TOOL WEAR ESTIMATION WITH A SELF-LEARNING ADAPTIVE NEURO-FUZZY SYSTEM IN COPY MILLING

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Abstract. *Tool wear sensing plays an important role in the optimisation of tool exchange and tip geometry compensation during automated machining in flexible manufacturing system. The focus of this work is to develop a reliable method to estimate flank wear during end milling process. A neural-fuzzy scheme is applied to perform one-step-ahead prediction of flank wear from cutting force signals obtained from a dynamometer. Because cutting force signals have more informations than acoustic emission signals, the relationship between the cutting force components and flank wear was examined. In our research we also discussed the construction of a neuro-fuzzy system that seeks to provide a linguistic model for the estimation of tool wear from the knowledge embedded in the neural network. Neuro-fuzzy modeling proved to be effective in modeling such complex systems. With the developed approach it is also possible to estimate the tool condition pretty accurately if the feeed and thrust cutting forces are measured at identical cutting conditions.*

Keywords: *Estimation, Tool wear, End-milling, Neuro-fuzzy interference system*

1. INTRODUCTION

Tool wear sensing plays an important role in the optimisation of tool exchange and tip geometry compensation during automated machining in flexible manufacturing system. Much of the previous research is concerned with the classification of wear states (fresh and worn), which is not enough for control purposes; estimation of tool wear length is thus required and plays an essential role in the control of geometric accuracy and surface roughness in finish machining (Chryssolouris et al., 1988). Although flank wear has been long recognized to be crucial to the surface quality in finish-machining, little work has been reported on the detection and estimation methods for this type of tool wear because the estimation of tool wear length not an easy matter, owing to the lack of an effective estimator for tool wear in the machining processes. However, several different approaches have been proposed to automate the tool monitoring function. These include classical statistical approaches as well as fuzzy systems and neural networks. For instance researchers (Emel, 1992) developed an approach based on the least-squares regression for estimating tool wear in machining while (Li et al., 1992) have, respectively, used fuzzy expert systems and fuzzy pattern recognition for monitoring tool wear over a limited range of cutting conditions. The use of neural networks in machining research has been extensive in the past decade to estimate the tool wear in milling. Neuro-fuzzy modeling proved to be effective in modeling such complex systems. 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, axial/radial depth of cut, and number of flutes) on the flank wear. ANFIS system is used to predict the flank wear of the tool in a milling process.

2. PROBLEM STATEMENT

A human operator can often predict the condition of the tool by observing the machining conditions and by utilizing his sensory perceptions. However in manufacturing the relationship between process characteristics and tool wear is difficult to capture. This is due to the complexity of the relationship between tool wear and process characteristics. 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 tool wear prediction models. 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 tool wear prediction models.

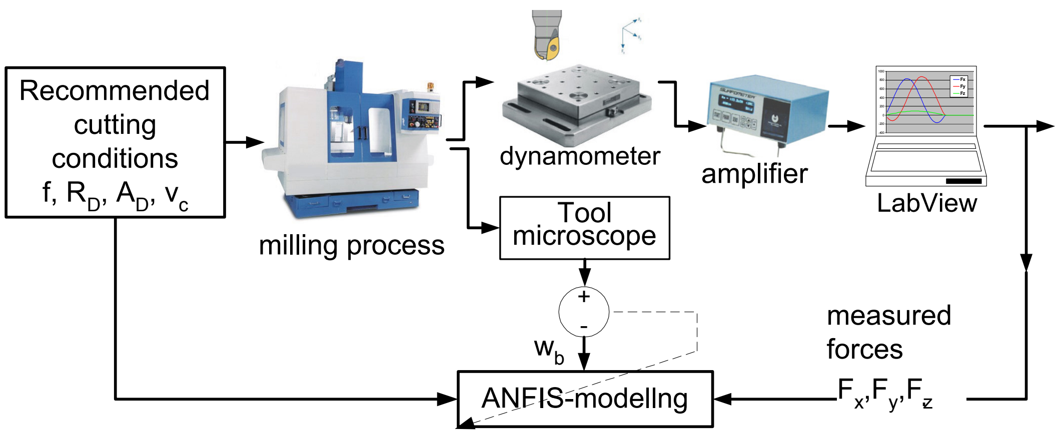

Figure 1- Experimental set-up.

