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Estimation of cutting temperature using machine learning based on signal information received from power analyzer in vortex machining conditions

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ABSTRACT

Cutting temperature directly determines power consumption by influencing tool wear and workpiece quality. Especially for workpieces that cause high heat generation due to low thermal conductivity coefficients, such as Ti6Al4V, it is a challenge to control and determine the cooling method and cutting parameters accordingly. Pre-process modeling and estimation of the cutting temperature due to the cutting variables is necessary for effective process planning and machining efficiency. In this study, it is aimed to use various signal information received from the power analyzer as input features to effectively model and estimate by using the machine learning method the cutting temperature occurring in the turning using various cooling environments of Ti6Al4V workpieces. The features extracted from the four signal information were used both individually and by obtaining hybrid signal features where all the features are combined. While individual signals were used directly in establishing the models, hybrid signals were ranked using the feature ranking method according to six different importance levels. As a result of the study, it was determined that the cutting temperature could be predicted with high success by modeling it according to the features extracted from the signal information obtained from the power analyzer.

1. Introduction

Ti6Al4V titanium alloy has a good strength-to-weight ratio because of its exceptional strength and minimal density [1]. This feature enables Ti6Al4V to have a wide range of uses in the aviation, space, defense, automotive, energy, and biomedical sectors [2]. However, because of this alloy's limited thermal conductivity and strong strength, machining is difficult [3]. One of the primary causes of titanium alloys' poor machinability is high cutting temperatures in the cutting zone [4]. Temperature increase negatively affects machining production by causing cutting tool wear, increased cutting forces, increased energy consumption, and resulting in workpieces with poorer surface quality [5]. Therefore, optimizing the temperatures occurring during processing will help optimize other output responses with a synergistic effect, thus increasing processing efficiency.

Studies in the literature were conducted under various machining settings in order to lower cutting temperatures in the machining region. In an experimental study, it was determined that micro-grooves opened on rake surfaces in dry turning of Ti6Al4V alloy reduced the cutting temperature significantly compared to conventional cutting tools [6]. An experimental study showed that textured tools combined with MQL cooling significantly reduced cutting temperatures compared to conventional tools and cooling methods [7]. Machining experiments were carried out in dry, cryogenic N_2LQL (cLQL), nanofluid LQL (nLQL), and oil Low Quantity Lubrication (oLQL) environments and at various speeds and feeds, and it was determined that the LN_2 method gave acceptable results [8]. In another study, the effects of high-pressure cooling on the tool and chip contact temperature in the turning of Ti6Al4V alloy were investigated [9]. The study found that using two coolant jets reduced cutting temperature and increased tool life by 55–60 % compared to dry machining. It was determined that the cutting temperature in LN_2 machining environment was 55 % lower than MQL and dry cutting [10]. The cutting zone temperature in turning under LN_2 + MQL, LN_2, MQL, and dry machining conditions was investigated,

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and the minimal cutting temperature was achieved under the LN_2 + MQL condition [11]. An experimental study found that MQL resulted in the highest cutting zone temperature, while MQL + LN2 produced the lowest [12]. As a result of the literature research, dry, flood, MQL, high-pressure cooling, and cryogenic cooling methods were utilized to reduce the cutting temperature. However, these methods have some limitations. During dry machining, higher friction increases interaction between the insert and workpiece, raising tool temperatures [13]. This reduces tool durability, wear resistance, and useful life [14]. This situation is not preferred because it causes negative effects on the dimensional accuracy, surface integrity, and surface quality of the machined parts [15]. Cutting fluids have several advantages in the machining process, including eliminating heat, prolonging tool life, and enhancing surface smoothness [16]. However, these fluids account for a significant portion (approximately 17 %) of processing costs [17]. At the same time, they lead to additional costs due to difficulties in disposal [18] and their degradation at high temperatures [19]. Many studies have been conducted to show that conventional cutting fluids are harmful to the environment and human health [20]. Researchers state that the MQL method has disadvantages such as high investment cost, maintenance requirements, lack of chip removal, difficulties in delivering sufficient amounts of lubricant to the cutting zone, and mist filtration and disposal problems [21]. High-pressure cooling needs advanced tools, is costly, and generates noise [22]. Cryogenic cooling systems identified in the literature require special equipment. These equipments are complex, and these systems are more difficult to install, maintain, and operate [23]. Therefore, there is a need for innovative coolers that are environmentally friendly, do not harm human health, are simple to maintain and use, have low investment costs, and are green for processing purposes. The most popular of these coolers is the Ranque-Hilsch Vortex Tube (RHVT) cooling. RHVT cooling is a method used to cool the cutting zone in machining processes. RHVT cooling offers an environmentally friendly, low-cost and efficient alternative in machining applications [24]. It has great environmental advantages, especially since it eliminates the use of chemical refrigerants. In the RHVT system, water vapor, carbon dioxide, nitrogen, and air are utilized as coolants or gas lubricants. Since these gases are present in the atmosphere, they are very useful for green processing and sustainable manufacturing. Furthermore, applying the cooling process to the contact areas of the cutting tool, chip, and workpiece increases tool life while decreasing cutting costs [25]. Due to these features, it has become a very popular topic in recent years within the scope of Industry 4.0 and sustainable manufacturing. However, more research needs to be done to obtain consistent and generalizable results that reflect the overall machining industry.

Due to the many advantages of the RHVT cooling method, researchers have attempted to overcome the limitations of traditional cooling and lubrication techniques. According to an experimental investigation, RHVT cooling reduced tool flank wear by 20 % and tool-chip temperature by 7 % [26]. The RHVT, MQL, and dry machining settings had the smallest cutting region temperatures, respectively [27]. Compared to the dry machining environment, the RHVT machining environment produced a cutting temperature that was 62 % lower [28]. According to certain reports, RHVT cooling is more ecologically friendly than dry machining and lowers tool tip temperature and tool flank wear [29]. It has been demonstrated that the cutting temperature is significantly impacted by the cold air supplied by the vortex tube [30]. In another study, dry, flood, and RHVT methods were compared, and it was stated that the use of cold air in the RHVT system significantly reduced the cutting edge and workpiece surface temperature [31]. Although there are various studies on RHVT in the literature, the scope of the subject and its effects need to be clarified with more studies. In order to control temperatures during processing and take proactive measures, modeling the cutting process before the process and estimating the temperature is very important in terms of processing efficiency and process planning.

Various methods have been employed to optimize cooling techniques and cutting parameters in the turning of Ti6Al4V material. For instance, one study utilized Taguchi and ANOVA methods to optimize cutting parameters [32]. Another study relied on experimental and analytical approaches [33,34]. Additionally, response surface methodology (RSM) and adaptive neuro-fuzzy inference system (ANFIS) methods were applied [35], while finite element analysis (FEA) was also explored as a potential tool [36]. However, when the literature is examined regarding the modeling of cutting temperature in the turning of Ti6Al4V using machine learning, it is not at the desired quality and sufficient level. Machine learning methods are useful for modeling and predicting temperature in the turning of titanium alloys due to their powerful ability to reveal relationships between input and output and capture complex relationship patterns. Cutting parameters [37], depth of cut and different cooling methods [38], feed rate and cutting speed [39], different cutter coatings, and cutting forces [40] were taken into account as input features in the modeling of temperature during turning with machine learning-supported modeling methods. However, in addition to these input parameters, there is a need for innovative methods that monitor the machining process in real time. For example, in the modeling of the cutting temperature, various signals, such as the current and k factor received from the power analyzer, were not taken into account as input features in the modeling of the temperature. However, it is stated that the signals received from the power analyzer strongly reflect the cutting process [41]. Additionally, approximately 63 % of the energy consumed in machine tools is spent during the cutting process [42]. Therefore, it is evaluated that signal information such as current and k factor obtained from the power analyzer can be used successfully in estimating the cutting temperature by modeling with machine learning. Furthermore, models are constructed by adding one feature at a time and ranking a huge number of input features based on their importance. The results are then compared [43]. Methods such as random forest (RF) [44], Shapley additive explanations (Shap) [45], permutation feature important (Pfi) [46], principal component analysis (PCA) [47], recursive feature elimination (RFE) [48], and Pearson correlation coefficient (Pcc) [49] are used to rank the features according to their importance. Usually, the performance of each feature ranking method is evaluated individually. However, it is rare to compare the mentioned methods with each other for the same dataset. Therefore, comparative examination of popular feature ranking methods according to importance is very important for improving model performance and more generalizable models.

