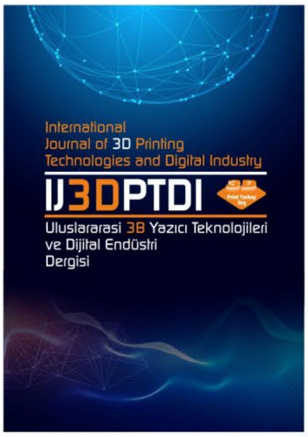

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Yazarlar (Authors): Gencay Sarıışık*, Ahmet Sabri Öğütlü

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OPTIMIZATION OF ENERGY CONSUMPTION IN CNC MARBLE PROCESSING: STATISTICAL AND MACHINE LEARNING APPROACHES

Gencay Sarıışık[a]*, Ahmet Sabri Öğütlü[a]

[a] Harran University, Engineering Faculty, Industrial Engineering Department, TÜRKİYE

* *Corresponding Author:* gsariisik@gmail.com

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ABSTRACT

This study aims to evaluate the specific energy consumption during marble processing on CNC machines both by traditional statistical methods and machine learning models. It presents an analytical framework that examines the effects of process parameters to improve energy efficiency in CNC machining processes. In the experimental part, a data set of 5400 obrervations was obtained considering different machining types, depths of cut and feed rates. Analysis of Variance (ANOVA) and regression models confirmed the decisive role of material removal rate (MRR) on specific energy consumption. The study comprehensively analyzed the performance of four different machine learning models (Gradient Boosting, Random Forest, XGBoost, LightGBM) to predict the specific energy consumption during marble processing on CNC machines. The findings show that specific energy consumption is an important parameter for energy efficiency and cost reduction. The accuracy of the models was evaluated with metrics such as R^2, RMSE and MAE, and as a result, it was found that Gradient Boosting and XGBoost models outperformed the others in the Spiral machining type. These findings provide a solid basis for developing strategies to improve energy efficiency in marble processing on CNC machines. The study provides important information that can help make strategic decisions to save energy and improve environmental sustainability. Providing valuable guidance for future research, this study demonstrates the potential use of machine learning models to improve energy efficiency in the natural stone industry.

Keywords: Marble, Energy Consumption, Specific Energy, CNC Machines, Machine Learning.

1. INTRODUCTION

Natural stones are frequently preferred by architects in modern building designs due to their aesthetic properties, durability and sustainability. These stones are especially suitable for indoor and outdoor use with their variety of colors, patterns and natural textures. With the impact of technological developments, two-dimensional (2D) and three-dimensional (3D) designs are processed in line with higher precision and quality requirements, and these processes are usually carried out with Computer Aided Control (CNC) machines. CNC machines play a critical role in responding to the increasing design demands and quality expectations in the natural stone industry. In particular, vertical machining centers are preferred in the production of architectural decorative products (sculptures, column capitals, reliefs, carvings, frescoes, etc.), and with these machines, precise and detailed 3D machining becomes possible. CNC technology enables the production of high quality products by offering small depth cutting and fine detailed machining in the x, y, z axes. This gives companies the opportunity to produce high value-added products and gain a competitive advantage in the global market. Nowadays, research on the determination of optimum machining parameters in CNC machines to achieve more efficient production in natural stone processing processes is increasing [1-2].
Studies on the cutting process of natural stones and the performance of CNC machines make important contributions both to increase

productivity in the stone processing industry and to obtain quality products. In these studies, many parameters affecting the cutting process and the performance of CNC machines have been analyzed. These parameters include the geometry of cutting tools, cutting speeds, feed rates and the use of coolants. Modeling the forces generated during the cutting process in CNC machines is of great importance for the optimization of the cutting process. Mathematical and simulation-based models are frequently used to calculate cutting forces and energy consumption. Especially recent studies have investigated in detail the effects of parameters such as cutting forces and specific cutting energy on both energy efficiency and surface quality [3-14].

The wear of the tools used during the cutting process and its effect on the machining quality is also of great importance. The hardness and durability properties of natural stones can cause rapid tool wear, which can adversely affect surface quality. Research to minimize tool wear has focused on the development of new tool materials and coatings. However, elastic and plastic deformations that occur during the cutting of stones are also among the factors that determine the process quality. Plastic deformations, especially in hard stones, can increase the forces used during the cutting process and increase energy consumption. Therefore, the correct selection of machining parameters minimizes both tool wear and deformations, resulting in more efficient and high quality cutting operations [15-19].

Recent research shows that process efficiency can be improved by customizing CNC technologies in natural stone machining processes. The performance of diamond and carbide tools has been studied along with their effects on cutting parameters. While diamond tools are preferred for machining hard stones due to their high hardness and wear resistance, the optimum cutting parameters were determined by cooled cutting experiments. Low cutting speed and feed rate were found to improve machinability for diamond tools. The relationship between cutting forces and energy consumption was also investigated and the optimum process parameters were determined. It has been observed that diamond tools improve the surface quality, while carbide tools may lead to loss of efficiency in hard stones [20-26].

