A Neuro-Genetic Approach for Multi-Objective Optimization of Process Variables in Drilling

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***Abstract*—The present paper focuses on a hybrid neural network coupled with controlled elitist type genetic algorithm for multi-response optimization in a traditional drilling process. Firstly a Back Propagation Neural Network (BPNN) structure is developed to predict the output responses like flank wear, thrust force and torque and then the multi-objective genetic algorithm (MOGA) is applied for minimizing the responses obtained from the BPNN to have an optimized cutting condition. The proposed approach is found efficient and robust as the simulated results have a close match with the experimental data.**

***Index Terms*—Drill Wear, Process Modeling, Back-Propagation Neural Network, Multi-Objective Genetic Algorithm, Optimization.**

I. INTRODUCTION

Your Product quality of the work piece has been an issue of primary concern to the manufacturing industry. From the various factors that affect the product quality, tool wear is the most important one. Drilling is one of the conventional material removal processes which almost cover 40% of all machining processes. Drill wear is categorized as flank wear, chisel wear, corner wear and crater wear. Flank wear is the most important of all. Drill wear has a negative effect on the surface finish and dimensional accuracy of the work piece. Generally thrust force and torque are developed in the operations which try to unclamp the job and create vibrations. As the flank wear increases, for the same set of speed and feed the forces will increase which is not desired at all. For long these cutting parameters which give minimum flank wear with minimum thrust force and torque are decided by experience and the optimum parameters could not be guaranteed and taken for granted. Now-a-days software packages have come out for help.

Researchers have tried implementing software and found out outstanding results and the literature is quite rich. Thrust force and torque were established as a function of material hardness, average flank wear and feed rate by Cook et.al [1]. Jalai et.al [2] observed that when machining the last hole, the thrust force and torque are 50% larger than while machining the first hole. These results show that both thrust force and torque increases as the drill wear increases. Lin and Ting [3] studied the effect of drill wear as well as other cutting parameters on current force signals and established the relationship between the force signals and drill wear with other cutting parameters. Lianyu Fua et.al [4] used input impedance to predict the drill breakages in micro drilling promptly and accurately by recognising the wave form. Neural networks and fuzzy sets have been used for the prediction of surface finish and tool life while optimisation for various goals is carried out using real coded GA by D.K. Ojha et.al [5] in a turning operation.

A neuro-fuzzy model was developed by S.S.Roy[6] for a drilling operation which can produce optimal knowledge base of fuzzy system for predicting tool life, torque and thrust force in drilling operation. In a work by P. Bhattacharyya et.al [7] combinations of signal processing techniques for real-time estimation of tool wear in face milling using cutting force signals are presented. Optimization techniques of GA like Multi-objective genetic algorithm (MOGA) is applied for reactive power optimization by P.Aruna Jeyanthy[8] effectively.

In latest researches in this field S.N.Joshi et.al [9] integrated finite element method (FEM) with neural networks and GA to optimize the process parameters in a electric discharge machining (EDM). B.Latha et.al [10] used multi-objective optimization of genetic algorithm with neural networks to optimise the process parameters of a composite drilling. All these research activities are done in sophisticated computer numerical controlled (CNC) machines.

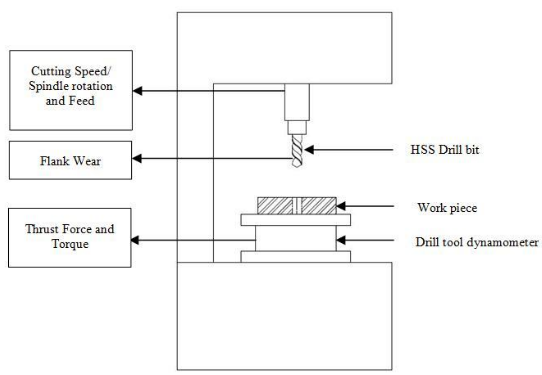
II. SCOPE

The present work focuses on a multi-response optimization model of drilling on the traditional machines as well as on sophisticated machines where generally job shop type or batch type production takes place. Here an offline procedure of drill wear monitoring is adopted where the method is based on acquisition of process variables and establishing a relationship between tool wear and process variables instead of an online method which will be an expensive deal for above mentioned type of production units. The input parameters like cutting speed and feed influences most to the flank wear along with the thrust force and torque keeping other cutting conditions constant. For minimizing the flank wear with thrust force and torque simultaneously by GA, a function or equation is needed which describes a relationship between the input variables and the responses. Here we select the Back propagation artificial neural network model to work as the objective function for GA. Thus an integrated approach is formed to model the process and optimise the cutting parameters.

