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Predictive Modeling of Surface Roughness in Manufacturing A Study Using Multiple Machine Learning Techniques

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ABSTRACT

This study provides an in-depth study advanced machining processes and their optimization using various machine learning algorithms. The study focuses on key machining parameters such as cutting speed (m/min), feed rate (mm/rev), and cutting depth (mm), and rotation speed (RPM), investigating their effects on surface roughness (Ra) in manufacturing operations. This research addresses emerging challenges in modern manufacturing, particularly in the processing of advanced engineering materials for the aerospace, automotive, and precision industries. These algorithms were selected for their ability to manage complex and non-linear relationships in manufacturing data and for their proven performance in predictive modeling. The study explores how these methods can overcome traditional limitations in process planning and optimization, especially in situations where conventional empirical models are inadequate. Special attention is paid to the theoretical foundations of each algorithm, in which linear regression serves as a basic model, random forest regression provides improved predictive capabilities through ensemble learning, and support vector regression provides robust optimization through its ε-insensitive loss function approach.

The research also explores the important relationship between machine parameter optimization and surface quality, emphasizing the importance of parameter optimization in achieving desired surface properties while maintaining production efficiency. This study advances the field by providing a structured methodology machine parameter optimization, particularly relevant to computer-aided process planning and advanced manufacturing processes. These findings have significant implications for industries requiring high-precision manufacturing, providing insights into How can machine learning methods be used effectively? optimize machining processes, reduce production costs, and improve surface quality in modern manufacturing operations.

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Introduction

High-performance engineering Materials including polymers, ceramics, composites, and super alloys, are becoming increasingly important in modern manufacturing, particularly in the aerospace, automotive, cutting tool and printing industries. However, high machine costs and potential material damage during processing pose significant challenges, limiting their applications. Furthermore, stringent design requirements present significant The obstacles facing the manufacturing industry, including precision machining of complex objects geometries, such as the aerofoil sections of turbine blades and intricate cavities in dies and melds, as well as special Drilling specifications include non-circular and fine-scale, deep, curved, or burr-free holes. Additional difficulties arise in machining low-rigidity structures, micro- or neon-scale components with tight tolerances, hard-to-reach areas and honeycomb structured materials.

Manufacturing of micro-electromechanical systems and the achievement of neon-coating surface integrity further complicate manufacturing. To address these demands, Unconventional or advanced mechanical processes developed after World War II, are used for complex and specialized shaping needs [1]. Modelling techniques are widely used in manufacturing engineering, including planning, optimization, and control. However, modelling manufacturing processes presents many challenges, such as the complexity of machine operations, the multidimensional and nonlinear nature of machining, inherent randomness, and poorly understood relationships between parameters.

In addition, the lack of reliable data further complicates the process, making modeling a valuable tool for addressing these issues. One possible approach to addressing these challenges it involves the use of basic models derived from mechanical science principles. However, despite advances in process modeling, completely accurate models for manufacturing processes are not available. Heuristic models, often based on empirical rules, are primarily Qualitative decision making is used for evaluation, while empirical models derived from experimental data are important in manufacturing process modeling. In addition, artificial neural networks serve as useful operational models due to their high nonlinearity, ability to handle multiple parameters, and incomplete data. With Due to their inherent learning ability, ANNs can adjust to variations manufacturing environment and are particularly useful when the exact relationships between various product parameters are unknown [2].

Process planning serves as the key interface between product design and manufacturing. It defines the sequence of required operations and specifies essential parameters such as machine dimensions, tolerances, machine and tool selection, and machining conditions to facilitate part production. In traditional process planning, an experienced planner manually creates process plans on an ad hoc basis, which often results in discrepancies in production output. The lack of optimization in this approach leads to high planning and production costs. However, with modern computer advancements, this task can now be efficiently automated. Computer-aided process planning (CAPP) has emerged as a significant advance in manufacturing engineering. A key aspect of the CAPP process is selection most cost-effective combination of machine conditions. This is accomplished through optimization models that balance variables such as production time, cost, metal removal rate, and profit, maximizing or minimizing them as needed. Like other optimization models, these have an objective function and a set of constraints.

Given their typically nonlinear nature, choosing the appropriate optimization method depends on these specific problems [3]. Machining is an important practice in the manufacturing industry, which involves the mechanical cutting of materials using specialized tools. It is generally classified into two types: Traditional and modern machining. Common traditional machining operations include turning, drilling, milling, and grinding. In contrast, advanced machining techniques such as abrasive water jet machining, electrical discharge machining, and electrochemical machining represent modern machining methods.

In machining operations, achieving the optimal balance between maximizing Improve productivity, reduce operating costs, and improve profitability margin presents a significant challenge. Various soft computer Optimization techniques such as ant colony optimization, simulated annealing, particle swarm optimization, and genetic algorithms are classified as single-objective optimization methods and have been successfully applied in real-world situations. MO GA has emerged as a new trend in recent research focusing on optimizing machine process parameters. Unlike single-objective GA-optimization techniques, where conflicting objectives often lead to unbalanced outcomes, MO GA allows for the optimization of multiple objective functions simultaneously [4].

This study examines the impact of electromagnetic radiation human body, focusing on a new concept called electromagnetic asymmetry (EA), which examines the imbalance between uplink and downlink in mobile communication systems. As mobile communication services evolve, many, especially high multimedia services, will become asymmetric, with the downlink demand significantly exceeding the uplink demand in both total transmission volume and transmission rate. This paper explains the electromagnetic asymmetry (EA) caused by this imbalance between uplink and downlink. The environmental impact of electromagnetic radiation has long been a topic of debate. As mobile communications become more widespread, the overall levels of electromagnetic radiation will rise, leading to a reassessment of the social consequences of mobile communications.

The influence of electromagnetic radiation is a key factor in the research and design of mobile communication systems. This paper examines the asymmetric properties of mobile communication systems as they are affected by electromagnetic radiation [5]. In sand casting, components are formed by pouring molten metal into a sand meld. Casting quality is significantly affected by the properties of the casting sand. As a result, ensuring optimal sand properties is crucial for industrial applications. Halter and colleagues it is documented that there were approximately 103 million tons of metal are used annually to produce cast parts worldwide. Proper mixing of silica sand with chemical binders initiates a catalytic reaction, solidifying the meld. Chemically bonded silica sand allows melds with complex shapes and precise dimensions to be created at ambient temperatures.

