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Implementation of Machine Learning Approaches for the Modeling and Predictive Turning Maintenance Operations Incorporating Lubrication and Cooling in Systems of Manufacturing

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ABSTRACT

The cutting force is a vital parameter in the metal cutting process, which serves as a cornerstone in the production and manufacturing industries for the creation of high-quality products. It is imperative for all Activities related to production and manufacturing to establish A technological advancement, such as a The system for lubrication or cooling is located at the area of cutting during The process of cutting metal. This research Emphasizes the importance of the development of a machine learning algorithm that employs A trio of distinct variations regression techniques: Gaussian process regression (GPR), polynomial regression (PR), and support vector regression (SVR). These methods are intended to forecast reduction in cutting pressure, force, and power by regulating essential Elements such as cutting speed, depth of cut, and feed rate. Furthermore, The process of cooling or lubricating plays a significant role Within the machining phases. Maintaining minimum qualifications for effective operation High-pressure coolant (HPC) and minimum quality lubrication (MQL) are essential. The artificial neural network (ANN) algorithm was utilized to evaluate various parameters, which were optimized for cutting force.

Keywords: *Turning, Multi Objectives Optimization, SVR, GPR, polynomial regression, ANN*

1. INTRODUCTION

Industry 4.0 incorporates several techniques, including Blockchain, artificial intelligence, machine learning, and the Internet of Things. These innovations in technology are being Assessed to improve The performance and excellence of diverse industrial fields. Currently, numerous Production process sectors are developing Advanced manufacturing technologies that incorporate various sensors within their machinery. These sensors are interconnected with different systems via the Internet of Things (IoT) and are utilized for diverse predictive management purposes. Metal cutting predictive models possess significant qualities due to their ability to predict outcomes based on A single or multiple input parameters. The modeling and predicting the cutting force during the process of turning depend on The number of parameters taken into account. Furthermore, obtaining the requisite power for the machine tool entails navigating a complex array of parameters that pose challenges in model development. Over the past few years, several predictive techniques have been utilized to formulate the complete model. The significance of cutting force is paramount in the matching process, especially when it comes to the judicious selection of parameters. The difficulty we encounter is in achieving precise modeling of the details, given that all input parameters are interrelated. Conventional machinery is progressively incorporating intelligent technology to mitigate errors. This examination primarily seeks to deepen the understanding of the system, which will aid in the creation of models for machine learning, including Gaussian process regression (GPR), support vector regression (SVR), and polynomial regression, to function as instrumental tools for the system. The concept of cutting force is complex, as it requires the selection of multiple Elements such as cutting pressure monitoring and machine tools and fixtures is notably Testing. The overarching goal is to accurately model and construct the intricate process of cutting complex shapes by connecting these variable and employing machine learning for predictive analysis. This study explores Distinct lubrication scenarios at varying levels.

Experimental Set Up

This research centers Concerning the system for lubrication and cooling. The study employed Approaches utilizing High-pressure coolant (HPC) and minimum quality lubricant (MQL). Both methods are integrated with lathe machines. Figure 1 illustrates The schematic representation of the various machining parameters and modeling. The material of the workpiece is SS304 steel, measuring 300 mm in length and 120 mm in diameter. The lathe equipment is equipped with a motor that has a power rating of 8 kW to facilitate the rotation of the workpiece. Following the installation of the workpiece onto A cooling or lubrication system is then connected to the lathe machine. The process of minimum quality lubrication (MQL) involves the mixing of water with compressed air at a pressure of 4 bar. The fluid is administered at a 35 ml/h flow rate, utilizing a spray technique from 40 mm away from the tooltip, at 40 and 80 degree angles. A system using high-pressure coolant (HPC) utilizes a mixture of water and compressed air at a pressure of 40 bar. The nozzle features a diameter of 0.5 mm and operates at a flow rate of 20 liters per minute. It is positioned 20 mm away from the tooltip, with an angle ranging from 4 to 7 degrees. In the operation of the lathe machine, it is crucial to monitor the feed rate, depth of cut, and cutting speed, all of which are under the operator's control. According to basic principles, we establish three levels for cutting speed and cut depth, along with three levels for the feed rate. Consequently, we can conduct nine experiments, each utilizing different lubricant and cooling conditions. The measurement of cutting forces is conducted using a Kistler component dynamometer. This device, which is affixed The custom tool holder adapter is utilized to connect to the lathe, ensures accurate monitoring of cutting forces. With the values obtained, we can proceed to prepare the data sets. It is important to allocate 76% of the data sets for training, while the remaining portion will be utilized as the test data set for model validation. We will randomly select 9 Data sets for training obtained based on the experimental findings, with the rest being Employed as evaluation models. The MQL and HPC machining procedures will be covered by the test data. parameters of machining and their corresponding Table 1 provides an overview of the responses.

