ADAPTIVE NETWORK BASED INFERENCE SYSTEM FOR ESTIMATION OF SURFACE ROUGHNESS IN END-MILLING

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Abstract:
This paper presents a new approach for surface roughness (Ra) prediction during milling by using dynamometer to measure cutting forces signals and cutting conditions. End milling machining process of hardened die steel with carbide end mill, was modeled in this paper using the adaptive neuro fuzzy inference system (ANFIS) to predict the effect of machining variables (spindle speed, feed rate and axial/radial depth of cut) on surface roughness. In this contribution we also discussed the construction of a ANFIS system that seeks to provide a linguistic model for the estimation of surface roughness from the knowledge embedded in the neural network. The predicted surface roughness values determined by ANFIS were compared with experimental measurements. The comparison indicates that the performance of this method turned out to be satisfactory for evaluating Ra, within a 6% mean percentage error and 96% accuracy rate.

Keywords: Estimation, Surface roughness, Milling, ANFIS.

1. INTRODUCTION

Many parameters influence surface roughness in milling. Feedrate, cutting speed and tool geometry are controllable parameters, while tool wear, vibrations and workpiece/tool variability are uncontrollable.

In manufacturing the relationship between process characteristics and surface roughness is difficult to capture. This is due to the complexity of the relationship between surface roughness and process characteristics. In workshops, inspection of surface finish is accomplished by off-line or on-line measurements.

Both approaches are uneconomical. Therefore, an in-process method based on prediction model is required for the real time monitoring process.

Several models have been proposed to estimate the surface roughness. These include classical statistical approaches as well as fuzzy systems and neural networks. For instance researchers [1,2] developed an approach based on the least-squares regression for estimating surface roughness in machining while [3] have, respectively, used fuzzy expert systems and fuzzy pattern recognition for monitoring surface roughness over a limited range of cutting conditions. The capacity of artificial neural networks to capture nonlinear relationships in a relatively efficient manner has motivated a number of researchers to pursue the use of these networks in developing surface roughness prediction models.

But in such models, the nonlinear relationship between sensor readings and surface roughness embedded in a neural network remains hidden and inaccessible to the user [4].

In this research we attempt to solve this situation by using the ANFIS system to predict the surface roughness. This model offers ability to estimate surface roughness as its neural network based counterpart but provides an additional level of transparency that neural networks fails to provide. We try to investigate the possibility and effectiveness of predicting surface roughness with ANFIS method. It uses training examples as input and constructs the fuzzy if–then rules and the membership functions of the fuzzy sets involved in these rules as output. Three milling parameters have been selected. Specifically the relationship between the sensor signals and surface roughness is first captured via a neural network and is subsequently reflected in linguistic form with the help of a fuzzy logic based algorithm. In this model, we adopted two different types of membership functions for analysis in ANFIS training and compared their differences regarding the accuracy rate of the surface roughness prediction. After training the estimator, its performance was tested under various cutting conditions. Test data sets collected from a wide range of cutting conditions in end milling were applied to the estimator for evaluating the Ra. The obtained result for predicting surface roughness has a highly correct rate. The results also indicate that the triangular MF rather than the trapezoidal MF has a higher correct rate of prediction.

2. EXPERIMENTAL DESIGN

In order to develop the surface roughness prediction model, experimental results were used. The experiments with the end milling cutter were carried out on the CNC milling machine (type HELLER BEA1). Material Ck 45 and Ck 45 (XM) with improved machining properties was used for tests. The solid end milling cutter (R216.24-16050 IAK32P) with four cutting edges, of 16 mm diameter and 10° helix angle was selected for machining. The corner radii of the cutter is 4 mm. The cutter is made of ultra fine carbide grade coated with TiN/TiCN coating. The coolant RENUS FFM was used for cooling. The cutting forces were measured with a piezoelectric dynamometer (Kistler 9255) mounted between the workpiece and the machining table. The data acquisition package used was LabVIEW. The surface roughness was measured by 7061 MarSurf PS1 Surface Roughess Tester. The set up can be seen in Fig. 1. The experiments were carried out for all combinations of the chosen parameters [5], which are radial/axial depth of cut, feedrate, spindle speed and tool wear. Other parameters such as tool diameter, rake angle, etc. are kept constant. Three values for the radial/axial depth of cut have been selected for use in the experiments: R_{D1} = 1d, R_{D2}=0.5d, R_{D3}=0.25d; A_{D1} = 2mm, A_{D2}=4mm, A_{D3}=8mm; d- cutting parameter (16 mm).

