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Particle Size Effects of the Boric Acid in the Machining of AISI 1040 STEEL

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A B S T R A C T

Importance propels have been made in understanding the conduct of designing materials while machining at higher cutting conditions from useful and hypothetical points of view. Material expulsion measures includes age of high cutting powers and temperatures. Utilization of legitimate grease is a significant viewpoint to diminish slicing powers and temperatures and to improve surface completion. In the current work, the impact of nano measured strong grease (boric corrosive) in the machining is examined. To examine the impact of strong grease molecule size different turning tests are directed on AISI 1040 steel utilizing tungsten carbide apparatus embeds. Varieties in cutting powers, apparatus temperatures and surface unpleasantness are concentrated to evaluate the impact of molecule size and weight level of boric corrosive. Tentatively acquired outcomes are utilized in the preparation of neural organization and to build up the ANN model. The multilayer feed forward neural organizations can incredibly accommodating in catching the tentatively noticed strong grease conduct. The neural organizations sum up all alone. The organization can anticipate yield esteems for the given obscure and never seen inputs. This may decrease the expense of investigations. Relapse model was additionally evolved to catch the strong oil molecule size conduct. Examination of neural organization model with relapse model is additionally done. The outcomes uncover that the anticipated cutting powers, instrument temperatures and surface harshness with test brings about completely tried cases show that the blunder is under 4% for ANN model and under 8% for relapse model. From this, we can presume that ANN model gives better forecast esteems with less error%..

Keywords: Electric field, Conductor, Insulator, Coulomb's law, Static electricity

1. Introduction

1.1 Introduction to Metal Cutting: Parameters of Machining

1. Cutting speed
2. Feed
3. Depth of cut

1.2 Machining Operations

There are several operations, which can be done on lathe. Some of there are:

Turning, Step turning, Drilling, Reaming, Boring

1.3.1 Rough and Finish turning:

Unpleasant turning is the term utilized for the cycle of hefty stock evacuation to save machining time. In this cycle, further cut is taken and heavier feed is

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utilized. Notwithstanding, inflexibility of the machine ought to be considered prior to settling on the feed rate and profundity of cut. The surface created will, clearly unpleasant. Barely removable stock ought to be left over the work piece for completing cut. A sharp edged weighty turning device with a solid forefront is utilized in this activity so it is sufficiently able to take profound cuts and is equipped for bearing the hefty cutting powers.

When the bigger piece of the abundance materials has been eliminated through unpleasant turning, it is trailed by Finish turning activity to carry the work to current measure and give a fine surface completion on it. The measure of overabundance material to be taken out through this activity is less and the more modest profundity of cut is utilized and the heavier device is supplanted by a get done with turning apparatus.

1.3.2 Surface unpleasantness of machining surfaces:

The nature of surface is regularly of most extreme significance for the interface working of machine parts. For moving surfaces (running sliding fit), the completion influences both grating and wear if they are greased up. On account of finding surfaces, the completion likewise influences change and impedance fits, for if the surfaces are unpleasant, the territory of commitment might be decreased and correspondingly debilitated.

1.3.3 Reasons for the surface harshness:

The feed checks or edges by the cutting instrument and the sections of developed edge shed on the work surface in cycle of chip arrangement. Surface completion can be improved by lessening the stature of the feed edges and the size of the developed edge.

1.4 Methods of machining measures

In view of the application different kinds of cutting cycles are utilized in the businesses. They are:

- Dry cutting cycle

- Wet cutting cycle

1.4.1 Dry cutting

Dry cutting is a machining strategy wherein no grease or coolant is utilized during the machining time frame. In this strategy, the surface completion got is low where as the temperatures and warmth created is extremely high at the device work interface and the instrument wear is high bringing about lesser apparatus life.

1.4.2 Wet cutting

To conquer the challenges in dry cutting, cutting liquids (greases/coolants) are utilized which diminishes the temperatures and coefficient of erosion between instrument work interface just as apparatus chip interface in this manner bringing about better surface completion and more device life. This sort of machining measure is known as wet cutting.

1.4.2.1 Types of cutting fluids

- Liquids
- Solids
- Gases

1.4.2.2 Purpose of cutting fluids

- Reduce friction
- Transfer heat
- Carry away contaminants & chips
- Protect tool against wear
- Prevent corrosion

1.4.3 Advantages of dry machining over wet machining

Though dry cutting has the above disadvantages, it is preferred for the following reasons:

- Dry cutting reduces environmental pollution caused since cutting fluids.
- Dry cutting is cost effective compared to wet cutting.
- No extra effect is required to maintain clean lubricant in the machine thus reducing the machine parts as well as the labour on it.

1.3.1 Rough and Finish turning:

Unpleasant turning is the term utilized for the cycle of hefty stock evacuation to save machining time. In this cycle, further cut is taken and heavier feed is utilized. Notwithstanding, unbending nature of the machine ought to be considered prior to settling on the feed rate and profundity of cut. The surface delivered will, clearly harsh. Barely removable stock ought to be left over the work piece for completing cut. A sharp edged substantial turning device with a solid front line is utilized in this activity so it is sufficiently able to take profound cuts and is equipped for bearing the weighty cutting powers.

