Optimization of Milling Parameters of Gun Metal Using Fuzzy Logic and Artificial Neural Network Approach

Visnu Sasindran¹, Vignesh M¹, Arvind Krishna S¹, Madusudhanan A¹ and Gokulachandran J¹

¹Department of Mechanical Engineering, Amrita School of Engineering, Amrita Vishwa Vidyapeetham, India

Abstract. Growing importance is dedicated towards effective pollution control in industries and much attention has been focused on industrial applications and practices that consume large amounts of energy and release carbon emissions into the atmosphere. Besides this, industries are looking for effective analysis to reduce costs, improving productivity and product quality. This report proposes a systematic approach to analyse milling parameters of gunmetal using Computer Numeric Controlled (CNC) vertical milling machine. milling is one of the most advanced and widely used manufacturing processes. Hence an effective analysis to optimize milling process parameters would have a significant positive impact on manufacturing productivity. In this study two soft computing models have been developed using the results obtained from the conduction of the experiments on gunmetal. The experiment is designed using Taguchi Method and the model development is done using Fuzzy Logic and Artificial Neural Network (ANN) approach. The results obtained from both the methods are compared and the error is tabulated. The more suitable model developer is suggested to be used in industries to determine optimum machining parameters for better surface finish, minimal power consumption and carbon emission.

1. Introduction

Gunmetal is a material that is becoming increasingly used in several manufacturing processes such as valves, hydraulic castings, gears, etc. due to its high machinability and corrosion resistance property. An extensive literature survey revealed that very limited amount of work has been conducted in machining of gunmetal. The research on model development of milling process on gunmetal using appropriate software, for multiple input and output parameters is restricted in scope [1]. In this project report, face milling parameters on gunmetal is analyzed. The input variables are speed, feed and depth of cut. The parameters studied are machining time, net cutting power consumption, surface finish (roughness) and carbon emission. Using model development software such as Fuzzy Logic and Artificial Neural Network, the optimum machining parameters can be determined effectively [2].

Taguchi method of orthogonal arrays are often used in several industrial processes to analyze the effects of control factors. It is a structured approach to determine the best combination of inputs to produce a product or service. It is based on Design of Experiment (DoE) methodology for determining different levels of parameters. The most important step in the Design of Experiment is the selection of appropriate control factors and their levels. Taguchi method, through statistical principles, reduces number of experiments and minimizes the effect of noise factors. After conducting the experiment, analysis is done using two soft computing techniques Fuzzy logic and Artificial Neural Network (ANN).

Fuzzy Logic is a method of reasoning that resembles human reasoning. It reciprocates the manner in which humans make decisions, that involves all intermediate possibilities between digital values YES and NO. It includes 0 and 1 as extreme cases of truth, but also includes various states of truth in between,
assigned as degrees if truth. A basic concept of Fuzzy Logic is that of a fuzzy IF-THEN rule, which is commonly called, fuzzy rule. It serves as the basis for what is called the Fuzzy Dependency and Command Language (FDCL).

Artificial neural networks are computing systems developed from the concept of biological network systems that constitute animal brains. Such systems undergo “learning” of tasks without task-specific programming, by observing data sets. In this manner, ANN is used as a random function approximation tool. The basic unit of an artificial neural network is called an artificial neuron (similar to biological neurons in an animal brain). An artificial neuron receives signal, processes it, and transmits it to other neurons connected to it. ANN is considered to be a non-linear statistical data modelling tool, where complex relations between input and output values are analyzed and outputs are modelled. It has three inter-connected layers. The first layer consists of input neurons. These send the data to the second layer, which in turn send it to the third layer- the output. Training of ANN involves selecting from pre-set for which there are numerous associated algorithms.

2. Literature Survey

Congbo Li et al [3] developed an analytical model to determine the carbon emission for different machining parameters in turning process of a cylindrical workpiece. The equipment used in the experiment was C26136HK with a P10 Carbide turning tool. The workpiece material was EN8 steel. The parameters varied were spindle speed and feed, while the depth of cut was maintained at a constant 2 mm. The optimum condition for minimum carbon emission was determined graphically. The results indicated that carbon emissions generated by power consumptions and cutting fluid decrease with increase in spindle speed. The carbon emission of cutting tool increases with increase in spindle speed. It also suggested that there exists an optimal cutting speed that strikes a balance between process efficiency and carbon emissions. Rehan R et al [4] has studied on the contribution of industries to global carbon dioxide emissions. The report analysis traditional and emerging policies that affect carbon emissions and discusses their merits and demerits. Mohamad Farizal Rajemi [5] conducted an investigation of energy consumption in manufacturing processes and energy footprints of machines. The study was on turning and milling processes for a range of materials. The results showed that optimization of cutting parameters in reducing the energy footprint of machining processes.

