Modelling And Analysis Of Machining Characteristics Of En-8 Steel In Drilling Process

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***Abstract*— En-8 steel is used for forging automobile components like bolts, rods, crank shafts, automobile axle beams, connecting rod etc. when this material is subjected to machining operations, the criterion of minimization of lubricant or coolant is used for pollution free working environment and also to reduce the possible damages of the machine tool slide ways by corrosion. In this, work is divided in three phases. In the first phase the controllable parameters (Spindle speed, feed rates, type of drill tool types (Uncoated HSS, Coated TiN, Coated TiALN), cutting environment (dry, vegetable oil, cutting fluid) 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 to develop to predict the responses. The developed ANN model is to be trained and tested with experimental data of drilling process. ANN tested results are compared with experimental results. In the second phase, the ANN predicted results are analyzed by performing Taguchi's S/N ratio analysis. In the third phase, the analysis of variance (ANOVA) is employed to analyze the effect of input parameters on output parameters. This work is useful in predicting the responses while cutting En8 steel materials in drilling processes.**

***Keywords*— Neural Approach, Taguchi, ANOVA, Torque, cutting force, Power, MRR and Surface roughness.**

I. INTRODUCTION

In the present aera 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 and generates large amount of heat and temperature at the chip-tool interface which ultimately reduces dimensional accuracy, tool life and 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 types and methods of application of cutting fluid have been found to become less effective with the increase in cutting velocity and fee 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 [1].

The modern industries are therefore looking for possible means of dry (near dry), clean, neat and pollution free machining and grinding. 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/hour-which 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 Minimum Quantity Lubrication (MQL), sometimes referred to as 'near dry lubrication' or 'micro lubrication' [1,2].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" [3, 4, 9] Performance studies on Oblique Cutting Using Conventional Methods and Neural Networks in [8,11,12]. Learning Speed of 2-Layer Neural Networks is improved by choosing initial values of the adaptive weights"[2,6,21]. Surface roughness and dimensional deviation cutting forces and vibrations in turning process are studied [22].Neural network based adaptive control and is used to optimize the milling Process [17, 18]. Essentially, traditional experimental design procedures are too complicated and not easy to use. A large number of experimental works have to be carried out when the number of process parameters increases. To solve this problem, the Taguchi method uses a special design of orthogonal arrays to study the entire parameter space with only a small number of experiments [15, 16]. In the present work, Taguchi method is combined with ANN for effective data representation in wide range with low experimental cost, to predict responses in drilling of En8.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 2 Issue 11, November - 2013

TABLE1

MECHANICAL PROPERTIES OF En8 Steel

Poisson's ratio	0.3
Elastic modulus (Gpa)	202
Hardness(HB)	243
Density(1000kg/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

2.0 EXPERIMENTAL WORK AND DATA GENERATION

The drilling tests have been carried on En8 steel of size 1000mmx40mmx16mm using standard uncoated and coated HSS tools at different levels of Input parameters like spindle speeds (V), feed rates (f), and type of drill tool (tt) and type of cutting environment (ce) as shown in (Table 2) according to full factorial Experimental design. During machining trials torque and cutting force are measured by the drill tool dynamometer and surface roughness values of drilled hole surface are measured by Talysurfmeter. The original experimental setup is shown in Figure 1(a).This data have been used for training and testing of Neural Network.

TABLE2
INPUT PARAMETERS AND THEIR LEVELS

Levels	*Process parameters*			
	Spindle speed(v) (rpm)	*Feed (f) (mm\rev)*	*Tool types(tt)*	*Cutting environments (ce)*
1	*250*	*0.15*	*Uncoated Hss*	*Dry*
2	*300*	*0.2*	*Hss +TiN*	*Vegetable Oil*
3	*350*	*0.3*	*Hss+ TiAlN*	*Cutting Fluid*

