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RESEARCH ARTICLE

Multi-Objective Optimization of the Surface Grinding Process for Heat-Treated Steel

V. Nguyen[1], **D. Nguyen**[1], **D. Do**[1], **and T. Tran**[2]*

[1]Faculty of Engineering, Vietnamese-German University, HCM City, Vietnam
[2]School of Science, Engineering & Technology, RMIT University, Vietnam

ABSTRACT – This paper effectively integrates Taguchi, Response Surface Methodology (RSM), and Genetic Algorithm (GA) approaches for both single and multi-objective optimization, delivering low-cost, high-effectiveness solutions for grinding. It examines the effects of three factors—depth of cut in coarse grinding, depth of cut in fine grinding, and the number of spark-outs—on three objectives: surface roughness, grinding time, and the deviation between the desired and actual grinding depth for SKD61 steel. Through in-depth analysis, the paper describes the impact of these factors and their interactions with the responses. It also proposes the optimal parameter setup for each objective. The optimal grinding time is achieved at 950 seconds with a coarse grinding depth of 0.007 mm, fine grinding depth of 0.004 mm, and zero spark-out. The minimal deviation and surface roughness were obtained at 0 mm and 0.144 µm, respectively, using the optimal setup of a coarse grinding depth of 0.004 mm, fine grinding depth of 0.001 mm, and 10 spark-outs. By applying GA, the paper provides a Pareto solution set, offering multiple combinations of optimal factors for minimizing grinding time, deviation, and surface roughness. These solutions serve as useful references for users seeking the best trade-offs in multi-objective scenarios. This paper contributes to improving customer satisfaction by enhancing the quality and efficiency of the machining process while reducing production costs for grinding machines. Its methodology can also be applied to other optimization fields.

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1. INTRODUCTION

Grinding machines are used in many applications, such as in the automotive industry, aerospace technology, and medical manufacturing fields. The grinding machine can remove only a small amount of material, flatten burrs, to produce a surface with low roughness, and achieve high accuracy in the dimensions. When compared to turning or milling, accuracy and surface polish produced by grinding are approximately about 10 times greater [1]. Besides ensuring tight tolerances, highly accurate dimensions, and smooth surface finishes for the products, the grinding machines can adapt to various materials and applications and are essential tools across different industries, including metalworking, plastics, ceramics, and more. One common type of grinding is the surface grinding machine, which uses an abrasive wheel to smooth and refine surfaces. Surface grinding operations involve removing material from a workpiece to achieve precise flatness and surface finish. It is a fundamental technique in metalworking and precision engineering. The grinding process is continuously improved and optimized to meet the ever-growing demands of precision engineering. Researchers and manufacturers study grinding process optimization for manufacturing efficiency, product quality, and sustainability. They mentioned that parameter setup has significantly influenced the machining process and outcome.

Factors in the grinding processes, such as cut depth, feed rate, wheel speed, and coolant flow, play distinctive roles in determining the outcome of the grinding operation, affecting responses such as surface finish, material removal rate, precision, and tool wear [2, 3]. Recent works in [4] investigated the effectiveness of grinding parameters on the surface finish of EN8 steel. In this work, they came up with the conclusion in which, grinding wheel material and grade play an essential role in the cylindrical and surface grinding technology. Li et al. [5] did great work by reducing surface roughness and the material removal rate (MRR) in the belt grinding process. The paper optimally determined values of abrasive size, contact force, belt linear speed, and feed speed. Optimizing parameter setup for varied materials in the grinding process is challenging and vital due to their complex interactions, especially in multi-objective problems. Achieving an optimal balance between objectives in the grinding process involves considering trade-offs; for instance, increasing material removal may come at the expense of surface quality. Recently, many publications have proposed different approaches to tackle the scope of multi-objective optimization. Lee et al. [6] optimize the parameters setup of feed rate, depth of cut, and grit size to maximize the MRR and minimize surface roughness in silicon carbide grinding. They used particle swarm optimization and compared the results with the GA approach. The design of experiment method, in addition to response surface methodology and Taguchi design in [7-10], is used wisely to implement to find solutions in optimization problems. They help reduce experimental time and build reliable models for analyzing and predicting output. The Taguchi method is a powerful statistical tool developed by Genichi Taguchi, a Japanese engineer, to optimize and improve the quality of processes and products [11]. It is a design of experiments technique that systematically explores the effects of various

***CORRESPONDING AUTHOR | T. Tran** | ✉ thanh.tran37@rmit.edu.vn

factors on responses while minimizing the number of experiments needed. Taguchi Orthogonal Array (OA) systematically arranges factors and their levels in a matrix structure. The orthogonal nature of the arrays ensures that each factor is varied independently, allowing for the isolation of individual factor effects, and each level appears the same number of times.

The RSM, investigated and introduced in 1951, is used to investigate the correlations between selected parameters and output parameters. It is a tool, and its primary purpose is to optimize outputs [11]. Box and Wilson later improved the method by introducing a second-order model of polynomials. Although this model is not an exact model, it can predict possible outputs and enormously impact industrial manufacturing. Using a method of experimental study is an easy technique to estimate a first-degree polynomial model. The first-order model is utilized as the approximation function if a first-order function can adequately characterize response [11].

$$y = \alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \cdots \alpha_k x_k + \varepsilon \tag{1}$$

Another model with 2nd order function is used if the system is curved [11].

$$y = \alpha_0 + \sum_{i=1}^{k} \alpha_i x_i + \sum_{i=1}^{k} \alpha_{ii} x_i^2 + \sum \sum_{i<j=2}^{k} \alpha_{ij} x_i x_j + \varepsilon \tag{2}$$

Many RSM issues adopt one or both of these approximation polynomials. Pawan Kumar et al. applied RSM in their experiment to find optimum values of grinding speed and cut depth. This brings us to solve the problems of minimizing the surface roughness and maximizing the metal removal rate [12]. Aravind and Periyasami [13] adopted the Taguchi design and RSM in their research to find minimum surface roughness with optimal grinding parameters. In this paper, an L27 orthogonal array is chosen, then signal-to-noise (S/N) ratio is used for analysis, and RSM is used to model the results. Taguchi method and RSM vary significantly in that the former can predict the ideal circumstances for decreasing processing faults in a quick approach. The Taguchi technique needs fewer experiments than RSM, which saves time and effort. The Taguchi technique permits the examination of many processing parameters and effectiveness on many responses, whereas RSM concentrates on examining correlations between all variables and each response. Other effective methods to solve optimization problems are listed as GA, TOPSIS, DE, and the ant colony algorithm [14-17]. GA has many advantages for solving multi-objective optimization problems compared to other methods [18]. GA adopts the process of genetic evolution to navigate solution spaces efficiently. It can efficiently explore the Pareto front and provide diverse solutions that represent trade-offs between conflicting objectives. GA excels in global search, preventing convergence to local optima in complex optimization landscapes. Many papers prove its adaptability to complex, non-linear relationships between parameters and objectives, which makes it well-suited to tackle complex problems [18]. In recent years, the combination of GA and other methods has proven advantageous in dealing with complicated optimization problems. The work [19] adopted a hybrid optimization method combining the PSO-ANN algorithm with a GA to optimize the welding parameters of 304L stainless steel spot welds. By integrating these two powerful algorithms, the study enhances the accuracy and efficiency of correlating predicted values with experimental data, which can significantly improve spot weld strength. The authors also implemented a hybrid approach combining different methods to estimate the quality of the finished product, such as expense and operation supply during the milling of alloy 2017A. The results emphasize the effectiveness of this combined approach for predicting multiple different conditions on quality, expense, and other factors compared to the RSM method and suggest possible enhancements in the machining of 2017A alloy [20]. In grinding process optimization, combining hybrid algorithms with traditional methods often raises questions about the precision of estimated models and a few experimental runs required for statistical reliability. The regression model may lack precision when dealing with a limited number of experiments. Finding a way to enhance the model's accuracy while reducing cost is still a concern that needs more studies. Many other works [21]-[25] have been proposed in recent years in aiming to improve the quality of the grinding surface process with different approaches. These proposals have proven to perform well in different working conditions. However, these works still have some limitations and need to be further developed to have better working conditions.

