**Manufacturing Technologies and Applications**
**MATECA**

# Optimisation of Energy Consumption in Milling of Inconel 718 Alloy and Prediction Model with Machine Learning

Hakan Yurtkuran[1,*], Güven Demirtaş[1], Birol Yazarlı[1], Ahmet Sertan Özpak[1], Semih Zorlu[1]

[1]*Yozgat Bozok University, Akdağmadeni Vocational School, Yozgat, Turkey*

## ABSTRACT

This study aims to optimize power consumption observed while milling Inconel 718 superalloy—well known for its poor machinability—and to develop machine learning-based prediction models. Experiments were carried out on a Taksan TMC 500 V CNC milling machining center at three cutting speeds (40, 60, and 90 m/min) under four distinct cutting conditions: dry, Minimum Quantity Lubrication (MQL), cryogenic, and cryogenic+MQL. Energy consumption was monitored in real-time using a KAEL Multiser signal analyzer and the collected data were analyzed through ANOVA and regression approaches. The ANOVA results revealed that cutting speed is the most significant factor influencing energy demand ($p<0.001$), whereas cooling/lubrication strategies exhibited no statistically significant effect. To address class imbalance the dataset was augmented via a SMOTE-based method and ensemble and regression-based ML models (Random Forest, Gradient Boosting, Linear Regression) were trained for power prediction. The findings indicated that the Gradient Boosting algorithm consistently achieved superior accuracy across all cutting environments with performance levels reaching $R^2 \approx 0.97$ and RMSE≈7 W. Results indicate that combining experimental data with computational methods is effective for decreasing energy consumption in machining and advancing sustainable production goals. The proposed methodology contributes to enhancing both efficiency and environmental sustainability in the industrial processing of Inconel 718.

***Keywords:*** *Milling, Energy Consumption, MQL, Machine Learning, SMOTE*

# Inconel 718 Alaşımının Frezelenmesinde Enerji Tüketiminin Optimizasyonu ve Makine Öğrenmesi ile Tahmin Modeli

## ÖZET

Bu çalışma işlenebilirliği zor olarak bilinen Inconel 718 süperalaşımının frezelenmesi sırasında ortaya çıkan güç tüketimini optimize etmeyi ve aynı zamanda makine öğrenmesi tabanlı tahmin modelleri geliştirmeyi amaçlamaktadır. Deneyler üç farklı kesme hızı (40, 60 ve 90 m/dak) ve dört farklı kesme koşulu (kuru, Minimum Miktarda Yağlama (MQL), kriyojenik ve kriyojenik+MQL) altında Taksan TMC 500 V CNC dik işleme merkezinde yürütülmüştür. Enerji tüketimi KAEL Multiser sinyal analizörü kullanılarak gerçek zamanlı olarak kaydedilmiş elde edilen veriler ise ANOVA ve regresyon yöntemleri ile analiz edilmiştir. İstatistiksel analiz sonuçları, enerji talebini belirleyen en önemli faktörün kesme hızı olduğunu ($p<0{,}001$), soğutma/yağlama stratejilerinin ise istatistiksel olarak anlamlı bir etki göstermediğini ortaya koymuştur. Ayrıca, veri kümesindeki sınıf dengesizliğini gidermek için SMOTE tabanlı bir veri çoğaltma yöntemi kullanılmış ve ardından güç tüketimi tahmini amacıyla topluluk (ensemble) ve regresyon tabanlı makine öğrenmesi modelleri (Rastgele Orman, Gradient Boosting ve Doğrusal Regresyon) eğitilmiştir. Bulgular Gradient Boosting algoritmasının tüm kesme ortamlarında en yüksek doğruluk seviyesine ulaştığını, performans değerlerinin $R^2 \approx 0{,}97$ ve RMSE≈7 W olduğunu göstermiştir. Elde edilen sonuçlar deneysel verilerin hesaplamalı yöntemlerle birleştirilmesinin talaşlı imalatta enerji tüketimini azaltmada etkili olduğunu ve sürdürülebilir üretim hedeflerine katkı sunduğunu kanıtlamaktadır. Bu yaklaşım Inconel 718'in endüstriyel işlenmesinde hem enerji verimliliği hem de çevresel sürdürülebilirlik açısından önemli bir yöntem önermektedir.

***Anahtar Kelimeler****: Frezeleme, Enerji Tüketimi, MMY, Makine Öğrenimi, SMOTE*

## 1. INTRODUCTION

Nickel-based superalloys form a unique material group characterized by superior strength and significant resistance to creep at elevated temperatures, as well as their stability against surface degradation, corrosion, and oxidation. Among them, Inconel alloys represent Ni–Cr based superalloys with diverse compositions and

*Corresponding author, e-mail: hakan.yurtkuran@bozok.edu.tr

*Received 28.09.2025; Revised 29.10.2025; Accepted 08.12.2025*
*https://doi.org/10.52795/ mateca.1792370*
*To cite this article: H. Yurtkuran, G. Demirtaş, B. Yazarlı, A. S. Özpak, S. Zorlu, Optimisation of Energy Consumption in Milling of Inconel 718 Alloy and Prediction Model with Machine Learning, Manufacturing Technologies and Applications 6(3) (2025) 296–307.*

mechanical characteristics [1–3]. Typically these alloys contain approximately 50–55% nickel while chromium and iron appear as the second most common elements [4]. Inconel 718 a widely used member of this family includes more than 50% nickel by weight together with alloying elements such as Mo and Co which support the formation of intermetallic phases and Ti, Al, and Nb which contribute to the stabilization of austenitic structures [5–7]. Although these properties make Inconel alloys highly attractive for demanding applications they also lead to considerable challenges in machining. The presence of hard and abrasive constituents accelerates tool wear their low ability to conduct heat results in significant temperature rise within the cutting region [8,9]. Milling remains one of the most prevalent and adaptable techniques in manufacturing particularly for processing such materials. In this method the workpiece is secured on the machine table by clamping elements and a multi-toothed rotary tool performs the cutting operation [10]. In milling processes, the required energy serves two main purposes: facilitating chip removal through plastic deformation and compensating for frictional forces at the tool–workpiece interface. This energy originates from the machine's motor [11]. The cutting tool which is connected to the spindle rotated by the motor both plastic deforms the workpiece and overcomes the friction forces in the cutting zone thanks to its rotational movement [12]. The extensive use of machine tools means they contribute significantly to industrial energy requirements. As electricity in our country is still predominantly produced from fossil fuels with low efficiency and high emissions the necessity of monitoring and optimizing energy consumption in machine tools is becoming ever more pressing [13–15]. Each type of machine tool has a unique energy profile depending on its design, intended function, and auxiliary subsystems. Therefore it is essential to establish specific consumption characteristics for each individual machine [16,17]. To enhance machinability and promote environmentally friendly manufacturing advanced lubrication/cooling techniques for instance MQL and cryogenic cooling are commonly employed. MQL involves delivering a controlled volume of lubricant directly to the cutting interface under pressure, thereby reducing unnecessary consumption while providing effective lubrication. Conversely cryogenic cooling makes use of liquid nitrogen directed at the cutting zone to dissipate the considerable heat generated when machining difficult materials. From the perspective of data analysis statistical and machine learning methods are widely used to evaluate machining experiments. Analysis of Variance (ANOVA) is a hypothesis testing approach that examines whether the means of multiple groups differ significantly by comparing inter-group and intra-group variances, thus revealing the significance of factor effects and their interactions [18,19]. On the other hand SMOTE short for Synthetic Minority Oversampling Technique is designed to balance uneven class distributions. issues in datasets by generating artificial minority samples through interpolation in feature space, thereby improving classifier performance and generalizability [20,21].

