Efficiency assessment of ANFIS in surface topology prediction in diamond turning of RSA443 optical aluminum using Small Datasets

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Abstract. This paper presents an assessment of the efficiency of the ANFIS model in surface topology prediction of RSA 443 optical aluminium using small datasets. The experiments are designed and conducted based on the Taguchi L9 orthogonal array. The single point diamond turning procedure has been carried out on Nanoform 250 Precision CNC machine. Cutting speed, feed rate and depth of cut together with acoustic emission signal root mean square, dominant frequency and peak rate are the ANFIS model input parameters. The function that gave the best results was the sigmoidal membership function, hence it is used in this paper. To evaluate model performance, the measured surface roughness results are compared to ANFIS predicted results based on the Mean Absolute Percentage Error (MAPE) and prediction accuracy. The MAPE values show that the ANFIS prediction accuracy of surface topology is 79.42%. This value is within the upper quartile range, indicating the high predicting accuracy of ANFIS even in the absence of enough training data. The model can be reliably utilized in surface roughness prediction using small datasets while its prediction accuracy can however be improved by using larger datasets.

1. Introduction

Advances in manufacturing technologies have resulted in the widespread use of automated manufacturing systems. Such advances have led to the advent of system compatible computational intelligence-based surface topology prediction models. The Adaptive Neuro-Fuzzy Inference System (ANFIS) model is one such computational intelligence-based surface topology prediction method that has gained ground over recent years. Components are manufactured for predefined applications; therefore, the target surface finish is also predefined. Proper selection of manufacturing process and machining parameters must be expertly done since there is a strong relationship between product surface finish and in-service performance characteristics [1].

Diverse researches on suitability of ANFIS as a surface roughness prediction model during single point diamond turning have been carried to date. The universal conclusion from the researches is that ANFIS is more accurate than other fuzzy expert systems when dealing with large data sets. This desirable quality is attributed to the adaptability of the ANFIS model in dealing with non-linear data traits [2-4]. An audit of the researches carried out reveals that much focus has been on ANFIS performance on large data sets. The size of data set and the type of membership function used in the ANFIS model have an influence on prediction accuracy. ANFIS model performance is enhanced by...
using larger data sets [5]. This research paper focuses on the efficiency assessment of ANFIS in surface topology prediction of RSA 443 optical aluminium using small datasets.

1.1. Membership Function.
A fuzzy inference system requires that crisp variables be converted to fuzzy variables before they can be processed. During the fuzzification stage, every resultant fuzzy variable is assigned a group to which it belongs. This group which specifies the degree to which a given variable belongs to a set is called a membership function (MF) [6]. While a crisp element either belongs to a set or not, a fuzzy element’s degree of membership to a set varies from 0 to 1 [7]. Membership functions are crucial in converting crisp variables into fuzzy variables and vice versa. In this research, the MATLAB ANFIS toolbox is used for prediction. The membership function utilized is the Sigmoidal Membership. A sigmoidal membership function is defined by two parameters: \( a \) and \( c \) in (Eq. 1). The parameters determine the transitional area width and transitional area center respectively. The shape of a Sigmoidal Membership function is illustrated by Figure 1.

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F(x; a, c) = \frac{1}{1 + e^{a(x-c)}}
\]

1.2. Adaptive Neuro-Fuzzy Inference System.
According to Jang [8], an Adaptive Neuro-Fuzzy Inference System is a hybrid of Artificial Neural Networks (ANN) and Fuzzy Inference Systems (FIS). Unlike in fuzzy logic systems where fuzzy rules are obtained from human expert knowledge, ANFIS automatically generates the fuzzy if then rules [9]. The use of human expert knowledge gets complicated in terms of time and number of rules to be generated, as the system to be modelled becomes bigger. ANFIS combines the advantages of both Fuzzy Logic systems and ANN. The two types of fuzzy inference systems are Sugeno-Takagi and Mamdani systems. The five data transformation stages of ANFIS are fuzzification, fuzzy operator application and defuzzification.

2. Experimental setup and procedure
The first step in this study was to design the experiment using the Taguchi L9 orthogonal array design (Table 1). This stage is followed by the experimental setup of Nanoform 250 machine (Figure 2). Cutting speed, feed rate and depth of cut are the primary cutting parameters used during the turning process while acoustic emission signals are captured using a piezoelectric sensor. The captured AE signals are processed to determine parameters that are used together with the primary cutting parameters in training and validating the ANFIS model. However, for the purpose of enhancing ANFIS training, three extra data sets (experiment numbers 10,11 and 12) that were not part of the L9
orthogonal array design have been included (Table 2). Various membership function shapes and numbers are tried to find the most accurate one.

