MULTI-OBJECTIVE OPTIMIZATION TO REDUCE ENERGY CONSUMPTION AND TO IMPROVE SURFACE QUALITY OF BOVINE HORNS IN MACHINING PROCESS

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Abstract
Efficiency in manufacturing sector is one of the major challenge due to it has great impact on environment. Machining process is a vital part in manufacturing sector in term of product creation. In most of the cases large amount of energy and resource consumed by machining process and it leads environment pollution. For the sustainable goals, it is important to reduce energy consumption in this process. At the same time, it is required to achieve product specifications objective. In addition, machining process extended beyond the regular practice. Natural material could have open the door for future product development. Bovine horn is one of the promising material that is environment friendly and sustainable. Therefore, in this study, a multi-objective optimization process has been employed in order to reduce energy consumption and surface roughness for bovine horns using Taguchi and Artificial Neural Networks (ANN). Face milling process has been performed for the data collection. There were 3 cutting parameters has been take into account for the optimization. The cutting parameters are depth of cut, spindle speed and feed rate. Firstly, the energy consumption data has been taken by using direct method with a watt meter. After that the machined bovine horn part has been used for measuring surface roughness using surface tester. The results indicates the influence of cutting parameters in energy consumption and surface roughness. For the energy consumption spindle speed has the significant influence. For the surface roughness, mixed condition found that influence in the process. The optimum value of machining parameters is obtained by feed rate 155mm/min., Spindle speed 1400rpm and 2mm for the depth of cut. In addition, a 3-25-2-2 ANN architecture provided the highest accuracy that was 95%. The output of this research can be utilized for further development of bovine horns industrial applications.

Keywords: Bovine horns, Natural Material, Artificial Neural Networks, Industrial Applications, Green Manufacturing.

1. Introduction

Optimization of energy consumption in machining has a high priority in manufacturing sector in term of reducing cost and the impact on environment. In most of the cases, a large amount of energy and resource consumed by the manufacturing processes and that leads environmental emission. In the Figure 1, shows the consumption of energy in various manufacturing processes[1] where machining process consume highest amounts of energy per unit among the others. It is shows a strong relationship between energy and machining process. Due to reduction of energy consumption beneficial for economy and to improve the environmental impact on the manufacturing process; therefore, to achieve sustainable manufacturing goal, reducing energy consumption in machining is an important factor[2].

There is a high demand in the machining process to have better surface finish with minimum processing time and energy. In addition, better surface roughness is compulsory for the sustainable machining process performance. Defect of surfaces cause much more product failures. As a result, it is worthwhile that the problems are pointed out. Moreover, it is well known that the reliability of the surface and quality of the product heavily affects the functional performance of the product[3]. Therefore, it is important to maintain the surface quality in term of better product performance.

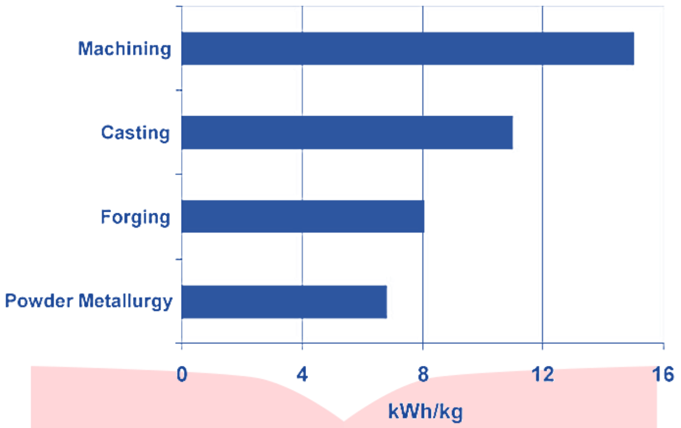

Figure 1. Consumption of energy in different manufacturing process[1]

Surface roughness and energy consumption heavily influenced by machining parameters. When surface roughness decrease, then the process consumed higher energy. Figure *2* shows that surface roughness decreased by increasing spindle speed and logically higher spindle speed is the indication of higher energy consumption. Furthermore, increase in feed rate results high MRR that makes machining faster with less processing time. It is indicates the interaction between surface roughness and energy consumption in machining process due to different cutting parameters. For that reason, optimizing the parameters is essential to balance between good surface quality with relatively small energy consumption.

