Optimization of the Tungsten Carbide OD Grinding Process by Design of Experiment and Artificial Neural Network Approach

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Abstract

Tungsten carbide holds immense significance in contemporary industries such as aerospace, manufacturing, medicine, and cutting tools. Within these sectors, precision machining and grinding processes are pivotal and often rely on powder metallurgy techniques. However, these procedures frequently suffer from prolonged time requirements, increased expenses, and elevated rejection rates post-sintering. While previous research has made attempts to address these challenges through methodologies such as Design of Experiments (DOE), only a handful have taken a holistic approach that integrates these techniques with Artificial Neural Networks (ANN) to effectively identify root causes. This study aims to mitigate the cost and time constraints associated with grinding processes and tackle the primary contributors to rejection rates. The experimental framework involves comprehensive testing at each grinding stage, incorporating in-depth analysis of surface roughness, material removal rate and process time. Results obtained from multi-objective optimization and analysis of variance (ANOVA) indicate that optimal component quality can be achieved through a spindle speed of 3000 rpm, a depth of cut of 0.013mm, and a feed rate of 1 mm/s resulting in better MRR, process time and surface roughness. The predictions generated by the ANN align with simulation outcomes and are supported by strong validation performance at the fifth epoch. Regression values of 0.99891, 0.99135, and 0.99779 for validation, testing, and the overall neural network model, respectively, further validate the findings. The close correlation between ANN approximations and DOE results highlights the significance of proper grinding wheel selection, adherence to standardized parameters, and careful powder handling in these processes.

Keywords: *Tungsten carbide, Artificial neural networks, Grinding process*

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1.0 Introduction

Tungsten carbide has gained considerable interest across various applications including aerospace, automotive, and manufacturing due to its exceptional properties such as highly resistant to wear and abrasion, high compressive strength, resistance to corrosion, and good thermal conductivity [1-2]. In numerous scenarios, tungsten carbide components undergo precision machining processes which include surface grinding, grinding of outer diameter (OD) and inner diameter (ID) [3]. These techniques are indispensable for achieving dimensional accuracy, surface quality, and geometrical precision required across diverse industries [4]. Also, precision grinding of tungsten carbide surfaces, OD, and ID requires careful monitoring of parameters such as grinding wheel grade selection, spindle speed, feed rate, and depth of cut. The kinematic interaction between the workpiece and the grinding wheel with the proper combination of these parameters results in the improved surface quality and material removal rate [5]. Improving the grinding of carbide tools requires a combination of advanced grinding methods, abrasives, and grinding fluids. The use of high-speed grinding, low-frequency vibration, and abrasive suspensions have all been shown to be effective in improving the surface finish of carbide tools. Further research is needed to optimize these methods for specific applications and materials to ensure the best results [6].

The grinding process is a surface finishing method employed to refine surfaces by removing a controlled amount of material from pre-machined surfaces. Among these methods, cylindrical grinding, which falls under the category of abrasive machining, is a widely used technique for precise material removal from a workpiece's surface, achieved by interacting with abrasive particles of various shapes [7].

In ongoing research, the Taguchi method, a form of Design of Experiments, has been employed to optimize the parameters inherent to cylindrical grinding. These parameters include wheel speed (measured in rpm), work speed, feed rate (measured in mm/min.), depth of cut, and the application of cutting fluid. The primary focus of this optimization is to enhance the Material removal rate, a critical aspect of grinding process efficiency [8].

N. Alagumurthi et al [9-10] from predicted optimal grinding conditions for Al_2O_3 grinding wheel. The following values: a depth of cut of 0.02mm, a work speed of 300rpm, and a wheel speed of 1750rpm. These settings resulted in an optimal surface roughness value of 0.46μm. Additionally, the estimated total grinding cycle time, which encompasses coarse cutting time, fine cutting time, forward and return movements, load and unload times, and setup time, was determined to be 6 minutes and 20 s, with the regression R^2 value, which assesses the variance explained by the variables, exhibited a significant and impressive result, surpassing 90% and more precisely, hovering at approximately 91.82%. K. Leo Dev Wins et al [11] developed predictive model for the surface roughness of a silicon carbide grinding wheel using Artificial Neural Network (ANN) methodology. The optimal combinations of speed 1000 rpm, depth of cut 0.03 mm and feed 0.8mm/s were found to predict a minimum surface roughness of 0.58 µm. Numerous studies have investigated the factors contributing to grinding wheel wear, forming a substantial body of research. Understanding the elements that accelerate wear underscores the importance of closely monitoring the grinding wheel's performance during processing, as highlighted in reference [12].

