Optimized Prediction and Modeling Under End Milling Machining By ANOVA And Artificial Neural Network

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Abstract

. In recent times, the need for characterization of surface roughness in an end milling machining process is essential. Accordingly a better approach can provide accurate machining for post casting of rolled Aluminium which often requires better dimensional tolerances. In present work the study for development of surface roughness model for rolled Aluminium is described. Experimental data is collected as per L18 orthogonal array with three levels defined for each of the factor by design of experiment approach. Analysis of variance (ANOVA) is used to test the adequacy of the developed mathematical model. Further, ANN analysis with multilayer feed forward perceptron structure using graphical user interface (GUI) under MATLAB is adopted with the experimental values as input-output pairs. Back Propagation algorithm using the input cutting conditions viz. Spindle Speed, Feed rate and Depth of Cut is being constructed and the surface roughness of the machined component is been taken as output response. The effect of feed rate is found to be the highest influence on surface roughness followed by the cutting speed and depth of cut. The result revealed the close correlation between the measured values and the model output in much lesser time and with a high accuracy.

Keywords: Dimensional tolerances, Machining, Surface Roughness, ANOVA, Artificial Neural Network

1. Introduction

To meet the need of precise dimensional tolerances through process planning, thus to achieve maximum productivity, an optimal metal removal process must be designed. The basic approach identified earlier, in order to obtain better surface finish, is the selection of proper cutting parameters before the actual machining takes place. The design specification for considering the material properties like fatigue strength, wear resistance, reliability of performance for any material undoubtedly, is surface quality and thus an important factor in evaluation of performance index for a machine tool. With the application of industrial development computer aided manufacturing (CAM) associated with CNC (Computer Numeric Control) has widely been accepted to result more accurate machining data and provide the most optimum production .The increase in utilization of machinability data systems for the selection of optimum cutting parameters has attracted the machinists for the machining processes such as milling. The most common machining operations in industries are milling operations, which is generally used for finishing, material removal processes. Many researchers have studied the effects of optimal selection of machining parameters of end milling which requires the simultaneous considerations of multiple objectives, including maximum tool life, desired surface roughness of the machined surface, metal removal rate etc. The investigations by El Bardie discussed the development of surface roughness prediction models for turning EN 24T steel and adopted the most conventional approach namely D.O.E in metal cutting which includes the experiment observations conclusion strategy.

Yang J, attempted the two purposes in the research. The first was to demonstrate a systematic procedure of using Taguchi parameter design in process control of individual milling machines. The second was to demonstrate a use of the Taguchi parameter design in order to identify the optimum surface roughness performance with a particular combination of cutting parameters in an end milling operation. Indrajit M successfully applied the RSM, a tool under design of experiment for prediction and optimization of cutting parameters. Yang Y K, applied the Taguchi method and the analysis of variance (ANOVA) approach to optimize parameters i.e. groove difference and the roughness average at the bottom plane of the inside groove in end milling for high-purity graphite under dry machining. It is mapped to achieve the objective of maximization or minimization of the output properties.

The theoretical surface roughness in end milling operations is dependent on the various parameters viz. cutting conditions, workpiece material, cutting tools etc. The D.O.E indicates the series of steps for the experiment planning for better understanding of product or process performance. In order to develop the techniques to predict the surface roughness of a product before the actual machining the evaluation of robustness of machining parameters such as feed rate, spindle speed, depth of cut etc. must be evaluated. Thus the best suited prediction technique must be employed for keeping the desired surface roughness and high product quality.

Hence, by this study an attempt has been made to develop a model to predict surface roughness in end milling of rolled aluminum, which is commercially available and known for the multiple uses in domestic as well as high precise industrial use. The research may be summarized by its purpose, as illustrated below:

(i) To study the effect of machining parameters on the surface roughness of the machined product.
(ii) To develop the surface prediction model by multiple regression technique.
(iii) To prepare the surface roughness model further by employing Artificial neural network and compare with the actual surface roughness achieved earlier,
(iv) To provide a solution of optimization problem for the selection of the best control setting to reduce the surface roughness.

