REST Journal on Emerging trends in Modelling and Manufacturing
Vol: 11(2), June 2025
REST Publisher; ISSN: 2455-4537 (Online)
Website: https://restpublisher.com/journals/jemm/
DOI: https://doi.org/10.46632/jemm/11/2/8

Surface Roughness Prediction and Parameter Optimization CNC utilizing the Response Surface Method to convert EN8 steel and Advanced Regression Models

Kedar Narayan Choudhary
Dilkap Research Institute of Engineering and Management Studies, Neral, Maharashtra, India.
*Corresponding Author Email: k_n_chy@yahoo.com

Abstract: *This study examines Improving machine parameter selection for turning operations enhance manufacturing efficiency and product quality. The research focuses on key factors including Spindle speed, feed rate, and depth of cut effects on important performance indicators includes elements including surface quality, machining time, and material removal rate finish, with a particular focus on its importance it significantly influences component functionality, Durability against wear, fatigue resistance and corrosion resistance investigation employs various analytical techniques Using Response Surface Method, Taguchi Method, and Artificial Neural Networks to model and predict optimal machine parameters. EN8 steel, widely used in manufacturing shafts, crankshafts, and connecting rods, serves as the primary material under examination. The research highlights that conventional machining techniques often struggle to meet quality requirements for advanced materials, necessitating the use of Computer Numerical Control (CNC) machines for precision operations. Statistical prediction methods are implemented to develop reliable models that can determine optimal machining parameters without extensive experimental testing. The study demonstrates that proper selection of cutting conditions significantly improves surface roughness, while appropriate modelling techniques enhance the efficiency of mechanical processes, particularly when manufacturers face multiple conflicting objectives.*

Keywords: *Surface finishing, response surface method, turning processes and machining Parameters, Artificial Neural Network (ANN), EN8 Steel, CNC Machining, cutting depth, material input rate, and spindle speed.*

1. INTRODUCTION

Casting, welding and forging are classified as primary manufacturing processes, while machining falls under secondary manufacturing processes. This work includes the verification of key factors in the selection of objectives. Machine time and material removal rate are key factors crucial for manufacturing efficiency, while Surface roughness is an important parameter that must be carefully considered minimized to prevent failure of mating parts due to friction. This study focuses on Machine Surface roughness is influenced by variables like spindle depth of cut reaction, feed rate, and speed. A surface roughness study was conducted using MATLAB and Using an artificial neural network, identify optimal machine parameters number of neurons is advisable to improve network performance [1]. Turning is a commonly used mechanical process that eliminates material from a work piece's exterior, allowing it to form various shapes including conical, curved, cylindrical and straight geometries. Various parameters, including Machining quality It is affected by characteristics including cutting speed, feed rate, depth of cut, and fluid cutting conditions. Therefore, these factors must be optimized in order to enhance cutting performance efficiency, cutting forces affect Work piece deformation, dimensional accuracy, chip formation and overall machine stability of processed structure. In this machining, surface roughness is crucial, affecting Fatigue strength, wear resistance and corrosion resistance are important factors. Therefore, it is necessary to measure the shear forces and surface roughness. Material studied, EN8 Steel is widely used in manufacturing components such as shafts, crankshafts, automobile axle beams, connecting rods, and lightly loaded gears due to its high tensile strength. Significant research has focused on optimizing the machining process parameters [2]. In contrast, the response surface methodology is an analytical approach that widely accepted, user-friendly technique for predicting and optimizing responses. For example, Hessenia et al. used RSM to predict surface roughness In hard turning, the main control variables are cutting speed, feed rate, depth of cut and tool vibration. The machining experiment was conducted under dry conditions using RSM and ANOVA, along with surface and regression plots, verified the accuracy He created a predictive model and obtained the regression coefficient for surface roughness, a regression coefficient of 99.9% was attained. RSM, supported by ANOVA, served as the primary statistical analysis method [3]. Therefore, it is very important for industries to understand these parameters when machining specific grade engineering materials. Optimizing Predicting tool wear based on process parameters provides an effective solution industrial applications. However, implementing an online tool wear monitoring system is complex, it is costly as well as time-consuming. Consequently, it is essential to create a prediction model with high accuracy. Response surface methodology and various optimization techniques can be used effectively address this need. Experimental data are analysed and fitted using statistical principles and regression modelling to establish a reliable predictive function. [4]. Acilturk and Akkus Taguchi used the method Leads to identifying optimal cutting parameters such as cutting speed, feed rate, and depth of cut a minimum surface roughness. Tests were conducted in Machining of hardened AISI 4140 steel bars with coated carbide inserts. The response surface method is widely accepted as one of the most commonly used computational approaches techniques for investigating metal cutting processes. Analysis, modelling and selecting machining processes, its performance is limited when dealing with discrete inputs, parallel operations, or more complex and nonlinear processes [5]. The hard turning process, as highlighted in the literature, offers many benefits, including improved product quality and reduced operating time. However, it also presents significant challenges during cutting operations, which can impact the ability to achieve High-quality products. The high cutting temperatures generated during hard turning are a major challenge process. In hard turning operations, the challenges are compounded by the high hardness Significant heat produced during work piece material and machining operation combination of thermal and mechanical effects accelerates Tool wear reduces tool life and increases machining costs, while increasing cutting forces and tensile residual stresses. These factors negatively affect Surface quality also the development of a white layer, which adversely affects the product's surface polish and lowers its fatigue strength [6]. Surface roughness can be optimized for specific parameters using techniques such as the Taguchi method, response surface method, and genetic algorithms, and artificial neural networks (ANN). Mathematical modelling a streamlined process reduces optimization effort and improves efficiency efficient implementation, leading to significant savings in both cost and time. Numerous studies have used ANN modelling for this purpose; however, such models are specific to machine tools and process parameters, requiring customization for each machining process. A literature review reveals that various Techniques such as genetic algorithms and response surface approach, statistical regression, and artificial neural networks are commonly used to create models and predict surface roughness. However, in all in some cases, the accuracy and reliability of the model are of paramount importance essential for this achieve reliable predictions [7]. The ANN predictions were in close agreement in line by comparing with experimental results, the influence of cutting parameters on dry turning of Al 7075 hard ceramic composite was investigated to evaluate the surface roughness. Experimental design and analysis were carried out using the response surface methodology. Optimal surface quality was achieved at low feed rates. AISI 3040 work pieces were machined using a cubic boron nitride insert, and the influence of process parameters on surface roughness was analysed. The study identified the random forest regression model as a useful approach, traditional regression model [8]. In the manufacturing sector, surface roughness has a significant impact on product performance and quality. Achieving the lowest possible surface roughness essential to meet growing consumer demands for high-quality, cost-effective products with low friction, improved lubrication, and minimal wear. It is a key factor affecting both the performance and manufacturing costs of mechanical components. Process modelling and optimization are important aspects of manufacturing. These processes involve a large number of dynamic interacting variables, which makes surface roughness modelling particularly challenging as it depends on many factors. Recently, various Systems for modelling, simulation, and optimization are created using a variety of cutting parameters and techniques to improve surface roughness prediction [9]. Manufacturing industries, often at the expense of product quality, prioritize increasing production within a very short period of time. These two factors are linked to various industrial objectives, making it challenging to select optimal process parameters. While relying on worker experience or industry guidelines can help achieve many objectives, introducing new materials often leads to errors. Numerous Research has been carried out to ensure accurate selection of process parameters. Kumar et al. improved the turning operations of Al7075 using PCD cutting tools for GFRP composites. Saha and Mandal et al. concentrated on optimizing various responses during the turning process. Suresh and associates developed an empirical model using the RSM-GA approach to determine the optimal Ra values in mild steel machining [10]. While RSM was used to evaluate the impact of particular parameters, Makadia and Nanavati used the Taguchi method to examine how turning parameters and nose radius affected surface roughness method. These parameters are fundamental in turning operations and should be optimized to increase productivity, reduce manufacturing costs and extend Tool life. RSM created empirical models to estimate output responses [11]. Therefore, selecting appropriate cutting circumstances can greatly raise the surface roughness.

