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SURFACE ROUGHNESS MONITORING IN CUTTING FORCE CONTROL SYSTEM

Uros ZUPERL[1,*], Tomaz IRGOLIC[2], Franc CUS[3]

[1)] Assist. Prof., researcher, University of Maribor, Faculty of mechanical engineering, Maribor, Slovenia
[2)] B.Sc., researcher, University of Maribor, Faculty of mechanical engineering, Maribor, Slovenia
[3)] Full. Prof., University of Maribor, Faculty of mechanical engineering, Maribor, Slovenia

Abstract: *The aim of this contribution is to present a reliable cutting force control system in end milling with the main focus on the integrated surface roughness prediction model. In this control system, cutting force sensor is used to control the milling process by digital adaptation of cutting parameters.*
The main goal of this paper is to present a new method for surface roughness (Ra) prediction by using measured maximum cutting forces signals and initial cutting parameters. End milling machining process of hardened die steel with carbide end mill was modeled using the adaptive neuro-fuzzy inference system (ANFIS). The purpose of ANFIS model is to predict the effect of machining variables and maximal cutting force on surface roughness during machining. The surface roughness tester is used to observe the actual surface roughness of the machined surface after the machining tests. The comparison between the predicted surface roughness values determined by ANFIS and experimental measurements indicates that the performance of this method turned out to be satisfactory for evaluating Ra, within a 3% mean percentage error and 96% accuracy rate. The developed model is used to monitor milling operations and provide warnings to the operator. The ANFIS model can also stop the machining process for tool change based on a pre-set surface roughness limits.

Key words: *force control, prediction, surface roughness, milling, ANFIS.*

1. INTRODUCTION

In high speed end-milling is very difficult to monitor surface roughness on-line. Despite many research, there are no available method for monitoring surface roughness in high-speed end-milling.

In milling the relationship between process characteristics and surface roughness is also difficult to capture. This is due to the complexity of the relationship between surface roughness and process characteristics. Therefore, an in-process method based on prediction model is required for the real time monitoring process.

In this study, we attempt to solve this situation by employing the Adaptive Neuro-Fuzzy Inference System (ANFIS) to predict the surface roughness based on measured cutting forces and cutting conditions. A new prediction model is integrated with the existing cutting force control system. The traditional ability of the operator to determine the quality of the machined surface based on his experiences and senses is now the expected role of the predictive model in the upgraded system. The role of the operator is now supervisory.

A neuro-fuzzy algorithm is investigated, for the purpose of surface roughness predicting. The cutting forces were measured with piezoelectric table dynamometer. The sensor signals were sent to the neuro-fuzzy algorithm, which had been trained to predict and display actual surface roughness.

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 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.

2. ADAPTIVE CUTTING FORCE CONTROL STRUCURE

The adaptive control system shown in Fig. 1 is a cutting force feedback loop where the feedrate adjusts itself to the actual cutting force F, and varies according to the changes in work conditions during machining.

* Corresponding author:
University of Maribor, Faculty of mechanical engineering, Smetanova 17, 2000 Maribor, Slovenia
Tel.: 0038622207621
Fax: 0038622207990
E-mail address: *uros zuperl@um.si*

