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# Integrated machine learning and PSO framework for optimization of grinding forces in advanced manufacturing

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In modern precision machining, optimization of the grinding process is vital to improve product quality, surface integrity, and machining efficiency. This research puts forward a data-driven solution that uses a combination of machine learning and Particle Swarm Optimization (PSO) to predict and minimize grinding forces in external cylindrical grinding processes. Experiments were conducted on EN31 steel with varying machining parameters depth of cut (DOC), feed rate (FR), work speed (WRS), wheel speed (WHS) and four coolant conditions: dry, flooded, MQL with HP KOOLKUT40, and MQL with HP SYNTHCOOL100. Three machine learning algorithms XGBoost, Multilayer Perceptron (MLP), and Support Vector Regression (SVR) were trained on a dataset of 115 experiments and validated with Mean Squared Error (MSE) and $R^2$. XGBoost worked best among the rest, particularly for shoulder force prediction, with an MSE of 0.0373 and an $R^2$ of 0.9324. This better model was combined with PSO to determine the best grinding parameters that had minimum total force. The PSO gave a minimum predicted force of 4.22 N with XGBoost, affirming its stability. Further, cooling condition analysis showed that MQL with HP SYNTHCOOL100 provided the most effective force reduction. In general, the investigation proves effective in demonstrating the suitability of integrating metaheuristic optimization and predictive modeling for intelligent process control in grinding.

KEYWORDS

**grinding forces, machine learning, XGBoost, PSO, cooling conditions, smart manufacturing, optimization**

## 1 Introduction

Maintaining high-quality standards of mechanical products is an essential requirement of current manufacturing due to its pivotal impact on product performance, operating reliability, and lifespan durability (Prakash et al., 2025). Therefore, precise prediction of critical quality characteristics has become important in sustaining competitiveness and conforming to strict industry norms. Production systems are generally classified into intermittent and continuous types, with mass production under continuous systems allowing automation and uniform machine settings for high-volume production, and job shop production under intermittent systems providing customized, small-batch

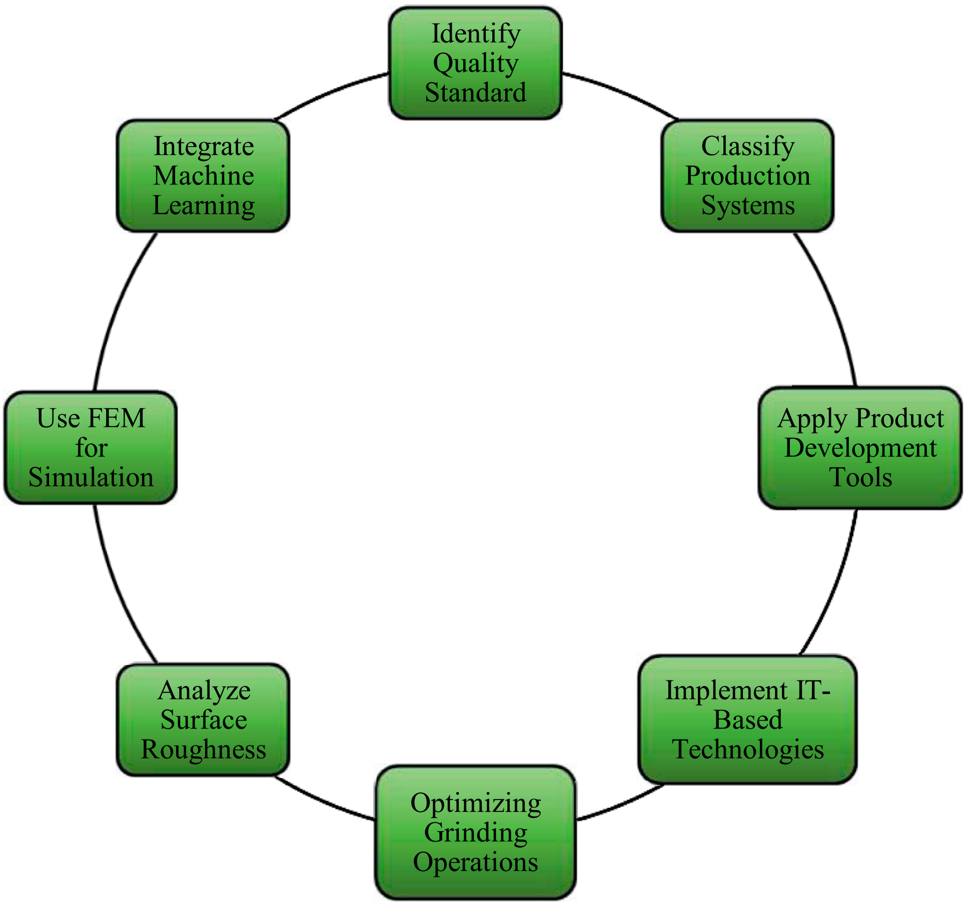


FIGURE 1
Manufacturing process and quality control.

manufacturing involving frequent setup changes. The cycle of product development encompasses activities including design, simulation, and process planning, taking advantage of sophisticated tools such as Design of Experiments (DOE), Finite Element Analysis (FEA), Design for Manufacturing (DFM), and Design for Assembly (DFA) and is supported increasingly by IT-based technologies such as Product Data Management (PDM) and Product Lifecycle Management (PLM) in compliance with Industry 4.0 guidelines (Rubi et al., 2024). Among different machining operations, grinding is a very accurate abrasive process, commonly employed in finishing manufacturing operations for creating smooth and precise surfaces. Grinding is especially ideal for machining hardened materials, with high precision and efficiency, but its optimization is difficult because of the nonlinear and complex nature of parameters like material removal rate, feed rate, wheel speed, and depth of cut (Kim et al., 2024). Grinding is also important in high-precision sectors such as aerospace, automotive, and defense, and is used on hard-to-machine materials such as glass ceramics. Surface roughness, an important quality characteristic influencing fatigue resistance, corrosion, and aesthetics, is determined by process parameters as well as external influences such as material properties, cooling conditions, and tool wear (Charde et al., 2025). To meet this, researchers have proposed predictive models and investigated sustainable grinding techniques, such as cryogenics, hybrid lubrication, and force-based data-driven roughness prediction (Charde et al., 2020). Further, surface integrity, dimensional accuracy, and tool life in subtractive manufacturing require greater understanding of cutting mechanics. The Finite Element Method (FEM) has turned out to be an advanced simulation tool in this area, supporting research into tool wear, residual stresses, and chip formation dynamics using different mesh-based methods. Though valuable for research, FEM's application in real-time use within manufacturing environments is restricted due to computationally intensive requirements, particularly in 3D simulations, although simplified 2D models offer some alternatives (Reeber et al., 2024). To counter the intricacies involved in optimizing such complex machining operations, current studies have increasingly relied on advanced computational methods. Specifically, the blend of machine learning and data-driven modeling has proven to be an exciting path for improving grinding efficiency and predictive performance. Figure 1 depicts a cyclical model that captures the major elements of manufacturing process and quality control. The cycle starts with the determination of quality standards and moves on to categorizing production systems, utilizing product development tools, and the adoption of IT-based technologies. It goes on to refine grinding processes, study surface roughness, FEM simulation of processes,

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and finally incorporates machine learning for increased efficiency and accuracy. This feedback mechanism focuses on continuous manufacturing improvement through data-driven and technology-infused strategies. Table 1 describes the methodology adopted by different authors and their outcomes.

Grinding is one of the most essential manufacturing processes in today's industry, appreciated for its potential to generate high-precision surfaces as well as increase productivity. Nevertheless, optimizing grinding parameters is a challenging task because nonlinear dynamics are involved. To solve this, an ML-based data-driven system coupled with metaheuristic optimization algorithms was suggested for internal cylindrical grinding performance enhancement. This framework combines a fault detection model and a Gaussian process-based cycle time estimator, resulting in considerable fault rate and cycle time reductions by 77.83% and 17.64%, respectively tested and validated using real-world experiments and expert opinions (Charde et al., 2020). Likewise, machine learning models like LightGBM, Random Forest, and Gradient Boosting have been used for surface roughness prediction based on critical parameters such as depth of cut, feed rate, work speed, and wheel speed. LightGBM performed best, with small error values, which proves the importance of predictive modeling in enhancing surface finish quality (Reeber et al., 2024).

Beyond grinding, there have been various studies investigating ML applications in various machining conditions. In orthogonal cutting of AZ91 magnesium alloy using MQL assistance, for instance, there have been machine learning models such as XGBoost, Decision Tree, and Random Forest applied to predict machinability. XGBoost proved to be the highest accuracy, performing better than other models in reducing MSE and MAE (Bukhari et al., 2025). In a different study, physics-informed ensemble learning strategy combining finite element simulations and machine learning models such as AdaBoost and SVR was employed for cutting temperature and force prediction during machining IN625 superalloy. AdaBoost and SVR attained the maximum accuracy for predicting temperatures and forces, respectively, with negligible validation errors (Karthik and Rao, 2025). Similarly, XGBoost also emerged as the best model in predicting mechanical characteristics of ultrathin niobium strips as compared to RF, MLP, and GBDT models at large in generalization performance (Wang et al., 2024). Regarding green manufacturing, XGBoost has also been utilized to predict and reduce carbon footprints in a three-axis mill machine with backup from SHAP analysis that reflected spindle speed to be the determining factor (Mishra et al., 2024). Finally, for cutting force prediction in thin-walled milling, a new framework integrating time-series analysis, the Imperialist Competitive Algorithm, and Multi-View Embedding was proposed, which showed high predictive accuracy with errors less than 17% even under unstable cutting conditions (Pour and Fallah, 2024). A recent large scale bibliometric analysis, highlighting the effect of artificial intelligence in advanced manufacturing through AI-enabled predictive maintenance and monitoring; 20% reductions in energy use and accuracy/stability improvements in machining (Kaur et al., 2025). In welding, while traditional evolution algorithms have typical been the go-to optimizations, with the introduction of reinforcement learning based optimization frameworks, faster bead geometries have been obtained resulting in significantly fewer experiments, total cost, waste and emissions when optimizing welds (Ma et al., 2024).

