Machine Learning Based Energy Consumption Modeling of Machining Process-approach for Sustainability

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Abstract: According to U.S. Energy Information Administration (EIA) energy consumption and carbon emission are projected to increase globally. In metal manufacturing there is continuous increase in energy demand and carbon emission. Machining is one of them which is widely used in discrete manufacturing sector. The performance of the machining process depends upon cutting parameters. These parameters are selected based on various criteria like minimum cost, maximum production rate, maximum material removal rate, and minimum energy consumption. For this, experiments have been conducted and based on collected data of input parameters cutting speed ,feed and depth of cut and corresponding energy consumption, modeling has been done. In the present work algorithms related to machine learning have been applied to the experimental data for modeling to predict energy consumption The performance of algorithms has been compared using mean squared error (MSE), mean absolute error (MAE) and R^2 value. The four favorable algorithms have been compared in terms of accuracy with the experimental data. Among the models tested, the Lasso Regression with Cross-Validation performed the best with lowest mean squared error (MSE) 158.9, mean absolute error (MAE) 8.37 and highest R^2 value 0.991.

Keywords: Machine learning; Data set; Regression models; Minimum energy criteria; Machining process; Energy consumption; Performance evaluation

1. Introduction

For sustainable development, pollution should be minimal, and resources should be used prudently so that it should be available for future generations also. As a considerable part of industry, metal manufacturing consumes a large amount of resources and energy in product manufacturing process and leads to serious [1)]environmental emissions. According to U.S. Energy Information Administration (EIA) projections, energy use and carbon emission are continuously increasing[1)].

As per International Energy Outlook 2021[2)] there is a trend of increase in energy consumption, petroleum, and liquid fuel consumption as well as electricity consumption in the industrial sector, as a result, carbon emission will also increase. Therefore, need of sustainable development has been felt by the many countries around the world. Several program to reduce energy consumption have been launched by many governments worldwide , these program are known as Industrial Energy Efficiency program (IEEPs)[3)].

Machining is one of the largest energy consumers and carbon emitters in the world, from manufacturing sector. As production and consumption of machine tools used in machining are continuously increasing due to their use in particularly discrete manufacturing segments like Railways, Automobiles, Electronics, Defense, Plastic machinery, Medical etc.

Machining contributed major energy consumption in the manufacturing sector. In recent years, regarding energy reduction the focus is on machining processes The research studies related to manufacturing process energy reduction are focusing on to develop energy-efficient machining processes[4)]. To develop an energy efficient process, it is essential to study and analyze the energy consumption pattern of the system. For these different techniques have been applied by the researchers.

2. Literature Review

To develop energy efficient method, energy consumption pattern of the system should be known. For these two types of mathematical models i.e. theoretical and experimental have been used. While developing a mathematical model of the machining process either total energy or specific energy consumption have been calculated.

Various theoretical models have been given by researchers. According to Gutowski et al. energy consumption consists of two parts i.e. constant and variable energy , where variable energy consumption is proportional to the material removal rate (MRR)[5)]. According to Li et al. spindle speed has major effect in energy consumption and a new model has been proposed[6)]. Liu et al. suggested a new model to estimate the SEC with better accuracy. In this model various time period have been considered like cutting period along with idle period, air-gap period, and energy required in tool changing[7)]. As per model developed by Chen et al.[8)] energy consists of direct energy and indirect energy. Direct energy is energy consumed by spindle and feed motors during machining process. The energy used in the production of cutting tools and cutting fluids refers to as indirect energy. As per Imani et al.[9)] Milling machine can be considered as a thermodynamic system where power consumption can be stated in terms of spindle speed, feed rate and MRR.

For machining processes, cheap and important energy conservation strategies is parameter optimization. As per Rajemi et. al.[10)] in case of shortage of fund, parameter optimization may be used to improve the energy efficiency of the machine tool under consideration. Li and Kara[11)] shows relationship between MRR and SEC using inverse model.The Paper by Berillinger et al.[12)] (2023) predicts the energy demand of machining of parts during the design phase itself by giving relation between SEC and MRR using some constants. The values of constants can be determined using regression function from process maps, developed using energy consumption models available in literature.

Newman et al. noted that energy consumption in machining process has been noticeably effected by changing the cutting settings[13)].

In machining operations like in turning, drilling milling etc the empirical relationship between input–output parameters are determined based on experimental data[14)]. Design of experiment techniques are used to generate the large sets of data with a minimum no of experiments. Generally, in any literature many experimental techniques are there like RSM, Box-Behnken design (BBD) or central composite design (CCD), Taguchi method etc. Several modelling techniques have been used[15–19,20)], the most popular is RSM[21,22)]. In the paper by Sangwan et. al.[23)] orthogonal array and RSM has been used to design experiments and energy prediction modelling respectively.

As per Wang, Qi et. al. precise model of energy consumption is required for energy efficiency improvement in machining[24)]. With the advancement in techniques, various modelling techniques related to machine learning have been used for predictive maintenance, quality control, tool wear prediction, real-time monitoring and control of machining process and energy efficiency.

Sarswatula et al.[25)] explored the modelling of energy consumption using machine learning techniques, highlighting the effectiveness of various algorithms for the prediction of energy consumption in various industries like in metal, plastic, and food manufacturing industry.

Artificial intelligence techniques like Machine learning (ML) and deep learning (DL) have also been used widely in machining industry in recent years. These techniques offer opportunities to enhance machining processes, improve energy efficiency, and support decision-making in smart manufacturing environments (Table 1). In a review paper by Kim Dong-Hyeon et al.[26)] and Preez a du et al.[27)] ML algorithms applied by many researchers in conventional and nonconventional machining for tool wear monitoring, tool life prediction, surface roughness prediction and energy consumption prediction etc have been discussed.

According to Nasir and Sassani[28)], ML and DL techniques have emerged as powerful tools for intelligent machining and tool monitoring in smart manufacturing. These techniques enable automation in engineering, handling of large and high-dimensional data, optimal sensor fusion, and the development of hybrid intelligent models.