However, during the casting process, these melds release Hazardous toxic emissions (i.e., chemicals), leading to environmental pollution and significant health risks to humans [6]. Electrochemical machining is a sophisticated process that operates on the principles of electrochemical processes principles. It involves the controlled Removal of anodic work piece material by a catholic electrode device, following Faraday's laws of electrolysis govern the process. Unlike electroplating, ECM extracts material from the work piece without depositing it on the cathode, which is achieved by ensuring a continuous flow of electrolyte in the gap between the electrodes. This process produces a nearly mirror-like reproduction of the tool shape work piece. To maintain a constant electrode gap under equilibrium or steady state conditions, the catholic tool must advance toward the work piece at the same rate as the material is removed. In manual ECM machines, the tool advance rate present, allowing the IEG to adjust toward its stable equilibrium point. In contrast, automatic ECM systems can detect the IEG and regulate it in real time using a closed-loop control mechanism such as a servo system [7].Wire electric Extrusion machining is a high-precision thermal machining process designed for the precision machining For machining hard materials with complex geometries, this is a straightforward method for manufacturing tools and melds and is very useful for producing fine-scale components with exceptional Accuracy in dimensions and surface quality.

Molybdenum wire is used in special applications requiring high tensile strength to provide adequate load-bearing capacity in fine diameterswires. Experimental studies are necessary to assess the impact Influence of process parameters on accuracy, volumetric material removal rate, and surface texture. Since the process is dependent on many factors, evaluating the performance of all parameters presents a significant challenge [8]. Electric discharge machining is a commonly used unconventional material removal method. The primary a major advantage of this process is its independence from the mechanical properties of the material and the elimination of shear forces. Forces.

As a result, even materials with Materials with high hardness, brittleness, or strength can be efficiently machined to achieve the desired shape. Since EDM is an expensive process, it is necessary to Adjust process parameters to increase production efficiency and reduce machine time. Since each parameter affects performance metrics differently, determining the best set of process parameters is challenging [9]. The demand for greater efficiency and precision in manufacturing has led to the development of the next generation class of multifunctional computer numerical control (CNC) machine tools called turning machines. These machines can perform multiple operations simultaneously using multiple turrets and spindles. In a turning machine, the three-jaw chuck is referred to as the part holding location (PHL), while the turret, which is driven by Servo motors are referred to as power turrets. Turning machines have recently gained popularity due to their ability to perform both turning and turning operations. By requiring fewer setups for many tasks, they significantly reduce work piece transfer and setup time.

This reduction in setups reduces setup errors, which leads to improved product accuracy. In addition, turning machines offer improved manufacturing capabilities, including simultaneous and simultaneously machine. In the initial machine mode, two power turrets (PTs) can perform the same feature or function at the same time. Traditionally, conventional machine tools only allow one function at a time. Thus, a turning machine tool serves as a viable alternative to two traditional machines, such as a milling machine and a lathe [10]. Genetic algorithms are widely used heuristics that have proven Skilled in addressing various types of optimization challenges. They help maintain the consistency of mathematical models. Scheduling involves allocating limited resources to tasks over time are a strategic decision-making process that considers activities, time, costs, and overall organizational objectives. It also requires integrating different types of data. Scheduling involves modelling processes, defining task-resource relationships, setting goals and performance metrics, and establishing data structures that tie all components together. Schedules assign resources to tasks at specific times, which can range from mechanical operations to software development. Resources include personnel, machinery, and raw materials. Typical objectives include reducing project duration, increasing net present value, or reducing the number of products delivered beyond the deadline.

In For project scheduling problems with multiple implementation approaches, the genetic algorithm proved to be more effective than deterministic methods and finite numerical search methods [11]. However, these values serve as initial guidelines rather than optimal settings. Optimizing cutting parameters is often a challenging task that involves several key aspects: understanding machining processes, using Empirical formulas are used to define practical constraints for the tool life, forces, power, surface finish, etc. An essential aspect of any optimization procedure is the identification of the key output, which is called the Optimization objective or criterion. In manufacturing processes, a commonly used optimization criterion is specific cost, which has been used by many researchers since the early stages field to recent studies [12]. In our study, we discuss Tool path length, tool selection, and planning techniques for a turning operation, with particular focus on tool path length and cutting force, and key machine parameters for rotating work pieces prepared for optimization within the MATLAB environment. The optimization process involves determining tool paths for each length segment Rotary machine designs can be represented as 2D models, determined by the geometry of the work pieces, although more complex geometric models (3D machining operations) can be created to account for machine complexity. In this context, the tool path length can be optimized by turning, and the best tool selection is determined based on the machine geometry to achieve the optimal tool path length.

In addition, in our study, the machine parameters, including depth of cut, feed rate, and cutting speed, are optimized using a genetic algorithm. This section focuses on optimizing path length for a rotating work piece, especially for External turning involves primary and secondary machining processes. The primary machining process involves turning, while secondary machining includes processes such as chamfering, facing, radii, creating concave and convex shapes, tapering, and cylindrical shaping. Secondary turning operations include grooving, drilling, turning, threading, and cutting [13]. When appropriate tool life equations are available, optimization analysis can also be applied to milling processes. Fortunately, numerous Researchers have developed equations for real-world grinding processes, which include a wide range of process variables. Detailed milling process models and the advancement of computer-aided manufacturing has laid the foundation for optimizing grinding parameters. Previous studies on optimizing grinding parameters have primarily focused on approaches to improve control during the grinding process. A technique for optimizing both grinding and dressing parameters to increase work piece material removal rates, while maintaining controls on work piece burnout and surface finish, is discussed in the reference. In addition, the use of quadratic programming to optimize grinding parameters under multi-objective operations is reported in another reference. In the authors' previous research, a genetic algorithm-based optimization approach was effectively implemented to address surface grinding process problem, focusing on a single objective function [14]. The WEDM process is a thermal-electrical machining method Material is removed from the work piece by a series of discrete sparks that occur between the work piece and a wire electrode (tool).Dimensional and geometric accuracy the accuracy of the cutting profile depends on the accuracy of the wire control mechanism.

