Tool flank wear prediction in CNC turning of 7075 AL alloy SiC composite

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Production Engineering

Prod. Eng. Res. Devel. (2011) 5:37–47
DOI 10.1007/s11740-010-0282-x

PRODUCTION PROCESS

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Received: 10 July 2010 / Accepted: 15 October 2010 / Published online: 2 November 2010

Abstract Flank wear occurs on the relief face of the tool and the life of a tool used in a machining process depends upon the amount of flank wear; so predicting of flank wear is an important requirement for higher productivity and product quality. In the present work, the effects of feed, depth of cut and cutting speed on flank wear of tungsten carbide and polycrystalline diamond (PCD) inserts in CNC turning of 7075 AL alloy with 10 wt% SiC composite are studied; also artificial neural network (ANN) and co-active neuro fuzzy inference system (CANFIS) are used to predict the flank wear of tungsten carbide and PCD inserts. The feed, depth of cut and cutting speed are selected as the input variables and artificial neural network and co-active neuro fuzzy inference system model are designed with two output variables. The comparison between the results of the presented models shows that the artificial neural network with the average relative prediction error of 1.03% for flank wear values of tungsten carbide inserts and 1.7% for flank wear values of PCD inserts is more accurate and can be utilized effectively for the prediction of flank wear in CNC turning of 7075 AL alloy SiC composite. It is also found that the tungsten carbide insert flank wear can be predicted with less error than PCD flank wear insert using ANN. With Regard to the effect of the cutting parameters on the flank wear, it is found that the increase of the feed, depth of cut and cutting speed increases the flank wear. Also the feed and depth of cut are the most effective parameters on the flank wear and the cutting speed has lesser effect.

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Keywords Flank wear · CNC turning · Artificial neural network · Co-active neuro fuzzy inference system

1 Introduction

Metal matrix composites are formed by combination of metal matrix and stiff and hard reinforcing phase. Incorporation of silicon carbide particles enhances the properties like adhesive, abrasive, diffusion wear resistance, thermal properties, hardness, and stiffness. The mechanical properties can be fine tuned to the requirement by choosing the size, shape, and distribution of reinforcement particles. In the last decades, SiC/Al composites have been increasingly used in the aerospace industry and advanced arm systems such as satellite bearing, inertia navigation system, and laser reflector. Due to the addition of reinforcing materials, which are normally harder and stiffer than matrix, machining of SiC/Al composites becomes significantly more difficult than those of conventional materials [1].

The productivity of a machining system and machining cost, as well as quality, the integrity of the machined surface and profit strongly depend on tool wear and tool life. Sudden failure of cutting tools leads to loss of productivity, rejection of parts and consequential economic losses.

Tool flank wear occurs on the relief face of the tool and is mainly attributed to the rubbing action of the tool on the machined surface. The tool flank wear predominantly occurs in cutting tools, so the life of a particular tool used in the machining process depends upon the amount of flank wear. As the flank face of the cutting tool performs a rubbing action against the work piece material, the surface finish of the machined work piece primarily depends upon the amount of flank wear. An increase in the amount of flank wear leads to a reduction in nose radius of the cutting tool, which reduces the surface finish in turn.

The maximum utilisation of cutting tool is one of the ways for an industry to reduce its manufacturing cost. Hence, tool wear has to be controlled and should be kept within the desired limits for any machining process [2]. Due to its nonlinear and stochastic nature, predicting tool wear is a difficult task [3].

Regression, artificial neural networks (ANNs) and neuro-fuzzy systems (NFSs) have been widely used in modelling and control of many practical industrial nonlinear processes. Recently, Chandrasekaran et al. [4] reviewed research work on the application of soft computing methods in modelling and optimization of machining processes, spanning for approximately two decades. Palanisamy et al. [2] predicted tool wear of carbide cutter in CNC milling of AISI 1020 steel using regression and ANN models. They found that the predictive neural network model offers better tool flank wear predictions within the trained range. An artificial-neural-networks-based in-process tool wear prediction (ANN-ITWP) system was proposed and evaluated by Jacob Chen and Joseph Chen [5]. Results showed that the system could predict the tool wear online with an average error of 0.037 mm. Diagnosis of tool wear based on cutting forces and acoustic emission measures as inputs to a neural network was performed by Jemielniak et al. [6]. Seeman et al. [7] in a part of their research modeled flank wear in turning process of particulate aluminum metal matrix composite using regression analysis. Harber et al. [8] proposed an intelligent supervisory system to predict tool wear in milling operation in real time under actual cutting conditions using the residual generation approach on the basis of a process model. The attained results showed the suitability and potential of this supervisory system for industrial applications. Two types of neural networks, Bayesian support vector machines for regression (BSVR) and Bayesian multilayer perceptrons (BMLP), were applied for tool wear estimation in CNC milling process by Dong et al. [9]. The comparison between the estimation results from the two neural networks showed that the BSVR method is more accurate in estimating flank wear than BMLP, but at the cost of a higher computing load. A genetic algorithm-based fuzzy estimator obtained by a fuzzy inference algorithm to evaluate the minor flank wear length in finish milling was introduced by Ming et al. [10]. The proposed system turned out to be effective for estimating minor flank wear length, and its mean error was less than 13%.