Aggogeri et al.[29)] discussed recent advances in ML applications in machining processes and addressed challenges such as the limited use of semi-supervised methods and the complexity of reinforcement learning. Von Hahn and Mechefske[30)] identified best practices for implementing ML effectively in the machining industry, emphasizing the importance of data infrastructure, simple model development, and avoidance of data leakage.

Work has been done by the researchers in which they use different ML algorithm and compare the accuracy of the results obtained. The selected research papers shed light on the potential of ML and DL techniques to optimize machining operations, predict energy consumption, and enable intelligent manufacturing systems[31)]. By examining the findings of these studies, we can better understand the methods, opportunities, and challenges associated with the implementation of ML and DL in the machining industry.

In the paper by Zoran Jurkovic et al.[32)] the performances of machine learning methods i.e. support vector regression (SVR), polynomial (quadratic) regression, and artificial neural network (ANN) have been compared to predict surface roughness, cutting force, and tool life in a high-speed turning process.

In the paper by Jinkyoo et al.[33)] the energy prediction modelling for CNC milling machine has been done by using Gaussian process . For this data has been collected for different machining operations. With this data values, optimum input parameters are identified for model selection. The proposed model can be used for estimating and comparing the energy required for machining a generic part. An accuracy of 95 % has been achieved on the total predicted energy.

As per He et al.[34] energy prediction modelling of machine tools have a crucial role in managing the energy consumption as well as conservation of energy in the manufacturing industry. In this area machinery data-based models of machine tools have achieved outstanding results. The results of deep learning-based model show improvement from 64.89% to 85.61% for the milling machine and 19.14% to 74.13% for the grinding machine. Brillinger et al.[35] focused on energy prediction for CNC machining using machine learning and demonstrated the successful prediction of energy demand without the need for dedicated experiments. Xiao et al.[17] conducted a comparative study on energy efficiency modelling by considering two cases one is using a model with experimental data using an ML algorithm and another considering the real situation with experimental data using a convolutional neural network. The model of the case II has better accuracy.

In energy prediction modelling work by Muhammad Rizwan Awan[36] the performance of Gaussian process regression was good out of three supervised learning techniques i. e. Gaussian process regression, regression trees, and ANN during validation and testing with minimum errors. The correlation coefficient was 0.98 while predicting specific energy consumption. The input parameter considered were cutting thickness, feed rate and type of cutting tool. In the present research, by Abbas et. al.[37] model between input machining parameters (speed, depth of cut and feed) and outputs (material removal rate, surface roughness, power consumption, and temperature) using orthogonal array approach has been development. The ML method has been used to predict the output parameters, and error was calculated between experimental and predicted data. To normalize all output parameters into single performance index, technique for order of preference by similarity to ideal solution (TOPSIS) approach has been used. The maximum percentage error using the above method was 3.43% between experiment results and proposed values.

In the paper by Vignesh et. al.[38] to obtain the machine tool information of working status accurately, a smart energy monitoring method based on a 1-dimensional convolutional neural network (1D-CNN) has been used. The performance of the model was also compared with DL and ML algorithms. Results show that 1D-CNN performs better than other algorithms.

It is important to predict energy consumption to develop energy efficient machining method. The insights obtained from this can help human operators better decide the input parameters needed to obtain the desired energy consumption strategy in advance.

In the present work number of ML regression algorithms have been applied for modelling to predict energy consumption in machining. Performance of different models have been evaluated using MSE, MAE and R^2 value. The results of best model have been compared with RSM model to validate result.

Table 1. Comparison of work done by researchers in machining area.

Reference (year)	**Application Area**	**Key Findings**	**ML/DL Algorithms Used**	**Performance Metrics**
Jinkyoo Park et. al. (2015)[33]	Energy prediction in CNC machining	Construct the energy prediction model using Gaussian process	Gaussian process	Accuracy 95%
Zoran Jercovic et. al. (2018)[32]	For predicting output parameters in machining	Support vector regression (SVR), polynomial (quadratic) regression, and artificial neural network (ANN)	Support vector regression (SVR), polynomial (quadratic) regression, and artificial neural network (ANN)	Polynomial regression is geed for surface roughness and cutting force, ANN has the best performance in the case of
M. Brillinger et. al. (2021)[35]	Energy prediction for CNC machining	Predicting energy demand based on machining strategy using ML algorithms	Random Forest	NA
Q. Xiao et. al. (2021)[17]	Energy efficiency modelling for machining	Comparative study of ML algorithms, considering spindle motor ageing and tool wear, prediction accuracy, stability,	Artificial neural networks, support vector regression, Gaussian process	Prediction accuracy, stability, computational efficiency

Muhammad Rizwan Awan (2022)[36]	Modelling energy consumption	Prediction of energy using three ML algorithm	Gaussian process regression, artificial neural network (ANN) and regression trees	Specific energy consumption was calculated using predicted value of energy consumption, correlation coefficient 0.98.
T. von Hahn et. al. 2022[30]	ML in CNC machining: Best practices	Best practices for ML system development in tool wear detection, emphasis on data infrastructure, simple models, data leakage prevention, open-source software usage, and computational power leverage	Random Forest	True positive rate, true negative rate
Abbas et. al.(2023)[37]	Milling process	The output parameters - material removal rate (MRR), surface roughness (Ra, Rt, and Rz), temperature and power consumption (PC)	ML- TOPSIS approach	maximum percentage error was 3.43% between the experimental and predicted values
Vignesh Selvaraj et. al. (2023)[38]	Operation monitoring of a CNC machine using energy data	Monitoring machine using 1-dimensional convolutional neural network	1-dimensional convolutional neural network	NA

3. Methodology

The methodology includes data preprocessing, feature engineering, and rigorous model evaluation. The experimental setup utilized energy sensors and standardized machining operations to ensure reliable data collection. Following section presents the methodology of this work as shown in Fig. 1.