Pavan Singh et al [6] incorporated Taguchi method of orthogonal arrays into the optimization of milling process parameters in the case of face milling. The parameter to be optimized was Material Removal Rate (MRR). The input parameters were spindle speed, feed and depth of cut. L-27 orthogonal array was used. The experiment was carried out on a 1.5HP CNC vertical milling centre. The tool was a 60mm diameter four-flute face milling cutter with inserts of grade 1C28M40. The workpiece used was 6061-T6 Aluminium. Response surface methodology was used to analyze the data set. The results obtained indicated that the MRR was influenced by all the three process parameters viz. spindle speed, feed and depth of cut, and the MRR increased by increasing any of the three parameters. Abhang L B et al [7] worked on optimization of turning process operation on EN-31 steel by Taguchi method. The aim was to find the optimal parameters based on S/N ratio and further performing ANOVA analysis. The conclusion drawn from the study was that surface finish improves on the application of a coolant lubricant, besides provisions for higher depth of cut if the temperature of the lubricant is lowered. Muataz Hazza Faizi Al-Hazza et al [8] conducted a study regarding optimization of surface roughness for hardened steel D2. The input parameters were feed, speed and depth of cut. L9 table was designed for the experiment and the results were analyzed using JMP software. It was found that feed rate was the most effective parameters among the three in controlling surface roughness.

Biswajit Das et al [9] used the fuzzy logic model for the optimization of milling parameters. The input parameters considered were cutting speed, feed and depth of cut and the response parameters were surface roughness and cutting force. L-25 orthogonal array was used. The material used for experimentation was Al–4.5%Cu–TiC of dimension 30mm x 30mm x 80mm. An end mill cutter of length 75mm and diameter 8mm was used for the milling operation. The results obtained were verified by doing the confirmatory experiment. They concluded from experiment that fuzzy logic model can be
effectively utilized for multi characteristic optimization of process parameters. And they also concluded that the optimization procedure significantly improved their milling process. Ahmed A. D. Sarhan et al [10] used fuzzy logic model development to analyze improvements in quality of machined surfaces. The process studied was glass milling and the input parameters were lubrication pressure, spindle speed, feed and depth of cut. The fuzzy logic model developed was proved to have an accuracy of over 90%. Saleh M. Amaitik [11] studied the application of fuzzy logic models to select machining parameters in automated process planning systems. The fuzzy values were compared to standard values from machining data handbook. The results showed a good fit and a promising approach to develop new process planning systems.

Girish Kant et al [12] used the artificial neural network technique to predict the optimal value of machining parameters, leading to minimum surface roughness. The machining parameters were cutting speed, feed per tooth, depth of cut and flank wear. The milling was conducted on AISI 1060 steel workpiece with 125mm diameter, on a 14kw vertical milling machine. And a tool microscope was used measure the width of flank wear land. The results from artificial neural network were compared with the experimental data using relative error analysis. They concluded from their experiment that artificial neural network model has satisfactory goodness of fit. They also concluded that artificial neural network model outperform the regression and fuzzy logic models. Deepa Bharathi Kannan et al [13] incorporated artificial neural network modeling to study drilling process. A comparison of two optimization techniques - Genetic Algorithm (GA) and Partial Swarm Optimization (PSO) was done. The results obtained showed that GA gave better results for thrust force and surface roughness while PSO gave better results for ovality and machining time. Nilesh Pohokar et al [14], studied End Milling process optimization using ANN. the experiment was conducted through a CNC milling machine on AISI 1040 MS plate and the input parameters were rake angle, cutting speed, feed and depth of cut. The obtained accuracy of the ANN values when compared to the experimental values during validation was approximately 90% indicating that ANN is an effective tool for machining optimization.

From the literature survey, it is revealed that very limited research has been conducted on process optimization of gunmetal in relation to machining processes such as face milling. Both fuzzy logic and ANN model developments are identified to have sufficient degree of accuracy. Hence a comparison between the two is necessary in selecting the most effective technique to optimize machining parameters in face milling process.