Table 1: Cutting Specifications and Their Responses.

Exp No.	Cutting Parameter Level			Response					
				MQL			HPC		
	Cutting Speed	Feed Rate	Depth of Cut	Machining Force in (N)	Cutting power (kW)	Cutting Pressure (N/mm2)	Machining force in (N)	Cutting power in (kW)	Cutting pressure in (N/mm2)
1	1	1	1	970	3.87	3.56	950	2.55	2.55
2	1	2	2	1070	2.2	2.2	1098	3.78	3.08
3	1	3	3	1243	3.08	3.02	1266	4.2	4.08
4	2	1	3	1657	5.28	5.26	1425	4.45	3.09
5	2	2	1	960	4.96	4.96	1102	3.88	3.56
6	2	3	2	1145	3.15	3.08	1533	5.16	4.98
7	3	1	2	1765	2.02	2.24	1704	6.18	6.08
8	3	2	3	1333	4.92	4.34	1678	5.89	5.06
9	3	3	1	1876	6.04	6.38	1988	6.08	5.98

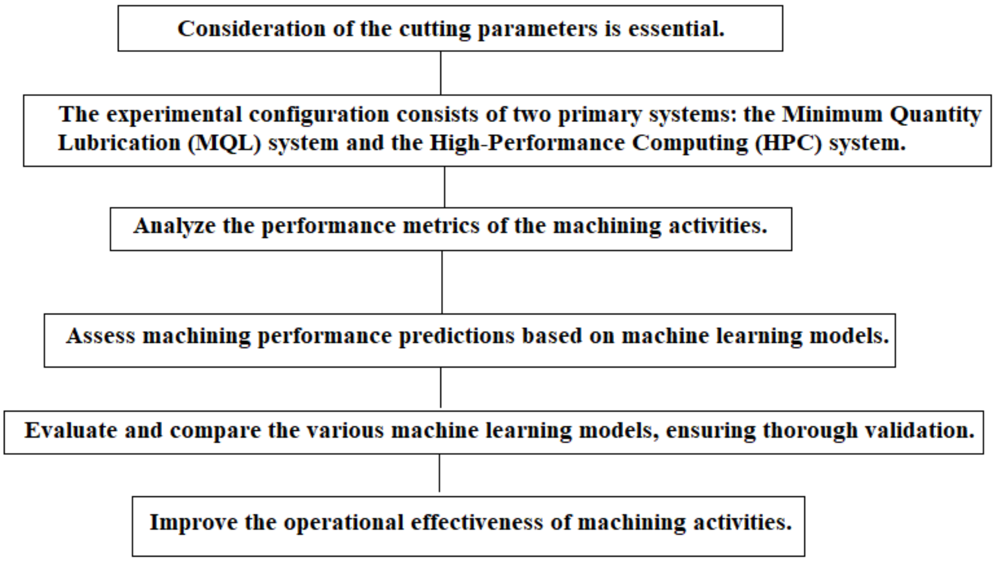

Figure 1: Diagram illustrating machining parameters and modeling processes.

