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Prediction of Drill Flank Wear Using Radial Basis Function Neural Network

S. S. Panda[1], # D. Chakraborty[1], S. K. Pal[2]
[1]Department of Mechanical Engineering,
Indian Institute of Technology, Guwahati, 781039, Assam, India.
[2] Department of mechanical Engineering
Indian Institute of technology Kharagpur, 721302,WB, India.

Abstract
In the present work, different type of artificial neural network (ANN) architectures have been used in an attempt to predict flank wear in drill bits. Flank wear in drill bit depends upon speed, federate, drill diameter and hence these parameters along with other derived parameters such as thrust force and torque have been used to predict flank wear using ANN. The results obtained from different ANN architectures have been compared and some useful conclusions have been made.
***Keywords**: neuron; cluster; center vector; Sensor signal; Flank wear*

Corresponding author. Tel No.: +91-361-2582666; fax: +91-361-2690762
E-mail address: chakra@iitg.ernet.in

1 Introduction

In order to achieve improved productivity and better quality of the product in drilling operation, monitoring of drill bit wear is an important issue. Since wear on drill bit affects the hole quality and tool life of the drill bit, online monitoring and prediction of drill wear is an important area of research. For improving the performance of decision making in tool condition monitoring, different type of intelligent system has been prepared by many authors. Following paragraph describes some of the relevant research in this direction.

Lin and Ting [1] studied the effect of drill wear as well as other cutting parameters on the current force signals, and established the relationship between the force signals and drill wear with the other cutting parameters. In another work, Lin and Ting [2] used the neural network model to study the drill wear and observed that the training error in case of sample mode converges faster than that in case of batch mode. Lee *et al.* [3] used the abductive network modeling in drilling process for predicting the drilling performance (tool life, thrust force and torque). Li and Tso [4] monitored the tool wear based on current signals of spindle motor and feed motor using regression model. Tsao [5] used the radial basis function network (RBFN) and adaptive based radial basis function network (ARBFN) to predict the flank wear, and compared their results with experimental observation. Ertunc and Loparo [6] used decisions fusion center algorithm (DFCA) for monitoring online tool wear condition in drilling process, and used number of numerical methods for predicting the condition of tool wear land. Abbu [7] predicted wear rate in drilling using FFT of vibration signature as an input to ANN. Multiple objectives linear programming models for optimizing drill hole quality with different cutting conditions such as speed and feed rate was proposed by Kim and Ramulu [8]. A.K Singh *et al.* [9] used back propagation neural network for prediction of flank wear of High Speed Steel drill bit in a copper work piece using spindle speed, feed rate, drill diameter, thrust force and torque as input parameters and maximum flank wear as output parameter to neural network. S.S Panda *et al.* [10] used back propagation neural network for prediction of flank wear of High Speed Steel drill bit in a mild steel work piece using the spindle speed, feed rate, drill diameter, thrust force, torque and chip thickness as input parameters and maximum flank wear as output parameter to neural network and concluded that including chip thickness as input parameter to network can predict flank wear very well. Li *et al.* [11] proposed hybrid learning for monitoring of drill wear using a combination of fuzzy system and neural network. Kuo and Kohen [12] applied a modified fuzzy neural network for detecting the defective sensor signal using membership function at the input node and fuzzy rule base. Lo [13] described the tool state in turning operation using artificial neuro fuzzy inference system (ANFIS) architecture, and concluded that higher accuracy could be achieved in the case of triangular and bell shape membership function. Hashmi *et al.* [14] proposed a fuzzy model for correlating the drilling speed with hardness of work material. They have used triangular membership function with fuzzy rule base in there analysis. Chung-Chen Tsao [15] used radial basis function network to forecast the flank wear of different coated drill bit using hybrid learning rule i.e combination of least square method and gradient descent method. G.H Lim [16] in his work correlate the flank wear of tool and acceleration amplitude of vibration signature in turning operation and he concluded that vibration acceleration produces two-peak amplitude just before tool failure. Tamas Szecsi [17] has proposed a cutting force model in machining operation using neural network. E.O.Ezugwu *et al.* [18] correlate cutting parameters like cutting speed, feed rate cutting time and coolant pressure with cutting process parameter like cutting force, feed force, flank wear and power consumption etc. and used neural network with marquardt learning algorithm. Marek Balazinski *et al.* [19] used three artificial intelligence (AI) methods: feed forward back propagation neural network, fuzzy decisions support system and an artificial neural network based fuzzy inference system to monitor the flank wear in turning operation. Toshiyuki Obikawa *et al.* [20] used unsupervised and self-organizing neural network Adaptive Resonance Theory (ART2) for monitoring of flank wear in high speed machining operation. C. Chungchoo *et al.* [21] used fuzzy neural network model for online tool wear estimation in CNC turning. D.K Sonar *et al.* [22] used radial basis function neural network for predicting the surface roughness in turning operation

The aim of the present work is to study the efficiencies of different ANN architectures in predicting drill wear.

2 Radial basis function network

(a) Architecture of radial basis function network

Basically radial basis function network is compose of large number of simple and highly interconnected artificial neurons and can be organized into several layer, i.e input layer, hidden layer, and output layer [23].

Input layer:

An input pattern enters the input layer and is subjected to direct transfer function and output from input layer is same as input pattern. Number of nodes in the input layer is equal to the dimension of input vector L.

Output from input layer with element $I_{i(i=1\,to\,L)}$ is I_i.

