

ANFIS Modeling of the Surface Roughness in Grinding Process

H. Baseri, G. Alinejad

Abstract—The objective of this study is to design an adaptive neuro-fuzzy inference system (ANFIS) for estimation of surface roughness in grinding process. The Used data have been generated from experimental observations when the wheel has been dressed using a rotary diamond disc dresser. The input parameters of model are dressing speed ratio, dressing depth and dresser cross-feed rate and output parameter is surface roughness. In the experimental procedure the grinding conditions are constant and only the dressing conditions are varied. The comparison of the predicted values and the experimental data indicates that the ANFIS model has a better performance with respect to back-propagation neural network (BPNN) model which has been presented by the authors in previous work for estimation of the surface roughness.

Keywords—Grinding, ANFIS, Neural network, Disc dressing.

I. INTRODUCTION

GRINDING is a complex surface finishing process and surface roughness is one of the most important factors in assessing the quality of a ground component. Grinding has a large number of parameters that influence each other. The ground surface is affected by the wheel surface. The wheel should be dressed before the machined surface deteriorates beyond a quality limit of surface integrity. In order to achieve the best wheel surface, dressing parameters must be optimally set.

There have been a number of attempts to develop and apply mathematical models of surface roughness in grinding. Tonshoff et al. [1] reviewed all theoretical and experimental models for surface roughness dated from 1952 to 1992. They showed that various models considered many grinding variables, and proposed some basic general models that cover many of the variables. In more recent works new grinding models have been developed by Badger and Torrance [2,3] which predicted the number of active grits per unit area and their statistical average slope. These are predicted from the single point dressing conditions and wheel properties and then compared with the measured topography. The predicted topography is then used to calculate forces and workpiece roughness. Hou and Komanduri [4] developed a model using stochastic approaches to approximate the grinding wheel

topography. The model attempts to determine the total number of grains of a certain size within the wheel, rather than a physical mapping of the surface. Baseri et al. [5,6] developed a new stochastic model of the prediction of wheel topography by diamond disc dresser. Then the effects of a disc dressing parameter which affect the wheel topography, specific energy, and workpiece surface roughness were evaluated. Dressing conditions with various speed ratio, cross feed rate and depth of dressing were investigated. In each case, the grinding forces and the surface roughness were experimentally measured, and then the effect of changing disc dressing parameters on the surface roughness was analyzed.

Ali and Zhang [7] have been presented a fuzzy model for prediction of the surface roughness produced by surface grinding operations. The effectiveness and performance of the model have been demonstrated by a worked example. Nandi and Kumar [8] developed a method for automatic design of fuzzy logic controller (FLC) using a genetic algorithm (GA) and a new approach for designing the knowledge base of an FLC (using a GA) was proposed. Govindhasamy [9] developed a neural model-based control strategy for the optimization of an industrial aluminum substrate disk grinding process. Kumar and Choudhury [10] predicted the wheel wear and surface roughness using two techniques, namely design of experiments and neural network.

In this paper an adaptive neuro-fuzzy inference system (ANFIS) is used to correlate the disc dressing parameters to surface roughness in grinding process using the data generated based on experimental observations. The results of the experiments were also compared with those of the ANFIS predictions.

II. DISC DRESSING PROCESS

Dressing is needed when the cutting edge of the grinding wheel deteriorate. It consists of sharpening the active grits by removing wear flats and adhering metal. During the dressing process, grinding wheel surface is generated by fracture of the grain at bond and fracture within the grain. These are referred to, respectively, as bond fracture and grain fracture.

For dressing, a single point dresser, a roll dresser and a disc dresser can be used. Fig. 1(a) shows the schematic disc dressing process which is used in this work to generate the wheel topography. Also Fig. 1(b) shows the sectional view of the disc dresser.

The disc dressing process has 3 variables as dressing speed

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ratio, dressing cross-feed rate and dressing depth. Dressing speed ratio q is defined as:

$$q = \frac{v_r}{v_s} \quad (1)$$

where v_r is surface speed of the disc dresser and v_s is surface speed of the grinding wheel. Due to the dressing cross feed rate and dressing depth, the dresser tip contacts the wheel grits.

Average mean square roughness of the surface is defined as follows [11]:

$$R_a = \frac{1}{L} \int_0^L |Z(x)| dx \quad (2)$$

where Z is height of the surface profile about the mean line and L is the sample length.

