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REGULAR ARTICLE

Optimization of Cutting Conditions for the Metallic Surfaces of 50CrNi3Mn Alloy Steel Using Box-Behnken Design, ANOVA, and Desirability Function (Box-ANOVA-DF)

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This work aims to model the performance factor of metallic surfaces (surface roughness *Ra*) and optimize cutting conditions (rotation speed *N*, feed rate *f*, and lubrication type) during the boring of holes in an alloy steel (50CrNi3Mn) using a carbide reamer. The combination of the Box-Behnken Design and ANOVA was applied with 15 experiments based on the L15 orthogonal design, using the following factors: rotation speed (22 (m/min) and 43 (m/min)), feed rate *f* (1.67, 3.33, and 5 mm/sec), and lubrication type (dry, air, and oil). A statistical analysis of the results was performed based on ANOVA to identify the most significant parameters affecting the experimental responses. A desirability function approach was established to find the optimal factors to minimize *Ra*. The optimal conditions obtained according to the three chosen criteria are as follows: $V_c = 22.261$, $f = 1.796$ (mm/sec) with oil lubrication. The optimized surface roughness is $Ra = 3.463$ µm.

Keywords: Metallic surfaces, Roughness, Optimization, ANOVA, Box-Behnken, Desirability Function

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1. INTRODUCTION

Metallic surfaces, particularly steel, are integral in various applications due to their strength, durability, and versatility [1, 2]. Alloy steel, known for its corrosion resistance and durability, is a widely used alloy in industries ranging from construction to food processing. The design and optimization of metallic surfaces, especially in contact with hardening fresh concrete, have been the focus of recent research to enhance bonding and performance in construction applications [3, 4]. Steel, an alloy of iron and carbon, offers improved strength and fracture resistance, making it a fundamental material in numerous sectors such as infrastructure, transportation, and manufacturing. The use of different grades of steel, including stainless steels and alloy steels, allows for tailored properties to meet specific application requirements. Understanding the surface finishes and treatments of steel, as well as its production standards, is crucial for ensuring quality and performance in various steel applications [5]. Recent studies have highlighted the importance of steel surfaces and their treatment in achieving optimal performance and longevity in diverse industrial and construction settings [6, 7].

The precise characterization and adjustment of cut-ting parameters are crucial for achieving optimal metal surface quality. Recent research has demonstrated that meticulous control of these parameters can minimize the formation of surface defects such as scratches, burrs, and residual stresses [8]. The integration of cut-ting parameter optimization in the manufacturing sec-tor results in a significant improvement in the quality of steel parts while reducing costs associated with finishing operations [9, 10].

Traditional optimization methods, focusing on varying one factor at a time, are often laborious and costly, and hindering effective exploration of parameter inter-actions. Conversely, Taguchi experimental designs pro-vide a structured framework to identify key factors influencing a process or product while minimizing the number of trials.

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This method utilizes pre-defined or-thogonal tables to select parameter combinations for testing, maximizing information with minimal experimentation. Subsequently, analysis of variance (ANOVA) quantifies each factor's contribution and their interactions on the studied response. This robust statistical approach distinguishes actual parameter effects from random variations, providing a solid foundation for optimization. Compared to traditional methods, Taguchi experimental designs coupled with ANOVA yield considerable time and cost savings, ensuring better understanding of underlying phenomena for efficient process and product optimization [11-14].

This study aims to optimize cutting conditions, including cutting speed, feed per revolution, and lubrication type (dry, air, and oil), using the Desirability Function (DF) approach, during the boring of holes in an alloy steel (50CrNi3Mn), to assess their impact on surface roughness (Ra) using factorial design methodology. Additionally, an analysis of variance (ANOVA) was conducted to determine the influence of each parameter on the responses. It is worth noting that very few studies have employed these analyses to thoroughly evaluate the quality of metallic surfaces used in various industrial sectors for enhancing their physical and mechanical properties.

