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Development and analysis of machine learning-based hybrid optimization framework for cutting temperature-based energy consumption estimation in turning of titanium alloys

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ABSTRACT

This study develops a machine learning-based hybrid optimization framework to predict energy consumption from cutting temperature in turning of Ti6Al4V alloy under different cooling environments. Due to the poor thermal conductivity of titanium alloys, heat accumulation in the cutting zone increases energy consumption and reduces process efficiency. Cutting temperatures were recorded in real time using a thermal camera, and energy consumption was measured with a power analyzer. Statistical features extracted from temperature data served as inputs for energy prediction. A hybrid optimization framework was developed by integrating feature selection methods, machine learning algorithms, and hyperparameter optimizers. Among six algorithms evaluated, CatBoost combined with SHAP-based feature selection and Optuna hyperparameter optimization achieved the best performance. The proposed hybrid model (CAT+SHAP+Optuna) provides a 91% improvement in Mean Squared Error compared to the benchmark model, demonstrating high accuracy in energy consumption estimation. This approach offers significant potential for enhancing energy efficiency and promoting sustainable manufacturing in the machining of difficult-to-cut materials.

1. Introduction

In recent decades, the manufacturing sector has become a central actor in global energy transitions and climate mitigation strategies, as industrial activities account for a substantial share of global energy consumption and carbon emissions [1]. Metal industries represent one of the most energy-intensive segments due to material extraction, processing, and machining operations [2]. Therefore, improving energy efficiency in machining is no longer merely a technical objective but a strategic necessity for low-carbon industrial transformation and sustainable economic resilience [3]. Sustainable manufacturing practices—supported by digitalization and resource-efficient models—strengthen economic competitiveness while reducing environmental burdens [4]. The integration of energy modeling and data-driven decision systems aligns with governance frameworks aimed at enhancing resource productivity in metal value chains [5]. In this context, machining difficult-to-cut alloys such as Ti6Al4V becomes critical from both environmental and socio-economic perspectives. Ti6Al4V is widely used in aerospace and biomedical sectors, yet its poor machinability and high specific cutting energy demand contribute to elevated production costs and environmental footprints [6]. Reducing energy consumption during machining supports economic gains through cost minimization and lowers carbon intensity per manufactured component [7]. In sustainable and smart machining operations, the simultaneous monitoring and control of energy consumption is paramount to prevent the rapid depletion of limited resources, decreased processing efficiency, and increased operational costs [1]. The manufacturing sector is a predominant global energy consumer, accounting for approximately one-third of total energy use [8]. Within this context, energy consumption is fundamentally determined by two key factors: the average power demand of the machine tool and the total processing time, both of which are directly influenced by cutting

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parameters [2]. Optimizing these parameters is thus critical, with studies indicating potential energy savings of up to 40% [9]. This pursuit of efficiency extends beyond economics, encompassing broader sustainability goals that include environmental impact and worker health, driving the trend towards cleaner and greener production [10–12]. The challenge of energy-efficient machining is particularly acute for difficult-to-machine materials like titanium alloys, especially Ti6Al4V, which are indispensable in aerospace, automotive, and medical sectors due to their superior strength-to-weight ratio, corrosion resistance, and biocompatibility [13–15]. Their characteristically low thermal conductivity, however, leads to significant heat accumulation in the cutting zone [16]. This accumulation accelerates tool wear, increases friction forces, and can cause workpiece deformation. Crucially, the resulting elevation in cutting temperature creates a detrimental cycle, further escalating energy consumption in an uncontrolled manner—a significant concern given that the cutting operation itself constitutes nearly 63% of a machine tool's total power usage [17]. Therefore, for titanium alloys, cutting temperature emerges as a critical, indirect determinant of energy consumption. Consequently, online monitoring and modeling of both cutting temperature and energy usage are vital for enhancing process efficiency and achieving sustainable manufacturing. This direct link explains the focused research on various cooling/lubrication strategies, as controlling cutting temperature is a primary pathway to managing and reducing energy consumption in machining Ti6Al4V.

Various studies have been conducted on different coolants used to provide energy efficiency by reducing cutting temperatures. In an experimental study, energy consumption in high-speed turning of 7075-T6 aluminum alloy in dry and minimum quantity lubrication (MQL) machining environments was investigated [18]. As a result, it is stated that energy consumption is 20% lower in the MQL environment. According to the ANOVA analysis performed on the processing of American Iron and Steel Institute (AISI) 1045 steel, it was stated that the most effective parameters on power consumption were cutting speed and cutting depth, respectively [19]. As a result of the study conducted for the optimization of power consumption of AlSI P20 steel in different processing environments and cutting parameters, it was stated that the most effective parameters on power consumption are cryogenic environment, speed, and depth of cut, respectively [20]. In order to obtain maximum material removal rate with minimum energy usage in the turning of AISI 6061 alloy, it was stated that the feed rate and cutting depth should be at the highest and the cutting speed should be at the lowest values; thus, a 14.41% reduction in energy consumption was achieved [21]. It has been reported that energy consumption is reduced by approximately 15% in the optimum parameter combination as a result of the optimization of cutting parameters to obtain the best surface property in the dry turning of AISI 316 material with minimum cost and tool wear [22]. It was concluded that the inclination angle, feeds, and speeds parameters were effective on energy usage in the machining of AISI 4140 [23]. Tool radius, feed, speed, and cutting depth all have an effect on machine tool power consumption while turning European Norm (EN-31) steel, with lower values consuming less power [24]. Energy usage in turning 7075-T6 material under compressed air, dry, and (Ranque-Hilsch Vortex Tube) RHVT conditions was tested. According to the study's findings, the dry processing environment consumed the most energy, while the RHVT processing environment consumed the least. It was observed that the energy consumption in the RHVT environment was 4.4% and 3.2% lower compared to dry cutting [25]. Beyond technical comparisons among cooling strategies, dry machining offers distinct sustainability advantages. Although cutting fluids increase tool life, they contain petroleum-derived substances that become harmful waste and pose health risks, including respiratory illnesses from evaporating chemicals [26–28]. Eliminating cutting fluids reduces chemical waste, disposal costs, and operator exposure to hazardous aerosols [26,28]. Additionally, dry machining produces coolant-free chips, enabling direct recycling and supporting material circularity in metal value chains [29]. These benefits align with responsible production (UN SDG 12) [30] and safer working environments (UN SDG 3) [31]. In parallel with experimental studies on cooling strategies, significant research has been undertaken to model and estimate energy use in machining. In these studies, energy consumption was modeled by considering the input features of the cutting insert coating and geometry [32], depth of cut, speed, and feed [33], different cooling environments [34], the effect of different workpiece materials [35], and tool flank wear [36]. However, despite its significant effects on workpiece quality and occupational safety, no study has been found on the effect of cutting temperature on energy consumption. This study aims to fill the gap in the literature. Thus, the impacts of different input features on the prediction performance in the modeling of energy consumption can be taken to a further level. Because by modeling energy consumption according to cutting temperature, the optimum coolant type can be determined and machining efficiency can be increased. In addition, proactive measures can be taken by better modeling the cutting process with a synergistic effect. Thermal cameras are used to display and record the cutting temperature in real time. By examining the thermal images taken, the temperature formation occurring during the cutting process can be better modeled. While creating the models, feature engineering is used to select and sort the features. Because all the determined features may not reflect the cutting process accurately. Therefore, selecting and determining effective input features is very important for establishing effective models and predictive performance. There are methods such as Pearson correlation coefficient (PCC) [37], recursive feature elimination (RFE) [38], permutation feature important (PFI) [39], shapley additive explanations (SHAP) [40], random forest (RF) [41], boruta [42], lasso [43], and mutual information (MI) [44] to select and rank the features according to their importance. There are also many machine learning algorithms for building models, such as Catboost [45], XGBoost (XGB) [41], Gradient Boosting (GB) [46], Theilsen (TS) [47], Automatic Relevance Determination (ARD) [48], and Extra Trees (ET) [49]. The performance of these algorithms is significantly improved with hyperparameter optimization [50]. Apart from methods such as grid search and random search, there are various optimizers such as Optuna [51], Hyperopt [52], Bayesopt [53], and Skopt [54] that have become popular recently. It is very difficult to create the most effective energy consumption estimation model in such a deep search space in a short time. Various methods, such as multi-objective optimization and real-time optimization, are used to achieve this [55,56]. In these studies, the performance obtained by the fusion of previously determined methods is compared. However, the effort spent on developing the most effective hybrid optimization framework constitutes the most innovative aspect of this work.

This study proposes a novel measurement and modeling paradigm that advances the context of energy monitoring in machining. While existing energy consumption models in the literature predominantly rely on direct electrical measurements or empirical correlations with cutting parameters, the causal link between cutting zone thermodynamics and energy use has not been fully leveraged. This research directly addresses this gap by utilizing cutting temperature as a primary input variable for a machine learning model to predict energy consumption with high accuracy. The proposed approach transforms real-time thermal imaging data from a passive monitoring metric into an active, information-rich tool. By extracting and analyzing statistical features from temperature profiles and integrating them with advanced feature selection (e.g., SHAP) and hybrid optimization techniques, the methodology enables a deeper, physics-informed understanding of the energy-temperature nexus and provides actionable insights for process optimization, thereby significantly enriching the measurement and analysis framework. To realize this paradigm, the current study aims to build and analyze a hybrid optimization framework for predicting temperature-based energy consumption in turning Ti6Al4V alloys under various coolant conditions. The turning process under different cooling environments was monitored in real time using a thermal camera and a power analyzer. Statistical features extracted from the thermal image

data served as inputs for modeling energy consumption. The framework involves a comprehensive comparison of multiple feature selection and ranking methods, regression algorithms, and hyperparameter optimizers to identify the most effective hybrid combination. The effectiveness and robustness of the proposed method have been verified by experimental results.