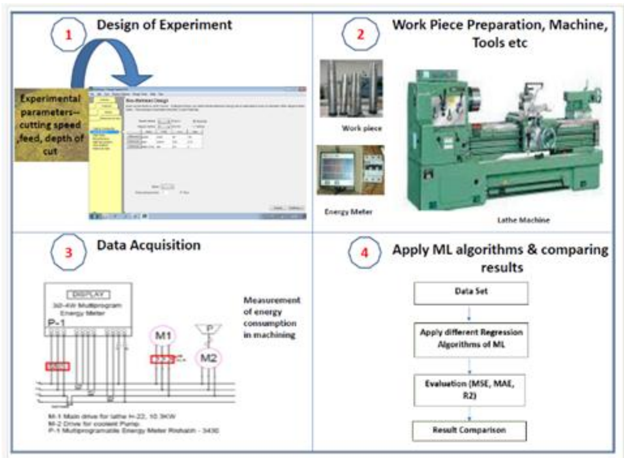

Fig. 1: Methodology

3.1 Experimental Setup

A lathe machine has been used to machine a job of AISI1045 steel using a carbide tool. A carefully controlled dry machining process was employed to collect the dataset. The input cutting parameters i e cutting speed (m/min), feed (mm/rev), and the depth of cut (mm), have been varied within a range of values. The processing energy has been calculated in kJ by measuring current, voltage and time using an energy meter and stopwatch respectively. The experimental setup ensured consistent operating conditions and robust data collection. Comparative methods, such as analyzing baseline models, enhanced the reliability of the results

3.2 Dataset

The dataset used in this study consists of 17 observations of cutting speed, feed, depth of cut, and processing energy[39]. Although the dataset size is limited, it provides a valuable foundation for developing and evaluating regression models to predict the processing energy based on the given input parameters.

3.3 Regression Models

In the pursuit of accurately predicting processing energy based on various input parameters, a comprehensive analysis utilizing a diverse array of regression models has been conducted. This analysis encompassed traditional and advanced methodologies, starting with Linear Regression, which serves as the foundational model for understanding relationships between variables. To accommodate non-linear patterns and complex data structures, more sophisticated models have also employed, including Support Vector Regression and Decision Tree Regressor, which offer flexibility in handling diverse data types. The ensemble techniques, such as Random Forest Regressor and Gradient Boosting Regression, further enhanced prediction accuracy by aggregating decisions from multiple models. Moreover, the study explored the potential of neural network-based MLP Regression and the powerful XG Boost Regression, known for its efficiency and effectiveness in various prediction tasks.

To refine predictions and manage overfitting, Lasso Regression with Cross-Validation was utilized, alongside its integration with polynomial features to capture more complex relationships. Similarly, Random Forest Regression has been examined under the lens of Grid Search to optimize its parameters, and this approach was further extended to include polynomial features for capturing intricate data patterns. The ensemble strategy has not been limited to traditional methods; a stacking ensemble combining XG Boost and MLP models has also tested, aiming to leverage the strengths of both approaches.

The cross-validation technique is a recurrent theme in enhancing model reliability, applied not just to Lasso and Ridge Regressions, but also to Random Forest and Gradient Boosting Regressions, ensuring that the models' performance is robust across different data subsets. Finally, an ambitious Ensemble model incorporating Lasso, Ridge, Random Forest, and Gradient Boosting has been developed, aiming to synergize the predictive capabilities of individual models for superior accuracy. This exhaustive exploration of regression models signifies a rigorous approach for understanding and predicting processing energy, highlighting the importance of leveraging a variety of techniques to address the complexity of real-world data.

3.4. Performance Evaluation

To assess the performance of each regression model, several evaluation criteria have been employed. These criteria include Mean Squared Error (MSE), Mean Absolute Error (MAE), and R-squared (R^2) coefficient of determination. Accuracy, precision, and goodness of fit of the models in predicting the processing energy can be assessed based on the required cutting parameters.

3.5. Experimental Analysis

The results obtained from the regression models have been analyzed to gain a comprehensive understanding of their performance. The evaluation criteria have been compared across different models to find out the most favorable model for predicting the processing energy. Additionally, insights have been drawn by examining the relative importance of the input variables in the selected models. Models also provide valuable information regarding the effect of cutting speed, feed, and depth of cut on the energy prediction.

3.6. Cross-Validation

To ensure the robustness and generalization capability of the selected models, cross-validation techniques are applied. This involved dividing the dataset into training and testing sets and performing number of rounds of training and evaluation to estimate the models' performance on unseen data. A 5-fold cross-validation methodology was used to evaluate the models, ensuring robustness and reducing the risk of overfitting. This technique divided the dataset into five subsets, iteratively using four for training and one for validation. The fold size was chosen to balance between bias and variance. Cross-validation helped validate the models and assess their reliability in predicting the processing energy for new observations.

4. Results & Discussion

The objective of this research is to predict the processing energy based on input factors: cutting Dataset consisting of 17 observations has been used for the analysis shown in Table 2.

Table 2. Data set used for energy-predicting models[39].

S No	Cutting Speed m/min	Feed mm/rev	Depth of cut mm	Processing Energy kJ
1	150	.09	2	262.12
2	90	.09	2	427.66
3	120	.05	2	593.5
4	120	.13	2	267.22
5	150	.09	.5	237.89
6	120	.13	.5	202.32
7	120	.05	.5	511.37
8	90	.09	.5	283.46
9	90	.05	1.25	700.35
10	120	.09	1.25	353.12
11	120	.09	1.25	356.57
12	120	.09	1.25	342.97
13	120	.09	1.25	347.33
14	120	.09	1.25	353.55
15	150	.05	1.25	505.19
16	90	.13	1.25	315.60
17	150	.13	1.25	262.38

Table 3 presents the performance results of the models using multiple ML algorithms. The performance of each model has been evaluated using MSE, MAE, and R^2 values as per Alateyah et al.[40] and with n< 20 as described in paper[41]. The graph in Fig 2 shows variation of MAE and R^2 value for all the regression algorithms.

Table 4 shows the results of four most favorable algorithms.

Table 3. Performance of regression models.