When some studies on Inconel 718 alloy and energy consumption are examined, Ali, M.A.M. et al. They compared the effects of different cooling strategies (dry, vortex-cold air, nano-fluid MQL) on the specific cutting energy in the machinability of Inconel 718 material. In the study, it was determined that machining with nano-fluid MQL significantly reduced the specific cutting energy compared to dry cutting [22]. In another study evaluating sustainable methods in turning with energy consumption and surface quality, it was reported that energy consumption decreased and surface roughness improved when sustainable lubrication techniques were used [23]. Barış Özlü et al. investigated the effects of cutting speed and feed rate on Specific Energy Consumption (SEC) in milling of Ti6Al4V alloy and reported that SEC generally decreases as cutting speed and feed rate increase [24]. Parida, A.K. et al. They experimentally and numerically investigated the effect of turning process on cutting force and specific energy of Inconel 718 material. As a result of the study, material hardness decreased with increasing temperature and lower force and energy requirements were achieved [25]. Zhou, Z. et al. in their study titled "Parameter optimisation and strategy suggestions for increasing energy efficiency in milling process" stated that significant reductions in energy consumption were observed with optimum parameter combinations [26]. Eco-friendly machining of Inconel 718 via minimum quantity lubrication amount of lubrication: In an artificial intelligence-based process modelling study, Farooq, M.U. et al. In the MQL environment, it provided a 20-25% reduction in energy consumption. The team also concluded that the artificial intelligence-based model successfully predicts energy consumption and helps to determine the optimum conditions [27]. In another study analysing energy consumption during machining of Inconel 718 for different geometric profiles and developing power prediction models using multi-sensor data, it was stated that energy consumption can be directly controlled by cutting parameters [28]. Frifita et al. In their study titled Optimisation of machining parameters in turning Inconel 718, they found the parameter set that provides the lowest energy consumption and optimum surface quality with Response Surface Methodology (RSM). It was also stated that while increasing the feed rate reduces energy consumption very high values negatively affect the surface quality [29]. When these findings are evaluated holistically it is concluded that green lubrication methods such as MQL, hot working strategies and statistical/computational optimisation approaches are effective tools to reduce energy consumption in the processing of Inconel 718.

In this study it is aimed to optimise the energy consumption of milling Inconel 718 alloy in four different cutting conditions (dry, mql, cryo and cryo+mql). In addition the obtained energy consumption data will be reproduced using SMOTE and the reproduced data will be modelled with machine learning algorithms.

## 2. MATERIAL AND METHOD

The experimental work was executed on a Taksan TMC 500 V CNC vertical machining tool. Inconel 718 material with prismatic geometry was used in the experiments. APMT11 T0308 PDSR-MM coded PVD coated carbide inserts were used as cutting tools and AEM90-AP11-D20-W20-L150-Z03-H coded clamping type tool was used as tool holder. The inserts and tool holder were supplied by Korloy company and a new insert was used in each experiment to keep the tool performance standardised. Energy consumption values were recorded using a KAEL Multiser 02-PC TFT Network Analyser. Three 60/5A current transformers are integrated into the measurement system and the Phase CNC machine draws approximately 30 A current from the mains, resulting in a significant saving in energy consumption. According to the manufacturer's technical documentation the power and energy measurement accuracy of the device is ±0.5 %. The system is factory calibrated and was verified to operate within ±1 % accuracy by comparative measurement with a reference clamp meter (Fluke 376 FC) prior to the experiments. Therefore the total measurement uncertainty of the energy data is considered to be below ±1.5 % and this level of accuracy is sufficient for machining energy analyses.

The experiments were carried out under four different cutting environments: dry cutting, Minimum Quantity Lubrication (MQL), cryogenic (Cryo) and cryogenic-MQL (Cryo-MQL). Power consumption was monitored instantaneously under these conditions. In order to improve the accuracy of the measurements the cutting tool was expected to fully penetrate the workpiece to ensure that the chip removal occurred evenly on both cutting edges.

Werte-STN15 dual channel micro-lubrication system manufactured by SBH was used for MQL applications. Mineral based WerteMist supplied by the same company was used as cutting fluid. Optimum conditions in the MQL system were obtained by reducing the 8 bar pressure from the air compressor to 5 bar with the help of a control valve. The aerosol mixture was delivered to the tool-shaving interface through a single nozzle positioned approximately 30 mm from the cutting edge and inclined at 45° to the chip surface. Liquid nitrogen ($LN_2$) tank was used in cryogenic experiments and $LN_2$ flow was provided through 3 mm diameter nozzles under 0.5 bar pressure. The nozzles were placed at a distance of approximately 40 mm from the cutting zone and at an inclination of 30° towards the chip surface. Both systems were operated simultaneously in CRYO-MQL hybrid mode.

In all experiments the feed rate was kept constant at 0.05 mm/rev and the chip depth at 0.5 mm. Only the cutting speed was varied at three levels, 40, 60 and 90 m/min. Three different cutting speeds were applied for each machining environment and 12 experiments were performed in total (4 environments × 3 different cutting speeds). The experimental design is summarised in Table 2.1.

Cutting parameters were determined by taking into account the values recommended by the tool manufacturer (Sandvik Coromant) literature information on the machining of Inconel 718 alloy and preliminary machinability experiments. The chemical composition and mechanical properties of the alloy used in the experiments are given in Tables 2.2 and 2.3. The experimental design is shown in Figure 2.1. Figure 2.2 shows the workflow diagram for machine learning algorithms.

