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PERFORMANCE OF BORIC ACID (H3BO3) AS LUBRICANT IN MACHINING

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ABSTRACT

Considerable progress has been achieved in comprehending the behaviour of engineering materials at increased cuttin g settings, both theoretically and practically.The removal of material requires the production of high temperatures and cutting forces.To lower cutting forces and temperatures and enhance surface smoothness, it's crucial to use the right lu bricant.The impact of a solid lubricant that is nanosized (boric acid) on machining is examined in this paper.Tungsten carbide tool inserts are used in AISI 1040 steel turning experiments to investigate the impact of solid lubricant particle size.The impact of boric acid weight % and particle size is evaluated by examining changes in cutting forces, tool te mperatures, and surface roughness.Results from experiments are utilised to build the ANN model and train neural net works.

The behaviour of solid lubricants found in experiments may be greatly captured by the multilayer feed forward neura l networks.On their own, neural networks generalise.For inputs that are unknown and have never been seen before, the network can forecast output values.This might lower the expense of the trials.Additionally, a regression model was cr eated to represent the behaviour of solid lubricant particle size.Additionally, a comparison between regression and two rk models is done.The findings show that, in all investigated scenarios, the error is less than 4%for the ANN model an d less than 8% for the regression model based on the anticipated cutting forces, tool temperatures, and surface roughne ss compared to experimental data.We may infer that the ANN model produces higher prediction values with a lower er ror percentage based on this.

1. INRODUCTION

Techniques used in machining operationsDifferent kinds of cutting techniques are used in the industries depending on the application.They are as follows:Procedure of dry cutting,Wetcutting techniqueCuts without moistureDuring the ma chining process, no coolant or lubricant is utilised when using the dry cutting method.This approach yields a low surfa ce polish but produces very high temperatures and heat at the tool work contact, as well as excessive tool wear and decreased tool life.Most Cutting fluids (lubricants/coolants) are used to address the challenges of dry cutting. Thes e fluids lower temperatures and the coefficient of friction at the toolwork and toolchip interfaces, improving surface s moothness and extending tool life. This kind of machine-work procedure is known as wet cutting.

Purpose of cutting fluids:Reduce friction,Transfer heat,Carry away contaminants & chips,Protect tool against wear,PreventcorrosionDry machining has advantages over wet machining.Despite the aforementioned drawbacks, dry cutting is recommended for the following reasons:Because Since cutting fluids are used, dry cutting lessens environme ntal contamination.Dry cutting is more economical than wet cutting.Because no additional effort is needed to keep the machine's lubricant clean, less machine parts and labour are needed.

Solidlubrication: Turning is a common metal removal technique in the manufacturing sector that generates high temp eratures and cutting pressures.In order to reduce the impact of these stresses and temperatures on the cutting tool and work piece, lubrication becomes essential.There are some environmental and financial constraints on the usage of tradi tional cutting fluids used in machining.The creation of environmentally friendly lubricants is becoming more and mor e important.Applying solid lubricants has shown to be a workable substitute for traditional cutting fluids in this situati on.Boric acid is employed as a lubricant in the turning process in the current work.

Artificial neural networks

The literature contains a wide variety of ANN architecture types.

For engineering and prediction purposes, however, a back propagation multilayer feedforward network is the most co mmonly utilised.In addition to having input and output layers, these networks also feature one or more hidden layers, which are intermediate layers.Any number of hidden levels are possible.Hidden neurons, or hidden units, are the comp utational units that make up the hidden layer.Before sending the input to the output layer, the hidden layer assists in ca

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rrying out helpful intermediate computations.Inputhidden layer weights are the weights on the links connecting the ne urons in the input layer to the neurons in the hidden layer.Once more, the weights corresponding to the links between t he hidden layer neurons and output layer neurons are alluded to.
as the layer with hidden output weighs.The multilayer feed forward network is shown in figure 1.2. It has three neuron s in the input layer, two neurons in the output layer, and four hidden neurons in the hidden layer.

2. 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.

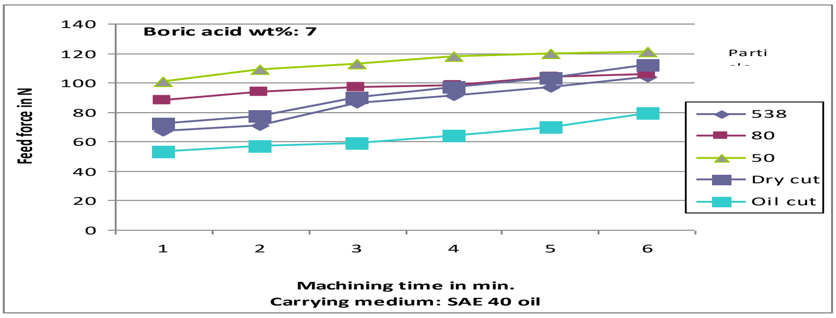
Dhar et al. used the minimum quantity lubrication technique in turning process of medium carbon steel and concluded that, in some cases, a mixture of air and soluble oil has been shown to be better than the overhead flooding application of soluble oil. The review of the literature suggests that minimum 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.

