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MONITORING OF DRILL FLANK WEAR IN THE TIME DOMAIN

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ABSTRACT
The present work deals with drill wear monitoring using artificial neural network. A back propagation neural network (BPNN) has been used to predict the flank wear of high speed steel (HSS) drill bit for drilling holes on copper work-piece. Experiments have been carried out over a wide range of cutting conditions and the effect of various process parameters like feed-rate, spindle speed, drill diameter on thrust force and torque in the time domain has been studied. The data thus obtained from the experiments have been used to train a BPNN for wear prediction.

KEYWORDS
Flank wear, artificial neural network, Drilling, Chip-thickness

1 INTRODUCTION
Drilling is one of the machining operations extensively used in manufacturing industries. Tool wear has significant influence on the performance of a machining operation. In case of drilling, wear is categorized as flank wear, chisel wear, corner wear, and crater wear. Wear on the drill has a definitive influence on the hole quality and tool life of a drill bit. Therefore monitoring of drill wear is a very important issue in manufacturing industries, and thus an emergent area of research. Many works have been reported in the broad field of tool condition monitoring.

Noori-Khajavi and Komanduri [1] developed a model for online tool wear monitoring of drilling operation and observed that only one signal is sufficient to monitor the tool wear. Lin and Ting [2] used the force signal to monitor online drill wear. They used the least square method for determining the thrust force and torque as a function of spindle speed, feed-rate, drill diameter and average flank wear. Lin and Ting [3], in another work used back propagation neural network with sample and batch mode, and observed faster convergence of error in the case of sample mode. They also observed that neural network with two hidden layers with same number of nodes converge faster than that with one hidden layer and reported that at higher learning rate error produced is less. Das *et al.* [4] used back propagation algorithm for measuring flank wear of carbide tool in turning operation. Lee *et al.* [5] used the abductive network modeling for drilling process for predicting the tool life, tool wear and surface roughness. The network has number of polynomial functional nodes. Optimal network architecture is prepared based on predicted square error criterion. Choudhury *et al.* [6] developed a three-layer feed forward back propagation neural network for predicting the flank wear in turning operation. He used the geometrical relation in correlating the flank wear on cutting tool with change in work-piece dimension. Li and Tso [7] used the regression model for monitoring the tool wear based on current signal of spindle motor and feed motor. Choudhury and Raju [8] developed a regression model to measure the flank wear and corner wear of a drill bit in cutting operation. Tsao [9] used the radial basis function network (RBFN) and adaptive based radial basis function network (ARBFN) to predict the flank wear in both the cases and compared their result with experimentally obtained value. Chien and Tsai [10] used the back propagation neural network for prediction of tool wear and determining the optimum cutting condition in turning operation, they used the genetic algorithm in the optimizing model as well as Taguchi method to find the optimum parameter for both the model.

Purpose of the present research is to identify the flank wear in the drill bit at different cutting conditions like feed-rata, spindle speed, thrust, torque, chip thickness, depth of cut and drill diameter.

2 BACK PROPAGATION NEURAL NETWORK

Back propagation neural network (BPNN) has been used in the present work. It is composed of a large number of highly interconnected processing elements (neuron) working in parallel to solve the specific problems. The commonest type of artificial neural network consists of three groups, or layers, of units: a layer of *"input"* units is connected to a layer of *"hidden"* units, which is connected to a layer of *"output"* units. Input layer receives information from the external sources, and passes this information to the network for processing. Hidden layer receives information from the input layer, and does all the information processing, and output layer receives processed information from the network, and sends the results out to an external receptor. The number of hidden layer and the number of node in a hidden layer is a variable quantity, which depends upon the convergence criteria of results. The input signals are modified by interconnection weight, known as weight factor V_{ij}, which represents the interconnection of i^{th} node of the first layer to j^{th} node of the second layer. The sum of modified signals (total activation) is then modified by a transfer function. Batch mode type supervised learning has been used in the present case. In batch mode all the pattern is presented at a time to network and weight is updated using average gradient information. During training the calculated output is compared with the desired output and the mean square error is calculated. If mean square error is more than a prescribed limiting value error it is back propagated i.e., from output to input, weights are further modified till the error is within a prescribed limit.