2. Machine Learning Models and Methods

In this study, it is proposed to determine the highest-performing machine learning algorithm according to various feature selection and ranking methods and then to create the highest-performing hybrid optimization model as a result of hyperparameter optimization of the most successful algorithm with various optimizers. The superiority of the hybrid optimization framework is highlighted by comparing the proposed model with the traditional model. Energy consumption estimation according to cutting temperature using the proposed method has shown higher performance success. Fig. 1 shows the process of the high-impact energy consumption prediction model according to the cutting temperature. It illustrates the overall workflow of the proposed methodology. The process begins with the acquisition of temperature signals during the machining experiments, followed by statistical feature extraction from the recorded thermal data. These features are then evaluated using SHAP-based feature importance analysis to identify the most informative variables. The selected features are subsequently used to train the CatBoost regression model, while Optuna is employed to optimize the model hyperparameters. Finally, the performance of the optimized model is evaluated using multiple statistical metrics to assess prediction accuracy. Based on the full factorial combination of input parameters, a total of 81 experimental conditions were obtained. For each condition, statistical features were extracted from the time-dependent cutting temperature data, forming a final dataset consisting of 81 observations. The data was then split into training and test sets in a 70% to 30% ratio, which were subsequently used for model construction and testing, respectively. The split was performed using stratified random splitting based on the cooling condition variable. In this study, the performance of regression models was evaluated using a comprehensive set of six metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Coefficient of Determination (R^2), Standard Deviation of errors (STD), and Mean Absolute Percentage Error (MAPE). MAE represents the average absolute deviation between the predicted and actual cutting temperature values. MSE and RMSE penalize larger errors more heavily, thereby highlighting the model's sensitivity to outliers. Expressing RMSE in the original physical unit enhances the interpretability of the results. The R^2 metric indicates the proportion of the total variance in the target variable that is explained by the model, quantifying its explanatory power. STD measures the dispersion of the prediction errors, providing insight into the stability and consistency of the model. MAPE expresses the error as a percentage, facilitating relative performance comparisons across different models and studies. The calculation formulas were taken from the literature [45]. All metrics were calculated on an independent test set that was not used during the model training process.

The modeled system consists of various stages. In the first stage, cutting temperature and energy consumption data were accumulated in real time. In the second stage, temperature information in thermal images was collected and listed. Total energy consumption for the relevant experiment was recorded. In the third stage, statistical features were extracted from the temperature information in the time domain by feature engineering. The benchmark model utilized for comparison in this study represents a reference model constructed without any feature selection or hyperparameter optimization. This benchmark employs a total of 24 input features, comprising 20 temperature-based statistical features and 4 cutting parameters. The model was trained using regression algorithms with their default hyperparameter settings. A comparison between the proposed models (e.g., CAT+SHAP and CAT+SHAP+Optuna) and the benchmark model was conducted under identical train-test data splits and the same evaluation protocol. All performance metrics were calculated on a fixed, held-out test set for each model, thereby ensuring that the comparative analysis remained

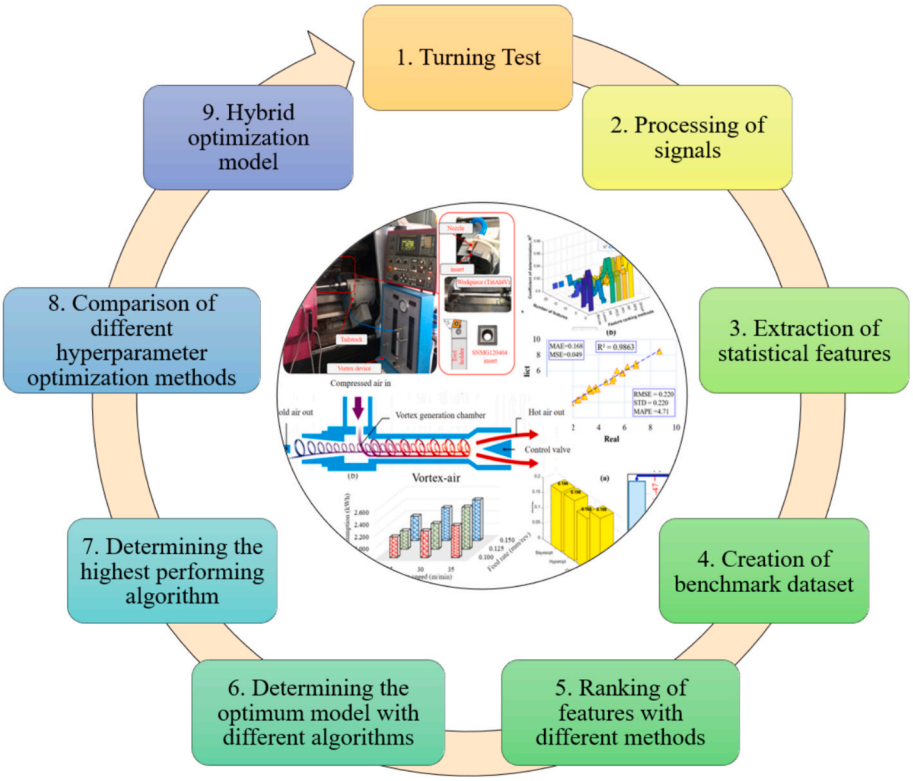


Fig. 1. Energy consumption hybrid optimization process.

fair, consistent, and unbiased. The benchmark dataset was obtained by adding cutting parameters to the extracted statistical features. The benchmark performance represents the best-performing algorithm among these models without applying feature selection or hyperparameter optimization. This approach allows a fair comparison to evaluate the effectiveness of the proposed framework, which integrates feature selection and Optuna-based hyperparameter optimization to improve predictive performance. In the fourth step, the features were graded by importance using PCC, RFE, PFI, SHAP, RF, MI, Boruta, and Lasso methods. A huge number of dataset subsets were generated by including a single attribute at a time to the ranking achieved using each approach. In the fifth stage, all datasets were modeled with Catboost, XGBoost, Gradient Boosting, Theilsen, ARD Regressor, and Extra Trees algorithms, and the most effective machine learning regressor was determined. In the sixth stage, hyperparameter optimization for the determined regressor was performed with Optuna, Hyperopt, Bayesopt, and Scopt and the highest-performing hybrid optimization model was determined. Based on the mentioned steps, energy consumption estimation can be performed with high success.

In this study, the term “optimization” refers to the systematic enhancement of multiple stages within the modeling pipeline, with the objective of maximizing energy consumption prediction performance. Specifically, the input space composed of temperature-based and process parameters is first optimized using SHAP-based feature selection. Following this, the hyperparameters of the CatBoost regression algorithm are fine-tuned with advanced hyperparameter optimization methods. The hybrid approach describes the sequential and integrated combination of feature selection, regression modeling, and hyperparameter optimization steps. This multi-stage optimization strategy results in the concurrent improvement of both prediction accuracy and model stability.

The primary methodological novelty of this work lies in systematically integrating feature selection, regression modeling, and hyperparameter optimization into a single, unified hybrid framework for cutting temperature prediction. While SHAP-based feature analysis, CatBoost regression, and Optuna-based hyperparameter optimization are frequently addressed in the literature as independent components or in pairwise combinations, this study incorporates these methods within a sequential, end-to-end optimization strategy. In the proposed approach, the SHAP method is employed not merely to enhance model interpretability but also as a data-driven, model-aware feature selection mechanism. This process effectively eliminates redundant or low-impact features, thereby reducing model complexity. Subsequently, the CatBoost algorithm's inherent capacity to handle categorical and numerical data efficiently is synergistically combined with Optuna-based hyperparameter optimization, yielding a refined structure that demonstrates improvements in both predictive accuracy and model stability. Furthermore, the systematic comparative analysis of different hyperparameter optimization methods and the joint evaluation of the computational cost–predictive performance trade-off constitute distinct original contributions of this study to the existing body of knowledge. In these respects, the study provides a novel and applicable hybrid optimization framework for energy consumption estimation problems. It offers significant methodological and practical contributions to the relevant literature by delivering an interpretable, highly accurate, and deployable modeling pipeline.

2.1. Machine learning algorithms analyzed for energy consumption prediction

To model energy use, this study used a variety of machine learning methods. CatBoost is an overfitting-resistant gradient boosting algorithm that works particularly effectively with categorical data; however, it can be slow on large datasets [45]. XGBoost, on the other hand, adapts well to the dataset with its high computational speed and regularization mechanisms, but hyperparameter settings can be complex and require high memory usage on large datasets [41]. The gradient boosting algorithm offers high accuracy by building sequential models to reduce the error rate, but this process can be slow on large datasets and requires careful tuning [46]. Theil-Sen Regressor is a regression method that is robust against extreme values. Although it gives reliable results in small and noisy data sets, the computation time may be longer in large data sets [47]. ARD Regressor reduces complexity by determining the importance of features with its Bayesian-based structure; however, its performance may be limited in data sets with intense non-linear relationships [48]. Finally, Extra Trees provides a highly diverse model that is robust to overfitting due to the randomness in the number of trees but may exhibit low stability on some datasets [49].

2.2. Methods for selecting features and ranking them according to their importance

In this study, feature selection and importance ranking methods were used to model energy consumption. PCC is particularly effective in linear relationships by measuring the linear relationship between two continuous variables but is limited in nonlinear relationships [37]. RFE optimizes model performance by extracting the least contributing feature at each step; however, if there are a large number of features, the processing time may be longer [38]. PFI determines the importance of features by measuring their impact on model accuracy. Although it is compatible with all types of data structures, it may require complex calculations in large data sets [39]. SHAP requires high computational power when precisely quantifying feature contribution in complex models [40]. RF is effective in multidimensional datasets and is powerful in identifying the features that contribute most to the model, but the processing time can be long [41]. Boruta identifies significant contributions of features with its random forest algorithm, and while it provides reliable results, it can be time-consuming on datasets containing a large number of features [42]. Lasso reduces unnecessary features to zero by adding regularization and reduces the complexity of the model, but it may result in the elimination of some important features [43]. MI is effective in complex datasets by providing an entropy-based measure that can also capture nonlinear relationships, but processing time can be long [44]. The use of these methods is important to increase model accuracy by determining whether the features in the data set are effective in estimating energy consumption. Fig. 2 visualizes the strategies used in the suggested hybrid optimization framework. This study implemented a rigorous evaluation protocol to reliably assess model generalization performance and to prevent data leakage. The dataset was first split into training and test sets, with the test set kept completely independent throughout the entire model development process. All steps, namely feature ranking, feature subset creation, comparison of machine learning algorithms, and hyperparameter optimization, were performed using only the training data. To this end, k-fold cross-validation was applied on the training set, and within each training fold, feature ranking methods were recalculated to construct subset data. The processes of algorithm selection and hyperparameter optimization, using tools such as Optuna, Hyperopt, BayesOpt, and Skopt, were also conducted exclusively within the training folds. Following the completion of all internal optimization steps, the final model was retrained on the entirety of the training data with the selected feature set and optimized hyperparameters. Evaluation was performed on the independent test set only at this final stage. This approach conforms to the principle of nested cross-validation, thereby enabling an unbiased and generalizable reporting of model performance.