A review of existing literature [1-12] reveals a significant body of research dedicated to optimizing the grinding process. This study primarily focuses on reducing grinding time and associated costs while maintaining product quality. Simultaneously, it aims to decrease the rate of rejected products and explore the factors leading to rejections, along with strategies for their mitigation. To achieve these goals, a comprehensive optimization strategy is employed, incorporating techniques such as the design of experiments, and quality control tools. This study harnesses Artificial Neural Networks (ANNs) to enhance optimization efforts, offering a means to analyze complex data and patterns to identify optimal parameters and configurations for the grinding process. This paper delves into the realm of grinding process optimization, drawing from a diverse array of methodologies and tools. Its integrative approach seeks not only to enhance efficiency and reduce costs but also to address quality concerns and rejection rates, ultimately contributing to an improved and streamlined grinding process.

2.0 Experimental Method

2.1 Experimental Layout for DOE

Experimental design is a critically important tool in the engineering world for improving the performance of manufacturing processes or developing trials for new experiments. It also has an extensive application in the development of new processes. The application of experimental design techniques early in process development can result in, improved process yields, reduced variability, closer conformance to nominal or target requirements, reduced overall costs, and reduced development time.

To conduct this investigation, opted for an L9 array in Minitab's 'Three Level Design' feature, allowing us to accommodate three factors, each with three variability levels. In this project, Table 1 presents choices for spindle speed (ranging from 2200, 2500 and 3000 rpm), depth of cut (varying between 0.008, 0.01 and 0.013 mm), and feed rate (set at 0.25, 0.5, and 1.0 mm/s). These selections represent the three levels of each factor for outer diameter grinding.

Optimizing material removal while minimizing time consumption ideally involves spindle speeds in the range of 2200 to 3000 rpm. For micro-finishing grinding, where precision levels as low as 0.008 mm and up to 0.013 mm can be achieved, the depth of cut should be within this range. Furthermore, it is recommended to adhere to the standard feed rate specifications commonly used in the WC grinding process.

Table 1. Factors and their corresponding variability levels for OD grinding

Sl. No.	Factors	Unit	Levels		
			1	2	3
1	Spindle speed	rpm	2200	2500	3000
2	Depth of cut	mm	0.008	0.01	0.013
3	Feed rate	mm/sec	0.25	0.5	1.0

Table 2 shows the experimental layout obtained through Minitab statistical software. The combinations of factors are shown in 1st column and responses namely material removal rate, process time, and surface roughness are shown in 2nd column respectively. Table 6 refers to the data related to 1st and 2nd set of experimental results. This table provides a comprehensive understanding of key parameters, including material removal rate, processing time, and surface roughness factors, within the context of a complete fractional factorial design. It offers valuable insights into how these variables interact and influence the overall outcome of the experimental setup, facilitating a deeper comprehension of the design's performance characteristics.

The material removal rate (MRR, mm^3/s) is given by equation 1 as shown

$$MRR = \frac{S(rpm)\ X\ F\left(\frac{mm}{s}\right) X\ DOC\ (mm)}{60} \tag{1}$$

Where, MRR – Material removal rate in mm^3/s, S – Spindle speed in rpm, F– Feed rate in mm/s, DOC– Depth of cut in mm

Table 2. Experimental Planning by L_9 Orthogonal Array

Sl. No.	Spindle Speed (RPM)	Depth of cut (mm)	Feed rate (mm/s)	MRR (mm3/s)	Process time (min)	Surface roughness (μm)
1	2200	0.008	0.25	0.07333	16.19	0.8585
2	2200	0.01	0.5	0.18333	18.11	0.787
3	2200	0.013	1	0.4767	18.16	0.8403
4	2500	0.008	0.5	0.16667	16.19	0.8955
5	2500	0.01	1	0.4167	16.2	0.813
6	2500	0.013	0.25	0.13542	16.2	0.7945
7	3000	0.008	1	0.4	15.17	0.7635
8	3000	0.01	0.25	0.125	15.13	0.7795
9	3000	0.013	0.5	0.325	15.16	0.7335

3.0 Results and Discussion

The crucial objective is to mitigate the bottleneck that has been significantly impeding the grinding phase, thereby alleviating a substantial challenge.

3.1 Material Removal Rate

The analysis of variance (ANOVA) presented in Table 3 gives clear trend that feed rate stands out as the primary factor influencing material removal rate (MRR). This assertion is rooted in the observation that the F-value notably surpasses the P-value. The pronounced F-value emphasizes the feed rate's substantial impact on MRR, substantiating its significance in the process. In contrast, the influence of spindle speed emerges as relatively minor. This is further accentuated by the fact that even variations in the depth of cut wield a more pronounced effect on MRR than spindle speed.

Fig.1 depicts the main effect plot for material removal rate, which highlights that spindle speed has a direct impact on the material removal rate in OD grinding. Elevating the spindle speed from 2200 to 3000 rpm typically results in an augmented material removal rate from 0.248 to 0.29 mm^3/sec, thereby enhancing overall efficiency and productivity The phenomenon was explained by the presence of fine abrasives that came into contact with the workpiece at high speeds, resulting in a kinetic action that caused rubbing, which, in turn, led to a higher material removal rate. Increasing the spindle speed often led to an increase in material removal rates, but it was crucial to find a careful balance to preserve the lifespan of the cutting tool, attain a desired surface finish, and maintain overall machining quality.

