四海學報 14 :1-22

The Study of Tool Failure Detection in Turning

Ship-Peng Lo

ABSTRACT

The cutting process is a major material removal process. Hence, it is important to search for ways of detecting tool failure. This paper describes results of the application of Adaptive-Network-based Fuzzy Inference System(ANFIS) for tool failure detection in a single point turning operation. In turning operation, wear and failure of the tool are usually monitored by measuring cutting force, load current, vibration, acoustic emission(AE) and temperature. One of them, the AE signal and cutting force signal provides useful information concerning the tool failure condition. Therefore, five input parameters of the combined two kinds of signals(AE signal and cutting force single) have been used in the ANFIS model to detect the tool state. In this model, We adopted three different types of membership functions for analysis in ANFIS training and compared their differences regarding the accuracy rate of the tool state detection. The obtained result for successful classification of tool state with respect to only two classes(normal or failure) has highly correct rate. The results also indicate that the triangular MF and generalized bell MF have higher correct rate of detection.

Keywords: Tool failure detection

1. Introduction

The development of efficiency, productivity and high quality in the manufacturing industry, tool failure is highly undesirable because it severely degrades the quality of machined surfaces and causes undesirable and unpredictable change in work geometry. Therefore, the detection of tool failure plays most important roles in improving reliability and to promoting automation of manufacturing processes.

Various methods[1] for tool failure detection have been proposed and evaluated in the past, even though none of these methods were universally successful due to the complex nature of machining processes. Generally speaking, these methods can be classified into two categories, namely direct and indirect methods. The direct method can be implemented by means of optical devices to measure the geometry and to recognize the morphology of wear land. ITV camera[2] is a typical equipment employed to monitor the tool failure. Jean and Kim[3] used the optoelectronic method for on-line monitoring of the flank wear of cutting tools. The serious problem of the techniques which directly measure the dimensions of tool wear zone, is that it is very difficult to get on-line measurement of the very small wear zone under shop environments. The indirect methods is based on the acquisition of a variable process from which tool wear or tool failure can be estimated by using a known relationship. Liang and Dornfeld[4] detect the tool wear by time series analysis of acoustic emission. In their study, a signal processing scheme is developed, which uses an autoregressive time-series to model the acoustic emission generated during cutting. Cuppini etc. [5] analyzed tool wear based on cutting power measurement. The implementation of a continuous indirect method based on experiment relationships between wear and cutting power has been described. Ravindra etc. [6] developed a mathematical model to describe the wear-time and the wear-force relationships during turning operation. Cutting force components have been found to correlate well with progressive wear and tool failure. It also eliminates variation in material properties, which was identified as a major noise source in signals measured during machining. Moriwaki[7], in his study, the acoustic emission monitoring was applied to in-process detection of the tool failure during the interrupted cutting on a NC lathe which the feed was automatically stopped. The acoustic emission signals were also measured during the static and the dynamic fractures of the tool materials and compared with those associated with the failures during the metal cutting. Most of the indirect methods suffer from the fact that the measurements are influenced not only by tool wear but also by various process parameters, such as the geometry of the cutting tool and the cutting condition.

Recently, the application of neural networks to detecting tool failure has attracted great interest. The superior learning, the noise suppression, and the parallel computation abilities are the major advantages of the neural network method. Lin and Ting[8] used a neural network method to integrate information from dynamometer and cutting parameters including spindle rotational speed, feedrate, and drill diameter in order to estimate tool wear. Dornfeld[9] described the design and implementation of a neural network-based system combining the outputs of several sensors(an acoustic emission, force and spindle motor current) for monitoring progressive tool wear in a single point turning operation. Prohaszka[10] studied different approaches to apply neural network techniques for modelling and monitoring of machining processes(turning, milling) by sensor integration. Back propagation networks are used for state classification of tools, estimation of the tool wear and inverse modelling of the cutting process. Das etc.[11] used the back propagation algorithm for training the neural network of 5-3-1 structure. The technique shows close matching of estimation of average flank wear and directly measured wear value.

Based on the above mentioned studies, it can be seen that most studies regarding the detection of cutting tool state obtained such items as the tool failure and the tool wear value from experiment measurement or neural network training system. Very few researchers used the adaptive-network based fuzzy inference system(ANFIS) to detect the tool failure. Further, the impact of different membership functions which are utilized in the ANFIS model on the correct rate of detection was not investigated yet.

In this paper, we try to investigate the possibility and effectiveness of detecting cutting tool failure with a new approach method called adaptive network based fuzzy inference system(ANFIS). Five cutting parameters of two kinds of monitored signals(AE signal and cutting force signal) have been selected, The parameters and their meanings are listed in Table 1[12]. Based on these five cutting parameters, and another important parameter-tool state(failure tool or normal tool), we investigate how to use ANFIS for tool failure detecting. In this model, We adopted three different types of membership functions for analysis in ANFIS training and compared their differences regarding the accuracy rate of the tool state detection. The obtained result for successful classification of tool state with respect to only two classes(normal or failure) has highly correct rate. The results also indicate that the triangular MF and generalized bell MF have higher correct rate of detection.

2.Theoretical foundation

In this section, we will describe primarily the ANFIS architecture and its learning algorithm for the Sugeno fuzzy model[13]. For simplicity, we assume the fuzzy inference system under consideration has two inputs m and n and one output f. For a first-order Sugeno fuzzy model, a typical rule set with two fuzzy if–then rules can be expressed as:

Rule 1：If (m is A_1) and (n is B_1) then $f_1 = p_1 m + q_1 n + r_1$ (2.1)

Rule 2：If (m is A_2) and (n is B_2) then $f_2 = p_2 m + q_2 n + r_2$ (2.2)

Where p_1 、 p_2 、 q_1 、 q_2 、 r_1 and r_2 are linear parameter. A_1 、 A_2 、 B_1 and B_2 are nonlinear parameter.

The corresponding equivalent ANFIS architecture is as shown in Fig. 1. The entire system architecture consists of five layers, namely, the fuzzy layer, product layer, normalized layer, de-fuzzy layer and total output layer. The following sections discuss in depth the relationship between the output and input of each layer in ANFIS.

Layer 1 is the fuzzy layer, in which m and n are the input of nodes A_1, B_1 and A_2, B_2, respectively. A_1, A_2, B_1 and B_2 are the linguistic labels used in the fuzzy theory for dividing the membership functions. The membership relationship between the output and input functions of this layer can be expressed as below:

$$\begin{aligned} O_{1,i} &= \mu_{A_i}(m) \qquad ,i=1,2 \\ O_{1,j} &= \mu_{B_j}(n) \qquad ,j=1,2 \end{aligned} \tag{2.3}$$

where $O_{1,i}$ and $O_{1,j}$ denote the output functions and μ_{A_i} and μ_{B_j} denote the membership functions.

Layer 2 is the product layer that consists of two nodes labeled II. The output W1 and W2 are the weight functions of the next layer. The output of this layer is the product of the input signal, which is defined as follows:

$$O_{2,i} = w_i = \mu_{A_i}(m)\mu_{B_i}(n) \qquad ,i=1,2 \tag{2.4}$$

where $O_{2,i}$ denotes the output of Layer 2.

The third layer is the normalized layer, whose nodes are labeled N. Its function is to normalize the weight function in the following process:

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2} \qquad ,i=1,2 \tag{2.5}$$

where $O_{3,i}$ denotes the Layer 3 output.

The fourth layer is the de-fuzzy layer, whose nodes are adaptive. The output equation is $\overline{w}(pm+qn+r)$, where p_i, q_i and r_i denote the linear parameters or so-called consequent parameters of the node. The de-fuzzy relationship between the input and output of this layer can be defined as follows:

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i(p_i m + q_i n + r_i) \qquad ,i=1,2 \tag{2.6}$$

where $O_{4,i}$ denotes the Layer 4 output.

The fifth layer is the total output layer, whose node is labeled as Σ. The output of this layer is the total of input signals, which represents the tool state (normal or failure) detection result. The results can be written as below:

$$O_{5,i}=\Sigma_i \overline{w}_i f_i=\frac{\Sigma_i w_i f_i}{\Sigma_i w_i} \qquad ,i=1,2 \tag{2.7}$$

where $O_{5,i}$ denotes the Layer 5 output.

