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Prediction and analysis of multi responses in drilling of EN8 steel under MQL using ANN-Taguchi approach

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ABSTRACT

This work has been done in two phases. In the first phase, the controllable parameters (cutting speeds, feed rates, type of drill tool, cutting fluids) which influence the responses (torque, cutting force, surface roughness, material removal rate, power) in drilling of En8 steel are identified and an Artificial Neural Network (ANN) model has been developed to predict the responses. The developed ANN model has been trained and tested with experimental data of drilling process which is conducted under Minimum Quantity Lubrication (MQL) condition. ANN tested results are closely matched with experimental results. In the second phase, the ANN predicted results are analyzed by performing Taguchi's S/N ratio analysis and optimum combinations of input parameters are determined. Further, the analysis of variance (ANOVA) is employed to find the contribution of input parameters on output parameters. This work is useful in predicting the multi responses while cutting different materials in different processes.

Introduction

In the present era of globalization, manufacturers are facing the challenges of higher productivity, quality and overall economy in the field of manufacturing by machining. To meet the these challenges in a global environment, there is an increasing demand for high material removal rate (MRR) and also longer life and stability of the cutting tools, but high production machining with high cutting speed, feed which generates large amount of heat and temperature at the chip-tool interface and ultimately reduces dimensional accuracy, tool life, surface integrity of the machined component. This temperature needs to be controlled at an optimum level to achieve better surface finish and ensure overall machining economy. The conventional type of cutting fluid systems have been found to become less effective with the increase in cutting velocity and feed when the cutting fluid cannot properly enter into the chip-tool interface to cool and lubricate the interface due to bulk plastic contact of the chip with the tool rake surface. It requires serious concern on the use of cutting fluid, particularly oil-based type cause for pollution of the working environment, water pollution, soil contamination and possible damage of the machine tool slide ways by corrosion [Kelly JF and Cotterell MG (2002)].

The modern industries are therefore looking for possible means of dry (near dry), clean, neat and pollution free machining . Minimum Quantity Lubrication (MQL) refers to the use of cutting fluids of only a minute amount-typically of a flow rate of 50-500 ml/hourwhich is about three to four orders of magnitude lower than the amount commonly used in flood cooling, for example, up to 10 liters of fluid can be dispensed per minute. The concept of MQL, sometimes referred to as 'near dry lubrication' or 'micro lubrication' [Kelly JF and Cotterell MG (2002); Nouari M et al(2003)]. Machining under minimum quantity lubrication (MQL) condition is perceived to yield favorable machining performance over dry or flood cooling condition. Accurate Modeling and Prediction of Surface Roughness by Computer Vision in Turning Operations Using An Adaptive Neuro-Fuzzy Inference System[Chen WC and Tsao CC (1999); Zhao H (1994); Furness RJ et al. (1996)] Performance studies on Oblique Cutting Using Conventional Methods and Neural Networks in [Pirtini M, Lazoglu I (2005); Nouari M et al. (2005); Haan DM et al. (1997)]. Learning Speed of 2-Layer Neural Networks is improved by choosing initial values of the adaptive weights [Nouari M et al. (2003); Basile SA (1993); Yang JL, Chen JC (2001)]. Surface roughness and dimensional deviation cutting forces and vibrations in turning process are studied [Phadke MS (1989)].Neural network based adaptive control is used to optimize the milling Process [Ross PJ (1996); Bagci E and Aykut Ş (2006)].

The literature reveals that little work has been done regarding to the application of Artificial neural networks for prediction of multi-responses in drilling process. This paper focused on development of a neural network model to predict the multi-responses and to study the influence of input parameters on output parameters for determining the optimum input parameters combination using Taguchi method.

Experimental work and data generation

The drilling tests have been carried on En8 steel (Table.1)of size 1000mmx40mmx16mm using standard uncoated and coated HSS tools at different levels of process parameters like cutting speeds (V), feed rates (f), and type of drill tool and type of cutting fluids (MQL with flow rate of 150 ml/hour) according to full factorial Experimental design (Table.3). During machining trials torque and force are measured by the drill tool dynamometer and surface roughness values of hole surface are measured by Talysurf for the different combinations of input parameters (Table.2), this data have been used for training and testing of Neural Network. The experimental setup of Radial drilling machine with MQL provision is shown in Fig.1.

