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ORIGINAL ARTICLE

Prediction of cutting tool wear during a turning process using artificial intelligence techniques

Mohsen Marani [1] · Mohammadjavad Zeinali [2] · Jules Kouam [3] · Victor Songmene [3] · Chris K. Mechefske [1]

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Abstract

In the manufacturing industry, cutting tool failure is a serious event which causes damage to the cutting tool and reduces the quality of the product, which increases the cost of production. A reliable, intelligent, tool wear monitoring system is required in the metal cutting manufacturing process to mitigate these negative effects. This study presents a model-based approach for tool wear monitoring based on an adaptive neuro-fuzzy inference system (ANFIS) for a cold-finished steel bar 1215 turning process. A three-input cutting force (F_x, F_y and F_z) and single-output (tool flank wear) model was designed and implemented using the ANFIS approach. The forces were measured using a piezoelectric dynamometer and data acquisition system. Flank wear was also monitored using a tool maker's microscope. The model prediction results show that it is accurate enough to perform online monitoring of the turning process and can detect wear while operating.

Keywords Turning process · Cutting force · Tool flank wear · ANFIS · TCM

1 Introduction

The main goal of industrial companies is to manufacture high-quality parts at a minimum price in the minimum time. Monitoring machining operations contribute significantly to the automation of the manufacturing process and minimise human factor costs [1]. In the past, predicting tool failure and tool changing strategy were based on operator experience and played an important role during the machining process [2]. However, these days, a tool condition monitoring (TCM) system is essential in the manufacturing process. The degree of tool wear may be determined from signals related to cutting force, acoustics, vibration of both the workpiece and the tool, spindle motor current and temperature [3].

Fu et al. [4] studied the optimisation problem of the cutting parameters in milling NAK80 mild steel and found that the depth of cut was the most influential factor for cutting force in the milling process. Shi et al. [5] investigated using the cutting sound signal for tool breakage detection in the machining process and determined that the proposed method was capable of separating cutting sound signals from other source components related to a normal insert and a broken one.

Seemuang et al. [6] monitored tool wear in the turning process using spindle noise. It was found that machining parameters such as cutting speed, feed rate and depth of cut had a substantial effect on the amplitude of the spindle noise, making it possible to use spindle noise to identify tool flank wear in the machining process. It was also found that using simple and inexpensive instrumentation could produce data for condition monitoring of the process. García-Ordás et al. [7] proposed a new online, low-cost and fast approach based on computer vision. They claimed that the decision about whether a cutting edge is serviceable or disposable is based on the number of sub-regions classified as worn.

Lu et al. [8] studied high-frequency sound signals for tool wear monitoring in milling and found that there was a significant variation between sharp and worn tools. The maximum amplitude of the sound signal was related to worn tools. Zhang et al. [9] proposed a tool wear model based on a least squares support vector machine (LS-SVM) analysis procedure combined with machining parameters to predict tool wear of different positions at the tool cutting edge for a milling operation.

✉ Mohsen Marani
marani.mohsen@gmail.com

1 Department of Mechanical and Materials Engineering, Queen's University, Kingston, Ontario K7L 3N6, Canada

2 Malaysia–Japan International Institute of Technology, Universiti Teknologi (UTM), 54100 Kuala Lumpur, Malaysia

3 École de Technologie Supérieure (ÉTS), 1100 Notre-Dame Street West, Montreal, QC H3C 1K3, Canada

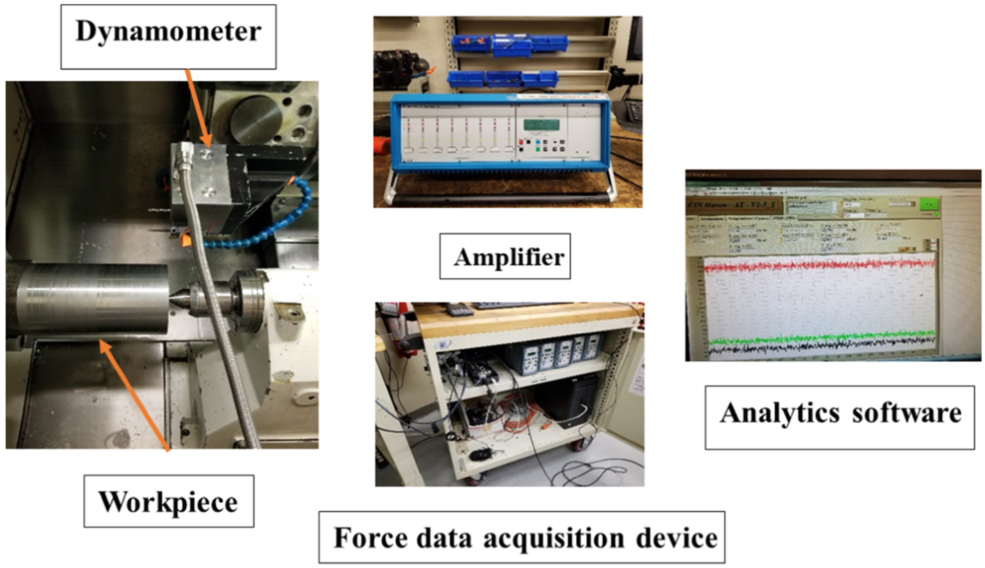


Fig. 1 Experimental setup

It has been reported that cutting force has a direct effect on machinability such as surface roughness, vibration and tool flank wear during the machining of alloys and composites [10–13]. Shankar et al. [5] reported that cutting force is the most accurate measurement for the online TCM. Boud et al. [14] investigated the application of multi-sensor signals for monitoring tool wear and reported that tool wear was identified by the cutting force, pressure and table displacement signals. They developed techniques in tool wear monitoring using a combination of sensors. In addition, they saved costs for industry by introducing high levels of automation along with improving the quality of final products.