The dimensional and geometric accuracy of the cutting profile is affected by the accuracy of the wire control mechanism. Selecting appropriate Optimizing process parameters is crucial to improving the overall performance of the WEDM process is a useful method to overcome the challenge of linking process parameters to performance metrics, but a review of the literature indicates that previous studies have not incorporated any modeling approaches [15]. CNC machines are widely used in industry today, but their operation can be expensive due to the many parameters involved. It is well established that in order to maximize machining efficiency, it is necessary to select optimal cutting conditions, including feed rate, cutting speed, and depth of cut, considering productivity and overall manufacturing cost per component. Agape developed the optimal machining conditions using the Elder-Mead simplex method. The objective function involves It is a combination of minimum production cost and minimum production time, with production cost being prioritized based on their weight coefficients. A fixed multiplier is used to normalize the objective function. Physical constraints related to the cutting parameters are also taken into account.

The performance of the combined objective function compared to single-scale objective functions ratio [16]. To achieve High surface quality and precise shape accuracy work piece, meld polishing is a finishing process that uses bonded abrasive materials. In a meld machine, surface polishing often takes a considerable amount of time and is usually performed by skilled operators. As a result, the development of a specialized meld polishing tool is a practical solution. Polishing systems based on industrial robotic architectures offer many advantages, including a large work area, great flexibility, and the ability to effectively control both force and position. However, unlike computer numerical control (CNC) machines, they face challenges in planning and tracking free-form surfaces, and have relatively large tracking errors. On the other hand, parallel polishing machines are generally faster and more powerful than traditional joint polishing robots, but their work areas are usually much smaller. This type of mechanical system faces problems related to inaccuracy of movement due to low rigidity. Polishing of axial surfaces is usually carried out using elastic polishing, which involves a relatively small polishing force, thereby reducing the requirements on the rigidity and accuracy of the machine [17]. To remain competitive in the market, it is essential to analyze and reduce Time and cost to increase the efficiency of part production manufacturing process.

These methods include Taguchi method, fuzzy logic algorithm, artificial intelligence, genetic algorithm, artificial neural networks, artificial bee colony algorithm, ant colony optimization and matching search algorithm. [18]. Process planning defines how a product, from semi-finished goods to finished parts, will be manufactured using available manufacturing resources. It is a key component in coordinating design and downstream manufacturing processes. In general, process planning involves two main tasks: selecting operations and sequencing those operations. Operation selection is based on the geometric features and technical requirements of the part, including selecting the appropriate machine, calculating the cutting tool, and machining parameters. Operation sequencing focuses on organizing the machining operations into a series of steps that produce each feature of the part while meeting the technical constraints outlined in the part drawing.

Typically, the operation sequence in process planning should aim to achieve some objective, such as minimizing the combined costs of machines, cutting tools, and changeover devices. This objective involves complex properties and complex priority relationships, which makes solving the operation sequence problem challenging [19]. Despite advances in modern machining technologies, grinding remains an important process. As with other manufacturing methods, the roughness of the ground surface significantly affects operational characteristics product. A high-quality ground surface is known to improve Fatigue resistance and corrosion durability. Surface roughness also affects friction and light reflection, lubricant retention, Electrical and thermal contact resistance, aesthetics and cost. An excellent surface finish often eliminates the need for further machining, reduces power consumption, and environmental impact.

Therefore, it is crucial to understand the factors that determine surface roughness and accurately predict it. Influencing parameters are classified into controlled and uncontrolled factors. The main the regulated cutting parameters include spindle speed, feed rate, and depth of cut. However, there are many uncontrolled factors, such as Vibrations, tool wear, machine movement errors, material inconsistencies in both the tool and work piece, and chip formation are difficult to control, and their interactions are challenging to accurately predict [20].

2. MATERIAL AND METHODS

Material

Cutting speed (m/min) (x1): Cutting speed, Measured in meters per minute (m/min), this refers to the relative motion between the cutting tool and the work piece machining. It plays a key role in determining tool longevity, surface finish, and overall machine performance. The ideal cutting speed is influenced by factors such as material properties, tool composition, coolant use, and machine stability. While higher speeds increase productivity, they can also cause rapid tool wear or thermal damage. Conversely, lower speeds extend tool life but compromise performance. Selecting the appropriate cutting speed ensures optimal performance, while maintaining accuracy and surface quality in turning, milling, and drilling.

Feed rate (mm/rev) (x2): The feed rate, expressed in millimeters/revolution (mm/rev), represents the distance the cutting tool moves forward with each spindle revolution. It has a significant impact on surface finish, cutting forces, and tool life. The ideal feed rate is influenced by factors such as work piece material, tool design, machine rigidity, and cutting conditions. Higher feed rates improve material removal efficiency but can lead to rougher finishes and accelerated tool wear. Conversely, lower feed rates improve surface quality but reduce machining speed. Selecting the correct feed rate ensures optimal machining performance, accuracy, tool life, and cost-effectiveness in turning, milling, and drilling.

Depth of cut (mm) (x3): It has a major impact on mechanization efficiency, Tool life, surface quality and cutting forces. Optimum depth of cut influenced by factors such as work piece material, tool strength, machining efficiency, and cutting conditions. A higher depth of cut increases material removal but increases cutting forces, tool wear, and vibration. Conversely, a shallower cut improves surface quality and accuracy but reduces productivity. Choosing the appropriate depth ensures a balance between performance, tool longevity, and machine efficiency in turning, milling, and drilling.

Rotational speed (RPM) (x4): Rotational motion refers to the motion in which an object moves about its own axis without any change in its spatial position. The Rotational speed is measured in radians per second or revolutions per minute. It is defined by angular displacement, angular velocity, and angular acceleration. RPM, which stands for revolutions per minute, is a measure of how many complete revolutions an object makes around a fixed axis in one minute. Rotational speed, also known as angular velocity, it refers to the number of cycles a system performs in a given period of time. It usually measured in rev/s (s^{-1}), while pump speeds are often given in min^{-1} (RPM).