In this study, it is aimed to use the signals received from the power analyzer as input features to estimate the cutting temperatures occurring in the turning operations of Ti6Al4V workpieces in different coolant environments by modeling them with machine learning before the process. To achieve this, turning experiments were conducted at various machining parameters. Real-time force signals during the machining process were collected for all experiments. In addition, the cutting area was recorded in real time with a thermal camera. Models were established by creating datasets with different input features and different feature ranking methods, and their prediction performances were evaluated. It is suggested to use the current (I), K factor (KF), current negative-phase unbalance factor (Iunb), and total harmonic current distortion factor (Ithd) signal information obtained from the power analyzer for modeling and estimating the cutting temperature. To minimize the effects of high cutting temperatures on materials with low thermal conductivity, such as Ti6Al4V, it is crucial to determine appropriate cooling methods and cutting parameters. In our study, we highlight how machine learning methods provide an innovative approach to accurately model cutting temperatures. By predicting cutting temperatures, this approach offers a valuable solution to enhance machining efficiency and optimize process planning. The distinctive contributions of the current study to the literature are listed below.

- Machine learning techniques were used to model cutting temperatures that occurred during the machining in various cooling settings. Models were also presented for pre-process prediction.
- For modeling the cutting temperature, four different signal information received from the power analyzer was used separately and as hybrid input features.
- The contributions of the changes in the cutting parameters to the changes in I, KF, Iunb, and Ithd signals were investigated.
- Six different feature ranking methods were examined and compared for modeling the input features by ranking them according to their importance.

The study's remaining sections are organized as follows: Details regarding data collection and the suggested methodology are provided in Section 2. In Section 3, the experimental findings are discussed by analyzing in depth in terms of cutting parameters, signal information, and machine learning models. In Section 4, the results obtained and future work planned are given.

2. Data collection and proposed methodology

2.1. Experimental setup

Turning experiments were carried out on commercially available Ti6Al4V superalloy with dimensions of Ø40x300 mm. The most important properties of Ti6Al4V alloys are their high resistance to corrosion, hardness, and durability. The chemical composition of the material (by weight) is 5.9 % Al, 4.00 % V, 0.09 % Fe, 0.14 % O, 0.01 % N, 0.002 % H, 0.01 % C, and the rest is Ti. The density of the alloy is 4.4 g/cm^3, tensile strength is 880–920 MPa, thermal conductivity is 7.1 W/mK, and hardness is 36 HRC. While these superior properties increase the preference of the material, they negatively affect its workability. Tests were performed on a Johnford TC-35 brand CNC lathe with a Fanuc control unit and 10 Kw machine power. In the turning process, Sumitomo brand SNMG120404 geometry and AC5015S quality PVD (AlTiSiN) coated carbide tool and PSBNR2525M12 tool holder with 75° approach angle were used.

The experiments were carried out using dry conditions, vortex tube CO_2, vortex tube air cutting conditions (CC). In determining the cutting parameters, the tool manufacturer's catalog data and literature information were taken into account. Accordingly, different cutting lengths (Cl) (5–10-15 mm), different speeds (Vc) (25–30-35 m/min), different feeds (f) (0.15–0.125-0.1 mm/rev), and fixed depth of cut (Doc) (0.75 mm) were determined. During the turning tests, the workpiece was fixed between the chuck and the rotary tailstock to avoid any vibration and rigidity. The stages of the experimental study are given in Fig. 1.

In the tests, a Ranque-Hilsch vortex tube (RHVT) of the Acgreiff brand was used. The selected cooling temperatures and pressures were determined to increase tool life by providing effective cooling in the cutting zone. -2 °C and 4.5 bar are a starting condition chosen considering the portability and economy of the chilled air. Cooling with CO_2 gas at −40 °C and 4.5 bar was applied to investigate the effect of much lower temperatures on the processing performance. These choices were determined as a result of the methods and preliminary experiments used in similar studies in the literature. The cold air exit nozzle was placed five millimeters away from the cutting insert in every trial. The total energy used in various turning parameters was measured in this investigation using a Hioki brand 9340 model power analyzer. The device was connected to the main power input of the CNC lathe, as seen in Fig. 1, and energy consumption was recorded in real time during each machining cycle. The temperature values released during the cutting operation were accumulated using a FLIR T440 thermal camera. This thermal camera, which can detect temperatures ranging from 0 to 1200 °C at a measure of 25 cm to the insert, was used to make the measurements. The emissivity (Ɛ) value is the most important parameter when taking measurements using a thermal camera. The temperature measuring device in this investigation was calibrated and set at Ɛ = 0.04. The calibration technique was validated by measuring the surface temperature of the Ti6Al4V workpiece after 24 h at room temperature using a digital thermometer's sensitivity of ±0.01 °C. The video recording recorded with the thermal camera was then examined frame by frame using a computer program. The frame rate of the thermal camera is 30 Hz. That means there are 30 images per second. The temperature change of the cutting environment depending on time was

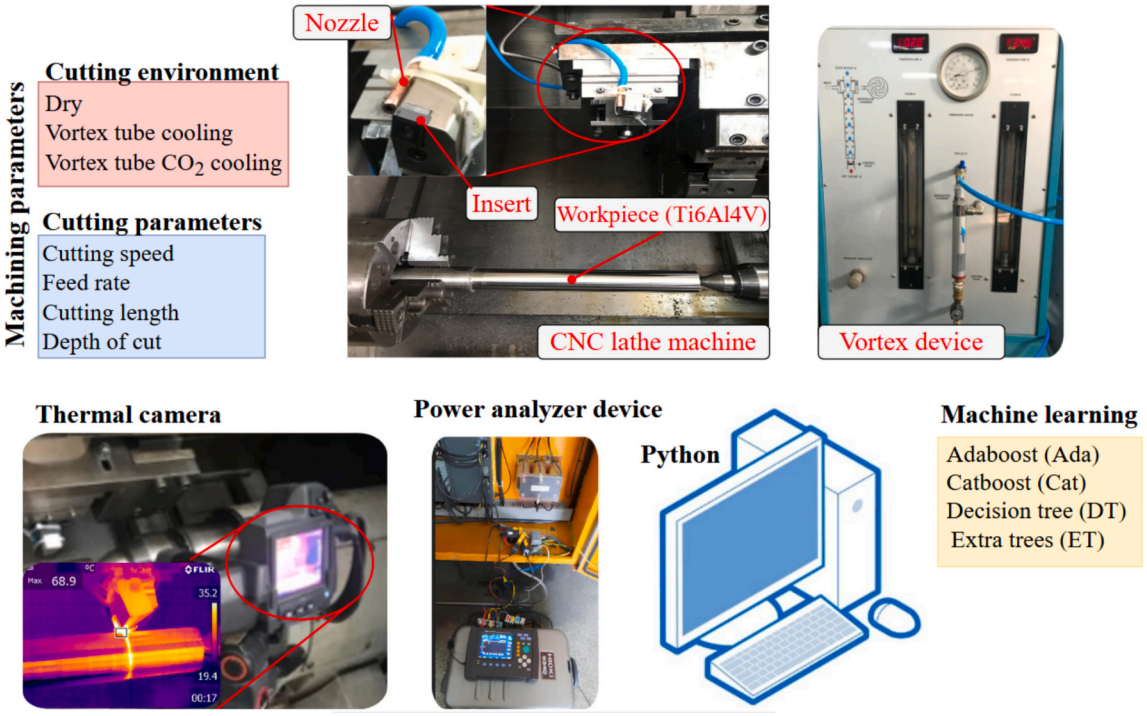


Fig. 1. Stages of the experimental study.

obtained by averaging the maximum temperature data taken from these images.