Hidden layer:

The hidden layer does all the important process these nodes satisfy a unique property being radially symmetry. Being *radially symmetry* it must have the following

a. *A center vector* v_j in the input space, made up of cluster center with element $v_{ji(j=1\, to\, M)}$.' $M \leq P$ ' where M is the number of center vectors and P is number of training patterns. The vector typically is store as weight factors from input layer to hidden layer.

b. *A distance measure* to determine how far an input pattern with element I_i is from cluster center v_{ji}. We have used Euclidean distance norm for this purpose.

Euclidean distance $ed_j = \left\| I - v_j \right\| = \sqrt{\sum_{i=1}^{L} (I_i - v_{ji})^2}$ (1)

c. *A transfer function* which transfer Euclidean distance to give output for each node. In our case we used the gaussian function for this purpose.

$$output_j = \exp(ed_j^{\,2} \div \sigma^2) \quad (2)$$

Where σ is the spread parameter determined [24]

$$\sigma = \max(ed) / \sqrt{M} \quad (3)$$

Where $\max(ed)$ is maximum Euclidean distance between selected centers and M is no of center

Output layer:

There are weight factor $w_{kj(k=1\, to\, N,\, j=1\, to\, M)}$ between k[th] nodes of output layer and j[th] nodes of hidden layer.' N 'is the dimension of output vector. Output from output layer transferred through a transfer function like log sigmoid or tan sigmoid.

Output from the output layer is given by

$$output_k = f(\sum_{k=1}^{N} w_{kj} \times output_j) \quad (4)$$

(b) Training RBFN

Two kind of training has been considered as fixed centers and self-organizing selection of centers.

(i) Fixed center selected at random

1. Location of center vector is choosen randomly from the training data set. A sufficient number of centers were choosen in order to ensure adequate sampling of input space.
2. Euclidean distance was calculated as per eq[n] (1)
3. Spread parameter was calculated as per eq[n] (3)
4. Initialize the weight of output layer to small random values, and output from output layer was calculated as per eq[n] (4).
5. Then MSE training sample was calculated and if the MSE training is not reaching the goal specified then weight is updated based on gradient descent method. The weight updated based on sample as well as batch mode.
6. The process was carried out for a definite number of iteration.

(ii) Self-Organized selection of centers

1. It is a self-organizing network known as '**SOM**' in which initial centers vector was choosen randomly v_j. The only restriction is that these intial values must be different.
2. Read the training sample and Euclidean distance was calculated for the initial center vector as per eq^n (1)
3. The corresponding center vector was modified closest to the training sample as

$$\begin{aligned} & v_j^{new} = v_j^{old} + \alpha \times (I_{pi} - v_j^{old}) \\ & P = training\ sample \\ & j = no\ of\ centre\ vector \\ & i = input\ node \\ & \alpha = learning\ rate\ i.e\ 0 < \alpha < 1 \end{aligned} \tag{5}$$

4. This process was continued for fixed number of iteration until no noticeable change was for the center vector v_j. This is known as ***k-means clustering*** algorithm [23], a special case of competitive (winners takes all) learning process.
5. Spread parameter was calculated as per eq^n (3)
6. Initialize the weight of output layer to small random values, and output from output layer was calculated as per eq^n (4).
7. Then MSE training sample was calculated and if the MSE training is not reaching the goal specified then weight updated based on gradient descent method. The weight was updated based batch mode.
8. The process was carried out for a definite number of iteration.

3 Experimental Set-up

Fig. 1 shows a schematic representation of the experimental set up used in this work. In the present work, a radial drilling machine (Batliboi Limited, BR618 model) is used for the drilling operation. High speed steel (HSS) drill bits with different diameters have been used for drilling in copper work piece at different cutting conditions. Root mean square (RMS*)* values of thrust force and torque signal are recorded through a piezo-electric dynamometer (Kistler, 9272). Signals from the dynamometer were passed through low pass filter, amplified through charge amplifier (B&K, 2525), and stored in the computer through a data acquisition system (Advantech, PCL 818 HG, 100 KHz sampling rate). The digital microscope along with Carl-Zeiss software interfacing have been used to measure flank wear. The maximum flank wear is used as the criterion to characterize the drill condition, and is obtained by measuring the wear at different points on either of the cutting edges.

4 Results and Discussion

Drilling operations have been conducted over a wide a range of cutting condition. Spindle speed has been varied in the range 315 *rpm* to 1000 *rpm* in six steps. Feed rate has been varied from 0.13 to 0.71 *mm/rev* in six steps. High speed steel (HSS) drill bit of three different diameter size of 5*m*, 7.5*m* and 10*m* have been used for drilling hole in a copper plates. Various combination of spindle speed, feed rate and drill diameter has been used to perform 49 different drilling operations for copper plate. For each of these conditions, thrust force and torque have been measured using the dynamometer, and the data are stored in the computer through the data acquisition system. Corresponding to each cutting condition, maximum flank wear has also been measured. The results from the present experiment are tabulated in Table 1.

(a) Wear predictions by radial basis function network

After shuffling the 49 data set, 34 have been selected at random for training the network, and remaining 15 are used for testing. The normalized data sets are used for training the network. The data sets are normalized in the range of 0.1 to 0.9 using

$$y = 0.1 + 0.8\left(\frac{x - x_{\min}}{x_{\max} - x_{\min}}\right) \tag{6}$$

where,

x = Actual value,

$x_{\max}$ = Maximum value of x,

$x_{\min}$ = Minimum value of x,

y = Normalized value corresponding to x.

Radial basis function neural network architecture, considered in the present work, comprises of five input nodes with the input parameters as spindle speed, feed rate, drill diameter, thrust force and torque. The output parameter of the network is flank wear, and hence the number of neuron in output layer is one.

(i) Fixed center selected at random

After shuffling the 49 data set, 35 have been selected at random for training the network, and remaining 14 are used for testing. The normalized data sets are used for training the network. The data sets are normalized in the range of 0.1 to 0.9 as per eq^n (6).