Machine Learning Technique.

Second-Degree Polynomial Regression Analysis.

Typically, the regression model defines The differentiation between independent variables and dependent variables. Linear regression establishes a linear correlation between these variables. Our study is concentrated on polynomial regression, which expresses the relationship in a polynomial form. In this context, we consider a second-order polynomial equation for our analysis.

$$\sum_{i=1}^{K} k_j \; L_j \; + \; \sum_{i=1}^{K} k_j \; L_j \; + € \qquad (1)$$

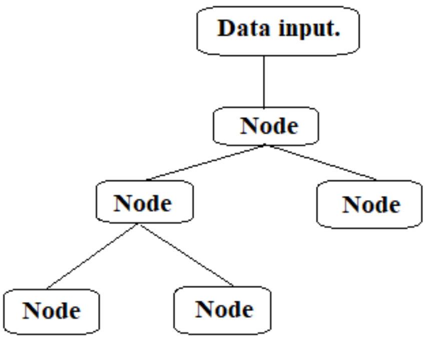

Figure 2 illustrates the configuration of the decision tree.

The framework for Support Vector Regression (SVR)

Regression utilizing support vectors distinguishes itself as An instance of the premier machine learning methods in supervised algorithms. It delivers optimal solutions, which negates the need for conducting experiments to obtain results. A support vector machine classifies data points according to their respective classes, utilizing A hyperplane situated within a space of high dimensions to establish two distinct hyperplanes that separate these classes. In instances where the dimensional space is expanded, the classifier may experience errors during the generation process. Therefore, it is crucial to pursue an optimal solution via the hyperplane, indicating the greatest separation from the various classes' data elements. The aspects that are present nearest They are referred to as support vectors to the separating hyperplane.. The application of the SVM process is feasible in any field of engineering. The key benefit is the capability to construct a model through the use of certain variable, for instance, the cost function, loss function, and kernel function. Initially, the Support Vector Machine (SVM) was created exclusively for classification purposes. At present, we are engaged in developing a regression problem that utilizes a loss function to ascertain the distance between hyperplanes. This method of addressing regression issues The method known as Support Vector Regression (SVR) is derived from Support Vector Machines.

Gaussian Process Regression Overview.

Gaussian process regression stands out as an excellent technique for tackling intricate issues that involve high dimensions, nonlinear relationships, and a reduced set of training parameters. Its efficacy has been recognized in a variety of engineering applications.

Model of Artificial Neural Networks.

The ANN methodology has been established to replicate the characteristics of human neural systems. A significant number of researchers are focusing on the ANN model because of its versatility in multiple fields. This model demonstrates exceptional intelligence in resolving nonlinear functions. We are currently working on an ANN model aimed at connecting The machining operation characterized by distinct parameters. Our constructed artificial neural network will feature three primary layers: The input layer, the output layer, and the hidden layer are the first three layers.. Each segment comprises A distinct group of neurons, with each individual neuron is able to enhance and assess performance using one or several processing methodologies. The results produced by the Artificial Neural Network (ANN) approach can be fine-tuned by altering the weights. These weights are determined by Enhancing the output of the artificial neural network alongside the existing response vector. The backpropagation algorithm stands out as one of the most proficient techniques utilized within the ANN framework.

Optimization with Multiple Objectives.

This research involved the development of a machine learning model utilizing a range of methodologies. The method employed is a multiobjective approach distinguished by challenging nonlinear functions, which cannot be accomplished efficiently addressed Utilizing established methods machine learning techniques. Therefore, Building a relationship is essential Utilizing polynomial regression for multiobjective optimization facilitates the relationship between the input and output.

2. RESULTS AND DISCUSSION.

the results section, the effectiveness of An analysis of models for machine learning was performed and evaluated based on the precision of each specific model. The predicted values for MAPE, MaxAPE, MAE, and R2 are consolidated in Table 2.

