Predictive model development and optimization of surface roughness parameter in milling operations by means of fuzzy logic and artificial neural network approach

Vignesh M’, Visnu Sasindran’, Arvind Krishna S’, Madusudhanan A’ and Gokulachandran J’
"Department of Mechanical Engineering, Amrita School of Engineering, Coimbatore, Amrita Vishwa Vidyapeetham, India

E-mail: vigneshvikki003@gmail.com

Abstract. The advancement of artificial intelligence in the field of manufacturing has led to innovative methods to enhance productivity. Introduction of soft computing and machine learning techniques in industries have played a major role in reducing costs and increasing process efficiency. Optimization of machining processes such as surface finish brings about significant reduction in manufacturing costs. This research paper develops an optimization model by comparing two approaches – fuzzy logic and artificial neural network (ANN). The experiment is designed using Taguchi approach and the model is developed using fuzzy logic and ANN techniques. The validation is done for both the techniques and the one that provides minimal error is selected for predictive and optimization analysis. The selected method is suggested to be used in industries to optimize surface finish.

1. Introduction
Designers and industrialists constantly design products than run faster, smoother and operate with precision. Therefore there is a need to develop products with high surface finish and accuracy to avoid malfunctioning. However, manufacturers pay negligible attention to geometrical accuracy and surface finish, and hence proper study should be done at the design and manufacturing stages. Surface roughness plays a major role in controlling other factors such as corrosion resistance, increasing fatigue life and aesthetics, etc.

Traditionally, machining parameters are selected based on tooling data and other machining handbooks, or in certain cases, through human experience. This is a very ineffective and inefficient method and has led to significant losses in productivity. The losses are more significant in processes involving CNC machines. Surface finish depends on several factors such as cutting speed, tool wear, coolant flow and temperature, feed, depth of cut, etc. and a small variation in these parameters will lead to variations in surface roughness values. Therefore, a scientific methodology to select the optimum parameters must be studied thoroughly and developed [1].

Model development using artificial intelligence has recently been proved to be easier to analyze and also have sufficient degree accuracy. Several approaches have been used to develop artificial intelligence models such as fuzzy logic, Artificial Neural Network (ANN), Genetic Algorithm (GA) and Support Vector Machine (SVM) [2]. There is an increasing interest towards predictive and optimization model development using such artificial intelligence techniques as a replacement to traditional approaches.

In this paper, the effect of machining parameters- speed, feed and depth of cut on face milling process is studied on duralumin alloy. Duralumin has traditionally been used to manufacture aircraft products due to its light weight, machinability and corrosion resistance. Today, duralumin is used to manufacture a variety of products ranging from wires, rods and bars for screw machining to heavy duty forgings. Thus, an efficient analysis on its process parameters will significantly reduce production costs for industries.
2. Literature Survey
Pang J S et al., [3] used Taguchi method in the optimization of machining parameters in end milling operation. The material used was halloysite nanotubes hybrid composite. The input parameters were speed, feed and depth of cut and the response parameters were cutting force and surface roughness. The study showed that Taguchi technique can be used to obtain the optimum parameters for minimal surface roughness and cutting force. João Eduardo Ribeiro et al., [4] also applied the same approach to optimize surface roughness in milling operation. The control parameters were cutting speed, feed rate, axial depth and radial depth. L16 orthogonal array was used to design the experiment and the influence of each parameters was studied by applying analysis of variation (ANOVA). Results showed that radial and axial depth of cut were the most prominent parameters in controlling surface finish. Lin C L [5] used Taguchi approach combined with grey relational analysis for optimization of turning process. The inputs were cutting speed, feed and depth of cut and the responses were tool life, cutting force and surface roughness. The optimal parameter were obtained using a grey relational grade as the performance index.

Pandu R Vundavalli et al., [6] model a fuzzy logic system for abrasive water jet machining process. The control parameters were pressure of water jet, focusing nozzle diameter, transverse flow rate of the jet and mass flow rate of the abrasive particles. Three approaches- construction of mamdani fuzzy logic inferring system, database and rule-base fuzzy logic system, and automatically evolved fuzzy logic systems were developed and compared. The results showed that the automatic fuzzy logic systems are more accurate than the other two. Pathak A D et al., [7] modeled a Taguchi approach based fuzzy logic model to optimize dry turning process. The effects of cutting speed, feed, nose radius and depth of cut on parameters such as cutting force and surface roughness were studied thorough ANOVA and optimization was carried out using fuzzy logic technique. Rajamani D et al., [8] studied wear characteristics of Selective Inhibition Sintering (SIS) on high density polyethylene (HDPE) material. Validation of fuzzy logic model developed from experiments conducted using pin-on-disc wear testing apparatus revealed that fuzzy systems show sufficient degree of accuracy in automated manufacturing processes.

