



The Lubricant Performance of Boric Acid (H_3BO_3) in Machine Operations

¹Penta. Shreenivasarao, ¹Ch. Venkata Lakshmi, ²K. Bhanu Prasad, ³K. Praveen Kumar, ⁴R. Pavan Kumar, ⁵M. Akarsh

^{1,1} Associate Professor in Mechanical Engineering Department, Satya Institute of Technology and Management

^{2,3,4,5} Students of Satya Institute of Technology and Management

Email: pshreenivasarao@gmail.com

Doi: <https://doi.org/10.55248/gengpi.5.0424.1094>

ABSTRACT

Importance propels have been made in understanding the way of behaving of designing materials while machining at higher cutting circumstances from useful and hypothetical angles. Material expulsion processes includes age of high cutting powers and temperatures. Use of appropriate oil is a significant viewpoint to lessen slicing powers and temperatures and to work on surface completion. In the current work, the impact of nano estimated strong grease (boric corrosive) in the machining is explored. To concentrate because of strong ointment molecule size different turning tests are directed on AISI 1040 steel utilizing tungsten carbide instrument embeds. Varieties in cutting powers, device temperatures and surface unpleasantness are examined to evaluate the impact of molecule size and weight level of boric corrosive. Tentatively acquired results are utilized in the preparation of brain organization and to foster the ANN model. The multi-facet feed forward brain organizations can very accommodating in catching the tentatively noticed strong oil conduct. The brain networks sum up all alone. The organization can anticipate yield values for the given obscure and never seen before inputs. This might lessen the expense of examinations. Relapse model was additionally evolved to catch the strong oil molecule size conduct. Correlation of brain network model with relapse model is additionally done. The outcomes uncover that the anticipated cutting powers, device temperatures and surface unpleasantness with trial brings about totally tried cases demonstrate that the mistake is under 4% for ANN model and under 8% for relapse model. From this, we can infer that ANN model gives better expectation values with less error%

INTRODUCTION

1 Dry cutting

Dry cutting is a machining technique where no oil or coolant is utilized during the machining time frame. In this strategy, the surface completion got is low where as the temperatures and intensity produced is exceptionally high at the device work interface and the apparatus wear is high bringing about lesser device life.

1.1 Wet cutting

To beat the troubles in dry cutting, cutting liquids (oils/coolants) are utilized which lessens the temperatures and coefficient of contact between device work interface as well as apparatus chip interface hence bringing about better surface completion and more instrument life. This sort of machining process is known as wet cutting.

1.2 Kinds of cutting liquids: Fluids, Solids, Gases

1.3 Reason for cutting liquids

Lessen grating, Move heat, Divert foreign substances and chips, Safeguard device against wear, Forestall consumption

1.3 Benefits of dry machining over wet machining

However dry cutting has the above weaknesses, it is liked for the accompanying reasons:

Dry cutting lessens ecological contamination caused since cutting liquids. Dry reducing is expense compelling contrasted with wet cutting.

No additional impact is expected to keep up with clean ointment in the machine subsequently decreasing the machine parts as well as the work on it.

1.4 How dry machining should be possible effectively

To accomplish the upsides of both dry machining and wet machining Close dry machining like least amount oil (MQL) is viewed as one of the arrangements. The minimization of slicing liquid additionally prompts conservative advantages via saving oil expenses and work piece/device/machine cleaning process duration. By utilizing an eco amicable ointment even the natural as well as risk to the administrator's wellbeing can be decreased or even disposed of.

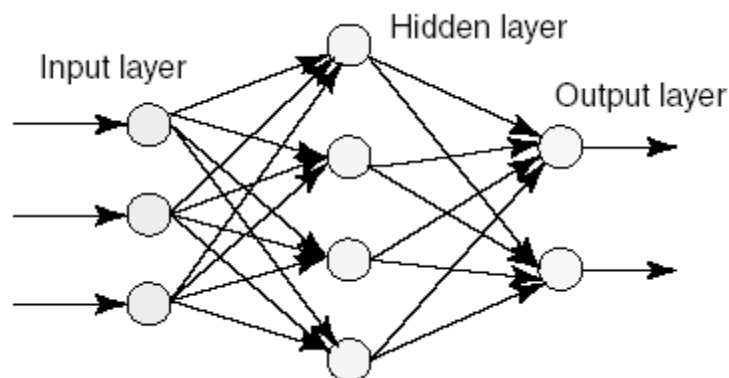
1.5 Strong grease

Turning is a broadly utilized metal evacuation process in assembling industry that includes age of high cutting powers and temperatures. Grease becomes basic to limit the impacts of these powers and temperatures on cutting instrument and work piece. The customary cutting liquids utilized in machining have specific impediments with respect to their utilization for natural and financial reasons. Improvement of oils that are eco cordial is obtaining significance. In this specific situation, use of strong greases has ended up being a doable option in contrast to the ordinary cutting liquids. In the current work, boric corrosive is utilized as a grease in turning process. Throughout the course of recent years, a few strong ointments have been found to decrease grating and wear during sliding contact essentially. A large portion of these ointments, which incorporate graphite, molybdenum disulphide and tungsten disulphide, have a place with a particular class of materials known as lamellar solids. Boric corrosive is another frequently ignored lamellar strong that has been viewed as a powerful oil. This viability can be credited to boric acids low grating and shear strength values. As detailed in the writing, the shear strength of boric corrosive has not entirely settled to be 23 MPa, and its coefficient of grinding has been estimated to be under 0.02 in surrounding conditions. These qualities are basically the same as the more regularly utilized molybdenum disulphide, which has a deliberate shear strength worth of 24 MPa.