When the bigger piece of the overabundance materials has been eliminated through harsh turning, it is trailed by Finish turning activity to carry the work to current estimate and give a fine surface completion on it. The measure of abundance material to be eliminated through this activity is less and the more modest profundity of cut is utilized and the heavier instrument is supplanted by a get done with turning apparatus.

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2. Literature Review

2.1 Literature Review Regarding the Metal Cutting

Vamsi Krishna pasam et al investigated the performance of the boric acid as the solid lubricant in the machining of hardened steel. Varied the size of the particle in the micron range and tested its performance by mixing it with SAE 40 oil. The results were stated to improve the machining performance with decrease in the particle size of boric acid.*Kabir et al* analyzed a green particulate-fluid lubricant that is produced by mixing two environmentally benign components- canola oil and boric acid powder to study the behavior of the sliding surfaces. The boric acid used was around 100 to 350 microns which was mixed in Canola oil in different weight percentages from 3.5 to 21%. The results were stated to improve the machining performance with increase in particle size.

Sumaiya, Islama, Mohammad Kamruzzamanb suggested the minimum quantity lubrication method to combine the advantages of both dry machining and wet machining. Minimum quantity lubrication (MQL) refers to the use of cutting fluids of only a minute amount typically of a flow rate of 50 to 500 ml/hour, which is an about three to four order of magnitude less than the amount commonly used in flood cooling condition. This would not only reduce the environmental hazards but also reduce the operating costs of the machining process.

Dhar et al. used the minimum quantity lubrication technique in turning process of medium carbon steel and concluded that, in some cases, a mixture of air and soluble oil has been shown to be better than the overhead flooding application of soluble oil. The review of the literature suggests that minimum quantity lubrication provides several benefits in machining. Therefore, it appears that MQL, if properly employed, not only provides environment friendliness but can also improve the machinability characteristics.

2.2 Literature Review Regarding the ANN In Metal Cutting

Tugrul Ozel, Yigit Karpat, utilizes neural network modeling to predict surface roughness and tool flank wear over the machining time for variety of cutting conditions in finish hard turning. Regression models are also developed to capture the process parameters. Trained neural network models were used in predicting the surface roughness and tool flank wear for other cutting conditions. A comparison of neural networks model with regression models is also carried out. *Dejan Tanikic, Miodrag Manic, Drgon mancic*, showed the possibility of implementation of artificial intelligence based systems in metal cutting process. Modeling of cutting process was performed using experimentally obtained data and artificial intelligence based approach (ANNs and Neuro fuzzy systems). For some unknown values of input, system can predict some output parameters of interest. *Mr. Harshit K.Dave, Dr. Keyur P.Desai, Dr. Harit K.Raval* conducted experiments on Electro discharge machine using copper tool and MS plate work piece. Material removal rate and Surface roughness are calculated for various combinations of current and tool diameter. Predictions of the response variables are made using Regression analysis and ANN techniques. The values obtained by both the methods are compared with the experimental values of the response variables to decide about the nearness of the predictions with the experimental values. The percentage error found in ANN model range from -1.71% to 4.48%, while the same obtained through regression equations range from 10.87% to 12%. It is found that the artificial neural network predicts better than the regression analysis.*E.O. Ezugwu, D.A. Fadare, J. Bonney, R.B. Da Silva, W.F. Sales* developed an artificial neural network model for the analysis and prediction of the relationship between cutting and process parameters during high-speed turning of nickel-based, inconel 718, alloy. The input parameters of the ANN model are the cutting parameters: speed, feed, depth of cut, cutting time and coolant pressure. The output parameters of the model are seven process parameters measured during the machining trials, namely cutting force, feed force, spindle motor power consumption, surface roughness, average flank wear, maximum flank wear and nose wear. The multilayer network with two hidden layers having 10 'tangent sigmoid' neurons trained with Levenberg-Marquardt algorithm combined with Bayesian regularization was found to be the optimum network for the model developed in this study. A very good performance of the neural network, in terms of agreement with experimental data, was achieved. *U.Esme, A.Sagbas and F.Kahraman* were used two techniques, namely factorial design and neural network for modeling and predicting the surface roughness of AISI 4340 steel. Surface roughness was taken as a response variable measured after wire erosion discharge machining (WEDM). The mathematical relation between the work piece and surface roughness and WEDM cutting parameters were established by regression analysis method. This mathematical model may be used in estimating the surface roughness without performing any experiments. Finally, predicted values of surface roughness by techniques, NN and regression analysis, were compared with the experimental values and their closeness with the experimental values determined. Results show that, NN is good alternative to empirical modeling based on full factorial design.

