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Response Surface Methodology Optimization of Wear Rate Parameters in Metallic Alloys

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***Abstract**: The optimization of wear rate parameters in metallic alloys using Response Surface Methodology (RSM) has been experimentally performed. The wear rate, a critical factor affecting the durability and performance of metallic components, served as the response parameter, while track diameter, sliding speed, and mass difference were considered as independent variables. The Central Composite Design (CCD) experimental method systematically explored the response surface and optimizes the wear rate. A mathematical model was developed, revealing a significant p-value of 0.043 in the ANOVA table, indicating the collective influence of the independent variables on wear rate at a significance level of 0.05. Furthermore, the model demonstrates a substantial explanatory power, with R-squared of 69.45% and adjusted R-squared of 51.95%. The p-value calculated to be 0.60 for the statistical Lack of fit indicated a satisfactory model. These findings highlight the effectiveness of RSM in optimizing the experimental input values and offer valuable insights for enhancing the durability and performance of metallic alloys in various industrial applications. The obtained result addresses the problem of uncertainty inherent in optimal levels of input parameters wear experimentation.*

***Keywords:** Response Surface Methodology, Response parameter, Wear rate, ANOVA, Optimization, p-value.*

1. INTRODUCTION

Wear is a natural phenomenon that occurs when two surfaces slide or rub against each other. In industrial applications, excessive wear can lead to equipment failure, increased maintenance costs, and compromised safety. Optimizing wear rates in metallic alloys is crucial for enhancing the performance and longevity of components in various applications [1].Wear is a significant concern in various industries where metallic alloys are used, such as automotive, aerospace, manufacturing, and biomedical sectors. It refers to material removal from a solid body due to mechanical action, often resulting from friction between two surfaces in contact [2]. Wear can lead to decreased performance, increased maintenance costs, and even catastrophic failures in critical components [3].There are numerous factors that affect the behavioural pattern of wear in solid materials. Such factors are load applied, nature of material, sliding distance, speed rate of disc and voltage. Traditional methods of wear rate optimization often involve extensive experimental trials, which are time-consuming and inability to explore the complex interactions between input parameters [4].

Process and parameter optimization has found considerable efficient statistical application in Response Surface Methodology. The statistical tool has been widely deployed to optimizing processes and understanding complex relationships between input variables and response variables. It involves the use of statistical models in describing some behavioural patterns inherent in systems while aiming to optimize response variables by adjusting input variables within certain constraints [5]. Experimental design is the process of planning the structure of the experiments to be conducted. It involves selecting the appropriate experimental factors (independent variables), determining their levels or settings, and defining the experimental conditions [6]. Common DOE platforms for predicting responses are Factorial Design, RSM and Taguchi Method. Response variables measures and evaluate the effect of the factors. Responses can be quantitative (e.g., fatigue strength, tensile strength, wear rate) or qualitative (e.g., product quality ratings, customer satisfaction scores). The choice of responses depends on the experimental objectives and the variables being studied. The rate of wear of the metallic alloy was used as the response parameter in the course of this study. In the context of metallic alloys and wear rate optimization, RSM offers a systematic approach to study the effects of various factors, such as composition, processing parameters, surface treatments, and environmental conditions, on wear resistance. By designing experiments, collecting data, and analyzing response surfaces, researchers can identify optimal combinations of factors that minimize wear rate and enhance the durability and performance of metallic alloys [7].

"Response Surface Methodology Optimization of Wear Rate Parameters in Metallic Alloys" delves into a sophisticated approach to optimizing wear rates in metallic alloys, a critical concern in various industries ranging from aerospace to automotive, where components are subjected to severe mechanical stresses [8]. This methodology offers a systematic and efficient way to understand the relationship between input parameters and wear rates, ultimately leading to the development of more durable and reliable materials [9]. RSM is a statistical technique widely used in engineering and scientific research to optimize processes and improve product quality. It involves experimental design, statistical modelling of response and input parameters. As regards wear optimization, the statistical technique presents an optimal setting which tends to minimize the mechanical property [10]. RSM is statistical technique used for modeling and optimizing processes, systems, and products. It provides a systematic and efficient approach to understanding the relationship between multiple input variables (factors) and one or more response variables (responses). RSM has wide applications across various fields including engineering, chemistry, biology, agriculture, and manufacturing. RSM allows researchers to explore the response surface using a relatively small number of experiments compared to traditional one-factor-at-a-time (OFAT) methods. By systematically varying input variables and fitting mathematical models, RSM maximizes information gain while minimizing experimental effort and resource consumption [11]. RSM begins with the design of experiments to systematically vary the input variables within a defined range. The prominent statistical designs used in RSM are CCD and BBD. These designs allow researchers to efficiently explore the response surface and capture curvature and interaction.