Looking at its actual qualities, boric corrosive is the normal term for orthoboric (or boracic) corrosive H_3BO_3 , which is a hydrate of boric oxide B_2O_3 . At the point when in touch with water, boric oxide will promptly hydrate, switching over completely to the lamellar strong boric corrosive. Under climatic tension, boric corrosive dries out (for example returns to boric oxide) over 170 degrees. Boric oxide is known to mellow around 400 deg at barometrical tension. The basic sub-atomic construction of boric corrosive permits it to go about as a viable strong ointment film. At the point when solidified, boric corrosive structures feeble Vander Walls connections between individual layers areas of strength for and (covalent) bonds inside a layer. Such a holding structure makes the underlying properties of boric corrosive profoundly anisotropic. At the point when extraneously stacked, the individual lamellae slide generally effectively more than each other. This is rather than the typical bearing where the boric corrosive has a general high burden conveying limit. Thus, when appropriately lined up with a substance, boric corrosive will show negligible contact and give powerful partition between surfaces. Truth be told, it has been shown that the erosion coefficient of sliding points of interaction with a boric corrosive film diminished with expanding pressure. Two of the main qualities of boric corrosive for use as an oil are that it is promptly accessible and ecologically protected. In its strong structure, boric corrosive is a pitifully acidic white powder that is dissolvable in water (around 27% by weight in bubbling water and around 6% at room temperature), delicate, bendable, steady, free streaming and effortlessly dealt with. It is exceptionally reasonable, as finely ground specialized grade boric corrosive powder (>99% unadulterated) is financially accessible for US\$ 2 for each pound. The Natural Insurance Organization has laid out that boric corrosive is harmless and the Perfect Water Act doesn't characterize it as a poison. Truth be told, a weaken water arrangement of boric corrosive is likewise normally utilized as a gentle germicide and eyewash. Furthermore, the modern commercial center has previously acknowledged boric corrosive as a designing material. The current business sectors for boric corrosive and boric oxide in the US incorporate glass making (78%), fire retardants (9%), farming manures (4%) and other modern applications like metal plating and getting done, paints and shades, electroplating and beauty care products (9%). The US is world's biggest maker of boron compounds, as huge homegrown stores of boron materials live in lake dregs and salt waters.

Multi-facet Feed forward Organization

There are many sorts of ANN models in the writing. Be that as it may, a back proliferation multi-facet feedforward network is the most generally utilized for expectation and designing applications. These organizations have an info and result layer and furthermore have at least one mediator layers called secret layers. There can be quite a few secret layers. The computational units of the secret layer are known as covered up neurons or secret units. The secret layer supports performing valuable middle person calculations prior to guiding the contribution to the result layer. The info layer neurons are connected to the secret layer neurons and the loads on these connections are input-stowed away layer loads. Once more, the secret layer neurons are connected to the result layer neurons and the comparing loads are alluded to as covered up yield layer gauges. The accompanying figure 1.2 addresses the multi-facet feed forward network gangs an info layer with three neurons, a result layer with two neurons, and one secret layer with four secret neurons.



Multilayer feed forward network

The expansion in the quantity of secret layers brings about the computational intricacy of the organization. Accordingly, the time taken for union and to limit the mistake might be extremely high. The inclination is accommodated both the covered up and yield layer, to follow up on the net contribution to be determined.

Back propagation. Back proliferation is a precise technique for preparing multi-facet fake brain organizations. It has a numerical establishment that is sufficient while perhaps not profoundly commonsense. It is a multi-facet feedforward network utilizing expand slope plummet based delta-learning rule, ordinarily known as back proliferation (of blunders) rule. Back spread gives computationally effective technique to changing the loads in a feed forward network, with differentiable enactment capability units, to become familiar with a preparation set of info yield models. GE Hinton, Rumelhart and R.O. Williams previously presented back proliferation network in 1986. What makes the back engendering calculation not the same as different calculations is the interaction by which the loads are determined during the learning period of the organization. The organization is prepared by managed learning strategy. The point of this organization is to prepare the net to accomplish a harmony between the capacity to answer accurately to the information designs that are utilized for preparing and the capacity to give great reactions to the information that are comparative.

1.6 Training Algorithm of back propagation

The training algorithm of back propagation involves four stages.

Initialization of weights, Feed forward, Back propagation of errors, Updation of the weights and biases. Writing survey with respect to the ANN in metal cutting

2. Literature review regarding the metal cutting and ANN:

Tugrul Ozel, Yigit Karpat, uses brain network demonstrating to anticipate surface harshness and device flank wear over the machining time for assortment of cutting circumstances in finish hard turning. Relapse models are likewise evolved to catch the cycle boundaries. Prepared brain network models were utilized in anticipating the surface unpleasantness and device flank wear for other cutting circumstances. An examination of brain networks model with relapse models is likewise completed.