2.2. Data collection

Machine learning models were established to model the cutting temperature with high accuracy and to achieve high prediction success. The Ti6Al4V workpiece was turned with different machining parameters. During the turning experiments, energy consumption data were recorded in real time with a power analyzer connected to the machine tool. Unlike previous studies in the literature, it is proposed to use different signal information received from the power analyzer. In this study, it is suggested to use the current (I), K factor (KF), current negative-phase unbalance factor (Iunb), and total harmonic current distortion factor (Ithd) information recorded in real time by the power analyzer. This information was used as individual and hybrid features in building machine learning models. This signal information was recorded for all 3 phases, separately for each phase output. In the simplest definition, I represents the motion of particles carrying electrical charges, while KF represents the effects of harmonic distortions. Iunb is used to measure the imbalance between phase currents in three-phase systems. Ithd is used to measure the total harmonic distortion of the current. The maximum, minimum, and average values of this signal information are calculated by the power analyzer and automatically calculated through the program. A total of thirty features was extracted from the statistical information. Additionally, when the cutting environment, feeds, speeds, and depth of cut information were added, 34 input features were obtained for one data point, as shown in Table 1.

The formulas for the signal information automatically calculated by the power analyzer are in Eqs. (1)–(3). I_h denotes the rms current at harmonic number h, I_R is the rms rating of load current at fundamental frequency, and h represents harmonic order. I_{md} denotes the maximum deviation from the average current, whereas I_{ave} represents the average current.

$$KF = \sum_{h=1}^{h=max} h^2 \left(\frac{I_h}{I_R}\right)^2 \tag{1}$$

$$I_{unb} = \frac{I_{md}}{I_{ave}} \times 100 \tag{2}$$

$$I_{thd} = \frac{\sqrt{\sum_{h=2}^{h=max} I_h^2}}{I_R} \times 100 \tag{3}$$

Different methods were used to determine the importance of these extracted features and to clarify their effects on modeling and prediction success. The features were ranked in order of importance using the RF, Pfi, Pcc, Shap, PCA, and RFE techniques. More advanced information about these methods can be obtained from the relevant resources for RF [44], Shap [45], Pfi [46], RFE [48], PCA [47], and Pcc [49]. Although these methods are used in separate studies in the literature, their detailed comparison for the same dataset is suggested in this study.

Table 1
Features extracted and used from signals.

Signal	Number	Extracted features
I	9	MaxIrms1, MaxIrms2, MaxIrms3, MinIrms1, MinIrms2, MinIrms3, AvgIrms1, AvgIrms2, AvgIrms3
KF	9	MaxKF1, MaxKF2, MaxKF3, MinKF1, MinKF2, MinKF3, AvgKF1, AvgKF2, AvgKF3,
Iunb	3	MaxIunb, MinIunb, AvgIunb
Ithd	9	MaxIthd1, MaxIthd2, MaxIthd3, MinIthd1, MinIthd2, MinIthd3, AvgIthd1, AvgIthd2, AvgIthd3,
Turning parameters	4	f, CC, Vc, CL

Thus, it will be clarified which feature ranking method contributes to achieving higher performance success. As a result, utilizing the six methods described above, 34 input features were rated in order of importance. Then, one feature was added at a time for each method, creating 34 datasets per method. $34 \times 6 = 204$ datasets were obtained for the comparison of feature ranking methods. The datasets were modeled using four different machine learning techniques and estimated using $204 \times 4 = 816$ models. To model and predict each 4 signal information using 4 distinct machine learning methods, $4 \times 4 = 16$ models were created, and the prediction results were rigorously compared. As expressed in Fig. 2, a total of $816 + 16 = 832$ regression models were established, and the test prediction results were meticulously compared.

In the current investigation, the cutting temperature was determined as the output response. The cutting temperature was obtained by real-time recording of the cutting environment with the help of a thermal camera. Then, the cutting temperature averages were taken from the images determined according to the cutting length ranges, and the output response values were obtained. Since all input and output responses consist of numerical values, the cutting temperature was estimated by modeling with regression algorithms. In this study, Adaboost (Ada), Catboost (Cat), Decision Tree (DT), and Extra Trees (ET) were selected as machine learning algorithms. The mentioned methods were preferred because they showed high performance success in the dataset sizes used, especially in the field of machinability. Further information on the algorithms can be obtained from related works for Ada [50], Cat [51], DT [52], and ET [53]. 56 of the 81 data points were used for training and the rest for the test set. A 5-fold cross-validation procedure was used to get results that were more generalizable and did not overfit. The models were built, and their prediction success was performed with the Python programming language. The test prediction performances of the models are analyzed by comparing their MAPE, RMSE, and R^2 performance evaluation criteria.

2.3. Ranking of features according to importance

Features are ranked according to their importance using different methods. However, the comparison of these ranking methods with each other has not been made at the desired level. Table 2 shows the ranking results of different methods. The first and last 5 features of the ranking results are given. Feature rankings based on importance levels obtained by different methods often differ from each other. Therefore, comparing the performance of different methods on the same dataset will determine the performance of the models to be established. It is also clear that in modeling and estimating the cutting temperature, the significance levels of the features retrieved from the suggested signal information show comparable performance to the cutting parameters (f, Vc, CC, CL).

3. Experimental results and discussion

The current study aims to forecast with high accuracy the cutting temperature that occurs during the turning tests of Ti6Al4V workpieces in various cooling settings using high-precision modeling. To achieve this, it is aimed at using the signals accumulated in real time with the help of a power analyzer as input features. Additionally, the accumulated signal features were used to create individual and hybrid datasets. Afterwards, the hybrid features obtained from all signal information were ranked according to their importance with six different methods, and the prediction performances of the established models were investigated in depth. Using the obtained findings, it was carefully investigated whether the cutting temperature could be predicted by pre-process modeling with high accuracy. It is determined that the suggested approach can be used for process planning, boosting processing efficiency, and sustainable manufacturing in the context of Industry 4.0.

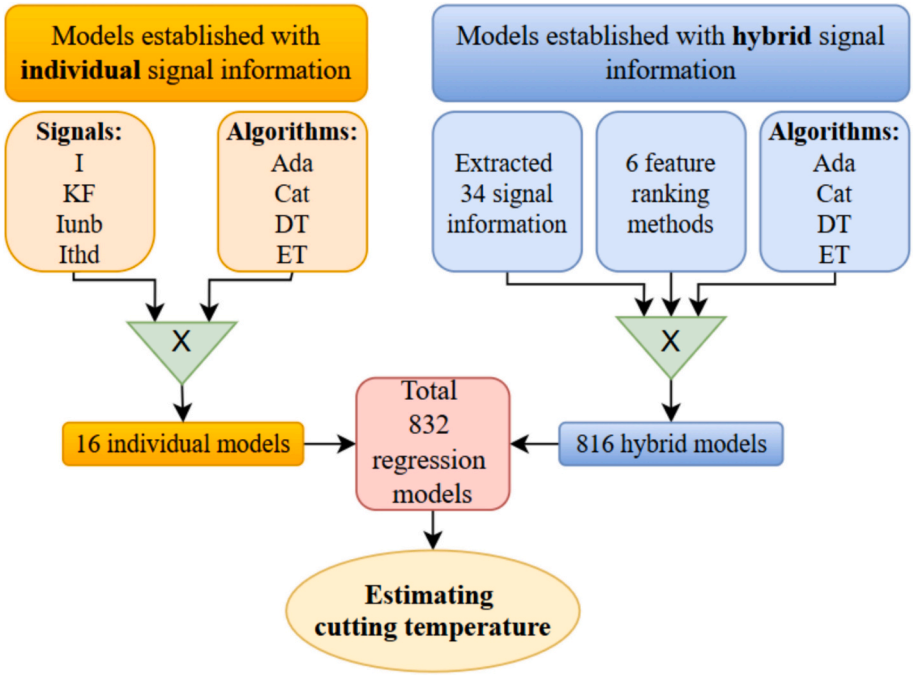


Fig. 2. Regression models established based on signal information.

Table 2
Ranking the features according to their importance with different methods.