3. Experimental equipment and procedure

The experimental setup for in-process detection of the tool failure schematically illustrated in Fig. 2 [12]. A NC lathe was employed for the interrupted cutting of an alloy steel plate which was fixed to the work holder and was turned by employing a longitudinal feed. The cutting tool used in this test is the carbide tool p20 and the cutting speed, the depth of cut and the feed are 250 m/min, 1.5 mm and 0.3 mm/rev respectively. A commercially available acoustic emission sensor was attached to the end of the tool shank employing a magnet. The frequency range of the sensor employed for the cutting test was 50 KHz-1 MHz. The sensed AE signal was amplified to employ the pre-amplifier, and then passed through the band pass filter which had a wide frequency range of pass band from 20 KHz- 1 MHz. Cutting force signal was monitored by cutting force recorder, then recorded by data recorded, and handled with computer after being changed by A/D.

Table 2 shows the experimental results of the six parameters. The experimental results will be used in ANFIS model for training and testing. In each cutting cycle, 30 signals were recorded. So 30 data groups were obtained, each of which has five continuous values(parameters Sx, Sy, Sz, Dx and Dy)and one discrete value(parameter Dz). The meaning of the Dz(tool state)in Table 2 is the result of the detection from the cutting process. "0" means the tool is normal, and "1" means the tool is failed[14].

4. Results and Discussion

In this paper, we randomly selected 24 sets of data from the 30 sets (as listed in Table 2) obtained from the cutting experiment. We input these 24 sets data in ANFIS for training. After training is completed, the remaining 6 sets data were used in a test to validate the accuracy of the detection of tool state(normal or failure). Fig. 3 shows the flowchart of using ANFIS to detect tool state.

Fig. 4 shows the fuzzy rule architecture of the ANFIS that adopts the triangular membership function. There are a total of 243 fuzzy rules in the architecture. During the training in ANFIS, 24 sets of experimental data were used to conduct 200 times of learning. The step size for parameter adaptation had an initial value of 0.01. The step size adaptation figure for the cutting parameters from the training results is shown in Fig. 5. Among the architecture, each input parameter's membership function is divided into three regions, namely, the small, medium and large regions. Figures 6 to 10 show the initial and final membership functions of the five experimental cutting parameters derived by the triangular membership function training. Fig. 6 shows little change between the initial and final membership functions of cutting parameter Sx. However, in Fig. 7, which shows the initial and final membership functions of cutting parameter Sy, we can see a considerable change in the final membership function after training. The change is especially evident in the small region and large region. Fig. 8 shows the initial and final membership functions of cutting parameter Sz. It also shows a distinctive change in the final membership function of Sz. Though the change is also present in the medium and large regions, it is greater in the small region. Fig. 9 shows the initial and final membership functions of cutting parameter Dx. As shown in this figure, the change of the final membership function is more evident in the medium region than in the small region. As for the parameter Dy, Fig. 10 shows a more evident change of the final membership function in the medium region and a slight change in the large region. The analysis from the above five figures indicates that the factor among the cutting parameters bearing the most impact on tool state detection is Sy, followed by Sz. This phenomenon is evident from the above figures showing the final membership functions of these parameters.

Figures 11 to 15 show the initial and final membership functions of the cutting parameters Sx, Sy, Sz, Dx and Dy derived from the bell membership function. Among these figures, we find that changes of the final membership function of cutting parameter Sy in Fig. 12 and that of Sz in Fig. 13 are most distinctive of all. As shown in Fig. 12, there is considerable change, especially in the small region, in the final membership function of Sy as compared with the initial membership function, more than the final membership function of any other parameters. This analytical result is the same as that concluded from Fig. 7. Fig. 13 shows the initial and final membership functions of cutting parameter Sz. It is easy to detect from this figure that changes also occur in the small and large regions of the final membership function. Besides, we also learn from changes of the final membership functions shown in Figures 15 and 16 that parameter Dy has a greater impact on tool state detection than parameter Dx.

Figures 16 to 20 show the initial and final membership functions of the cutting parameters Sx, Sy, Sz, Dx and Dy derived from the trapezoidal membership function. The physical phenomena shown in these figures are similar to those shown in Figures 6 to 10 and Figures 11 to 15. In other words, changes of the final membership function of cutting parameter Sy in Fig. 17 and that of Sz in Fig. 18 are the most distinctive among this set of five figures. Based on the above results and discussions, we know that regardless of the type of membership function adopted for training analysis, the physical phenomena obtained are more or less identical. That is, parameters Sy and Sz have a greater impact on tool state detection, and parameter Dy has a greater effect on tool state detection than Dx.

Table 3 lists the measure values and estimate values derived from the simulation of tool failure detection by ANFIS through the adoption of different membership functions. Among the 30 sets of cutting experimental data, 24 sets were randomly selected for training. The remaining 6 data sets were used as testing data. By entering the five cutting parameters of any of the 6 data sets into the already trained ANFIS, we obtain an output value. This output value is then used to determine whether the tool is normal or has failed. ANFIS outputs are not binary, but rounded. In other words, ANFIS predicted values below 0.5 are rounded to 0, which indicates the tool is normal. On the contrary, those values above and including 0.5 are approximated to 1, which indicates tool failure [15]. The results are presented in Table 3. Based on the above judgement criteria, results shown in Table 3 indicate that the adoption of triangular or bell membership function in ANFIS obtained a 100% accurate tool state detection rate, whereas the adoption of trapezoidal membership function only achieved a 67% accuracy rate. Based on these results, the 100% accurate tool state detection rate may have been the result of only 6 sets of testing data. Given more testing data sets, the results may come closer to the actual phenomena. Nevertheless, we can still draw a conclusion from the results shown in Table 3. That is, by adopting the triangular or bell membership function to conduct system training, ANFIS can obtain a higher accuracy rate of tool state detection.

5. Conclusion

In this study, we used ANFIS to conduct training, and tested the accuracy rate of tool state detection. We adopted three different types of membership functions for analysis in ANFIS training and compared their differences regarding the accuracy rate of the tool state detection. Based on the above descriptions and discussions, we may draw the following conclusions:

1. In our analytical model, by adopting the triangular or bell membership function to conduct system training, ANFIS can obtain a higher tool state detection accuracy rate.
2. Among the five cutting parameters, parameter Sy as the greatest impact on tool state detection, followed by Sz. Besides, parameter Dy has a greater impact than Dx.
3. The combination of AE signals and cutting force signals can be used effectively in the detection of tool state (normal or failure).

REFERENCE

1. Dan, Li. and Mathew, J., Tool wear and failure monitoring techniques for turning-a review. Int. J. Mach. Tools Manufact., Vo1. 30, pp.579-598, 1990.
2. Uehara, K. and Kanda, Y., On the chipping phenomena of carbide cutting tools. Annals of the CIRP, 25, 1, 1977.
3. Jeon, J. U. and Kim, W., Optical flank wear monitoring of cutting tools by image processing. Wear, 127, pp. 207-217,1988.
4. Liang, S. Y. and Dornfeld, D. A., Tool wear detection using time series analysis of acoustic emission. ASME, Journal of Engineering for Industry, Vol. 111, pp. 199-203, 1989.
5. Cuppini, D., D'errico, G. and Rutelli, G., Tool wear monitoring based on cutting power measurement. Wear, 139, pp. 303-311, 1990.
6. Ravindra, H. V., Srinivasa, Y. G. and Krishnamurthy, R., Modelling of tool wear based on cutting forces in turning. Wear, 169, pp. 25-32, 1993.
7. Moriwaki, T., Detection for cutting tool fracture by acoustic emission measurement. Annals of the CIRP, Vol. 29, 1, pp. 35-40, 1980.
8. Lin, S. C. and Ting, C. J., Drill wear monitoring using neural networks. Int. J. Mach. Tools Manufact., Vol. 36, pp. 465-475, 1996.
9. Dornfeld, David A., Neural network sensor fusion for tool condition monitoring. Annals of the CIRP, Vol. 39, pp.101-105, 1990.
10.Prohaszka, J., A step towards intelligent manufacturing: modelling and monitoring of manufacturing processes through artificial neural networks. Annals of the CIRP, Vol. 42, pp.485-488, 1993.
11.Das, S., Roy, R. and Chattopadhyay, A. B., Evaluation of wear of turning carbide inserts using neural networks. Int. J. Mach. Tools Manufact., Vol. 36, pp. 789-797, 1996.12.Jin, D. and Kakazu, Y., Tool failure detecting by ID3. Int. J. Japan Soc. Prec. Engng., Vol. 29, pp. 140-145, 1995.
13.Roger Jang, J. S. and Sun, C. T., Neuro-fuzzy modeling and control. Proceedings of the IEEE, Vol. 83, pp.378-404, 1995.
14.Venkatesh, V. C. and Satchithanandam, M., A discussion of tool life criteria and total failure causes. Annals of the CIRP, Vol. 29, pp.19-23, 1980.
15.Dimla, E., Dimla, JR, Paul M. Lister and Nigel J. Leighton, Automatic tool state identification in a metal turning operation using MLP nerual networks and multivariate process parameters, Int. J. Mach. Tools Manufact., Vol. 38, pp.343-352, 1998.