The One popular statistical prediction method for modelling is the response surface method (RSM) surface roughness and identify the ideal machining settings needed to accomplish the desired effect results. Several studies have successfully implemented Response surface method is used to estimate surface roughness. In particular, Sahin and Motor cu developed Surface roughness model for TiN-coated AISI 1040 mild steel turning process using RSM. The model includes three machine Factors such as feed rate, cutting speed, and depth of cut. This research used a centre joint design as a selection. RSM approach [12]. Historically, industries have relied primarily Relying It relies on the skill and experience of operators to achieve optimal settings and maintain the desired quality and performance efficiency. Then, traditional methods such as Taylor's tool life equation were introduced, along with various analytical and experimental optimization techniques. These approaches have been used to address optimization challenges, with moderate success. Currently, the focus has shifted to using more accurate modern or unconventional techniques to solve the same problem. Methods such as Fuzzy logic, scatter plot techniques, genetic algorithms, Taguchi method, and simulated annealing and Response Surface Methodology has been used to some extent to enhance the turnaround process's effectiveness and quality. However, continuous evolution of new materials and process technologies, more research is necessary to equip industries with adequate knowledge of products, processes and manufacturing methods. This will help maintain product quality, improve productivity and uphold the reputation of the company [13]. Response Surface Methodology is a specific design of experiment technique that uses quantitative data from carefully planned experiments to generate and solve a series of equations. It establishes a relationship between response variables such as With input parameters such as Power consumption, tool life, cutting force, surface roughness, depth of cut, feed rate, and cutting speed in turning operations. Graphical representations of these equations are called response surfaces, help analyse the Relationships between input Factors and their influence on output variables. RSM is widely used in product and process design and development. Numerous studies have used various standard methods for Ra modelling and various techniques to optimize process parameters. Recently, artificial neural networks (ANN) have attracted attention in scientific research due to their strong predictive capabilities. Alagarswamy and Raja Kumar proposed an effective approach to optimize turning conditions Using the Taguchi method with the response surface methodology, their study investigates application of Taguchi method for reducing and improving Ra material removal rate Material Removal Rate (MRR) During machining of Al-7075 alloy with tungsten carbide (TNMG 115 100) inserts [14]. Product reliability has a direct impact on the consumption Natural resources in production. Mohammed et al. Vegetable oils offer significant advantages as lubricants for mechanical applications. Environmentally sustainable manufacturing requires a strong focus on product design and reliability, which becomes increasingly challenging as products grow more complex. In this context, most industries strive to produce complex components while maintaining high standards of safety and quality. In machining operations, Cutting temperature, Surface roughness and cutting force are crucial factors key factors main factors affecting product quality. An increase in these parameters results in increased power consumption and deformation, which have a detrimental effect on cutting tool performance, dimensional accuracy, and overall product quality [15]. This process offers significant advantages Compared to other manufacturing methods such as casting, forging and rolling, especially in achieving better surface finish. With the development of advanced materials, conventional machining techniques often fail to meet The desired product quality and the full application of Computer Numerical Control (CNC) machines in various fields have not yet been mastered. In the current industry landscape, Key production processes are still largely carried out on conventional machinery; however, CNC machines are used whenever precision and accuracy are essential. In machining operations, surface properties are an important quality indicator. As noted by many researchers, improved surface properties contribute to improved aesthetics, Corrosion resistance, fatigue strength and long life a material. Therefore, achieving excellent surface properties is crucial to ensuring the desired product quality [16]. Multi-discipline optimization often involves the use of several mathematical techniques, including model generation and optimization. Model generation serves as the initial step in machine optimization. Since the It is typically unclear how cutting parameters and process performance indices relate to one another essential to create trustworthy equations that can be used as control or objective functions. In many cases, process becomes cost-effective because a significant number of experiments are required to ascertain the connection between cutting parameters and observed responses. Address this challenge, researchers often use the Response Surface Method (RSM) to evaluate how cutting settings affect mechanical effects through carefully designed experiments, generating data suitable for efficient statistical analysis. This helps to generate reliable models and objective conclusions [17]. Computer numerical control (CNC) machines, such as CNC lathes, play a key role in the machining industry. These high-precision turning machines can process various types of raw materials, including metals and alloys, wood, composites, and plastics. This capability allows for the production of complex components with tight tolerances and consistent quality, which are often challenging to achieve using conventional machines. Traditional machining methods rely heavily on operator experience and often require multiple test runs, as workers must have a deep understanding of the process to minimize errors. In contrast, CNC machines, with their advanced automation and visualization systems, help reduce human error, predict appropriate specifications, and reduce production costs [18]. When manufacturers face multiple conflicting objectives, modelling techniques can improve the efficiency of mechanical processes. While many theoretical models rely on simplifications, assumptions, and approximations to represent real-world machinery, they often fail to account for undesirable imperfections in the process. As a result, analytical solutions are not easily applicable in practical situations, making proper modelling essential for qualitative predictions in cutting conditions. Modelling using Response Surface Method and Artificial Neural Networks have proven effective be effective. To be a useful approach for product and process optimization and has received significant attention from researchers over the past two decades [19].