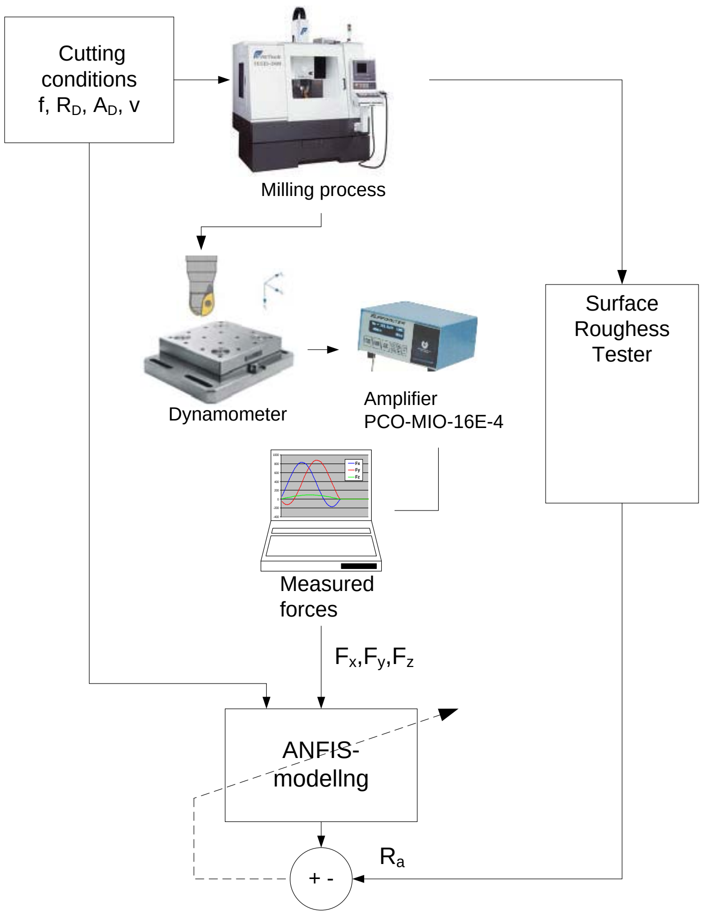

Fig. 1: Experimental set-up.

In the experiments the following values for feedrate and spindle speed were varied in the ranges from 0.05-0.6 mm/tooth and 125 –350 min^{-1}, respectively. In this way two sets of data groups were generated, one for learning and other for estimation tests.

3. ANFIS ARCHITECTURE

By given input/output data set, the ANFIS method constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using either a backpropagation algorithm alone, or in combination with a least squares type of method. This allows fuzzy systems to learn from the data they are modeling. FIS Structure is a network-type structure similar to that of a neural network, which maps inputs through input membership functions and associated parameters, and then through output membership functions and associated parameters to outputs.

FIS Structure is a network-type structure similar to that of a neural network, which maps inputs through input membership functions and associated parameters, and then through output membership functions and associated parameters to outputs. ANFIS applies two techniques in updating parameters. For premise parameters that define membership functions, ANFIS employs gradient descent to fine-tune them. For consequent parameters that define the coefficients of each output equations, ANFIS uses the least-squares method to identify them. This approach is thus called Hybrid Learning method since it combines the gradient descent method and the least-squares method. ANFIS modeling process starts by obtaining a data set (input-output data pairs) and dividing it into training and checking data sets. The training data set is used to find the initial premise parameters for the membership functions by equally spacing each of the membership functions. A threshold value for the error between the actual and desired output is determined. The consequent parameters is found using the least-squares method. Then an error for each data pair is found. If this error is larger than the threshold value, update the premise parameters using the gradient decent method as the following ($Q_{next}=Q_{nov}+\eta_d$, where Q is a parameter that minimizes the error, η the learning rate, and d is a direction vector). The process is terminated when the error becomes less than the threshold value. Then the checking data set is used to compare the model with actual system. A lower threshold value is used if the model does not represent the system.

Fig. 1 shows the flow chart for predicting the surface roughness via ANFIS. The findings are analyzed and discussed in the following chapter.

Fig. 3 shows the fuzzy rule architecture of ANFIS when the triangular membership function and the trapezoidal membership function is adopted, respectively. The structure shown in Fig. 2 consist of 36 fuzzy rules.