Researchers have used various intelligent techniques, including neural network, fuzzy logic, neuro-fuzzy, etc., for the prediction of machining parameters and to enhance manufacturing automation. The motivation for hybridization is the technique enhancement factor, multiplicity of application tasks and realizing multi-functionality [11]. ANFIS, CANFIS and TWNFIS are of these hybrid techniques.

ANFIS is a fuzzy inference system implemented in the framework of neural networks. Several ANFIS models for predicting in machining operations have been developed [11–19]. For example, Kumanan et al. [11] were using adaptive ANFIS and radial basis function neural network-fuzzy logic (RBFNN-FL) for the prediction of surface roughness in end milling. Dweiri et al. [12] presented a model for down milling operation of Alumic-79 using the ANFIS to predict the effect of machining variables on the surface roughness. Caydas et al. [13] introduced the ANFIS model for the prediction of the white layer thickness (WLT) and the average surface roughness achieved as a function of the process parameters in wire-EDM.

With regard to tool wear prediction by using neuro-fuzzy based models, Uros et al. [20] developed a model to predict flank wear during end milling process using ANFIS. The error of the tool wear values predicted by ANFIS with the triangular membership function was 4%. Balazinski et al. [21] studied CNC tool wear detection using neurofuzzy classification system. He adopted three different types of membership function for analysis for ANFIS training and compared their differences regarding the accuracy rate of the turning tool-state detection. Gajate et al. [22] proposed the application of a Transductive-Weighted Neuro-Fuzzy Inference System (TWNFIS) to obtain local models for predicting tool wear in a turning process. Kuo [23] introduced an ANFIS-based methodology, designed to operate under varying cutting conditions, for on-line estimation of flank wear rate based on cutting force measurement. Cutting forces and cutting conditions including speed, feed, rake angle and depth of cut have been usually employed as input units in these prediction models. Tool wear monitoring using genetically-generated fuzzy knowledge bases in face-milling operations was done by Achiche et al. [24]. Cutting tool wear estimation in turning operations using ANFIS was performed by Sharma et al. [3]. Their presented model performed quite satisfactory results with the actual and predicted tool wear values.

Co-active neuro fuzzy inference system (CANFIS) is a dynamic-statistical model that incorporates classification and regression trees with a neuro-fuzzy inference system. CANFIS has been mostly used in areas like earth and weather sciences [25–32].

In the present work, the effect of cutting parameters (i.e. feed rate, depth of cut and cutting speed) on the flank wear (VB) of tungsten carbide and PCD inserts in CNC turning of 7075 AL alloy SiC composite has been investigated using the main effect plot and the interaction plot. In continuation, artificial neural network and co-active neuro fuzzy inference system models were used to assess flank wear of tungsten carbide and PCD inserts. The input parameters were selected to be as feed rate, depth of cut and cutting speed and the outputs were the flank wear of tungsten carbide and PCD inserts. In order to construct the models, the experimental data presented by Bhushan et al. [1] is used. The results of neuro-fuzzy model are compared with the results of ANN model in order to specify which model is more accurate.

2 Experimental procedure

The experiments were performed on 7075 AL alloy and 10 wt% SiC (particle size 20–40 µm) composites. Figure 1 shows the microstructure of the cast Al alloy and SiC composite before the machining operation was performed. The diameter and length of the workpiece material are 27 and 100 mm, respectively. Two types of inserts (tungsten carbide and PCD inserts) were used at different cutting speeds (180, 200, 220, and 240 m/min), feed rates (0.1, 0.2, 0.3, and 0.4 mm/rev), and depths of cut (0.5, 1.0, 1.5, and 2.0 mm). Details of inserts and tool holders are given in Table 1. CNC Turning Machine (Model TC 20) was used for the experiments [1].

The extent of flank wear (VB) can be measured as the distance between the top of the cutting edge and the bottom of the area where flank wear occurs. Carbide turning tools are usually replaced when the width of the flank wear area reaches some pre-defined limit. The 1993 international standard (ISO 3685) stipulates a flank wear width of 0.76 mm width for rough turning and 0.38 mm for finish turning (Fig. 2).

Figure 3a indicates a carbide insert before machining. Figure 3b represents a carbide insert after machining for 7 min at cutting speed of 180 m/min, feed rate of 0.4 mm/rev, and depth of cut of 2 mm. The optical inspection of the flank face of the cutting inserts revealed the beginning of the flank wear. No substantial groove wear was observed; insert experience relatively wider, but shallower nose deformation with mild erosion of material over the tool [1]. ISO 3685 was followed for measurement of flank wear. Machining was continued for 7 min for carbide and PCD inserts for all the parameters considered. Each experiment was repeated three times and average values were taken [1]. Flank wear of carbide and PCD inserts while machining 7075 AL alloy with 10 wt% SiC composite is shown in Table 2.

The main effects of the flank wear of carbide and PCD inserts during turning of 7075 AL alloy composite have been plotted in Figs. 4 and 5 by using Minitab 15 software. A main effect plot is a plot of the mean response values at each level of a design parameter or process variable [33]. From Figs. 4 and 5, it can be observed that:

- The increase of the feed, depth of cut and cutting speed increases the flank wear.
- The minimum flank wear values pertains to feed of 0.1 mm/rev, depth of cut of 0.5 mm and cutting speed of 180 m/min.
- The feed and depth of cut are the most effective parameters on the flank wear; the cutting speed has lesser effect.