2. MATERIALS AND METHODS

The material used in this study is an alloy steel ($50CrNi_3Mn$), with its chemical composition presented in Table 1. This experimental research aims to model machining performance parameters, particularly surface roughness (Ra), and to optimize cutting conditions such as rotation speed, feed per revolution, and lubrication type (dry, air, and oil) during the boring of holes in this alloy steel. The tool used is a $W_{18}Cr_4V$ carbide reamer with a diameter of 17.2 mm and a length of 180 mm, ideal for precision boring of holes in hard and resistant materials due to its superior hardness and wear resistance. The machining center used is a Tongtai VTX-5 vertical model, suitable for machining medium to large-sized parts in difficult materials, ensuring high precision and productivity thanks to its advanced technical features.

ANOVA analyses were conducted to determine the most influential factors in the responses, using F and P values to assess the significance of each parameter. Subsequently, linear regression analysis was employed to develop mathematical models for each response based on the independent factors. Optimal parameter levels were then determined using the desirability function to minimize surface roughness Ra.

This study is divided into two parts: the first focuses on modeling output responses, particularly surface roughness (*Ra*), using response surface methodology (RSM). ANOVA is utilized to assess the impact of cut-ting parameters such as cutting speed (V_c), feed rate (f), and lubrication type on output parameters. The final part of the work is dedicated to optimization using the Response Surface Methodology (RSM) approach, employing the Desirability Function (DF) to find the optimal values of input parameters.

3. EXPERIMENTAL RESULTS

Table 2 presents the experimental data of surface roughness (*Ra*) of drilled holes, based on three primary cutting parameters: cutting speed, feed rate, and lubrication type (1: dry, 2: air, 3: oil). These values were obtained from various combinations of cutting parameters according to an experimental design plan (L15) during the drilling of holes in $50CrNi_3Mn$. Analysis of the results from Table 1 reveals that the surface roughness (*Ra*) falls within a range of values between 3.662 and 5.922 μm.

3.1 Analysis of Surface Roughness (*Ra*) Results

Table 3 provides detailed results of the analysis of variance (ANOVA) for surface roughness (*Ra*). The aim is to assess the impact of the main factors on *Ra*. It is evident from this table that lubrication is the most significant factor influencing surface roughness (*Ra*), with a contribution of 96.76 %. Following this, cutting speed (V_c) contributes 4.66 %, and feed rate (f) contributes 1.59 %. These findings highlight the importance of lubrication in controlling surface roughness, followed by cutting speed and feed rate similar results show the importance of lubrication [15-17].

3.2 Films Characterization

Fig. 1 illustrates the effects of cutting parameters on surface roughness (*Ra*) under various cutting conditions. Analysis of the graphs reveals that oil lubrication stands out as the most influential factor affecting surface roughness (*Ra*). This is evident from the significant improvement in surface quality when changing the lubrication type. Following lubrication, cutting speed (V_c) and feed rate (f) also exhibit noticeable effects on surface roughness, albeit to a lesser extent. This observation highlights the importance of carefully selecting and optimizing lubrication strategies to achieve the desired surface quality in machining processes.

3.3 Regression Equation for (*Ra*)

The relationship between the arithmetic mean surface roughness (*Ra*) and the independent variables examined (V_c and f) for the three types of lubrication (Air, Dry, and Oil) has been formulated using a linear mathematical model. This model is represented by equations (1, 2, and 3), where the correlation coefficients are respectively 99.73 % and 99.36 % for R^2 and adjusted R^2. These equations enable quantification of the relationship between cutting variables and surface roughness, thus providing a precise understanding of their influence on the quality of the machined surface.

- Lubrification Air

$$Ra = 3.92608 + 0.000909\ Vc + 0.001240 f \quad (3.1)$$

Table 1 – Chemical composition of steel 50CrNi$_3$Mn

C	Mn	Si	P	S	Cr	Mo	Ni	Al	Co	Cu	Nb	Ti	N	Fe	Cr+NI
0.55	0.75	0.21	0.009	0.005	0.224	0.0863	0.0934	0.0322	0.0291	0.0592	0.0040	0.0103	0.0093	97.817	2.59

Table 2 – Factorial Design Matrix Planning Table (L15)