3. Methodology
The methodology of study applied in this research is elaborated in the flow chart shown in figure 1.

![Methodology Flow Chart](image-url)

**Figure 1.** Methodology of study
4. Experimental Work
The first step in the experimentation process is to select the appropriate Taguchi’s orthogonal array [15] and the levels of input parameters. The experiment is conducted based on the values entered in the orthogonal array. The results are then analyzed. The machine specification, workpiece specification and workpiece composition is described in the Table 1 and Table 2.

| Table 1. Specification of CNC machine, cutting tool, and workpiece |
|------------------|------------------|
| Table clamping area | 350 x 600 mm |
| Distance from table to spindle face | 150 – 500 mm |
| Distance from spindle to column face | 150 – 500 mm |
| Spindle power | 5.5 kW |
| Spindle speed | 8000 rpm |

| Table 2. Workpiece specification |
|---------------------------------|
| ELEMENT | Copper | Lead | Zinc | Tin | Nickel | Aluminium | Phosphorus | Manganese |
| PERCENTAGE COMPOSITION | 80.419 | 10.159 | 3.349 | 4.009 | 0.349 | 0.037 | 0.1 | Balance |

4.1. Selection of factors
The parameters to be studied in this project, i.e., surface roughness, carbon emission and net machining power depends on several factors such as cutting speed, cutting fluid, tool geometry and hardness, working table inclination, cutting tool wear, etc. Considering all the above factors will not be cost effective and will lead to unnecessary time consumption. From the literature survey, it is evident that the major input factors that determine the values of the aforementioned output parameters are speed, feed and depth of cut. Therefore, these are the factors that are taken into consideration for the experiment.

4.2. Selection of number of levels of the input variable
For the present study, three levels of each input parameter are considered as shown in Table 3. A minimum of three levels of process parameters is desired in order to achieve sufficient degree of accuracy of the obtained outputs.

| Table 3. Selected Levels for Milling |
|-------------------------------------|
| Process Variable | Units | Notation | Levels |
| Spindle speed | rpm | v | 1 (min) | 2 (med) | 3 (max) |
| Feed | mm/min | f | 200 | 600 | 900 |
| Depth of cut | mm | d | 0.05 | 0.5 | 1 |

4.3. Determination of output parameters
From the standard array, there are 27 experimental runs that need to be conducted for factors with different combination of levels. The surface roughness was measured using surface roughness testing machine and the values were shown in Table 4.
Table 4. Obtained surface roughness

| Trial No | Speed (rpm) | Feed (mm/min) | Depth of cut (mm) | Time (sec) | Surface roughness (micron) |
|----------|-------------|---------------|-------------------|------------|--------------------------|
| 1        | 800         | 200           | 0.05              | 22.61      | 0.4                      |
| 2        | 800         | 600           | 0.05              | 7.1        | 0.6975                   |
| 3        | 800         | 900           | 0.05              | 4.19       | 1.1675                   |
| 4        | 800         | 200           | 0.5               | 22.08      | 0.5334                   |
| 5        | 800         | 600           | 0.5               | 6.94       | 0.7267                   |
| 6        | 800         | 900           | 0.5               | 4.72       | 1.043                    |
| 7        | 800         | 200           | 1                 | 21.79      | 0.568                    |
| 8        | 800         | 600           | 1                 | 6.76       | 0.864                    |
| 9        | 800         | 900           | 1                 | 4.46       | 1.152                    |
| 10       | 1600        | 200           | 0.05              | 20.45      | 0.4434                   |
| 11       | 1600        | 600           | 0.05              | 6.77       | 0.6934                   |
| 12       | 1600        | 900           | 0.05              | 4.94       | 0.7467                   |
| 13       | 1600        | 200           | 0.5               | 22.08      | 0.2434                   |
| 14       | 1600        | 600           | 0.5               | 7.4        | 0.2825                   |
| 15       | 1600        | 900           | 0.5               | 4.06       | 0.3425                   |
| 16       | 1600        | 200           | 1                 | 22.8       | 0.2567                   |
| 17       | 1600        | 600           | 1                 | 7.78       | 0.2767                   |
| 18       | 1600        | 900           | 1                 | 4.78       | 0.3375                   |
| 19       | 2500        | 200           | 0.05              | 22.29      | 0.2634                   |
| 20       | 2500        | 600           | 0.05              | 6.14       | 0.25                     |
| 21       | 2500        | 900           | 0.05              | 4.25       | 0.32                     |
| 22       | 2500        | 200           | 0.5               | 22.41      | 0.2434                   |
| 23       | 2500        | 600           | 0.5               | 7.19       | 0.2334                   |
| 24       | 2500        | 900           | 0.5               | 3.54       | 0.27                     |
| 25       | 2500        | 200           | 1                 | 23.2       | 0.2467                   |
| 26       | 2500        | 600           | 1                 | 7.13       | 0.265                    |
| 27       | 2500        | 900           | 1                 | 4.24       | 0.285                    |