Model	MSE	MAE	R^2
Linear Regression	10292.8	94.99	-0.497
Support Vector Regression	9486.36	88.42	-0.38
Random Forest Regression	5037.41	60.04	0.267
MLP Regression	26547.2	142.68	-2.861
XG Boost Regression	3605.66	52.32	0.476
Lasso Regression with Cross validation	5906.73	56.33	0.141
Random Forest Regression with grid search	5172.85	59.66	0.248

Gradient Boosting Regression	4442.57	61.55	0.354
Lasso Regression with polynomial features	16770.2	111.43	-1.439
Random Forest Regression with polynomial features	2916.66	42.13	0.576
Gradient Boosting Regression with Polynomial Features	3338.56	43.18	0.514
Stacking Ensemble of XGBoost and MLP	5395.35	54.3	0.215
Lasso Regression with Cross-Validation	158.9	8.37	0.991
Ridge Regression with Cross-Validation	585.79	17.66	0.966
Random Forest Regression with Cross-Validation	4829.68	48.7	0.208
Gradient Boosting Regression with Cross-Validation	4361.61	44.47	0.078
Ensemble of Lasso, Ridge, Random Forest, and Gradient Boosting	6778.95	57.8	-1.904

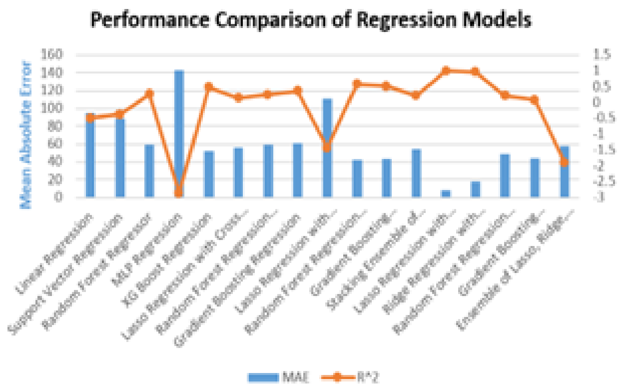

Fig. 2: Performance comparison of different regression models.

Table 4. Performance comparison of four selected regression models.

Algorithm	MSE	MAE	R^2
Gradient Boosting Regression with polynomial features	3338.56	43.18	0.514
Random Forest Regression with polynomial features	2916.66	42.13	0.576
Ridge Regression with Cross-Validation	585.79	17.66	0.966
Lasso Regression with Cross-Validation	158.9	8.37	0.991

The Figure 3, Figure 4 and Figure 5 shows the comparison of mean squared error, mean absolute error and R squared value respectively for four regression models, showing favorable results.

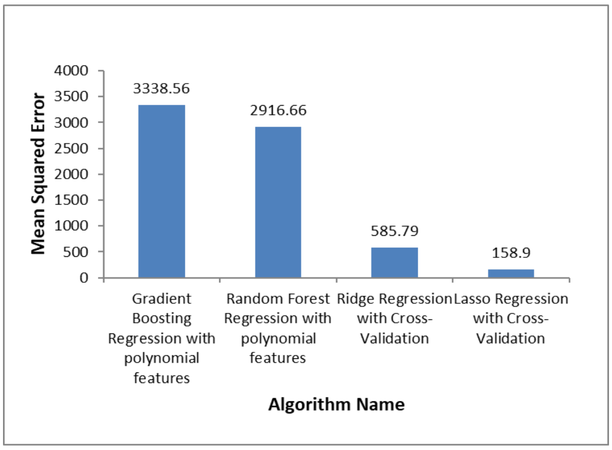

Fig. 3: Variation of mean square error for various ML algorithms.

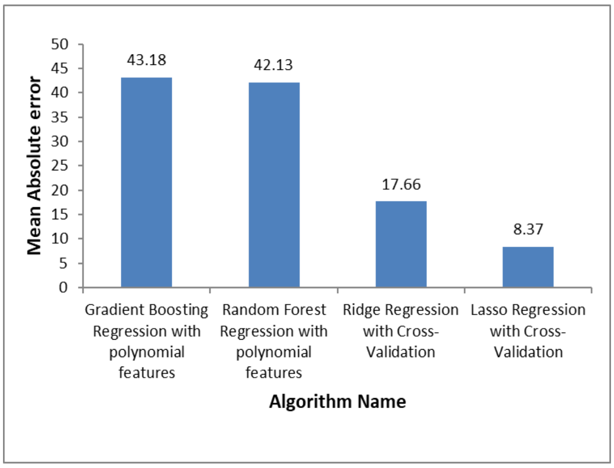

Fig. 4: Variation of mean absolute error for various ML algorithms.

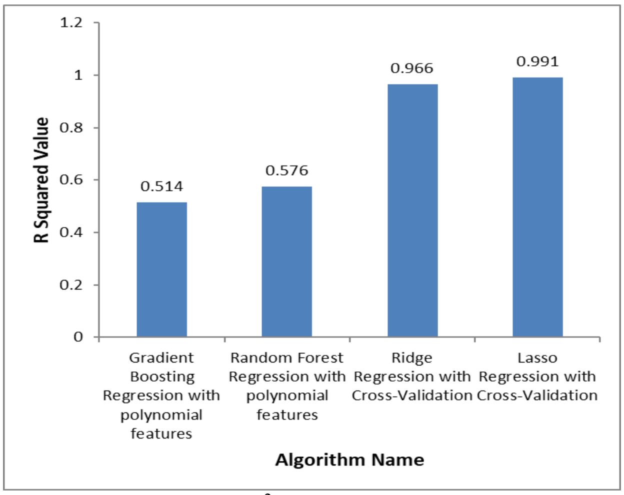

Fig. 5: Variation of R^2 value for various ML algorithms.

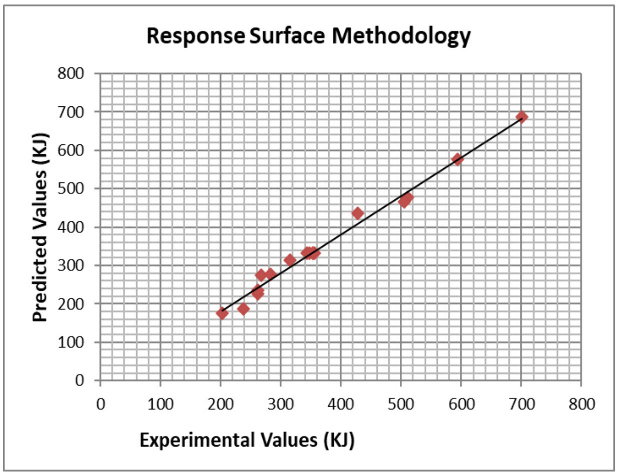

Fig. 6: Experimental and predicted value of energy consumption.