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Figure1 (a) Radial drilling machine

Figure1 (b) Drill Tool dynamometer

Figure 1 (c). Talysurf surface meter

Figure1 (d).En8 steel specimen after drilling

Figure1 (e).Drill bits

Figure1 Experimental setup and drilled work piece

ANN-Taguchi approach

This approach (see Fig.2) consists of two phases. In the first phase an Artificial Neural Network (ANN) model has been developed to predict the responses or output parameters. In the second phase, the ANN predicted results are analyzed by performing Taguchi's S/N ratio analysis.

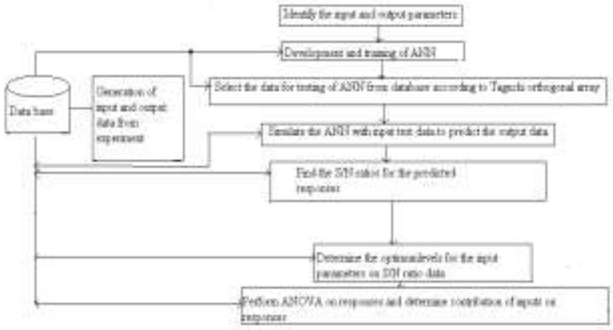

Figure 2 ANN-Taguchi approach

Phase-I: Development of ANN

Steps in the development of ANN are: pre-processing of generated data, ANN modelling, training of ANN, simulation of ANN for prediction of responses

Pre-processing of generated data

In the present study, the input parameters for ANN are cutting speed, feed rate, tool type and condition of cutting fluid, while the output parameters are surface roughness, torque, cutting force, MRR and power. Before input-output dataset are fed to network, pre-processing steps like formation of data patterns and normalization are required on the data obtained from experiments. The input-output dataset are normalized within the range of -1 to +1. Afterwards training and testing pattern vectors are formed, each pattern is formed with an input condition vector (Pi) and the corresponding target(output) vector (Ti), as shown in the below.

P_i = [v, f, tool type, condition of coolant]

T_i = [Torque, cutting force, surface roughness, MRR, Power]

Experiment data of 81 patterns was divided randomly into two categories: training dataset which consist of 75% of the generated data and test dataset which consist of 25% the generated data. Based on this 72 data patterns are considered for training of ANN and 9 data patterns are considered for testing ANN.

ANN modeling

In this work, multilayer back-propagation neural network has been developed for the prediction of responses in drilling of En8. A neural network model has been modeled using MATLAB with four neurons in input layer and five neurons in the output layer as per number of input and output parameters as shown in Fig.3.

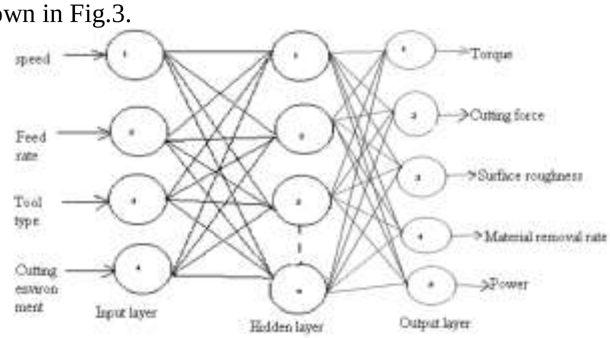

Figure 3. Proposed ANN model

In order to model best network architecture, selection of number of hidden layers and number of neurons in each hidden layer, training algorithms and transfer functions for the input, hidden and output layers are very important issues. The issue of determining the optimum number of hidden neurons is a crucial and complicated is neuronal network modeling. In the case of one hidden layer network, several practical guidelines exist. These include 2n+1, 2n, n\2 where n is the number of input nodes. Lawrence and Fredrick suggested that the number of hidden neurons are (n_1+n_2), where n_1 and n_2 are the number of input and output nodes respectively. The most common approach in determining the number of hidden neurons (nodes) is via trial and error has been used in the present work. Using trial and error method, the suitable transfer functions for input, hidden and output layers are sigmoid, tansig, purelin respectively have been selected.