Table 1 parameters used in ANFIS [12]

Parameter	Meaning
Sx	average RMS of AE
Sy	maximum amplitude of demodulated AE
Sz	averaged amplitude of AE
Dx	mean main force
Dy	ratio of feed force to main force
Dz	tool state (normal tool or failure tool)

Table2 Experimental results of AE and cutting force signals

Test No.	Experimental results					
	Sx	Sy	Sz	Dx	Dy	Dz
1	8.010	0.057	0.139	1.180	0.510	0
2	10.31	0.043	0.167	1.090	0.470	0
3	12.57	0.056	0.049	1.000	0.500	0
4	18.03	0.089	0.117	0.930	0.550	0
5	25.11	0.071	0.088	1.110	0.600	0
6	32.00	0.083	0.128	1.250	0.490	0
7	32.18	0.100	0.115	1.170	0.530	0
8	41.91	0.093	0.100	0.990	0.600	0
9	50.71	0.125	0.065	1.200	0.630	0
10	50.01	0.131	0.080	1.080	0.590	0
11	49.88	0.107	0.104	1.000	0.710	0
12	43.01	0.111	0.098	1.050	0.720	0
13	39.57	0.122	0.157	1.200	0.690	0
14	37.53	0.250	0.360	1.410	0.800	1
15	53.69	0.201	0.261	1.380	0.750	1
16	40.17	0.213	0.202	1.270	0.830	1
17	35.99	0.266	0.271	1.300	0.850	1
18	47.36	0.289	0.197	1.420	0.700	1
19	54.51	0.199	0.248	1.490	0.750	1
20	53.73	0.358	0.224	1.290	0.880	1
21	51.94	0.271	0.348	1.500	0.810	1
22	40.00	0.353	0.313	1.470	0.800	1
23	39.65	0.375	0.200	1.220	0.890	1
24	48.01	0.277	0.256	1.530	0.930	1
25	28.01	0.158	0.163	1.210	0.800	0
26	44.55	0.130	0.109	1.190	0.780	0
27	47.11	0.171	0.200	1.000	0.600	0
28	47.77	0.300	0.219	1.520	0.830	1
29	43.17	0.291	0.308	1.380	0.900	1
30	29.81	0.250	0.195	1.410	0.900	1

Table 3 Comparison of tool state measured and estimated from ANFIS trained with different MF

Test No	Experimental results						Membership function type		
	Sx	Sy	Sz	Dx	Dy	Dz	trangular	trapezoidal	bell
V1	28.01	0.158	0.163	1.210	0.800	0	0.3153 (0)	0.5195 (1)	0.3294 (0)
V2	44.55	0.130	0.190	1.190	0.780	0	0.1463 (0)	0.0650 (0)	0.1226 (0)
V3	47.11	0.171	0.200	1.000	0.600	0	0.0550 (0)	0.00165 (0)	0.0546 (0)
V4	47.77	0.300	0.219	1.520	0.830	1	0.9438 (1)	1.03600 (1)	1.0509 (1)
V5	43.17	0.291	0.308	1.380	0.900	1	1.0118 (1)	0.62820 (1)	0.7997 (1)
V6	29.81	0.250	0.195	1.410	0.900	1	0.6376 (1)	0.35110 (0)	0.6636 (1)
					correct rate		100%	67 %	100%