Table 2.2. Chemical composition of Inconel 718 alloy

| **Element** | **Ni** | **Cr** | **Fe** | **Nb** | **Mo** | **Ti** |
|---|---|---|---|---|---|---|
| **wt.%** | 52.5 | 19.0 | 18.5 | 5.1 | 3.0 | 1.0 |
| **Element** | **Al** | **Co** | **Mn** | **Si** | **C** | |
| **wt.%** | 0.5 | 0.2 | 0.2 | 0.1 | 0.04 | |

Table 2.1. Experimental design

| Experiment No. | Cutting Conditions | Cutting speed (m/min) | Feed rate (mm/rev) | Cutting depth (mm) |
|---|---|---|---|---|
| 1 | DRY | 40 | 0,05 | 0,5 |
| 2 | DRY | 60 | 0,05 | 0,5 |
| 3 | DRY | 90 | 0,05 | 0,5 |
| 4 | MQL | 40 | 0,05 | 0,5 |
| 5 | MQL | 60 | 0,05 | 0,5 |
| 6 | MQL | 90 | 0,05 | 0,5 |
| 7 | CRYO | 40 | 0,05 | 0,5 |
| 8 | CRYO | 60 | 0,05 | 0,5 |
| 9 | CRYO | 90 | 0,05 | 0,5 |
| 10 | MQL-CRYO | 40 | 0,05 | 0,5 |
| 11 | MQL-CRYO | 60 | 0,05 | 0,5 |
| 12 | MQL-CRYO | 90 | 0,05 | 0,5 |

Table 2.3. Mechanical properties of Inconel 718 alloy

| Property | Value | Unit |
|---|---|---|
| Tensile strength (UTS) | 1240 | MPa |
| Yield strength | 1030 | MPa |
| Elongation | 12–15 | % |
| Hardness | 45–48 | HRC |
| Density | 8.19 | g/cm³ |

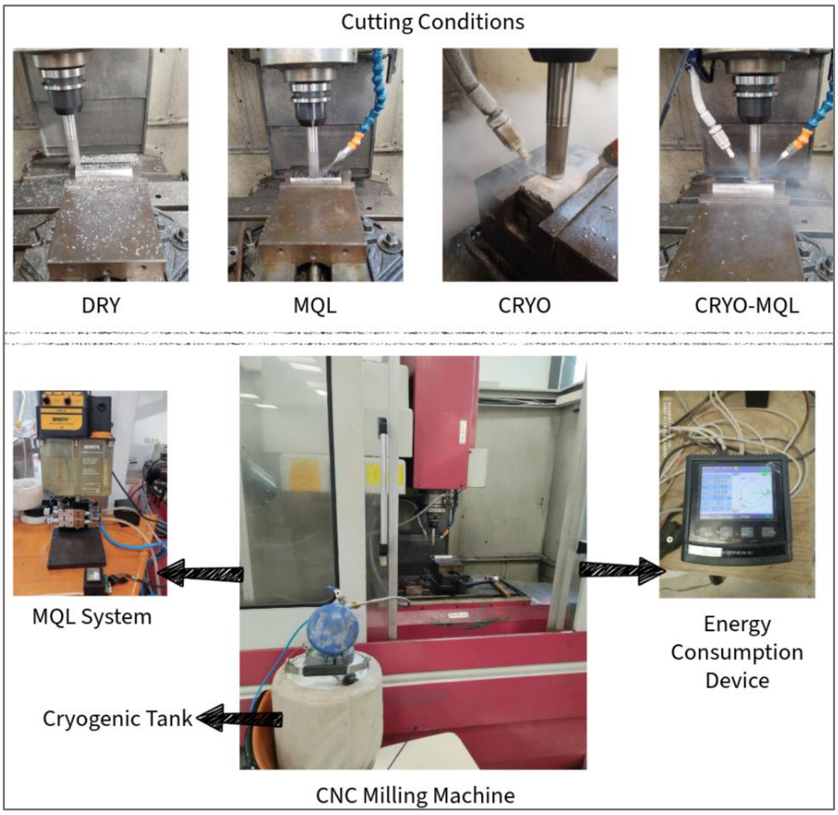


Figure 2.1. Experiment design

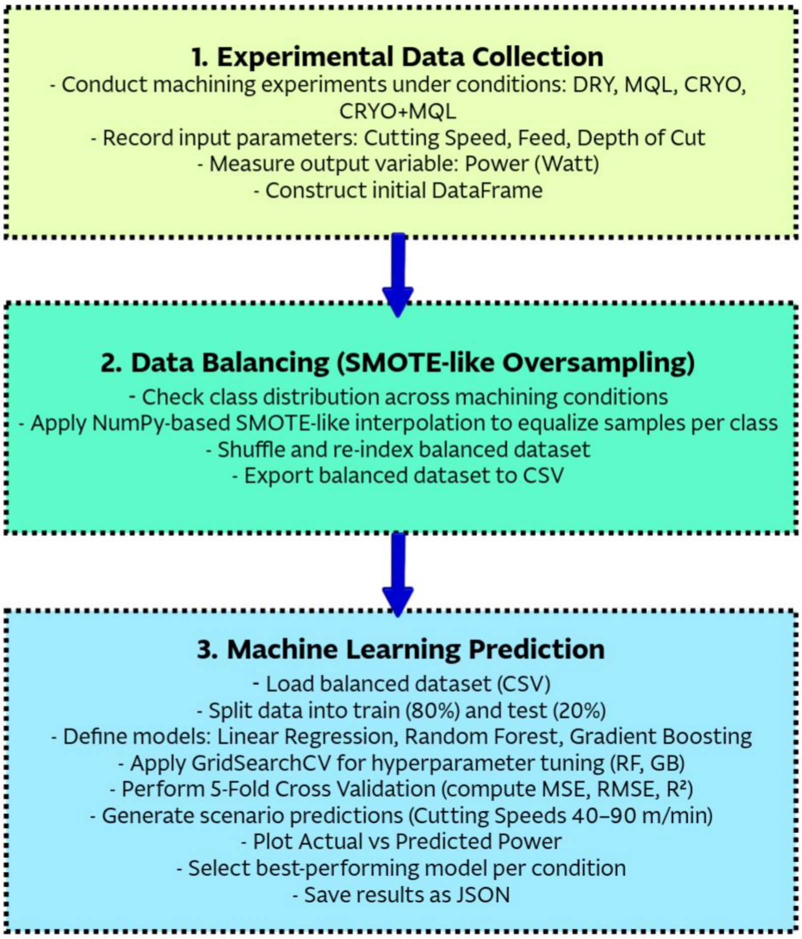


Figure 2.2. Work flow

## 3. RESULTS AND DISCUSSION

### 3.1. Energy Consumption

Energy consumption is a critical indicator of machining efficiency and sustainability in cutting operations. The figure below illustrates how energy demand varies with cutting speed under different cooling and lubrication conditions. This comparison provides a clear understanding of how process parameters and cutting environments influence power requirements [30]. The values obtained as a result of the study are given in Figure 3.1.