Best network architecture (i.e. number of center vectors in the hidden layers, learning rate and momentum coefficient) has been obtained by trial and error based on mean square error in training, testing, and the number of iterations. Large number of runs were given for selecting the best architecture in sample and batch mode, and few of these are shown in Table 3. The best network architecture arrived at in the present model in case of sample mode is 5-20-1 with η=0.3 and α=0.3 and in case of batch mode is 5-20-1 with η=0.7 and α=0.4. Fig. 2 shows the mean square errors for training and testing with number of iteration for sample mode and fig. 4 shows the mean square errors for training and testing with number of iteration for batch mode. It is observed that training in sample mode is much more faster than that of batch mode It could be observed from the fig. 3 and 5 that flank wear predicted by the present radial basis function network is very close to $\pm 15\%$ of the actual values in case of sample mode and $\pm 20\%$ in case of batch mode of training. Most of the values are within the $\pm 10\%$ error band.

(b) Self-Organized selection of centers

After shuffling the 49 data set, 35 have been selected at random for training the network, and remaining 14 are used for testing. The normalized data sets are used for training the network. The data sets are normalized in the range of 0.1 to 0.9.

Best network architecture (i.e. number of center vectors in the hidden layers, learning rate and momentum coefficient) has been obtained by trial and error based on mean square error in training, testing, and the number of iterations. Large number of runs were given for selecting the best architecture and few of these are shown in Table 2. The weight is updated based on batch mode. The best network architecture arrived at in the present model is 5-15-1 with η=0.1 and α=0.9. Fig. 6 shows the mean square error in training and testing with number of iteration. It could be observed from the Fig. 7 that flank wear predicted by the present radial basis function network is very close to $\pm 15\%$ of the actual values. Most of the values are within the $\pm 10\%$ error band.

5 CONCLUSION

Radial basis function neural network have been tested for prediction of flank wear in drill bits. It has been observed that radial basis function neural network can be trained well and the trained network can predict drill were within an error of $\pm$ 15%. It has also been concluded from the present work that fixed center radial basis function neural network can learn much faster when the trained data is fed in sample mode compared to batch mode data feeding and also compared to self organized method (SOM).

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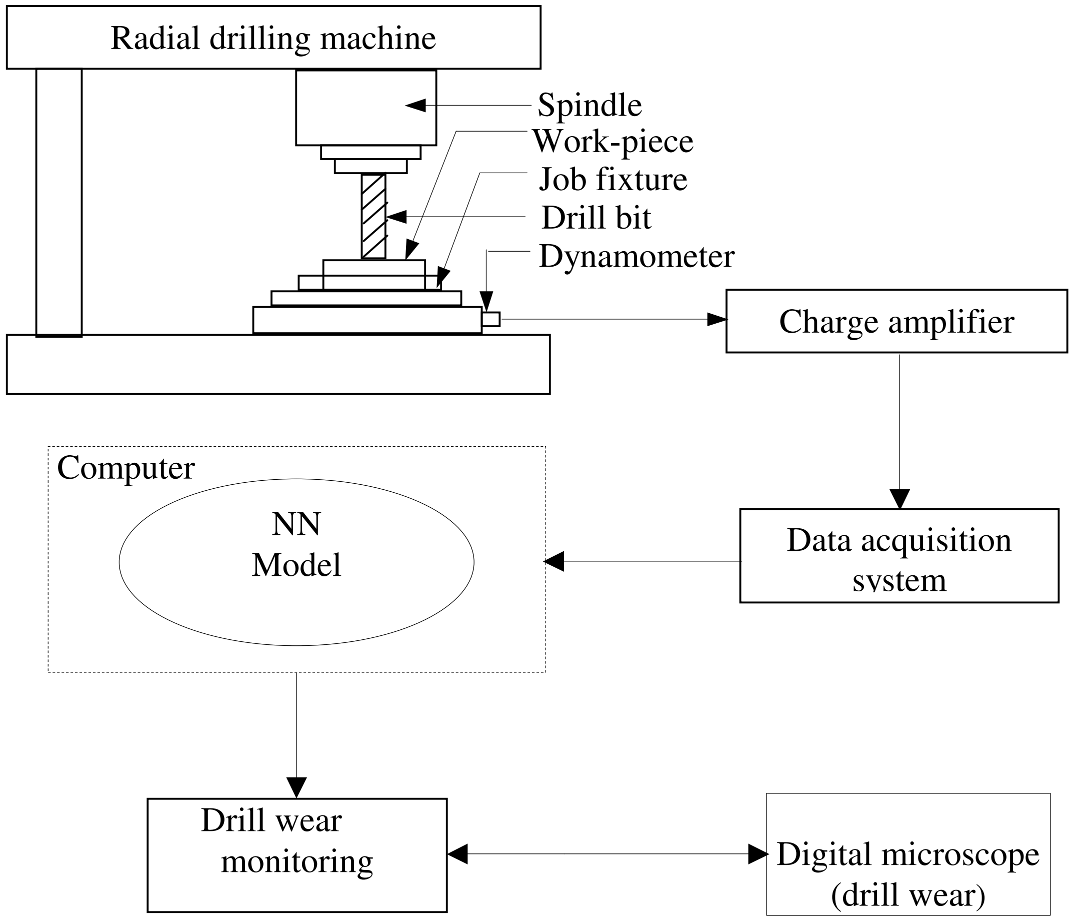

Fig. 1: Schematic diagram of the experimental set-up.