Table 1. Experimental design using L9 Taguchi orthogonal array

| Exp No. | Speed, [rpm] | Feed, [mm/min] | Depth, [µm] |
|---------|--------------|----------------|-------------|
| 1       | 1250         | 7.5            | 5           |
| 2       | 1250         | 15.0           | 15          |
| 3       | 1250         | 22.5           | 25          |
| 4       | 1750         | 7.5            | 15          |
| 5       | 1750         | 15.0           | 25          |
| 6       | 1750         | 22.5           | 5           |
| 7       | 2500         | 7.5            | 25          |
| 8       | 2500         | 15.0           | 5           |
| 9       | 2500         | 22.5           | 15          |

Figure 2. Experimental setup on Nanoform 250 ultra-high precision machine-tool

Table 2. Extra experimental runs for better ANFIS training

| Exp. No. | Speed, [rpm] | Feed, [mm/min] | Depth, [µm] |
|----------|--------------|----------------|-------------|
| 10       | 1250         | 7.5            | 15          |
| 11       | 1750         | 15             | 5           |
| 12       | 2500         | 22.5           | 25          |
The following experiment numbers were used during the model training stage: 2, 3, 9, 10, 11 and 12. The remaining datasets are used to validate the ANFIS model performance. The selection of which datasets to use as either training or testing data has been done judiciously. In this investigative research, a two-layered Sugeno-Style feed-forward ANFIS architecture with six inputs is used to predict the surface roughness of single point diamond turned RSA 443. MATLAB ANFIS toolbox is utilized in this research. The proposed ANFIS model learning information is presented in Table 3.

Table 3. ANFIS learning information

| Learning scenario                  | Value  |
|-----------------------------------|--------|
| Number of Nodes                   | 161    |
| Number of linear Parameters       | 64     |
| Number of Non-Linear Parameters   | 48     |
| Total Number of Parameters        | 112    |
| Number of Training Data Pairs     | 6      |
| Minimal Training RSME             | 0.000001 |
| Number of Fuzzy Rules             | 64     |

3. Results and Discussion

Table 4 is a normalized presentation of the experimental results. The input data and manually measured surface roughness values were standardized for better results. The following acronyms are used to denote the parameters: CS (cutting speed), F (feed), DC (depth of cut), AE_{rms} (acoustic emission root mean square), DF (dominant frequency), PR (peak rate) and Ra (surface roughness parameter). Figure 3, is a screen shot of the Fuzzy Inference System test plot against training data. The experimental values of surface roughness are shown by the blue dots while predicted values are shown by red dots. The overlapping of plots depicts high prediction accuracy. The MAPE value and prediction accuracy are presented in Table 5.

Table 4. Normalized Experimental Results

| Speed, [rpm] | Feed, [mm/min] | Depth, [µm] | AE_{rms},[V] | DF, [Hz] | PR, [/min] | Ra, [nm] |
|--------------|----------------|-------------|--------------|----------|------------|---------|
| 0.00         | 0.00           | 0.00        | 0.95         | 1.00     | 0.89       | 0.28    |
| 0.00         | 0.50           | 0.50        | 0.60         | 0.54     | 0.49       | 0.56    |
| 0.00         | 1.00           | 1.00        | 1.00         | 1.00     | 0.10       | 1.00    |
| -0.40        | 0.00           | 0.50        | 0.55         | 0.61     | 0.34       | 0.17    |
| -0.40        | 0.50           | 1.00        | 0.52         | 0.61     | 0.35       | 0.50    |
| -0.40        | 1.00           | 0.00        | 0.49         | 0.04     | 0.34       | 0.56    |
| 0.00         | 0.00           | 1.00        | 0.48         | 0.52     | 0.29       | 0.00    |
| -1.00        | 0.50           | 0.00        | 0.00         | 0.00     | 0.00       | 0.17    |
| -1.00        | 1.00           | 0.50        | 0.58         | 0.61     | 0.40       | 0.33    |
| 0.00         | 0.00           | 0.50        | 0.95         | 1.00     | 0.89       | 0.36    |
| -0.40        | 0.50           | 0.00        | 0.62         | 0.61     | 0.35       | 0.34    |
| -1.00        | 1.00           | 1.00        | 0.58         | 0.61     | 0.40       | 0.48    |
The prediction accuracy value illustrates ANFIS model’s high efficiency when using training data. Figure 4 is a screen shot of the Fuzzy Inference System test plot against testing data.
data. The experimental values of surface roughness are shown by the blue dots while predicted values are shown by red dots. The MAPE value and prediction accuracy are presented in Table 6.

The prediction accuracy of the ANFIS model using testing data is relatively lower than when using training data. The lower prediction accuracy is attributed to the small data set used to train the model. The highest MAPE value of 40.00% is obtained on experimental run 5 while the lowest MAPE value of 0.00% is attained on experimental run 7.

Table 6. Surface roughness prediction using testing data

| Exp. No. | Measured Ra, [nm] | Predicted Ra, [nm] | Absolute error (%) |
|----------|-------------------|--------------------|--------------------|
| 1        | 0.28              | 0.36               | 28.57              |
| 4        | 0.17              | 0.15               | 11.76              |
| 5        | 0.50              | 0.30               | 40.00              |
| 6        | 0.56              | 0.45               | 19.64              |
| 7        | 0.00              | 0.00               | 0.00               |
| 8        | 0.17              | 0.21               | 23.53              |

Mean absolute error (%) 20.58
Prediction accuracy 79.42

4. Conclusion
The efficiency of ANFIS model in surface topology prediction of RSA 443 optical aluminium using small datasets was assessed in this study. The ANFIS model was first used to predict the surface roughness of training datasets and the prediction accuracy was 99.20%. This shows that the ANFIS model is extremely accurate when using training data. When the ANFIS model was used to predict the surface roughness of testing datasets, the prediction accuracy was found to be 79.42%. The model’s prediction accuracy is relatively lower than the training dataset result. However, this value is classified as good since it lies within the upper quartile range. In light of the result, ANFIS model can reliably be used to model the surface roughness of RSA 443 in the absence of sufficient datasets. Further researches to compare the performance of the ANFIS model and a Fuzzy PID controller are recommended.

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