III. EXPERIMENTATION

A. Experimental Setup, Materials and Test Conditions

The experiment was carried out on a Batliboi BVR-5 radial drilling machine. The work piece material was a mild steel plate and the drill depth was maintained at 30 mm for each experimental run. The drill bit used was a HSS twist drill of 10 mm diameter. The mechanical properties of the work piece and the chemical composition of the twist drill are given on the table I and table II respectively. A Kistler 9272 drill tool dynamometer was used to have the readings of the thrust force and torque developed. Flank wear of the drill was measured using a Mitutoyo Tool Makers Microscope TM-500. The schematic diagram of the experimental arrangement is shown in Fig. 1.



Figugre 1 Schematic view of the experimental setup.

TABLE I. MECHANICAL PROPERTIES FOR MILD STEEL

Ultimate Tensile Stress (MN/m^2)	Yield Stress (MN/m^2)	Density (Kg/m^3)	Elongation (%)	Hardness (VHN)
300	170	7850	42	140

TABLE II .CHEMICAL COMPOSITION FOR HSS (% WEIGHT)

W	Cr	V	Co	Mo	C	Hardness (BHN)
18	4.3	1.1	5	0.65	0.75	290

To acquire data for various cutting speeds and feeds also considering the availability of spindle speeds in the radial drill BVR5, spindle rotations were selected as 250, 355, 500, 710, 1000 and 1400 rpm for a 10mm drill, and feed rate were selected as 0.10, 0.15, 0.34, 0.50 and 0.70 mm/rev. The other parameters that affect flank wear, including tool hardness, tool geometry, work piece hardness, temperature and rigidity of machine tool were assumed as constant in the different set of test and the number of holes ranged from 1 to 30. 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 cutting edges.

B. Pre-Processing the Data

As there is a considerable variation in the input data range in terms of numerical value, it will be convenient to bring the data to a uniform scale for input to any soft computing methods and this is been achieved by normalising, using (1) for a range varying from 0.1 to 0.9.

$$y = 0.1 + 0.8\left(\frac{x - x_{min}}{x_{max} - x_{min}}\right) \quad (1)$$

Where, x = actual value,

x_{max}= maximum value of x,

x_{min}= minimum value of x,

y= normalized value corresponding to x.

The normalised value of data selected for training and validation are tabulated on table III.

IV. MODELING NEURAL NETWORK

Artificial neural network is an accepted tool for predicting the output when the input and output are not related linearly or relations are complex. An ANN may be seen as a black box which contains hierarchical sets of neurons (e.g., processing elements) producing outputs for certain inputs. Each processing element consists of data collection, processing the data and sending the results to the relevant consequent element. The whole process may be viewed in terms of the inputs, weights, the summation function, and the activation function.

The training and test data have been prepared using experimental patterns. In this study, we have 30 patterns obtained from the experiments. Among them, 16 patterns have been selected by considering two factors and four levels in the Design of Experiments (DOE) and used as the training data and rest are divided equally and randomly as validation and testing data.

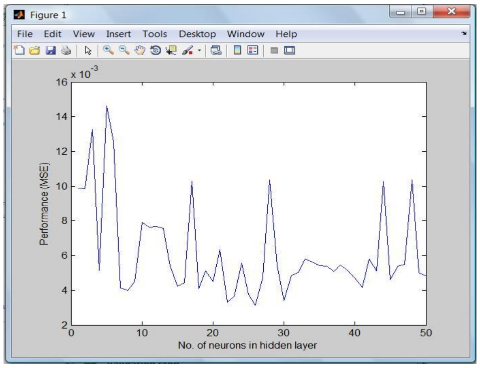


Figure 2. Variation of Mean Squared Error with ANN Architecture.