This paper will investigate the effects of processing grinding parameters that need to be worked in different conditions. The aim is to minimize these factors for the efficient grinding of heat-treated steel. This study uses the Taguchi orthogonal array for experiment design and uses RSM to build mathematical models representing the relationship between inputs and responses. First, the Taguchi orthogonal array for experimental design is employed, significantly reducing the number of required experiments while maintaining statistical integrity. The optimal parameter sets are predicted through Taguchi analysis and then validated through actual experiments, and the validated sets are integrated into the original Taguchi table. This refined table is then used in RSM to build a more accurate regression model. The approach minimizes the number of experiments while enhancing model precision. An ANOVA table and plots will be used to support the study on the influences of main factors and their interaction with the objectives. Finally, GA is used for multi-objective processing. The results are listed as a Pareto solution set with multiple combinations of optimal factors for minimizing objectives, which will help increase the quality and efficiency of the machining process as well as reduce production costs for grinding machines. In addition, it allows for a more flexible and adaptable decision-making approach. The decision-maker can choose a solution directly from the Pareto front based on their priorities and preferences.

2. EXPERIMENTAL STUDY AND OPTIMIZATION APPROACH

2.1 Experimental Setup

Stainless steel is tough to grind due to its toughness and tendency to work hardening, but it is manageable with the right quality of grinding wheels. In this study, the workpieces made from SKD61 steel with dimensions of 130.45 mm x 20.45 mm x 12.12 mm in length, width, and thickness, respectively, are used. SKD61 with heat-treated and hardened processing to achieve high hardness and wear resistance is used for this study. It can be used to create high accuracy. Table 1 describes the parameters and features of the proposed steel.

Table 1. Composition of SKD61

C(%)	Si(%)	Mn(%)	P(%)	S(%)	Cr(%)	Mo(%)	V(%)
0.35-0.42	0.80-1.20	0.25-0.50	Max 0.030	Max 0.020	4.80-5.50	1.00-1.50	0.80-1.15

The Meister V3 grinding machine in Figure 1, with a 200mm outside diameter, width of 13mm, and bore of 31.75 mm grinding wheel, has been chosen for this experiment. Its maximum grinding speed is 63 m/s, and it can be used to grind medium to hard steel (HRc > 50).

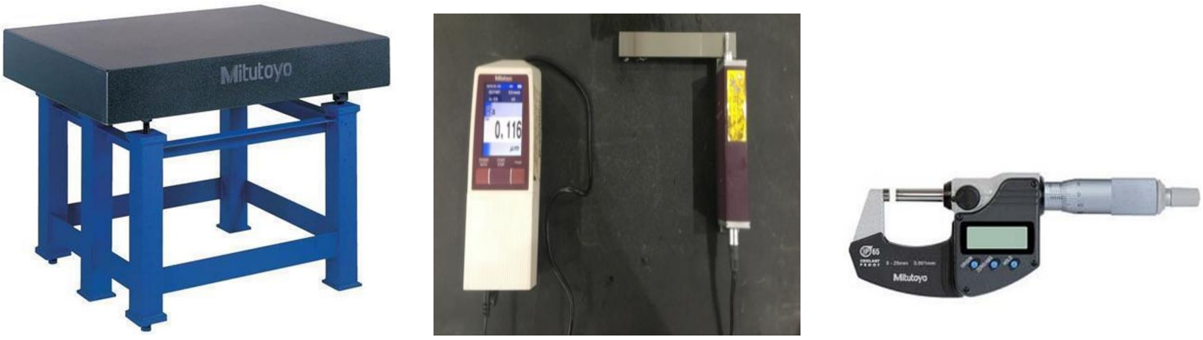
Figure 1. Inside Meister V3 machine

Choosing parameters for coarse and fine grinding is especially important and influences the quality of the final product. While coarse pick determines how to remove significant material quickly to reshape a workpiece, fine grinding helps increase precision and surface finish. The number of spark-outs is often implemented at the end of the grinding cycle to ensure that the workpiece reaches a stable and consistent dimension. "Spark out" refers to the additional grinding passes without further infeed. Adjusting these three factors allows control of removed steel and the final conditions that ensure the workpiece meets the desired surface finish and achieves consistent dimensions with tight tolerance specifications. This research examines the main factors that are mentioned at the beginning of the paper. Levels of the parameters are chosen based on the manufacturers' recommended range and are shown in Table 2.

Table 2. Factors and their levels

Control Factors	Unit	Level 1	Level 2	Level 3
A. Coarse grinding	mm	0.004	0.0055	0.007
B. Fine grinding	mm	0.001	0.0025	0.004
C. Number of Spark-out	No	0	5	10

Table 3 indicates parameters and levels used in an experimental design of the Taguchi L9 method. Nine grinding experiments are implemented, in which a combination of the control factors and level parameters are dependent on the design matrix. After grinding, the dimensions, roughness of workpieces, and processing time are measured and recorded. The assessment of final quality is then proposed and estimated by using the tool of the Mitutoyo SJ-210 model. This model will help us in estimating the finished quality of the post-grinding surface. A high-precision measurement equipment, Panme Mitutoyo 293-240-30 (0-25 mm), is used to define the difference from the expected parameters to real grinding depth in Figure 2. Grinding time is recorded directly from the machine.



a. Mitutoyo granite table b. Mitutoyo roughness tester c. Panme Mitutoyo 293-240-30

Figure 2. Measurement equipment

Table 3. Design matrix L9 and Experimental results

Sample No.	Coded values			Uncoded value			Y1	Y2	Y3
	A	B	C	Coarse grinding	Fine grinding	Spark-out	Time	Deviation	Roughness
				(mm)	(mm)	(-)	(Second)	(mm)	(µm)
1	1	1	1	0.0040	0.0010	0	2308	0.006	0.174
2	1	2	2	0.0040	0.0025	5	2318	0.003	0.171
3	1	3	3	0.0040	0.0040	10	1674	0.005	0.162
4	2	1	2	0.0055	0.0010	5	2214	0.001	0.180
5	2	2	3	0.0055	0.0025	10	1965	0.003	0.171
6	2	3	1	0.0055	0.0040	0	1252	0.002	0.199
7	3	1	3	0.0070	0.0010	10	2166	0.007	0.180
8	3	2	1	0.0070	0.0025	0	1518	0	0.177
9	3	3	2	0.0070	0.0040	5	1228	0	0.169

In the next part, the research will focus on analyzing the effectiveness of input factors on the outputs through the Taguchi response table, graphs, and response surface analysis. The study will first implement nine treatment combinations following the Taguchi L9 array. The Taguchi approach is prioritized with input factor importance and predicts optimal combinations. Then, the predicted sets are used in the L9 dataset, where a regression function is developed by using the proposed approach. This approach shows effectiveness as combined factors are implemented. The approach will be analyzed at three different levels, in which 27 experimental uses are generated for the study. In the paper, the hybrid use with Taguchi-RSM leads to a decrease in experimental numbers, whereas 15 runs will be used from full factorial designs.