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.

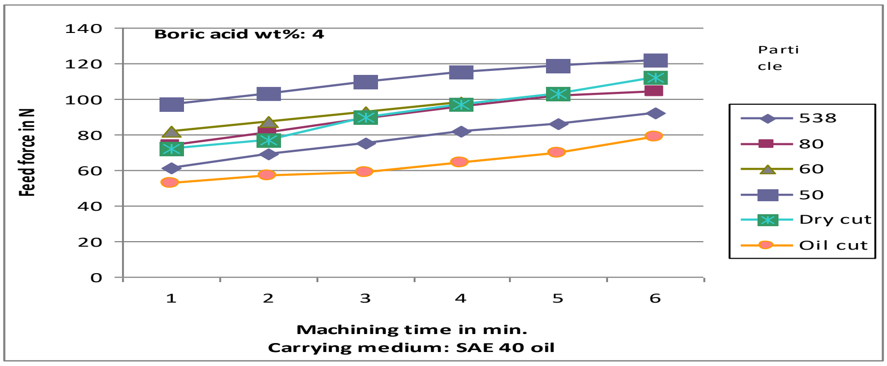
4. Problem definition

• High cutting forces and temperatures are typically generated during material removal procedures.
To lower cutting forces and temperatures and enhance surface smoothness, it's crucial to use the right lubricant.• The g oal of this work is to examine how machining is affected by a solid lubricant that is nanosized (boric acid).• Tungsten carbide tool inserts will be used in AISI 1040 steel turning tests to investigate the impact of solid lubricant particle siz e.• In order to evaluate the impact of particle size, variations in cutting forces, tool temperatures, and surface roughnes s must be investigated.• Results from experiments are suggested for application in neural network training and ANN m odel development.• On their own, neural networks generalise.The systemcan forecast output values for unknown and p reviously unseen inputs.This could lower the expense of the experiments.• A regression model is also suggested for de velopment in order to obtain the mathematical relationship between the independent and dependent variables as well a s to capture the behaviour of solid lubricant particle sizes.• A comparison between regression and neural network mod els needs to be done.

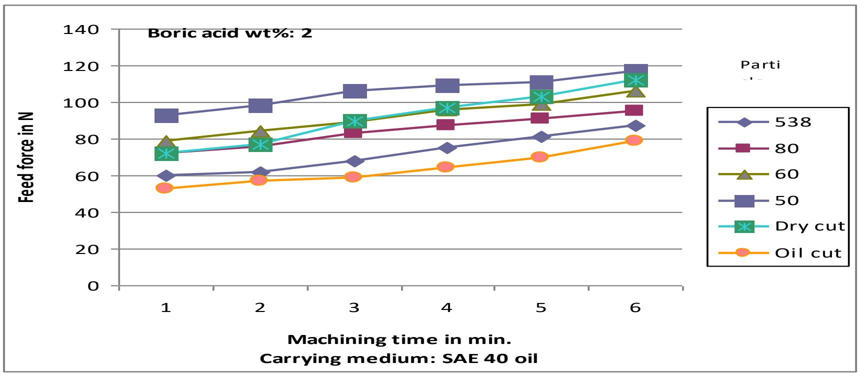
Variation of cutting forces at 7% boric acid



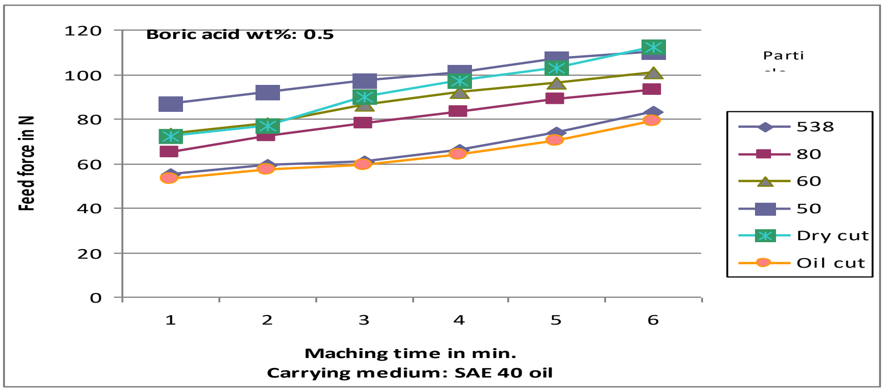
Variation of cutting forces at 4% boric acid



Variation of cutting forces at 2% boric acid



Variation of cutting forces at 0.5% boric acid



- Notes from Cutting Forces:The following observations were drawn from the cutting force variation graphs abov
- By varying the % weight of boric acid, feed forces, cutting forces, and thrust forces were also evaluated in relatio n to variations in particle size at the nanoscale.
- As the particle size decreased from 538 nm to 50 nm, all three force components increased.
- The findings of Kabir et al. appear to be supported by the possibility that this phenomena is caused by an increase in coefficient of friction with a decrease in particle size.
- Cutting forces have decreased as a result of the solid lubricant's weight percentage changing from 7 to 0.5.
- The increased use of boric acid, which raises the coefficient of friction, could be the cause of this phenomena.
- Notes on Tool Temperatures
- The following observations were drawn from the tool temperature variation graphs shown above.
- By varying the weight percentage of boric acid, tool temperatures were also monitored in relation to variations in the nanoscale particle size of boric acid.
- As the particle size decreased from 538 nm to 50 nm, tool temperatures were raised.
- The findings of Kabir et al. appear to be supported by the possibility that this phenomena is caused by an increase in coefficient of friction with a decrease in particle size.
- When the weight percentage of boric acid was changed from 7 to 0.5, the tool's temperature decreased.• A lower c oefficient of friction could be the result of using less boric acid, which would explain this behaviour.

