0.7
Magnesium (Mg)	0.855	0.08-1.20
Mangan (Mn)	0.0075	Max 0.15
Silicon (Si)	0.617	0.40-0.80

Source: ASM Aerospace Specification Metals Inc. (2018)

Table 4-1 and Table 4-2 show the percentage composition results for Brass C3604 are 58.5% for Copper, 3.37% for Plumbum, 0.319% for Ferrum, 0.466% for Tin (Sn) and

35.8% for Zinc. Meanwhile, the percentage composition results for Aluminium 6061 is 96.8 % for Aluminium, 0.0855% for Chromium, 0.271 % for Copper, 0.205 % for Ferrum, 0.855% for Magnesium 0.0075% for Mangan and 0.617% for Silicon. Based on the results, both materials composed the acceptable range of materials composition percentage as provided by Daechang Co and ASM Aerospace. The percentage of the composition also reflects the originality of the samples for both Aluminium 6061 and Brass C3604.

4.4 Theoretical Calculation Results – Economics Criteria

4.4.1 Raw Material Cost

Prior to the cost calculation on raw materials used, it is important to figure out the total cost based on ringgit per volume unit. It shall be noted that both Aluminium 6061 and Brass C3604 used in this study are in the hexagon bar shape and thus, the volume of the hexagon can be calculated using simple mathematical formula (Equation 3-2) where a hexagon is made of six 60 degree triangle. Particularly for this shape, the base and tall values obtained are defined based on the sketch in Figure 4.5.

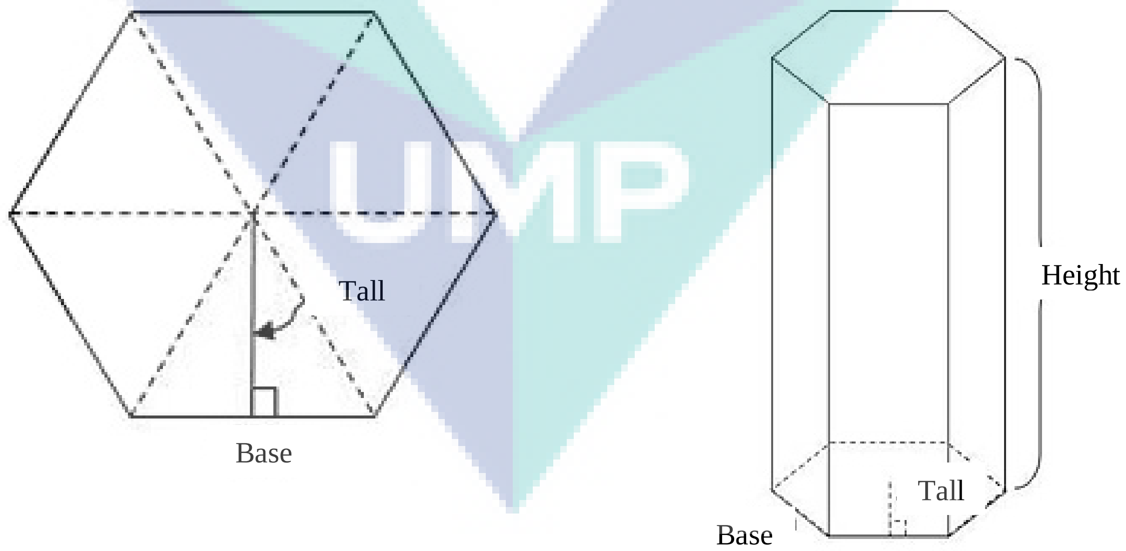


Figure 4.5 The classification of tall, base and height in hexagon volume calculation.

The base and tall values are obtained from the data specification provided by the supplier with the base and tall values are 1.40 and 0.95cm, respectively. The density of

Aluminium 6061 and Brass C3604 are 2.70 and 8.43 g/cm^3, respectively. The cost of raw material is obtained by multiplying the raw material mass with raw material price as shown in Equations 3-3 to 3-4. According to the sale price quoted by the supplier, the standard price for 1.00 m Aluminium 6061 is RM 67.21 while for Brass C3604 is RM 272. Therefore, the standard price for 1.00 g Aluminium 6061 is RM 0.06 and 1.00 gram Brass material is RM 0.05. The calculation examples of raw material cost for Aluminium 6061 and Brass C3604 are as follow. The required length was measured by using vernier caliper.

$$\text{Volume}_{\text{Aluminium}} = \left(\frac{\text{Base} \times \text{Tall}}{2} \times 6 \times \text{Raw Material Length (Height)}\right)$$

$$= \frac{1.40 \times 0.95}{2} \times 6 \times 5.50 = 21.945\text{cm}^3$$

$$\text{Mass}_{\text{Aluminium}} = \text{Volume} \times \text{Density} = 21.945 \times 2.70 = 59.2515 \text{ gram}$$

$$\text{Raw Material Cost}_{\text{Aluminium}} = 59.2515 \times \text{ RM } 0.06215724 = \text{RM } 3.6829$$

$$\text{Volume}_{\text{Brass}} = \left(\frac{\text{Tall} \times \text{Base}}{2} \times 6 \times \text{Raw Material Length (Height)}\right)$$

$$= (\frac{1.50 \times 1.25}{2} \times 6 \times 5.50 = 30.9375\text{cm}^3)$$

$$\text{Mass}_{\text{Brass}} = \text{Volume} \times \text{Density} = 30.9375 \times 8.43 = 260.8031 \text{ gram}$$

$$\text{Raw Material Cost}_{\text{Brass}} = 260.8031 \times \text{RM } 0.05695589 = \text{RM } 14.8542$$

Based on the calculation above, the raw material cost for Aluminum 6061 and Brass C3604 is RM 3.6829 and RM 14.8542, respectively.

4.4.2 Coolant and Lubricant Cost

In the following stage, both the cost for coolant and lubricant are determined using Equations 2-6 to 2-8. The assumption that has been made here is that the amount of coolant and lubricant needed for both materials is the same. Hence only one calculation example was done. According to Okuma's catalogue, the capacity of the coolant and lubricant tanks in OKUMA LB 15 CNC Turning Machine are 150 and 40 liters (Okuma Machinery Works Ltd, 1987), respectively.

Based on Zhang & Haapala (2015) calculation method, the coolant and lubricant loss rate range is between 10 % to 30 %. In the present study, the loss rate for both coolant and lubricant is 15% or at pH 8.08 scale for coolant quality (Inc, 2017). According to the advice given by the supplier, the coolant and lubricant need to be changed regularly to maintain the optimum quality and functions. Hence, the coolant and lubricant are changed for every six and three months, respectively. At the same time, two working shift per day with 22 working days per month and the daily average output is 120 units/ shift are assumed. Based on the price list for 'buy items' provided by the faculty, the coolant and lubricant costs are RM 44.24 / liter and RM 25.0209 / liter, respectively. Therefore, the example of cost calculation for coolant for both materials are as follow:

$$\text{Make Up Volume}_{\text{Coolant}} = \frac{\text{Coolant Tank Capacity} \times \text{Coolant Loss Rate}}{1 - \text{Coolant Loss Rate}}$$

$$= \frac{150 \times 0.15}{1 - 0.15} = 26.47059 \text{ L}$$

$$\text{Coolant Volume} = \frac{\text{Coolant Tank Capacity (L)} + \text{Make Up Volume (L)}}{\text{Months Used} \times \text{Average Daily Output}}$$

$$= \frac{150 + 26.47057}{6 \times (3 \times 22 \times 120)} = 0.0055704 \text{ L}$$

$$\text{Coolant Cost} = \text{Coolant Volume} \times \text{Coolant Cost Rate}$$

$$= 0.0055704 \times \text{RM } 44.24 = \text{RM } 0.246435$$

The calculations for the cost of lubricant are as follows:

$$\text{Make Up Volume}_{\text{Lubricant}} = \frac{\text{Lubricant Tank Capacity} \times \text{Lubricant Loss Rate}}{1 - \text{Lubricant Loss Rate}}$$

$$= \frac{40 \times 0.15}{1 - 0.15} = 7.058823 \text{ L}$$

$$\text{Lubricant Volume} = \frac{\text{Lubricant Tank Capacity (L)} + \text{Make Up Volume (L)}}{\text{Months Used} \times \text{Average Daily Output}}$$

$$= \frac{40 + 7.058823}{3 \times (3 \times 22 \times 120)} = 0.002970 \text{ L}$$

$$\text{Lubricant Cost} = \text{Lubricant Volume} \times \text{Lubricant Cost Rate}$$

$$= 0.002805 \times \text{RM } 25.0209 = \text{RM } 0.074334$$

Based on the calculation above, the coolant and lubricant cost used for both types of raw material is RM 0.246435 and RM 0.0774334, respectively.

4.4.3 Energy Cost

In this case, the energy cost is equal to the amount of energy used during the machining process of pneumatic nipple hose connector multiply with the industrial energy rate per kilowatt-hour, as shown in Equation 2-4. The amount of energy used in the present study is shown in the environmental impact calculation (Aluminium 6061 by using cutting parameter Option 1), where it consists both of chip re-cycling and energy impact. The industrial energy rate used in this study is RM 0.38 per kWh based on Tenaga Nasional Berhad (TNB) tariff starting from 1st January 2014. The tariff is based on low voltage industrial tariff where for the price for the first 200 kWh per month is RM 0.38 and for more than 200 kWh, the energy tariff is RM 0.4410 for each kWh. In the present study, it is assumed that the energy tariff is flat at RM0.38 / kWh and the energy cost is RM 4.1837; the energy cost calculation is shown below for Aluminium 6061 material using cutting parameter option 1 where the total energy used is based on total energy data obtained in sub-topic 4.6.

$$\text{Energy Cost} = \text{Total Energy Used (kWh)} \times \text{Industrial Electricty} \left(\frac{\text{RM}}{\text{kWh}}\right)$$

$$= 11.00962 \text{ kWh} \times \text{RM } 0.38 = \text{RM } 4.1837$$

4.4.4 Labor Cost

The labor cost is calculated based on the average daily output for one shift for both aluminium 6061 and brass C3604 materials, as shown in Equation 2-5. In the present study, it is assumed that the operator is a highly skilled worker and his/her salary is RM 2,500 per month. The minimum salary used by Malaysia Government is RM1100 for basic skill worker. The production line output for one shift daily handled by one operator is 120 units and there are 22 working days per month for both materials. The estimated labor cost per unit product is RM 0.9469 as shown in the next page.

$$\text{Labor Cost} = \frac{\text{Salary}}{\text{Working Days Per Month} \times \text{Average Shift Output}}$$

$$= \frac{\text{RM 2500}}{22 \times 120} = \text{RM } 0.9469$$

4.4.5 Tool Cost

Generally, the tool cost can be calculated using Equation 2-3, as discussed in Chapter Two. In this study, Equation 2-3 is used only for the turning process, while Equation 3-5 is used for the drilling operation using the High-Speed Steel (HSS) drill bit. If the machining process involves more than one types of the cutting tool, all cutting tool involved in the machining process must be considered in determining the tool cost. The machining process employed Mitsubishi cutting tools bought from the supplier. The detail specifications and price for each cutting tool are shown in Table 4-3.

Table 4-3 Cutting tool price bought from the supplier.

Tool Name	Price (RM/Piece)	Number of points used
TNMG160408 Coated Carbide Insert	40.28	3
VCMT160404 Coated Carbide Insert	66.78	2
16ERG60 Thread Insert	66.78	3
HSS Center Drill ∅ 3.00 mm	13.78	2
SDD 1000 Mitsubishi HSS Drill ∅ 10.00mm	56.18	1
SDD 1000 Mitsubishi HSS Drill ∅ 13.00mm	73.46	1
SDD 1000 Mitsubishi HSS Drill ∅ 14.50mm	72.72	1

As shown in Table 4-3, the cutting tool cost per piece is quite expensive. However, the quality of that cutting tool in terms of physical shape and the ability to perform work more than one point leverage the advantages of it. For example, TNMG160408 turning insert can be used at three different points of locations. For VCMT160404 turning insert, the shape is a rhombus and it can only be used to cut aluminum and brass at two points. For 16ERG60 thread insert, the general shape is rectangular and the thread cutting process can be done at three points. For center drill cutting tool, it can be used at two points before being disposed at the end of its tool life, while for the drill cutting tool, it can be used only at one point. In the present study, the re-grinding of the cutting tool is not taking into account because the inset is too small and difficult to grind.

To calculate the tool cost, the first thing we need to do is to determine the tool life of the cutting tool and then the machining time for each of the cutting tools. Based on the literature survey, none of the researchers determines the exact tool life inserts required based on the cutting parameter used as described in the present study. Hence, a simple experiment conducted using Fanuc 400 CNC turning machine located in CNC Laboratory at the Faculty of Mechanical Engineering Universiti Malaysia Pahang (UMP) is used to determine the inserts tool life. Meanwhile, for the drill cutting tool, the machine involved is CNC RoboDrill machine using the cutting parameters mention in Chapter Three and the workpiece used are Aluminium 6061 and Brass C3604. The next subsection discussed the tool life of Option 1 (refer to Table 3-1 for cutting parameters value) cutting tool involved in the machining process using Aluminium 6061 workpiece as an example in details.

4.4.5.1 Insert Tool Life Results

Based on Equations 2-3 and 3-5 described in Chapter Two and Three, the importance of cutting tool life in calculating the tool cost involved in the machining process is discussed here. The tool life data are divided into two parts, that are, inserts tool life and drilling tool life. The inserts tool life used in the present study are discussed here and the drill cutting tool life was discussed under the sub-topic 4.4.5.2. The workpiece involved in the experiment is Aluminium 6061. Only Aluminium 6061 sample is to determine the tool life in this part as an example of how tool life is determined. It is worth to note here that the tool life is not the main focus of this thesis based on the objective stated in Chapter One. However, it is necessary to include the results here to obtain accurate and precise tool cost outcomes.

As previously mentioned in Chapter Three, there are three types of insert cutting tool involved in the present study. They are TNMG160408 turning insert, used in rough cutting and finishing process, and VCMT160404 turning insert is used in the finishing process and the 16ERG60 thread insert is used in cutting the pneumatic connector thread. The workpiece used in this experiment is Aluminium 6061 material in a cylindrical shape with a dimension of diameter 27.5 mm x 250 mm. The cutting length for each raw material is 230 mm. Figure 4.6 shows the sample of Aluminium 6061 workpiece used in this study.

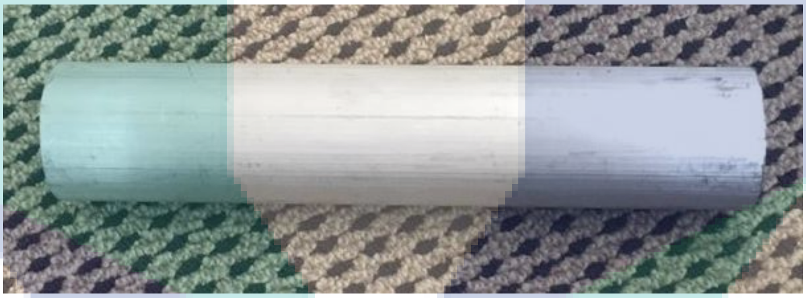


Figure 4.6 Aluminium 6061 raw material used in the tool life experiment.

Based on the experiment, the tool life for TNMG 160408 with the 0.50 mm depth of cut is 75.5 minutes where the surface roughness used is closed to 8.400 µm, while the tool life for TNMG 160408 with 0.25 depth of cut is 113.25 minutes where the surface roughness is 1.600 µm. The tool life for VCMT 160404 with 0.25 depth of cut is 66.2 minutes with the surface roughness value is 1.600 µm and the tool life for 16ERG60 thread insert is 69.4 minutes. Table 4-4 and Table 4-5 summarised the surface roughness results of tool wear for TNMG 160408 coated carbide inserts with 42.00 m/min cutting speed and the federate is 0.10 mm/rev.

Table 4-4 Surface roughness values for TNMG 160408 insert till tool wear with the depth of cut of 0.50 mm.

Pass	Reading 1st	2nd	3rd	Average
1st	0.572	0.581	0.594	0.582
2nd	1.093	1.081	1.102	1.092
3rd	1.614	1.632	1.627	1.624
4th	2.136	2.148	2.152	2.145
5th	2.657	2.664	2.673	2.665
6th	3.178	3.185	3.198	3.187
7th	3.700	3.718	3.726	3.715
8th	4.221	4.245	4.237	4.234
9th	4.742	4.755	4.763	4.753
10th	5.264	5.281	5.273	5.273
11th	5.785	5.804	5.798	5.796
12th	6.306	6.327	6.314	6.316
13th	6.827	6.839	6.845	6.837
14th	7.349	7.355	7.361	7.355
15th	7.870	7.883	7.892	7.882
16th	8.420	8.360	8.410	8.397

Table 4-5 Surface roughness values for TNMG 160408 insert till tool wear with the depth of cut of 0.25 mm.

Pass	Reading 1st	2nd	3rd	Average
1st	0.315	0.278	0.304	0.299
2nd	0.345	0.357	0.361	0.354
3rd	0.419	0.413	0.422	0.418
4th	0.482	0.470	0.465	0.472
5th	0.529	0.526	0.539	0.531
6th	0.587	0.583	0.592	0.587
7th	0.632	0.639	0.647	0.639
8th	0.689	0.696	0.692	0.692
9th	0.757	0.752	0.763	0.757
10th	0.815	0.809	0.821	0.815
11th	0.876	0.866	0.872	0.871
12th	0.934	0.922	0.928	0.928
13th	0.972	0.978	0.969	0.973
14th	1.029	1.035	1.041	1.035
15th	1.095	1.091	1.102	1.096
16th	1.136	1.148	1.154	1.146
17th	1.207	1.201	1.213	1.207
18th	1.254	1.261	1.269	1.261
19th	1.312	1.317	1.309	1.313
20th	1.368	1.374	1.381	1.374
21st	1.427	1.431	1.421	1.426
22nd	1.495	1.487	1.482	1.488
23rd	1.548	1.543	1.552	1.548
24th	1.586	1.592	1.601	1.593

On the other hand, Table 4-6 shows the surface roughness of tool wear for VCMT160404 coated carbide insert using similar cutting speed and feedrate but with the depth cut of 0.25 mm. Based on these results, the surface roughness value is increasing as the machining time is longer due to the occurrence of tool wear during the machining process. Therefore, the obtained machining time with the surface roughness close to 1.600 µm for VCMT 160404 insert is 66.20 minutes.

Table 4-6 Surface roughness values for VCMT 160408 insert till tool wear with the depth of cut of 0.25 mm.

Pass		**Reading**		
	1st	**2nd**	**3rd**	**Average**
1st	0.295	0.314	0.306	0.305
2nd	0.408	0.423	0.416	0.416
3rd	0.517	0.523	0.53	0.523
4th	0.625	0.645	0.637	0.636
5th	0.734	0.747	0.751	0.744
6th	0.798	0.806	0.811	0.805
7th	0.897	0.889	0.901	0.896
8th	0.992	0.983	0.972	0.982
9th	1.055	1.061	1.076	1.064
10th	1.132	1.155	1.148	1.145
11th	1.187	1.182	1.158	1.176
12th	1.275	1.267	1.289	1.277
13th	1.383	1.378	1.286	1.382
14th	1.597	1.599	1.605	1.600

The tedious part in determined the tool life is to calculate the tool life of 16ERG60 Thread insert. These are due to the difficulty in measuring the surface roughness of the thread area as the cutting area is too small and the smallest surface roughness that the machine can reach cannot fit in the slot correctly. Hence, the graphical method is used to determine the tool life, as shown in Figure 4.7. For Aluminum 6061 sample, the tool wear is at 69.40 minutes and for Brass C3604 the tool wear occurs at 60.20 minutes where the tool wear conditions are around the end of the tip and at the side of the cutting tool. Figure 4.7 (a) shows the graphical results of Aluminium 6061. In the figure, at the tip of the cutting tool, we can see the sharp edge was torn down. Besides that, there is a scratch and a bit of Aluminium 6061 material adhesion at the wall of the thread tool. For the Brass C3604 material in Figure 4.7 (b), we can see that the tip of the cutting tool become blunt but there are no scratches at the wall of the cutting tool. This phenomenon already expected because Aluminium 6061 materials is a soft material based on its technical characteristics compared to Brass C3604.

(a) Thread tool wears conditions when machining Aluminium 6061 Material.

(b) Thread tool wears conditions when machining Brass C3604 Material.

Figure 4.7 The 16ERG60 Thread insert conditions upon the tool wear for (a) Aluminium 6061 (b) Brass C3604 Materials.

4.4.5.2 Drilling Cutting Tool Tool Life

As stated in Chapter Three, there are four types of drilling cutting tool involved in the present study. The center drill diameter is 3.00 mm while the drill diameters are 10.00 mm, 13.00 mm and 14.5 mm. The workpiece used in this experiment is Aluminium 6061 in cubical shape with a dimension of 200 mm x 200 mm x 55 mm. The 55.00 mm workpiece thickness is chosen because it represents the deepest hole that needs to be drilled as needed in the pneumatic connector. All the drilling experiment were done using similar Aluminium 6061 workpiece grade as shown in Figure 4.8 starting with the center drill diameter of 3.00 mm, followed by drill diameter of 10.00 mm, 13.00 mm and 14.50 mm tool. In total, there are five blocks of Aluminium 6061, such as shown in Figure 4.8.

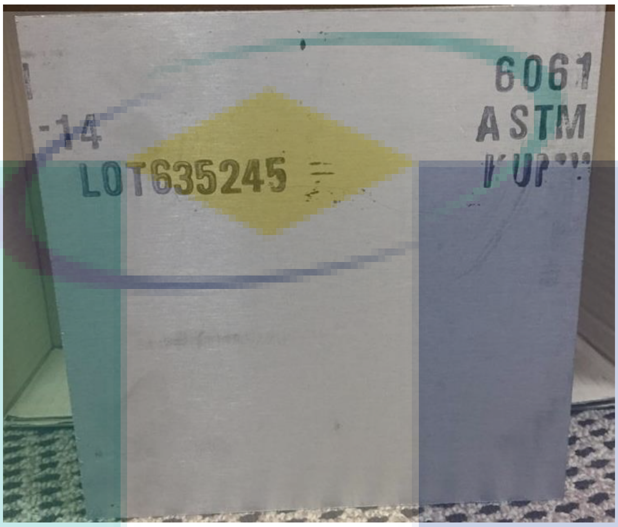


Figure 4.8 Aluminium 6061 block dimension 200 mm x 200 mm x 55 mm.

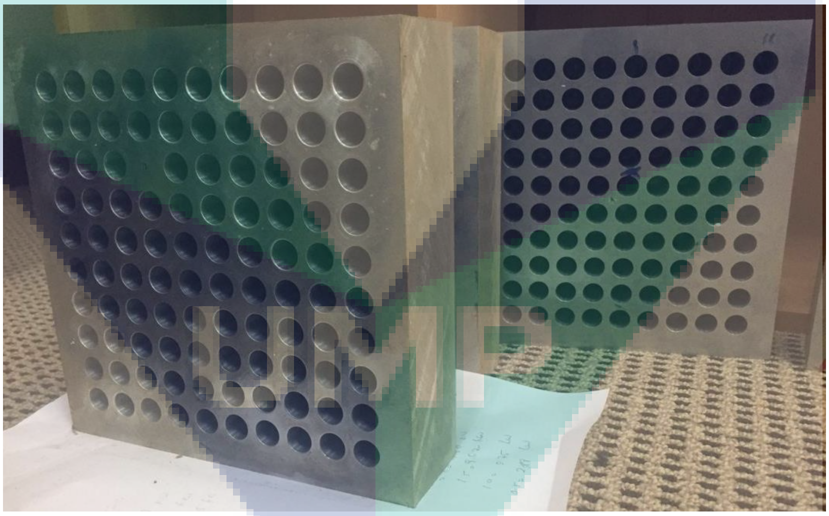


Figure 4.9 Samples of the completed experiment workpiece.

Experimentally, the tool life for center drill diameter of 3.00 mm took place when 476 drilled holes are completed. Based on the supplier catalogue, the maximum acceptable tolerance is +0.05 mm when the maximum diameter measurement is 3.05 mm. During the machining process at the 470th hole, it is found that the drilling process sound is abnormal as compared to the 469th hole. After machining the 477th hole completed, the center drill broke down and scattered into the workpiece, as shown in Figure 4.9.

After the center drill broke down, the diameter of the hole is measured using vernier calliper and the summary of the measurement results are shown in Table 4-7. Based on Table 4-7 results, it shows that the measurement of diameter is almost equal to the maximum acceptable tolerance at 0.05 mm and then brake down. The tool life of the first drilling process usually not very long due to the high force needed to ensure the part of drilling tool remain in the workpiece (Ghasemi et al., 2018). Besides that, the tendency for the drilling tool being chipped off at the tip of the drilling tool also caused the drilling tool to break down. Besides that, the holes produced before broken down is slightly larger than 3.00 mm because the tendency for the drill tool to bent is small due to the high force act at the tip of the tool. A similar phenomenon is observed in the remaining drilling tool. The hole diameter of 10.00 mm is machined until the 250th hole number is reached. For 13.00 mm hole diameter, it can be done until the hole number is 485 while, the 14.50 mm hole diameter is machined for the 499th hole number before all drilling tools started produced an abnormal sound during drilling and the dimension of the hole became larger.

Table 4-7 Average hole diameter measurement for Aluminium 6061 workpiece when drilling by using High-Speed Steel Center Drill tool with cutting speed of 9.426 m/min, federate 0.10 mm/rev and 0.10 mm depth of cut.

Pass	**Reading**			
	1st	**2nd**	**3rd**	**Average**
1st	3.000	3.000	3.000	3.000
5th	3.001	3.000	3.000	3.000
10th	3.000	3.001	3.003	3.001
20th	3.004	3.006	3.004	3.005
30th	3.008	3.006	3.007	3.007
40th	3.010	3.009	3.009	3.009
50th	3.010	3.009	3.011	3.010
100th	3.013	3.014	3.012	3.013
150th	3.017	3.015	3.016	3.016
200th	3.018	3.019	3.016	3.018
250th	3.024	3.025	3.025	3.025
300th	3.026	3.028	3.028	3.027
350th	3.032	3.034	3.031	3.032
400th	3.038	3.036	3.037	3.037
450th	3.043	3.047	3.046	3.045
476th	3.046	3.045	3.048	3.046

Tables 4-8 and 4-9 show the measured hole for a cutting tool with a diameter of 10.00 mm and the measured boring performance using drill cutting tool with a diameter of 13.50 mm. Meanwhile, Table 4-10 shows the measured hole boring performance using drilling cutting tool with a diameter of 14.50 mm, cutting speed of 30.00 m/ min, federate of 0.10 mm/rev and depth of cut 1.00 mm until the hole formed. The max accepted hole diameter is 14.50 with the depth of cut 21.00 mm.