Importance rank	PCA	Pcc	Pfi	RF	RFE	Shap
1	MinKF1	MinIrms3	MinIrms1	MinIrms1	MinIrms1	MinIrms1
2	MaxIrms1	AvgIrms3	f	f	MaxIunb	f
3	AvgKF1	MinIrms2	MinIthd1	MaxIunb	MinIrms2	MinIthd1
4	MaxKF1	MaxIunb	MaxIunb	MinIthd1	MaxKF2	AvgIunb
5	MaxKF3	AvgIunb	MinIunb	AvgIunb	f	MinIrms2
…	…	…	…	…	…	…
30	AvgIunb	MaxKF3	AvgIthd2	AvgKF3	AvgKF2	MaxIthd2
31	f	MinKF2	AvgKF3	MinKF3	MinIthd3	MinKF3
32	CC	MaxKF1	MinIthd2	Vc	AvgIthd3	AvgIthd2
33	Vc	AvgKF2	AvgIrms3	MinIthd3	Vc	AvgIrms3
34	CL	MaxKF2	MinIthd3	AvgIrms3	AvgIrms3	MinIthd3

3.1. Experimental findings and analysis

A large portion of the energy spent during chip removal turns into heat, and this heat negatively affects tool life, cutting forces, chip shape, and surface quality. Coolants are used to reduce these harmful effects of heat and increase the efficiency of machining. Cutting tool life is negatively affected due to the heat generated in dry machining. In order to overcome these limitations, the air cooling method's Vortex tube cooling procedure is notable for being user-friendly and environmentally friendly. Studies have shown that applying cold air to the tool interface will have a positive effect on the cutting process. In this context, many researchers have conducted studies to reveal the advantages of the Vortex method [24]. Fig. 3 shows how cutting factors affect cutting temperature. According to the figure, the lowest and highest cutting temperature values were measured for dry medium. The maximum temperature in dry medium was 311 °C at 25 m/min and 0.1 mm/rev of feed, and the minimum was 119 °C at 30 m/min and 0.15 mm/rev of feed. When Fig. 3 is evaluated at various speeds, the average cutting temperature measured under all cutting mediums at a speed of 25 m/min is 239 °C. A rise of 20 % in speed, the situation shifted to a 2.2 % increase at 30 m/min cutting speed, which occurred at 244 °C. It was observed that the amount of increase was the same with a 40 % rise in speed and a 35 m/min speed. When the speed rose from 30 m/min to 35 m/min, the average cutting zone temperature remained constant. While the machining temperature was 258 °C on average at 0.100 mm/rev for all feed rates, it decreased by 6.2 % on average at 0.125 mm/rev and was 242 °C. The average cutting temperature was determined as 228 °C with a 5.8 % decrease trend at 0.150 mm/rev compared to 0.125 mm/rev feed. With the increase of 25 % and 50 % in the feed rate, a decrease of 6.2 % and 11.7 % in the cutting temperature was observed, respectively.

It is observed that the cutting zone temperature exhibits a decreasing trend under dry cutting conditions, while it exhibits an increasing trend depending on the Vortex-Air and Vortex-CO_2 cooling conditions. For the experiments conducted under dry cutting conditions, maximum temperatures were measured at low feed rates. According to the literature, chip evacuation tends to increase with the increase in feed rate [54]. It is stated that approximately 80 % of the heat is discharged through sawdust [55]. As a result, it was determined that increasing the feed rate reduced the temperature during dry cutting. Yağmur [56] found that a low feed rate causes heat to concentrate on the tool, resulting in high cutting zone temperatures due to slow heat removal. It is also stated that when machining titanium material at low feed and cutting depths, the chip does not break but wraps around the tool/workpiece and the measured temperature fluctuates. Fig. 4 shows the maximum temperature images obtained at the maximum cutting parameters of 0.150 mm/rev feed and 35 m/min speed. It was underlined that while using a thermal camera to monitor temperature, the cutting zone cannot be measured, but the wrapped around chip can [57]. It has been evaluated

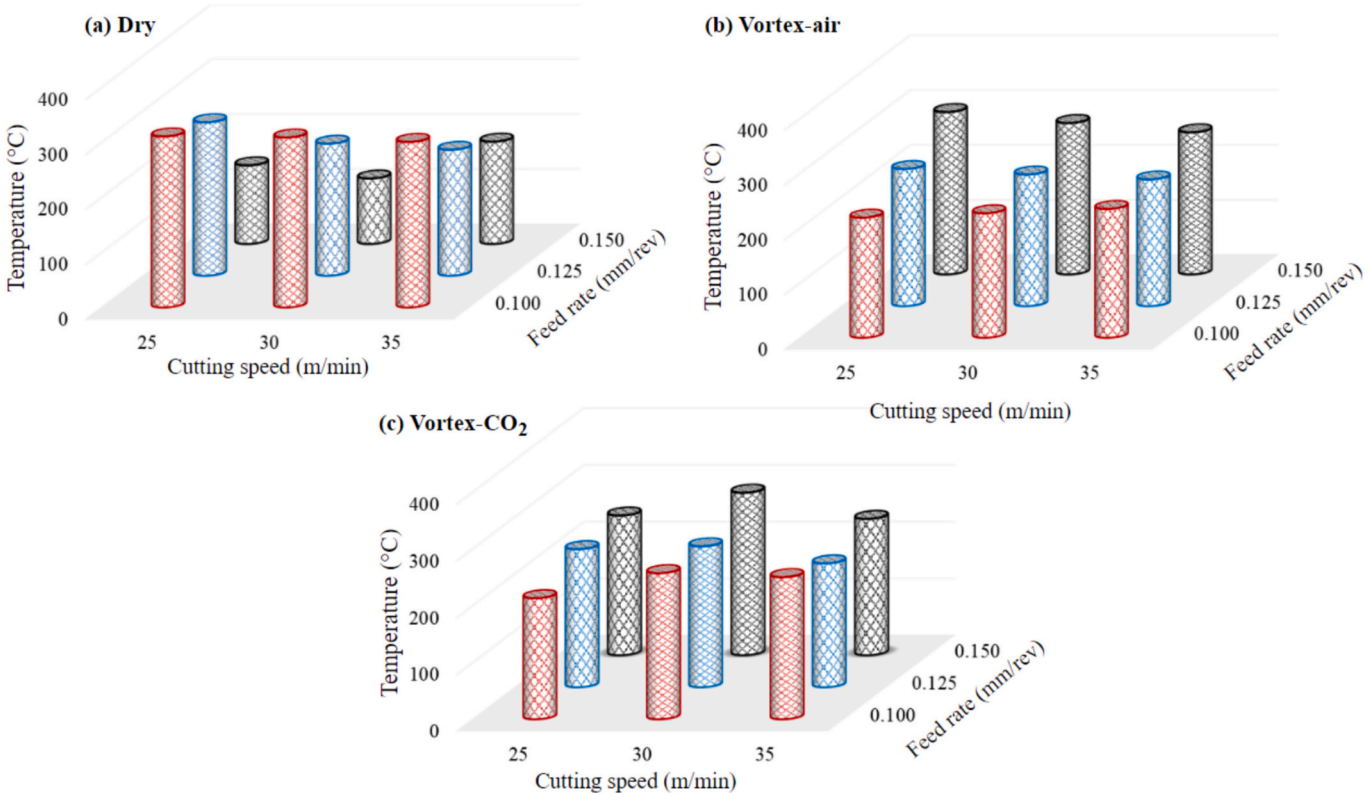


Fig. 3. Maximum cutting temperature values depending on cutting parameters and processing medium a) dry b) Vortex-air c) Vortex-CO_2.