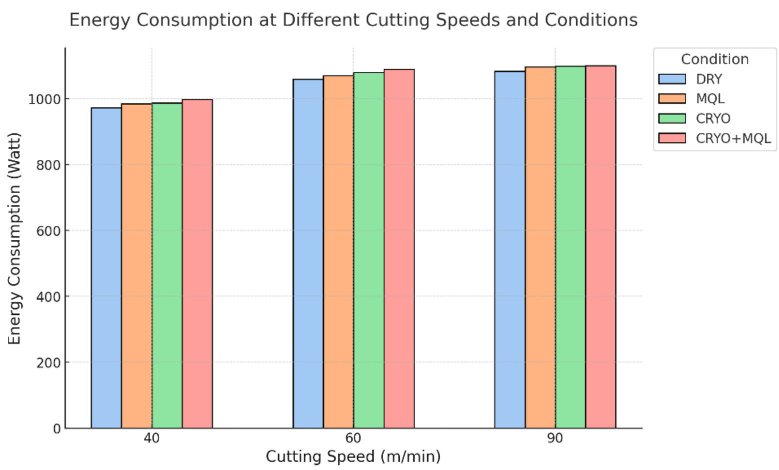


Figure 3.1. Energy consumption values in four different cutting conditions

Figure 3.1 clearly shows that the energy consumption increases with increasing cutting speed. While at 40 m/min the energy requirement is relatively low the consumption increases steadily as the speed increases to 60 and 90 m/min. When the cutting conditions are compared it is noticeable that the CRYO+MQL method causes slightly higher energy consumption compared to the others especially at high speeds [31]. This may be due to the effects of cooling and lubrication on the cutting forces. On the other hand energy consumption is lowest in dry cutting conditions. One of the reasons for this is the additional power requirement of auxiliary units such as air compressor/oil pump for MQL [32]. The other situation is the decrease in the thermal softening of Inconel 718 as a result of the decrease in the temperature in the cutting zone. However the yield stress shows an increase. These changes may increase the specific cutting energy. In addition at higher cutting speeds the strain rate and work hardening of the machined surface become more pronounced which further elevates the energy demand of the process. Under cryogenic and MQL-assisted conditions the improvement in cooling efficiency can alter the heat partition between the tool, chip, and workpiece, causing variations in frictional behavior and shear zone temperature. As a result the mechanical load on the cutting edge and the overall energy requirement may differ from those in dry cutting. Especially in cryogenic conditions, the friction-reducing effect of lubrication may be partially or even completely suppressed in some cases [33]. Overall the results show that although sustainable methods such as MQL or cryogenic support may provide advantages in terms of tool life and process stability, they may lead to a small increase in energy consumption.

### 3.2. ANOVA Results and Regression Model Prediction Performance for Energy Consumption

For statistical evaluation of the cutting parameters effect on energy demand an ANOVA test was performed. The results indicate which factors significantly affect the energy demand during machining [34]. Table 3.1 presents the ANOVA results for energy consumption under different cutting parameters. Regression analysis was applied to model the relationship between cutting parameters and energy consumption. The developed model enabled the estimation of the power requirement under different experimental conditions and made it comparable with the measured values. Figure 3.2 shows the ANOVA results for the relationship between cutting parameters and energy consumption.

Table 3.1. ANOVA results for the the relationship between cutting parameters and energy consumption

| Factor | DF | Seq SS | Adj SS | Adj MS | F-Value | p-value | Contribution (%) | Significance |
|---|---|---|---|---|---|---|---|---|
| **Cutting Speed** | 2 | 24.092 | 24.092 | 12.046 | 120.4637 | 0.000 | 96.71 | (p<0.001) |
| **Condition** | 3 | 0.018 | 0.018 | 0.006 | 0.0907 | 0.9631 | 0.07 | ns |
| **Error** | 6 | 0.600 | 0.600 | 0.100 | - | - | 2.41 | - |
| **Total** | 11 | 24.710 | - | - | - | - | - | - |

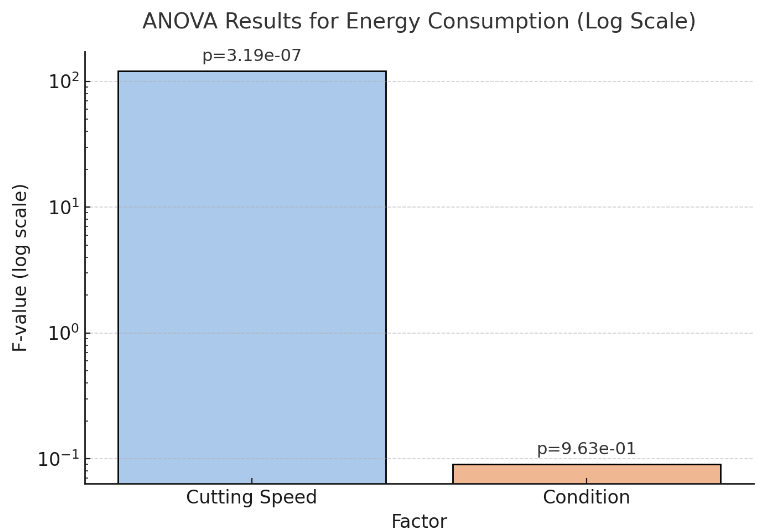


Figure 3.2. ANOVA results for the effect of cutting parameters on energy consumption.

ANOVA analysis shows that cutting speed has a highly significant effect on energy consumption ($p < 0.001$), while cutting conditions have no statistically significant effect ($p > 0.05$). This result shows that the variation in energy demand is mainly due to the cutting speed while the cooling/lubrication strategy does not play a significant role [35]. The F-value is quite high 120.46 indicating that most of the variance is due to the cutting speed. Its contribution to the total variance is 96.71% meaning that almost all of the energy consumption can be explained by this parameter. However the F-value of the machining condition factor is quite low (0.0907) and the p-value is 0.9631. This shows that the effect of machining condition on energy consumption is statistically insignificant. The contribution rate is only 0.07 per cent, which is negligible. A multivariate linear regression model was developed to predict energy consumption depending on the cut-off parameters. The general mathematical form of the model is given in Equation (1). Where $P$ is the estimated energy consumption, $v$, $f$ and $ap$ are the cutting speed, feed rate and depth of cut respectively. Cutting condition C which is a categorical variable is included in the model with dummy variables. Figure 3.3 shows the prediction performance of the regression model for energy consumption.

$$P = \beta_0 + \beta_1 \cdot v + \beta_2 \cdot f + \beta_3 \cdot a_p + \beta_4 \cdot C + \varepsilon \qquad (1)$$

Where:
P = Energy consumption (Watt)
v = Cutting speed (m/min)
f = Feed rate (mm/rev)
$a_p$ = Depth of cut (mm)
C = Cutting condition (categorical variable, dummy coded)
$\beta_i$ = Regression coefficients
ε = Error term

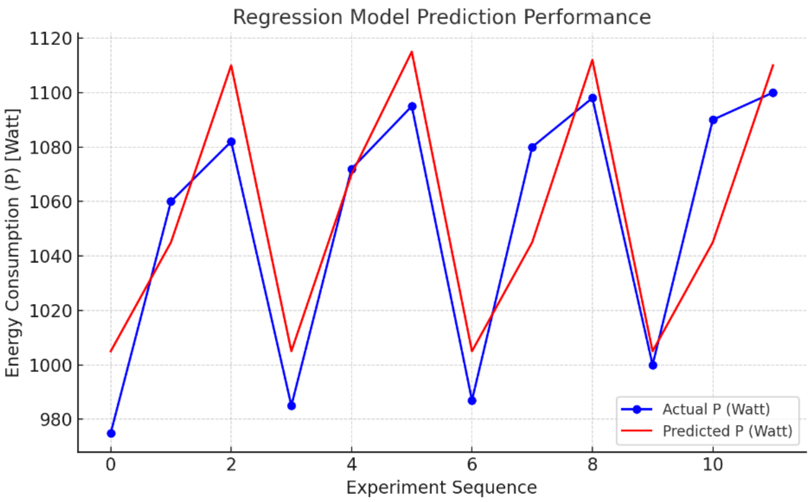


Figure 3.3. Regression model prediction performance for energy consumption.

