A Comparative study in heat-assisted machining of Inconel 718 and Hastelloy-276 using machine learning techniques

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KEYWORDS

Inconel 718,
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ABSTRACT

Machining parameters have an important role in material removal, tool wear, and surface finish. The manufacturers need to obtain optimal operating parameters with a minimum set of experiments and minimize the simulations to reduce machining set up costs. Due to more demanding manufacturing systems, the focus is on applying machine learning (ML) algorithms in heat-assisted turning in which critical process parameters are predicted. Based on the predictions, the machining parameters can be altered to avoid essential conditions of the process. The experimental results of Inconel 718 and Hastelloy C-276 are analyzed to compare the surface roughness and flank wear using ANN and SVR methods of machine learning. The performance of the models in predicting the parameters is presented to improve further the machining process. Finally, ANN showed a more accurate and effective method in predicting the heat assisted turning responses for the selected machining parameters.

1. Introduction

The machining process is a special technique that transforms the particular material into a required component for an application with desired accuracy, reliability, and surface quality. It is consisting of turning, milling, drilling, and grinding processes. Some of these processes are complex because it accounts for a large percentage of the entire volume removed. In the fabrication of mechanical components, these processes have considerable economic implications. Super alloys are tested high-performance materials used in various industries due to their superior properties like high strength to weight ratio, high tensile and compressive strength, lower density, higher fatigue resistance in sea and air, and high corrosion resistance. Super alloys are classified as difficult-to-machine materials because of their non-favourable properties such as poor thermal conductivity, low modulus of elasticity, strong chemical reaction to tool materials at higher temperatures. Due to an increase in super alloys usage in aerospace and other applications, their fabrication with higher efficiency, safety, and reliability shows a lot of importance. In the machining system, cutting tools, work piece, and machine and cutting tools play an important role because the cutting speed relies upon the cutting tool materials to a greater extent. Researchers are continuously exploring the tool-work piece interaction for getting a better-machined surface. In this regard, efforts have been made for developing novel tool materials that can sustain extreme conditions in the cutting zone. One of the objectives of machining research is to optimize the cutting conditions to lower operational costs and improve product quality. Yang W.H. and Tarng Y.S [1] proposed that using the Taguchi method, a powerful tool to design optimization for quality, is used to find the optimal cutting parameters for turning operations. The optimal cutting parameters for turning operations can be obtained through this study, but the main cutting parameters that affect the cutting performance in turning operations can be found. Experimental results are provided to confirm the effectiveness of this approach. Dash, S.K [2] investigated that the experiment has been carried out dry turning (without using cutting fluid). The ranges of process cutting parameters are cutting speed (11.86,18.65,30.52m/min), feed rate (0.044,0.089,0.178 mm/rev), depth of cut (0.5,0.75,1.0mm). This study highlights applications of Fuzzy logic and the use of the Taguchi experiment design to optimize the