4.4. Calculation

**Net Machining Power**

Net machining power is the total power consumed for the milling process. It is the product of cutting force and tool velocity.

**Trial 1**

\[ \text{Net Machining Power, } P_v = V_w \times w \ \text{kW} \]  \hspace{1cm} (4.1)

where \( V_w \) = Stock Removal Rate
\( V_{wp} \) = Specific stock removal rate
\( w \) = wear factor
\[ V_w = \frac{50 \times 0.05}{22.61} = 5.528 \text{ mm}^3/s \]

\[ V_{wp} = \frac{1}{k_c} = \frac{1}{756 \text{ N/mm}^2} \text{ (For gunmetal)} \]

\[ w = 1.1 \text{ (For face milling)} \]

\[ P_e' = \frac{5.51 \times 756}{2 \times 1.1} = 0.0046 \text{ kW} \]

**Carbon Emission**

Carbon emission footprint is defined as the total emissions caused by a process expressed in terms of carbon dioxide equivalent.

**Trial 1**

\[ Carbon \ Emission = \text{Net Machining Power} \times \text{CEF ton of CO}_2/s \]

where CEF = Carbon Emission Factor = 0.82 ton of CO\(_2\)/MWhr (For India)

**Carbon Emission** = \[ \frac{0.0046 \text{ kW} \times 0.82}{3.6} = 0.0010 \text{ ton of CO}_2/s \]

5. **Fuzzy Model Development**

Fuzzy logic model development involves multivalued logic operations rather than bi-valued operations which includes only 0 and 1. The first step in fuzzy logic is to identify the input and determine the range of values. The values within the range are divided into fuzzy subsets, and each subset is assigned a membership function. There are several membership functions available such as Gaussian, trapezoidal, etc. In this study, triangular membership function is selected, as it had a higher degree of accuracy.

In fuzzy logic model development, the input values undergo a process called fuzzification. In fuzzification, the crisp input value is transformed into a fuzzy value [17]. Crisp inputs are scalar input values measured by sensors and transmitted to the fuzzy control system. The transformation of crisp value into fuzzy value is achieved by membership functions called as fuzzifiers. The fuzzified input data is sent to a fuzzy inferencing system that applies predefined set of rules to produce fuzzy output in linguistic form. The fuzzy output is converted into a crisp output by the process called defuzzification. The inferencing system selected is mandani. The crisp inputs are feed, speed and depth of cut. The output parameters are surface roughness, carbon emission and net machining power. Given below are the linguistic variables for fuzzification:

i. Surface roughness – very smooth, smooth, medium, rough, and very rough
   ii. Carbon emission – very low, low, medium, high, and very high
   iii. Net machining power – very low, low, medium, high, and very high

The Fuzzy Logic Model undergoes training by selecting appropriate fuzzifiers (membership functions). The rule base for training the model consists of a series of IF-THEN statements with three inputs values (x1, x2, x3) and one output value (y), i.e.,

Rule 1: IF x1 is A1 and x2 is B1 and x3 is C1 THEN y is D1 else
Rule 2: IF x1 is A2 and x2 is B2 and x3 is C2 THEN y is D2 else
…………………………………………………………………….
Rule n: IF x1 is An and x2 is Bn and x3 is Cn THEN y is Dn

Where Ai, Bi, Ci, Di are fuzzy subsets defined by corresponding fuzzifiers. For this project, three fuzzy subsets are allotted to the three input variables and five fuzzy subsets are allotted to each of the three
output parameters. The triangular membership function was assigned for the input variables (speed, feed, depth of cut) and for the output responses (surface roughness, carbon emission, and net machining power). An example is shown in Figure 2.

![Figure 2. Membership function for carbon emission](image)

6. Artificial neural network (ANN) model development

Artificial Neural Network Toolbox performs dynamic system modelling. Its models can handle more variability in input values as compared to other traditional model development networks. The most important use of ANN is as a recognizer of patterns which plays a vital role in quality control [18].