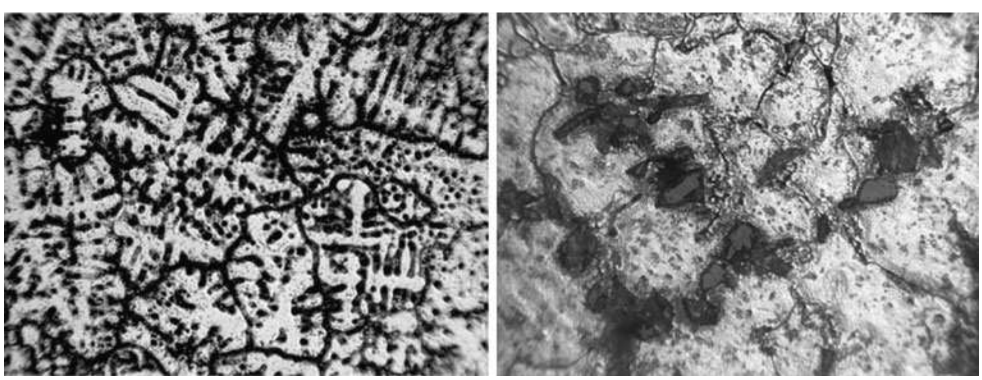

Fig. 1 Microstructure of 7075 aluminium alloy and 10 wt.% SiC-p composite [1]

Table 1 Cutting tools used in the experiments [1]

Turning tool holder	Type of insert	Clearance angle (degree)	Rake angle (degree)	Nose radius (mm)	Feed (mm/rev)	Depth of cut (mm)
PCLNL 2525 M12 KT 809	Carbide insert CNMG 120408EM grade 6630	0°	7°	0.8	$f_{\min} = 0.15$; $f_{\max} = 0.60$	$a_{p\min} = 1.0$; $a_{p\max} = 6.0$
SVJBL 2525 M16 WIDAX	PCD Insert VCMW 160404 FN	7°	0°	0.4	$f_{\min} = 0.1$; $f_{\max} = 0.14$	$a_{p\min} = 0.4$; $a_{p\max} = 2.0$

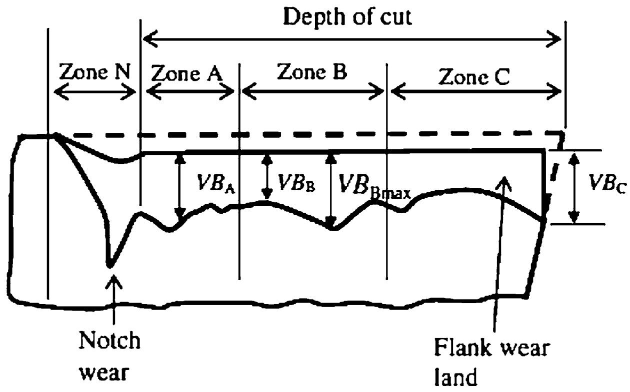

Fig. 2 Side view of cutting tool showing flank wear (ISO3685)

Figures 6 and 7 show the interaction effect of feed, depth of cut and cutting speed on the flank wear of carbide and PCD inserts. An interactions plot is a powerful graphical tool which plots the mean response of two factors at all possible combinations of their settings. If the lines are parallel, then it connotes that there is an interaction between the factors. Non-parallel lines is an indication of the presence of interaction between the factors [33].

From the Figs. 6 and 7, it is clearly found that there is no interaction between the factors.

3 Neuro-fuzzy systems theory and model

3.1 Adaptive neuro-fuzzy inference systems

Advantages of fuzzy logic control (FLC) are explicitness and flexibility in linguistic control based on if–then rule set, but problem of determining the shape and location of membership function for each fuzzy variable can be solved by

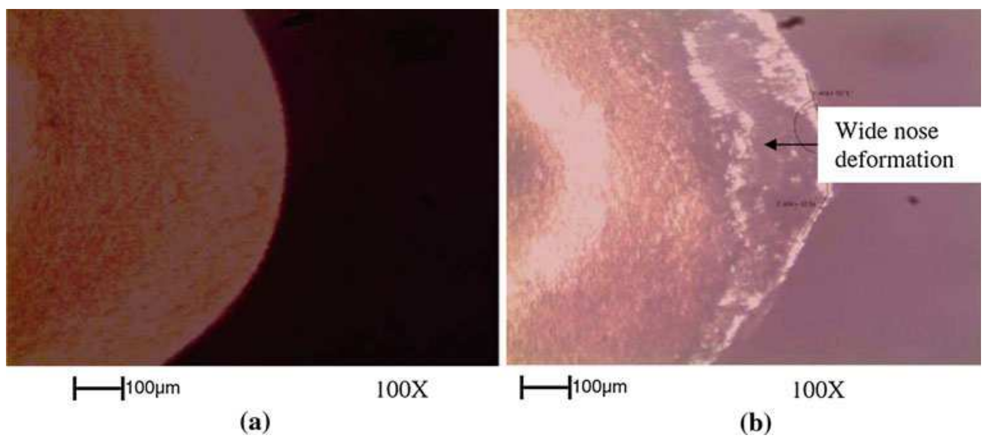

Fig. 3 **a** Carbide insert before machining. **b** Carbide insert after machining at cutting speed of 180 m/min [1]