In recent years, Machine Learning (ML) applications in CNC machine tools have been investigated with increasing interest and future research areas have been identified [27-31]. ML is an important revolution in computer science and enables the optimization of various manufacturing processes in CNC machines. Especially in areas such as cutting forces, cutting tool wear prediction and optimization of machining parameters, the use of ML algorithms can significantly increase production efficiency. In addition, advanced machine learning systems are also used to improve the surface quality of machined parts and to predict and prevent errors that may occur during production. It has been emphasized that the use of ML algorithms in CNC machines contributes to energy efficiency and cost savings by predicting cutting forces and extending tool life [32-33]. It is predicted that such technologies will contribute to the development of autonomous production processes and the achievement of industry 4.0 targets in the future.

Electrical energy is a fundamental element of social and economic development and an integral part of industrial production. Accurate forecasting of electricity generation is critical for energy planning and efficient use; in this context, machine learning (ML) algorithms have become prominent in the energy sector thanks to their ability to analyze complex relationships and make accurate forecasts [34]. Similarly, ML algorithms are also effective for optimizing resource utilization in logistics and manufacturing processes [35]. Environmental sustainability has become an increasing focus in the manufacturing sector. Especially in energy-intensive systems such as CNC machines, comprehensive approaches such as accurate estimation of energy consumption, waste reduction strategies and regular maintenance are important to reduce the carbon footprint. With these strategies, 23% energy savings and 14% waste reduction can be achieved, while practices such as regular maintenance and operator training contribute to energy efficiency by extending machine life [36-38]. These studies demonstrate the potential of ML algorithms and sustainability-oriented approaches to increase efficiency in energy and resource management.

Evaluating the performance of machine learning models is critical to understanding and optimizing their effectiveness. This paper comprehensively analyzes the performance of different machine learning models in predicting energy consumption. Using the Python programming language, the actual specific energy values are compared with the values predicted by the models, and an objective evaluation is performed using performance metrics such as coefficient of determination (R^2), mean absolute error (MAE) and root mean squared error (RMSE) of each model. By examining the outputs of the XGBoost model, the analysis revealed that the material removal rate (MRR) is the most critical factor and accordingly, the performance of different prediction models such as XGBoost, Gradient Boosting, Random Forest and LightGBM based on MRR were compared. All models were found to perform with high accuracy, with XGBoost in particular standing out with the highest coefficient of determination (R^2). These findings provide important strategies to improve energy efficiency and reduce costs and highlight the potential of machine learning methods to optimize energy consumption in CNC machines. The findings of the study provide important insights into how machine learning methods can be used to improve energy efficiency, providing a valuable foundation for future research.

2. MATERIALS AND METHODS

2.1. Methodology

CNC machines have undergone significant advancements in recent years, particularly through the integration of artificial intelligence (AI), which has greatly enhanced the optimization of machining performance, reduced errors, and improved efficiency [40]. In addition, the adoption of cloud-based platforms has enabled faster and more reliable access to production processes, thus fostering greater collaboration among teams [41]. The integration of robotic technologies, particularly collaborative robots, with CNC machines has not only increased production speeds but also enhanced workplace safety [42]. Furthermore, the application of Internet of Things (IoT) technologies in CNC systems has allowed for inter-machine communication, enabling predictive maintenance and the optimization of production schedules [43]. These technological advancements have contributed to making CNC machines more intelligent, precise, and adaptive, improving production efficiency across industries such as aerospace, automotive, and medical sectors. As these innovations continue to evolve, CNC machines are expected to offer even more advanced solutions and further enhance industrial production quality.

In this study, experiments were carried out on CNC machines using different machining parameters on marble and the effects of these parameters on material machining performance were investigated. A load cell tester fixed to the CNC machine table was used to measure the forces generated during the experiment. The general methodology followed during the experimental study is shown in Figure 1.

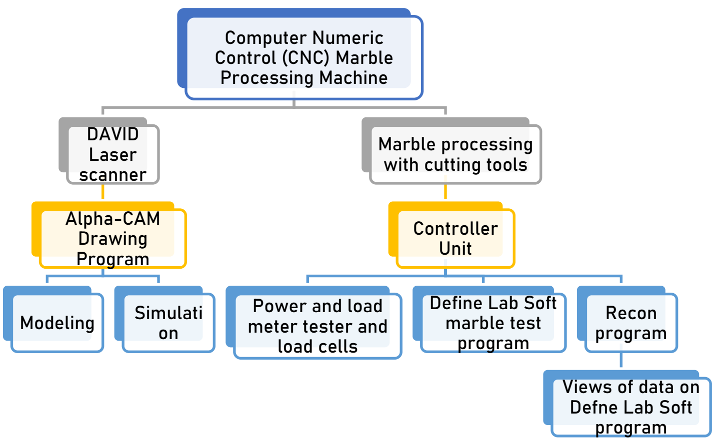

Figure 1. Methodology followed during the experimental study phase [1]