Table 4-8 Average hole diameter measurement for Aluminium 6061 workpiece when drilling through the hole by using High-Speed Steel Drill tool diameter 10.00 mm with cutting speed of 30.00 m/min, federate 0.10 mm/rev with the depth of cut of 1.00 mm.

Pass	**Reading**			
	1st	**2nd**	**3rd**	**Average**
1st	10.000	10.000	10.000	10.000
5th	10.000	10.000	10.001	10.000
10th	10.002	10.000	10.001	10.001
20th	10.007	10.005	10.003	10.005
30th	10.010	10.009	10.008	10.009
40th	10.010	10.012	10.011	10.011
50th	10.015	10.014	10.016	10.015
100th	10.018	10.023	10.023	10.021
150th	10.025	10.024	10.026	10.025
200th	10.039	10.035	10.036	10.037
250th	10.050	10.050	10.050	10.050

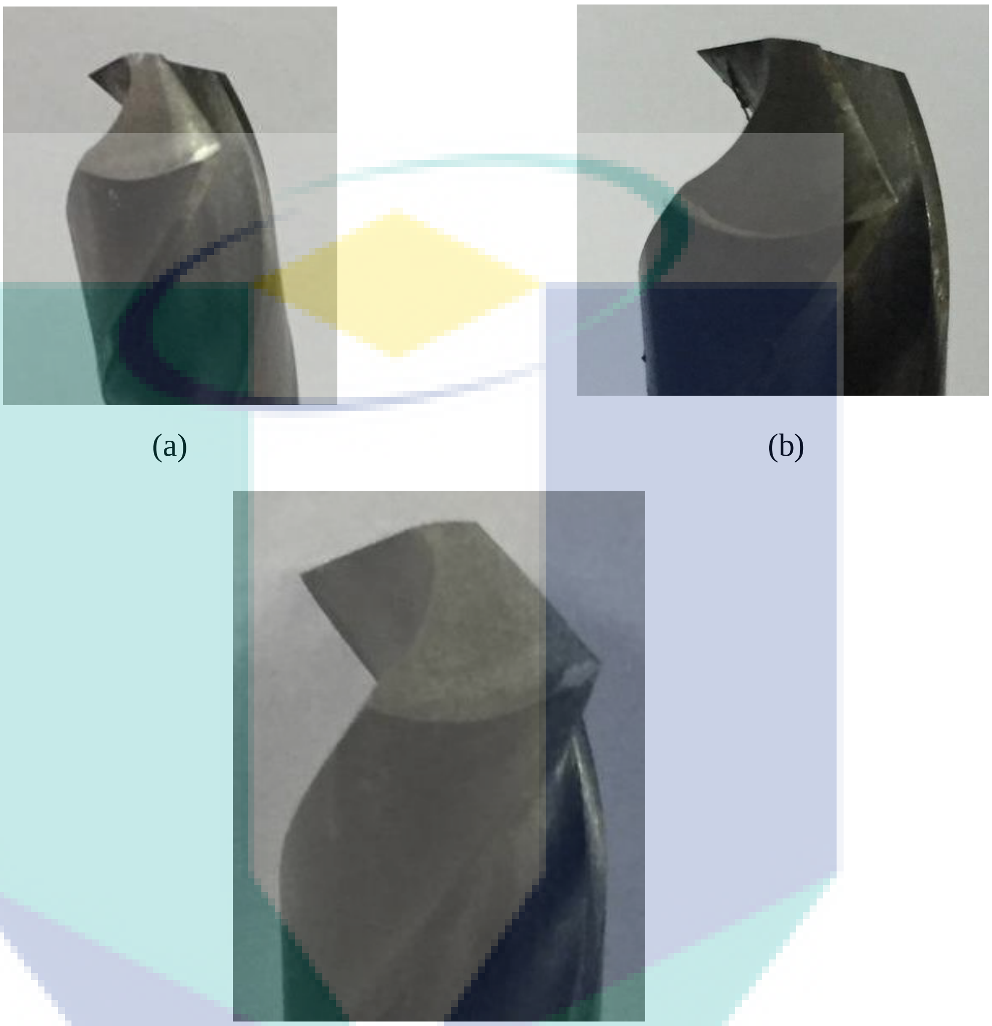
Table 4-9 Average hole diameter measurement for Aluminium 6061 workpiece when drilling through the hole by using High-Speed Steel Drill tool diameter 13.00 with cutting speed of 30.00 m/min, federate 0.10 mm/rev with the depth of cut of 1.00 mm.

Pass	**Reading**			
	1st	**2nd**	**3rd**	**Average**
1st	13.000	13.000	13.000	13.000
5th	13.001	13.000	13.000	13.000
10th	13.001	13.001	13.000	13.001
20th	13.002	13.002	13.001	13.002
30th	13.003	13.002	13.004	13.003
40th	13.004	13.005	13.006	13.005
50th	13.005	13.003	13.007	13.005
100th	13.010	13.011	13.009	13.010
150th	13.015	13.016	13.018	13.016
200th	13.020	13.022	13.021	13.021
250th	13.025	13.025	13.024	13.025
300th	13.031	13.029	13.034	13.031
350th	13.036	13.037	13.035	13.036
400th	13.041	13.037	13.042	13.040
450th	13.042	13.045	13.047	13.045
485th	13.050	13.050	13.049	13.050

Table 4-10 Average hole diameter measurement for Aluminium 6061 workpiece when drilling through the hole by using High-Speed Steel Drill tool diameter 14.50 mm with cutting speed of 30.00 m/min, federate 0.10 mm/rev with the depth of cut of 1.00 mm.

Pass	Reading 1st	2nd	3rd	Average
1st	14.500	14.500	14.500	14.500
5th	14.500	14.501	14.500	14.500
10th	14.502	14.500	14.502	14.501
20th	14.503	14.501	14.502	14.502
30th	14.503	14.504	14.501	14.503
40th	14.505	14.503	14.504	14.504
50th	14.505	14.508	14.504	14.506
100th	14.510	14.507	14.509	14.509
150th	14.514	14.516	14.518	14.516
200th	14.520	14.528	14.531	14.520
250th	14.525	14.523	14.526	14.525
300th	14.530	14.528	14.531	14.530
350th	14.535	14.536	14.533	14.535
400th	14.540	14.541	14.538	14.540
450th	14.545	14.546	14.545	14.545
499th	14.550	14.549	14.550	14.550

Based on typical drilling condition using center drill cutting tool, the drilling process is stopped when the machining started to produced abnormal sound because of the safety precautions and also to avoid the CNC RoboDrill machine from breakdown. Then, the holes are measured using vernier calliper and showed that for all three different tool diameters, the reading is closer or exceed the maximum tolerance. Figure 4.10 shows the results of the drilling tool after the machining process stopped.



(a) (b) (c)

Figure 4.10 The drill cutting tool conditions after the machining process where (a) is for 10.00 mm, (b) 13.00 mm and (c) 14.50 mm in diameter.

The tool tends to build up the edge or tool worn in the second cutting tool cycle during the central drill machining process as shown in Figure 4.10(a) which is accorded to the one reported by Ghasemi et al., (2018). This is mainly due to the central drill cutting which is used to guide the drilling process and is limited to a particular drill depth. As the drilling tool with a diameter of 10.00 mm which aligned with center drill hole started, the drilling process continued until the depth is more than 3.00 mm. The tip of the drilling tool plays its role to build-up the edge or the side worn around the tooltip. Similar situations also observed for Brass material.

For drill tool with diameters of 13.00 and 14.50 mm, the tip of the drilling tool is free from the machining during the boring process. Thus, the absence of tool worn around the tip of the drilling tool is observed. The cutting process only occurred at the diameter of 10.00 mm and above for drill tool with diameters of 13.00 and 14.50 mm. At the starting drilling area, the drilling tool is worn and scratches appeared around the areas as shown in Figure 4.10 (b) and (c). The tip of the drill tool diameter of 10.00 mm became chipped off as shown in Figure 4.11, similar to the one reported by Ghasemi et al., (2018). At the same time, it is observed that the drilling tool is not correctly aligned after the hole surface was touched just before the machining took place. These might be the main reason for the formation of a larger hole diameter size.

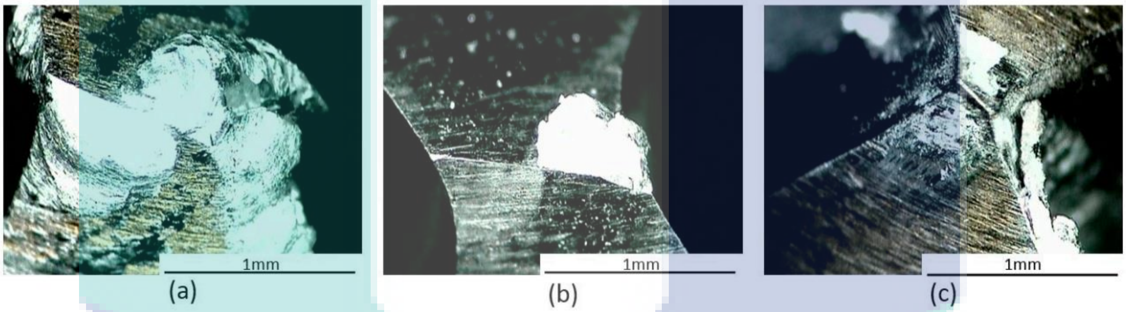


Figure 4.11 Drill tool worn findings by Ghasemi et al., (2018).

Prior to the calculation of the tool cost, the machining time or machine-tool contact time needs to be determined. The machining time is calculated using the machining time formula as shown in Equations 4-1 and 4-2, adopted from Kalpakjian and Schmid (2015).

$$\text{Machining Time (Minutes)} = \frac{\text{Length To Be Machined (mm)}}{\text{Feedrate}\left(\frac{\text{mm}}{\text{rev}}\right) \times \text{Spindle Speed (rpm)}} \qquad 4\text{-}1$$

where:

$$\text{Spindle Speed(rpm)} = \frac{\text{Cutting Speed}\left(\text{V}_\text{c}\right) \times 1000}{\pi \times \text{Material Diameter}\left(\text{D}_\text{c}\right)} \qquad 4\text{-}2$$

For these equations, the total contact time during machining process for each insert or other cutting tools is equal to the total machining time. For TNMG 160408 insert, there are two machining process involved. The first process is the hose and thread parts roughing process which the depth cut is 0.50 mm and labeled as TNMG 1. Secondly, the second thread machining process for finishing process used the depth cut is 0.25 mm and labeled as TNMG2. The spindle speed calculation includes the diameter of the materials used and that the value is based on the raw material diameter at the clamping side. For TNMG 1 insert where it cuts the roughing hose part, the raw material diameter is referred to as 27.5 mm and as the threaded part is removed, the material diameter at the clamping side remain 27.5 mm. Here, the calculation for machining time is based on the energy consumption criteria, the tool cost for TNMG1 and TNMG2 as follows:

$$\text{Tool Cost}_{\text{TNMG1}} = \frac{\text{Machining Time (Minutes)}}{\text{Tool Life (Minutes)}} \times \text{Tool Cost}\left(\frac{\text{RM}}{\text{point}}\right)$$

$$= \frac{4.1145 + 1.5430 \text{ minutes}}{75.5 \text{ minutes}} \times \text{RM } 13.43 = \text{RM } 1.0064$$

$$\text{Tool Cost}_{\text{TNMG2}} = \frac{\text{Machining Time (Minutes)}}{\text{Tool Life (Minutes)}} \times \text{Tool Cost}\left(\frac{\text{RM}}{\text{point}}\right)$$

$$= \frac{0.6172 \text{ minutes}}{75.5 \text{ minutes}} \times \text{RM } 13.43 = \text{RM } 0.0732$$

The VCMT 160404 insert used for finishing cut has the depth of cut of 0.25 mm around the hose part. The area created a stepping shape and labeled as VCMT, as shown in Figure 3.3. The material diameter at the clamping side is 27.5mm and the tool cost is:

$$\text{Tool Cost}_{\text{VCMT}} = \frac{\text{Machining Time (Minutes)}}{\text{Tool Life (Minutes)}} \times \text{Tool Cost}\left(\frac{\text{RM}}{\text{point}}\right)$$

$$= \frac{3.0859 \text{ minutes}}{66.20 \text{ minutes}} \times \text{RM } 33.39 = \text{RM } 1.5565$$

On the other hand, the threaded cutting insert tool cost is calculated as follows based on the 27.5 mm material diameter at the clamping side.

$$\text{Tool Cost}_{\text{Thread}} = \frac{\text{Machining Time (Minutes)}}{\text{Tool Life (Minutes)}} \times \text{Tool Cost}\left(\frac{\text{RM}}{\text{point}}\right)$$

$$= \frac{9.4317 \text{ minutes}}{69.4 \text{ minutes}} \times \text{RM } 22.26 = \text{RM } 3.0379$$

Equation 3-5 determined the center drill tool cost calculation for Aluminium 6061 workpiece with a depth of 3.00 mm. The center drill tool cost is:

$$\text{Tool Cost}_{\text{Center}_{\text{Drill}}} = \frac{1}{\text{Total Number of Holes}} \times \text{Tool Cost}\left(\frac{\text{RM}}{\text{point}}\right)$$

$$= \frac{1}{476} \times \text{RM } 6.89 = \text{RM } 0.01447$$

For the cost of drilling cutting tool with a diameter of 10.00 mm for Aluminium 6061 workpiece, one hole is calculated as:

$$\text{Tool Cost}_{\text{Drilld10}} = \frac{1}{\text{Total Number of Holes}} \times \text{Tool Cost}\left(\frac{\text{RM}}{\text{point}}\right)$$

$$= \frac{1}{250} \times \text{RM } 56.18 = \text{RM } 0.22472$$

For the cost of the drill cutting tool with a diameter of 13.00 mm for Aluminium 6061 workpiece, one hole is calculated as:

$$\text{Tool Cost}_{\text{Drilld13}} = \frac{1}{\text{Total Number of Holes}} \times \text{Tool Cost}\left(\frac{\text{RM}}{\text{point}}\right)$$

$$= \frac{1}{485} \times \text{RM } 74.46 = \text{RM } 0.1515$$

Lastly, the cost of drill cutting tool with a diameter of 14.50 mm for Aluminium 6061 workpiece, one hole with a depth cut of 21.00 mm is calculated as:

$$\text{Tool Cost}_{\text{Drilld14.5}} = \frac{1}{\text{Total Number of Holes}} \times \text{Tool Cost}\left(\frac{\text{RM}}{\text{Point}}\right)$$

$$= \frac{1}{499} \times \text{RM}72.72 = \text{RM}0.1457$$

Hence, the total tool cost to produce one Aluminium 6061 pneumatic nipple connector is as follows:

$\sum$ Tool $Cost_{Aluminium}$ = Tool $Cost_{TNMG1}$ + Tool $Cost_{TNMG2}$ + Tool $Cost_{VCMT}$ +
Tool $Cost_{Thread}$ + Tool $Cost_{Center\_Drill}$ + Tool $Cost_{Drilld10}$ +
Tool $Cost_{Drilld13}$ + Tool $Cost_{Drilld14.5}$ = 1.0064 + 0.0732 + 1.5565 +
1.379   0.014474 + 0.224720 + 0.151500 + 0.145700=RM 6.2103

Thus, the Total Manufacturing Cost for Aluminium 6061 material using option 1 cutting parameter is calculated as follows:

$\sum$Manufacturing $Cost_{AluminiumOption1}$ = Raw Material Cost + Coolant Cost + Lubricant Cost + Tool Cost + Labor Cost + Energy Cost =
3.6829 + 0.246435 + 0.074334 + 6.2103 + 0.9469 + 4.1837 = RM 15.3446

4.5 Theoretical Calculation Results - Environmental Impact Criteria

4.5.1 Chip Re-cycling Impact

The second criteria evaluated in the present study is environmental impact criteria. As stated in Chapter Three, this study only considers chip re-cycling impact and energy impact because the number of product produced using the same cutting tool is higher compared to the weight of a cutting tool. Hence it can be neglected (Dahmus & Gutowski, 2004). The same situation occurs for coolant and lubricant usages, where they only changed when periodic maintenance takes place for 3 to 6 months. Due to this, both evaluations are neglected. The assessment of chip recycling impact is adopted from Narita (2012) using Equation 2-12 and the chip re-cycling constant used for Aluminium 6061 and Brass C3604 are 8.19 $kgCO_2$, 2.42 $kgCO_2$ respectively (Hammond & Jones, 2008). For theoretical calculations, the data of raw material weight is obtained from the raw material cost (subtopic 4.4.1) in which for Aluminum 6061 raw is 59.2515 gram. The weight of the finished product is obtained from the SolidWorks software with the weight is 24.35 gram. Hence, the chip recycling impact for Aluminium 6061 and Brass C3604 is:

$$\text{Chip Recycling Impact, } Ch_{e_{Aluminium}} = \frac{\text{Raw Material Weight} - \text{Finished Product Weight}}{1000} \times \text{Aluminium Chip Recycling Constant}$$

$$= \left(\frac{59.2515 - 24.35}{1000}\right) \times 8.19\,kgCO_2 = 0.2858\,kgCO_2$$

$$\text{Chip Recycling Impact, } Ch_{e_{Brass}} = \frac{\text{Raw Material Weight} - \text{Finished Product Weight}}{1000} \times \text{Brass Chip Recycling Constant}$$

$$= \left(\frac{260.8031 - 83.46}{1000}\right) \times 2.42\,kgCO_2 = 0.4292\,kgCO_2$$

4.5.2 Energy Impact

The amount of carbon released into the air is calculated using the amount of energy used multiply with the electricity environmental burden constant that is 0.747 $kgCO_2$ (Lojuntin, 2015). Hence, the amount of carbon released into the air during the machining process is calculated as:

$$\text{Amount of Carbon Released} = \frac{\text{Energy Used During Machining}}{1000} \times \text{Electricity Environment Burden Constant}$$

$$= \left(\frac{11009.621}{1000}\right) \times 0.7470\,kgCO_2 = 8.2242\,kgCO_2$$

The calculation for total environmental impact for pneumatic nipple hose connector A1uminium 6061 machined using Option 1 cutting parameters is:

$$\sum \text{Environmental Impact} = \text{Chip recycling Impact} + \text{Energy Impact}$$

$$= 0.2858\,kgCO_2 + 8.2242\,kgCO_2 = 8.5100\,kgCO_2$$

4.6 Theoretical Calculation Results – Energy Consumed Criteria

In Okuma LB 15 turning machine, five types of electrical motor contribute to the power consumed during the machining process (Okuma Machinery Works Ltd, 1987). They are main spindle drive motor with a rating of 15 kW for 30 minutes running, z-axis drive motor with a rating of 2.4 kW for 60 minutes running, x-axis drive motor with rating of 1.5 kW for 60 minutes running, hydraulic pump motor with rating of 1.5 kW for 60 minutes running and coolant pump motor with a rating of 0.25 kW for 60 minutes running.

Although the power rating for each motor has stated in the technical specification, not all the machine used during the machine setup, there is a flow of energy in the machine although all of the motors are idle. Hence, the best way to measure the energy consumed during the machine setup is by using Fluke 437-II power harmonic analyzer and the average energy consumed obtained 900 watts for 30 minutes. The details machine setup energy consumed is shown in Table 4-11.

Table 4-11 Energy consumed during machine set up process.

	Reading			
	1	**2**	**3**	**Average**
Energy Used (watt)	888	907	905	900

Here the assumption used for average output per shifts for both materials is 120, which to the one shift consists of 10 working hours plus 1.5 hours for a break and 0.5 hours for machine setup. Hence, the setting up machine energy is calculated as follows:

$$\text{Setting Up Machine Energy} = \frac{900}{10 \times 120} = 0.75 \text{ watt}$$

Next, the time needed for the cutting tool to complete one movement from the starting point to the workpiece surface and back to the starting point again is taken using a stopwatch. The average results for both total time movement are 2.00 seconds. The energy used during this time needs to be added because the energy only occurs when there is work (friction) between the cutting tool and the workpiece as noted in the metal cutting theory by Kalpakjian & Schmid (Kalpakjian & Schmid, 2014).

Although there is no cutting process take place, the tool movement from the starting point to the workpiece surface and back to the starting point requires energy. Therefore, the energy used during these movements is included based on the rating power supply for the main spindle drive motor, *z*-axis drive motor, *x*-axis drive motor, hydraulic pump motor and coolant pump motor. The electrical rating for all five electrical motors for 1 second is 8.33 watt for the main spindle drive motor, 0.67 watts for the z-axis drive motor, 0.42 watt for the x-axis drive motor, 0.42 watt for hydraulic pump motor and 0.0694 watts for the coolant pump motor.

As the workpiece is clamped at the chuck, a stopwatch is used to records the time taken to clamp the workpiece and the recorded average time is 5.00 seconds. The calculation for clamping workpiece energy usage is:

$$\text{Clamping Workpiece Energy Usage} = 5 \times 8.33 = 41.65 \text{ watt}$$

Next, the turning process is performed. The Aluminum 6061 workpiece has 27.5 mm in diameter based on the Option 1 parameter. The Option 1 parameter involves in this calculation are the spindle speed which is 42 m/min, the feed rate is 0.10 mm/ rev, specific cutting force (K_c) is 650 N/mm^2 for Aluminum 6061 and 550 N/mm^2 for Brass C3604 (Sandvik Coromant, 2017). The depth cut used is 0.5 mm for roughing and 0.25 mm for finishing processes. Since the workpiece material is Aluminium 6061 and the cutting parameters used is Option 1, the sample is labeled as A1. The spindle speed, energy consumed and the machining time for this process is:

$$\text{Spindle Speed, } n = \frac{\text{Cutting Speed, } V_c \times 1000}{\pi \times D_m} = \frac{42 \times 1000}{3.142 \times 27.5} = 486.08 \text{rpm}$$

$$T_{roughhoseturning} = \frac{1}{f_n \times n} \times 8 = \frac{25}{0.10 \times 486.08} \times 8 = 4.114 \text{ minutes}$$

$$P_{roughhoseturning} = \frac{V_c \times a_p \times f_n \times K_c}{60000} \times 8 \times 1000 = \frac{42 \times 0.5 \times 0.10 \times 650}{60000} \times 8 \times 1000 = 182 \text{ watt}$$

Moreover, the energy consumed during the tool movement with no cutting process involved is

$$\text{Energy consumes during tool movement (no cutting process)}$$
$$= (8.33 + 0.67 + 0.42 + 0.42 + 0.0694) \times (8 \times 2.00) = 9.9094 \times 16.00 = 158.5504 \text{ watt}$$

Next, to produce the stepping shape, the diameter is reduced from 19.5 mm to 16.5 mm with the raw material diameter at the clamping side is 27.5 mm. The turning process is done for six passes using 42 m/min cutting speed, 0.25 mm the depth cut and 0.10 mm/rev federate. The energy consumed during the machining, spindle speed and the machining time of hose area is as follow

$$\text{Spindle Speed, } n = \frac{\text{Cutting Speed, } V_c \times 1000}{\pi \times D_m} = \frac{42 \times 1000}{3.142 \times 27.5} = 486.08\text{rpm}$$

$$T_{\text{finehoseturning}} = \frac{1}{f_n \times n} \times 6 = \frac{25}{0.10 \times 486.08} \times 6 = 3.0859 \text{ minutes}$$

$$P_{\text{finehoseturning}} = \frac{V_c \times a_p \times f_n \times K_c}{60000} \times 6 \times 1000 = \frac{42 \times 0.25 \times 0.10 \times 650}{60000} \times 6 \times 1000 = 68.25 \text{ watt}$$

The energy consumed during the tool movement with no cutting process involved is:

$$\text{Energy consumes during tool movement (no cutting process)}$$
$$= (8.33 + 0.67 + 0.42 + 0.42 + 0.0694) \times (6 \times 2.00) = 9.9094 \times 12.00 = 118.9128 \text{ watt}$$

Once the workpiece clamp is released, it is rotated to 180° and clamp again with the raw material diameter at the clamping side is 16.5 mm. The releasing, rotating and clamping activities time are taken using the stopwatch and the recorded average time is 5.00 seconds. Thus, the energies used to released and clamped are 41.65 watts for each. Next, for the threaded part, the workpiece diameter is reduced from 27.5 mm to 22.5 mm. The energy used during the rough cutting process and the cutting time is as follow:

$$\text{Spindle Speed, } n = \frac{\text{Cutting Speed, } V_c \times 1000}{\pi \times D_m} = \frac{42 \times 1000}{3.142 \times 27.5} = 486.08\text{rpm}$$

$$T_{\text{roughthreadturning}} = \frac{1}{f_n \times n} \times 5 = \frac{15}{0.10 \times 486.08} \times 5 = 1.5430 \text{ minutes}$$

$$P_{\text{roughthreadeturning}} = \frac{V_c \times a_p \times f_n \times K_c}{60000} \times 5 \times 1000 = \frac{42 \times 0.5 \times 0.10 \times 650}{60000} \times 5 \times 1000 = 113.75 \text{ watt}$$

The energy consumed during the tool movement with no cutting process involved is

Energy consumes during tool movement (no cutting process)

$$= (8.33 + 0.67 + 0.42 + 0.42 + 0.0694) \times (5 \times 2.00) = 9.9094 \times 10.00 = 99.094 \text{ watt}$$

Next, the workpiece diameter is reduced from 22.50 mm to 21.50 mm for the fine cutting process and the energy used during the machining process, spindle speed and the cutting time is as follow:

$$\text{Spindle Speed, } n = \frac{\text{Cutting Speed, } V_c \times 1000}{\pi \times D_m} = \frac{42 \times 1000}{3.142 \times 27.5} = 486.08\text{rpm}$$

$$T_{\text{finethreadturning}} = \frac{1}{f_n \times n} \times 2 = \frac{15}{0.10 \times 486.08} \times 2 = 0.6172 \text{ minutes}$$

$$P_{\text{finethreadeturning}} = \frac{V_c \times a_p \times f_n \times K_c}{60000} \times 2 \times 1000 = \frac{42 \times 0.25 \times 0.10 \times 650}{60000} \times 2 \times 1000 = 22.75 \text{ watt}$$

The energy consumed during the tool movement with no cutting process involved is as follow:

Energy consumes during tool movement (no cutting process)

$$= (8.33 + 0.67 + 0.42 + 0.42 + 0.0694) \times (2 \times 2.00) = 9.9094 \times 4.00 = 39.6376 \text{ watt}$$

For the thread cutting, the cutting tool used is 16ERG60 with the cutting speed setting is 26 m/min, the feed rate is 0.1 mm/rev and depth of cut is 0.0612 mm for 19 passes to obtain 1.162 thread depth. The spindle speed, machining time and energy consumed during the thread cutting process are as follow:

$$\text{Spindle Speed, } n = \frac{\text{Cutting Speed, } V_c \times 1000}{\pi \times D_m} = \frac{26 \times 1000}{3.142 \times 27.5} = 300.91\text{rpm}$$

$$T_{\text{threadturning}} = \frac{1}{f_n \times n} \times 19 = \frac{15}{0.10 \times 300.91} \times 19 = 9.4712 \text{ minutes}$$

$$P_{\text{threadeturning}} = \frac{V_c \times a_p \times f_n \times K_c}{60000} \times 19 \times 1000 = \frac{26 \times 0.0612 \times 0.10 \times 650}{60000} \times 19 \times 1000 = 32.7255 \text{ watt}$$