Table 2 Flank wear of carbide insert and PCD inserts [1]

Feed (mm/rev)	Depth of cut (mm)	Cutting speed (m/min)	Flank wear (mm) using carbide insert	Flank wear (mm) using PCD insert
0.1	0.50	180	0.08	0.0040
0.1	0.50	200	0.11	0.0044
0.1	0.50	220	0.14	0.0046
0.1	0.50	240	0.19	0.0052
0.2	1.00	180	0.16	0.0056
0.2	1.00	200	0.18	0.0058
0.2	1.00	220	0.22	0.0062
0.2	1.00	240	0.28	0.0068
0.3	1.50	180	0.23	0.0068
0.3	1.50	200	0.26	0.0070
0.3	1.50	220	0.31	0.0076
0.3	1.50	240	0.38	0.0084
0.4	2.00	180	0.41	0.0086
0.4	2.00	200	0.45	0.0090
0.4	2.00	220	0.48	0.0094
0.4	2.00	240	0.54	0.0102

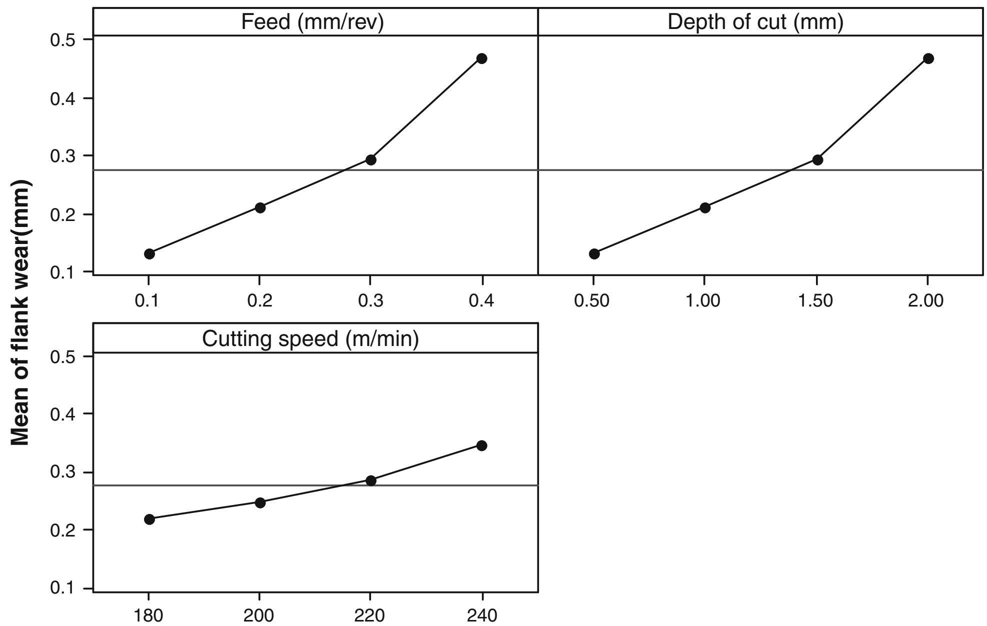

Fig. 4 Main effect plot of the cutting parameters on flank wear for the carbide insert

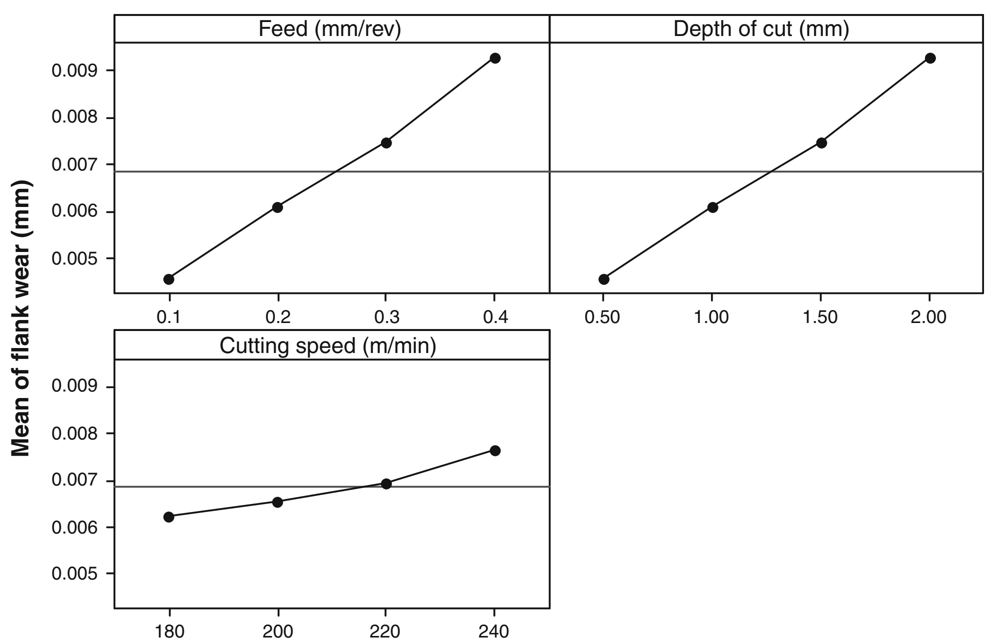

Fig. 5 Main effect plot of the cutting parameters on flank wear for the PCD insert

''trial-and-error'' method only. Numerical computation, adaptive and learning capability are strong points of NN, however, it is not easy to obtain the optimal structure (number of hidden layer and number of neuron in each hidden layer) of constructed NN and NN also performs numerical rather than symbolic computation. In order to enhance strong points as well as to limit weak points of both approaches, Jang combined both FLC and NN to produce a powerful processing tool named NFSs with many representation methods and the most common one is ANFIS. An ANFIS model is an adaptive NN which represents a particular type of fuzzy inference system (FIS). There are three types of FIS represented by an ANFIS model as follows:

Type 1: A FIS whose overall output is the weighted average of each rule's crisp output. The output membership functions are monotonic functions.