Figure 1(a): Radial drilling machine

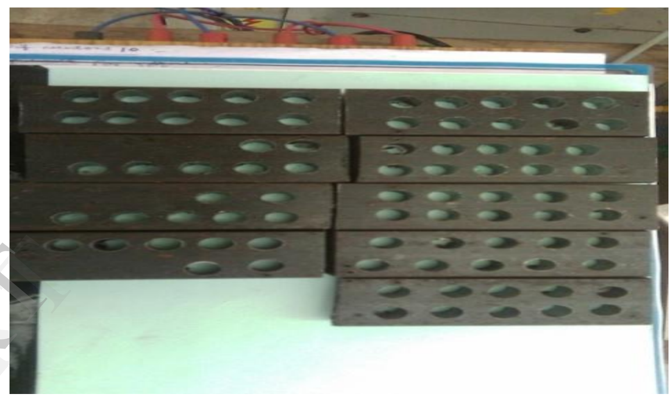

Figure 1(b): EN8 Steel Specimen after Drilling

3.0 PHASE -1: ANN APPROACH

This approach 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.

3.1 Designing of the Neural Network Architecture

A Generalized feed forward networks is used for developing ANN model. These networks are used for a generalization of the MLP (Multi-layer perceptron) such that connections can jump over one or more layers. The network has four inputs of Spindle speed, feed, tool type, Cutting Environment and five outputs of Torque, Cutting Force, Power, surface roughness and MRR. The size of hidden layer is two of the most important considerations when solving actual problems using multi-layer feed forward network. Two hidden layer was adopted for the present model. Attempts have been made to study the network performance with a different number of hidden neurons. A number of networks are constructed, each of them is trained separately, and the best network is selected based on the accuracy of the predictions in the testing phase. The general network is supposed to be 4-n-n-5, which implies 4 neurons in the input layer, n neurons in the two hidden layer and two neurons in the output layer. Using a neural network package developed in Neuro Solution 6.0, different network configurations with different number of hidden neurons were trained, and their performance is checked. The performance of the different networks is checked with the means square error and best network is selected which has the lowest mean square error among the different networks. In this study 4-8-8-5 network was selected which has the minimum mean square error.

The optimal neural network architecture 4-8-8-5 was used in **Neuro Solutions 6.0** and shown in Figure 2. The network consists of one input, two hidden and one output layer. The input layer has four neurons, two hidden layer has eight, eight neurons and output layer has five neurons respectively. Since Torque, Cutting Force, Power, surface roughness and MRR prediction in terms of spindle speed, feed, tool type, Cutting Environment was the main interest in this research. Neurons in the input layer corresponding to the spindle speed, feed, tool type, Cutting Environment, the output layer corresponds to Torque, Cutting Force, Power, surface roughness and MRR. The input layer, hidden and output layer will apply a Tangent activation function.

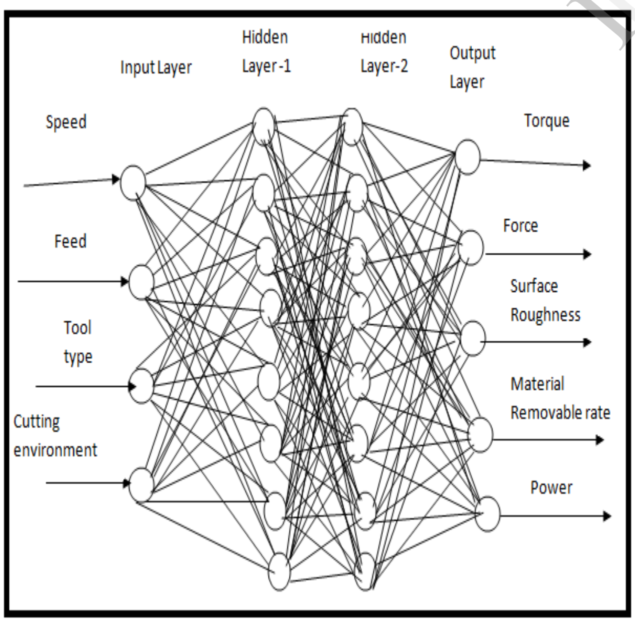

Figure 2:.Proposed ANN model

3.2. Generation of Train and Test Data

In creating the ANN models, a new data set obtained from 81 data sets is utilized. The new data set consists of 81analysis results and corresponds to the combination of five most important process parameters affecting the Torque, Cutting Force, Power, surface roughness and MRR. The seventy data set used for training of the developed model. The eleven data set used for testing of the developed model. The training data and test data were found by analyses which were done by **Neuro Solutions 6.0** software.