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multi-response parameters on turning operation. For this experiment, the Taguchi design of experiment was carried out to collect the data for surface roughness and tool vibration. The results indicate the input factors' optimum values, and a confirmatory test confirms the results. Srinivas.P and Choudhury [3] stated that the present work aims to develop a reliable method to predict flank wear precisely in a turning process by developing a mathematical model and comparing it with the experimental results. Manoj Kumar B.V., Ram Kumar J [4] observed that TiCN–Ni-based cermets are attractive cutting tools because of the combination of high hardness and wear resistance with improved toughness. The present work reports the effect of TiCN–20 wt.% Ni cermets against boiler steel. The cutting force was measured on-line using a dynamometer, concerning varying cutting speed and feed rate, in dry and orthogonal cutting conditions. The principal aim of the present investigation is to evaluate the dominant mechanisms, using SEM-EDS. The cutting performance of TiCN–Ni cermet is observed to improve with the addition of WC content up to 10 wt.%. A V N L. Sharma et al. [5] have evaluated the surface roughness, and tool wear is one of the most specified customer requirements in a machining process. To predict the surface roughness and tool wear, the Genetic Algorithm & Image processing model was designed through MATLAB 7.1 software for the data obtained. Venkatesh G et al. [6] analyze the multi-response optimization of machining parameters in hot turning of Inconel 718 based on Taguchi based grey relational analysis technique. Cutting parameters such as cutting speed, feed rate, and depth of cut and temperature of work piece were taken as process parameters, whereas surface roughness, tool wear, and material removal rate (MRR) were considered as performance characteristics for the present study. From the Taguchi based grey relational, an optimum level of cutting parameters has been identified. Furthermore, analysis of variance (ANOVA) has been carried out and identified that the feed rate is the dominant process parameter on multiple performance characteristics. A K Kumar et al. [7] performed a simulation of heat assisted machining of Inconel 718 in order to predict the influence of preheating temperature along with machining conditions on cutting force and in which the results indicate that the cutting force has got reduced at preheating (600^0C) compared to room temperature. Cica et al. [8] applied ANN and ANFIS in predicting tool life and surface roughness in hard turning of the 100Cr6 steel under the HPC environment. Models developed to train and validate the experimental data got imposing prediction values and good agreement with experimental results. Mia and Dhar [9] employed ANN methods in predicting surface roughness under different coolant environments in hard turning of EN-24T steel. In addition to cutting parameters, it also considered the material's hardness and determined the best model. Kamruzzaman et al. [10] formulated the ANN model of cutting temperature as a dependent parameter in terms of independent parameters cutting speed, feed rate, depth of cut, work piece materials (C-60, 17CrNiMo4, and 42CrMo4), and cutting environments (dry, wet and HPC), and obtained 97.3% accuracy. Mia et al. [11] developed an ANN-based predictive model of surface roughness in MQL-assisted turning, wherein MQL flow rate, in addition to cutting parameters inputted. Their prediction results obtained 97.5% accuracy in the ANN model. SG Barad et al. [12] carried out a case study in implementing a neural network approach in order to monitor the performance of combined mechanical and performance pertaining to a developmental power turbine. Mia et al. [13] implemented Support Vector Regression (SVR) to predict the best combination of parameters in obtaining the average surface roughness through MQL assisted turning of high hardness steel. The developed model shows 95.04% accuracy to predict the output responses. In the present work, SVR is a regression-based machine learning technique and ANN technique deployed in contrast to | past works, the prediction of chosen machining responses was carried out for heat-assisted machining conditions. Furthermore, selected machine learning techniques are used for the relative evaluation of machining responses to arbitrate the best method based on model accuracy.

2. Experimental Details

In this work, turning is carried out on Inconel 718 and Hastelloy C276 with 16mm diameter and 220mm length. The turning experiments were conducted on NAGAMATI-175 Lathe machine shown in Fig. 1. The chemical composition is shown in Table 1(a) and 1(b) and the properties of both materials are shown in Table 2. Carbide insert with CNMG 120408 NC6210 specification is used as a cutting tool. The input parameters range was selected on basis of machine capacity and preliminary experiments. The range of input parameters is shown in Table 3.

Table 1(a)
Chemical composition of Inconel 718.

Alloy	Percent	Ni	Cr	Fe	Mo	Nb	Co	C	Mn	Si		Cu	A	Ti
718	Min.	50	17	balance	2.8	4.75							0.2	0.7
	Max.	55	21		3.3	5.5	1	0.08	0.35	0.35		0.3	0.8	1.15

Table 1(b)
Chemical composition of hastelloy C276.

Element	Ni	Co	Cr	Mo	Fe	W	Mn	V	Cu
Wt %	57 max.	2.5	16	16	5	4	1max.	0.35	0.5 max

Table 2
Mechanical properties of inconel 718 and hastelloy C276.

S. No	Parameter	Inconel 718	Hastelloy C276
1	Density(kg/m^3)	8195	8890
2	Young's Modulus(GPa)	200	229
3	Poisson ratio	0.3	0.307
4	Thermal conductivity(W/m^{0}C)	11.4	10.2
5	Specific heat(J/Kg/^{0}C)	430	427

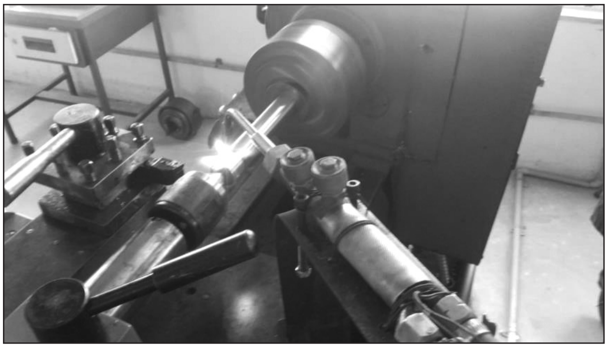

Fig. 1. Machine setup.