Training of ANN

The modeled neural network has been trained with training data set using a feed forward back propagation algorithm. The network performs two phases of data flow. First the input information is propagated from the input layer to the output layer and, as a result it produces an output. Then the error signals resulting from the difference between the networks predicted values and the actual values are back propagated from the output layer to the previous layers for them to update their weights accordingly. The updating of weights continues until the network error goal is reached. The number of neurons in the hidden layer is intentionally chosen to start with five neuron and afterwards neurons are added to the hidden layer incrementally. The addition of hidden neurons continues until there is no significant progress in network performance. The performance of the network is evaluated by mean squared error (MSE) between the experimental and the predicted values for every output parameter in respect of training the network as shown in Fig.4.

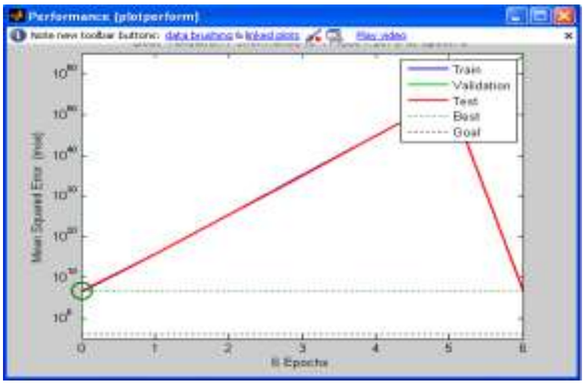

Figure 4. Performance graph

The feedback value from that processing is called the "average error" or "performance". The momentum constant and learning rate used in this model is 0.5 and 0.1 respectively. The maximum number of training epochs that was set is 10,000 and the training error goal was 0.0001. After the training, the actual weight values are stored in a separate file. Finally a best ANN, 4-10-5 has been designed, it consists of four neurons in input layer, ten neurons in hidden layer and five neurons in the output layer.

Simulation of ANN and prediction of responses

The network has been simulated (tested) with the input test data sets that have not been used in training of the network (raw untrained data) but are in the same range as those used for training. This enables to test the network with regard to its capability of interpolation regarding unseen data.

The output parameter values obtained from the simulation of neural network for the corresponding input are shown in Table 4.

Phase-2: Taguchi's Signal-to-Noise ratios analysis on predicted responses

In the second phase, S/N ratios are calculated and are listed in the Table.5, by using Eq.1 and Eq.2, for responses obtained from neural network (Table 4) and the optimum combination of input parameters are determined based on the quality requirement such as Smaller-The-Better and Larger-The-Better.

i) *Smaller-The-Better*

In drilling process, the response characteristics such as cutting force, torque, surface roughness and power should be low for better quality, hence smaller S/N ratios are considered for these parameters.

Signal-To-Noise ratio for the Smaller-The-Better

S/N = -10 *log (mean square of the response)

$$S/N = -10\log_{10}\left(\frac{\sum y^2}{n}\right) \qquad (1)$$

ii) Larger-The-Better

In drilling process, the response characteristic like material removal rate should be high for better quality. Hence larger S/N ratios are considered for this kind of parameters.

Signal-To-Noise ratio for Larger-the-better

S/N = -10*log (mean square of the inverse of the response)

$$S/N = -10\log_{10}\left(\frac{1}{n}\sum\frac{1}{y^2}\right) \qquad (2)$$

Analysis of Variance (ANOVA) on predicted results

ANOVA has been performed using MINITAB software to determine the influence of input parameter on the output parameters and ANOVA results are shown in the Table 6.

Results and concluding remarks

In the present paper, the developed ANN model has been trained and tested with experimental data of drilling process. ANN tested results are compared again with experimental results (see Fig5). The validity of this approach for parameter optimization is well established. The concluding remarks as follows.