The depth of cut is intrinsically linked to the material removal rate in OD grinding. Increasing the depth of cut from 0.008 to 0. 013 mm generally leads to a higher material removal rate from 0.21 to 0.32 mm^3/sec, increasing efficiency. This phenomenon is attributable to the greater force exerted on the workpiece by the grinding wheel, leading to a larger surface area coming into contact and thereby increasing the likelihood of achieving a higher Material Removal Rate (MRR). This also contributes to achieving a superior surface finish.

Furthermore, the feed rate directly governs the material removal rate in OD grinding. Elevating the feed rate from 0.25 to 1.00 mm/s usually yields a greater material removal rate of 0.10 to 0.44 mm^3/sec. This phenomenon occurs when the cutting tool rapidly advances towards the workpiece, resulting in a heightened material removal. This outcome was anticipated, as the material removal rate naturally rises with an increased feed rate, owing to the reduction in machining time. However, this enhancement must be pursued with careful consideration to maintain precision, achieve the desired surface finish, and curb wheel wear, all within well-defined boundaries. [13]

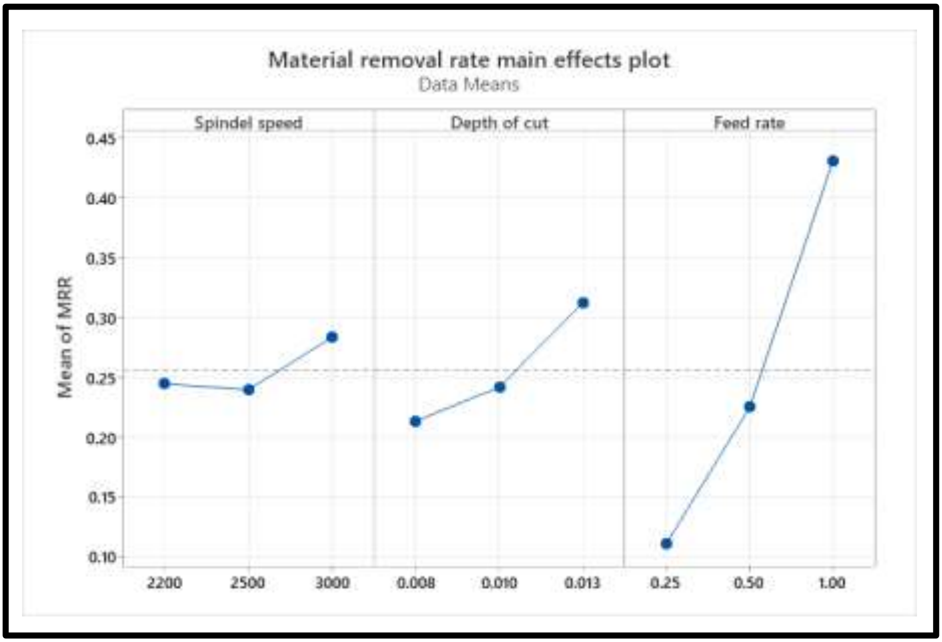

Fig. 1. Main effect plot for MRR

Table 3. Anova table for MRR

Analysis of Variance					
Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	3	0.175725	0.058575	111.18	0
Spindle Speed in RPM	1	0.002708	0.002708	5.14	0.073
Depth of cut in mm	1	0.015359	0.015359	29.15	0.003
Feed rate in mm/s	1	0.157658	0.157658	299.25	0
Error	5	0.002634	0.000527		
Total	8	0.178359			

The relationship between the outer diameter grinding parameters and the responses was modelled using RSM. The general first-order RSM model used to predict the influence of grinding parameters on the response factor is given by Eq. (2)

$$Yi = \beta 0 + \beta 1Xi1 + \beta 2Xi2 + \ldots\ldots\ldots \beta qXiq + \epsilon i(i = 1,2 \cdots N) \quad (2)$$

where Y_i is the response factor and X_{ij} are the values of i^{th} observation and j^{th} level of the grinding parameters. The terms β_i are the regression coefficients. For the modelling, the higher-order linear effects are considered and the interactive effects are not considered. The residual ϵ is a measure of the experimental error. The response surface represents the material removal rate, process time, and surface roughness (MRR, PT, SR) as a function of outer diameter grinding parameters such as spindle speed (SS), depth of cut (DOC), and feed rate (FR) an be represented by Eq. (3)

$$GR = \beta 0 + \beta 1(SS) + \beta 2(DOC) + \beta 3(FR) \quad (3)$$

Based on the experimental results of outer diameter grinding, the mathematical relationship established for correlating material removal rate (MRR) and the grinding parameters is presented as Eq. (4)

$$MRR = -0.3345 + 0.000053\,SS + 20.10\,DOC + 0.4245\,FR \quad (4)$$

R^2 value for model 98.52%

3.2 Process time

The analysis of variance (ANOVA) in Table 5 illustrates a distinct pattern indicating that spindle speed has a more significant influence. Increasing the spindle speed holds the potential for substantial improvements in process time, while the impacts of feed rate and depth of cut are relatively less significant when compared to spindle speed.