Type 2: A Mamdani FIS where the centroid defuzzification operator is replaced by a discrete version which calculates the approximate centroid of area.

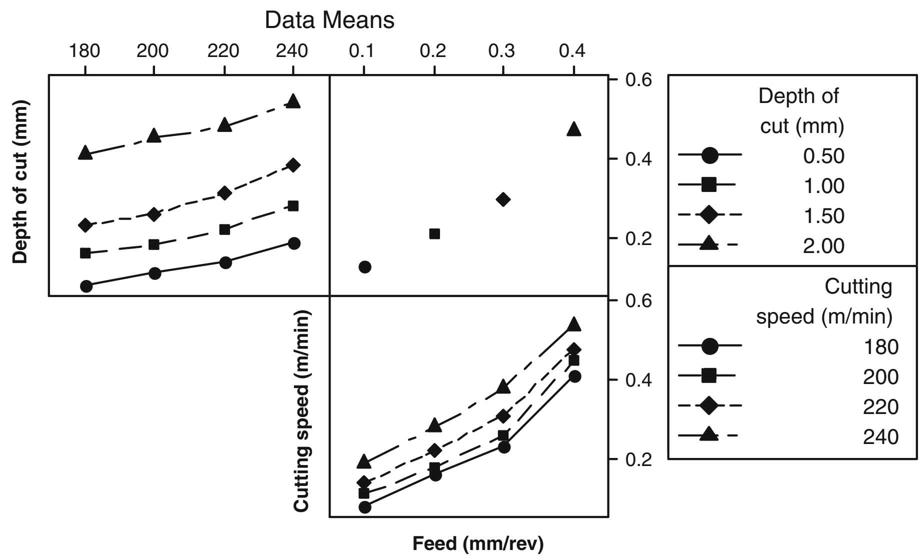

Fig. 6 Interaction plot of factors for flank wear of carbide insert

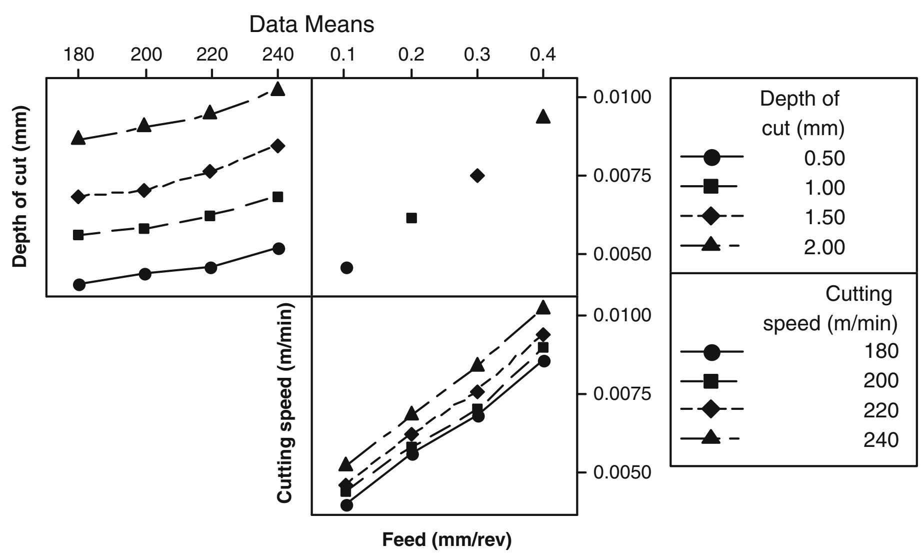

Fig. 7 Interaction plot of factors for flank wear of PCD insert

Type 3: A Sugeno-type FIS whose output is a linear combination of the input variables plus a constant term.

Jang presented an ANFIS architecture, a special case of Type 3 system, which is briefly explained as following.

Assume that the considered FIS has two inputs (x and y) and one output f. For a first-order Sugeno fuzzy model, a common rule set with two fuzzy if–then rules is as follows:

Rule 1: If x is $A1$ and y is $B1$; then

$$f_1 = p_1 x + q_1 y + r_1, \tag{1}$$

Rule 2: If x is $A2$ and y is $B2$; then

$$f_2 = p_2 x + q_2 y + r_2, \tag{2}$$

Figure 8a illustrates the reasoning mechanism for the Sugeno model. The corresponding equivalent ANFIS architecture is shown in Fig. 8b. In this diagram, the output of the ith node in layer l is denoted as $O_{l,i}$.