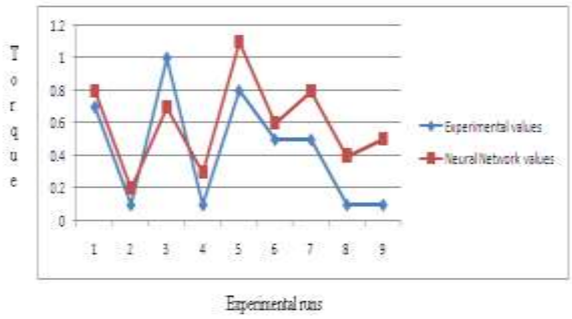

Figure 5(a) Torque Vs Experimental runs

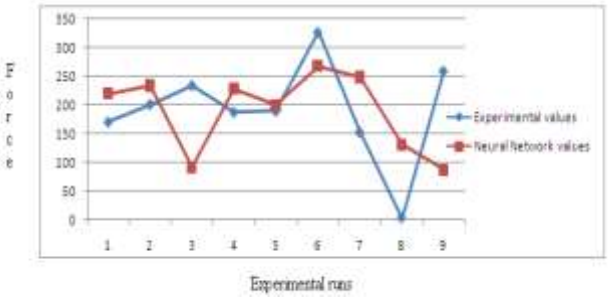

Figure 5(b) Cutting force Vs Experimental runs

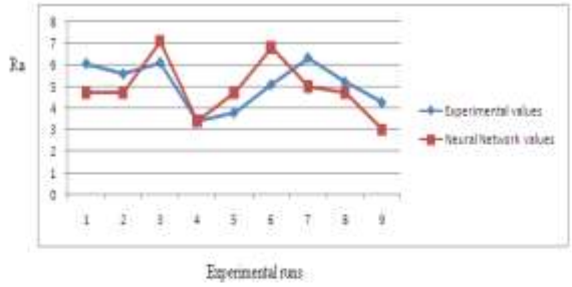

Figure 5(c) Surface roughness Vs Experimental runs

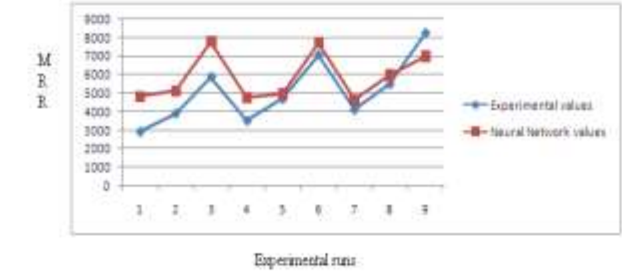

Figure 5(d).Material removal rate Vs Experimental runs

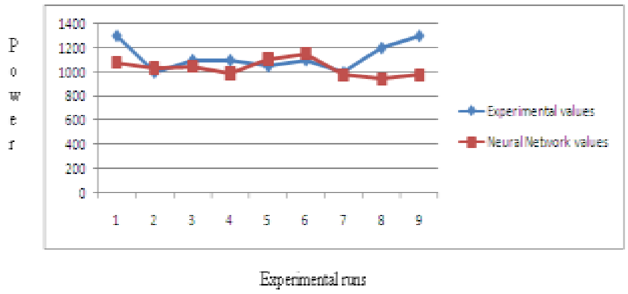

Figure5(e).Power Vs Experimental runs

Figure5.Graphs between experimental and network result values

From ANN

The developed ANN model has been trained and tested with experimental data of drilling process. ANN tested results are closely matched with experimental results (refer Fig.5)