2. MATERIALS AND METHODS

Spindle Speed: Spindle speed refers to the rotation rate of the rotational speed of the engine, usually measured in revolutions per minute. It is an important factor in machining, affecting surface finish, tool longevity, and material removal efficiency. Higher speeds work well with softer materials for smoother cutting, while lower speeds help reduce heat build-up and tool wear in harder materials. Choosing the right Spindle speed is affected by factors such as cutter diameter, material properties, and cutting conditions. Advanced CNC machines offer adjustable spindle speeds for optimal results. Improper speed settings can lead to tool failure or poor quality finishes, making precise adjustments necessary for accuracy and efficiency.
Feed: Feed refers to the rate of movement of a cutting tool or workpiece during machining, which affects surface quality, tool life, and overall performance. Expressed in mm/rev or mm/min, it varies based on the kind of instrument, the substance, and the cutting circumstances. Selecting the correct feed increases accuracy, reduces tool wear, and improves CNC machining performance.
Depth of cut: Measured perpendicular to the work's surface, the thickness of material removed in a single machining pass is known as the depth of cut piece. It significantly affects Cutting force, tool longevity and surface quality. Higher depths improve material removal but increase cutting stress, while shallower cuts improve accuracy and finish. The optimal depth depends on material hardness, tool life, and machining parameters. CNC machines offer precise depth control for improved performance. Selecting the correct depth increases productivity, extends tool life, and ensures excellent machining results with minimal defects.
Cutting Environment: The cutting environment encompasses the conditions under which machining occurs, including temperature, lubrication, chip removal, and workpiece stability. Proper cooling and lubrication help reduce heat build-up, reduce tool wear, and improve cutting performance. Effective chip management ensures consistent operations and prevents damage. Factors such as dry cutting, wet cutting, or coolant use affect machining accuracy. Improving the cutting environment increases productivity, extends tool life, and improves accuracy, making it essential for achieving better production results.
Surface roughness: Surface roughness describes the texture and unevenness of the surface a machined surface, measured in micrometres (µm). It the function of a plays a key role in defining wear resistance and durability aesthetic quality component. Factors Including cutting speed, feed rate, tool position and other factors material properties affect roughness levels. Smooth surfaces reduce friction, increase fatigue resistance, and improve performance in critical applications, while excessive roughness can cause premature wear and reduced performance. Measurement methods include profilometers and optical techniques. Proper machining parameters, tool selection, and lubrication help achieve the desired result. Controlling roughness is critical to ensuring accuracy, durability, and superior production results.

Instructions for Machine Learning

Regression Analysis: Linear regression is a data analysis technique that estimate unknown Values obtained from known data points. Easy linear regression estimates the dependent variable derived from one independent variable dependent variable, with prediction accuracy improving as the linear relationship becomes stronger. This method determines the best-fit line that represents their mathematical relationship. Widely used in business, education, and scientific fields such as biology, behavioural sciences, and social sciences, linear regression is a reliable tool for data-driven predictions. Training a linear regression model involves a gradient descent optimization algorithm, which adjusts Model parameters are adjusted to reduce mean square error (MSE). While Simple linear regression involves analysing the relationship between variables, whereas it specifically focuses on involves a single independent variable, multiple linear regression extends this concept by including multiple features into the equation. General equation of multiple linear regression has additional weights and inputs for each variable, which are represented as follows: Y(Ks)=P0+P1S1+P2S2+…+P(N)Ks(N) This extended approach enables the analysis of complex datasets, improving prediction accuracy in various domains.

Random Forest Regression: This machine learning ensemble technique combines several results trees to increase prediction accuracy and decrease over fitting. As opposed to a single choice tree, which is highly variable, using various data sources, Random Forest generates several decision trees subsets and averages their outputs their outputs for more consistent and reliable predictions. The algorithm selects each tree is constructed using training data and random subsets of selected features, which promotes diversity among the models. During prediction, each tree independently estimates the target value is obtained by averaging the predictions from all models, ensuring a more accurate final output approach reduces errors and improves generalization to missing data. Due to its robustness against noise and ability to capture nonlinear relationships, Random Forest Regression Commonly used in fields such as finance and healthcare, and engineering. It handles large datasets and missing values efficiently, but may require more computational resources than simpler models. Important Hyper parameters such minimum samples per tree, tree depth, and number of trees partition, can be fine-tuned to improve performance. Despite its complexity, Random Forest a robust and understandable resilience model that is reliable and provides accurate predictions in a variety of applications.