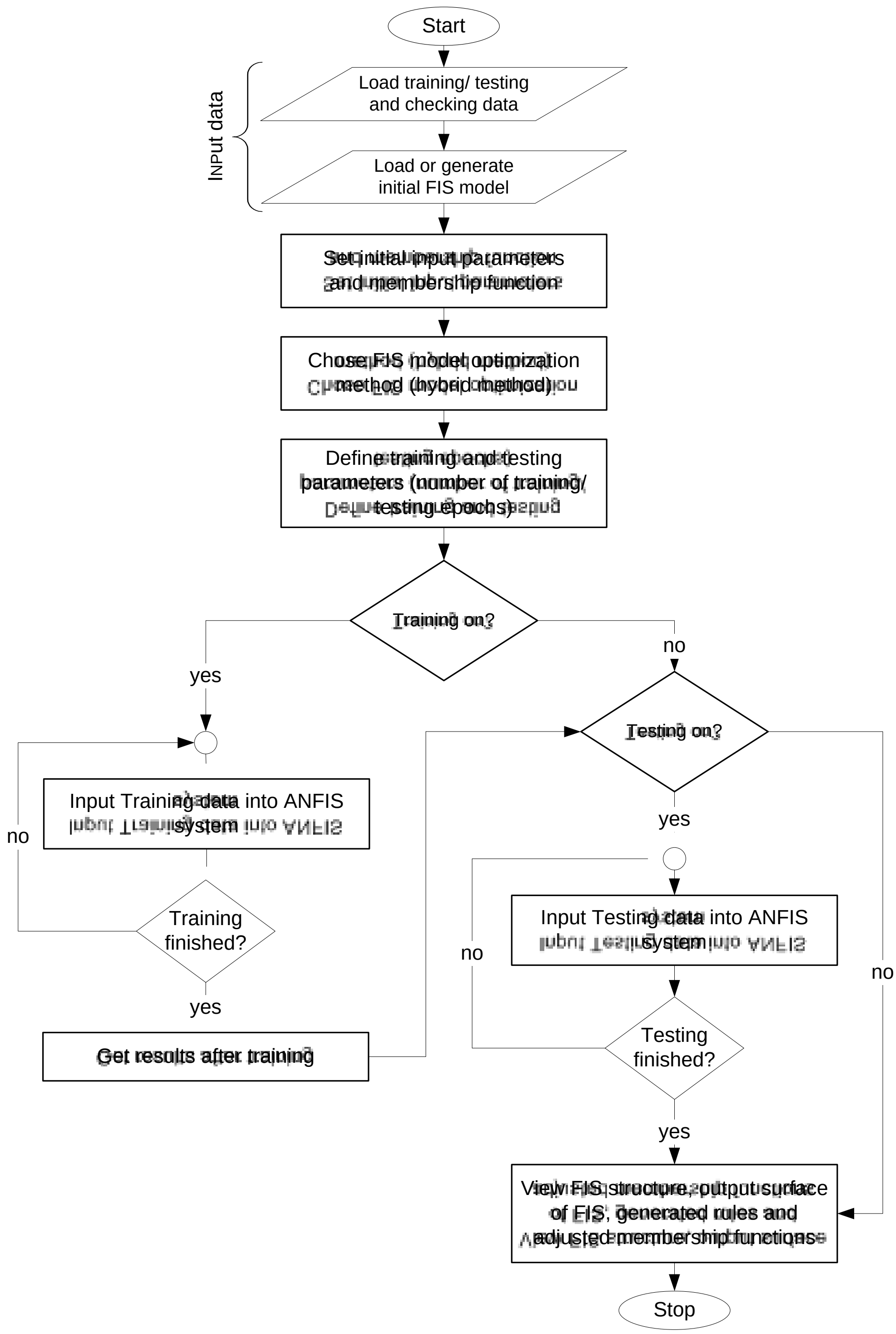

Fig. 2: Flowchart of surface roughness prediction of ANFIS system

During training in ANFIS, 160 sets of experimental data were used to conduct 350 cycles of learning.

4. DISCUSSION OF RESULTS

In this study, a trained ANFIS algorithm is used to predict the surface roughness during the milling of hardened steel workpieces. The major advantage of ANFIS predictions is that the models can estimate surface roughness very fast and accurately, once the cutting forces are known. In conclusion, predicted surface roughness was found significantly sensitive to the measured cutting forces, especially the thrust cutting component.

A total of 100 sets of data were selected from the total of 150 sets obtained in the end milling experiments [6,7] for the purpose of training in ANFIS.