Dejan Tanikic, Miodrag Hyper, Drgon mancic, showed the chance of execution of computerized reasoning based frameworks in metal cutting cycle. Displaying of cutting cycle was performed utilizing tentatively got information and man-made brainpower based approach (ANNs and Neuro fluffy frameworks). For a few obscure upsides of info, framework can anticipate a few result boundaries of interest.

Mr. Harshit K. Dave, Dr. Keyur P. Desai, Dr. Harit K. Raval led investigates Electro release machine utilizing copper instrument and MS plate work piece. Material expulsion rate and Surface harshness are determined for different blends of current and apparatus breadth. Expectations of the reaction factors are made utilizing Relapse examination and ANN strategies. The qualities acquired by both the strategies are contrasted and the exploratory upsides of the reaction factors to figure the closeness of the expectations with the trial values out. The rate mistake found in ANN model reach from - 1.71% to 4.48%, while similar got through relapse conditions range from 10.87% to 12%. It is found that the fake brain network predicts better compared to the relapse examination.

E.O. Ezugwu, D.A. Fadare, J. Bonney, R.B. Da Silva, W.F. Deals fostered a counterfeit brain network model for the examination and expectation of the connection among cutting and cycle boundaries during fast turning of nickel-based, inconel 718, composite. The info boundaries of the ANN model are the cutting boundaries: speed, feed, profundity of cut, cutting time and coolant pressure. The result boundaries of the model are seven interaction boundaries estimated during the machining preliminaries, to be specific cutting power, feed force, axle engine power utilization, surface harshness, normal flank wear, greatest flank wear and nose wear. The multi-facet network with two secret layers having 10 'digression sigmoid' neurons prepared with Levenberg-Marquardt calculation joined with Bayesian regularization was viewed as the ideal organization for the model created in this review. A generally excellent exhibition of the brain organization, regarding concurrence with exploratory information, was accomplished.

U. Esme, A. Sagbas and F. Kahraman were utilized two methods, in particular factorial plan and brain network for displaying and anticipating the surface harshness of AISI 4340 steel. Surface harshness was taken as a reaction variable estimated after wire disintegration release machining (WEDM). The numerical connection between the work piece and surface harshness and WEDM cutting boundaries were laid out by relapse investigation technique. This numerical model might be utilized in assessing the surface harshness without playing out any analyses. At last, anticipated upsides of surface unpleasantness by procedures, NN and relapse examination, were contrasted and the exploratory qualities and their closeness with the not set in stone. That's what results show, NN is great option in contrast to observational displaying in view of full factorial plan.

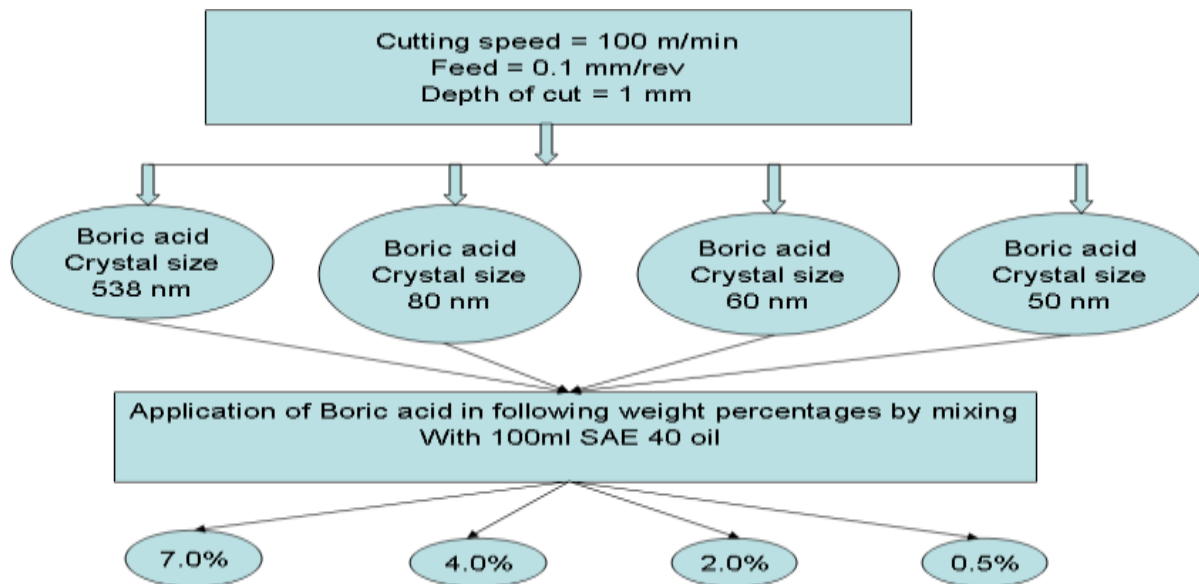
A. John presin kumar and D. Kingsly jeba singh involved brain networks in forecast of wear misfortune amounts of A390 aluminum compound has been concentrated on in the current work. The material is exposed to dry sliding wear test utilizing nail to circle mechanical assembly at room conditions. Impacts of burden, sliding velocity and time have been examined by utilizing counterfeit brain organizations. The exploratory outcomes were prepared in an ANNs program and the outcomes were contrasted and trial values. It is seen that the trial results harmonized with ANN results.