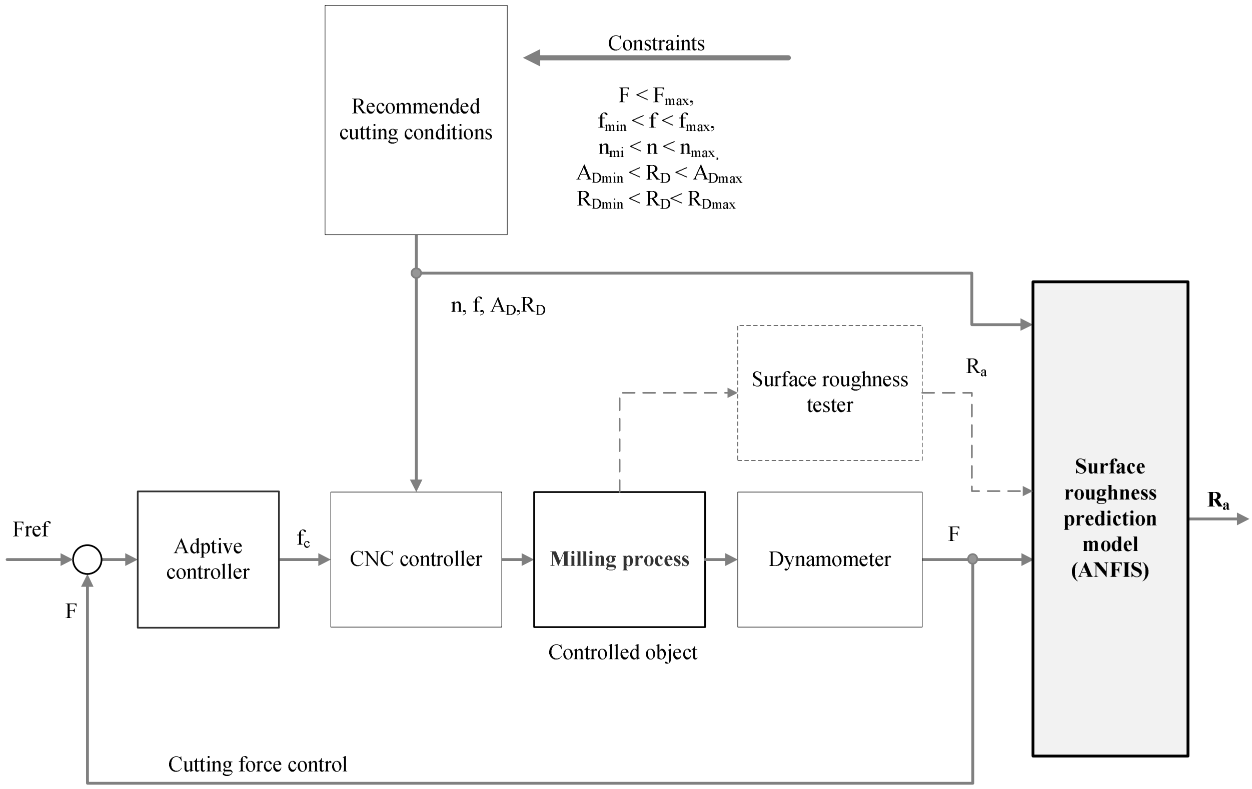

Fig. 1. Integration of surface roughness predication model in the adaptive force control system.

The actual maximal cutting force is sampled every 0.01 seconds and converted to a digital signal. This signal is immediately compared with a predetermined reference cutting force *Fref*. In order to determine the reference force for the system controller the milling forces are measured using the dynamometer. The maximum measured force is a good starting value for the reference force *Fref*. The difference between the F and *Fref* is the control error. The control error is used as the input to the system controller.

The controller adjusts the federate override percentage and sends the determined federate command signal to the federate routine in the CNC controller. A positive error increases the programmed feedrate and consequently increases the produced actual cutting force. A negative error decreases the programmed feedrate and consequently decreases the actual cutting force.

The adaptive controller determines the federate command value to maintain the cutting force at a prescribed reference force.

The controller is connected with the CNC controller of a four axis machining center, as shown in Fig. 1. The federate control is achieved through Feed override commands. In order for the controller to regulate peak force, force information must be available to the control algorithm at every 20 ms.

Data acquisition software (LabVIEW) and the algorithm for processing the cutting forces are used to provide this information. Based on this presented control system, very complicated processes can be controlled more easily and accurately compared to standard approaches.

The objective of the developed combined control system is keeping the metal removal rate (MRR) as high as possible and maintaining cutting force as close as possible to a given reference value. When spindle loads are low, the system increases feeds above and beyond preprogrammed values, resulting in considerable reductions in machining time and production costs. When spindle loads are high the feed rates are lowered, safeguarding cutting tool from damage and breakage.

Sequence of steps for the cutting force control of the milling process is presented below.

1. The pre-determined cutting conditions are sent to CNC controller of the milling machine.
2. The measured cutting forces are sent to adaptive controller.
3. The surface roughness is predicted based on measured cutting forces.
4. Adaptive controller adjusts the feedrates and sends it back to the machine tool,
5. Steps 2 to 5 are repeated until termination of machining.

When the adaptive controller is turned on, the feedrates generated by the CNC controller are sent to the feed drive servo-unit and the surface roughness prediction model.