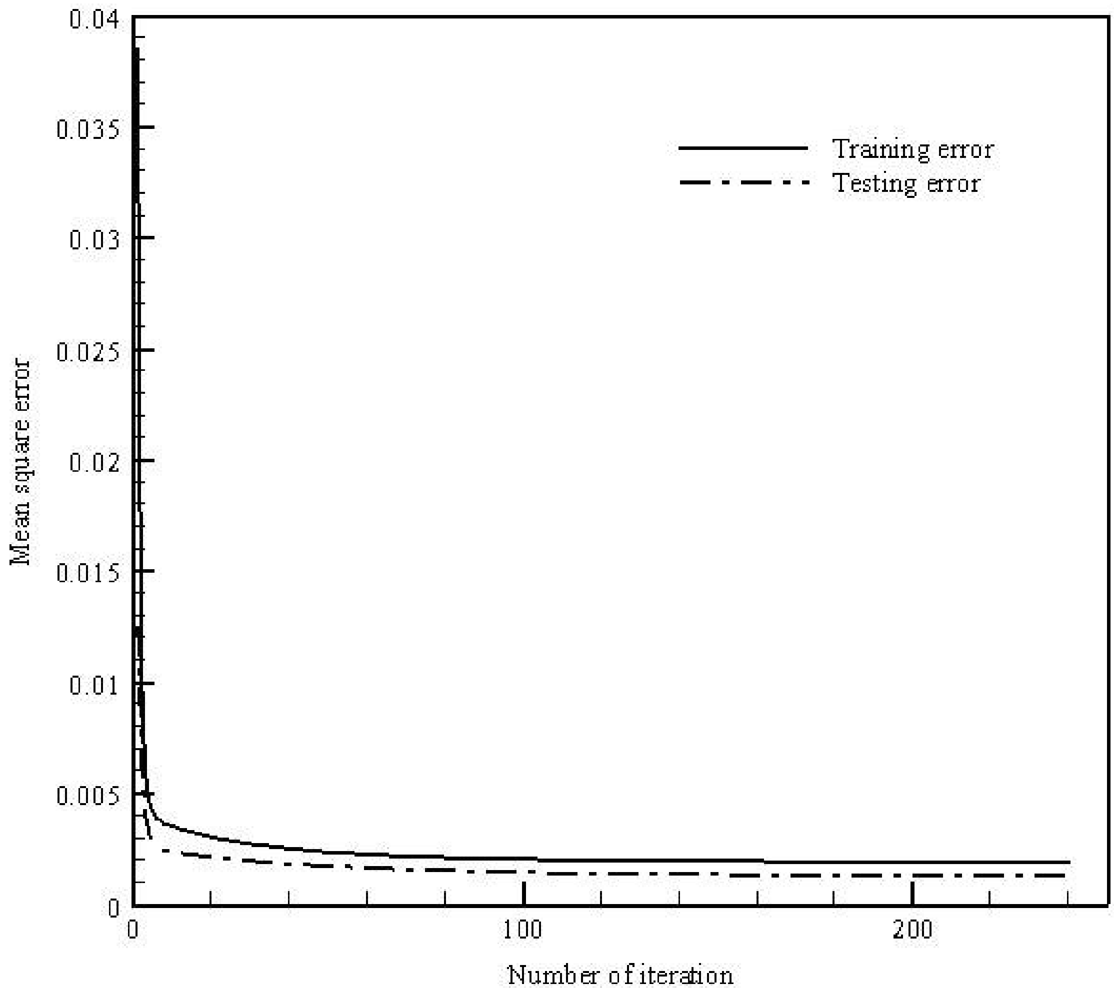

Fig.2: Variation of mean square error with number of iteration of 5-20-1 architecture fixed center selection in sample mode

(for α =0.3, η =0.3).