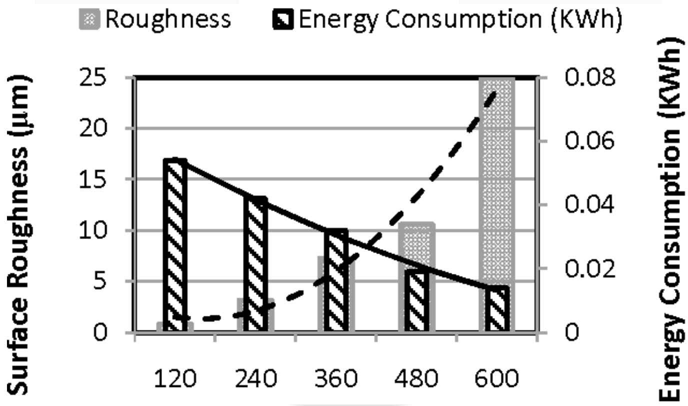

Figure 2. Correlation between surface roughness and energy consumption; Pervaiz et al. (2013)

The issue of optimizing machining parameters with ultimate goals of reducing energy consumption and maintaining surface quality refers to the characteristic of multi-objective optimization. A multi-objective optimization works together with the collection of objective functions, which is systematic and simultaneous. Two types of approaches are used in the development of multi-objective optimization model namely conventional and non-conventional. As machining operation is a very complex process where different types of parameter are involved, therefore it is essential to develop a comprehensive model involving all parameters in the machining process. Recently, numbers of research has carried out using artificial intelligence techniques as an alternative of non-conventional way[5][6][7][8][9][10].

ANN is the most desired technology that uses in many different types of engineering applications including optimization of cutting parameters[11]. ANN model is works with the functions of human brain neurons. This network consist of few elements. For propagating signals through the network, there are weighted interconnections, Processing units, activation rule. ANN have ability to learn and develop model of non-linear complex relationship that is common in real life application[12]. Overall, stated advantages are makes ANN most suitable for specific problems solution and so current study is expected to utilize the capability of ANN algorithm in optimizing machining parameters of a unique material.

Having said that the characteristic and properties of bovine horns that may suit other industrial applications, flexibility in performing manufacturing process is vital. Therefore, applying machining process to current conventional method of producing the product of bovine horns may significantly escalate the productivity of the producers. Finally, knowing the benefits of applying ANN in solving the multi-objective problems of optimizing machining parameters, and the potential of bovine horns product diversification, current study aims to describe and implement the ANN model optimization on machining of bovine horns. In addition to the fact that very limited study on the machining of bovine horns, the outcome of this study is expected to be beneficial for the capacity development of current creative industry worldwide.

2. Literature Review

2.1 Sustainable Manufacturing

Sustainable manufacturing refers as "developing technologies to transform materials and products with reduced emission of greenhouse gases, reduced use of non-renewable or toxic materials, and reduced generation of waste" [13]. According to the sustainable statement of united nation, the three fundamentals (economy, environment & social) are interconnected and mutually dependent on each others (**Error! Reference source not found.**). A small change in any one area will influence the other two. Non-renewable natural resources and production of harmful emissions required for economic growth, howerver, both of them affect environment and social well-being. Usage of energy in manufacturing industry has significantly increased over last two decades which indicates this sector as energy-inclusive with significant CO_2 emission in the environment [13]. Therefore, energy consumption in this sector is the big factor due the interrelation between electricity and manufacturing indutry.

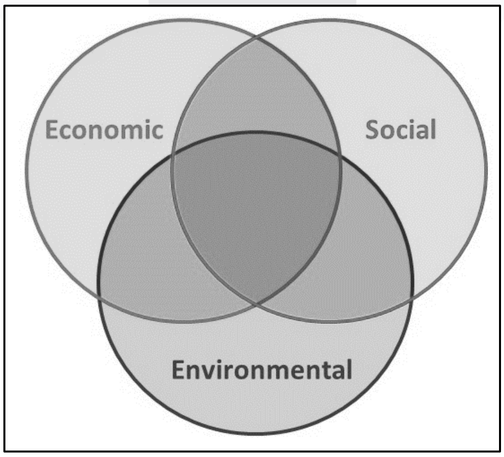

Figure 3 Overlapping circles of sustainability [14]

