Optimization and Prediction of Parameters in Face Milling of Al-6061 Using Taguchi and ANN Approach

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Abstract

In this paper, Taguchi Method has been used to identify the optimal combination of influential factors in the milling process. Milling experiment has been performed on Al 6061 material, according to Taguchi orthogonal array (L₁₆) for various combinations of controllable parameters viz. speed, feed and depth of cut. The surface roughness (Rₐ) is measured and recorded for each experimental run and analyzed using Taguchi S/N ratios and the optimum controllable parameter combination is identified. An Artificial neural network (ANN) model has been developed and trained with full factorial design experimental data and a combination of control parameters have been found from ANN for the surface roughness (Rₐ) value, obtained from confirmation test, for the optimum control parameters which are obtained from Taguchi S/N ratios analysis. Taguchi method and ANN found different sets of optimal combinations but the confirmation test revealed that both got almost same Rₐ values.

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Keywords: Controllable parameters; Al-6061; milling; Taguchi method; S/N ratio analysis; Artificial Neural Networks.

1. INTRODUCTION

Roughness is often a good predictor of the performance of a mechanical component since irregularities in the surface may form nucleation sites for cracks or corrosion. Although roughness is usually undesirable, it is difficult and expensive to control during manufacturing. Decreasing roughness of a surface will usually exponentially increase its manufacturing costs. This often results in a trade-off between the manufacturing cost of a component and its performance in application. Increasing the productivity and the quality of the machined parts are the main challenges of metal-based industry. There has been increased interest in monitoring all aspects of the machining process. Quality of machining can be judged by surface roughness. Higher the surface finish higher will be the quality. Surface finish mainly depends on cutting speed, Depth of cut, Feed. Most of the operators use trial and error method to find the appropriate cutting condition.

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It is not the effective way to find out optimal cutting parameters. So the main objective of the study is to find the optimum parameters (speed, feed, depth of cut) so that surface roughness is optimized. Aluminium has much application in industries. Also automotive aircraft and train companies need to replace steel and cast iron with lighter metal like aluminum. So, it is important to know the machining behaviour of aluminium. There are various optimization techniques like Genetic Algorithm, Artificial Neural Network, Grey Analysis, Utility Concept, Response Surface Methods, Taguchi technique, Fuzzy Logic, etc. to find out optimum cutting conditions.

2. LITERATURE REVIEW

Şeref Aykut [1] developed an ANN model to predict the surface roughness of Castamide material after machining process. In the study, experiments on Castamide were done in CNC milling using high speed steel and hard metal carbide tools. Dr. Mike S. Lou et al. [2] developed a multi-regression model that can predict the surface roughness on the surface of the specimen (Al-6061) on which end milling operation has been carried out using a CNC machine. Surasit Rawangwong et al. [3] investigated the effects of cutting parameters on the surface roughness in semi-solid AA 7075 face milling. The results of the research could be applied in the manufacture of automotive components. Mathew A. Kuttolamadom et al. [4] studied the effects of machining feed on surface roughness in milling Al-6061. A controlled milling experiment on 6061 aluminium depicted the relationship between feed and surface quality. Yang Yang et al. [5] proposed a method based on gene expression programming (GEP) to construct the prediction model of surface roughness. GEP combines the advantages of the genetic algorithm (GA) and genetic programming (GP). Bharat chandra Routara et al. [6] studied a multi-objective optimization problem by applying utility concept coupled with Taguchi method through a case study in CNC end milling of UNS C34000 medium leaded brass. The study aimed at evaluating the best process environment which could simultaneously satisfy multiple requirements of surface quality. B. Vijaya Krishna Teja et al. [7] conducted an experimental study on performance characteristics of AISI 304 stainless steel during CNC milling process. The work represents multi-objective optimization of milling process parameters using Grey-Taguchi method in machining of AISI 304 stainless steel. Sanjit Moshat et al. [8] studied the highlights of optimization of CNC end milling process parameters to provide good surface finish as well as high material removal rate (MRR).

In this paper, Taguchi method is adopted experimentally to investigate surface roughness influenced by the control parameters such as speed, feed and depth of cut. And also it presents an ANN approach for prediction of control parameters for surface roughness in face milling.