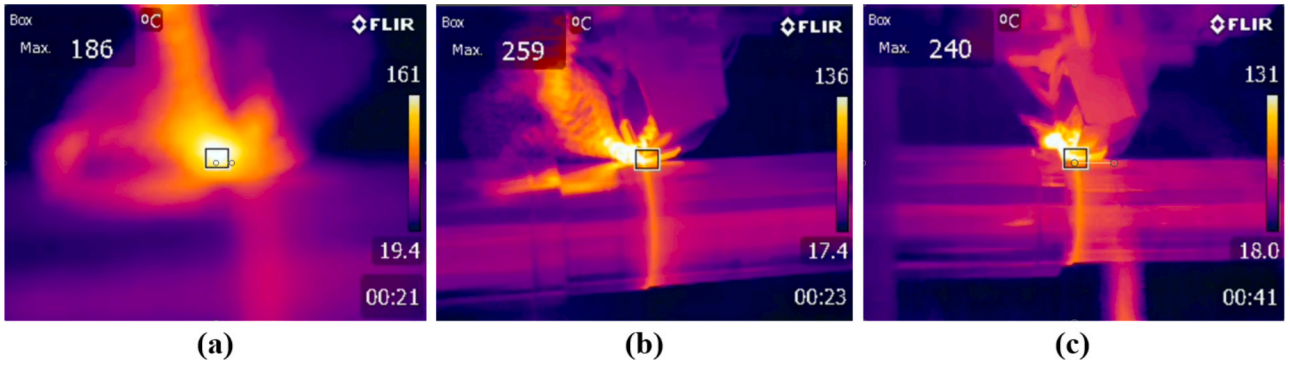


Fig. 4. (a) Dry, (b) Vortex air, (c) Vortex CO_2.

that most of the heat generated when vortex coolers cool the cutting zone may have been transferred to the chip. Therefore, higher temperature values may have occurred for Vortex coolers when measuring temperatures with a thermal camera. It is also considered that as the feed grows, so does the amount of chip removed. In terms of Vortex coolers, lower temperatures were achieved with the Vortex CO_2 cooling method compared to Vortex air. It has been assessed that this situation is caused by the more intense cooling effect of CO_2.

Fig. 5 depicts visuals of the insert and chips produced during turning. Although less temperature formation was seen in the cutting temperature area, the rake face of the insert employed in the dry cutting procedure wore out faster. As a result, the majority of cutting heat generated during dry machining is transferred to the cutting tool and workpiece rather than being eliminated with the chip. Thus, it was evaluated that the cutting edge was exposed to high temperatures. Because there is no coolant or air flow during dry machining, the temperature generated by the turning accumulates directly at the insert-workpiece interface. This accumulated heat surpasses the thermal resistance of the insert, particularly when cutting hard materials at high speeds, resulting in rapid wear [58]. These thermal stresses increase problems such as cracking and deformation at the tool edge, reducing tool life. Even in a test with a new insert, such wear may cause more serious damage to the cutting process that follows. Therefore, it is considered that cutting in dry conditions is not suitable. Under other cooling conditions, no significant wear occurred on the rake surface. When the chip images are examined, the saw-tooth-like formation on the edges of the chips in the Vortex air cooling process attracts attention. Sawtooth-like chip formation is caused by high stress and temperature changes occurring on the material, especially during the machining of titanium and hardened steels [59]. During the cutting process, the material heats up rapidly at the points in contact with the cutting tool and cools down when contact is broken. These cyclic temperature changes cause the material to compress and relax [60]. This creates small protrusions that resemble sawtooth as the material breaks. Saw-tooth chip formation causes reduced quality of the machined surface, increased tool wear, and fluctuations in cutting forces [61]. It has also been

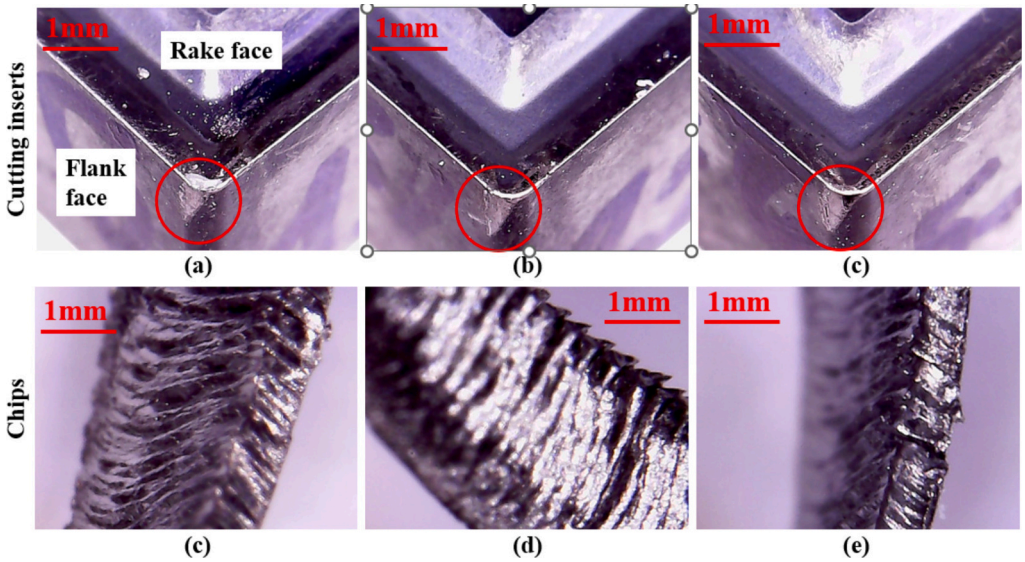


Fig. 5. Vc = 35 m/min f = 0.150 mm/rev (a, c) dry, (b, d) Vortex air, (c, e) Vortex CO_2.

suggested that the speed is affected in the development of this chip type, with the saw-tooth degree decreasing as the speed grows [62]. Therefore, considering the negative effects of dry machining, such as increased wear on the cutting tool and Vortex air causing saw-tooth chip formation, it was determined that the Vortex CO_2 cooling method gave more acceptable results.