3.3 Network Training

For calculation of weight variables, often referred to as network training, the weights are given quasi-random, intelligently chosen initial values. They are then iteratively updated until convergence to the certain values using the gradient descent method. Gradient descent method updates weights so as to minimize the mean square error (MSE) between the network prediction and training data set as shown below:

$$W_{ij}^{new} = W_{ij}^{old} + \Delta W_{ij}$$

$$\Delta W_{ij} = -\eta \sum_{t=1}^{k} \alpha^{k-t} \frac{\partial E}{\partial W_{ij}} out_j$$

Where E is the MSE and out_j is the j^{th} neuron output. η is the learning rate [step size, momentum] parameter, controlling the stability and rate of convergence of the network. The learning rate [step size 1.0, momentum 1] selected and the training process takes place on an Intel(R) premium(R) D CPU 3.4 GHz 3.39GHz processor PC for 1,000 training iterations. The MSE was obtained after training of the network with 1000 epochs and multiple training (three times) as 2.41E-06, depicts the average MSE with standard deviation boundaries for three runs and convergence of MSE with epochs. The comparison between ANN model output and experimental output for training data sets are presented. In Order to judge the ability and efficiency of the model to predict the Torque, Cutting Force, Power, surface roughness and MRR values percentage deviation (Ø) and the average percentage deviation ($\bar{\phi}$) were used and defined as

$$\varphi_i = \frac{|Experimental - Predicted|}{Experimental} \times 100\%$$

Where φ_i = percentage deviation of single sample data

$$\bar{\varphi} = \frac{\sum_{i=1}^{n} \varphi_i}{n}$$

Where $\bar{\varphi}$ = average percentage deviation of all sample data and n= size of the sample data.

3.4 Neural Network Testing

The ANN predicted results are in good agreement with experimental results and the network can be used for testing of the network. Hence the testing data sets are applied which were used in the training process. The results predicted by the network were compared with the experimental results.