Surface roughness (Ra): Surface roughness, referred to as Ra, measures the texture of a machined surface by evaluating deviations from a smooth surface. Ra Cutting speed is affected by mechanical factors such as feed rate, depth of cut, and tool geometry. Smaller Ra values indicate a smoother finish, whereas larger values indicate a rougher surface. Controlling surface roughness is essential to meet functional and aesthetic standards in manufacturing and to ensure optimal performance in industries such as automotive, aerospace, and precision engineering.

Instructions for machine learning

Linear Regression: A Statistical Method Used valuable technique for predicting quantitative outcomes and has been extensively studied in numerous textbooks over time. Although it may seem less exciting than modern statistical learning methods, it is widely used and very relevant. In addition, it serves as a foundation for more advanced techniques, as many sophisticated statistical learning methods can be seen as extensions or generalizations of linear regression. Therefore, a solid understanding of linear regression is essential before exploring more complex approaches. This chapter examines the basic concepts of linear regression and the least squares method, which is commonly used to build a model. Regression serves two primary purposes. First, it is widely used for forecasting and prediction, often with significant overlap with machine learning applications.

Second, in some cases, regression analysis helps identify causal relationships between independent and dependent variables. Through regression analysis, the dependent variable 'y' is predicted based on different values of the independent variables. variable 'x'. This paper focuses on linear regression and multinomial regression, both of which are well suited for predictive modelling. Regression can take the A type of regression that can be simple linear regression or multiple regression. Simple linear regression involves a model in which single independent variable to determine its effect on a dependent variable. It is represented by the equation □ = β□ + β□□ + □, which describes the relationship between the variables. In addition, simple regression helps to distinguish the impact of independent variables from the interactions within the dependent variables.

Random Forest Regression: Random forest regression is a powerful supervised machine learning method used for predictive modeling. It falls under the category of ensemble methods and is built on the basis of decision tree algorithms. In this approach, multiple decision trees are trained on different dataset subsets, and their outputs are averaged to improve prediction accuracy method not only improves performance, but also reduces the computational burden associated with training, storing, and predicting with multiple individual models. Due to its efficiency, random forests are very useful for regression tasks, where they are typically used to predict continuous values. The random forest method works by creating a "forest" of multiple independently constructed decision trees, with the final prediction obtained by averaging the outputs of all the trees. By exposing each tree to slightly different data, this approach helps reduce variance and increase over fitting, ultimately improving the generalize ability of the model.

Support Vector Regression: A regression problem extends a classification problem, where the model produces a continuous-valued output instead of selecting from a set of defined categories. Simply put, a regression model predicts a continuous multivariate output relationship. Support vector machines (SVMs) are designed as convergent optimization tasks to address binary classification problems (Vapnik, 1998). The goal is to identify an optimal hyper plane that maximizes the edge when classifying the maximum training points accurately. This hyper plane is defined using support vectors. Due to their sparse solution and strong generalization capabilities, SVMs are also well suited for regression tasks. The transition from Support vector regression extends SVM by incorporating a ε-insensitive part called a ε-pipe. As a result, a multi-objective function is created that encompasses both the loss function, together with the geometric properties, model.

3. RESULT AND DISCUSSION

TABLE 1. Machining process optimization genetic algorithm

x1	x2	x3	x4	Ra
1250	533.4	76.2	1725.29	2.4892
1250	533.4	127	1845.55	2.667
1000	228.6	25.4	911.13	2.3368
1000	228.6	76.2	1225.66	2.4384
1000	228.6	127	1425.78	2.5908
1000	381	25.4	1000.77	3.2766
1000	381	76.2	1486.15	2.7432
1000	381	127	1597.07	2.3368
1000	533.4	25.4	1033.83	3.7846
1000	533.4	76.2	1679.39	3.683
1000	533.4	127	1687.24	2.8448
750	228.6	25.4	930.96	2.7686
750	228.6	72.6	1254.68	2.5146
750	228.6	127	1171.25	2.413
750	381	25.4	950.24	3.175
750	381	76.2	1513.81	3.0988
750	381	127	1529.82	2.6416
750	533.4	25.4	1135.16	4.5212
750	533.4	76.2	1624.06	4.1402
750	533.4	127	1658.57	3.81

Table 1 illustrates how Spindle speed (x_1), feed rate (x_2), depth of cut (x_3), and cutting speed (x_4) collectively affect determine Ra values. Higher spindle speeds, such as 1250 rpm, generally yield lower Ra values, ranging from 2.4892 to 2.667. Conversely, lower spindle speeds, such as 750 rpm, tend to increase Ra, with values exceeding 4.5 under certain conditions. Feed rate also plays an important role; at 533.4 mm/min and 25.4 mm depth of cut, Ra reaches 4.5212, the highest in the dataset, indicating that excessive feed rate combined with low spindle speed worsens surface quality. However, at 1000 rpm, at 381 Feed rate mm/min and cutting depth 127 mm, Ra reaches a minimum of 2.3368, indicating an optimal balance. Depth of cut and cutting speed affect each other because is evident in variations in the same spindle speeds and feed rates. For example, at 1000 rpm and 381 mm/min, increasing the cutting depth from 25.4 mm to 127 mm reduces Ra 3.2766 to 2.3368. This indicates that a modest increase in depth of cut can improve surface quality when combined with appropriate spindle speed and feed rate. Genetic algorithms help identify these optimal conditions by analysing complex parameter interdependencies, helping to reduce Ra while maintaining machine efficiency. By optimizing such parameter interactions, manufacturers can fine-tune machine settings to achieve better surface results, demonstrating the importance of interoperable factors in machining process optimization.