3.2. Analysis of signals

The cutting parameters and time-dependent changes of the signal

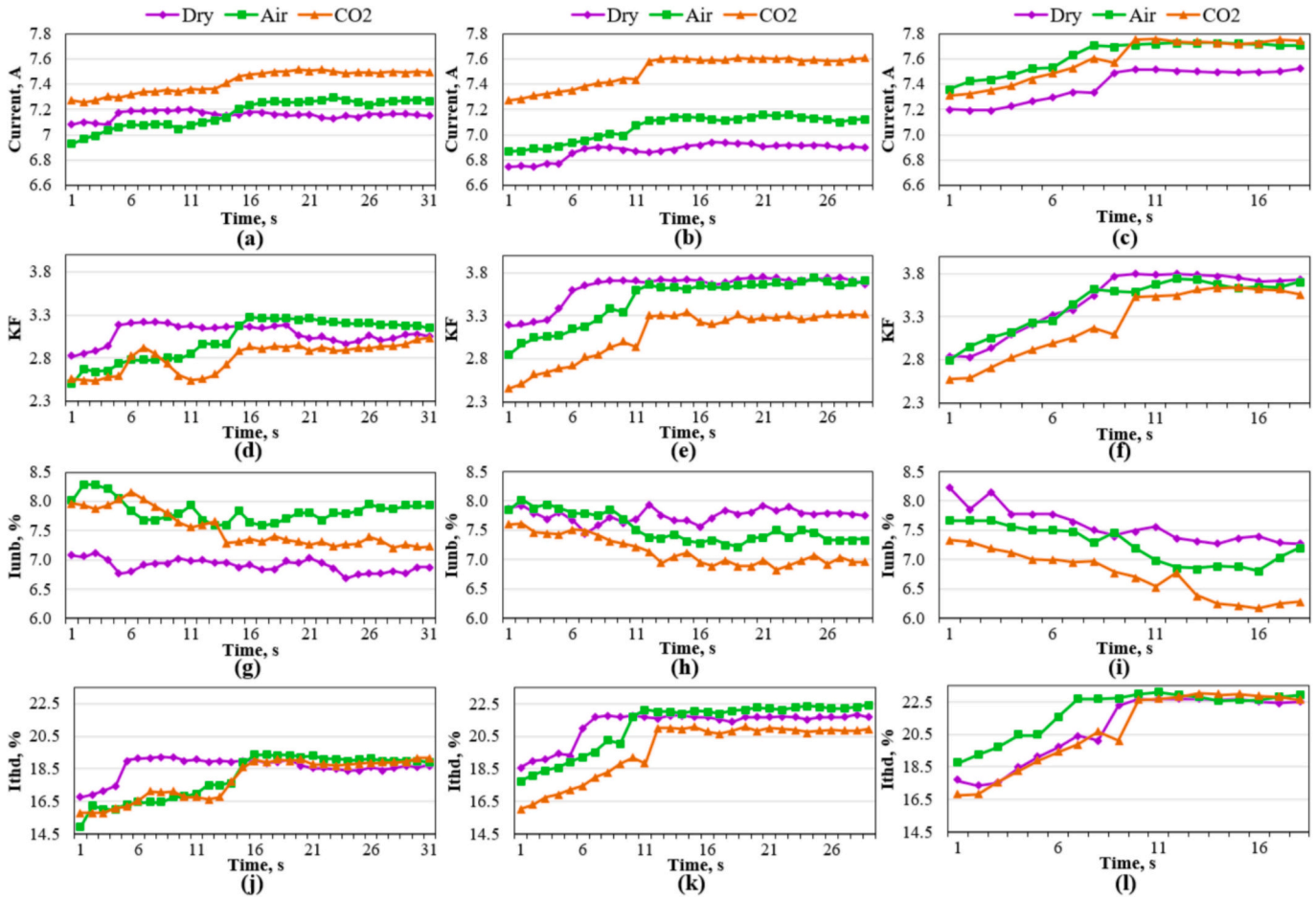


Fig. 6. Change of signals depending on time and cutting parameters (a-d-g-j) Vc = 25 m/min-f = 0.1 mm/r, (b-e-h-k) Vc = 30 m/min-f = 0.125 mm/r, (c-f-i-l) Vc = 35 m/min-f = 0.15 mm/r.

information received from the power analyzer are shown in Fig. 6. The signals in the figure were obtained by taking the average of three phases. Parallel to the changes in the cutting parameters, different trends occur in the signals. The Iunb signal tends to decrease with time, while the other signals tend to increase. When the interaction between increasing cutting parameters and signal information according to cooling methods was analyzed in terms of current, the CO_2 cooler increased, while the dry and air coolers decreased and then increased in medium cutting settings. The KF and Ithd signals tend to grow with the increase of the turning parameters. For the Iunb signal, it tends to increase in dry conditions, while for air and CO_2 gases, it tends to decrease. Different coolants and different cutting parameters used in the turning process cause various effects on the signals, so it was evaluated that they can be used for modeling the cutting process.

3.3. Comparison of machine learning and feature ranking methods

It is aimed to use the signal information received from the power analyzer as input features to estimate the cutting temperature by modeling it with machine learning. The MAPE values of the test prediction performance of the models established with four machine learning algorithms are given in Fig. 7. According to the models established with all algorithms, the signal that showed the highest performance was signal I. For algorithms other than the DT algorithm, the second best performing signal was Iunb, while the worst performing signal was Ithd. Cat and ET algorithms are the best performing algorithms. The algorithm with the worst performance was the DT algorithm. According to the signal information, the best performing algorithms were the Cat algorithm for I and the ET algorithm for the other signals. Therefore, it was evaluated that the signal information received from the power analyzer can be used to estimate the cutting temperature. Thus, it was evaluated that the team status can be monitored according to real-time signal information.

The test prediction performance of the I signal and the Cat algorithm, which showed the highest performance among individual signals, is shown in Fig. 8. The agreement between the actual values and the predicted values for the test set is quite high. Although the percentage error is relatively high at some data points, it is clear that the overall performance is at an acceptable level. The MAPE value of 9.29 also confirms this result. Therefore, it is clear that the I signal can be used successfully in modeling and estimating the cutting temperature.

In addition to the test prediction performances of individual signal features, it was evaluated that it would be useful to examine the effects of using hybrid features obtained from all signal information together on modeling and prediction performance. When all signals are brought together, a total of 34 features are obtained. However, using a large number of features can increase model complexity [63]. In addition, some features may cause negative results in prediction performance [64]. Various methods are used in the literature to obtain the most optimum properties. A careful comparison of these methods is very important for establishing high-performance models and making strong predictions. Fig. 9 shows the test set prediction performances of feature ranking methods. Models were built by including one feature at each stage, working from most important to least important. For example, the number 5 was generated by taking the first five attributes as input features and ranking them according to their significance. The value of 10 indicates that the model was created by establishing the features whose importance is in the first 10. When the figures are examined, the first point that draws attention is the MAPE value of the models established with PCA. It resulted in higher MAPE values compared to other methods. The algorithms exhibited different trends with each feature ranking method.

The performances of different feature ranking methods according to machine learning algorithms are given in Table 3. When the R^2 value was examined, different feature ranking methods showed better performance for each machine learning algorithm. RFE for the Ada algorithm, Shap for the Cat algorithm, Pcc for the DT algorithm, and RF method for the ET algorithm showed greater performance. The quantity of attributes demonstrated varying performances based on the algorithms. Therefore, the feature ranking method must be determined in accordance with the algorithm to be used. The feature ranking method that showed high performance for one algorithm did not show the same success for the other algorithm. In the studies in the literature, models are created by ranking them intensively according to the Pcc method [43]. However, in the current study, only the DT algorithm showed relatively high prediction performance. It has also been determined that various signals received from the power analyzer can be successfully used as input features in modeling the cutting temperature.

The comparison of test prediction performance indicators of the optimal algorithm and feature ranking methods is given in Fig. 10. The top-level performance for both R^2 and RMSE indicators was achieved with the ET algorithm and RF feature ranking method. Cutting temperature can be estimated with high performance using 9 features.

The highest-performing models of feature ranking methods are given in Table 4. When all methods were compared, the worst performance was obtained with PCA, while the best performance was obtained with RF. The algorithm with the highest performance other than the Pcc method was ET. The optimum number of features for Pfi, RF, and Shap methods was determined as 9. It can be said that the ET algorithm, RF feature ranking method, and 9 feature count can be used successfully to effectively model and predict the cutting temperature. In the finite element analysis conducted during the turning process of Ti6Al4V

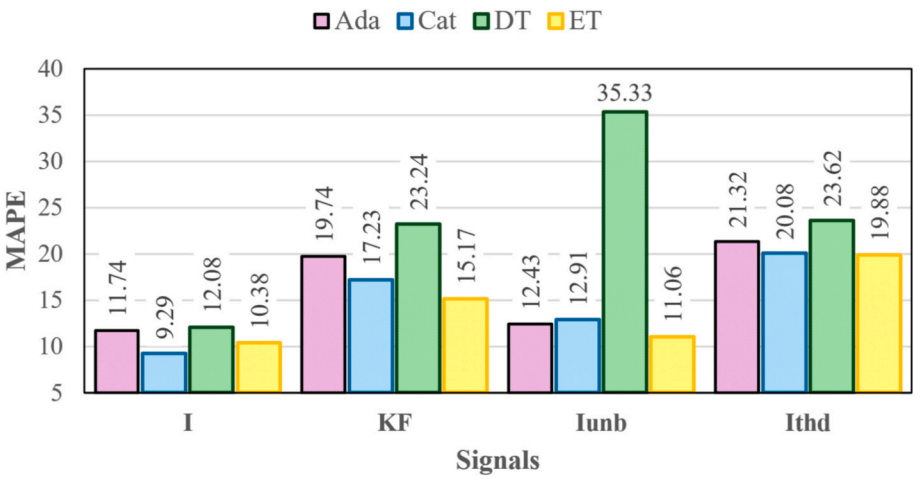


Fig. 7. Test estimation performances of signal information received from power analyzer.

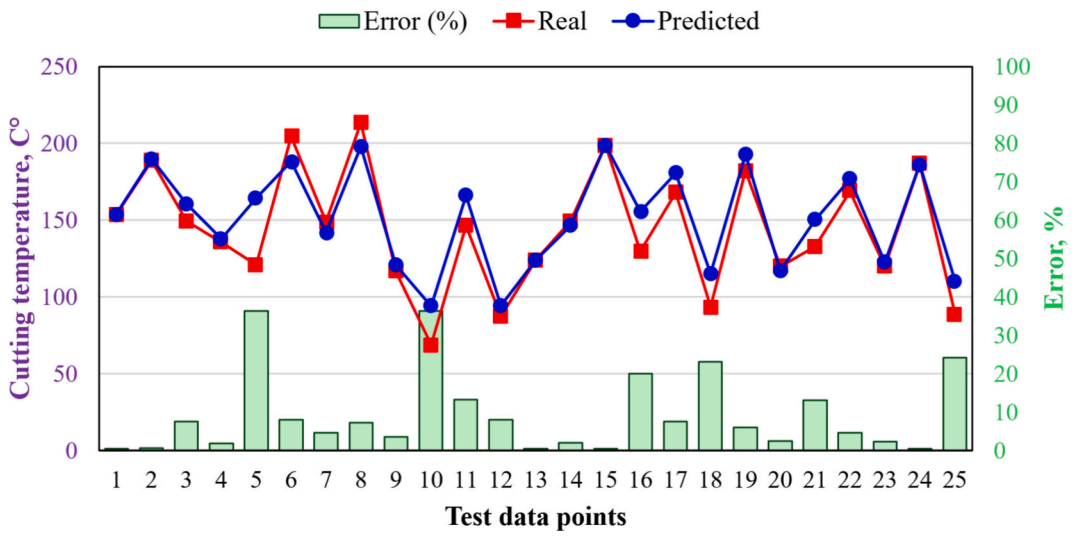


Fig. 8. Prediction performance of test data points for the model established with I signal and Cat algorithm.