Bahaa Ibraheem Kazem, Nihad F.H. Zangana planned and carried out a successful brain network model for turning process distinguishing proof as well as a brain network regulator to follow an ideal vibration level of the turning machine. Multi-facet perceptron brain network design with Levenburg

Marquardt calculation has been used to prepare the turning system identifier. The vibration signal got by the trial work has been to prepare a brain network for recognizable proof and control of the turning system.

H.Solimanimehr, M.J. Nategh, S. Amini fostered a counterfeit brain network for expectation of aluminum work pieces surface harshness in ultrasonic vibration helped turning (UAT). Apparatus wear as the primary driver of surface unpleasantness was likewise examined. ANN was prepared through exploratory information acquired based on full factorial plan of examinations. It was outlined that multi-facet perceptron brain organization could productively demonstrate the surface harshness as the reaction of the organization, with a blunder under 10%. The exhibition of the prepared organization was confirmed by additional investigations.

Flow chart



Validation of proposed models

The proposed models (ANN & Regression models) are validated by comparing the predicted results with the experimental results.

Validation of feed force results with the ANN & Regression models

The figure represents the feed 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.

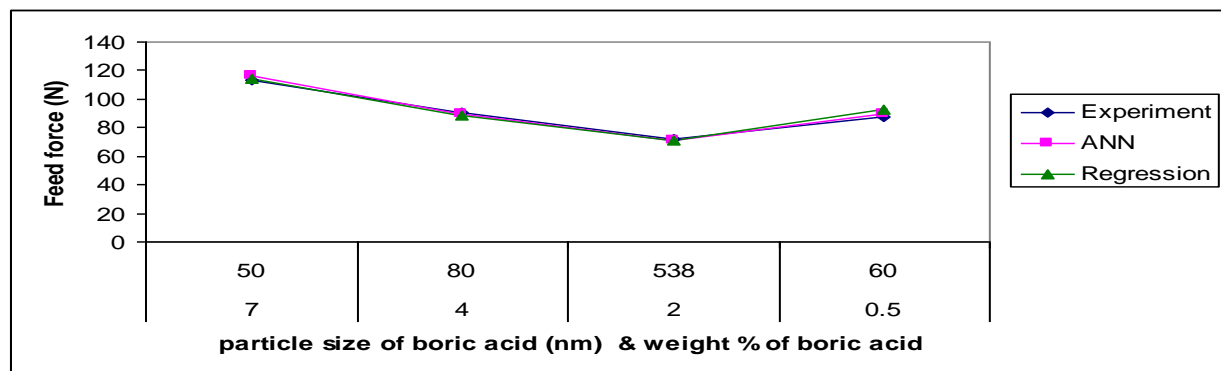


Figure : Comparison between experimental and predicted values of feed force at different particle sizes and weight % of boric acid

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

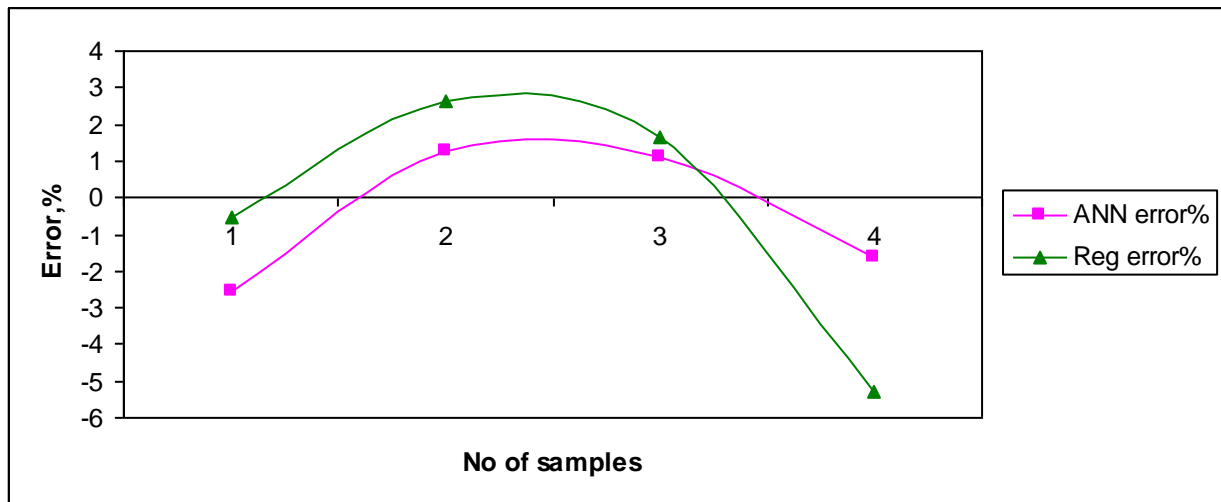


Figure : Percent errors obtained for feed force based on ANN and regression models

From the figure 7.2, it is observed that maximum error is 2.5558 for neural network model and 5.2967 for regression model.

Validation of cutting force results with the ANN & Regression models

The figure 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.