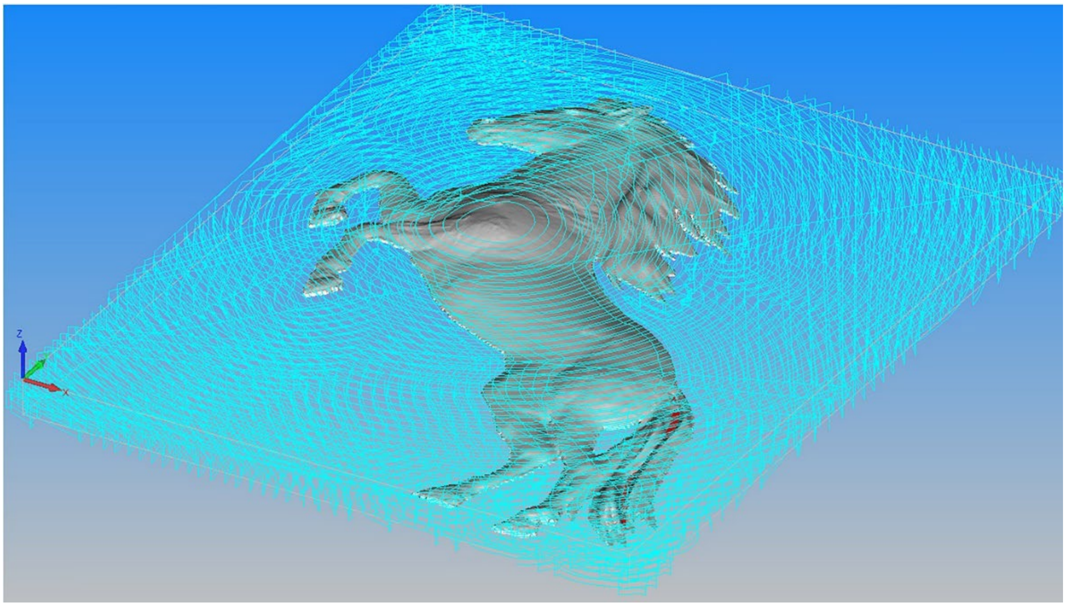

Figure 2. 3D product design in Alpha-CAM software [1]

The modeling of a horse figure was scanned using a 3D laser scanner and the resulting STL file was imported into Alpha-CAM design software (Figure 2).

The laser scanner used was DAVID Professional Version-3 software, known for its high scanning speed and resolution. Alpha-CAM software, which has 3D surface processing and simulation features, was preferred because it allows the drawings to be compatible with different programs. The specimens used in the experiments were modeled in Alpha-CAM software with dimensions of 125x100 mm. Different cutting parameters were determined for each figure and the experiments were tested with simulations beforehand.

The load meter tester consists of load cells, measurement and control units and is integrated with Defne Lab-Soft software. Before the experiments, the specimens were fixed to the device with a quick-clamping apparatus. There are a total of eight load cells in the system, four of which are used for force measurement in the Z axis and the other four are used for force measurement in the X and Y axes. Defne Lab-Soft software allowed the input of parameters such as specimen type, size, diameter, weight, machining type, depth of cut, spindle speed, cutting speed, feed rate, tool sinking speed and water content.

For each experiment, the Numerical Control (NC) codes generated in Alpha-CAM software were transferred to the CNC machine control unit via RSP (Recon Software Program). For each measurement, 100 data were collected per second from each 60x60 mm square for a period of 60 seconds, totaling 600 data. This high-resolution data collection method provided the precision needed to analyze in detail the effects of machining parameters on marble cutting performance.

2.2. Process Parameters

In this study, cutting forces (Fc), depth of cut (Ft) and energy consumption (Ec) were used as effective cutting parameters to monitor the performance of cutting tools for optimization of marble processing. Experimental models were used to determine the process conditions. The process parameters and values used in the experimental studies are presented in Table 1.

Table 1. Process parameters used in the experiments

Process Parameters	SI	Values
Milled Tool Diameter	*mm*	4.0
Spindle Speed	*d/min*	10,000
Plunge Speed	*d/min*	1000
Cutting Speed	*m/min*	125.6
Cutting Width	*mm*	2.0
Depth of Cut	*mm*	1.0-1.5-2.0
Feed Speed	*mm/min*	2000-2500-3000

The machining parameters are defined by variables such as cutting speed (Vc), feed rate (Va), equivalent depth of cut (heq) and material removal rate (MRR). The cutting parameters Fc, Ft and Ec were calculated with the equations (Equations 1 to 4) proposed by Sarıışık and Özkan (2018)[2]. Furthermore, the equations presented by Polini and Turchetta (2004) and Teale (1965) (Equations 5 to 16 and 17 to 18) were also used to calculate the parameters of the machining process[19,33] (Table 2).