Dinesh Kumar Kasdekar et al., [9] used artificial neural network technique to study electro chemical machining (ECM). The specimen used was AA6061 (T6). The experiment was conducted by varying the most important factors which influence material removal rate. ANOVA and ANN was adopted to study the response. The results indicated that ANN was efficient in predicting ECM process responses. Yilmazkaya E et al., [10] applied ANN technique and regression models to predict performance characteristics of mono-wire cutting.

3. Experimental Procedure
In this research, soft computing models such as Artificial neural network and Fuzzy logic techniques have been developed to analyze the surface roughness. Face milling experiments are conducted on duralumin work material with carbide tool on vertical milling machine. The specification of the machine, tool and work piece is shown in table 1. The composition of the workpiece is shown in table 2. The experiments are conducted by changing three machining parameters: speed (v), feed rate (f) and depth of cut (d). Three levels of each input parameter are considered. The standard L27 orthogonal array was selected and the values are assigned. The output response (surface roughness) is measured using the surface roughness tester. Table 4 shows the surface roughness readings displayed by the tester for 27 sets of inputs.
Table 1. Specification of CNC machine, cutting tool, and workpiece

| Specification                  | Value          |
|-------------------------------|----------------|
| 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 |
| Traverse X – Y – Z             | 450 – 350 – 350 mm |
| Feed rates                    | 1 – 10000 m/min|
| Spindle power                 | 5.5 kW         |
| Spindle speed                 | 8000 rpm       |
| Maximum tool length           | 200 mm         |
| Machine weight                | 3500 Kg        |

Cutting Tool Specification

| Material used | Carbide |

Workpiece Specification

| Material used | Duralumin |
|---------------|-----------|
| Dimensions(mm)| 150 x 50 x 50 |

Table 2. Workpiece composition

| ELEMENT                                      | PERCENTAGE COMPOSITION (%) |
|----------------------------------------------|----------------------------|
| Aluminium                                    | 93.2                       |
| Copper                                       | 4.16                       |
| Manganese                                    | 0.93                       |
| Silicon                                      | 0.74                       |
| Magnesium                                    | 0.76                       |
| Iron                                         | 0.148                      |
| Nickel                                       | 0.01                       |
| Zinc                                         | 0.014                      |
| Chromium, Tin, Boron, Vanadium, Cadmium      | Balance                    |

For the research, the input parameters are categorized into 3 levels-minimum, medium and maximum. Categorizing the parameters into 3 levels would provide sufficient degree of accuracy for the predicted model. The categorization of input parameters is shown in table 3.
### Table 3. Selected Levels for Milling

| Process Variable | Units | Notation | Levels |
|------------------|-------|----------|--------|
| Spindle speed    | rpm   | v        | 1600   |
|                  |       |          | 2600   |
| Feed             | mm/min| f        | 100    |
| Depth of cut     | mm    | d        | 0.5    |
|                  |       |          | 1      |
|                  |       |          | 1.5j   |

### Table 4. Obtained surface roughness

| SL No: | SPEED (rpm) | FEED (mm/min) | DEPTH OF CUT (mm) | SURFACE ROUGHNESS (micron) |
|--------|-------------|---------------|-------------------|-----------------------------|
| 1      | 1600        | 200           | 0.5               | 0.35                        |
| 2      | 1600        | 600           | 0.5               | 0.45                        |
| 3      | 1600        | 900           | 0.5               | 0.57                        |
| 4      | 1600        | 200           | 1                 | 0.22                        |
| 5      | 1600        | 600           | 1                 | 0.37                        |
| 6      | 1600        | 1000          | 1                 | 0.90                        |
| 7      | 1600        | 200           | 1.5               | 0.22                        |
| 8      | 1600        | 600           | 1.5               | 0.74                        |
| 9      | 1600        | 1000          | 1.5               | 0.79                        |
| 10     | 2600        | 200           | 0.5               | 0.15                        |
| 11     | 2600        | 600           | 0.5               | 0.31                        |
| 12     | 2600        | 1000          | 0.5               | 0.73                        |
| 13     | 2600        | 200           | 1                 | 0.12                        |
| 14     | 2600        | 600           | 1                 | 0.34                        |
| 15     | 2600        | 1000          | 1                 | 0.68                        |
| 16     | 2600        | 200           | 1.5               | 0.13                        |
| 17     | 2600        | 600           | 1.5               | 0.39                        |
| 18     | 2600        | 1000          | 1.5               | 0.54                        |
| 19     | 3600        | 200           | 0.5               | 0.13                        |
| 20     | 3600        | 600           | 0.5               | 0.21                        |
| 21     | 3600        | 1000          | 0.5               | 0.55                        |
| 22     | 3600        | 200           | 1                 | 0.16                        |
| 23     | 3600        | 600           | 1                 | 0.22                        |
| 24     | 3600        | 1000          | 1                 | 0.64                        |
| 25     | 3600        | 200           | 1.5               | 0.15                        |
| 26     | 3600        | 600           | 1.5               | 0.19                        |
| 27     | 3600        | 1000          | 1.5               | 0.69                        |
4. Fuzzy Logic Modelling

