Hindawi
Advances in Materials Science and Engineering
Volume 2022, Article ID 9289320, 10 pages
https://doi.org/10.1155/2022/9289320

Research Article

Machine Learning-Based Modelling and Predictive Maintenance of Turning Operation under Cooling/Lubrication for Manufacturing Systems

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Received 27 May 2022; Revised 24 June 2022; Accepted 4 July 2022; Published 18 July 2022

Academic Editor: Samson Jerold Samuel Chelladurai

Cutting force is one of the significant parameters in the metal cutting process. The metal cutting process is the primary in the production and manufacturing industry to produce high-quality products. Every production and manufacturing needs to develop a technology, i.e., a cooling or lubrication system at the cutting zone while doing the metal cutting process. This current work focuses on developing the machine learning algorithm by using three different types of regression processes, namely, polynomial regression process (PR), support vector regression (SVR), and gaussian process regression (GPR). These three processes are developed to predict the machine learning force, cutting power, and cutting pressure by controlling primary factors (cutting speed, depth of cut, and feed rate). The cooling or lubrication process also affects the machining process. We need to maintain the minimum qualifications to perform under minimum quality lubrication (MQL) and high-pressure coolant (HPC). The ANN algorithm was used to run different parameters, and these parameters are optimized for cutting force.

1. Introduction

In industry 4.O, some techniques are used, i.e., IoT, machine learning, artificial intelligence, blockchain technology, etc. These technologies are tested to enhance the quality and productivity of the industries [1]. Now, several manufacturing industries are working on intelligent manufacturing techniques integrated with several sensors with the machines. These manufacturing sensors were synchronized with the various systems through the IoT and used for different prediction management [2, 3].

Metal cutting predictive models have some excellent characteristics because of prediction by using one or more input parameters to get the output parameters. Modelling and forecasting the cutting force in the turning process is related to the number of parameters [4]. Also, it is the getting of power needed for the machine tool, in any way number of parameters challenging to develop the model. Several predictive methods have been used in the last few years to create the entire model [5, 6]. Cutting force is more important in the matching process through the proper selection of parameters. The challenge we face is modelling the details accurately because all input parameters are integrated.

Every conventional machine has started integrating with intelligent technology to reduce errors. This study's main objective is to develop a deeper understanding of the system to develop the machine learning models, i.e., polynomial regression, SVR, and GPR, to act as tools for the system [7, 8].

In the 21st century, every industry wants to set efficient production strategies by controlling and monitoring every process in each stage. Especially in metal cutting, it is a convenient issue to prevent the quality of production, which influences the parameters and better machining process. Many related/interrelated parameters influence the cutting force, so it is tough to develop an accurate model. This research uses machine learning to predict the process using different models.

Cutting force is difficult to understand because they need to select various parameters such as machine tools and fixtures, and monitoring the cutting pressure is very challenging. Finally, the main aim is to model/develop the exact complex shape-cutting process by interrelating the parameters and prediction using machine learning. In this paper, different lubrication conditions are considered with different levels.

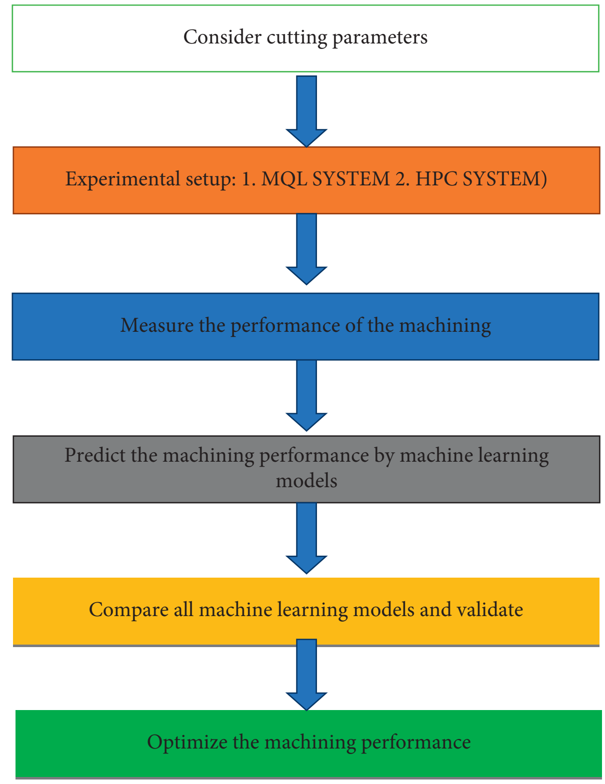

Figure 1: Flow chart machining parameters and modelling.