A.John presin kumar and D.Kingsly jeba singh used neural networks in prediction of wear loss quantities of A390 aluminium alloy has been studied in the present work. The material is subjected to dry sliding wear test using pin-on-disc apparatus at room conditions. Effects of load, sliding speed and time have been investigated by using artificial neural networks. The experimental results were trained in an ANNs program and the results were compared with experimental values. It is observed that the experimental results coincided with ANN results.

Bahaa Ibraheem Kazem, Nihad F.H. Zangana designed and implemented an effective neural network model for turning process identification as well as a neural network controller to track a desired vibration level of the turning machine. Multilayer perceptron neural network architecture with Levenburg Marquardt algorithm has been utilized to train the turning process identifier. The vibration signal obtained by the experimental work has been to train a neural network for identification and control of the turning process.

H.Soliemanimehr, M.J. Nategh, S. Amini developed an artificial neural network for prediction of aluminum work pieces surface roughness in ultrasonic vibration assisted turning (UAT). Tool wear as the main cause of surface roughness was also investigated. ANN was trained through experimental data obtained on the basis of full factorial design of experiments. It was illustrated that multilayer perceptron neural network could efficiently model the surface roughness as the response of the network, with an error less than ten percent. The performance of the trained network was verified by further experiments. From the above literature survey, one can observe the importance of artificial neural networks in the metal cutting process. Thus, the present investigation analyzes the influence of boric acid particle size in Nano dimensions and solid volume fraction on the proposed lubricant performance in machining of hardened steel. The tool forces, tool temperatures & surface roughness were taken as the parameters. The experimental behavior was applied to the artificial neural networks and observed the generalization capability. Two input parameters and five output parameters were used in the ANN model. The experimental behavior was also applied to the Regression model. The artificial neural networks results were validated with regression analysis.

3. Experimentation

3.1 Flow chart

In the accompanying figure 3.1, it has been indicated that the stream diagram speaking to the system of directing tests. Analyses have been directed under dry cutting, oil cutting and utilizing combination of SAE 40 oil with boric corrosive to examine the device powers, apparatus temperatures and surface unpleasantness in turning.The cutting velocity, feed rate and profundity of cut are kept steady and consequently the precious stone sizes are diminished slowly alongside changing the rates of boric corrosive to be blended in SAE 40 oil as demonstrated in stream outline and the cycle boundaries are tried.

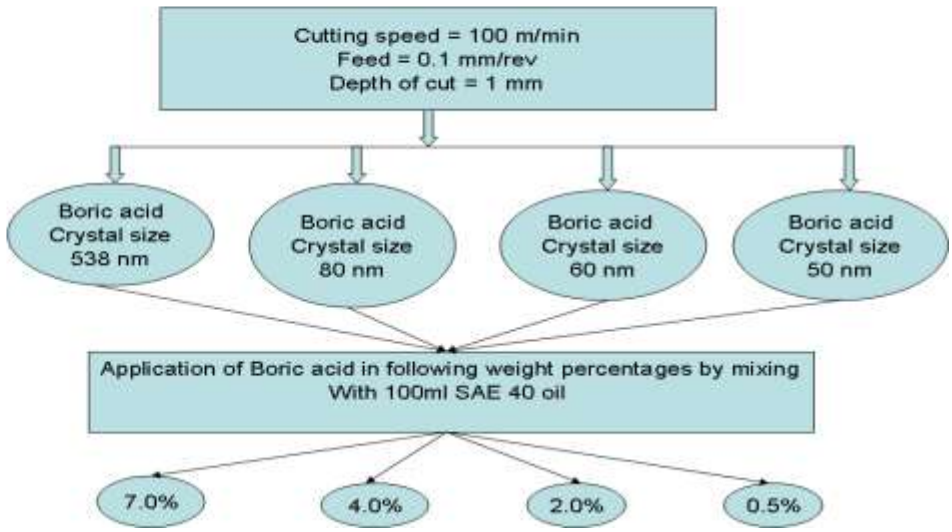

Figure 3.1: Flow chart representing the methodology of conducting experiments

3.2 Machining conditions

The table 4.1 represents machining conditions, which are applied while conducting experiments. The liquid lubricant SAE 40 oil is mixed with the solid lubricant and is used as carrying medium. The cutting conditions (Cutting speed, feed rate and depth of cut) are kept constant while doing experiments.

Table 4.1: Machining conditions

Work material	AISI 1040 steel (0.35-0.4% C, 0.6-1.0% MN)
Material Size	50 mm diameter, 300 mm length
Tool material	WC-Co Inserts (8-12% Co)
Liquid lubricant	SAE 40 oil
Solid lubricant	Boric acid
Cutting conditions	Cutting speed – 100 m/min, Feed rate - 0.1 mm/rev, Depth of cut – 1 mm.

3.3 Instrumentation

The accompanying instruments are utilized to locate the cutting powers, apparatus temperatures and surface unpleasantness of the work piece while directing analyses.