Table 2. Equations and explanations of processing parameters

No	Equation	**Description**
1	$F_x = \lvert F_{x1} \rvert + \lvert F_{x2} \rvert$	F_x cutting force
2	$F_y = \lvert F_{y1} \rvert + \lvert F_{y2} \rvert$	F_y cutting force
3	$R = \sqrt{F_x^2 + F_y^2}$	Resultant force R(N), the sum of the cutting forces F_x and F_y
4	$\beta = tan^{-1}\left(\frac{F_y}{F_x}\right)$	Beta angle, inverse tangent of the ratio of the cutting forces F_y and F_x
5	$\theta = cos^{-1}\left(1 - \frac{2d_p}{d}\right)$	Contact angle between cutting tool and material θ
6	$F_c = Rsin\delta$	Tangential force F_c (N) is calculated with resultant force R and angle δ
7	$F_t = Rcos\delta$	The radial force F_t (N) is calculated by the resultant force R and angle δ
8	$\delta = \beta - Z\theta$	Angle δ is the difference of beta angle and $Z\theta$ angle
9	$Z = \frac{AB}{AC}$	Parameter Z determines the position of the application point of the resultant force in the contact spring
10	$h_{eq} = \frac{d_p \times V_a}{V_t}$	Equivalent depth of cut heq (mm) is calculated by depth of cut dp and feed rate Va
11	$V_t = \frac{\pi \times D \times n}{1000}$	Cutting speed Vt (m/min) is calculated with spindle speed n and cutter diameter D
12	$V_a = f_z \times z \times n \times f_2$	Calculated with feed rate Va (mm/min), feed per tooth fz, number of inserts z, spindle speed n and correction factor $f2$
13	$E_c = \frac{F_c \times V_t}{V_a \times d_p \times b}$	Energy consumption Ec (J) is calculated by tangential force Fc, cutting speed Vt, feed speed Va, depth of cut dp and width of cut b
14	$MRR = V_a \cdot d_p \cdot b$	Material removal rate MRR (mm³/min) is calculated by feed rate Va, depth of cut dp and width of cut bb
15	$MRR = h_{eg} \cdot V_t \cdot b$	Material removal rate MRR (mm³/min) is calculated by equivalent depth of cut h□□, cutting speed Vt and cutting width b
16	$h_{eg} = \frac{MRR}{V_t \, . \, b}$	Equivalent depth of cut heq (mm) is calculated by material removal rate MRR, cutting speed Vt and cutting width b
17	$Q_w = b \times l \times d_p$	Chip volume (mm³) is calculated.
18	$S_e = \frac{\frac{\sum_{j=1}^{n} pj}{n} \times \sum_{j=1}^{n} tj}{Q_w}$	The total specific energy (J/mm³) is calculated.

These equations allow us to analyze the efficiency and energy consumption of cutting tools in the marble processing process, contributing to the determination of optimal processing conditions. This data will help to develop strategies to improve the machinability of marble.

2.3. Machine Learning

Machine learning includes various algorithms used to analyze data and identify patterns and offers various approaches to solve different problems such as regression and classification. In this study, popular machine learning models such as XGBoost, Gradient Boosting, Random Forest and LightGBM will be used to evaluate energy consumption.

The XGBoost model is an optimized version of the Gradient Boosting algorithm. It uses quadratic functions for calculating the loss function, allowing for a faster and more optimized training process compared to standard methods [43-46]. Gradient Boosting, on the other hand, is a decision-tree-based learning algorithm that converts weak learners into strong learners through gradient boosting, offering a transparent and comprehensible framework [44-45,47]. Random Forest, is widely used for both regression and classification tasks. It performs well by reducing variance without the need for complex hyperparameter tuning [44,48-49]. LightGBM is a machine learning algorithm based on histograms, which discretizes continuous variables to minimize computational costs. Its leaf-oriented growth strategy accelerates the learning process [50-51].

In evaluating each model's performance, the dataset was partitioned into a 70% training set and 30% test set, enabling reliable model validation and comparison. Key metrics such as Mean Squared Error (MSE) and R-squared (R^2) were used to assess predictive accuracy, ensuring each model’s effectiveness in estimating energy consumption under varied machining conditions. Cross-validation techniques, particularly k-fold cross-validation, were applied to reinforce model robustness and reduce overfitting risks, thereby enhancing generalizability. Each model’s predictive capacity was rigorously validated through cross-validation to produce robust and consistent findings. This systematic evaluation process highlighted the predictive strengths and limitations of each model, establishing a clear understanding of how different algorithms respond to machining conditions and contributing substantially to the optimization of CNC processes.

3. RESULTS

3.1. Experimental Study and Energy Consumption Analysis

In the experimental study, data were obtained from power consumption (W) measurements depending on the processing time of the marble. Three different feed rates and three different depths of cut were used in the processing of three-dimensional products. In total, a data set of 5400 observatıons ~~was~~ used in the experiments (3 processing types x 3 depth of cut x 3 feed rate x 600 data points). For specific energy, the MRR process parameters were analyzed statistically usıng ANOVA in the different experiments of marble (Table 3). In this context, it was observed that MRR was effective on the specific energy values of three-dimensional marble products in all experiments ($p<0.001$).

