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RESEARCH ARTICLE-MECHANICAL ENGINEERING

# Sustainable Machining of Nimonic 80A: Machine Learning-Driven Optimization of Energy Consumption Under Environmentally Conscious Cooling Strategies

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**Abstract**
Machining advanced materials like Nimonic 80A in a way that is both environmentally friendly and energy efficient is becoming more important around the world. However, achieving an acceptable level of machining performance without harming the environment remains challenging. The present study is focused on resolving this issue. Machine Learning (ML) was employed to predict and optimize cutting power and specific cutting energy (SCE). Four novel sustainable cooling and lubrication (C/L) environments were studied which are dry, minimum quantity lubrication (MQL), cryogenic $CO_2$, and hybrid $CO_2$ + MQL configuration. The main contribution of the study is the systematic comparison of ML techniques such as support vector machine (SVM), random forest (RF), and multi-layer perceptron (MLP) for getting the prediction and optimization of the cutting power and SCE among different C/L environments. Among all C/L environments, the hybrid ($CO_2$ + MQL) environment produced the best results, significantly reducing power consumption and SCE. Under the best conditions, the hybrid method used about 47% less power and about 80% less SCE than dry machining. ML analysis showed the superior predictive capability of the MLP model, which achieved the lowest error rates and highest coefficients ($R = 0.9996$ for power; $R = 0.9873$ for SCE). These results demonstrate the strong potential of combining hybrid cooling with intelligent ML prediction for sustainable and energy-efficient machining of Nimonic 80A.

**Keywords** Sustainable machining · Energy efficiency · Nimonic 80A · Advanced cooling strategies · Machine learning · Specific cutting energy · Cryogenic $CO_2$

## 1 Introduction

Manufacturing industries are continuously seeking innovative machining solutions to improve product quality and process efficiency in response to growing consumer and market demands for better products, as well as procedures for quality and efficiency [1]. Simultaneously, high-tech engineering goods, such as wind turbines and aviation products, that operate with physical boundaries are becoming increasingly optimized [2]. Over the past 30 years, a few firms have shown the importance of quality in becoming competitive. These firms are effective in understanding customer needs and translating them into finished goods. The basic definition of quality in manufacturing is making goods that meet the needs of customers [3], but the industry still has problems with integrating new technologies, using resources wisely, and meeting sustainability goals. Manufacturers are widely using AI data management in their production processes to stay competitive [4–6]. In accordance with the current trend, this study focuses on the machine learning application in manufacturing, especially in machining advance material (Nimonic 80A) to make the process environmentally friendly.

Difficult to machine material such as Nimonic 80A always presents significant challenges to the sustainability of the process. Machining difficulty to cut materials generally creates high temperature at the cutting zone that increases tool wear and hinders surface integrity. Furthermore, lubricating oil or coolant used to reduce this temperature creates environmental issues and dry machining will have significant

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amount of energy consumption [7–10]. These limitations have negative impact on both process efficiency and product quality. Hence, sustainable machining strategies using environmentally friendly cooling/lubrication (C/L) techniques together with application of machine learning-based optimization have found attraction all around the globe [11, 12]. Improvement in tool life, surface finish, together with energy efficiency have been reported while machining under hybrid and cryogenic environments [13–15]. However, the studies on integration of these conditions with machine learning-based optimization have been rarely reported for Nimonic 80A.

From the literature, it is evident that sustainable machining is an important part for sustainable manufacturing. However, sustainable machining of difficult-to-cut materials like Nimonic 80A is particularly challenging. Machining of Nimonic 80A has been associated with high cutting temperatures, poor surface finish, inadequate surface integrity, and high tool wear. It is due to its poor conductivity of heat and presence of hard particles like carbides. Furthermore, it is found to be very tough at high temperatures. Novel C/L methods (MQL, cryogenic $CO_2$, and hybrid $CO_2$ + MQL) have been developed to minimize these effects by reducing cutting temperatures and minimizing friction. Furthermore, using better suited ML techniques for optimizing parameter or power consumption will contribute significantly to the sustainable machining of hard to cut materials.

### 1.1 Artificial Intelligence in Machining

In recent times, manufacturers are not only concentrating on environmentally friendly C/L in machining strategies but also focusing on the optimization of critical machining parameters as well as energy consumption. To do that, AI (Artificial Intelligence) has taken the center stage which has given encouraging results already [15, 16]. Methods like Deep Learning (DL) and ML already gained attention and have been used in machining [17]. ML uses data such as cutting forces and cutting temperatures to apply algorithms to predict and optimize the machining process. DL, which is an extension of ML, uses neural networks that are organized in levels. These networks can find complicated patterns in machining datasets to make accurate models of things like how tools wear out over time or how surface finishes change [18, 19].

Recent works show AI and ML frameworks being used in many machining applications. These include tool-condition monitoring, chip formation analysis, surface-roughness prediction, cutting-force estimation, and optimizing C/L parameters [20–22]. These implementations directly contribute to sustainable machining by improving tool life, enhancing surface integrity, cutting power consumption (SCE), and enabling real-time optimization (Fig. 1).

### 1.2 Nimonic 80A in Manufacturing

Super alloys are desperately needed in today's high-precision nuclear reactor and aircraft manufacturing industries to produce various components at high production levels. Because of their superior creep resistance properties compared to readily available stainless austenitic steels, as well as their long-lasting strength and toughness at high temperatures, nickel (Ni)-based superalloys gain more advantages in gas turbines [23]. Figure 2 presents the cross section of a jet engine; from the image, it is clear that major parts are produced with the help of Ni alloys. Ni's remarkable phase stability in its face-centered cubic (FCC) matrix is one of its main advantages as an alloy base. These qualities promote the use of superalloys based on nickel in a wide range of applications. Due to their strong chemical affinity toward cutting tools, Ni alloys are not easily machined, which can lead to chipping and early tool failure [8]. Because Ni alloys have a low conductivity during cutting, the temperature at the workpiece (W/p)-tool tip rises, directly affecting the cutter life [9]. Nimonic 80A, a material in the Ni alloy family, is extremely difficult to machine because it has poor conductivity and high chemical reactivity. These properties lead to surface defects, rapid cutter wear, and higher cutting forces. Therefore, to improve the surface characteristic, cutting fluid (CF) must be applied to reduce heat and friction. Chavan et al. [24] report on the machinability of the Nimonic 80A superalloy when using alumina-based ceramic inserts. During the process of machining Nimonic 80A, adhesion and abrasion are the primary factors that lead to tool failure. When the cutting speed is reduced, the component of tool wear plays a more significant role in the surface finish. In addition, the thermally triggered wear that occurs at tool surfaces gradually increases when the cutting speed reaches higher levels [24]. Because of its low heat diffusivity and high chemical attraction, Nimonic 80A is difficult to mill using conventional techniques. Ross et al. [12] conducted research on the hybrid cooling/lubrication (C/L) method for machining Nimonic 80A. Lower temperatures, increased microhardness, compressive residual stress, and surface quality were all achieved through the simultaneous action of chilling and lubricating. Another study by Ross et al. [13] examined the viability of machining Nimonic-80A in a hybrid C/L environment in comparison with other cutting conditions, such as cryogenic and MQL. SCE was lowered because of the hybrid cutting strategy and reduced burr development was seen [13].

### 1.3 Machine Learning in Machining of Metal Parts

ML techniques are increasingly used in machining because they can effectively model the complex, nonlinear relationships between process parameters and responses. ML algorithms learn directly from experimental data to predict

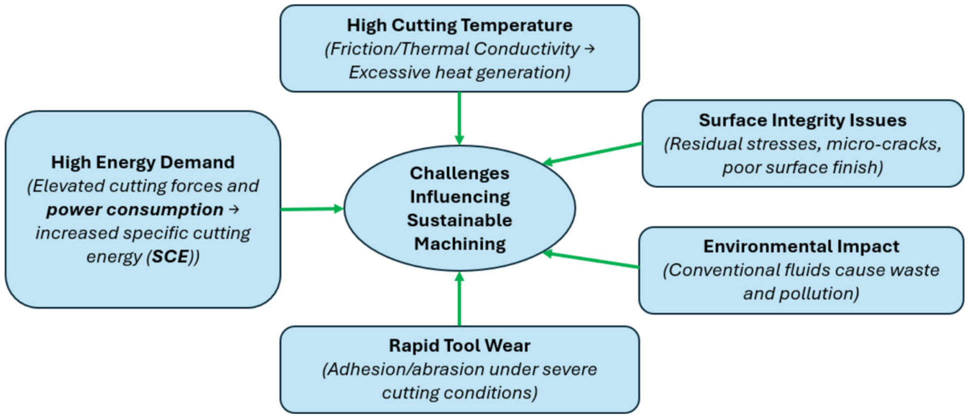


**Fig. 1** Challenges in sustainable machining processes

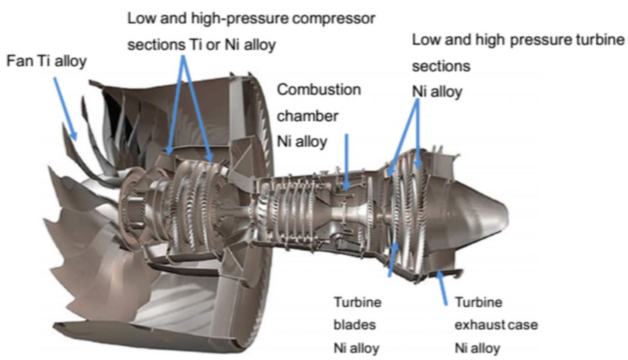


**Fig. 2** Cross section of jet engine [25]

outputs like cutting power, SCE, surface roughness, and tool wear. Improving surface integrity, optimizing cutting conditions, and making processes more sustainable by using fewer resources are all possible due to these data-driven approaches [26–28]. For example, Brillinger et al. [26] predicted energy consumption using real-time CNC data by employing a random forest model. In another study, energy consumption was predicted using the GPR and ANN method [27].