In such models, the nonlinear relationship between sensor readings and tool wear embedded in a neural network remains hidden and inaccessible to the user. In this research we attempt to solve this situation by using the ANFIS system to predict the flank wear. This model offers ability to estimate tool wear 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 tool wear with ANFIS method. Four milling parameters have been selected. 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 flank wear prediction. The obtained result for predicting flank wear 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.

3. EXPERIMENTAL EQUIPEMENT

In order to develop the tool wear prediction model, experimental results were used. The cutting forces were measured with a piezoelectric dynamometer (Kistler 9255) mounted between the workpiece and the machining table. 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 were 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 cutting tool flank wear was continuously measured with tool microscope of 0.01 mm accuracy. The data acquisition package used was LabVIEW. The set up can be seen in Fig. 1. The experiments were carried out for all combinations of the chosen parameters, 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 (16mm). 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 (cus et al., 2000). In this way two sets of data groups were generated, one for learning and other for estimation tests.

4. ARCHITECTURE OF ANFIS SYSTEM

Using a 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 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, update the premise parameters using the gradient decent method as the following ($Qnext=Qnov+\eta d$, 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. Figure 2 shows the flow chart for predicting the flank wear via ANFIS. Figure 3 shows the fuzzy rule architecture of ANFIS when the triangular membership functions and the trapezoidal membership function is adopted, respectively.

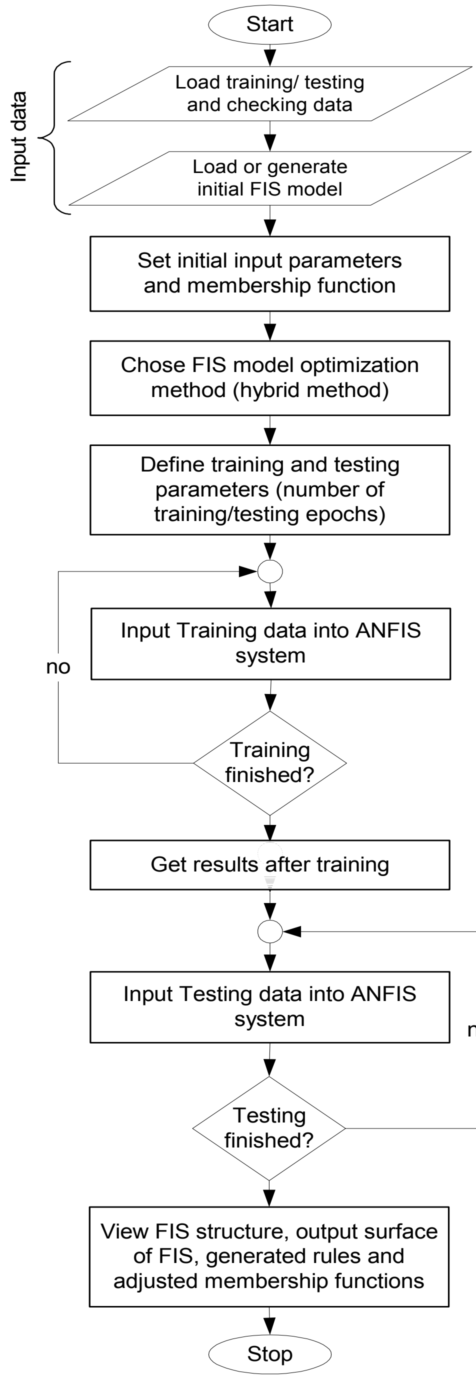

Figure 2- Flowchart of flank wear prediction of ANFIS system.