The fuzzy model is developed using the fuzzy logic toolbox. The rules have been constructed using input parameters which are the feed rate, speed and depth of cut on the workpiece. Surface roughness of the milled surface is the output parameter. Three membership functions are used for each input variable, which are high, medium and low. Five membership functions are selected for the output response (surface roughness): very smooth, smooth, medium, rough and very rough. Mamdani inferencing system [11] is selected for model development as shown in figure 1.

![Figure 1. Mamdani inferencing system](image)

4.1. Membership Functions for Fuzzy Variables

Fuzzy logic toolbox has several membership functions such as triangular, trapezoidal, sigmoid, etc. In this model, Gaussian membership function is selected for both input and output variables to train the model. The input variables have been divided into three ranges and output variable into five ranges depending on the experimental results. Membership functions for both the input as well as the output parameters are shown in figure 2 and figure 3.

![Figure 2. Input membership function](image)

![Figure 3. Output membership function](image)
The rule base for twenty seven fuzzy rules has been built based on the experimental result. The rule base assigned for surface roughness is shown in figure 4.

![Figure 4. Rule editor for surface roughness](image)

5. Artificial Neural Network (ANN) Modeling

Artificial neural networks (ANNs) work similar to the neurons present in the human brain. In neural network these artificial neurons are linked to each other to form a model analogous to the biological nervous system. Neural networks trains itself in such a way that a particular input undergoes machine learning and produces specific output target [12]. In neural network, many input and target sets are established to train the model network. After machine learning, the validation is done by giving a sample of experimental values as input. ANN Network model used for study is shown in figure 5.

![Figure 5. ANN Network Model](image)

5.1. Methodology

The developed ANN model comprises of three layers of neurons (input, hidden and output) with different sets of neurons in each layer. The input, hidden and output layers have three, four and one neuron respectively. Out of the 27 experimental readings, 22 sets are selected for training the neural network model and validation is done with the remaining 5 sets. The training function, adaptive learning function and performance function selected were TRAINLM, LEARNGDM and MSE respectively. The training tool and the regression plot for surface roughness are shown in figure 6 and figure 7 respectively. The training tool (Figure 6) performs the function of machine learning and produces the regression plot.
(Figure 7). The regression plot shows the best fit produced by the model after analysing the experimental readings. The value of correlation coefficient (R) is close to 1 which indicates the ANN model has sufficient correlation with the experimental values.

6. Result
In this section, the values of surface roughness obtained experimentally as well as from fuzzy logic and artificial neural network model developments are compared. The percentage error of the values obtained from the fuzzy logic and ANN models were determined with respect to the experimental readings and the values were studied.

6.1. Determination of error in fuzzy logic and ANN model
Percentage error is the deviation of model development values when compared to experimentally obtained readings. The percentage error is calculated based on equation 6.1. The comparison between experimental values and values obtained from fuzzy logic and ANN models are shown in table 5 and table 6 respectively.

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\text{Percentage error} = \frac{(\text{Fuzzy}/\text{ANN value} - \text{actual value}) \times 100}{\text{Actual value}} \quad (6.1)
\]
Table 5. Estimation of error in fuzzy logic model