This model predicts surface roughness on-line and displays the value to the operator. If the value of the surface roughness exceeds the predetermined limits, the warning message is sent to the operator.

3. ANFIS BASED SURFACE ROUGHNESS PREDICTION MODEL

The aim of this study is to develop an accurate and reliable model for predicting surface roughness during end milling process. The surface roughness prediction model is built according to the ANFIS method described

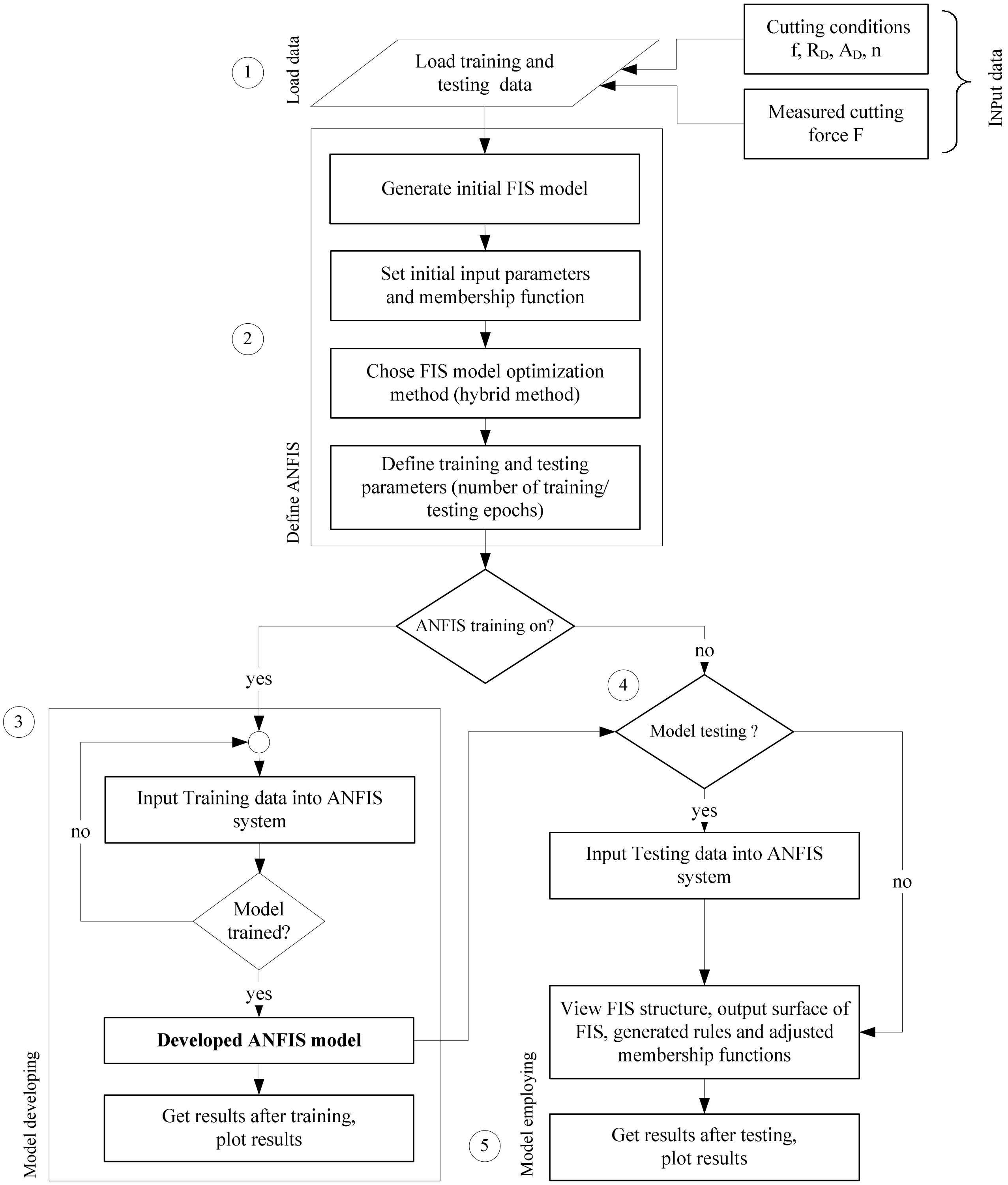

Fig. 2. Algorithm for developing and employing of the ANFIS based surface roughness model.

in this section. The ANFIS method seeks to provide a linguistic model for the prediction of surface roughness from the knowledge embedded in the trained neural network.