Test N°	cutting speed (Vc)(m/*min*)	Avance *f* (mm/sec)	Lubrification	Experimentally values *Ra* (μm)	predicted Values *Ra* (μm)
1	22	1.67	Air	4.416	4.41368
2	43	5	Air	5.038	5.02528
3	22	5	Oil	3.47	3.50259
4	43	3.33	Dry	5.922	5.86582
5	43	1.67	Oil	3.662	3.61819
6	22	1.67	Air	4.416	4.41368
7	22	5	Oil	3.47	3.50259
8	43	5	Oil	3.845	3.8661
9	43	1.67	Dry	5.625	5.74182
10	43	5	Air	5.038	5.02528
11	43	1.67	Oil	3.662	3.61819
12	43	3.33	Air	4.909	4.90128
13	22	3.33	Dry	5.533	5.50222
14	22	3.33	Dry	5.533	5.50222
15	43	1.67	Air	4.741	4.77728

Table 3 – ANOVA Results for (Ra)

Source	Sum of Squares	*df*	Mean Square	*F*-value	*p*-value		% of contribution
Model	9.96	4	2.49	928.21	< 0.0001	significant	99.79 %
Vc	0.4651	1	0.4651	173.41	< 0.0001	significant	4.66 %
f	0.1589	1	0.1589	59.24	< 0.0001	significant	1.59 %
lub	9.66	2	4.83	1801.57	< 0.0001	significant	96.76 %
Residual	0.0268	10	0.0027				0.26 %
Cor Total	9.98	14					100 %

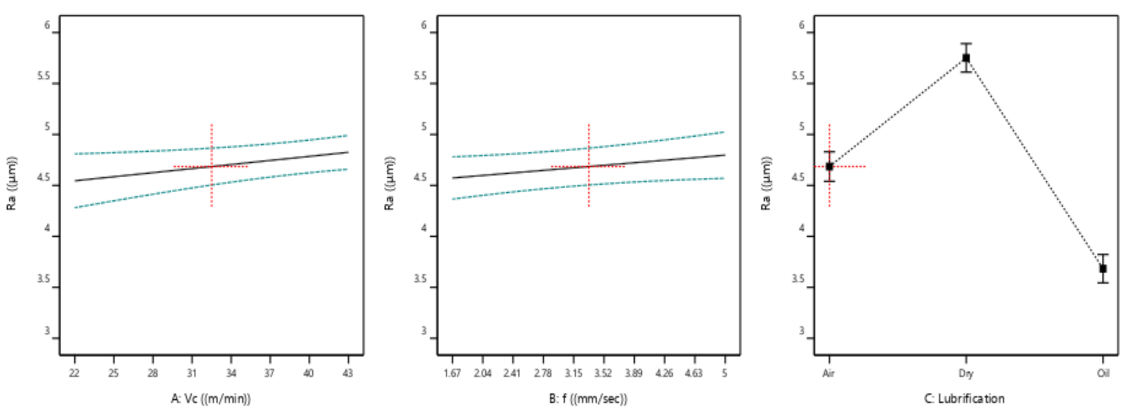


Fig. 1 – Effects of cutting parameters on surface roughness (*Ra*)

- Lubrification Dry

$$Ra = 4.89062 + 0.000909Vc + 0.001240f \qquad (3.2)$$

- Lubrification Oil

$$Ra = 2.76699 + 0.000909Vc + 0.001240f \qquad (3.3)$$

Fig. 2 and Fig. 3 depict the disparity between experimentally measured values and predicted values of surface roughness (*Ra*). Analysis of the results reveals a significant closeness between predicted and experimental data, highlighting the accuracy of the developed model. Furthermore, these graphs allow visualization of error distribution, providing insight into the overall consistency between observed and anticipated values by the model.