TABLE 2. Descriptive Statistics

	x1	x2	x3	x4	Ra
count	20	20	20	20	20
mean	912.5	396.24	78.56	1369.321	3.01371
std	167.7051	129.8816	41.95856	305.0954	0.650989
min	750	228.6	25.4	911.13	2.3368
25%	750	228.6	25.4	1109.828	2.50825
50%	1000	381	76.2	1455.965	2.7559
75%	1000	533.4	127	1632.688	3.3782
max	1250	533.4	127	1845.55	4.5212

The descriptive statistics in Table 2, machine parameters and their impact on the surface roughness (Ra). With an average spindle speed (x_1) of 912.5 rpm and a standard deviation 167.71, the dataset primarily consists of values ranging from 750 to 1250 rpm. Similarly, the feed rate (x_2) varies between 228.6 and 533.4 mm/min, with an average of 396.24 mm/min, indicating a uniform distribution of low and high feed rates. The cutting speed (x_4) shows significant variation from 911.13 to 1845.55 mm/min, with an average of 1369.32 mm/min. These parameters interact to affect Ra, which the mean value is 3.0137 and the standard deviation is 0.6509, indicating moderate variation in surface roughness under different machining conditions. The minimum Ra is 2.3368, which occurs at optimal parameter settings, while the highest Ra of 4.5212 indicates a condition where machining inefficiencies such as excessive feed rate or improper spindle speed negatively affect the surface finish. The quartile distribution also reveals that 25% of the Ra values are below 2.5082 and 75% are below 3.3782, indicating that most conditions yield acceptable surface roughness. The interplay between these variables shows that optimizing machining parameters can significantly reduce Ra while maintaining performance. For example, medium-range spindle speeds (1000 rpm) and moderate feed rates (381 mm/min) often result in low Ra values, which are reflected in the 50th percentile (2.7559). By understanding these relationships, manufacturers can use genetic algorithms to refine machining processes, ensuring better surface finishes and operational efficiency.

Effect of Process Parameters

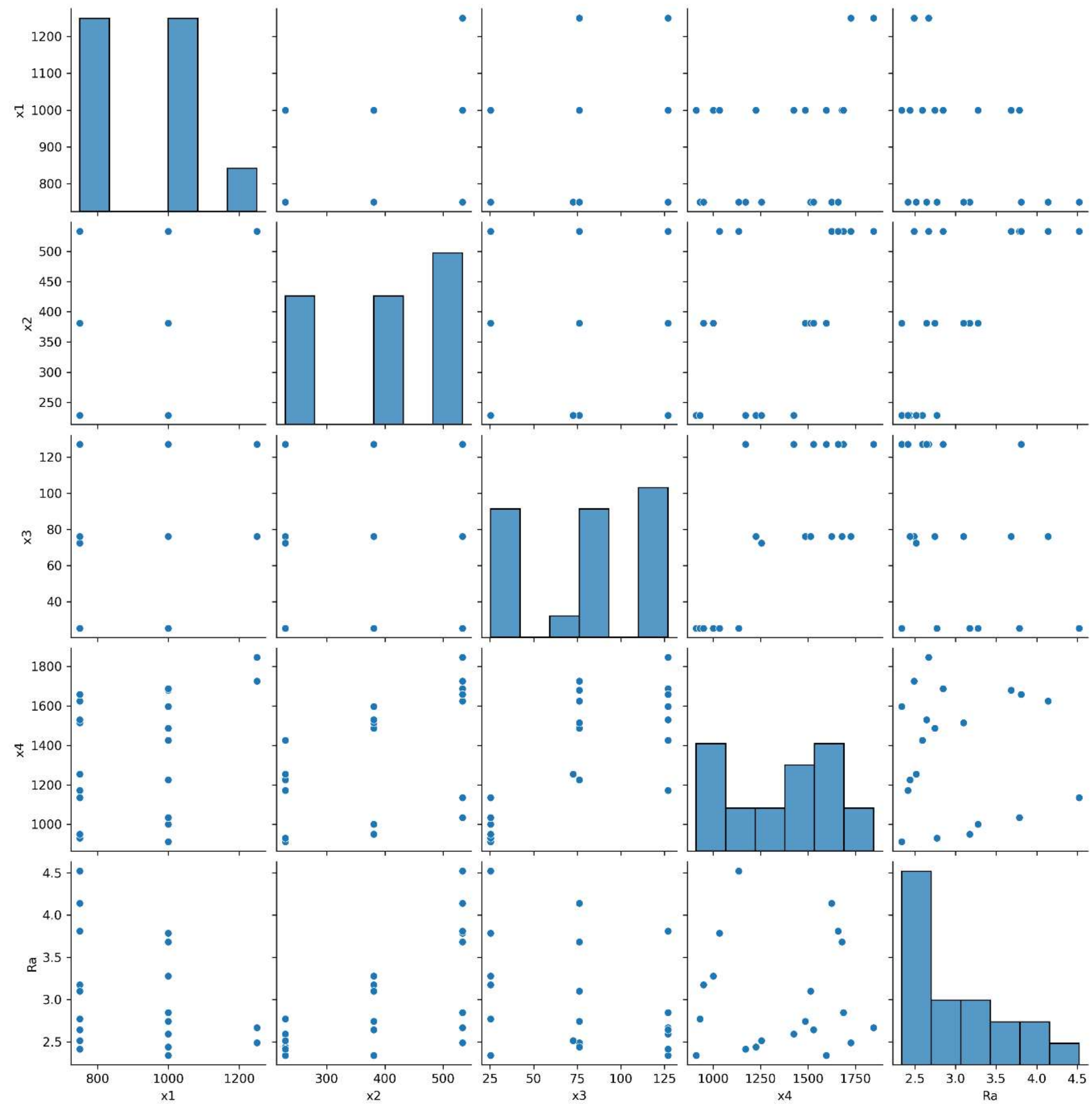


FIGURE 1. Scatter plot of the various Machining process optimization genetic algorithm

Figure 1 presents a scatter plot matrix illustrating the interaction between machine parameters (x□, x□, x□, and x□) Surface roughness (Ra) during the optimization process using genetic algorithm diagonal histograms depict the distribution of each variable, revealing the spread of specific parameter values. For example, the spindle speed (x□) is concentrated around 750, 1000, and 1250 rpm, while the feed rate (x□) shows distinct groups at 228.6 mm/min, 381 mm/min, and 533.4 mm/min. Depth of cut (x□) and cutting speed (x□) show a categorical nature, indicating predefined parameter positions. The scatter plots highlight the relationships between the variables, showing how different machine parameters affect Ra. Ra values at various Depth of cut and feed rate indicates that these parameters interact with each other to influence the surface finish. In particular, a cluster of low Ra values near specific parameter combinations indicates optimal machining conditions.By analysing these interactions, genetic algorithms can refine machining settings, ensuring efficiency and improved surface quality. This visualization underscores the importance of parameter interaction in improving machining performance.