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.

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

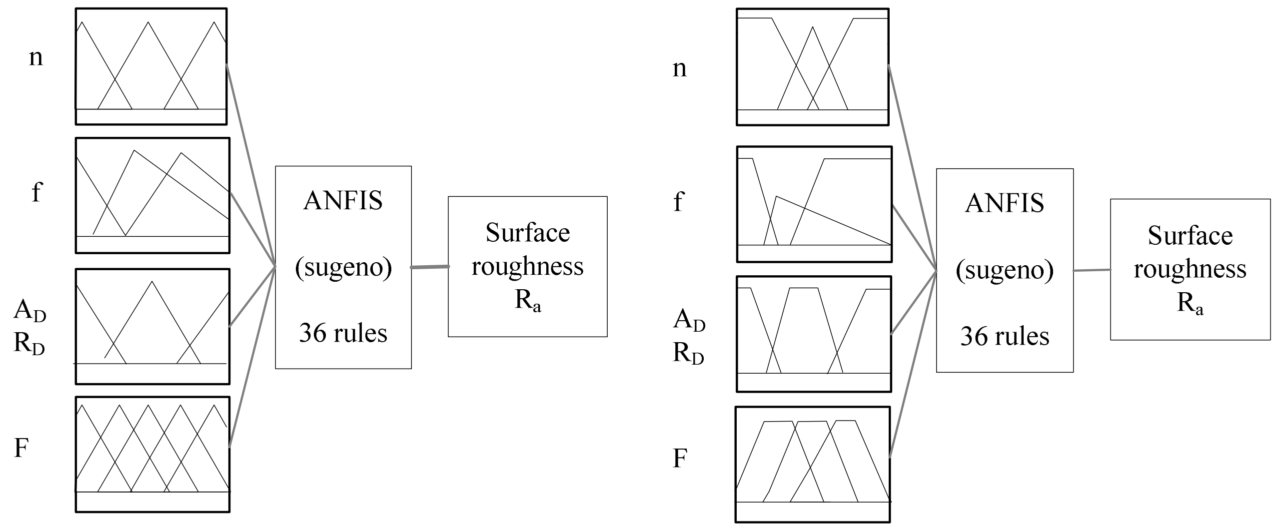

Fig. 3. Architecture of FIS system with triangular and the trapezoidal membership function.

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 are found using the least-squares method. Then an error for each data pair is found. If this error is larger than the threshold value, the premise parameters using the gradient decent method are updated as the following ($Q_{next} = Q_{nov} + \eta d$, where Q is a parameter that minimizes the error, η the learning rate, and d 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. 2 shows the basic flow chart for predicting the surface roughness via ANFIS. It has surface roughness generalization capability.

The system continuously monitors the signal of surface roughness. If the surface roughness limit is exceeded, a warning is declared within 10 ms.

Five steps are required to develop an ANFIS system. In step 1, the training and testing data are loaded to the system. The process variables are force sensor readings (F), spindle speed (n), feed rate (f), depth of cut (A_D, R_D), and measured surface roughness. The domain of definition of these variables is normalized in the range (0, 1), where 1 corresponds to the maximal value of that variable. All the data were scaled. The whole data set is divided into the training and the testing set. 350 data points were used in this study.

The FIS architecture and training parameters were defined in step 2. The optimization method, the tolerance error, the maximal number of epoch, the number of membership functions and the membership functions types are defined. Finding the proper membership function and associated parameters is very difficult and time consuming task. The ANFIS architecture is explained in detail in [5]. The fuzzy inference system under consideration has 5 inputs and one output. Neuro fuzzy algorithm needs to be trained with a set of training data to be able to predict surface roughness based on input-output data. The inputs are cutting force sensor signal, and the cutting conditions. The output is surface roughness provided by the surface roughness tester.

In step 3, the training phase is accomplished. With the input–output data, the neuro-fuzzy algorithm is trained, and the unknown parameters are identified.