Support Vector Regression: A machine learning method for predicting continuous values is called support vector regression. Unlike conventional regression models, the aim of SVR is to find a function that closely fits the data while maintaining a defined tolerance level range rather than just minimizing the error. SVR transforms Transforming Transforms input features into a high-dimensional space using kernel functions, which help capture complex, nonlinear relationships. The model then determines a hyper plane that maximizes the edge on which most of the data points fall, penalizing significant errors while ignoring small deviations. Frequently used Linear, polynomial, and radial basis functions are examples of kernel functions, which allow SVR to adapt to a variety of data formats. SVR's primary strength is its capacity to handle high-dimensional data effectively and noise while minimizing the risk of over fitting. It is widely used in areas such as financial forecasting, biomedical signal processing, and engineering simulations. However, SVR Can be computationally challenging, especially for large datasets, and fine-tuning of hyper parameters Kernel type, regulatory parameter (C), and epsilon (ε) is required to improve performance. Despite these problems, SVR remains a very useful regression technique, especially for datasets with complex patterns and limited observations.

3. RESULTS AND DISCUSSION

TABLE 1. Using RSM and GA to optimize machine settings for EN 8 steel turning.

Spindle speed	Feed rate	Depth of cut	Cutting environment	Surface roughness
900	0.33	1	20	3.69
900	0.25	1	25	3.52
800	0.3	0.5	23	2.58
800	0.3	1.5	23	4.85
730	0.25	1	30	3.48
1000	0.2	0.5	27	2.69
800	0.2	0.5	33	2.68
900	0.25	1	25	3.52
1000	0.3	0.5	20	2.59
900	0.25	1	25	3.49
900	0.17	1	35	3.5
900	0.25	1	25	3.33
800	0.2	1.5	33	4.46
900	0.25	1	25	3.46
1000	0.2	1.5	27	4.13
900	0.25	1.84	25	4.85
900	0.25	1	25	3.47
900	0.25	0.16	24	2.51
1000	0.3	1.5	19	4.64
1060	0.25	1	21	3.71

Optimizing turning parameters for EN 8 steel Using response surface methodology and genetic algorithm involves assessing the cutting environment, depth of cut, feed rate, and spindle speed are all modified to achieve optimal surface roughness. As shown Table 1, surface roughness values range from 2.51 to 4.85, depending on the cutting conditions. For example, with under cutting parameters of 0.5 mm cutting depth, 0.3 mm/rev feed rate, and 800 RPM spindle speed 23, the surface roughness measured 2.58. Similarly, at 1000 RPM, with a 0.3 mm/rev feed rate and a 0.5 mm cutting depth at 20, The roughness of the surface was measured to be 2.59 lowest roughness value of 2.51 occurred at 900 RPM, with The depth of cut is 0.16 mm, and the feed rate is 0.25 mm/rev, and the cutting environment is 24. Findings indicate that reducing the depth of cut and feed adjustment rates significantly enhance surface finish. Additionally, spindle speeds between 800 and 1000 RPM, combined with moderate Lower Surface quality is enhanced by feed rate and depth of cut factors. This research emphasizes the critical significance of choosing the right parameters to reduce surface roughness and improving machining performance.

TABLE 2. Descriptive Statistics

	Spindle speed	Feed rate	Depth of cut	Cutting environment	Surface roughness
count	20	20	20	20	20
mean	899.5	0.25	1	25.5	3.5575
std	84.13492	0.041549	0.423718	4.394973	0.736027
min	730	0.17	0.16	19	2.51
25%	875	0.2375	0.875	23	3.17
50%	900	0.25	1	25	3.495
75%	925	0.2625	1.125	27	3.815
max	1060	0.33	1.84	35	4.85

Table 2 presents a summary of the descriptive statistics for turning parameters and surface roughness when EN 8 steel is being machined. The dataset includes 20 observations for surface roughness, cutting environment, depth of cut, spindle speed, and feed rate. Average spindle speed 899.5 RPM, with a standard deviation of 84.13, and it ranges from 730 RPM to 1060 RPM with an average 0.25 mm/rev feed rate, with values varying between 0.17 Cutting depth, mm/rev and 0.33 mm/rev values vary from 0.16 mm to 1.84 mm, with a standard deviation of 0.42 and an average of 1 mm. The cutting environment varies from 19 to 35, with an average value of 25.5. The surface roughness the range is 2.51 to 4.85, the mean is 3.56, and the standard deviation is 0.74. A quarterly analysis shows that 50% of the data falls within the 875–925 RPM spindle speed range, feed rates ranging from 0.2625 mm/rev to 0.2375 mm/rev, cutting depth varies from 0.875 mm to 1.125 mm. These statistical insights provide valuable information on parameter variations and their impact on machine performance, aiding in Process refinement and improvement.

Effect of Process Parameters:

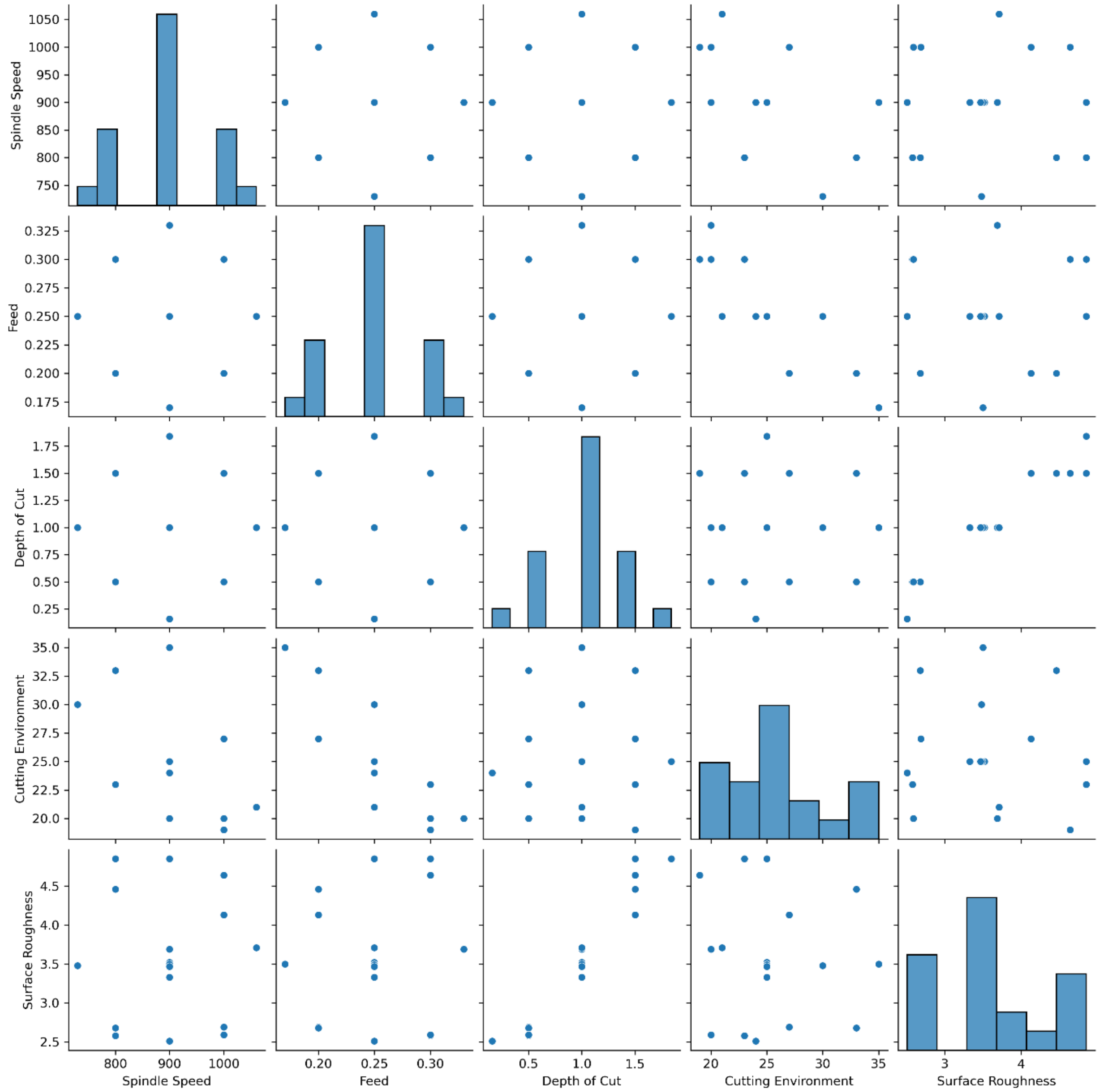


FIGURE 1. Scatter plot of the various Response surface technology was used to optimize the turning parameters for EN 8 steel machining and genetic algorithm.

Figure 1 presents a scatterplot matrix that illustrates the relationships between various turning parameters for Response Surface Methodology and Genetic Algorithms for EN 8 Steel Optimization. The matrix includes Surface roughness, cutting environment, spindle speed, feed rate, and depth of cut all contribute identify possible interactions among the variables. The diagonal histograms display the distribution of each parameter, while the scatterplots highlight potential trends and correlations between them. This figure offers valuable insights into how machining parameters interact and impact the final results, supporting the optimization process. Notably, Surface roughness variations are influenced by the feed rate and cut depth.

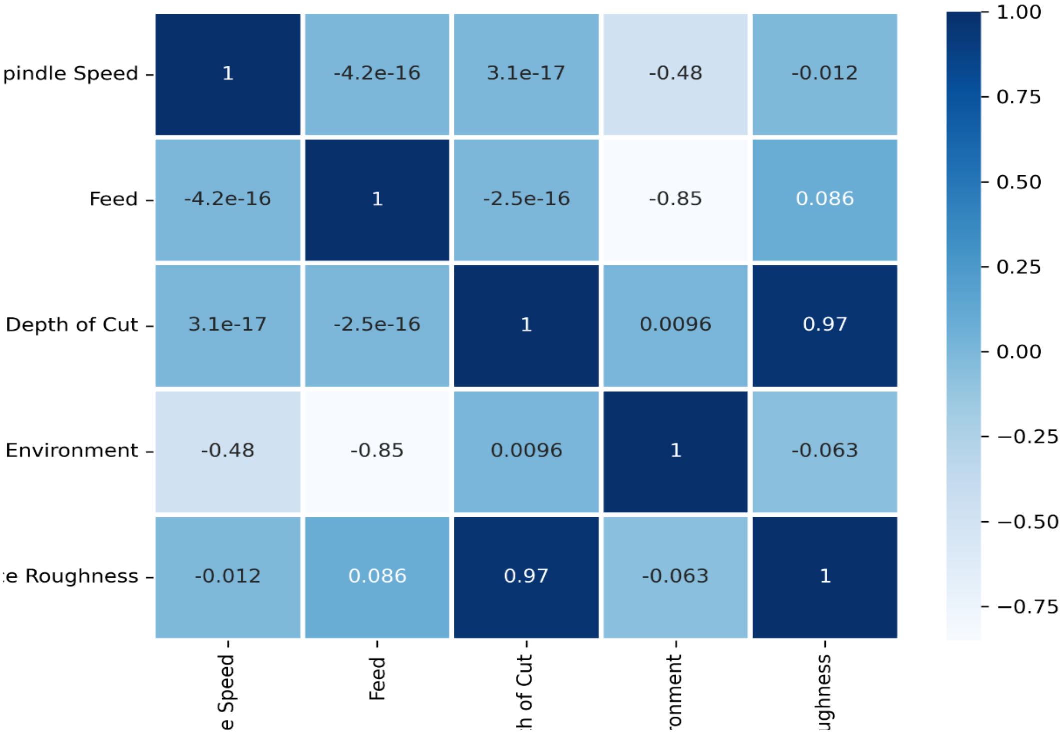
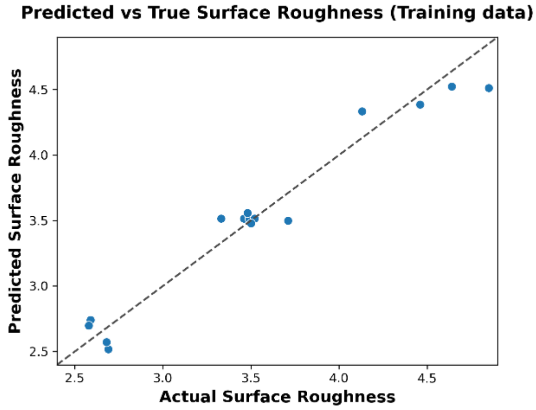