2.2 Data Collection and Result Analysis

The Response Table for Means in Table 4 is constructed based on the average value calculated for responses, i.e., Grinding Time, Deviation, and Surface Roughness, corresponding to each control factor at their various levels. For example, the calculation of the response means of A (coarse grinding) at level 1 related to Time is shown in Eq. (3). At A = 0.004 mm:

$$\overline{Y1} = \frac{2308 + 2318 + 1674}{3} = 2100 \tag{3}$$

Table 4. Response table for means

Level	Grinding Time (Y1)			Deviation (Y2)			Surface Roughness (Y3)		
	A	B	C	A	B	C	A	B	C
1	2100	2229	1693	0.004667	0.004667	0.002667	0.1692	0.1780	0.1833
2	1810	1934	1920	0.002000	0.002000	0.001333	0.1837	0.1731	0.1737
3	1637	1385	1935	0.002333	0.002333	0.005000	0.1752	0.1770	0.1711
Delta	463	845	242	0.002667	0.002667	0.003667	0.0144	0.0049	0.0122
Rank	2	**1**	3	2.5	2.5	**1**	**1**	3	2

After calculating for means, the delta values are computed by comparing the smallest mean value with the highest in the same factor, and the factor with the highest delta values has the most influence on the response value. Based on these delta values, the influence ranks of various elements are established. For example, compared to A (Coarse grinding) and C

(Spark-out), B (Fine grinding) has the most significant influence on the variance of Time. While A has the highest impact on surface roughness, changing value C can create the largest variant of Deviation. Graph 3 shows the average mean repose value variant at each factor level. From this, we can find that the predicted treatment combination for minimizing Time is 0.007 mm Coarse grinding, 0.004mm Fine grinding, and 0 Spark-out, while the suggested parameters for minimizing Deviation are 0.0055 mm Coarse grinding, 0.0025mm Fine grinding, and 5 Spark-out. The estimated minimum values of the SR are 0.004 mm coarse grinding, 0.0025 mm fine grinding, and 10 spark-outs in Table 5. Sets of these found minimum values are employed to record experimental values and add them to the L9 original table for further modeling by RSM.

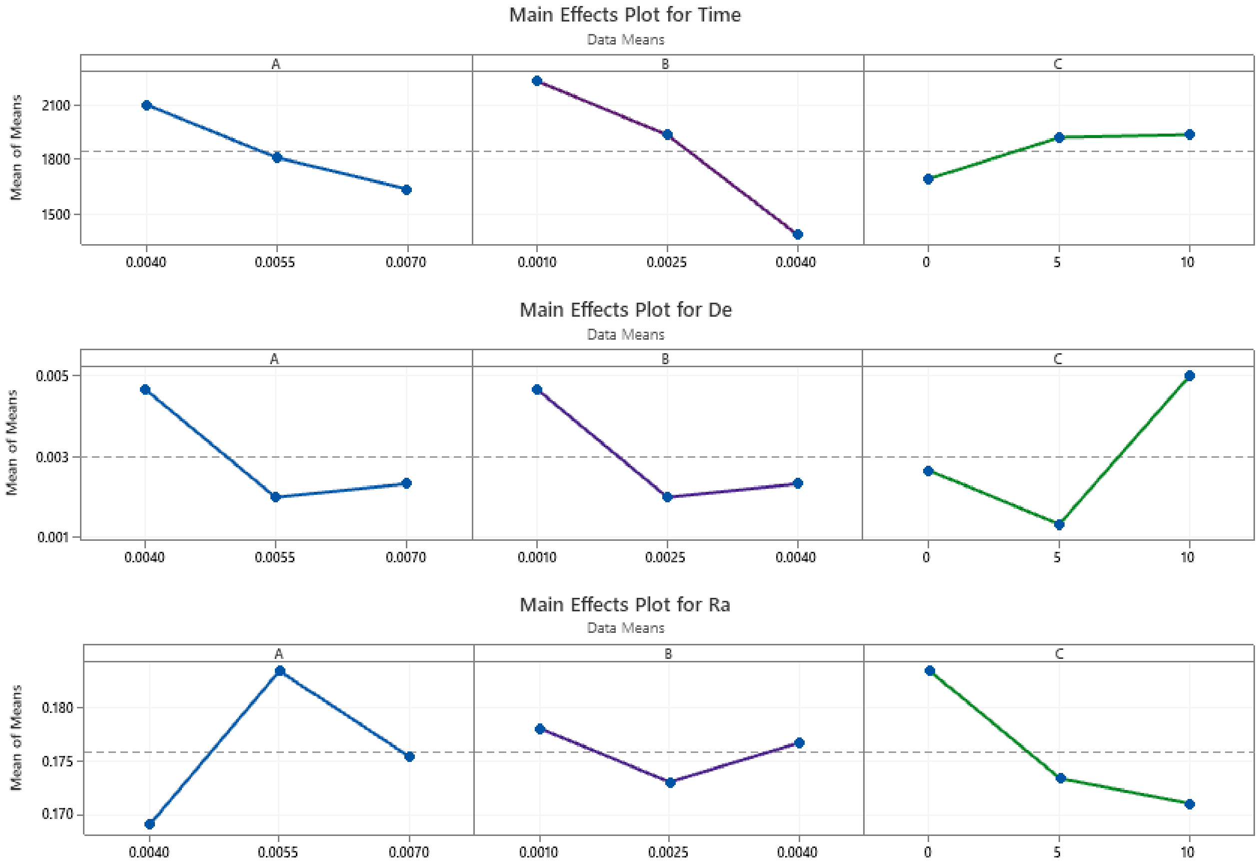


Figure 3. Main effects plot for Means

Table 5. Predicted optimal parameter sets by Taguchi and their experimental results

	Taguchi optimal set for Time	Taguchi optimal set for Deviation	Taguchi optimal set for Surface Roughness
(A) Coarse grinding (mm)	0.007	0.0055	0.0040
(B) Fine grinding (mm)	0.004	0.0025	0.0025
(C) Spark-out (No.)	0	5	10
Experimental value	T= 950 (s)	De = 0.002 (mm)	Ra= 0.152 (μm)

In the paper, RSM approach is selected to improve models. This paper uses Minitab 19 to generate the regression models in Eq. (4) based on the data collected above. The ANOVA tables for responses are studied at a 95% reliability. A p-value that is smaller than 5% signifies a considerable impact of processing inputs on the response. Besides, a p-value that is bigger than 5% shows inadequate evidence between processing factors and responses.

A second-degree polynomial model is used for the Time with the achieved R-squared (or the coefficient of determination) at 99.05%.

$$Time\ (s) = 3651 - 413194 * A + 9583 * B + 70.4 * C + 23166667 * A * A - 59055556 * B * B - 4.49 * C * C \tag{4}$$

From the ANOVA in Table 6 and Figure 4, we can see that the influence of A, B, and C on grinding time is independent. They all strongly impact the grinding time (P value <0.05). The influence order will be A (the most impact), followed by B, then C. Increasing A tends to reduce grinding time. Similarly, fine grinding with smaller depths of cut will extend the grinding time. Lager A and B will significantly increase the material removal rate, meaning faster processing. On the other hand, a higher number of spark-outs will make grinding time longer.