2.2 Energy Consumption in Machining

Energy consumption is one of the key issue for both machining process cost and environmental impact. Then in the first stage, understanding the concept of energy consumption is more important than practical improvement. An energy-flow concept can be the crucial step to understand this issue. Peng et al. (2014), provides energy flow information in machining process. Machine tool, cutting tool, material supply and auxiliary equipment are the four basic energy consumed parts (Figure 4). Even though most of the research carried out on machine tool, but then overall attention kept on the total energy consumption in this process.

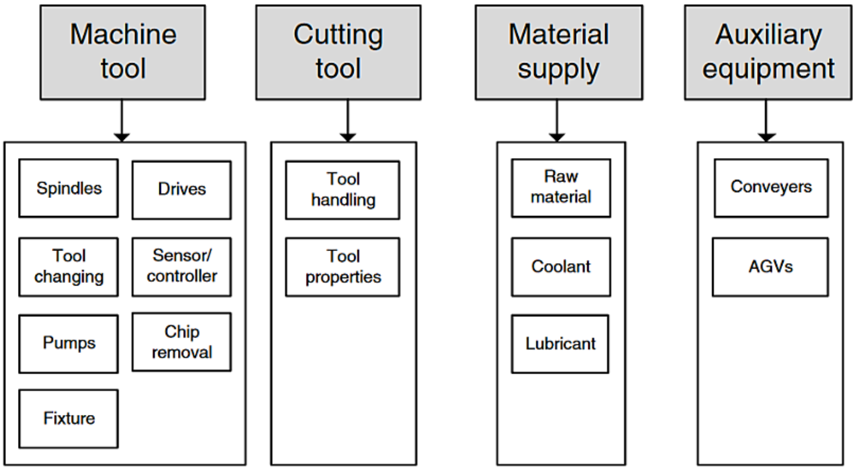

Figure 4. Overview of energy consuming parts in machining [15]

2.3 Surface Roughness

Surface roughness is a widely used index of product quality and it is one of the technical requirement for mechanical products[16]. In the machining process, surface roughness should be considered as the important characteristics to fulfill machined parts functionality. There may have many factors that influence this decision. Desired luster, adhesion, friction are few of them[17].

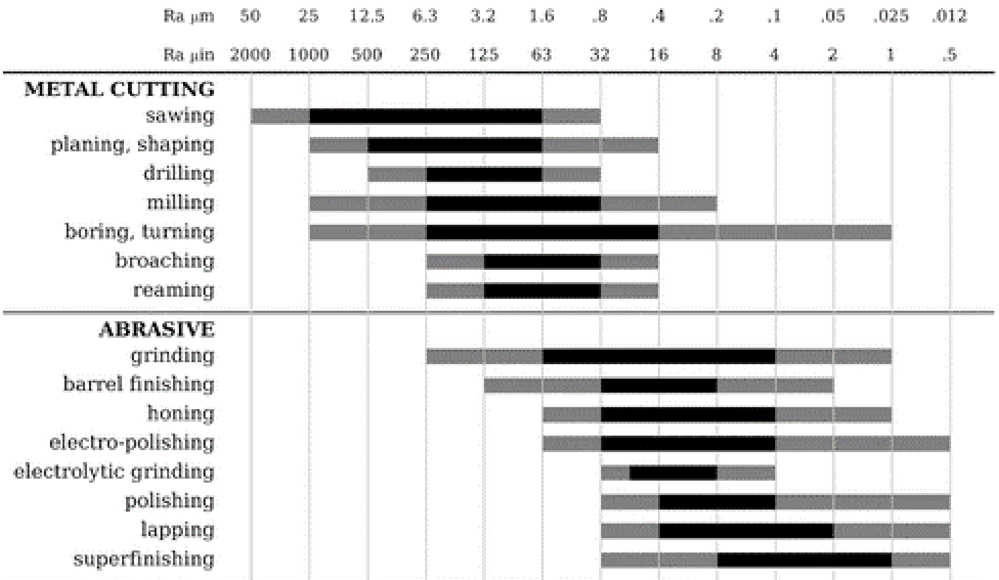

Figure 5. Typical surface finish in machining process [17]

A clear understanding about the performance requirements may lead to choose best manufacturing process and measurement parameters. The process machining process will be chosen, once the surface finish requirements decision has made. A large number of parameters such as, cutting tool properties, materials, machining parameters, etc. makes it difficult for surface finish even in simple machining process like milling, turning etc. The achievable surface finish in different machining process is shown in
Figure 5.