Fig 2 depicts the main effect plot for process time, demonstrates the typical direct correlation between spindle speed and process time in OD grinding. Increased spindle speeds from 2200 to 3000 rpm often lead to reduced process times from 18.1 to 15.2 min due to heightened material removal rates. This phenomenon can be described as follows: as the spindle speed increases, the removal of material accelerates because the sharp abrasive particles make high-speed contact with the workpiece, resulting in a higher Material Removal Rate (MRR). However, achieving a reduction in process time necessitates a balanced approach that carefully considers factors such as speed, tool durability, surface quality, and overall machining quality.

The depth of cut exhibits an inverse relationship with process time in OD grinding. Elevating the depth of cut from 0.008 to 0.013 mm holds the potential to slight increase in process time from 16.49 to 16.53 min by amplifying the material removal rate. This phenomenon could be linked to the precise point of contact between abrasive particles and the component, with the increased volume being a significant factor. In such situations, the spindle's speed takes on a primary role in the effort to decrease the processing time.

Likewise, the feed rate directly influences process time in OD grinding. Swifter feed rates from 0.25 to 1.00 mm/s generally yield slight larger process time of 16.49 to 16.5 min due to elevated material removal rates. The feed rate in the outer grinding process directly impacts process time. A higher feed rate reduces process time as it moves the workpiece more rapidly past the grinding wheel, while a lower feed rate extends process time as it slows down the workpiece advancement, affecting the overall efficiency of the grinding operation [14].

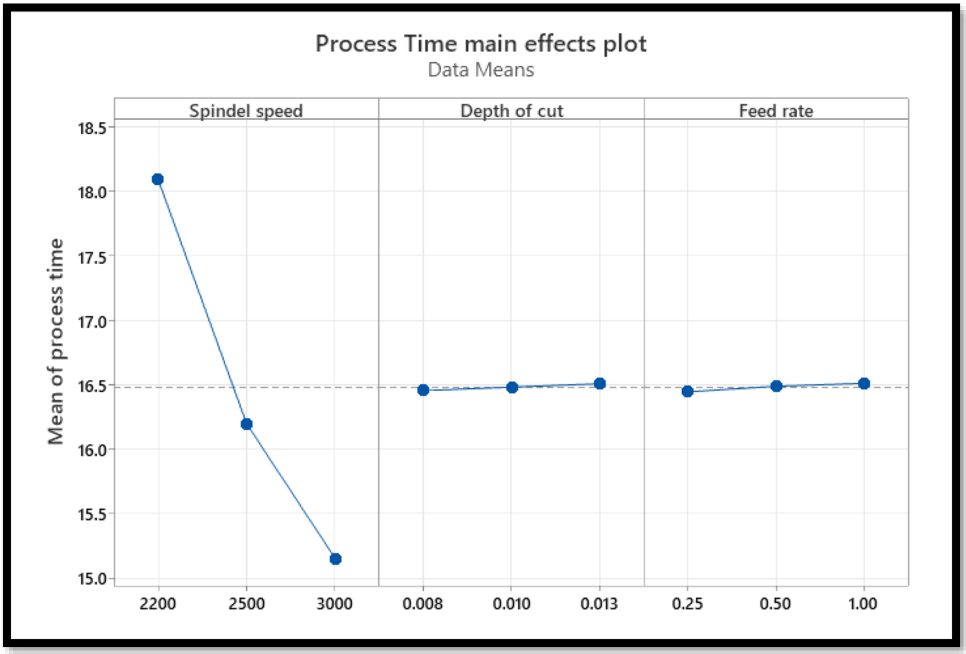

Fig 2. Main effect plot for process time

Table 4. Anova table for process time

Analysis of Variance					
Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	3	12.0783	4.0261	16.32	0.005
Spindle Speed in RPM	1	12.0681	12.0681	48.93	0.001
Depth of cut in mm	1	0.0042	0.0042	0.02	0.901
Feed rate in mm/s	1	0.006	0.006	0.02	0.882
Error	5	1.2333	0.2467		
Total	8	13.3116			

RSM model developed for process time. Based on the experimental results of outer diameter grinding, the mathematical relationship established for correlating process time (PT) and the grinding parameters is presented as Eq. (5)

$$PT = 25.33 - 0.003509\,SS + 10.5\,DOC + 0.083\,FR \qquad (5)$$

R^2 value for model 90.74%

3.3 Surface roughness

The analysis of variance (ANOVA) in Table 6 underscore the crucial role that spindle speed plays in achieving the specified surface finish standards, which require maintaining a surface finish within the defined range of 1.68 µm. As spindle speed increases, there is a noticeable improvement in surface roughness, bringing it into closer alignment with the targeted standards. In contrast, the impact of depth of cut and feed rate on surface finish appears relatively subtle as demonstrated.