In recent years, artificial intelligence (AI) techniques have been utilised in TCM [15, 16]. The network based on an adaptive neuro-fuzzy inference system (ANFIS) comprising both fuzzy and artificial neural networks (ANN) has been verified as a robust system recognition tool with the capacity to forecast accurately [17]. Shankar et al. [18] investigated the applicability of predicting cutting tool wear using AI techniques. The flank wear of the tool was found to be assessed precisely with the ANN model. Saglam [19] proposed a three-level ANN based on the cutting force for intelligent TCM in the milling process. A close match was found between the model output and directly measured wear of the flank. The ANN model was suitable even for research with insufficient data.

Mohtaram et al. [20] studied how to detect tool breakage using a combination of neural decision and an ANFIS tool wear predictor. They found that their proposed model enables monitoring of the cutting process with high reliability. It was also found that an ANFIS model can estimate tool flank wear progress quickly and accurately. Therefore, in this research, ANFIS is used to predict flank wear of a tool in the turning process for machining a steel alloy. The cutting forces are used as the indicator of the tool flank wear variation.

The paper is organised as follows: After the introduction, Section 2 introduces the methodology used for monitoring of tool flank wear. Section 2.1 describes turning experiments. This section provides a description of the material, tool and experimental setup. Section 2.2 provides a description of the ANFIS model. Section 2.3 presents ANFIS structure and membership function selection. Section 2.4 describes the TCM structure in detail. The result and discussion are presented in Section 3. The tool wear measurement results are explained in Section 3.1. Section 3.2 presents feature extraction and correlation with tool condition states. Sections 3.3 and 3.4 describe ANFIS training and ANFIS prediction results, respectively. Finally, the conclusion is listed in Section 4.

2 Methodology

2.1 Turning experiments

Turning experiments were conducted on a Mazak CNC (Nexus 100-II M) which has a maximum spindle speed of

Table 1 Experimental conditions

Machining type	Turning	
Tool	CVD/TiCN-coated carbide	
Workpiece	Material	Steel 1215
	Size	100 mm × 300 mm
	Hardness	150–170 (BHN)
Cutting conditions	Spindle speed	250 m/min
	Feed rate	0.15 mm/rev
	Depth of cut	1.5 mm
Number of pass	36 passes	
Sampling frequency	1000	

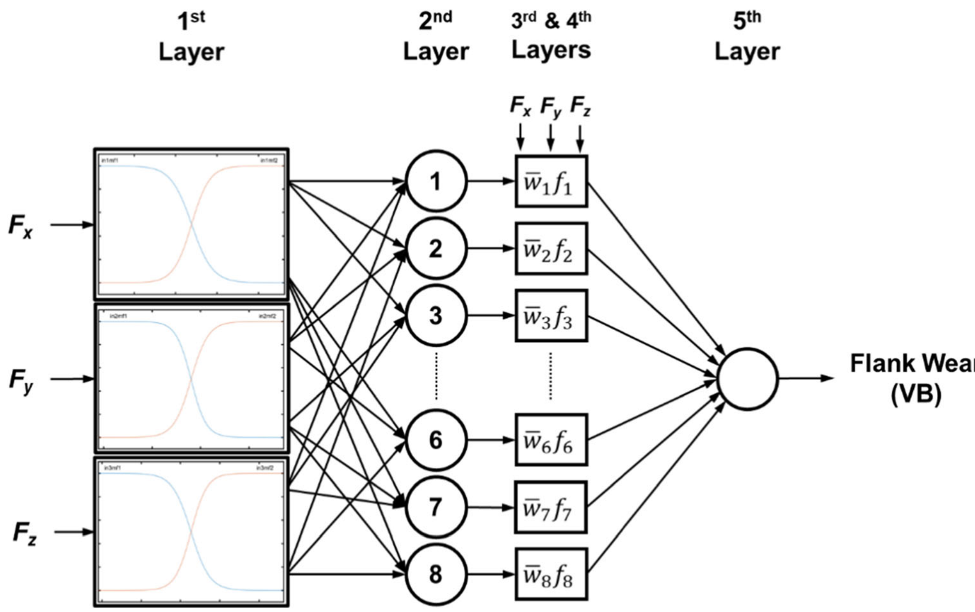


Fig. 2 Schematic of ANFIS model

8000 rpm. A three-component piezoelectric dynamometer (Kistler, Type 9255C) was used to record the cutting forces during the turning operations. The dynamometer was connected to charge amplifiers (type 5010) that measured the cutting forces along the x, y and z axes, recorded as F_x, F_y and F_z. LabView (Cut Pro 8.0) software was used to record and monitor all signals independently. All cutting force signals were exported to Matlab software for further analysis.

A cold-worked steel bar (1215) having a diameter of 100 mm and an overall length of 300 mm was used as a workpiece during the turning process. The cutting tool used for this research work was a CVD/TiCN-coated carbide tool having a 7° relief angle and a nose radius of 0.7 mm. Figure 1 shows the experimental setup. The experimental conditions are summarised in Table 1. The turning tool cuts the workpiece 36 times with the same machining conditions. Therefore, a total of 36 profiles of the turning force signals were gathered.

2.2 Adaptive neuro-fuzzy inference system

An adaptive neuro-fuzzy interface system (ANFIS) is an artificial neural network–based Takagi Sugeno fuzzy interface system which integrates both artificial neural networks (ANN) and fuzzy logic principals in a single frame [21]. The goal of ANFIS is to find a model to correlate the inputs and output correctly. ANFIS is an essential and intelligent tool for building efficient models for complex processes and datasets with uncertainty [22]. It has been found that ANFIS is useful for establishing a model with a complex data distribution under uncertainty [23].

2.3 ANFIS structure and membership function selection

The ANFIS architecture has five layers, as shown in Fig. 2. Every individual layer has a specific function to modify the incoming signals from the previous layer. The Matlab environment was employed to build up the ANFIS model using 36 pairs of data (27 were used for training and 9 were used for testing). As can be seen in Fig. 2, three different inputs, which are F_x, F_y and F_z with two membership functions (MFs) were considered in the proposed ANFIS model. In addition, 2^3 rules were considered for the structure of the recommended model.