Fig. 3 shows the inputs, membership functions, and the fuzzy inference system for surface roughness prediction. During the training stage, the ANFIS adjusts its internal structure to give correct output results according to the input features. Using a given input/output data set, the ANFIS method constructs a fuzzy inference system (FIS) whose membership function parameters are adjusted by using the backpropagation algorithm. This allows fuzzy systems to learn from the data they are modeling. It consists of 131 fuzzy rules.

During training in ANFIS, 350 sets of experimental data is used to conduct 500 cycles of learning.

Finally, in the fourth step the trained ANFIS is used to predict surface roughness. After the training, the inference system could estimate surface roughness from cutting force measurement and cutting conditions in real time. The developed ANFIS model can guide system or operator in tool change decisions making.

4. EXPERIMENTAL DESIGN FOR SURFACE ROUGHNESS MODELLING

Experiments were performed on a CNC machining platform Heller with FAGOR CNC controller. 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 radius of the cutter is 4 mm.

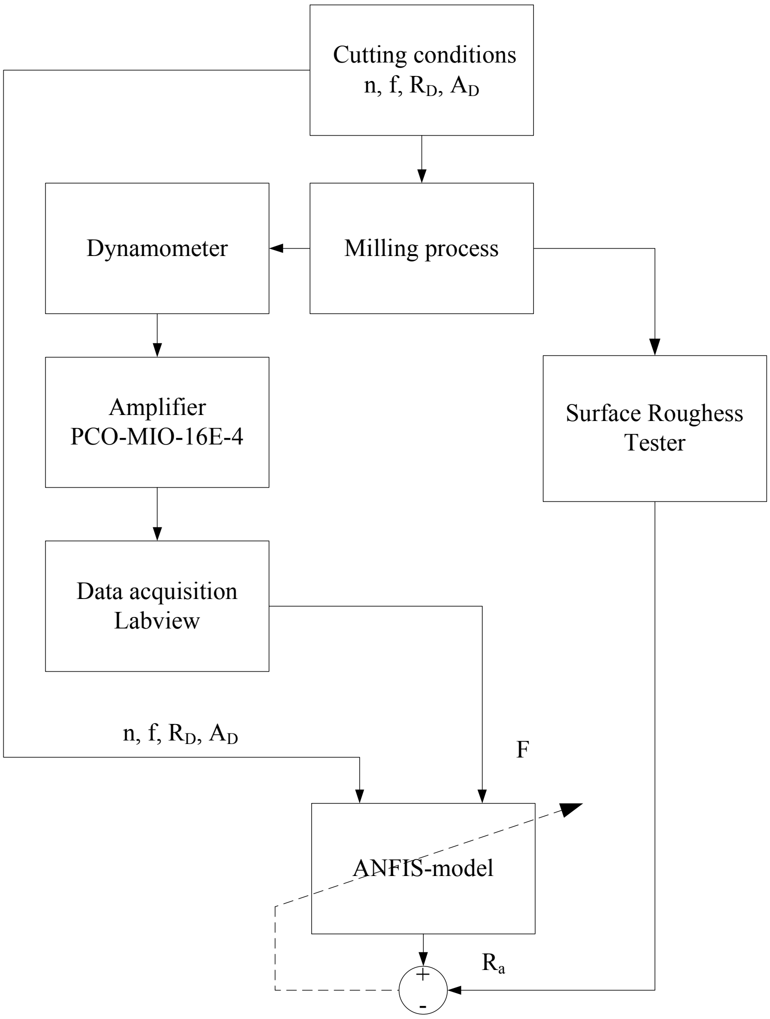

Fig. 4. Experimental set –up for surface roughness modeling.

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 experimental set up can be seen in Fig. 4.

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} = 2 mm, A_{D2} = 4 mm, A_{D3} = 8 mm; d – cutting parameter (16 mm). In the experiments, the following values for feed 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 training and other for testing.

The dynamometer was mounted on the machining table and connected to a three channel charge amplifier.

Charge amplifier (Kistler 5001) converts the charge signals into voltage signals.

The signals were monitored by using a fast data acquisition card (National Instruments NI 9215 A) and software written with the National Instruments CVI programming package.

The surface roughness was measured by 7061 MarSurf PS1 Surface Roughess Tester.

5. RESULTS AND DISCUSSION

In conclusion, predicted surface roughness was found significantly sensitive to the measured cutting forces, especially the thrust cutting component.