Table 2: Evaluation of Various Machine Learning Processes.

Environment for cutting	Response	Method	M A P E	Max A P E	M A E	R2
MQL	FR	PR	1.5	3.2	2.2	0.9923
		SVR	1	1.8	12.24	0.9978
		GPR	1	2.2	11.98	0.9962
		ANN	0.82	1.2	9.82	0.9923
	PC	PR	2.5	9.2	0.123	0.9924
		SVR	1	1.7	0.059	0.998
		GPR	1	2.7	0.068	0.9977
		ANN	0.88	2.2	0.06	0.9922
	KS	PR	1.4	2.8	27.88	0.9902
		SVR	1.1	2.2	22.98	0.9823
		GPR	1	2.88	18.56	0.9876
		ANN	0.92	2.6	15.67	0.9854
HPC	FR	PR	1.3	2.1	18.44	0.9978
		SVR	0.94	2.5	12.68	0.9989

		GPR	0.82	1.8	9.78	0.9992
		ANN	0.72	1.4	10.78	0.9962
	PC	PR	2.1	7.6	0.122	0.9968
		SVR	1	2.9	0.068	0.9992
		GPR	0.84	2.9	0.056	0.9956
		ANN	0.68	1.3	0.042	0.9994
	KS	PR	1.35	3.1	29.55	0.9657
		SVR	0.92	2.2	15.15	0.9855
		GPR	0.92	2.6	16.88	0.9678
		ANN	0.78	2.6	14.78	0.9756

Prediction Response Utilizing Machine Learning Techniques.

This section employs four predictive methods to ascertain he turning procedure performed with various cooling methods and lubrication conditions. Figure 3 presents an illustration of The model of the machine learning framework.

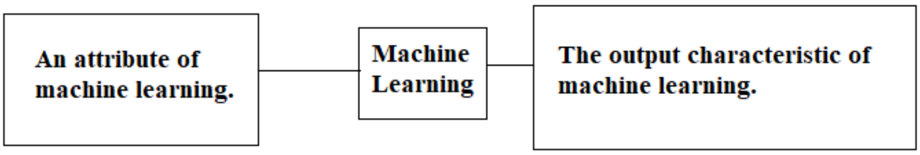

Figure 3: Framework for Machine Learning.

To construct An example based on polynomial regression, we generate a total of 30 data sets. Out of these, 9 data sets are utilized to formulate The equation representing the regression analysis, while the remaining 9 are employed to evaluate The mathematical expression in order to obtain precise results. The development of the Support Vector Regression (SVR) model incorporates inputs including feed rate, depth of cut, and cutting speed. The model employs the Radial Basis Function (RBF) kernel. Key components such as The c-value and its associated loss function are vital for the operation of the SVR model within the kernel context. The RBF kernel is configured automatically produced using The subsampling method available in MATLAB. We have chosen The grid search method employed for this Support Vector Regression (SVR) model, as it is well-suited for solving medium-sized issues. The grid search technique involves setting a fixed step size for each parameter, allowing us to assess the performance of the entire set through various production methods. In the context of turning SS 304, a predictive model was formulated with DEFORM 3D to estimate machining parameters such as cutting force and the temperature at the cutting edge of the insert. The 2D wavelet transform effectively breaks down a surface image that has been machined into multiresolution representations that capture different surface features, thus serving as a useful method for surface assessment. This research seeks to identify the optimal c-value and loss function for each model within the framework of Support Vector Regression (SVR) through a grid selection approach. In the context of the Gaussian Process Regression (GPR) model, obtaining precise hyperparameter values under Minimum Quantity Lubrication (MQL) and High-Pressure Coolant (HPC) conditions is a complex task. The influence of Main parameters on the GPR model is significant. The optimization of the neural network in the artificial neural network (ANN) model is vital, as it comprises various hidden layers and numerous nodes per layer. This optimization is conducted through an error correction approach, which necessitates the modification of any errors detected. A linear transfer function is applied to amend these errors. The training of the network is conducted over 10000 epochs, with a momentum of 0.089 and a learning rate of 0.035, resulting in an error between the actual outputs that remains well below 0.0001 during the training process.