Pimenov et al. [28] demonstrated the integration of ML and with machining parameters and found encouraging results toward sustainable machining process. Researchers have also predicted tool wear, surface finish, cutting temperature, and energy consumption during machining of superalloys by employing SVM, ANN, RF, and GPR [9, 29, 30]. Biswas et al. [29] employed ML in machining of nickel-based superalloys to study sustainability of the process. Wang et al. [9] worked tool-wear mechanisms in nickel alloys and identified predictive modeling as a promising avenue for future research. Furthermore, Gupta et al. [30] also studied at green cooling strategies for machining titanium. They showed how choosing the right parameters can make tools last longer and use less energy. Hybrid frameworks that use both ML and metaheuristic algorithms, like genetic algorithms, have also been better at tuning parameters for long-lasting uses [31].

In summary, ML-based approaches are a promising tool for promoting sustainable machining through precise prediction and optimization. However, most current studies focus on individual cooling or lubrication techniques. There is limited research that comparatively evaluates multiple eco-friendly strategies using ML models to assess energy efficiency. Our investigation aims to fill this specific gap.

### 1.4 Aim and Scope of the Study

The rapid expansion of research integrating machine learning-based optimization with sustainable cooling and lubrication (C/L) strategies in machining has produced a wide spectrum of outcomes across different materials and process conditions. Nevertheless, the focus of these investigations remains somewhat fragmented, highlighting the need to consolidate the major research directions and pinpoint persisting challenges. To present an overview of published studies which clearly shows the existing research gap, Table 1 compiles the recent works on sustainable machining and machine learning applications.

From the literature summarized above, it is evident that while many studies have employed machine-learning techniques for predicting tool wear, surface roughness, or process parameters, most were limited to single cooling or lubrication strategies and did not evaluate energy-efficiency metrics. Only a few studies combined ML prediction with experimental validation for comparative analysis. The present research addresses these gaps by integrating experimental energy measurement with ML-based prediction for sustainable machining optimization of Nimonic 80A.

The primary objective of this study is to develop and validate machine learning-based predictive models for optimizing cutting power and specific cutting energy (SCE) during end-milling of Nimonic 80A under four sustainable cooling and lubrication (C/L) conditions i.e., Dry, MQL, $CO_2$, and Hybrid $CO_2$ + MQL. The proposed framework integrates experimental analysis with intelligent prediction

**Table 1** Summary of key literature related to sustainable machining and machine learning applications

| References | Material/ process studied | ML technique used | Focus area | Limitation/gap identified |
|---|---|---|---|---|
| Brillinger et al. [26] | CNC machining | Random Forest | Energy-consumption prediction from production data | Focused only on energy modeling; no cooling/lubrication or superalloy analysis |
| Awan et al. [27] | Grinding of steel | ANN, GPR | Prediction of specific energy consumption | Lacked multiple cooling strategies and experimental validation |
| Wang et al. [9] | Nickel-based superalloys (milling) | Review | Tool-wear mechanisms and machinability overview | Review study; no ML or sustainability modeling |
| Danish et al. [32] | Inconel 718 (turning, Cryo-MQL) | Not used (Experimental) | Hybrid lubri-cooling for improved tribology | Did not include ML prediction or energy optimization |
| Gupta et al. [30] | Titanium alloys (turning) | Not used (Data comparison) | Tool wear and SCE under hybrid & green cooling | No ML-based optimization; limited to titanium alloys |
| Ross et al., 2022 [13] | Nimonic 80A (milling, $CO_2$ + MQL) | Not used (Empirical ANOVA) | Effect of hybrid cooling on surface morphology | No ML or energy-efficiency modeling |
| Pimenov et al. [28] | Various materials (Review) | Multiple ML methods | Energy consumption and sustainable machining optimization | Broad review; no hybrid C/L experimental studies |
| Biswas et al., 2025 [29] | Nickel-based superalloys (Review) | ANN, SVM, RF | ML modeling for sustainable superalloy machining | No experimental validation of energy performance |
| Balasudhakar et al. [33] | AISI H11 – end milling under three cooling conditions | ANN, SVM | ML prediction of surface roughness under varied C/L strategies | Focused on surface quality; no energy or SCE analysis |
| Tóth et al. [34] | General machining processes | Physics-informed ML | Resource-efficient machining and energy optimization | Did not compare different C/L conditions or superalloy applications |
| Current study | Nimonic 80A (end milling) | SVM, RF, MLP | Prediction of cutting power and SCE under Dry, MQL, $CO_2$, and Hybrid $CO_2$ + MQL | Integrates experimental and ML approaches for energy-efficient sustainable machining |

to provide a comparative evaluation of these strategies and to support data-driven sustainable machining of superalloys.

## 2 Materials and Methods

### 2.1 Experimental Setup

In this work, Nimonic 80A was used as a workpiece (W/p). Its exceptional thermo-mechanical qualities are specifically tailored for highly specialized application domains within the aerospace and automotive sectors [35]. Figure 3 presents the experimental procedure. The main qualities of the work material are its resistance to corrosion, less thermal expansion, and reliability at high temperatures. During the testing, the work material with dimensions of 150 × 100 × 10 $mm^3$ was employed. Table 2 lists the chemical components found in the W/p.

Due to their use in specialized applications requiring high surface smoothness, the end milling technique was employed. The YCM EV20 Machining Center was used for the milling investigations that were conducted. End milling was carried out with the assistance of a PVD-TiAlN-coated APMT 1135 PDTR mounted on a 20-mm-diameter end-mill holder. The insert has a standard positive-rake geometry with an approximate nose radius of 0.8 mm, suitable for machining nickel-based superalloys [11, 36]. It was determined that the process parameters, which include Cutting speed (*Vc*, m/min) and feed rate (*fr*, mm/tooth), and cooling environment, were

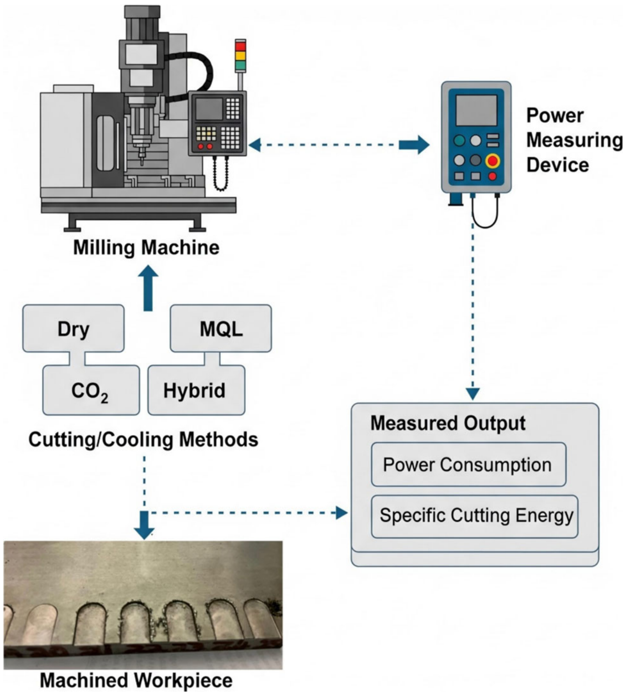


**Fig. 3** Experimental setup

selected based on past research and manufacturing procedures [37, 38]. Specifically, the selected cutting speeds and feed rates were chosen within the ranges reported by previous studies on Nimonic 80A machining and validated through preliminary test cuts to ensure process stability and representative cutting behavior [39, 40]. Information regarding the experimental particulars and the cutting settings can be found in Table 3.

## 2.2 Machining Conditions

Vegetable oil (VO) was sprayed into the cutting area using the minimum quantity lubrication (MQL) system, along with a mist of air. Olive oil was selected as the MQL base fluid due to its excellent lubricating ability, high flash point, biodegradability, and non-toxic nature, which make it environmentally safer and highly effective for sustainable machining operations. A flow control valve transports the oil from the tank into the chamber where it mixes. The adjusted air pressure helps the oil reach the cutting region to a greater extent. The gap between the cutting place nozzle and the nozzle outlet (2 mm) contributed to the excellent wettability at the cutting area. The position of the nozzle is maintained at 45 degrees.