Selection of transfer function and learning function along with the number of hidden neurons affects the quality of prediction. As there are two input variables namely spindle speed and feed there will be two neurons in the input layer so also to predict three output variables namely flank wear, thrust force and torque the output layer will consist three neurons.

For selecting the best size of the hidden layer, a code was developed in Matlab-R2010b with normalised inputs and outputs considering minimum Mean Squared Error (MSE) criteria for a set of hidden neuron numbers. The performances of network i.e. MSE is plotted against number of neurons in a graph shown in Fig. 2.

It is clear from the graph that the network having 26 neurons in the hidden layer [2-26-3] is having minimum MSE. So the network [2-26-3] is selected for further analysis. From the different transfer functions, 'logsig' and 'purelin' is selected for transfer function to the hidden and output layer respectively whereas 'trainlm' is selected as training function by trial and error method. The schematic view of the developed network is shown in Fig. 3. The simulation results of the test data are tabulated in table IV.

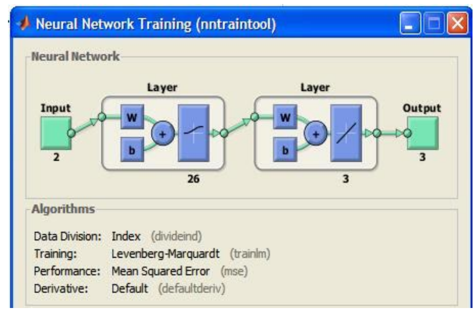


Figure 3. View of Neural Network used.

TABLE III. TRAINING AND VALIDATION DATASET

Data Group	Experiment No.	Real data					Normalized data				
		Spindle speed (rpm)	Feed (mm/rev)	Flank wear (mm)	Thrust force (N)	Torque (N-m)	Spindle speed	Feed	Flank wear	Thrust force	Torque
Training	1	250	0.1	0.14	3800	62.7	0.1	0.1	0.1	0.614	0.543
	2	250	0.34	0.19	4105	74.5	0.1	0.42	0.35	0.728	0.811
	3	250	0.5	0.2	4150	75.8	0.1	0.633	0.4	0.745	0.841
	4	250	0.7	0.21	4275	78.4	0.1	0.9	0.45	0.792	0.9
	5	500	0.1	0.2	3570	62	0.274	0.1	0.4	0.528	0.528
	6	500	0.34	0.24	4012	69.7	0.274	0.42	0.6	0.694	0.702
	7	500	0.5	0.25	4315	70.3	0.274	0.633	0.65	0.807	0.716
	8	500	0.7	0.3	4564	75.1	0.274	0.9	0.9	0.9	0.825
	9	1000	0.1	0.15	2425	43.21	0.622	0.1	0.15	0.1	0.1
	10	1000	0.34	0.16	3048	47.7	0.622	0.42	0.2	0.33	0.202
	11	1000	0.5	0.18	3547	51.32	0.622	0.633	0.3	0.520	0.284
	12	1000	0.7	0.18	4021	56.24	0.622	0.9	0.3	0.697	0.396
	13	**1400**	**0.1**	**0.14**	**2523**	**47.72**	**0.9**	**0.1**	**0.1**	**0.137**	**0.203**
	14	1400	0.34	0.16	2773	45.51	0.9	0.42	0.2	0.23	0.152
	15	1400	0.5	0.16	2813	47.24	0.9	0.633	0.2	0.245	0.192
	16	1400	0.7	0.2	2915	48.11	0.9	0.9	0.4	0.283	0.211
Validation	17	355	0.1	0.14	4075	63.75	0.173	0.1	0.1	0.717	0.567
	18	355	0.15	0.18	4105	65.76	0.173	0.167	0.3	0.728	0.613
	19	355	0.34	0.18	4172	69.21	0.173	0.42	0.3	0.753	0.691
	20	710	0.1	0.18	3154	54.65	0.42	0.1	0.3	0.373	0.360
	21	710	0.15	0.19	3290	60.62	0.42	0.167	0.35	0.424	0.496
	22	710	0.34	0.2	3695	64.12	0.42	0.42	0.4	0.575	0.575
	23	1400	0.15	0.14	2615	44.81	0.9	0.167	0.1	0.171	0.136