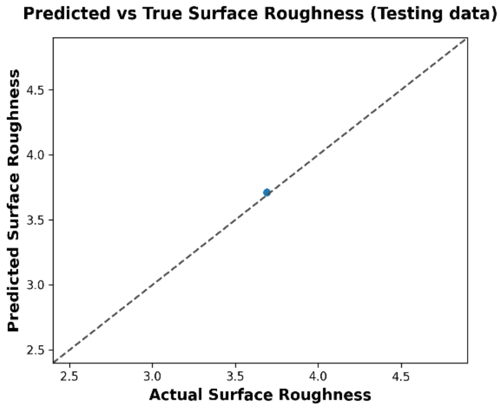
FIGURE 2. Correlation heat map on process parameters and effects

Figure 2 presents a correlation heat map that depicts the connection between EN 8 steel's surface roughness optimization and mechanical characteristics. The heat map shows Surface roughness, cutting environment, cut depth, spindle speed, and feed rate in relation to each other through correlation coefficients. Darker shades indicate stronger interactions, while lighter shades reflect weaker interactions. Notably, the depth of cut exhibits a strong positive correlation with surface roughness (0.97), emphasizing its substantial influence. In contrast, feed rate and cutting environment show negative correlations with certain parameters. This visualization offers valuable insights into parameter interdependencies, aiding in the selection of optimal machining conditions for enhanced surface finish.

Linear Regression (LR)



a)

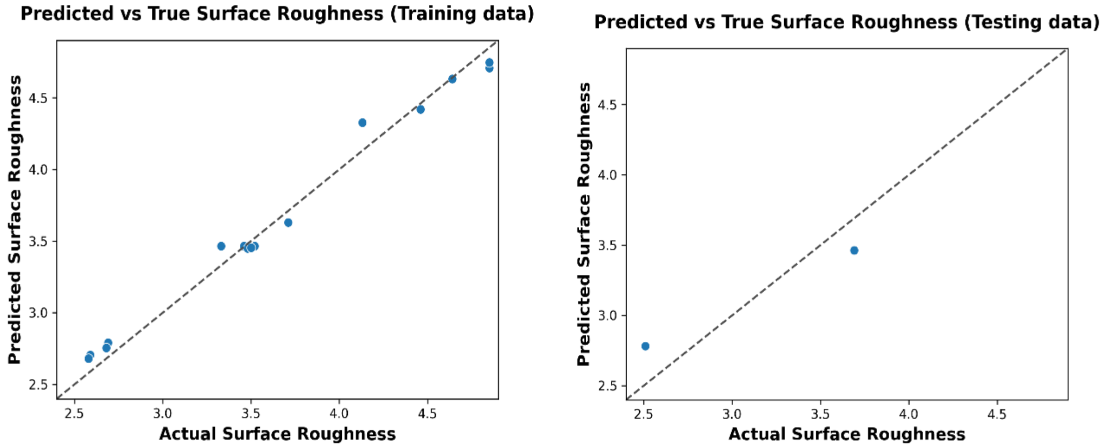


b)

FIGURE 3. Predictive accuracy of linear regression model in Optimizing turning process parameters for EN 8 steel using response surface methodology and genetic algorithm. (a) training; (b) testing.

Figure 3 illustrates the Accuracy of predictions in a linear regression model in optimizing turning parameters for EN 8 steel using Response Surface Methodology and Genetic Algorithm. Substructure (a) displays the training data, while substructure (b) shows the experimental data. The scatter plots compare the predicted surface roughness values with the actual measurements, with the dashed line representing the ideal prediction. In the training data, most points are closely aligned with the diagonal, indicating strong model performance. Similarly, the experimental data shows a good fit, validating the model's reliability. These findings illustrate how well the model predicts surface roughness for machining optimization.

Random Forest Regression

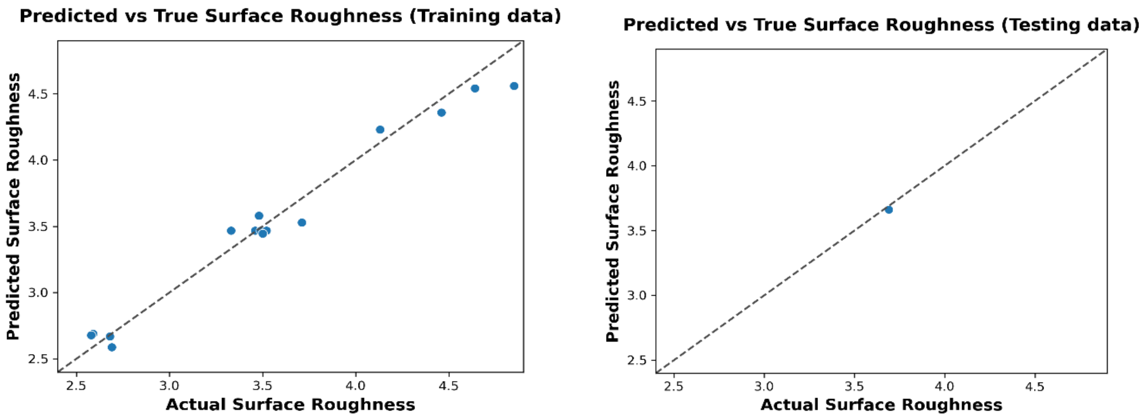


a) b)

FIGURE 4. Predictive accuracy of the random forest regression model in Optimizing turning process parameters for EN 8 steel using response surface methodology and genetic algorithm a) train b) test

Figure 4 demonstrates Predictive accuracy of the random forest regression model in optimizing turning parameters for EN 8 steel using Response Surface Methodology and Genetic Algorithm. Subset (a) represents the training data, while subset (b) represents the experimental data. The scatter plots compare the predicted surface roughness values with the actual measurements, with the dashed diagonal line indicating the ideal prediction. The training data aligns closely with the diagonal, signifying high model accuracy. Similarly, the experimental data shows a good alignment, further confirming the model's reliability in predicting surface roughness for machining optimization.