2.4 Artificial Neural Networks (ANN)

Artificial Neural Networks (ANN) is a computational modeling tool that simulates the structure or function of the biological neural network [18]. ANN has been implemented in engineering such as optimization, classification, and prediction based on the ability to learn input and outputs relationship. The architecture of ANNs includes a combination of layers which is neuron based. It establishes for a prediction problem, and there is no rule in determining the number of the hidden layer and hidden neurons. ANN is trained to learn the unknown relationship between model variables and to find the best weights connection between the neurons that located in the layer's network to obtain the output[19].

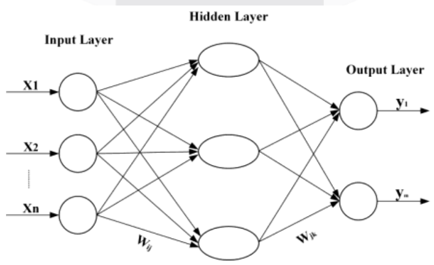

Figure 6. A simple ANN Structure [20]

ANN can learn their environment, the advantages of that Artificial neural network can be used for various tasks like function approximation, classification, filtering, clustering, processing, etc. more complex the data more chance to success that leads to problems in process of learning[21]. Choosing the right artificial neural network topology depends on the type of the application and data representation of a given problem. Optimization works by the artificial neural network (ANN) on the machining process of engineering material have been investigated by several earlier studies. Some of the investigations are listed in Table 1.

Table 1. Optimization works on the Machining Process

No	Author(s)	Material	Optimization Technique
1.	[9]	Magnesium Alloy	ANN
2.	[5]	Brass	ANN and Analysis Regression
3.	[22]	Wood	ANN
4.	[23]	Steel alloy	ANN
5.	[7]	Titanium Alloy	ANN-GA
6.	[24]	Aluminum	ANN-RSM

2.5 Bovine Horns

Bovine horn is one of the strong natural material because of its mechanical properties. It is also called as natural composite material. The uniqueness of bovine horn may be explained by its mechanical properties. Empirical data shows that the strength of the bovine horn is affected by its water contents[25]. At 0 wt % of water content, the horn acts similar to a ceramic material, with high strength but minimal elongation. However, once the water content reaches 19 wt %, the behavior changes drastically. The material becomes similar to the typical characteristic of the polymeric material. Thus, the application of lubrication in the machining needs to be reconsidered. Similarly, wood experiences similar condition as its moisture level differs[26].

Figure 7 Typical condition of bovine horns

In summary, the ANN modelling approach is a promising method of modelling and predicting of machining process. Even though the natural material (e.g. Bovine horns) mechanical properties are a function of its water level, the capability of ANN is expected to suppress the machining variation. The self-learning function of ANN may able to optimize the parameters and able to produce a highly accurate model for future prediction.

3. Discussion

3.1 Workpiece Material

In this study, workpiece material was used that is bovine horns (tanduk kerbau) acquired from the regional sources. As a natural material, it is sustainable and there are several application potentials in industrial sectors. 27 experimental run were performed as mentioned in the experimental design section. The fourteen workpieces were machined from bovine horn. Each of the workpiece dimensions of 35mm length and 45mm width and the height is about 40mm. Each workpiece used to perform two experiments. Therefore, only the upper and bottom faces were used to conduct the machining process. In each experiment, the only 20x20mm area was machined. Once machining process done, the workpiece kept for the further process which was prepared for surface roughness data collection step.

3.2 Machine Tool

The face milling experiments were carried out in the dry condition using HauwGen conventional milling machine. It has a maximum spindle speed of 1400 rpm and spindle power of 3.5 kW. In the machining process, the workpiece was held in between the chuck and the milling experiments were conducted by the right direction movement of workpiece material and clockwise spindle rotation shown in Figure 8.