Table 2 describes the function of each layer. The cutting forces as the inputs of the model are acquired to predict tool

Table 2 Equations applied at each layer

Layer number	Equation	Layer number	Equation
1	$\mu_{1i}(F_x)$, $\mu_{2j}(F_y)$, $\mu_{3k}(F_z)$	4	$\bar{w}_r f_r = \bar{w}_r(p_r F_x + q_r F_y + r_r F_z + s_r)$
2	$w_r = \mu_{1i}(F_x) \times \mu_{2j}(F_y) \times \mu_{3k}(F_z)$	5	$VB = \sum_{r=1}^{8} \bar{w}_r f_r$
3	$\bar{w}_r = \frac{w_r}{\sum_{r=1}^{8}(w_r)}$		

Table 3 Specification of MFs employed in ANFIS model

Membership function	Equation
Sigmoidal	$\frac{1}{1+e^{-a_1(x-c_1)}}-\frac{1}{1+e^{-a_2(x-c_2)}}$
Triangular	$\max\left(\min\left(\frac{x-a}{b-a},\frac{c-x}{c-b}\right),0\right)$
Gaussian	$e^{\frac{-(x-c)^2}{2\sigma^2}}$
Bell-shaped	$\frac{1}{1+\left\lvert\frac{x-c}{a}\right\rvert^{2b}}$

flank wear as output. The model splits the inputs F_x, F_y and F_z into various spaces using two MFs in the first layer.

Four different MF types, Sigmoidal, Triangular, Gaussian and Bell-shaped, were implemented to determine the most accurate model. Table 3 shows the function of these applied MFs. An AND rule is applied in the second layer to execute the multiplication of the outgoing signals from the first layer and then the relative weights of every rule are obtained in the third layer using the equation described in Table 2. A linear function of the inputs F_x, F_y and F_z is involved in the fourth layer of the model as defined in Table 3. Finally, in the fifth layer, the outgoing signals of the fourth layer are aggregated to obtain the predicted tool flank wear.

2.4 TCM structure

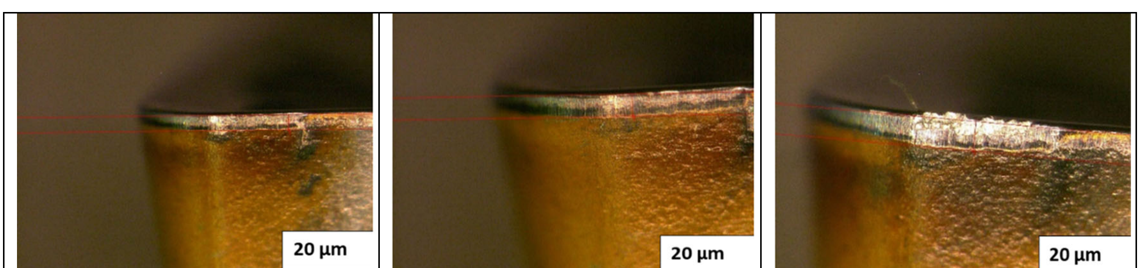
The purpose of TCM is to adopt corresponding sensor signal processing techniques to monitor and predict the cutter state during the machining process. A powerful TCM system can improve productivity and guarantee product quality, which has a considerable influence on machining efficiency. Hence, TCM is considerably important in the manufacturing industry [24]. In the current study, two main steps were considered for the proposed approach. First, a set of data obtained during an actual machining test on the turning machine was used to develop an ANFIS model of tool wear. Then, the trained ANFIS model for the tool wear was used for estimating specific tool wear condition as either initial, workplace or dull.

The force sensor was used to collect the signals during the turning process through a data acquisition module. The machining signals were analysed using a signal processing module for extracting features sensitive to tool wear. The data set was created by the features to be used as input to the decision system and estimator in order to map the input features to the current state of the tool. The data were divided into a training set and a testing set with a random pattern classifier module. The training set was used for learning, while the testing set was used to test the performance of the decision system [25]. A machining test was carried out with three different tools: a new tool, a working tool and a dull tool. To expedite the development of tool wear during the turning experiments, a set of machining conditions was applied according to the suggestion of a toolmaker company for steel alloys.

3 Results and discussion

3.1 Tool wear measurement results

For tool wear measurement, nine turning passes, including the 4th, 8th, 12th, 16th, 20th, 24th, 28th, 32nd and 36th passes, were selected from among the total of 36 passes. When measuring the tool wear, the turning process was paused after finishing each selected pass, and the tool was detached for measurement. Thus, an actual tool condition after each turning pass could be identified. A



8 passes	20 passes	36 passes
0.06 mm	0.11mm	0.18 mm

Fig. 3 Images of the flank wear of tool after cutting turning process and their measured values