2. Experimental Setup

This experimentation is focused on the lubrication/cooling system. The minimum quality lubrication (MQL) and high-pressure coolant (HPC) operating techniques were used for this research work. These two techniques are attached to the lathe machines. Figure 1 shows flow chart machining parameters and modelling.

Workpiece material is AISID6 steel, size 120 mm diameter 300 mm long [9]. The lathe machine has an 8 kW power motor to turn the workpiece. The workpiece is fitted to the lathe machine after that lubrication or cooling system is attached [10]. For the minimum quality lubrication (MQL) process, water is mixed with the compressed air of 3 bar. Fluid was supplied at 30 ml/h by spraying at a distance of 30 mm away from the tooltip, at an angle of 30 and 90 degrees [11].

For a high-pressure coolant (HPC) system, water is mixed with compressed air of 50 bar. The nozzle diameter supplies 0.4 mm, and the flow rate is 21/min. This nozzle is fixed at a distance of 30 mm away from the tooltip at an angle of 5-6 degrees [12, 13].

When we run the lathe machine, we need to control the cutting speed and depth of the cut feed rate; the operator owns these parameters [14]. As per the basic knowledge, we consider three levels of cutting speed and cut depth and four feed rate levels. We can run $(3 \times 3 \times 4)$ 36 experimentations that can run each lubricant/cooling condition.

A Kistler component dynamometer is used to measure the cutting forces. Cutting force is precisely monitored with this dynamometer, which is attached to the lathe through a custom-designed tool holder adapter [13, 15]. Now, by using the above values, we can start the preparation of data sets. In the data sets, 75% of data sets should be prepared for training data sets; the remaining all are considered as test data set to validate the model [16]. Now, we can select 26 random training data sets from the experimental data, and the remaining are used as test models. Test data should consider from the MQL and HPC machining process. The machining parameters and responses are presented in Table 1.

3. Machine Learning Method

3.1. Polynomial Regression/Second-Order Polynomial Regression Model. Generally, the regression model gives the relation between dependent and independent variables. Linear regression will provide a connection between dependent and separated linearly. Our work focuses on the polynomial regression, which means that it will give the relation between the dependent and independent in a polynomial manner. The polynomial equation needs the number of linear regressions. For that purpose, the second-order polynomial equation is considered in our research [15, 17, 18].

$$\sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ij} x_{ij}^2 + \sum_{ij} \beta_{ij} x_{ij} + \varepsilon. \quad (1)$$

To fit the second-order polynomial equation, consider the least square method. The structure of the decision tree is

Table 1: Cutting parameters and response.