The regression model shows a strong agreement between actual and predicted energy consumption values. The curves of the experimental and predicted values follow a broadly similar trend with only minor deviations at some experimental points. This result reveals that the regression method can reliably predict the energy demand in machining processes.

### 3.3. SMOTE

In the data set obtained experimentally in the study it was observed that the number of samples was low in some cutting conditions (DRY, MQL, CRYO, CRYO+MQL). In order to overcome this situation, a method inspired by In this study, the Synthetic Minority Oversampling Technique (SMOTE) was implemented. The classical SMOTE algorithm generates new synthetic examples through linear interpolation by selecting binary combinations from observations in classes with a small number of examples [36].

In this study the same logic is implemented with a NumPy-based SMOTE-like application. For each condition new data points were generated by randomly selecting among the available samples and linearly interpolating the coefficient (λ) between them. In cases where there was only one sample new samples were generated by adding very small random noise. In the last stage all samples were mixed and re-indexed to create an extended data set containing 50 samples for each condition. Thanks to this method balance between classes was achieved and the machine learning models trained with the obtained data showed a high accuracy of $R^2 \approx 0.99$ in power estimation (Figure 3.4.). A comparison table showing the experimentally obtained results and the prediction values obtained from SMOTE data is given in Table 3.2.

Table 3.2. Comparison of experimental results and SMOTE data.

| Condition | Cutting Speed (m/min) | Experimental P (W) | Predicted P (W, SMOTE) | Absolute Error (%) |
|---|---|---|---|---|
| DRY | 40 | 973 | 979.09 | 0.63 |
| DRY | 60 | 1059 | 1068.14 | 0.86 |
| DRY | 90 | 1083 | 1094.21 | 1.03 |
| MQL | 40 | 985 | 993.01 | 0.81 |
| MQL | 60 | 1070 | 1078.56 | 0.80 |
| MQL | 90 | 1097 | 1102.23 | 0.48 |
| CRYO | 40 | 987 | 980.42 | 0.67 |
| CRYO | 60 | 1080 | 1074.55 | 0.51 |
| CRYO | 90 | 1099 | 1107.68 | 0.79 |
| MQL+CRYO | 40 | 998 | 1001.33 | 0.33 |
| MQL+CRYO | 60 | 1089 | 1085.44 | 0.33 |
| MQL+CRYO | 90 | 1100 | 1098.81 | 0.11 |

Table 3.2 shows the comparison between the experimentally measured energy consumption values and the values predicted using the SMOT algorithm. It can be seen that the predicted results are in very high agreement with the experimental data and the average absolute error is less than 1%. This shows that the SMOTE-based regression model can predict the cutting energy with high accuracy under different cooling and lubrication conditions. The highest agreement was obtained for the CRYO+MQL condition where the difference between the experimental and predicted values was less than 0.2%.

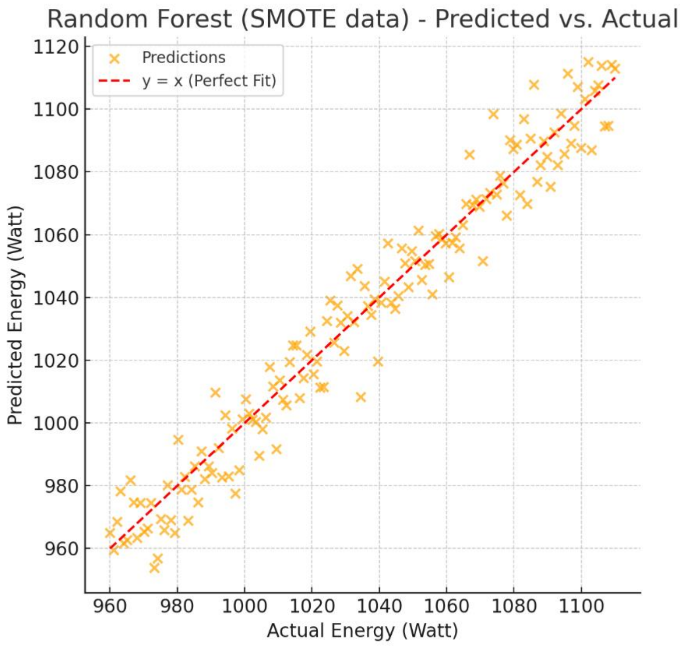


Figure 3.4. Power estimation results of the Random Forest algorithm on data balanced with SMOTE.

As can be seen in the figure the predicted energy values and the actual energy values overlap at a high level. The clustering of the points close to the red dashed line (perfect fit line) shows that the model produces highly successful predictions. Similar to some studies in the literature [37,38] these results confirm that the dataset extended with SMOTE provides a significant contribution to machine learning models and the prediction performance obtained is at the level of $R^2 \approx 0.99$.

### 3.4. Machine Learning

In this study a machine learning approach was applied for power prediction under different cutting conditions. First the experimental dataset was balanced using a SMOTE-based method to generate an equal number of samples for each condition. The balanced dataset was then utilized to train machine learning algorithms [39]. The dataset was split into training (80%) and testing (20%) *subsets (train_test_split(test_size=0.2, random_state=42))*. To assess the generalization performance of the models 5-Fold Cross Validation was applied *(KFold(n_splits=5, shuffle=True, random_state=42))*.

Hyperparameter optimization for Random Forest and Gradient Boosting was carried out using GridSearchCV. For RF, the parameter grid *included n_estimators [50, 100, 200*], *max_depth [None, 10, 20]*, and *min_samples_split [2, 5]*. For Gradient Boost, the parameter grid comprised *n_estimators [50, 100, 200]*, *learning_rate [0.01, 0.1]*, and *max_depth [3, 5]*. The *negative mean squared error (neg_mean_squared_error)* was used as the scoring function to identify the optimal hyperparameters.