Figure 3(a-e): COMPARISON GRAPHS FOR TESTING DATA SET AND PREDICTED OUTPUT

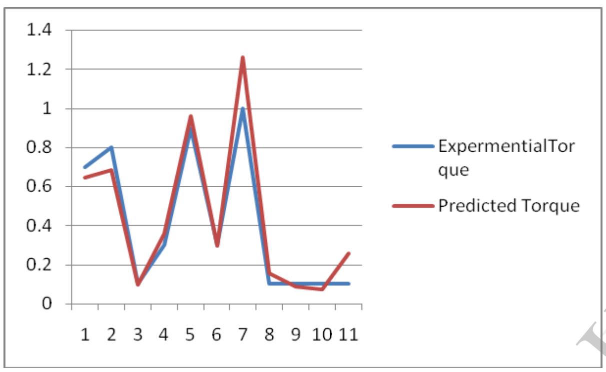

Figure 3(a): Experimental Torque Vs predicted Torque

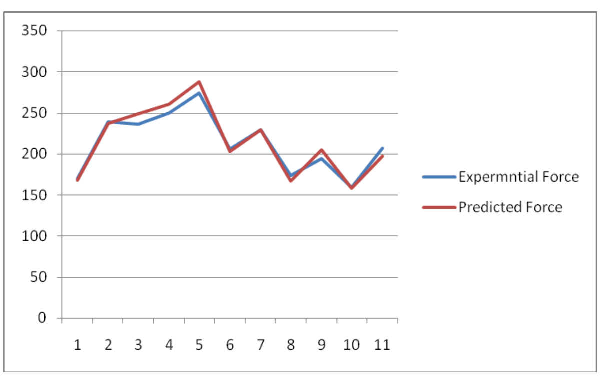

Figure 3(b): Experimental force Vs predicted force

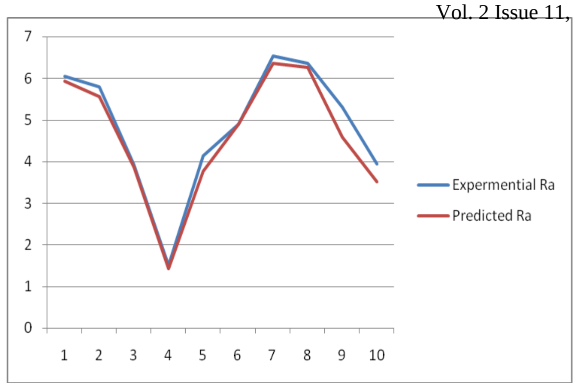

Figure 3(c): Experimental Ra Vs predicted Ra

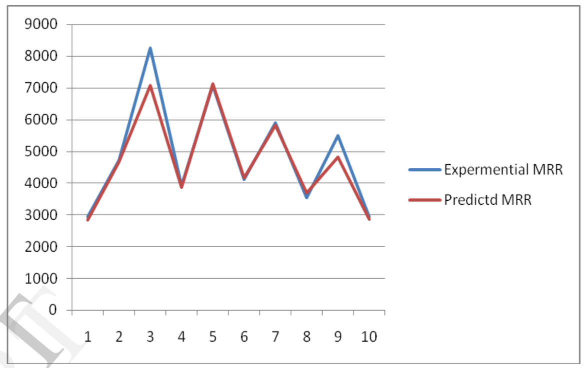

Figure 3(d): Experimental MRR Vs predicted MRR

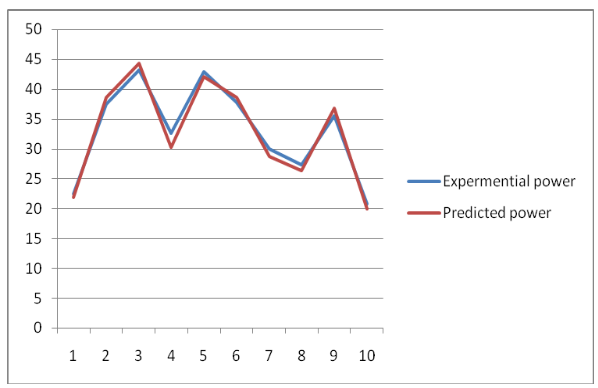

Figure 3(e): Experimental power Vs predicted Power

4.0 PHASE-2:TAGUCHI'SSIGNAL-TO-NOISE RATIO ANALYSIS

In the second phase, In Taguchi method the term "signal" represents the desirable value and "noise" represents the undesirable value. The objective of using S/N ratio is measure of performance to develop products and processes insensitive to noise factors .The S/N ratio indicates the degree of the predictable performance of a product or process in the presence of noise factors. Process parameters setting with highest S/N ratio always yield the optimum quality with minimum variance. The S/N ratio for each parameter level is calculated by averaging the S/N ratios obtained when the parameter is maintained at that level and the optimum combination of input parameters are determined based on the quality requirement such as Smaller-The-Better, Larger-The-Better.

i) Smaller-The-Better

In drilling process, the response characteristics such as cutting force, torque and surface roughness 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 X log (mean square of the response)

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

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 the Larger-the-better

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

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

Table 3 (a-e): Response table for Signal to Noise ratios

.