Support Vector Regression



a) b)

FIGURE 5. Predictive accuracy of support vector regression model in Optimizing turning process parameters for EN 8 steel using response surface methodology and genetic algorithm a) train b) test

Figure 5 illustrates Predictive performance of the support vector regression model in optimizing turning parameters for EN 8 steel using Response Surface Methodology and Genetic Algorithm. Subset (a) represents the training dataset, while subset (b) corresponds to the test dataset. The scatter plots compare the predicted surface roughness values with the actual ones, with the dashed diagonal line indicating ideal predictions. The training data shows a strong alignment with the diagonal, signifying high model accuracy. Similarly, the test data also demonstrates good accuracy, further validating the effectiveness using the SVR model for surface prediction roughness for machining optimization.

TABLE 3. Regression Model Performance Metrics (Training Data)

Data	Symbol	Model	R2	EVS	MSE	RMSE	MAE	Max Error	MSLE	Med AE
Train	LR	Linear Regression	0.958452	0.95845	0.02108	0.14518	0.11672	0.33814	0.00095	0.11256
Train	RFR	Random Forest Regression	0.984104	0.98421	0.00806	0.08980	0.07336	0.19620	0.00039	0.06500
Train	SVR	Support Vector Regression	0.975157	0.97575	0.01260	0.11226	0.09001	0.28982	0.00054	0.09997

Table 3 presents the performance metrics of different regression models used to optimize turning parameters in EN 8 steel machining. The evaluated models include linear regression, random forest regression, and support vector regression. Key metrics such as the explained variance score, coefficient of determination, mean square error, mean absolute error, and root mean square error (R^2), maximum error, median Both mean square logarithmic error (MSLE) (Med AE) and absolute error are presented.. Among these, RFR achieves the highest prediction accuracy with an R^2 of 0.984, the lowest MSE (0.00806), and an RMSE of 0.0898, indicating its superior ability to model machining parameters. SVR also performs well, with an R^2 of 0.975 and an RMSE of 0.11226. In contrast, LR shows the lowest R^2 (0.958) and the highest RMSE (0.14518), reflecting lower accuracy. These results establish RFR as the most effective model for minimizing errors and enhancing predictive performance, making it the preferred choice for surface roughness prediction in machining optimization.

TABLE 4. Regression Model Performance Metrics (Testing Data)

Data	Symbol	Model	R2	EVS	MSE	RMSE	MAE	Max Error	MSLE	Med AE
Test	LR	Linear Regression	0.564986	0.76479	0.15143	0.38914	0.28614	0.54987	0.01453	0.28614
Test	RFR	Random Forest Regression	0.818305	0.81983	0.06325	0.25149	0.25044	0.27347	0.00405	0.25043
Test	SVR	Support Vector Regression	0.650436	0.84481	0.12168	0.34883	0.26012	0.49254	0.01145	0.26012

Table 4 presents the performance metrics of different regression models applied to experimental data for optimizing turning parameters in EN 8 steel machining. The evaluated models include Random forest regression, linear regression, and support vector regression were evaluated utilizing key indicators such as the explained variance score, the coefficient of determination, maximum error, median absolute error, mean square logarithmic error, mean absolute error, mean square error, and root mean square error (Med AE). Among these, RFR achieves the highest prediction accuracy, with an R^2 of 0.818, the lowest MSE (0.06325), and the smallest RMSE (0.25149), demonstrating its strong predictive capability and minimal error rate. SVR ranks second with an R^2 of 0.34883 and an RMSE of 0.650, suggesting a moderate level of accuracy. In contrast, LR exhibits the weakest performance, recording the lowest R^2 (0.564) along with the highest MSE (0.15143) and RMSE (0.38914), reflecting significant predictive errors. These results establish RFR as the most accurate and reliable model Predicting and creating surface roughness in machining optimization the preferred choice for analysing experimental data.

4. CONCLUSION

The Using reaction surface technique to maximize EN8 steel turning parameters and genetic algorithm (GA) has demonstrated significant improvements in manufacturing efficiency and product quality. This research investigated the critical The connection between the cutting parameters (feed rate, depth of cut, cutting environment, and surface roughness) and spindle speed), which is essential for ensuring component functionality, Test findings highlight resistance to corrosion, fatigue strength, and wear depth of the cut revealed the highest correlation with surface roughness (0.97), indicating its dominant influence on the final surface quality. Lower cut depths (about 0.16–0.5 mm) consistently produced superior surface finishes, with the ideal settings for minimizing surface roughness is 2.51 μm. Of these three regression models employed linear regression, random forest regression, and support vector machine regression are Random Forest model demonstrated superior predictive capabilities with the highest R^2 values (0.984 for training and 0.818 for testing) and lowest error metrics. This confirms RFR's the ability to model complex, nonlinear interactions between machine parameters and surface quality, making it an ideal choice for optimization in industrial applications. This research emphasizes the importance of statistical prediction techniques in building reliable models determine optimal machining parameters without extensive experimental testing. The research addresses the challenges faced by modern manufacturing industries that often struggle to meet quality requirements for advanced materials using conventional machining techniques. The findings emphasize that precise selection of cutting conditions significantly improves surface roughness, while appropriate modelling techniques enhance the efficiency of mechanical processes, particularly when manufacturers face multiple conflicting objectives. This work contributes valuable insights to the optimization of turning operations, enabling more efficient production with higher quality outcomes, reduced tool wear, and improved overall manufacturing performance.