Si no	Cutting parameters			Response						Type
				MQL			HPC			
	Cutting speed in (m/min)	Depth of cut in (mm)	Feed rate in (mm/rev)	Machining force in (N)	Cutting power in (kW)	Cutting pressure in (N/mm^2)	Machining force in (N)	Cutting power in (kW)	Cutting pressure in (N/mm^2)	
1	200	1	0.2	975	2.79	2.78	954	2.76	2.46	T
2	200	1	0.25	1088	3.19	3.19	1067	3.16	2.87	T
3	200	1	0.3	1254	4.05	4.01	1233	4.02	3.69	L
4	200	1	0.35	1546	4.38	4.37	1525	4.35	4.05	T
5	200	1.2	0.2	1026	3.38	3.38	1005	3.35	3.06	T
6	200	1.2	0.25	1225	3.95	3.95	1204	3.92	3.63	L
7	200	1.2	0.3	1654	5.11	5.04	1633	5.08	4.72	L
8	200	1.2	0.35	1862	5.58	5.52	1841	5.55	5.2	T
9	200	1.5	0.2	1325	4.11	4.13	1304	4.08	3.81	T
10	200	1.5	0.25	1456	4.81	4.84	1435	4.78	4.52	T
11	200	1.5	0.3	2015	6.2	6.19	1994	6.17	5.87	T
12	200	1.5	0.35	2022	6.84	6.95	2001	6.81	6.63	T
13	300	1	0.2	955	4.04	4.15	934	4.01	3.83	T
14	300	1	0.25	1055	4.74	4.65	1034	4.71	4.33	L
15	300	1	0.3	1244	5.94	5.05	1223	5.91	4.73	T
16	300	1	0.35	1016	6.7	6.65	995	6.67	6.33	T
17	300	1.2	0.2	1215	5.1	5.04	1194	5.07	4.72	T
18	300	1.2	0.25	1644	6.01	6.01	1623	5.98	5.69	L
19	300	1.2	0.3	1852	7.61	7.62	1831	7.58	7.3	T
20	300	1.2	0.35	1854	8.44	8.45	1833	8.41	8.13	T
21	300	1.5	0.2	1315	6.25	6.32	1294	6.22	6	T
22	300	1.5	0.25	1445	7.2	7.2	1424	7.17	6.88	L
23	300	1.5	0.3	2011	9.16	9.26	1990	9.13	8.94	T
24	300	1.5	0.35	2015	10.23	10.32	1994	10.2	10	T
25	400	1	0.2	945	4.7	4.84	924	4.67	4.52	T
26	400	1	0.25	1044	5.44	5.45	1023	5.41	5.13	L
27	400	1	0.3	1233	7.13	7.12	1212	7.1	6.8	T
28	400	1	0.35	1006	7.84	7.85	985	7.81	7.53	L
29	400	1.2	0.2	1205	6.38	6.35	1184	6.35	6.03	T
30	400	1.2	0.25	1635	7.42	7.42	1614	7.39	7.1	L
31	400	1.2	0.3	1842	9.74	9.32	1821	9.71	9	T
32	400	1.2	0.35	1844	10.34	10.35	1823	10.31	10.03	T
33	400	1.5	0.2	1300	7.92	7.95	1279	7.89	7.63	L
34	400	1.5	0.25	1425	9.12	9.13	1404	9.09	8.81	T
35	400	1.5	0.3	1990	11.54	11.52	1969	11.51	11.2	T
36	400	1.5	0.35	2011	12.81	12.84	1990	12.78	12.52	T

*L, learning data set; *T, training data set.

shown in Figure 2. Where Y is the dependent variable, X_i, and Y_j are the independent variables.

3.2. Support Vector Regression (SVR) Method. Supportive vector regression is one of the best machine learning methods for the supervised algorithm. It will give the best optimal solutions so that there is no need to do the experimentation to find the answer [19].

A supportive vector machine divides the data point according to the claves, which are mapped by the hyperplane in a high-dimensional space, to create two hyperplanes between the classes [20]. If there is a larger space, generating means an error is achieved in the classifier. Due to that regression, we should try to get an optimal solution by the hyperlink, which is the most significant distance to data points of the different classifiers. The data points on the boundaries closest to separating the hyperplane are called a supportive vector [20, 21].

This SVM process can apply in any engineering area. The primary advantage is getting the model by using some parameters; parameters are kernel function, loss function, cost function, etc. [22, 23].

The SVM was developed for the classifier regression only. We are now developing a regression problem with a loss function that will help find the distance between the hyper lines. This solving regression problem through the SVM is called supportive vector regression (SVR) [24].

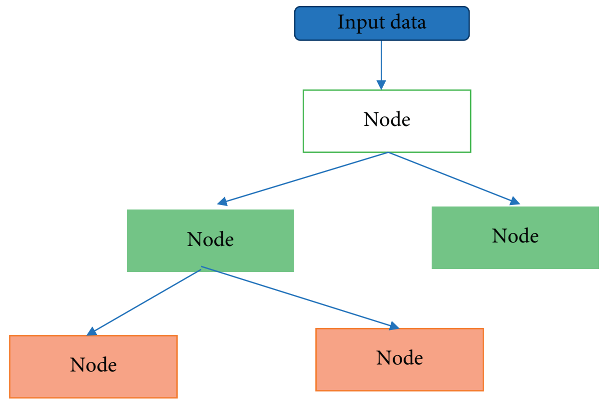

Figure 2: Structure of decision tree.

Table 2: Performance of different machine learning process.