The energy consumed during the tool movement with no cutting process involved is:

Energy consumes during tool movement (no cutting process)

$$= (8.33 + 0.67 + 0.42 + 0.42 + 0.0694) \times (19 \times 2.00) = 9.9094 \times 38.00 = 376.5572 \text{ watt}$$

Next, the center drill machining takes place to mark the center point using center drill cutting tool with a diameter of 3.00 mm. The cutting speed used is 9.426 m/min or equivalent to spindle speed of 1000 rpm, the feed rate is 0.1 mm/rev and the drilling depth is 1.00 mm at each pass. The spindle speed, drilling time and energy consumed during the center drill process are:

$$\text{Spindle Speed, } n = \frac{\text{Cutting Speed, } V_c \times 1000}{\pi \times D_m} = \frac{9.426 \times 1000}{3.142 \times 3.00} = 1000 \text{ rpm}$$

$$T_{centerdrill} = \frac{1}{f_n \times n} \times 3 = \frac{3.00}{0.10 \times 1000} \times 3 = 0.09 \text{ minutes}$$

$$P_{centerdrill} = \frac{V_c \times a_p \times f_n \times K_c}{240000} \times 3 \times 1000 = \frac{9.426 \times 3.00 \times 0.10 \times 650}{240000} \times 3 \times 1000 = 22.9759 \text{ watt}$$

Generally, a good drilling practice involved no interruption of up and down movement, which referring to peck drill. The peck drill is required to prevent the cutting tool from damage caused by the cutting tool burning out due to high friction between the cutting tool and the workpiece. Also, important to ensure the chips produced during the drilling process is short. The total interruption movement time for one cycle without involving the cutting process is 0.50 second in average is taken using a stopwatch. The energy consumed during the center drilling process movement without involved cutting process is:

$$\text{Energy consumes during tool movement (no cutting process)}$$
$$= (8.33 + 0.67 + 0.42 + 0.42 + 0.0694) \times (0.50 \times 3) = 9.9094 \times 1.50 = 14.8641 \text{ watt}$$

Next, the hole drilling used 10.00 mm diameter drill tool bit with a cutting speed of 30.00 m/min with the feed rate of 0.10 mm/rev and the depth of 1.00 mm until the maximum drilling depth of 60.00 mm. The spindle speed, drilling time and energy consumed during the drilling process for 10.00 mm diameter are:

$$\text{Spindle Speed, } n = \frac{\text{Cutting Speed, } V_c \times 1000}{\pi \times D_m} = \frac{30 \times 1000}{3.142 \times 10.00} = 954.81 \text{ rpm}$$

$$T_{drilld10} = \frac{1}{f_n \times n} \times 60 = \frac{1.00}{0.10 \times 954.81} \times 60 = 0.6284 \text{ minutes}$$

$$P_{drilld10} = \frac{V_c \times a_p \times f_n \times K_c}{240000} \times 60 \times 1000 = \frac{30 \times 10.00 \times 0.10 \times 650}{240000} \times 60 \times 1000 = 4875 \text{ watt}$$

The energy consumed during tool movement with no cutting process involved is

$$\text{Energy consumed during tool movement (no cutting process)}$$
$$= (8.33 + 0.67 + 0.42 + 0.42 + 0.0694) \times (60 \times 0.50) = 9.9094 \times 30 = 297.282 \text{ watt}$$

Next, for 13.00 mm diameter hole, the drilling process Used the cutting speed at 30 m/min, the drilling depth of 1.00 mm, the feed rate of 0.1 mm/rev and the maximum drilling depth of 60.00 mm. Although the second hole is drilled using a similar 13.00 mm diameter drill bit, theoretically it is not considered as part of the drilling process. It is known as a boring process. Hence, the energy consumed considered at this stage and onwards is calculated using the boring process equation, as shown in Equation 3-9. The energy consumed and drilling time is:

$$P_{boring13} = \frac{V_c \times a_p \times f_n \times K_c}{60000} \times 1 - \frac{a_p}{D_c} \times 60 \times 1000$$

$$= \frac{30 \times 1.50 \times 0.10 \times 650}{60000} \times 1 - \frac{1.5}{13.00} \times 60 \times 1000 = 2587.5 \text{ watt}$$

The energy consumed during tool movement with no cutting process involved is

$$\text{Energy consumed during tool movement (no cutting process)}$$
$$= (8.33 + 0.67 + 0.42 + 0.42 + 0.0694) \times (60 \times 0.50) = 9.9094 \times 30 = 297.282 \text{ watt}$$

Lastly, for 14.50 mm diameter hole with a depth of 21.00 mm, the drilling process used the cutting speed of 30 m/min, the drilling depth for each movement of 1.00 mm and the feed rate of 0.1 mm/rev. The energy consumed during the drilling process and the machining time are

$$P_{boring14.5} = \frac{V_c \times a_p \times f_n \times K_c}{60000} \times 1 - \frac{a_p}{D_c} \times 21 \times 1000$$

$$= \frac{30 \times 0.75 \times 0.10 \times 650}{60000} \times 1 - \frac{0.75}{14.50} \times 21 \times 1000 = 485.40 \text{ watt}$$

The energy consumed during tool movement with no cutting process involved is

Energy consumes during tool movement (no cutting process)

$$= (8.33 + 0.67 + 0.42 + 0.42 + 0.0694) \times (21 \times 0.50)$$

$$= 9.9094 \times 11.50 = 104.0487 \text{ watt}$$

After pneumatic nipple hose machining process completed, the clamping button is pushed to release the workpiece and the time taken to do the work is taken using a stopwatch with the average time is 3.00 seconds. Hence, the released clamping workpiece energy usage is:

$$\text{Released clamping workpiece energy usage} = (3 \times 8.33) = 24.99 \text{ watt}$$

Hence, the total amount of energy used in the machining process to produce aluminium 6061 nipple hose connector by using Option 1 cutting parameter is

Total amount of energy used

$$= 0.75 + 41.65 + 182 + 158.5504 + 68.25 + 118.9128 + 41.65 + 113.75 + 99.094 + 22.75 + 39.6376 + 35.86 + 376.5572 + 22.98 + 14.8641 + 4875 + 297.282 + 2587.5 + 297.282 + 485.40 + 104.0487 + 24.99 = 10008.75 \text{ watt}$$

According to Sandvik Coromant (2017), the 10008.75 Watt energy is a raw data where the machine efficiency assumption is 100%. The machine efficiency needs to be considered in the calculation because as there is a delay in time due to unexpected downtime. Hence, the machine efficiency used in the present study is 90% as the CNC Turning machine is a computerized machine and the total energy consumed after including the machine efficiency is 11009.62 watt for Aluminium 6061 material by using option1 cutting parameter.

4.7 Theoretical Calculation Results – The NIOSH Revised Weight Lifting Index

Lastly, the fourth criterion is social equity. In this section, the NIOSH Revised Weight Lifting Index equation is used with some modification as proposed by Muslim et al., (2013), which is based on the South East Asia male worker capacity. The assumption used is that one pallet weighted of 1.00 kg consists of 24 pieces of raw material need to be lifted from the floor and walked about 5.00 meters and placed it on a rack. Based on the 59.2515 gram theoretical raw material weight, the total amount of weight to be lifted in one pallet is shown as follows:

Total Weight = (59.2515 gram × 24) + 1000 gram = 2422.04 gram = 2.4220 kg

where:

RWL = LC × HM × VM × DM × AM × FM × CM

Here, there are a few assumptions been made to measure the NIOSH weight lifting index. The load weight is a summation of pallet weight and 24 pieces of raw materials which equal to 2.4220 kg. The LC is load constant, which is equal to 23.00 kg. For Horizontal Multiplier (HM), the horizontal distance used in the present study is 30 cm. Hence the HM value is calculated as 25/30 = 0.833. For Vertical Multiplier (VM) measurement, the measured method follows Muslim et al., (2013) as the measurement is based on the South East Asian Male worker capacity while the original measurement equation used European anthropometric data. Noted that the VM equation used is VM = 1-0.0310083 (|68-V|) and the vertical distance (V) of the worker used in this study is 68 centimeters. Hence, the VM value is 1-0.0310083 (|68-68|) = 1.00.

The Distance Multiplier equation is equal to (0.82 + (4/5D)). The pallet needs to be lifted about 40 to50 cm in the distance. Hence, the distance multiplier obtained is 0.93. The Asymmetric Multiplier used in the present study is 60 to70° or equal to 0.81 and the Frequency Multiplier used is 0.65 with the working duration is between 2 to 8 hour, the vertical distance is more than 30 inch and the F is set to 2 since the lifting is less frequently than once in 5 minutes. The coupling multiplier is considered good for a box pallet design which has an optimal handle design of 5.00 cm clearance with a smooth and non-slip surface. Hence, the coupling multiplier value is 1.00. Hence, the recommended weight lifting is

$$RWL = LC \times HM \times VM \times DM \times AM \times FM \times CM$$
$$= 23 \times 0.833 \times 1.00 \times 0.93 \times 0.81 \times 0.65 \times 1.00 = 9.3811$$

The NIOSH revised weight lifting index is

$$\text{Weight Lifting Index} = \frac{\text{Load Weight (kg)}}{\text{Recommended Weight Limit}}$$

$$\text{Weight Lifting Index}_{\text{Aluminium}} = \frac{2.4220}{9.3811} = 0.2582$$

The overall summary of the theoretical calculation data for manufacturing cost, environmental impact, amount of energy used and ergonomics assessment are shown in Table 4-12. Please note that A1 stands for Aluminium option cutting parameter 1 and B1 stands for Brass option cutting parameter 1.

Table 4-12 Overall summaries of the theoretical data for manufacturing cost, amount of energy used, environmental impact and ergonomics assessment.

Sample	Manufacturing Cost (RM)	Energy (kWh)	Environmental ($kgCO^2$)	Ergonomics (Index)
A1	15.3446	11.0062	8.5100	0.2582
A2	15.4322	11.4316	8.8253	0.2582
A3	14.2392	11.4215	8.8177	0.2582
A4	14.5510	12.2622	9.4457	0.2582
B1	27.8839	9.7900	7.7423	0.7738
B2	27.9046	10.2664	8.0982	0.7738
B3	26.3701	10.2551	8.0897	0.7738
B4	26.6279	11.1966	8.7930	0.7738

Based on the theoretical calculation results in Table 4-12, it shows that for either Aluminium 6061 or Brass C3604 alone, when the cutting speed increased while the feedrate is fixed, the manufacturing cost decreased, such as shown in sample A1 and A3; B1 and B3 (Kalpakjian & Schmid, 2014). The amount of energy used is increased when the cutting speed is increased while the feed rate is fixed (Camposeco-Negrete, 2015). The same pattern recorded for the environmental impact assessment while for ergonomics, there are no changes since the raw material weight is assumed fixed in these calculations. At the same time, the finished product weight is assumed the same for each material types because they are determined theoretically by using Solidworks software.

When comparing both Aluminium 6061 and Brass C3604 material pneumatic connector, the manufacturing cost of the brass C3604 pneumatic connector is higher than Aluminium 6061 pneumatic connector because of the brass price is more expensive than Aluminium. On the other hand, the energy used during machining process is higher when machining Aluminium 6061 material compared to brass C3604 because of the specific cutting force (K_c) value for Aluminium 6061 is 650 N/mm^2 while Brass C3604 is 550 N/mm^2 (Sandvik Coromant, 2017). The values of ergonomics index (The Revised NIOSH Weight Lifting Index) of Brass is higher compared to Aluminium 6061 because the Brass C3604 density is higher than Aluminum 6061.

4.8 Experimental Results

The summary of the experimental data collected is shown in Table 4-13.

Table 4-13 Summary of the experimental data conducted in this study; where A = Aluminium 6061, B = Brass C3604, the number represents the cutting parameters option and the number in a bracket represents the number of the experiment.

Sample	Manufacturing Cost (RM)	Energy (kWh)	Environmental ($kgCO^2$)	Ergonomics (Index)
A1(1)	15.4786	11.1519	8.6143	0.2588
A1(2)	15.4244	11.1713	8.6290	0.2589
A1(3)	15.6227	11.1854	8.6438	0.2598
A2(1)	15.5393	11.5809	8.9394	0.2585
A2(2)	15.6527	11.5837	8.9376	0.2583
A2(3)	15.7002	11.5924	8.9518	0.2596
A3(1)	14.3821	11.5809	8.9350	0.2589
A3(2)	14.4793	11.5892	8.9485	0.2584
A3(3)	14.5186	11.5975	8.9488	0.2597
A4(1)	14.7256	12.4317	9.5751	0.2600
A4(2)	14.7577	12.4294	9.5781	0.2595
A4(3)	14.8344	12.4399	9.5834	0.2599
B1(1)	28.0557	9.9365	7.8500	0.7741
B1(2)	28.0609	9.9443	7.8561	0.7739
B1(3)	28.0726	9.9664	7.8740	0.7741
B2(1)	28.1005	10.4513	8.2342	0.7742
B2(2)	28.1009	10.4406	8.2273	0.7743
B2(3)	28.1011	10.4538	8.2361	0.7741
B3(1)	26.5517	10.4306	8.2204	0.7739
B3(2)	26.5607	10.4240	8.2157	0.7742
B3(3)	26.5583	10.4331	8.2224	0.7740
B4(1)	26.7094	11.3805	8.9294	0.7741
B4(2)	26.8254	11.3758	8.9262	0.7744
B4(3)	26.8359	11.3861	8.9331	0.7741

When comparing the results based on the cutting parameter sets, the higher the cutting speed, the manufacturing cost will be lower, but the energy used during machining and the environmental impact assessment is higher for both Aluminium 6061 and Brass C3604 materials compared to theoretical results. This phenomenon has already explained by Kalpakjian and Schmid in their book which stated that as the cutting speed and feed rate increased, the energy used to machine the pneumatic connector will be higher and it will reflect the environmental impact contribute by the energy (Kalpakjian & Schmid, 2014). Besides that, when machined the raw material in reality, sometimes the chip getting stuck to the cutting tool and machining process need to be stopped for a while to pull away from the chips. Stopping the machine for a while will contribute to the increasing amount of energy used since more machining time needed and there is energy being used at the idle machining state when troubleshooting the problem. If we neglected the amount of energy consumed during the machine idle for troubleshooting, the amount of energy used is still higher compared to theoretical calculation method because the amount of energy used by the controller and others takes into account when performing the machining process, but not in the theoretical method. When the cutting speed increased, the total manufacturing cost will be lower because the time needed to complete the machining process is getting shorter and it directly reflects the reduction of the tool cost which contributes directly to the total manufacturing cost.

The ergonomic assessment using the revised NIOSH weight lifting index results shows scatter patterns for both Aluminium 6061 and brass C3604 materials. The range values for Aluminium 6061 is between 0.2583 to 0.2600 and for Brass C3604 material the range is between 0.7739 to 0.7744. The ergonomics assessment pattern scatters because of the weight of the raw material used in the study. Theoretically, the raw material length is assumed fixed at 5.50 cm and the weight is 59.2515 gram for Aluminium 6061 and 260.8031 gram for Brass C3604 materials. However, when experimenting, the raw material weight is determined by using the digital weight scale and the results are varied compared to theoretically calculated because the raw material length produces by using electrical sawing machine is not exactly 5.50 cm which may be caused by vibration activities during the machining process such as shown in Figure 4.12. The summary of raw material weight recorded in the experimental method is shown in Table 4-14.

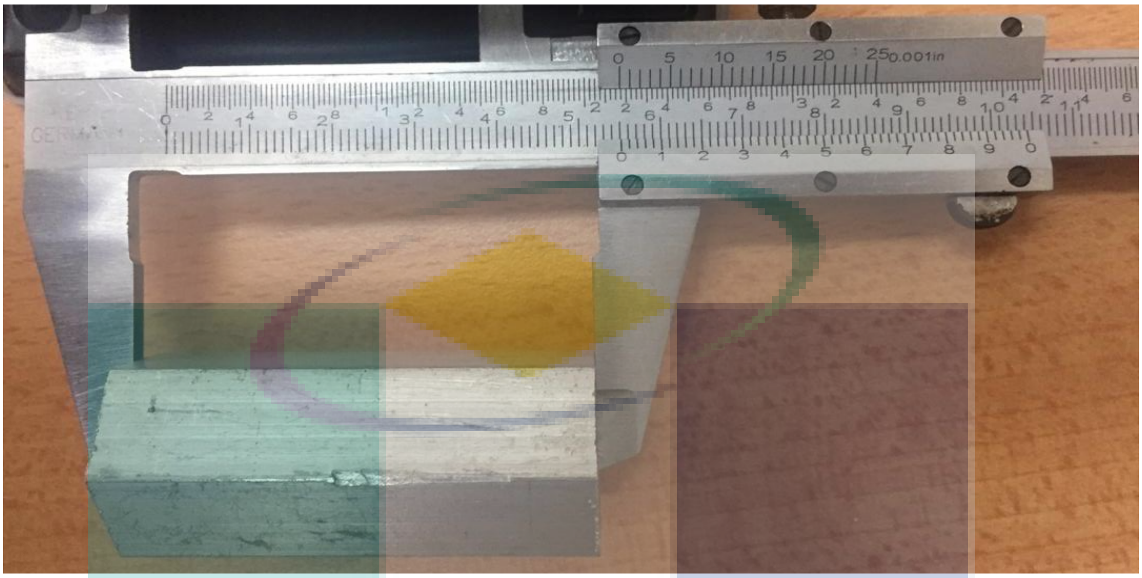


Figure 4.12 Raw material sample length measured at 5.54 cm.

Table 4-14 The summary of raw material weight recorded in the experimental method.

Aluminum 6061	Weight (g)	Brass C3604	Weight(g)
A1(1)	59.5073	B1(1)	260.8967
A1(2)	59.5273	B1(2)	260.8297
A1(3)	59.8873	B1(3)	260.8997
A2(1)	59.3709	B2(1)	260.9423
A2(2)	59.2909	B2(2)	260.9923
A2(3)	59.7909	B2(3)	260.9123
A3(1)	59.5327	B3(1)	260.8455
A3(2)	59.3227	B3(2)	260.9655
A3(3)	59.8627	B3(3)	260.8855
A4(1)	59.9740	B4(1)	260.9076
A4(2)	59.7774	B4(2)	261.0176
A4(3)	59.9140	B4(3)	260.9076

Table 4-15 Summary of the percentage difference between theoretical and experimental data for Manufacturing Cost, Energy, Environmental and Ergonomics criteria.

Sample	Manufacturing Cost (RM)			Energy (kWh)		
	Theory	Experiment	Difference (%)	Theory	Experiment	Difference (%)
A1(1)	15.3446	15.4786	0.8733	11.0096	11.1519	1.2925
A1(2)	15.3446	15.4244	0.5200	11.0096	11.1713	1.4687
A1(3)	15.3446	15.6227	1.8124	11.0096	11.1854	1.5968
A2(1)	15.4322	15.5393	0.6943	11.4316	11.5809	1.3055
A2(2)	15.4322	15.6527	1.4290	11.4316	11.5837	1.3305
A2(3)	15.4322	15.7002	1.7370	11.4316	11.5924	1.4065
A3(1)	14.2392	14.3821	1.0033	11.4215	11.5809	1.3953
A3(2)	14.2392	14.4793	1.6858	11.4215	11.5892	1.4685
A3(3)	14.2392	14.5186	1.9617	11.4215	11.5975	1.5407
A4(1)	14.5510	14.7256	1.2001	12.2622	12.4317	1.3822
A4(2)	14.5510	14.7577	1.4207	12.2622	12.4294	1.3634
A4(3)	14.5510	14.8344	1.9475	12.2622	12.4399	1.4486
B1(1)	27.8839	28.0557	0.6163	9.7900	9.9365	1.4966
B1(2)	27.8839	28.0609	0.6349	9.7900	9.9443	1.5764
B1(3)	27.8839	28.0726	0.6767	9.7900	9.9664	1.8022
B2(1)	27.9046	28.1005	0.7020	10.2664	10.4513	1.8008
B2(2)	27.9046	28.1009	0.7035	10.2664	10.4406	1.6969
B2(3)	27.9046	28.1011	0.7042	10.2664	10.4538	1.8254
B3(1)	26.3701	26.5517	0.6886	10.2551	10.4306	1.7117
B3(2)	26.3701	26.5607	0.7226	10.2551	10.4240	1.6474
B3(3)	26.3701	26.5583	0.7136	10.2551	10.4331	1.7364
B4(1)	26.6279	26.7094	0.3061	11.1966	11.3805	1.6421
B4(2)	26.6279	26.8254	0.7419	11.1966	11.3758	1.6008
B4(3)	26.6279	26.8359	0.7814	11.1966	11.3861	1.6922

Table 4-15 Continued

Sample	Environmental Impact (kgCO2)			Ergonomic (Index)		
	Theory	Experiment	Difference (%)	Theory	Experiment	Difference (%)
A1(1)	8.5100	8.6143	1.2256	0.2582	0.2588	0.2535
A1(2)	8.5100	8.6290	1.3984	0.2582	0.2589	0.2733
A1(3)	8.5100	8.6438	1.5723	0.2582	0.2598	0.6300
A2(1)	8.8253	8.9394	1.2928	0.2582	0.2585	0.1183
A2(2)	8.8253	8.9376	1.2725	0.2582	0.2583	0.0390
A2(3)	8.8253	8.9518	1.4342	0.2582	0.2596	0.5345
A3(1)	8.8177	8.9350	1.3297	0.2582	0.2589	0.2786
A3(2)	8.8177	8.9485	1.4832	0.2582	0.2584	0.0706
A3(3)	8.8177	8.9488	1.4862	0.2582	0.2597	0.6056
A4(1)	9.4457	9.5751	1.3701	0.2582	0.2600	0.7159
A4(2)	9.4457	9.5781	1.4016	0.2582	0.2595	0.5211
A4(3)	9.4457	9.5834	1.4570	0.2582	0.2599	0.6565
B1(1)	7.7423	7.8500	1.3915	0.7738	0.7741	0.0309
B1(2)	7.7423	7.8561	1.4707	0.7738	0.7739	0.0088
B1(3)	7.7423	7.8740	1.7019	0.7738	0.7741	0.0319
B2(1)	8.0982	8.2342	1.6796	0.7738	0.7742	0.0460
B2(2)	8.0982	8.2273	1.5947	0.7738	0.7743	0.0626
B2(3)	8.0982	8.2361	1.7036	0.7738	0.7741	0.0361
B3(1)	8.0897	8.2204	1.6153	0.7738	0.7739	0.0140
B3(2)	8.0897	8.2157	1.5580	0.7738	0.7742	0.0537
B3(3)	8.0897	8.2224	1.6399	0.7738	0.7740	0.0272
B4(1)	8.7930	8.9294	1.5505	0.7738	0.7741	0.0345
B4(2)	8.7930	8.9262	1.5143	0.7738	0.7744	0.0709
B4(3)	8.7930	8.9331	1.5927	0.7738	0.7741	0.0345

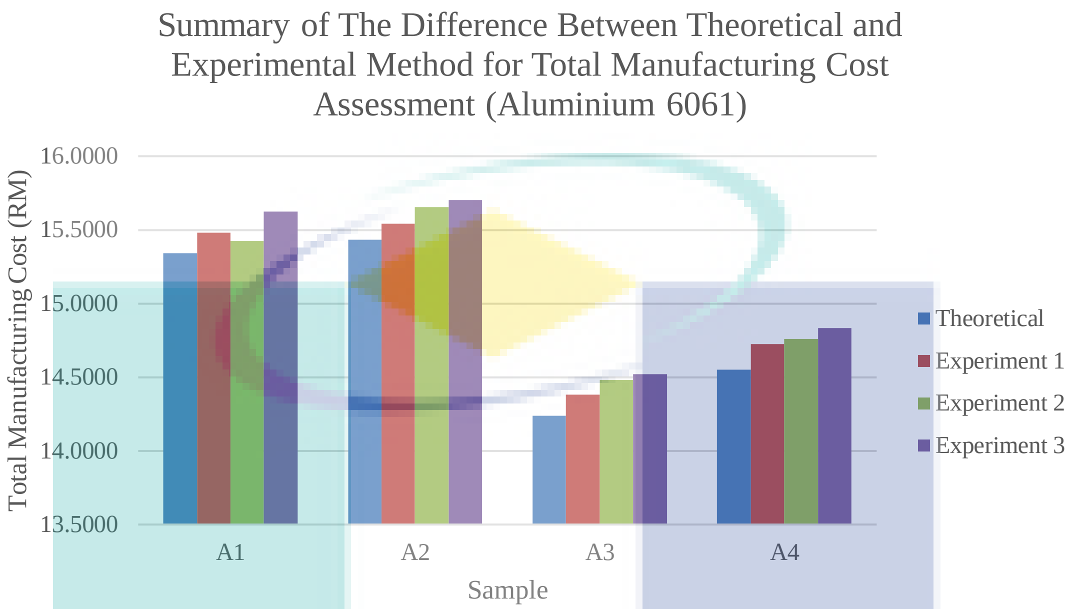


Figure 4.13 Summary of total manufacturing cost comparisons between theoretical and experimental for Aluminium 6061 nipple hose connector.

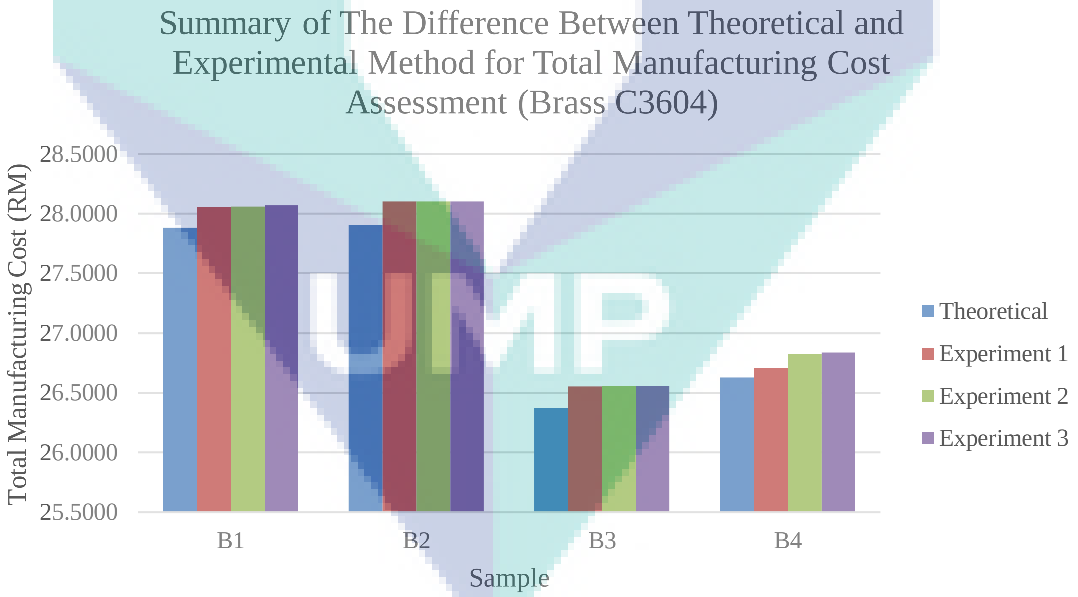


Figure 4.14 Summary of total manufacturing cost comparisons between theoretical and experimental for Brass C3604 nipple hose connector.