By employing ensemble machine learning models with techniques of statistical method and interpretability in the CNC machining of marble produces extremely accurate predictions ($R^2 > 0.98$), while identifying the primary components to energy efficient machining; that is; removal rate of material and machining strategy (Sariişik and Öğütlü, 2025). The hard turning of tool steels demonstrated substantial heat treatment impacting performance on machinability, generating significant improvements in surface qualities, tool life, and power consumptions in addition to displaying high potential applicability to industrial needs (Tlija et al., 2025).

These studies often focus on a single parameter at a time when modelling their predictive power, such as determining surface finish based solely on surface roughing parameters or measuring tool wear based solely on data related to tool-wear measurements. In addition, many existing models use a conventional machine learning approach and do not support a single framework that can manage the dynamic non-linearities of grinding systems in real-time. In contrast, the proposed architecture uses both hybrid learning and metaheuristic techniques in order to be adaptable for high-precision automated control on the production floor. Existing limitations in these existing approaches highlight the importance of a more complete, robust and production-ready optimisation framework.

The rest of the paper is organized as in Section II there is a discussion about the material used and the setting up of the experimental setup, Section III discusses about the methodology where process from data collection and description to the optimization process is discussed in detail. Moving further in the paper Section IV discusses about the Results obtained from the methodology and Section V is the conclusion of the paper.

# 2 Material and experimental setup

## 2.1 Workpiece material and specifications

The base materials for testing were made of the material known as EN 31 steel with 50 HRC hardness. The chemical make-up of EN 31 steel is 1% Carbon, 0.50% Manganese, 1.40% Chromium, 0.3% Sulphur, 0.20% Silicon, and 0.025% Phosphorus. The size of the workpiece is 60 mm in length with a major diameter of 80 mm and minor diameter of 60 mm. Different machining operations, such as facing, turning, and step turning, are performed on the workpiece prior to hardening through a hot oil deep hardening process. Thermocouples are also inserted in the workpiece through Electrical Discharge Machining (EDM) for temperature measurement during the grinding processes.

## 2.2 Grinding conditions and process parameters

### 2.2.1 Control parameters

The four major parameters of the machining process determined to be in focus for this study were subsequently investigated to understand their effect on cylindrical grinding performance. The

TABLE 1 Data-driven and machine learning approaches in machining process optimization and prediction.

| Ref. No. | Material used | Model/ Algorithm used | Machining process | Performance metrics | Input parameters | Key findings | Results |
|---|---|---|---|---|---|---|---|
| Kim et al. (2024) | Internal Grind | ML + Gaussian Process + Metaheuristic Optimization | Internal Cylindrical Grinding | Fault Rate Reduction, Cycle Time Reduction | DOC, FR, WRS, WHS | Proposed a data-driven system integrating ML for fault detection and optimization using real-world data | Fault rate ↓ by 77.83%, Cycle time ↓ by 17.64% |
| Reeber et al. (2024) | - | Random Forest, Gradient Boosting, LightGBM | Grinding | MSE, MAE, RMSE, $R^2$ | DOC, FR, WRS, WHS | LightGBM performed best in surface roughness prediction; Gradient Boosting had the highest error | LightGBM: MSE 0.0047, MAE 0.064, RMSE 0.09, $R^2 \approx -0.02$ |
| Bukhari et al. (2025) | AZ91 magnesium alloy | Decision Tree, Bayesian Opt., RF, XGBoost | Orthogonal Cutting (MQL) | MSE, MAE, $R^2$ | Feed, Cutting Speed, MQL Flow Rate | XGBoost showed superior predictive accuracy; rare literature in AZ91 under MQL | XGBoost: MSE ↓ 34.1%, MAE ↓ 17.1% vs. Decision Tree; MSE ↓ 19.8% vs. RF |
| Karthik and Rao (2025) | IN625 superalloy | AdaBoost, SVR, RF, GPR, FEM-based Data Augmentation | Milling/Turning (General) | Accuracy (%), Error (%) | FE Simulations, Cutting Parameters | AdaBoost best for temperature; SVR best for cutting force; ML models validated with experimental data | AdaBoost: 99.89% acc. temp.; SVR: 100% acc. force; Validation error: 4% temp., 7% force |
| Wang et al. (2024) | Ultrathin Niobium Strips | XGBoost, RF, MLP, GBDT | Rolling | $R^2$, MAE, RMSE, MAPE | Strip Thickness, Microstructure Features | XGBoost achieved highest $R^2$ and lowest error; effective for predicting mechanical properties | $R^2$: 0.944 (TS), 0.964 (YS); Lowest MAE, RMSE, MAPE across models |
| Mishra et al. (2024) | - (Carbon analysis) | XGBoost, SHAP | 3-Axis Milling | RMSE, MAE, $R^2$ | Cutting Params, Flowmeter Rate | XGBoost best for emission prediction; SHAP identified spindle speed as dominant factor | RMSE: 0.0007129, MAE: 0.0004476, $R^2$: 1 |
| Pour and Fallah (2024) | Flexible Thin-Walled Workpiece | Imperialist Competitive Algorithm + MVE | Milling (Force Prediction) | Peak-to-Peak Error (%) | Cutting Parameters, Modal Characteristics | Rapid cutting force prediction using dynamic state-space and time series analysis | Force prediction error: <8% (stable), <17% (unstable) |
| Kaur et al. (2025) | Various machining materials (182 studies across machining, manufacturing, and prognostics) | AI, ML, DL; clustering using VOSviewer; algorithms include predictive models, neural networks, optimization algorithms | Machining processes; predictive maintenance; monitoring; digital twins; sustainable manufacturing | Efficiency, accuracy, sustainability; energy consumption; tool wear prediction; process stability | Keywords-derived clusters: sensing, prognostics, sustainability, optimization, neural networks, tool wear, CNC, digital twins | AI/ML/DL significantly enhance predictive maintenance, real-time monitoring, energy optimization (up to 20% energy reduction); improve tool wear prediction and machining accuracy | Identified 8 thematic clusters; major gaps include data quality, adaptability, and system integration; roadmap proposed for scalable intelligent machining |

(Continued on following page)

TABLE 1 (*Continued*) Data-driven and machine learning approaches in machining process optimization and prediction.

| Ref. No. | Material used | Model/ Algorithm used | Machining process | Performance metrics | Input parameters | Key findings | Results |
|---|---|---|---|---|---|---|---|
| Ma et al. (2024) | Welding samples (material not specified; welding bead geometry studied) | Machine Learning model for bead geometry prediction; Reinforcement Learning – SPO (Stochastic Policy Optimization); Genetic Algorithm (GA) for benchmarking | Welding optimization; WPS development | Penetration depth, bead area, material deposition, computational time, prediction error | Process parameters affecting bead geometry; constraints for two optimization tasks (setpoint-based and setpoint-free) | ML model correlates parameters to bead geometry; SPO RL algorithm outperforms GA in accuracy and computational efficiency; reduces number of physical welding experiments | Setpoint optimization: solved in 8 min, MPAE = 2.48% (vs. GA: 42 min, 3.42%). No-setpoint optimization: 30 s vs. GA's 6 min; RL reward 5.8 vs. 3.6; Reduced cost, waste, and emissions |
| Sariişik and Öğütlü (2025) | Marble | CatBoost, LightGBM, XGBoost, K-means clustering, Gradient Boosting (classification); ANOVA statistical analysis | CNC machining of marble under different toolpath strategies (external, linear, spiral) | Specific Energy (Se), Material Removal Rate (MRR), $R^2$ scores, AUC, classification accuracy, feature importance | Cutting depth, feed rate, toolpath type, cutting force, energy metrics | Significant effects of depth, feed rate, toolpath on Se; MRR strongly reduces Se; MRR most important feature (96.05% importance by XGBoost); Ensemble ML models achieved $R^2$ > 0.98; SHAP validated interpretability | CatBoost best predictor ($R^2$=0.983). Toolpath accuracy ranking: external > linear > spiral. Gradient boosting: accuracy = 0.75, highest AUC. Strong correlations ($R^2$=0.70) for Se with depth/feed; weak with MRR ($R^2$=0.16) |
| Tlija et al. (2025) | DC53 tool steel (compared with AISI D2) using Xcel CBN tool | Artificial Neural Networks (ANNs); NSGA-II (Non-Sorting Genetic Algorithm) for multi-objective optimization | Hard part turning | Tool life, surface roughness, MRR, power consumption, temperature; $R^2$; optimized trade-offs | Workpiece hardness (heat treatment), cutting speed, feed rate, depth of cut | Heat treatment is the dominant factor (e.g., 74.63% effect on tool life); ANN models accurately predict machinability ($R^2$ > 0.97); NSGA-II identifies optimal compromises | Optimized results: +92.05% tool life, +91.83% material removed, −33.33% roughness, −26.73% power consumption, −9.61% temperature; strong prediction and optimization framework |