3 EXPERIMENTAL SET-UP

Experiments over a wide range of cutting conditions has been performed. Radial drilling machine (Batliboi Limited, BR618 model) is used for the drilling operation. HSS drill bits with different diameters have been used for drilling in the copper work-piece at different cutting conditions.

Thrust force and torque are recorded through a piezo-electric Kistler 9272 dynamometer during drilling. Signal from the dynamometer is amplified through charge amplifier, and is stored in the computer through data acquisition system. Charge amplifiers of B&K 2525 model have been used in this work. Advantech PCL 818 HG model data acquisition system is used in present work.

Flank wear is measured by digital microscope with the help of Karl-Zeiss software interfacing. 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 edge.

4 RESULTS AND DISCUSSION

Drilling operation has been conducted over a wide a range of cutting conditions. Spindle speed has been varied in the range 630 rpm to 1000 rpm in three steps. Feed-rate has been varied from 0.13 to 0.25 mm/rev in three steps. HSS drill bit of 8, 10, 12 and 14 mm diameters have been used for drilling hole in a copper plate. Various combination of spindle speed, feed-rate and drill diameter has been used to perform 28 different drilling operations. For each of this condition, thrust force and torque signal have been measured using the data acquisition system, and is stored in the computer. Machine condition has a definitive effect of environment during the time domain so change in thrust force and torque signal (known as delta thrust and delta torque) with respect to time scale is taken as one of the input parameters to the network. Also corresponding to each cutting condition, maximum flank wear has been measured using digital microscope with interface of Karl-Zeiss software .The result of the experiment are tabulate in Table 1.

5 WEAR PREDICTIONS BY NEURAL NETWORK

Back propagation neural network algorithm with batch mode has been used in the present work. To train the neural network delta thrust, delta torque, feed-rate, drill diameter and spindle speed is used as input parameters and corresponding maximum flank wear has been used as the output parameter. A comparative study is carried out including chip thickness as one of the input parameter to network. From the 28 data sets obtained from the experiment, 21 have been selected at random for training the network and remaining 7 are used for testing. Shuffling the data sets different sample of data sets is prepared. The normalized data sets are used for training the network. The data sets are normalized in the range of 0.1 to 0.9.

The number of nodes in the hidden layer, learning rate and momentum coefficient are decided by trial and error. Large number of neural network architecture has been tried and is prepared in Table 2 and 3 based on the convergence rate of mean square error for training and testing as well as the number of iteration. The optimal network without chip-thickness and with chip thickness is selected from the table 2 and 3 based on mean square error. It has been observed that without chip thickness mean square for testing is converged to a value of 0.0026 with only 511 iteration, but adding chip thickness mean square error of testing converged to 0.0009 with 2827 iteration which are shown Figure 1 and 3 respectively. It has been observed that without chip thickness wear predicted by optimal network is within ±14% of the experimental value. But adding chip thickness as one of the input parameter to neural network predicted wear reduces to approximately ±8% of actual value as compared in Figure 2 and 4.

5 CONCLUSION

Back propagation neural network based drill wear prediction methodology has been adopted using various important parameters like delta thrust, delta torque, drill diameter, spindle speed, chip thickness and feed rate influencing the drill wear. Chip thickness as input parameter has a better influence of the network to learn. Neural network could learn well the pattern and could be used for future prediction of drill wear.

REFERENCES

[1] Noori-Khajavi A, Komanduri R (1995) Frequency and time domain analyses of sensor signal in drilling-II, Investigation on some problems associated with sensor signal. International journal of machine tool manufacturer 35: 795-815

[2] Lin SC, Ting CJ (1995) Tool wear monitoring in drilling using force signals. International journal of machine tool manufacturer 180: 53-60

[3] Lin SC, Ting CJ (1996) Drill wear monitoring using neural network. International journal of machine tool manufacturer 36: 465-475

[4] Das S, Roy R, Chottopadhyay AB (1996) Evaluation of wear of turning carbide inserts using neural network. International journal of machine tool manufacturer 36:789-797