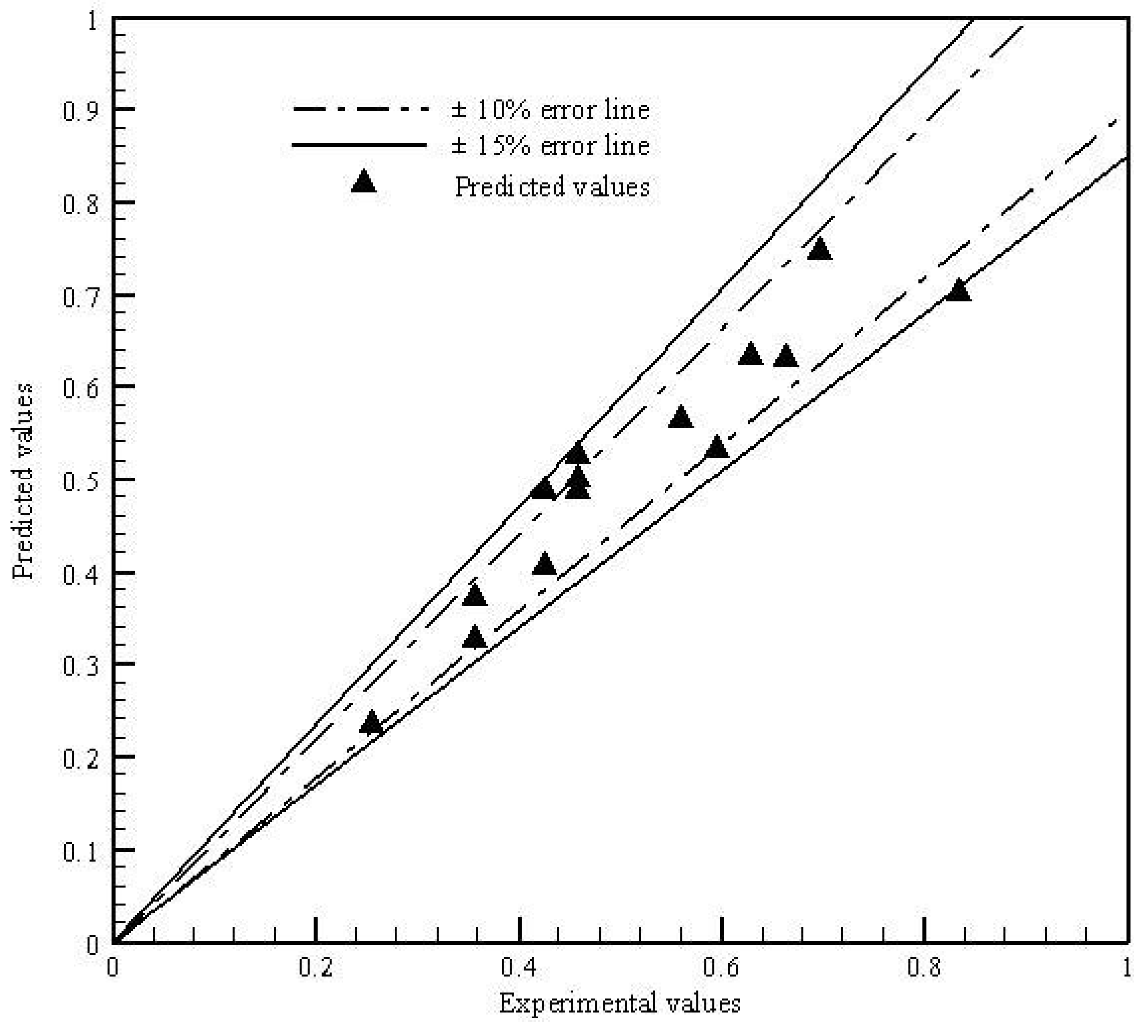

Fig. 3: Comparison between experimental values with predicted values of flank wear by 5-20-1 architecture fixed center selection in sample mode (for α =0.3, η =0.3).

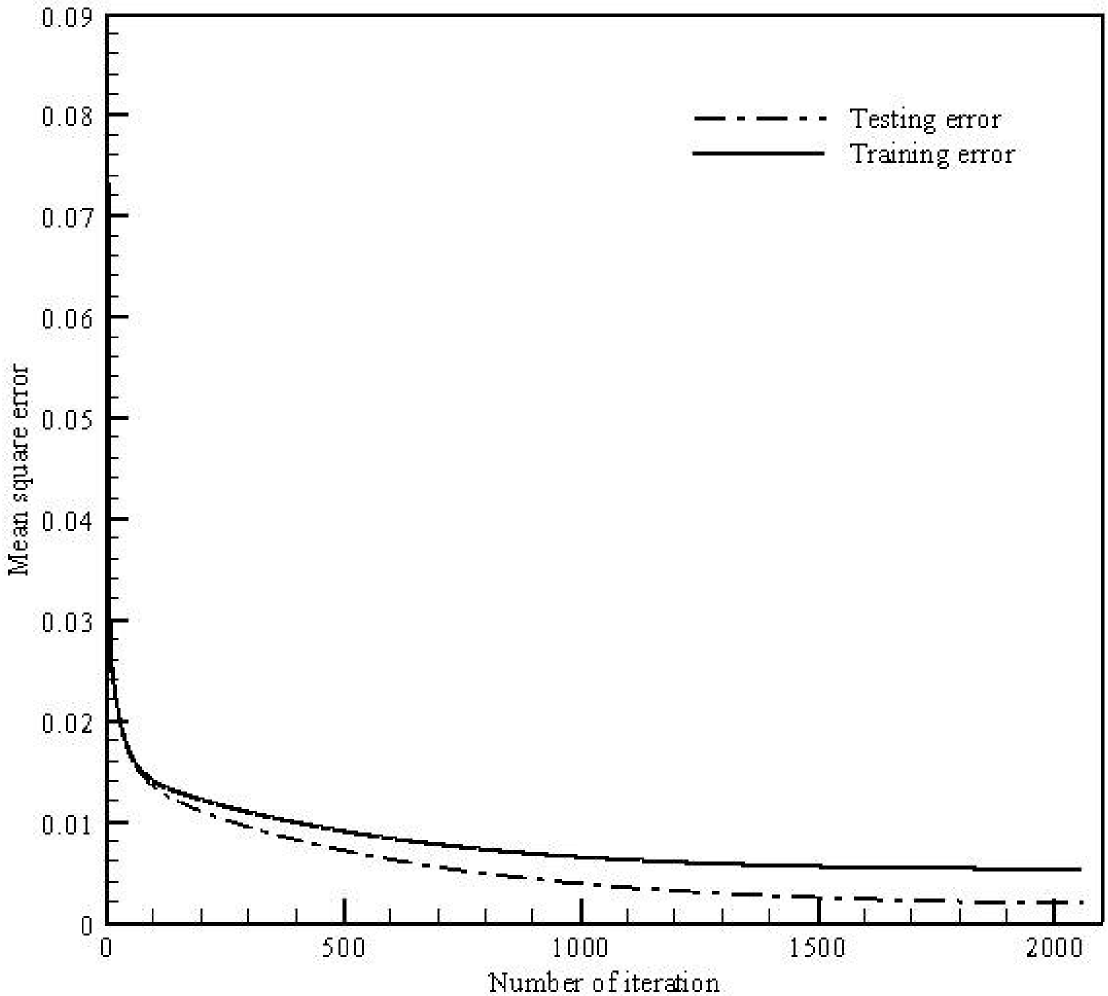

Fig. 4: Variation of mean square error with number of iteration of 5-20-1 architecture fixed center selection in batch mode (for α =0.4, η =0.7).