2.3. Hyperparameter optimizers

Optimizing hyperparameters is crucial to maximizing the performance of machine learning models. In this study, Optuna, Hyperopt, Bayesopt, and Skopt optimization tools were used to provide hyperparameter optimization. These optimizers increase model accuracy by

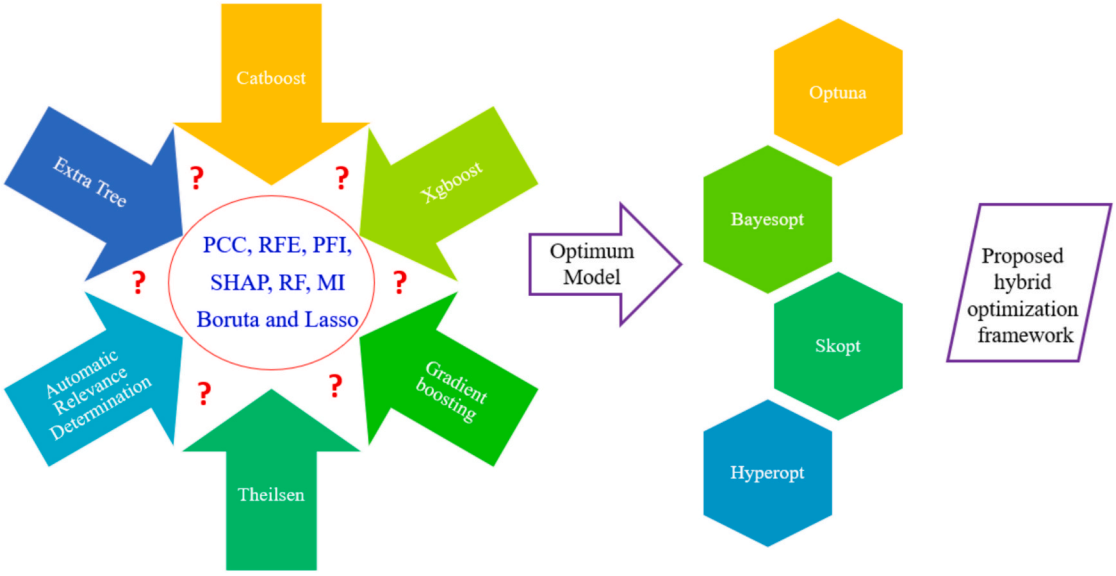


Fig. 2. Methods used for the proposed hybrid optimization framework.

applying different strategies to find the best combinations in the hyperparameter space. Performance differences between the optimization methods were compared based on results obtained under identical data splits and random number generation conditions. All optimization procedures were executed using 5-fold cross-validation on the training data, with a fixed random seed to ensure methodological consistency and reproducibility.

2.3.1. Optuna

Optuna is an open-source optimization tool designed to simplify and speed up hyperparameter search [51]. Optuna defines a dynamic search space using a "define-by-run" approach and uses model-based optimization algorithms such as the Tree-structured Parzen Estimator (TPE) to perform an efficient hyperparameter search. Optuna offers fast results even in complex search areas with its flexible and scalable structure.

2.3.2. Hyperopt

Hyperopt is a tool that facilitates hyperparameter optimization, especially in large search spaces [52]. This optimizer evaluates combinations of hyperparameters using random search and TPE algorithms. Hyperopt allows defining ranges for parameters to be optimized and can produce results quickly on large datasets. Since it uses the TPE algorithm, it increases efficiency by exploring more combinations with high potential in terms of performance.

2.3.3. Bayesopt

Bayesopt is a tool that performs hyperparameter search based on Bayesian optimization [53]. It can produce efficient results, especially when there are a limited number of hyperparameter evaluation rights. BayesOpt strategically directs subsequent search steps using statistical modeling techniques such as the Gaussian Process to find the best value of a function. This approach aims to reach the best parameter combinations with fewer evaluations by using information from previously tested parameters.

2.3.4. Skopt

Skopt is a hyperparameter optimization tool based on Bayesian optimization and has a particularly simple and user-friendly structure [54]. Skopt enables rapid determination of optimum parameters by applying the sequential best search strategy. As with other Bayesian optimization tools, it explores the hyperparameter space with a given modeling method (e.g., Gaussian Process) and utilizes available data to determine parameters close to the optimum value.

3. Experiments and methods

3.1. Turning experiments

The experimental study was carried out in dry, vortex tube air cooling and vortex tube CO_2 cooling environments. A vortex tube is a cooling device that uses compressed air to separate it into hot and cold air streams [57]. The working principle of this device is presented in Fig. 3. In the machinability tests, a cooling system called Acgreiff brand RHVT was used.

In the vortex system, cooling is provided with 4.5 bar pressure, and the vortex nozzle is positioned 5 mm away from the cutting insert which was determined through preliminary experiments and literature recommendations as the optimal distance for effective cooling without interfering with the cutting process [59]. The titanium alloy Ti6Al4V was preferred as the workpiece material in the experiments. The hardness of the Ti6Al4V alloy is 36 HRC, and the dimensions of the test sample are ∅40×400 mm. The alloy has a chemical content of 4.0% V, 0.09% Fe, 5.9% Al, 0.14% O, 0.01% C, 0.01% N, 0.002% H, and the balance Ti and has a density of 4.4 g/cm^3, a thermal conductivity of 7.1 W/mK, and a tensile strength of 880-920 MPa. In the machinability tests, PVD (AlTiSiN)-coated carbide inserts with AC5015S quality and SNMG120404 geometry from the Sumitomo company were used. These tools can be mounted using a tool holder, which has a 75° approach angle. The selection of this specific insert was based on its proven performance in machining titanium alloys: the AlTiSiN coating provides excellent high-temperature resistance, oxidation resistance, and a low coefficient of friction, which are critical for maintaining stable cutting conditions when processing Ti6Al4V. Furthermore, the AC5015S grade and SNMG120404 geometry constitute a widely adopted industrial standard for titanium machining, which enhances the practical relevance, representativeness, and comparability of the experimental results obtained in this study. To isolate the effects of cooling environment and cutting parameters on energy consumption, a fresh cutting insert was used for each experimental condition, thereby eliminating tool wear progression as a confounding variable. This approach ensured that all measurements commenced with identical tool conditions, allowing direct attribution of observed energy differences to the controlled factors. In this study, the experimental design was configured as a full factorial arrangement to generate reliable data for machine learning and

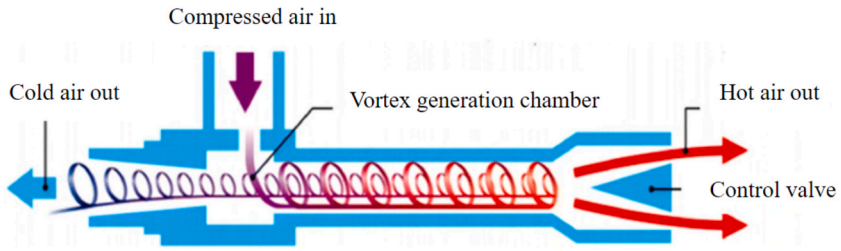


Fig. 3. Vortex tube internal working mechanism [58].

comprehensively analyze the effects of cutting parameters. The cutting parameters were selected based on tool manufacturer recommendations, preliminary experiments, and literature research. Within this scope, four control factors were examined, each at three levels: cooling environment (dry, vortex-air, vortex-CO_2), cutting speed (25, 30, and 35 m/min), feed rate (0.100, 0.125, and 0.150 mm/rev), and cutting length (5, 10, and 15 mm), all varied systematically. The depth of cut was held constant at 0.75 mm for all experiments. Since the primary focus of this study is to model the relationship between cutting temperature and energy consumption, the depth of cut was kept constant to maintain a manageable number of control factors and to isolate the effects of the parameters of interest (cooling environment, cutting speed, feed rate, and cutting length) on the temperature-energy relationship. Among these factors, cutting length requires particular clarification regarding its role in energy consumption. The cutting length parameter refers to the length of cut per pass along the workpiece axis. This factor was included in the experimental design because it directly influences the total processing time and, consequently, the cumulative energy consumption. For a given cutting speed and feed rate, longer cutting lengths result in extended machining time, leading to higher total energy consumption. Additionally, as cutting length increases, the progressive tool wear may affect instantaneous power demand. Therefore, cutting length was considered as a control factor to capture both the time-dependent and wear-dependent variations in energy consumption. This range of parameter combinations enabled the reliable evaluation of both main and interaction effects on energy consumption and cutting temperature, while simultaneously providing a dataset with sufficient diversity and robustness for the developed machine learning models. In the experiments, the workpiece was positioned between the tailstock and the chuck to prevent runout and vibration. The studies were conducted using a Johnford TC35 industrial-use CNC lathe capable of producing 10 KW of power and reaching a maximum speed of 3500 rpm. During the cutting process, the cutting region's temperature was recorded using a FLIR T440 infrared thermal camera with a measurement range of 0-1200°C, operating at a spatial resolution of 320 × 240 pixels and a recording frequency of 30 Hz. The camera was calibrated using an emissivity value of 0.4 for the Ti6Al4V surface, and the device data was subsequently acquired. It is well documented in the literature that the emissivity of Ti6Al4V alloy can vary between 0.3 and 0.6 depending on surface oxidation and temperature. The emissivity value of $\varepsilon = 0.4$ used in this study is based on the value recommended and experimentally validated for machined Ti6Al4V surfaces in relevant literature [60]. The obtained temperature data exhibited a measurement uncertainty of ±4.6°C. The average temperature was 159.81°C, with a standard deviation of 41.04°C. The 95% confidence interval for the mean temperature was calculated to be between 150.73°C and 168.88°C. The calculation of features derived from temperature data across multiple consecutive frames serves to mitigate the influence of measurement noise. Concurrently, the inherent structure of machine learning models, which relies on relative patterns rather than absolute values, has limited the impact of measurement uncertainty on prediction performance. Energy consumption is critical to both cost-effectiveness and environmental sustainability in the manufacturing industry, varying according to cutting settings, tool type, workpiece hardness, and machine efficiency. In this study, a Hioki 3390 power analyzer with a class 0.5 accuracy was connected in series to the primary electrical circuit of the CNC machine tool to measure the energy consumed under different processing parameters. Instantaneous active power (kW) was recorded at a 1-second sampling interval, and simultaneous energy consumption measurements were made for each processing cycle. It is important to define the system boundary for the energy consumption reported in this study. The energy values presented herein represent the process energy (also referred to as cutting energy), which is the electrical energy consumed by the machine tool exclusively during the material removal phase. This was calculated by multiplying the instantaneous active power (kW) recorded during cutting by the processing time (hours). This measurement includes the power drawn by the spindle drive, axis servomotors, and other components directly involved in the cutting operation. However, it excludes the energy consumption of auxiliary equipment such as the coolant pump, hydraulic unit, or the external air compressor required for the vortex tube cooling system. This system boundary was deliberately chosen to focus the analysis on the thermomechanical relationship between the cutting zone temperature and the net energy required for material removal, thereby enhancing the physical interpretability of the developed machine learning model. Data acquisition was synchronized by starting both the thermal camera and the power analyzer simultaneously at the beginning of each experimental cycle. Post-processing involved automatically extracting the maximum temperature value from each frame of the thermal video and calculating the average power corresponding to the cutting duration from the power analyzer data. The total energy consumption (kWh) for each cycle was then obtained by multiplying this average power by the processing time. Fig. 4 shows a schematic interpretation of the methodology utilized in the current investigation.