Fig 3 depicts the main effect plot for surface roughness. Elevated spindle speeds from 2200 to 3000 rpm typically result in smoother surface finish of 0.829 to 0.757 µm due to heightened abrasive action and improved rates of material removal. This phenomenon can be attributed to the use of a fine abrasive wheel, which, when in contact with the workpiece at higher speeds, maximizes material removal rates while simultaneously achieving a finer surface finish.

The depth of cut increases from 0.008 to 0.013 mm is intricately linked to pivotal factors such as surface quality reduced from 0.84 to 0.79 µm, material removal rate, and precision. Deliberating upon considerations like the intended surface finish, workpiece composition, grinding wheel attributes, and other relevant elements becomes pivotal when determining the most suitable depth of cut. This approach ensures the achievement of optimal grinding outcomes without compromising the quality of the workpiece.[15]

Furthermore, the feed rate increases from 0.25 to 1.00 mm in OD grinding bears a direct impact on crucial aspects such as surface quality from 0.815 to 0.809 µm, material removal rate, and precision. This phenomenon due to more aggressive material removal and coarser abrasive actions involved. While higher feed rates can enhance productivity in certain situations, it's essential to maintain a careful balance with other factors to avoid compromising the desired surface finish and overall workpiece quality. It's important to note that the maximum allowable roughness as per the standard is 1.65µm.

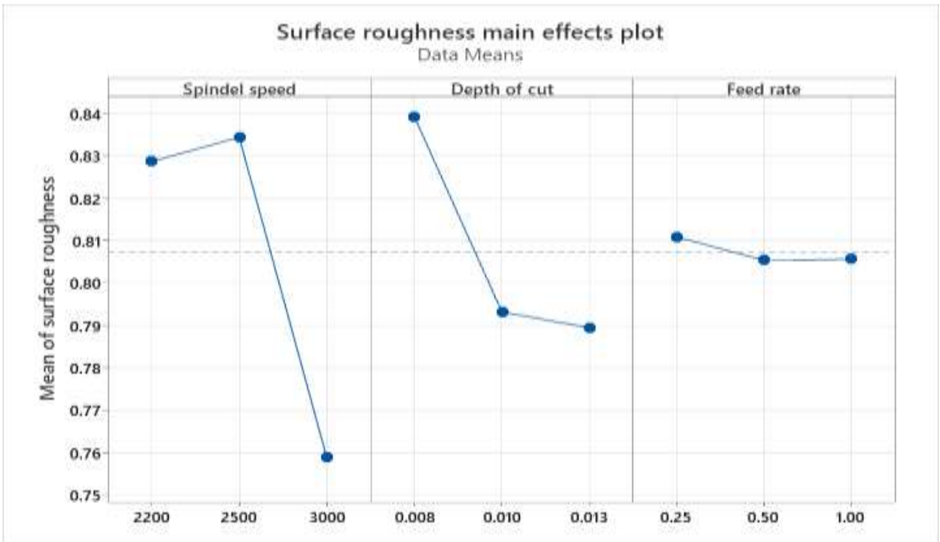

Fig. 3. Main effect plot for surface roughness

Table 5. Anova table for surface roughness

Analysis of Variance					
Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	3	0.011896	0.003965	2.38	0.186
Spindle Speed in RPM	1	0.00861	0.00861	5.16	0.072
Depth of cut in mm	1	0.003257	0.003257	1.95	0.221
Feed rate in mm/s	1	0.00003	0.00003	0.02	0.898
Error	5	0.008342	0.001668		
Total	8	0.020238			

RSM model developed for surface roughness. Based on the experimental results of outer diameter grinding, the mathematical relationship established for correlating surface roughness (SR) and the grinding parameters is presented as Eq. (6)

$$SR = 1.147 - 0.000094\, SS - 9.26\, DOC - 0.0059\, FR \qquad (6)$$

R^2 value for model 83.26%

3.4 ANN (Artificial Neuron Networks)

The effectiveness of an ANN model hinges on the precise selection of input-output process parameters, pivotal for achieving efficient forecasting or interpolation capabilities. The essence of learning and pattern recognition revolves around training the neural network to execute specific functions by finely adjusting inter-element weight values [16]. Neural networks are often fine-tuned, or trained, to map specific input data to desired target output results. The schematic depiction of a typical neural network architecture can be observed. These models incorporate a hyperbolic tangent sigmoid function within the hidden layer and a linear activation function within the output layer realize their construction [17].

Fig 4 illustrates an artificial neural network model with three input parameters: spindle speed, depth of cut, and feed rate. This model comprises three hidden layers and is trained on 70% of the data for MRR, process time, and surface roughness, with the remaining 15% each allocated for validation and test data.