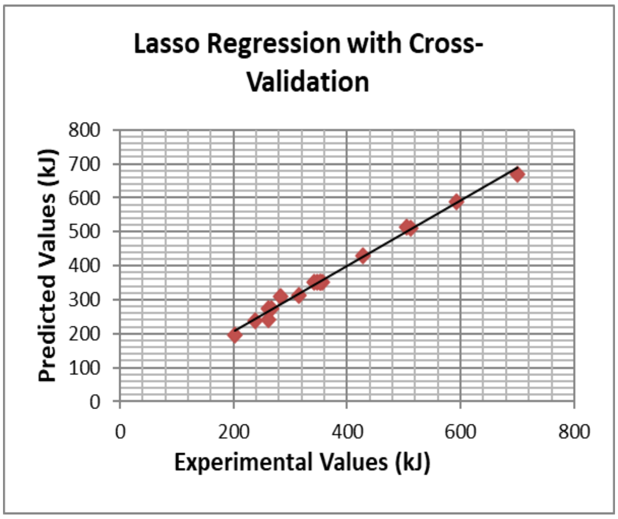

Fig.7: Experimental and predicted value of energy consumption.

On the basis of analysis, the Lasso Regression with Cross-Validation model exhibited the best performance in terms of MSE, with a value of 158.9, showing low deviation between predicted and experimental values as in Fig. 7 and almost in line with trend in Fig. 6. It also achieved the lowest MAE of 8.37 and a high R-squared value of 0.991. Lasso Regression, which includes feature selection, outperformed other models due to its ability to simplify the model by penalizing less significant features.

Random Forest Regression with polynomial features and Ridge Regression with Cross-Validation are Intermediate Accuracy Models, showing comparison of experimental and predicted model as shown in Fig. 8 and Fig. 9 respectively.

The comparative analysis revealed that simpler models like Ridge and Lasso Regression outperformed more complex models such as Random Forest and Gradient Boosting. This outcome is attributed to the dataset's small size, where simpler models with strong regularization are less prone to overfitting[42]. In machining processes, Ridge and Lasso are effective in maintaining stability and interpretability under constrained data conditions. Conversely, complex models tend to overfit due to their reliance on more training data. Insights from study[31] validate the suitability of simpler models for resource-intensive machining scenarios with limited data.

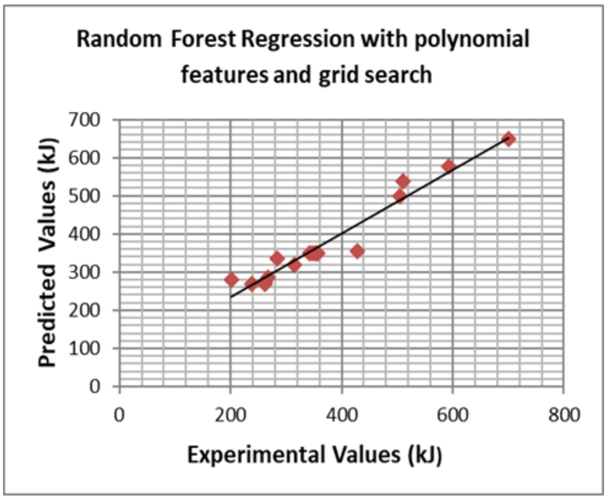

Fig. 8: Experimental and predicted value of energy consumption

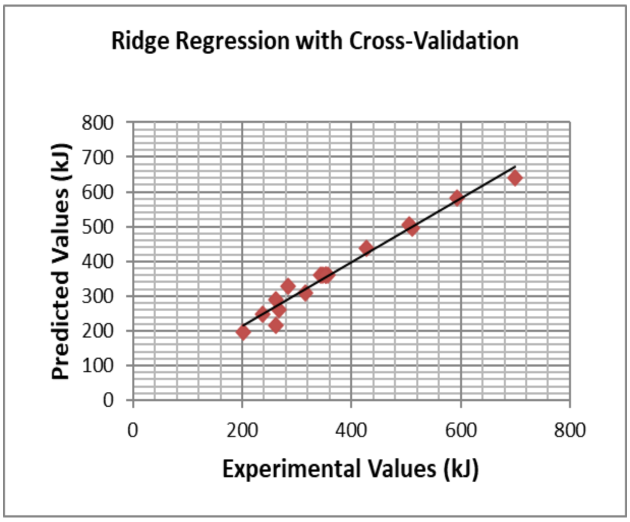

Fig. 9: Experimental and predicted value of energy consumption.

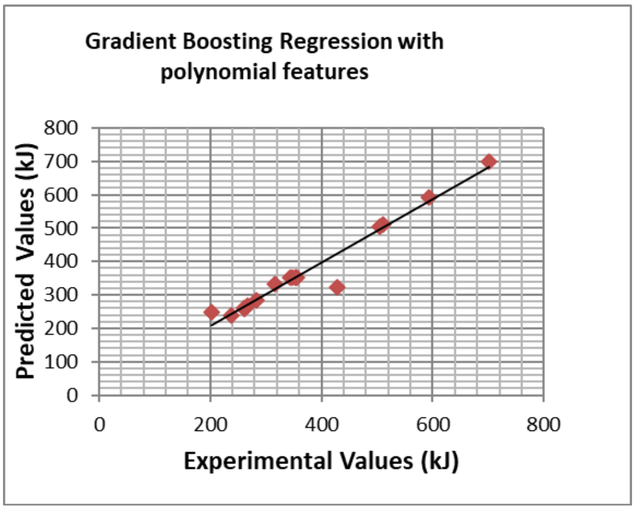

Fig. 10: Experimental and predicted value of energy consumption.