The other 50 sets were then used for testing after the

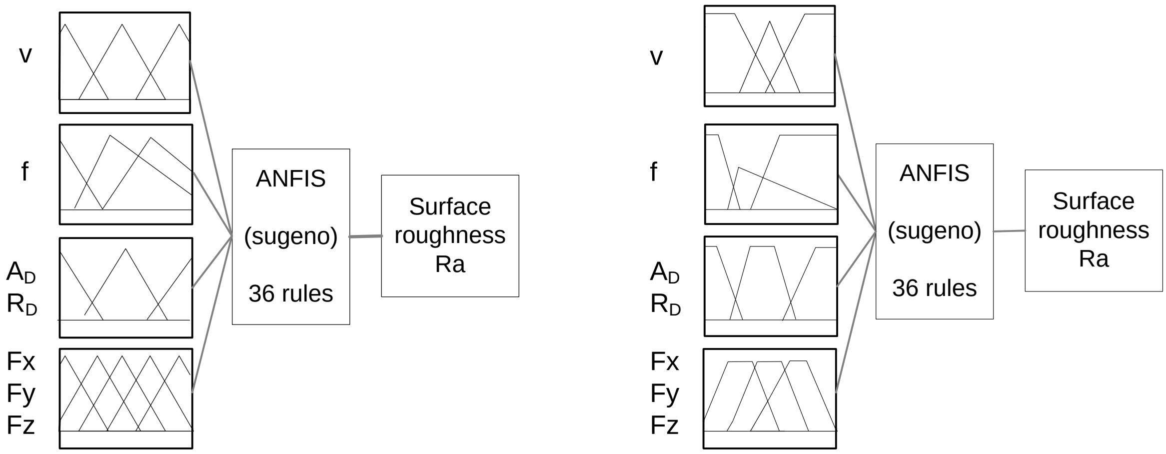

Fig. 3: Architecture of fuzzy ruls for the triangular and the trapezoidal membership function.

training was completed to verify the accuracy of the predicted values of surface roughness. The average error of the prediction of surface roughness is around 4% when triangular membership function is used in ANFIS. The accuracy is as high as 96%.

The prediction accuracy of ANFIS when the triangular membership function is used is higher than that when the trapezoidal membership function is used. Fig. 4 shows the scatter diagram of the predicted values and measurement values of the surface roughness of 50 sets of testing data when triangular membership functions are used in ANFIS.

It shows that the predicted values of surface roughness between 100 and 170 all follow the 45. line very closely. In other words, the predicted values are not far from the experimental measurement values.

5. CONCLUSION

In this contribution ANFIS system is used to predict the surface rougnes in end-milling process.

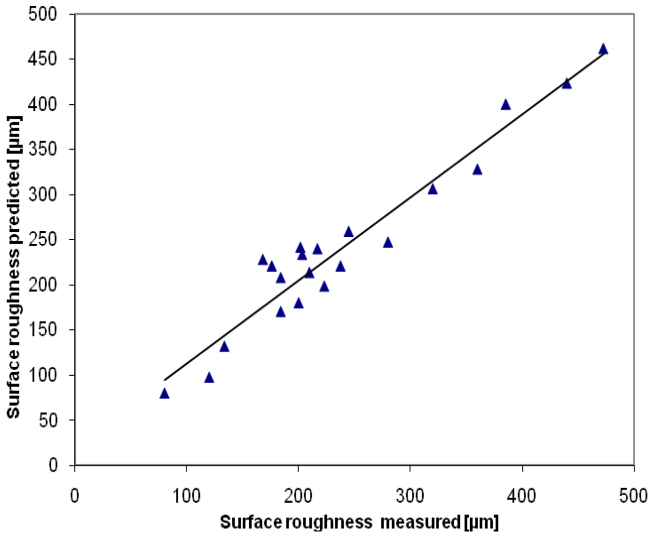

Fig. 4: Scatter diagram of measured Ra and predicted for testing data using the triangular membership function.

The experimental results indicate that the proposed ANFIS model has a high accuracy for estimating surface roughness with small computational time. The surface roughness values predicted by ANFIS are compared with the measurement values derived from the 150 data sets in order to determine the error of ANFIS. The following conclusions can be drawn from the above analysis: The error of the surface roughness values predicted by ANFIS with the triangular membership function is only 4%, reaching an accuracy as high as 96%. When the trapezoidal membership function is adopted the average error is around 6.4%, with an accuracy of 94%. The results indicate that the training of ANFIS with the triangular membership function obtains a higher accuracy rate in the prediction of surface roughness.

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