Cutting environment	Statistical model						
	Response	Method	MAPE	Max APE	MAE	NRMSE	R^2
MQL	Fr	PR	1.6	3.4	2.22	0.99	0.9956
		SVR	1	1.9	13.5	0.066	0.9975
		GPR	1	2.5	12.08	0.058	0.9998
		ANN	0.8	1.3	9.79	0.055	0.9985
	Pc	PR	2.8	9.6	0.156	0.075	0.9998
		SVR	1	1.8	0.058	0.026	0.9989
		GPR	1	2.8	0.065	0.025	0.9987
		ANN	0.9	2.5	0.057	0.33	0.99899
	Ks	PR	1.5	2.9	28.78	0.386	0.9909
		SVR	1.2	2.4	23.98	0.445	0.9722
		GPR	1	2.98	19.51	0.318	0.976
		ANN	0.9	2.5	16.58	0.275	0.9788
HPC	Fr	PR	1.4	2.5	19.22	0.086	0.9992
		SVR	0.9	2.4	11.89	0.058	0.9995
		GPR	0.8	1.9	10.78	0.048	0.9995
		ANN	0.7	1.5	9.98	0.048	0.9959
	Pc	PR	2.2	6.8	0.123	0.59	0.9998
		SVR	1	2.8	0.065	0.33	0.09998
		GPR	0.8	2.8	0.058	0.035	0.9997
		ANN	0.7	1.4	0.045	0.019	0.9999
	Ks	PR	1.5	3.2	28.55	0.48	0.9575
		SVR	0.9	2.1	16.15	0.351	0.9755
		GPR	0.9	2.4	15.99	0.254	0.9687
		ANN	0.8	2.4	13.65	0.254	0.9745

$$
\begin{aligned}
&Minimize\, C\,\frac{1}{N}\sum_{i=1}^{N}\left(\epsilon_i+\epsilon_i^*\right)+\frac{1}{2}\|W\|^2,\\
&W=\sum_{i=1}^{N}\left(\beta_i-\beta_i^*\right)\varnothing\left(X_i\right),\\
&f(X)=\sum_{i=1}^{N}\left(\beta_i-\beta_i^*\right)K\left(X_i,X_j\right)+b,\\
&K\left(X_i,X_j\right)=\varnothing\left(X_i\right).\varnothing\left(X_j\right),\\
&K\left(X_i,X_j\right)=\exp\left(-\frac{\left\|X_i-X_j\right\|^2}{2\sigma^2}\right).
\end{aligned}
\tag{2}
$$

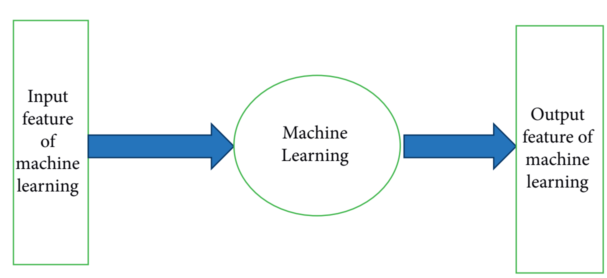

Figure 3: Machine learning framework.

3.3. Gaussian Process Regression. It is the best regression process to solve complex problems with high dimension, nonlinear, and fewer training parameters. So that we will get good performance output by the gaussian process regression