2. Experimental set up & Procedure

2.1 Experimental Design

The factors whose effects were studied are depth of cut (inch), cutting speed/spindle speed (rpm), feed rate (inch/min.) on the quality characteristic surface roughness (R_a) in an end milling operation. With the involvement of 2 or more factors the response affect may be interacted; so for considering the effect the possible factor level combinations has been considered. The procedure adopted for preparing a model of the process is as illustrated:

(a) Selection of factors & their levels in the process
(b) Conducting the experiments at possible factor level combinations randomly
(c) Analyze the data by ANOVA
(d) Building of Ist order multiple regression model
(e) Validating of the model

For the investigation to be carried out and in order to reduce the number of experiments to a practical level, partial factorial design with L18 orthogonal array is proposed.

2.2 Experimental Procedure

The set up employed a VMC (Vertical Milling Centre), two 4-flute and 80 mm diameter SGS-48554 cemented carbide end mill cutters. The machining performed in dry environment. (Table 4).
The cutting process parameters and their levels selected are as shown in table 1.

Table 1: Cutting Process Parameters and their Levels

Process Parameters (units)	Levels		
	1	2	3
Depth of cut (inch)	0.02	0.038	0.046
Cutting Speed (rpm)	2500	3800	5000
Feed Rate (inch/mm)	2.0	3.5	5.0

The machining specimen is made at 18 different factor level combinations as representing the conduction of 18 experiments in table 3. The dimension of work material is taken as 80 mm x 75 mm x 15 mm. The specification of the work material is as follows (Table 2).

Table 2: Specification of Work Material

Particulars	Value
Material	Rolled Aluminium
Elastic limit	48.1 MN/m^2
Modulus of elasticity	66.7 MN/m^2
Modulus or resilience	0.280 MJ/mm^2
Izod No. (Impact Strength)	7.9
Hardness (BHN)	250
Weight	230 gm.

Table 3: Process Parameters & their Levels

Exp. No.	Column No.			
	1 Depth of cut (inch)	2 Cutting speed (rpm)	3 Feed Rate (inch/mm)	4 Avg. Surface roughness, R_a (μ-inch)
1	0.02	2500	2.0	80.3
2	0.02	5000	3.5	111.7
3	0.038	3800	5.0	76.0
4	0.046	2500	2.0	39.3
5	0.046	5000	3.5	61.0
6	0.02	3800	3.5	65.3
7	0.038	2500	5.0	69.3
8	0.038	5000	3.5	93.67
9	0.046	3800	5.0	22.3
10	0.02	2500	2.0	137.67
11	0.02	5000	5.0	42.0
12	0.038	3800	2.0	58.0
13	0.046	2500	3.5	62.7
14	0.046	5000	3.5	72.0
15	0.02	3800	5.0	31.3
16	0.038	2500	2.0	88.3
17	0.038	5000	5.0	40.0
18	0.046	3800	3.5	48.3

The experimental conditions are given in table 4 as follows.

Table 4: Experimental Conditions

Particulars	Experimental conditions
Machine	Vertical milling center, AGNI BMV 45. MODEL No. 4000SPE
Tool	4 flute, 8.0 diameter, SGS 48554, Cemented carbide end mill cutter
Collet	Size 8-9 mm
Cutting parameters	Depth of cut, Cutting speed, Feed rate
Surface roughness tester	Profilometer, Federal Pocketsurf-3 Piezoelectric contact type stylus, Stylus travel: 0.1 inch/2.54 mm, Maximum stylus force: 15 MN, Measuring capacity: R_a or R_{max}/R_y or R_z
Coolant	Dry machining

The surface roughness was measured at three different spaced locations along the length of the specimen and the average was taken as response values. The mean response values for experimental data are shown in table 5 as given below.