selected parameters varied from 0.025 mm to 0.04 mm for the depth of cut and were directly proportional to the amount of material removed per pass; the rate of feed that was taken into account, especially concerning the material removal rate and surface finish; the work speed, whose variations were 100–250 rpm, and it was said to be in favour of keeping the right balance of heat generation and wear rate of the grinding wheel; similarly, the wheel speed was maintained between 948 rpm and 1186 rpm and exerted a great influence on the size of abrasive chips and the subsequent thermal effect on the workpiece. The ranges of the parameters included in this study were determined by the machining capabilities of EN31 steel and the operational limits of the AHG-60 × 300 CNC grinding machine. The allowable combinations for the experiment were selected such that they all met the safe and industrially valid parameters. The ranges of the parameter values used are also representative of those used in previous grinding research, and this allows for comparison to published results. To accomplish this, the 29-lateral Taguchi L29 orthogonal array was selected, as it allows four factors to be assessed simultaneously at various levels and, due to the L29's architecture, constrains the number of required experimental tests from hundreds to 29. By having 29 test configurations, the evaluation of parameter interactions will be statistically meaningful, and the workload will be manageable because, as indicated by the previous use of the L29 array, simultaneous measurement of force, temperature and cooling conditions produces a large volume of data in addition to the amount of time involved. In an ordered approach, the investigation established a systematic method of analysis of these parameters through the Taguchi L29 orthogonal array as the experimental design for an effective investigation of combinations of parameters by conducting 29 designed experiments. The optimization approach was based on the Smaller-the-better quality objective, aiming toward minimizing the critical output responses like temperature and surface roughness to render the grinding process much more upgraded in terms of its quality and integrity.

## 2.3 Experimental setup and measurement techniques

Face and shoulder grinding operations are carried out with the aid of the AHG-60 × 300 CNC grinding machine that can hold

TABLE 2 Specifications of face and shoulder grinding machine used.

| | |
|---|---|
| Machine type | AHG- 60 × 300 CNC<br>Maximum width of the work piece to be grind=60 mm<br>Maximum distance between centers = 300 mm |
| Manufactures Name | Parishudh Machines Pvt. Ltd |
| Capacities | Centre Height: 130 mm<br>Distance between centers: 300 mm |
| External Wheel Head | Grinding Wheel (OD x ID) = ϕ500 mm X ϕ 254 mm<br>Maximum Width: 60 mm |
| Work Head (Dead) | Spindle Motor (AC induction Motor): 7.5 Kw<br>Grinding Speed: 45 m/s<br>Spindle Speed (infinitely variable):50–650 rpm<br>Spindle motor (AC Servo Motor): 6NM |
| Infeed Slide (X-Axis) | Total stroke: 200 mm<br>Rapid Feed rate: 10 m/min<br>Feed A. C. Servo Motor: 6NM<br>Input Resolution: 0.0001 mm |
| Table (Z-Axis) | Total Stroke: 400 mm<br>Rapid feed rate: 10 m/min<br>Feed A. C. Servo motor: 6NM<br>Input Resolution: 0.001 mm |
| Tail Stock Assembly | Travel: 40 mm<br>Centre: MT 4 |
| General | Coolant Pump Motor: 1.5 KW<br>Total power requirement: 25 Kw<br>Total Weight of the machine: 4000 kg |

several features such as a 60 mm maximum workpiece width and 45 m/s grinding wheel speed as per the Table 2. Experimental testing incorporates the utilization of slip rings, thermocouples, and a brush assembly to capture and store temperature readings during grinding. These elements collaborate to allow precise monitoring and measurement of temperatures during the grinding processes of the face and shoulders.

In this experiment, we used an array of strain gauges in an assembly that was mounted between the support of the work piece and the support of the machine as shown in Figure 2 to measure the grinding force at the shoulder and the end face of a cylinder. This created the ability to obtain data in real-time during the cylinder grinding process on both radial and axial directional forces of the grinding wheel.

## 2.4 Grinding under various cooling conditions

In the dry condition, there is grinding in the absence of any coolant, and consequently, there is high temperature generation. High temperatures are liable to cause thermal damage to the workpiece in the form of tensile residual stresses and crack formation. Contrarily, in the flooded coolant condition, there is grinding through an oil-in-water emulsion or neat oil, and it is supplied to the grinding zone at low pressure. This cooling method is particularly beneficial for low-speed grinding, and it controls heat more effectively. Furthermore, in the Minimum Quantity Lubrication (MQL) condition, a small amount of lubricant, typically 100 mL/h or lower, is delivered directly to the cutting zone by an air-oil stream. This reduces the overall coolant usage but provides an acceptable surface finish with lower thermal damage. The lubricants used in this operation are HP KOOLKUT 40 and HP SYNTHCOOL 100 whose properties are described in Tables 3, 4.

## 2.5 Force measurement during grinding at face and shoulder

The forces generated in grinding are measured by a force measuring system that has been specifically designed using strain gauges, an octagonal ring, and a digital display. The system is capable of measuring both the radial and axial forces generated during grinding. The forces are detected at the workpiece extension end where strain gauges are mounted on the ring. These measured forces are subsequently digitally presented, with real-time data available for examination. The force measurement system is designed to be integrated into the grinding process in such a way as not to close the process while continuously monitoring face and shoulder grinding forces.

# 3 Methodology

## 3.1 Dataset description

The information for this study was collected from a series of experimental grinding tests conducted with four various cooling conditions: dry, flooded coolant, MQL with HP KOOLKUT, and MQL with HP SYNTHCOOL. There are a few input parameters in

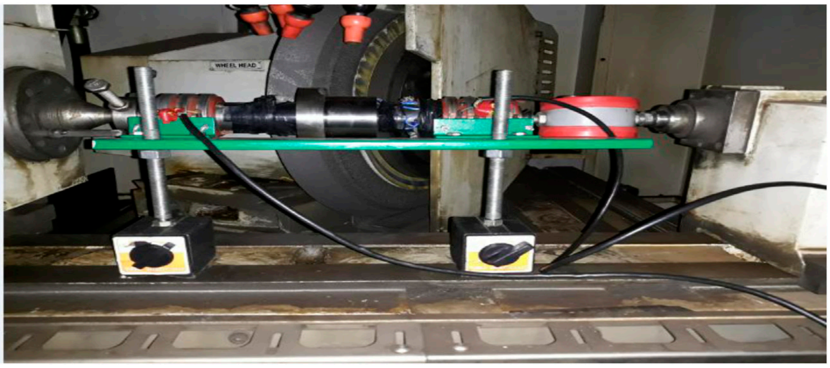

FIGURE 2
Experimental Setup for Measuring Forces in Face and shoulder Grinding Operation.

TABLE 3 Physio-chemical properties of HP KOOLKUT 40.

| S. No. | Properties | HP KOOLCUT 40 |
|---|---|---|
| 1 | Colour After Emulsification | Milky White |
| 2 | Kinematic Viscosity at 40 °C, Min, CST | 20 |
| 3 | Flash Point, COC °C, Min | 150 |
| 4 | Copper Corrosion at100 °C, Min | 1 |
| 5 | Cast Iron Corrosion Test, 20:1 Emulsion with 400 PPM Hard Water Max | 0/1–1 |

TABLE 4 Physio-chemical properties of HP SYNTHCOOL 100.

| S. No. | Properties | HP SYNTHCOOL 100 |
|---|---|---|
| 1 | Appearance | Fluorescent yellow |
| 2 | Copper Strip Corrosion 3Hr 1 at 100 °C, Max | 1 |
| 3 | 1:40 in Distilled Water | 0/1–1 |
| 4 | 1:40 in Hard Water-200 PPM | 0/1–1 |

each record, including the depth of cut (DOC), feed rate (FR), work speed (WRS), wheel speed (WHS), and the cooling condition, which is defined as a categorical variable. The measured outputs are surface roughness, temperature, and force, all of which were measured at the shoulder and face of the workpiece during grinding. The data set consists of 115 experiments each representing a unique combination of the input parameters. These combinations were grouped based on an L29 orthogonal array such that various settings of the parameters were well covered in the data set.

## 3.2 Data pre-processing

Data pre-processing followed a few steps to clean the dataset before analysis. The categorical feature, cooling condition, was one-hot encoded to transform it into numerical form that can be utilized well in machine learning models. The input features were normalized with standard scaling so that all variables are on the same scale, thus avoiding any feature from controlling the model based on magnitude differences. Missing values in the data were deleted, and any column formatting inconsistencies were resolved to preserve the integrity of the data. New features were also introduced for optimization purposes, like the calculation of the total force, i.e., the addition of forces at the face and shoulder. This total force feature was most beneficial in the following optimization models, where total grinding force reduction was one of the main goals.

## 3.3 Predictive modeling of grinding forces

Machine learning was a very important part of the methodology aimed at building robust predictive models that could accurately forecast the grinding forces at the workpiece face and shoulder. The three algorithms to be used were chosen because they had demonstrated ability in regression applications and their potential to accommodate non-linear interactions among variables: Extreme Gradient Boosting (XGBoost), Multilayer Perceptron (MLP), and Support Vector Regression (SVR). XGBoost, a high-performance gradient-boosted decision tree implementation, was used because of its ability, scalability, and regularization, which assist in overcoming overfitting and generalization.