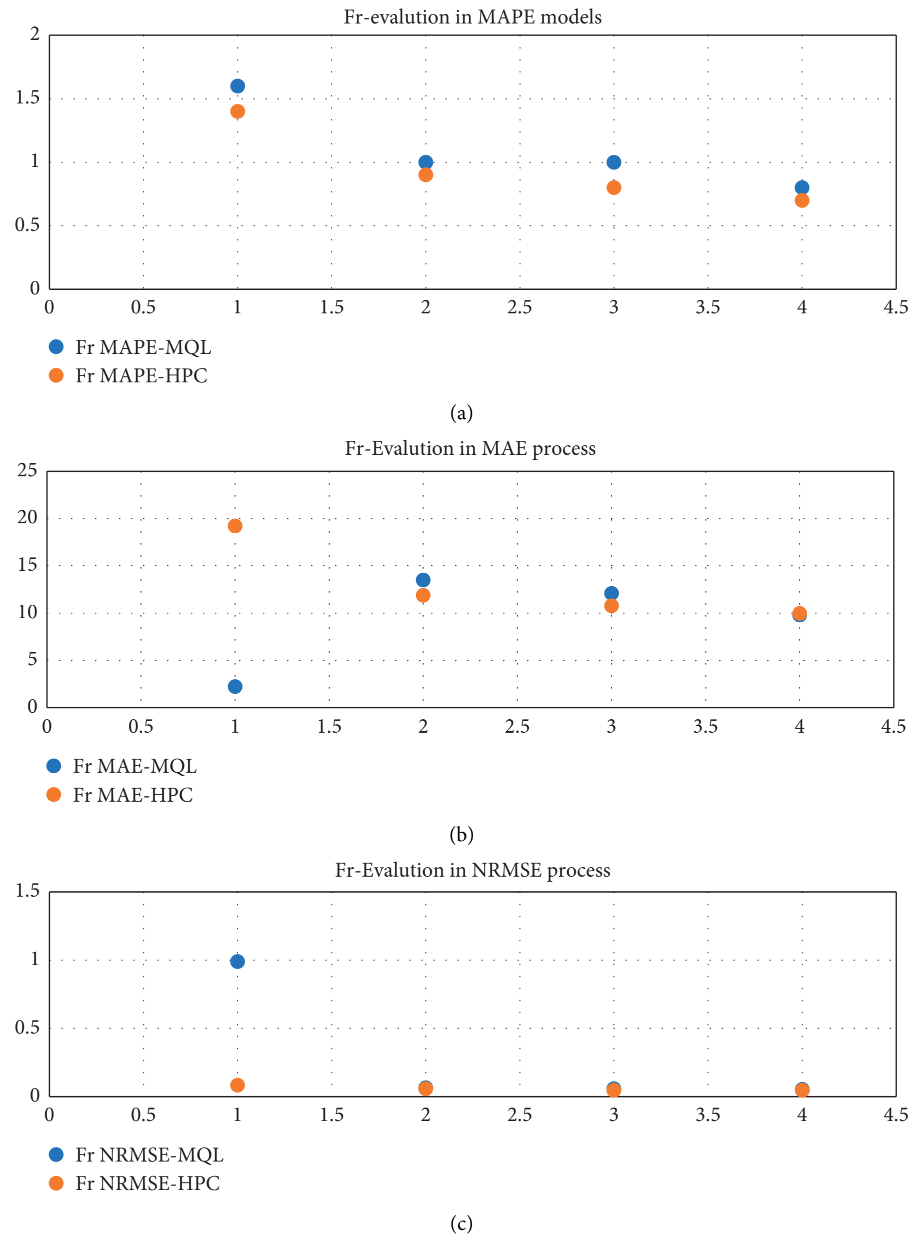

Figure 4: (a–c) Machine learning performance for reducing machining force. (a) Fr-evaluation in MAPE models. (b) Fr-evaluation in MAE process. (c) Fr-evaluation in NRMSE process.

which has been widely applied in various areas of engineering [24, 25].

$$\log\left(\rho\left(y/X,\theta\right)\right) = \frac{1}{2}y^{T}\left(K+\sigma^{2} I\right)^{-1} y - \frac{1}{2}\log\left|K+\sigma^{2} I\right| - \frac{n}{2}\log 2\pi. \quad (3)$$

3.4. ANN Model. ANN method developed like a human neuron system. Many researchers work on the ANN model because it can apply to all fields. The ANN model has a superior intelligence to solve the nonlinear functions. We were developing an ANN model to interlink the machining process with different parameters.

In our developed ANN model, we will consider three layers: (1) input layer, (2) output layer, and (3) hidden layer. Each layer has different neurons, and each neuron can simplify and calculate the performance by one or several varieties of processing methods [1, 4, 24].

The output of the ANN method can adjust by using the weights. The weights are designed by optimizing the ANN output and current respond vector. The back propagation algorithm is one of the best techniques in the ANN model [25].

3.5. Multiobjective Optimization. In this research, we developed a machine learning model using different methods; this method is a multiobjective method characterized by