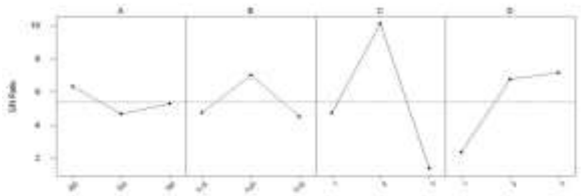

Figure 6(a) S/N ratio for torque

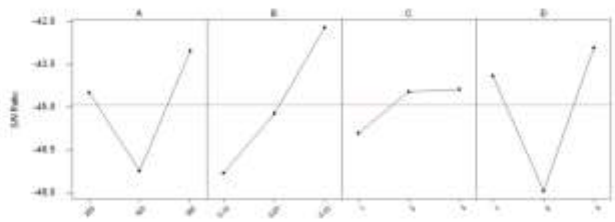

Figure 6(b) S/N ratio for force

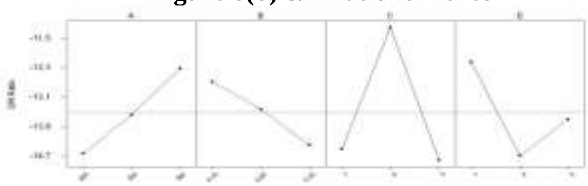

Figure 6(c).S/N ratio for surface roughness

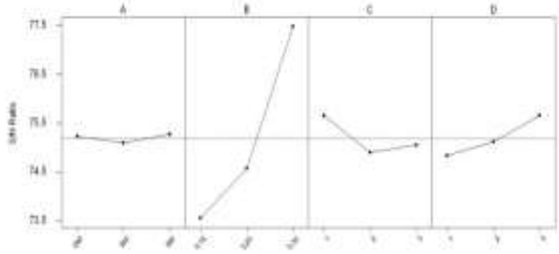

Figure 6(d) S/N ratio for material removal rate

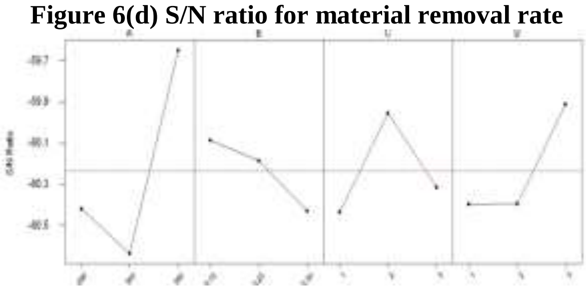

Figure 6(e) S/N ratio for power

Figure 6 Main effects plot for S/N ratio

From S/N ratio Analysis

The best input parameter combination for getting a best individual response is identified by Taguchi's S/N ratio analysis (Table 7 & Fig.6)

- For lower torque, the optimum parameters are v 250rpm,fe 0.2mm/rev ,tool type TiN , vegetable oil environment
- For lower cutting force, the optimum parameters are v 350 rpm,fe 0.3mm/rev, tool type TiAlN, cutting fluid environment.
- For lower surface roughness, the optimum parameters are v 350rpm,fe 0.15mm/rev,tool type TiN ,dry environment
- For higher material removal rate, the optimum parameters are v 350rpm,fe 0.3mm/rev,tool type HSS,dry environment.
- For lower power requirements optimum parameters are v 350rpm,fe 0.15mm/rev,tool type TiN ,cutting fluid environment

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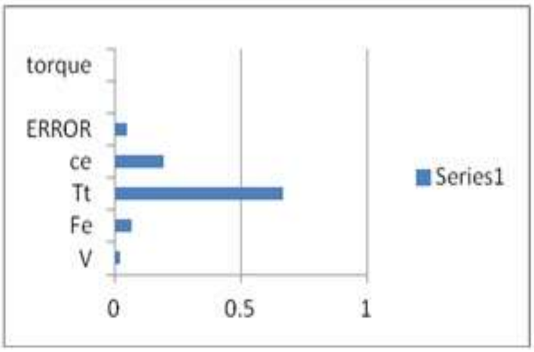