5. RESULTS

In this study, a trained ANFIS algorithm is used to predict the flank wear of the cutter during the cutting of hardened steel workpieces. The major advantage of ANFIS predictions is that the models can estimate flank wear progress very fast and accurately, once the cutting

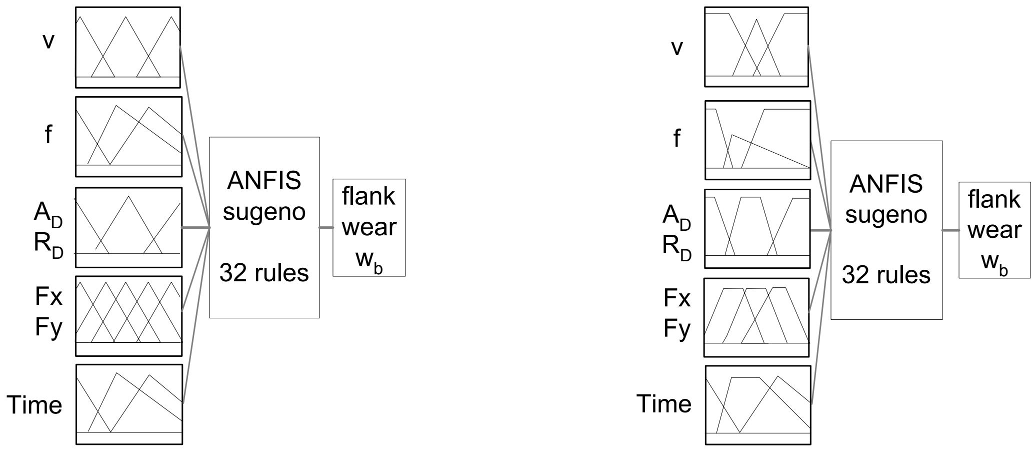

Figure 3- Fuzzy rule architecture of ANFIS system.

forces are known. The major advantage of the ANFIS predictions is that the algorithms can estimate flank wear progress quite accurately once the forces are known. A total of 75 sets of data were selected from the total of 140 sets obtained in the end milling experiments for the purpose of training in ANFIS. The other 65 sets were then used for testing after the training was completed to verify the accuracy of the predicted values of flank wear. Figures 4 and Fig. 5 show the initial and final membership functions of the main end milling parameters derived by training via the triangular function. Figure 4 shows the initial and final membership functions of parameter f. There is obviously a considerable change in the final membership function after training, regardless of the small, large or even medium area. Figure 5 shows the initial and final membership functions of parameter A_D. It shows that the final membership function after training experiences a smaller variation in the small areas, but slightly a greater variation in the medium area and large areas. The average error of the prediction of flank wear is around 4% when triangular membership function is used in ANFIS. The accuracy is as high as 94%. The prediction accuracy of ANFIS when the triangular membership function is used is higher than that when the trapezoidal membership function is used.