3.3.1 Tool power dynamometer:

Apparatus power dynamometer is utilized to discover the powers applied on the device in three ways bearing of cut, heading of feed, course of push. The device power dynamometer chips away at the guideline of strain checks connected to the instrument holding unit.

3.3.2 Thermocouple:

The temperature is detected by a thermocouple intersection embedded underneath the instrument bit. The thermocouple is embedded through a 2 mm opening bored under the apparatus holder.

3.3.3 Surface unpleasantness analyzer:

Surface harshness analyzer is utilized to quantify the surface completion of the work piece after the machining process.The table 4.2 speaks to the instruments utilized while directing analyses to gauge the cutting powers, apparatus temperatures and surface unpleasantness. The estimating scope of these instruments are likewise appeared.

3.4 Artificial neural organization displaying

The tentatively acquired information is utilized to prepare the organization and to build up the model. ANN model is created in the MATLAB Neural organization tool stash. The model can be created by graphical UI or by composing code. 12 datasets are utilized to prepare the neural organization. The info and yield joined information is called as dataset. Neural organizations are prepared utilizing preparing informational collection and their speculation limit is inspected by utilizing test sets. The preparation information never utilized in the test information. Number of neurons to be utilized in the shrouded layer of neural organization is basic to stay away from over fitting issue, which prevents the speculation ability of the neural organization. Number of concealed layer neurons is typically found with experimentation approach. In all the instances of the current work, multi layer feed-forward counterfeit neural organizations are utilized. In the current work, the accompanying advances are created:

1. Database assortment

2. Analysis and pre-handling of the information
3. Training of the neural organization

Test of trained network
1. Post processing of the data
2. Use of trained NN for simulation and prediction.

3.5 Schematic model of ANN for prediction of process parameters

The input parameters and the output parameters are needed to develop the artificial neural network model. The following figure 3.2 represents the input and output parameters have been used in the present work.

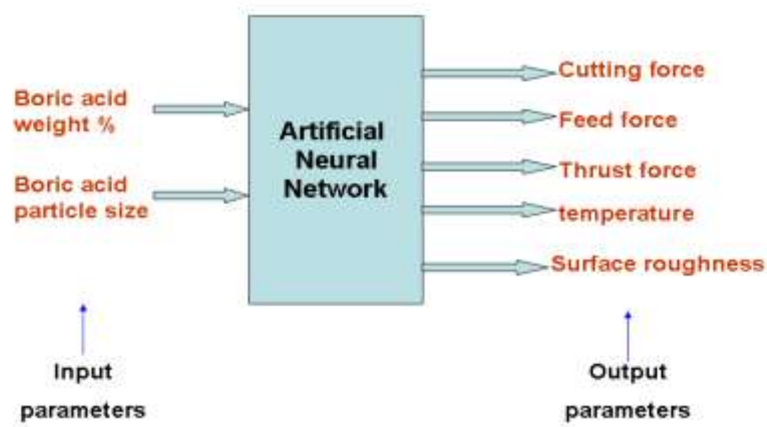

Figure 3.2 : Schematic model of ANN for prediction of process parameters

In the present work, the boric acid weight percentage and boric acid particle size are taken as input parameters; cutting force, feed force, thrust force, temperature and surface roughness are taken as output parameters

3.6 .Observations from ANN results

• Comparison of predicted cutting forces, tool temperatures and surface roughness with experimental results in all tested cases indicate that the error is less than 4% for ANN model.
• The average error percentage for all the predicted values in the ANN model is 1.897%.

3.7 Introduction to regression analysis

Regression is the process of fitting models to data. Regression is the statistical model that we use to predict continuous outcome based on one or more continuous predictor variables. Regression analysis is a mathematical measure of the average relationship between two or more variables in terms of the original units of the data. In regression analysis, there are two types of variables. The value whose value is influenced or is to be predicted is called dependent variable and the variable, which influences the values or is to be used for prediction is called independent variable.
Simple linear regression looks at one dependent variable in terms of one independent variable. When we want to explain a dependent variable in terms of two or more independent variables, we use multiple linear regression. The purpose of multiple linear regression is to establish a quantitative relationship between a group of predictor variables and a response variable. This relationship is useful for:

- Understanding which predictors has the greatest effect.
- Using the model to predict future values of the response when only the predictors are currently known.

3.7.1 Beta (standardized regression coefficients)

The beta value is a measure of how strongly each predictor variable influences the response variable (criterion variable). The beta is measured in units of standard deviation. For example, a beta value of 2.5 indicates that a change of one standard deviation in the predictor variable will result in a change of 2.5 standard deviations in the response variable. Thus, higher the beta value the greater the impact of the predictor variable on the response variable.