### 3.3.1 XGBoost (extreme Gradient Boosting)

XGBoost is an ensemble learning algorithm that constructs additive regression trees sequentially. To help control model complexity, the target functions have both loss terms and regularization constants. The objective function, regularization function and prediction step for XGBoost algorithm is represented by Equations 1-3.

Overall Objective Function:

$$\mathcal{L} = \sum_{i=1}^{n} l\left(y_i - \hat{y}_i^{(t)}\right) + \sum_{k=1}^{t} \Omega\left(f_k\right) \tag{1}$$

Here,

$\mathcal{L}$: total loss

$l\left(y_i - \hat{y}_i^{(t)}\right)$: training loss (e.g., Mean Squared Error)
$f_k$: individual regression tree at iteration $k$
$\hat{y}_i^{(t)}$: predicted value after $t$ trees
Regularization Term:

$$\Omega(f_k) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2 \tag{2}$$

Here,
$T$: number of leaves in the tree
$w_j$: weight of the $j$th leaf
$\gamma, \lambda$: regularization parameters
Prediction:

$$\hat{y}_i^{(t)} = \sum_{k=1}^{t} f_k(x_i) \tag{3}$$

### 3.3.2 Multilayer Perceptron (MLP)

Multilayer Perceptron's in artificial neural networks represent a series of feedforward neural network that includes the input layer, hidden layer, as well as the output layer, and is capable of learning increasingly complex nonlinear relationships by weighted sums and activation functions on various-layer transformations. The hidden layer computation is shown by Equation 4 with output layer and loss function represented by Equations 5, 6 respectively.

Hidden Layer Computation:

$$h_j = f\left(\sum_{i=1}^{n} w_{ij}^{(1)} x_i + b_j^{(1)}\right) \tag{4}$$

Output Layer:

$$\hat{y} = g\left(\sum_{j=1}^{m} w_j^{(2)} h_j + b^{(2)}\right) \tag{5}$$

Here,
$x_i$: input features (DOC, FR, WRS, WHS)
$h_j$: output of hidden node $j$
$w_{ij}^{(1)}, w_j^{(2)}$: weights of input-to-hidden and hidden-to-output layers
$b_j^{(1)}, b^{(2)}$: biases
$f(\cdot)$: activation function (e.g., ReLU or sigmoid)
$g(\cdot)$: linear activation for regression output
Loss Function (Mean Squared Error):

$$\mathcal{L}_{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 \tag{6}$$

### 3.3.3 Support Vector Regression (SVR)

Support Vector Regression (SVR) is effective in coping with highly dimensional data, model complexity as against prediction accuracy. In this way, the target values are estimated within a margin (ε) using kernel functions while ensuring the flatness of the model. SVR Optimization equation represented by Equations 7-9.

Optimization Objective:

$$\min_{w, b, \xi, \xi^\star} \frac{1}{n}\|w\|^2 + C\sum_{i=1}^{n}\left(\xi_i + \xi_i^\star\right) \tag{7}$$

Subject to:

$$y_i - \left(w^T \varnothing(x_i) + b\right) \le \varepsilon + \xi_i \tag{8}$$

$$\left(w^T \varnothing(x_i) + b\right) - y_i \le \varepsilon + \xi_i^\star; \quad \xi_i - \xi_i^\star \ge 0 \tag{9}$$

## 3.4 Model training and evaluation

All the models trained and tested on a stratified 80/20 train-test split were such that the data distribution in the underlying data was maintained in both training and test sets. This method, therefore, helped in realistic testing of models under reduced possibilities of bias. Prior to training, the input features were normalized to ensure that all features made equal contributions to the learning process, a process critical for algorithms like MLP and SVR that are sensitive to feature scaling. One-hot encoding was also applied to transform the categorical cooling condition variable to one appropriate for numerical computation.

Model performance was assessed using two common regression metrics Mean Squared Error (MSE), which measures the average squared difference between real and estimated force values, and the coefficient of determination ($R^2$ score), which measures the percentage of variance in the dependent variable that can be explained by the independent variables. These were chosen to adequately reflect both the accuracy and explanatory ability of the models. The comparative performance of the models not only gave us an understanding of their predictive capabilities but also set the stage for identifying the best model to be used for subsequent optimization. The best-performing model's output was then incorporated in a metaheuristic optimization framework to optimize the total grinding force, thus connecting predictive modeling with process improvement in an end-to-end intelligent manufacturing approach.

In order to ensure that model assessments are robust and to compensate for the drawbacks associated with only using MSE and $R^2$ as measures of performance; we also included other performance metrics in our evaluation. The MAE represents the average size of your prediction errors across all predictions and is not dependent on the presence of large outlier predictions, thus it provides a better estimate of prediction accuracy overall, on average. In addition, we have performed 5-fold cross validation to evaluate the generalization of each model to different training/test partitioning versus 1 train/test partition; therefore, allowing for greater confidence in the stability and predictive reliability of the models.

## 3.5 Optimization of grinding parameters through Particle Swarm optimization methodology

Particle swarm optimization (PSO) was deployed as a global optimization algorithm with high robustness and efficiency to reduce the overall machining grinding force. PSO derives its concept from the collective behavior in nature, especially from the behavior of bird flocks and fish schools. It works by initializing a set of possible solutions, known as particles, which iteratively search the solution space according to both individual and social experience. In this case, however, the PSO protocol was hence used to determine the best combination of grinding process parameters such as depth of cut (DOC), feed rate (FR), work speed (WRS), and wheel speed (WHS), which would give rise to least possible total force defined as the sum of the forces exerted on face and shoulder sides of the workpiece.

The process of optimization was organized over some search space characterized by machining experience with experimentally achievable limits about the minimum cut depth of 0.02–0.06 mm; a feed rate of 0.5–2.0 mm/s, a workpiece rotation speed of 50–300 rpm, and a wheel speed of 900–1,500 rpm. A population size of 20 particles was initialized, and 50 iterations were performed to ensure an adequate exploration over the multidimensional parameter space. Each particle represents a candidate solution expressed as a set of the four grinding parameters, and its fitness is evaluated by a trained machine learning model that predicts the total grinding force for that combination. The machine learning model is used in the fitness function, which was already selected in the previous predictive modeling iterations as it had a better prediction performance of force values with high accuracy.

The fitness function was used as a surrogate model, to enable quick evaluation on a number of parameters sets without having to do additional physical experimentation. In each step, particles updated their positions in the search space according to their own best-known position and the global best-known position found by the swarm, resulting in successive solution improvement towards the global optimum. This PSO-driven optimization platform delivered a viable mechanism for coupling data-driven modeling and intelligent search mechanisms to enable the creation of a smart manufacturing policy for process improvement in grinding operations. The method not only enabled the minimization of grinding forces but also presented a scalable process that could be tailored for optimization of other performance indicators like temperature or surface finish in future work.

The parameter setting for the Particle Swarm Optimization (PSO) method will be used throughout this study to provide us with a stable, reproducible basis for our work, as this is an important aspect of the overall methodology and one that is generally accepted and used in the area of machining technology. The inertia weight ($w$ = 0.7) was selected to provide a good balance between exploration (randomness) and exploitation (use of current knowledge). It is important to note that the cognitive and social learning coefficients were selected based on previous research to also assist the particles to learn from their own best experiences as well as from the global best solution, and set equal values ($c1$ = 1.5 and $c2$ = 1.5). The other two parameters, particle velocity, and position limits, were set in order to prevent any oscillatory behavior during the update process. Finally, the convergence of PSO was determined based on the following two criteria: either the improvement of the global best fitness was less than 10–6 for the last ten iterations, or the algorithm reached the maximum limit (50 iterations) and it had made no further improvements in the global best fitness since the last iteration. Using these parameters allowed for the development of a consistent, reliable method to analyse the nonlinear parameters in the grinding process.

Figure 3 depicts a robust workflow for grinding force optimization with machine learning and Particle Swarm Optimization (PSO) and model is named as MSX_PS. It starts with experimental setup and data collection, which includes measurement of forces on EN31 steel under various cooling conditions. Having pre-processed the data, machine learning models (XGBoost, MLP, SVR) are trained and tested using Mean Squared Error (MSE) and $R^2$. The model with the highest performance is utilized in PSO to find the best grinding parameters (DOC, FR, WRS, WHS) which reduce the total force and improve process efficiency.

# 4 Result and discussion

This section brings in the results for the evaluation performance of machine learning models on the Particle Swarm Optimization (PSO) process parameter tuning and a comparative view regarding different visualizations to understand the trends and efficiency of the presented methods.

## 4.1 Machine learning model evaluation

An evaluation was made of three machine learning algorithms-XGBoost, Multilayer Perceptron (Neural Network), and Support Vector Regression (SVM), to forecast grinding forces for shoulder and face operations. The models were trained and tested on an 80: 20 ratio, and performance measurement was by means of Mean Squared Error (MSE) and $R^2$ metrics.

Table 5 presents a comparison of the performance of XGBoost, Neural Networks, and SVM models in predicting grinding forces using various statistical error metrics. The predictive performance of XGBoost was significantly greater than that of both the Neural Network and SVM models. For example, the lowest MSE (0.02641), RMSE (0.1625), and MAPE (0.0698) were achieved using XGBoost, which had the highest coefficient of determination (R2 = 0.6640) among the three models. The Neural Networks and SVMs had higher values for each of these metrics, indicating a lower level of predictive accuracy and a lower level of explanatory power. These results suggest that tree-based ensemble learning provides the best modelling of grinding force behaviour.