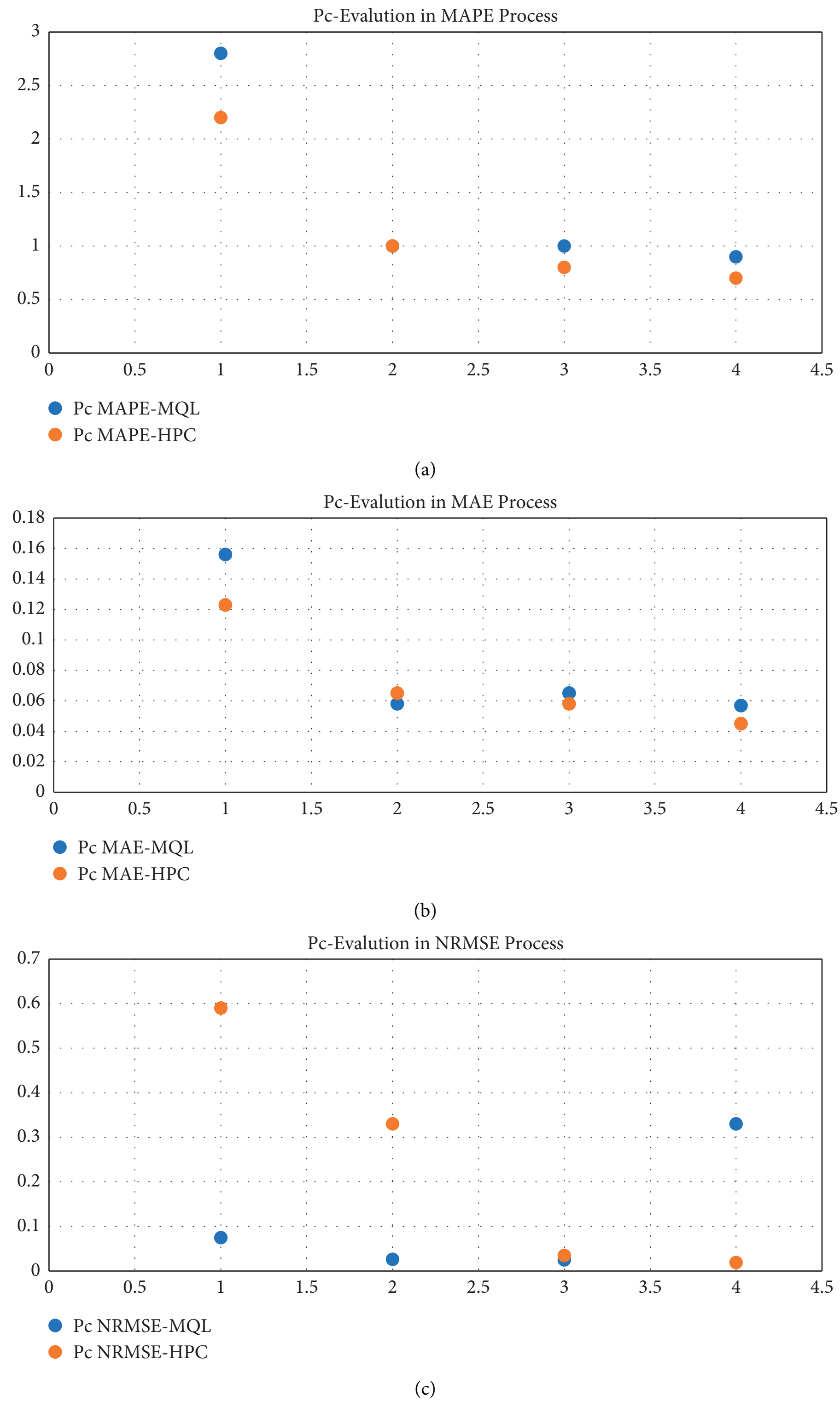

FIGURE 5: (a–c) Machine learning performance for reducing cutting power. (a) Pc-evaluation in MAPE models. (b) Pc-evaluation in MAE process. (c) Pc-evaluation in NRMSE process.

difficult nonlinear functions, and it is impossible to use with traditional methods in machine learning. So, we need to develop a correlation between the input and output by using polynomial regression multiobjective optimization.

4. Results and Discussion

In the result part, the capability of machine learning models was discussed and analyzed according to the accuracy of that