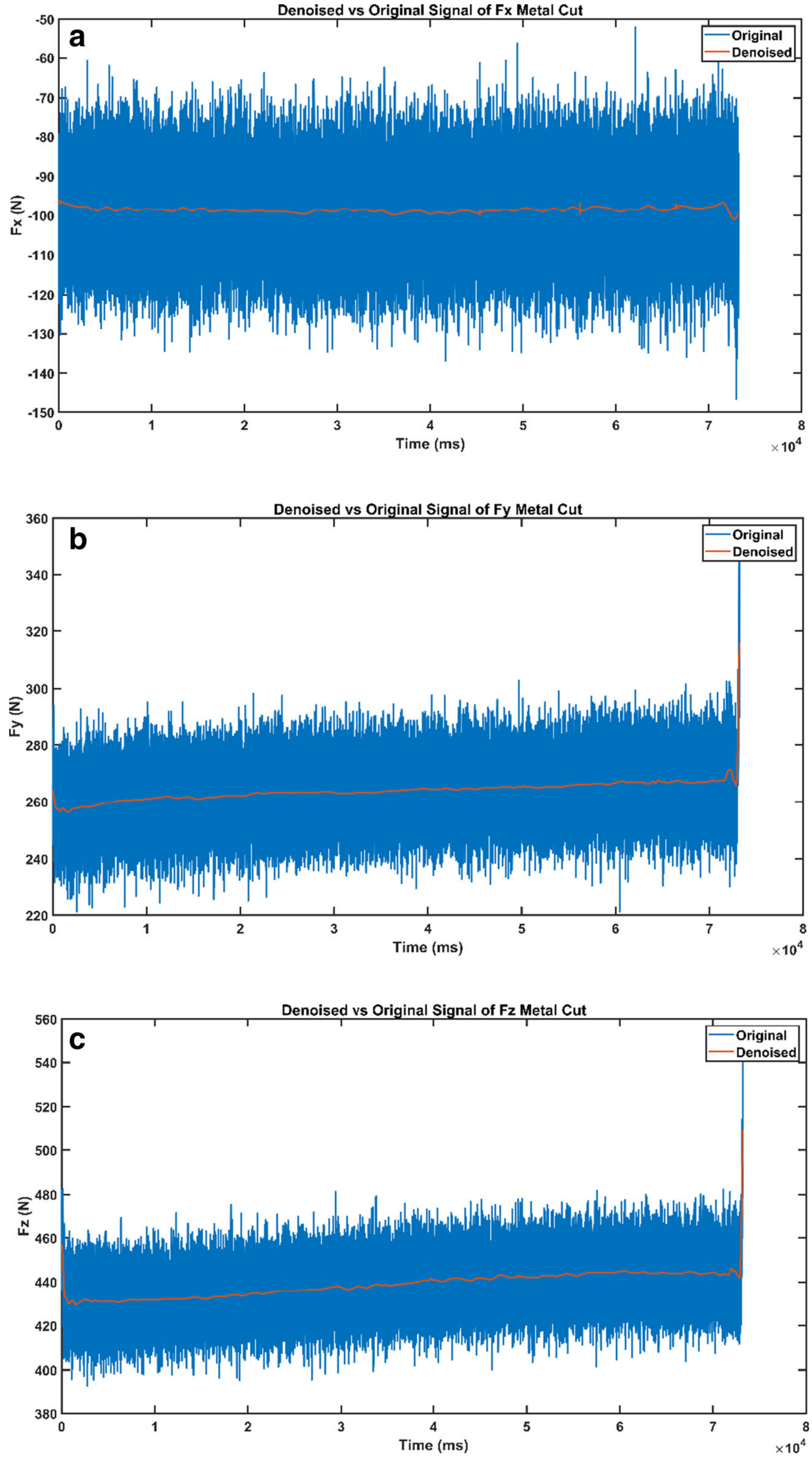


Fig. 4 Denoised and original cutting force signals for **a** F_x, **b** F_y and **c** F_z

microscope with image analyser software was used to take images after cutting each pass. The flank wear is a result of abrasion and adhesion wear on a tool's clearance face contacting with workpiece surface [26]. Figure 3 shows the optical images of the turning tool and measured flank wear values after machining the 8th, 20th and 36th passes. As can be seen in Fig. 3, flank wear values increased as the number of turning passes increased. For instance, after machining the 8th pass, the flank wear value was 0.06 mm, and it increased to 0.11 mm after machining the 20th pass. The flank wear also increased to 0.18 mm after machining the last pass (36th) for the steel alloy.