3.7.2 R, R Square, Adjusted R Square

R is a measure of the correlation between the observed value and the predicted value of the response (criterion) variable. R square is called coefficient of determination indicates explanatory power of any regression model. Its value lies between +1 and 0. It can be shown that R-square is the correlation between actual and predicted value. It will reach maximum value when dependent variable is perfectly predicted by regression. R Square is the square of this measure of correlation and indicates the proportion of the variance in the response (criterion) variable, which is accounted for by our model. In essence, this is a measure of how good a prediction of the criterion variable we can make by knowing the predictor variables. However, R square tends to somewhat over-estimate the success of the model when applied to the real world, so an Adjusted R Square value is calculated which takes into account the number of variables in the model and the number of observations (participants) our model is based on. This Adjusted R Square value gives the most useful measure of the success of our model. If, for example we have an Adjusted R Square value of 0.75 we can say that our model has accounted for 75% of the variance in the response (criterion) variable.

3.7.3 Correlation coefficients

The connection coefficient framework speaks to the standardized proportion of the strength of direct connection between factors. The connection coefficients range from - 1 to 1, where

•Values near 1 propose that there is a positive direct connection between the information sections.

•Values near - 1 propose that one segment of information has a negative straight relationship to another section of information (anticorrelation).

•Values near or equivalent to 0 propose there is no direct connection between the information segments.

3.8 Mathematical displaying

Numerical model was created in the relapse examination utilizing MATLAB Statistical tool kit. The measurement tool kit gives us four models in relapse investigation.

1) Linear: $Y = \beta0 + \beta1x1 + \beta2x2$

2) Interactions: $Y = \beta0 + \beta1x1 + \beta2x2 + \beta3x1x2$

3) Pure quadratic: $Y = \beta0 + \beta1x1 + \beta2x2 + \beta3x1^2 + \beta4x2^2$

4) Full quadratic: $Y = \beta0 + \beta1x1 + \beta2x2 + \beta3x1x2 + \beta4x1^2 + \beta5x2^2$

- Here a reaction variable Y is displayed as a blend of consistent, direct, cooperation and quadratic terms shaped from two indicator factors x1& x2.
- Given information on x1, x2 and Y, relapse gauges the model boundaries.

3.9 Commands utilized for relapse examination in MATLAB

Regstats: The regstats work plays out various straight relapse and figures more insights. The measurements for each metal cutting cycle boundary were found. Punctuation: regstats (yield, input, 'model');

3.10 Coefficient assurance (R-square) estimations of Regression models:

Coefficient of assurance (R-square) shows informative force of any relapse model. Its worth lies somewhere in the range of +1 and 0. It tends to be demonstrated that R-square is the connection among's real and anticipated worth. It will arrive at most extreme worth when subordinate variable is consummately anticipated by relapse. The above coding referenced in the segment 6.3 will give the coefficient assurance (R-square) values .The table 6.1 speaks to the coefficient assurance estimations of various relapse models.

Table 6.1: R-Square values of different Regression models:

	Linear	Interaction	Pure quadratic	Quadratic
Feed force	0.7167	0.7260	0.9516	0.9548
Cutting force	0.8169	0.8373	0.9310	0.9611
Thrust force	0.6656	0.6661	0.9517	0.9524
Tool temperatures	0.7225	0.7663	0.8114	0.8683
Surface roughness	0.5491	0.5523	0.9018	0.9142

3.11 Correlation coefficients

The connection coefficient lattice speaks to the standardized proportion of the strength of direct connection between factors. The connection coefficients range from - 1 to 1, where

•Values near 1 propose that there is a positive straight connection between the information sections.

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2) Interactions: $Y = \beta 0 + \beta 1x1 + \beta 2x2 + \beta 3x1x2$
3) Pure quadratic: $Y = \beta 0 + \beta 1x1 + \beta 2x2 + \beta 3x1^2 + \beta 4x2^2$
4) Full quadratic: $Y = \beta 0 + \beta 1x1 + \beta 2x2 + \beta 3x1x2 + \beta 4x1^2 + \beta 5x2^2$