3.2. Collection of experimental data and preparation of datasets

Cutting temperatures and energy consumption data were collected in real time during the Ti6Al4V workpiece turning trials. The values of each experiment were obtained by averaging the energy consumption data with respect to time. Cutting temperatures were recorded by a thermal camera placed directly in the tool-chip interface. The frame size of the camera is 320×240, and the frame rate is 30 Hz. Therefore, 30 visual images were received per second. These images were processed manually one by one, and the maximum values of the cutting temperature were digitized. The emissivity value was fixed at 0.4 and was consistently employed across all experiments. During post-processing, a region of interest (ROI) encompassing the tool-chip contact zone was manually defined for each thermal video frame. The maximum temperature values within these ROIs were recorded to construct time-dependent temperature series. All temperature measurements were conducted using the manufacturer's calibration. The consistency of the obtained temperature values with existing literature was also verified. Statistical features in the time domain were extracted from the digitized cutting temperature data by feature engineering. The extracted statistical features are minimum, maximum, mean, median, kurtosis, skewness, interquartile range, coefficient of variation, geometric mean, harmonic mean, mean absolute deviation, standard error, RMS,

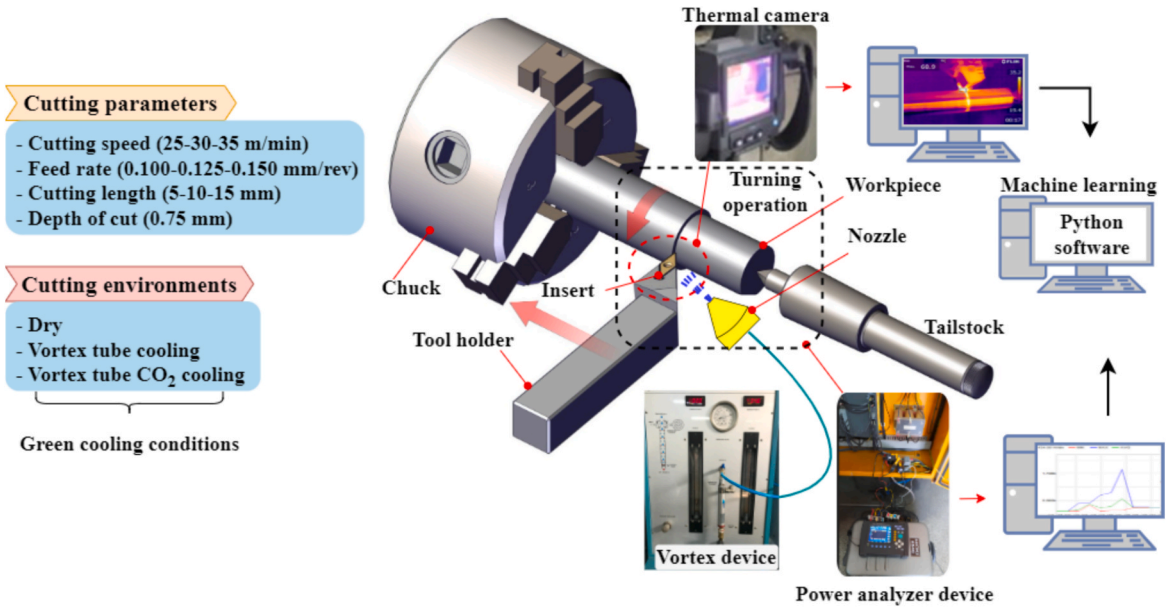


Fig. 4. Schematic interpretation of the procedure utilized in the experimental investigation.

variance, signal power, peak-to-peak, crest factor, pulse indicator, average curve length, and shape factor. Formulas used in calculating statistical properties and further information can be found in the relevant source and appendix Table A.1 [40]. Four cut-off parameters were added to the 20 statistical features extracted, and a total of 24 input features were obtained. The dataset obtained with these 24 features was determined as the benchmark dataset. The 24 attributes in this benchmark dataset are ranked separately based on their value level, using eight different techniques. Dataset subsets were generated by including a single attribute at a time in the order determined by each feature ranking technique. A total of 222 datasets were obtained: six for the Boruta feature ranking method and 24 datasets for each of the other nine methods. Each of the 222 datasets was created using six methods, and a total of 1332 model installations were executed. The most optimum model was determined by comparing the prediction performance of these models with various performance metrics. The detected model algorithm was processed with four different hyperparameter optimizers, and the hybrid optimization model for the most effective energy consumption estimation was determined.

4. Experimental Findings and Discussion for the Hybrid Optimization Framework

The aim of this study is to effectively predict the energy consumption in the cutting of Ti6Al4V in various coolant mediums with a hybrid optimization framework based on real-time cutting temperature information. Various datasets have been created to achieve this. Then, the prediction performance of machine learning algorithms based on the datasets were evaluated with the help of various performance metrics. Hyperparameter optimization for the algorithm that showed the highest performance was performed with the help of different optimizers. The results were examined, and the most successful model was tried to be obtained.

4.1. Experimental findings and analysis

Experiments were conducted in this work to assess the usage of energy associated with the turning of Ti6Al4V superalloy under various cutting circumstances. The energy utilized by the machine tool during the turning process of the Ti6Al4V superalloy was attempted to be calculated using tests. Determining the energy demanded by machine tools is critical in terms of production costs and sustainability. The prevalence of machining operations places significant danger on the ecosystem owing to the usage of energy and accompanying carbon emissions. The total power needed for machining comprises both the power utilized by the machine before it begins cutting and the power spent on extracting material from the workpiece (cutting power-AVG). Energy saving is based on an accurate assessment of energy usage in machining [35]. In this study, air and carbon dioxide (CO_2) gas were sprayed from the vortex tube into the cutting area, and the power consumed during the cutting process was compared with the dry cutting condition. As a result of the experiments, the average maximum energy consumption values depending on the cutting speed, feed rate, and processing conditions are given in Fig. 5. In terms of cutting conditions, the lowest energy consumption values were measured under dry cutting conditions. In terms of Vortex cooling methods, the highest energy consumption was determined in the Vortex-CO_2 cooling method. While the average energy consumption was 2.20 kWh depending on the cutting parameters in dry cutting conditions, it was 2.28 kWh with a 3.7% increase compared to the dry cutting condition in the Vortex-air cooling method. According to the dry cutting condition, an energy consumption of 2.36 kWh was achieved with a 7.1% increase in the vortex-CO_2 cooling method. This can be explained by the fact that the Vortex-CO_2 cooling method cools the cutting zone more than other conditions [58]. As the temperature increases in the cutting zone, the material being processed can be deformed more easily, resulting in decreases in cutting forces [61]. Therefore, the lowest energy consumption values were measured under dry cutting conditions. It is also seen in the literature [62] that vortex air cooling (11.3%) increases energy consumption compared to dry cutting conditions. In terms of vortex cooling methods, lower energy consumption (3.4%) was achieved in vortex-air conditions, which provide less cooling compared to vortex-CO_2. When the shape is inspected according to feed and speed, it is shown that energy consumption tends to grow as the speed and feed increase. This scenario can be explained by the fact that tool wear grows with speed.

Fig. 6 depicts inserts utilized in various machining conditions and with the greatest cutting settings. It was observed that the wear occurred at the highest level of speed, and feed was greater. As cutting speed rises, so do the friction and temperature created between the cutting insert and the workpiece. This accelerates tool wear and shortens tool life. It should be noted that the tool wear images presented in Fig. 6 represent the condition of each cutting insert after a single experimental run under