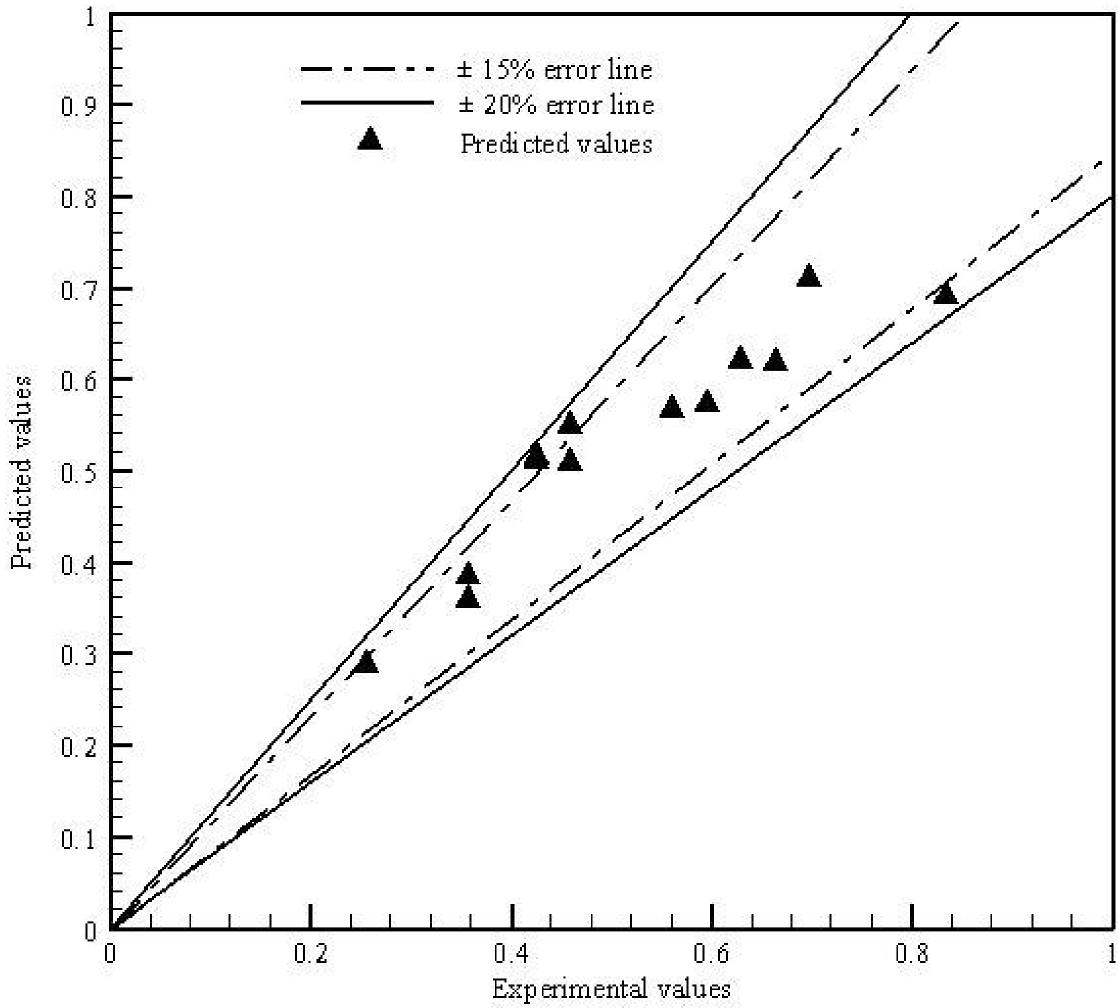

Fig. 5: Comparison between experimental values with predicted values of flank wear by 5-20-1 architecture fixed center selection in batch mode (for α =0.4, η =0.7).