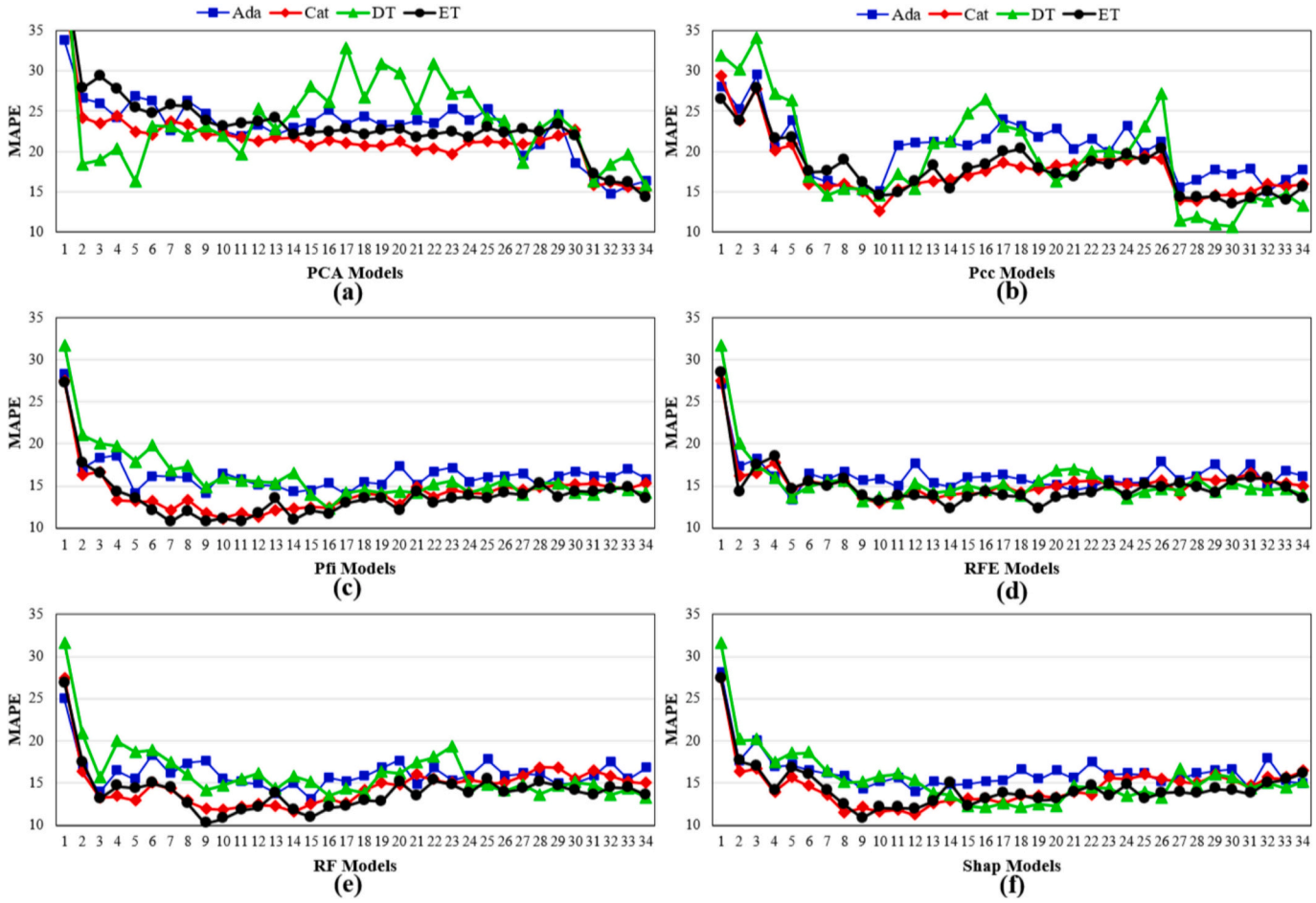


Fig. 9. Comparison of feature ranking methods.

material, the MAPE value between the actual and estimated values was found to be approximately 16 % in the dry environment and around 12 % in the coolant environment [36]. In another study, the average cutting temperature estimation error using the RSM method was about 18 % [35]. Based on these results, it was concluded that the values obtained with the proposed method in this study fall within highly acceptable ranges.

Table 5 displays the first nine characteristics identified using feature ranking techniques. When the features are examined, there are features from all signals and cutting parameters. According to the RF feature ranking method, the first 9 features are MinIrms1, f, MaxIunb, MinIthd1, AvgIunb, MinIrms2, MinIunb, MaxIrms1, CC, in that order. Therefore, using all signals received from the power analyzer as a hybrid and making predictions by establishing models according to the most

Table 3
Performances of feature ranking methods according to algorithms.

Model's PERFORMANCE		PCA	Pcc	Pfi	RF	RFE	Shap
Ada	MAPE	14.72	15.09	14.04	13.07	13.33	13.88
	RMSE	23.18	24.88	21.42	19.80	19.20	20.85
	R^2	0.749	0.611	0.765	0.798	**0.833**	0.778
	Feature count	32	10	17	15	5	12
Cat	MAPE	15.32	12.70	11.14	11.57	13.00	11.19
	RMSE	23.80	20.53	18.28	18.19	20.27	17.45
	R^2	0.773	0.795	0.842	0.853	0.816	**0.876**
	Feature count	34	10	10	14	10	12
DT	MAPE	15.83	10.68	12.25	13.32	13.05	12.04
	RMSE	25.54	17.44	21.54	21.66	23.47	20.83
	R^2	0.669	**0.803**	0.730	0.749	0.719	0.740
	Feature count	34	30	16	34	11	16
ET	MAPE	14.35	13.44	10.73	10.20	12.24	10.82
	RMSE	23.92	23.01	16.51	15.52	19.51	17.48
	R^2	0.716	0.730	0.873	**0.887**	0.802	0.842
	Feature count	34	30	9	9	14	9

Bold = Indicates the maximum R^2 value of the feature ranking methods.

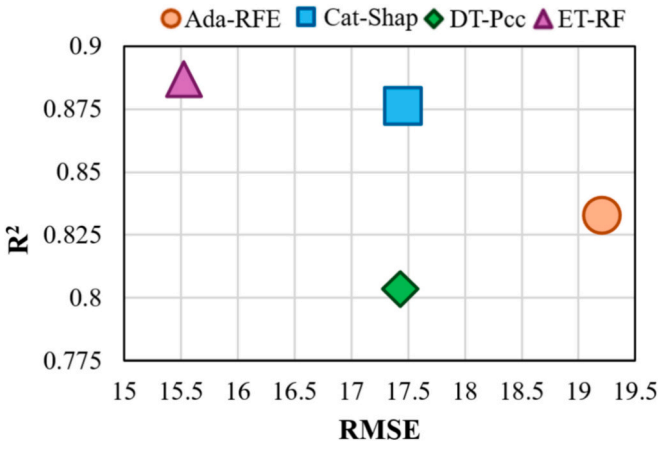


Fig. 10. Test prediction performance indicators of optimal algorithm and feature ranking methods.

Table 4
Models with the highest predictive performance of feature ranking methods.