**Table 3** Cutting conditions and parameters

| Parameter | Specification |
|---|---|
| Machine Tool | YCM EV1020A |
| Workpiece | Nimonic 80A |
| Cutting tool | PVD—TiAlN (APMT) |
| Radial DOC ($a_e$) | 12 mm |
| Axial DOC ($a_p$) | 0.75 mm |
| Length of cut | 25 mm |
| Cutting speed (Vc) | 60–120 m/min |
| Feed rate (*fr*) | 0.5–1.5 mm/rev |
| Environment | Dry, MQL, $CO_2$ and $CO_2$ + MQL (Hybrid) |
| MQL Oil | Olive oil |

The MQL system employed pure olive oil as the biodegradable vegetable-oil-based lubricant, sprayed with compressed air at a pressure of 2 bar and a flow rate of 60–80 ml/hr. A large portion of friction is reduced due to the fatty-acid composition of olive oil, which enhances lubricity and cooling performance in sustainable machining studies [41]. The heat generated at the cutting area is immediately controlled by the cryo environment, which also releases it into the surrounding air without leaving any residue behind. It complies with the three main requirements of sustainable practices: economic, social, and ecological. To control the amount of fluid, a pressure regulator is attached to the hose. The nozzle output was used to create a cryogenic $CO_2$ flow at 3 bars of pressure. Under hybrid conditions, the researchers made use of both $CO_2$ and MQL conditions, which can curtail heat and increase lubrication.

## 2.3 Measurement of Responses

The power consumption (*Pc*) during the metal cutting was measured with the help of the HTC to make clamp meter. The specific cutting energy (SCE) in KJ/mm$^3$ is computed using Eqs. (1) and (2) [30].

$$SCE = \frac{Pc}{MRR} \tag{1}$$

$$MRR = Vc \times fr \times DOC \tag{2}$$

Material removal rate (MRR) in mm$^3$ and DOC in mm were utilized. The analyzer then aggregated and recorded the

**Table 2** Chemical composition of Nimonic 80A alloy (in wt.%)

| Element | Ni | Cr | Fe | Ti | Al | Others |
|---|---|---|---|---|---|---|
| wt.% | 73.21 | 19.35 | 2.5 | 2.49 | 1.55 | Balance |

power consumed by the CNC device, which was measured individually across the three phases. Although current study was primarily focused on energy-related parameters, the machining conditions, cutting tool, and process parameters were selected based on prior validated studies on Nimonic 80A to ensure that surface integrity and dimensional quality remained within industrially acceptable limits. Previous investigations under comparable cooling environments have confirmed that the selected parameter range yields acceptable surface finish and minimal tool wear [11, 13].

## 3 Results and Discussion

### 3.1 Power Consumption

The power demand of machine tools can be broken down into three distinct groups: constant, variable, and cutting power. Machine tools serve a variety of applications and have a wide range of capabilities. Auxiliary equipment that uses electricity at a set pace regardless of material processing inputs is responsible for the "constant" power requirement. Operator-controlled machine tool components account for "variable" power consumption. Together, the constant and variable power demands create the machine tool's "tare" power demand, which is the lowest power required for a certain set of process parameters, whether material is cut [42]. The material type, material removal rate, cutting tool, and other factors influence the cutting power consumption. The variations in milling power with different Vc and fr values offer insightful information about the machining process [12].

According to the experimental data, under all cutting strategies, milling power generally rises with higher fr and Vc. Figure 4a, b and c presents power consumption with distinct speed–feed combinations under different cooling conditions. When the environment is dry, the power rises, as Vc and fr rise as well. At a Vc of 60 m/min, power consumption increases from 1122 W at a fr of 0.05 mm/rev to 1181.4 W at 0.15 mm/rev. At greater speeds, this tendency continues, and at 120 m/min and 0.15 mm/rev, power usage reaches 1232 W. The increased contact between the cutting tool and the workpiece (W/p) under dry conditions leads to higher frictional heat and adhesion at the tool chip interface, increasing cutting forces and hence power consumption [43, 44]. Higher heat loads and a corresponding demand for energy are due to this. MQL effectively minimizes tool–chip friction and cutting zone temperature by delivering a thin lubricant film directly at the cutting interface, thereby improving tribological performance and reducing power demand [44].

Under MQL, power consumption dropped significantly to 860.2 W (at 60 m/min, 0.05 mm/rev), a major reduction from the dry cutting condition. This improvement is due to the reduction of friction at cutting interface due to lubrication thereby reducing heat generation and power consumption. The power consumption rose to 926.2 W with an increase in the feed rate in MQL conditions, but this was still lower than in dry conditions. This could be due to the presence of the lubricant in MQL, which keeps the cutting area cool and reduces friction.

When cryogenic conditions are applied to the same set of parameters, power consumption falls significantly lower than dry and MQL conditions. It dropped to 756.8 W at 60 m/min and 0.15 mm/rev. This reduction in power is attributed to better cooling performance in the cutting zone which lowers the thermal stresses and results in lower power consumption. It has been reported that cooling the cutting zone helps reduce tool wear and makes cutting easier [41].

The hybrid conditions ($CO_2$ + MQL) were found to be most effective in reducing the power consumption (646.8 W) during the machining operation (60 m/min and 0.15 mm/rev) of Nimonic 80A. This substantial reduction in power consumption is due to the positive effects of high-cooling ($CO_2$) and lubrication (MQL) occurring simultaneously. It means, lubrication is provided by MQL to minimize the friction, while the cutting zone is significantly cooled by the $CO_2$ environment. The combination of these two environments (Hybrid) makes machining more energy efficient, reduces tool wear, and leads to enhanced surface finish [32]. It is important to note that the cutting temperature was not measured directly. But its effects can be seen in power consumption and in SCE data comparison with other machining environments. This is because both things are very sensitive to the heat during the machining process which is evident from the literature [32, 45].

### 3.2 Specific Cutting Energy

Machining operations generally need high power consumption which is significantly influenced by machining parameters and environments. SCE is an important measure of machining efficiency, as it calculates the energy required to remove a unit volume of material (see the schematic of the cutting process in Fig. 5a and b) [46].

In the current study, the experiments were conducted with varying feed rates (0.05–0.15 mm/rev) and cutting speeds (60–120 m/min) in all machining environments. Figure 6 shows the SCE results obtained for all machining conditions. It was observed that SCE decreased as the feed rate increased in all machining conditions.

The highest levels of SCE were found in dry cutting. For example, at cutting speed of 60 m/min, when the feed rate was increased from 0.05 to 0.15 mm/rev, it was found that SCE was reduced from 2493.33 to 875.11 J/mm$^3$. This approves that material removal efficiency improves with higher feed rates.