Table 3
Input parameters.

Machining Parameters	Level 1	Level 2	Level 3
Cutting speed (m/min)	40	65	100
Feed (mm/rev)	0.051	0.055	0.059
Pre heating Temperature (^{0}C)	30	300	600

Full factorial experiments, L27 orthogonal array has been selected which can reduce the experimental cost. Experiments are conducted under different cutting parameters, which are cutting speed, feed and preheating temperature while depth of cut is kept constant of 0.5. The ranges of these parameters were selected based on the recommendations of the cutting tool manufacturer and in accordance with previous studies. Moreover, the parameter ranges were also extended in order to achieve higher productivity and to investigate machining responses in different machining environments.

3. Machine Learning Techniques

3.1 Support Vector Regression (SVR)

Support vector regression and support vector machine (SVM) are supervised machine learning methods. The further one is used for regression problems, and the latter method is used in classification problems [14]. SVM provides distinguishing features, particularly kernels like linear, Radial Basis Function (RBF), sigmoid, and polynomial, which makes prediction effective. In the present work, three different kernels (linear, RBF, and polynomial) are implemented to determine the performance in predicting the responses in heated assisted machining of Inconel 718 and Hastelloy C276. The model is trained with 80 percent dataset and 20 percent for testing using python language. In data pre-processing, normalization is done using a standard scaler, which helps achieve better prediction. The Kernel function can be replaced by any function satisfying the Mercer's condition. The SVR model is implemented using linear, polynomial, and

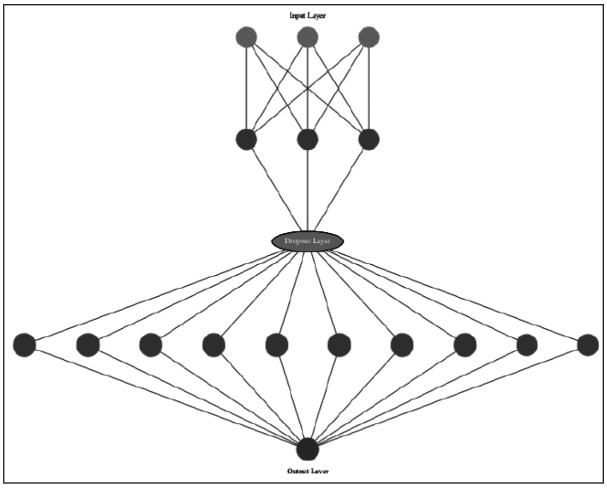

Fig. 2. ANN Model architecture.

RBF kernels in predicting surface roughness and flank wear. Mean Squared Error (MSE) and Root Mean Square Error (RMSE) metrics used in evaluating the model's performance for each kernel.

3.2 ANN

Machine learning techniques, mainly artificial neural networks (ANN), have attracted many researchers in virtually all engineering fields in recent decades [15]. In an attempt to achieve human-like efficiency, ANN was influenced by human brain information [16]. In the literature, various ANN models have been suggested, but the most commonly used is the multi-layer perceptron (MLP). MLP is a type of neuronal feed-forward ANN divided into three layers: the input layer, an output layer, and hidden layers. In the present work, a multi-layer feed-forward ANN based on the back propagation using selected is shown in Figure 2. Keras library files are imported into python when constructing ANN models where the tensor flow is used in the backhand. Dense modules are imported from Keras, of which Sequential is the first to initialize the model, and then the second module, to add separate layers to the ANN model. The number of neurons=10, input dimensions=3, and activation function = relu are the input and hidden layers' parameters with output layer activation taken as linear to predict the continuous variables.