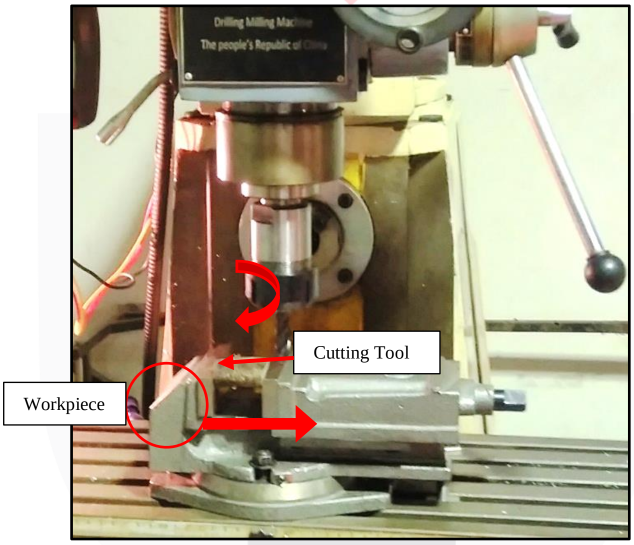

Figure 9. Position of Tool holder and Workpiece Material

3.3 Design of Experiment

A proper data collection is important for any experimental investigation in term of the results. It is common practice for the researchers to utilize a full factorial set of experiments. The experimental design carried out all the possible combinations of the variables and the levels. While it measures the response of each possible combination and analysis of response, provide a picture of the combination and interaction effect. Design of Experiment in the study for three milling parameters with its three levels determined by the Taguchi L_{27} orthogonal array. L_{27} orthogonal array frequently used and it has 27 trials with 26 degrees of freedoms, which is more than 18 degrees of freedoms. According to Taguchi's experimental design, the total degrees of freedoms must be larger than or equal to the degrees of freedoms needed for the experiment[27].

3.4 Energy Consumption Measurement

In this study, energy consumption has been measured through direct measurement technique by using a wattmeter. A clamp meter used to measure the energy that consumed by the machine tool. Figure 10 shows PeakMeter clamped on 3-phase of spindle motor and a rs232 cable attached with clamp meter and laptop. Schematic of experimental procedure to measure energy consumption shown in the. Real time data displayed on the laptop with the graphs. In every experimental run, energy measurement was made during the milling cycle. After that, the average of all readings was used for analysis.

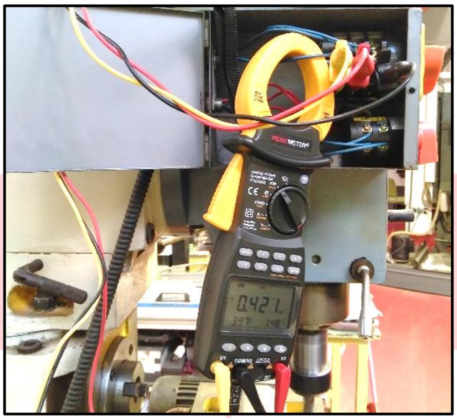

Figure 10 Wattmeter used for measuring energy consumption

3.8 Surface Roughness Measurement

The workpiece shown in Figure 11, used to measure the surface roughness in the experiment. Mitutoyo SJ410 surface roughness tester used as a tool for measuring finished surface of the machined workpiece. The workpiece placed in between a holder to achieve stability in the time of measurement. According to the manufacturer data, the surface measurement tool capability to measure relatively accurate measurement and that found when the tool calibrated a high precision workpiece. The specification of the surface measurement tool has given in [28].