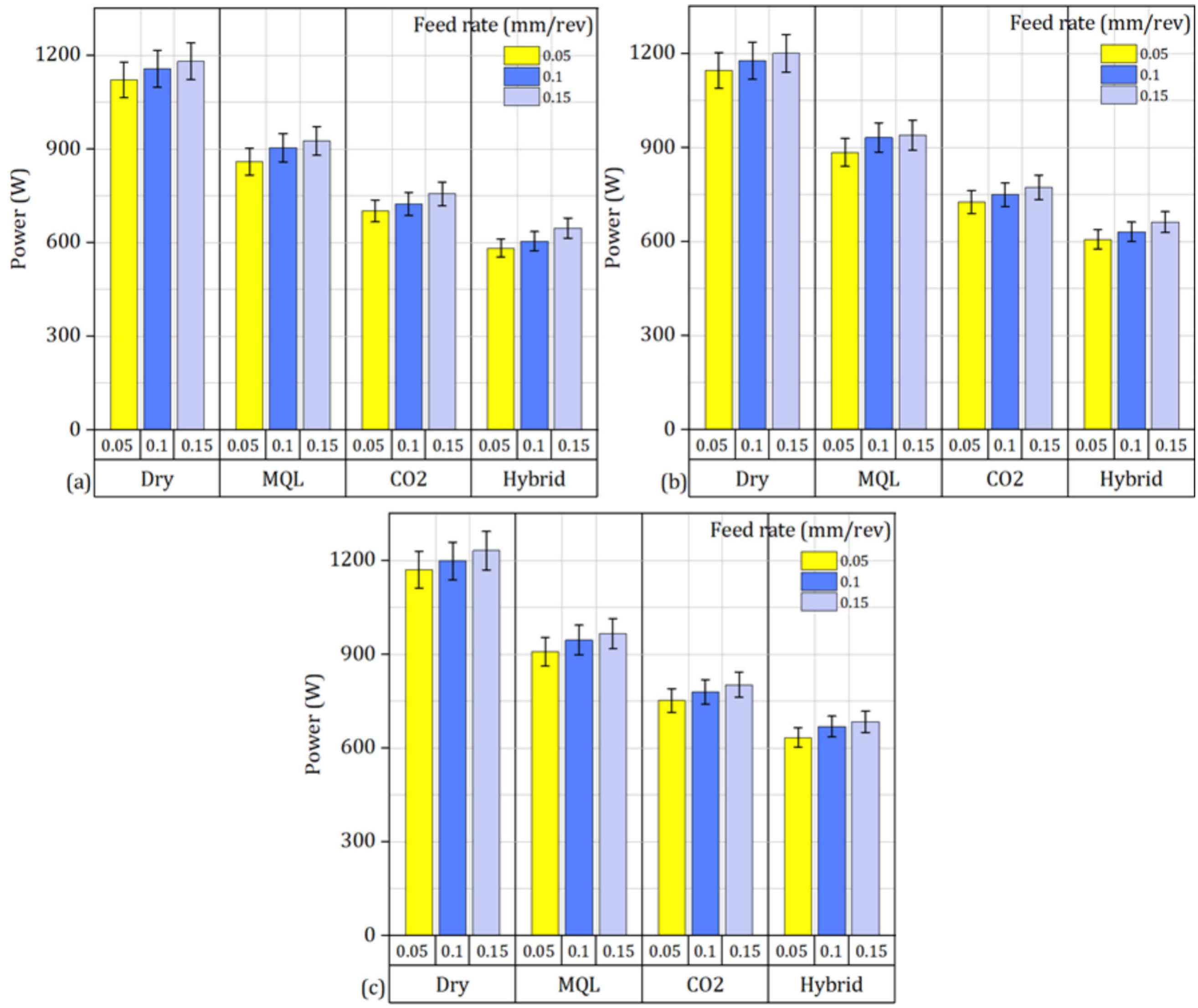


**Fig. 4** Power consumption with distinct speed–feed combinations under different cooling conditions

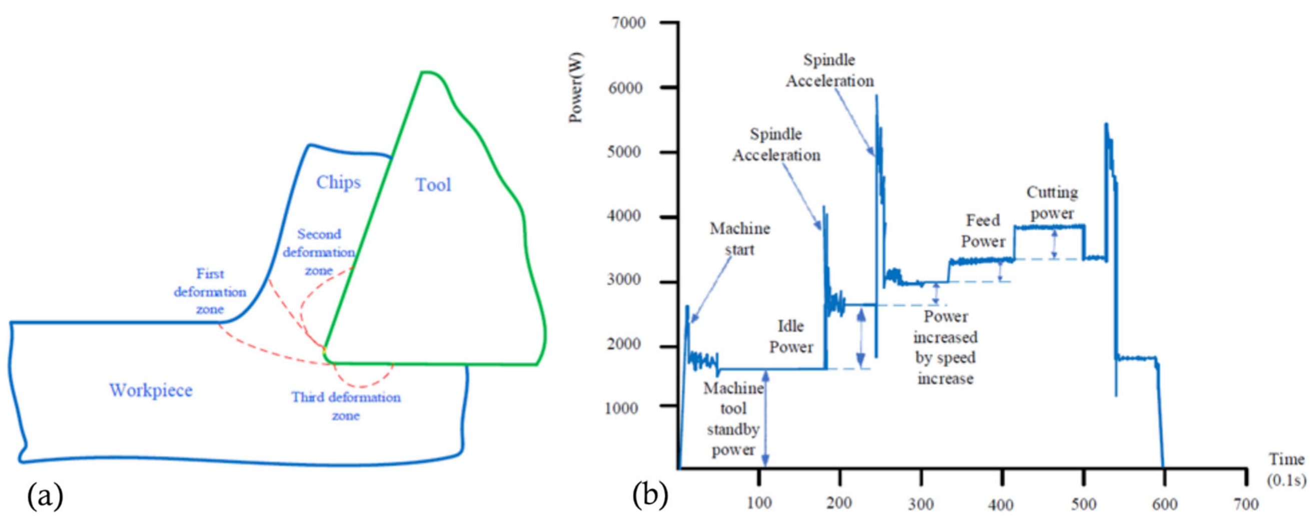


**Fig. 5** **a** Metal cutting and **b** Energy used in metal cutting [40]

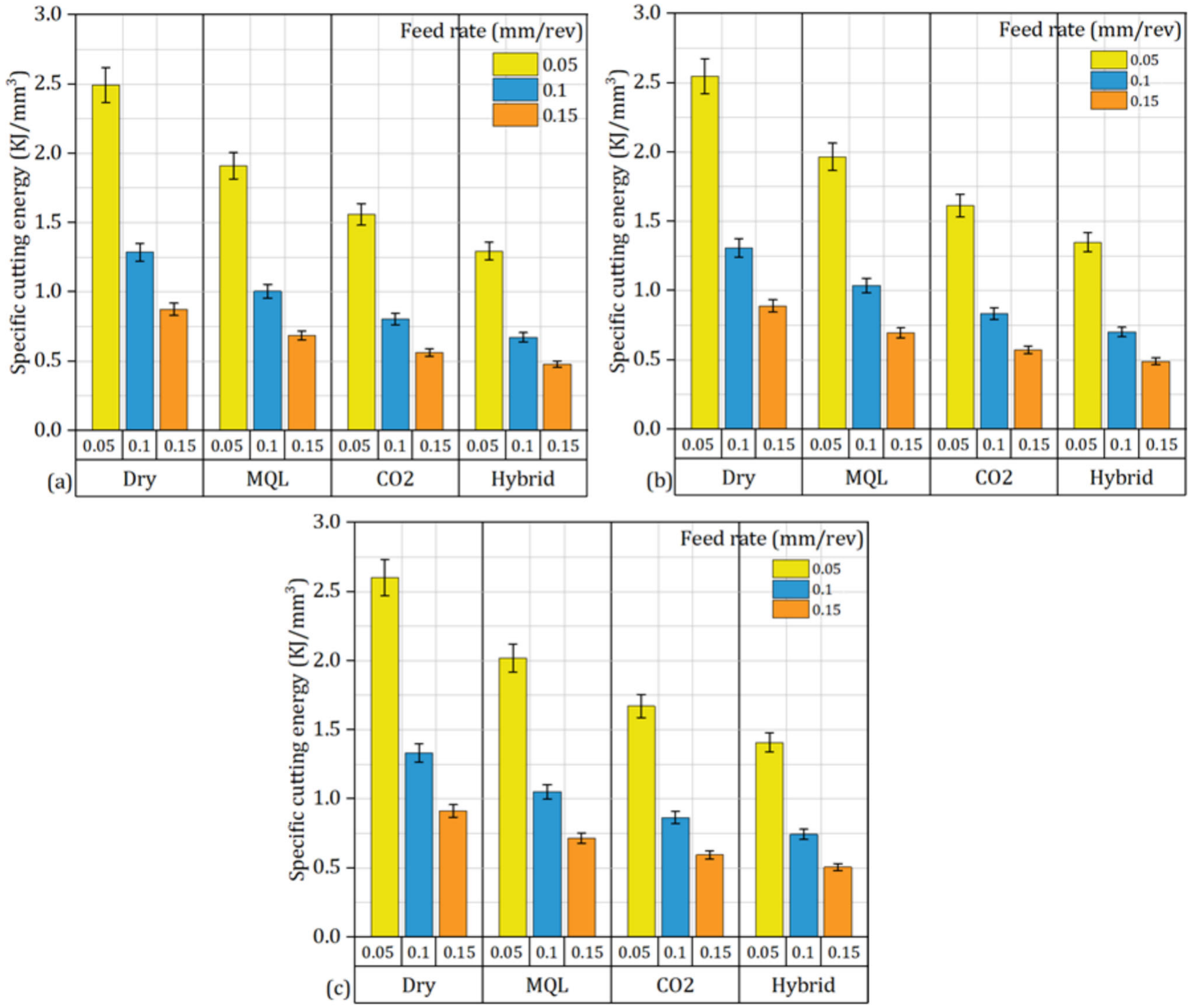


**Fig. 6** Specific cutting energy with distinct speed–feed combinations under different cooling conditions

Similar trends of decreasing SCE with increasing feed rates were observed in other machining conditions as well. However, the magnitude of SCE was different for each machining conditions. For instance, in MQL environment, at same machining parameters (60 m/min and 0.05 mm/rev), the SCE was found to be 686.07 J/mm$^3$ compared to 1911.56 J/mm$^3$ during the dry machining. This is the attribute of lubrication effect caused by the oil which not only reduces the friction but also helps in removing the heat from the cutting zone. For the same set of machining parameters, when Cryogenic ($CO_2$) condition was employed during the machining, the SCE further reduced to just 560.59 J/mm$^3$. Cryogenic $CO_2$ cooling was the most effective strategy, achieving the lowest SCE values. At 60 m/min and 0.15 mm/rev, the SCE fell to just 560.59 J/mm$^3$. This superior performance is due to its enhanced heat removal capability, which reduces the thermal load on the tool and workpiece, thereby decreasing the energy needed for cutting [39].

The hybrid (Cryo-MQL) machining environment further reduced the SCE thereby produced best results among all machining environments. The significant decrease in SCE can be attributed to the combined effects of high-cooling ($CO_2$) and lubrication (MQL) occurring at the same time. This approach involves the use of MQL to provide lubrication, thereby reducing friction, while the $CO_2$ environment significantly cools the cutting zone. The lowest value of SCE was observed while machining the Nimonic 80A in hybrid machining environment. It was found to be 479.11 J/mm$^3$ at cutting speed of 60 m/min and feed rate of 0.15 mm/rev. This further proves that by employing hybrid C/L during the machining operation enhances the machining efficiency by minimizing the SCE [10].