RSM employs statistical techniques such as ANOVA to analyze experimental data and assess the significance of model terms. This statistical rigor ensures that conclusions drawn from the experiments are robust and reliable, enhancing confidence in the validity of the optimization results [12]. RSM reduces the number of experiments required compared to traditional methods, saving time and cost. RSM allows researchers to systematically explore the effects of multiple input variables and their interactions on wear rate. It facilitates the identification of optimal parameter settings that minimize wear rate while meeting performance requirements. The optimization of wear rate parameters in metallic alloys is crucial for ensuring the durability and performance of engineering components across various industries. In recent years, RSM has emerged to be a statistical technique for optimizing wear rate parameters by exploring the complex relationships between input variables and wear behaviour. This literature review aims to provide an overview of the key findings and advancements in the application of RSM for wear rate optimization in metallic alloys. The utilization of RSM in the optimization of wear parameters traces back to the late 20th century, with early studies focusing on understanding the effects of individual alloying elements, heat treatment conditions, and surface treatments on wear behavior [13]. These studies laid the groundwork for the development of more comprehensive optimization approaches using RSM.

Numerous studies have focused on designing efficient experimental layouts for RSM-based wear rate optimization. Design of Experiments (DOE) which comprises of RSM and Taguchi methods was widely employed to systematically vary input parameters while minimizing the number of experiments required. Additionally, researchers have developed sophisticated mathematical models, including regression models and polynomial equations, to describe the relationship between input variables and wear rate accurately [14].Through RSM-based optimization studies, researchers have identified several critical parameters that significantly influence wear behavior in metallic alloys. These parameters include alloy composition, microstructure, hardness, material roughness, lubrication conditions, sliding velocity, and force applied. Understanding the effects of these parameters and their interactions is essential for developing predictive models and optimizing wear effect.

A plethora of case studies have demonstrated the effectiveness of RSM in optimizing wear rate parameters in specific metallic alloys and industrial applications. These studies span various sectors, including aerospace, automotive, manufacturing, and biomedical engineering. For example, RSM has been used to optimize the wear resistance of aluminium alloys for aerospace components, improve the durability of engine components in automotive applications, and enhance the longevity of orthopedic implants [15].Despite its effectiveness, the application of RSM in tribology faces certain challenges, including the need for accurate modeling of complex wear mechanisms, putting environmental factors into perspectives, and validation of optimized parameters under real-world conditions. Future research directions may involve the integration of advanced spectrographic test, microstructural analysis and computational modeling to enhance the predictive capabilities of RSM-based optimization approaches [16].

In addition, the predictive model study highlights the significant advancements and contributions of RSM in optimizing wear rate parameters in metallic alloys. A notable novel of this study is the RSM optimization of wear response influenced by mass difference, track diameter and sliding speed. For a very a long time Taguchi and Factorial designs had always been the most employed tools for determining optimal levels of various mechanical properties. An optimization of dry sliding wear using Taguchi Design to determine the optimal levels of the input parameters was carried out by [6]. Also, [17] applied Genetic Algorithm in optimizing the optimal levels of input parameters in a machine removal operation. Recent works have shown that RSM provides a wide coverage of experimental runs that eventually converges into an optimal setting which is the direction maintained in this study. By systematically exploring the complex relationships between input variables and wear behavior, RSM offers a powerful and efficient approach to improving durability, reliability, and performance of engineering components across various industrial sectors. Continued research efforts targeted at addressing challenges and advancing optimization methodologies are essential for further enhancing the effectiveness of RSM in wear rate optimization [18].

2. MATERIALS AND METHODS

The materials deployed in this study were stop watch, mild steel specimen, variable weights and the statistical software. The machine shown in Figure 1 was used to conduct the wear test. Design of Experiment (DOE) platform was applied in conducting experiments [19].

Figure 1: The experimental wear test machine

2.1 Method

Mild steel specimen attached to the specimen holder was made to maintain contact with the rotating circular disc of the machine. The contact was as a result of the placement of loads to bring the required force. The specimen pin had its weight taken before and after the experiment with a beam balance built within the machine. The experiment was carried out with a circular disc rotation of between 1000rpm to 1500 rpm. During experimentation, it was observed that the rubbing of the specimen pin on the rotating disc brought about detachment of metallic particles from the mild steel material.