The gradient boosting regression with polynomial features exhibited the highest MSE of 3338.56, indicating a larger deviation between predicted and actual values shown in Fig. 10. It also had the highest MAE of 43.18, indicating higher average absolute differences. The R-squared value of 0.514 indicates that the MLP Regression model did not fit the data well and its predictions were poor in explaining the variance in processing energy. In Fig. 11 the results of all four ML algorithms have been compared.

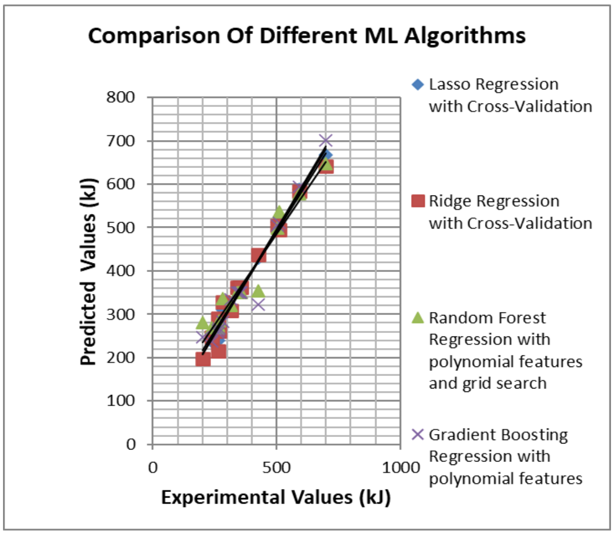

Fig. 11: Comparison of performance of different ML algorithms for experimental and predicted value of energy consumption.

Overall, the Lasso Regression with Cross-Validation model emerged as the best performer, providing the most accurate predictions of processing energy with 0.991 R^2 and MSE 158.9 which is in line with the result in the paper by the author[39] using RSM with 0.991 R^2 and $p < 0.05$. The results of prediction model using RSM and Lasso regression with cross validation can be seen in Fig. 6 and Fig. 7. Researchers may use this ML algorithm for energy predictions in machining. However, further investigation is required to see the performance of the other algorithms using a larger data set.

The dataset used in this study consisted of 17 observations, which limits its generalizability to larger and more diverse machining scenarios. The small dataset size restricts the model's ability to learn complex relationships and patterns effectively. This limitation can be addressed in future research by scaling the dataset with more comprehensive data collected from industrial grade setups. Findings from the paper[43] suggest that parameter optimization and diverse data collection can enhance generalizability, enabling better model performance in varied contexts.

It is noteworthy that some of the models, such as Ridge Regression with Cross-Validation (R^2 = 0.966, MAE = 17.66) and Lasso Regression with Cross-Validation (R^2 = 0.991, MAE = 8.37), already demonstrate excellent performance despite the dataset limitations. These results suggest that even with the current dataset, certain models effectively generalize within the scope of the study. They are likely to maintain or improve their performance when applied to larger and more diverse datasets, given their robustness and ability to minimize error

While the current dataset is small, the proposed models are scalable to larger datasets. As per study[44] managing scalability in ML applications ensures adaptability to industrial-scale challenges.

Potential sources of error in the modeling process include variations in machining parameters, environmental factors etc. For instance, inconsistencies in tool wear or material properties could lead to prediction errors. To mitigate these, robust error-handling strategies, such as outlier detection and sensitivity analysis, were employed.

5. Conclusions

In the present study, several regression models have been compared to predict processing energy in machining processes. Among the models tested, the Lasso Regression with Cross-Validation performed the best with lowest MSE, MAE, and highest R^2 value. This model showed superior accuracy and the ability to explain the variance in processing energy. The findings emphasize the importance of model selection in optimizing cutting processes and minimizing energy consumption. The study highlights the significance of energy-efficient machining as a step toward sustainable industrial practices[45] The findings contribute to the global effort to optimize manufacturing energy consumption, resource optimization which leads to carbon foot print reduction. The study supports international initiatives focused on sustainable industrial growth, as discussed[31].

By integrating machine learning with conventional machining, long-term benefits include reduced operational costs and enhanced productivity. However, Adopting ML frameworks in traditional machining industries may face challenges such as high initial costs, lack of skilled personnel, and resistance to change. Addressing these barriers requires training programs and cost-benefit analyses to demonstrate the long-term value of ML

The proposed models can be applied in real-world scenarios such as CNC machining and other machining operations, enabling precise energy consumption predictions These applications demonstrate the practicality of integrating machine learning into machining processes for enhanced operational efficiency.

The modeling framework can be seamlessly integrated with IoT-enabled systems for real-time energy monitoring. For instance, sensors can feed live data into the model, enabling dynamic adjustments to machining parameters

Future research should focus on increasing the dataset and finding out additional factors to further enhance the accuracy of the predictive models.

6. Future Scope

It is important to address the limitations of the study. The small size of the dataset may impact the generalizability of the findings. Furthermore, the extent of the study is limited to the specific cutting process and parameter range considered. Extrapolation of the results to different cutting conditions should be done with caution. Future research should aim to collect larger datasets and explore additional features to enhance the accuracy and applicability of the models. So future work should focus on:

1. Expanding datasets with diverse machining contexts.
2. Exploring advanced ML models like deep learning for larger datasets.
3. Integrating the framework with IoT for real-time adjustments.
4. Conducting material-specific studies to broaden applicability.

