A neuro-fuzzy approach to select cutting parameters for commercial die manufacturing

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Abstract

Surface roughness is a quality index for machined surfaces. In this study an algorithm has been developed to determine the feasible solutions for cutting parameters in order to obtain desired surface roughness for three dimensional dies. Here the average surface roughness values for a commercial die material EN24 after ball end milling operation have been measured after experiments with different cutting parameters. These datasets have been used for training and testing different prediction models like artificial neural network (ANN), response surface methodology (RSM), adaptive neuro-fuzzy inference system (ANFIS) and mathematical equation based on machining theories. ANFIS model has been selected as better prediction model because it has shown minimum value of root mean square error (RMSE) and mean absolute percentage error (MAPE) for training and testing datasets. This ANFIS model has been used further for predicting surface roughness of a typical die made of EN24 after ball end milling operation.

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1. Introduction

The main objective of today’s manufacturing industries is to produce low cost, high quality products in short time. The selection of optimal cutting parameters is a very important issue for every machining process in order to enhance the quality of machined products and reduce the machining costs. It is expected that the next decade

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machine tools will be intelligent machines with various capabilities such as prediction of self set up required parameters to reach to the best surface qualities. Unlike turning, face milling or flat end milling operations, predicting surface roughness for ball end milling by mathematical models is very difficult. In recent years the trends are towards modeling of machining processes using artificial intelligence due to their advanced computing capability. Researchers have used various intelligent techniques, including neural network, fuzzy logic, neuro-fuzzy, RSM, ANFIS, etc., for the prediction of machining parameters and to enhance manufacturing automation.

This research focuses on surface quality of commercial dies. Primarily research was planned to conduct for different die materials. Survey among the commercial die manufacturers reveals that dies are mainly commercially manufactured using EN24 and Hot die steel. This study attempts to design Adaptive Network-based Fuzzy Interface System (ANFIS) for modeling and predicting surface roughness in ball end milling of a die material; and developing an algorithm to preset the cutting parameters for a desired level of surface roughness. The developed model can be effectively used to predict the surface roughness in three dimensional machining of EN24 within the ranges of variables studied. The results are compared with the ANN and RSM results and results from theoretical equations. Comparison of results shows that the ANFIS results are superior to others.

2. Literature review

The quality of surface finish mainly depends on the interaction between the workpiece, cutting tool and the machining system. Due to the above reasons, there have been a series of attempts by researchers to develop efficient prediction model for surface roughness before machining. Survey on previous surface roughness research reveals that most of the researches proposed multiple regression method to predict surface roughness. Some research applied neural network, fuzzy logic, and neural-fuzzy approaches. Optimization of surface roughness prediction model, developed by multiple regression method, with a genetic algorithm is presented in some journals.

For the prediction of surface roughness, a feed forward ANN was used for face milling of high chromium steel (AISI H11) by Rai et al. [1] and AISI 420 B stainless steel by Bruni et al. [2]. Bruni et al. proposed analytical and artificial neural network models. Yazdi and Khorram [3] worked for selection of optimal machining parameters (i.e., spindle speed, depth of cut and feed rate) for face milling operations in order to minimize the surface roughness and to maximize the material removal rate using Response Surface Methodology (RSM) and Perceptron neural network. In 2009, Patricia Munoz-Escalona et al. [4] proposed the radial basis feed forward Neural Network model and generalized regression for surface roughness prediction for face milling of Al 7075-T735. Zhanjie et al. [5] used radial basis Function Network to predict surface roughness and compared with measured values and the result from regression analysis. Experiments have been carried out by Brecher et al. [6] after end milling of steel C45 in order to obtain the roughness data and model ANN for surface roughness predictions. Seref Aykut [7] had also used ANN to predict the surface roughness of cast-polyamide material after milling operation. Khorasani et al. [8] have conducted study to discover the role of machining parameters like cutting speed, feed rate and depth of cut in tool life prediction in end milling operations on Al 7075 by using multi layer perceptron neural networks and Taguchi design of experiment.

Mahdavinejad et al. [9] used combination of adaptive neural fuzzy intelligent system to predict the surface roughness in turning process. Shibendu Shekhar Roy [10] designed Adaptive Network-based Fuzzy Inference System (ANFIS) for modeling and predicting the surface roughness in end milling operation. Reddy et al. [11] also used ANFIS to prediction surface roughness of aluminum alloys but for turning operation. The ANFIS results are compared with the RSM results and comparison showed that the ANFIS results are superior to the RSM results. Kumanan et al. [12] proposed the application of two different hybrid intelligent techniques, adaptive neuro fuzzy inference system (ANFIS) and radial basis function neural network- fuzzy logic (RBFNN-FL) for the prediction of surface roughness in end milling. A neural fuzzy system was used to predict surface roughness in milling operations by Cabrera et al. [13]. From the literature review, it was observed that majority of the work in the area of Artificial Intelligence application has been conducted for turning and flat end or face milling operation. Due to this fact and also considering the importance of ball end milling operation this research was designed for machining commercial die materials.
3. Methodology