- Here a reaction variable Y is displayed as a blend of consistent, straight, cooperation and quadratic terms framed from two indicator factors x1& x2.
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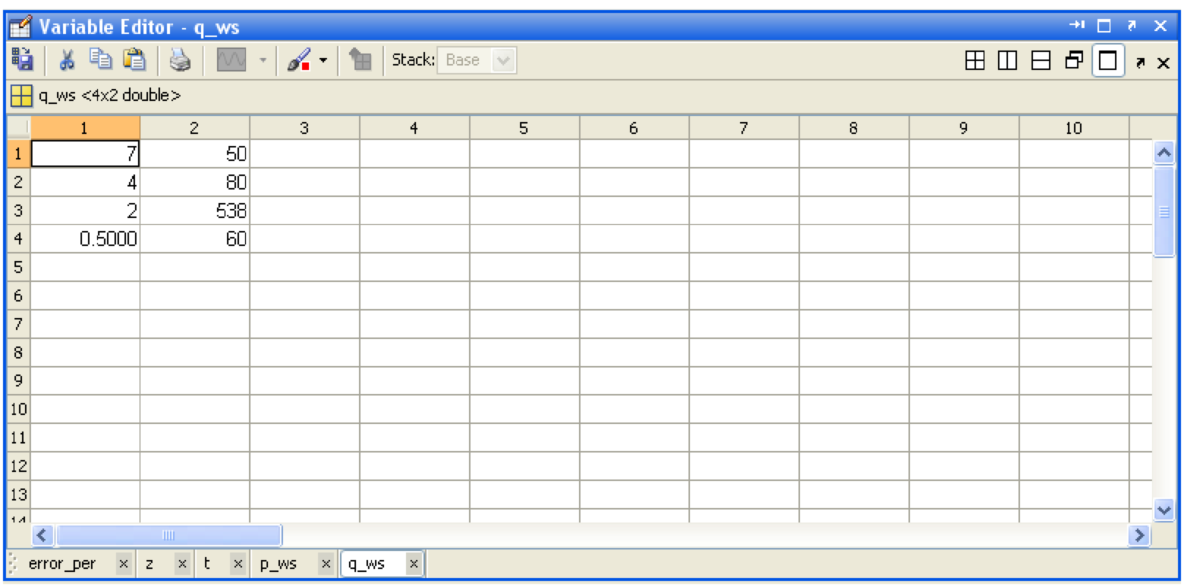

Figure 3.3: Testing input data for Regression analysis

4. Results and Discussion

4.1 Validation set utilized for Neural Network and Regression investigation

Testing legitimacy of the neural organizations and relapse investigation is made utilizing the information boundaries. Four datasets are utilized for approval. The accompanying table 7.1 speaks to the test results, ANN results and the relapse investigation results. The test results are contrasted and the counterfeit neural organization model and the relapse investigation for the approval and the blunder rate is determined.

- Comparison of anticipated cutting powers, instrument temperatures and surface unpleasantness with test brings about completely tried cases show that the mistake is under 4% for ANN model and under 8% for relapse model.

- The normal mistake rate for all the anticipated qualities in the ANN model is 1.897%, though in the relapse model is 2.94%.

Table 7.1: Validation of ANN and Regression Results with the Experimental Results

Output	Experiment number	Experimental value	ANN model		Regression analysis	
			Predicted value	Percentage Error	Predicted value	Percentage error
Feed force	1	113.66	116.5649	-2.5558	114.2544	-0.5229
	2	91	89.8371	1.2779	100.3525	2.2858
	3	72.16	71.3675	1.0983	118.9878	7.9754
	4	87.66	89.0789	-1.6187	92.0588	3.6739
Cutting force	1	102.7	103.1024	-0.3918	1.6818	6.0433
	2	80.16	82.2229	-2.5734	88.5851	2.6538
	3	70.16	67.6841	3.5289	82.6407	-3.0947
	4	73.83	75.6014	-2.3993	101.3173	1.4423
Thrust force	1	129.3	128.8119	0.3775	81.2906	-5.1216
	2	102.8	99.4464	3.2623	1.3950	1.0634
	3	87.83	88.0447	-0.2444	70.9877	1.6246
	4	91.33	93.7550	-2.6552	69.6757	0.6902
Tool temperature	1	95.57	99.1036	-3.6974	89.2346	-1.5993
	2	77.33	79.8798	-3.2973	73.8643	0.6266
	3	74.33	72.6692	2.2343	1.2285	-2.8921
	4	73	71.4656	2.1019	92.3031	-5.2967
Surface roughness	1	1.79	1.7558	1.9110	76.0559	-3.0150
	2	1.41	1.4034	0.4695	95.3468	-4.3982
	3	1.194	1.1733	1.7344	72.4643	0.7338
	4	1.363	1.3560	0.5103	1.4192	-4.1226

4.2. Approval of proposed models

The proposed models (ANN and Regression models) are approved by contrasting the anticipated outcomes and the test results.

4.2.1 Validation of feed power results with the ANN and Regression models

The figure 4.1 speaks to the feed power consequences of neural organization model and relapse model are contrasted and the test results with various weight % of boric corrosive and distinctive molecule sizes

experimental results.

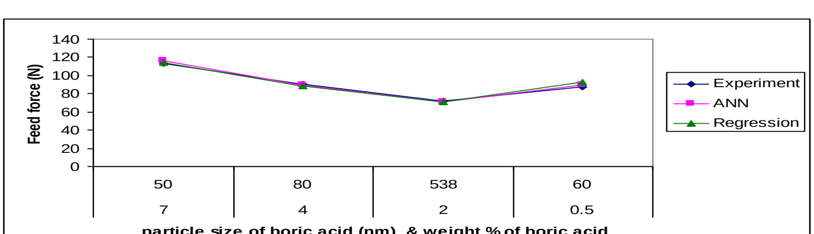

Figure 4.1: Comparison between experimental and predicted values of feed force at different particle sizes and weight % of boric acid

The percent errors obtained for feed force from neural network model and regression model are presented in the figure 4.2.