Table 3: ANOVA table for lınear regressıon between mrr and spesıfic energy

Process Type	Dependent variable	Model	Sum of Squares	df	Mean Square	F	Sig.
External lines	MRR	Regression	6902,923	1	6902,923	32220,88	0,001
		Residual	320,928	1498	0,214		
		Total	7223,851	1499			
Linear	MRR	Regression	4800,926	1	4800,926	8698,315	0,001
		Residual	826,802	1498	0,552		
		Total	5627,729	1499			
Sprial	MRR	Regression	1682,361	1	1682,361	21115,84	0,001
		Residual	119,350	1498	0,080		
		Total	1801,711	1499			

In Figure 3, the effect of MRR (Material Removal Rate) parameter on specific energy according to the processing type is analyzed in detail. In this analysis, linear regression analysis was performed to determine the relationship between MRR and specific energy for each processing type. According to the results, the coefficient of determination (R^2) for contour machining was 0.956, which indicates that 95.6% of the variance in specific energy values is explained by MRR. The R^2 value for linear processing was 0.853, indicating that 85.3% of the variance in specific energy in this type of processing was explained by MRR. For spiral processing, the R^2 value was calculated as 0.934, indicating that 93.4% of the specific energy variance was explained by MRR. These results provide important findings for understanding the impact of MRR on specific energy in different processing types. The highest R^2 value was achieved in outline machining, indicating that the specific energy in this type of machining is largely influenced by MRR. Linear and spiral processes also show a significant effect of MRR on specific energy with high R^2 values.

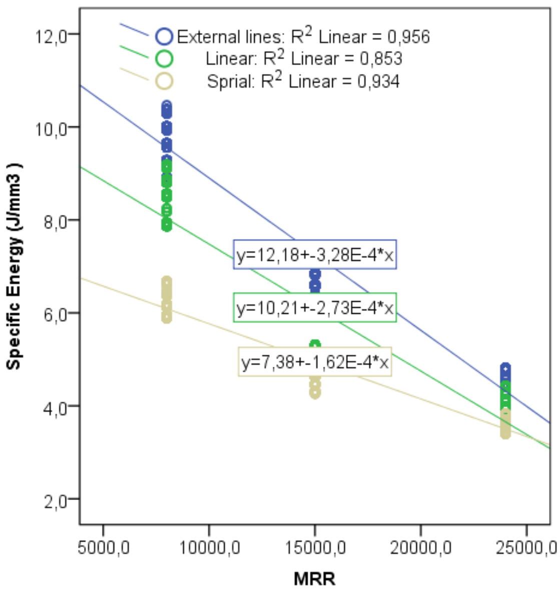

Figure 3. Regression plot showing the relationship between specific energy and MRR parameters by processing type

This research presents a comprehensive analysis using ANOVA to evaluate the specific energy consumption during marble processing on CNC machine. The ANOVA results revealed significant differences between the processing types. However, considering the complexity of the available dataset and the non-linear relationships between variables, it is also proposed to apply machine learning models to gain a deeper understanding. In this context, the use of machine learning methods can be important to more accurately estimate specific energy consumption and enable optimization of processing parameters. For example, advanced regression models such as Gradient Boosting, Random Forests, LightGBM and XGBoost can provide higher accuracy predictions by better capturing non-linear relationships and interactions. The application of these models will allow the development of potential strategies to improve energy efficiency and reduce costs in CNC machines. In conclusion, this study provides important insights for improving energy efficiency in CNC marble machining processes by evaluating the effects of MRR on specific energy according to machining types. This approach, supported by advanced analysis methods, will provide a valuable basis for future studies.

3.2. Machine Learning Model Analysis and Performance Evaluation

In this section, the performance of the previously introduced machine learning models on the specific energy dataset is analyzed in detail. During the evaluation process, comparisons were made between the actual specific energy values and those predicted by the machine learning algorithms. To assess the effectiveness and accuracy of each model, performance metrics such as the coefficient of determination (R^2), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) were used. These metrics help evaluate how successful the machine learning models are in predicting specific energy and provide important insights into the reliability of the models.

In Figure 4, the outputs of the XGBoost model are analyzed, and the effect of the input features on the model is discussed in detail.

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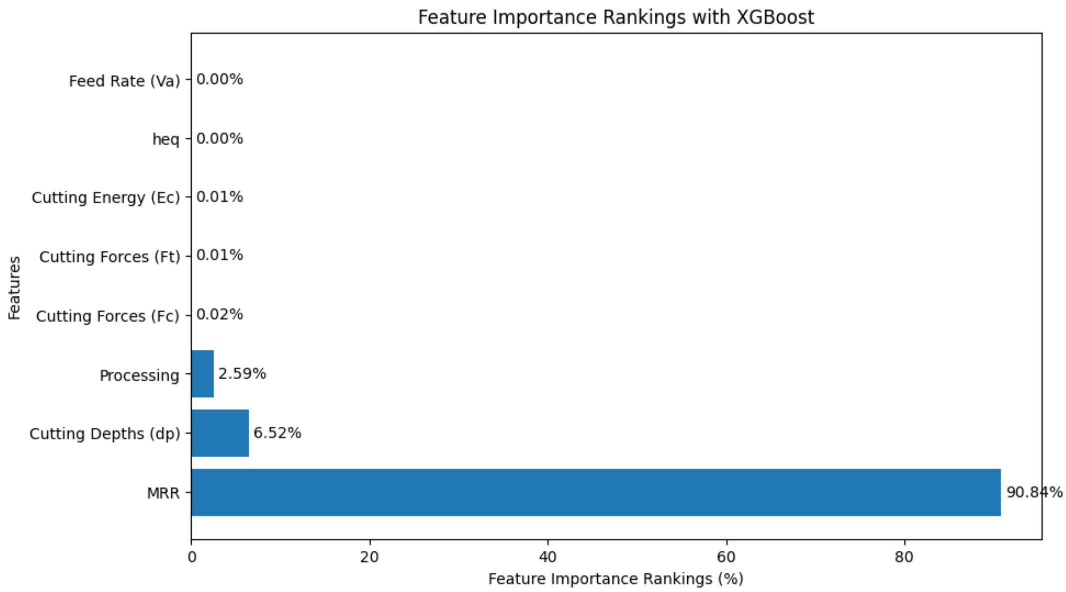