A comparison of the performance (in terms of MSE, RMSE, MAE, MAPE, and $R^2$) of XGBoost, NeuralNet, and SVM in predicting the face grinding force can be seen in Figure 4. Overall, XGBoost performed the best and produced the lowest MSE (0.02641), RMSE (0.1625), MAE (0.1286), and MAPE (0.0698) values for predicting the face grinding force. XGBoost also produced the highest $R^2$ value of 0.6640 which shows that it has better predictive capabilities compared to both NeuralNet and SVM whose $R^2$ values are 0.6250 and 0.6395, respectively. Furthermore, the visual representations of the predictive models in Figure 4 show that the XGBoost predictive model has a much better generalization ability than both NeuralNet and SVM.

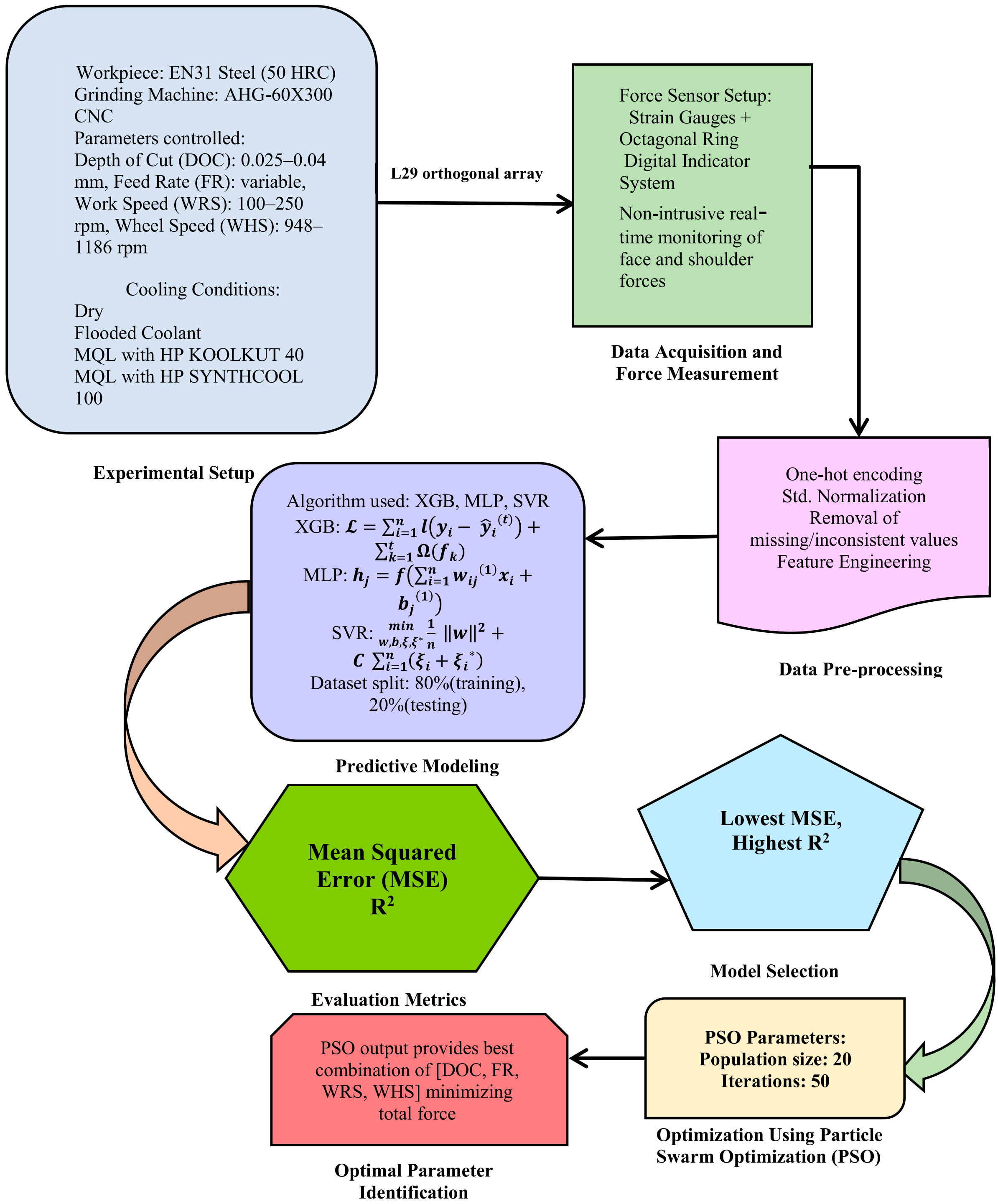


FIGURE 3
Framework for predictive modeling and optimization of grinding forces using MSX_PS model.

Table 6 provides a comparison of XGBoost, Neural Network and SVM models based on predictive performance for grinding force prediction, measured using common performance metrics. In Table 6, XGBoost produced the best prediction accuracy, having the lowest Mean Squared Error (MSE = 0.03730), Root Mean Squared Error (RMSE = 0.1931) and Mean Absolute Percentage Error (MAPE = 0.0462). The R-squared ($R^2$) value of XGBoost (0.9324) is much higher than the $R^2$ value of the other two models (Neural Network and SVM), which indicates lower predictive power. As a result, this study demonstrates the efficacy of ensemble methods for predicting grinding force in the shoulder.

In modeling the shoulder force prediction, there were significant differences in performance when comparing the results between three different predictive models. Figure 5

TABLE 5 Comparative performance of machine learning models for grinding force prediction at face.

| Model | MSE | RMSE | MAE | MAPE | $R^2$ |
|---|---|---|---|---|---|
| XGBoost | **0.02641** | 0.1625 | 0.1286 | 0.0698 | **0.6640** |
| NeuralNet | 0.02948 | 0.1717 | 0.1383 | 0.0768 | 0.6250 |
| SVM | 0.02834 | 0.1683 | 0.1348 | 0.0769 | 0.6395 |

Note: Highlighted values represent the best performance parameters.

shows the XGBoost model again demonstrated its superiority over the other two models in terms of accuracy and the received mean square error (MSE) at 0.03730, root mean square error (RMSE) at 0.1931, mean absolute error (MAE) at 0.1192, mean absolute percentage error (MAPE) at 0.0462, and strong correlation coefficient ($R^2$ = 0.9324). In comparison to the high $R^2$ value of XGBoost, the Neural Network and SVM models had respectively lower $R^2$ values of 0.6361 and 0.6325 that corresponded to their respective RMSE values of approximately between 0.448 and 0.450, and MAE values of approximately between 0.346 and 0.359 for both Neural Network and SVM models. The results from this study demonstrate that XGBoost provides a more stable and stronger predictive performance than either Neural Network or SVM for modeling complex behaviors of shoulder force.

The present investigation is specifically dedicated to the prediction and optimization of grinding forces (face and shoulder components) using the experimentally established ranges of depth of cut, feed rate, work speed, wheel speed, and coolant condition. In contrast, most contemporary machine-learning studies in grinding including the work of Charde et al. (2020) are designed around different output variables such as grinding temperature, surface roughness, tool-wear progression, or thermo-mechanical responses, each governed by its own physical behavior and parameter sensitivity. Because our experimental work incorporates a distinct response type and parameter configuration focused entirely on force generation, the numerical indicators reported in temperature- or roughness-based studies do not correspond directly to the predictive outcomes obtained in the present XGBoost–PSO framework.

## 4.2 PSO-based process parameter optimization

With the predictive models, Particle Swarm Optimization (PSO) was used to optimize the total grinding force to the minimum. The objective function was set as the predicted total force, integrating face and shoulder forces. Input parameters like depth of cut (DOC), feed rate (FR), work speed (WRS), and wheel speed (WHS) were optimized within practical ranges in industry.

Particle Swarm Optimization (PSO), a population-based global optimization method that draws inspiration from the social behaviour of bird flocks and fish schools, was utilized to determine optimal machining parameters that reduce the total grinding force. The optimization problem was framed within a specified search space with four key input variables: depth of cut (DOC), feed rate (FR), work speed (WRS), and wheel speed (WHS). Each variable was limited in experimentally certified machining limits DOC between 0.02 and 0.06 mm, FR from 0.5 to 2.0 mm/s, WRS between 50 and 300 rpm, and WHS between 900 and 1500 rpm. The PSO algorithm processed with a population of 20 particles for 50 iterations to meet global convergence. The optimization process was guided by the fitness function that was defined as the total grinding force predicted, computed as the sum of face and shoulder forces, as estimated by the machine learning model. This setup provided a well-balanced exploration of the input space and facilitated robust convergence to optimal process settings.

Optimization using Neural Network resulted in an exceptionally high predicted force because of issues with convergence and thus became unusable for optimization. Out of all models, XGBoost provided the most applicable and efficient parameter set with the least predicted force, reiterating its effectiveness in parameter optimization.