Figure 11 Workpiece used for measuring surface roughness

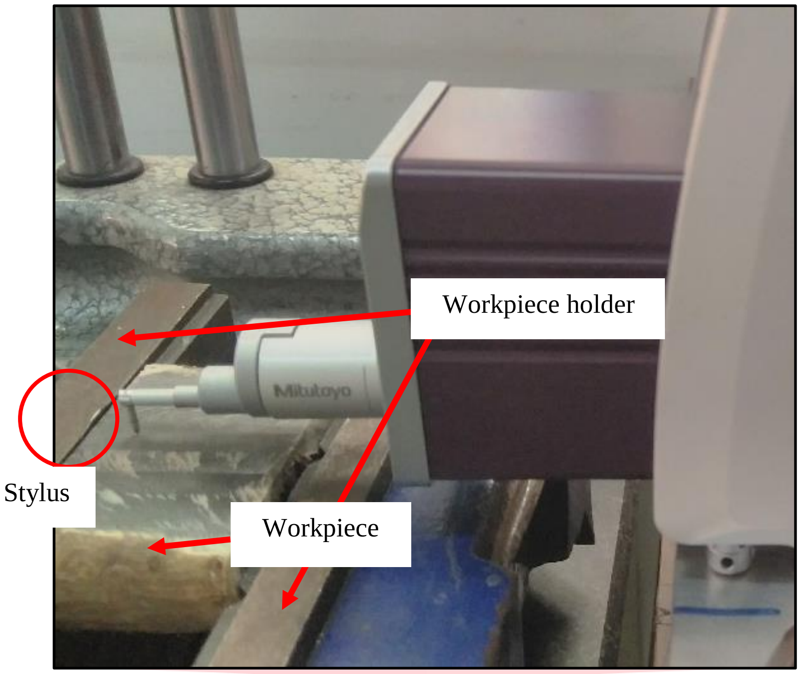

Figure 12 Detail of the surface roughness measurement process

3.9 Machine Learning

Machine learning has been carried out in this study to create an optimum prediction model for the cutting parameter optimization. An artificial neural network (ANN) model was developed in order to predict process parameters. There were a few steps in an ANN model such as preparing datasets, training the datasets, validation, testing. In developing the prediction model, required to determine the appropriate number of datasets (input and output), number of neurons and number of hidden layers. In this research, data includes input, which is consists of cutting parameters and the outputs used in the ANN model were energy consumption and surface roughness data.

3.10 ANN Outcomes

Best prediction model obtained by selecting minimum error in training. Based on experiment, best model was M8 because of the minimum error in prediction. In the networks, training phase, the networks decrease the error smoothly till epoch 3, then slightly moved MSE to 10^{-16} at the time of epoch 5. On the other hand, from the epoch 0 to 1, MSE of validation and test was going down till 10^{-1}. After that it was remaining constant. In addition, according to the FFBP-LM, the learning process will be stop in minimum level of error for the three component which are training, validation and testing. In the learning process, the model recorded the minimum error in epoch 3, even though the process run until epoch 5. The situation is usual to run further due to find minimum error. Therefore, the best performance has been chosen at epoch 3, while the value of MSE is 0.0501 for test and validation.