Figure 4. Importance ranking of the parameters affecting specific energy

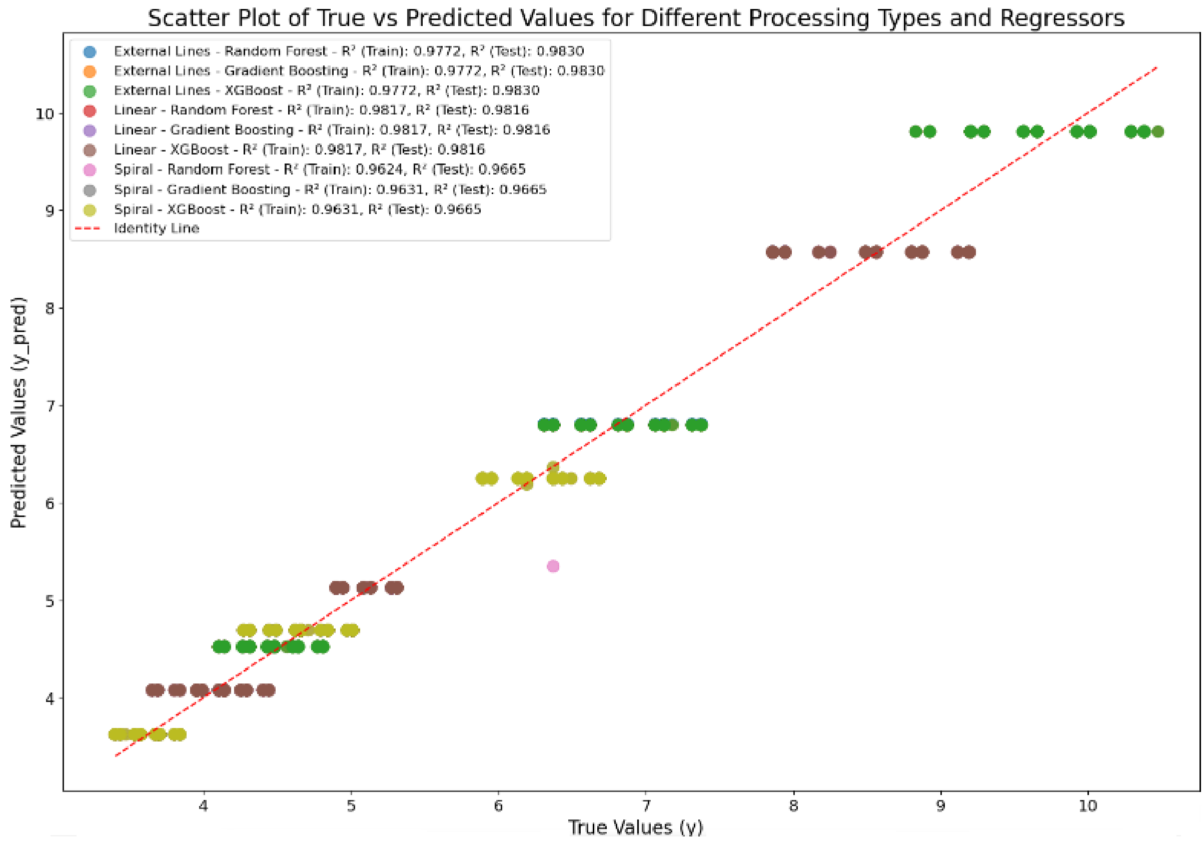

Figure 5. Prediction models according to the effect of specific energy on material lift ratio

This analysis provides an important perspective on the contribution of each input feature to the prediction results. For specific energy, the Material Removal Rate (MRR) is found to be the most influential factor, affecting the model output by 90.84%. This finding highlights the critical role of MRR in the model's prediction of specific energy. This information helps us understand the model's sensitivity to certain input features and serves as an important resource for optimizing predictions and enhancing the model's reliability. This analysis is highly valuable for professionals in the natural stone industry and researchers working to improve energy consumption predictions in CNC machine operations.

In Figure 5, the effect of mmr on spesıfıc energy is analyzed by using four different prediction models and the prediction results are obtained. This analysis aims to evaluate how accurate the different models are in predicting specific energy. The models are specifically designed to analyze various input characteristics in specific energy forecasts. The coefficient of determination (R^2) obtained in the training set was 0.9817 and 0.9816 in the test set. This comprehensive comparison helps us to understand how accurately each model predicts the impact of MRR in specific energy forecasts.