Figure 6 shows the minimum predicted overall grinding force obtained by Particle Swarm Optimization (PSO) by three machine learning models: XGBoost, Neural Network, and SVM. XGBoost yielded the smallest predicted force of 4.22 N, closely followed by SVM with 4.69 N, suggesting good convergence and trustworthy modeling. As a comparison, the Neural Network model produced an

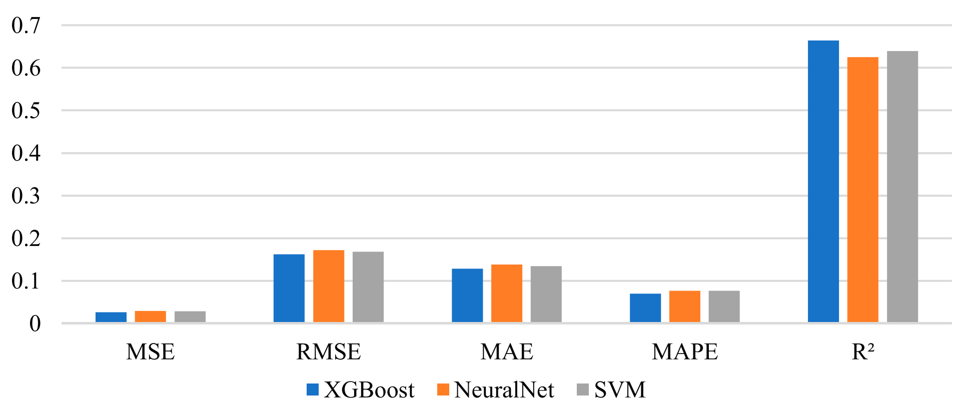


FIGURE 4
Comparative performance of machine learning models for face force prediction.

TABLE 6 Comparative performance of machine learning models for grinding force prediction at shoulder.

| Model | MSE | RMSE | MAE | MAPE | $R^2$ |
|---|---|---|---|---|---|
| XGBoost | **0.03730** | 0.1931 | 0.1192 | 0.0462 | **0.9324** |
| NeuralNet | 0.20079 | 0.4481 | 0.3457 | 0.1313 | 0.6361 |
| SVM | 0.20280 | 0.4503 | 0.3591 | 0.1421 | 0.6325 |

Note: Highlighted values represent the best performance parameters.

excessively high predicted force of 532.84 N, indicating instability and optimization problems. The optimized input values (DOC, FR, WRS, WHS) utilized by each model serve to further indicate the parameter sensitivity of the outcomes. By and large, the Table 7 conclusively identifies XGBoost as the most stable and precise model for force minimization in grinding operations.

Figure 7 shows a pair plot that illustrates the pairwise relationships between important machining parameters Depth of Cut, Feed Rate, Work Speed, Wheel Speed and the resulting grinding forces at the face and shoulder. The diagonal plots indicate the distribution of each variable, and the scatter plots below indicate correlations between pairs of variables. A visible linear correlation is evident between force at the shoulder and force at the face, indicating a high dependency. Other input factors such as feed rate and depth of cut also exhibit patterns affecting the output forces. Visualization helps in finding trends, clusters, and outliers, if any, and serves as a baseline tool for feature selection in predictive modeling.

## 4.3 Comparative analysis

The visual analysis offered extensive support for the model optimization and evaluation conclusions. Bar charts illustrating comparisons of Mean Squared Error (MSE) and $R^2$ scores Figure 6 showed that XGBoost performed better than the Neural Network and Support Vector Machine (SVM) models consistently, especially in shoulder force prediction, where it had the highest $R^2$ and lowest MSE. Such improved predictive power justified the validity of using XGBoost for process optimization applications. Moreover, the output of the Particle Swarm Optimization (PSO) was plotted in Figure 7, wherein XGBoost again demonstrated a significant lead by having the lowest predicted total grinding force among other models, once again proving its strength and credibility in reducing machining forces.

Figure 8 shows the distribution of grinding forces at the shoulder and face. The face force has a more concentrated distribution around 1.8–2.2 N, while the shoulder force has a broader range with a peak around 3.5 N, reflecting greater variability in shoulder force during grinding.

Figure 9 compares Mean Squared Error (MSE) for XGBoost, NeuralNet, and SVM over face and shoulder force predictions. XGBoost strongly indicates the lowest MSE for both face and shoulder forces, whereas NeuralNet and SVM have much higher shoulder MSEs (~0.2), demonstrating their poorer predictive accuracy for this output.

Figure 10 shows $R^2$ values for the same models and targets. XGBoost is on top with the highest $R^2$ of ~0.93 for shoulder force and ~0.66 for face force, which suggests high correlation and

TABLE 7 PSO-based optimization results for minimum predicted total grinding force.

| Model | Optimized input [DOC, FR, WRS, WHS] | Predicted min force (N) |
|---|---|---|
| XGBoost | [0.0283, 0.6829, 131.01, 1119.64] | 4.22 |
| NeuralNet | [0.0214, 1.6216, 292.69, 900.11] | 532.84 |
| SVM | [0.0296, 0.7825, 284.46, 925.95] | 4.69 |

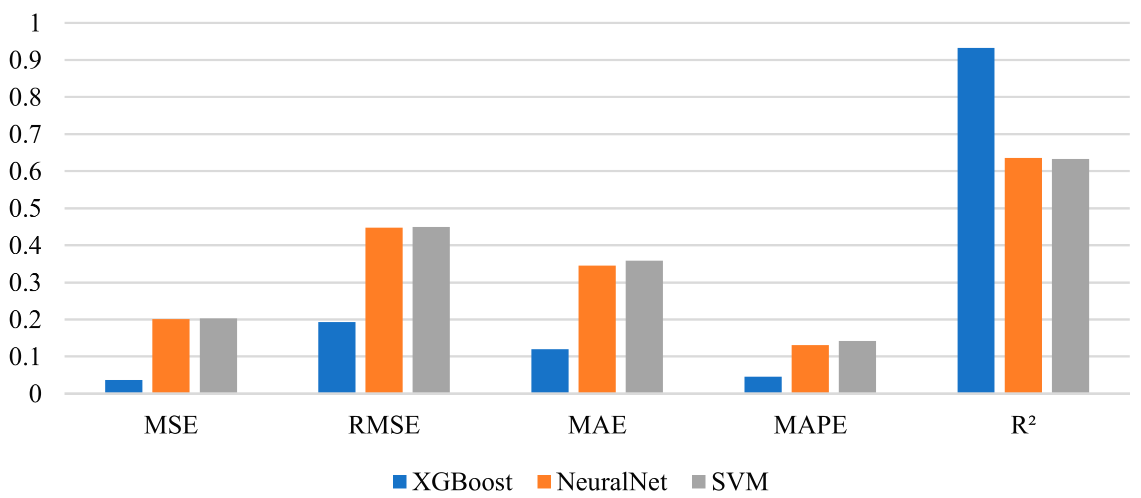


FIGURE 5
Comparative performance of machine learning models for shoulder force prediction.

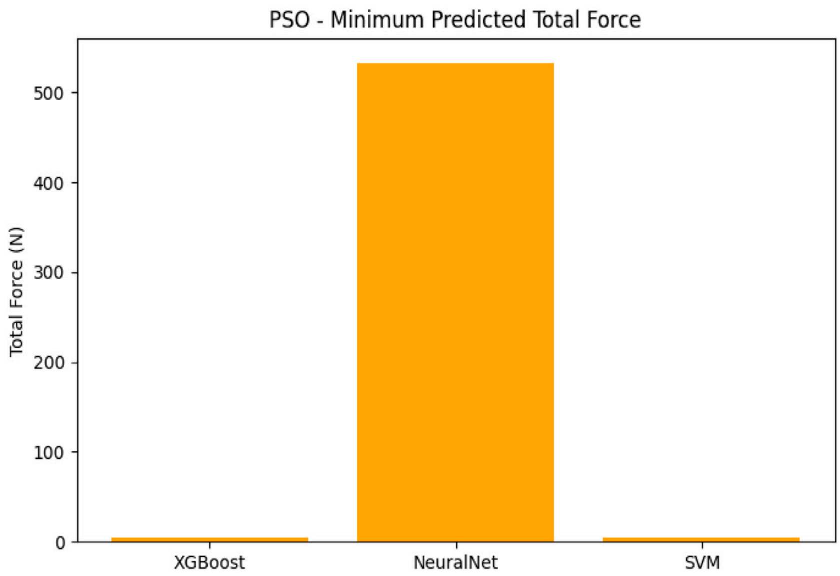


FIGURE 6
PSO–minimum predicted total force using different machine learning models.