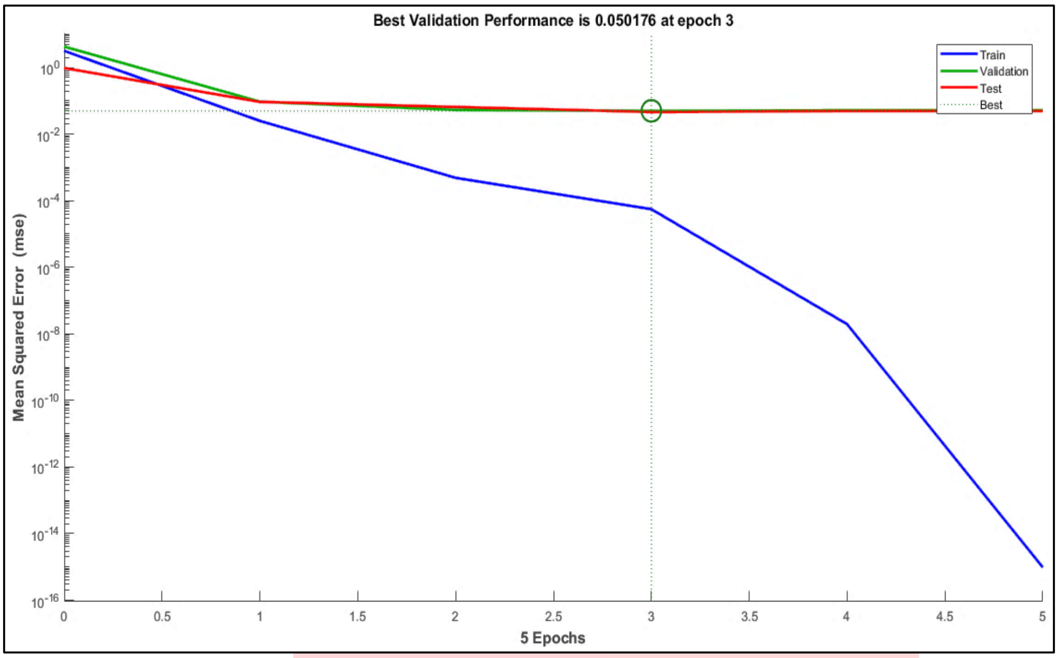

Figure 13 Error analysis in the networks

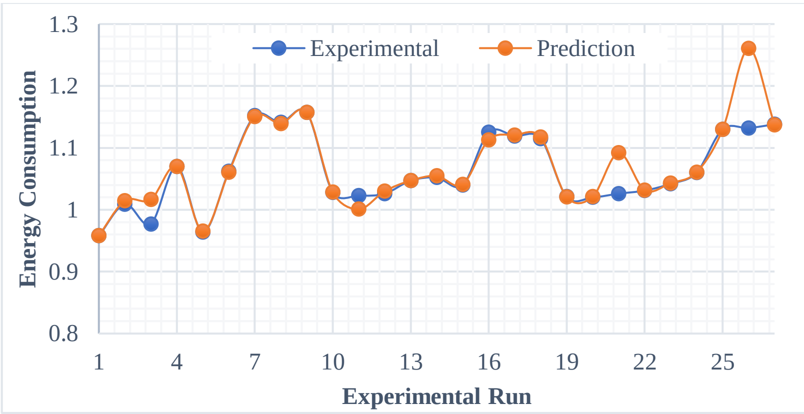

Figure 14 Experimental and predicted value for energy consumption

The differences between experimental and ANN model prediction data for energy consumption and surface roughness data are shown in Figure *14* and Figure *15*. In energy consumption output, most of the predicted result are almost closed to the experimental value. It is found that the average error for energy consumption prediction is 0.79%.

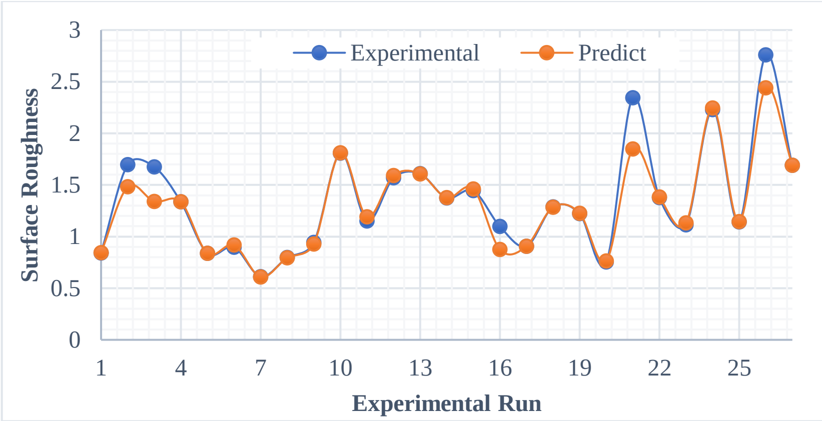

Figure 15 Experimental and predicted value for surface roughness

Similar results can be seen for surface roughness prediction too (Figure *15*). Therefore, it is one of the indication of model's prediction capability. This section represented the theoretical analysis that the prediction model is valid in term of experimental and prediction values.

3.11 Multi-Objective Optimization

As the part of multi-objective optimization, Figure *16* shows the main impact of machining parameters on multi-objective function. The figure represents that feed rate and depth of cut has the highest impact on the multi-objective function. While feed rate is at level 1, level 3 for spindle speed and depth of cut level 2, then multi-objective function is maximized. Therefore, better surface quality and minimum energy consumption can be obtained as the objective of the is study at a feed rate 155mm/min., spindle speed 1400 rpm and depth of cut 2mm.