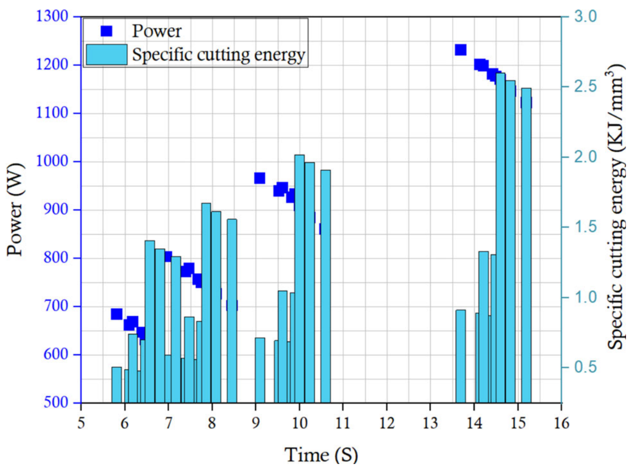


**Fig. 7** Comparison of power consumption and SCE in relation to time

### 3.3 Comparison of Power Consumption with SCE

Figure 7 shows the power consumption and specific cutting energy (SCE) for each experiment, relative to the total machining time. The machining time for each trial was found to range from 5.81 to 15.19 s. This is due to the different cutting parameters, as these parameters also influence the machining time. The range of machining time here is also because of these different set of cutting parameters especially the feed rate. Higher the feed rate lower will be the machining time. Power consumption was also found to have wide range across the experiments where peak value was observed to be 1232 W and lowest value was found to be 583 W. The lower values were because of C/L condition used for machining operations as it reduces friction and takes away the heat from cutting zone. Similarly, SCE also had a wide range across the experiments which is from 2.60 to 0.479 kJ/mm$^3$.

The important thing to note here is the different values of SCE for some experiments having similar power consumption which shows the complex nature of machining operation. This could be due to other factors like tool wear, material properties, and cutting speed which was reported to influence the efficiency of machining Nimonic 80A [11].

These findings are also in agreement with previous studies. In previous studies, it was reported that, by employing the C/L environment during machining operation, surface quality was improved, burr formation was reduced, and tool wear was decreased as well [12, 13, 32]. Furthermore, the reduction in power consumption and SCE while employing C/L environments during the machining operation will support the idea of having environmentally friendly C/L environments during machining operations of hard to cut materials like Nimonic 80A making the process efficient as well.

### 3.4 Environmental and Sustainability Considerations

The goal of sustainable machining is to minimize the overall environmental impact while maximizing process efficiency [14, 47]**.** Therefore, the impact of each C/L strategy on energy use, waste generation, and disposal was assessed qualitatively in this study [14]**.**

The main environmental benefit of dry machining is that it does not use cutting fluids, which reduces chemical waste and the need for cleaning. However, the high friction and heat in the cutting zone increase tool wear, shortening tool life. This is a concern for sustainability because replacing tools rapidly demands more materials and energy, hindering the benefits of cutting fluid and overall sustainability [14, 47, 48].

MQL provides an effective solution to the disadvantages of dry machining. Using a very small quantity of biodegradable, vegetable-based oil per minute significantly reduces lubricant consumption, emissions, and wastewater treatment. These non-toxic fluids also eliminate the health and environmental hazards associated with mineral oils [14, 44, 49].

Cryogenic $CO_2$ cooling takes a different approach. It markedly lowers temperatures and tool wear. While it requires high-pressure gas systems, the $CO_2$ is typically recovered from industrial exhaust, making the process near carbon neutral. Its main environmental advantage is that the $CO_2$ sublimates, leaving no liquid residue and eliminating all coolant disposal requirements [10, 32, 50].

Cryogenic $CO_2$ cooling uses a different approach. It significantly reduces temperatures and tool wear. Although high-pressure gas systems are required, the $CO_2$ is usually recovered from industrial exhaust, which makes the process almost carbon neutral. The main environmental advantage is that the $CO_2$ evaporates, leaving no liquid residue and eliminating the need to dispose of coolant [14, 23, 49].

Overall, the present study confirms that the hybrid $CO_2$ + MQL configuration offers the most sustainable solution. By successfully integrating energy efficiency, waste minimization, and ecological compatibility, this method (which uses reclaimed $CO_2$ and eco-friendly oil) paves the way for the cleaner machining of difficult-to-cut alloys such as Nimonic 80A [23, 24, 47].

### 3.5 Machine Learning

ML is increasingly used to improve productivity and streamline the machining of nickel-based superalloys, which are challenging due to their high strength and wear resistance [40, 51]. As shown in Fig. 8, AI methods are becoming very important in modern manufacturing.

ML models, i.e., neural networks, SVM, and decision trees can use data from power measurement instruments to predict

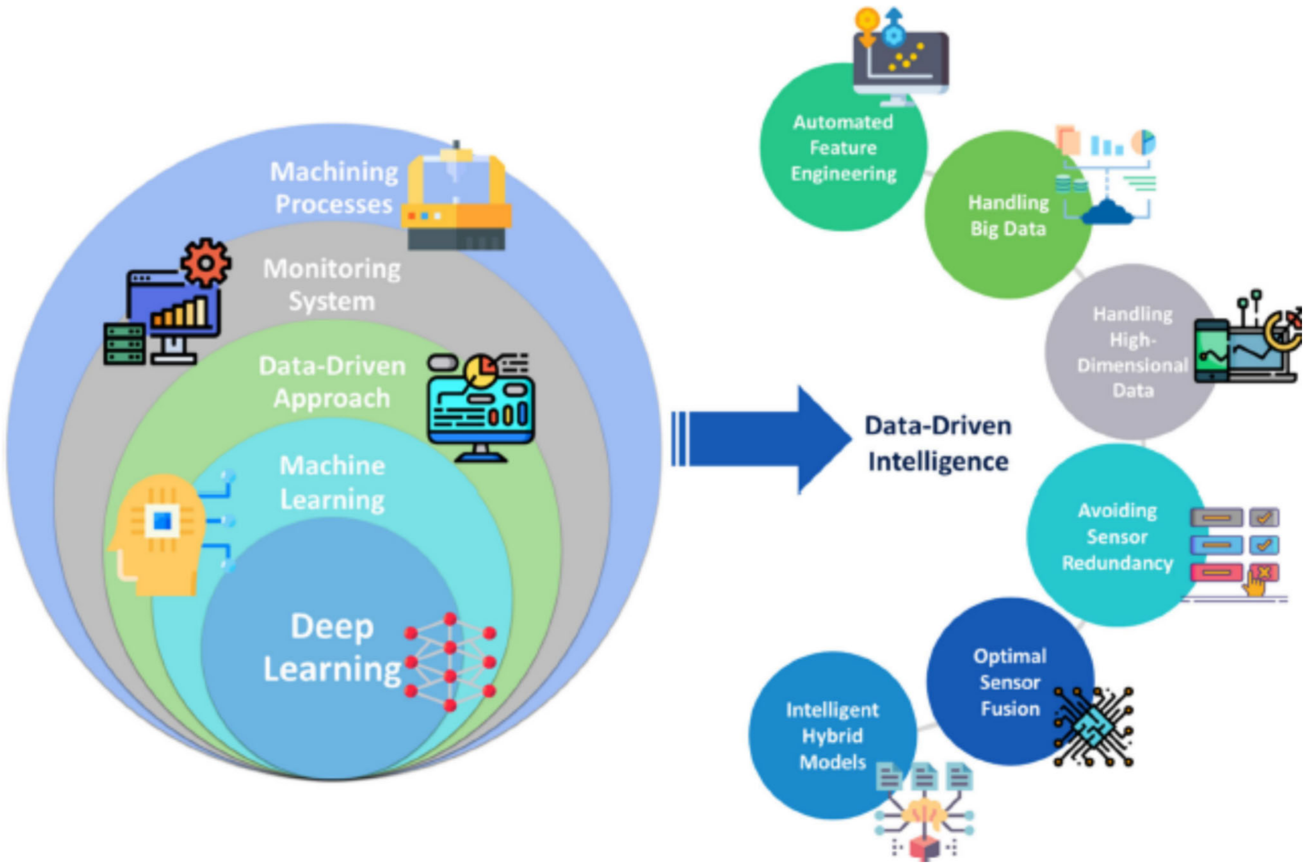


**Fig. 8** AI techniques in manufacturing [51]

outcomes like surface roughness and tool wear. This predictive power allows for real-time parameter adjustments, helping to extend tool life, reduce costs, and ensure surface quality. ML can also be used in adaptive control systems to change the conditions of machining in real time. This makes operations more accurate and less wasteful, which is better for the environment.

To further interpret our experimental trends, we developed ML models specifically to predict cutting power and specific cutting energy (SCE) under the different cooling conditions. The following subsections present this model-based prediction and analysis as an extension of our experimental discussion.

### 3.5.1 Model Development and Algorithm Selection

SVM, RF, and MLP models were selected because they represent three widely used and complementary machine-learning approaches in manufacturing applications like kernel-based, ensemble-based, and neural-network-based methods, respectively. These algorithms are known for their robust performance with limited datasets and nonlinear relationships, which makes them particularly suitable for machining-process prediction where experimental samples are often few and noise-prone [52, 53]. The selected models thus provide a balanced evaluation of three distinct learning mechanisms for energy-efficiency prediction in sustainable machining.