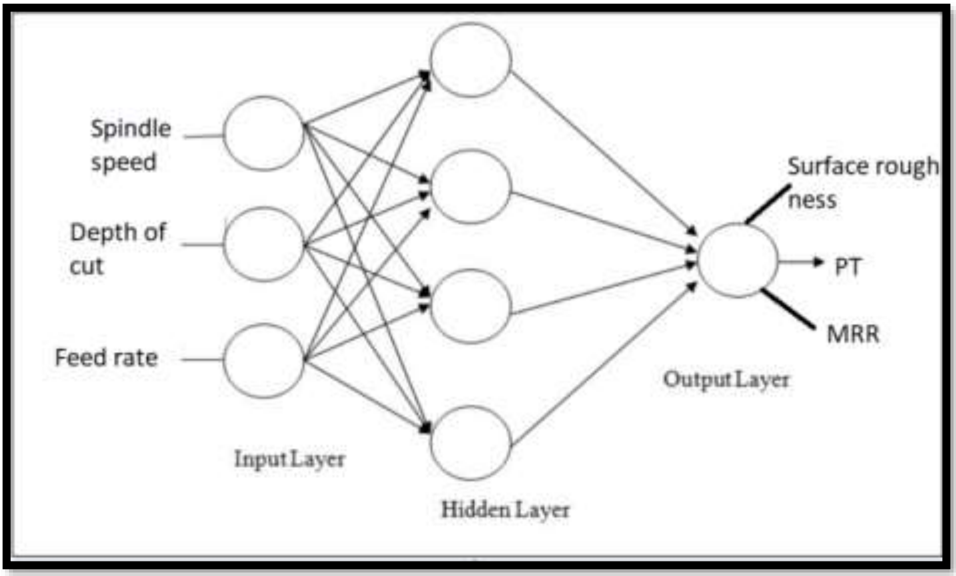

Fig. 4. Neural network with three input nodes and output nodes

In this investigation, the Levenberg-Marquardt algorithm is chosen for training the network, and the final network model is chosen based on attaining the lowest MSE value. In Fig.5, the evolution of mean square error (MSE) across the network's iterations is presented, covering training, testing, and validation phases. It's worth highlighting that the graph reveals an optimal point with minimal validation performance, which corresponds to epoch 2 and signifies a pivotal moment. Following this juncture, the training process continued for an additional 6 iterations before concluding, echoing the pattern observed in OD grinding.

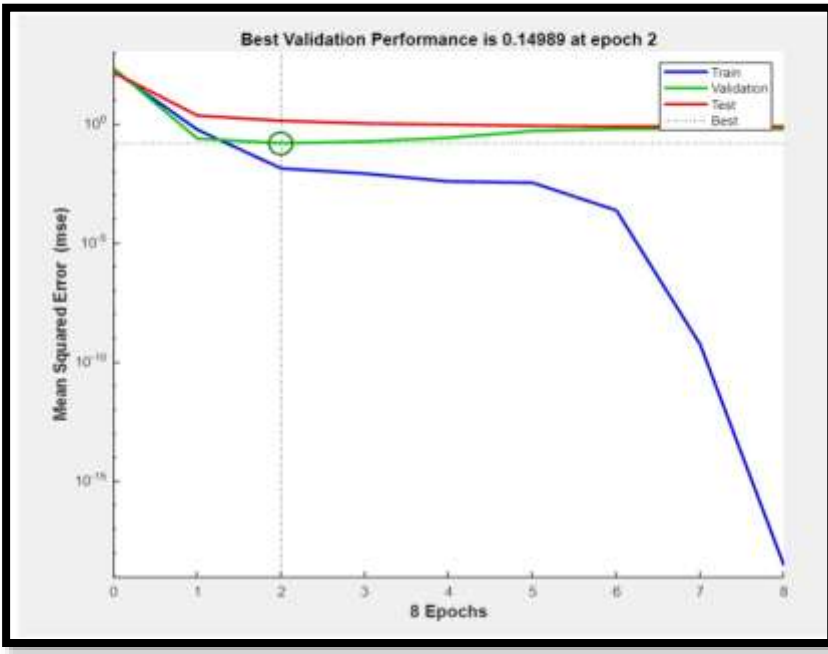

Fig. 5. Variation of MSE with number of iterations for OD grinding

Fig. 6 showcases the regression plot that spans the training, validation, and testing phases. This visual effectively captures the dynamic interaction between the network's output and the desired target values Remarkably, an R-value surpassing 0.9 signifies a noteworthy alignment between projected values and actual values of MRR, process time, and surface roughness values. Regression analysis reveals a significant correlation coefficient (R) of 0.999 for training, 0.989 for validation, and 0.994 for testing in the context of outer diameter grinding. This analysis culminates in an overall R-value of 0.995.