4. Results and Discussion

In the ANN model, the neurons and hidden layers are selected through a trial and error method to adjust the converged error. After examining different neural network architectures, the result

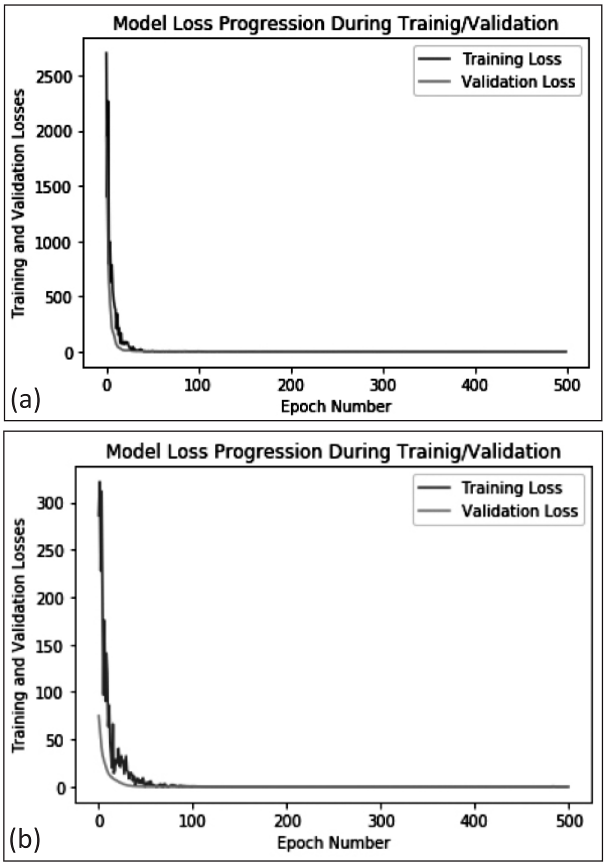

Fig. 3. (a) Model loss plot (Hastelloy 276)
(b) Model loss plot(Inconel 718).

showed that network structure with two hidden layers of three and ten neurons was found to be accurate and efficient in the current study. The loss propagation during training and validation is shown in Figure 3(a) and 3(b) for both Inconel 718 and Hastelloy C276 materials. This indicates that both training and validation got good agreement as there is no over fitting in the model and the loss propagation is also very minimal.

The developed model accuracy was evaluated in terms of RMSE and MSE metric methods, the equations are shown as follows.

$$RMSE = \sqrt{\sum_{i=0}^{n} \frac{\left(y^{pred} - y^{actual}\right)^2}{n}} \quad \text{---Eq.(1)}$$

$$MSE = \sum_{i=0}^{n} \frac{\left(y^{pred} - y^{actual}\right)^2}{n} \quad \text{---Eq.(2)}$$

where y^{pred} = predicted value from ANN, y^{actual} = experimental value, n= number of samples. RMSE and MSE were used to measure the variation between the experimental and

Table 4
Performance evaluation of Machine Learning methods.

Material	Output Response	Model	Metrics	
			MSE (%)	RMSE (%)
Inconel 718	SR	ANN	0.064	0.253
		SVR (RBF)	0.062	0.248
		SVR (linear)	0.023	0.153
		SVR (Poly)	0.039	0.198
	FW	ANN	0.011	0.033
		SVR (RBF)	0.029	0.054
		SVR (linear)	0.026	0.040
		SVR (Poly)	0.029	0.050
Has-telloy C276	SR	ANN	0.175	0.418
		SVR (RBF)	0.520	0.721
		SVR (linear)	0.256	0.506
		SVR (Poly)	0.170	0.412
	FW	ANN	0.026	0.074
		SVR (RBF)	0.075	0.087
		SVR (linear)	0.029	0.077
		SVR (Poly)	0.046	0.081

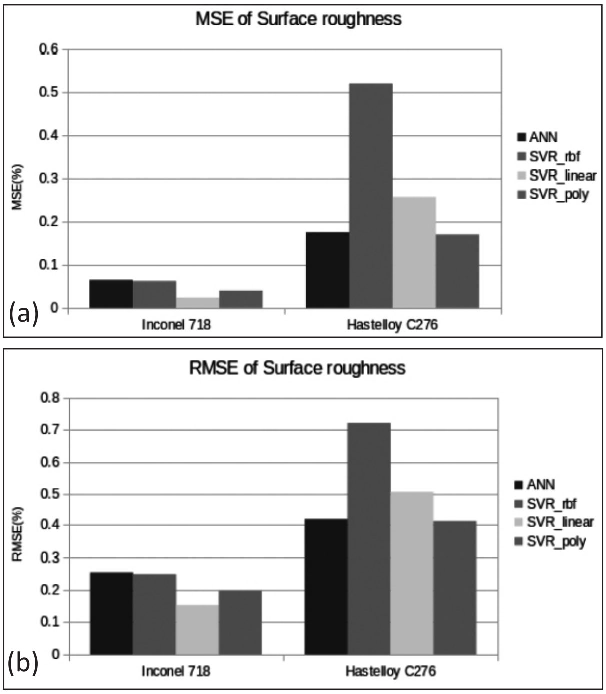

Fig. 4. (a) & (b) Comparison of ML techniques performance for SR.