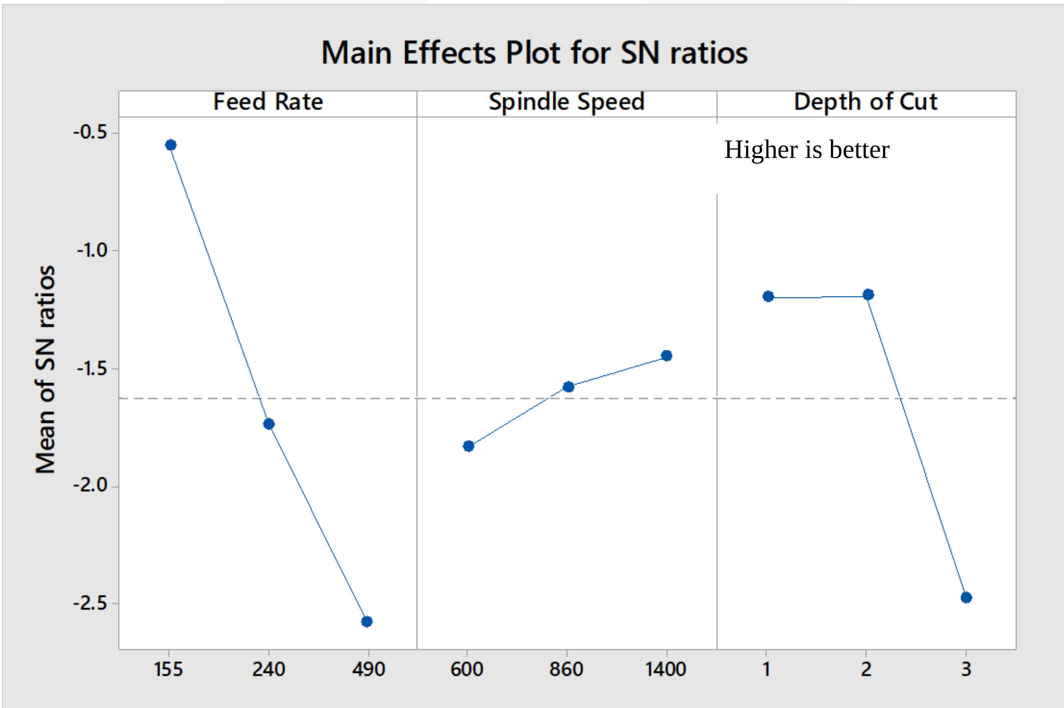

Figure 16 Effects of machining parameters on multi-objective function

3.12 Prove of the Prediction Model Effectiveness

According to the research goal, it is required to prove that developed ANN model is capable to predict energy consumption and surface roughness. To do this, the step that need to do is to apply in the real experiment. Therefore, the prediction model has been used for predicting experimental data. Results in the Table 2 shows the comparison of actual data from the experiment and predicted data that achieved from the proposed ANN based prediction model. The results of experimental and predicted data has represented the capability of prediction using proposed model. In addition, results shows the close relationship between experimental and predicted results. As it is indication of validness of the prediction model.

Table 2 Prove of prediction capability

Method	Optimum Machining Parameters			Energy consumption (kW)	Surface Roughness (R_a)
	f (mm/min.)	*v (rpm)*	*d (mm)*		
Best experimental run	155	1400	2	1.1410	0.797
Proposed model	155	1400	2	1.1392	0.795

4. Conclusion

In this study, a multi-objective optimization to improve surface quality and reduce energy consumption in bovine horn machining process. As mentioned earlier, there is no such research has been done before on bovine horn especially for machining processes. The major contributions of this research are given below:

1. An artificial neural network based predictive modelling to predict surface roughness and energy consumption of bovine horn. The results show the accuracy of the model is 95% approximately.
2. As a promising material, bovine horn has the opportunity to use in different fields. This work provides an optimization work in term of better surface quality with a minimum energy consumption. The optimum value of machining parameters is obtained by feed rate 155mm/min., Spindle speed 1400rpm and 2mm for the depth of cut.

The output of this research can be utilized for further development of bovine horns industrial applications. Finally, according to prediction accuracy with the experimental results and optimum cutting parameters, this study successfully achieve the goals of this research that is optimization of machining parameters to reduce energy consumption and to improve surface quality of bovine horn in machining process.

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