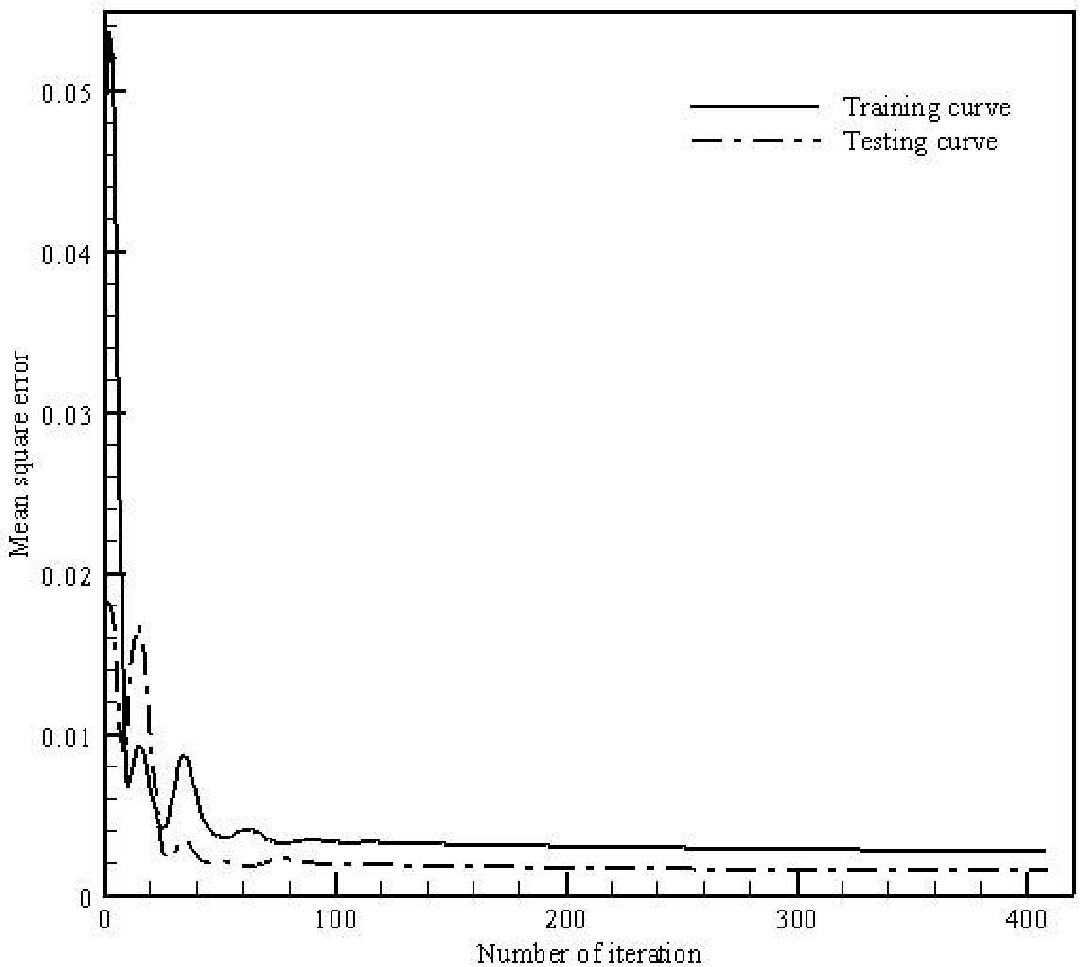

Fig. 6: Variation of mean square error with number of iteration of 5-15-1 architecture in SOM (for α =0.9, η =0.1).

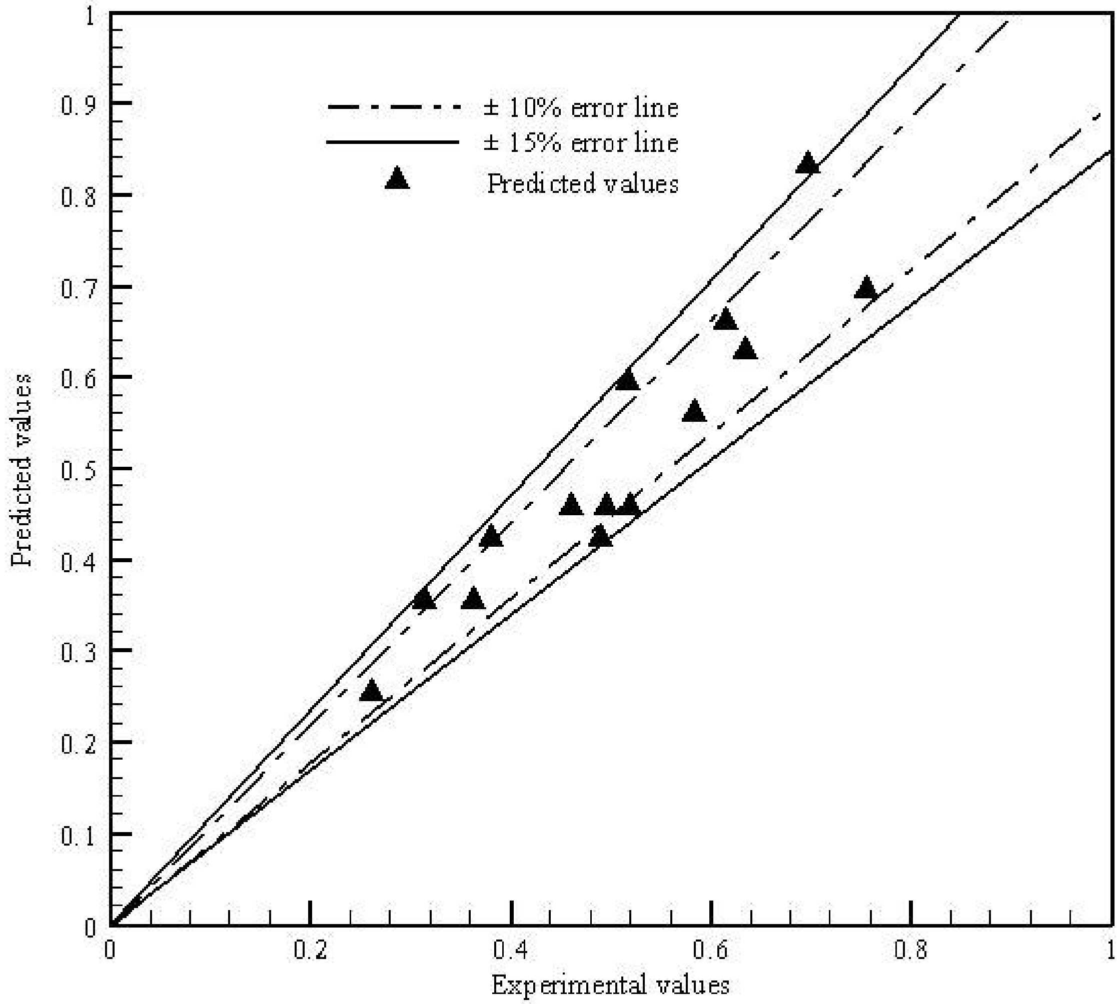

Fig. 7: Comparison between experimental values with predicted values of flank wear by 5-15-1 architecture in SOM (for α =0.9, η =0.1).