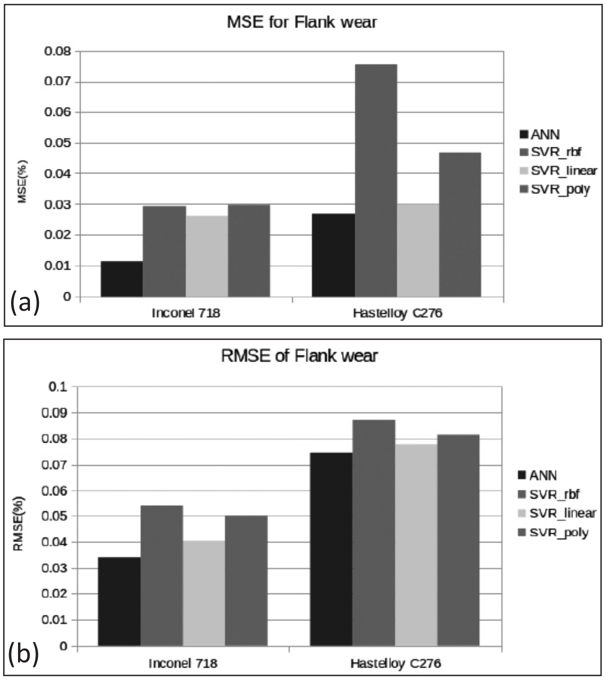

Fig. 5. (a) & (b) Comparison of machine learning techniques performance for flank wear.

predicted values. The predicted values will be nearer to experimental values if the values of these metrics are minimal. The machine learning techniques performances using metric measures for the test data are shown in Table 4. Performance comparison of SVM and ANN models for surface roughness and flank wear prediction of both Inconel 718 and Hastelloy C276 are also shown in Figs. 4(a), 4(b), 5(a), and 5(b) respectively.

The plots show that the MSE values for surface roughness ranging from 0.023 to0.064 for Inconel material and for Hastelloy, it is 0.175 to 0.520. The values of MSE in case of surface roughness of Inconel, almost all the methods are performing well; however, SVR with the linear kernel is outperforming slightly compared to other methods. Whereas in the case of Hastelloy, the ANN model is showing better performance, and also SVR model with poly Kernal is almost the same as ANN performance. The metric values of RMSE and MSE are proportional since it is obtained by taking the square root of MSE, so the values for Inconel ranging from 0.153 to 0.253, and for Hastelloy, the range is from 0.033 to 0.054. For flank wear, the ANN model is outperforming as the MSE and RMSE values are very small for both materials, and SVR with RBF Kernal is showing higher values among all the models.

Based on the data review, it is clear that all considered machine learning techniques are reliable, effective for estimating the surface roughness and flank wear for both materials. The comparison of machine learning techniques based on the regression method of support vector machine of different Kernals also showed better performance, particularly linear kernel showed better accurate results than RBF and Poly Kernals. ANN model is performing even better in almost all cases.

5. Conclusions

In the present work, the two machine learning methods were compared for surface roughness and flank wear prediction in hot machining of Inconel 718 and Hastelloy C276, and the conclusions drawn are as follows.

- The machinability of super alloys is low, and it involves high machining cost and increased lead time due to inherent properties; hence the machine learning techniques play a crucial role in improving the machinability by minimizing the number of experiments through better prediction of responses.
- ANN model is more efficient and reliable compare to other machine learning methods. The loss propagation of the model during training and validation has no much variance, representing no over fitting of the data.
- The metrics analysis clearly shows that the ANN model's error percentage is significantly less in almost all the cases, and the error percentage is more for SVR RBF. In some instances, SVR with linear kernel performance is virtually matching with ANN.
- The metrics values of MSE and RMSE are very low for surface roughness and flank wear models in the test data set of Inconel 718, whereas the values are high for HastelloyC276. Hence the percentage of error is too small; the model performance is too high.

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