The prediction performance of the developed machine learning models was evaluated with Mean Square Error (MSE), Root Mean Square Error Squared (RMSE) and Coefficient of Determination ($R^2$) values. MSE and RMSE indicate the average magnitude of prediction errors. The formulae for MSE and RMSE are given in Eq. 2 and Eq. 3. Low values indicate that the model accuracy is high. The $R^2$ value shows how well the predicted values fit the actual data and as it approaches 1 the explanatory power of the model increases. $R^2$ formula is given in Eq. 4. Related metrics are calculated with the following equations.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{2}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{3}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \tag{4}$$

For each cutting condition (CRYO, DRY, MQL, CRYO+MQL), separate models were developed using cutting speed (m/min) as the input feature and power consumption (P, Watt) as the output variable. Model performance was evaluated in terms of Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and the Coefficient of Determination ($R^2$). Additionally scenario-based predictions were generated for cutting speeds in the range of 40–90 m/min, and visualizations were created to compare predicted and actual values. Analyses and comparisons are given in Table 3.3.

Table 3.3. Analysis and comparison of machine learning models algorithms for power prediction under different cutting conditions

| Cutting Condition | Algoritma | $R^2$ | MSE | RMSE |
|---|---|---|---|---|
| CRYO | Random Forest | 0.85 | 193.17 | 13.81 |
| | Gradient Boosting | 0.96 | 75.55 | 8.21 |
| | Linear Regression | 0.84 | 202.37 | 13.37 |
| DRY | Random Forest | 0.87 | 167.19 | 11.81 |
| | Gradient Boosting | 0.97 | 73.55 | 7.04 |
| | Linear Regression | 0.89 | 114.55 | 10.02 |
| MQL | Random Forest | 0.82 | 236.41 | 14.46 |
| | Gradient Boosting | 0.91 | 106.45 | 11.04 |
| | Linear Regression | 0.83 | 224.29 | 14.02 |
| CRYO+MQL | Random Forest | 0.88 | 137.84 | 11.24 |
| | Gradient Boosting | 0.97 | 73.32 | 7.01 |
| | Linear Regression | 0.88 | 124.55 | 10.52 |

Comparative results for the power estimation performance of machine learning algorithms under different cutting conditions are given in Table 3. In the study different machine learning methods were evaluated only for power estimation based on cutting speed. The results show that the Gradient Boosting algorithm significantly outperforms the other methods in all shear conditions. Especially in the CRYO+MQL condition, the lowest error level was reached with $R^2 \approx 0.97$ and RMSE≈7.01. In the DRY condition the Gradient Boosting algorithm provided similarly high accuracy with RMSE≈7.04 while in the CRYO condition, the error value remained at RMSE≈8.21. On the other hand the error metrics were relatively higher in the MQL condition with RMSE≈11.04. These results show that in a univariate configuration (cutting speed only) the effect of lubrication and cooling conditions on power can be reflected to a limited extent, but the Gradient Boosting algorithm shows superior performance in capturing non-linear relationships. Figure 3.5 shows the Actual and Predicted Power plots obtained with the Gradient Boosting algorithm under different cutting conditions.

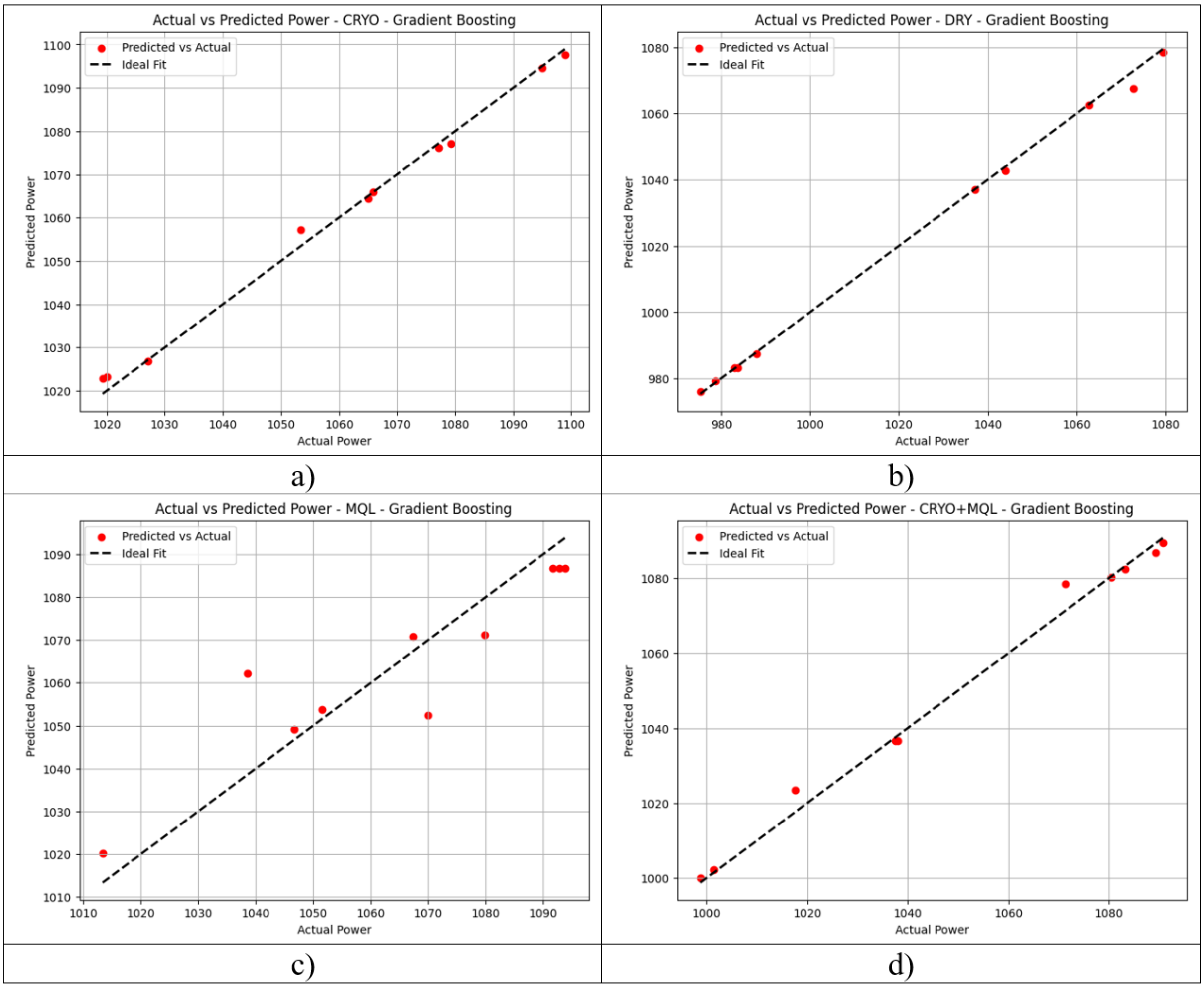


Figure 3.5. Actual and Predicted Power graphs obtained with Gradient Boosting algorithm.
a)CRYO b)DRY c) MQL d)CRYO+MQL

Figure 3.5 shows the relationship between the predicted power values obtained by the Gradient Boosting algorithm and the actual power values under four different cut-off conditions. In the graphs the red dots represent the predicted values and the dashed line represents the ideal fit. In CRYO+MQL (d) and DRY (b) conditions the predicted values are very close to the ideal line. In the CRYO (a) condition the results show similarly high accuracy but it is noteworthy that the deviations are more pronounced in the MQL (c) condition. These findings reveal that the Gradient Boosting algorithm offers high reliability in power estimation, especially in CRYO+MQL and DRY conditions while the margin of error increases relatively in the MQL condition.