$$MAPE = \frac{1}{N}\sum\frac{B_i - Y_1}{B} \text{ x } 100 \qquad (2)$$

$$maxMAPE = max\sum\frac{B_i - Y_1}{B} \text{ x } 100 \qquad (3)$$

$$MAE = \frac{1}{N}\sum B_i - Y_1 \qquad (4)$$

Here, N indicates The overall quantity of training variables, and B and Y refer to the results obtained from the experiments. The performance of various machine learning models is illustrated through a comparison with five additional models for the datasets, as presented in Table 2.

Regarding the MQL process:

MAPE values are observed to be between 0.82% and 2.5%. The MAXAPE values fall within the range of 1.7% to 9.2%. The MAE is recorded from 0.059 to 27.88%. The highest value detected was 2.5 from PR. It is evident that the SVR and GPR methodologies are obsolete when In contrast to PR. The ANN method showed a marginal improvement, while both SVR and GPR methods exceeded the performance of PR. Despite the machining force and cutting power values being considerably high, the cutting pressure is relatively lower.

The analysis conducted using High-Performance Computing (HPC) presents the following results: (1) MAPE values range from 0.72% to 2.1%, (2) MAXAPE values are found between 1.4% and 2.9%, and (3) MAE values extend from 0.042 to 18.44%. (4) When the PR method is implemented, the highest MAPE and MAXAPE values are observed in the cutting power model, mirroring the MQL cutting conditions. (5) The findings indicate that SVR and GPR methods provide better performance than the PR approach. (6) Moreover, ANN is increasingly accurate

The findings from this analysis suggest that machine learning algorithms are quite precise. A comparison of the models indicates that Support Vector Regression (SVR) and Gaussian Process Regression (GPR) performed similarly, while the Polynomial Regression (PR) model reached a high level of accuracy. The Artificial Neural Network (ANN) demonstrated superior accuracy compared to all regression methods. In conclusion, the analysis was conducted effectively, and the results are deemed satisfactory. Additionally, the PR method is faster in execution, as it necessitates fewer parameters.

3. CONCLUSIONS

In this investigation, we created several models that incorporate cutting parameters as the input data. The output generated, which represents the prediction, assesses the quality of lubrication and cooling within Machining settings. By executing these various Frameworks, we seek to ascertain The correlation coefficient, mean fundamental error, peak absolute error, total absolute error percentage, and root mean square error against the values that have been empirically observed. The formulated model yields accurate prediction values regardless of the conditions in Table 2.

1. The MAPE values for MQL and HPC vary between 2.5% and 0.72%.
2. The values of MaxAPE vary from 0.72% to 2.1% for both MQL and HPC.
3. An examination of Table 2 reveals that the greatest cutting power is utilized in PR.
4. The analysis of PR, MAE, and NRMSE revealed that SVR and GPR exhibit superior performance compared to PR.
5. The model based on artificial neural networks is achieving greater accuracy compared to traditional machine learning model.
6. The model that has been developed yields the accepted results and is expected to minimize the time and costs involved in the experimental process.

List of abbreviations:

MAPE: The mean absolute percentage error

MAE: Mean Absolute Error

NRMSE: The normalized root mean squared error

SVR: Support Vector Machine

MAXAPE: Maximum The mean absolute percentage error

MQL: minimum quantity lubrication

GPR: Gaussian process regression

HPC: high-pressure coolan

Declarations

1. Acknowledgements

The authors wish to indicate that no individuals or organizations need to be recognized for their contributions to this work.

2. Data availability

The concept of data sharing is not applicable to this article, as there was no creation or analysis of new data in this study.

3. Competing interests

There are no competing interests that need to be disclosed.

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