[5] Lee BY, Liu H S, Tarng YS (1998) Modelling and optimization of drilling process. Journal of material processing technology 74: 149-157

[6] Choudhury SK, Jain VK, Rama Rao ChVV (1999) On-line monitoring of tool wear in turning using neural network. International journal of machine tool and manufacture 39: 489-504

[7] Li Xiaoli, Tso S.K (1999) Drill wear monitoring based on current signals. Wear 231: 172-178

[8] Choudhury SK, Raju G (2000) Investigation into crater wear in drilling. International journal of machine tool manufacturer 40: 887-898

[9] Tsao CC (2002) Prediction of flank wear of different coated drills for JIS SUS 304 stainless steel using neural network. Journal of material processing technology 123: 354-360

[10] Chien W T, Tsai C S (2003) The investigation on prediction of tool wear and the determination of optimum cutting conditions in machining17-4 PH stainless steel. Journal of material processing and technology 140: 340-34

Table 1: Experimental data sets

Drill diameter *(mm)*	Speed *(RPM)*	Feed-rate *(mm/rev)*	RMS of thrust *(N)*	RMS of torque *(N-cm)*	Abs RMS of delta thrust *(N)*	Abs RMS of delta torque *(N-cm)*	Chip thickness *(mm)*	Flank wear *(μm)*
8	630	0.13	302.1360	173.2582	243.9321	117.4846	1.340	9
8	630	0.18	368.8668	196.7067	280.2943	116.5424	1.34	10
8	630	0.25	424.0121	249.7400	179.2039	47.7866	1.34	13
8	800	0.13	213.2314	104.2341	26.8021	72.8714	1.415	12
8	800	0.18	309.2489	187.9397	152.4617	61.8451	1.385	15
8	800	0.25	324.5988	244.1572	172.3974	61.7673	1.365	16
8	1000	0.13	177.8196	119.9028	22.5935	79.2308	1.246	17
8	1000	0.18	258.3172	161.6020	47.9875	74.0186	1.233	20
8	1000	0.25	328.7271	186.6766	102.5257	63.2135	1.170	23
10	630	0.13	322.7427	234.5440	243.4622	117.7749	1.415	8
10	630	0.18	386.4270	250.1095	243.1373	90.4861	1.332	12
10	630	0.25	432.7161	255.0504	111.4878	45.5968	1.275	14
10	800	0.13	270.2510	134.6798	17.0838	108.2325	1.225	10
10	800	0.18	361.6624	220.7611	130.2710	78.2321	1.160	16
10	800	0.25	433.9120	242.5445	45.2026	24.7938	1.125	18
10	1000	0.13	184.9971	123.8156	2.4614	80.5026	1.0	17
10	1000	0.18	267.4196	212.3019	151.1116	40.6836	1.440	19
12	630	0.13	340.3940	259.5553	208.2819	135.6040	1.825	8
12	630	0.18	399.7980	320.5312	230.9828	69.4281	1.4	12
12	630	0.25	479.9599	337.3189	137.3384	36.7033	0.96	13
12	800	0.13	289.0885	227.7611	61.2862	114.2321	1.455	11
12	800	0.18	379.5711	278.9677	83.4265	68.9167	1.363	15

12	800	0.25	478.0625	303.4089	88.8650	55.0684	1.220	17
12	1000	0.13	216.9482	142.2341	55.6672	85.331	1.150	17
12	1000	0.18	307.0	243.6705	122.9572	39.7383	1.1	19
14	630	0.13	390.1036	295.0981	208.0963	173.3156	1.360	16
14	630	0.18	456.2198	439.5404	223.0519	97.9018	1.083	17
14	630	0.25	598.3699	454.0336	128.8578	65.5759	0.923	22

Table 2: Network architecture without chip thickness

Network architecture	Learning rate	Momentum coefficient	MSE training	MSE testing	Number of iteration	Maximum error (%)	Minimum error (%)
5-1-1	0.6	0.4	0.0279	0.0043	1893	18.07	-3.16
5-2-1	0.6	0.4	0.0273	0.0051	2763	19.60	0.51
5-3-1	0.6	0.4	0.0255	0.0044	1261	-20.13	3.5
5-5-1	0.6	0.4	0.0274	0.0038	1142	16.72	6.13
5-5-1	0.4	0.4	0.0272	0.0039	1761	18.00	7.15
5-3-1	0.5	0.6	0.0294	0.0029	963	14.20	-1.13
5-3-1	0.7	0.8	0.0306	0.0026	511	-14.06	-1.18