## 4. RESULTS

This study investigated the energy consumption behavior of Inconel 718 during milling under different cutting conditions and developed machine learning-based models for reliable prediction. The experimental and computational results provide valuable insights into sustainable manufacturing practices. The main conclusions can be summarized as follows:

- Cutting speed was identified as the dominant parameter influencing energy consumption while cooling/lubrication methods had no statistically significant impact.

- Although MQL and cryogenic-assisted conditions improve tool life and process stability the additional power demand of auxiliary units and the reduced thermal softening of Inconel 718 can slightly increase overall energy consumption.
- The regression model demonstrated a strong correlation between actual and predicted energy consumption values indicating that the proposed approach can reliably capture the overall energy demand trend in machining operations.
- SMOTE-based data augmentation significantly improved the performance of machine learning models by balancing the dataset.
- Gradient Boosting outperformed Random Forest and Linear Regression achieving the highest prediction accuracy ($R^2 \approx 0.97$, RMSE≈7 W), particularly under CRYO+MQL and DRY conditions.

## ACKNOWLEDGMENT

This research was supported by a project carried out within the scope of TÜBİTAK 2209-A.

## REFERENCES

[1] M. Shahwaz, P. Nath, I. Sen, A critical review on the microstructure and mechanical properties correlation of additively manufactured nickel-based superalloys, J. Alloys Compd. 907 (2022) 164530. https://doi.org/https://doi.org/10.1016/j.jallcom.2022.164530.

[2] X. Wang, Y. Ding, Y. Gao, Y. Ma, J. Chen, B. Gan, Effect of grain refinement and twin structure on the strength and ductility of Inconel 625 alloy, Mater. Sci. Eng. A 823 (2021) 141739.

[3] D. Dubey, R. Mukherjee, M. K. Singh, A review on tribological behavior of nickel-based Inconel superalloy, Proc. Inst. Mech. Eng. Part J J. Eng. Tribol. 238 (2024) 706–732. https://doi.org/10.1177/13506501241235724.

[4] Y. Xie, D.M. Artymowicz, P.P. Lopes, A. Aiello, D. Wang, J.L. Hart, E. Anber, M.L. Taheri, H. Zhuang, R.C. Newman, K. Sieradzki, A percolation theory for designing corrosion-resistant alloys, Nat. Mater. 20 (2021) 789–793.https://doi.org/10.1038/s41563-021-00920-9.

[5] H. Wang, Q. Guo, C. Li, L. Cui, H. Yao, Y. Liu, Microstructural evolution and strengthening mechanisms of inconel 718 alloy with 1wt.% Ti2AlC addition fabricated by laser powder bed fusion, Mater. Sci. Eng. A 925 (2025) 147872.https://doi.org/https://doi.org/10.1016/j.msea.2025.147872.

[6] H. Zhang, Y. Liu, X. Liu, K. Zhu, T. Xiao, Z. Zhang, K. Feng, L. Chai, S. Guo, N. Guo, Laser weldability and interface microstructure of CoCrNi-based medium-entropy alloy to Inconel 718 superalloy, Mater. Charact. 216 (2024) 114290.https://doi.org/https://doi.org/10.1016/j.matchar.2024.114290.

[7] P. Sun, N. Yan, S. Wei, D. Wang, W. Song, C. Tang, J. Yang, Z. Xu, Q. Hu, X. Zeng, Microstructural evolution and strengthening mechanisms of Inconel 718 alloy with different W addition fabricated by laser cladding, Mater. Sci. Eng. A 868 (2023) 144535.https://doi.org/10.1016/j.msea.2022.144535.

[8] M.S. Alsoufi, S.A. Bawazeer, Predictive Modeling of Surface Integrity and Material Removal Rate in Computer Numerical Control Machining: Effects of Thermal Conductivity and Hardness, Materials (Basel). 18 (2025). https://doi.org/10.3390/ma18071557.

[9] M.R.D.D. Carvalho, A.Í.S. Antonialli, A.E. Diniz, A machinability evaluation based on the thermal and mechanical properties of two engine valve steels, Int. J. Adv. Manuf. Technol. 110 (2020) 3209–3219. https://doi.org/10.1007/s00170-020-06108-w.

[10] S. Chauhan, R. Trehan, R.P. Singh, State of the art in finite element approaches for milling process: a review, Adv. Manuf. 11 (2023) 708–751.https://doi.org/10.1007/s40436-022-00417-x.

[11] M.P. Sealy, Z.Y. Liu, D. Zhang, Y.B. Guo, Z.Q. Liu, Energy consumption and modeling in precision hard milling, J. Clean. Prod. 135 (2016) 1591–1601.https://doi.org/10.1016/j.jclepro.2015.10.094.

[12] A. Czán, R. Joch, M. Šajgalík, J. Holubják, A. Horák, P. Timko, J. Valíček, M. Kušnerová, M. Harničárová, Experimental Study and Verification of New Monolithic Rotary Cutting Tool for an Active Driven Rotation Machining, Materials (Basel). 15 (2022).https://doi.org/10.3390/ma15051630.

[13] N. Sihag, K.S. Sangwan, A systematic literature review on machine tool energy consumption, J. Clean. Prod. 275 (2020) 123125.https://doi.org/10.1016/j.jclepro.2020.123125.

[14] R. Çakıroğlu, M. Günay, Analysis of surface roughness and energy consumption in turning of C17500 copper alloy under different machining environments and modellings with response surface method, Proc. Inst. Mech. Eng. Part E J. Process Mech. Eng. 237 (2022) 207–219. https://doi.org/10.1177/09544089221101368.

[15] M.E. Korkmaz, M.K. Gupta, E. Çelik, N.S. Ross, M. Günay, A sustainable cooling/lubrication method focusing on energy consumption and other machining characteristics in high-speed turning of aluminum alloy, Sustain. Mater. Technol. 40 (2024) e00919.https://doi.org/10.1016/j.susmat.2024.e00919.

[16] J. Lv, R. Tang, S. Jia, Y. Liu, Experimental study on energy consumption of computer numerical control machine tools, J. Clean. Prod. 112 (2016) 3864–3874.https://doi.org/10.1016/j.jclepro.2015.07.040.