Figure 7(a) Torque

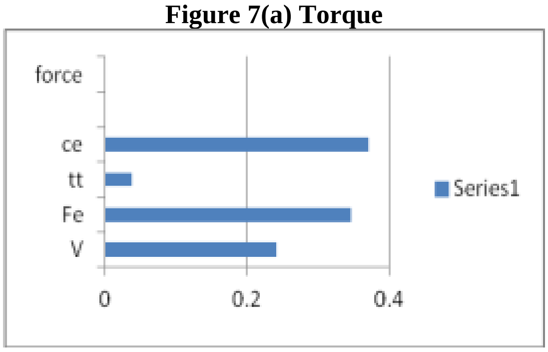

Figure 7(b) Cutting force

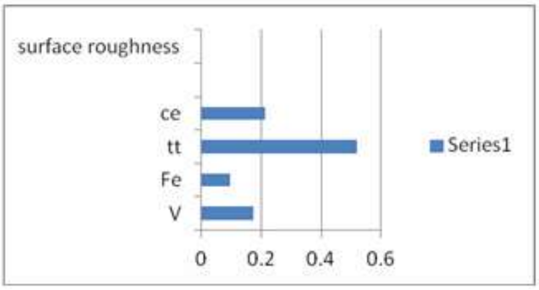

Figure7(c) Surface roughness

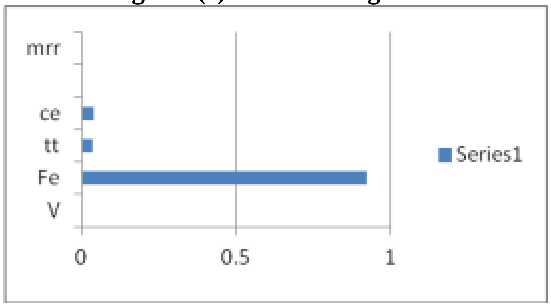

Figure7 (d) Material removal rate

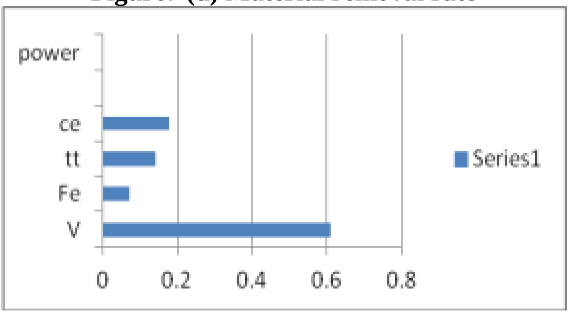

Figure 7(e) Power

Figure 7 Percentage contribution charts for outputs from ANOVA

From ANOVA

The contributions of input parameters on individual response are identified by ANOVA. The influence of input parameters on output parameters is shown in Table 6 and Fig.7.

- Surface finish and torque are mostly affected by types of drill tools
- Cutting force is mostly affected by cutting environment
- Material removal rate is mostly affected by feed rate
- Power is mostly affected by cutting speed

This work is useful to predict the responses in wide range of input data and it can be further extended to other processes for cutting different materials. It may helps in reducing the experimental cost while modeling of complex machining process.

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Table 1.mechanical properties

Poisson's ratio	0.3
Elastic modulus (Gpa)	202
Hardness(HB)	243
Density(x1000kg/m^3)	7.845
Tensile strength (MPa)	518.8
Yield strength (MPa)	353.4
Elongation (%)	30.2
Reduction in area (%)	57.2
Impact strength (J)	44.3

Table 2 Process parameters and their levels

levels	Process parameters			
	Cutting speed(rpm)	**Feed(mm\rev)**	**Drill Tool type**	**Cutting environments**
1	250	0.15	Uncoated Hss	Dry
2	300	0.2	Hss+TiN	Vegetable Oil(MQL)
3	350	0.3	Hss+TiAlN	Cutting Fluid(MQL)

Table.3.Full factorial design and experimental data

Sl no	speed (rpm)	Feed (mm/rev)	Tool Type	Cutting environment	Torque (kgm)	Fc (kgf)	Ra (µm)	MRR (mm³/min)	Power (watt)
1	250	0.15	HSS	Dry	0.7	170	6.05	2943.75	1300
2	250	0.15	HSS	Vegoil	0.5	107	6.13	2943.75	1050
3	250	0.15	HSS	Cutfluid	0.2	188	6.28	2943.75	1100
4	250	0.15	TIN	Dry	0.1	182	5.52	2943.75	1050
5	250	0.15	TIN	Vegoil	0.1	153	5.96	2943.75	800
.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.
73	350	0.3	HSS	Dry	0.2	346	3.06	8242.5	1400
74	350	0.3	HSS	Vegoil	0.1	150	3.95	8242.5	1300
75	350	0.3	HSS	Cutfluid	0.2	298	1.37	8242.5	1350
75	350	0.2	HSS	Cutfluid	0.1	2.41	5.2	5495	1200
77	350	0.3	TIN	Vegoil	0.6	293	3.75	8242.5	1250
78	350	0.3	TIN	Cutfluid	0.7	295	6.23	8242.5	1200
79	350	0.3	TIAlN	Dry	0.8	269	5.57	8242.5	1150
80	350	0.3	TIAlN	Vegoil	0.1	236	3.93	8242.5	1200
81	350	0.3	TIAlN	Cutfluid	0.3	262	6.45	8242.5	1250