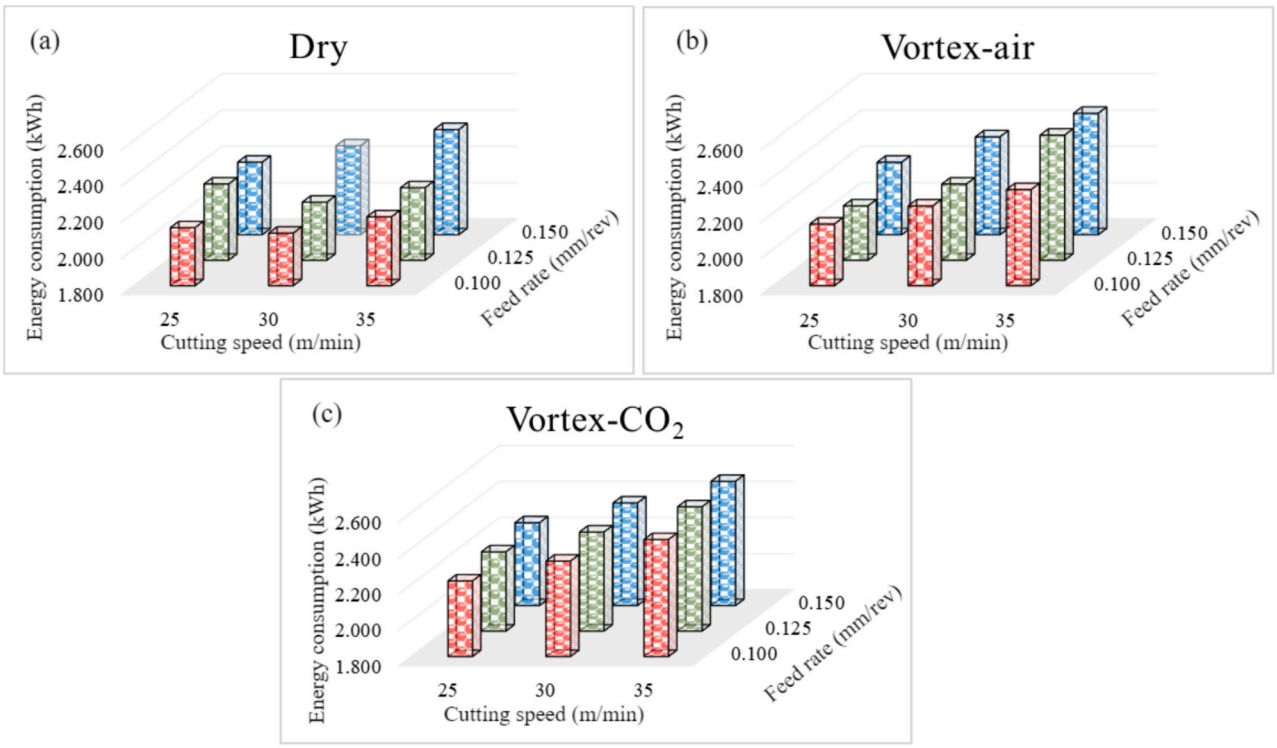


Fig. 5. Energy consumption values depending on parameters

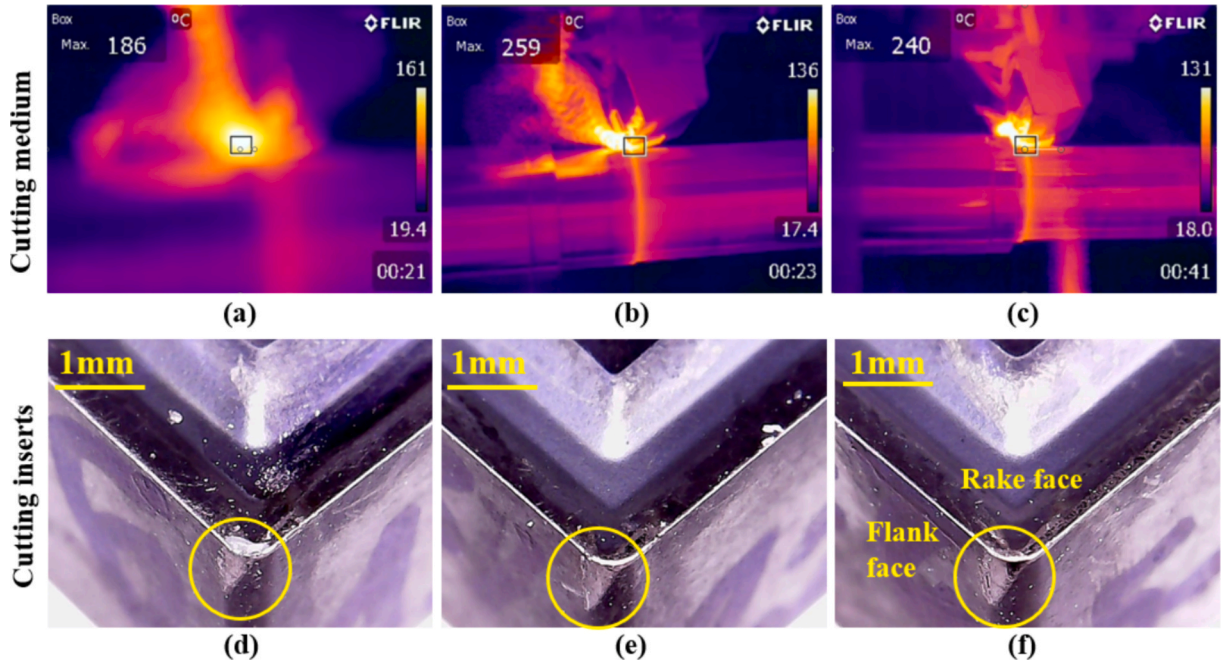


Fig. 6. Cutting environment and insert images (a, d) Dry, (b, e) Vortex air, (c, f) Vortex CO_2.

the specified conditions. Since a fresh insert was used for every experiment, the observed wear patterns are solely attributable to the cooling environment and cutting parameters applied during that specific test, and do not reflect cumulative wear effects across multiple experiments. Especially at high speeds, due to thermal effects, the tool may deform more rapidly, or microstructural changes may occur on the cutting surface [63]. Depending on the cutting speed, the average of all cutting conditions at 25 m/min cutting speed was 2.19 kWh. With a 20% increase in cutting speed, this situation changed by 3.1% at 30 m/min cutting speed and became 2.25 kWh. With a 40% increase in cutting speed, an energy consumption of 2.36 kWh occurred with a 7.8% increase at a cutting speed of 35 m/min. Once the speed was increased from 30 to 35 m/min, energy usage rose by 4.6%. This situation was realized as 2.23 kWh at 0.100 mm/rev, 2.27 kWh at 0.125 mm/rev, and 2.33 kWh at 0.150 mm/rev for the feed rate. With a 25% and 50% increase in feed rate, 10% and 15% increase in energy consumption were observed, respectively. This scenario may be explained by the rise in chip removal per unit time that occurs when speed and feed increase.

Literature research indicates that boosting the number of chips eliminated per unit time leads to a bump in power and strength levels [64].

The experimental findings indicate that the dry machining condition provides the most favorable performance in terms of both energy consumption and cutting temperature. Accordingly, dry machining offers significant sustainability advantages compared to vortex air and vortex CO_2 systems. The absence of additional cooling equipment, the elimination of environmental impact due to zero coolant consumption, lower energy requirements, improved chip recyclability, and a safer working environment for the operator are particularly noteworthy. From this perspective, when energy efficiency and environmental sustainability criteria are jointly considered, dry machining emerges as a more advantageous option compared to vortex-based cooling methods.

There may be several reasons why dry machining results in lower cutting temperatures compared to RHVT. Although active cooling is applied, the observation of higher maximum cutting temperatures relative to dry machining can be attributed to changes in the thermo-mechanical conditions within the cutting zone induced by the cooling effect. The low-temperature CO_2 jet and compressed air impinging on the cutting zone suppress the thermal softening behavior of the Ti6Al4V alloy, leading to higher material strength during cutting. This, in turn, increases cutting forces and specific cutting energy, thereby enhancing primary heat generation [65]. In addition, under RHVT conditions, heat transfer is governed predominantly by forced convection rather than conduction. The limited accessibility of the cooling flow to the narrow tool–chip contact region may cause localized heat accumulation, which can result in increased instantaneous temperature peaks measured during the process. Consequently, the heat removal capability of the cooling system may be outweighed by the increased heat generation associated with higher cutting forces and altered contact conditions, leading to higher maximum cutting temperatures compared to dry machining.

It is important to acknowledge that these findings are specific to the experimental conditions investigated in this study, namely Ti6Al4V alloy machined within the selected parameter ranges (cutting speed: 25-35 m/min, feed rate: 0.100-0.150 mm/rev). Under these conditions, the thermal softening effect facilitates chip formation and reduces cutting forces, thereby lowering energy consumption. However, this conclusion may reverse under different machining scenarios, and the findings must be interpreted within a broader sustainability framework that considers not only energy consumption but also tool life, surface quality, and material waste.

At significantly higher cutting speeds, the intense heat generation in the cutting zone may exceed the thermal softening benefits and accelerate tool wear, leading to increased friction and energy consumption [63]. As shown in Fig. 6, tool wear was qualitatively observed to be more pronounced under dry conditions, particularly at higher cutting speeds and feed rates. In such cases, effective cooling becomes essential to maintain tool integrity and process efficiency. Conversely, although RHVT and vortex-air cooling methods consume more energy during operation—7.1% and 3.7% more, respectively, compared to dry machining—they provide effective temperature control that can significantly extend tool life by reducing thermal and mechanical loads on the cutting edge [66,67]. Extended tool life translates to fewer tool changes, reduced tool consumption, and less tool-related waste, all of which contribute positively to sustainability. Similarly, for finishing operations where surface integrity and dimensional accuracy are critical, the absence of cooling and lubrication may result in higher surface roughness, thermal damage, and subsurface microstructural alterations, particularly in titanium alloys which are prone to work hardening and thermal degradation [16,68]. Under these conditions, minimum quantity lubrication (MQL) or cryogenic cooling may provide superior surface quality and part performance, potentially offsetting their higher energy consumption through extended tool life and reduced scrap rates [18,66]. Better temperature control may also improve surface integrity and dimensional accuracy, reducing scrap rates and material waste in high-precision applications. This trade-off between operational energy consumption and tool life highlights that energy efficiency alone is insufficient as a comprehensive sustainability metric. Furthermore, sustainability assessment should consider the entire lifecycle, including tool manufacturing, coolant production and disposal, and energy mix variations across different geographical regions [12,27]. In regions where the energy grid relies heavily on renewable sources, the environmental footprint of additional cooling equipment may be lower, potentially altering the comparative sustainability ranking. A multi-criteria assessment framework encompassing energy consumption, tool life, surface quality, material recyclability, and occupational health impacts is therefore necessary for holistic sustainability evaluation in machining processes. The optimal cooling strategy depends on the specific priorities of the manufacturing context: dry machining may be preferable when energy costs and carbon emissions are the primary concerns, while vortex cooling methods may be justified in high-productivity or high-precision applications where tool life and surface quality are critical. Future studies should incorporate quantitative tool wear monitoring and life cycle assessment (LCA) methodologies to quantify these trade-offs more precisely and develop multi-objective optimization frameworks that balance competing sustainability criteria [32,36]. Such approaches would enable manufacturers to select cooling strategies that align with their specific sustainability goals, whether minimizing energy consumption, extending tool life, or reducing overall environmental footprint.

To rigorously assess the statistical significance of the observed temperature differences under various cutting conditions, an analysis of variance (ANOVA) was conducted. The results are presented in the Appendix (Tables A.2 and A.3). The ANOVA model is highly significant (P-Value = 0.000), with an adjusted R^2 value of 96.81%, indicating that the model explains almost all of the variability in the cutting temperature data. Crucially, the main effects of Vc, f, CC, and Cl on cutting temperature are all statistically significant (P-Value = 0.000 for each). This confirms that the temperature variations observed across different experimental conditions, as illustrated in Fig. 5, are not random fluctuations due to the ±4.6°C measurement uncertainty of the thermal camera. The residual error accounts for only 0.64% of the total variance (Table A.2), demonstrating that the measurement uncertainty has a negligible impact on the overall model and that the observed temperature differences are indeed attributable to the controlled process parameters.

4.2. Selecting the best feature ranking method based on significance level.

It is aimed at determining the most effective input features so that energy consumption can be effectively modeled and estimated according to the initial dataset. There are many methods of selecting and ranking features according to their importance. However, choosing the most optimum method with respect to the dataset characteristics is necessary for establishing effective models. Most of the feature selection and ranking methods examined in various studies in the literature were evaluated within the scope of the current study. The coefficients of determination obtained by the ranking methods are given in Fig. 7.