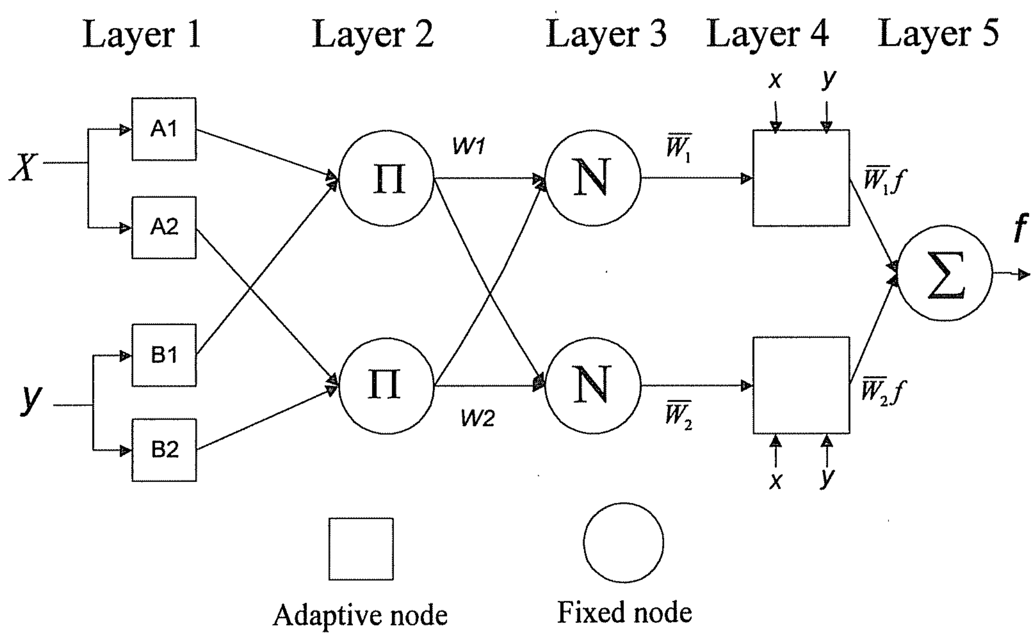

Fig. 1. ANFIS architecture

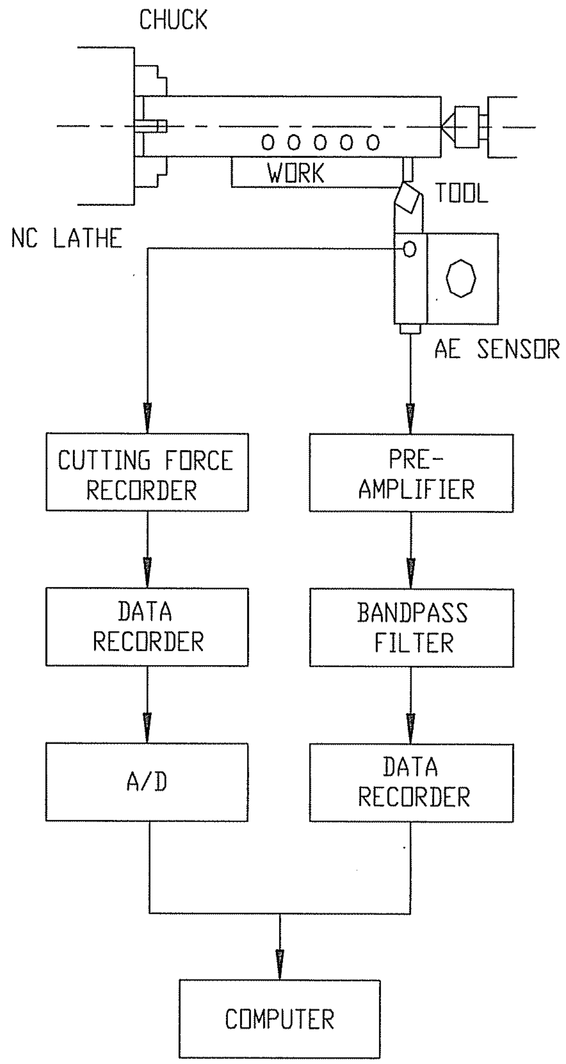

Fig. 2. Schematic illustration of experimental setup

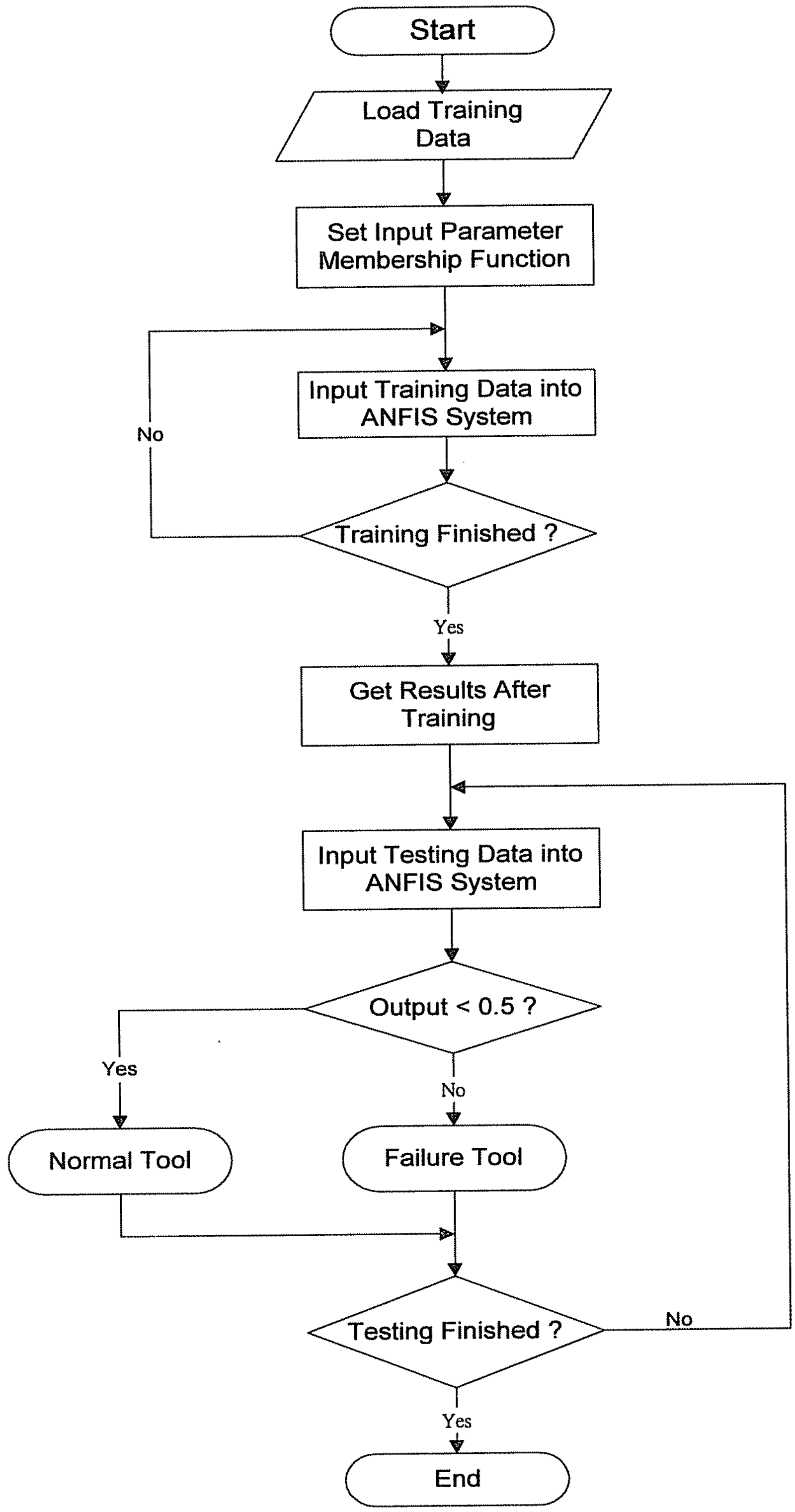

Fig. 3. Flowchart of tool state detection of ANFIS system

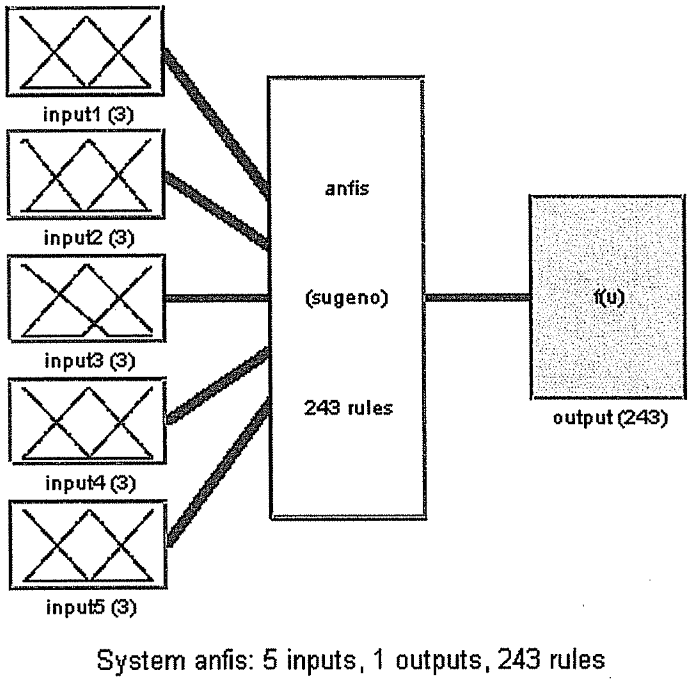

Fig. 4. Fuzzy rule architecture of the ANFIS model

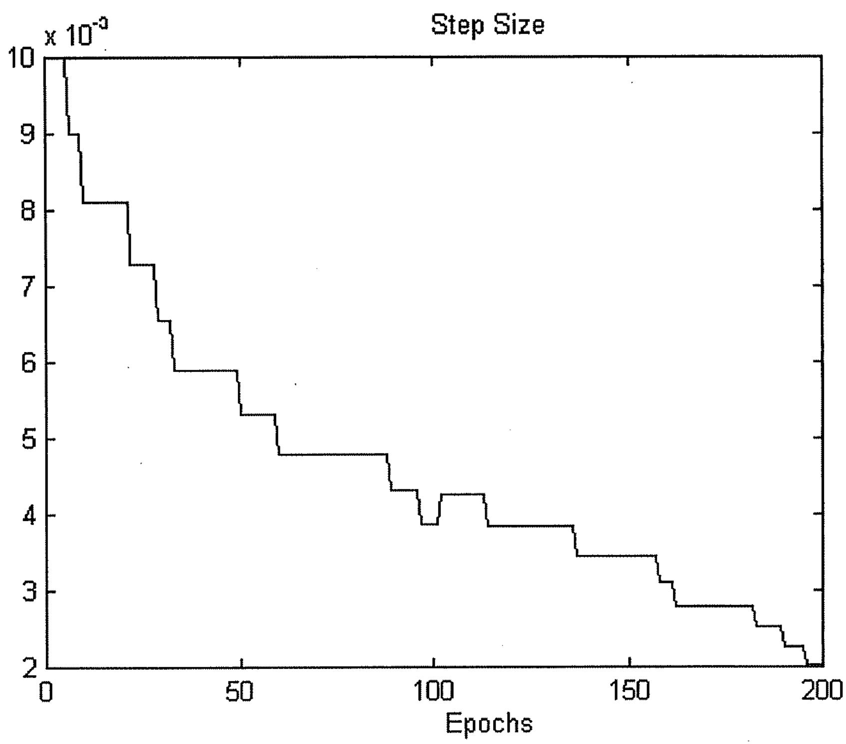

Fig. 5. Step size diagram of training process

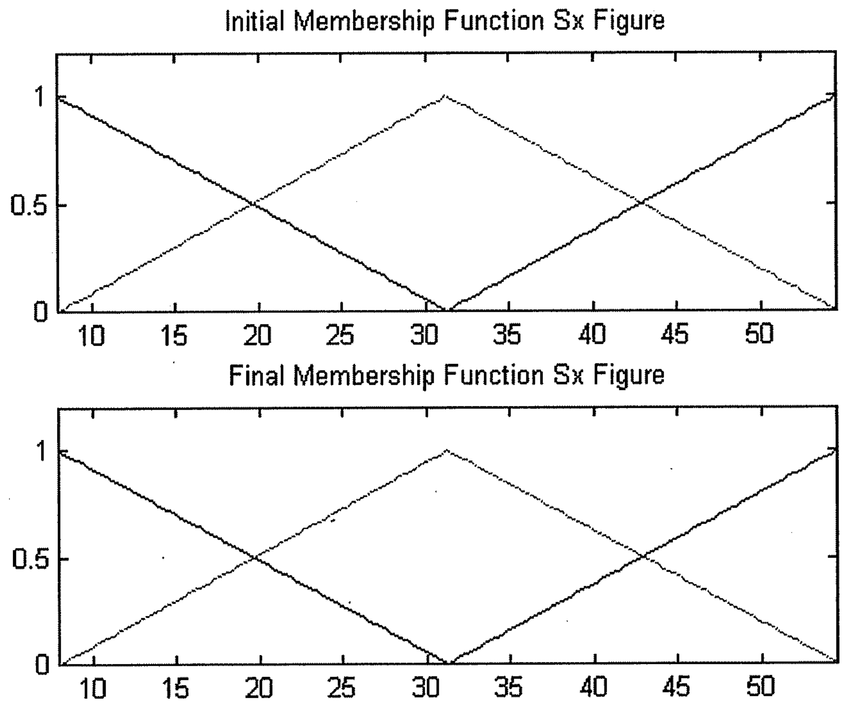