Layer 1: Including adaptive nodes.

$$O_{l,i} = \mu_{Ai}(x) \quad \text{for } i = 1, 2 \tag{3}$$

$$O_{l,i} = \mu_{Bi-2}(y) \quad \text{for } i = 3, 4 \tag{4}$$

Where $\mu_{Ai}(x)$ and $\mu_{Bi-2}(y)$: any appropriate parameterized membership functions. $O_{l,i}$: the membership grade of a fuzzy set A (=$A1$, $A2$, $B1$ or $B2$) and it specifies the degree to which the given input $x(y)$ satisfies the quantifier A.

Layer 2: Including fixed nodes labeled $\prod$, whose output is the product of all the incoming signals:

$$O_{2,i} = \mu_{Ai}(x) * \mu_{Bi}(y), \quad i = 1, 2 \tag{5}$$

Each node output represents the firing strength of a fuzzy control rule.

Layer 3: Including fixed nodes labeled N with function of normalization:

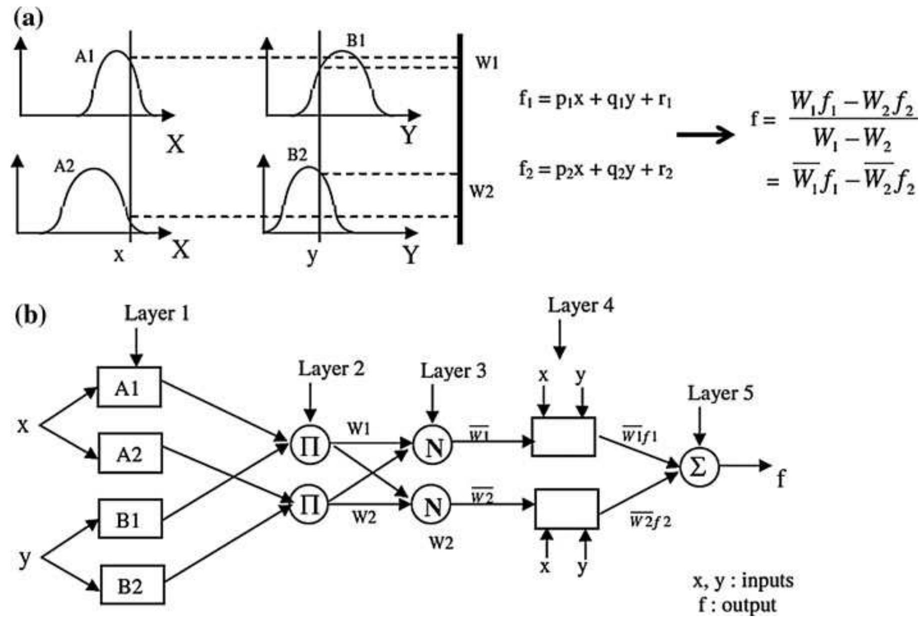

Fig. 8 **a** First-order Sugeno fuzzy model. **b** Equivalent ANFIS architecture [26]

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2 \tag{6}$$

Outputs of this layer are called normalized firing strengths.

Layer 4: Including adaptive nodes.

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i) \tag{7}$$

Layer 5: Including a single fixed node labelled $\sum$ with function of summation [26].

Overall output

$$O_{5,i} = \sum \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{8}$$

3.2 Coactive neuro-fuzzy inference system

Co-active neuro-fuzzy inference system (CANFIS) is a generalized ANFIS. ANFIS fuses the fuzzy system and neural network into a learning system, which would combine the benefits of the fuzzy system and neural network. The resulting neuro-fuzzy system, a hybrid, has fuzzy system architecture, but uses neural network learning techniques so that it can be trained automatically. For a given input/output dataset, ANFIS can construct a fuzzy inference system whose membership functions are tuned by using either a back propagation algorithm alone or in combination with the least square method [19].

CANFIS combines some single-output ANFIS models to produce a multiple-output model with nonlinear fuzzy rules which is an advantage of CANFIS model. There are many ways to form a CANFIS from ANFIS whereof one is illustrated in Fig. 9. This diagram is used to maintain the same antecedents of fuzzy rules among multiple ANFIS models. It means that fuzzy rules are constructed with shared membership values to express possible correlations between outputs in this diagram. Besides, we can also form a multiple ANFIS (MANFIS) by placing many ANFIS models side by side, in which, each ANFIS has an independent set of fuzzy rules [26].

In neuro-fuzzy based model, the number of input sets is equal to the input variants. For this system the feed rate, depth of cut and cutting speed are the input variations. So two input sets are selected. The model has two output variables respected to the predicted value of flank wear of tungsten carbide and PCD inserts. Four data sets are selected randomly as the testing data and the remaining twelve data sets are used for training. A developed CANFIS model used the gaussian membership function (MF) with three MFs per input, momentum (MOM) learning rule during training process and TSK fuzzy model proposed by Takagi, Sugeno and Kang for fuzzy part in these hybrid systems. MSE values of CANFIS model are summarized in Table 3. The number of epochs during training process was equal to 180.

4 Artificial neural network model and principle

ANN has been developed by simulating the biological structure of human brain. ANN is one of the most popular nonlinear mapping systems in artificial intelligence which has the ability to solve many problems including modelling, predicting, and measuring in experimental knowledge [34]. ANN structure is generally designed by multi layers: input layer, hidden layer, and output layers. The neurons, called as processing elements in layers, are linked by weighted interconnections, which resemble the intensity of bioelectricity transmitting among the neuron cells in real network [35].