[17] B. Li, X. Tian, M. Zhang, Modeling and Multi-objective Optimization Method of Machine Tool Energy Consumption Considering Tool Wear, Int. J. Precis. Eng. Manuf. Technol. 9 (2022) 127–141.

https://doi.org/10.1007/s40684-021-00320-z.

[18] D. Bergh, E. Wagenmakers, F. Aust, Bayesian Repeated-Measures Analysis of Variance: An Updated Methodology Implemented in JASP, Adv. Methods Pract. Psychol. Sci. 6 (2023) 25152459231168024. https://doi.org/10.1177/25152459231168024.

[19] R. Christensen, One-Way ANOVA BT - Plane Answers to Complex Questions: The Theory of Linear Models, in: R. Christensen (Ed.), Springer New York, New York, NY, 2011: pp. 91–103. https://doi.org/10.1007/978-1-4419-9816-3_4.

[20] G. Douzas, F. Bacao, F. Last, Improving imbalanced learning through a heuristic oversampling method based on k-means and SMOTE, Inf. Sci. (Ny). 465 (2018) 1–20.https://doi.org/10.1016/j.ins.2018.06.056.

[21] M. Mujahid, E. Kına, F. Rustam, M.G. Villar, E.S. Alvarado, I. De La Torre Diez, I. Ashraf, Data oversampling and imbalanced datasets: an investigation of performance for machine learning and feature engineering, J. Big Data 11 (2024) 87.https://doi.org/10.1186/s40537-024-00943-4.

[22] M.A. Mahboob Ali, A.I. Azmi, A.N. Mohd. Khalil, Specific cutting energy of Inconel 718 under dry, chilled-air and minimal quantity nanolubricants, Procedia CIRP 77 (2018) 429–432. https://doi.org/10.1016/j.procir.2018.08.290.

[23] N. Khanna, C. Agrawal, M. Dogra, C.I. Pruncu, Evaluation of tool wear, energy consumption, and surface roughness during turning of inconel 718 using sustainable machining technique, J. Mater. Res. Technol. 9 (2020) 5794–5804.https://doi.org/10.1016/j.jmrt.2020.03.104.

[24] B. Özlü, H.B. Ulaş, F. Kara, Investigation of the Effects of Cutting Tool Coatings and Machining Conditions on Cutting Force, Specific Energy Consumption, Surface Roughness, Cutting Temperature, and Tool Wear in the Milling of Ti6Al4V Alloy, Lubricants 13 (2025).https://doi.org/10.3390/lubricants13080363.

[25] A.K. Parida, K. Maity, Numerical and experimental analysis of specific cutting energy in hot turning of Inconel 718, Measurement 133 (2019) 361–369.https://doi.org/10.1016/j.measurement.2018.10.033.

[26] Z. Zhou, K. Liu, J. Zhou, Y. Xu, L. Wang, A highly energy-efficient milling of Inconel 718 via modulated short electric arc machining, J. Manuf. Process. 78 (2022) 46–58. https://doi.org/10.1016/j.jmapro.2022.03.051.

[27] M.U. Farooq, R. Kumar, A. Khan, J. Singh, S. Anwar, A. Verma, R. Haber, Sustainable machining of Inconel 718 using minimum quantity lubrication: Artificial intelligence-based process modelling, Heliyon 10 (2024) e34836. https://doi.org/10.1016/j.heliyon.2024.e34836.

[28] P. Adishesha, S. Allada, PB Dhanish, J. Mathew, D. L. K, Analysis of the power during machining of Inconel 718 for different geometrical profiles and the development of power prediction models using multisensor data, Proc. Inst. Mech. Eng. Part E J. Process Mech. Eng. (2024) 09544089241291743. https://doi.org/10.1177/09544089241291743.

[29] W. Frifita, S. Ben Salem, A. Haddad, M.A. Yallese, Optimization of machining parameters in turning of Inconel 718 Nickel-base super alloy, Mech. Ind. 21 (2020) 203.

[30] N. Khanna, P. Shah, R.W. Maruda, G.M. Krolczyk, H. Hegab, Experimental investigation and sustainability assessment to evaluate environmentally clean machining of 15-5 PH stainless steel, J. Manuf. Process. 56 (2020) 1027–1038.https://doi.org/10.1016/j.jmapro.2020.05.016.

[31] N. Khanna, P. Shah, N.M. Suri, C. Agrawal, S.K. Khatkar, F. Pusavec, M. Sarikaya, Application of Environmentally-friendly Cooling/Lubrication Strategies for Turning Magnesium/SiC MMCs, Silicon 13 (2021) 2445–2459.https://doi.org/10.1007/s12633-020-00588-x.

[32] A. Dttmann, J. de Oliveira Gomes, Adapted versus Projected Machining Centers Energy Consumption for MQL Technique, U. Porto J. Eng. 7 (2021) 78–87.

[33] J. Han, Y. Tang, L. Yue, X. Ma, H. Jia, N. Liu, P. Bai, Y. Meng, Y. Tian, Tribological Behavior of Polydiethylsiloxane (PDES) in a Si3N4 and M50 System under Low Temperatures from −80 to 25 °C, Lubricants 12 (2024).https://doi.org/10.3390/lubricants12050176.

[34] C. Camposeco-Negrete, Optimization of cutting parameters for minimizing energy consumption in turning of AISI 6061 T6 using Taguchi methodology and ANOVA, J. Clean. Prod. 53 (2013) 195–203.

[35] M. Jamil, N. He, W. Zhao, H. Xiang, M.K. Gupta, A. Iqbal, A.M. Khan, Assessment of energy consumption, carbon emissions and cost metrics under hybrid MQL-Dry ice blasting system: A novel cleaner production technology for manufacturing sectors, J. Clean. Prod. 360 (2022) 132111. https://doi.org/10.1016/j.jclepro.2022.132111.

[36] E. Aslan, Y. Özüpak, F. Alpsalaz, Z.M.S. Elbarbary, A Hybrid Machine Learning Approach for Predicting Power Transformer Failures Using Internet of Things-Based Monitoring and Explainable Artificial Intelligence, IEEE Access 13 (2025) 113618–113633.

[37] R. Hassanzadeh, M. Farhadian, H. Rafieemehr, Hospital mortality prediction in traumatic injuries patients: comparing different SMOTE-based machine learning algorithms, BMC Med. Res. Methodol. 23 (2023) 101. https://doi.org/10.1186/s12874-023-01920-w.

[38] J. Kim, J.H. Kim, W. Jang, J. Pyo, H. Lee, S. Byeon, H. Lee, Y. Park, S. Kim, Enhancing Machine Learning Performance in Estimating CDOM Absorption Coefficient via Data Resampling, Remote Sens. 16 (2024). https://doi.org/10.3390/rs16132313.

[39] F. Alpsalaz, Fault Detection in Power Transmission Lines: Comparison of Chirp-Z Algorithm and Machine Learning Based Prediction Models, Eksploat. i Niezawodn. – Maint. Reliab. (2025). https://doi.org/10.17531/ein/203949.