3. CONTROL PARAMETERS AND THEIR LEVELS

The parameters which influence the surface roughness of machined surface called control parameters such as speed, feed and depth of cut. In this work, three controllable parameters are considered and each parameter is set at four levels. The parameters and its levels are shown in Table 1.

| Levels | Control parameters |
|--------|--------------------|
|        | Speed (RPM) | Feed (mm/rev) | DOC (mm) |
| 1      | 900         | 125            | 0.1      |
| 2      | 1120        | 160            | 0.15     |
| 3      | 1400        | 200            | 0.2      |
| 4      | 1800        | 250            | 0.25     |

4. EXPERIMENTAL DESIGN AND MILLING OF WORK MATERIAL

In this work, Taguchi L16 design is used for conducting milling experiments (see Fig.1) on Al6061 work material by considering different speed, feed and depth of cut combinations and the values of surface roughness are measured using TalySurf surface tester (Fig 2) recorded in Table 2. And also experiments are conducted for full factorial design (Table.6) to train the developed ANN.
5. OPTIMIZATION OF MACHINING PARAMETERS USING TAGUCHI S/N RATIO ANALYSIS

The Experimental data of surface finish ($R_a$) is analyzed using Taguchi design in Minitab software and signal to noise (S/N) ratio values are determined. The optimum levels of influential parameters are determined based on the obtained S/N ratios.

| Exp. run | Speed (rpm) | Feed (mm/rev) | DOC (mm) | Surface roughness (μm) |
|----------|-------------|---------------|---------|-------------------------|
| 1        | 900         | 125           | 0.1     | 0.695                   |
| 2        | 900         | 160           | 0.15    | 0.82                    |
| 3        | 900         | 200           | 0.2     | 1.04                    |
| 4        | 900         | 250           | 0.25    | 1.13                    |
| 5        | 1120        | 125           | 0.15    | 1.205                   |
| 6        | 1120        | 160           | 0.1     | 0.7                     |
| 7        | 1120        | 200           | 0.25    | 0.33                    |
| 8        | 1120        | 250           | 0.2     | 0.535                   |
| 9        | 1400        | 125           | 0.2     | 0.745                   |
| 10       | 1400        | 160           | 0.25    | 0.62                    |
| 11       | 1400        | 200           | 0.1     | 0.53                    |
| 12       | 1400        | 250           | 0.15    | 0.485                   |
| 13       | 1800        | 125           | 0.25    | 0.59                    |
| 14       | 1800        | 160           | 0.2     | 0.605                   |
| 15       | 1800        | 200           | 0.15    | 0.355                   |
| 16       | 1800        | 250           | 0.1     | 0.115                   |

Figure 3: Main Effects Plot for S/N ratios
After determining the S/N ratio values (Table 3), the effect of each Machining parameter is separated based on S/N ratio at different levels and the values of S/N ratio for each level of the controllable parameters and the effect of parameter on response (Ra) in rank wise are summarized in Table-4. Basically, large S/N ratio means it is close to good quality, thus, a higher value of the S/N ratio is desirable. From the Table-3 and Fig.3 the cutting parameters with the best level are spindle speed at level-4, feed at level-4 and DOC at level-1. The optimal levels for the controllable parameters obtained from this methodology are verified by the conformation test, the surface roughness (Ra) value obtained for these optimum control parameters is 0.115 μm and as shown in Table-5.

Table 3: S/N ratios

| Exp. run | Surface roughness (Ra, μm) | S/N for Ra |
|----------|-----------------------------|------------|
| 1        | 0.695                       | 3.160      |
| 2        | 0.82                        | 1.723      |
| 3        | 1.04                        | -0.340     |
| 4        | 1.13                        | -1.061     |
| 5        | 1.205                       | -1.619     |
| 6        | 0.7                         | 3.098      |
| 7        | 0.33                        | 9.629      |
| 8        | 0.535                       | 5.432      |
| 9        | 0.745                       | 2.556      |
| 10       | 0.62                        | 4.152      |
| 11       | 0.53                        | 5.514      |
| 12       | 0.485                       | 6.285      |
| 13       | 0.59                        | 4.582      |
| 14       | 0.605                       | 4.364      |
| 15       | 0.355                       | 8.995      |
| 16       | 0.115                       | 18.786     |

Table 4: S/N ratio for each level of control parameters

| Levels | Speed | Feed | DOC |
|--------|-------|------|-----|
| 1      | 0.870 | 2.170| 7.639|
| 2      | 4.135 | 3.101| 3.846|
| 3      | 4.627 | 5.949| 3.003|
| 4      | 9.182 | 7.360| 4.186|
| Delta  | 8.311 | 5.190| 4.636|

Table 5: optimum control parameters values for S/N ratio analysis

| Speed (rpm) | Feed (mm/ min) | Depth of Cut (mm) |
|-------------|----------------|------------------|
| 1800        | 250            | 0.10             |