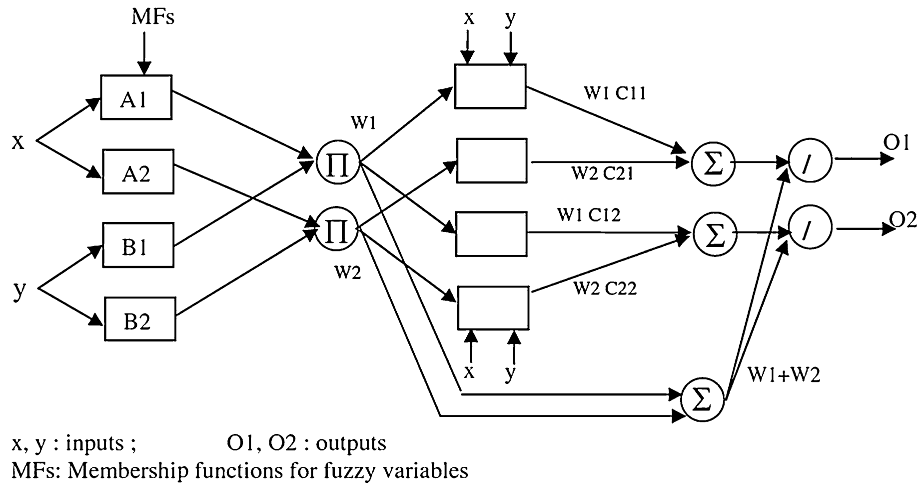

Fig. 9 Two-output CANFIS architecture with two rules per output [26]

Table 3 MSE values of CANFIS model for training and testing data

Data	MSE
Train	0.000841986
Test	0.001546375

Neural network determines the connection between input and output data by training. One of the basic benefits of neural network is their parallel structure. The ability of neural networks for solving the complex and non-linear problems causes to use them in machining processes which include such a phenomena.

In this study, the back propagation neural network was used, since it is considered to be a powerful technique for constructing non-linear functions between several inputs and one or more corresponding outputs, according to Klimasauskas et al. [36]. While being a relatively simple and flexible tool for data modelling and analysis, it is able to handle large amounts of data in complex problems.

The back propagation network typically has an input layer, an output layer and at least one hidden layer, with each layer fully connected to the succeeding layer. During learning, information is also propagated back through the network and used to update the connection weights. The following expressions give the basic relationships used for this analysis [36].

Let

$X_q^{[s]}$ = current output state of the qth neuron in layer

$\overset{q}{W}{}_{qp}^{[s]}$ = weight on the connection joining the Pth neuron in layer S − 1 to the qth neuron in layer S

$I_q^{[s]}$ = weighted summation of inputs to the qth neuron in layer S

A back propagation element therefore propagates its inputs as

$$X_q^{[s]} = f\left(\sum_p \left(W_{qp}^{[s]} \times X_p^{[s-1]}\right)\right) = f\left(I_q^{[s]}\right) \tag{9}$$

Where f is a differentiable function, but usually the sigmoid function given by

$$f(z) = (1.0 + e^{-z})^{-1} \tag{10}$$

A global error function E (which is a differentiable function of all the connection weights in the network), is needed to define the local errors at the output layer so they can be propagated back through the network. Here, the critical parameter that is passed through the layers is defined by

$$e_q^{[s]} = \frac{\partial E}{\partial I_q^{[s]}} = f\left(I_q^{[s]}\right) \times \sum_u \left(e_u^{[s+1]} \times W_{uq}^{[s+1]}\right) \tag{11}$$

which can be considered a measure of the local error at processing element q in level s (here, s + 1 is a layer above layer s). The aim of the learning process is to minimize the global error E of the system by modifying the weights. A given set of current weights $W_{qp}^{[s]}$ should then be increased or decreased, to decrease the global error. This can be done by using a gradient descent rule, as

$$\Delta W_{qp}^{[s]} = -l_c \times \frac{\partial E}{\partial W_{qp}^{[s]}} = l_c \times e_q^{[s]} \times X_p^{[s-1]} \tag{12}$$

where l_c is a learning coefficient. Each weight is to be changed according to the size and direction of negative gradient on the error surface.

In neural network designing process, the optimal structure of neural network (the right number of hidden layer as well as the right number of neuron in each hidden layer) can be found out by ''trial-and-error'' method only. More layers can give a better fit, but the training takes longer. Too few neurons give a poor fit, while too many neurons result in over-training of the net.