2.2 The Determination of Wear Rate

The wear rate was calculated by the use of Equation (1).

$$W_t = \frac{M_a - M_b}{S_l} \tag{1}$$

Where W_t= Wear rate

M_a= specimen mass before experimentation

M_b= specimen mass after experimentation

S_l=Sliding distance

A sliding distance is the product of the sliding speed and the track radius.

2.3 Design of Experiment

DOE is a technique applied in optimizing experimental settings in order to promote quality and understand the relationships between input variables and responses. DOE involves planning, conducting, and analysing controlled experiments in which the researcher manipulates one or more factors (independent variables) to observe their effect on a response (dependent variable), while keeping other factors constant [20].

The technique allows researchers to conduct experiments in a systematic and efficient manner, minimizing the number of experiments required to obtain meaningful results. By strategically varying factors and levels, DOE maximizes the amount of information obtained from each experiment, reducing time and resources needed for experimentation. DOE employs statistical techniques to analyze experimental data and draw conclusions about the relationships between factors and responses. Statistical analysis allows researchers to quantify the effects of factors, assess the significance of their interactions, and identify optimal conditions for achieving desired outcomes. Common statistical tools used in DOE include Analysis of Variance (ANOVA), Taguchi design, RSM and Multi linear regression. The independent variables and their levels applied are shown in Table 1, and were obtained from profound study of related literature. Each factor had multiple levels, representing different settings or values that the factor took during the experiment [17].

Table 1: Factor levels

Wear parameters	Levels	
	Low level	High level
Track diameter (mm)	50	100
Sliding speed (rpm)	1000	1500
Mass difference (mg)	3000	13000

2.4 Mathematical Model

Once the experiments are conducted, mathematical models are developed to describe the relationship between the input variables and the response(s). Typically, second-order polynomial models are used in RSM to capture linear, quadratic, and interaction effects. The general form of the model is for representing a 3-parameter response (Wr) in a Response Surface Methodology (RSM) is as given in Equation (2) obtained from Montgomery, (2007).

$$W_t = \beta_0 + \beta_1 A + \beta_2 B + \beta_3 C + \beta_4 A^2 + \beta_5 B^2 + \beta_6 C^2 + \beta_7 AB + \beta_8 AC + \beta_9 BC \qquad (2)$$

Where A=Track diameter
B=Sliding speed
C= Mass difference
W_t=wear rate response
"B_0, β_1,β_2,β_3,β_4-------------------------β_9 are the regression coefficients"

After developing the initial mathematical model, it is essential to validate its adequacy and accuracy. Model validation involves conducting additional experiments to test the predictive capability of the model. Techniques such as ANOVA evaluates the p-value, identify potential outliers, and the goodness-of-fit. Once validated, the mathematical model is used to optimize the input and output parameters. Optimization in RSM aims to find the global optimum within the experimental region defined by input variable ranges. Optimization techniques include gradient-based methods, response surface optimization, and desirability approach.

2.5 Genetic Algorithm Technique

Genetic algorithms are particularly useful for complex optimization problems with large solution spaces, where other optimization techniques may struggle due to their reliance on gradient information or other assumptions about the problem structure. GAs offer the advantage of being able to search a wide range of potential solutions simultaneously and are robust in finding good solutions even in the presence of noisy or incomplete information. Their relevance has been noticed in notable such as engineering, life, science, robotics etc. Optimization technique is inspired by the principles of natural selection and genetics. It proffers solutions to optimization and search problems where traditional methods struggle or are impractical. The natural principles are mutation, crossover, reproduction and selection [19].

3. RESULTS AND DISCUSSIONS

3.1 Central Composite Design Experimental Outcome

The experimental and statistical analysis of the wear test is reported in this section. The experimental design of the CCD applied in the experimentation of the wear had a wear response and three input parameters which are mass difference, track diameter and sliding speed. The Central Composite Experimental Design is displayed in Table 2.