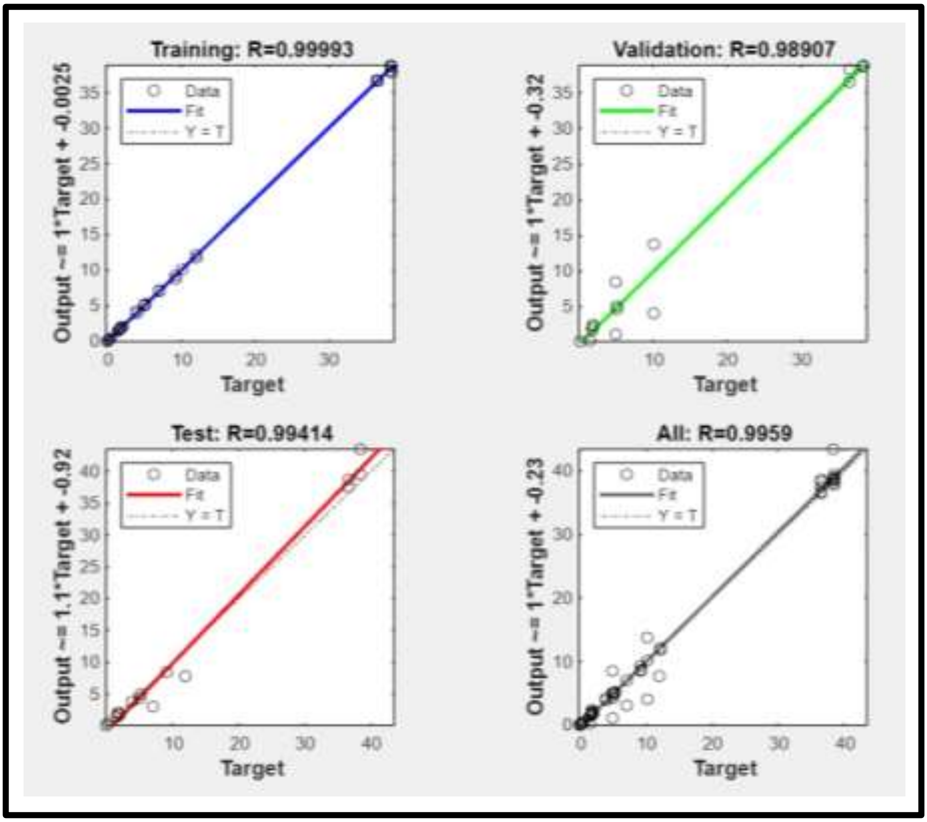

Fig. 6. Regression plot for training, validation, and testing for outer diameter grinding

The comparison between the experimental data and predictions generated by the Artificial Neural Network (ANN) has yielded a high level of satisfaction, indicating the effectiveness of the ANN model. This validation is further emphasized through the updated graphical representation in Fig.7-9, providing a comprehensive visualization of the comparison between the two datasets. These figures encompass critical output responses, including material removal rate, surface roughness, and process time, offering a holistic view of how well the ANN predicts these parameters based on the experimental inputs. This graphical analysis deepens our comprehension of the model's accuracy and its ability to capture complex relationships within the data. The alignment observed between the experimental results and the values predicted by the ANN underscores the ANN's potential as a valuable tool for optimizing and predicting these key output responses within the given process. The ensuing presentation encapsulates the experimental results, ANN predictions, and the disparities between the experimental data and ANN forecasts, meticulously catalogued in Table 6.

Table 6. Comparison of data between experimental v/s ANN predicted with error percentage

Sl No	Spindle Speed (RPM)	Depth of cut (mm)	Feed rate (mm/s)	MRR (mm^3/sec) Experiment	MRR ANN Predicted	MRR Error (%)	Process time (min) Experiment	Process time ANN Predicted	Process time Error (%)	Surface roughness µm Experiment	Surface roughness ANN Predicted	Surface roughness Error (%)
1	2200	0.008	0.25	0.07333	0.0745	1.60	16.19	17.48	2.89	0.8585	0.8456	1.50
2	2200	0.01	0.5	0.18333	0.18563	1.25	18.11	18.05	0.33	0.787	0.774	1.65
3	2200	0.013	1	0.4767	0.4815	1.01	18.16	18.06	0.55	0.8403	0.8312	1.09
4	2500	0.008	0.5	0.16667	0.1678	0.68	16.19	16.04	0.93	0.8955	0.8869	0.96
5	2500	0.01	1	0.4167	0.4236	1.66	16.2	16.11	0.56	0.813	0.81	0.37
6	2500	0.013	0.25	0.13542	0.1369	1.09	16.2	15.98	1.36	0.7945	0.7823	1.54
7	3000	0.008	1	0.4	0.412	3.00	15.17	15.01	1.05	0.7635	0.7512	1.61
8	3000	0.01	0.25	0.125	0.129	3.20	15.13	15.03	0.66	0.7795	0.7618	2.27
9	3000	0.013	0.5	0.325	0.331	1.85	15.16	15.1	0.40	0.7335	0.72369	1.34