3(a) Response table for Signal to Noise ratios (Smaller is better) for Torque

Level	v	f	tt	ce
1	7.669	9.706	9.706	8.345
2	9.320	13.979	20.00	10.630
3	15.340	8.674	2.653	13.333
Delta	7.641	5.306	17.347	4.988
Rank	2	3	1	4

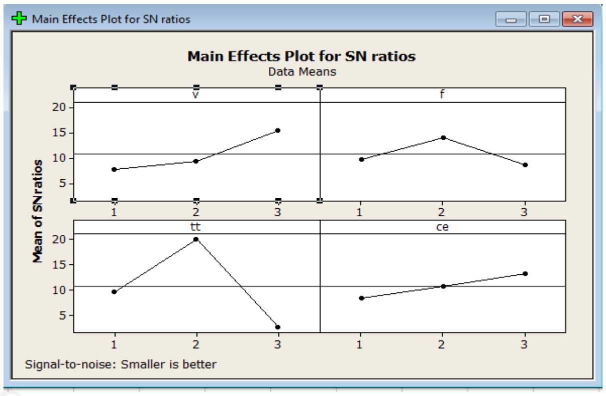

Figure 4(a): Mean S/N graph for Torque.

3(b) Response table for Signal to Noise ratios (Smaller is better) for Force

Level	v	f	tt	Ce
1	-46.02	-44.56	-47.51	-46.13
2	-47.09	-46.41	-46.51	-46.66
3	-46.51	-48.65	-45.52	-46.82
Delta	1.07	4.09	2.00	0.69
Rank	3	1	2	4

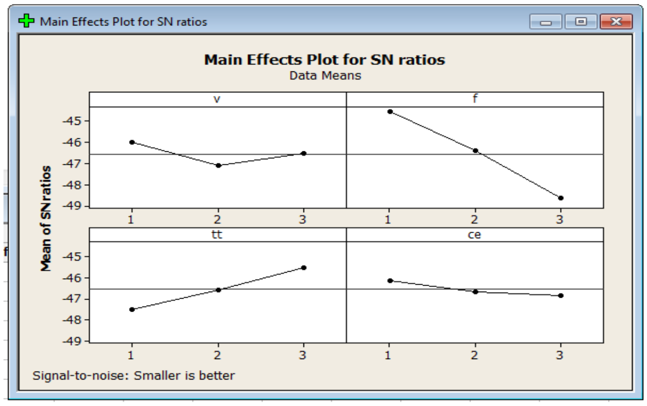

Figure 4(b): Mean S/N graph for Force

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 2 Issue 11, November - 2013

3(c) Response table for Signal to Noise ratios (Smaller is better) for surface roughness

Level	v	f	tt	Ce
1	-15.42	-14.09	-14.69	-13.27
2	-12.11	-13.62	-12.72	-15.02
3	-14.30	-14.14	-14.43	-13.55
Delta	3.31	0.52	1.97	1.74
Rank	1	4	2	3

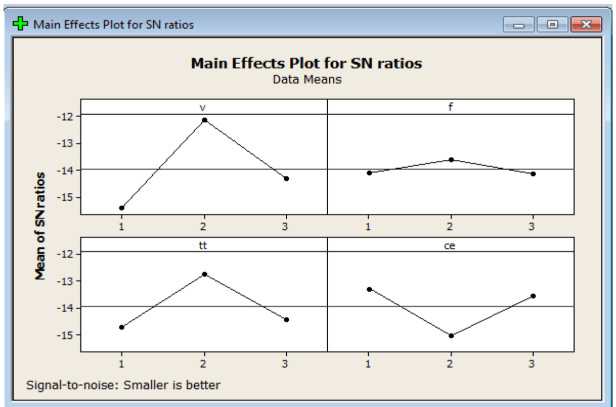

Figure 4(c): S/N ratio for surface roughness

3(d) Response table for Signal to Noise ratios (Larger is better) for material removal rate

Level	v	f	tt	ce
1	71.87	72.73	73.08	72.17
2	75.09	73.08	74.28	74.45
3	72.83	73.98	72.43	73.17
Delta	3.22	1.25	1.85	2.28
Rank	1	4	3	2