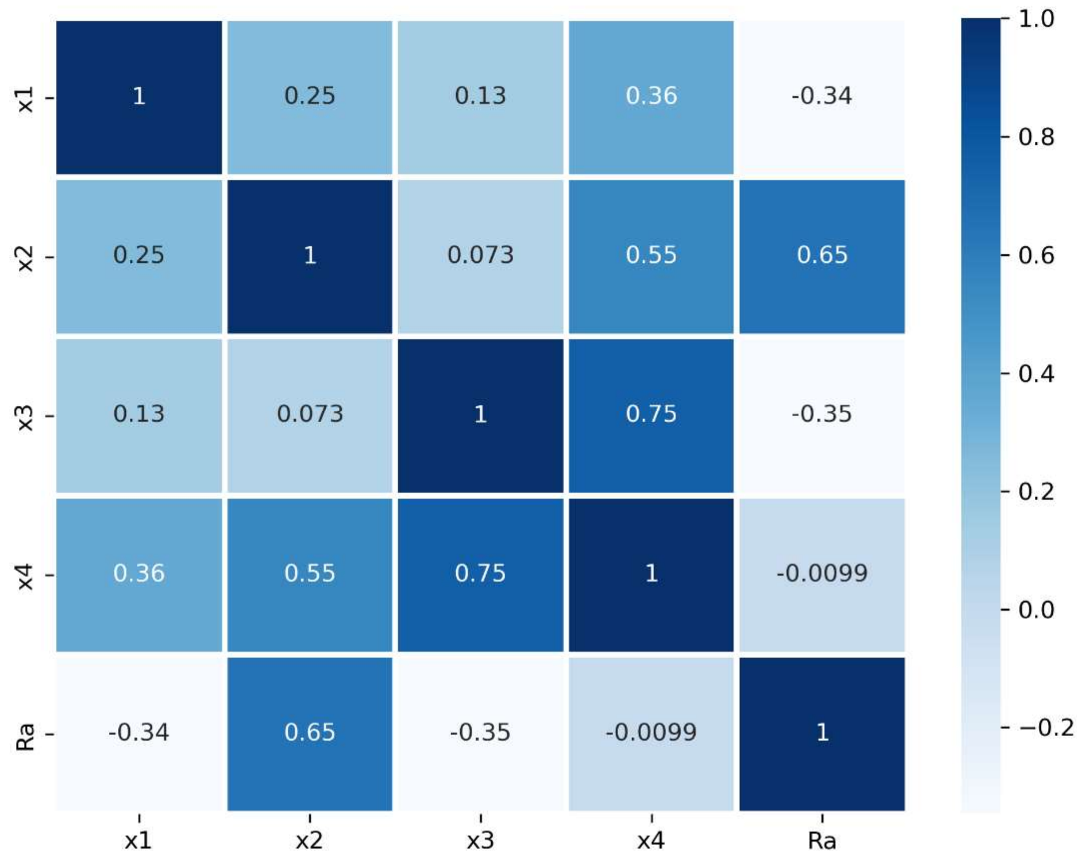
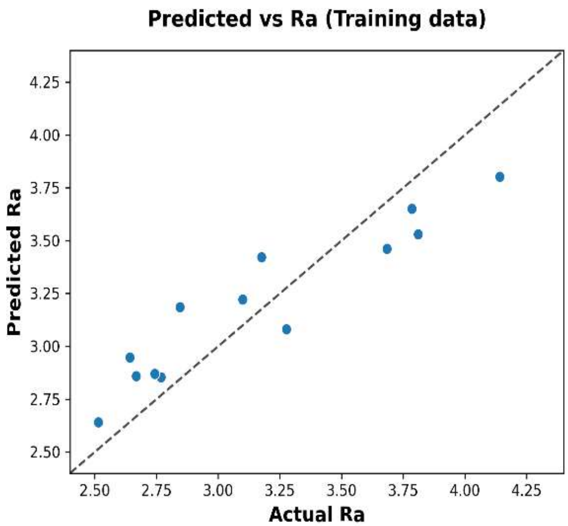
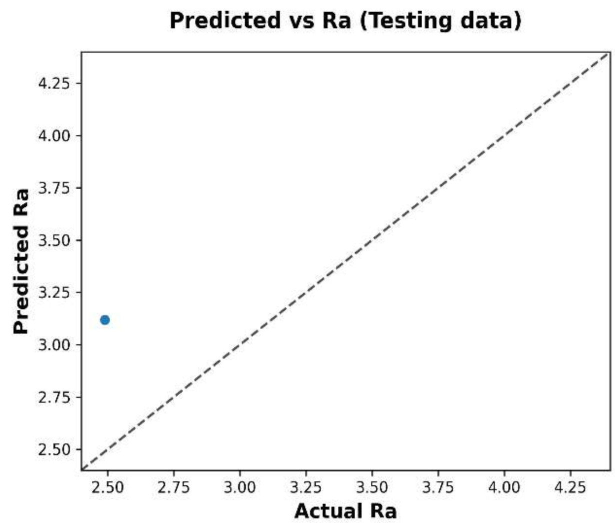


FIGURE 2. Correlation heat map between the process parameters and the responses

Figure 2 presents a correlation heat map illustrating the interaction between the machining parameters (x□, x□, x□, and x□) and surface roughness (Ra). The color gradient indicates the strength of the correlation, where darker shades indicate stronger relationships. Conversely, the spindle speed (x□) shows a moderate negative correlation with Ra (-0.34), indicating that increasing the spindle speed can help reduce surface roughness. The depth of cut (x□) also shows a weak negative correlation with Ra (-0.35), indicating that some machining conditions may allow deeper cuts without significantly degrading the surface finish. Interestingly, cutting speed (x□) has almost zero correlation (-0.0099) with Ra, indicating minimal direct influence on surface roughness. These correlations illustrate how machining parameters interact to affect surface quality. Understanding these correlations enables optimization through genetic algorithms, allowing fine-tuning of the spindle speed, feed rate, and depth of cut are adjusted to achieve the desired size Ra while maintaining machining efficiency.