	PCA	Pcc	Pfi	RF	RFE	Shap
MAPE	14.35	10.68	10.73	10.20	12.24	10.82
RMSE	23.92	17.44	16.51	15.52	19.51	17.48
R^2	0.716	0.803	0.873	0.887	0.802	0.842
Algorithm	ET	DT	ET	ET	ET	ET
Feature count	34	30	9	9	14	9

important features is very important for more generalizable results. Determining the most optimal one by using different feature ranking methods according to the dataset type is essential for making predictions with a high success rate.

The test data point prediction performance for model number 9 established with the ET algorithm and RF feature ranking methods is given in Fig. 11. When examining the factors affecting the model's performance under high temperature and challenging cutting conditions, it was found that the primary reason for error rates exceeding acceptable limits in certain machining scenarios is the dry machining of the Ti6Al4V workpiece. Due to the low thermal conductivity of Ti6Al4V, the high temperatures generated during cutting become especially pronounced under dry machining conditions. This excessive heat led to noise in the signal data, which negatively impacted the model's prediction accuracy. In the dry machining experiments, the model's ability to generalize was limited, resulting in higher error rates. This provides further evidence that dry machining conditions contribute to difficulties in processing Ti6Al4V material. Despite the elevated error deviations at a few data points, the overall performance of the model remains within acceptable limits. For the test dataset, the actual data points and the predicted data points exhibited a very consistent trend. Since most of the error percentages between the predictions are within acceptable limits, it can be said that the model's success is quite good. It has been found that high-level prediction performance can be achieved by sorting hybrid signals for cutting temperature using feature ranking.

To summarize, the prediction performance of the cutting temperature was examined by establishing models based on individual and hybrid signal information obtained from the power analyzer. By effectively modeling the cutting temperature based on individual signals, robust predictions are made. However, the most successful cutting temperature predictions were obtained with the I, Iunb, KF, and Ithd signal information order. Hybrid features, in which all signal information is used together, are ranked by feature ranking methods according to their importance. Models created by integrating a single attribute at each stage were rigorously compared. The model established for 9 features with the ET algorithm and RF ranking method showed the highest level of prediction performance. It has been concluded that the signal information obtained from the power analyzer can be used successfully

Table 5
The first 9 features determined by feature ranking methods.

Feature sorting	PCA	Pcc	Pfi	RF	RFE	Shap
1	MinKF1	MinIrms3	MinIrms1	MinIrms1	MinIrms1	MinIrms1
2	MaxIrms1	AvgIrms3	f	f	MaxIunb	f
3	AvgKF1	MinIrms2	MinIthd1	MaxIunb	MinIrms2	MinIthd1
4	MaxKF1	MaxIunb	MaxIunb	MinIthd1	MaxKF2	AvgIunb
5	MaxKF3	AvgIunb	MinIunb	AvgIunb	f	MinIrms2
6	MaxIrms2	MinIrms1	AvgIunb	MinIrms2	MinIthd1	MaxIunb
7	MinKF2	AvgIrms2	CC	MinIunb	MinIunb	CC
8	MinIthd2	MinIunb	MinIrms2	MaxIrms1	MaxIthd1	MaxIrms1
9	MinIrms1	AvgIrms1	MaxIrms1	CC	MaxIrms1	MaxIthd1

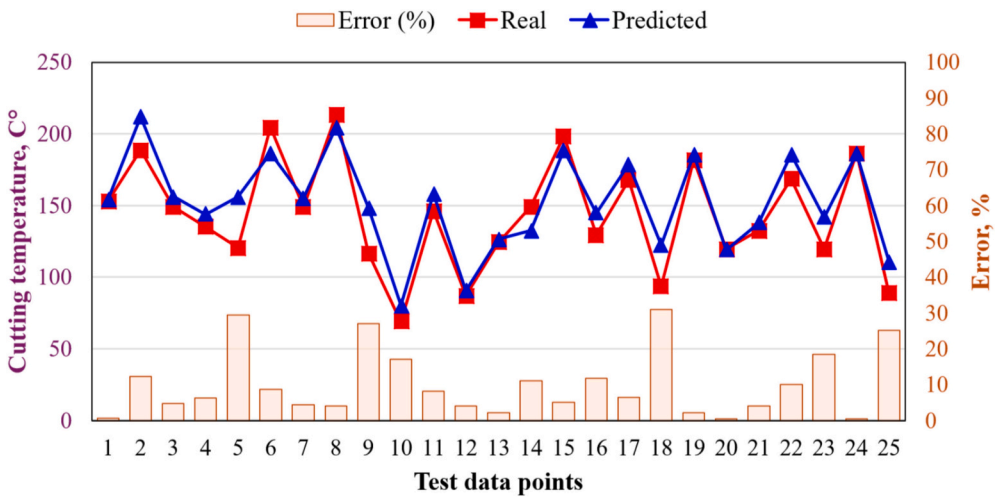


Fig. 11. Test data point prediction performance of ET algorithm and RF feature ranking methods for model 9.

in modeling and estimating the cutting temperature.

4. Conclusion

Cutting temperature has a very important place in cutting tool wear and workpiece quality. It is particularly decisive in terms of machining efficiency in the turning of alloys such as Ti6Al4V, where high cutting temperatures occur due to the low thermal conductivity coefficient. Therefore, establishing effective models and predicting the process beforehand is very important for process planning. The purpose of this study is to use various signal information acquired from the power analyzer as input characteristics to successfully model and estimate the cutting temperature occurring in the turning of a titanium workpiece in various cooling settings using the machine learning method. Four signal information, namely I, KF, Iunb, and Ithd, were received from the power analyzer. From these received signals, the minimum, maximum, and average values of the signals according to three phases were extracted. Firstly, these signals were used individually to model the cutting temperature. Then, 34 features extracted from all signals were used to establish models in the second stage. 34 features were ranked using the feature ranking method according to six different importance levels. The aim is to determine the optimum input features for modeling the cutting temperature by adding one feature at a time. Four machine learning regression algorithms, namely Ada, Cat, DT, and ET, were used in establishing the models. A total of 832 regression models were established to estimate cutting temperatures. As a result of this study, the following results were obtained:

- Cooling methods have a significant effect on cutting temperature. According to cutter wear, cutting temperature, and chip information, it was determined that the most effective cooling method was Vortex CO_2, then Vortex air, and finally dry conditions.
- It was determined that the I, KF, Iunb, and Ithd signal information obtained from the power analyzer changed according to the cutting parameters and could be used successfully in modeling and estimating the cutting temperature. The most efficient signal information in estimating the cutting temperature was the I, Iunb, KF, and Ithd signals, respectively. The MAPE value of 9.26 obtained confirms this result. The most effective algorithm for individual models was Cat.
- All signal information was ranked by six different methods according to their importance and compared in terms of cutting temperature estimation. In terms of hybrid features, the model established for 9 features with the ET algorithm and RF ranking method showed the highest level of prediction performance.
- As a result, it has been determined that the features extracted from the signal information obtained from the power analyzer can be successfully used for high-accuracy estimation by modeling the cutting temperature individually and hybridly.

This study demonstrated the usability of signal information obtained from the power analyzer in estimating the cutting temperature. In particular, the positive effects of advanced cooling methods such as Vortex CO_2 on cutter wear and cutting temperature can provide significant benefits such as longer tool life, better surface quality and reduced energy consumption in industrial applications. Modeling methods developed to predict cutting temperature can be used for real-time monitoring and process optimization in manufacturing processes. In particular, the effectiveness of the Cat algorithm and hybrid feature ranking approaches allows for more accurate prediction of the cutting temperature, preventing overheating situations and allowing for more efficient adjustment of machining parameters. In cases where similar challenges are encountered in industry, this study can contribute to the development of more sustainable and economical machining operations through modeling and prediction of cutting temperature. This is particularly valuable for its applicability in precision machining, high-speed machining applications and processes using cryogenic cooling.

In future studies, the effects of different signals received from the power analyzer on various output responses will be compared and examined in terms of various machining operations. In addition, the effects of the Vortex tube cooling method on machining outputs in different operations and with different gases are among the studies to be carried out. Deep learning models regarding tool wear or machining quality can be established that take into account power analyzer signal information.

CRediT authorship contribution statement

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

Data availability

The data is available on request.

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