| SI No | Speed (rpm) | Feed (mm/min) | Depth of Cut (mm) | Surface Roughness Deviation | Percentage error (%) |
|-------|-------------|---------------|------------------|------------------------------|----------------------|
|       |             |               |                  | Actual Value | Fuzzy Value | micron |                   |
| 1     | 1600        | 200           | 0.5              | 0.35          | 0.32        | -0.03   | -8.57               |
| 2     | 1600        | 600           | 0.5              | 0.45          | 0.51        | 0.06    | 13.34               |
| 3     | 1600        | 600           | 0.5              | 0.57          | 0.51        | -0.06   | -10.52              |
| 4     | 1600        | 200           | 1                | 0.22          | 0.21        | -0.01   | -4.54               |
| 5     | 1600        | 600           | 1                | 0.37          | 0.33        | -0.04   | -11.76              |
| 6     | 1600        | 1000          | 1                | 0.90          | 0.81        | -0.09   | -10                 |
| 7     | 1600        | 200           | 1.5              | 0.22          | 0.21        | -0.01   | -4.54               |
| 8     | 1600        | 600           | 1.5              | 0.74          | 0.70        | -0.04   | -5.40               |
| 9     | 1600        | 1000          | 1.5              | 0.79          | 0.81        | 0.02    | 2.53                |
| 10    | 2600        | 200           | 0.5              | 0.15          | 0.20        | 0.05    | 33.34               |
| 11    | 2600        | 600           | 0.5              | 0.31          | 0.33        | 0.02    | 6.45                |
| 12    | 2600        | 1000          | 0.5              | 0.73          | 0.70        | -0.03   | -4.10               |
| 13    | 2600        | 200           | 1                | 0.12          | 0.21        | 0.09    | 75                  |
| 14    | 2600        | 600           | 1                | 0.34          | 0.33        | -0.01   | -2.40               |
| 15    | 2600        | 1000          | 1                | 0.68          | 0.70        | 0.02    | 2.94                |
| 16    | 2600        | 200           | 1.5              | 0.13          | 0.21        | 0.08    | 61.54               |
| 17    | 2600        | 600           | 1.5              | 0.39          | 0.33        | -0.06   | -15.39              |
| 18    | 2600        | 1000          | 1.5              | 0.54          | 0.51        | -0.03   | 5.56                |
| 19    | 3600        | 200           | 0.5              | 0.13          | 0.19        | 0.06    | 46.15               |
| 20    | 3600        | 600           | 0.5              | 0.21          | 0.21        | 0       | 0                   |
| 21    | 3600        | 1000          | 0.5              | 0.55          | 0.51        | -0.04   | -7.27               |
| 22    | 3600        | 200           | 1                | 0.16          | 0.19        | 0.03    | 18.75               |
| 23    | 3600        | 600           | 1                | 0.22          | 0.21        | -0.01   | -4.54               |
| 24    | 3600        | 1000          | 1                | 0.64          | 0.70        | 0.06    | 9.375               |
| 25    | 3600        | 200           | 1.5              | 0.15          | 0.19        | 0.04    | 26.67               |
| 26    | 3600        | 600           | 1.5              | 0.19          | 0.21        | 0.02    | 10.52               |
| 27    | 3600        | 1000          | 1.5              | 0.69          | 0.70        | 0.01    | 1.45                |

Average error for fuzzy logic model = 8.32%

The plot representing the comparison between experimental values and fuzzy logic developed values is shown in Figure 8.
Average error for ANN model = 3.93%

The plot representing the comparison between experimental values and ANN developed values is shown in Figure 9.

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**Table 6. Estimation of error in ANN model**

| SI No. | Speed (rpm) | Feed (mm/min) | Depth of Cut (mm) | Surface Roughness Deviation | Percentage Error |
|--------|-------------|---------------|-------------------|----------------------------|-----------------|
|        |             |               |                   | Actual Value | ANN Value | Deviation | %             |
| 1      | 1600        | 600           | 0.5               | 0.45         | 0.37      | -0.08     | -17.77        |
| 2      | 1600        | 200           | 1.5               | 0.22         | 0.13      | -0.09     | -40.90        |
| 3      | 2600        | 1000          | 1                 | 0.68         | 0.74      | 0.06      | 8.82          |
| 4      | 3600        | 600           | 0.5               | 0.21         | 0.30      | 0.09      | 42.85         |
| 5      | 3600        | 20n0          | 1.5               | 0.15         | 0.19      | 0.04      | 26.67         |

**Figure 8.** Fuzzy logic deviation plot

**Figure 9.** ANN deviation plot
7. Conclusion
This research study presents a comparison between artificial neural network and fuzzy logic techniques to determine the levels of control parameters that produce optimum surface roughness. The results show that both the soft computing techniques have negligible error. This shows that artificial intelligence is a faster, easier and more effective substitute to predict optimal process parameters. The comparison and validation of both artificial neural network and Fuzzy logic developed model with respect to experimentally obtained values reveal that the ANN developed model has less significant error when compared to the fuzzy logic model. The percentage error calculated from both the models shows that neural network has superior accuracy. Hence ANN is considered to be the more efficient and effective model to control surface roughness and can be used in manufacturing industries to obtain the requisite surface finish and accuracy.

8. References
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