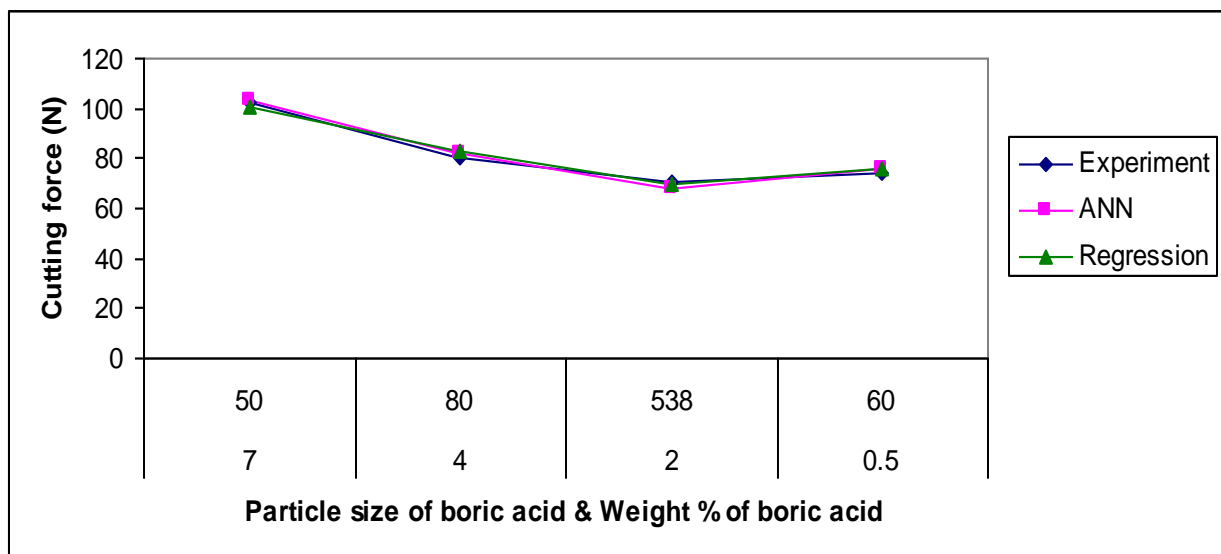


Figure : Comparison between experimental and predicted values of cutting force at different particle sizes and weight % of boric acid

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

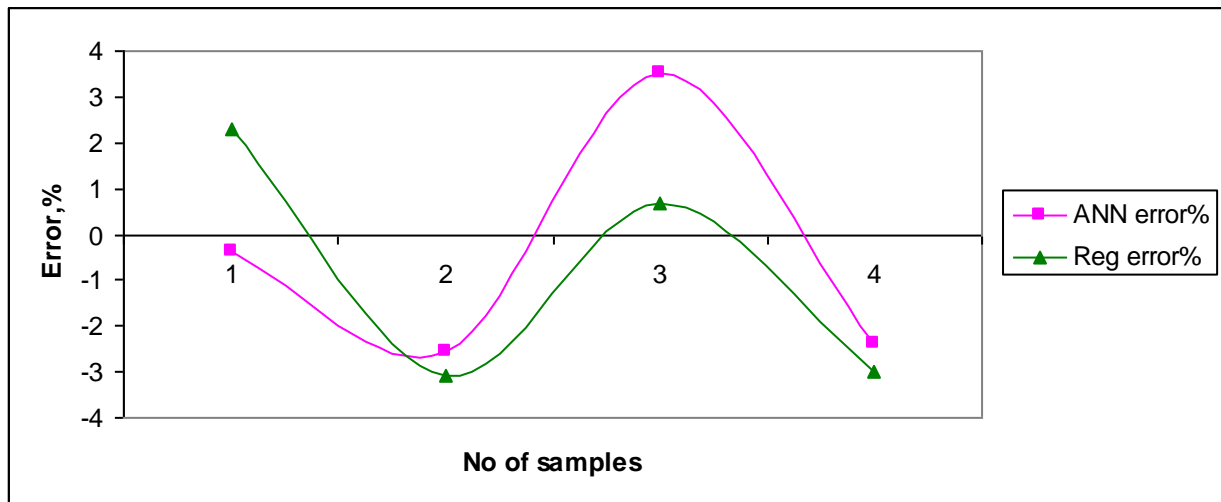


Figure : Percent errors obtained for cutting force based on ANN and Regression models

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

Validation of thrust force results with the ANN & Regression models

The figure 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.