Table 5: Mean response Table for Experimental Data

Levels	Depth of cut (inch)	Cutting speed (rpm)	Feed rate (inch/mm)
1	84.28	2.0	80.3
2	55.27	3.5	111.7
3	60.32	5.0	76.0
Max-min (δ)	29.01	2.0	39.3
Rank	3	2	1

The result of the analysis of variance of surface roughness is shown in table no. 6 as given below.

Table 6: ANOVA Table for Surface Roughness

Factor	Cutting parameter	DOF	Sum of squares	Mean square	F-test
A	Depth of cut (inch)	2	36.669	18.335	12.223
B	Cutting speed (rpm)	2	56.018	28.009	18.673
C	Feed rate (inch/mm)	2	160.485	80.243	53.495
Error	-	47	70.52	1.50	-
Total	-	53	323.694	-	-

2.3 Analysis of Variance

The purpose of the analysis of variance (ANOVA) is to determine which cutting parameter significantly affects the quality characteristic (R_a). Being an objective decision making tool it can provide a measure of average performance of group of items under test. This does not analyze the data directly, but rather determine the value- ability (variance) of the data. The F-test (Frequency test) a statistical measure to analyze the significant effect of the parameters expressing the quality characteristics table 7 shows the result of ANOVA analysis of raw data for surface roughness for a level of significance for 95 % level of confidence. From the table 7, it is apparent that the F-ratio values of factor A (depth of cut), Factor B (cutting speed) and factor C (feed rate) are all greater than $F_{0.05,2,45}$ = 3.2. Thus have statistical physical significance as the response variable (surface roughness).

Table 7: Mean Response Table for S/N ratio

Levels	Depth of cut (inch)	Cutting speed (rpm)	Feed rate (inch/mm)
1	-37.94	-37.492	-32.26
2	-34.55	-37.12	-36.477
3	-35.505	-33.38	-39.54
Max-min (δ)	3.39	4.11	7.28
Rank	3	2	1

The mean response and the mean signal to noise ratio for the depth of cut, cutting speed & feed rate are represented graphically & tabulated in Fig. 2 & table 5 and table 6. The optimal cutting parameters for surface roughness are A2–B3–C1. The predicted surface roughness is obtained by the following equation:

$$\mu = \mu + (\mu_A - \mu) + (\mu_B - \mu) + (\mu_C - \mu) \quad \textbf{(1)}$$

where, μ = Mean Surface Roughness

μ_A = Main effect due to A

μ_B = Main effect due to B

μ_C = Main effect due to C

Figure 1: Experimental and data aquisition setup

Table 8: Final Confirmation Experiment

	Exp. No.	A2-B3-C1-D2			R_a (µin.)	S/N Ratio
		R1	R2	R3		
N1	1*	17	21	22	20.0	-25.92
	2	20	22	25	22.3	-27.016
N2	1*	17	21	22	20.0	-25.92
	2	15	17	24	18.67	-25.60

3. Artificial Neural Network (ANN)

Among the most appropriate tools in artificial intelligence and widely accepted in all fields of engineering, modeling and optimization is ANN. ANN is used to predict the linear and nonlinear problems in machining field. Davim J P [12], developed and investigated the predicted models for Surface roughness using artificial neural network (EBPTA) during turning of free machining steel, 9SMnPb28k (DIN). Zain A.M [13,15] discussed the concept, application, abilities and limitations of Artificial Neural Network in the machining process modeling. The comparison been attempted between the conventional approaches such as statistical regression technique, explicit models with non conventional approaches or Artificial Intelligence techniques such as Artificial Neural Network, Fuzzy Logic and Genetic Algorithm based modeling. Muthukrishnan N, J. Paulo Davim [14], studied the surface roughness of Al–SiC (20 p) composite bars in turning operation using coarse grade polycrystalline diamond (PCD) insert under different cutting conditions. Experimental data collected, tested with ANOVA and artificial neural network techniques. Multilayer perceptron model has been constructed with back-propagation algorithm using the input parameters of depth of cut, cutting speed and feed. Output parameter is surface finish of the machined component.