The input parameters speed, feed and depth of cut are entered in matrix form. The experimental values of surface roughness, carbon emission and net power consumption are entered separately in the matrix form as target data. Out of the 27 experiments conducted, the values of 23 experimental values are selected for training the model and the remaining four values are used for validation purpose. Two layers of neurons are selected for training. Among them, one is a hidden layer which transforms the input parameters into a form the second layer—the output layer, can work on. The output layer transforms the data from the hidden layer into the required output form, based on the weightage given to each input. The training function, adaptive learning function and performance function selected were TRAINLM, LEARNGDM and MSE respectively.

The regression plot shows the relationship between the output and the target. The plot represents training, validation and testing data. The solid line represents the best fit, linear regression line between output and target. The correlation coefficient (R) indicates the nature and the strength of relationship between the output and the target. The value of R ranges from -1 to 1. The correlation coefficient equal to one represents a linear relationship between the output and target. The regression plot obtained from the experimental values shown in Figure 3 shows an approximate linear relationship.

![Figure 3. Regression plot for carbon emission](image)

7. Result

In this chapter, the values obtained of surface roughness, carbon emission and net machining power obtained experimentally as well as from fuzzy logic and artificial neural network model developments were compared. The percentage error of the values obtained from the fuzzy logic and ANN models were calculated with respect to the experimentally obtained readings and the values were analyzed.
7.1. Comparison and determination of error in fuzzy logic method and ANN method
Percentage error is the deviation of the values obtained from the model when compared to experimentally obtained values. The error is calculated based on Equation 7.1. The comparison between experimental values and fuzzy values are shown in Table 5.

\[
\text{Percentage error} = \frac{|\text{Experimental} - \text{Fuzzy Model}|}{\text{Experimental}} \times 100 
\]

(7.1)

| SI No: | Speed (rpm) | Feed (mm/min) | Depth of Cut (mm) | Surface Roughness (micron) | Carbon Emission (ton of CO2/hr) | Net Machining Power (kW) | Percentage error (%) | Surface Roughness | Carbon Emission | Net Machining Power |
|--------|-------------|---------------|-------------------|-----------------------------|---------------------------------|--------------------------|----------------------|------------------|----------------|------------------|
| 1      | 800         | 200           | 0.05              | 0.4                         | 0.001                           | 0.0046                   | 16                   | 762.53           | 755.71           |
| 2      | 800         | 600           | 0.05              | 0.6975                      | 0.0033                          | 0.0146                   | 0.22                 | 209.97           | 176.94           |
| 3      | 800         | 900           | 0.05              | 1.1675                      | 0.0056                          | 0.0247                   | -6.64                | 75.82            | 25.08            |
| 4      | 800         | 200           | 0.5               | 0.5334                      | 0.0107                          | 0.0469                   | -13.01               | 171.41           | 143.02           |
| 5      | 800         | 600           | 0.5               | 0.7267                      | 0.034                           | 0.1492                   | -3.81                | -14.69           | -23.62           |
| 6      | 800         | 900           | 0.5               | 1.043                       | 0.05                            | 0.2194                   | -10.55               | 14.04            | 2.08             |
| 7      | 800         | 200           | 1                 | 0.568                       | 0.0217                          | 0.0951                   | -18.31               | 33.92            | 19.92            |
| 8      | 800         | 600           | 1                 | 0.864                       | 0.0698                          | 0.3064                   | 7.99                 | 21.78            | 8.99             |
| 9      | 800         | 900           | 1                 | 1.152                       | 0.1058                          | 0.4645                   | -5.38                | -1.7             | -11.94           |
| 10     | 1600        | 200           | 0.05              | 0.4434                      | 0.0012                          | 0.0051                   | 4.65                 | 766.81           | 679.89           |
| 11     | 1600        | 600           | 0.05              | 0.6934                      | 0.0035                          | 0.0153                   | 0.81                 | 195.57           | 164.07           |
| 12     | 1600        | 900           | 0.05              | 0.7467                      | 0.0048                          | 0.0211                   | -6.52                | 109.39           | 88.39            |
| 13     | 1600        | 200           | 0.5               | 0.2434                      | 0.0107                          | 0.0469                   | 25.72                | 171.41           | 143.02           |
| 14     | 1600        | 600           | 0.5               | 0.2825                      | 0.0319                          | 0.14                     | 8.67                 | -9.04            | -18.55           |
| 15     | 1600        | 900           | 0.5               | 0.3425                      | 0.0581                          | 0.2551                   | 35.47                | -1.91            | -12.2            |
| 16     | 1600        | 200           | 1                 | 0.2567                      | 0.0207                          | 0.0909                   | 19.21                | 40.13            | 25.47            |
| 17     | 1600        | 600           | 1                 | 0.2767                      | 0.0606                          | 0.2663                   | 10.95                | 40.15            | 25.44            |
| 18     | 1600        | 900           | 1                 | 0.3375                      | 0.0987                          | 0.4334                   | 37.48                | 5.36             | -5.62            |
| 19     | 2500        | 200           | 0.05              | 0.2634                      | 0.0011                          | 0.0046                   | 15.79                | 841.02           | 743.6            |
| 20     | 2500        | 600           | 0.05              | 0.25                        | 0.0038                          | 0.0169                   | 22.8                 | 168.06           | 139.49           |
| 21     | 2500        | 900           | 0.05              | 0.32                        | 0.0056                          | 0.0244                   | 45                   | 79.42            | 60.85            |
| 22     | 2500        | 200           | 0.5               | 0.2434                      | 0.0105                          | 0.0462                   | 25.31                | 175.47           | 146.65           |
| 23     | 2500        | 600           | 0.5               | 0.2334                      | 0.0328                          | 0.1441                   | 31.53                | -11.62           | -20.86           |
| 24     | 2500        | 900           | 0.5               | 0.27                        | 0.0666                          | 0.2926                   | 12.96                | 27.54            | 14.15            |
| 25     | 2500        | 200           | 1                 | 0.2467                      | 0.0203                          | 0.0893                   | 23.63                | 42.59            | 27.67            |
| 26     | 2500        | 600           | 1                 | 0.265                       | 0.0662                          | 0.2905                   | 15.85                | 28.44            | 14.96            |
| 27     | 2500        | 900           | 1                 | 0.285                       | 0.1113                          | 0.4886                   | 7.02                 | -6.55            | -16.29           |
Average percentage error of values obtained from fuzzy logic model development for the three parameters = **93.02%**