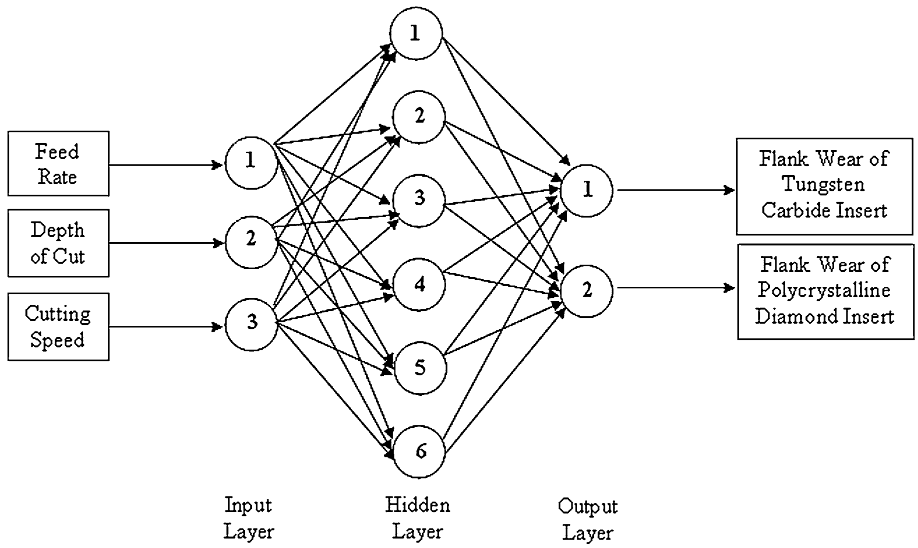

Fig. 10 Proposed neural network model

Feed rate, depth of cut and cutting speed are considered as the input variables and flank wear of tungsten carbide and PCD inserts are the outputs. Four data sets are selected randomly as the testing data and the remaining twelve data sets are used for specifying the neural networks. In order to have accurate models, several back propagation Multilayer Perceptron (MLP) neural networks, which are not shown in this section, have been used to obtain the best neural network architecture and learning coefficients.

For constructing the model, the tahnaxon transfer function and the momentum (MOM) learning rule were used for training this model. Network with three inputs, six neurons in hidden layer and two neurons in output layer, 3:6:2, has been considered. The proposed neural network model is shown in Fig. 10. The final MSE values for training and testing data are shown in Table 4. The number of epochs and momentum value during training process were 180 and 0.85, respectively.

It is noticeable that multilayer feed-forward back propagation is very sensitive to the initial weight assignments. Also, it suffers from a local minima issue. Different estimation results can be obtained even if the network structure and training data are kept constant.

5 Results

The validation of models was performed with the testing dataset. Relative errors obtained using CANFIS and MLP neural network methodologies have been compared, and the results of testing are shown in Tables 5 and 6. The results illustrate that the ANN model has much better predicting capability than the CANFIS model. The average relative errors of ANN model for flank wear of tungsten carbide and PCD inserts are 1.035 and 1.7%, respectively.

Table 4 MSE values of ANN model for training and testing data

Data	MSE
Train	0.002081227
Test	0.000823635

It means that the artificial neural network models are more applicable than the CANFIS models for the prediction of flank wear in CNC turning of 7075 AL alloy SiC composite. Also the results indicate that the predicted values of tungsten carbide insert flank wear using ANN are more accurate and better than the predicted values of PCD insert flank wear.

6 Conclusions

In this work, the effect of the cutting parameters on the flank wear of tungsten carbide and PCD inserts in CNC turning of 7075 AL alloy with 10 wt% SiC composite was studied. The following remarks can be pointed out:

- The increase of the feed, depth of cut and cutting speed increases the flank wear.
- The feed and depth of cut are the most effective parameters on the flank wear; the cutting speed has lesser effect.
- There is no interaction between the feed, depth of cut and cutting speed.

This research proposed two different intelligent techniques, artificial neural network (ANN) and co-active neuro fuzzy inference system (CANFIS), for the prediction of flank wear of tungsten carbide and PCD inserts in CNC turning of 7075 AL alloy SiC composite. The flank wear values predicted by CANFIS and ANN were compared

Table 5 Testing data and results that obtained using ANN and neuro-fuzzy based methods for tungsten carbide insert

Feed (mm/rev)	Depth of cut (mm)	Cutting speed (m/min)	Experiment flank wear (mm)	CANFIS	ANN	Relative error obtained by CANFIS (%)	Relative error obtained by ANN (%)
0.1	0.5	200	0.11	0.1175	0.1092	6.82	0.73
0.2	1	200	0.18	0.1865	0.1799	3.61	0.05
0.3	1.5	220	0.31	0.3249	0.3150	4.81	1.61
0.4	2	220	0.48	0.4845	0.4884	0.94	1.75
Average relative errors (%)						4.045	1.035

Table 6 Testing data and results that obtained using ANN and neuro-fuzzy based methods for PCD insert

Feed (mm/rev)	Depth of cut (mm)	Cutting speed (m/min)	Experiment flank wear (mm)	CANFIS	ANN	Relative error obtained by CANFIS (%)	Relative error obtained by ANN (%)
0.1	0.5	200	0.0044	0.004602	0.004446	4.59	1.04
0.2	1	200	0.0058	0.005920	0.005651	2.07	2.57
0.3	1.5	220	0.0076	0.007704	0.007758	1.37	2.07
0.4	2	220	0.0094	0.009384	0.009505	0.17	1.12
Average relative errors (%)						2.05	1.7

with the experimental results in order to determine the error of both models. The results indicated that the proposed ANN model has a high accuracy for estimating flank wear of tungsten carbide and PCD inserts. The obtained conclusions can be drawn as follows:

- The predictive ANN model was found to be much more accurate in predicting of tool flank wear when compared with the CANFIS model. The ANN model could predict the flank wear of tungsten carbide and PCD inserts for different cutting conditions with an average relative error of 1.035% and 1.7%, respectively.
- The predicted values of tungsten carbide insert flank wear using ANN are more accurate and better than the predicted values of PCD insert flank wear.

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