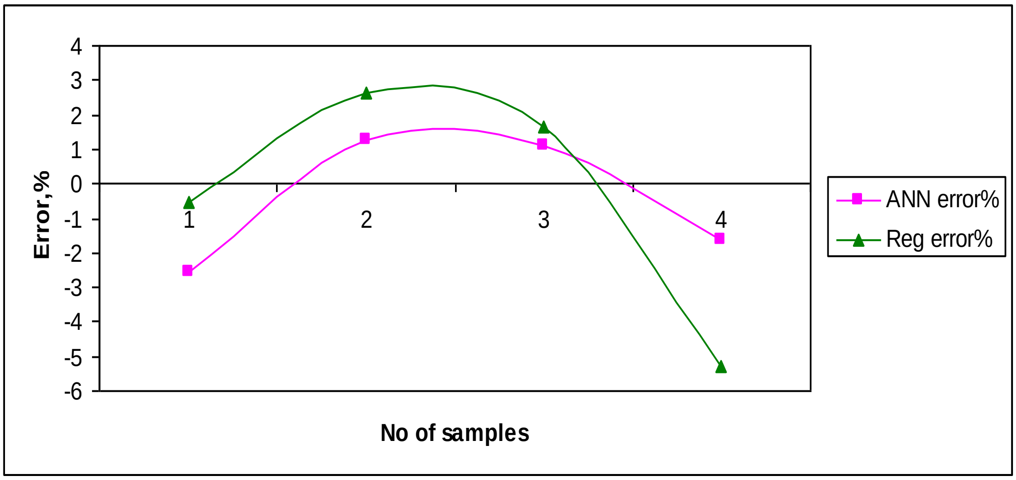

Figure 4.2: Percent errors obtained for feed force based on ANN and regression models

From the figure 4.2, it is observed that maximum error is 2.5558 for neural network model and 5.2967 for regression model.

7.2.2. Validation of cutting force results with the ANN & Regression models

The figure 7.3 represents the cutting force results of neural network model and regression model are compared with the experimental results with different weight % of boric acid and different particle sizes.

The percent errors obtained for cutting force from neural network model and regression model are presented in the figure 4.3.

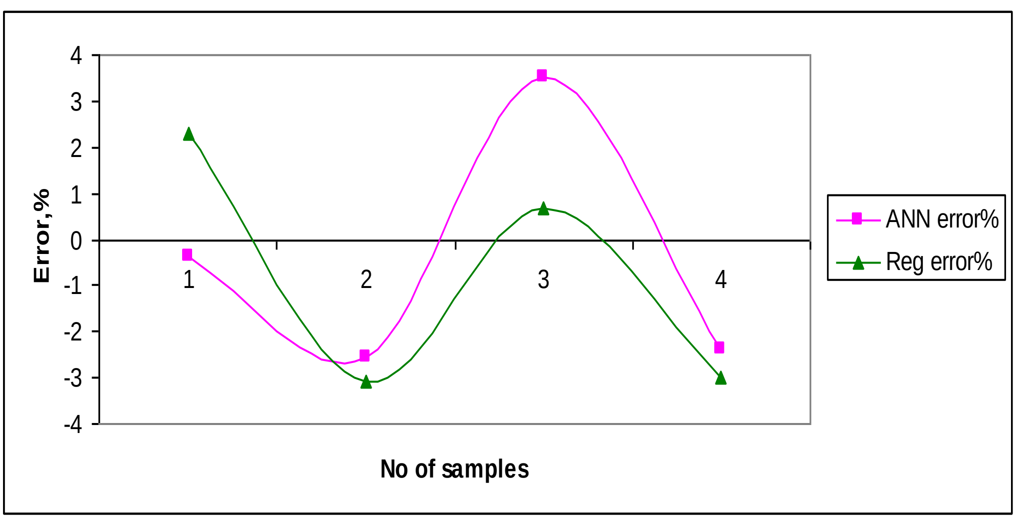

Figure 4.3 : Percent errors obtained for cutting force based on ANN and Regression models

From the figure 4.3, It is observed that maximum error is 3.5289 for neural network model and 3.0947 for regression model.

7.2.3 Validation of thrust force results with the ANN & Regression models

The figure 4.4 represents the thrust force results of neural network model and regression model are compared with the experimental results with different weight % of boric acid and different particle sizes.