### 3.5.2 Support Vector Machine

SVM is a supervised learning algorithm frequently used for classification problems [53]. Its main goal is to find the best possible hyperplane (a decision boundary) that clearly separates data points from different classes in a high-dimensional space. Figure 9 illustrates this conceptual approach. In a binary classification scenario, this hyperplane is mathematically defined as (Eq. (3)):

$$W.x + b = 0 \tag{3}$$

Here, $W$ is the weight vector (orthogonal to the hyperplane), $x$ is the input feature vector, and $b$ is the bias term. The main goal of SVM is to make the margin as big as possible. The margin is the shortest distance between the hyperplane and the closest data points from each class. These points are called “support vectors.” A wider margin makes

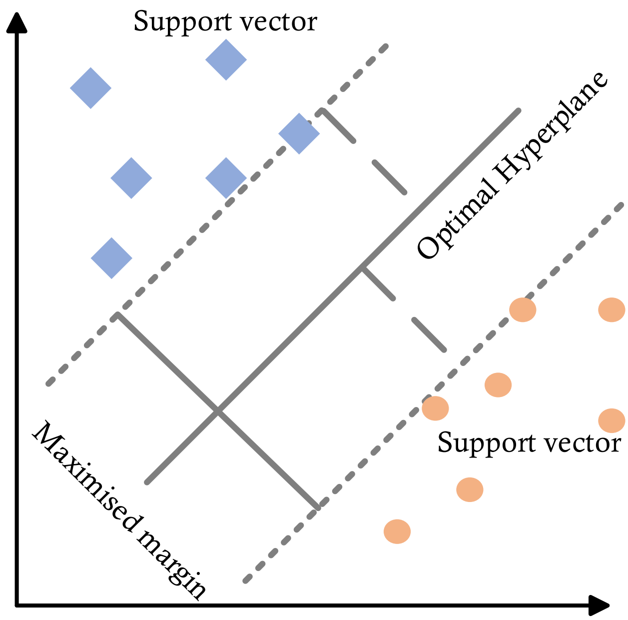


**Fig. 9** Schematic of SVM

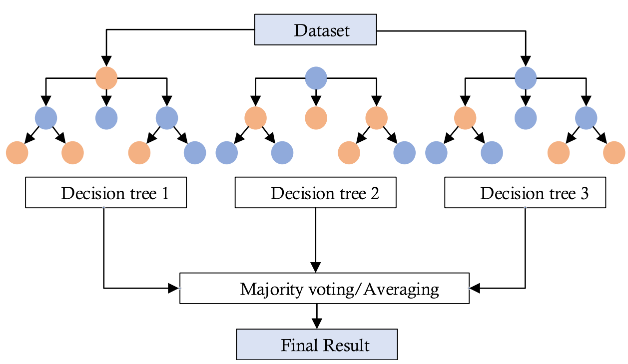


**Fig. 10** Schematic of RF

the model more robust and better at generalizing to new data. When the data are not linearly separable, SVM uses kernel functions. These functions project the input data into a higher-dimensional space. This change makes it possible to build a straight line in the new space, which makes it easier to separate classes more accurately.

### 3.5.3 Random Forest

RF employs an ensemble learning methodology, constructing multiple decision trees from diverse data subsets to improve prediction accuracy and robustness [38]. To evaluate each model's predictive performance, we calculated the correlation coefficient (R), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) as defined in Eqs. (4), (5) and

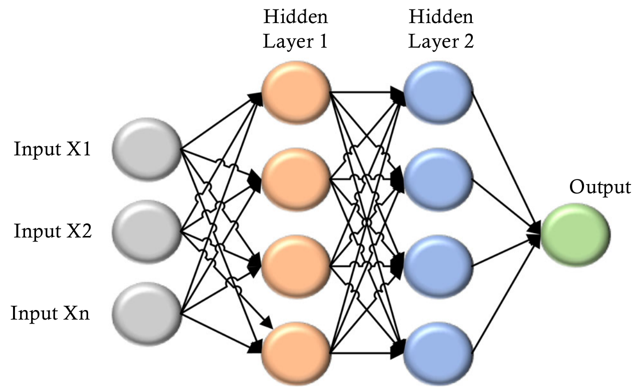


**Fig. 11** Schematic of MLP

(6) [7]:

$$R = \frac{\sum_{i=1}^{n}(y_i - \overline{y})(\widehat{y_i} - \overline{\widehat{y}})}{\sqrt{\sum_{i=1}^{n}(y_i - \overline{y})^2}\sqrt{\sum_{i=1}^{n}(\widehat{y_i} - \overline{\widehat{y}})^2}} \tag{4}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i})^2} \tag{5}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \widehat{y_i}| \tag{6}$$

where $y_i$ and $\hat{y}_i$ represent experimental and predicted values, respectively, and $\bar{y}$ and ˆ$\bar{y}$ denote their corresponding means. The R value expresses the linear correlation between predicted and experimental data, whereas the coefficient of determination ($R^2$) was also calculated to evaluate overall model-fit accuracy.

Figure 10 shows a schematic view of RF. Every tree in the RF is trained on a separate subset of the training data, obtained using bootstrapping sampling, a method where samples are randomly selected with replacement. Moreover, at every decision point, a random choice of features is used to increase system variation. This fluctuation reduces the link among trees, therefore producing a larger and more solid model. RF compiles all individual tree's outputs during the prediction stage.

This ensemble model does classification and regression tasks in different ways. For classification, the last label is given based on a "majority vote" from all the predictions (Eq. 7). For regression, the model finds the final output by taking the average of all the individual predictions (Eq. 8). This method of combining data is what really cuts down on overfitting and makes the model more accurate on new data.