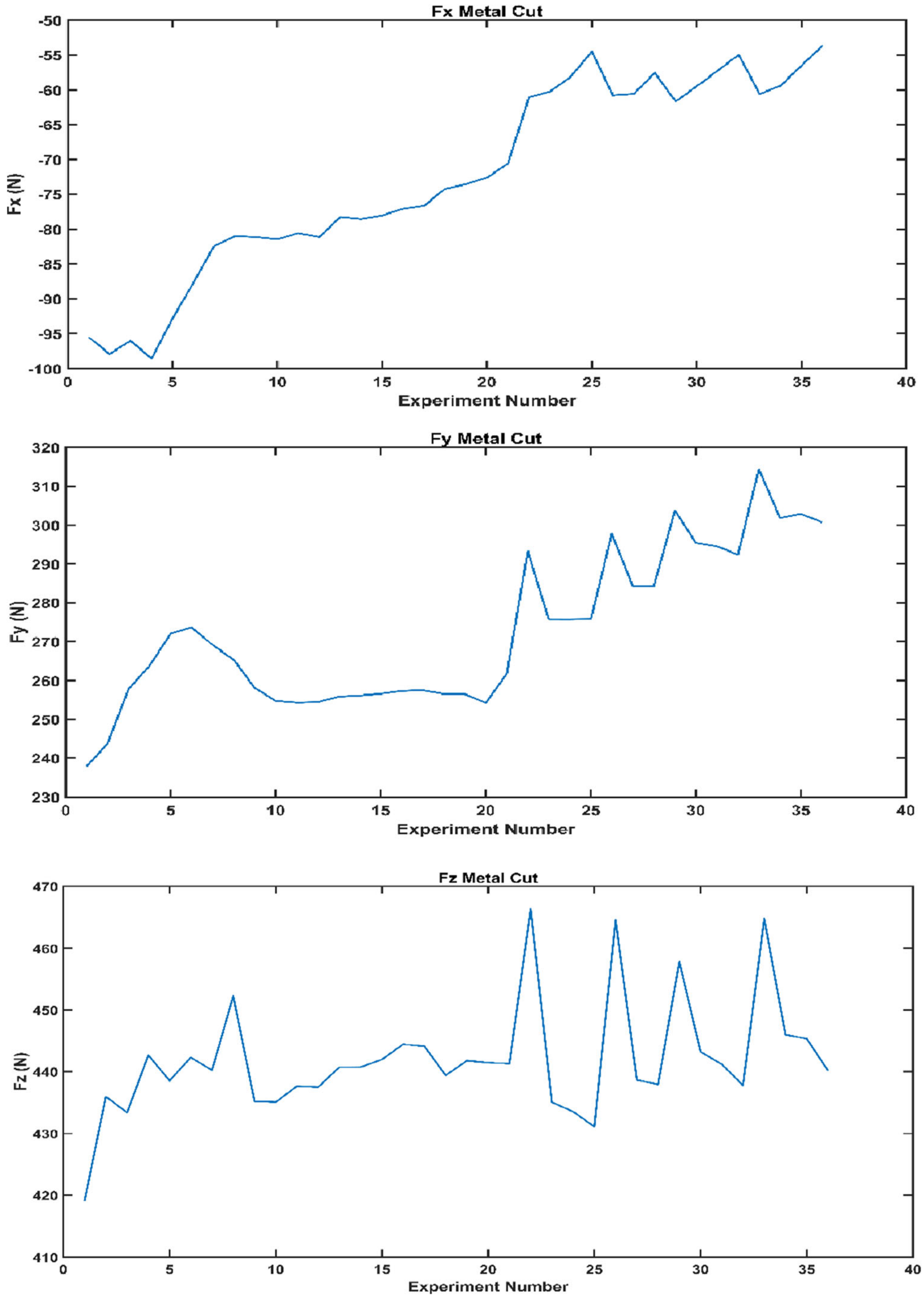


Fig. 5 Average cutting force signals for **a** F_x, **b** F_y and **c** F_z

3.2 Feature extraction and correlation with tool condition states

In this study, the data collected from the cutting forces was processed and classified to extract the main feature of machining operations from all data. One of the important steps of a TCM system is the application of signal processing which has been considered beside the data acquisition system [27]. The signal from the machining process is generally classified either in the time domain or in the frequency domain [28]. Some procedures such as signal conditioning, filtering and root mean square (RMS) computation are commonly used in time domain signal processing. The difference between normal and irregular behaviour of the machine is often obtained by frequency domain signal processing.

In this research work, the air-cut signals were extracted from the raw signals as they could be differentiated by their magnitude. Then, the features from the signals were extracted

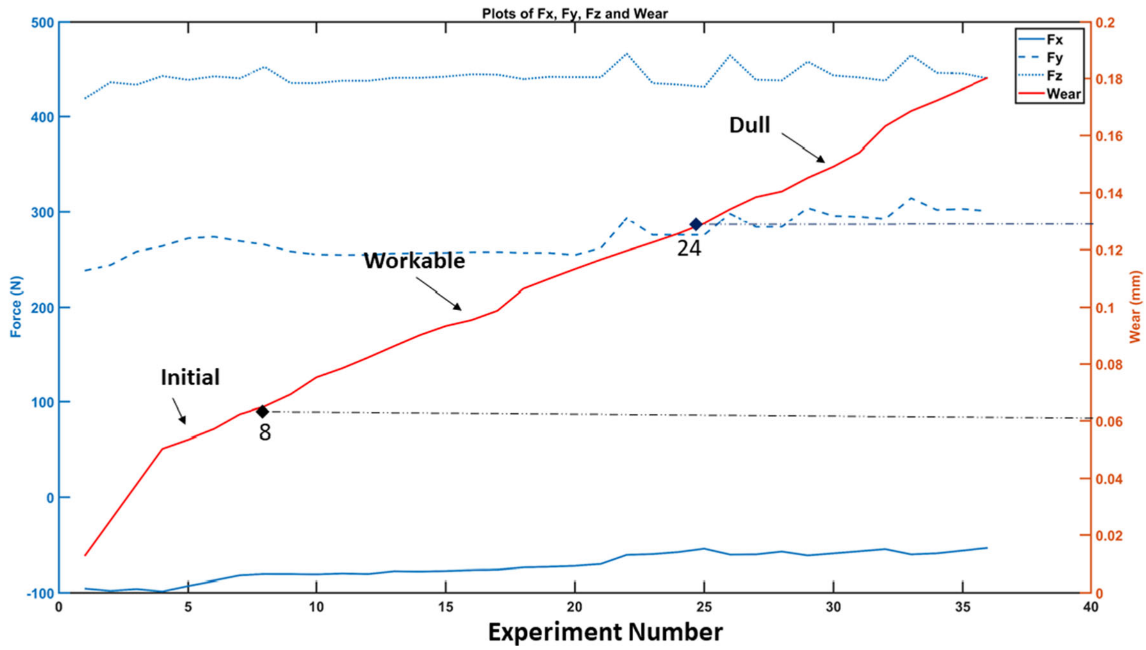


Fig. 6 Tool wear and corresponding turning forces based on cutting numbers

from the entry cut and the exit cut of the raw signals. It has been found that noise is the main obstacle to obtaining signals through sensor data acquisition [28]. Therefore, wavelet transformation was used for denoising the original cutting force signals for F_x, F_y and F_z as it is the most popular and most important method for signal analysis in the time-frequency domain [23]. Figure 4 shows cutting force signals and denoised signals. As can be seen in Fig. 4, tangential force (F_x) and radial force (F_y) are always smaller than the main cutting force (F_z).