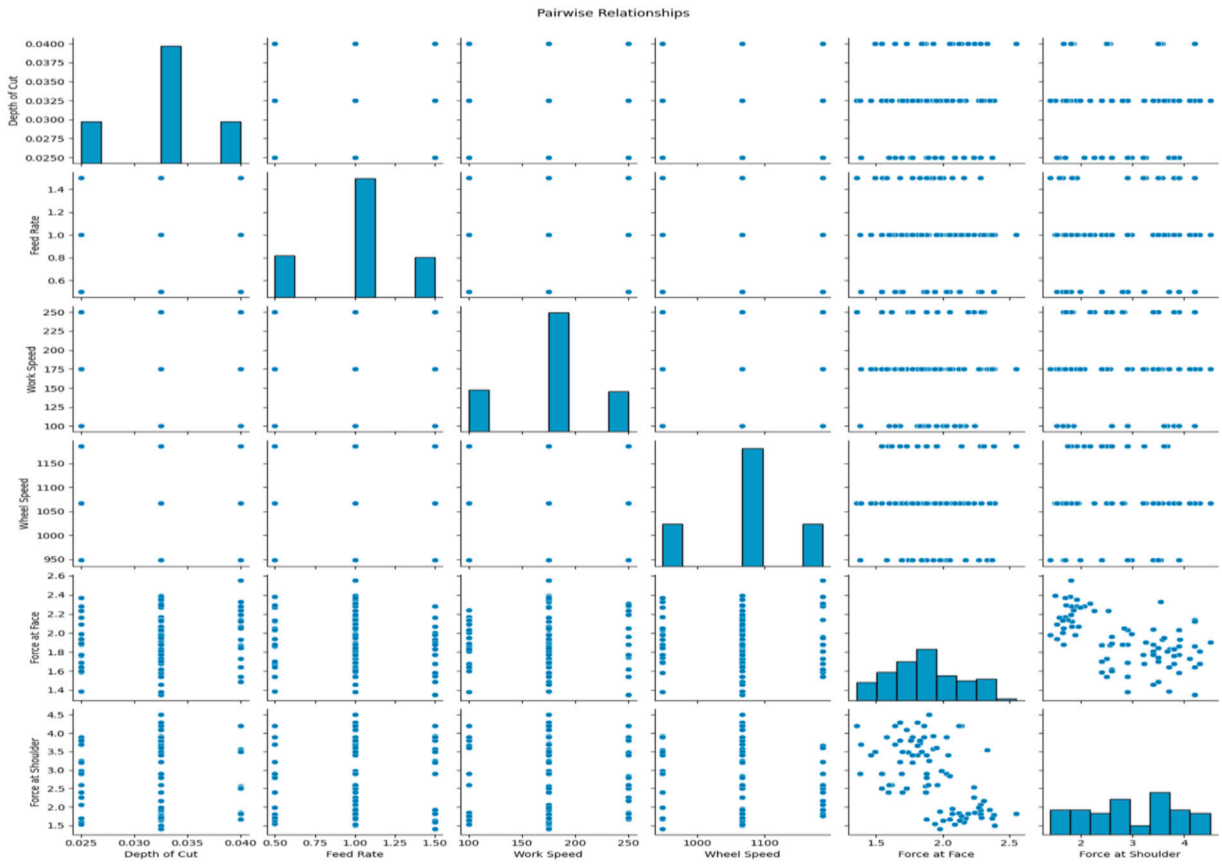


FIGURE 7
Pairwise relationships between machining parameters and grinding forces.

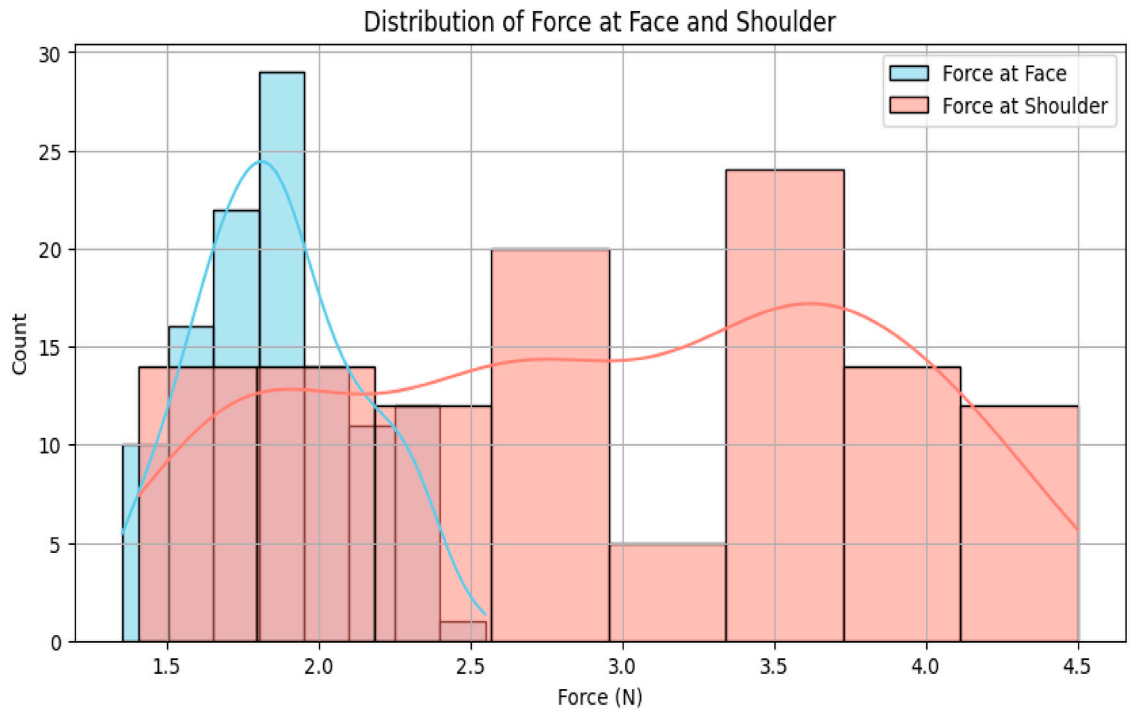


FIGURE 8
Distribution of force at face and shoulder.

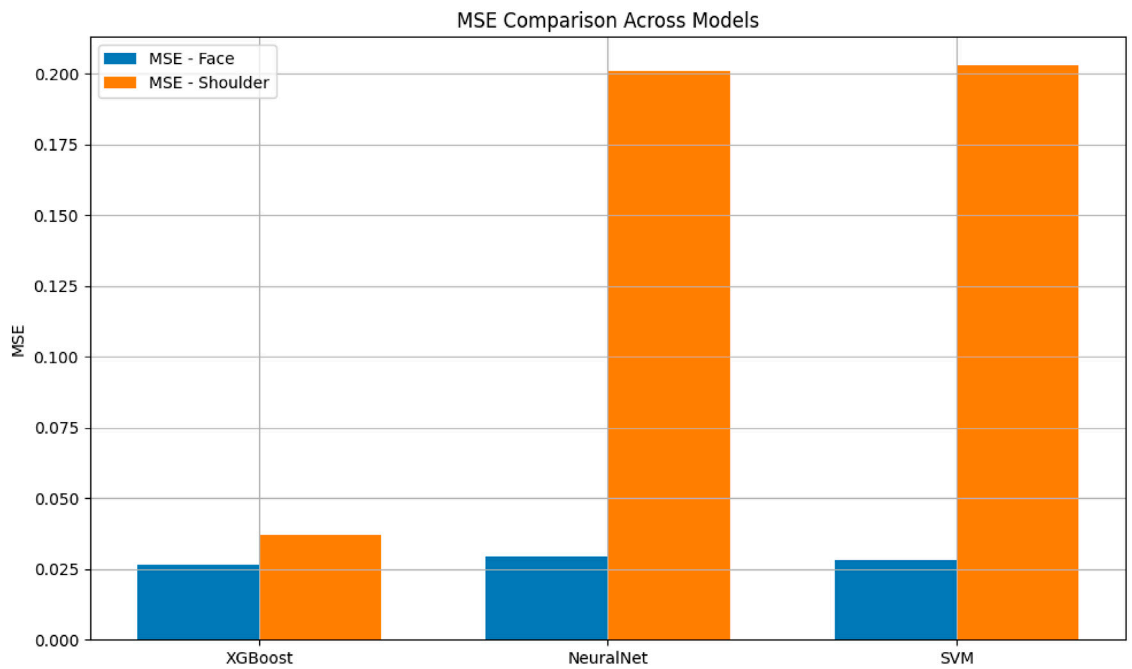


FIGURE 9
MSE comparison across models.

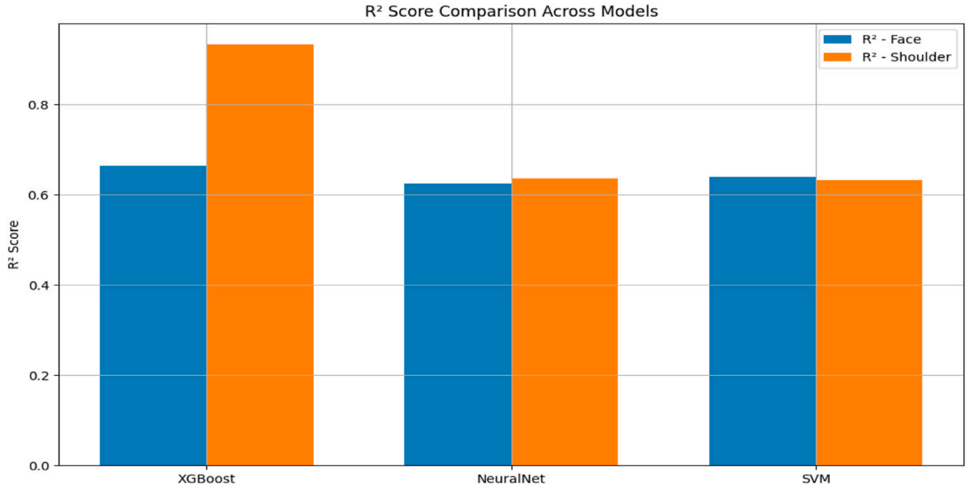


FIGURE 10
$R^2$ score comparison across models.