Table 6. ANOVA table for Time

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	6	2266082	377680	52.20	0.004
Linear	3	2030502	676834	93.55	0.002
A	1	373579	373579	51.63	0.006
B	1	1215876	1215876	168.05	0.001
C	1	107417	107417	14.85	0.031
Square	3	68574	22858	3.16	0.185
A*A	1	5609	5609	0.78	0.443
B*B	1	36451	36451	5.04	0.110
C*C	1	26071	26071	3.60	0.154
Error	3	21706	7235		
Total	9	2287788			

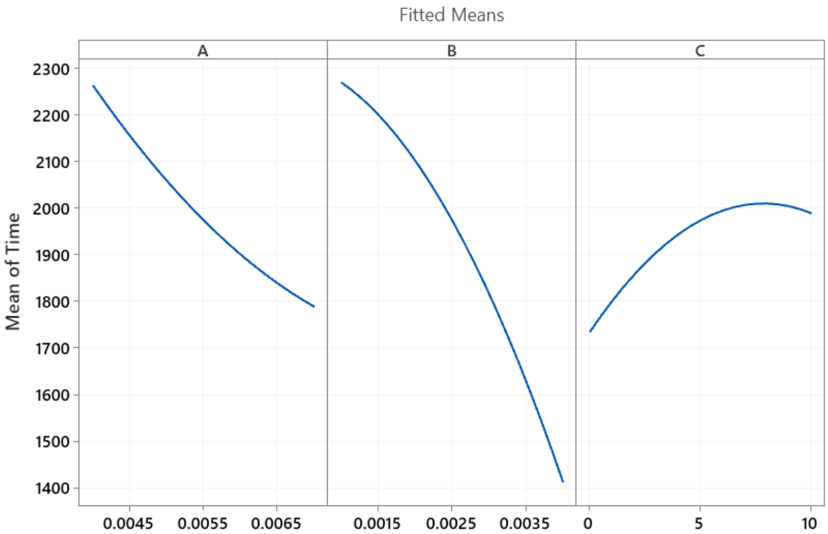


Figure 4. Main effects plot for time

For Deviation, a first-degree polynomial model in Eq. (5) included the impact of the main factor and interactions fit with the data set value. The R-squared value is 94.52%. From the ANOVA table (Table 7), the p-value of the model is 0.053, which is very close to the threshold of 0.05. Since it is a slight difference, the R-square value is also considered when deciding the model's utility. The R-squared value of 94.52% indicates that the model explains a large proportion of the variability in the dependent variable. It suggests the model fits the data well, even if the p-value is marginally above 0.05. Therefore, the deviation regression model, in this case, is still valuable and used to explain the relationship and prediction.

$$Deviation\ (mm) = -0.00159 + 1.460 * A + 8.32 * B - 0.004305 * C - 1714 * A * B + 0.590 * A * C + 0.362 * B * C \quad (5)$$

Table 7. ANOVA table for Deviation

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	6	0.000050	0.000008	8.62	0.053
Linear	3	0.000004	0.000001	1.24	0.432
A	1	0.000000	0.000000	0.10	0.774
B	1	0.000003	0.000003	2.98	0.183
C	1	0.000002	0.000002	1.58	0.298
2-Way Interaction	3	0.000026	0.000009	8.79	0.054
A*B	1	0.000017	0.000017	17.96	0.024
A*C	1	0.000023	0.000023	23.67	0.017
B*C	1	0.000009	0.000009	8.89	0.059
Error	3	0.000003	0.000001		
Total	9	0.000053			