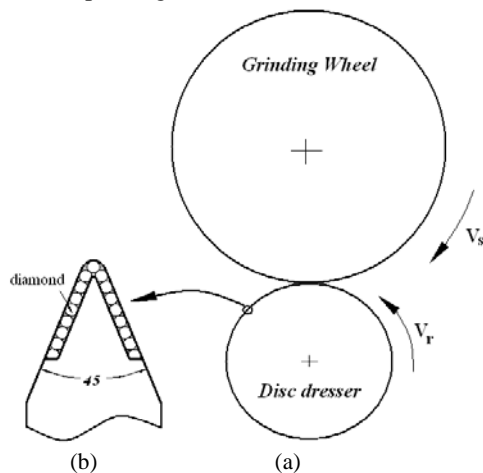


Fig. 1 Disc dressing process; (a) Schematic of process, (b) sectional view of the dresser tip.

III. EXPERIMENTAL SETUP

The vitrified aluminum oxide grinding wheel was dressed using the diamond disc dresser. The dressing system setup consists of a dressing disc that rotated with an electric motor with speed control. The device is placed on the table of the grinding machine (Hauni-Blohm HFS204). The axis of the dresser is parallel to the grinding wheel axis. During dressing, the disc is traversed across the wheel at a constant feed rate. Specification of the dresser and the grinding wheel is given in Table 1.

Three dressing parameters namely speed ratio, cross-feed rate and depth of dressing were varied to measure the surface roughness. The workpiece material was SPK 1.2080 with hardness 56 Rockwell C. Workpiece specimens were 100 mm long, 40 mm wide and 7 mm high. Five speed ratios, as listed in Table 1, were selected. At each speed ratio, four experiments with different cross-feed rates were conducted. At each set of speed ratio and cross-feed rate, three depths of dressing, were investigated. A total of 60 dressing conditions were carried out. For each set of dressing conditions the disc dresser was traversed across the wheel and surface roughness (R_a) were measured by a profilometer Taylor Hobson-TR240. In this procedure, grinding parameters are constant as listed in

Parameter	Value
Dresser size	130 mm diameter
Dresser tip	Diamond, 0.5 mm tip radius
Speed ratio	0.4, 0.7, 0.95
Dresser Cross feed rate	48, 96, 144, 192 mm/min
Dressing depth	0.03, 0.04, 0.05 mm
Wheel Type	A46K6V
Wheel Size	200 mm diameter, 20 mm width

Table 1.

IV. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

An Adaptive neuro-fuzzy inference system gives the mapping relation between the input and output data by using hybrid learning method to determine the optimal distribution of membership functions [12]. Both artificial neural network (ANN) and fuzzy logic (FL) are used in ANFIS architecture. Basically, five layers are used to construct this inference system. Each ANFIS layer consists of several nodes described by the node function. The inputs of present layers are obtained from the nodes in the previous layers. Figure 2 shows the ANFIS structure for a system with m inputs ($X_1 \dots X_m$), each with n membership functions (MFs), a fuzzy rule base of R rules and one output (Y). The network consisting of five layers is used for training Sugeno-type fuzzy interface system (FIS) through learning and adaptation. Number of nodes (N) in layer 1 is the product of numbers of inputs (m) and MFs (n) for each input, i.e., $N=mn$. Number of nodes in layers 2-4 depends on the number of rules (R) in the fuzzy rule base. Five Layers of ANFIS model are as follow:

Layer 1 (Fuzzification layer): It transforms the crisp inputs X_i to linguistic labels (A_{ij} , like small, medium, large etc.) with a degree of membership. The output of node ij is expressed as follows:

$$O_{ij}^1 = \mu_{ij}(X_i) \quad , \quad i = 1 \dots m \quad , \quad j = 1 \dots n \quad (3)$$

where μ_{ij} is the j th membership function for the input X_i .

Several types of MFs are used, for example, triangular, trapezoidal and generalized bell function. In this study it is selected a Gauss function by trial and error, as follows:

$$\mu(X) = \exp\left(\frac{-(X-c)^2}{2\sigma^2}\right) \quad (4)$$

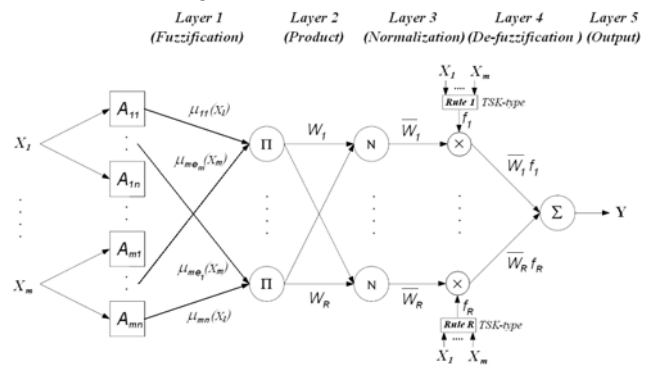


Fig. 2. Basic structure of ANFIS.