Table 4-15 showed a comparison on the percentage difference between theoretical and experimental data collected for total manufacturing cost of the experiment. For total manufacturing cost, the differences are between 0.3061% to 1.9617% for both materials and the detail comparison data between theoretical and experimental are shown in Figure 4.13 for Aluminium 6061 pneumatic nipple hose connector and Figure 4.14 for Brass C3604 pneumatic nipple hose connector. The theoretical results is lower compared to experimental because some of the wires used in the CNC Turning Machine are replaced with new wire sizes that are slightly larger than the old wires. Larger wire size allows more energy to go through the wire as the wire volume is bigger. Besides that, the machine spare parts such as gears and machine controllers have been replaced with new spare parts. New spare parts cause uncertainty to the energy usage because it was produced by other companies which are the not same as the original components. Sometimes, the machine also needs to be stopped for a while for simple trouble shotting but the amount of energy is included. For longer trouble shotting time, the energy counting will not take into account in the present study.

Meanwhile, for energy criteria, the differences are between 1.3055% to 1.8254% for both materials and the detail comparison data between theoretical and experimental are shown in Figure 4.15 and Figure 4.16. In this case study, the energy used during the machining process is a critical issue to looked at because it can give direct impact to manufacturing cost and environmental impact. The percentage differences recorded for Aluminium 6061 material is between 1.3055% to 1.6283%, and for Brass C3604 material the differences are between 1.4966% to 1.8254%. Since the theoretical method did not consider the energy used during machine downtime, the same principle is also applied to the experimental method.

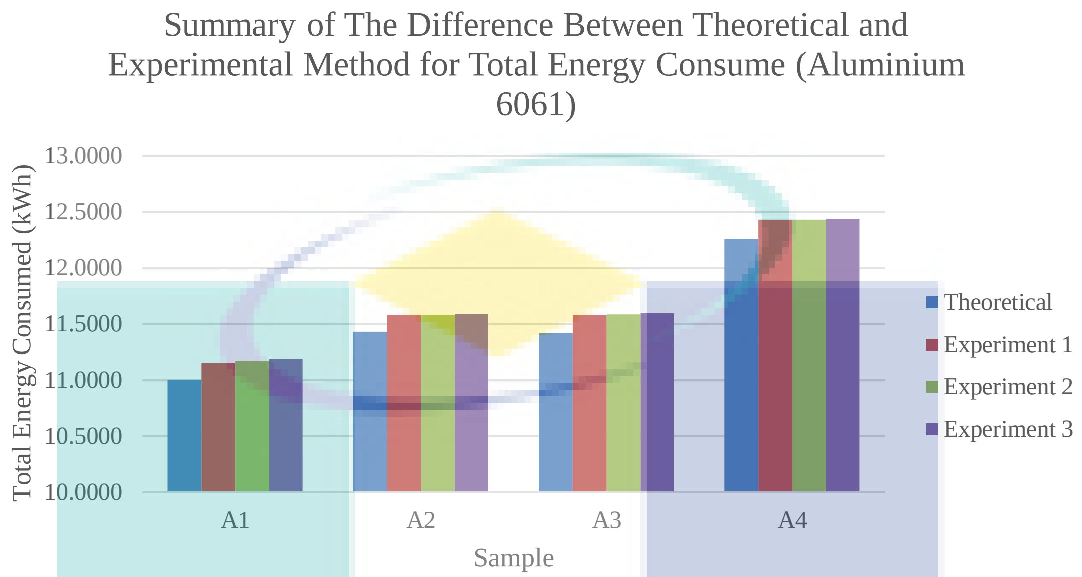


Figure 4.15 Summary of total energy consumed comparisons between theoretical and experimental for Aluminium 6061 nipple hose connector.

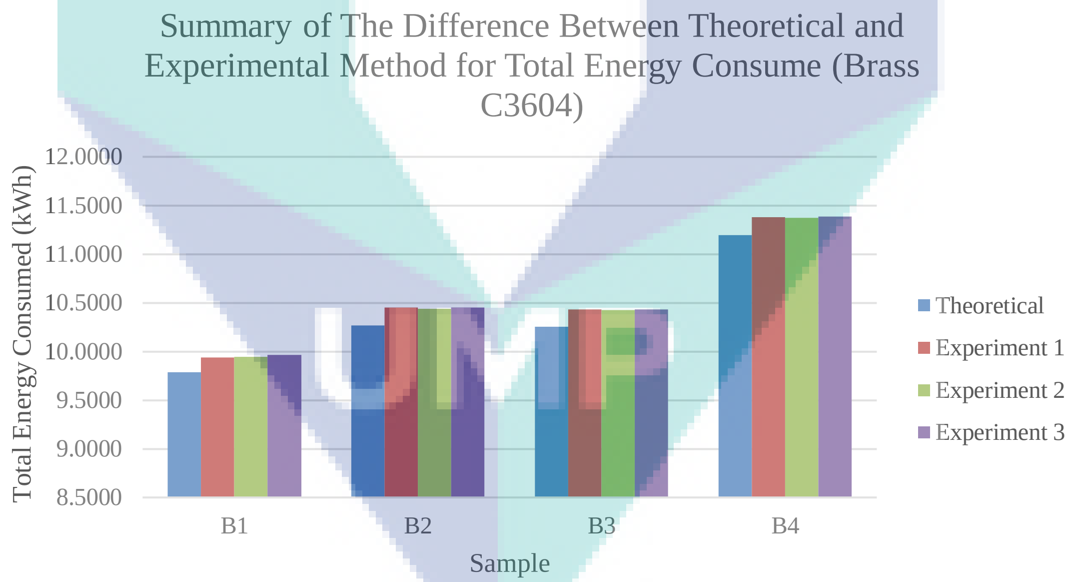


Figure 4.16 Summary of total energy consumed comparisons between theoretical and experimental for Brass C3604 nipple hose connector.

As the energy flows from the main power supply into the machine under dynamic supply state, the amount of energy moves in is not the same all the time (Jignesh Parmar, 2013; Mohassel et al., 2014). Hence, it is difficult to retain a stable energy reading in the machining process although it is essential to make sure that the energy data collected is in stable supply all the time. The dynamic movement of energy is also observed at the beginning of the experiment setup where it is found that the energy load is very high at the early in the morning as not many machines being used in the laboratory. However, in the afternoon, the energy flow becomes lesser since more machines are operated at the same time. Therefore, the machine is started from 10.00 am until 5.00 pm to run the samples accordingly and the energy consumption during the machining in the correct range is ensured.

The energy lost is inevitable when the energy travels from the main power supply into the machine. To prevent this, one machine is used to run all of the samples. The dynamic movement of energy and the energy loss phenomenon also highlighted by a group of researchers (Pervaiz et al., 2013). In the present study, the maximum range of error percentage is denoted as 12 % for energy criteria which also adopted by other researchers (Navani et al., 2012) and the obtained results is less than 12% difference.

Another factor that contributes to the energy difference is the assumption made when calculating the energy usage according to the theoretical method and experimental method. Theoretically, the machining process is assumed to be smooth during the machining process. However, in reality, the machine sometimes needs to be stopped for a while if there is a problem that occurs during machining. Stagnant energy is used as a factor and the machine efficiency in energy determination could help to obtain better energy results. However, it did not reflect the real situation. Stopping the machine for troubleshooting will increase the amount of energy used. Hence, it is essential to ensure the steps taken in the experiment is correct to avoid the energy increment due to the machine troubleshooting. Another thing that needs to be done is to make sure that the energy data is consistent during the idle state of the machine where there is no cutting process run at that time. In the present study, the amount of energy consumed during the trouble shutting is neglected to mimic the amount of energy used in the theoretical method.

When looking at the environmental impact criteria, the percentage difference is between 1.2556% to 1.7036% for both materials and the detail comparison data between theoretical and experimental are shown in Figures 4.17 and 4.18. When looked into detail, the main factor that contributes to the huge difference in the environmental impact assessment is the amount of energy used during the machining process because of the dynamic movement of energy in the wire.

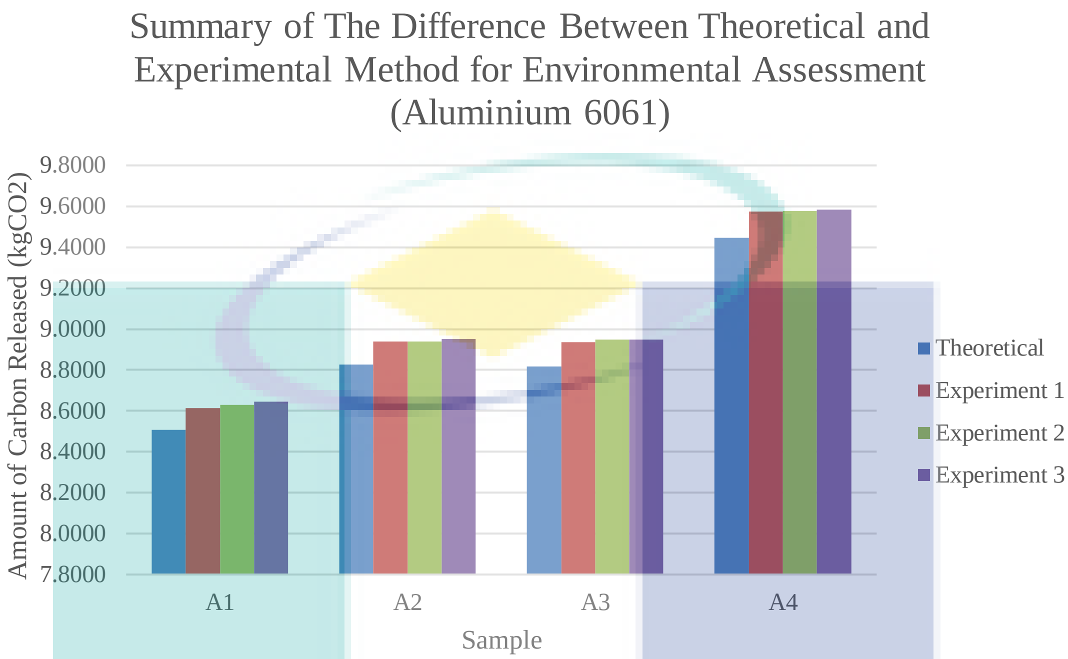


Figure 4.17 Summary of total environmental assessment comparisons between theoretical and experimental for Aluminium 6061 nipple hose connector.

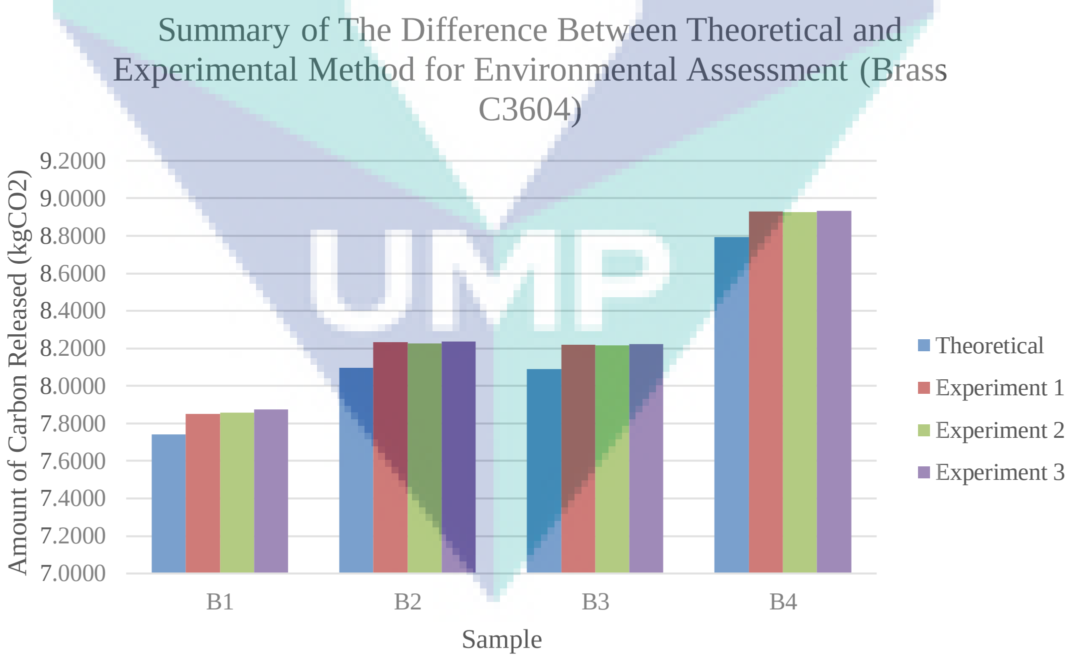


Figure 4.18 Summary of total environmental assessment comparisons between theoretical and experimental for Brass C3604 nipple hose connector.

If we looked at the ergonomics criteria, as stated in the methodology; the assessment is based on the NIOSH weight lifting index. Table 4-15 shows the percentage difference between theoretical and experimental data for ergonomic assessment is relatively small because the weight does not significantly change compared to energy as shown in Figures 4.19 and 4.20 for Aluminium 6061 pneumatic nipple hose connector and Brass C3604 pneumatic nipple hose connector, respectively. Hence, energy plays a vital role in determining the environmental impact assessment. Cutting tool, coolant and lubricant used in the present study are not included in the environmental impact assessment calculation. As the comparison is made between the number of products being produced to the number of the cutting tool, coolant and lubricant being used, the environmental impact produce from the cutting tool, coolant and lubricant are neglected as they are too small compared to the amount of energy and weight of the material being reduced (Dahmus & Gutowski, 2004).

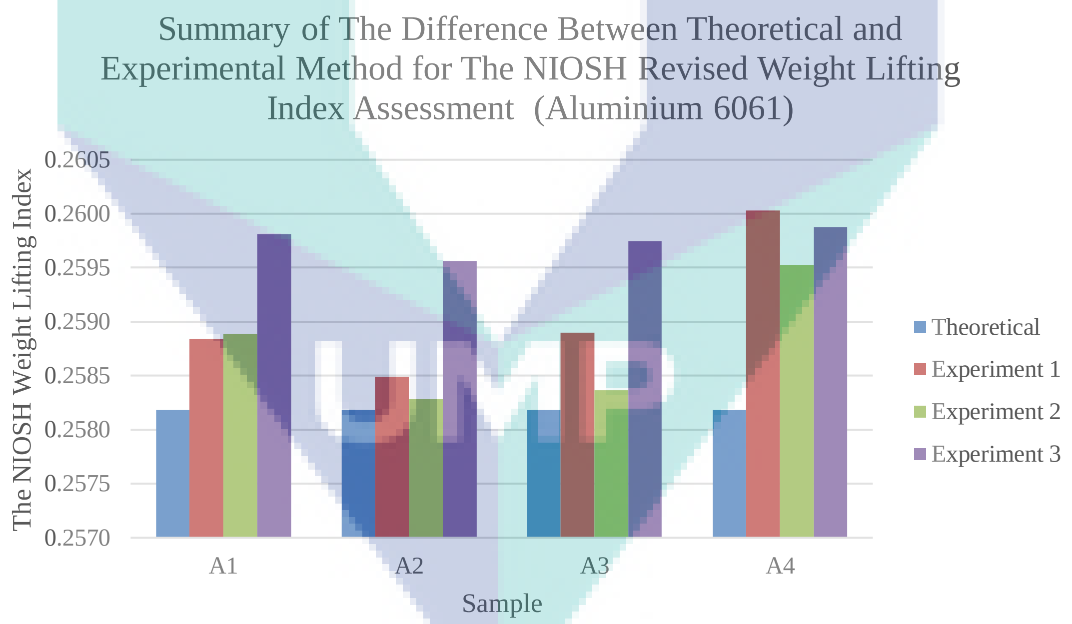


Figure 4.19 Summary of The NIOSH weight lifting index comparisons between theoretical and experimental for Aluminium 6061 nipple hose connector.

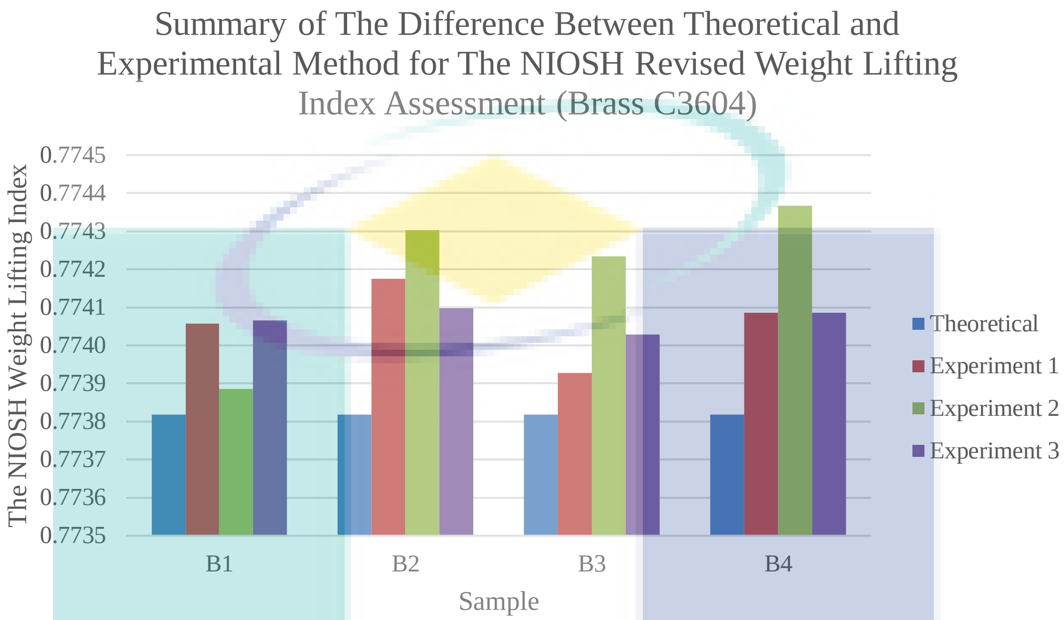


Figure 4.20 Summary of The NIOSH weight lifting index comparisons between theoretical and experimental for Brass C3604 nipple hose connector.

4.9 Predicted Results by Neural Network Model

The predicted results are obtained by using the neural network model generated by using Matlab software under the neural network fitting toolbox. Here, only the experimental data have been used to generate the neural network model. The main reason why only experimental data is used to generate the mathematical model because, in experimental data collected, the energy used during machining already included the energy used by the machine accessories such as machine monitor and controller. Besides that, the experimental data is based on real human performance. However, in the theoretical data, the energy used by machine monitor and controller is not included because it is difficult to be determined, but the machine efficiency is included to mimic the real performance.

At the beginning of generating neural network mathematical model, four inputs are being used; known as cutting speed, feed rate, raw material length and material types. When generating the predicted results, the proposed results are differences is enormous although it is in acceptable range results, the main problem occurs when to predict the optimum results where the proposed optimum results are out of the range of cutting parameter used in the case study. When the raw material length and material types being pulled out from the input data list, the results are in a good, acceptable range for prediction and optimization. The reasons behind it are that in this study, the raw material length is assumed fixed at 5.50 centimeter. Hence it can be neglected because of that reason. For the raw material types, the differences of material are assigned with a number, where one is for Aluminium 6061 and 2 for Brass C3604 which did not have any connections in this case study. Hence it will produce bias results when these types of data being used.

The number of hidden neuron used in this study is 5 for Aluminium and Brass. This figure is obtained by using Equation 2-24 proposed by Sheela & Deepa (2013), where n is the number of input used in this study. They added, if the results obtained are in a negative value, modulus should be used because the hidden number of neuron must be positive. The equation is adopted due to the intensive reviewed received on the development of how to determine the number of hidden neuron and at the same time, a lot of experiments proved the findings.

$$N_{haluminium} = \frac{(4n^2+3)}{(n^2-8)} = \frac{(4(2)^2+3)}{(2^2-8)} = \frac{19}{|-4|} \approx 5$$

$$N_{hbrass} = \frac{(4n^2+3)}{(n^2-8)} = \frac{(4(2)^2+3)}{(2^2-8)} = \frac{19}{|-4|} \approx 5$$

The Lavenberg – Marquardt algorithm that is the training algorithm is used in this study as it requires less time to compute and the training process is automatically stopped when generalization stop improving (Mathworks, 2018). When training the data by using Lavenberg – Marquardt algorithm, the regression R (R squared) value for Aluminium 6061 material is 0.999985 for training, 0.999993 for validation and 0.999952 for testing; while the mean square error (MSE) value for training is 9.05627 x e^{-4}, for validation is 5.85674 x e^{-4} and for testing is 5.09827 x e^{-3}. The regression R (R squared) value for Brass C3604 material is 0.999998 for training, 0.999999 for validation and 0.999998 for testing; while the mean square error (MSE) value for training is 2.57715 x e^{-4}, for validation is 1.72072 x e^{-4} and for testing is 3.68821 x e^{-4}. The nearer the R squared value to one, the better the correlation or results (Esfe et al., 2015; Kaytez et al., 2015; Were et al., 2015). Figure 4.21 and Figure 4.22 show the regression results obtained by using neural network fitting in the Matlab software for Aluminium 6061 and Brass C3604 materials, respectively.

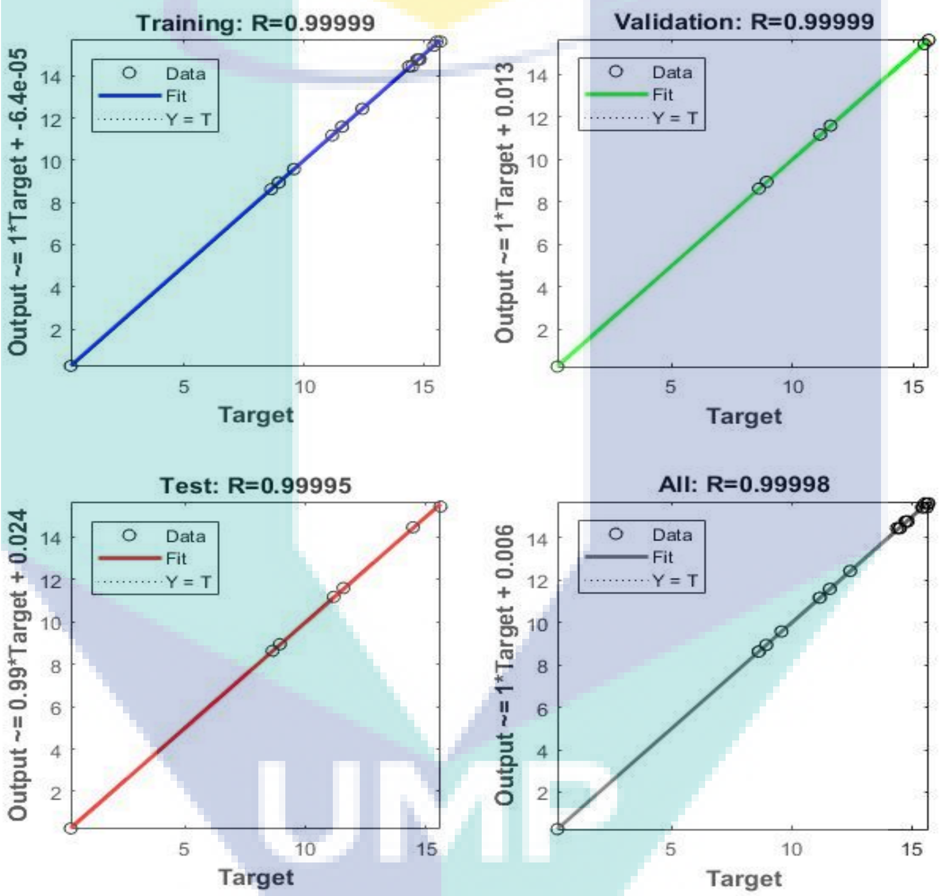


Figure 4.21 Summary of Training, Validation and Testing for Regression value for Aluminium 6061 material by using hidden neuron = 5.

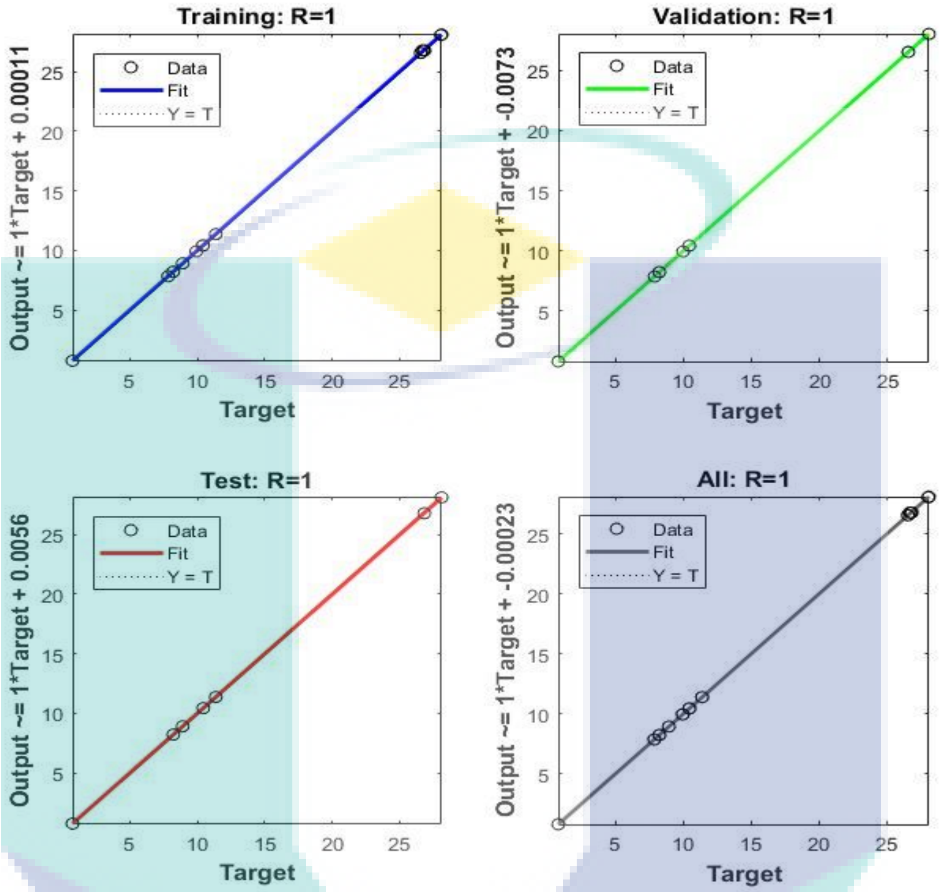


Figure 4.22 Summary of Training, Validation and Testing for Regression value for Brass C3604 material by using number of hidden neuron = 5.