According to the model performance comparison results, the XGBoost model has the highest accuracy in specific energy estimation with MRR, with an R^2 value of 0.9817, indicating that 98.17% of the specific energy variance is explained by MRR. The Gradient Boosting model, which has the second highest accuracy, has an R^2 = 0.9816 and explains 98.16% of the specific energy variance. The coefficient of determination of the Random Forest model was also found to be 0.9817, revealing that 98.17% of the specific energy variance is due to MRR. The LightGBM model successfully analyzed the relationship between energy consumption and MRR. The results confirm that MRR is an important factor in specific energy predictions in all models. These findings provide important insights to improve energy efficiency and reduce costs in CNC marble machining processes. The use of machine learning methods offers significant contributions to more accurately predict specific energy consumption and optimize machining parameters.

Table 4. Performance comparison of prediction models for different processing types

Processing	Model	R^2		MAE		RMSE	
		Train	**Test**	**Train**	**Test**	**Train**	**Test**
External lines	Gradient Boosting	0,9772	0,9830	0,2732	0,2501	0,3280	0,2976
	Random Forest	0,9772	0,9830	0,2729	0,2500	0,3281	0,2976
	XGBoost	0,9772	0,9830	0,2732	0,2501	0,3280	0,2976
	LightGBM	0,9772	0,9830	0,2732	0,2501	0,3280	0,2976
Linear	Gradient Boosting	0,9817	0,9816	0,1930	0,1948	0,2600	0,2687
	Random Forest	0,9817	0,9816	0,1931	0,1949	0,2600	0,2687
	XGBoost	0,9817	0,9816	0,1930	0,1948	0,2600	0,2687
	LightGBM	0,9817	0,9816	0,1930	0,1948	0,2600	0,2687
Spiral	Gradient Boosting	0,9631	0,9665	0,1727	0,1666	0,2094	0,2045
	Random Forest	0,9624	0,9665	0,1735	0,1665	0,2115	0,2044
	XGBoost	0,9631	0,9665	0,1727	0,1666	0,2094	0,2045
	LightGBM	0,9578	0,9664	0,1751	0,1670	0,2239	0,2047

Table 4 compares the performance of four different machine learning models (Gradient Boosting, Random Forest, XGBoost, LightGBM) for three different processing types (Outline, Linear and Spiral). Performance measures such as coefficient of determination (R^2), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are presented for both training and test sets. The R^2 values of all the models in the external lines processing type were found to be very high, 0.9772 in the training set and 0.9830 in the test set, indicating a good fit of the models to the data. The MAE values were approximately 0.2732 in the training set and 0.2501 in the test set, indicating that the prediction errors were quite low and accurate predictions were made. The RMSE values are around 0.3280 for the training set and 0.2976 for the test set, which indicate that no large errors were made. In the linear processing type, the R^2 values are 0.9817 in the training set and 0.9816 in the test set, indicating that the models continue to fit the data. The MAE values remained at a low level, approximately 0.1930 in the training set and 0.1948 in the test set, indicating that the predictions are close to reality. The RMSE values were approximately 0.2600 in the training set and 0.2687 in the test set, indicating that no large errors were made. In the Spiral processing type, R^2 values are slightly lower than the other processing types, 0.9631 in the training set and 0.9665 in the test set for the Gradient Boosting and XGBoost models; Random Forest and LightGBM show similar high performance. For the Spiral type, the MAE values are about 0.1727 in the training set and 0.1666 in the test set, which are also low. The RMSE values are approximately 0.2094 in the training set and 0.2045 in the test set, which are similarly low compared to the other processing types, confirming that the models do not make large errors.

The results obtained show that all models make efficient predictions with high R^2 values and low MAE and RMSE values. While there is no significant performance difference between the models for Outline and Linear machining, Gradient Boosting and XGBoost models give slightly better results for Spiral machining. Overall, the Gradient Boosting model, with its high accuracy and low error rates, was identified as the most suitable model for predicting the specific energy consumption during marble processing on CNC machines. These findings show that machine learning techniques can be effectively used in specific energy estimation.

This study presents valuable insights into the analysis and prediction of specific energy consumption in marble processing processes on CNC machines, while also providing several critical recommendations for advancing research and enhancing energy efficiency in this domain. First, it is recommended that deep learning techniques, such as artificial neural networks, be employed to more effectively model nonlinear relationships, which could further enhance the accuracy of the model. Additionally, incorporating other influencing parameters, such as machine maintenance and environmental conditions, into the model could improve prediction accuracy and overall energy efficiency. Expanding the dataset to include a broader range of processing parameters would enhance the model's generalization ability, particularly by considering different types of marble and processing methods. The investigation of hybrid models, which combine multiple machine learning algorithms, is also suggested, as these could offer higher accuracy and improved overall performance. Finally, in pursuit of energy conservation and sustainability, the development of strategies aimed at reducing energy consumption through machine learning-based optimization techniques is proposed. These recommendations serve as a guide for future research focused on improving energy efficiency and reducing costs in CNC machine operations.

4. DISCUSSION

Nowadays, machine learning (ML) methods play an important role in optimizing complex processes such as marble machining on CNC machines. This paper comprehensively investigates the performance of four different ML models such as Gradient Boosting, Random Forest, XGBoost and LightGBM to predict the specific energy consumption during marble processing. Specific energy consumption is a critical parameter to improve energy efficiency and reduce costs. The analysis is carried out using metrics such as R^2, RMSE and MAPE, which provide important data to evaluate the effectiveness and reliability of the models.

