QRMAES2007-National Conference on Quality, Reliability and Maintainability aspect in Engineering systems (2007), NIT Hamirpur

Simultaneous prediction of surface roughness and drill flank wear in drilling a mild steel work piece using ANN

S. S. Panda, Lecturer in the Department of Mechanical Engineering,
National Institute of Technology Rourkela, Rourkela-769008, India,
sspanda@nitrkl.ac.in , sspanda@iitg.ernet.in, Ph No-91-9853485749

Extended Abstract:

The reason for acquiring the drill wear state information is to enhance the predictive capability to allow the machine operator to schedule tool change or regrind just in time to avoid underused or overuse of tools. On the other hand, drill wear affects the ability of the hole cutting system to satisfy specified performance characteristics, such as hole roundness, centering, burr formation at drill exit, and surface finish.

The literature is rich with relevant studies. Noori-Khajavi and Komanduri (1995) developed a model for online tool wear monitoring of a drilling operation and observed that only one signal is sufficient to monitor the tool wear. EI-Wardany et al. (1996) used the vibration signal in predicting different type of drill wear. Lee et al. (1998) used the abductive network modeling for drilling process for predicting the tool life, tool wear and surface roughness. Tso and Xiaoli (1999) used the regression model for monitoring the tool wear based on current signals of spindle motor and feed motor. Lin and Ting (1995) studied the effect of tool wear as well as other cutting parameters on the current force signals, and established the relationship between the force signals and tool wear as well as the other cutting parameters.

In the present work cutting forces, vibration signals and chip thickness with others cutting process parameters (drill diameter, spindle speed, feed rate) have been used for on-line assessment of drill flank wear as well as hole roughness of the drilled hole surface. A multi input and multi output back propagation neural network (BPNN) model has been trained for subsequent monitoring of the maximum flank wear of the drill and the average surface roughness (CLA) of drilled hole in drilling of a mild steel work piece.

Experiment conducted in a radial drilling machine. Mild steel as work piece and high speed steel as drill are used to conduct the experiment along with different sensors attachment. Back propagation neural network architectures, prepared using various combination of input parameter such as spindle speed, feed rate, drill diameter, thrust force, torque, feed vibration, radial vibration and chip thickness for simultaneous prediction of drilled hole roughness and

the flank wear of the drill. The normalized data sets in the range 0.1 to 0.9 are used for training the network. Splitting of experimental data sample into training set, testing set and validation set is done on basis of result reported by Kearns (1996).Large number of neural network architecture has been tried with different combination of number of neurons in the hidden layers, learning rate (η) and momentum coefficient (α).

BPNN is tested with two output variable i.e. surface roughness and flank wear. It can be observed from the table 1 that maximum error predicted by both the validating (surface roughness and flank wear) sample has been averaged out and the mean of %age error is reported.

Table 1 Network architecture for BPNN with two outputs

η	α	Iteration	MSE training	MSE testing	Maximum % error of roughness	Maximum % error of flank wear	Mean % average error	Architecture L-M-N
0.1	0.9	6240	0.00024	0.000493	8.554	9.167243	8.860622	8-3-2
0.3	0.7	7084	0.000252	0.000437	8.279	6.158454	7.218727	
0.9	0.1	375	0.000422	0.000976	9.0981	8.616391	8.857246	
0.1	0.1	19811	0.000283	0.000539	6.652	6.455174	6.553587	**8-5-2**
0.7	**0.9**	**5465**	**0.000091**	**0.000362**	**7.44663**	**5.497016**	**6.471823**	
0.9	0.1	6321	0.000223	0.000384	8.83257	-8.547045	8.689808	
0.9	0.7	3177	0.000206	0.000369	7.37947	-7.835835	7.607653	8-8-2
0.1	0.7	19021	0.000236	0.000411	6.95711	-8.204795	7.580953	
0.3	0.3	20370	0.00023	0.000405	7.59947	-7.612494	7.605982	
0.5	0.1	20244	0.000204	0.000397	8.111375	-6.505143	7.308259	8-12-2
0.7	0.5	7048	0.000214	0.000396	6.733649	-6.29127	6.51246	
0.3	0.5	19900	0.000323	0.000449	8.082713	7.852634	7.967674	

Reference

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 & Manufacture 35:795–815.

EI-Wardany T.I., Goa D., Elbestawi M.A. (1996), Tool condition monitoring in drilling using vibration signature analysis International Journal of Machine Tool & Manufacture 36 (6) 687–711.

Lee B.Y., Liu H.S., Tarng Y.S. (1998), Modeling and optimization of drilling process, Journal of Material Processing Technology (74) 149–157.

Tso S.K., Xiaoli L. (1999), Drill wear monitoring based on current signals, Journal of Wear (231) 172–178.

Lin S.C., Ting C.J. (1995), Tool wear monitoring in drilling using force signals, International Journal of Machine Tool & Manufacture (180) 53–60.

Kearns, M. (1996), A bound on error cross validation using the approximation and estimation rates with consequences for training-test split, Advances in neural information processing systems (8) 183-189.