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Notes Regarding Surface Roughness

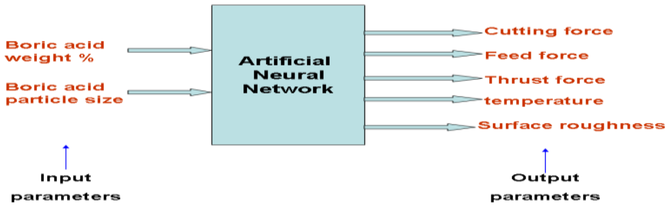
The following observations were drawn from the surface roughness variation graphs shown above.

• By varying the weight percentage of boric acid, surface roughness was also assessed in relation to changes in boric a cid particle size at the nanoscale.

• As the boric acid particle size decreased from 538 nm to 50 nm, surface roughness increased.

• Surface roughness has decreased when boric acid weight percentage is changed from 7 to 0.5.

In reality, the results of these experimental studies contradict the behaviour of particles at the micro level and show a d istinct phenomenon in the nano range of particle size



Schematic model of ANN for prediction of process parameters

3. VALIDATION SET USED FOR NEURAL NETWORK AND REGRESSION ANALYSIS

Testing validity of the neural networks and regression analysis is made using the input parameters. Four datasets are used for validation. The following table 7.1 represents the experimental results, ANN results and the regression analysis results. The experimental results are compared with the artificial neural network model and the regression analysis for the validation and the error percentage is calculated.

Table: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 tempera ture	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 roughn ess	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

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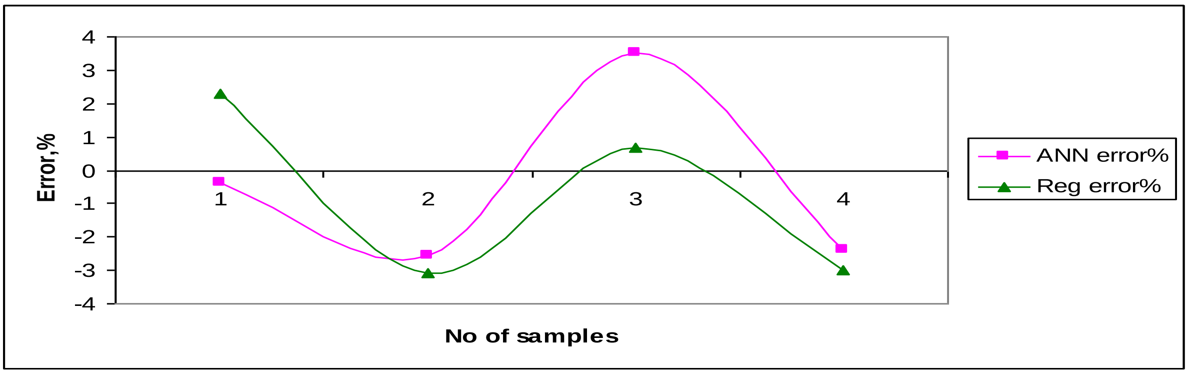
- Comparison of predicted cutting forces, tool temperatures and surface roughness with experimental results in all tested cases indicate that the error is less than 4% for ANN model and less than 8% for regression model.
- The average error percentage for all the predicted values in the ANN model is 1.897%, whereas in the regression model is 2.94%.



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

4. CONCLUSION

The removal of material requires the production of high temperatures and cutting forces.
To lower cutting forces and temperatures and enhance surface smoothness, it's crucial to use the right lubricant.The im pact of a solid lubricant with nanosize (boric acid) on machining was examined in the current study.Using tungsten car bide tool inserts, a variety of turning tests were performed on AISI 1040 steel in order to investigate the impact of soli d lubricant particle size.
The impact of boric acid weight percentage and particle size is evaluated by examining changes in cutting forces, tool temperatures, and surface roughness.The inaccuracy is less than 4% for the ANN model and less than 8% for the regre ssion model, according to comparisons of experimental outcomes with anticipated cutting forces, tool temperatures, an d surface roughness across all testing instances.In the regression model, the average error percentage for all predicted values is 2.94%, while in the ANN model, it is 1.897%.We can infer from this that the ANN model produces higher pr ediction values with a lower error percentage.Ultimately, it was discovered that the ANN model could forecast the met al cutting process parameters more accurately than the regression model, albeit only somewhat.

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