A total of 250 sets of data were selected from the total of 350 sets obtained in the end milling experiments [5] for the purpose of training in ANFIS. The other 100 sets were then used for testing after the training was completed to verify the accuracy of the predicted values of surface roughness. The best results were obtained when triangular membership functions were chosen for the neuro-fuzzy model. During training of the neuro-fuzzy algorithm the parameters of membership functions, the optimal rules and the output weights were determined.

The average error of the prediction of surface roughness is around 2.9% when triangular membership function is used in ANFIS. The accuracy is as high as 96%.

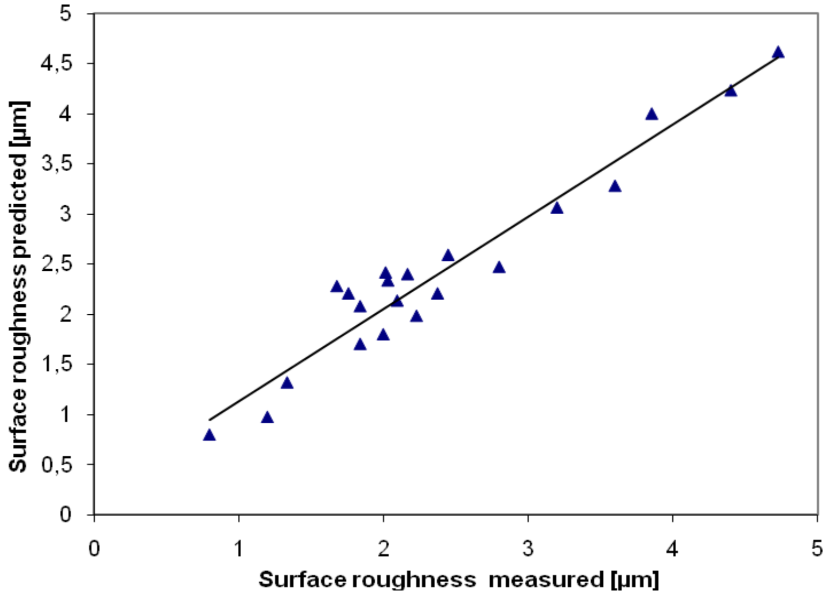

Fig. 5. Scatter diagram of measured *Ra* and predicted for testing data using the triangular membership function.

The training was very fast, and the error reached a constant value after about 45 epochs. In this case, there were 36 rules in the fuzzy inference system. The prediction accuracy of ANFIS when the triangular membership function is used is higher than that when the trapezoidal membership function is used.

When the trapezoidal membership function is adopted the average error is around 4.4%, with an accuracy of 94%. Figure 5 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.

The system with incorporated ANFIS model was capable of predicting the surface roughness in real time. The accuracy of the training data was 98.1%, and the accuracy of the testing data was 94.9%.

Wrong predictions accrued when the feed rate and rotational speed were low. This issue can change the cutting forces and affect the tool wear estimation via force signals. The force sensor gives a good estimation of the surface roughness

6. CONCLUSIONS

The purpose of this research was to develop a control system aimed at controlling the cutting force by digital adaptation of cutting parameters.

The connection between cutting force, cutting conditions and surface roughness were determined via ANFIS modeling. The presented ANFIS model predicts surface roughness with 96% accuracy. This model is the main element of cutting force control system. In this system, cutting force sensor was used as an input to the surface roughness prediction model. The trained ANFIS model is capable to predict surface roughness for various cutting conditions.

Surface roughness was measured after each cutting test with a Surface roughness tester. The sensor signals and the measured cutting force was analyzed off-line and applied to a neuro-fuzzy method to determine the membership functions and rules.

Once the neuro-fuzzy algorithm was trained, the cutting signals could be interpreted to determine the surface roughness through on-line analysis. The training of ANFIS with the triangular membership function obtains a higher accuracy rate in the prediction of surface roughness.

Comparison between the actual surface roughness and the simulated results from the neuro-fuzzy method showed good agreement.

The trained model can be used to monitor milling operations and provide warnings to an operator.

Experiments have also confirmed efficiency of the control system with integrated ANFIS model, which is reflected in improved surface quality.

The experimental results indicated that maintaining constant cutting force leads to better quality of surface.

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