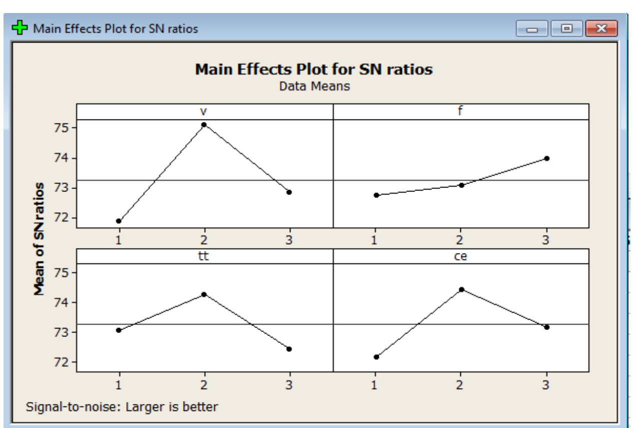

Figure 4(d): S/N ratio for material removal rate

3(e) Response table for Signal to Noise ratios (Smaller is better) for Power

Level	v	f	tt	ce
1	-28.39	-28.44	-31.39	-30.01
2	-31.01	-30.25	-30.43	-30.51
3	-31.78	-32.49	-29.36	-30.66
Delta	3.39	4.05	2.03	0.65
Rank	2	1	3	4

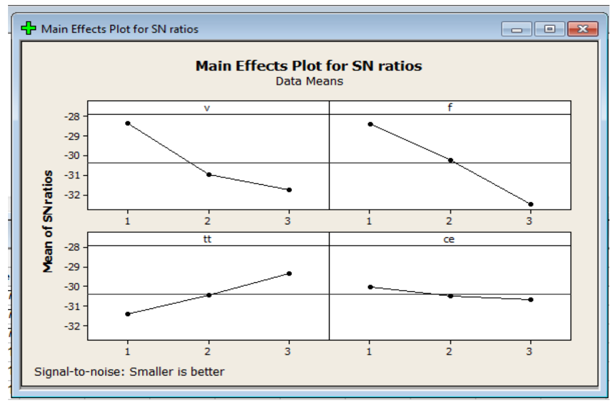

Figure 4(e): S/N ratio for Power

5.0 PHASE- 3: ANALYSIS OF VARIANCE (ANOVA) ON PREDICTED RESULT

ANOVA can be useful for determining the influence of input parameter on the output parameters.

TABLE 4 (a-e): ANOVA for predicted results

4(a) Results of ANOVA for S/N ratio of the Torque

Source	DF	Seq SS	Adj SS	Adj MS	F	P
V	2	0.38691	0.38691	0.19346	2.96	0.058
F	2	0.48099	0.48099	0.24049	3.68	0.000
tt	2	1.56617	1.56617	0.78309	12.00	0.030
ce	2	0.03062	0.03062	0.01531	0.23	0.792
Error	72	4.70000	4.70000	0.06528		
Total	80	7.16469				

Table 4(a) shows that the results of analysis of variance (ANOVA) for the S/N ratio of the Torque. The ANOVA table indicates that all the cutting parameters are significant F calculated values is more than the table value; F (0.05, 2,72)= 3.134 at 95% confidence level Also it is indicated that the most significant parameter is feed followed by tool type, Spindle speed and cutting environment is insignificant.

4(b) Results of ANOVA for S/N ratio of the cutting force

Source	DF	Seq SS	Adj SS	AdjMS	F	P
V	2	383	383	192	0.21	0.000
F	2	131139	131139	65569	71.73	0.810
tt	2	8528	8528	4264	4.66	0.012
ce	2	3306	3306	1653	1.81	0.171
Error	72	65819	65819	914		
Total	80	209175				

Table 4(b) shows that the results of analysis of variance (ANOVA) for the S/N ratio of the cutting force. The ANOVA table indicates that all the cutting parameters are significant F calculated values is more than the table value; F (0.05, 2,72)= 3.134 at 95% confidence level Also it is indicated that the most significant parameter is spindle speed followed by tool type, cutting environment and feed is insignificant.