As development of mathematical models are required for the prediction of decision variable and responses in decision making processes for industries[16], in this research work the attempt is made to model the machining parameters using artificial neural network. The developed model for the milling process derives the relationship between the input parameter and the output parameter in terms of mathematical equation. It is a multi layer feed forward network using gradient –descent based delta learning rule, commonly known as back propagation rule. Being a gradient descent method, it minimizes the total squared error of the output computed by the net. The network is trained by supervised learning method. The network achieves a balance between the ability to respond correctly to the input patterns that are used for training and the ability to provide good responses to the input.

Artificial neural networks are mathematical models of biological neural systems. It learns from examples through iteration, without requiring a priori knowledge of relationships between variables under investigation. Each example includes both inputs (information used to make a decision) and patterns (prediction or responses). ANN tries each example in turn using the inputs to calculate answers which it compares to provide pattern. If it is wrong, ANN corrects the network by making changes to internal connections (weights). The trial and error process continues until the network outputs are in good agreement with patterns to a certain specified level of accuracy.

In ANN modeling, MATLAB software was used for training and validating of neural network models. Multiple input and multiple output (MIMO) network models were developed for objective parameters and for sensory attributes. Standard Bayesian regularization back propagation training algorithm, trainbr function, was used for training the network. This training function updates the weight and bias values according to Levenberg – Marquardt algorithm. It is one of the best ways to improve generalization performance of network for function approximation problems. This is because it does not require that a validation data set be separated out of the training data set. It uses all of the data. This advantage is especially noticeable when the size of data set is small. It minimizes a linear combination of squared errors and weights and then determines the correct combination to produce network that generalizes well. The number of neurons in hidden layer [11], was determined by trial and error. The multi-layer feed forward ANN consisted of neurons divided into input layer, output layer and hidden layers. The neurons between the layers are connected by the links having synaptic weights. The error back-propagation training algorithm is based on weight updates so as to minimize the sum of squared error for *K*-number of output neurons, given as

$$E = \frac{1}{2}\sum_{k=1}^{K}(d_{k.p} - o_{kp})^2 \qquad \textbf{(2)}$$

Where, $d_{k,p}$ = desired output for the p_{th} pattern.

The weights of the links are updated as

$$w_{ji(n+1)} = w_{ji(n)} + \eta\delta_{pj}o_{pi} + \alpha\Delta w_{ji(n)} \qquad \textbf{(3)}$$

where *n* is the learning step, η is the learning rate, α is the momentum constant and δ_{pj} is error for output or input layer as,

$$\delta_{pk} = (d_{kp} - o_{kp})(1 - o_{kp}), \quad k=1,2,\ldots.K \qquad \textbf{(4)}$$

$$\delta_{pj} = o_{pj}(1 - o_{pj})\sum \delta_{pk} w_{kj}\,, \quad j=1,2\ldots\ldots J \qquad \textbf{(5)}$$

where, j is the number of neurons in the hidden layer.

The training process is initialized by assigning small random weight values to all the links. The input–output patterns are presented one by one and updating the weights each time. The mean square error (MSE) at the end of each epoch due to all patterns is computed as

$$MSE = \frac{1}{NP}\sum_{p=1}^{P}\sum_{k=1}^{K}(d_{kp} - o_{kp})^2 \qquad \textbf{(6)}$$

Where, NP = number of training patterns. The training process will be terminated when the specified goal of MSE or maximum number of epochs is achieved.