Table 4-16 summarizes the experimental results, predicted results and the percentage difference between predicted and experimental for manufacturing cost, energy, environmental and ergonomic criteria.

Table 4-16 Summary of experimental results, predicted results and the percentage difference between predicted and experimental for manufacturing cost, energy, environmental and ergonomic criteria.

Sample	Manufacturing Cost (RM)			Energy (kWh)		
	Experimental	Predicted by Neural Network	Difference (%)	Experimental	Predicted by Neural Network	Difference (%)
A1(1)	15.4786	15.4240	-0.3535	11.1519	11.1710	0.1711
A1(2)	15.4244	15.4240	-0.0023	11.1713	11.1710	-0.0032
A1(3)	15.6227	15.4240	-1.2883	11.1854	11.1710	-0.1292
A2(1)	15.5393	15.6203	0.5183	11.5809	11.5871	0.0541
A2(2)	15.6527	15.6203	-0.2075	11.5837	11.5871	0.0294
A2(3)	15.7002	15.6203	-0.5119	11.5924	11.5871	-0.0456
A3(1)	14.3821	14.4503	0.4722	11.5809	11.5892	0.0716
A3(2)	14.4793	14.4503	-0.2003	11.5892	11.5892	-0.0005
A3(3)	14.5186	14.4503	-0.4722	11.5975	11.5892	-0.0717
A4(1)	14.7256	14.7726	0.3178	12.4317	12.4337	0.0156
A4(2)	14.7577	14.7726	0.1005	12.4294	12.4337	0.0342
A4(3)	14.8344	14.7726	-0.4184	12.4399	12.4337	-0.0498
B1(1)	28.0557	28.0583	0.0092	9.9365	9.9404	0.0393
B1(2)	28.0609	28.0583	-0.0092	9.9443	9.9404	-0.0393
B1(3)	28.0726	28.0583	-0.0508	9.9664	9.9404	-0.2617
B2(1)	28.1005	28.1007	0.0007	10.4513	10.4459	-0.0511
B2(2)	28.1009	28.1007	-0.0008	10.4406	10.4459	0.0511
B2(3)	28.1011	28.1007	-0.0015	10.4538	10.4459	-0.0753
B3(1)	26.5517	26.5562	0.0169	10.4306	10.4273	-0.0316
B3(2)	26.5607	26.5562	-0.0169	10.424	10.4273	0.0317
B3(3)	26.5583	26.5562	-0.0079	10.4331	10.4273	-0.0559
B4(1)	26.7094	26.7727	0.2365	11.3805	11.3832	0.0245
B4(2)	26.8254	26.7727	-0.1969	11.3758	11.3832	0.0650
B4(3)	26.8359	26.7727	-0.2362	11.3861	11.3832	-0.0248

Table 4-16 Continued

Sample	Environmental (kgCO2)			Ergonomic (Index)		
	Experimental	Predicted by using Neural Network	Difference (%)	Experimental	Predicted by using Neural Network	Difference (%)
A1(1)	8.6143	8.6294	0.1746	0.2588	0.2579	-0.3506
A1(2)	8.6290	8.6294	0.0041	0.2589	0.2579	-0.3704
A1(3)	8.6438	8.6294	-0.1671	0.2598	0.2579	-0.7275
A2(1)	8.9394	8.9451	0.0641	0.2585	0.2581	-0.1458
A2(2)	8.9376	8.9451	0.0842	0.2583	0.2581	-0.0665
A2(3)	8.9518	8.9451	-0.0753	0.2596	0.2581	-0.5620
A3(1)	8.9350	8.9419	0.0772	0.2589	0.2596	0.2733
A3(2)	8.9485	8.9419	-0.0741	0.2584	0.2596	0.4802
A3(3)	8.9488	8.9419	-0.0771	0.2597	0.2596	-0.0519
A4(1)	9.5751	9.5789	0.0389	0.2600	0.2597	-0.1387
A4(2)	9.5781	9.5789	0.0079	0.2595	0.2597	0.0550
A4(3)	9.5834	9.5789	-0.0468	0.2599	0.2597	-0.0796
B1(1)	7.8500	7.8531	0.0391	0.7741	0.7742	0.0155
B1(2)	7.8561	7.8531	-0.039	0.7739	0.7742	0.0377
B1(3)	7.8740	7.8531	-0.2669	0.7741	0.7742	0.0145
B2(1)	8.2342	8.2307	-0.0418	0.7742	0.7746	0.0511
B2(2)	8.2273	8.2307	0.0418	0.7743	0.7746	0.0346
B2(3)	8.2361	8.2307	-0.0654	0.7741	0.7746	0.0610
B3(1)	8.2204	8.2181	-0.0283	0.7739	0.7739	-0.0008
B3(2)	8.2157	8.2181	0.0282	0.7742	0.7739	-0.0404
B3(3)	8.2224	8.2224	-0.0524	0.7740	0.7739	-0.0140
B4(1)	8.9294	8.9278	0.0211	0.7741	0.7742	0.0189
B4(2)	8.9262	8.9278	0.0568	0.7744	0.7742	-0.0174
B4(3)	8.9331	8.9278	-0.0204	0.7741	0.7742	0.0189

The comparison on the predicted results obtained from the neural network model with the experimental results shows that the percentage difference between the experimental and predicted results for manufacturing costs is -1.2883% to 0.4722 % for Aluminium 6061 and -0.2362% to 0.2362 % for Brass C3604 materials as shown in Figure 4.23 and Figure 4.24.

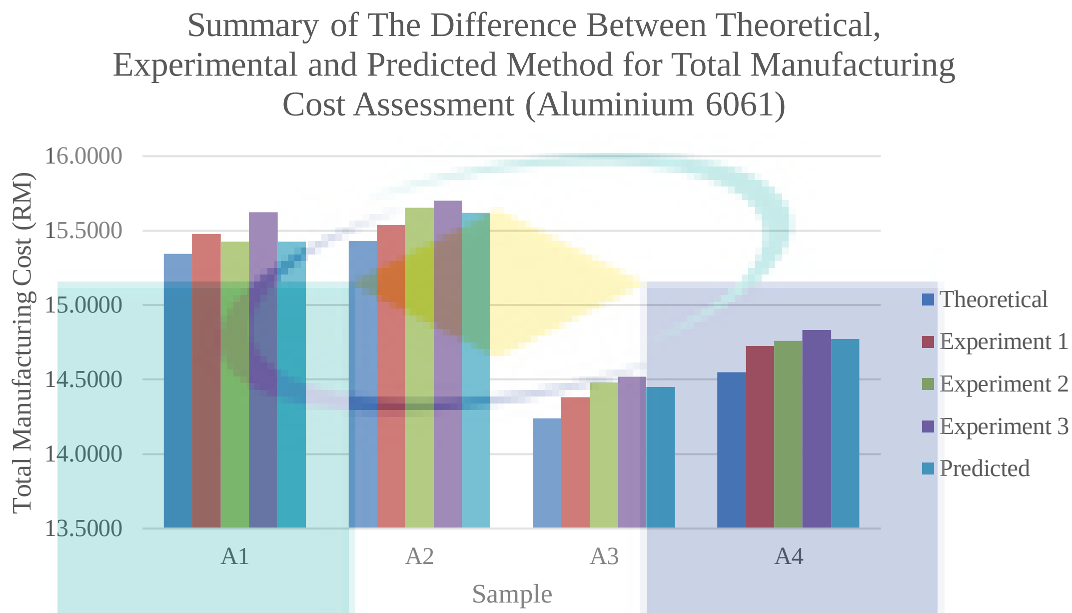


Figure 4.23 Summary of the total manufacturing cost comparisons between theoretical, experimental and predicted results for Aluminium 6061 nipple hose connector.

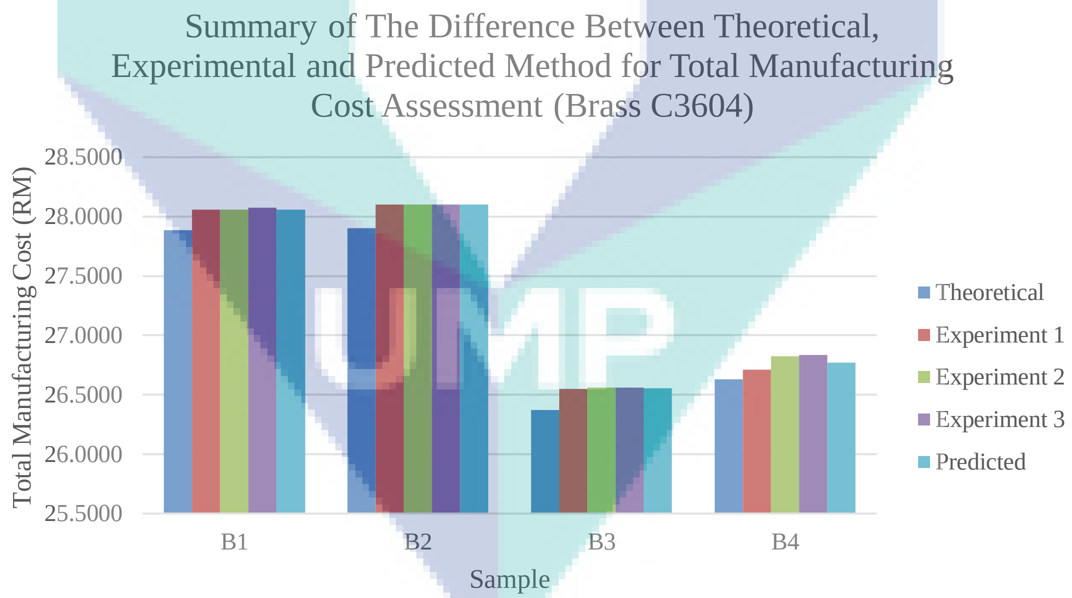


Figure 4.24 Summary of the total manufacturing cost comparisons between theoretical, experimental and predicted results for Brass C3604 nipple hose connector.

The percentage difference in energy assessment is between -0.1292% to 0.1711 % for Aluminium 6061 and -0.2617% and 0.0650 % for Brass C3604 materials as shown in Figure 4.25 and Figure 4.26, respectively.

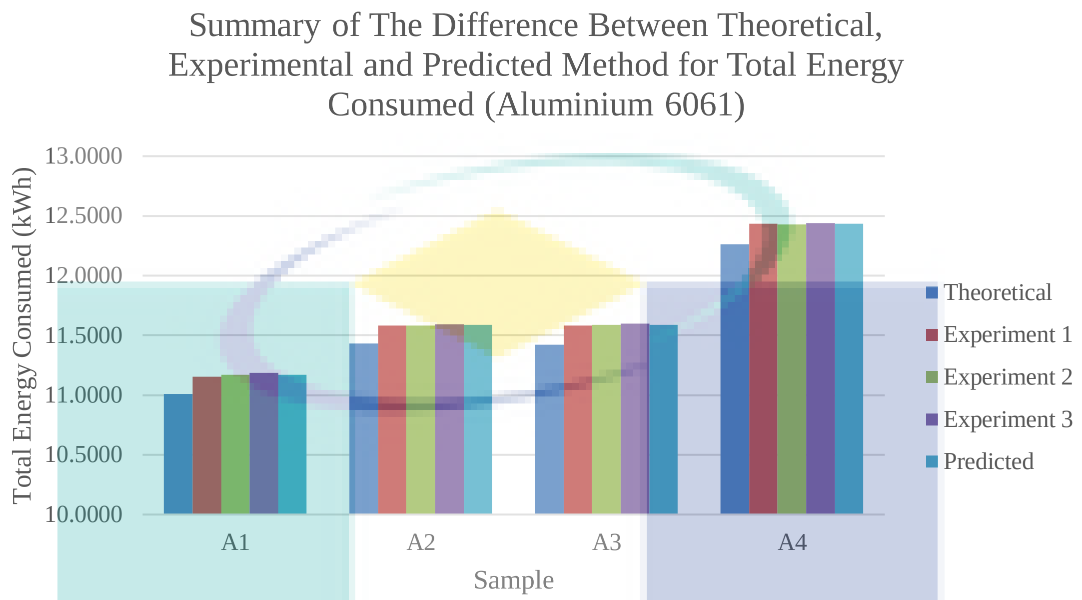


Figure 4.25 Summary of the total energy consumed comparisons between theoretical, experimental and predicted results for Aluminium 6061 nipple hose connector.

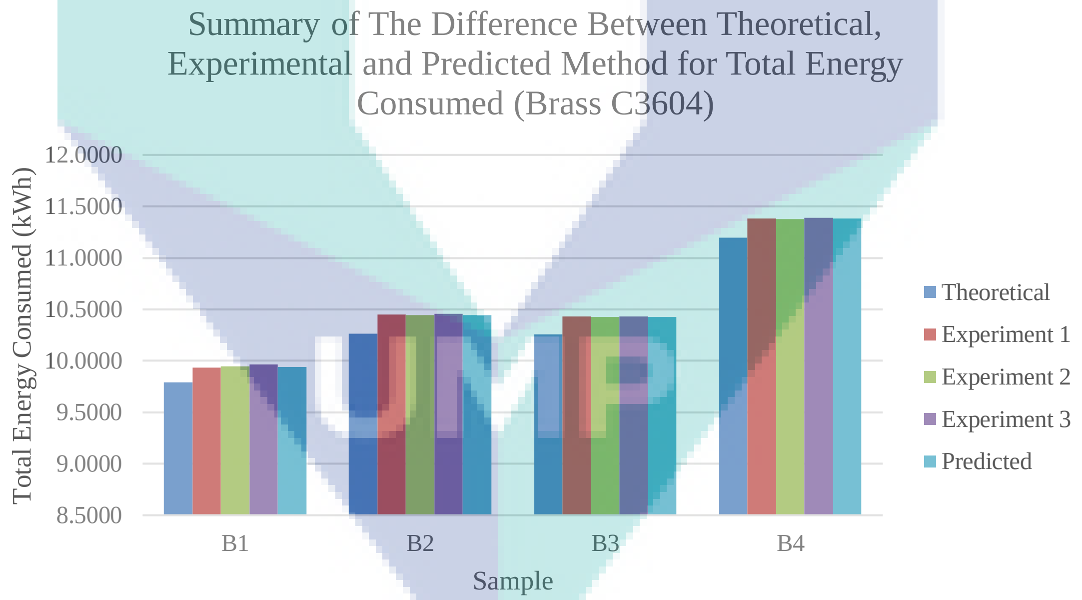


Figure 4.26 Summary of the total energy consumed comparisons between theoretical, experimental and predicted results for Brass C3604 nipple hose connector.

For environmental impact assessment, the percentage difference is between -0.1671% to 0.1746 % for Aluminium 6061 material and -0.2669% to 0.0568 % for Brass C3604 material such as shown in Figure 4.27 and Figure 4.28.

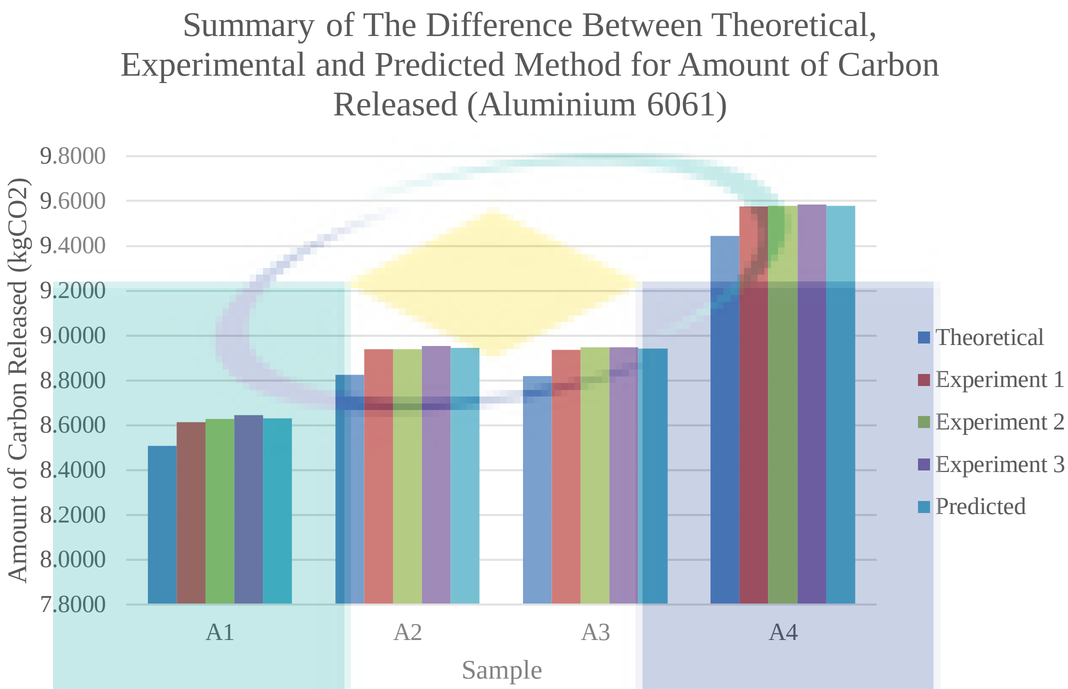


Figure 4.27 Summary of the amount of carbon released comparisons between theoretical, experimental and predicted results for Aluminium 6061 nipple hose connector.

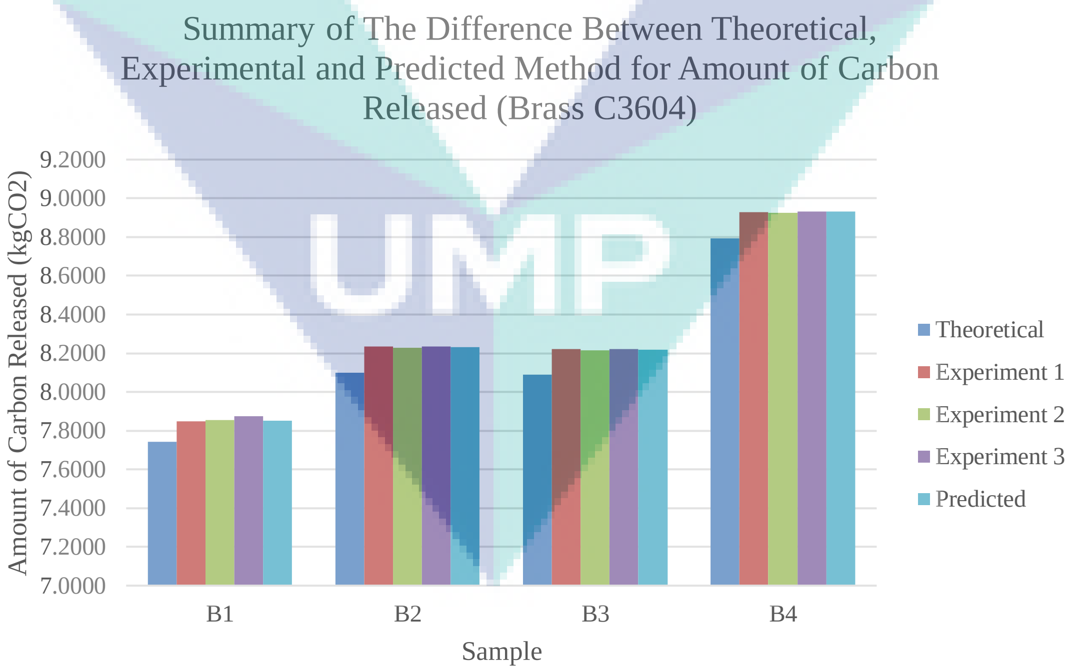


Figure 4.28 Summary of the amount of carbon released comparisons between theoretical, experimental and predicted results for Aluminium 6061 nipple hose connector.

Lastly, the percentage difference for ergonomics assessment is between -0.7275% to 0.4802 % for Aluminium 6061 material and -0.0404 to 0.0610 % for Brass C3604 material as shown in Figure 4.29 and Figure 4.30. It is concluded that the predicted neural network results is less than 5.00% which is lower than 5% used by Kant & Sangwan (2015). Hence the neural network model could be use to predict the manufacturing cost, environmental impact, energy used and the NIOSH weight lifting index.

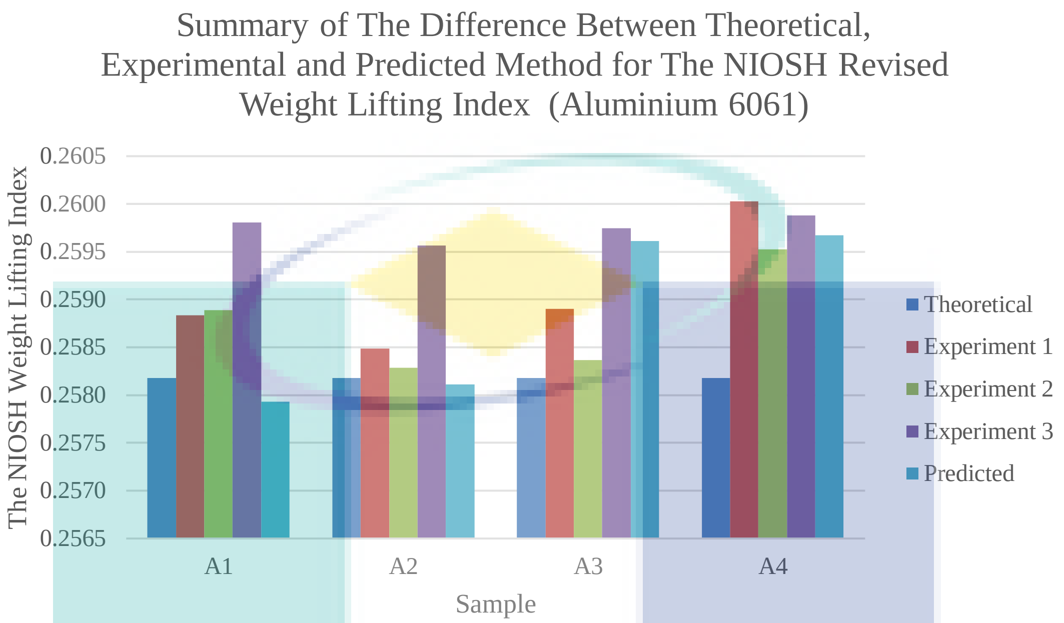


Figure 4.29 Summary of the NIOSH weight lifting index comparisons between theoretical, experimental and predicted results for Aluminium 6061 nipple hose connector.

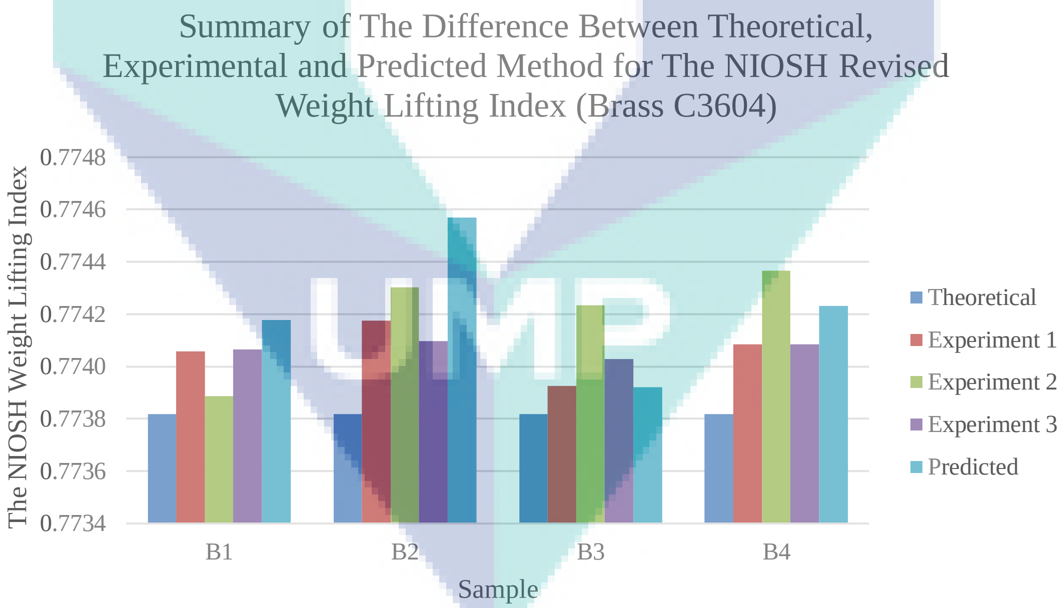


Figure 4.30 Summary of the NIOSH weight lifting index comparisons between theoretical, experimental and predicted results for Brass C3604 nipple hose connector.

4.10 The Inversed Neural Network Model Results

Since the predicted values and the experimental values differences are less than 5.00 %, it can be concluded that the neural network model generated based on the experimental data is a good and valid model and the data collected in the experiment is useful. The next thing to do is to inverse the neural network model to obtain the optimum cutting parameters that satisfy all the four criteria studied in this research. Based on the literature survey, it is possible to inverse the neural network model to obtain the optimum cutting parameters, such as proposed by Cortes (2009). The inversed neural network model can be done by changing the input to output and vice versa. Here, the number of inputs used at this stage is four because there are four criteria involved, manufacturing cost, environmental, energy and ergonomics. The number of hidden neuron used at this stage is calculated as follows for Aluminium 6061 and Brass C3604.

$$N_{haluminium} = \frac{(4n^2+3)}{(n^2-8)} = \frac{(4(4)^2+3)}{(4^2-8)} = \frac{67}{8} \approx 9$$

$$N_{hbrass} = \frac{(4n^2+3)}{(n^2-8)} = \frac{(4(4)^2+3)}{(4^2-8)} = \frac{67}{8} \approx 9$$

The present work tried to minimize all the four criteria, therefore, each minimum value for all the criteria is set as input based on predicted results. The input values used for Aluminium and Brass materials in this study are shown in Table 4-17 below.

Table 4-17 Input values used for the inversed neural network model to obtain the optimum cutting parameters.

Material	Manufacturing Cost (RM)	Energy (kWh)	Environmental (kgCO2)	Ergonomics (Index)
Aluminium	14.4240	11.171	8.6294	0.2579
Brass	26.5562	9.9404	7.8531	0.7739

The inversed neural network model also adopted the Lavenberg – Marquardt algorithm and the regression R (R squared) value for Aluminium 6061 material is 0.999999 for training, 0.999899 for validation and 0.992472 for testing; while the mean square error (MSE) value for training is 1.26125 x e^{-4}, for validation is 0.338357 and for testing is 95.34788. The regression R (R squared) value for Brass C3604 material is 0.999999 for training, 0.999997 for validation and 0.999980 for testing; while the mean square error (MSE) value for training is 3.26640 x e^{-5}, for validation is 8.74443 x e^{-3} and for testing is 1.84663. Figure 4.31 and Figure 4.32 show the summary of regression results obtained by using neural network fitting in the Matlab software for Aluminium 6061 and Brass C3604 materials, respectively.