For the ARD algorithm in Fig. 7a, Boruta, Lasso, and MI feature ranking methods could not show effective performance at low feature numbers, while other methods gave more successful results. While the most successful feature ranking method for the ARD algorithm is PCC, the optimum number of features is determined to be 12. In Fig. 7b, while the Lasso, MI, and PCC methods did not show effective performance for the CAT algorithm, more successful results were obtained with other methods. The most successful method was SHAP, and the optimum number of features was 7. In Fig. 7c, the Boruta, Lasso, and MI methods showed lower performance for the ET algorithm. The highest performance was obtained with SHAP and 7 features. In Fig. 7d, the highest performance success for the GB algorithm was achieved with the PFI method and 7 features. In Fig. 7e, the Boruta, Lasso, and MI methods

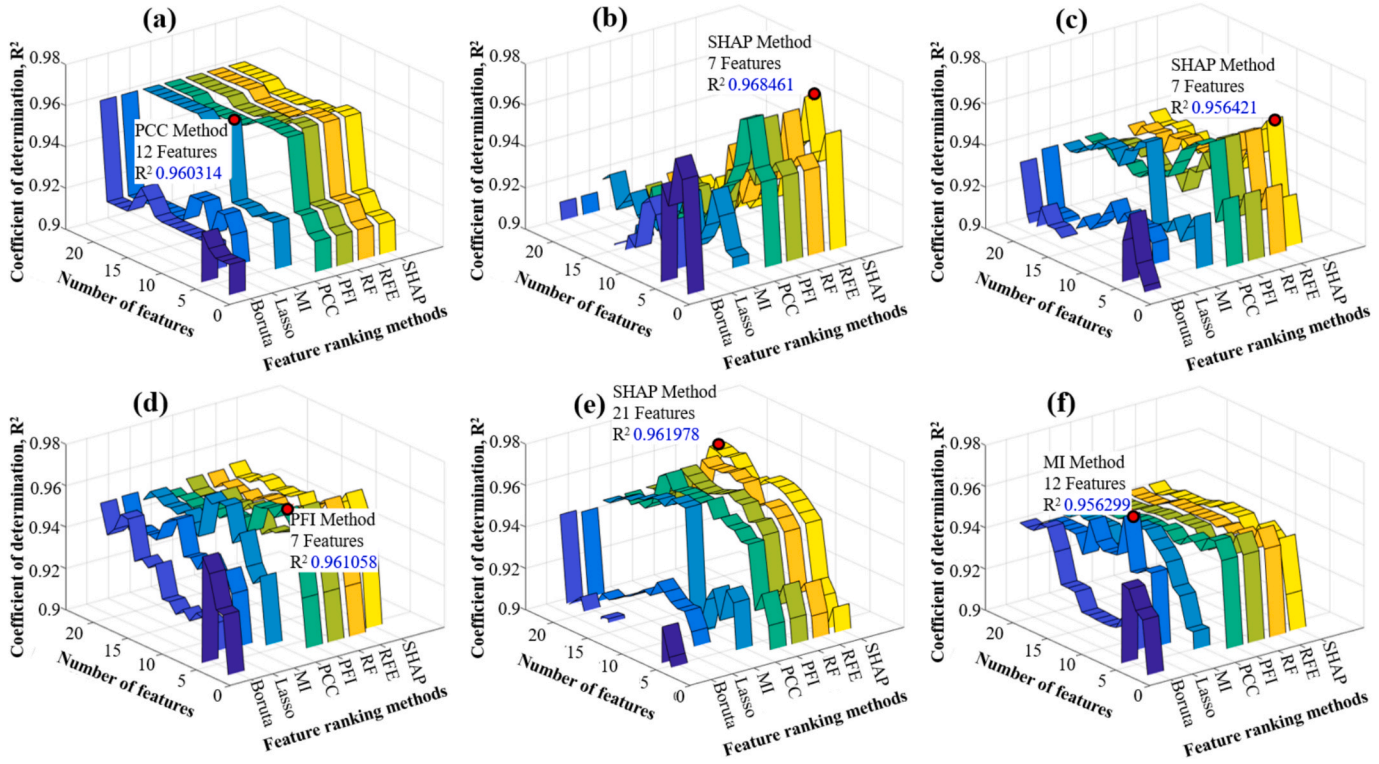


Fig. 7. Determination coefficients of ranking methods (a) ARD, (b) CAT, (c) ET, (d) GB, (e) TS, (f) XGB.

showed lower performance success for the TS algorithm. The highest performance was obtained with the SHAP method and 21 features. In Fig. 7f, the highest performance for the XGB algorithm was obtained with the MI method and 12 features. When the figure is evaluated in general, SHAP comes to the fore among the feature ranking methods according to the algorithms. The highest performance success for the three algorithms was achieved with the SHAP method. The Boruta and Lasso methods showed lower performance than other methods. For all algorithms, PFI, RF, RFE, and SHAP methods exhibited higher and closer performance to each other. The MI method is notable for showing the highest performance with the XGB algorithm while showing lower performance with other algorithms.

The performance of the feature ranking methods that showed the highest success according to the algorithms are given in Table 1. The highest performance was obtained for the CAT algorithm, the SHAP feature ranking method, and the R^2 value of 0.968 for 7 features. The SHAP ranking and importance values are found in Appendix Table A.4. Although the coefficient of determination obtained gives relatively successful results, it is desired to obtain results that are more effective and closer to the real values.

Hyperparameter optimization needs to be performed in the algorithms to perform more effectively and avoid overfitting models. Various methods are used for hyperparameter optimization. The most effective prediction model was the model established with the dataset having 7 features and the CAT algorithm. Therefore, the hyperparameters determined for the CAT algorithm were modeled and compared separately with Optuna, Hyperopt, Bayesopt, and Scopt optimizers. The optimum hyperparameters determined by the optimizers so that the CAT algorithm can show the most effective performance are given in Table 2. The hyperparameter space intervals are given in Appendix Table A.5. The hyperparameters used in the CAT algorithm provide important adjustments to optimize model performance and prevent over-learning. Bagging temperature increases the diversity of the model by adjusting the randomness of the sampling process; higher values provide more diversity, while lower values can make the model more stable. Border count controls the granularity of the algorithm by adjusting the number of boundaries used when determining the categorical levels of features. Depth determines the depth of decision trees, with deeper trees increasing the complexity of the model while shallower trees increasing the ability to generalize. “Iterations” refers to the number of iterations in the model's learning process, and generally higher values allow the model to learn better but increase the computational cost. L2 leaf regularization is used to prevent over-learning by regularizing the coefficients at the leaf nodes of the trees. The learning rate determines how much change the model will make at each step; at lower values, the learning process is slower and more stable, while at higher values, it speeds up, but the model runs the risk of overlearning. Random strength, on the other hand, reduces overfitting by increasing the randomness in the model and can improve overall performance. Different hyperparameter values have been suggested by optimizers. Therefore, it is very important to analyze and compare the contributions of these hyperparameters to the performance metrics in depth.

Table 3 and Fig. 8 provide a comparison of test prediction performance as a consequence of hyperparameter adjustment to get more generalizable outcomes by improving the CAT algorithm's prediction performance. The R^2 values and MAPE values obtained by all optimizers indicate that very successful predictions were made. According to performance metrics, the least successful optimizer was Skopt, while the

Table 1
Performance of the most successful feature ranking methods according to the algorithms.

Algorithms	Ranking methods	Number of features	Test R^2
ARD	PCC	12	0.960314
CAT	SHAP	7	**0.968461**
ET	SHAP	7	0.956421
GB	PFI	7	0.961058
TS	SHAP	21	0.961978
XGB	MI	12	0.956299

Bold = Best results.

Table 2
Hyperparameters optimized by optimizers in the CAT algorithm.

	Optimal hyper parameters						
Optimizer	bagging_temperature	border_count	depth	iterations	l2_leaf_reg	learning_rate	random_strength
Bayesopt	0.5439	63	4	788	4.2930	0.061	0.2458
Hyperopt	0.5896	41	4	163	0.0045	0.085	0.0008
Optuna	0.7614	14	4	453	0.0003	0.094	0.0045
Skopt	0.2299	186	4	1000	0.0001	0.047	0.0001

Table 3
Comparison of test prediction performance of optimizers.

Optimizer	MAE	MSE	RMSE	R^2	STD	MAPE
Bayesopt	0.194	0.060	0.244	0.9831	0.244	4.88
Hyperopt	0.196	0.058	0.242	0.9835	0.241	5.48
Optuna	**0.168**	**0.049**	**0.220**	**0.9862**	**0.220**	**4.71**
Skopt	0.198	0.062	0.249	0.9824	0.249	5.56

Bold = Best results.

most successful optimizer was Optuna.

Fig. 9 illustrates the convergence behavior of the MSE loss function, plotted against iterations, for the CatBoost algorithm optimized using four distinct hyperparameter tuning frameworks: Bayesopt, Hyperopt, Optuna, and Skopt. Across all methods, the loss value demonstrates a monotonic and stable decline as iterations progress, eventually converging to a stable minimum plateau after a specific number of iterations without exhibiting significant oscillations. The convergence profiles reveal distinct search characteristics: both Bayesopt and Optuna achieve rapid convergence in the early stages of the optimization process. In contrast, Hyperopt and Skopt exhibit a more gradual yet consistently stable convergence trajectory. The smooth and well-behaved nature of all convergence curves validates that the proposed hyperparameter search space is appropriately defined. Furthermore, it confirms that the high predictive performance of the final models is the result of a robust and stable training process, free from erratic optimization behavior.

Table 4 and Fig. 10 provide a performance comparison between the benchmark model and the models generated for the current investigation. When the SHAP ranking of features was applied to the benchmark model, a significant improvement in performance metrics occurred. Later, when the hyperparameter optimization method was applied to Optuna, a significant improvement was achieved compared to both the benchmark and the version with SHAP added. When the benchmark model is ranked with SHAP, the percentage improvement rates in MAE, MSE, RMSE, R^2, STD, and MAPE values are -44%, -72%, -47%, 9%, -47%, and -44%, respectively. When the Optuna optimizer was added, the improvement rates were -71%, -91%, -70%, 11%, -70%, and -73%, respectively. When the Optuna optimizer was added to the CS-coded model, the improvement in performance metrics was -49%, -67%, -78%, 2%, -78%, and -52%, respectively. Given the development rates, the suggested hybrid optimization strategy appears to be successful.

To clarify the individual contributions of the hybrid pipeline components, the performance differences between BM, CS, and CSO models were analyzed in a stepwise manner. The transition from BM (all features with default hyperparameters) to CS (SHAP-based feature selection with default hyperparameters) isolates the impact of model-aware feature selection, revealing that a substantial portion of the performance gain originates from eliminating redundant and low-contribution variables. Subsequently, the transition from CS to CSO (SHAP + Optuna optimization) reflects the isolated contribution of hyperparameter tuning, as both models rely on the same selected feature subset. The results

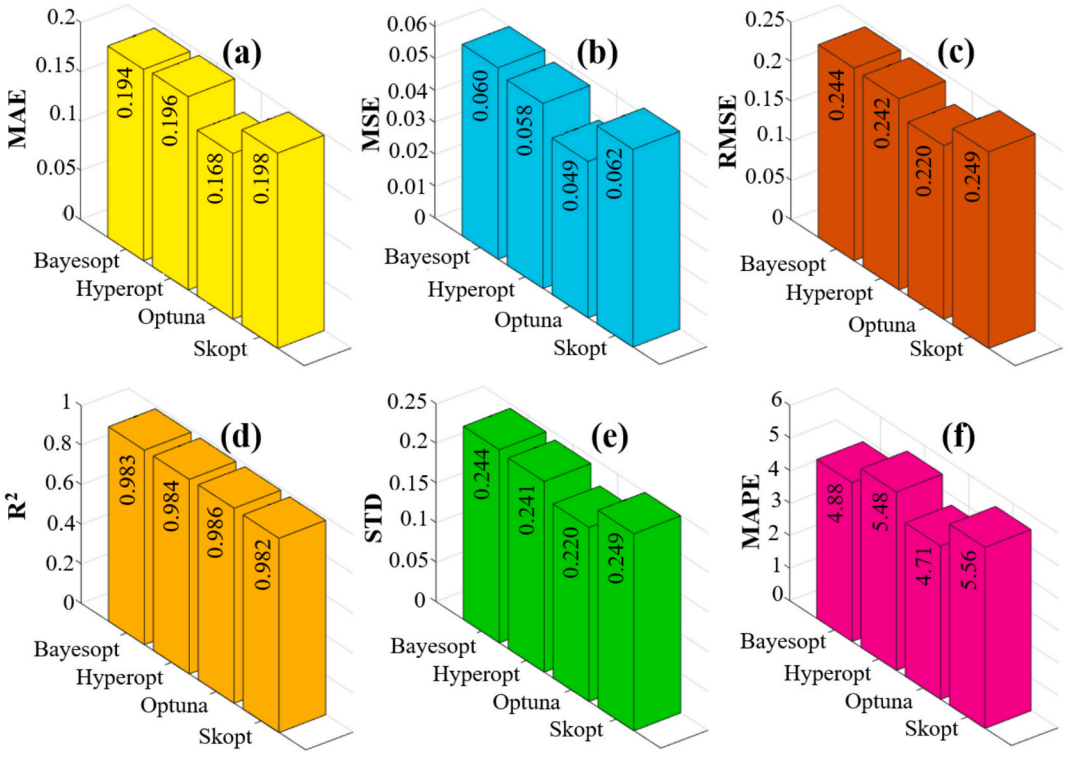


Fig. 8. Test prediction performance of optimizers (a) MAE, (b) MSE, (c) RMSE, (d) R^2, (e) STD, (f) MAPE.