Linear Regression (LR)



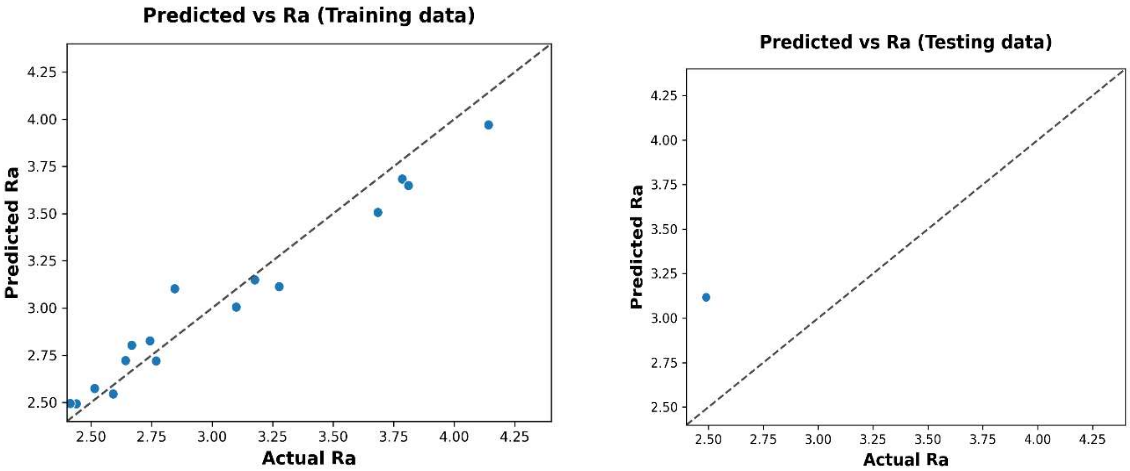


A) b)

FIGURE 3.Predictive accuracy of linear regression model in machining process optimization Genetic algorithm (a) training; (b) testing.

Figure 3 illustrates the Forecast accuracy of linear regression model in a genetic algorithm for machine process optimization. Subfigure (a) represents the training dataset, while subfigure (b) corresponds to the test dataset. The scatter plots compare the actual and predicted surface roughness (Ra) values, with the dashed line representing an ideal predictive scenario where the predicted Ra matches the actual Ra exactly. In the training dataset, the estimated values closely match the actual measurements, suggesting a strong model fit. The distribution of points on the diagonal indicates that the model effectively learns the relationship between machine parameters and Ra. However, small deviations suggest potential areas for further refinement. In contrast, the test dataset contains significantly fewer data points, making it challenging to comprehensively evaluate the generalize ability of the model. The single visible point deviates slightly from the ideal diagonal, indicating the difference between the actual and predicted Ra values, model may need further validation with a larger test set to ensure robustness. Overall, the model shows strong performance on the training data; however, results indicate that further evaluation is needed for reliable predictions on unseen events. Combining highly diverse test data and optimizing hyper parameters will improve prediction accuracy in machining process optimization.

Random Forest Regression

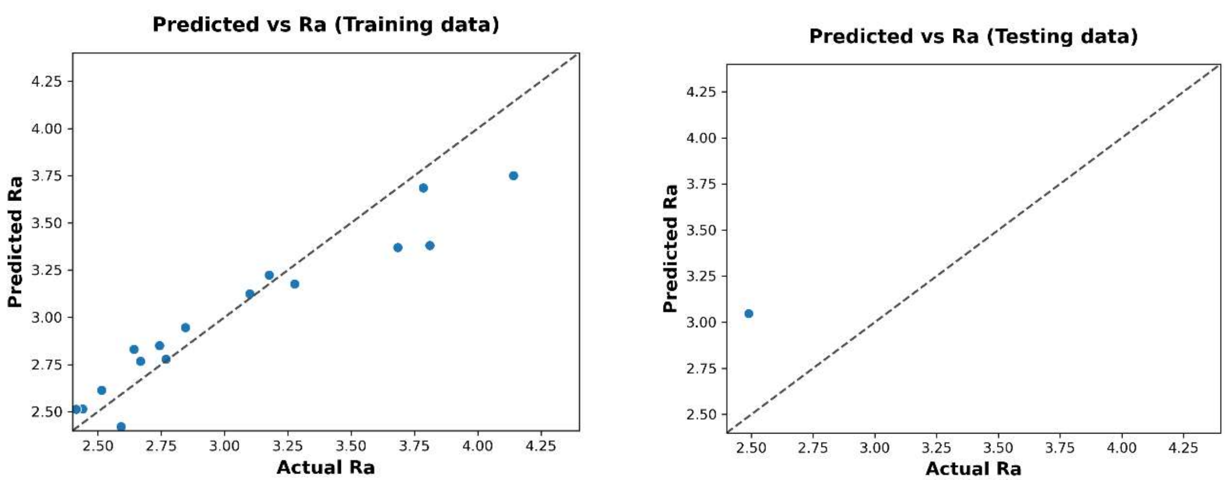


a) b)

FIGURE 4. Predictive accuracy of the random forest regression model in machining process optimization genetic algorithm a) train b) test

Figure 4 presents Forecast accuracy of the random forest regression model used for mechanical process optimization using genetic algorithm. Subset (a) presents the results for the training dataset, while (b) shows the results for the test dataset. The scatter plots are for the real and predicted values of surface roughness (Ra), with the dashed diagonal line representing the best case where the predictions match the actual values are accurately reflected. In the training dataset, the predicted Ra values closely match the actual measurements, forming a trend along the diagonal line. This indicates that the random forest model effectively captures the underlying relationships between the machine parameters and Ra, which provides high accuracy in training. Small variations indicate some residual errors, but overall, the model performs well at this stage. However, the test dataset presents a challenge, as only a single data point is available for evaluation. The predicted value deviates from the ideal diagonal, highlighting potential problems in model generalization. Limited experimental data preclude a comprehensive assessment of prediction reliability in unobserved cases. While the random forest model demonstrates strong predictive ability in training, further testing with a larger dataset is needed to validate its robustness. Additional hyper parameter tuning and cross-validation may improve generalization performance.