The error for ANN method is calculated based on Equation 7.2. The comparison of experimental values and ANN values are shown in Table 6. The average error for different output responses (surface roughness, carbon emission, power consumption) are shown in Table 7.

\[
\text{Percentage error} = \frac{(\text{Actual Value} - \text{ANN Value})}{\text{Actual Value}} \times 100
\]  

(7.2)

### Table 6. Comparison of experimental and ANN values

| Sl No: | Speed (rpm) | Feed (mm/min) | Depth of Cut (mm) | Surface Roughness (micron) | Carbon Emission (ton of CO₂/hr) | Net Machining Power (kW) |
|-------|-------------|---------------|------------------|----------------------------|---------------------------------|--------------------------|
|       | Actual Value | ANN Value     | Actual Value     | ANN Value                  | Actual Value                    | ANN Value                |
| 1     | 800         | 200           | 0.05             | 0.4                       | 0.51439                         | 0.0010                   | 0.0014149                | 0.0040                   | 0.01819                 |
| 2     | 1600        | 200           | 0.5              | 0.2434                    | 0.28607                         | 0.0100                   | 0.013101                 | 0.0430                   | 0.031878                |
| 3     | 2500        | 600           | 1                | 0.265                      | 0.26362                         | 0.0600                   | 0.0057386                | 0.2640                   | 0.41492                 |
| 4     | 2500        | 900           | 0.05             | 0.32                       | 0.2669                          | 0.0050                   | 0.066951                 | 0.0220                   | 0.015548                |

### Table 7. Percentage error from ANN model

| Parameter         | Average percentage error |
|-------------------|--------------------------|
| Surface roughness | 7.1%                     |
| Carbon emission   | 88.13%                   |
| Machining Power   | 15.42%                   |

Average percentage error of values obtained from ANN model development for the three parameters = **36.883%**

### 8. Conclusion

Surface finish, carbon emission and net machining power are important parameters in manufacturing processes and has to be optimized as much as possible. This project report proposes a model to determine these parameters for various combinations of feed, speed and depth of cut. Comparing the two models proposed by fuzzy logic and artificial neural network, the latter is found to give more accurate results. Hence artificial neural network model is considered to be more effective for carrying out further analysis.

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