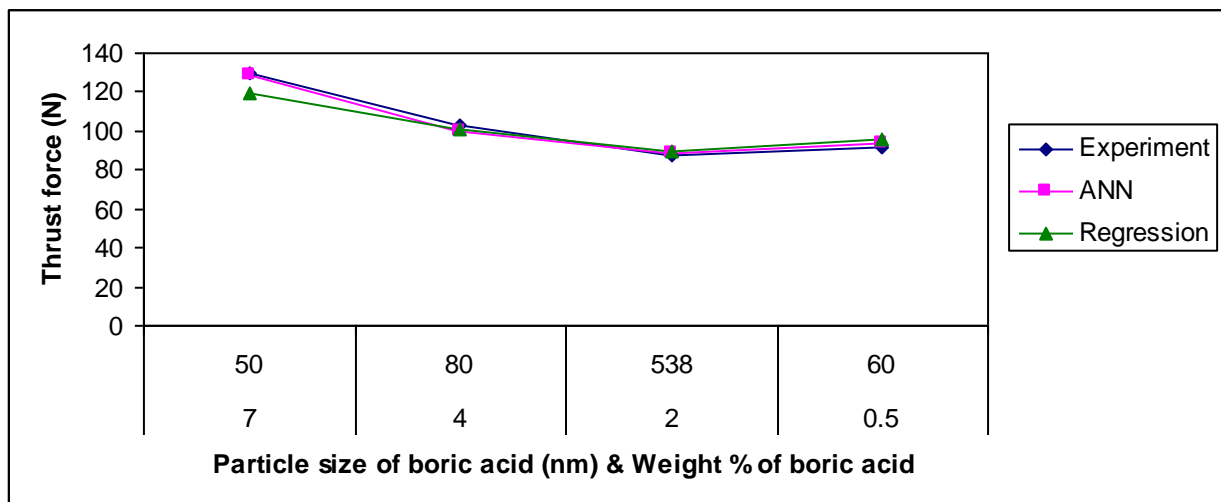


Figure : Comparison between experimental and predicted values of thrust force at different particle sizes and weight % of boric acid

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

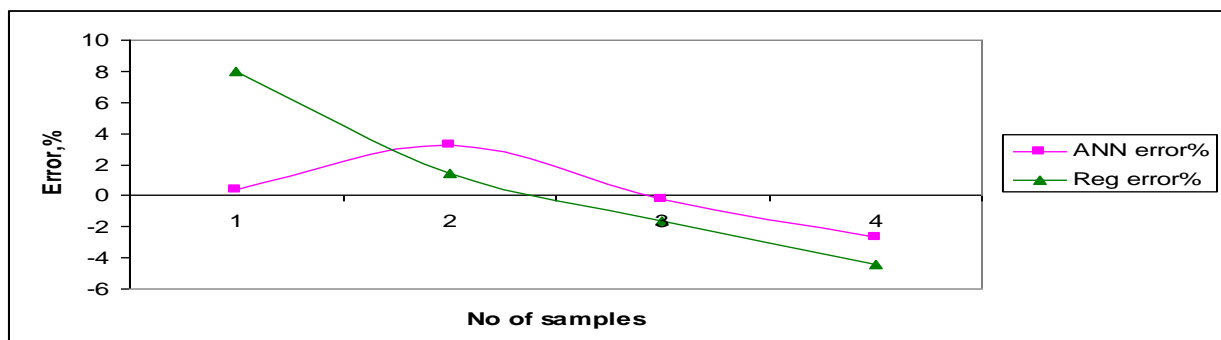


Figure : Percent errors obtained for thrust force based on ANN and Regression models

From the figure 7.6, it is observed that maximum error is 3.2623 for neural network model and 7.9754 for regression model.

Validation of tool temperature results with the ANN & Regression models

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

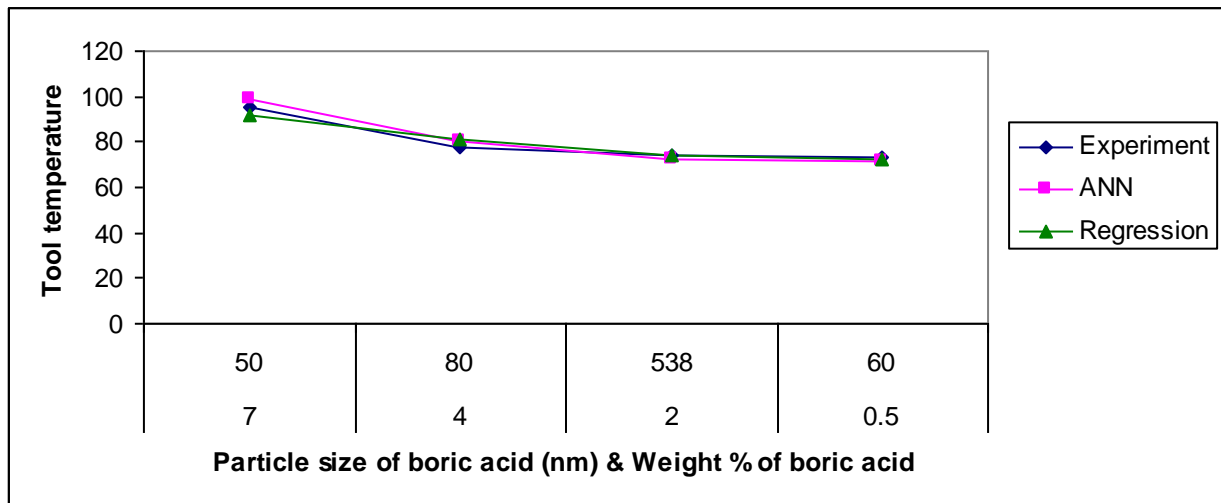


Figure : Comparison between experimental and predicted values of tool temperatures at different particle sizes and weight % of boric acid