Fig. 6. Initial and final trangular MF of cutting parameter Sx

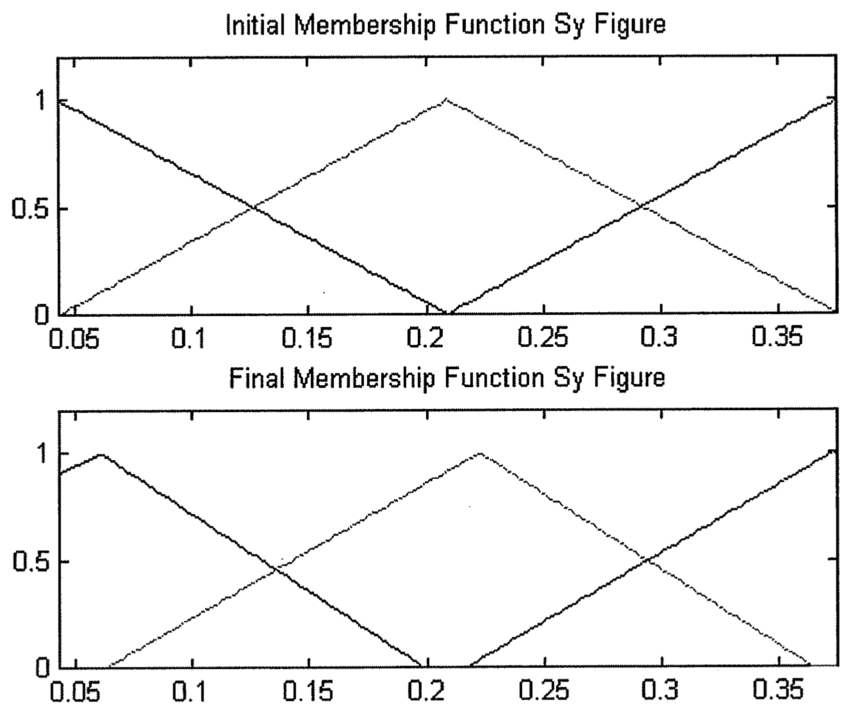

Fig. 7. Initial and final trangular MF of cutting parameter Sy

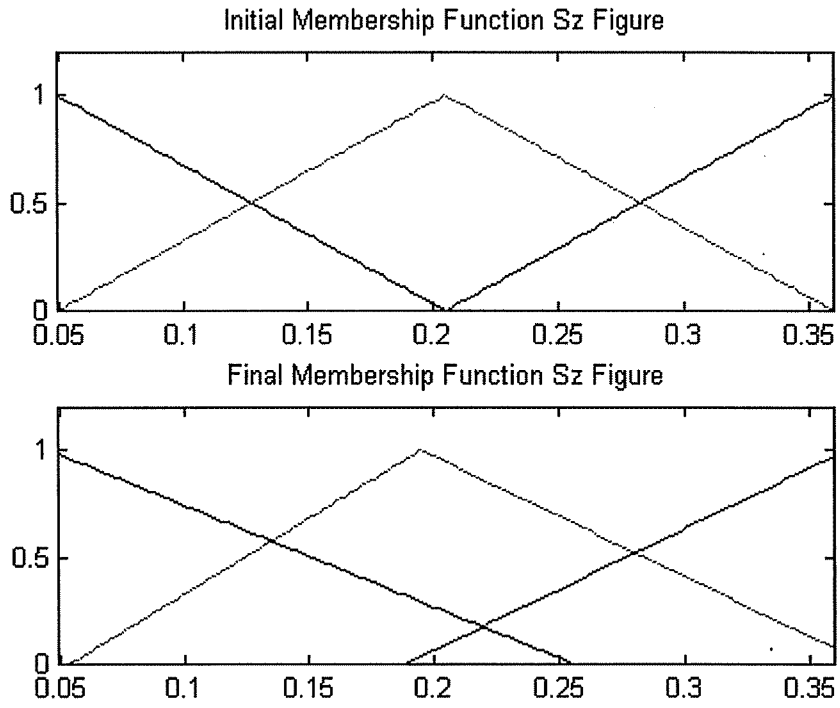

Fig.8. Initial and final trangular MF of cutting parameter Sz

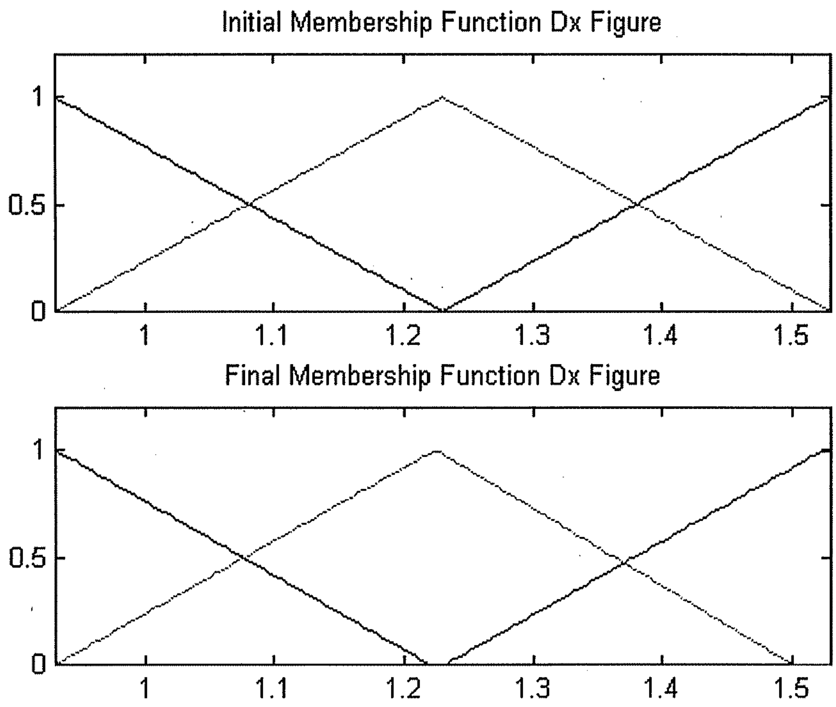

Fig.9. Initial and final trangular MF of cutting parameter Dx

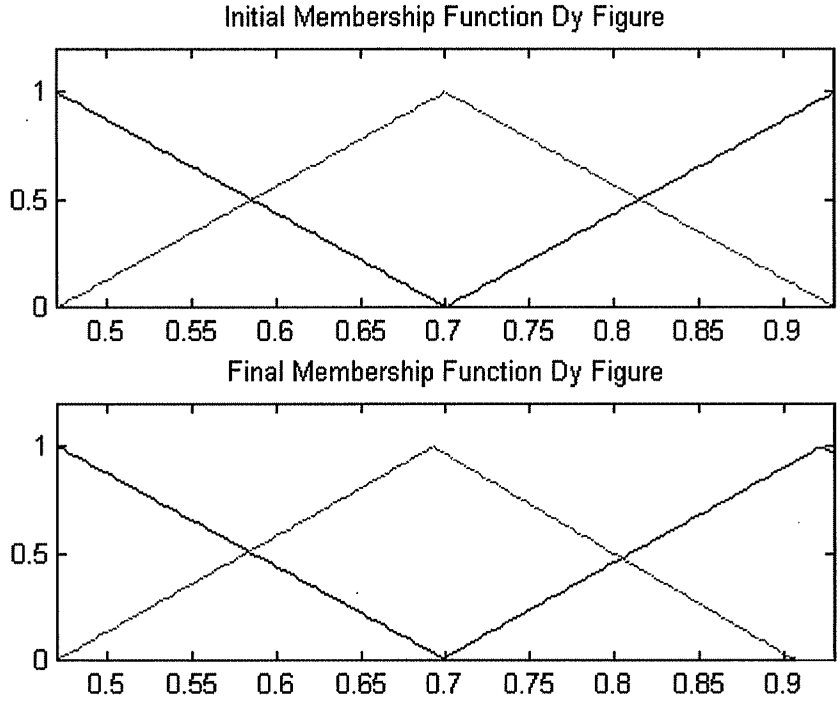

Fig.10. Initial and final trangular MF of cutting parameter Dy

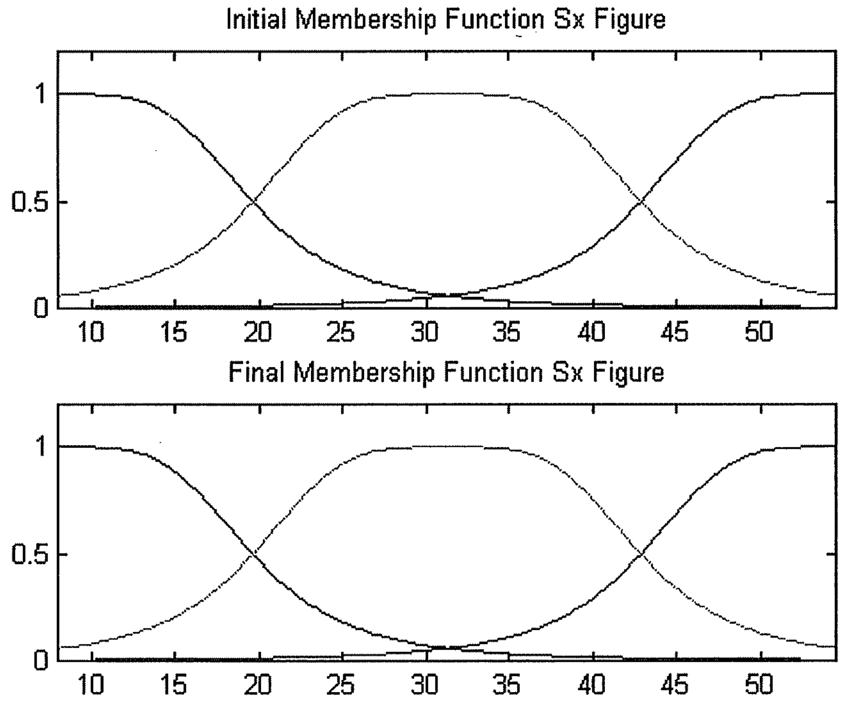