Table 2: CCD Experimental platform

Run order	STD order	Track diameter A (mm)	Sliding speed, B (rpm)	Mass difference C (mg)	Wear rate, Wr (mg/mm)
1	9	32.955	1250.00	8000.00	4.9
2	17	75.000	1250.00	8000.00	5.3
3	11	75.000	829.55	8000.00	5.4
4	1	50.000	1000.00	3000.00	5.3
5	13	75.000	1250.00	-409.00	5.2
6	7	50.00	1500.00	13000.00	4.9
7	14	75.000	1250.00	16409.00	5.7
8	20	75.000	1250.00	8000.00	5.6
9	6	100.000	1000.00	13000.00	5.6
10	18	75.000	1250.00	8000.00	5.8
11	5	50.00	1000.00	13000.00	5.6
12	3	50.00	1500.00	3000.00	5.6
13	4	100.000	1500.00	3000.00	5.5
14	15	75.000	1250.00	8000.00	5.5

Run order	STD order	Track diameter A (mm)	Sliding speed, B (rpm)	Mass difference C (mg)	Wear rate, Wr (mg/mm)
15	12	75.000	1670.45	8000.00	5.5
16	19	75.000	1250.00	8000.00	5.4
17	10	117.045	1250.00	8000.00	5.3
18	16	75.000	1250.00	8000.00	5.2
19	8	100.000	1500.00	13000.00	5.1
20	2	100.000	1000.00	3000.00	4.9

3.2 ANOVA Result

The ANOVA result of the CCD experimentation is shown in Table 2.

Table 3: ANOVA result

Source	DF	Adj SS	Adj. MS	F-value	P-value
Model	9	0.9483	0.1054	2.53	0.043
Linear	3	0.0516	0.0172	0.41	0.748
A	1	0.0102	0.0101	0.24	0.632
B	1	0.0013	0.0012	0.03	0.032
C	1	0.0402	0.0401	0.96	0.035
Square	3	0.2529	0.0845	2.02	0.175
A^2	1	0.2523	0.2523	6.05	0.034
B^2	1	0.0011	0.0010	0.03	0.087
C^2	1	0.0011	0.0010	0.03	0.087
2-way Interaction	3	0.6437	0.2145	5.14	0.021
AB	1	0.0312	0.0312	0.75	0.407
AC	1	0.0613	0.0612	1.47	0.254
BC	1	0.5513	0.5512	13.21	0.005
Error	10	0.4172	0.0417		
Lack of fit	5	0.1838	0.0367	0.79	0.600
Pure error	5	0.2333	0.0466		
Total	19	1.3655			

The R^2 and adjusted R^2 are 69.45% and 51.95% respectively. Explicitly, the model's R^2 and adjusted R^2 are measures of the dependent variable that is explained by the independent variables in the model [21]. The R^2 of 69.45%proves that this amount of variability in the dependent variable is explained by the independent variables applied in the model. This is a reasonable good fit to the data, as it explains a substantial part of the variability observed in the dependent variable. The adjusted R^2 value of 51.95% adjusts for the predictors in the model, displaying an estimate of the variance explained.

The calculated adjusted R^2 of 51.95% was found to be lower than the R^2 value; this is as a result of getting into the model only significant predictors that explains it. The significance of Table 2 is to determine the mathematical model adequacy.

3.3 Statistical Model

The statistical model developed from DOE experimentation is shown in Equation (3).

$$W_r = 3.18 + 0.0147\text{A} + 0.00123\text{B} + 0.000226\text{C} - 0.000212\text{A}^2 \quad (3)$$

Where A=Track diameter
B=Sliding speed
C= Mass difference

The developed mathematical model has a p-value of 0.043 as shown in the ANOVA table, indicating that at a significance level of 0.05, the model's overall fit is statistically significant. This is a pointer that the predictors have a strong influence on the response parameter.

The p-value is a measure of the probability of observing the data if the null hypothesis (i.e., no effect of the independent variables) were true. A p-value that has a selected significance level of less than 0.05 as in this case shows that there exists a sufficient evidence to turn down the null hypothesis and conclude that the model provides a better explanation of the data than a model with no independent variables. The statistical values obtained were similar to that obtained by [5].

3.4 Normality Plot

It is a graphical technique used to assess the extent at which the residuals of a statistical model follow a normal distribution. Ideally, when points on the plot align it shows normal distribution of the residuals. The developed Normal Probability plot shown in Figure 2 yields a p-value of 0.043 in the ANOVA results at a significance level of 0.05.