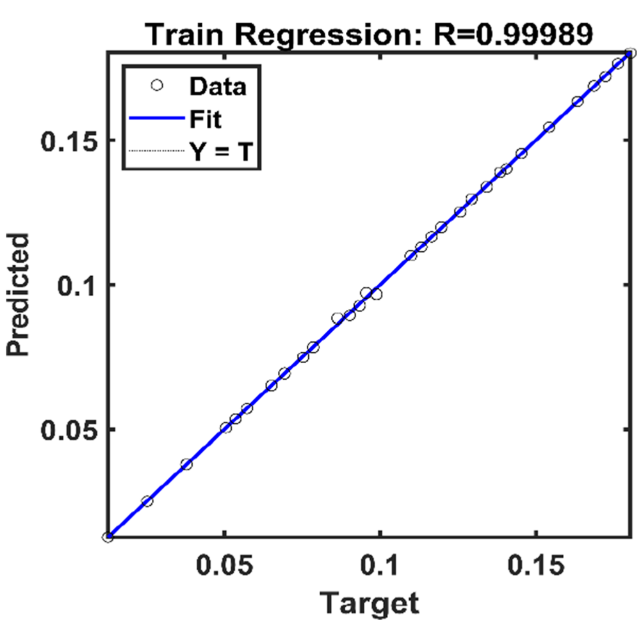
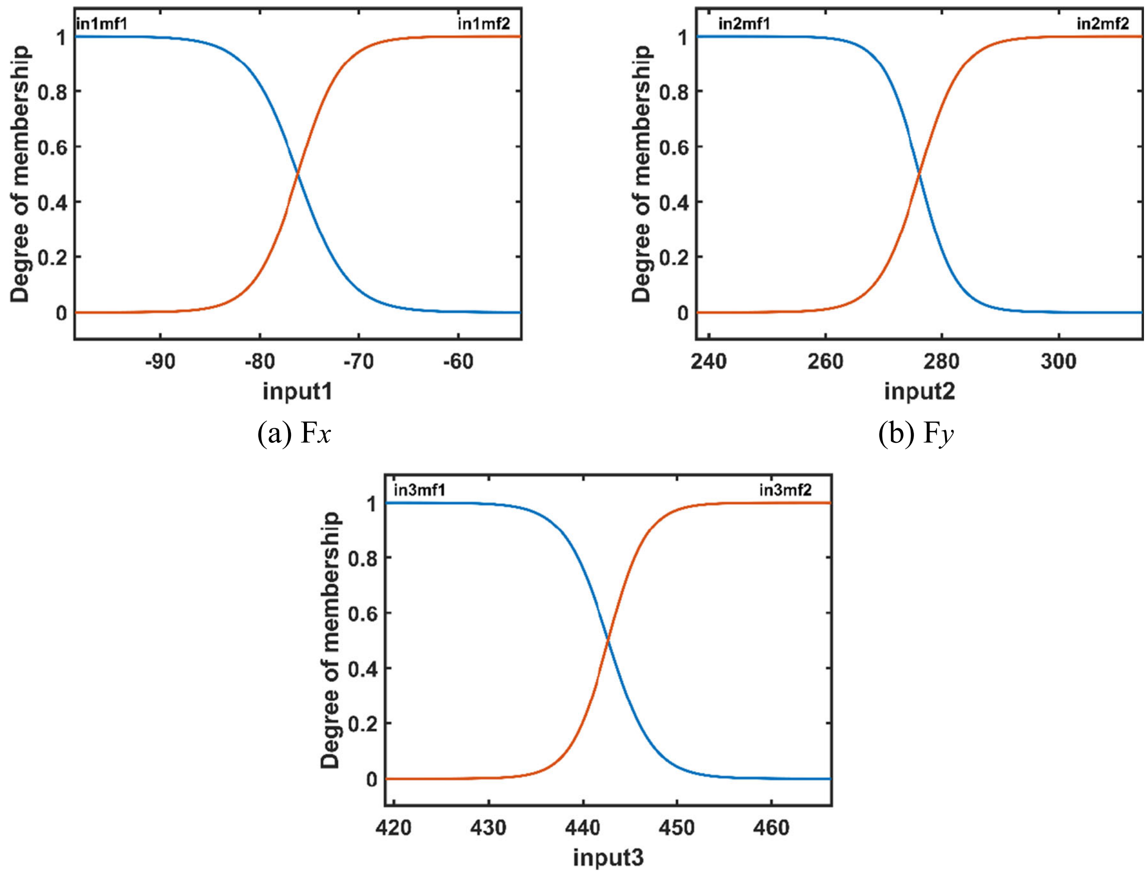


Fig. 7 Training regression plot of the ANFIS model with Sigmoidal MF

In addition, the mean values of the cutting force were calculated for F_x, F_y and F_z. Figure 5 illustrates the mean value of cutting force for all axes. As can be seen in Fig. 5, cutting forces increased with increasing number of machining pass. This means that cutting force signals increased with increasing machining time [27]. The measured turning signals were divided into 36 sections, one for each cutting pass of the tool. Observing the magnitudes of the measured turning force in different sections showed a sudden increase from the 24th pass and it fluctuated up and down between the 24th and 36th passes. In addition, the turning forces, F_x and F_y, increased significantly in this span. Since the measured tool flank wear also increased in this span, it was concluded that the turning process was not stable, and the tool was in a ‘dull’ condition.

A dull tool requires more power to cut the material due to the large contact area as well as friction between that tool and the workpiece which increases the magnitude of the main cutting force, F_z. Therefore, it was believed that measuring cutting force signals could be used to represent tool wear conditions in the turning process. As can be seen in Fig. 5, in the first section, from the 1st machining pass to the 8th pass, the measured turning cutting forces gradually increased, and it is observed that a new turning tool had become stabilised by turning the first six machining passes (Fig. 5a). Meanwhile, from the 8th pass to the 24th, the measured turning force signals had nearly constant magnitude, and measured tool wear values gradually increased (Fig. 5b). Therefore, in these sections, the turning process could be considered stable for machining the workpiece (workable). Finally, the dull state includes those from the 24th to the 36th passes. In this section, the measured turning force signals fluctuated sharply (Fig. 5c).



(c) Fz

Fig. 8 Plots of membership functions **a** F_x, **b** F_y and **c** F_z inputs in prediction model of tool flank wear

Figure 6 shows tool wear and turning forces in three directions, F_x, F_y and F_z. As can be seen in Fig. 6, the tool flank wear is about 0.2 mm at the end of the 36th machining pass. The tool flank wear conditions were defined along with the turning process: the initial state, workplace state and dull state. The turning forces increased with the increasing of flank wear values. The main cutting force (F_z) illustrates the highest turning force is about 450 N compared with the other forces. The tangential (F_x) and radial (F_y) forces were also consistent with the change in tool wear. The results illustrate that the influence of the tool's wear state on F_y is greater than its effect on F_x, which is related to the sever adhesion caused by tool wear deterioration, especially at the tool chip interface [29]. According to the classification of cutting tool conditions, the tool flank wear value below 0.06 mm was classified as the initial state, those between 0.06 and 0.13 mm were classified as the workplace state, and those larger than 0.13 mm were classified as the dull state.