Fig.11. Initial and final bell MF of cutting parameter Sx

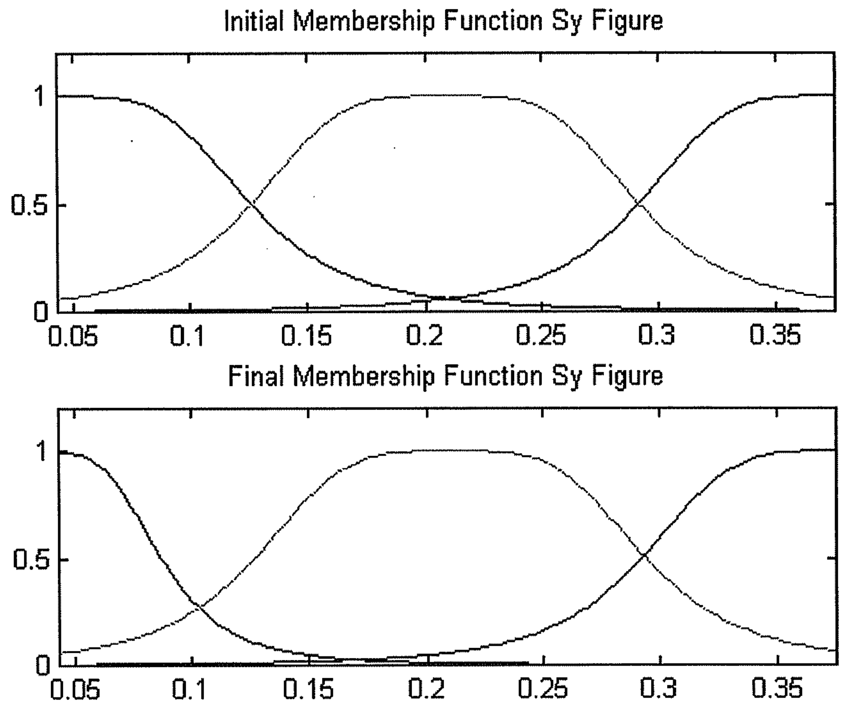

Fig.12. Initial and final bell MF of cutting parameter Sy

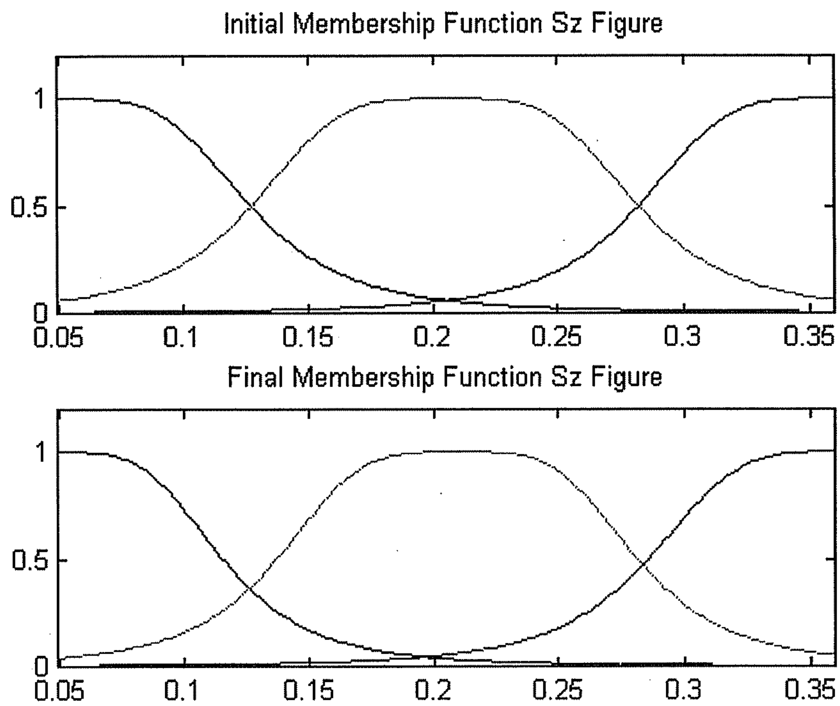

Fig.13. Initial and final bell MF of cutting parameter Sz

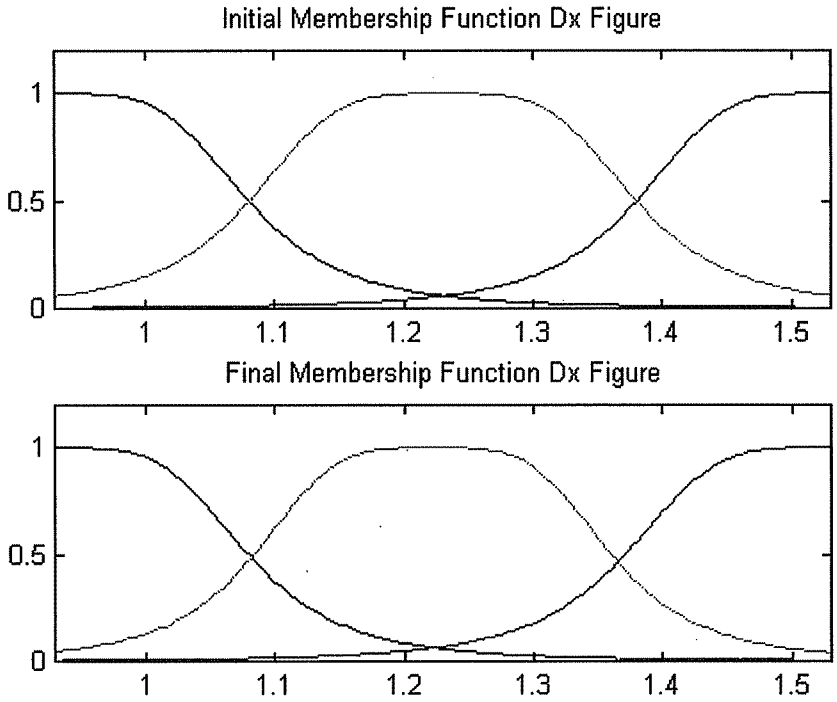

Fig.14. Initial and final bell MF of cutting parameter Dx

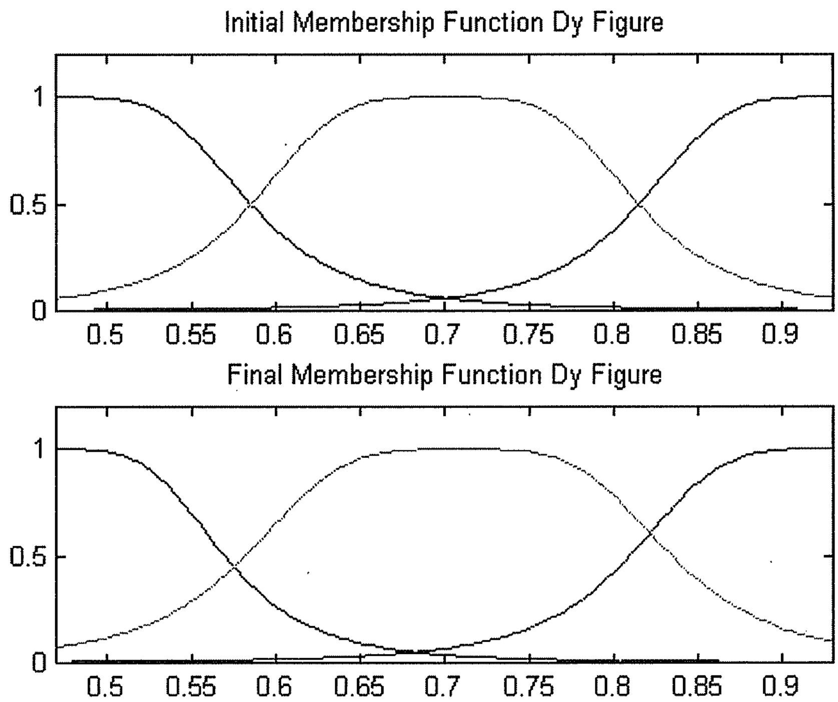

Fig.15. Initial and final bell MF of cutting parameter Dy

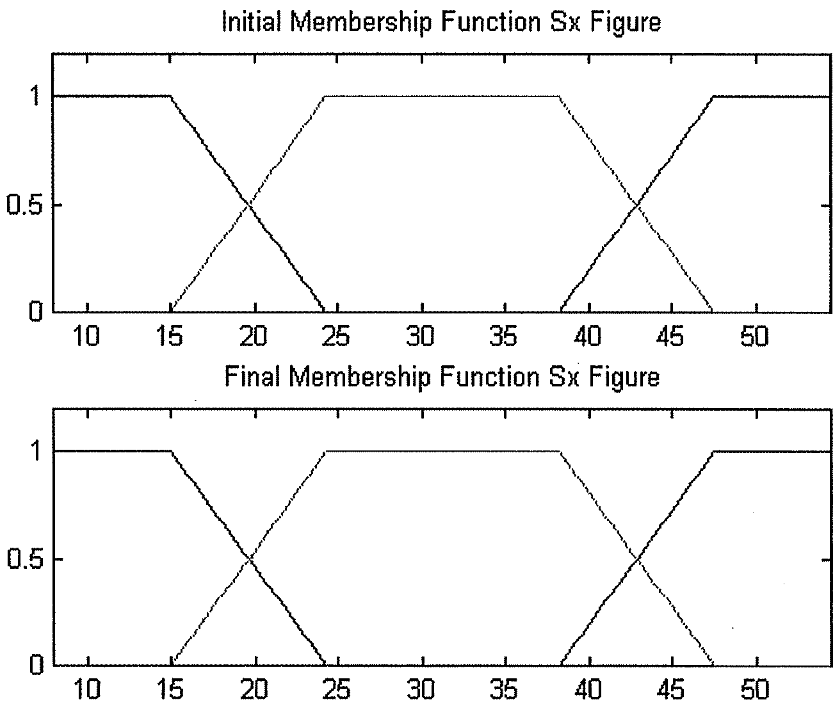