TABLE IV. NORMALIZED TESTING DATASET

Experiment No.	Spindle Speed	Feed	Flank wear by		Thrust force by		Torque by	
			Experiment	Prediction	Experiment	Prediction	Experiment	Prediction
24	0.1	0.167	0.2	0.1544	0.657	0.6416	0.652	0.6728
25	0.173	0.633	0.5	0.5387	0.760	0.7996	0.758	0.8085
26	0.173	0.9	0.6	0.6361	0.785	0.8213	0.807	0.8634
27	0.274	0.167	0.4	0.3397	0.543	0.5344	0.580	0.5348
28	0.420	0.633	0.4	0.5064	0.650	0.7294	0.634	0.5604
29	0.420	0.9	0.5	0.73	0.737	0.8643	0.669	0.7213
30	0.622	0.167	0.2	0.2198	0.195	0.2172	0.125	0.1985

V. OPTIMIZATION USING GENETIC ALGORITHM

For optimising i.e. minimising the three output responses (flank wear, thrust force and torque), a multi-objective genetic algorithm (MOGA) is applied using MatlabR2010b which uses a controlled Elitist Genetic Algorithm (GA) which is a variant of NSGA-II [11]. An elitist GA always favours individuals with better fitness value (rank). Two options, 'Pareto Fraction' and 'Distance Function' control the elitism. The other critical factors in GA are number of generations and population size. The best suitable values of the Pareto fraction, number of generation and population size could be found as 0.2 (Fig. 4), 50(Fig. 5) and 95 (Fig. 6) respectively. The criteria for selecting these sizes are the minimum average response which is calculated in fashion mentioned below:

Let, output of GA= F,

Where, 'F' is a matrix of size [n×3],

'n' is the number solutions in each output,

and, '3' is the number of output responses.

If, $$F = \begin{bmatrix} P_1 & Q_1 & R_1 \\ P_2 & Q_2 & R_2 \\ \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots \\ P_n & Q_n & R_n \end{bmatrix}$$

Where, P is the flank wear in normalised scale,

Q is the thrust force in normalised scale,

R is the torque in normalised scale.

Now the minimum average response (A_R) could be represented as (2).

$$A_R = min\left[\left(\frac{P_1 + Q_1 + R_1}{3}\right), \left(\frac{P_2 + Q_2 + R_2}{3}\right), \dots\dots\dots, \left(\frac{P_n + Q_n + R_n}{3}\right)\right] \quad (2)$$

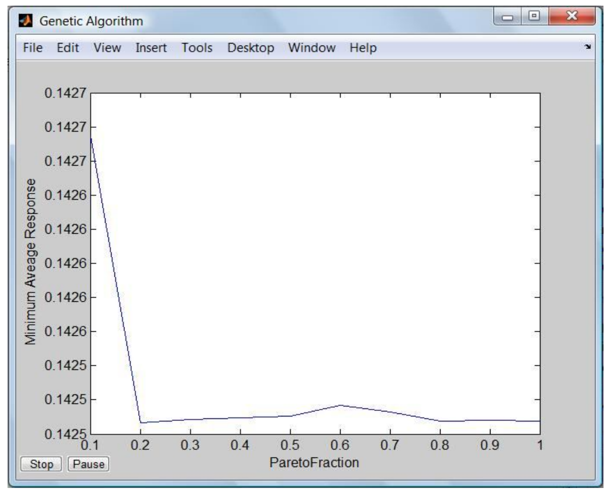


Figure 4. Variation of Minimum Average Response with Pareto Fraction.

After deciding the above factors, the genetic algorithm was simulated using the two type of distance measure function named as *'distance crowding - genotype'* and *'distance crowding - phenotype'*. The optimized results thus obtained are tabulated in table V. The other factors were kept at their default values as available with the GA tool box in MatlabR2010b.

VI. RESULTS AND DISCUSSION

A. Performance of the Artificial Neural Network Model

The result of the neural network tabulated in the table IV is quite satisfactory and acceptable as compared to the experimental data except few noisy data. The variations of those results may be due to insufficient number of training data which in this case is being restricted due to a traditional machine. The performance graph of the network in terms of MSE during training, validation and testing is shown in Fig. 7.