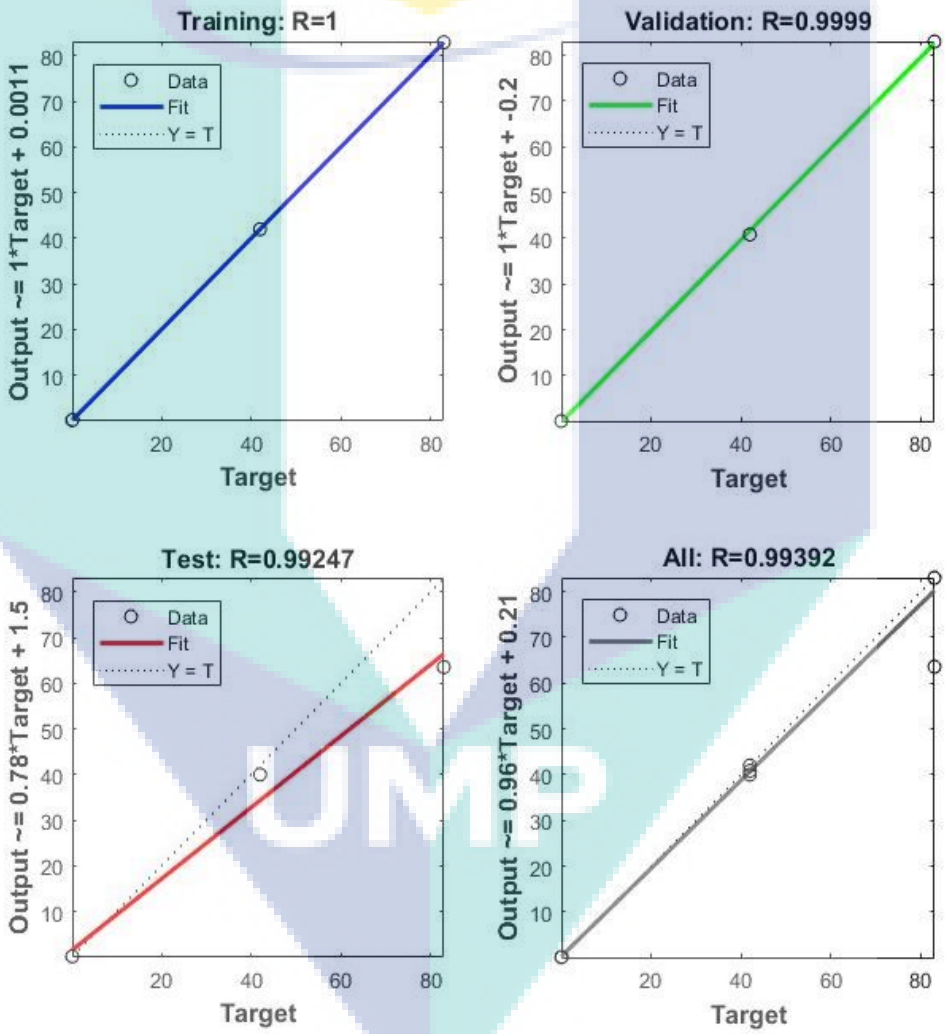


Figure 4.31 Summary of Training, Validation and Testing for inversed neural network regression value for Aluminium 6061 material by using number of hidden neuron = 9.

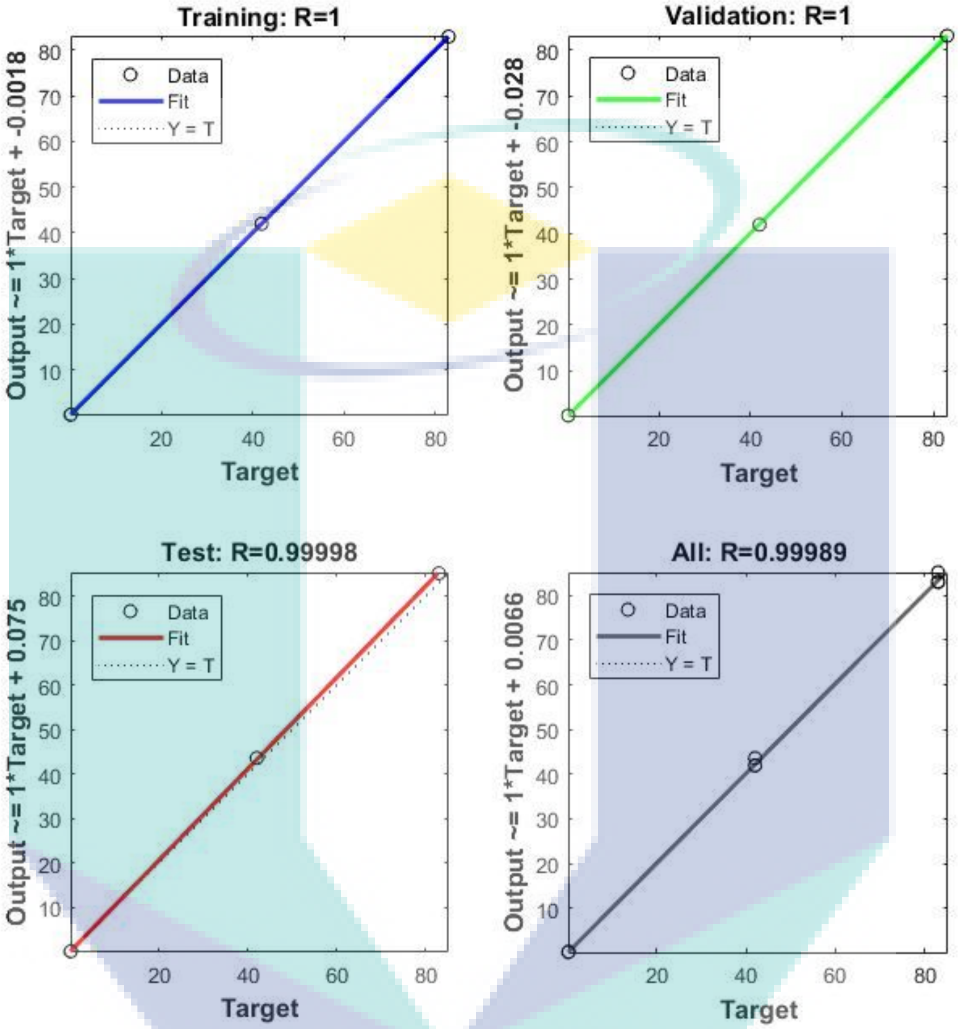


Figure 4.32 Summary of Training, Validation and Testing for inversed neural network Regression value for Brass C3604 material by using number of hidden neuron = 9.

The proposed results for optimization of cutting speed and feed rate is 55.25 m/min and 0.10 mm/rev for Aluminium 6061 material while Brass C3604 material the cutting speed is 82.00 m/min and the feed rate is 0.10 mm/rev. The obtained proposed optimum cutting parameters for each workpiece material is used to calculate the theoretical cutting speed and federate data of the four criteria results and at the same time another experiment being conducted to collect the experimental data to be verified and validated the proposed optimization cutting parameter. The results for both Aluminium 6061 and Brass C3604 materials are shown in Table 4-18 and Table 4-19.

Table 4-18 Summary of manufacturing cost, energy, environmental and ergonomics criteria results calculated theoretically by using optimized cutting parameters proposed by the neural network model.

Material	Theoretical Method			
	Manufacturing Cost (RM)	Energy (kWh)	Environmental (kgCO2)	Ergonomic (Index)
Aluminium	14.7621	11.1404	8.6077	0.2582
Brass	26.3896	10.2437	8.0812	0.7738

Table 4-19 Summary of manufacturing cost, energy, environmental and ergonomics criteria results determine experimentally by using optimized cutting parameters proposed by the neural network model.

Material	Experimental Method			
	Manufacturing Cost (RM)	Energy (kWh)	Environmental (kgCO2)	Ergonomic (Index)
Aluminium	14.8889	11.2621	8.6972	0.2582
Brass	26.5568	10.3861	8.1871	0.7739

Theoretically, when the proposed optimized cutting parameters in the theoretical assessment method is used, the manufacturing cost, energy, environmental impact and ergonomics results fall in between the range of minimum and maximum results for each criterion as predicted at the early stage in the theoretical method. The machining contact time is lower because the cutting speed is a bit high for Aluminium 6061 material and a bit low for Brass C3604 material, but, still, the results are in the minimum and maximum range of the theoretically determined results. The energy used is reduced when using the proposed optimized cutting parameters for Aluminium 6061 material. However, for Brass C3604, the energy used is slightly high compared to the lowest cutting parameter setup. A similar trend is recorded for the environmental impact in which the second lowest for Aluminium 6061 and for Brass C3604 the results is in between second and third place.

As highlighted in the discussions, the present study has achieved the proposed objectives in which a new sustainability assessment model is successfully developed that is eligible to obtain further optimum cutting parameters selection. The study also demonstrated the success of the new sustainability assessment application which is implemented at the manufacturing process level. The optimised cutting parameters for Aluminium 6061 is 55.25 m/min with the cutting speed and 0.10 mm/rev feedrate while for Brass C3604 material, the cutting speed is 82.00 m/min and the feed rate is 0.10 mm/rev.

4.11 Sustainability software / Tool Development

The results obtained from theoretical and experimental data are then transferred in a Microsoft Excel software. Five sheets are separated with each name Energy, Toolcost, Economic, Environmental and Social. For sheet “Energy” in Excel Workbook, the description of cutting parameters option, a specific cutting force for Aluminium 6061 and Brass C3604 material is shown. The evaluation is taking Option 1 calculation for Aluminium 6061 and Brass C3604 that described in this chapter. Here, energy consumed during machining process data is gathered for each process; turning, drilling and boring. The machining time, energy consumed, and idle energy (energy consumed during no tool movement) for theoretical result and energy consumed data for the experimental result is recorded in Excel as shown in Figure 4.33. The total energy consumed after including machine efficiency for both results is evaluated.

	Cutting speed (m/min)	Feedrate (mm/rev)	Depth of cut (mm)	
1	42	0.1	0.5	0.25
2	42	0.2	0.5	0.25
3	83	0.1	0.5	0.25
4	83	0.2	0.5	0.25

Material	Specific cutting force,Kc (N/mm^2)
Aluminium 6061	650
Brass C3604	550

			ALUMINIUM 6061				BRASS C3604			
			Theoretical			Experimental	Theoretical			Experimental
Process	Part		Machining Time(min)	Energy consumed(Watt)	Idle energy(Watt)	Energy consumed(Watt)	Machining Time(min)	Energy consumed(Watt)	Idle energy(Watt)	Energy consumed(Watt)
Turning	Hose	Rough	4.1145	182.00	158.5504		4.3390	154.00	158.5504	
		Fine	3.0859	68.25	118.9128		3.2542	57.75	118.9128	
	Thread	Rough	1.543	113.75	99.094		1.627	96.25	99.094	
		Fine	0.6172	22.75	39.6376		0.6508	19.25	39.6376	
		Threadcutting	9.4713	32.7522	376.5572		9.9879	27.7134	376.5572	
Drilling	3mm	Mark center point	0.09	22.9759	14.8641		0.09	19.4411	14.8641	
	10mm	Hole drilling	0.6284	4875.00	297.282		0.6284	4125.00	297.282	
Boring	13mm	First hole boring	0.7541	2587.50	297.282		0.7541	2189.4231	297.282	
	14.5mm	Second hole boring	0.2199	485.3987	104.0487		0.2199	410.7220	104.0487	
TOTAL :			20.5243	8390.3768	1506.2288		21.5515	7099.5496	1506.2288	

	Aluminium 6061	Brass C3604
Theoretical results		
Total amount of energy used (Watt)	10005.6456	8714.8184
Machine efficiency	90%	90%
Total energy consumed after including machine efficiency (Watt)	11006.21014	9586.3002
Experimental results		
Total energy consumed after including machine efficiency (Watt)	11169.53	9949.07

Energy | Toolcost | Economic | Environmental | Social | Sheet1

Figure 4.33 Energy sheet in Microsoft Excel.

For “Toolcost” sheet in Excel Workbook, calculation on tool cost based on tool life data and type of cutting tool are evaluated here. The total tool cost for an aluminium nipple hose connector and total tool cost for a brass hose connector is estimated which is

RM 6.2103 for one product of Aluminium 6061 material and RM 8.0427 for one product of Brass C3604. In this development, it is worth to note that some data are interrelated to other data for calculation. For instance, to calculate tool cost for TNMG1 in the rough cutting of turning process for hose part, data from energy sheet is needed which is machining time. At the same time, another sheet also uses other data from another sheet to evaluate all the criteria in sustainability assessment. The example of evaluation of tool cost is shown in Figure 4.34.

=(((Energy!$G$17)+(Energy!$G$19))/G8)*13.43

Cutting tool price bought from the supplier --> Cutting tool price

ALUMINIUM 6061				
Process	Part	Cutting tool	Tool Life (minutes)	Tool cost (RM)
Turning	Hose	TNMG1 (rough cutting)	75.5	1.0064
		TNMG2 (fine cutting)	113.25	0.0732
		VCMT (finishing cut)	66.2	1.5565
	Thread	16ERG60	69.4	3.0379
Drilling		Center Drill		0.01447
		Drill Diameter 10mm		0.22472
Boring		Drill Diameter 13mm		0.1515
		Drill Diameter 14.5mm		0.1457
				6.2103

BRASS C3604				
Process	Part	Cutting tool	Tool Life (minutes)	Tool cost (RM)
Turning	Hose	TNMG1 (rough cutting)	65.69	1.7520
		VCMT (finishing cut)	57.60	1.8864
	Thread	16ERG60	60.20	3.6943
Drilling		Center Drill		0.01914
		Drill Diameter 10mm		0.2957
Boring		Drill Diameter 13mm		0.2013
		Drill Diameter 14.5mm		0.1939

Total tool cost for an aluminium hose connector (RM)	6.2103
Total tool cost for a brass hose connector (RM)	8.0427

Energy | Toolcost | Economic | Environmental | Social | Sheet1

Figure 4.34 Tool cost sheet in Microsoft Excel.

For "Economic" sheet, every cost in manufacturing cost data theoretically and experimentally are gathered; raw material cost, labor cost, coolant and lubricant cost, tool cost and energy cost. For the raw material cost, the data collected for 1 gram cost (RM), material density (g/cm³), volume (cm³) and weight of an Aluminium 6061 and Brass C3604 raw material. The raw material cost is calculated based on the data acquired. In labor cost, the assumption that is mentioned in Chapter Three is listed in Excel Workbook to get a labor cost per pneumatic nipple hose connector. The cost stated is RM 0.9470. For coolant and lubricant cost, the assumption that stated in Chapter Three are gathered in this part to calculate both costs which is RM 0.2464 coolant and RM 0.0743 lubricant oil for one product. Tool cost has been calculated in "Toolcost" sheet and copied in "Economic" sheet. In energy cost, Based on Tenaga Nasional Berhad, the rate for tariff D small industry is assumed at RM 0.38 / kWh is multiplied with total energy consumed result which is taken from "Energy" sheet to acquire energy cost for both materials. The total manufacturing cost is shown in Figure 4.35.

Raw material cost

Type of method	Theoretical		Experimental	
Material	Aluminium 606	Brass C360	Aluminium 606	Brass C3604
1 gram cost (RM)	0.06216	0.05696	0.06216	0.05696
Material density (g/cm^3)	2.7	8.43		
Volume (cm^3)	21.9450	30.9375		
Mass (gram)	59.2515	260.8031	59.6406	260.875
Raw material cost (RM)	**3.6829**	**14.8543**	**3.7071**	**14.8584**

Labour Cost

Assumption :	
Total actual time work for one shift (hrs)	10
total shift(s) in one day	2
Output product in 1 hour	12
Working days/month	22
total products in a month	5280
basic salary (RM)	2500
Actual production quantity per month	5280
Labor cost per product (RM)	**0.9470**

Coolant and Lubricant Cost

	Coolant	Lubricant Oil
Cost rate/liter (RM)	44.24	25.0209
Loss Rate	15%	15%
Tank capacity (Liters)	150	40
Period for next change	6	3
Make Up Volume (Liters)	26.47059	7.05882
Volume (Liters)	0.0056	0.00297
Cost/product (RM)	**0.2464**	**0.07433**

Tool Cost

Tool cost for an Aluminium 6061 hose connector (RM)	6.2103
Tool cost for a Brass C3604 hose connector (RM)	8.0427

Tariff Industry Bill (TARIFF D)

Rate for bill (RM/kWh) 0.38

	Theoretical result		Experimental result	
	Aluminium	Brass	Aluminium	Brass
Total energy consumed (kWh)	11.0062	9.5863	11.17	9.95
Energy cost (RM)	**4.1824**	**3.6428**	**4.2444**	**3.7806**

TOTAL MANUFACTURING COST

	Aluminium 6061	Brass C3604
Theoretical result (RM)	**15.3433**	**27.8075**
Experimental result (RM)	**15.4296**	**27.9495**

Energy | Toolcost | Economic | Environmental | Social | Sh

Figure 4.35 Economic sheet in Microsoft Excel.

For “Environmental” sheet, energy and chip recycling impact are the aspects to be evaluated by gathering data from theoretical and experimental result. For energy impact, total energy consumed during machining process value from “Energy” sheet is taken for both materials and multiplying with carbon emission per kilowatt hour for

Semenanjung Malaysia that is 0.747 $kgCO_2$. At the same time, data for chip recycling also collected to acquire total carbon emission for aluminium and brass material. Figure 4.36 summarizes the sheet.

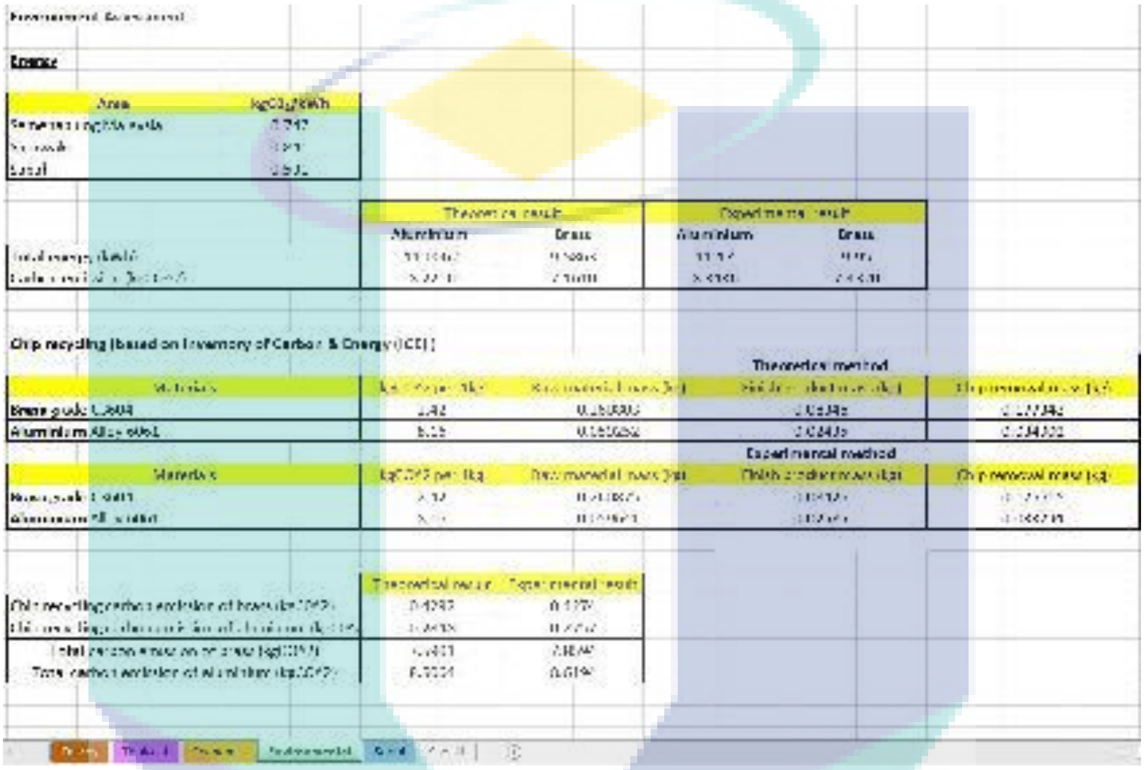


Figure 4.36 Environmental sheet in Microsoft Excel.

Lastly, "Social" sheet in Excel Workbook collected ergonomics data by using the revised NIOSH Weight Lifting Index equation. The assumption is stated here where pallet weight is 1 kg, total pieces of raw material in a pallet is 24 pieces and travel distance is 5 meters. All Recommended Weight Limit (RWL) value is assumed same for the theoretical and experimental result, while the difference is from the load weight of raw material for Aluminium 6061 and Brass C3604. The example of the data gathered for ergonomics assessment is shown in Figure 4.37.

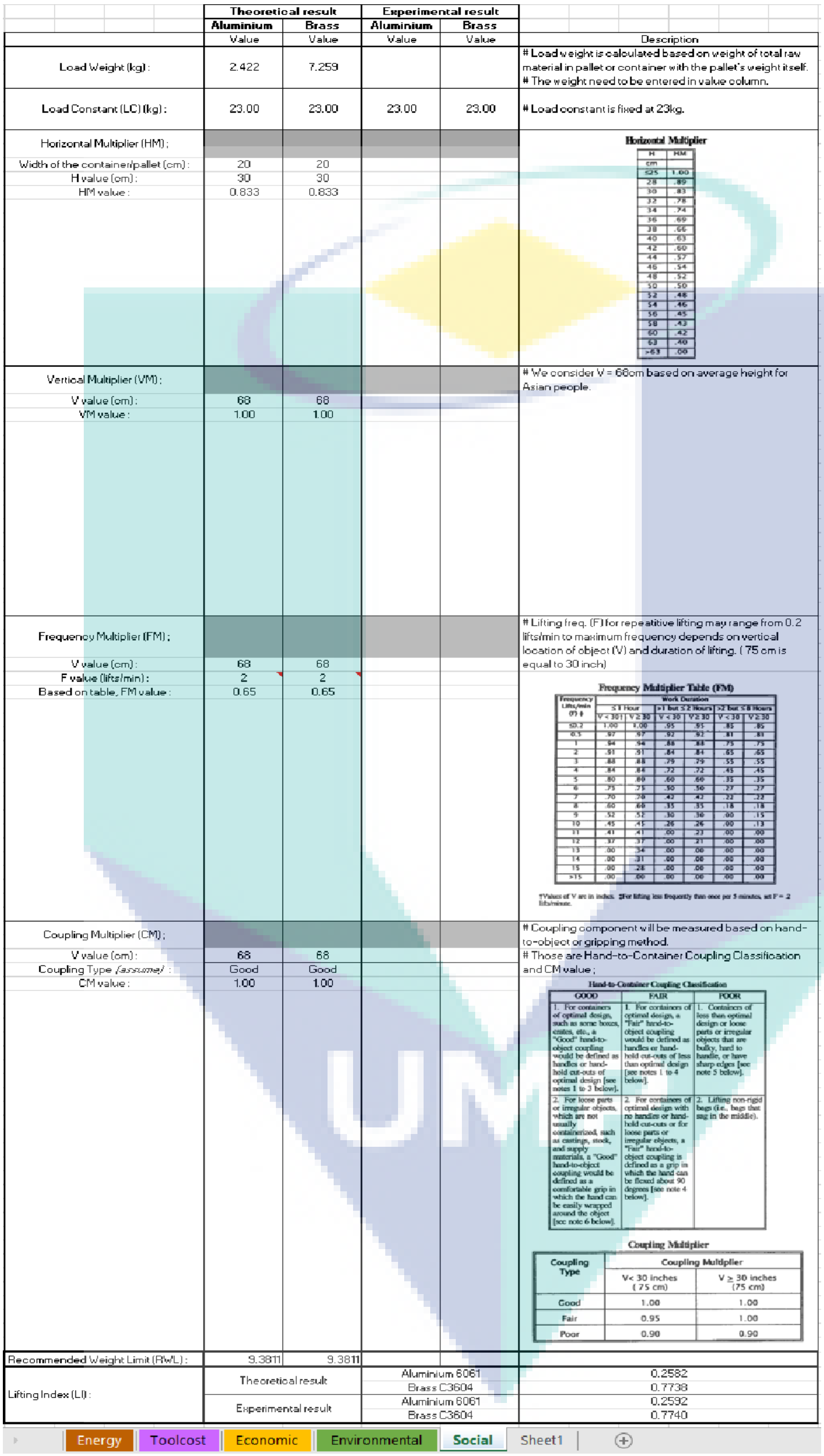


Figure 4.37 Social sheet in Microsoft Excel.

In order to create a simple tool that eases the user to evaluate the sustainability and their assessment, Microsoft Excel software is used with the development of its macro programming language; Visual Basic for Application (VBA). VBA will create a simple function Excel, user form and button control where the user can enter his/her data and value before evaluating. VBA code is typed and viewed in the VBA Editor in what we called as modules. Figure 4.38 shows the VBA Editor that can be opened by pressing Ctrl+F11.

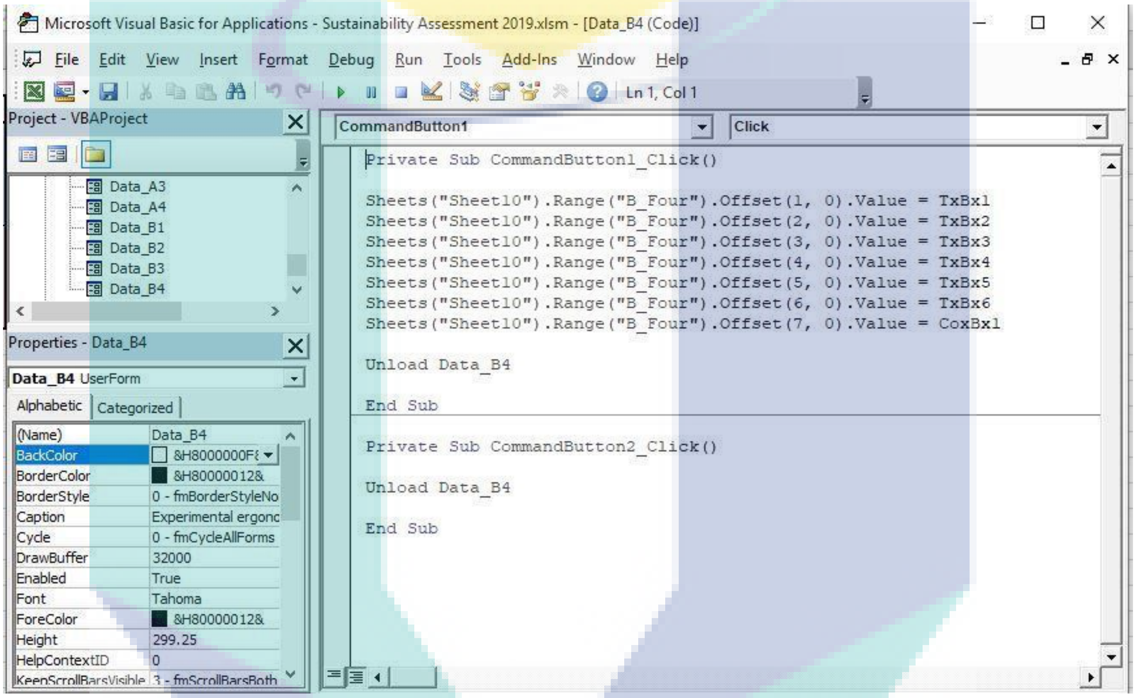


Figure 4.38 VBA Editor.