Table 4 shows Testing Data set and predicted output

S no	speed (rpm)	Feed (mm/rev)	Tool Type	Cutting environment	Torque (kgm)	Force (kgf)	Ra (µm)	MRR (mm³/min)	Power (watt)
1	250	0.15	HSS	DRY	0.8	220.4	4.7	4820.6	1076
2	250	0.2	TIN	VEGOIL	0.2	233.8	4.7	5132.1	1029.4
3	250	0.3	TIALN	CUTFLUID	0.7	91.8	7.1	7772	1043.7
4	300	0.15	TIN	CUTFLUID	0.3	228.7	3.4	4783.4	987
5	300	0.2	TIALN	DRY	1.1	199.7	4.7	4978.3	1100.3
6	300	0.3	HSS	VEGOIL	0.6	267.6	6.8	7714.6	1147.3
7	350	0.15	TIALN	VEGOIL	0.8	248.4	5	4664.2	970.7
8	350	0.2	HSS	CUTFLUID	0.4	130.7	4.7	5975.2	941.7
9	350	0.3	TIN	DRY	0.5	87.4	3	6982.6	969.3

Table.5 S/N ratios for test data

S no	Speed (rpm)	Feed (mm/rev)	Tool type	Cutting environment	S/N ratios				
					Toque	**Force**	**Surface roughness**	**MRR**	**Power**
1	250	0.15	HSS	DRY	1.9382	-46.8642	-13.442	73.662	-60.6362
2	250	0.2	TIN	VEGOIL	13.979	-47.3769	-13.442	74.2059	-60.2517
3	250	0.3	TIALN	CUTFLUID	3.098	-39.2569	-17.0252	77.8107	-60.3715
4	300	0.15	TIN	CUTFLUID	10.458	-47.1853	-10.6296	73.5947	-59.8863
5	300	0.2	TIALN	DRY	-0.8279	-46.0076	-13.442	73.9416	-60.8302
6	300	0.3	HSS	VEGOIL	4.437	-48.5497	-16.6502	77.7463	-61.1935
7	350	0.15	TIALN	VEGOIL	1.9382	-47.903	-13.9794	73.3755	-59.7417
8	350	0.2	HSS	CUTFLUID	7.9588	-42.3255	-13.442	75.527	-59.4783
9	350	0.3	TIN	DRY	6.0206	-38.8302	-9.5424	76.8803	-59.7292

Table 6.ANOVA results for the output parameters in the drilling of En8 steel

Parameters	DOF	SS	MS	P-VALUE
TORQUE				
V	2	4.168338	2.084169223	0.023808
Fe	2	11.51085	5.755424463	0.065746
Tt	2	116.8362	58.41811266	0.667324
ce	2	33.85326	16.92662995	0.193357
error		8.713012	4.35650616	0.049765
FORCE				
V	2	27.61801	13.80900738	0.242069
Fe	2	39.54027	19.77013505	0.346566
tt	2	4.427695	2.213847701	0.038808
ce	2	42.50551	21.25275721	0.372556
Surface roughness				
v	2	8.057851547	4.028925773	0.173306
fe	2	4.470439387	2.235219693	0.096149
tt	2	24.06534051	12.03267025	0.517591
ce	2	9.90123936	4.95061968	0.212953
mrr				
v	2	0.046430409	0.023215204	0.001715
fe	2	25.04473768	12.52236884	0.925101
tt	2	0.949899469	0.474949734	0.035087
ce	2	1.031356976	0.515678488	0.038096
power				
v	2	1.614071227	0.807035613	0.609953
fe	2	0.187474667	0.093737333	0.070846
tt	2	0.374116027	0.187058013	0.141377
ce	2	0.47055962	0.23527981	0.177823

Table.7. Response table for output parameters

Response table for Torque				
level	V	Fe	TT	CE
1	6.338533	4.778	4.778	2.376967
2	4.6889	7.036767	10.15253	6.784867
3	5.305867	4.518533	1.402767	5.1646
Response table for Force				
1	-44.4993	-47.3175	-45.9131	-43.9007
2	-47.2475	-45.2367	-44.4641	-47.9432
3	-43.0196	-42.2123	-44.3892	-42.9226
Response table for Surface Roughness				
1	-14.6364	-12.6837	-14.5114	-12.1421
2	-13.5739	-13.442	-11.2047	-14.6905
3	-12.3213	-14.4059	-14.8155	-13.6989
Response table for MRR				
1	75.2262	73.54407	75.6451	74.82797
2	75.0942	74.55817	74.89363	75.10923
3	75.26093	77.4791	75.0426	75.64413
Response table for Power				
1	-60.4198	-60.0881	-60.436	-60.3985
2	-60.6367	-60.1867	-59.9557	-60.3956
3	-59.6497	-60.4314	-60.3145	-59.912