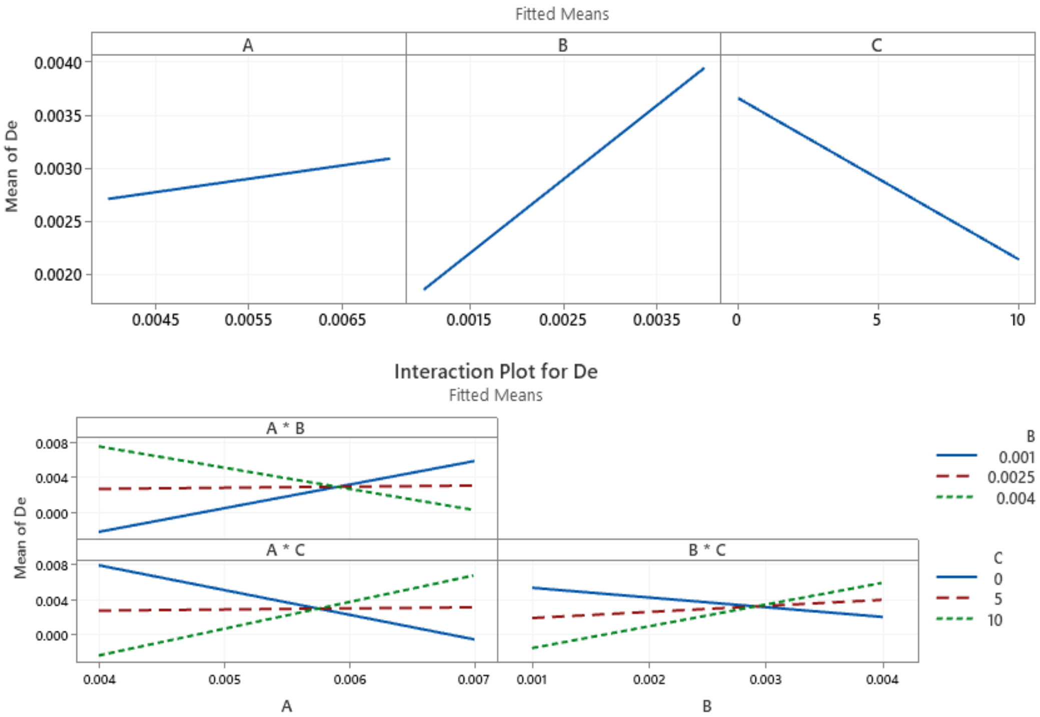


Figure 5. Main effects and interactions plot for Deviation

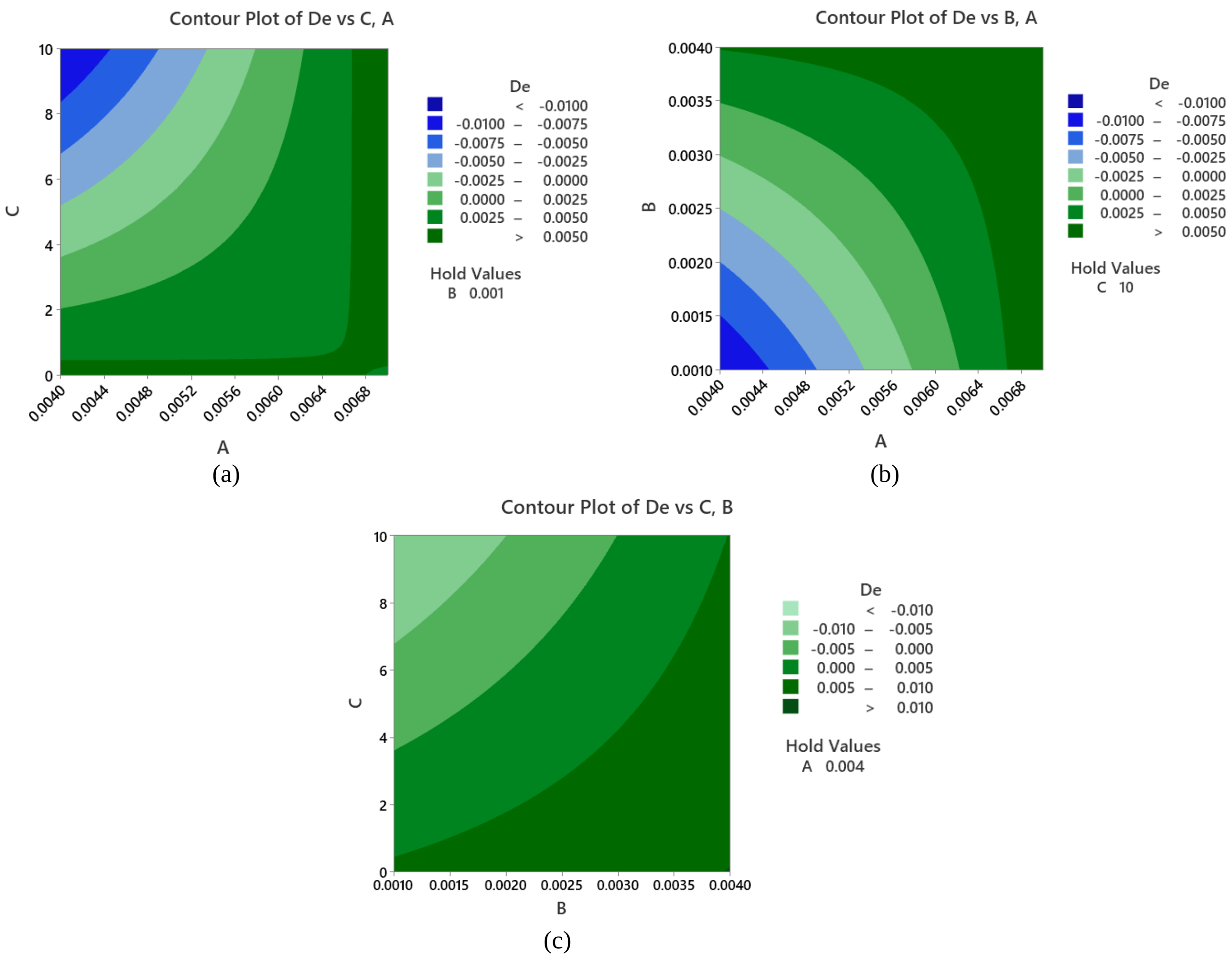


Figure 6. Contour plots for Deviation

Table 7 shows that the interactions of factors strongly impact the Deviation. The individual main factors have p-values larger than 0.05, indicating that they do not significantly affect the response variable. However, their interaction terms have p-values smaller than 0.05, showing that the combined effect of the two main factors strongly influences the dependent variable. Because the interaction term depends on the presence of the corresponding main factors, the main factors are kept in the model to avoid bias and ensure interpretability. Figure 5 shows that the precision of the grinding process is reduced when increasing A and B. The number of spark-outs can also have a positive impact on grinding accuracy. The additional passes during spark-out cycles contribute to precise results. From the interaction plots, we can see that the magnitude of the influence of one factor on the precision variance depends on the others. The precision can be achieved at small depths of cut in coarse and fine grinding and with a high number of spark-outs. At a five-value C, the variance in the values of A and B does not very much impact the value of De. When the number of spark-outs is 10, increasing A and B will linearly increase De or reduce the precision. Meanwhile, the grinding precision is significantly reduced at a small value of C, i.e., 0. The influences of these interactions are shown clearly in the contour plot in Figure 6. It describes the range of values of the De response corresponding to the values of pairs of parameters when the third one is set at a fixed value.

For Surface Roughness, a second-degree polynomial model in Eq. (6) is adopted. It achieved an impressive R-squared of 99.8%.

$$Ra\ (\mu m) = 001699 + 54.36\,A + 26.19\,B - 0.007013\,C - 4385\,A*A - 4046\,A*B + 1.0450\,A*C - 0.3533\,B*C \tag{6}$$

The processing factors in Table 8 clearly indicate that the inputs of variables C and B are statistically significant in relation to the SR of the finished product. Additionally, the second-order effect of factor A shows a high correlation with the variation in SR. From this result, we suggest that a U-shaped expression of inputs A, AB, and AC exhibits a substantial impact on Ra. Comparatively, BC exerts weaker influences. Figure 7 shows that the interactions of factors significantly impact its value. Considering only the main factors, a bigger A value will result in worse surface roughness. A smaller B value generally contributes to a smoother surface finish. In addition, increasing the C contributes to a better surface finish. However, the magnitude and direction impact of one factor on Ra depends very much on the value of others. When B is higher than 0.0025, A's variation has less influence on Ra. Ra depends more on B, where increasing B creates a worse surface roughness. At low B values (smaller than 0.025), smaller A values result in a smoother Ra, while increasing A makes Ra rougher. When the number of spark-outs (C) is high, it results in smoother Ra. Higher C values result in a better Ra. Increasing A has a slightly negative impact on Ra at a spark-out count of 10. At a spark-out count of 5, varying A or B almost does not impact Ra significantly. With 0 spark-outs, Ra is high. Increasing B will result in a linear increase in the value of roughness.

Figure 8 gives us an indication of the correlation between processing parameters and output responses. Figure 8 indicates a variation of surface roughness value in terms of these proposed processing parameters and provides us a visualization of the effect of the inputs on the response. Then, we can adapt to have a better quality of the response.

Table 8. ANOVA table for Surface Roughness

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	7	0.001373	0.000196	237.63	0.004
Linear	3	0.000582	0.000194	234.93	0.004
A	1	0.000015	0.000015	18.28	0.051
B	1	0.000041	0.000041	49.61	0.020
C	1	0.000515	0.000515	624.50	0.002
Square	1	0.000173	0.000173	209.09	0.005
A*A	1	0.000173	0.000173	209.09	0.005
2-Way Interaction	3	0.000397	0.000132	160.37	0.006
A*B	1	0.000179	0.000179	217.11	0.005
A*C	1	0.000168	0.000168	203.05	0.005
B*C	1	0.000013	0.000013	16.01	0.057
Error	2	0.000002	0.000001		
Total	9	0.001375			