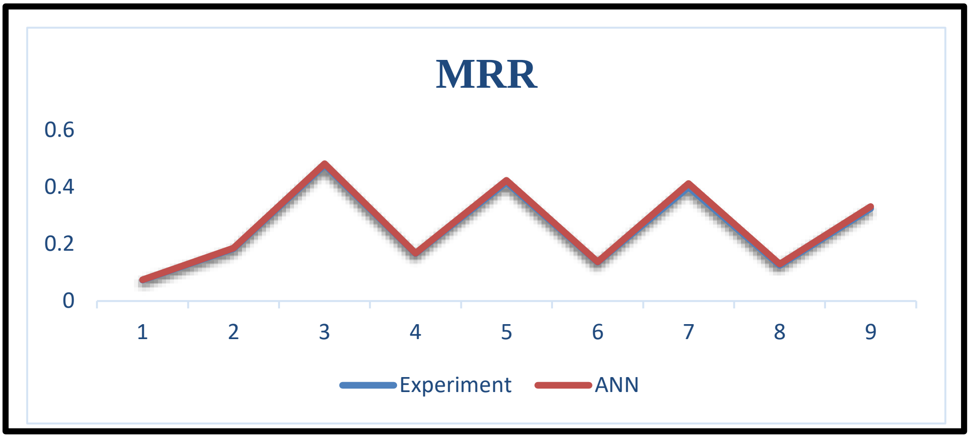

Fig. 7. Graphical representation of experiment and predicted MRR

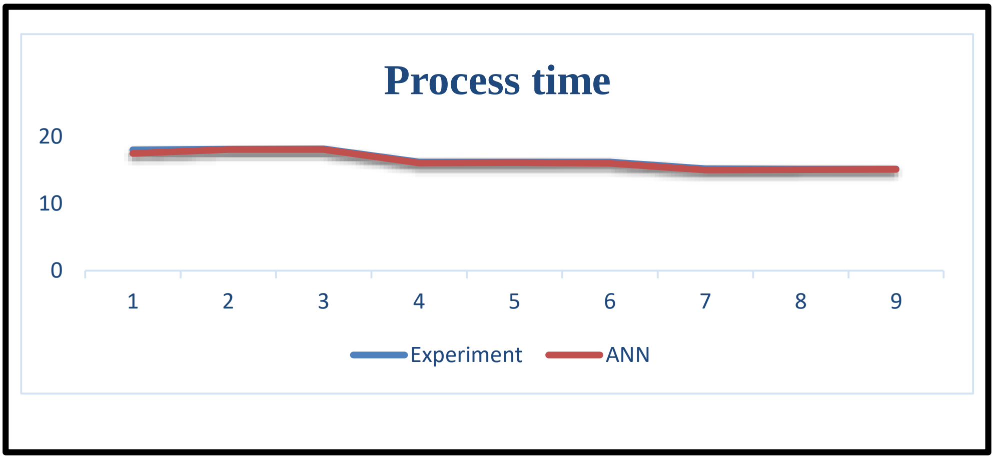

Fig. 8. Graphical representation of experiment and predicted Process time

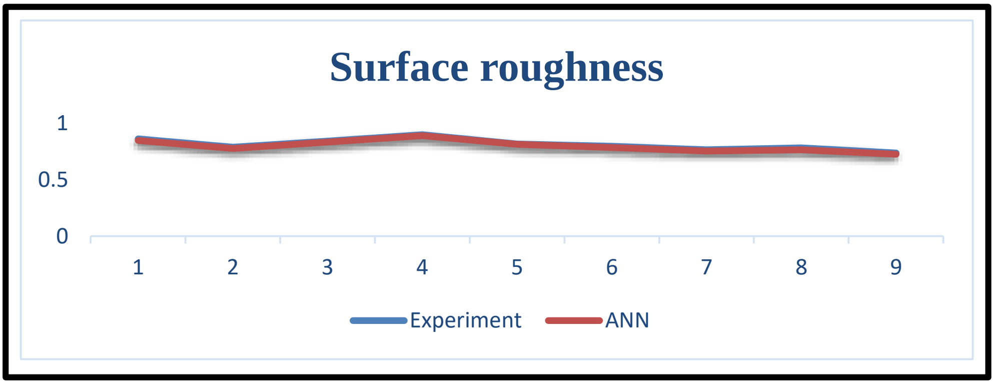

Fig. 9. Graphical representation of experiment and predicted surface roughness

4.0 Conclusion

This paper presents a comprehensive exploration of cost-effectiveness and time optimization in OD grinding through the application of Design of Experiments (DOE). DOE played a crucial role in optimizing OD grinding by manipulating spindle speed, depth of cut, and feed rate. These variables directly impact Material Removal Rate (MRR), process duration, and surface roughness. Using Taguchi L9 array fractional factorial design, optimal parameters were determined: spindle speed at 3000 rpm, depth of cut at 0.013 mm, and feed rate at 1 mm/sec, resulting in improved MRR (0.47 mm^3/s), reduced process time (15 min 13 sec), and enhanced surface finish (0.73μm). ANOVA confirmed regression up to an R^2 of 92.23%. Artificial neural network (ANN) models exhibited strong alignment with the data, indicated by high correlation coefficients (close to unity) for training (0.99993), validation (0.98907), and testing (0.99414) in outer diameter grinding. The overall R-value of 0.9959 underscores the significant effectiveness of employing DOE methodologies to enhance cost-effectiveness and time efficiency in these processes

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