Support Vector Regression



b)

FIGURE 5. Predictive accuracy of support vector regression model in machining process optimization genetic algorithm a) train b) test

Figure 5 illustrates the predictive performance of the support vector regression (SVR) model in mechanical process optimization using genetic algorithm. Substructure (a) presents the predicted and actual surface roughness (Ra) for the training data, showing a strong correlation with the diagonal reference line, indicating accurate predictions. Most of the data points align closely with this line, demonstrating the model's effectiveness in capturing the underlying patterns. In contrast, subsystem (b) shows predictive performance on the test data, where only one data point is available, which limits the assessment of generalization ability. The lack of more test data points indicates potential data constraints, which makes it challenging to comprehensively assess the prediction accuracy. Nevertheless, the SVR model appears promising in training performance, although further validation on a larger test dataset is necessary for reliable results.

TABLE 3. Regression Model Performance Metrics (Training Data)

Data	Symbol	Model	R2	EVS	MSE	RMSE	MAE	MaxError	MSLE	MedAE
Train	LR	Linear Regression	0.7940	0.7940	0.0624	0.2498	0.2208	0.5710	0.0044	0.1938
Train	RFR	Random forest regression	0.9413	0.9415	0.0178	0.1333	0.1174	0.2578	0.0011	0.0968
Train	SVR	Support Vector Regression	0.8590	0.8590	0.0427	0.2067	0.1636	0.4290	0.0025	0.1003

Table 3 shows the evaluation metrics various regression models applied to the training data for machine process optimization. The evaluated models include linear regression, random forest regression, and support vector regression, with key metrics such as R^2, explained variance score, mean square error, root mean square error, mean absolute error, maximum error, mean square logarithmic error, and mean absolute error (Med AE). Among these models, RFR demonstrates the best predictive performance with the highest R^2 (0.9413) and EVS (0.9415), indicating strong explanatory power. It also achieves the lowest MSE (0.0178), RMSE (0.1333), and MAE (0.1174), indicating minimal predictive errors. In contrast, LR exhibits a much weaker performance, with 0.7940 R^2 and high error values, reflecting its limited ability to capture complex relationships in the data. SVR outperforms LR, but falls short of RFR, reaching 0.8590 R^2 and achieving moderate error metrics. Notably, RFR also records the lowest MSLE (0.0011) and Med AE (0.0968), which reinforces its robustness. While these results show that SVR and LR have reasonable predictive capabilities, RFR outperforms both in accuracy and reliability, indicating that it is a more suitable model for machine process optimization.

TABLE 4. Regression Model Performance Metrics (Testing Data)

Data	Symbol	Model	R2	EVS	MSE	RMSE	MAE	MaxError	MSLE	MedAE
Test	LR	Linear Regression	0.6824	0.6860	0.3279	0.5726	0.5694	0.6304	0.0185	0.5694

Test	RFR	Random forest regression	0.5576	0.5596	0.4567	0.6758	0.6742	0.7198	0.0235	0.6742
Test	SVR	Support Vector Regression	0.5952	0.6020	0.4179	0.6464	0.6410	0.7249	0.0209	0.6410

Table 4 presents the performance metrics of three regression models, linear regression, random forest regression, and support vector regression, on the test data for machine process optimization. The metrics include R^2, explained variance score, mean square error, and root mean square error, mean absolute error, maximum error, mean square logarithmic error, and mean absolute error (Med AE). Among these models, LR shows the highest R^2 (0.6824) and EVS (0.6860), indicating better explanatory power compared to RFR and SVR. In addition, LR achieves the lowest MSE (0.3279), RMSE (0.5726), and MAE (0.5694), indicating better prediction accuracy on the test set. However, the relatively high errors in all models indicate challenges in generalization. Interestingly, RFR, which performed well on the training data, did not perform well on the test data, showing the lowest R^2 (0.5576) and the highest MSE (0.4567), RMSE (0.6758), and MAE (0.6742). This indicates possible over fitting, where the model captures the training patterns well but struggles with the missing data. SVR performs slightly better than RFR, with an R^2 of 0.5952 and moderate error values. However, both RFR and SVR exhibit higher maximum error values (0.7198 and 0.7249, respectively) compared to LR (0.6304), indicating higher deviations in the predictions. Overall, although LR shows better generalization, the higher errors across all models highlight the need for further adjustments or alternative approaches to improve the predictive reliability in machine process optimization.

4. CONCLUSION

Through the analysis Cutting speed, feed rate, depth of cut, and rotation speed, several key findings emerge: Descriptive statistics revealed that machining parameters significantly affect surface roughness, with Ra values ranging from 2.3368 to 4.5212. Correlation analysis showed that feed rate has a strong positive correlation (0.65) with surface roughness, while spindle speed demonstrated a moderate negative correlation (-0.34), indicating that higher spindle speeds generally contribute to better surface finish. Among the three machine learning models among the evaluated models (linear regression, random forest regression, and support vector regression), random forest regression showed the highest performance on the training data, achieving the maximum value of 0.9413 and the lowest error indicate excellent model performance. Metrics (MSE: 0.0178, RMSE: 0.1333, MAE: 0.1174).

However, the experimental results revealed different patterns, with linear regression showing the best generalization ability ($R^2 = 0.6824$) compared to both random forest regression ($R^2 = 0.5576$) and support vector regression ($R^2 = 0.5952$). This discrepancy between training and experimental performance indicates possible over fitting in more complex models, highlighting the importance of model selection and validation in practical applications. The genetic algorithm optimization approach proved valuable in identifying optimal parameter combinations that reduce surface roughness while maintaining machining efficiency. The results indicate that moderate spindle speeds (around 1000 rpm) combined with appropriate feed rates and depths of cut can achieve optimal surface finish. The study also highlighted the importance of parameter interactions in determining surface quality. For example, the relationship the relationship between cutting depth and cutting speed is a strong positive correlation (0.75), indicating their interdependence in affecting machining effects.

For practical applications, these findings suggest that manufacturers should:

a) Carefully consider feed rate settings, as they significantly affect surface roughness

b) Optimize spindle speed to achieve better surface finish

c) Take parameter interactions into account when adjusting machining conditions

d) Use appropriate machine learning models based on available data and desired outcomes

Future research should focus on expanding the experimental dataset to improve model validation, exploring additional machine parameters, and developing more robust prediction models that maintain high accuracy while avoiding over fitting. The integration of real-time monitoring and adaptive control systems can further improve the optimization process and improve production outcomes.

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