3.3 ANFIS training results

After construction of the ANFIS model, the values of the model coefficients were defined by using training data. In fact, every prediction model needs to initially learn the phenomenon. The data used in the learning (training) process must be different from the data which will be used to evaluate the predictive ability of the model. Therefore, 75% of the whole data was used to train the ANFIS model. In this step, the ANFIS model can learn the process with adequate accuracy if the model complexity is at a similar level with the process complexity. In this study, the ANFIS model was designed using 36 pairs of data (27 were used for training and 9 were used for testing). Various error analysis tools were used to determine the quality of the learning process in which regression analysis was selected as an appropriate and reliable method in this study.

Figure 7 shows the train regression plot of the prediction model with Sigmoidal MF. The regression coefficient of 0.99989 illustrates that the prediction model learns the relationship between flank wear and cutting forces efficiently.

There are two types of coefficients: premise coefficients which are the parameters of the MFs, and consequent coefficients which are the parameters of the linear function in the fourth layer (see Tables 2 and 3). The training stage can provide us with a good understanding of the process. For

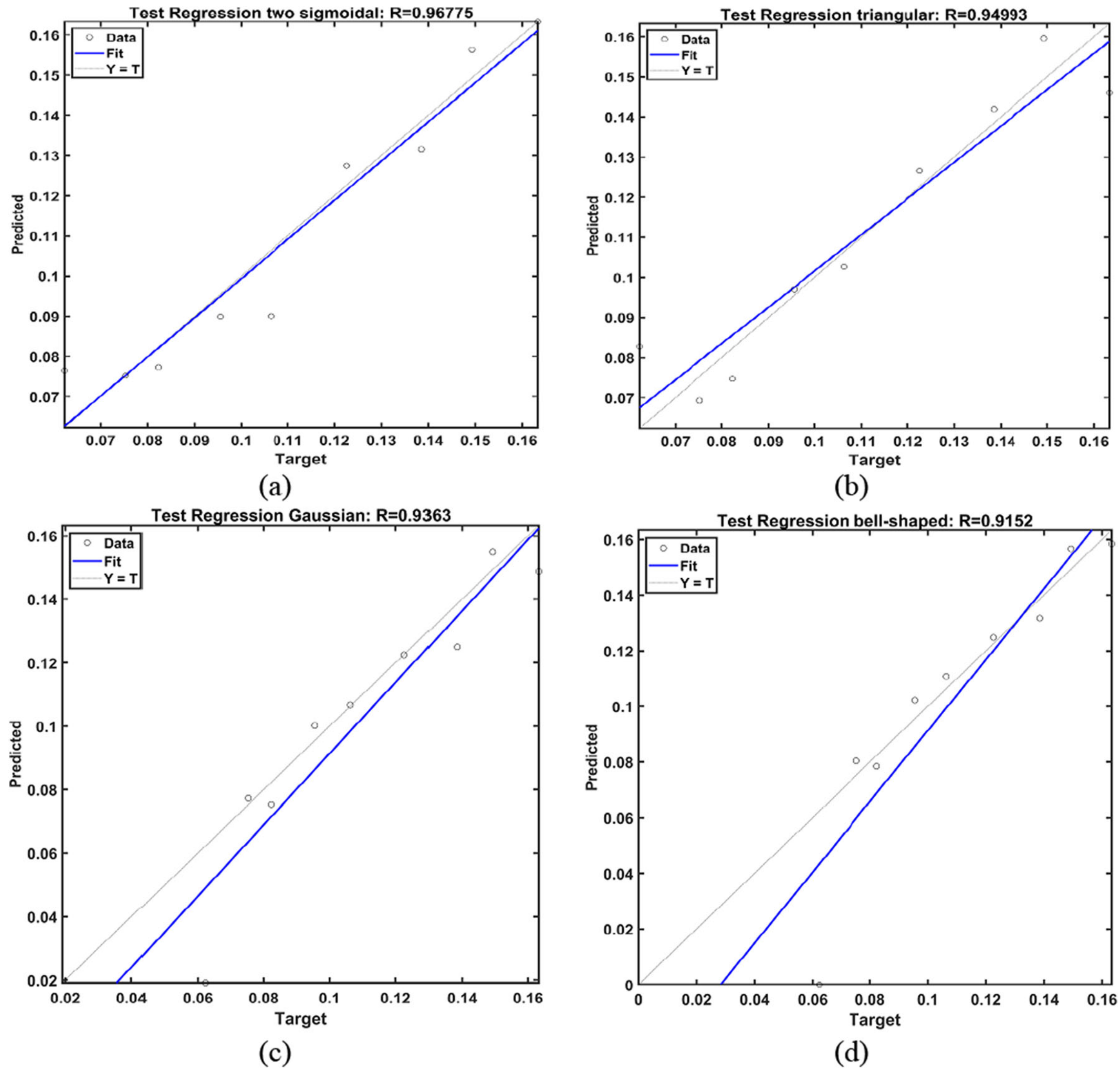


Fig. 9 Test regression plots for the prediction models with Sigmoidal, Triangular, Gaussian and Bell-shaped MFs

instance, as can be seen in Fig. 8, the behaviour of the MFs for F_x, F_y and F_z inputs during the training stage is similar. Therefore, the complexity of the process with regard to all inputs is similar and the consequent parameters have a vital role in characterising the tool flank wear. This feature is considered as an advantage of using ANFIS to predict complex phenomena.