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

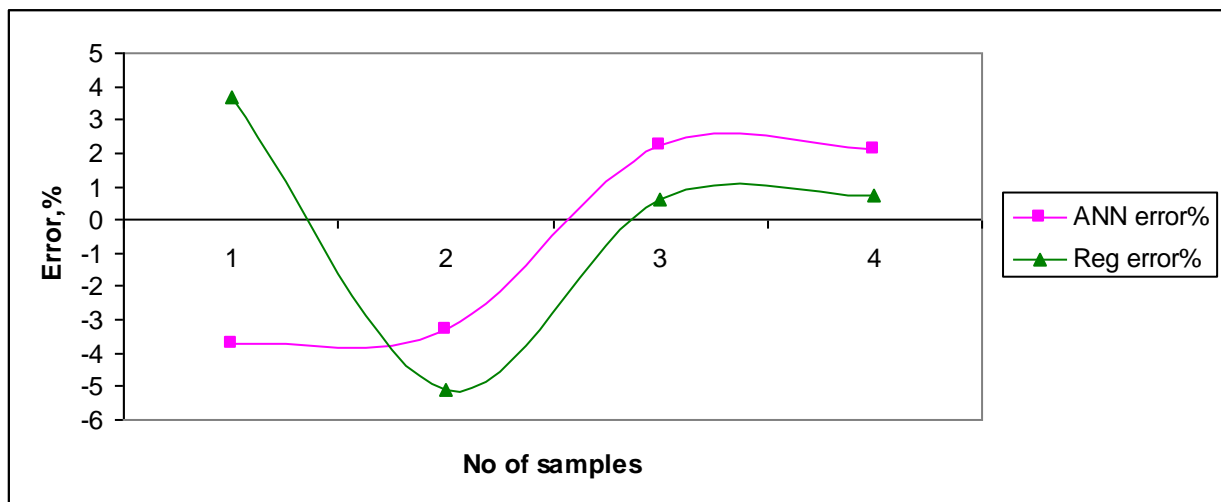


Figure : Percent errors obtained for tool temperatures based on ANN & Regression models

From the figure, it is observed that maximum error is 3.6974 for neural network model and 5.1216 for regression model.

Validation of surface roughness results with the ANN & Regression models

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

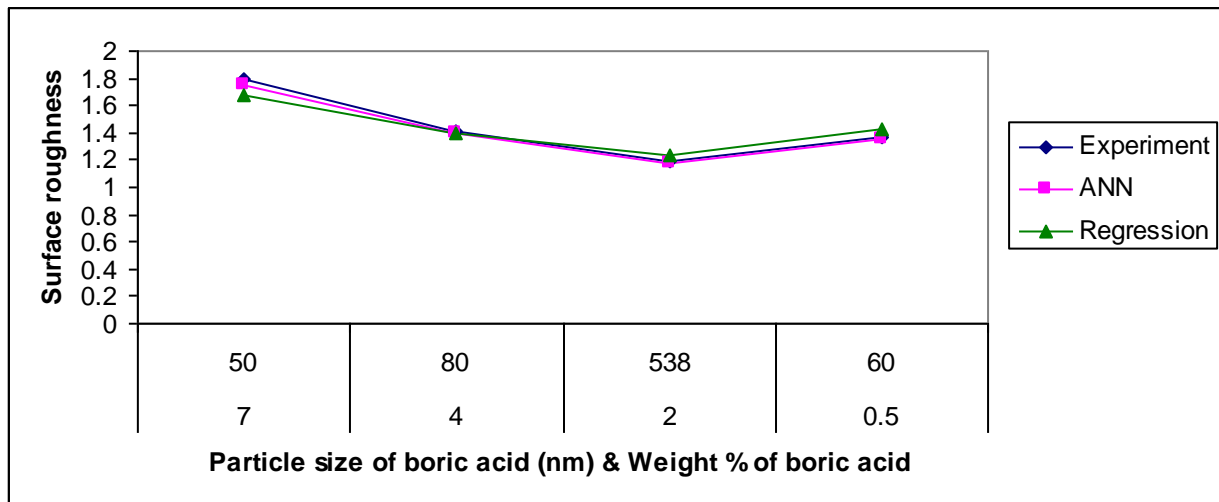


Figure : Comparison between experimental and predicted values of surface roughness at different particle sizes and weight % of boric acid

The percent errors obtained for surface roughness from neural network model and regression model are presented in the figure .