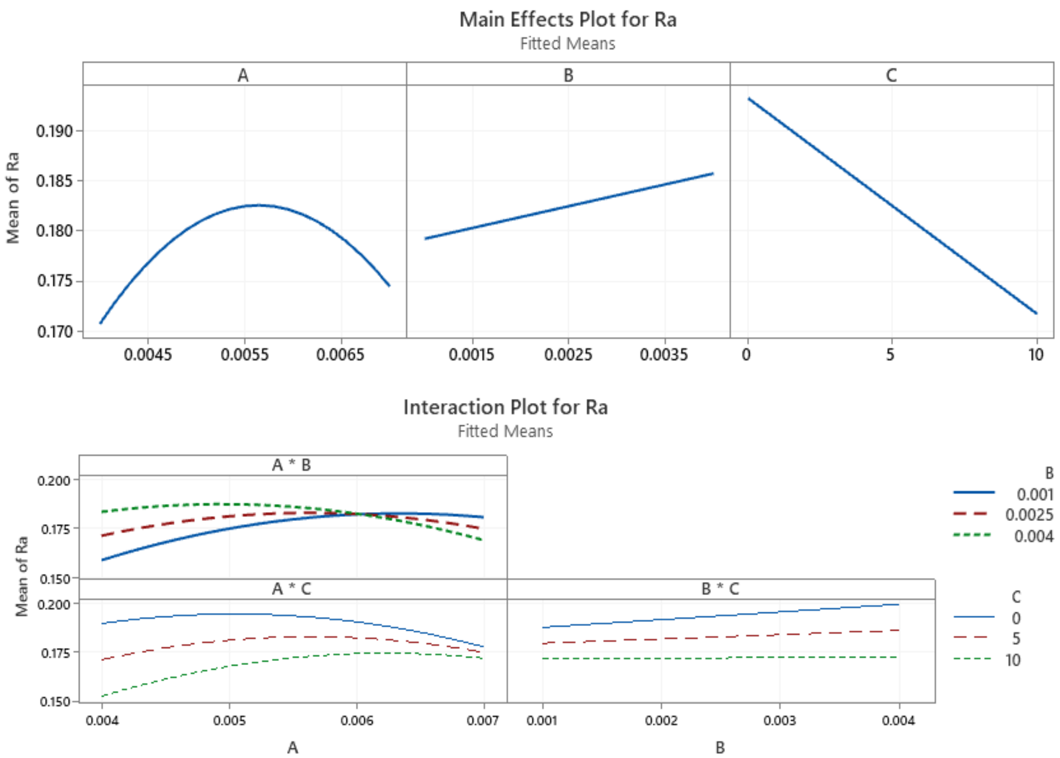
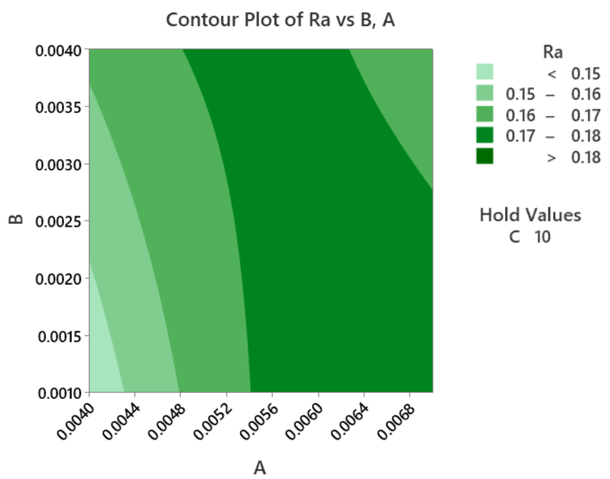
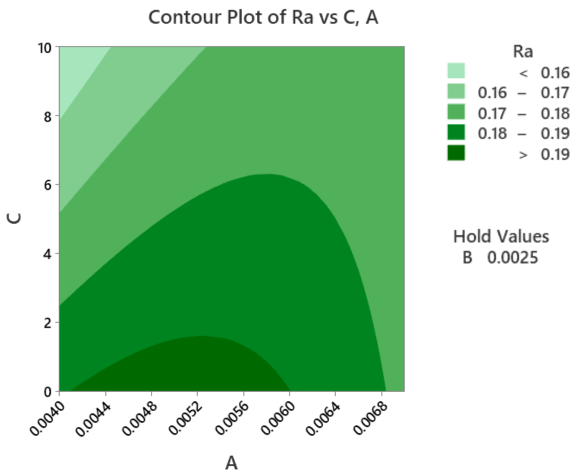


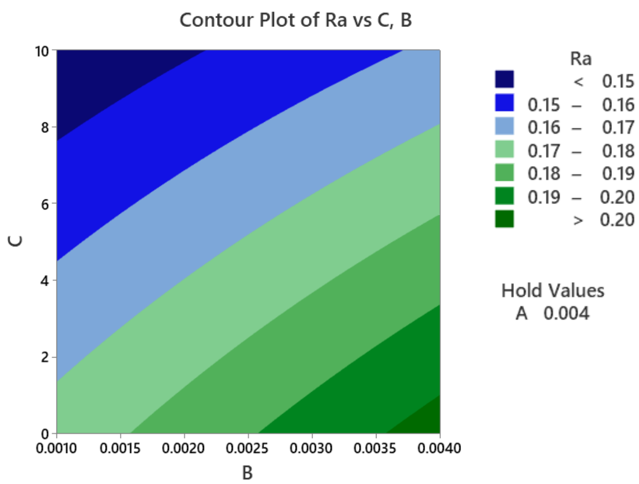
Figure 7. Main effects and interactions plot for Surface Roughness



(a)



(b)



(c)

Figure 8. Contour plots for Surface Roughness

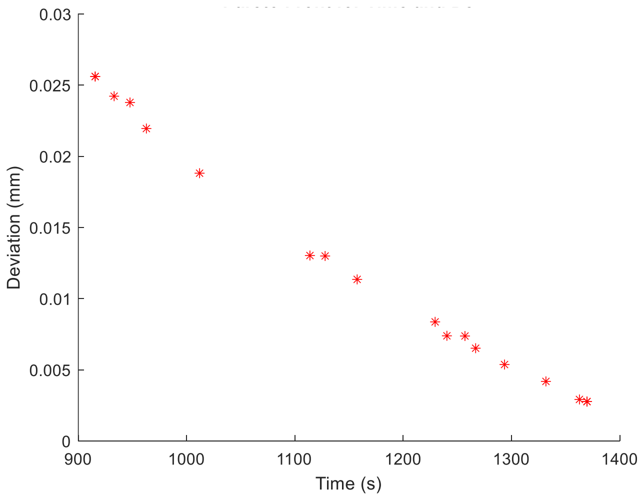
Optimizing the regression models (4), (5), and (6) separately by the tool in MATLAB and MINITAB, the optimal parameter sets are achieved in Table 9, whereas optimal grinding time is predicted at 987.25 seconds when setting up a coarse-grinding parameter of 0.007 mm, fine-grinding parameters of 0.004 mm, and zero spark-out. The minimal Deviation and surface roughness were predicted at 0 mm and 0.1424 µm, respectively. They were obtained at 0.004 mm for coarse grinding, 0.001 mm for fine grinding, and 10 for spark-outs number. The achieved parameters are validated experimentally, with the proposed parameter sets implemented. The validated grinding time, deviation, and surface roughness are 987.25 s, 0 mm, and 0.144 µm, respectively. The error difference between proposed values and real values is only 3.7%, 0%, and 1.1 %, corresponding to errors in grinding time, deviation, and surface roughness.

Table 9. Experimental validations

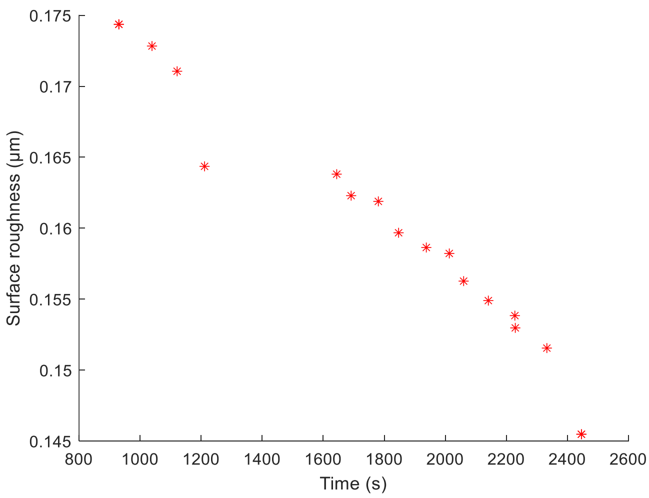
	RSM optimal set for Time	RSM optimal set for Deviation	RSM optimal set for Surface Roughness
(A) Coarse grinding (mm)	0.007	0.004	0.004
(B) Fine grinding (mm)	0.004	0.001	0.001
(C) Spark-out (No.)	0	10	10
Predicted value	T= 987.25 (s)	De=0 (mm)	Ra= 0.1424 (µm)
Validate value	T= 950 (s)	De=0 (mm)	Ra= 0.144 (µm)
Percentage Error	3.8%	0%	1.1%