The parameters for Gauss represent the parameters σ and c .

The Gauss shaped functions vary while the values of this parameter are changing. These parameters are named as premise parameters.

Layer 2 (Product layer): For each node k in this layer, the output represents weighting factor (firing strength) of the rule k. The output W_k is the product of all its inputs as follows:

$$O_k^2 = W_k = \mu_{1e_1}(X_1)\mu_{2e_2}(X_2)\dots\mu_{me_m}(X_m) \quad (5)$$

$$k = 1 \dots R, \quad e_1, e_2, \dots, e_m = 1 \dots n$$

Layer 3 (Normalized layer): The output of each node k in this layer represents the normalized weighting factor \bar{W}_k of the kth rule as follows:

$$O_k^3 = \bar{W}_k = \frac{W_k}{W_1 + W_2 + \dots + W_R} \quad (6)$$

Layer 4 (De-fuzzification layer): Each node of this layer gives a weighted output of the first order TSK-type fuzzy if-then rule as follows:

$$O_k^4 = \bar{W}_k f_k \quad (7)$$

where f_k represents the output of kth TSK-type fuzzy rules as follows:

$$If(X_1 \text{ is } A_{1e_1}) \text{ and } (X_2 \text{ is } A_{2e_2}) \text{ and } \dots \text{ and } (X_m \text{ is } A_{me_m})$$

$$\text{Then } f_k = \sum_{i=1}^m p_{ie_i} X_i + r_k \quad (8)$$

where p_{ie_i} and r_k are called consequent parameters and $e_1, e_2, \dots, e_m = 1 \dots n, k = 1 \dots R$.

Layer 5 (Output layer): This single-node layer represents the overall output (Y) of the network as the sum of all weighted outputs of the rules:

$$O^5 = Y = \sum_{k=1}^n \bar{W}_k f_k \quad (9)$$

V. RESULTS AND DISCUSSION

A. Data preprocessing

Before the ANFIS can be trained and the mapping learnt, it is important to process the experimental data into patterns. Training/testing pattern vectors are formed. Each pattern is formed with an input condition vector and the corresponding target vector.

The scale of the input and output data is an important matter to consider, especially when the operating ranges of process parameters are different. The scaling or normalizing ensures that the ANFIS will be trained effectively, without any particular variable skewing the results significantly. As a result, all of the input parameters are equally important in the training of the neural network. The scaling is performed by mapping each term to a value between newmin and newmax using the following equation:

$$V_{nor} = newmin + \frac{V_i - V_{min}}{V_{max} - V_{min}}(newmax - newmin) \quad (10)$$

where V_{nor} is the normalized value, V_i is the value of a certain

variable (speed ratio, dressing depth and cross-feed rate), V_{max} and V_{min} are the maximum and minimum values of the independent variable. Additionally, "0.9" is its new maximum value (newmax), and "0.1" is the variable's new minimum value (newmin). The input pattern vectors are then formed, comprising 48 pairs of input/output ones for training the neural network on the basis of the previous mentioned experiments. The remaining 12 pairs are reserved for testing the trained network performance.

B. Training and testing performance criterion

The training performance of the ANFIS model can be checked by the root mean square error (RMSE) as follows:

$$RMSE = \sqrt{\frac{1}{M} \sum_{z=1}^M (S_z - Y_z)^2} \quad (11)$$

where M is the total number of training patterns (48 patterns), S_z is the target value, and Y_z is the ANFIS output value.

The testing performance accuracy of the ANFIS model can be checked by the error of network predictions. For the test data sets (12 patterns), neural network predictions are calculated. These are compared with the corresponding experimental values. The linear regression and statistical analysis is only effective for large quantities of data. In the current circumstances, it would have been better to use the root mean square error (RMSE) as presented in equation (11).

C. Network topology, training, and testing

Modeling of the process with an ANFIS model is composed of two stages: training and testing of the network with experimental data. The training data consist of dressing values for speed ratio, dressing depth and cross-feed rate and corresponding surface roughness. In all, 60 such data sets were used, of which, 48 data sets were selected randomly and used for training purposes, while the remaining 12 data sets were presented to the trained network as new application data for verifying or testing the predictive accuracy of the network model. Thus, the network was evaluated using data that had not been used for training.

The number of required rules and type of MF are very important considerations when solving actual problems using ANFIS network. To find the best network model that gives superior results in comparison with other networks topologies, a number of candidate networks with different number of rules and different MF types firstly were developed using the ANFIS editor of the Matlab 7.1 (14th release) software. Then, all ANFIS structures were trained based on the error goal (RMSE) of 0.001 and maximum number of 100 epochs. It means that the training epochs are continued until the RMSE fell below 0.001 or the epochs go up 100. As the RMSE criterion for all networks is the same, their actions are comparable. Then their testing performances were compared and the optimized model is selected based on its predictive accuracy in response to new input data in the testing phase

when compared with experimental values.