Fig.16. Initial and final trapzoidal MF of cutting parameter Sx

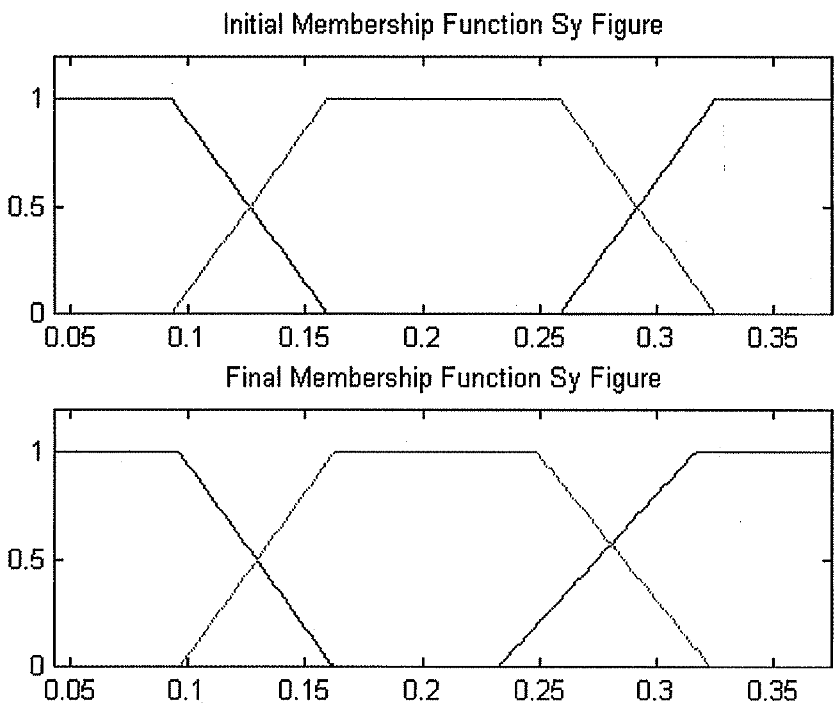

Fig.17. Initial and final trapzoidal MF of cutting parameter Sy

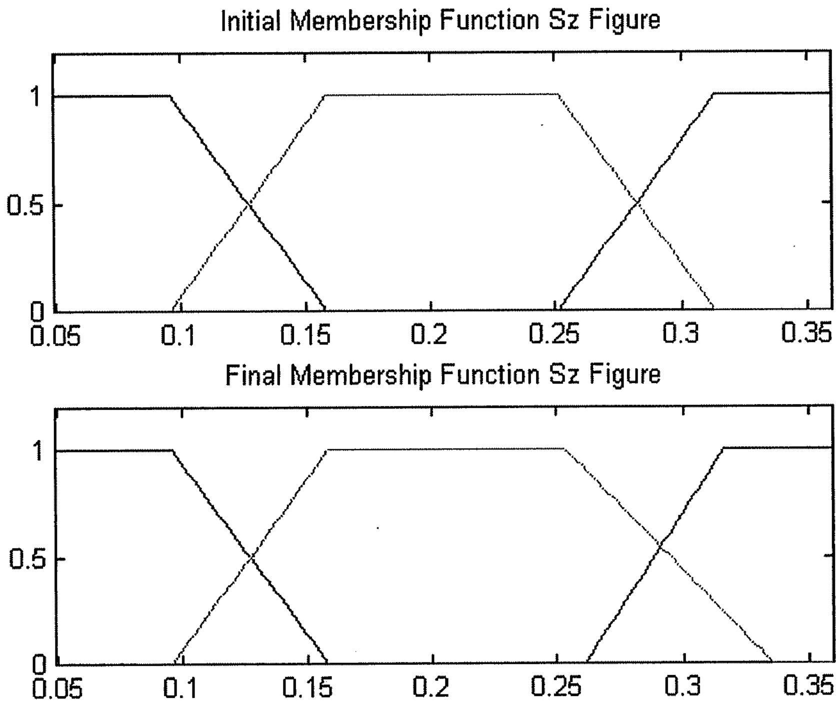

Fig.18. Initial and final trapzoidal MF of cutting parameter Sz

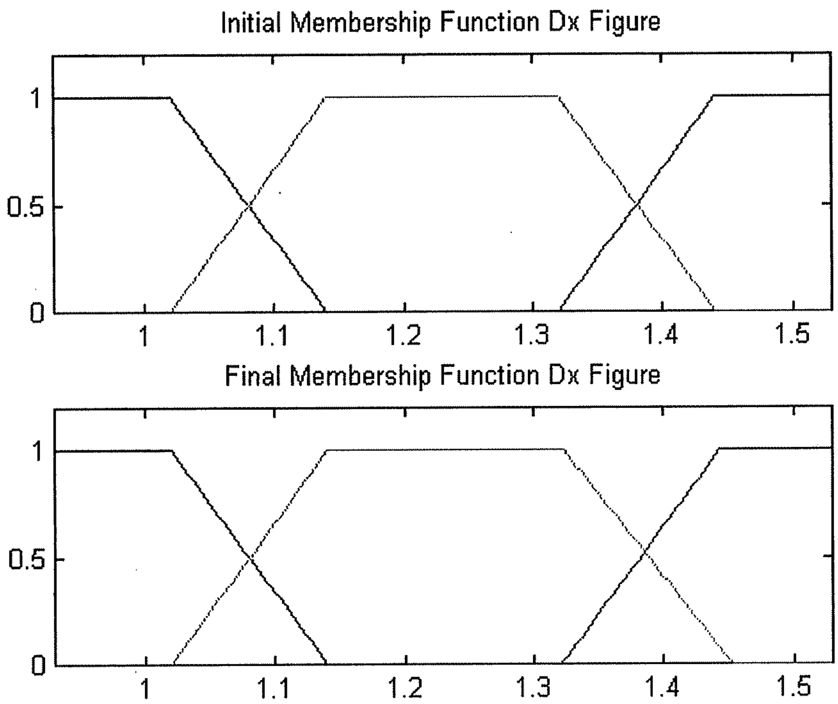

Fig.19. Initial and final trapzoidal MF of cutting parameter Dx

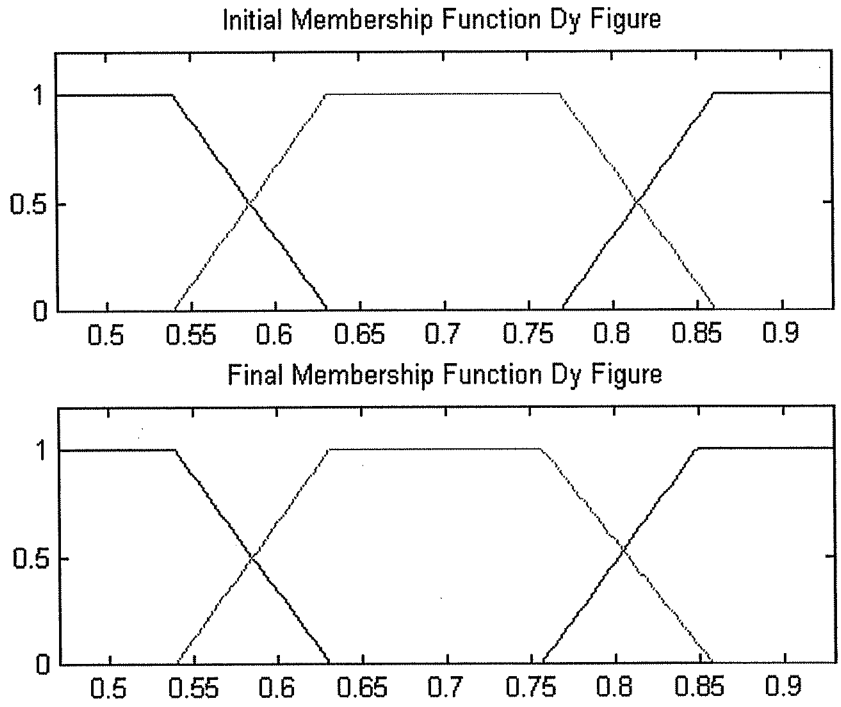

Fig.20. Initial and final trapzoidal MF of cutting parameter Dy

車削刀具損壞偵測上的研究