Table 1
Experimental data copper work-piece

Serial number	Drill diameter (mm)	Spindle speed (rpm)	Feed rate (mm/rev)	Thrust force (N)	Torque (N-cm)	Maximum wear (mm)
1	10	500	0.13	1925	19.253	0.11
2	7.5	500	0.13	510	7.1	0.06
3	5	500	0.13	245	2.5	0.03
4	10	500	0.18	3860	25.1	0.195
5	7.5	500	0.18	595	4.41	0.08
6	5	500	0.18	275	2.75	0.06
7	10	500	0.25	3740	27.44	0.21
8	7.5	500	0.25	539	5.39	0.105
9	5	500	0.25	386	2.9	0.095
10	10	400	0.13	2518	23.52	0.185
11	7.5	400	0.13	853	11.27	0.085
12	5	400	0.13	267	3.1	0.05
13	10	400	0.18	3921	26.78	0.2
14	7.5	400	0.18	646	12.64	0.1
15	5	400	0.18	451	3.96	0.085
16	10	400	0.25	4010	29.25	0.26
17	7.5	400	0.25	1051	16.54	0.1
18	5	400	0.25	505	1.96	0.07
19	10	630	0.13	1258	10.11	0.12
20	7.5	630	0.13	488	5.86	0.09
21	5	630	0.13	186	2.94	0.08
22	10	630	0.18	1470	13.23	0.125
23	7.5	630	0.18	524	3.95	0.1
24	5	630	0.18	187	2.64	0.07
25	10	630	0.25	3077	15.68	0.18
26	7.5	630	0.25	441	4.41	0.1
27	5	630	0.25	285	2.15	0.025
28	10	800	0.36	2234	22.34	0.16
29	7.5	800	0.36	1666	8.66	0.13
30	10	800	0.5	2548	24.1	0.19
31	7.5	800	0.5	1440	19.3	0.13
32	5	800	0.5	1087	11.27	0.09
33	10	315	0.36	3303	25.33	0.20
34	7.5	315	0.36	1866	12.74	0.16
35	5	315	0.36	592	7.72	0.1
36	10	315	0.5	3413	29.54	0.205
37	7.5	315	0.5	1688	15.19	0.14
38	5	315	0.5	1210	13.39	0.08
39	10	315	0.71	3920	36.22	0.24
40	7.5	315	0.71	1828	17.15	0.12
41	5	315	0.71	1282	16.66	0.1
42	10	1000	0.36	1460	12.25	0.14
43	7.5	1000	0.36	554	5.39	0.095
44	5	1000	0.36	421	4.21	0.06
45	10	1000	0.5	1960	18.13	0.13
46	7.5	1000	0.5	784	7.35	0.1
47	5	1000	0.5	651	6.17	0.07

48 49	10 7.5	1000 1000	0.71 0.71	2009 970	20.58 8.05	0.17 0.12

Table 2
Training error for different neural network architectures (Radial basis function network)

Serial No	Number of center vector	Momentum coefficient (α)	Learning rate (η)	MSE Training	MSE Testing	Number of iteration	Absolute maximum predicted error	Absolute minimum predicted error	Radial basis network type
1	10	0.90	0.6	0.002999	0.001703	842	21.53	2.38	SOM
2	10	0.10	0.6	0.00703	0.009292	4205	21.53	2.38	
3	**15**	**0.90**	**0.1**	**0.0027368**	**0.001575**	**409**	**16.43**	**0.33**	
4	15	0.90	0.3	0.002751	0.001988	268	18.97	1.76	
5	15	0.90	0.6	0.002576	0.001705	125	18.79	2.12	
6	20	0.90	0.1	0.002975	0.001621	119	23.98	1.10	
7	20	0.90	0.6	0.003013	0.001603	41	19.23	0.4	
8	25	0.90	0.1	0.002537	0.002086	182	31.66	0.89	
9	35	0.90	0.3	0.002336	0.001717	91	35	1.27	
10	35	0.90	0.6	0.002377	0.001853	130	27.8	0.2	

Table 3
Training error for SOM

Serial No	Number of center vector	Momentum coefficient (α)	Learning rate (η)	MSE Training	MSE Testing	Number of iteration	Absolute maximum predicted error	Absolute minimum predicted error	Radial basis network type	
1	15	0.1	.1	0.001924	0.002376	1196	23.84	3.0	Sample mode	Fixed center
2	20	.1	.1	0.0018	0.00156	1071	17.95	0.30		
3	20	.6	.1	0.001869	0.001461	498	16.94	0.18		
4	**20**	**.3**	**.3**	**0.001921**	**0.001337**	**241**	**15.64**	**0.66**		
5	20	.1	.3	0.001877	0.001388	317	16.33	0.35		
6	25	.3	.1	0.001689	0.001561	527	19.79	1.56		
7	25	.1	.9	0.001537	0.001726	6521	21.94	0.30		
8	30	.1	.1	0.001651	0.001688	614	18.41	1.12		
9	30	.3	.3	0.00149	0.001572	4127	21.77	1.71		
10	30	.1	.6	0.001482	0.00154	3852	22.06	1.16		
1	15	.1	.1	0.013264	0.009296	4012	38.80	0.07	Batch mode	
2	15	.7	.2	0.0047	0.002034	498	26.44	2.15		
3	15	.4	.6	0.007102	0.002938	2624	30.23	0.002		
4	20	.3	.7	0.006973	0.003166	11235	33.26	0.23		
5	**20**	**.4**	**.7**	**0.005367**	**0.001948**	**2060**	**21.52**	**0.94**		
6	25	.4	.6	0.006085	0.002217	2466	27.14	0.47		
7	25	.4	.1	0.006206	0.002359	12103	26.88	0.03		
8	35	.4	.6	0.009456	0.00383	1379	44.80	0.27		
9	35	.7	.1	0.00386	0.001999	8227	26.06	1.49		
10	35	.7	.5	0.003857	0.001999	1651	26.04	1.49		