4(c) Results of ANOVA for S/N ratio of the surface roughness

Source	DF	Seq SS	Adj SS	AdjMS	F	P
v	2	16.608	16.608	8.304	3.25	0.045
f	2	2.552	2.552	1.276	0.50	0.000
tt	2	2.543	2.543	1.272	0.50	0.610
ce	2	6.527	6.527	3.263	1.28	0.286
Error	72	184.244	184.244	2.559		
Total	80	212.474				

Table 4(c) shows that the results of analysis of variance (ANOVA) for the S/N ratio of the surface roughness. The ANOVA table indicates that all the cutting parameters are significant F calculated values is more than the table value; F (0.05, 2,72)= 3.134 at 95% confidence level Also it is indicated that the most significant parameter is feed followed by cutting environment ,spindle sped and cutting environment is insignificant.

4(d) Results of ANOVA for S/N ratio of the material removal rate

Source	DF	Seq SS	Adj SS	Adj MS	F	P
v	2	3909276	39092763	1954638	434.56	0.000
f	2	1748765	17487659 9	8743829	1943.9 7	0.002
tt	2	0	0	0	0.00	0.004
ce	2	0	0	0	0.00	0.057
Error	72	3238503	3238503	44979		
Total	80	2172078				

Table 4(d) shows that the results of analysis of variance (ANOVA) for the S/N ratio of the material remove rate. The ANOVA table indicates that all the cutting parameters are significant F calculated values is more than the table value; F (0.05, 2,72)= 3.134 at 95% confidence level Also it is indicated that the most significant parameter is spindle speed followed by feed ,tool type and cutting environment is insignificant.

4(e) Results of ANOVA for S/N ratio of the Power

Source	DF	Seq SS	Adj SS	Adj MS	F	P
v	2	2140.19	2140.19	1070.09	44.52	0.000
f	2	3258.95	3258.95	1629.48	67.80	0.003
tt	2	198.10	198.10	99.05	4.12	0.020
ce	2	84.68	84.68	42.34	1.76	0.179
Error	72	1730.51	1730.51	24.03		
Total	80	7412.42				

Table 4(e) shows that the results of analysis of variance (ANOVA) for the S/N ratio of the power. The ANOVA table indicates that all the cutting parameters are significant F calculated values is more than the table value; F (0.05, ,72)= 3.134 at 95% confidence level Also it is indicated that the most significant parameter is spindle speed followed by feed, tool type and cutting environment is insignificant.

6.0: RESULTS

i) ANN Results:

The developed ANN model has been trained and tested with experimental data of drilling process.

ANN tested results are closely matched with experimental results.

ii) Taguchi S/N ratio Analysis

The best input parameter combination for getting a best individual response is identified by Taguchi's S/N ratio analysis.

- For low torque, the optimum parameter values are v 350rpm,fe 0.2mm/rev ,tool type TiN ,cutting environment of cutting fluid.
- For producing low value of cutting force, the optimum parameter values are v 250, fe 0.15, tool type TiAlN, cutting environment of dry condition.
- For producing low value of surface roughness, the optimum parameter values are v 300, fe 0.2, tool type TiN, cutting environment of dry condition.
- For high value of material removal rate, the optimum parameter values are v 350, fe 0.3, tool type HSS, cutting environment of dry condition.
- For low value of power, the optimum parameter values are v 300, fe 0.15, tool type HSS+TIALN, cutting environment of Vegetable Oil.

iii) Results from ANOVA

- The contributions of input parameters on individual response are identified by ANOVA.
- From ANOVA(i)torque is mostly affected by feed(ii)cutting force is mostly affected by spindle speed(iii) surface roughness is mostly affected by feed (iv) material removal rate is mostly affected by spindle speed (v) power is mostly affected by spindle speed.

7.0 CONCLUSIONS

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. The validity of this approach for parameter optimization is well established. This work is used to predict the responses in wide range of input data and it can further be extended for other process while cutting different materials. Finally ANN is integrated with Taguchi method for improving its performance. From ANOVA torque is mostly affected by feed ,cutting force is mostly affected by spindle speed, surface roughness is mostly affected by feed ,material removal rate is mostly affected by spindle speed and power is mostly affected by spindle speed.

FUTURE SCOPE

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

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