The experiment was performed by using a vertical milling machine. The work-piece tested was an AISI 4340 plate of size 7cm×1cm×4cm. Tungsten carbide coated ball end mill cutters of two-flutes were used as the cutting tool. The diameters of the tools were 6, 8 and 10 mm. Some surfaces of 1cm×1cm were produced on the work-piece by machining with various input parameters. In order to detect the average surface roughness (Ra) value, experiments were carried out by varying the cutter axis inclination angle (θ) spindle speed (S rpm), the feed rate along y-axis (f_y mm/min), radial depth of cut namely feed along x-axis (f_x mm) and the axial depth of cut (t). Here varying Cutter Axis Inclination Angle the scenario of three dimensional machining could be seen. For every input variable the allowable and possible maximum and minimum values were identified based on tool supplier specifications and commercial die manufacturers. For designing the experiments Fractional Box-Behnken Design of Experiment (DoE) was used as suggested by Box and Behnken [14], because this is very useful for observing the interaction effects. This DoE yields 49 sets of experiments. Few more experiments (25 sets of experiment) have been conducted using random sets of input parameters within the range. For each of the experiments, three sample readings were taken and their average value was considered.

In this study ANN, RSM, ANFIS and theoretical equations were used for developing prediction models for Ra using the 49 train datasets. ANN and ANFIS models were developed using MATLAB 7.6 and RSM was developed using Minitab software. Theoretical equations were developed using machining theories. Using the 25 test datasets all of the prediction models were tested. Prediction errors (RMSE and MAPE) calculated in each models for the test and train datasets have been listed in Table 1. It can be observed that the prediction results for surface roughness are more accurate in ANFIS model if we consider both training and testing data. So finally the ANFIS model can be suggested as a better prediction model and can be used further for surface roughness prediction using ball end milling operation on commercial die making steel EN24. This ANFIS model consists, 2 two-sided Gaussian curve built-in (gauss2MF) membership functions for each of the six inputs and a linear output function. Grid partitioning method has been selected for FIS structure and rule generation; and hybrid optimization method used for training the FIS.

| Model       | For Training Data | For Testing Data |
|-------------|-------------------|------------------|
|             | RMSE              | MAPE (%)         | RMSE              | MAPE (%)         |
| Theoretical Model | 0.475             | 39.73            | 0.318             | 27.1             |
| ANFIS       | 4.2392×10^{-5}   | 0.00302          | 0.17024119        | 15.7941          |
| ANN         | 4.34×10^{-5}     | 0.0041           | 0.23445483        | 20.3422          |
| RSM         | 0.151             | 15.94            | 0.236             | 23.78            |

4. Application of the model and discussion

The models developed for the prediction of surface roughness of dies made of EN24 can be used for setting the cutting parameters to obtain a predetermined surface roughness. Here the die selected as an example is made of EN24 used for ceramic plate manufacturing. The surface quality of the die surface will affect the surface of the final ceramic plate. The post processing of a machined surface will cost higher if the machined surface is too much rough. As a result it is important that the die surface should be of low surface roughness.

In this example the surface roughness of the die is targeted to be smooth which is defined by triangular membership function, where the desired R_a should have smallest possible value of 0, most promising value of 0.76 and largest possible value 0.8 respectively. Only a ball end mill cutter of 8 mm diameter is being used for the machining. It was previously machined with rough cut for removing the maximum material and already given a near to desired shape. Now it is needed to machine for finishing and obtaining the final die. So, for the final machining operation with ball end mill, the average depth of cut is needed only 0.2 mm.

The shape of final die is shown in Fig. 1 (a). It is round shaped plate of 71.8 mm diameter. The center portion of the die is flat. The diameter of the center of the die (flat part BC) is 20 mm and outer round part (AB) of the die is as
an internal shape of a sphere of radius 100 mm. This spherical portion forms 15° angle at its center. Half of the cross section view and dimension of this die are shown in Fig. 1 (b). Our focus is on the surface roughness of the upper face (ABC) of the die as shown in Fig. 1 (b).

According to machine specification possible cutting parameters are as follows: Cutter Axis Inclination Angle or Inclination Angle of machining surface, \( \varphi = 0^\circ \) to \( 15^\circ \); Spindle Speed \( S = [316, 380, 433, 520, 596, 715] \) rpm; Tool Diameter \( d = 8 \) mm; Feed Rate \( f_y = [22, 34, 44] \) mm/min; Radial Depth of Cut or Feed along \( x \)-axis \( f_x = 0.2 \) mm; Depth of Cut \( t = 0.2 \) mm.