In ANFIS structure, it is used the Sugeno fuzzy rules, where the output is the linear combination of inputs. By testing the various ANFIS structure with different number of membership function, it is obtained the optimal structure with 64 membership function by trial and error method.

Also, different type of membership functions like bell, sigmoid, triangle and Gaussian were tested. Table II shows the training and testing RMSE of ANFIS model with different type of MFs. Results show that the Gaussian in comparison with others has least training and testing RMSE values. Therefore, the Gauss MF and 64 rules create the best architecture for ANFIS model. The experimental results under the same conditions as the training data are used to compare the measured results with those estimated by the ANFIS network, as shown in Fig. 3.

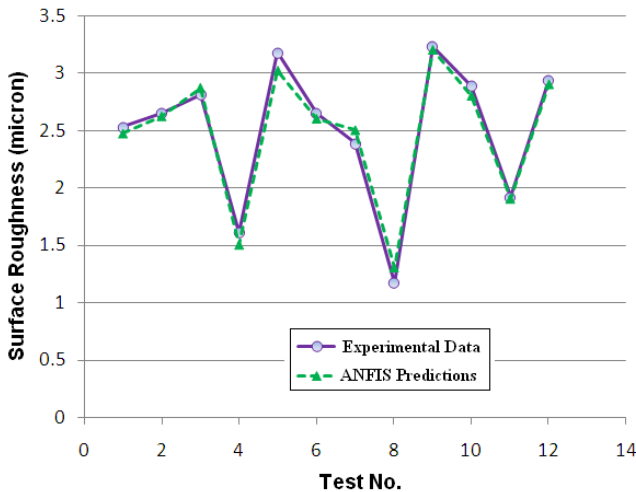


Fig. 3. Comparison of the measured and ANFIS predicted values of the surface roughness.

As shown in Fig. 3, the results predicted by simulation show a good agreement with experimental results for a wide range of operating conditions. They are acceptable, considering the limited amount of training data available and large error prone to measurements of surface roughness. Therefore, the adopted ANFIS can be used to acquire a function that maps input parameters to the desired process outputs in a wide range of grinding process.

Also Fig. 4 shows the experimental surface roughness for 12 test number and those predicted value by FFBP-NN model from the previous work by the authors [13].

Comparison of the Figs 3 and 4 shows the ANFIS model has a better performance with respect to BPNN model in prediction of the surface roughness. It is due to this fact that ANFIS model uses the neural network and fuzzy logic approaches for classification of experimental data. Therefore it can be predicted the surface roughness values more accurate than the back-propagation neural network model.

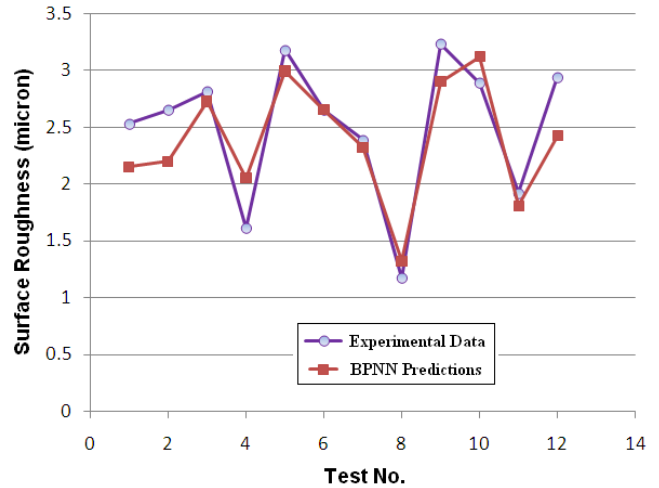


Fig. 4. Comparison of the measured and BPNN predicted values of the surface roughness. [13]

VI. CONCLUSIONS

In this paper, the surface roughness of workpiece in grinding process has been predicted using an ANFIS model. The disc dressing input parameters were considered to determine the effect of the grinding performance. The required training and test data have been obtained from experimental observation. An adaptive neuro-fuzzy interface system with 64 rules and Gaussian function was developed to enable the measures of surface roughness to be predicted in terms of three different dressing parameters of speed ratio, dressing depth and cross-feed rate. The ANFIS predicted surface roughness values show a good comparison with those obtained experimentally and also with respect to BPNN model in prediction of the surface roughness. It is evidence that the fuzzy logic technique can be help to better prediction of the experimental data.

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