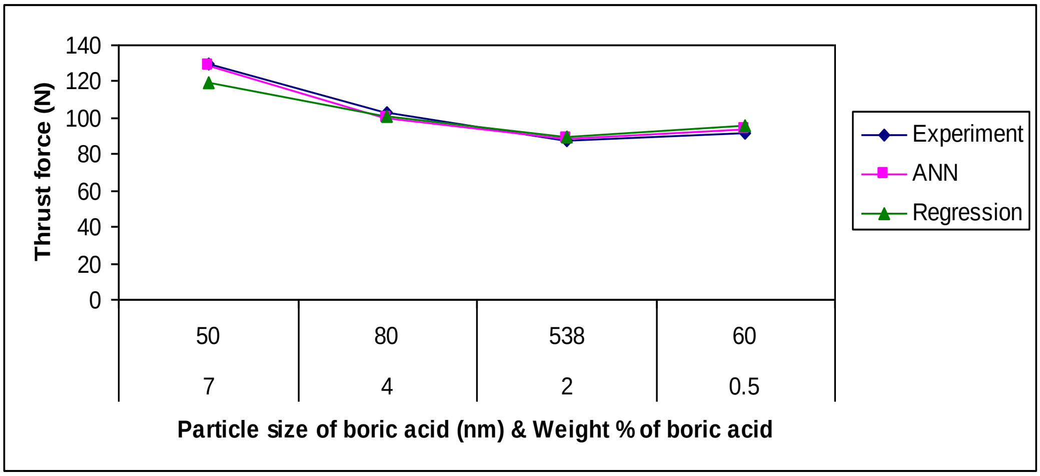

Figure 4.4: Comparison between experimental and predicted values of thrust force at different particle sizes and weight % of boric acid

The percent errors obtained for thrust force from neural network model and regression model are presented in the figure 4.5.

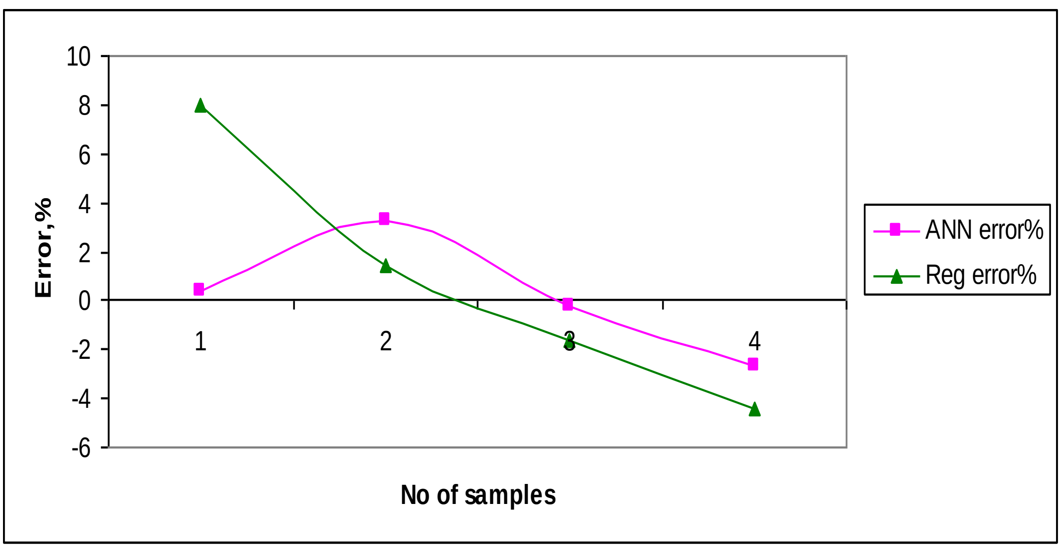

Figure 4.5: Percent errors obtained for thrust force based on ANN and Regression models

From the figure 4.5, it is observed that maximum error is 3.2623 for neural network model and 7.9754 for regression model.

5. Conclusion

Material evacuation measures includes age of high cutting powers and temperatures. Use of legitimate grease is a significant viewpoint to diminish slicing powers and temperatures and to improve surface completion. In the current work, the impact of nano estimated strong grease (boric corrosive) in the machining was researched. To contemplate the impact of strong grease molecule size different turning tests were directed on AISI 1040 steel utilizing tungsten carbide device embeds. Varieties in cutting powers, apparatus temperatures and surface unpleasantness are concentrated to survey the impact of molecule size and weight level of boric corrosive.

The trial information of estimated cutting powers, instrument temperatures and surface unpleasantness are used to prepare the neural organization models. Prepared neural organization models are utilized in anticipating cutting powers, instrument temperatures and surface unpleasantness for different strong oil (boric corrosive) molecule sizes and weight rates. The created forecast framework is discovered to be fit for precise cycle boundaries expectation for the reach it has been prepared. The neural organization models are additionally contrasted with the relapse models. As it was envisioned, the neural organization models gave better forecast capacities since they by and large offer the capacity to demonstrate more perplexing non-linearities and connections than direct and outstanding relapse models can offer.

Correlation of anticipated cutting powers, apparatus temperatures and surface harshness with exploratory outcomes in all testing cases demonstrate that the blunder is under 4% for ANN model and under 8% for relapse model. The normal mistake rate for all the anticipated qualities in the ANN model is 1.897%, while in the relapse model is 2.94%. From this assertion, we can infer that ANN model gives better expectation esteems with less mistake rate. At last, the ANN model was discovered to be fit for anticipating the metal cutting cycle boundaries with reasonable precision than the relapse model.

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