For the starting part, a module is selected in VBA Editor. Modules are made up of elemental building blocks called procedures, which is used to organize and run the code in a module. In VBA module procedures, all commands, variables and function will control Microsoft Excel and perform various some tasks. In the manufacturing part, VBA Editor set a macro for raw material data for the user to enter size; base, tall and height for hexagon shape of raw material for Aluminium 6061 and Brass C3604. After entering the value, a message box will pop-up to state the raw material cost for both materials. The example of the macro with the result is shown in Figure 4.39.

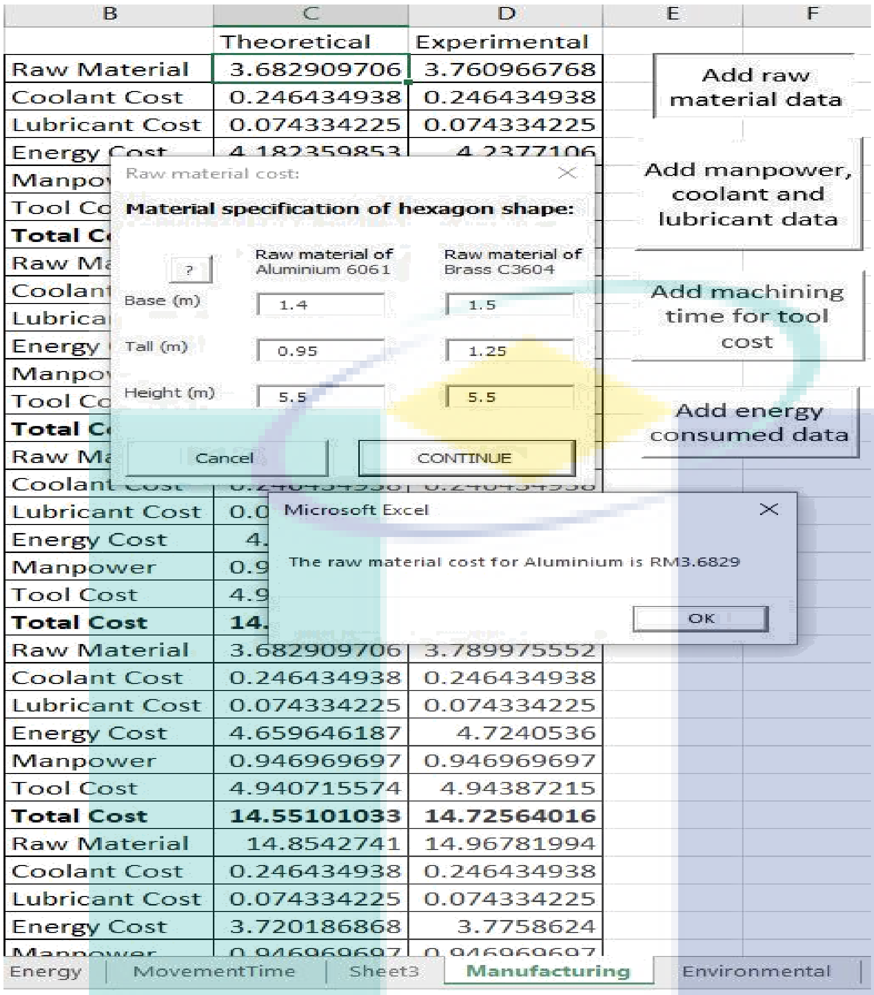


Figure 4.39 Macro by VBA Editor to evaluate raw material cost.

For manpower, coolant and lubricant cost, coding in VBA Editor produce a user form to enter the worker's salary in a month, the product output for an hour, total working hours, the total number of shift, and total working days in a month for manpower cost data. In coolant and lubricant cost data, the user needs to enter the value for their loss rate and also the price per liter. The example of data entered with the result is shown from Figure 4.40 to Figure 4.42.

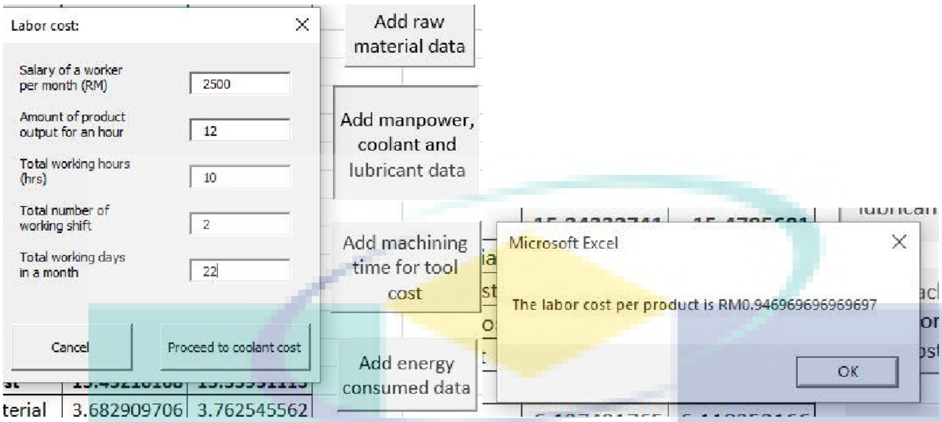


Figure 4.40 Macro by VBA Editor to evaluate labor cost.

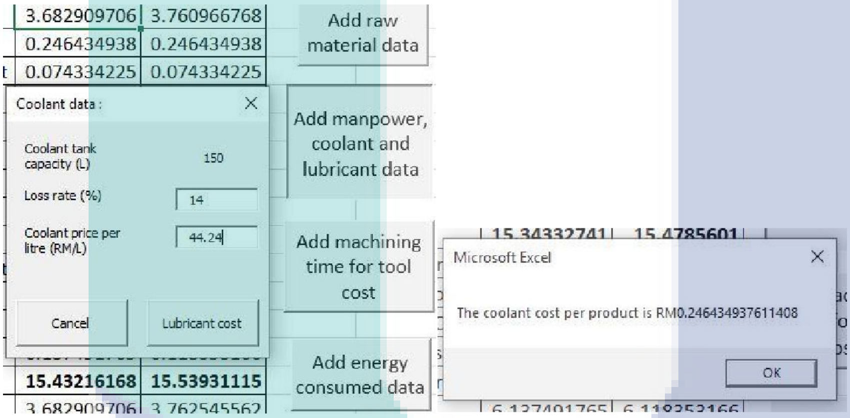


Figure 4.41 Macro by VBA Editor to evaluate coolant cost.

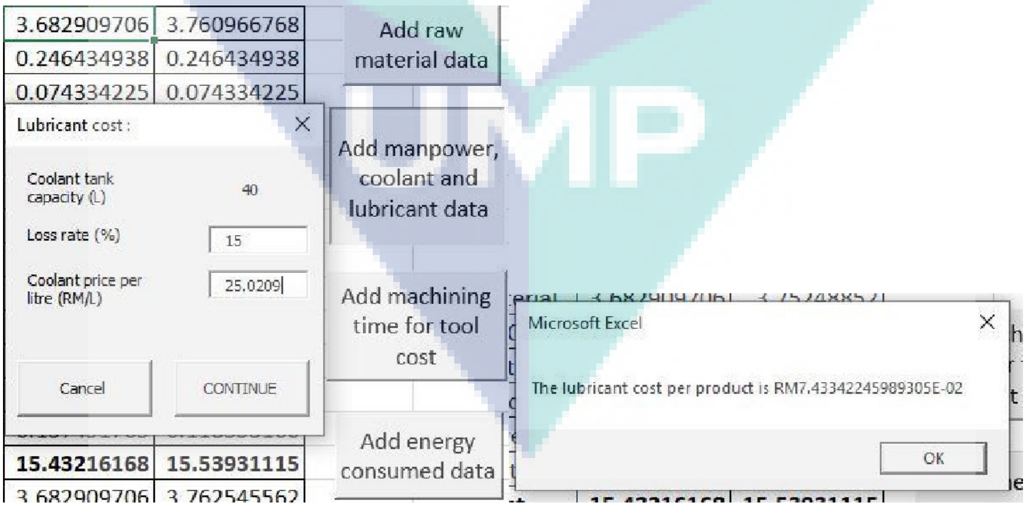


Figure 4.42 Macro by VBA Editor to evaluate lubricant cost.

In order to evaluate tool cost, on the other hand, the user needs to enter machining time for every cutting tool process; turning, drilling and boring for material Aluminium

6061 and Brass C3604. The message that shows the tool cost will pop-up after the user clicks the "CONTINUE" button. The example of data entered with the results is shown in Figure 4.43.

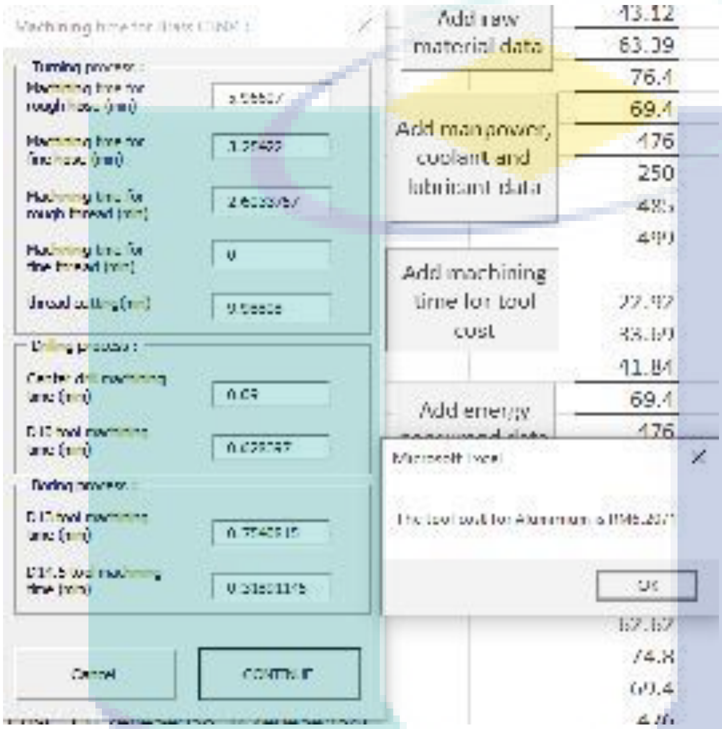


Figure 4.43 Macro by VBA Editor to evaluate tool cost.

For energy cost, VBA Editor runs the code for the macro so that the user can enter cutting speed and feed rate for every machining process. This value is needed to calculate the total energy consumed during nipple hose connector production. The energy cost will be showed up after the user clicking "CONTINUE" button. The example of the value entered with the results is shown in Figure 4.44.

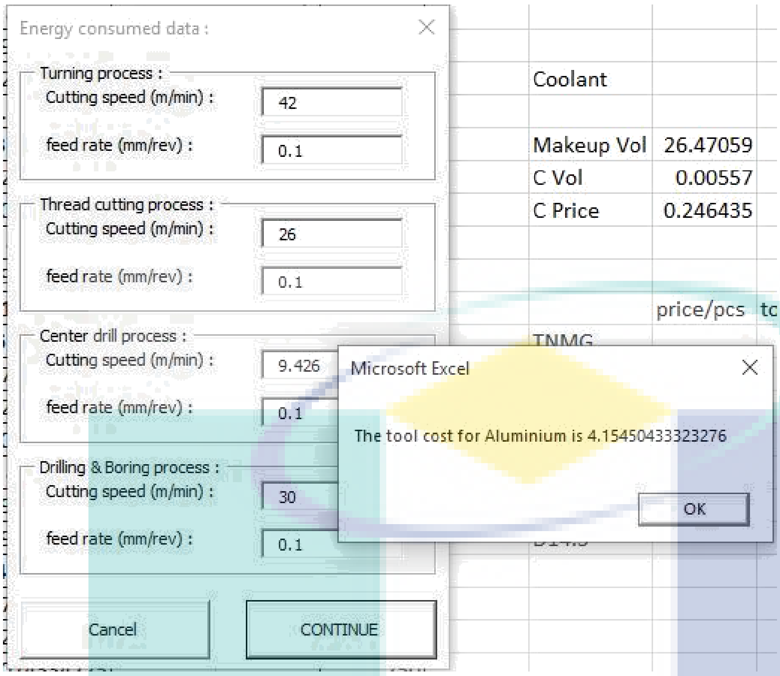


Figure 4.44 Macro by VBA Editor to evaluate energy cost.

In environmental sheet, the user just needs to click the "Check for energy impact" button or "Check for chip recycling impact" button to acquire the result. Figure 4.45 and Figure 4.46 summarize the output of macro VBA.

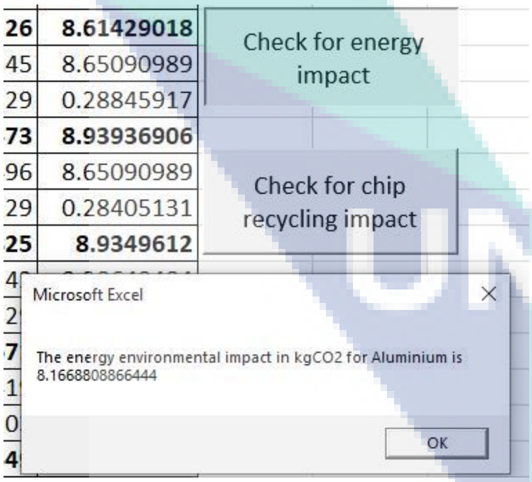


Figure 4.45 Macro by VBA Editor to evaluate energy environmental impact.

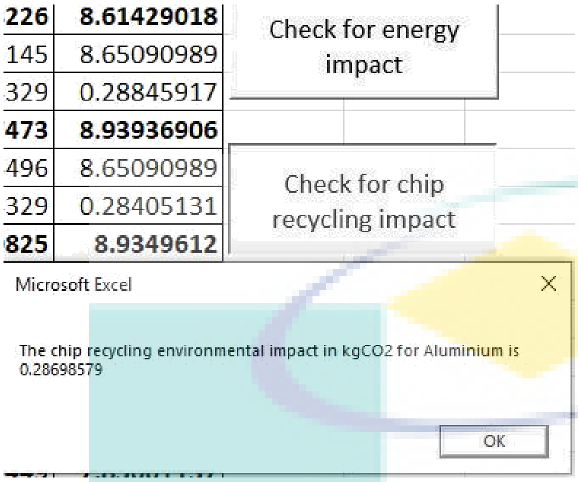


Figure 4.46 Macro by VBA Editor to evaluate chip recycling environmental impact.

Lastly, ergonomics sheet in sustainability software provides a macro button where the user needs to enter the value based on the Revised NIOSH Weight Lifting Index Equation to calculate the Lifting Index (LI). The value needed is mass of a product, HM, VM, DM, AM, FM and CM. The lifting index output will later pop-up to inform the user for the result as shown in Figure 4.47.

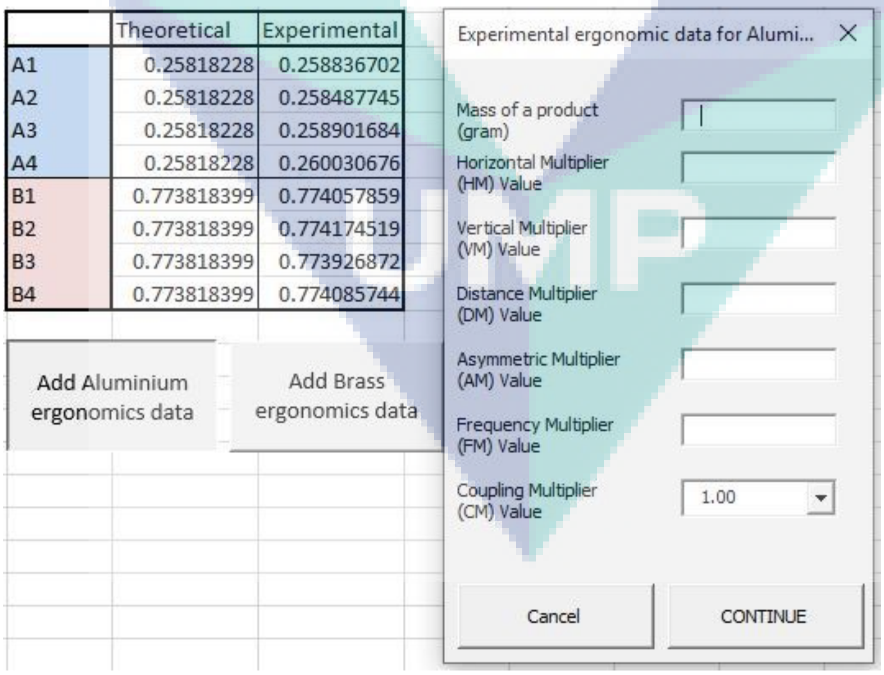


Figure 4.47 Macro by VBA Editor to evaluate ergonomics assessment.

CHAPTER 5

CONCLUSION

5.1 Introduction

This chapter presented the conclusion of the project study and the recommendation for future works that can be done to improve this research.

5.2 Conclusion

As a conclusion, the present project study successfully developed a new sustainability assessment model which can be used to select an optimum solution. This study also demonstrated the new assessment model which is suitable to apply at the production floor level. The approach used in this study is based on the integration of sustainability criteria and energy assessment using two methods, namely, theoretical assessment and experimental methods. The integration of conventional sustainability concept criteria with energy criteria is successfully done to overcome the disadvantages of the PCA concept especially for energy usage in dynamics data. Then results obtained from both method are compared to validate the results obtained whether it is reliable or not with the valid percentage error should be less than 12% (Navani et al., 2012).

The sustainability software / tool development being done in this project only covers the teoretical calculation by using microsoft excel platform. Further, the data produce can be optimised by using Matlab software which is capable to use the data produced by the sustainability tool developed.

Later on, the experimental data are employed for the development of sustainability performance model using neural network method. The experimental data are used since it includes all the energy used during the machining process compared to the theoretical assessment method. In the next step, the developed model is tested with the similar input data to make sure the predicted results mimic the experimental data with a percentage error of 5% (Kant & Sangwan, 2015).

Then, the input and output data obtained are employed for inverse calculation and another sustainability performance model is developed to obtain optimum cutting parameters (cutting speed and feedrate). To test the proposed cutting parameters, theoretical assessment and experimental methods are carried out and both results are compared to make sure the percentage error obtain is not more than 5% (Kant & Sangwan, 2015). The optimum cutting speed and feedrate is 55.25 m/min and 0.10 mm/rev for Aluminum 6061 and 82.00 m/min and 0.10 mm/rev for Brass C3604 material.

Using the proposed method, lack of sustainability performance at the manufacturing shop floor can be solved and selecting optimum cutting parameter (cutting speed and feedrate) can be done where the total manufacturing cost, the energy used during the machining process, the environmental impact and the ergonomic assessment are compromised. This method can be used to ensure the success of any companies to sustain in their business, saving the environment and provides a good living quality of the workers. The summary of the proposed manufacturing sustainability performance model is shown in Figure 5.1.

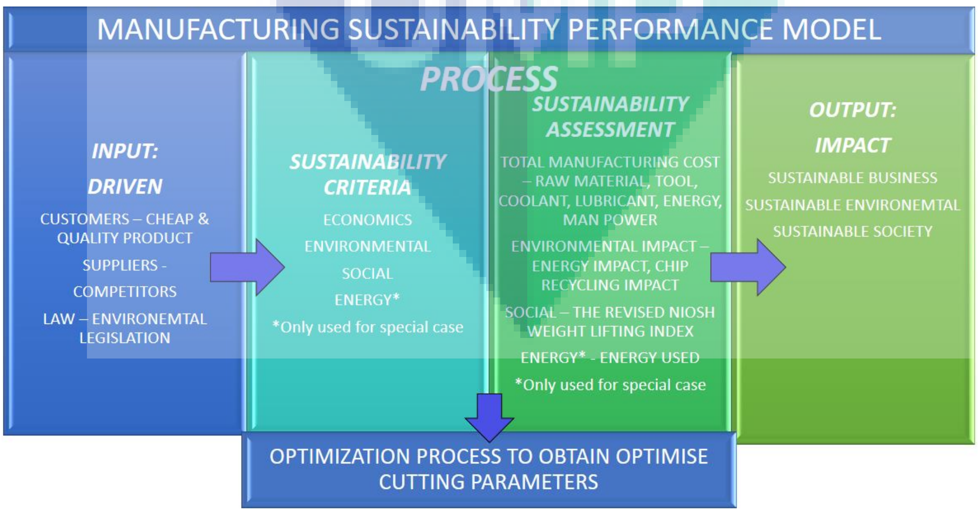


Figure 5.1 Summary of proposed manufacturing sustainability performance model

5.3 Recommendation for Future Works

There are a few things that can be done to enhance this study to obtain better results such as:

1. The machine setup parameters to collect the energy consumption data should be enhanced in order to avoid the CNC Turning machine back door opened during the machining process which it can interrupt the machining process caused by the sensors attached to the machine.

2. The machining process to collect the data need to be planned well to obtain a good energy consumption outputs. Based on the conducted experiment, there is a tendency that the energy usage data collected is different due to the change of the surrounding environment.

3. Since this project only capable to produce a basic sustainable assessment software/tool because of time constranit, for future works; this software / tool can be enhance by adding the development of neural network assessment by using microsoft excel platform.

4. The proposed evaluation method could be applied to other various machining processes, which then could help the small-medium industry in Malaysia to market their product globally after fulfilling the export government environmental legislation.

5. Company management and engineers are suggested to use appropriate assessment methods that could fit their goal and scope. This is necessary as every industry possess different problems in measuring sustainability performance. The needs to find the best assessment method to measure their product sustainability performance are crucial. Similar needs to be considered for the social criteria and the assessment methods used, where both aspects need proper selection based on major company concerns and regulatory requirements from the government.

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APPENDIX A
QUESTIONNAIRE

Sustainability Questionnaire

Sustainability concept can be defined as activities that meet the needs of the present generation without compromising the ability of future generation to meet their own needs. Sustainability also refers to the considerations of environmental, economic and social issues in the highlight of cultural, historical, retrospective, prospective and institutional perspective. There are three criteria measured in sustainability known as economic, environmental and social criteria. Economics criteria can be described as something analogous to a net financial profit or loss that can be calculated using an uncontroversial formula and used by any business firm. Environmental criteria refer to the respective company should ensure that the raw material and energy used to produce a product give less impact to the environment. Lastly, the social criteria is referring to social dimensions of a community or regional area and include life quality, access to resources, health and education. The objective of this questionnaire is to collect data from respondents regarding a suitable assessment to be used for each criterion.

1. What is your name?

   ____

2. How old are you?

   ____

3. What is your highest education background?

   a) Diploma b) Degree c) Master d) PhD e) Executive Diploma

4. Where is your current work?

   ____

5. What is your position?

   ____

6. Working experience: How many years?

   ____

7. Have you ever heard about sustainability?

   ____

8. From your opinion, which assessment method is suitable to evaluate:

a. Economics Criteria:
   1) Raw Material Cost
   2) Energy Cost
   3) Tooling Cost
   4) Lubricant Cost
   5) Coolant Cost
   6) Man Power (Salary) Cost
   7) Others (reason):

   ____

b. Environmental Criteria:
   1) Water Pollution
   2) Land Pollution
   3) Air Pollution
   4) Energy Impact
   5) Coolant Impact
   6) Lubricant Impact
   7) Cutting Tool Impact
   8) Chip re-cycling Impact
   9) Others (reason):

   ____

c. Social Criteria:
   1) Salary
   2) Medical Certificate
   3) REBA
   4) RULA
   5) The Revised NIOSH Weight Lifting Index
   6) Others (reason):

   ____

Thank you for your co-operation

APPENDIX B
PUBLICATION PAPER

Sustainability performance model: A case study of pneumatic nipple hose connector

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Abstract. Sustainability concept was first introduced by Dr Harlem Brundtland in 1980's promoting the need to preserve today's mother nature for the sake of our future generations. There are three main evaluation criteria's involved in sustainability approach namely economics, environmental and social. In consumer product manufacturing industry, the economics criteria are measured by consider the total manufacturing costs where it evaluates the economic sustainability of a company in a long term. The impact to the environment during manufacturing process can be used to measure the environment criteria. The social criteria are complicated to evaluate. But focusing at production line workers' health who works at the production line can be used to evaluate the social criteria because it gives direct impact to their performance. In this paper, the sustainability concept is applied at the production line in the production of a pneumatic nipple hose connector. The evaluation criteria which has been considered are total manufacturing costs, environmental impact, ergonomics impact and also energy used for manufacturing. This study involves machine learning optimization by using neural network model which carried out in two stages. The first stage is to predict the results based on experimental works. The second stage is by using inversed neural network model to determine the optimum cutting parameters so that it can be used to manufacture the pneumatic nipple hose connector. Through these stages, optimization of the manufacturing procedures to produce pneumatic nipple hose connector already considered the criteria for sustainability.

Keywords. Sustainability; Economics; Environmental; Social and performance model.

1. Introduction

Sustainable development concept was introduced by Harlem Brundtland in 1980's after he witnessed the consequence of industrialization to the nation, environmental and impact to the community. She defined sustainable development as meeting the needs of the present generations without compromising the ability of future generations to fulfil their own needs [1]. To achieved sustainability, a company must strive to operate efficiently according to the three pillars of susainability namely economical, environmental and social [2].

In order to fulfil the three pillar of sustainability, manufacturing company need to ensure that their company operates with minimal impact to the enviroment, produce a good quality of social life with a minimal cost to produce a product (1). When producing a product, the impact to the environment, community (social) and also the economics of the production for the product need to be measured and optimised in order to achieve the sustainbaility state (2).

Many researchers have put lots of effort to measure sustainability [3]. However, only some of the theoretical works [4, 5] were appropriately documented. For example, Harik [3] stated that among the indicator which has been used to measure economics are money waste, branding strategy, foreign labor percentage and customer satisfaction. On the other hand, Green House Gas (GHG) emissions, water consumption, land used, environmental fines, energy usage and waste treatment method can be used as environmental indicators. Lastly for social indicators, among of the indicators are average salary, employee ergonomics consideration, gender and average time employee work with the company.