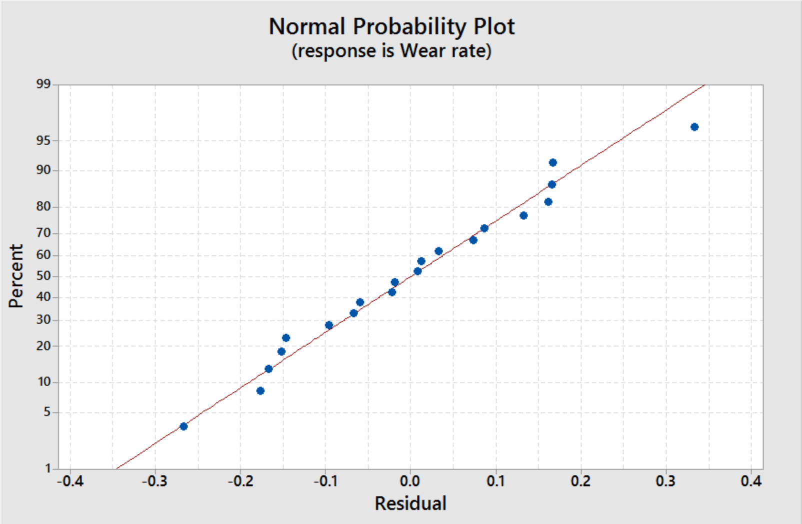

Figure 2: Normal probability plot

3.5 Genetic Algorithm Optimization

The Genetic algorithm technique was used to predict the optimal levels of the independent variable. The developed mathematical model was inputted into the Genetic Algorithm toolbox of MATLAB software. The lower boundaries were the low levels of the process parameters, while the high levels taken to be the upper boundaries. The obtained optimal levels are shown in Table 4.The wear rate shown in Figure 3 is 5.824 mg/mm.

Table 4: Genetic algorithm optimal levels

Parameters	Optimal Levels
Track diameter (mm)	50.05
Sliding speed (rpm)	1000.06
Mass difference (mg)	3000.05
Wear rate (mg/mm)	5.824

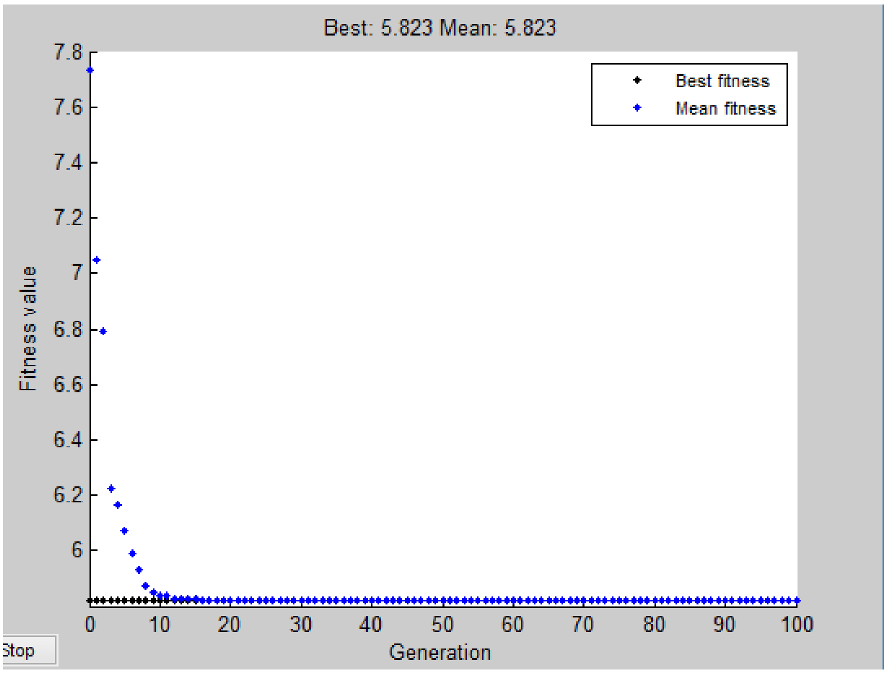

Figure 3: Fitness value against generation plot

3.6 Validation of the Model

In further validating the developed model a scattered plot between the run order and the experimental wear rates was developed as shown in Figure 4. Also, a plot between the run order and the predicted values was graphically presented as shown in Figure 5. The two plots show high level of graphical similarity as a result of the closeness of their data.