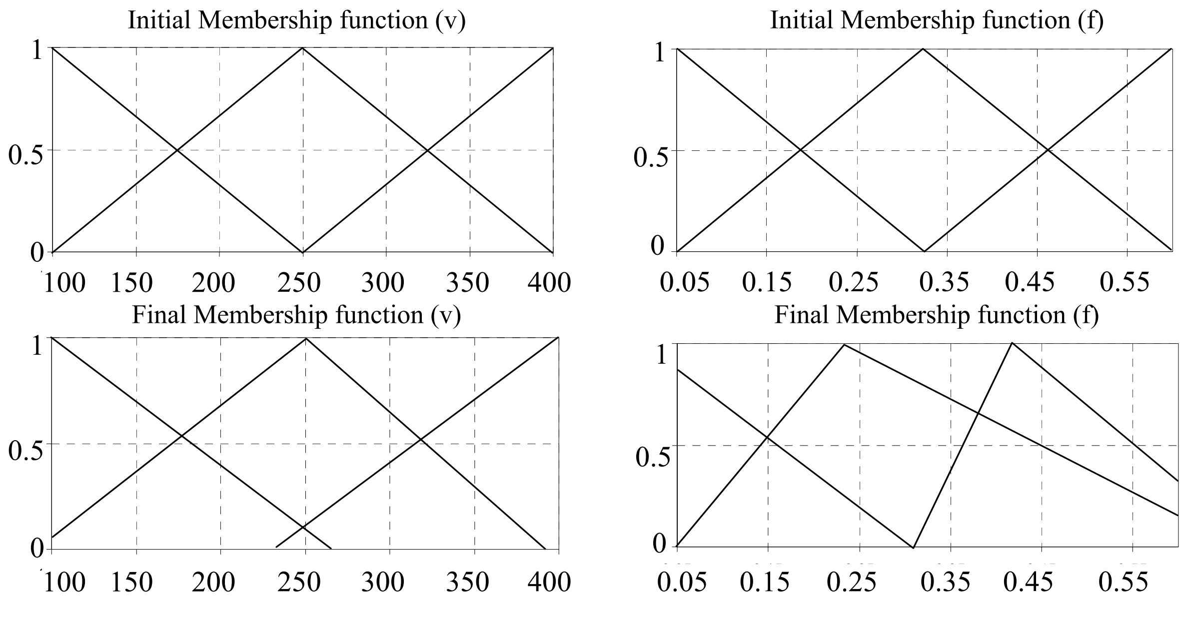

Figure 4- Initial and final triangular MF of parameter v and f.

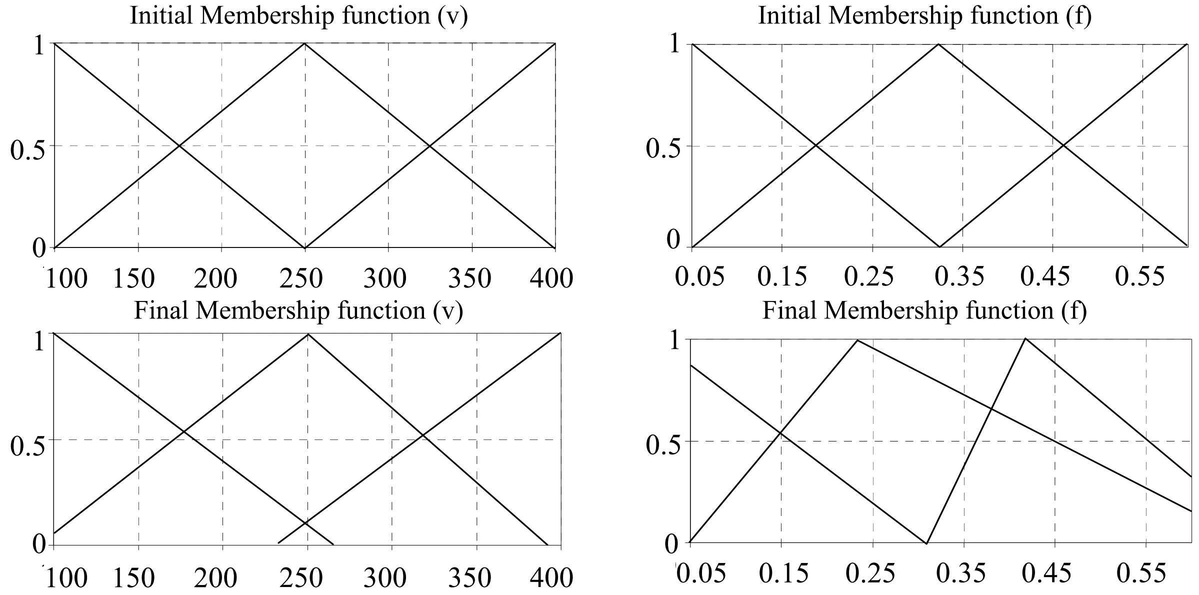

Figure 5- Initial and final triangular MF of parameter A_D and F_x (thrust force).

6. CONCLUSION

The experimental results indicate that the proposed ANFIS model has a high accuracy for estimating flank with small computational time. Comparisons between the wear maps generated by ANFIS and those obtained experimentally show good agreement in the trends of wear-rate variation against machining conditions.

The flank wear values predicted by ANFIS are compared with the measurement values derived from the 120 data sets in order to determine the error of ANFIS. The following conclusions can be drawn from the above analysis: The error of the tool wear values predicted by ANFIS with the triangular membership function is only 4%, reaching accuracy as high as 94%.

When the trapezoidal membership function is adopted the average error is around 5.4%, with an accuracy of 92%.

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