Dubey et al. [6] stated that among the indicators which can be used to assess economics are economical perspective, technology transfer and production and manufacturing technologies. Among the indicators which have been used to assess environmental are design for environment, energy conservation, government legislation and life cycle assessment; while for social indicators, the assessment method can be used are society perspective, health perspective and ergonomics factor.

Therefore, further study is required so that an alternative way could be proposed to obtain the relationship between each pillar (criterion) in sustainability as demonstrated in the present study. Additionally, the optimization study not only based on the theoretical determination method but also include data generated from experimental work as a validation which is shown in this study.

2. Literature Review

Sustainability refers to the considerations of environmental, economic and social issues to highlight the cultural, historic, retrospective, prospective and institutional perspective [7]. During the production of a product, manufacturer needs to minimize the impact to the environment and strive for sustainable facilities management which enables building and working areas to be more efficient in terms of minimizing waste and resource [3]. Sustainability also can be defined as creation of manufactured goods through the use of a series of manufacturing process that minimize the negative impact to the environment, conserve energy and natural resources which are safe for employee to handle with minimal impact [6].

Susainability can be divided into three criteria known as economical, environmental and social [2]. There are a few indicators that can be used to assess sustainability economically, for example, money waste, branding strategy, foreign labor percentage and customer satisfaction. For environmental, the criteria that can be used for consideration are GHG emissions, water consumption, land use, environmental fines, energy usage and waste treatment method (1, 3). Lastly for social criteria, among of the indicators are average salary, employee ergonomics consideration, gender and average time employee work with the company (2).

Economics criteria can be described as something analogous to a net financial profit or loss that can be calculated by using the uncontroversial formula that could be used by any business firm [8]. Economics criteria can be referred to Life Cycle Costing (LCC) where it can be defined as a methodology where cost of a given product / asset is considered throughout their life cycle [9]. Another definition of LCC is a summation of all costs related to the production of a product such as material cost, tool cost, energy cost and labor cost [4]. These costs can be represented as total manufacturing cost as shown in equation (1).

Total manufacturing cost (RM) = Material cost + Tool cost + Energy cost + Labor cost + Coolant Cost (1)

where:

Material Cost = Standard size price (RM/gram) x required size (gram) (2)

Tool Cost = Tool cost (RM/point) x (Tool contact time / tool life) (3)

Energy Cost = Amount of energy used to machining a product (kWh) x commercial electrical tariff (RM/kWh) (4)

Labor Cost = Monthly Salary / number of product produce per month (5)

Makeup volume = (Coolant tank capacity x coolant loss rate) / (1-Coolant loss rate) (6)

Coolant volume = (Coolant tank capacity (L) + Makeup Volume) / (month used x actual output) (7)

Coolant Cost = (Coolant volume x Coolant cost (RM/L)) (8)

In environmental impact criteria, one of the assessment can be used is to ensure that the raw material being used has less impact on the environment (4). It can be assessed by using the Life-cycle assessment (LCA) method. LCA is an attempt to quantify the overall environmental and economic impact in terms of material and energy consumption during the manufacturing process, carbon footprint, etc. Environmental impact assessment in a production line can be calculated by using the amount of carbon released into the environment which consider the impact of producing raw materials, energy consumed to process raw materials into finished product, scrap produced during the manufacturing process and disposal of tools, coolant and lubricant used during manufacturing process (2). On the other hand, Narita et al. (5) stated that environmental impact also can be measured by using energy consumption impact, coolant impact, lubricant impact and chip recycling impact by using equation (9) - (12).

$$Ee = LCI(e) \times (PSm + PFM + \sum PP) \tag{9}$$

where E_e is machine power consumption impact; *LCI (e)* is electricity emission intensity; *PSm* is spindle motor power consumption; *PFM* is feed motor power consumption; ΣPP is peripheral device power consumption.

$$C_e=[(LCI(cp))+LCI(cd)\times Tc+LCI(w)\times Tw]\times[Mt/MTTR] \tag{10}$$

where C_e is coolant impact consumption; *LCI (cp)* is coolant production emission intensity; *LCI (cd)* is coolant disposal emission intensity; *Tc* is total coolant amount; *LCI (w)* is water distribution emission intensity; *Tw* is total water amount; *Mt* is machining time and *MTTR* is Mean time to replenish coolant.

$$LOe = [Mt/MTTD] \times Ld \times (LCI(lp) + LCI(LD)) \tag{11}$$

where LO_e is lubricant oil impact consumption; *Mt* is moving parts running time; *MTTD* is mean time to discharge lubricant; *Ld* is amount of lubricant discharge; *LCI (lp)* is lubricant production emission intensity; *LCI (LD)* is lubricant disposal emission intensity.

$$Ch_e = (WpV - pV \times LCI(M) \tag{12}$$

where Ch_e is chip recycling impact; *WpV* is workpiece volume; *pV* is product volume; *d* is material density; *LCI (M)* is metal chip recycling emission intensity.

Social criteria refer to social dimensions of a community or regional area and could include quality of life, access to resources, health and education (6-9). When implement it at the production floor level, social criteria can be assessed by using ergonomics assessment methods which consider human safety in the production line and societal benefit (2). According to the Department of Safety and Health (DOSH) Malaysia (10), manufacturers are responsible to create a safe and healthy working environment taking into consideration injuries, illumination, noise level and safety protection. Based on the statement, among the social criteria assessment methods that can be used are number of injuries occur, illumination level, noise level and NIOSH Revised Weight Lifting Index.

The revised National Institute of Occupational Safety and Health (NIOSH) weight lifting index was introduced in 1993 purposely to identify the hazardous lifting activity and as an attempt to minimize the hazards (11). The equation used in the evaluation is shown in equation (13) and (14).

$$\text{Lifting Index (LI)} = \text{Load weight (kg)} / \text{Recommended Weight Limit} \tag{13}$$

$$\text{Recommended Weight Limit} = LC \times HM \times VM \times DM \times AM \times FM \times CM \tag{14}$$

where *LC* is load constant = 23kg; *HM* is Horizontal Multiplier; *VM* is Vertical Multiplier; *DM* is Distance Multiplier; *AM* is Asymmetric Multiplier; *FM* is Frequency Multiplier, and *CM* is Coupling Multiplier and their values can be obtained by referring to the tables 1.

There are many tools developed by non-profitability organizations or private companies with the aim to evaluate their product in terms of sustainability and environmental impact. The U.S Environmental Protection Agency has come out with Electronics Product Environmental Assessment Tool (EPEAT) and Energy Tracking Tool (ETT) evaluation tools to help their industry to evaluate their product sustainability [18].

Sustainable Manufacturing Toolkit was developed by Organization for Economic Co-operation and Development (OECD) with the aim to provide a practical starting point for businesses around the world to improve the efficiency of their production processes and products enabling them to contribute to sustainable development and green growth. The Cambridge University have come out with Cambridge Sustainable Design Toolkit which designed to provide both a theoretical learning experience as well as action based support [19].

Currently, there are a few sustainable or environmental impact software's available in the market developed by private organization for example Eco-It and SimaPro software. Eco-It software was developed by Pre Sustainability [20]. This software is suitable to be used when mass production data is involved and the results will be presented as carbon emission (kg CO2 or Pt). On the other hands, SimaPro provides a tool to collect, analysed and monitor the sustainability performance of products and services. SimaPro is integrated with various databases and impact assessments, and used for a variety of LCA applications such as Carbon footprint, Water footprint, Product design and eco-design (DfE), Environmental Product Declarations (EPD) and Determination of key performance indicators (KPIs) [21].

Neural network is a mathematical model that tries to simulate the functionality of biological nervous system [22]. The system consists of a group of interconnected neurons and process information by using a connectionist approach to computation [23]. Neural network is an adaptive system that change its structure based on the given information in terms of data either based on internally or externally that flows in the network during the learning phase [22]. Neural network can be used to model complex relationship between inputs and outputs or vice versa to find patterns in the data set [23].

There are three basic rules in developing the mathematical model which known as multiplication, summation and activation [22]. Each inputs value in neural network will be multiplied with a specific weight. These weight inputs will be added with a bias term and both weights will be transformed using an activation function to compute the output. According to Mohamed [22], the weight that associated with each inputs provide the strength of the synapse. The higher the strength of synapse value means the stronger the input.

One of the major problem faced by researchers who used neural network technique are to determine the right number of hidden neuron to be used so that their developed mathematical model will not be either under fitting or over fitting [24, 25]. Sheela and Deepa [25] added, there are a few methods proposed by researcher to determine the correct number of hidden neurons, but most of them based on trial on rule. Besides that, they also review a few other methods to determine the number of hidden neuron from other researchers starts from the year 1995 to 2013. In their paper, Sheela and Deepa [25] presents their proposed method on how to determine the number of hidden neuron as shown in Equation (15) where n is the number of inputs.

$$N_h = \frac{(4n^2+3)}{(n^2-8)} \tag{15}$$

According to Baghirli [26], there are three learning algorithm that can be used to train the collected data in order to obtain the mathematical model in the Matlab Software. They are Lavenberg-Marquardt backpropagation algorithm, Scaled Conjugate Gradient algorithm and Bayesian Regularization algorithm.

Lavenberg-Marquardt backpropagation algorithm was developed by Kenneth Lavenberg and Donald Marquardt where it provides a numerical solution to minimize a non-linear function problem [27]. This algorithm is suitable to be applied to the small and medium size problems where it can process very fast and has a stable convergence.

Baghirli added, the conjugate gradient algorithm adjusted the step size in each iteration where the step size is determined by the search made along the conjugate gradient direction where it directly minimize the function performance along the line. Bayesian regularization algorithm update the weight and bias values according to Lavenberg-Marquardt optimization [26]. He added that this algorithm minimizes a combination of squared errors and weights and then determines the correct combination to produce a generalized network

3. Methodology

The steps taken in conducting these study were adopt from Maxim [28] and modified accordingly where the process flow chart are shown figure 1. This study starts with identifying a set of manufacturing process to be assessed based on the existing literature review. From there, all relevant indicators were identified for each of the criteria involved. At the same time, informal discussions with engineers in a few companies were conducted to get their opinion on the relevant sustainability indicators to be used at the production floor. Based on their feedback, the indicator selection outcomes are measurable, independent, consistent and comparable.

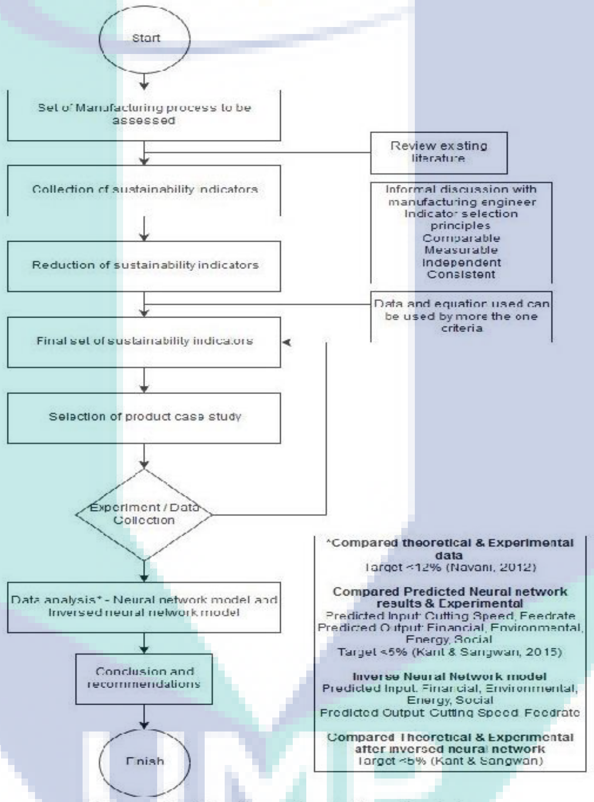

Figure 1. The flow chart of methodology.

The next step is to reduce the number of indicators that can be applied at the production floor. Here, engineers who involved in the informal discussion were asked to select the best indicator to be used in this study as a final decision. The product case study selected is Pneumatic nipple hose connector as shown in figure 2. This product was selected because the demand is high and it has been used in many industries to connect high compressed air hose for multi-purpose usage [1].

Figure 2. Pneumatic nipple hose connector.

The machining process involved are rough and fine turning; thread turning; center drill and drilling of three different holes' size by using CNC turning machine. The tool used for rough and fine turning process is TNMG160408, VCMT160404 and 16ERG60. The tool used for drilling is the center drill diameter 3.0 mm, drill diameter 10.0 mm, 13.0 and 14.5 mm with feed rate of 0.1 mm/rev and cutting speed of 30 m/min for drilling process and 9.426 m/min feedrate 0.3 mm/rev and depth of cut of 3.00 mm for center drill. Lastly, for thread operation, both cutting and thread depth is 0.25mm while the cutting speed is 30 m/min. Machining parameters used for turning process in this study follows recommendation from Kalpakjian and Schmid [29] and also recommendation by the tool manufacturers as shown in table 1.

Table 1. Machining parameters used.

Option	Description
1	Cutting Speed: 42m/min; Feedrate: 0.1mm/rev; Depth of Cut: 0.50, 0.25mm
2	Cutting Speed: 42m/min; Feedrate: 0.2 mm/rev; Depth of Cut: 0.50, 0.25mm
3	Cutting Speed: 83m/min; Feedrate: 0.1mm/rev; Depth of Cut: 0.5, 0.25mm
4	Cutting Speed: 83m/min; Feedrate: 0.2 mm/rev; Depth of Cut: 0.50, 0.25mm

There are three sustainability criteria known as financial, environmental and social criteria. Based on the engineer selection, the total assessment method being used is four where total manufacturing cost assessment will be used for financial criteria, environmental impact and energy assessment will be used for environmental criteria and The NIOSH revised weight lifting index for social criteria. The first criteria to be evaluated is financial criteria. Here, the total manufacturing cost approach was adopted because it represents the cost needed to produce a pneumatic nipple hose connector. The calculation method was modified from Zhang & Haapala [4] as shown in equation (1) with lubricant cost was added as shown in equation (16).

$$\textit{Total manufacturing cost} = \textit{Material cost} + \textit{Tool cost} + \textit{Coolant cost} + \textit{Lubricant cost} + \textit{Energy cost} + \textit{Labor cost} \tag{16}$$

The method to determine the material, tool, coolant, energy and labor cost are shown in equation (2) – (8); while calculation to determine the lubricant cost can be adopted from equation (6) – (8).

The second criteria are environmental. According to Narita et al [30], environmental assessment in a production line consists of cutting tool impact, chip recycling impact, disposal of coolant and lubrication impact; and energy impact. In present study, only chip re-cycling impact and energy impact is considered because according to Dahmus and Gutowski [31] the number of chips being produced when using one same cutting tool is higher compared to the weight of a cutting tool; hence it can be neglected. The same situation happened for coolant and lubricant usage where it only change when doing periodically maintenance from 3 to 6 months.

The chip recycling impact is assessed from Narita et al. (12) as shown in equation (12). The energy impact for CNC turning process is given by equation (17) - (21) as adopted from Sanvik Coromant (13):

$$P_{c\ turn}=((V_C \times a_p \times f_n \times K_c)/60000) \tag{17}$$

$$P_{c\ drill}=((V_C \times a_p \times f_n \times K_c)/240000) \tag{18}$$

$$P_{c\ boring}=((V_C \times a_p \times f_n \times K_c)/60000) \times (1-(a_p/D_c)) \tag{19}$$

$$\sum P_{c\ Total} = \sum P_{c\ turn} + \sum P_{c\ drill} + \sum P_{c\ boring} \tag{20}$$

$$E_e = \sum P_{c\ total} \times 0.747\ kgCO_2 \tag{21}$$

where P_{c_turn} is power required to perform training; P_{c_drill} is power required to perform drilling; P_{c_boring} is power required to perform boring; $\sum P_{c\_total}$ is the total power used in the machining process; E_e is total energy impact in (kgCO2); Vc is cutting speed (m/min); a_p is depth of cut (mm); f_n is federate (mm/min); K_c is Specific cutting force (N/mm2) for Brass C3604 is 550 and Dc is drill diameter. The second assessment for environmental is energy used during the machining process. The data can be obtained by using equation (17) to (20).

The third criteria are social equity. In this study, ergonomic assessment is considered since it is related to human machine interaction especially in the production floor level. The main reason for choosing ergonomic assessment is because it reflects the immediate impact on labor at the production floor [33]. The assessment is based on the revised Lifting Equation with some modification as proposed by Muslim et al. [34] specifically for south east asia male worker, where the evaluation method is based on equation (13) and (14).

After each of the cutting parameter results have been determined theoretically, a series of experiment are conducted by using Brass C3604 material and all the criteria assessment data were collected. The first analysis being done is comparing the theoretical data with the experimental data. The maximum percentage of error taken at this stage is less than 12% following work which was carried out by Navani [35]. Then, by using the experimental data and Neural Network method in Matlab software, the predicted neural network model is obtained and tested to check the predicted neural network model results. At this stage, the inputs are cutting speed and feedrate while the outputs are total manufacturing cost, environmental impact, energy and The NIOSH Revised weight lifting index. The equation used to determine the number of hidden neurons follows Sheela & Deepa [25] as shown in equation (15). The percentage of error targeted is less than 5% follows Kant & Sangwan [36] since it only compared the experimental data with the predicted neural network data.

The next thing to do is to obtain the optimised cutting parameters. In order to do that, the predicted neural network model need to be inversed like the work which was done by Cortes [37]. At this stage, the inputs will be the total manufacturing cost, environmental impact, energy and the NIOSH Revised weight lifting index while the output is cutting speed and feedrate. The cutting parameters results were then used in both of theoretical calculation and the experimental method to obtain the final answers and being compared with targeted error of less than 5 %.

4. Results and discussion

Figure 3 to 6 shows the comparison results for theoretical, experimental data and predicted neural network model data while table 2 to 5 shows the values for each data.

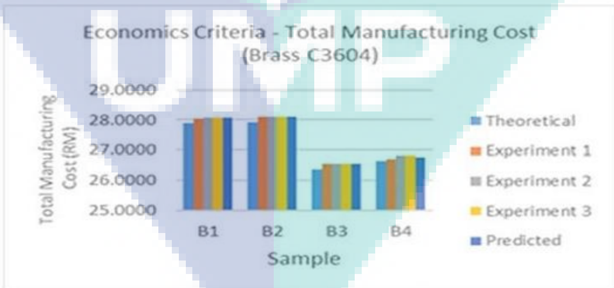

Figure 3. Total manufacturing cost comparison for Brass C3604.

Table 2. Total manufacturing cost comparison data for Brass C3604.

Sample	Theory	Exp 1	Exp 2	Exp 3	Predicted
B1	27.8839	28.0557	28.0609	28.0726	28.0583
B2	27.9046	28.1005	28.1009	28.1011	28.1007
B3	26.3701	26.5517	26.5607	26.5583	26.5562
B4	26.6279	26.7094	26.8254	26.8359	26.7727

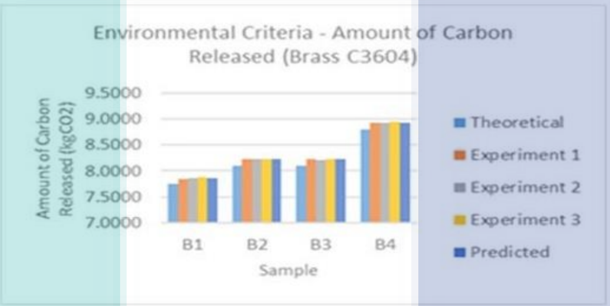

Figure 4. Amount of carbon released for Brass C3604.

Table 3. Amount of carbon released data for Brass C3604.

Sample	Theory	Exp 1	Exp 2	Exp 3	Predicted
B1	7.7423	7.8500	7.8561	7.8740	7.8531
B2	8.0982	8.2342	8.2273	8.2361	8.2307
B3	8.0897	8.2204	8.2157	8.2224	8.2181
B4	8.7930	8.9294	8.9262	8.9331	8.9312

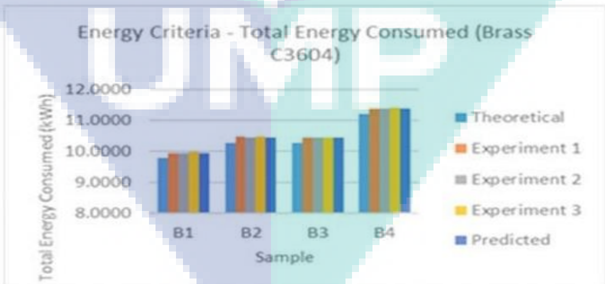

Figure 5. Total energy consumed for Brass C3604.

Table 4. Total energy consumed data for Brass C3604.

Sample	Theory	Exp 1	Exp 2	Exp 3	Predicted
B1	9.7900	9.9365	9.9443	9.9664	9.9404
B2	10.2664	10.4513	10.4406	10.4538	10.4459
B3	10.2551	10.4306	10.4240	10.4331	10.4273
B4	11.1966	11.3805	11.3758	11.3861	11.3832

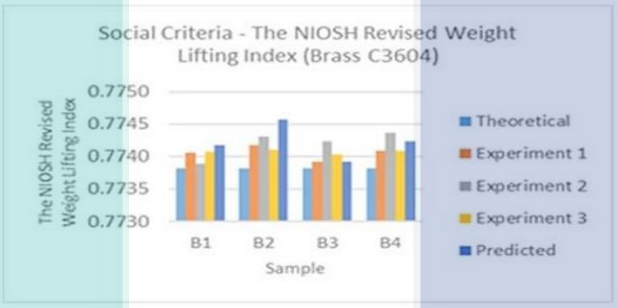

Figure 6. The NIOSH revised weight lifting index for Brass C3604.

Table 5. The NIOSH revised weight lifting index data for Brass C3604.

Sample	Theory	Exp 1	Exp 2	Exp 3	Predicted
B1	0.7738	0.7741	0.7739	0.7741	0.7742
B2	0.7738	0.7742	0.7743	0.7741	0.7746
B3	0.7738	0.7739	0.7742	0.7740	0.7739
B4	0.7738	0.7741	0.7744	0.7741	0.7742

According to the results based on cutting parameter (figure 3), the higher the cutting speed, the manufacturing cost will be lower, but the energy used (figure 5) and the environmental impact produced (figure 4) is higher in experimental results compared to theoretical results. This phenomenon has already been explained by Kalpakjian and Schmid [29] in their book which stated that as the cutting speed and feed rate increased, the energy used to machine the pneumatic connector will be higher and it will reflect the environmental impact contributed by the consumed energy [29]. Sometimes the chip produced during machining gets stuck and curled at the area of machining near the cutting tool which require the machining process to be stopped to remove the chips. These situations will contribute to higher amount of energy used since more machining time are needed. In addition, while the machine is idle for troubleshooting period, energy is being used too at this time. When the cutting speed increased, the total manufacturing cost will be lower because the time needed to complete the machining process is getting shorter and it directly reflects the reduction of the tool cost which contributes directly to the total manufacturing cost.

The ergonomics assessment by using the revised NIOSH weight lifting index results shows a scatter patterns for Brass C3604 materials. The range is from0.7739 to 0.7744. This happened because of the weight of the raw material used in the study. Theoretically, the raw material length was kept fixed at 5.50 cm and the weight calculated is 260.8031 gram; but when the raw material weight was determined experimentally by using the digital weight scale, the weight range is between 260.8297 to 261.0176 gram. Overall, the percentage difference between experimental and theoretical is less than 12%.

Predicted results are obtained by using the neural network model generated by using Matlab software. Here, only the experimental data have been used to generate the neural network model because in experimental data, the energy used during machining already considered dynamic movement of electricity where in the theoretical calculation the electricity movement is assumed same all the time.

Two inputs are being used in the development of neural network prediction model; cutting speed and feed rate. The number of hidden neuron used in this study is 5 which determined by using equation (15). The training algorithm used in this study is Lavenberg – Marquardt algorithm because it requires less time to compute and the training process is automatically stopped when generalization stop improving. The regression R (R squared) value for Brass C3604 material is 0.999998 for training, 0.999999 for validation and 0.999998 for testing which are desirable; while the mean square error (MSE) value for training is 2.57715 x e^{-4}, for validation is 1.72072 x e^{-4} and for testing is 3.68821 x e^{-4}.

Based on all four evaluated criteria, the percentage difference is less than 5%. This result is similar to the finding as reported by Kant & Sangwan [36]. Therefore, the neural network model which has been designed in this work can be concluded as valid to be used to predict the manufacturing cost, environmental impact, energy used and the NIOSH weight lifting index assessment for the four criteria.

The inversed neural network model can be done by changing the input to output and vice versa to obtain the optimum cutting speed and feedrate [37]. The number of inputs used at this stage is four because there are four criteria assessment involved, training algorithm used is Lavenberg – Marquardt and the number of hidden neuron used is 9. Since this study try to minimize all the four criteria, each minimum value for all criteria is set as an input based on predicted results where the input values used are shown in table 6.

Table 6. Input values used for the inversed neural network model.

Material	Manufacturing Cost (RM)	Energy (kWh)	Environmental (kgCO2)	Ergonomics (Index)
Brass	26.5562	9.9404	9.9404	0.7739

The regression R (R squared) value is 0.999999 for training, 0.999997 for validation and 0.999980 for testing which is desirable; while the mean square error (MSE) value for training is 3.26640 x e^{-5}, for validation is 8.74443 x e^{-3} and for testing is 1.84663. The proposed results for optimization of cutting speed and feed rate is 82.00 m/min and 0.10 mm/rev. Then, the optimized cutting parameters will be used to calculate the four criteria results theoretically and at the same time another experimental work was conducted to verify and validate the proposed optimization cutting parameter. The results are shown in table 7.

Table 7. Theoretical and experimental results based on optimum cutting parameters.

Method	Manufacturing Cost (RM)	Energy (kWh)	Environmental (kgCO2)	Ergonomics (Index)
Theory	26.3896	10.2437	8.0812	0.7738
Experiment	26.5568	10.3861	8.1871	0.7739

Based on the proposed optimized cutting parameters in the experimental assessment method, the manufacturing cost, energy, environmental impact and ergonomics results falls between the range of minimum and maximum results for each criteria as predicted at the early stage in the theoretical method.

5. Conclusions

This study managed to develop an approach for assessing sustainability performance, focuses on the production floor level. The approach for integrated sustainability assessment and decision making using a general common sense to solve the manufacturing shop floor problem especially in selecting a good cutting parameters. These cutting parameter can optimize the total manufacturing cost, the energy used during machining process, the environmental impact and reduce the ergonomics criteria index in order to make sure the company can sustain in their business, saving the environment and gives human a good living quality.

Acknowledgement
The authors are most grateful to Research Management Center (RMC), Universiti Malaysia Pahang (UMP) for the funding of the research under RDU1703215.

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