3. MULTI-OBJECTIVE OPTIMIZATION AND RESULT ANALYSIS

A conflict may exist between the objectives, which creates challenges for users. In this paper, grinding time, deviation (precision), and surface roughness are the objectives that need to be optimized simultaneously. The paper uses the NSGA-II built-in function in MATLAB to find the optimal solutions for the optimized objective. The developed mathematical regression models (4), (5), and (6) are applied. GA is set as follows: A population size is set by 500; the method is repeated and produced with 1000 generations; the method uses the value of a crossover probability of 0.8 and the value of mutation probability of 0.2. Figure 9 describes the optimal Pareto sets for simultaneously optimizing two pairs of objectives: grinding time-deviation (Figure 9(a)) and time-surface roughness (Figure 9(b)). Figure 10(a) visualizes the optimal sets for minimizing deviation and surface roughness. The Pareto Front for three objectives is illustrated in Figure 10(b). The Pareto-optimal solutions for three objectives are indicated in Table 10. The best combination of grinding parameters is chosen based on the user's needs. For this three-objective optimization, the Pareto-optimal solutions offer the best trade-off options.

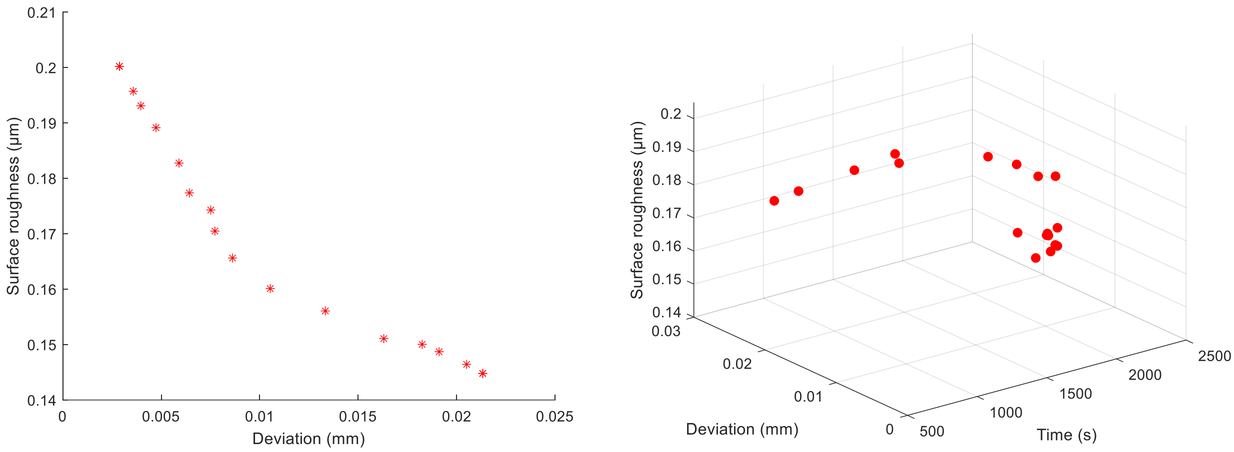


(a)



(b)

Figure 9. (a) Pareto Front for Time & Deviation; (b) Pareto Front for Time & Surface Roughness



(a) (b)
Figure 10: (a) Pareto Front for De and Ra; (b). Pareto Front for three objectives

Table 10. Pareto value set of grinding time, deviation, and surface roughness optimization

No.	Factors			Responses		
	Coarse grinding	Fine grinding	Spark-out	Time	Deviation	Roughness
	(mm)	(mm)	(No.)	(Second)	(mm)	(µm)
1	0.0070	0.0040	0	898.5886	0.0265	0.1741
2	0.0040	0.0040	0	1370.4896	0.0017	0.2042
3	0.0040	0.0010	10	2485.4691	0.0208	0.1444
4	0.0040	0.0010	8	2499.5200	0.0190	0.1480
5	0.0068	0.0040	0	952.8196	0.0242	0.1787
6	0.0043	0.0040	0	1300.3541	0.0043	0.2048
7	0.0041	0.0022	8	2268.3054	0.0135	0.1577
8	0.0044	0.0037	8	1686.3462	0.0077	0.1740
9	0.0042	0.0029	8	2043.8746	0.0106	0.1670
10	0.0061	0.0039	1	1071.6538	0.0186	0.1891
11	0.0041	0.0033	7	1924.2794	0.0081	0.1701
12	0.0043	0.0022	7	2229.5452	0.0128	0.1644
13	0.0056	0.0038	0	1153.6833	0.0145	0.1972
14	0.0040	0.0032	0	1728.9942	0.0033	0.1951
15	0.0059	0.0036	1	1264.6297	0.0161	0.1916
16	0.0043	0.0027	8	2094.4783	0.0116	0.1648
17	0.0041	0.0035	1	1622.6895	0.0036	0.1959
18	0.0041	0.0017	8	2384.8361	0.0161	0.1541

4. CONCLUSIONS

This research proposed the integration of Taguchi, RSM techniques, and genetic algorithms in single- and multi-objective optimization for the grinding process. The study centers on three major factors, as presented in the abstract. The paper also indicates the impact of these processing parameters on the optimized objectives, i.e., grinding time, deviation, and surface roughness. In the paper. a Taguchi L9 method is used to set up the processing parameter for the experimental study. Basically, nine datasets are proposed for the experiments, and the Taguchi is used to initially examine the importance of selected parameters. With the proposed inputs, the paper will analyze and estimate the possibility of the possible combinations of the processing parameters. These predicted optimal parameter sets are experimented with and combined with the original L9 design matrix. With this approach, for three factors with three levels each, instead of conducting 27 experimental runs, the experimental set was reduced to just nine original experiments plus three validated runs. The updated design table is used for the RSM approach to construct three regression models for three corresponding objectives. The precision of these regression models is remarkable, with the r-square 99.05%., 94.52%, and 99.8%, respectively. In addition, when solving single objectives, the error difference between estimated optimal values and real achieved values are only 0.037, 0, and 0.011, corresponding to differences in grinding time, deviation, and surface roughness. Therefore, the models have been proven suitable for explaining the variation in the relationship between inputs and outputs through statistical factors and validation results.

The paper also analyzes the influences of control factors and their interaction with the responses using ANOVA tables. Factors A, B, and C strongly impact grinding time. An increase in A tends to reduce grinding time, while finer grinding with smaller cut depths increases grinding time. Larger values of A and B significantly boost the material removal rate, leading to faster processing. Conversely, a higher number of spark-outs lengthens the grinding time. Interestingly, the main factors alone do not significantly affect the deviation objective, but their interaction terms strongly influence the dependent variable. Factors A, B, and C are all statistically significant in surface roughness. The interaction between AB and AC exhibits a substantial impact on Ra. Comparatively, BC exerts weaker influences. Considering only the main factors, a bigger A value will result in worse surface roughness. A smaller B value generally contributes to a smoother surface finish. In addition, increasing the C contributes to a better surface finish. While the impact of A, B, and C on grinding time is independent, the magnitude and direction impact of one factor on De or Ra depends very much on the value of others.

The paper applies GA to optimize three objectives simultaneously and provides a Pareto set for this multi-objective problem. The discovery of a Pareto-optimal set of solutions that balance multiple conflicting objectives contributes to grinding multi-objective optimization. Choosing a solution from the Pareto front based on priorities is a valid and often practical approach, especially when decisions need to be made quickly or when the decision-maker has clear preferences that guide their choice. By integrating the proposed methodologies, the paper helps minimize the number of necessary experiments, reducing cost and time while guaranteeing effectiveness. The paper's analysis and results can be a valuable reference for users in the grinding process and can be further applied in other optimal machining fields.