Nomenclature

Abbreviation	Full Form
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
BBD	Box Behnken Design
CCD	Central Composite Design
CNC	Computer Numerical Control
CNN	Convolutional Neural Network
DL	Deep Learning
IEEPs	Industrial Energy Efficiency Program
MAE	Mean Absolute error
ML	Machine Learning
MRR	Material removal rate
MSE	Mean Squared error
RSM	Response Surface Methodology
SEC	Specific energy consumption
SVR	Support Vector Regression
TOPSIS	Technique for order of preference by similarity to ideal solution

References

1) M. Bowman, “EIA projects global energy consumption will outpace efficiency gains in most cases,” *U.S Energy Information Administration*, (2023).
2) EIA, “International energy outlook 2021,” *International Energy Outlook*, 1–42 (2021). www.eia.gov/outlooks. (Accessed 2 January 2024)
3) S. Safarzadeh, M. Rasti-Barzoki, and S.R. Hejazi, “A review of optimal energy policy instruments on industrial energy efficiency programs, rebound effects, and government policies,” *Energy Policy*, 139 (*February*) 111342 (2020). doi:10.1016/j.enpol.2020.111342.
4) J.R. Duflou, J.W. Sutherland, D. Dornfeld, C. Herrmann, J. Jeswiet, S. Kara, M. Hauschild, and K. Kellens, “Towards energy and resource efficient manufacturing: a processes and systems approach,” *CIRP Annals - Manufacturing Technology*, 61 (*2*) 587–609 (2012). doi:10.1016/j.cirp.2012.05.002.
5) T. Gutowski, J. Dahmus, and A. Thiriez, “Electrical energy requirements for manufacturing processes,” *Proceedings of the 13th CIRP International Conference on Life Cycle Engineering, LCE 2006*, (*Cvd*) 623–628 (2006).
6) L. Li, J. Yan, and Z. Xing, “Energy requirements evaluation of milling machines based on thermal equilibrium and empirical modelling,” *Journal of Cleaner Production*, 52 113–121 (2013). doi:10.1016/j.jclepro.2013.02.039.
7) N. Liu, Y.F. Zhang, and W.F. Lu, “A hybrid approach to energy consumption modelling based on cutting power: a milling case,” *Journal of Cleaner Production*, 104 264–272 (2015). doi:10.1016/j.jclepro.2015.05.049.
8) X. Chen, C. Li, Y. Jin, and L. Li, “Optimization of cutting parameters with a sustainable consideration of electrical energy and embodied energy of materials,” *International Journal of Advanced Manufacturing Technology*, 96 (*1–4*) 775–788 (2018). doi:10.1007/s00170-018-1647-0.
9) R. Imani Asrai, S.T. Newman, and A. Nassehi, “A mechanistic model of energy consumption in milling,” *International Journal of Production Research*, 56 (*1–2*) 642–659 (2018). doi:10.1080/00207543.2017.1404160.
10) M.F. Rajemi, P.T. Mativenga, and A. Aramcharoen, “Sustainable machining: selection of optimum turning conditions based on minimum energy considerations,” *Journal of Cleaner Production*, 18 (*10–11*) 1059–1065 (2010). doi:10.1016/j.jclepro.2010.01.025.
11) S. Kara, and W. Li, “Unit process energy consumption models for material removal processes,” *CIRP Annals - Manufacturing Technology*, 60 (*1*) 37–40 (2011). doi:10.1016/j.cirp.2011.03.018.

12) M. Brillinger, M. Wuwer, B. Smajic, M. Abdul Hadi, S. Trabesinger, B. Oberegger, and M. Jäger, "Novel method to predict the energy consumption of machined parts in the design phase to attain sustainability goals," *Journal of Manufacturing Processes*, 101 (*March*) 1046–1054 (2023). doi:10.1016/j.jmapro.2023.05.086.
13) S.T. Newman, A. Nassehi, R. Imani-Asrai, and V. Dhokia, "Energy efficient process planning for cnc machining," *CIRP Journal of Manufacturing Science and Technology*, 5 (*2*) 127–136 (2012). doi:10.1016/j.cirpj.2012.03.007.
14) I. Mukherjee, and P.K. Ray, "A review of optimization techniques in metal cutting processes," *Computers and Industrial Engineering*, 50 (*1–2*) 15–34 (2006). doi:10.1016/j.cie.2005.10.001.
15) M.R. SOLEYMANI YAZDI, and A. KHORRAM, "Modeling and optimization of milling process by using rsm and ann methods," *International Journal of Engineering and Technology*, 2 (*5*) 474–480 (2010). doi:10.7763/ijet.2010.v2.167.
16) N. V Prajina, "Multi response optimization of cnc end milling using response surface methodology and desirability function," 6 (*6*) 739–746 (2013).
17) Q. Xiao, C. Li, Y. Tang, and X. Chen, "Energy efficiency modeling for configuration-dependent machining via machine learning: a comparative study," *IEEE Transactions on Automation Science and Engineering*, 18 (*2*) 717–730 (2021). doi:10.1109/TASE.2019.2961714.
18) Y. Lee, A. Resiga, S. Yi, and C. Wern, "The optimization of machining parameters for milling operations by using the nelder-mead simplex method," *Journal of Manufacturing and Materials Processing*, 4 (*3*) 1–22 (2020). doi:10.3390/jmmp4030066.
19) R. Kumar, P.S. Bilga, and S. Singh, "Multi objective optimization using different methods of assigning weights to energy consumption responses, surface roughness and material removal rate during rough turning operation," *Journal of Cleaner Production*, 164 45–57 (2017). doi:10.1016/j.jclepro.2017.06.077.
20) R. Kumar, P.S. Bilga, and S. Singh, "An investigation of energy efficiency in finish turning of en 353 alloy steel," *Procedia CIRP*, 98 654–659 (2021). doi:10.1016/j.procir.2021.01.170.
21) A.K. Srivastava, M. Maurya, A. Saxena, N.K. Maurya, and S.P. Dwivedi, "Statistical optimization by response surface methodology of process parameters during the cnc turning operation of hybrid metal matrix composite," *Evergreen*, 8 (*1*) 51–62 (2021). doi:10.5109/4372260.
22) "ARDAMBIRHARPREETKAURR3-21.pdf,"
23) K.S. Sangwan, and G. Kant, "Optimization of Machining Parameters for Improving Energy Efficiency using Integrated Response Surface Methodology and Genetic Algorithm Approach," in: Procedia CIRP, Elsevier B.V., 517–522 (2017). doi:10.1016/j.procir.2016.11.162.
24) Q. Wang, D. Zhang, K. Tang, and Y. Zhang, "Energy consumption model for milling processes considering auxiliary load loss and its applications," *International Journal of Advanced Manufacturing Technology*, 105 (*10*) 4309–4323 (2019). doi:10.1007/s00170-019-04479-3.
25) S.A. Sarswatula, T. Pugh, and V. Prabhu, "Modeling energy consumption using machine learning," *Frontiers in Manufacturing Technology*, 2 (*July*) 1–8 (2022). doi:10.3389/fmtec.2022.855208.
26) D.H. Kim, T.J.Y. Kim, X. Wang, M. Kim, Y.J. Quan, J.W. Oh, S.H. Min, H. Kim, B. Bhandari, I. Yang, and S.H. Ahn, "Smart machining process using machine learning: a review and perspective on machining industry," *International Journal of Precision Engineering and Manufacturing - Green Technology*, 5 (*4*) 555–568 (2018). doi:10.1007/s40684-018-0057-y.
27) A. du Preez, and G.A. Oosthuizen, "Machine learning in cutting processes as enabler for smart sustainable manufacturing," *Procedia Manufacturing*, 33 810–817 (2019). doi:10.1016/j.promfg.2019.04.102.
28) V. Nasir, and F. Sassani, "A review on deep learning in machining and tool monitoring: methods, opportunities, and challenges," *International Journal of Advanced Manufacturing Technology*, 115 (*9–10*) 2683–2709 (2021). doi:10.1007/s00170-021-07325-7.
29) F. Aggogeri, N. Pellegrini, and F.L. Tagliani, "Recent advances on machine learning applications in machining processes," *Applied Sciences (Switzerland)*, 11 (*18*) (2021). doi:10.3390/app11188764.
30) T. von Hahn, and C.K. Mechefske, "Machine learning in cnc machining: best practices," *Machines*, 10 (*12*) 1–27 (2022). doi:10.3390/machines10121233.
31) R. Kumar, S. Rani, and S. Singh Khangura, "Machine Learning for Sustainable Manufacturing in Industry 4.0," (2023). doi:10.1201/9781003453567.
32) Z. Jurkovic, G. Cukor, M. Brezocnik, and T. Brajkovic, "A comparison of machine learning methods for cutting parameters prediction in high speed turning process," *Journal of Intelligent Manufacturing*, 29 (*8*) 1683–1693 (2018). doi:10.1007/s10845-016-1206-1.
33) J. Park, K.H. Law, R. Bhinge, N. Biswas, A. Srinivasan, D.A. Dornfeld, M. Helu, and S. Rachuri, "A Generalized Data-Driven Energy Prediction Model With Uncertainty for a Milling Machine Tool Using Gaussian Process," in: ASME International, (2015). doi:10.1115/msec2015-9354.
34) Y. He, P. Wu, Y. Li, Y. Wang, F. Tao, and Y. Wang, "A generic energy prediction model of machine tools using deep learning algorithms," *Applied Energy*, 275 (2020). doi:10.1016/j.apenergy.2020.115402.
35) M. Brillinger, M. Wuwer, M. Abdul Hadi, and F. Haas, "Energy prediction for cnc machining with machine learning," *CIRP Journal of Manufacturing Science and Technology*, 35 715–723 (2021). doi:10.1016/j.cirpj.2021.07.014.
36) M.R. Awan, H.A. González Rojas, S. Hameed, F. Riaz,