6. PREDICTION OF VALUES USING ANN

A three-layer feed-forward network with sigmoid hidden neurons and linear output neurons can fit multi-dimensional mapping problems arbitrarily well, given consistent data and enough neurons in its hidden layer. The network is trained with Levenberg-Marquardt back propagation algorithm (trainlm). The structure of artificial neural network with input and output parameters is shown in Fig. 4(a). Cutting speed, Feed rate and depth of cut are taken as the input parameters whereas surface roughness (Ra) is taken as output parameter.
As shown in Fig. 4, the ANN has three layers, input layer, hidden layer, and output layer. The hidden layer consists of 10 neurons and the output layer consists of only one neuron. The experimental values of full factorial design (Table 6) are used for training (ref. Fig. 4) the network. A well-trained ANN is well generalized which gives proper output for those input also which has never been encountered with the network while training. Training a network is nothing but to set optimum weights of the links of two neurons. These weights, activation function, number of layers and neurons in a layer decide how well nonlinearity can be defined. The performance plot and regression plots are shown in Figure 5 and 6 respectively. The best performance is obtained at epoch 6.
The confirmation test results for the optimal parametric combination obtained in Taguchi S/N ratio analysis is given as input to the trained ANN, and the network predicted the control parameter values as speed: 1800 rpm, feed: 250 mm/rev and depth of cut: 0.5 mm. Again confirmation test has been conducted for this parameter combination. The surface roughness (Ra) value obtained for these optimum control parameters is 0.113 μm (see Table 7).

Table 6: Experiments for Full factorial design

| Run | Speed (rpm) | Feed (mm/rev) | DOC (mm) | Ra (µm) |
|-----|-------------|---------------|---------|---------|
| 1   | 900         | 125           | 0.1     | 0.695   |
| 2   | 900         | 125           | 0.15    | 0.708   |
| 3   | 900         | 125           | 0.2     | 0.852   |
| 4   | 900         | 125           | 0.25    | 1.042   |
|     |             |               |         |         |
| 60  | 1800        | 200           | 0.25    | 0.098   |
| **61** | **1800** | **250** | **0.1** | **0.115** |
| 62  | 1800        | 250           | 0.15    |         |
| **63** | **1800** | **250** | **0.2** |         |
| 64  | 1800        | 250           | 0.25    | 0.155   |

Table 7: Confirmation test results

| Combination of controllable parameters | Ra (µm) |
|---------------------------------------|---------|
| Speed (rpm) | Feed (mm/rev) | DOC (mm) | Predicted value | Exp. Value |
| ANN | 1800 | 250 | 0.2 | --- | 0.113 |
| Taguchi | 1800 | 250 | 0.1 | N.A | 0.115 |

7. CONCLUSION

Among the consider parameters, speed has the most influence on the surface finish of the work-piece. The trained ANN is able to predict the Ra values with reasonable accuracy. Taguchi S/N ratio analysis and ANN are useful to find the optimum combination of parameters for getting a good surface finish.
REFERENCES

[1] Şeref Aykut, “Surface Roughness Prediction in Machining Castamide Material Using ANN” (2011), Acta Polytechnica Hungarica, Vol. 8, No. 2, PP 21-32.

[2] Dr. Mike S. Lou, Dr. Joseph C. Chen & Dr. Caleb M. Li, (1999), “Surface roughness prediction technique for CNC End-milling”, Journal of industrial technology, Vol-15.

[3] Surasit Rawangwong, Jaknarin Chatthong, Romadorn Burapa, and Worapong Boonchouyetan, “An investigation of optimum cutting conditions in face milling semi-solid AA7075 using carbide tool” (2012), International journal of innovation, Vol-3, No. 6, PP 692-696.

[4] Mathew A. Kuttolamadom, Sina Hamzehlouia, M. Laine Mears, “Effect of machining feed on surface roughness in cutting 6061 aluminum” (2010), International center for automotive research, Clemson university, 2010-01-0218.

[5] Yang Yang, Xinyu Li, Ping Jiang and Liping Zhang, “Prediction of surface roughness in end milling with gene expression programming”, Proceedings of the 41st International Conference on Computers & Industrial Engineering, PP 441-446.

[6] Bharat chandra routara, Saumya darsan mohanty, saurav datta, Asish bandyopadhyay and siba sankar mahapatra, “Optimization in CNC end milling of UNS C34000 medium leaded brass with multiple surface roughness characteristics”, Sadhana, Indian Academy of Sciences, Vol. 35, Part 5, October 2010, pp. 619–629.

[7] B. Vijaya Krishna Teja, N. Naresh and K. Rajasekar, “Multiple response optimization of Milling parameters on AISI 304 Stainless steel using grey-taguchi method” (2013), International Journal of Engineering Research and Technology, Vol-2, issue 8, PP 2335-2341.

[8] Sanjit Moshat, Saurav Datta, Asish Bandyopadhyay and Pradip Kumar Pal, “Optimization of CNC end milling process parameters using PCA-based taguchi method” (2010), International Journal of Engineering, Science and Technology, Vol-2, No-1, PP 92-102.