![Fig. 1. (a) Die for a ceramic plate(b) Dimension of the die (Arc AB forms 15° angle at its centre).](image)

All of the possible combinations of input parameters would be used to find corresponding \( R_a \) using already developed ANFIS model for EN24, which is constructed with 2 two-sided Gaussian curve built-in (gauss2MF) membership functions for inputs and a linear membership function for output \( R_a \). As the target is to obtain a surface roughness less than 0.8 \( \mu m \) there may be a lot of combinations of the input parameters which results the required roughness value. But it can be observed from the correlation analysis that low values of feed \( f_x \) (radial depth of cut) will produce smoother surface. As a result the \( f_x \) has been set to its minimum value (0.2) within its range. The value of \( \varphi \) will change after every round pass of the cutter as a function of \( f_x \), tool diameter \( (d=8mm) \) and radius of the spherical portion of the die \( (R=100mm) \), at a rate \( \theta \), as shown in equation (1).

\[
\theta = 2 \sin^{-1} \left( \frac{f_x}{2 (R - d/2)} \right)
\]  

(1)

| Machining points | \( \Phi \) | \( S \) | \( D \) | \( f_x \) | \( f_y \) | \( t \) | \( R_a \) |
|-----------------|----------|------|------|-------|-------|------|--------|
| 1               | 0        | 596  | 8    | 22    | 0.2   | 0.2  | 0.6346 |
| 2               | 1.15     | 715  | 8    | 44    | 0.2   | 0.2  | 0.7993 |
| 3               | 2.301    | 715  | 8    | 44    | 0.2   | 0.2  | 0.7876 |
| 4               | 3.4516   | 715  | 8    | 44    | 0.2   | 0.2  | 0.7764 |
| 5               | 4.602    | 715  | 8    | 44    | 0.2   | 0.2  | 0.7666 |
| 6               | 5.7527   | 715  | 8    | 44    | 0.2   | 0.2  | 0.7591 |
| 7               | 6.9032   | 715  | 8    | 44    | 0.2   | 0.2  | 0.7556 |
| 8               | 8.0537   | 715  | 8    | 44    | 0.2   | 0.2  | 0.7581 |
| 9               | 9.2043   | 715  | 8    | 44    | 0.2   | 0.2  | 0.7690 |
| 10              | 10.355   | 596  | 8    | 22    | 0.2   | 0.2  | 0.7568 |
| 11              | 11.505   | 596  | 8    | 22    | 0.2   | 0.2  | 0.7975 |
| 12              | 12.656   | 316  | 8    | 44    | 0.2   | 0.2  | 0.7679 |
| 13              | 13.806   | 715  | 8    | 34    | 0.2   | 0.2  | 0.7722 |
| 14              | 14.957   | 433  | 8    | 22    | 0.2   | 0.2  | 0.7516 |
| 15              | 15       | 433  | 8    | 22    | 0.2   | 0.2  | 0.7839 |
| **Average Roughness of the round surface of the die** |          |      |      |       |       |      | **0.7624** |
So, after every round pass, the cutting tool will move to both vertical and horizontal direction whose resultant vector sum is equal to the radial depth of cut \( f_x \). \( \varphi \) will have an increment by \( \theta = 1.15006^\circ \). So, the curved surface can be divided into 15 machining points. For each value of \( \varphi \) all possible combinations of other input parameters are used for simulating the ‘anfis’ model. To conduct this simulation ANFIS code ‘evalfis’ was used as, “evalfis ([input dataset], anfis)”. Now among them, output \( R_a < 0.8 \) are stored along with corresponding input parameters. Again among these stored dataset the \( R_a \) nearest to the most promising value 0.76 and its corresponding machining parameters are finally considered and presented in Table 2. The average of the ‘\( R_a \)’ value 0.7624 \( \mu \)m presented in Table 2 would be the final roughness of round part AB of the die which was targeted. The process described above has been summarized with a flowchart shown in Fig. 2.

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**Fig. 2. Flow chart for obtaining desired \( R_a \) of a spherical surface of a die.**
From Table 2, we can observe that as the value of $\varphi$ increases feed rate $f_y$ and speed $S$ cannot be maintained at a consistent value, rather these have to be changed to meet the desired surface roughness. The solution may be obtained in a different way and that may result different combination of cutting parameters. The process described above is producing one of many feasible solutions. Moreover here many other constraints have not been considered. As low value of $f_y$ causes higher machining time, higher values of $f_y$ can be taken for further calculations till $R_a$ at any point of the curved surface remains below desired level, to obtain more economic solutions.

5. Conclusion

Engineered components especially commercial dies must satisfy surface texture requirements and, traditionally, surface roughness (arithmetic average, $R_a$) has been used as one of the principal methods to assess quality. It is quite obvious from the results of the predictive models that the predicted accuracy was good and the predicted results matched well with the experimental values. In this research an application with ANFIS model for prediction of $R_a$ of a die made of EN24 is also presented. As cutting parameters can be preselected for a particular level of surface finish, the values of cutting parameters can be changed during production phase of a die. It is not only an application of Artificial Intelligence but also a framework for the commercial die manufacturers in order to implement the Computer-Aided Tools and Methodologies for achieving the desired surface finish of the dies. The model developed in the research will help the die manufacturing industries to reduce their production lead time indeed through predicting the desired surface roughness and selecting the right combination of cutting parameters. As the correlation between the machining parameters and the surface roughness is strongly dependent on the material being machined, there is an imminent need to develop a generic predictive platform to predict surface roughness. The present investigation is a step in this regard.

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