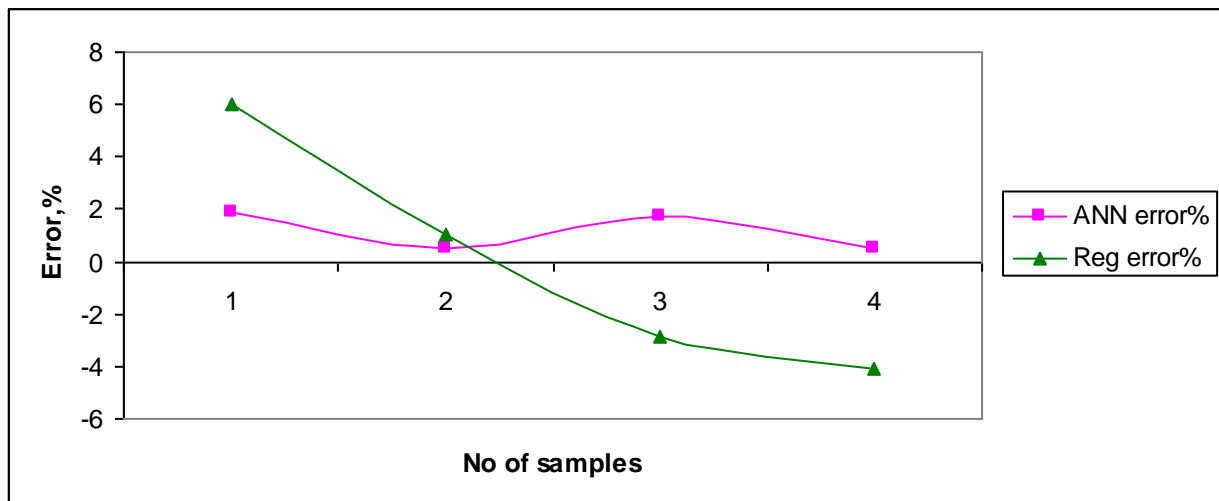


Figure : Percent errors obtained for surface roughness based on ANN & Regression models

From the figure it is observed that maximum error is 1.911 for neural network model and 6.0433 for regression model.

CONCLUSION:

Material evacuation processes includes age of high cutting powers and temperatures. Utilization of legitimate grease is a significant viewpoint to diminish slicing powers and temperatures and to work on surface completion. In the current work, the impact of nano measured strong ointment (boric corrosive) in the machining was examined. To concentrate because of strong grease molecule size different turning tests were directed on AISI 1040 steel utilizing tungsten carbide apparatus embeds. Varieties in cutting powers, device temperatures and surface harshness are considered 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 brain network models. Prepared brain network models are utilized in anticipating cutting powers, apparatus temperatures and surface unpleasantness for different strong grease (boric corrosive) molecule sizes and weight rates. The created expectation framework is viewed as fit for precise cycle boundaries forecast for the reach it has been prepared. The brain network models are likewise contrasted with the relapse models. As it was expected, the brain network models gave better forecast capacities since they by and large proposition the capacity to show more complicated non-linearities and cooperations than direct and outstanding relapse models can offer.

Examination of anticipated cutting powers, device temperatures and surface unpleasantness with trial brings about all testing cases show that the blunder is under 4% for ANN model and under 8% for relapse model. The typical blunder rate for every one of the anticipated qualities in the ANN model is 1.897%, while in the relapse model is 2.94%. From this assertion, we can reason that ANN model gives better expectation values with less

blunder rate. At last, the ANN model was viewed as equipped for anticipating the metal cutting cycle boundaries with fair precision than the relapse model.

REFERENCES

- [1] Dejan Tanikic, Miodrag manic, Goran Radenkovic, Dragan Mancic, "Metal cutting process parameters modeling: an artificial intelligence approach", *Journal of scientific and industrial research* vol 68, June 2009, pp. 530-539.
- [2] Turgul Ozel, Yigit Karpaz, "Predictive modeling of surface roughness and tool wear in hard turning using regression and neural networks", *International journal of machine tools and manufacture* 45 (2005), pp. 467-479.
- [3] E.O. Ezugwu, D.A. Farade, J.Bonney, R.B. Da Silva,, "Modeling the correlation between cutting and process parameters in high-speed machining of Inconel 718 alloy using an artificial neural network", *International journal of machine tools & manufacture* 45 (2005), pp. 1375-1385.
- [4] Mr. Harshit K. Dave, Dr.Keyur P.Desai, Dr. Harit K.Raval "Investigations on prediction of MRR and surface roughness on electro discharge machine using regression analysis and artificial neural network programming" *Proceedings of the world congress on engineering and computer science 2008 WCECS 2008, October 22-24, 2008, San Fransisco, USA.*
- [5] A.john presin kumar, D.kingsly jeba singh, "Artificial neural network - based wear loss prediction for A390 aluminium alloy", *journal of theoretical and applied information technology*, 2005-2008,JATIT.
- [6] Sakir Tasdemir, suleyman Neseli, Ismail Saritas, Suleyman Yaldiz, "Prediction of surface roughness using artificial neural network in lathe", *International conference on computer systems and technologies – compsysstech '08.*
- [7] H. Soleimanimehr, M.J.Nategh, S. Amini, "Modeling of surface roughness in vibration cutting by Artificial neural network", *World Academy of Science, Engineering and Technology* 52 2009.
- [8] A.Antic, J.Hodolic, M.Sokovic, "Development of an intelligent system for tool wear monitoring applying neural networks", *Journal of achievements in materials and manufacturing engineering*.
- [9] A pin-on-experimental study on a green particulate- fluid lubricant 1040 steel- M.A.Kabir, C.Fred Higgs, Michael R.love11, *journal of tribology, copyright by ASME october 2008.*
- [10] The influence of solid lubricant particle size on machining parameters in turning – P.Vamsi krishna, D. Nageshwar rao, *international journal of machine tools and manufacture available online 4 August 2008.*
- [11] Pushkarraj Deshmukh, Michael Lovell, W. Gregory Sawyer, Anton Mobley, "On the friction and wear performance of boric acid lubricant combinations in extended duration operations", *Elsevier wear* 260 (2006) 1295-1304.
- [12] Neural networks ----- Simon Haykin.
- [13] Introduction to neural networks using MATLAB 6.0 S ----- S N Sivanandam S Sumathi S N Deepa.
- [14] Probability and statistics for Engineers ----- Jay L. Devore.
- [15] Manufacturing technology ----- P.N.Rao.