Table 3: Network architecture with chip thickness

Network architecture	Learning rate	Momentum coefficient	MSE training	MSE testing	Number of iteration	Maximum error (%)	Minimum error (%)
6-3-1	0.4	0.8	0.0480	0.0017	599	12.08	-0.50
6-1-1	0.4	0.5	0.0489	0.0012	8524	8.28	-0.74
6-3-1	0.4	0.5	0.0388	0.0030	2988	-17.54	-1.61
6-6-1	0.4	0.5	0.0438	0.0025	2376	15.08	-3.09
6-5-1	0.5	0.6	0.0421	0.0020	1387	-11.65	-1.15
6-1-1	0.6	0.6	0.0501	0.0009	2827	-7.96	-2.94
6-1-1	0.6	0.7	0.0537	0.0009	1517	-8.65	-0.05

Figure1: Comparison of optimal network mean square error without chip thickness

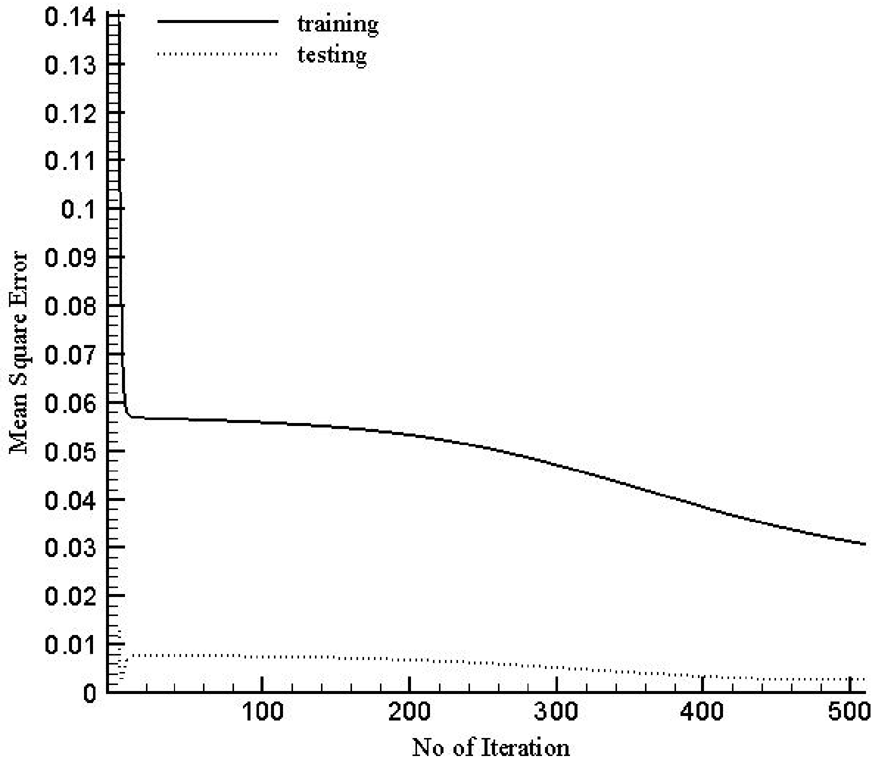

Figure 2: Scattering of predicted results without chip thickness

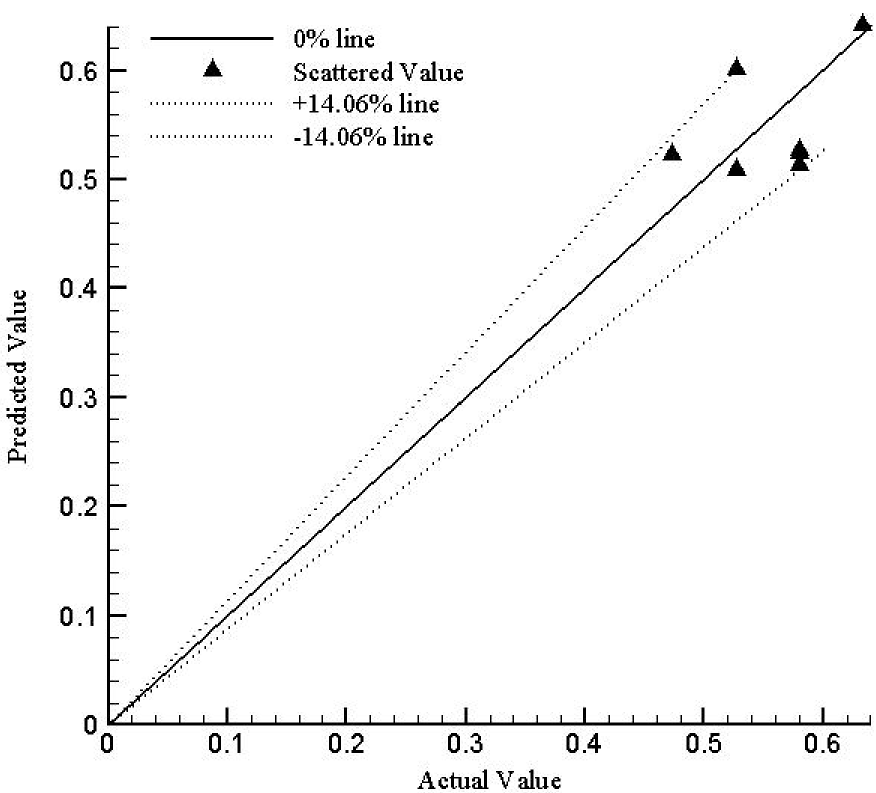

Figure 3: Comparison of optimal network mean square error with chip thickness

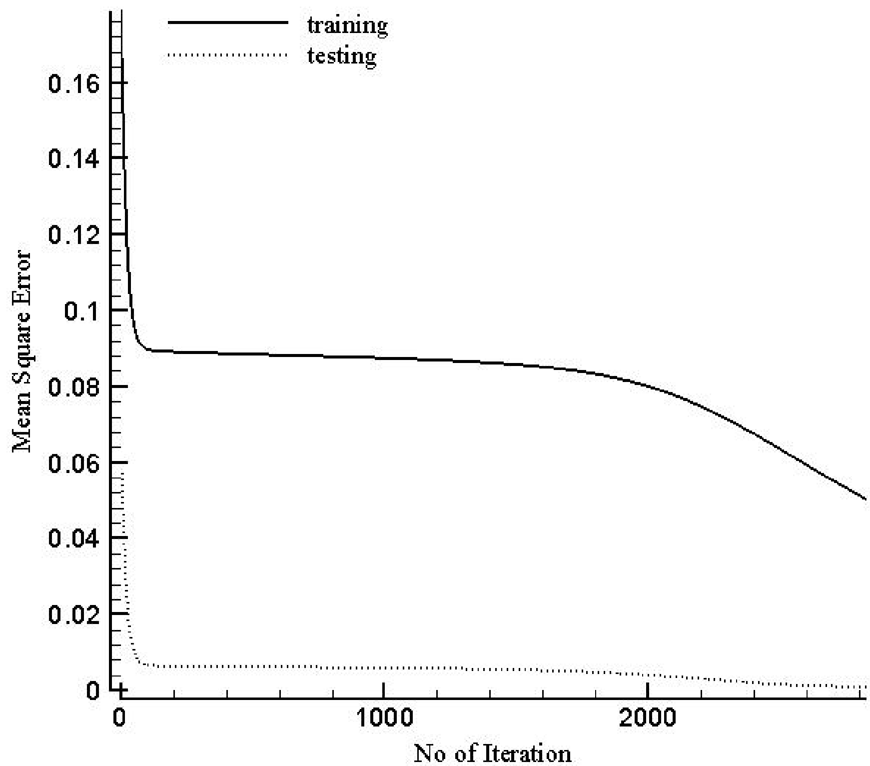

Figure 4: Scattering of predicted results with chip thickness