$$\widehat{y} = mode(y1,\ y2,\ \ldots.yn) \tag{7}$$

$$\widehat{y} = \frac{1}{n}\sum_{i=1}^{n} y_i \tag{8}$$

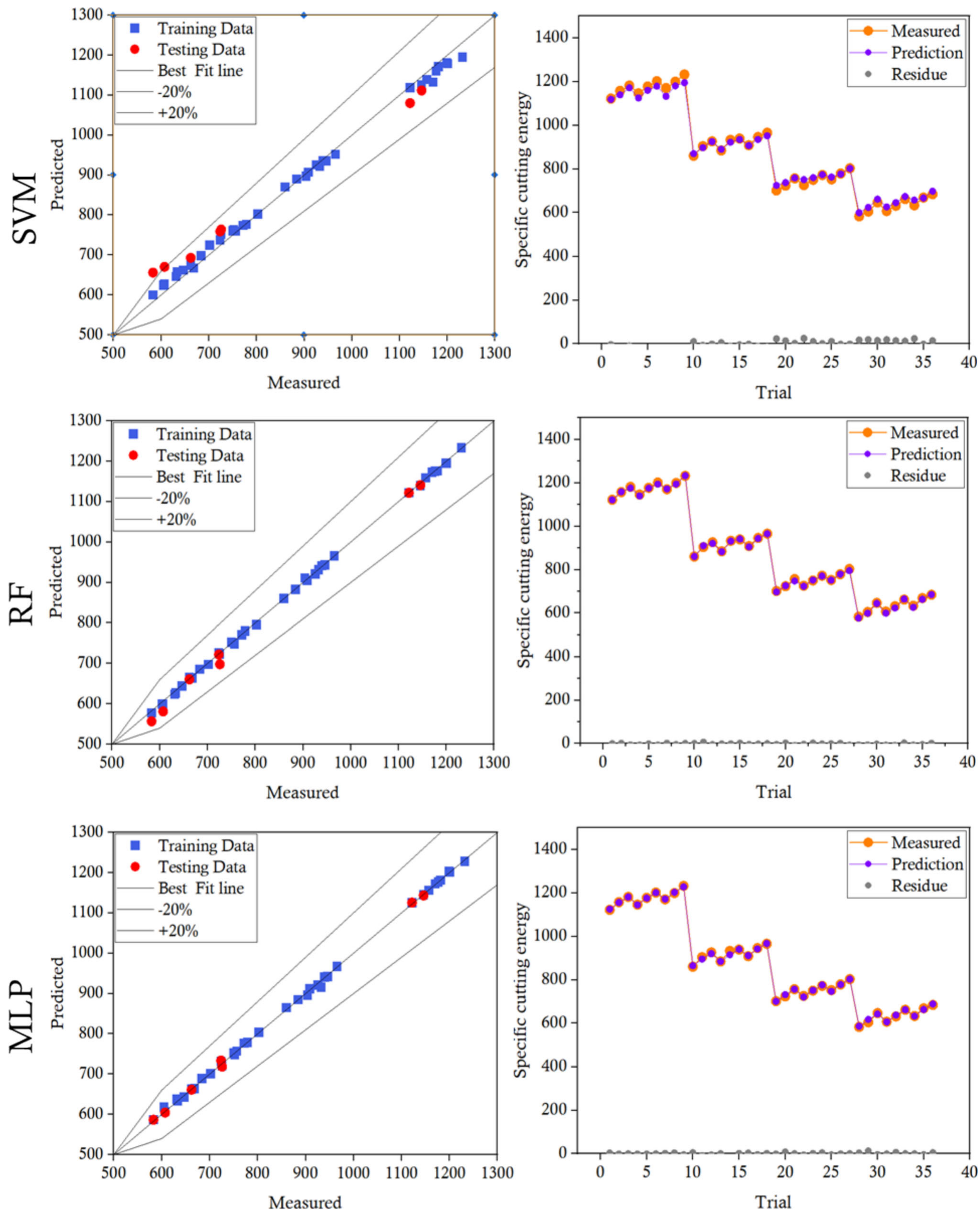


**Fig. 12** Predictive model for power consumption with distinct ML models

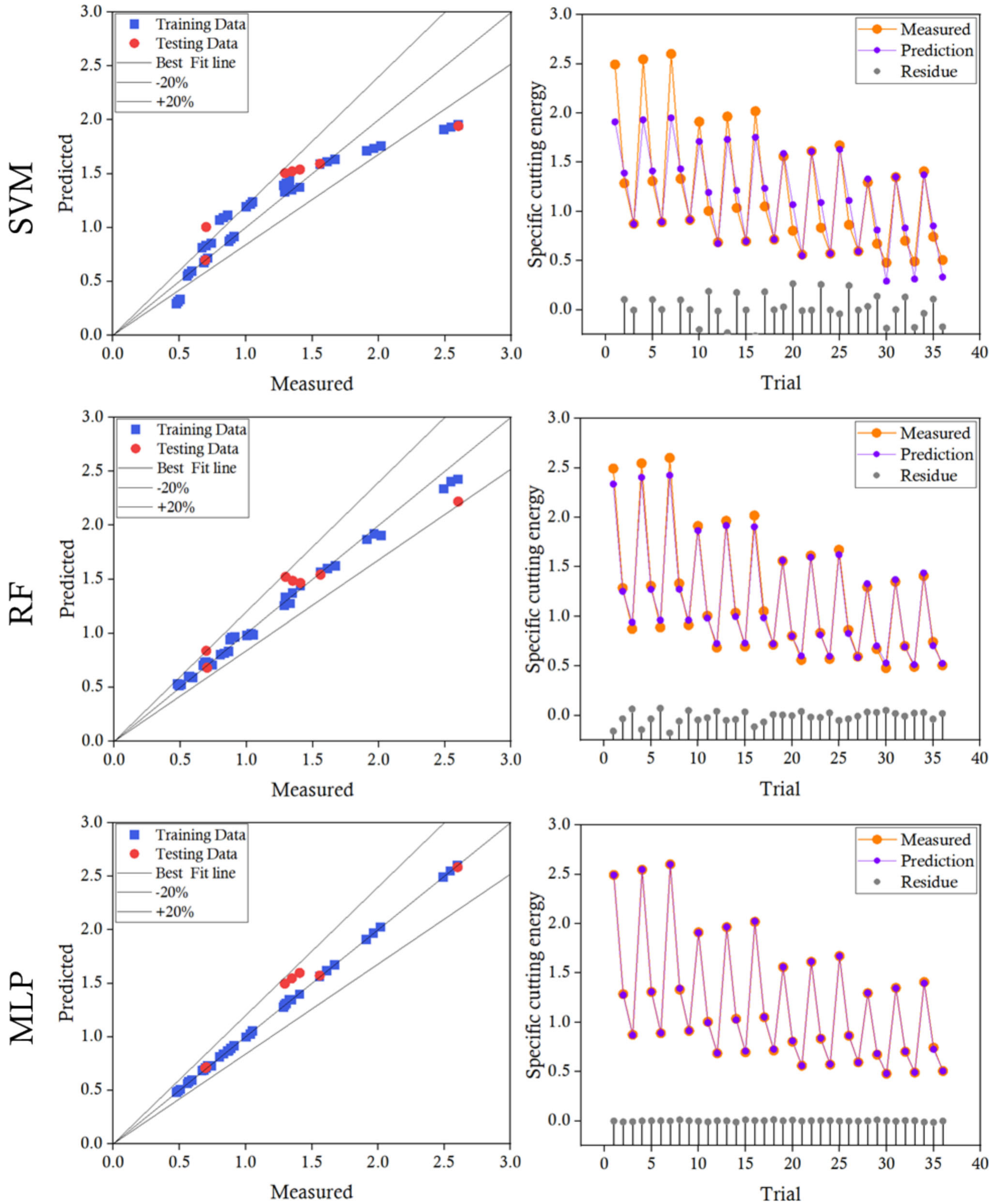


**Fig. 13** The Predictive model for SCE with distinct ML models

#### 3.5.4 Multi-Layer Perceptron (MLP)

As shown in Fig. 11, MLP neural networks have an input layer, one or more hidden layers, and an output layer [52, 54]. Through weighted connections, each neuron gets input, processes it, and sends it to the next layer. This computation involves two key steps: i) a net input calculation and ii) an activation function. The net input to any given neuron is calculated as (Eq. (9)):

$$Z_i = \sum_j w_{ij} x_j + b_i \tag{9}$$

here, $x_j$ represents the input from the previous layer, $w_{ij}$ is the weight assigned to that input, and $b_i$ is the bias term.

The weighted sum, $Z_i$, establishes the overall input to the neuron and is essential for recognizing patterns in the data. Activation functions are used to introduce nonlinearity and enable the model to learn intricate functions. A frequently used activation function is the Rectified Linear Unit (ReLU) (Eq. (10)):

$$ReLU(Z_i) = \max(0,\ Z_i) \tag{10}$$

ReLU produces an output of 0 for negative inputs and outputs $Z_i$ for positive inputs. This feature helps the model to control a wider range of inputs and speed convergence during training. MLP uses backpropagation and optimization methods to continually change weights and biases, thereby reducing a loss function that gauges the difference between predicted and actual outputs and so strengthening the network.

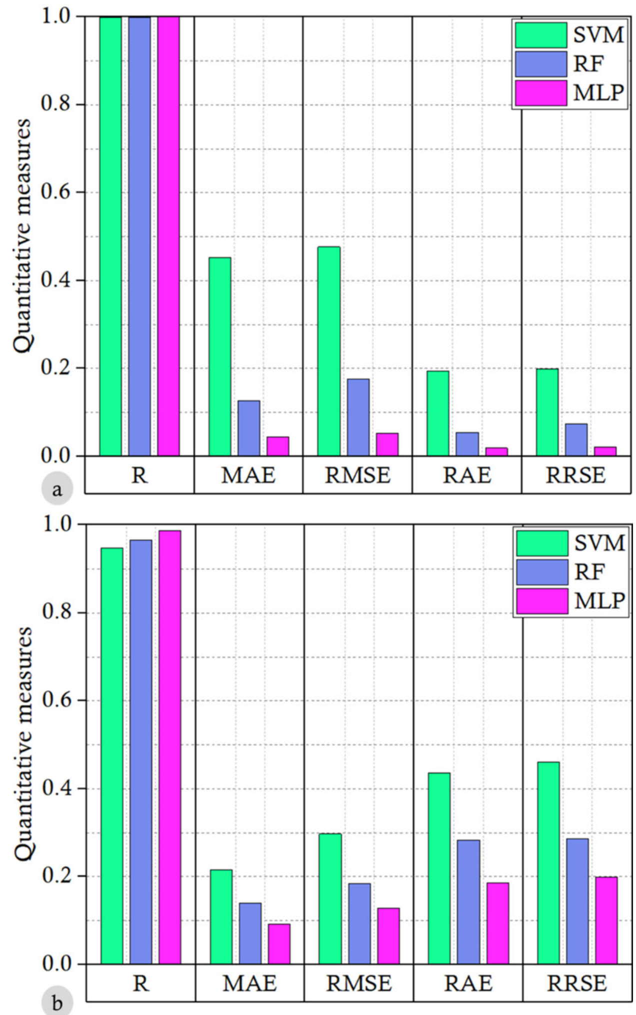


**Fig. 14** Quantitative measures for **a** power consumption and **b** SCE

### 3.6 ML Analysis

#### 3.6.1 Prediction with ML Models

For both SCE and power consumption, the MLP method provided the strongest predictive performance. Figure 12 (power consumption) and Fig. 13 (SCE) show the comparative forecasts for all machine learning techniques used. The MLP model had the best correlation between predicted and actual values and had the fewest errors on all tests. This makes it the most reliable and accurate forecasting model, which makes it a good choice for monitoring processes in real time. SVM, on the other hand, did the worst. It had higher error rates and more variability in its predictions, which means that the model had trouble figuring out how to apply the complex relationships between machining inputs and outputs. This finding aligns with the research conducted by Danish et al. [43], which similarly emphasized MLP's superior efficacy in milling. MLP's ability to find complex nonlinear patterns gives it a clear edge in accuracy when making predictions, which makes it an essential tool for getting the most out of energy use in machining.

#### 3.6.2 Quantitative Measures

In present paper, we evaluated the model performance using R, RMSE, MAE, RAE, and RRSE. The quantitative findings for power consumption and SCE are illustrated in Fig. 14 a and b.

The MLP model demonstrated superior performance across the board. For power prediction, it achieved the highest correlation (R = 0.9996) and the lowest errors (i.e., MAE = 0.0443, RMSE = 0.0527, RAE = 0.0190, and RRSE = 0.0221). It also led in SCE prediction, with the highest R (0.9873) and lowest error metrics (i.e., MAE = 0.0917 and RMSE = 0.1284).