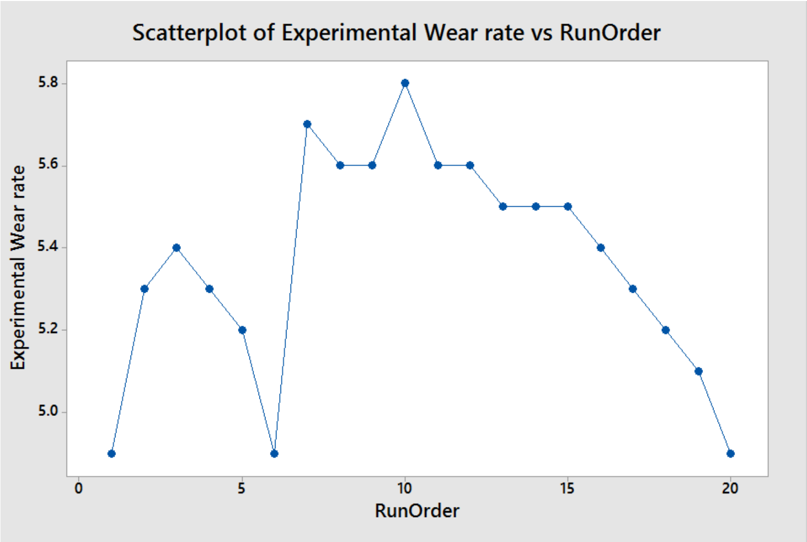

Figure 4: A scatter plot of experimental wear rate against run order

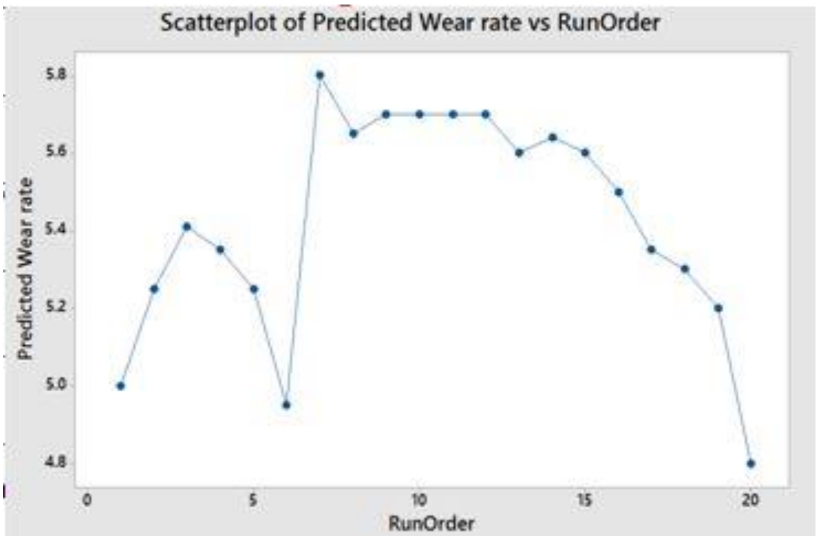

Figure 5: A scatter plot of predicted wear rate against run order

4. CONCLUSION

The application of RSM for the determination of optimal levels of wear rate parameters in metallic alloys, with a track diameter, sliding speed, and mass difference as independent variables, has yielded significant insights and outcomes. The study employed the Central Composite Design (CCD) experimental method, which enabled systematic exploration of the response surface and facilitated the optimization process.

The developed statistical and mathematical model demonstrated promising results, with a p-value of 0.043 in the ANOVA table, indicating statistical significance at the 0.05 significance level. This suggests that the predictors collectively have a great effect on the wear rate response. Furthermore, the R^2 of 69.45% proves that this amount of variability in the dependent variable is explained by the independent variables applied in the model. The adjusted R^2 value of 51.95% adjusts for the predictors in the model, displaying an estimate of the variance explained.

The Lack of Fit model, with a p-value of 0.60, indicates that the model adequately fits the data, and there is no significant lack of fit. This enhances confidence in the reliability of the developed model for predicting wear rate in metallic alloys based on the specified independent variables.

Overall, the findings of this study underscore the effectiveness of Response Surface Methodology in optimizing wear rate parameters, providing valuable insights of the design and development of metallic alloys with enhanced durability and performance. The optimized model offers practical implications for industries reliant on metallic components subjected to wear, such as aerospace, automotive, and manufacturing sectors. Further research may focus on validating the optimized model under real-world conditions and exploring additional factors that could influence wear rate for comprehensive optimization strategies

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