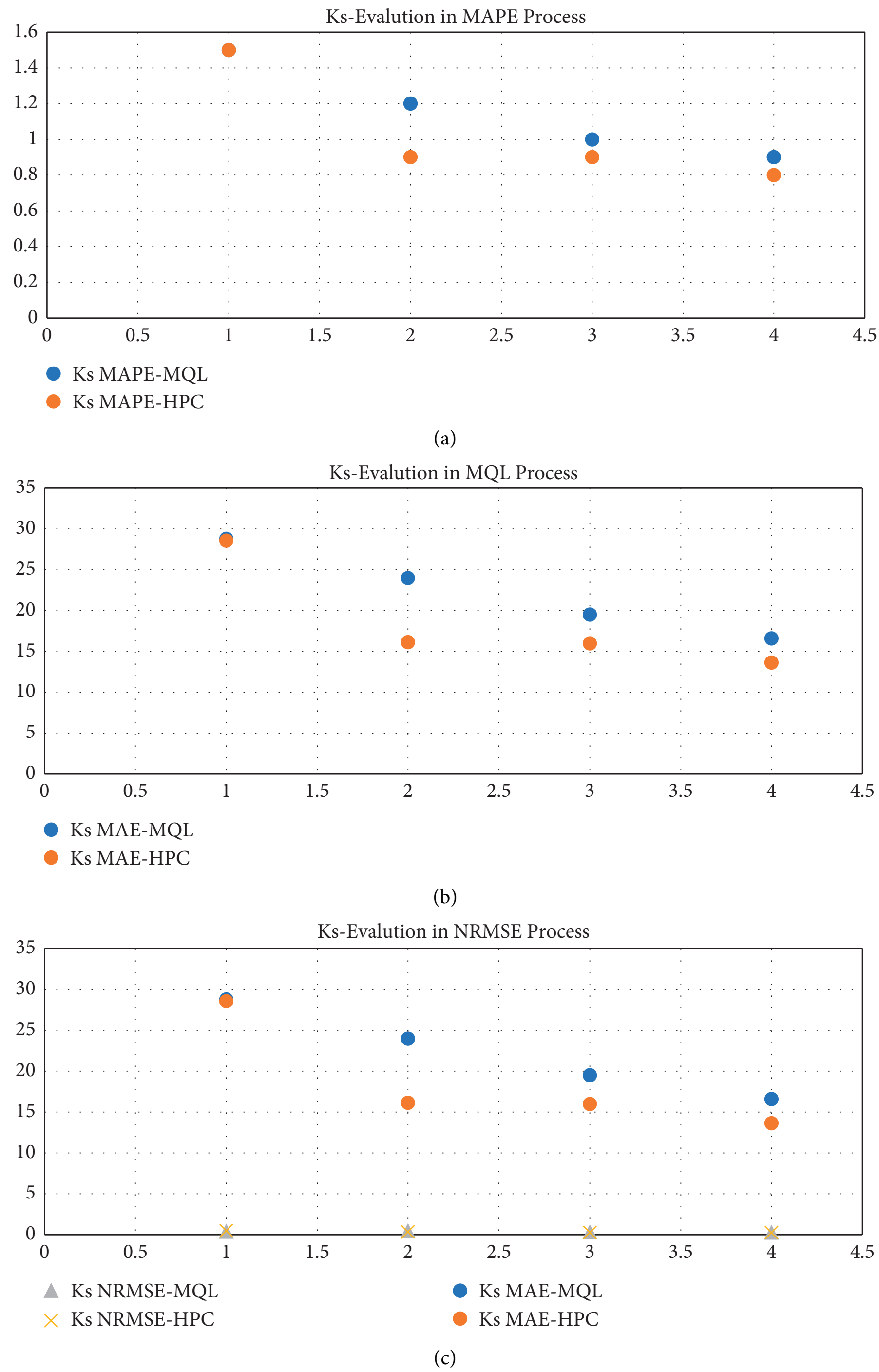

FIGURE 6: (a–c) Machine learning performance for reducing cutting pressure. (a) Ks-evaluation in MAPE models. (b) Ks-evaluation in MQL process. (c) Ks-evaluation in NRMSE process.

particular model. MAPE, MaxAPE, MAE, NRSME, and R2 predicted values are summarized in Table 2.

4.1. Machine Learning-Based Prediction Response. This section uses four prediction methods to determine the turning operation under different cooling/lubricating conditions. The machine learning framework model is shown in Figure 3.

To develop a polynomial regression model, we produce 36 data sets. In that, 27 data sets are used to create the regression equation; the remaining nine are used to test the equation to get an accurate output.

