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 sustainability 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].

Sustainability 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).

\[
\text{Total manufacturing cost (RM)} = \text{Material cost} + \text{Tool cost} + \text{Energy cost} + \text{Labor cost} + \text{Coolant Cost}
\] (1)

where:
\[
\text{Material Cost} = \text{Standard size price (RM/gram) x required size (gram)}
\] (2)
\[
\text{Tool Cost} = \text{Tool cost (RM/point) x (Tool contact time / tool life)}
\] (3)
\[
\text{Energy Cost} = \text{Amount of energy used to machining a product (kWh) x commercial electrical tariff (RM/kWh)}
\] (4)
\[
\text{Labor Cost} = \text{Monthly Salary / number of product produce per month}
\] (5)
\[
\text{Makeup volume} = (\text{Coolant tank capacity x coolant loss rate}) / (1-\text{Coolant loss rate})
\] (6)
\[
\text{Coolant volume} = (\text{Coolant tank capacity (L) + Makeup Volume}) / (\text{month used x actual output})
\] (7)
\[
\text{Coolant Cost} = (\text{Coolant volume x Coolant cost (RM/L)})
\] (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).

$$E_e = LCI(e) \times (PSm + PFM + \sum PP)$$

where $E_e$ is electricity emission intensity; $LCI (e)$ is electricity emission intensity; $PSm$ is spindle motor power consumption; $PFM$ is feed motor power consumption; $\sum PP$ is peripheral device power consumption.

$$C_e = \left\{ \frac{(LCI(cp)) + LCI(cd) \times Tc + LCI(w) \times Tw}{Mt/MTTR} \right\} \times [Mt/MTTD]$$

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.

$$LOe = \left\{ \frac{Mt}{MTTD} \times Ld \times LCI(lp) + LCI(LD) \right\}$$

where $LOe$ 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.

$$Che = (WpV - pV \times LCI(M))$$

where $Che$ 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).

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

$$Recommended \ Weight \ Limit = LC \times HM \times VM \times DM \times AM \times FM \times CM$$

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.

\[
N_h = \frac{(4n^2+3)}{(n^2-8)}
\]

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 feed rate 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).

\[
\text{Total manufacturing cost} = \text{Material cost} + \text{Tool cost} + \text{Coolant cost} + \text{Lubricant cost} + \text{Energy cost} + \text{Labor cost}
\]  

(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):

\[
P_{e, \text{turn}} = \frac{(V_C \times a_p \times f_s \times K_c)}{60000}
\]  

(17)

\[
P_{e, \text{drill}} = \frac{(V_C \times a_p \times f_s \times K_c)}{240000}
\]  

(18)

\[
P_{e, \text{boring}} = \frac{(V_C \times a_p \times f_s \times K_c)}{60000} \times (1 - \frac{a_p}{D_c})
\]  

(19)

\[\sum P_e = \sum P_{e, \text{turn}} + \sum P_{e, \text{drill}} + \sum P_{e, \text{boring}}\]

(20)

\[E_e = \sum P_{e, \text{total}} \times 0.747 \text{ kgCO}_2\]

(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; \( \Sigma P_{c \_total} \) is the total power used in the machining process; \( E_e \) is total energy impact in (kgCO2); \( V_c \) 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/mm²) for Brass C3604 is 550 and \( D_c \) 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.](image-url)
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 from 0.7739 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.

| 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 8.74443 x e^-3, for validation 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.

| 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.

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