The RF model was the clear runner-up. It was relatively inaccurate in power prediction compared to MLP (i.e., R = 0.9991, MAE = 0.4521 and RAE = 0.1939) and only

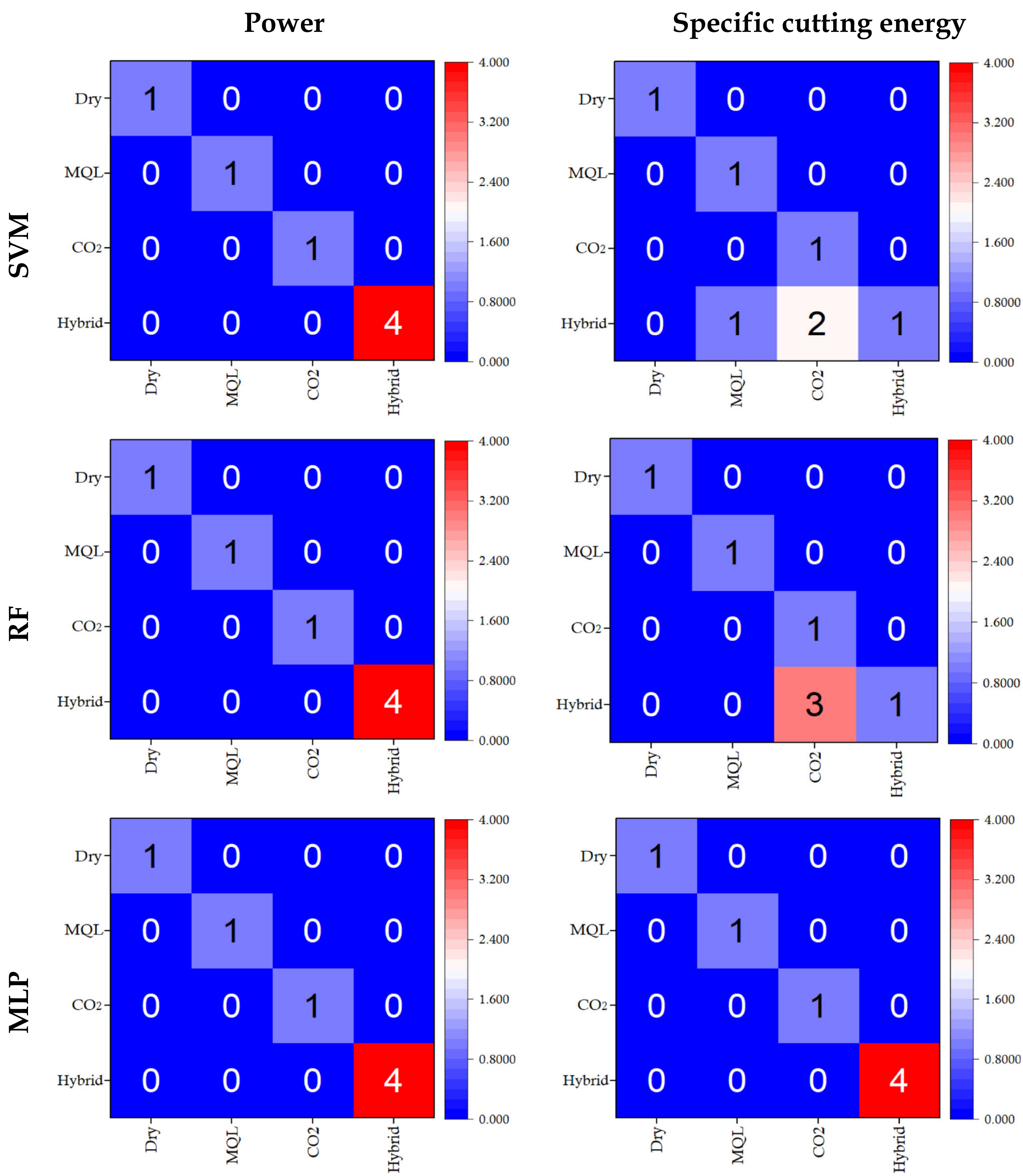


**Fig. 15** Confusion matrix under distinct ML algorithms for power and SCE for testing

**Table 4** Quantitative analysis for power

| Class | SVM | | | RF | | | MLP | | |
|---|---|---|---|---|---|---|---|---|---|
| | Precision | Recall | F-Measure | Precision | Recall | F-Measure | Precision | Recall | F-Measure |
| Dry | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| MQL | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| $CO_2$ | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Hybrid | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |

**Table 5** Quantitative analysis for SCE

| Class | SVM | | | RF | | | MLP | | |
|---|---|---|---|---|---|---|---|---|---|
| | Precision | Recall | F-Measure | Precision | Precision | Recall | F-Measure | Recall | Precision |
| Dry | 1 | 1 | 1 | 0.5 | 1 | 0.667 | 1 | 1 | 1 |
| MQL | 0.5 | 1 | 0.667 | 0 | 0 | 0 | 1 | 1 | 1 |
| $CO_2$ | 0.333 | 1 | 0.5 | 0 | 0 | 0 | 1 | 1 | 1 |
| Hybrid | 1 | 0.25 | 0.4 | 1 | 0.25 | 0.4 | 1 | 1 | 1 |

moderately successful in predicting SCE (i.e., R = 0.9665 and MAE = 0.1398).

The SVM model was consistently the least precise. For power prediction, it had high error values (i.e., MAE = 1.2646 and RMSE = 1.7598), and for SCE, it had the lowest predictive accuracy (i.e., R = 0.948, MAE = 0.2159 and RAE = 0.4368), indicating the most variation.

In short, the results consistently show that MLP surpasses SVM and RF for forecasting both power and SCE. The MLP's combination of the highest correlation coefficients and the lowest error percentages confirms it has the superior predictive accuracy with the least divergence from the observed values.

### 3.6.3 Confusion Matrix

In the study, we used three ML algorithms such as VM, RF, and MLP to predict power consumption and SCE, training each on our dataset and verifying them against a test set. To compare how well they classified things, we used confusion matrices (refer to Fig. 15) and standard metrics like Precision, Recall, and F-Measure [55].

The analysis for power consumption (refer to Table 4) was straightforward: All three models (i.e., SVM, RF and MLP) achieved perfect scores of 1.0 for Precision, Recall, and F-Measure across all classes. This indicates that all three algorithms were equally and fully effective at handling the power classification task.

The SCE analysis (refer to Table 5), however, revealed significant performance differences.

The MLP model was the clear top performer. It was the only model to maintain perfect 1.0 scores for Precision, Recall, and F-Measure across all four C/L classes (Dry, MQL, $CO_2$, and Hybrid).

The SVM model's performance was inconsistent. While it achieved a perfect F-Measure (1.0) for the Dry class, its precision dropped significantly for MQL (0.5) and $CO_2$ (0.333), and its recall collapsed in the hybrid class (0.25), resulting in a low F-Measure of 0.4.

The RF model was the least effective. Although it performed adequately for the Dry class (F-Measure 0.667), it failed completely for MQL and $CO_2$ (0 precision, 0 recall) and only matched the SVM's poor performance in the hybrid class (F-Measure 0.4).

These quantitative findings confirm that MLP surpassed both SVM and RF, establishing it as the most robust model for this task. This ML analysis complements our experimental results, confirming that the hybrid $CO_2$ + MQL strategy and the MLP model together provide the highest efficiency and predictive accuracy. This not only validates our experimental data but also demonstrates that the trained ML models can reliably predict machining responses for new parameter combinations, highlighting their value as genuine decision-support tools.

## 4 Conclusions

This study examined energy consumption behavior in Nimonic 80A milling utilizing four environmentally conscious cooling/lubrication strategies, i.e., dry, MQL, $CO_2$, and hybrid $CO_2$ + MQL, employing machine learning for predictive analysis.

The findings of the study confirm that the C/L strategy has a strong effect on energy consumption. Dry machining was the least efficient because it always used the most power and SCE because of friction and heat. MQL made a big difference over dry conditions by adding lubrication to the interface. Cryogenic $CO_2$ cooling was even better because it lowered the cutting zone temperature so much that it made energy use even more efficient than MQL.

However, the hybrid $CO_2$ + MQL strategy turned out to be the most energy-efficient. This synergistic approach, which improves both cooling and lubrication, led to the biggest drops in power use and SCE. These energy savings are in line with earlier studies that found better surface quality and tool life in similar hybrid conditions. This confirms that the method can improve both sustainability and product quality.

These energy responses were correctly predicted by the machine learning models (SVM, RF, and MLP). The MLP model was the best at making predictions, with higher correlation coefficients and lower error rates than RF and SVM. This shows that MLP is very good at finding complicated, nonlinear connections in the machining data.

This work is new because it directly and quantitatively compares these four C/L strategies, which was confirmed by predictive ML. The hybrid $CO_2$ + MQL configuration is the best way to cut down on energy use, and the MLP model ($R = 0.9996$, $RMSE = 0.162$) is the best way at making predictions. This combined method creates a strong, data-driven base for improving the sustainable machining of superalloys that are hard to cut.

Future efforts should focus on integrating comprehensive thermal and surface integrity assessments to develop a more comprehensive sustainability framework. An important step forward would be to use advanced deep learning architectures for adaptive optimization.

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