REFERENCES

[1]. Ganesh, N., M. Udaya Kumar, C. Vinoth Kumar, and B. Santhosh Kumar. "Optimization of cutting parameters in turning of EN 8 steel using response surface method and genetic algorithm." International Journal of Mechanical Engineering and Robotics Research 3, no. 2 (2014): 75.

[2]. Sridhar, G., and G. Venkateswarlu. "Multi objective optimisation of turning process parameters on EN 8 steel using grey relational analysis." Int. J. Eng. Manuf. (IJEM) 4, no. 4 (2014): 14-25.

[3]. Mia, Mozammel, and Nikhil Ranjan Dhar. "Prediction and optimization by using SVR, RSM and GA in hard turning of tempered AISI 1060 steel under effective cooling condition." Neural Computing and Applications 31 (2019): 2349-2370.

[4]. Ravuri, Manu, Y. Santhosh Kumar Reddy, and D. Harsha Vardhan. "Parametric optimization of face turning parameters for surface roughness on EN 31 material using RSM and Taguchi method." Materials Today: Proceedings 37 (2021): 769-774.

[5]. Meddour, Ikhlas, Mohamed Athmane Yallese, Hamza Bensouilah, Ahmed Khellaf, and Mohamed Elbah. "Prediction of surface roughness and cutting forces using RSM, ANN, and NSGA-II in finish turning of AISI 4140 hardened steel with mixed ceramic tool." The International Journal of Advanced Manufacturing Technology 97 (2018): 1931-1949.

[6]. Manjula Selvam, M. Ramachandran, Chandrasekar Raja, Sathiyaraj Chinnasamy, "Assessment of Material Selection Problem for Aircraft Parts Using the GRA method", Aeronautical and Aerospace Engineering, 2(1), March 2024, 7-15.

[7]. Routara, B. C., A. K. Sahoo, A. K. Parida, and P. C. Padhi. "Response surface methodology and genetic algorithm used to optimize the cutting condition for surface roughness parameters in CNC turning." Procedia engineering 38 (2012): 1893-1904.

[8]. Elsadek, Ahmed A., Ahmed M. Gaafer, Samah Samir Mohamed, and A. A. Mohamed. "Prediction and optimization of cutting temperature on hard-turning of AISI H13 hot work steel." SN Applied Sciences 2 (2020): 1-12.

[9]. Srivastava, Abhishek, Adarsh Sharma, Aditya Singh Gaur, Rahul Kumar, and Yashwant Kumar Modi. "Prediction of surface roughness for CNC turning of EN8 steel bar using artificial neural network model." Journal Européen des Systèmes Automatisés 52, no. 2 (2019): 185-188.

[10]. SK, Thangarasu, S. Shankar, and Devendran K. "Tool wear prediction in hard turning of EN8 steel using cutting force and surface roughness with artificial neural network." Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science 234, no. 1 (2020): 329-342.

[11]. Asiltürk, Ilhan, and Süleyman Neşeli. "Multi response optimisation of CNC turning parameters via Taguchi method-based response surface analysis." Measurement 45, no. 4 (2012): 785-794.

[12]. Narayanan, N. Sathiya, N. Baskar, and M. Ganesan. "Multi objective optimization of machining parameters for hard turning OHNS/AISI H13 material, using genetic algorithm." Materials Today: Proceedings 5, no. 2 (2018): 6897-6905.

[13]. Senthilkumar, N., T. Tamizharasan, and S. Gobikannan. "Application of response surface methodology and firefly algorithm for optimizing multiple responses in turning AISI 1045 steel." Arabian Journal for Science and Engineering 39 (2014): 8015-8030.

[14]. Kandananond, Karin. "Using the response surface method to optimize the turning process of AISI 12L14 steel." Advances in Mechanical Engineering 2 (2010): 362406.

[15]. Izelu, Christopher Okechukwu, Samuel Chikezie Eze, and Festus Ifeanyi Ashiedu. "Modeling and optimization of hard turning operation on 41Cr4 alloy steel using response surface methodology." Int. J. Mech. Eng. Appl 4, no. 2 (2016): 88-102.

[16]. Chinnasami Sivaji, M. Ramachandran, Vimala Saravanan, Ramya Sharma, "Space and Underwater Robots using the SPSS Method", Aeronautical and Aerospace Engineering, 2(1), March 2024, 17-26.
[17]. Abdulridha, H., A. Helael, and A. Al-duroobi. "Prediction the influence of machining parameters for CNC turning of Aluminum alloy using RSM and ANN." Eng. Technol. J. 38, no. 6 (2020): 887-895.
[18]. Usha, M., and G. S. Rao. "Optimization of multiple objectives by genetic algorithm for turning of AISI 1040 steel using Al2O3 nano fluid with MQL." Tribology in industry 42, no. 1 (2020): 70.
[19]. Kumar, Vidyanand, Manjeet Kharub, and Animesh Sinha. "Modeling and optimization of turning parameters during machining of AA6061 composite using RSM box-behnken design." In IOP Conference Series: Materials Science and Engineering, vol. 1057, no. 1, p. 012058. IOP Publishing, 2021.
[20]. Paiva, A. P., E. J. Paiva, J. R. Ferreira, P. P. Balestrassi, and S. C. Costa. "A multivariate mean square error optimization of AISI 52100 hardened steel turning." The International Journal of Advanced Manufacturing Technology 43 (2009): 631-643.
[21]. Nguyen, VI, Hieu Do, and Thanh Tran. "Experimental study and multi-objective optimisation of CNC turning parameters of AL6061 materials." Australian Journal of Mechanical Engineering (2024): 1-10.