羅仕鵬*

中文摘要

切削是主要移除材料的一種過程，因此，尋找各種能偵測出刀具損壞的方法是非常重要的。本文是描述適應性類神經模糊推論系統(ANFIS)在單鋒車削刀具損壞偵測上的應用。在車削過程中，刀具的損壞及磨耗通常是藉著量測切削力、負荷電流、震動、聲音放射(Acoustic emission)及溫度等之變化來判斷，而這些作為判斷刀具損壞或磨耗的量測方法中，以量測切削力變化或量測聲音放射訊號作為刀具損壞或磨耗的判斷時可獲得較佳的正確率。本文將切削力變化及聲音放射訊號等兩種不同的判斷方法，組合出五種不同的輸入參數，並將此五種不同的輸入參數應用於適應性類神經模糊推論系統(ANFIS)中，以判斷刀具的狀況。在 ANFIS 的分析模式中，應用三種不同的隸屬函數作推論系統的訓練，並分別比較此三種不同的隸屬函數對刀具損壞偵測的正確率。研究分析結果得知，本推論系統應用在刀具損壞或正常等兩種狀況的偵測上有相當高的正確率，此外，文中發現三種不同的隸屬函數中，以三角形及鐘形隸屬函數對刀具損壞的偵測有較高的正確率。

關鍵詞：刀具損壞偵測，適應性類神經模糊推論系統

羅仕鵬：機械工程科助理教授兼機械工程科主任