S. Hamid, and A. Hussain, “Machine learning-based prediction of specific energy consumption for cut-off grinding,” *Sensors*, 22 (*19*) (2022). doi:10.3390/s22197152.

37) A.T. Abbas, N. Sharma, Z.A. Alsuhaibani, A. Sharma, I. Farooq, and A. Elkaseer, “Multi-objective optimization of aisi p20 mold steel machining in dry conditions using machine learning—topsis approach,” *Machines*, 11 (*7*) (2023). doi:10.3390/machines11070748.

38) V. Selvaraj, Z. Xu, and S. Min, “Intelligent operation monitoring of an ultra-precision cnc machine tool using energy data,” *International Journal of Precision Engineering and Manufacturing - Green Technology*, 10 (*1*) 59–69 (2023). doi:10.1007/s40684-022-00449-5.

39) G. Agarwal, and M.K. Khare, “Multiobjective optimisation of cutting parameters in machining -a sustainable approach,” *Materials Today: Proceedings*, 46 (*xxxx*) 5535–5543 (2020). doi:10.1016/j.matpr.2020.09.272.

40) W.H. El-Garaihy, A.I. Alateyah, M. Shaban, M.F. Alsharekh, F.N. Alsunaydih, S. El-Sanabary, H. Kouta, Y. El-Taybany, and H.G. Salem, “A comparative study of a machine learning approach and response surface methodology for optimizing the hpt processing parameters of aa6061/sicp composites,” *Journal of Manufacturing and Materials Processing*, 7 (*4*) (2023). doi:10.3390/jmmp7040148.

41) B. Ghattas, and D. Manzon, “Machine learning alternatives to response surface models,” *Mathematics*, 11 (*15*) 1–27 (2023). doi:10.3390/math11153406.

42) R. Kumar, E. Althaqafi, S.G.K. Patro, V. Simic, A. Babbar, D. Pamucar, S.K. Singh, and A. Verma, “Machine and deep learning methods for concrete strength prediction: a bibliometric and content analysis review of research trends and future directions,” *Applied Soft Computing*, 164 (*June*) (2024). doi:10.1016/j.asoc.2024.111956.

43) A.S. Sidhu, S. Singh, R. Kumar, D.Y. Pimenov, and K. Giasin, “Prioritizing energy-intensive machining operations and gauging the influence of electric parameters: an industrial case study,” *Energies*, 14 (*16*) (2021). doi:10.3390/en14164761.

44) N. Ranjan, R. Kumar, R. Kumar, R. Kaur, and S. Singh, “Investigation of fused filament fabrication-based manufacturing of abs-al composite structures: prediction by machine learning and optimization,” *Journal of Materials Engineering and Performance*, 32 (*10*) 4555–4574 (2023). doi:10.1007/s11665-022-07431-x.

45) R.S. Chandel, R. Kumar, and J. Kapoor, “Sustainability aspects of machining operations: a summary of concepts,” *Materials Today: Proceedings*, 50 (*May*) 716–727 (2021). doi:10.1016/j.matpr.2021.04.624.