The SVR model was developed by the input of cutting speed, depth of cut, and feed rate. The RBF kernel function is established in the SVR model. The c-value and loss function are essential to perform the SVR model in the Kernel function. The RBF kernel function will generate automatically by the subsampling method, which is inbuilt in MATLAB. We select the grid search method for this entire SVR model because the medium-sized problem is key solves by this method. In the grid search method, we will fix every step by the size range, and we should compare the all-set performance using the production methods. In the turning of Nimonic C263 super alloy, a predictive model based on DEFORM 3D was developed to forecast machining attributes such as cutting force and insert cutting edge temperature [26]. The 2D wavelet transform can disintegrate a machined surface image into multiresolution depictions for a variety of surface characteristics, and it can be used to evaluate surfaces [27]. This current work will predict the optimal value for each model's c-value and loss function in SVR for the grid selection method [28]. In the GPR model, machining parameters in MQL and HPC conditions to get the accurate values of hyper parameters is a challenging step for the GPR model. This number of primary parameters influenced the GPR model.

In the ANN model, neuro network optimization is essential because there are several hidden layers and several nodes in the layer through an error method, so we need to adjust that error; the linear transfer function is used for adjusting the mistake. The network is well-trained at 10000 epoch with a learning rate of 0.04 and momentum is 0.09 error between the actual output is significantly less than 0.0001 at the training process [29, 30].

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{\left|A_1 - X_i\right|}{A_1}\right). 100,$$

$$MaxAPE = \text{Max}\left(\frac{|A - X|}{A} . 100\right),$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|A - X|, \tag{4}$$

$$= \frac{\sqrt{\sum_{i=1}^{n} (A - X)^2}}{\epsilon},$$

$$R^2 = \frac{\sum_{i=1}^{N}(A_1 - a_i)(X_i - x_1)}{\sqrt{\sum_{i=1}^{N} (A_1 - a_i)^2 \sum_{i=1}^{N} (X_i - x_1)^2}},$$

where N is the number of training variables, A and X are the experimental results, and a and x are the average values of experimental values.

Performance is shown in different machine learning models in terms of five other models for the data sets as shown in Table 2. For more clarity and visualization, a comparison in performance is shown in Figures 4–6.

From the MQL process:

(1) MAPE values 0.8 to 2.8%
(2) MAXAPE is 1.3 to 9.6%
(3) MAE is 0.57 to 13.5%
(4) NRMSE is 0.66 to 0.025%
(5) The max value found was 3.4 from PR
(6) It is concluded that SVR and GPR methods are outdated compared to PR
(7) ANN slightly outperformed; both SVR and GPR methods outperformed PR
(8) Machining force and cutting power values are very high, but cutting pressure is less.

From the HPC,

(1) MAPE values 0.7 to 2.2%
(2) MAXAPE is 1.4 to 6.8%
(3) MAE is 0.045 to 28.15%
(4) NRMSE is 0.019 to 0.59%
(5) When PR is employed, the maximum values are found in MAPE and MAXAPE in the cutting power model, just as in MQL cutting conditions
(6) We observed the best use of SVR and GPR over the PR method from the above points
(7) ANN is getting more accurate compared to the remaining methods
(8) We noted from the HPC method that the predicted machining force and cutting force were close, but the cutting pressure value was less.

Based on this entire prediction, machine learning algorithms are accurate. By comparing all models, SVR and GPR performed very closely, accuracy will reach in the PR model, and ANN is getting more accuracy than all regression methods. Finally, we conclude the analysis. All procedures are performed very well, and the results are pretty satisfactory. While comparing time, the PR method is faster because it does not need more parameters.

5. Conclusion

In the present study, we developed different models; input data are cutting parameters in this model. The output (prediction) is the quality check in lubrication and cooling machining environments. By performing the different models, we should find absolute error percentage, maximum absolute error, mean fundamental error, root square error, and correlation coefficient with practically observed values [31, 32].

By the developed model, it gets accurate prediction values under all conditions.

Table 2 and the graphs are shown in Figures 4(a), 5(a), and 6(a).

(1) MAPE values range from 2.8 to 0.7% for MQL and HPC.
(2) MaxAPE values range 3.4 to 1.3% for MQL and HPC.
(3) By observing Table 2, we can conclude that the highest cutting power is employed in PR.
(4) By comparing the PR, MAE, and NRMSE, we found that SVR and GPR performance is better than PR.
(5) The ANN model is also getting higher accuracy than machine learning models.

(6) Developed model gets the accepted result, and also it will reduce the time and cost of the experimentation.

(7) By multiobjective optimization, the best or optimal combination of machine performance is a cutting speed is 210 m/min, depth of cut of 1.5 mm, and feed rate of 0.224 mm/rev.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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