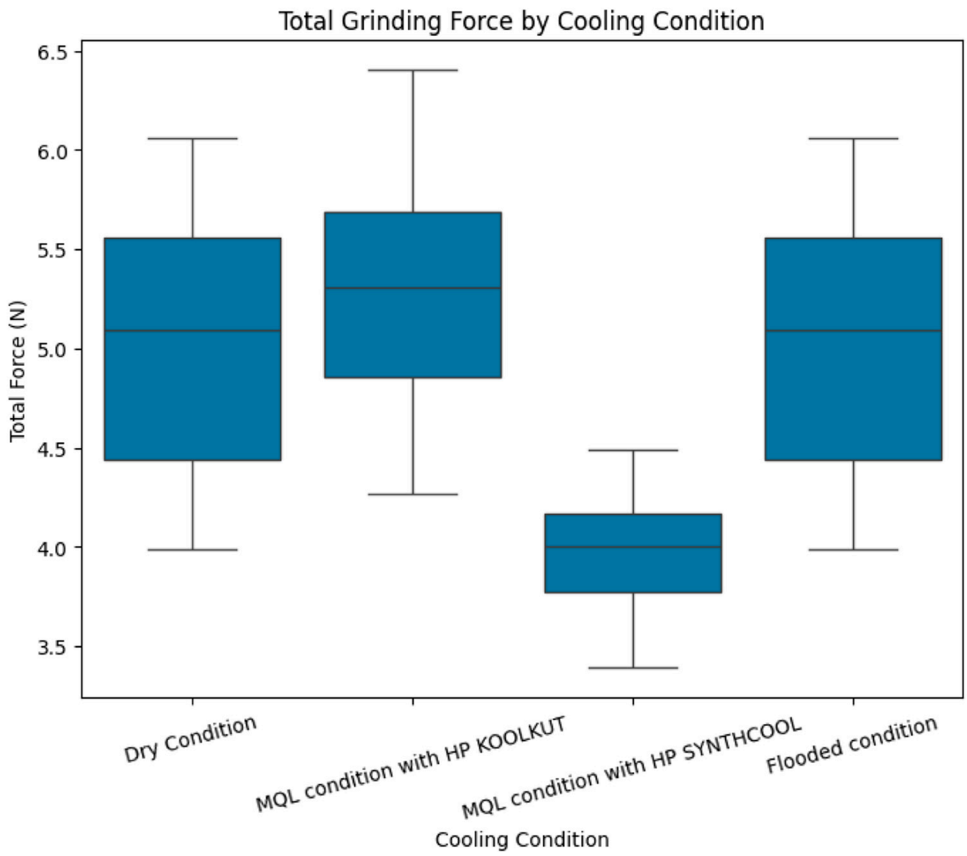


FIGURE 11
Total grinding force by cooling condition.

reliability. NeuralNet and SVM both report moderate $R^2$ values (~0.62–0.64), which indicate lower performance in explaining variance in the data. Overall, these graphs affirm that XGBoost is the most accurate and reliable model for grinding forces prediction.

Furthermore, how cooling conditions influenced grinding performance became apparent from boxplot analysis Figure 11. Dry grinding condition produced maximum force levels and variability, but MQL (Minimum Quantity Lubrication) and

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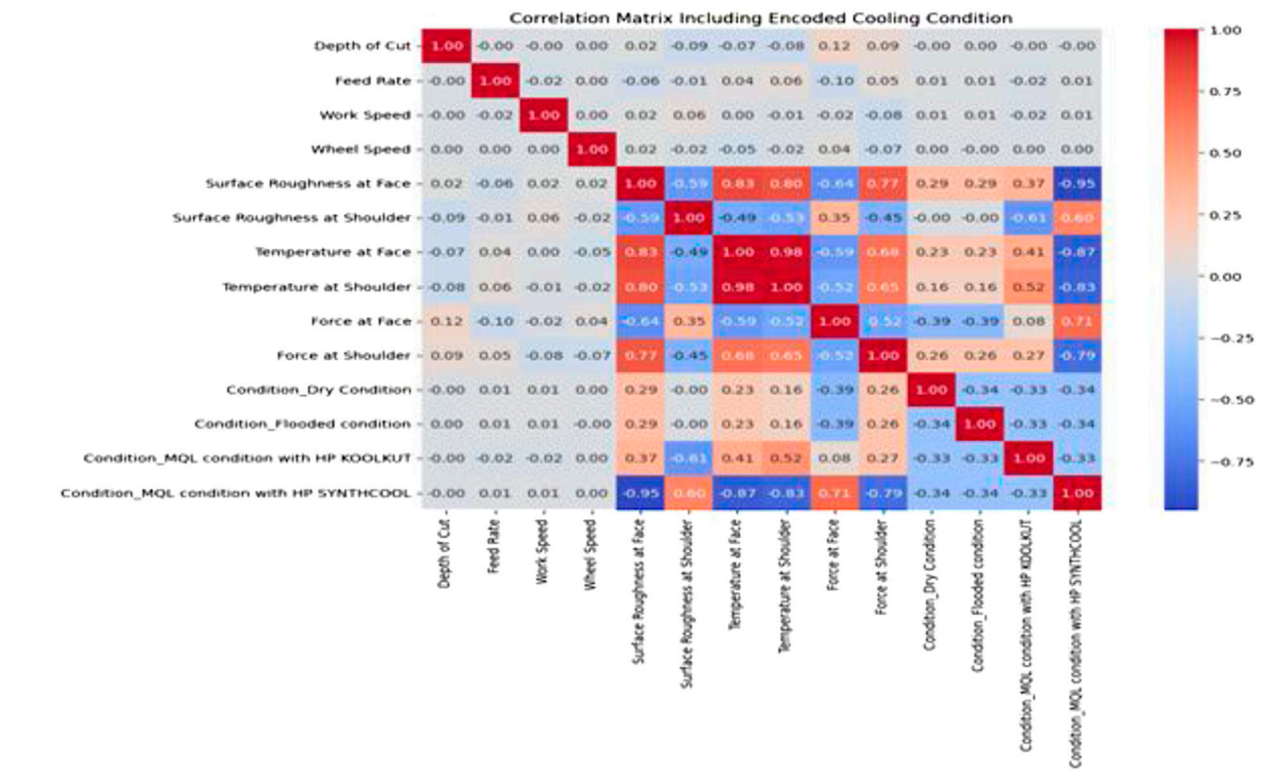


FIGURE 12
Correlation matrix including encoded cooling conditions.

flooded coolant approaches suppressed overall force drastically while providing better-stable performance. These observations speak volumes for the importance of coolant strategies for raising process efficiency and stability. Supporting this, the correlation heatmap Figure 12 showed strong positive correlations among force, temperature, and surface roughness suggesting that these output parameters are closely interconnected. This emphasizes the need for a comprehensive optimization strategy, where simultaneous consideration of thermal, mechanical, and surface quality parameters is crucial to realize optimal grinding performance.

Figure 11 shows a boxplot of the total grinding force for different cooling conditions. Among them, the MQL condition with HP SYNTHCOOL100 has the lowest and most stable force values, with a median slightly above 4 N and little variation. Dry and flooded conditions have larger variability and higher medians (~5.1–5.2 N), whereas MQL with HP KOOLKUT40 has a little larger range. This means that MQL with HP SYNTHCOOL100 provides better efficiency in minimizing grinding forces.

Figure 12 presents a heatmap of the correlation matrix, indicating relationships between machining parameters, surface features, temperatures, forces, and coded cooling conditions. There is a high correlation ($r \approx 0.98$) between temperature at shoulder and face, and between force at shoulder and face ($r \approx 0.77$). The matrix also indicates that MQL SYNTHCOOL100 is negatively correlated with both force outputs ($r = -0.79$ and $-0.71$), confirming its efficiency in reducing grinding forces. This matrix helps to determine key relationships for predictive modeling and parameter optimization.

# 5 Conclusion

This research is focused on meeting the demand for advanced data-driven intelligent optimization for the current state of modern manufacturing focusing specifically on precision grinding operations where the elements of high productivity, consistent quality and process stability are critically interdependent. The research is situated within the area of Smart Machining and the fourth industrial revolution (Industry 4.0) and is intended to advance the integration of machine learning based predictive models with metaheuristic optimization methods. Current methods of optimizing grinding processes are limited due to the empirical basis for selecting parameters, their reliance upon overly simplistic analytical assumptions, and their very limited capabilities for adapting to the nonlinear nature of grinding processes making it impossible to consider simultaneous optimization of force, temperature, surface finish and cooling. The primary goal of this work and research is to create and validate a machine learning-assisted framework for optimization that accurately predicts grinding forces and enables end users to optimise their grinding processes while reducing fault rates and production cycle times.

The Integrated XGBoost–PSO (Particle Swarm Optimization) framework was developed and tested to achieve the objective of accurately predicting the grinding forces throughout the shoulder and face, and to minimize the total grinding force via a combination of methods. It highlighted advantages in predictive accuracy and computational efficiency, time-to-solution, scalability, and applicability to Industry 4.0 concepts. It supports near real-time optimization and integration with Computer Numerical Control (CNC) and Digital Twin systems, as demonstrated by the combination of XGBoost with PSO. However, the framework has limitations in that it is based on a small experimental dataset and has a single-objective optimization focus. Subsequent research will concentrate on enhancing the framework and methods using larger and more diverse datasets, and creating a multi-objective optimization method, simultaneously considering the four factors associated with intelligent grinding/tool application (grinding force, temperature, surface integrity and tool wear), thus developing an enhanced intelligent grinding/tool application capability.

## Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

## Author contributions

MC: Conceptualization, Formal Analysis, Writing – original draft, Data curation, Project administration, Methodology. YB: Validation, Supervision, Software, Writing – review and editing, Visualization. LC: Writing – review and editing, Funding acquisition. SR: Investigation, Writing – review and editing, Resources. BS: Visualization, Supervision, Writing – review and editing.

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## Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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