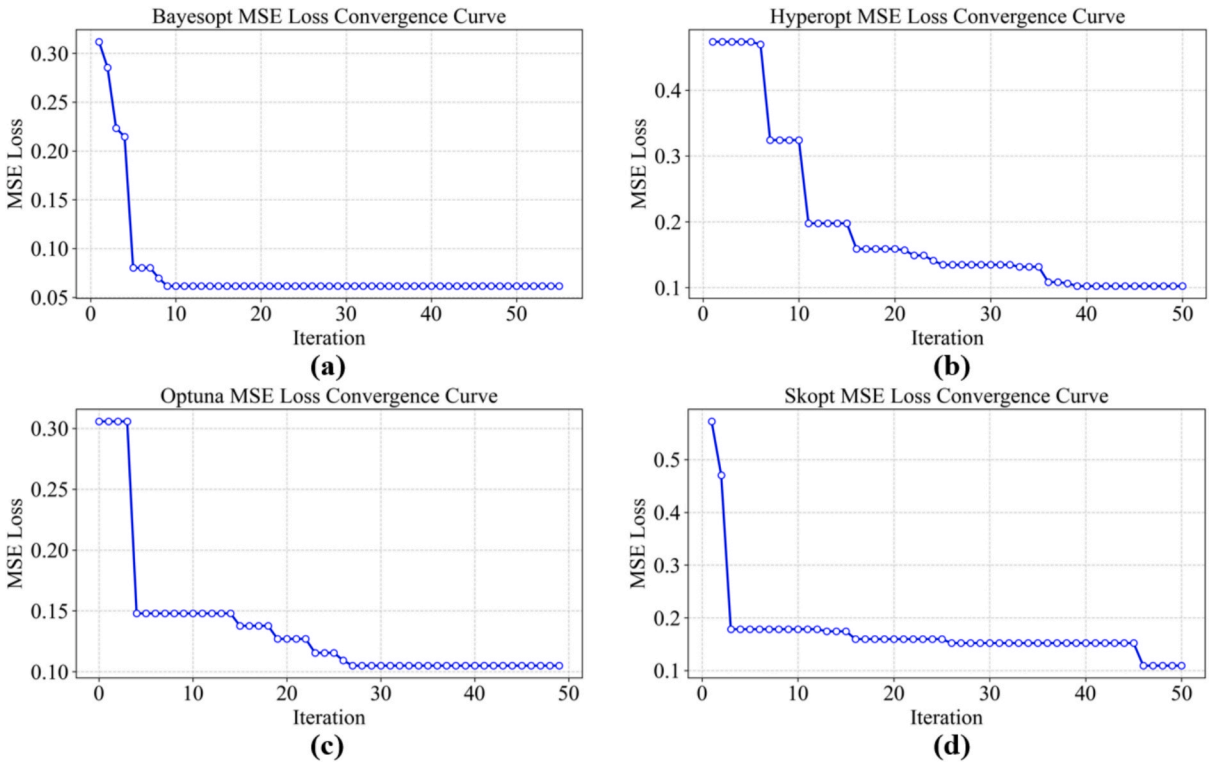


Fig. 9. MSE loss convergence curves (a) Bayesopt, (b) Hyperopt, (c) Optuna, (d) Skopt.

Table 4
Performance comparison of models created with the benchmark model.

Code	Models	MAE	MSE	RMSE	R^2	STD	MAPE
BM	Benchmark model	0.577	0.531	0.729	0.887	0.728	17.56
CS	CAT+SHAP	0.326	0.150	0.387	0.968	0.387	9.84
CSO	CAT+SHAP+Optuna	**0.168**	**0.049**	**0.220**	**0.986**	**0.220**	**4.71**

Bold = Best results.

in Table 4 indicate that the major share of the ~91% MSE improvement observed between BM and CSO is primarily attributable to SHAP-based feature selection, while Optuna-based hyperparameter optimization provides an additional but complementary refinement. This stepwise design demonstrates that performance enhancement is not solely due to hyperparameter tuning but largely driven by the construction of an informative and compact feature space prior to optimization.

Fig. 11 depicts the distributions of data points for both the benchmark and suggested models. With the proposed systems CAT+SHAP+Optuna, a significant improvement in performance metrics occurred, with data points showing a more balanced distribution. The fact that the MAPE value obtained with the proposed method is less than 5% is an indication that the proposed method can make very high-performance predictions. The estimation results for the proposed model based on real data points are given in Fig. 12. The trends of actual and forecast values across data points are quite similar and consistent. It can be said that the hybrid optimization model developed in this study can be used successfully for high-accuracy estimation of energy consumption. Although the overall prediction accuracy is high (MAPE ≈ 4.7%), a small number of data points in Fig. 12 exhibit relatively larger prediction errors. These deviations do not appear to be systematically associated with a specific cutting parameter such as feed rate or cutting speed. Instead, they are likely related to natural process variability and measurement uncertainties inherent in experimental machining studies. Nevertheless, identifying such higher-error observations is useful for understanding the potential boundaries of model reliability and may guide future data collection efforts toward conditions where additional experimental data could further improve model robustness. Due to the relatively small dataset (81 samples), the 70–30 train–test split resulted in a limited test set of approximately 24 samples. Although nested cross-validation was applied during the training phase to ensure robust model selection and to reduce the risk of overfitting, the performance metrics obtained from the independent test set may still exhibit some variance due to the small sample size. Therefore, the cross-validation results observed during the training process were also considered to assess the stability and consistency of the model performance. Future studies with larger datasets could provide a more comprehensive evaluation of model generalization.

To evaluate the computational efficiency of the proposed hybrid framework, all models were trained under identical hardware and software configurations, and their training durations were recorded. The benchmark CatBoost model, trained with default hyperparameters, exhibited an average training time of 1.91 s. The SHAP analysis applied during the feature selection stage constitutes a one-time preprocessing step, incurring a negligible additional computational cost of approximately 0.07 s. In contrast, the Optuna-based hyperparameter optimization, involving multiple trials, represents the most computationally intensive component of the proposed approach, with an average duration of 114.66 s. This overhead is considered typical for comprehensive hyperparameter fine-tuning. Consequently, the high predictive performance of the proposed method is achieved without introducing a prohibitive computational burden, making it feasible for real-time

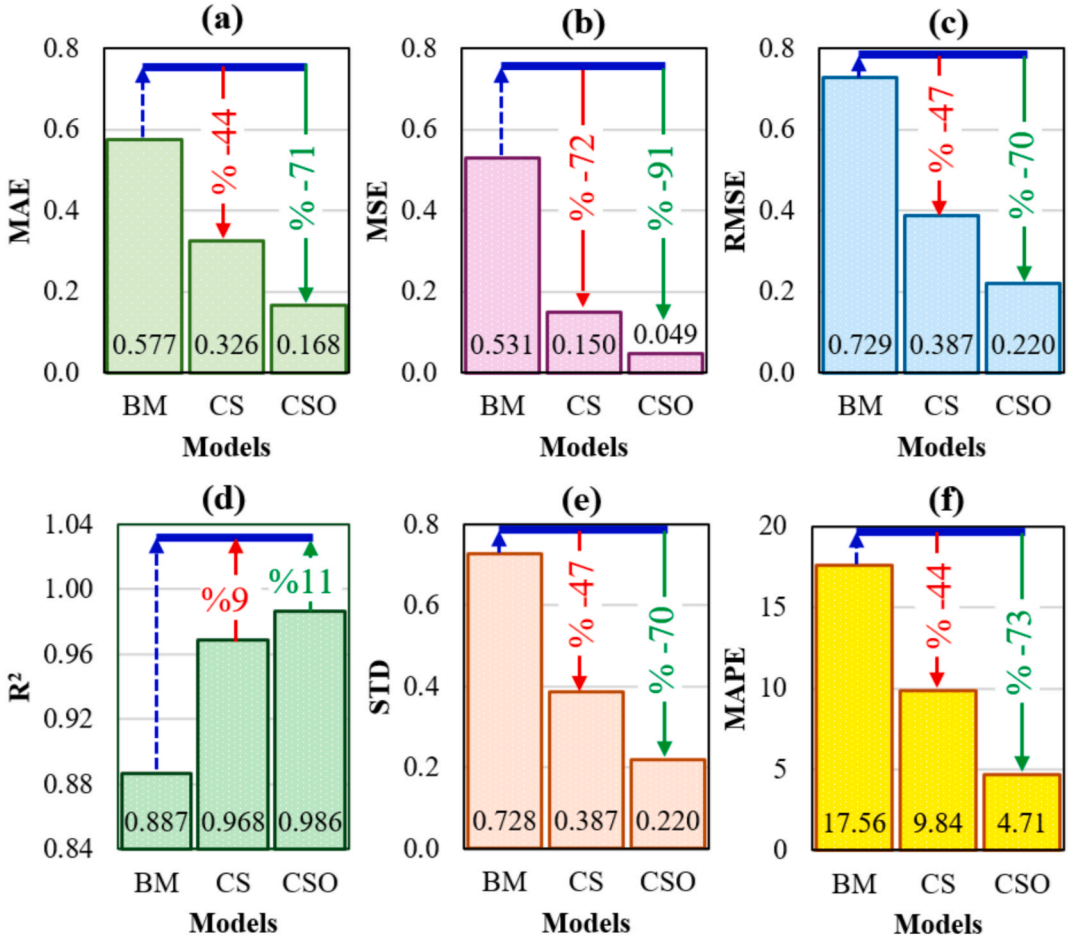


Fig. 10. Performance comparison of models developed with the benchmark model (a) MAE, (b) MSE, (c) RMSE, (d) R^2, (e) STD, (f) MAPE.