3.1 ANN Training

The training of ANN for the 18 inputs and output patterns has been used under MATLAB software. The multilayered feed forward ANN with 3 inputs (depth of cut, spindle speed, feed rate) and 1 output (R_a) is employed. The training simulations with following details are as under table 9. For each input pattern, the predicted value of R_a is compared with the respective experimental measured value and the $\%_{ge}$ absolute error is measured as equation 7.

$$\%_{ge}\, AbsoluteError = \left[\frac{y_{i.\exp} - y_{i.pred}}{y_{i.\exp}}\right] \times 100 \qquad \textbf{(7)}$$

Table 9: Factors assumed to train the Network

Particulars	Value
Number of nodes in input layer	3
Number of nodes in hidden layer	20
Number of nodes in output layer	1
Learning rate chosen	0.05
Momentum	0.9
Goal (MSE)	1e-05
Number of epochs	10000

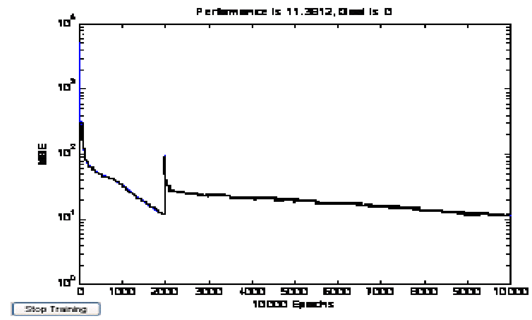

Figure 2: The variation of MSE with number of epochs

3.2 Model Verification

The training of the artificial neural network with different nodes in the hidden layer found to be 20.The performance of ANN after taking account of all the training and testing pattern is 11.38.Thus proven to be a significant A.I tool in order to predict the surface roughness in end milling machining process. The Fig. 5 shows the graph plotted using predicted and tested values for surface roughness. The correlation between the outputs and targets measures the variation in the outputs that may be related with targets. The correlation coefficient (RC value) for the output (R_a) is found to be 0.98, nearly equal to 1, which indicates the very good correlation. Further the validation of ANN model for the output (surface roughness, R_a) is performed with the data set of actual experimental values and the predicted surface roughness values in Fig. 4. The trend reveals that the predicted values following the actual values observed in experimental trials.

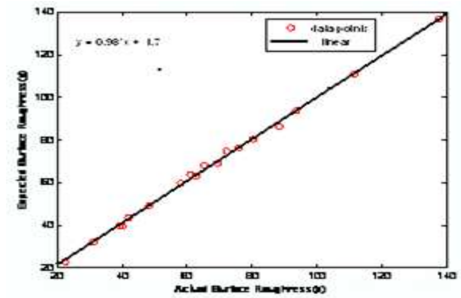

Figure 3: Correlation of the Training Pattern for R_a

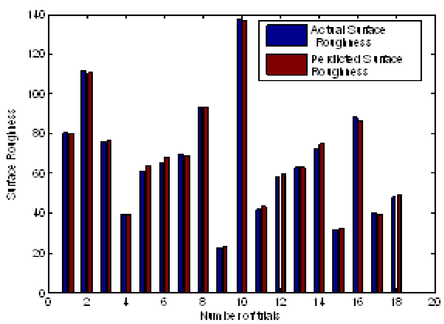

Figure 4: Validation of ANN Model for Surface Roughness

4. Conclusions

The 18 experiments were conducted on a VMC using cemented carbide end mill cutter; the surface roughness values were obtained with various factor-level combinations. The two modeling techniques, viz. ANOVA and ANN were explored for the prediction of surface roughness in an end milling machining. The outcome of the calculations and analysis by the ANOVA has depicted that the effect of feed rate represents the highest influence on surface roughness followed by the cutting speed and depth of cut. From the (Table 3) Average (Mean) Effect Response Table for the raw data, the factor (C) Feed rate represents the largest influence on surface roughness followed by factor (B) Cutting Speed, factor (A) Depth of Cut and finally factor (D) Type of tool which is further verified with the (table 4) Average Effect Response Table for S/N Ratio. Further, ANN with configuration of 18 patterns was trained. The result revealed the close correlation between the measured values and the model output in much lesser time and with a high accuracy. Finally it is concluded that ANN is a powerful tool for the modeling of linear and nonlinear relationship between the process response (surface roughness) and input parameters problems. Thus modeling using ANN is proven to be an effective method for the prediction of experimental patterns.

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