3.4 ANFIS prediction results

The results of tool condition monitoring and diagnosis models developed by the ANFIS approach are presented in this section. These results are compared with the turning experimental results under the machining condition given in Table 1.

As has been discussed in previous sections, four different ANFIS models were constructed with Sigmoidal, Triangular, Gaussian and Bell-shaped MFs. A regression analysis of test data was used to evaluate the accuracy of prediction models. Figure 9 shows the test regression plots of all prediction models with their regression coefficient values. As can be seen in Fig. 9a, the prediction model with Sigmoidal MF and regression coefficient value of 0.96775 is the most accurate model among all prediction models. Figure 9 b, c and d illustrate the regression coefficient values for Triangular, Gaussian and Bell-shaped models which are 0.94993, 0.9363 and 0.9152, respectively.

Figure 10 shows the comparison of prediction and experimental results of the models for the whole dataset including training and test data. As can be seen in Fig. 10a, the best prediction result can be obtained by the ANFIS model with Sigmoidal MF since its prediction value in the turning process showed a monotonic increasing trend according to the tool flank wear progression.

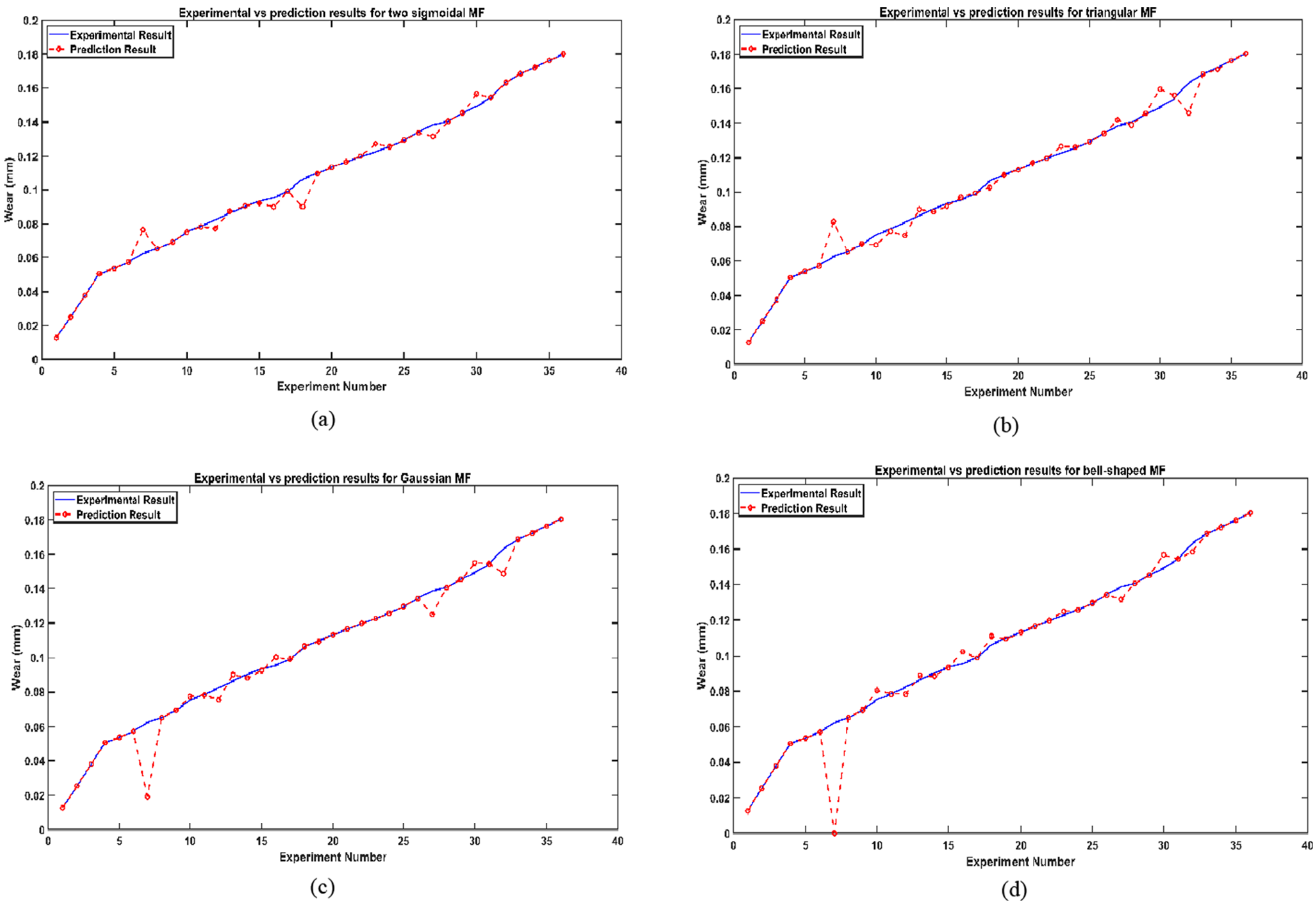


Fig. 10 Prediction vs experimental results of the tool condition monitoring and diagnosis based on ANFIS models **a** Sigmoidal, **b** Triangular, **c** Gaussian and **d** Bell-shaped

4 Conclusion

This research work was carried out to monitor tool condition with a sensor fusion technique by measuring cutting force during turning of cold-working steel 1215. The tool flank wear had three conditions: initial state, workplace state and dull state. The flank wear increased with an increasing number of experiments, which means that the flank wear increases with increasing machining time. It was found that a dull tool requires higher power to cut the material due to the larger contact area as well as friction between the tool and the workpiece which increased the magnitude of the main cutting force, F_z. The tool condition was predicted by using an ANFIS approach. It was indicated that, when the flank wear results exceed 0.13 mm, the condition becomes dull and the tool should be replaced for further machining processes. The prediction model with the Sigmoidal membership function was the best model for predicting wear compared with the other models. The ANFIS prediction of tool wear can be applied to develop a condition monitoring interface in industrial applications where tooling cost and part quality are important factors in the production system.

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