Previous studies have analyzed cutting forces and energy consumption in a similar framework; researchers have studied the physical and mechanical properties of natural stones, focusing on parameters such as cutting forces, specific energy and cutting energy. Our current study aims to evaluate the specific energy consumption during marble processing on a CNC machine, both with traditional statistical methods and machine learning models. This provides a more advanced and comprehensive approach to energy consumption estimation, unlike previous studies [1-2]. It also examines the application of machine learning and artificial intelligence techniques, focusing on issues such as energy consumption, cutting forces, and cutting tool wear in CNC machines, while providing recommendations to improve energy efficiency [32-33]. In this context, both studies point to important contributions in the field of CNC machines.

In our study, each machine learning model is analyzed for different processing types (external lines, linear and spiral). In particular, the accuracy and error rates of the models were evaluated using performance metrics such as coefficient of determination (R^2), mean absolute error (MAE) and root mean square error (RMSE). The results show that, in general, all four models perform well and the performance differences between them are quite small. However, in the case of spiral processing, Gradient Boosting and XGBoost perform better than the other models. This finding is due to the ability of these models to better capture complex and non-linear relationships.

These analyses provide critical data for understanding the effectiveness and reliability of machine learning models in various classification tasks. In conclusion, the use of machine learning methods for specific energy consumption prediction in CNC machines offers a strategic approach to improve energy efficiency and reduce costs. The current findings provide important insights to improve the performance of machine learning models and optimize their effectiveness in specific tasks. Future studies can conduct more in-depth analyses to evaluate model performance on more complex and dynamic datasets and contribute to developing more robust and reliable models for real-world applications. Research in this area has the potential to optimize energy consumption and improve efficiency in manufacturing processes.

5. CONCLUSION

This study provides a comprehensive analysis of the factors affecting specific energy consumption during marble processing on CNC machines, providing important information for improving energy efficiency. Based on three different feed rates and depths of cut used in the marble processing process, the analysis of 5,400 data points showed that Material Removal Rate (MRR) plays a critical role in determining specific energy consumption.

ANOVA on the experimental data revealed a significant effect of MRR on specific energy consumption ($p<0.001$). The R^2 values determined for each processing type by regression analyses show that a large part of the specific energy variance is explained by MRR. The R^2 values were 0.956, 0.853 and 0.934 for outline, linear and spiral machining, respectively, confirming the strong influence of MRR on specific energy. These high coefficients of determination emphasize how significant the impact of MRR on energy consumption in marble processing is.

Forecasting specific energy consumption using machine learning models has provided a better understanding of non-linear relationships and interactions between variables. Advanced regression models such as Gradient Boosting, Random Forest, LightGBM and XGBoost were analyzed for their prediction performance on the dataset. All models gave successful results with high accuracy and low error rates. The values of $R^2=0.9817$ in the training set and $R^2=0.9816$ in the test set indicate that the models are compatible with the data and have high generalization capabilities.

When the outputs of the XGBoost model are analyzed, it is seen that MRR has the most significant impact on the model (impact rate 90.84%) and this finding is a critical factor in specific energy forecasts. Analyses showing the ranking of the importance of model features provide important information for optimizing predictions and improving model reliability. In terms of performance metrics for different processing types, it was observed that the Gradient Boosting and XGBoost models performed slightly better, especially in the spiral processing type. However, all models perform well in the outline and linear processing types. The similar performances inthe training and test sets suggest that the models are not overfitting and have good generalization capabilities. Based on these evaluations, the Gradient Boosting model was identified as the best model due to its overall performance and superiority in specific processing types.

The findings of this study provide a valuable basis for developing important strategies to improve energy efficiency in marble processing processes on CNC machines. Future work can extend and deepen these analyses using more data and advanced algorithms. In particular, improving the performance of machine learning models and using these models in real-world applications to optimize energy consumption will lead to efficiency and cost effectiveness in industrial applications.

In conclusion, this research provides important insights for optimizing energy consumption in CNC marble machining processes by comprehensively evaluating the factors affecting specific energy consumption and their impact on energy efficiency. The use of machine learning models improves prediction accuracy, allowing the development of potential strategies to improve energy efficiency. These findings provide valuable guidance for natural stone industry professionals and researchers.

This study offers significant contributions to the natural stone industry, particularly in improving energy efficiency during CNC marble processing. By identifying Material Removal Rate (MRR) as the primary factor influencing energy consumption, this research provides a foundation for optimizing processing parameters to reduce energy costs. The application of machine learning models, including Gradient Boosting and XGBoost, demonstrates high accuracy in predicting specific energy consumption, offering valuable insights for real-world energy management strategies. Future work should focus on incorporating additional variables, such as machine maintenance and environmental conditions, to further enhance model accuracy and applicability. Additionally, exploring hybrid machine learning models and real-time optimization techniques can drive further advancements in energy conservation, helping the industry adopt more sustainable practices while lowering operational costs.

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