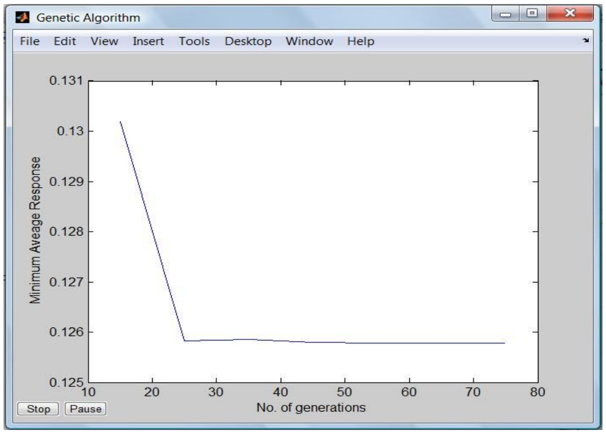


Figure 5. Variation of Minimum Average Response with no. of generation.

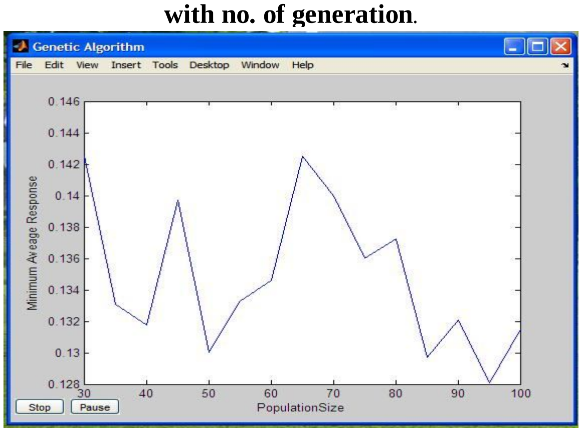


Figure 6. Variation of Minimum Average Response with population size.

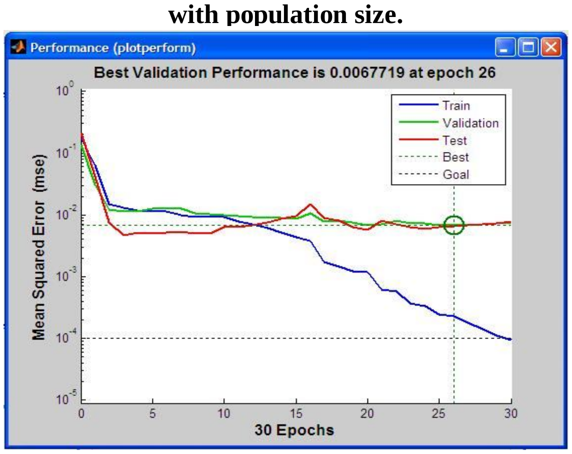


Figure 7 . Performance (MSE) Plot of ANN.

B. Performance of the Multi-Objective Genetic Algorithm

The GA converges to its best suitable minimum value of average response in the selected generation. The minimum value of the response parameters and the respective input parameters are given in table V for both the distance measure functions. It is observed that both results are equally acceptable and matches to our experimental data as in experiment number 13 as in table III.

TABLE V. OUTPUT OF GENETIC ALGORITHM IN NORMALIZED SCALE

Used distance measure function	Optimized input		Predicted output		
	Spindle Speed	Feed	Flank wear	Thrust force	Torque
Distance crowding (phenotype)	0.9	0.1031	0.1279	0.1363	0.1368
Distance crowding (genotype)	0.8999	0.1001	0.1276	0.1362	0.1368

VII. CONCLUSION

The recent work elaborates briefly the modeling of an offline drilling process for minimizing flank wear, thrust force and torque simultaneously and also predicting the same via neural networks for a particular kind of material with a particular type of drill bit and drill size. The network architecture and the parameters are selected carefully by choosing the minimum MSE and in case of GA by minimizing the average responses. The results closely match the experimental data so it can be used for prediction and optimization of the process parameters. By prediction we are able to change the tool as it reaches 0.3 mm flank wear [12] which is the standard for replacing the tool or can continue drilling in case of similar cutting conditions as in this experiment.

The model can be in a more generalised format if more input variables like drill size, type of material by hardness etc could be given and for GA the other default parameters are changed.

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