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CONFLICT OF INTEREST

The authors declare that they do not have any conflict of interest.

AUTHORS CONTRIBUTION

Dr. Vi Nguyen is a primary contributor to this research. She is responsible for research design, outcome analysis and integration. Mr. Duyen Do and Mr. Duc Nguyen are responsible for collecting and processing the data. Dr. Thanh Tran is responsible for supervising the research process and developing the paper. He also had some valuable comments on the research design and how to validate the result. In addition, Dr. Vi Nguyen and Mr. Duc Nguyen actively joined the discussion of the results of the paper and reviewed the manuscript for approval.

REFERENCES

[1] G. Guo, Z. Liu, Q. An, and M. Chen, “Experimental investigation on conventional grinding of Ti-6Al-4V using Sick abrasive,” *The International Journal of Advanced Manufacturing Technology*, vol. 57, pp. 135-142, 2011.

[2] N. Alagumurthi, K. Palaniradja, and V. Soundararajan, “Optimisation of process parameters in grinding on different dimensions and perspectives,” *International Journal of Industrial and Systems Engineering*, vol. 3, no. 4, pp. 447-473, 2008.

[3] M. Soori and M. Asmael, “A review of the recent development in machining parameter optimization,” *Jordan Journal of Mechanical and Industrial Engineering*, vol. 16, no. 2, pp. 205-223, 2022.

[4] D. Kumar Patel, D. Goyal, and B. Pabla, “Optimization of parameters in cylindrical and surface grinding for improved surface finish,” *Royal Society Open Science*, vol. 5, no. 5, p. 171906, 2018.

[5] F. Li, Y. Xue, Z. Zhang, W. Song, and J. Xiang, “Optimization of grinding parameters for the workpiece surface and material removal rate in the belt grinding process for polishing and deburring of 45 steel,” *Applied Sciences*, vol. 10, no. 18, p. 6314, 2020.

[6] T. Lee, T. Ting, Y. Lin, and T. Htay, “A particle swarm approach for grinding process optimization analysis,” *The International Journal of Advanced Manufacturing Technology*, vol. 33, pp. 1128-1135, 2007.

[7] K.R. Jagtap, S. Ubale, and M. Kadam, “Optimization of cylindrical grinding process parameters for AISI 5120 steel using Taguchi method,” *International Journal of Design and Manufacturing Technology*, vol. 2, no. 1, pp. 47-56, 2011.

[8] D. Pal, A. Bangar, R. Sharma, and A. Yadav, “Optimization of grinding parameters for minimum surface roughness by Taguchi parametric optimization technique,” *International Journal of Mechanical and Industrial Engineering*, vol. 1, no. 3, pp. 74-78, 2012.

[9] J. S. Kwak and I. K. Kim, “Parameter optimization of surface grinding process based on Taguchi and response surface methods,” *Key Engineering Materials*, vol. 306, pp. 709-714, 2006.

[10] P. Krajnik, J. Kopac, and A. Sluga, “Design of grinding factors based on response surface methodology,” *Journal of Materials Processing Technology*, vol. 162, pp. 629-636, 2005.

[11] V. Nguyen, F. Altarazi, and T. Tran, "Optimization of process parameters for laser cutting process of stainless steel 304: A comparative analysis and estimation with Taguchi method and response surface methodology," *Mathematical Problems in Engineering*, vol. 2022, p. 6677586, 2022.

[12] P. Kumar, A. Kumar, and B. Singh, "Optimization of process parameters in surface grinding using response surface methodology," *International Journal of Research in Mechanical Engineering & Technology*, vol. 3, no. 2, pp. 245-252, 2013.

[13] M. Aravind and D.S. Periyasamy, "Optimization of surface grinding process parameters by Taguchi method and response surface methodology," *International Journal of Engineering Research*, vol. 3, pp. 1721-1727, 2014.

[14] S.P. Kodali, R. Kudikala and D. Kalyanmoy, "Multi-objective optimization of surface grinding process using NSGA II," *2008 First International Conference on Emerging Trends in Engineering and Technology*, Nagpur, India, pp. 763-767, 2008.

[15] D.D. Trung, N. Thien, and N.-T. Nguyen, "Application of TOPSIS method in multi-objective optimization of the grinding process using segmented grinding wheel," *Tribology in Industry*, vol. 43, no. 1, p. 12, 2021.

[16] Y. Wang, X. Chen, W. Gui, and C. Yang. "A hybrid multi-objective differential evolution algorithm and its application to the optimization of grinding and classification," *Journal of Applied Mathematics*, vol. 2013, no. 1, p. 841780, 2013.

[17] N. Baskar, R. Saravanan, P. Asokan, and G. Prabhaharan, "Ants colony algorithm approach for multi-objective optimisation of surface grinding operations," *The International Journal of Advanced Manufacturing Technology*, vol. 23, pp. 311-317, 2004.

[18] Y. Yusoff, M.S. Ngadiman, and A.M. Zain, "Overview of NSGA-II for optimizing machining process parameters," *Procedia Engineering*, vol. 15, pp. 3978-3983, 2011.

[19] K. Bousnina, A. Hamza, and N. Ben Yahia, "Effect of vibration and welding parameters on spot weld resistance: modeling integrating PSO-ANN and GA algorithm," *Multiscale and Multidisciplinary Modelling, Experiments and Design*, vol. 7, no. 3, pp. 1755-1767, 2024.

[20] K. Bousnina, A. Hamza, and N.B. Yahia, "A combination of the particle swarm optimization-artificial neurons network algorithm and response surface method to optimize energy consumption and cost during milling of the 2017A alloy," *Energy Exploration & Exploitation*, vol. 42, no. 2, pp. 727-746, 2024.

[21] G. Zhang, M. Liu, J. Li, W.Y. Ming, X.Y. Shao and Y. Huang, "Multi-objective optimization for surface grinding process using a hybrid particle swarm optimization algorithm," *The International Journal of Advanced Manufacturing Technology*, vol. 71, pp. 1861–1872, 2014.

[22] N.T. Nguyen, D.H. Tien and H. Le Dang "A research on multi-objective optimization of the grinding process using segmented grinding wheel By Taguchi-dear method," *Eureka: Physics and Engineering*, vol. 1, pp. 67-77, 2021.

[23] A.T. Nguyen, T.T.N. Nguyen, Q.H. Tran, H.Q. Nguyen, H.A. Le, H.L. Nguyen, et al. "Multi-objective optimization for minimum surface roughness and maximum wheel life when external cylindrical grinding SKD11 steel. In *Advances in Engineering Research and Application: Proceedings of the International Conference on Engineering Research and Applications*, ICERA 2021, pp. 601-609. Springer International Publishing.

[24] X.L. Wang, L.M. Liu, L. Duan, and Q. Liao, "Multi-objective optimization for an industrial grinding and classification process based on PBM and RSM," *IEEE/CAA Journal of Automatica Sinica*, vol. 10, no. 11, pp. 2124–2135, 2023.

[25] S. Azim, S. Noor, Q.S. Khalid, A.M. Khan, D.Y. Pimenov, I. Ahmad, A.R. Babar, C.I. Pruncu. "Sustainable manufacturing and parametric analysis of mild steel grade 60 by deploying CNC milling machine and Taguchi method," *Metals*, vol. 10, no. 10, p. 1303, 2020.