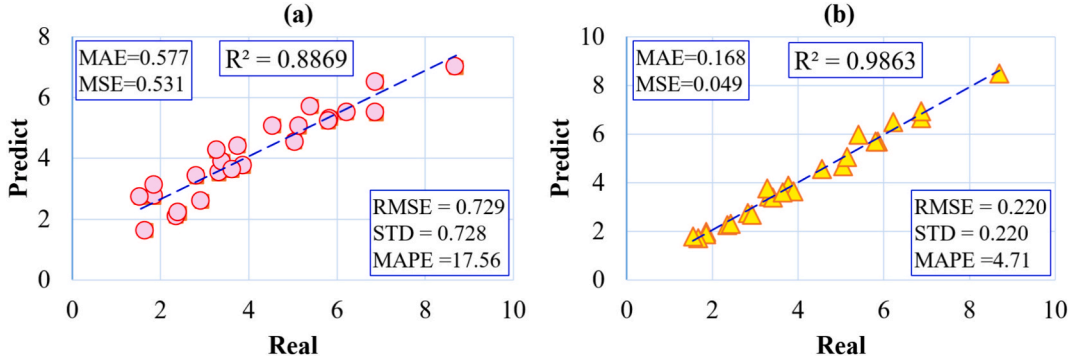


Fig. 11. Benchmark model and proposed model data points (a) Benchmark model, (b) Proposed model (CAT+SHAP+Optuna).

industrial applications.

It should be emphasized that the reported 114.66 s Optuna optimization time corresponds to a one-time offline training cost rather than a recurring real-time computation. Once the optimal hyperparameters are identified and the model is finalized, prediction (inference) is executed in milliseconds (ms), making the framework suitable for industrial monitoring applications. Therefore, the computational overhead is associated with model development or periodic recalibration rather than operational deployment. Considering the substantial reduction in prediction error achieved by the optimized pipeline, the additional training time represents a reasonable trade-off between computational cost and predictive accuracy, particularly for offline process optimization or condition-based monitoring scenarios.

From a practical manufacturing perspective, the proposed model can be interpreted as a decision-support tool for monitoring the energy behavior of the machining process through thermal signatures. Instead of relying solely on post-process energy measurements, the predicted energy consumption derived from temperature features can be used as an indicator of process efficiency during operation. For instance, if the predicted energy value for a given temperature profile exceeds a predefined reference level, the system could trigger a warning or alarm to indicate that the process may be operating under inefficient conditions. In addition, the SHAP-based interpretability analysis provides insights into which temperature-related features contribute most to the predicted energy consumption. Such information can help engineers identify critical thermal behaviors and focus on controlling the process

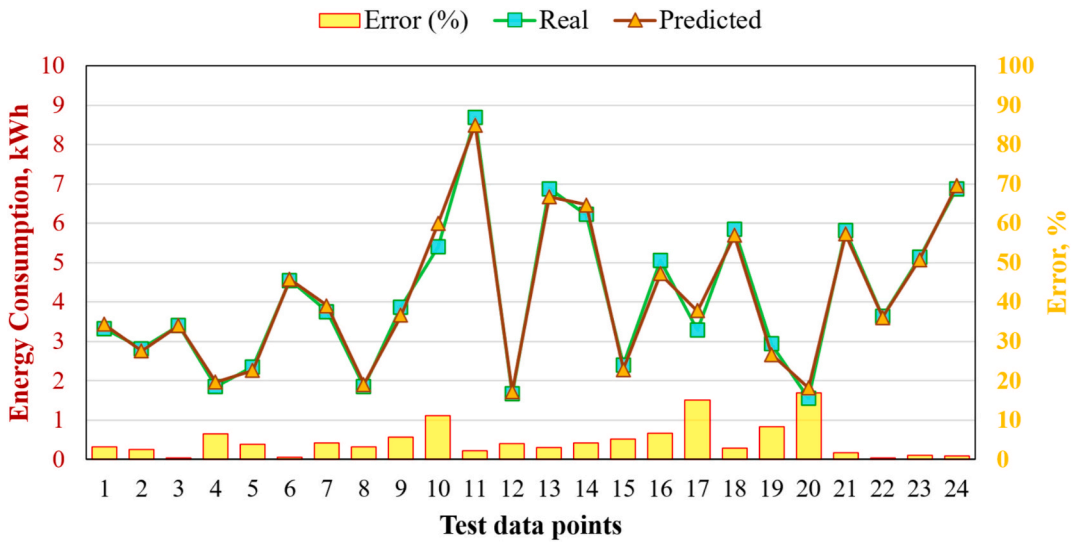


Fig. 12. Test data point estimates and error percentages of the proposed model.

parameters that influence these temperature characteristics, thereby supporting energy-aware process optimization.

5. Conclusion

This study provides an innovative contribution to the measurement context by advancing energy consumption monitoring and optimization in titanium machining across three fundamental dimensions. First, it achieves a methodological advancement by moving beyond traditional direct power measurement, establishing cutting temperature—a fundamental indicator of process efficiency—as a direct antecedent variable for energy prediction. Second, the developed hybrid optimization framework (CAT+SHAP+Optuna) not only ensures high prediction accuracy but also, through SHAP analysis, interpretably reveals which temperature features (e.g., maximum temperature, temperature variability) most significantly influence energy consumption, thereby linking measurement data to physical understanding. Third, the model possesses the potential to serve not merely for prediction but as the foundation for an intelligent manufacturing system capable of proactively controlling energy consumption based on real-time thermal monitoring data. Consequently, this research transforms measurement from a passive data collection activity into an active decision-support tool for sustainable and efficient production. The study's principal findings are presented here.

1. The experimental findings reveal a clear relationship between cooling method and process energy: dry machining resulted in both lower cutting temperatures and lower process energy compared to vortex-assisted methods. This counterintuitive result—where cooling increases rather than decreases process energy—is explained by the suppression of thermal softening, which increases material shear strength and cutting forces. This finding validates rather than contradicts the study's motivation, as it demonstrates that cutting temperature is not merely a consequence but also a determinant of energy consumption, and that this relationship can be accurately modeled using the proposed hybrid framework.
2. The increase in cutting temperatures caused a significant increase in energy consumption. This relationship revealed that cutting temperature is a critical input feature in energy consumption prediction models.
3. A total of 24 input features were obtained using 20 statistical features extracted from cutting temperatures and 4 cutting parameters. Analysis with feature ranking methods played an important role in determining the most effective features to improve energy consumption estimation performance. In feature selection, the SHAP method provided the highest success in terms of prediction performance.
4. The CAT algorithm outperformed the other algorithms in terms of performance success. It has been found that models developed with hyperparameter optimization provide significantly higher accuracy.
5. Optuna outperformed other hyperparameter optimizers in terms of performance.
6. The hybrid optimization framework developed by the fusion of CAT+SHAP+Optuna methods has exhibited superior performance. According to the benchmark model, approximately 91% improvement was achieved in the MSE criterion. This model has emerged as an effective tool for both estimating energy consumption and determining optimum cutting parameters.

The results of this study provide significant insights for reducing energy consumption and enhancing processing efficiency in machining. Specifically, identifying cutting conditions that minimize both energy use and heat accumulation offers substantial contributions to the manufacturing sector in terms of environmental sustainability and cost-effectiveness. The proposed hybrid optimization framework (CAT+SHAP+Optuna) presents a novel, data-driven approach for accurate energy consumption estimation during the turning of Ti6Al4V alloy, thereby contributing valuable knowledge to both the scientific literature and industrial practice.

Based on these findings, concrete proposals for industrial application can be made. The framework developed in this work offers directly applicable industrial strategies for facilities machining titanium alloys. Primarily, the developed CAT+SHAP+Optuna-based hybrid model can be utilized as an energy monitoring and prediction module integrated into CNC machine tools. Such a system could predict the energy consumption of each cutting cycle in real time, using only basic cutting parameters and thermal camera data, providing instant feedback to operators and enhancing process control. Furthermore, when coupled with an optimization algorithm, the model can automatically determine the optimal cutting speed and feed rate according to desired energy consumption or temperature limits, thereby reducing setup times while increasing production efficiency. Finally, the relationships established in this study enable the integration of energy- and temperature-based monitoring approaches into maintenance planning processes, offering significant advantages to businesses in terms of energy savings, process stability, and sustainable production goals.

It is important to emphasize that the quantitative results and conclusions regarding the superiority of dry machining, as well as the optimal model configuration, are validated for the specific experimental conditions of this work (Ti6Al4V alloy, cutting speed range of 25-35 m/min, feed rate range of 0.100-0.150 mm/rev, and dry/vortex cooling environments). For different workpiece materials, tool geometries, or machining scenarios—particularly at higher cutting speeds or in finishing operations requiring stringent surface integrity—the optimal cooling strategy and model parameters may differ. In such cases, the higher energy consumption of active cooling methods may be justified by improvements in product quality, tool life, or process reliability. The ultimate objective of this research is therefore not to prescribe a universal solution, but to provide a generalizable methodology for developing data-driven decision support systems in sustainable manufacturing. It should be noted that the proposed model was developed using 81 experimental observations obtained through a full-factorial design, which ensures systematic coverage of the cutting parameter space. Nevertheless, as with most data-driven approaches, the model performance depends on the representativeness of the training data. Factors such as sensor noise, variations in machine tool dynamics, or different tool wear conditions were not explicitly considered and may influence the temperature–energy relationship in practical applications. Therefore, when the framework is applied to different machining environments, retraining with new data may be required to maintain prediction accuracy.

Future research should focus on validating and extending this methodology by: (a) evaluating its applicability and robustness across materials with different machinability characteristics, (b) testing it under a wider array of cooling/lubrication strategies and broader cutting parameter spaces, and (c) further improving model performance. This includes planned comparisons with deep learning architectures (e.g., BiLSTM, Transformers, LSTM, and 1D-CNN) on larger datasets and more comprehensive SHAP-based explainability analyses to elucidate model decision-making processes with greater clarity.

CRediT authorship contribution statement

Aslan Akdulum: Writing – original draft, Visualization, Resources, Methodology, Conceptualization. **Yusuf Siyambaş:** Writing – review & editing, Writing – original draft, Resources, Methodology, Conceptualization. **Ramazan Çakıroğlu:** Supervision, Methodology, Formal analysis, Conceptualization. **Gültekin Uzun:** Writing – review & editing, Visualization, Resources, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.measurement.2026.121390.

Data availability

Data will be made available on request.

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