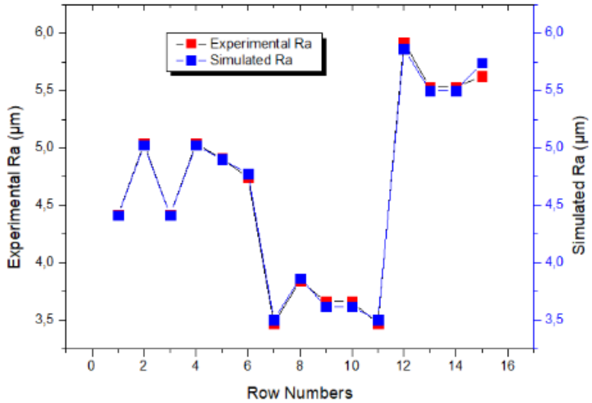


Fig. 2 – Comparison between Experimental and Simulated Values of *Ra*

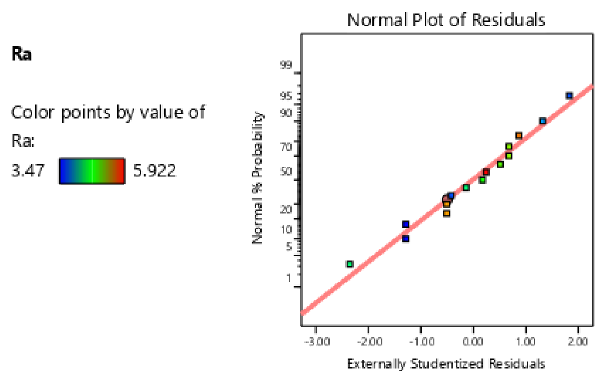
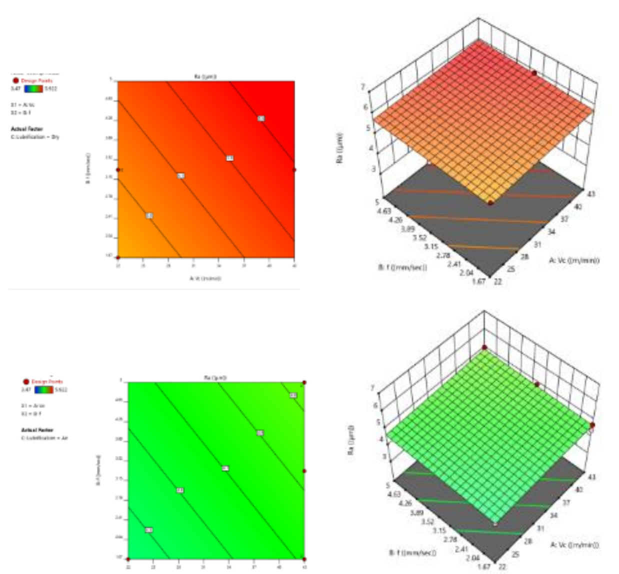


Fig. 3 – Predicted Values versus Experimental Values for *Ra*

3.4 Contour Plot and 3D Surface Plot

In Fig. 4, the type of lubrication appears to exert a predominant influence on surface roughness *Ra* compared to rotation speed and feed, particularly with the use of oil as a lubricant, during boring of holes in metallic surfaces in the alloy steel.



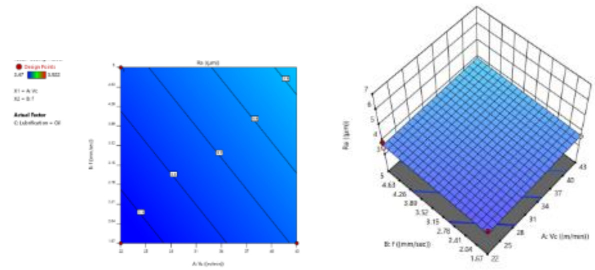


Fig. 4 – Contour and 3D surface plot for Ra

3.5 Optimization Using the Desirability Function (DF) Method

The Desirability Function method proves to be a valuable optimization tool for enhancing the quality of metal surfaces. By enabling the simultaneous optimization of multiple response variables, it identifies the optimal process parameters and accommodates various surface improvement techniques. Its systematic approach distinctly sets it apart from traditional optimization methods [18-21].

The optimal cutting conditions regimen identified consists of $V_c = 22.261$, $f = 1.796$ (mm/sec) with oil lubrication. Surface roughness achieves a minimal value of $Ra = 3.463$ (µm) with a desirability of 1. This scenario is particularly relevant for whole boring operations where high-quality standards are required (minimal roughness). Table 3 outlines the objective and parameter range for this optimization case. The top 5 responses of the roughness surface are presented in Table 3.

The relationship between the arithmetic mean surface roughness (*Ra*) and the independent variables examined (V_c and *f*) for the three types of lubrication (Air, Dry, and Oil) has been formulated using a linear mathematical model. This model is represented by equations (1, 2, and 3).

Fig. 5 presents the exact optimal values of the parameters (V_c, *f*, and lubrication type), as well as those of the studied output parameters (*Ra*) and desirability. This visualization offers a detailed insight into the precise configuration that yields the best performance in terms of surface roughness and overall desirability.

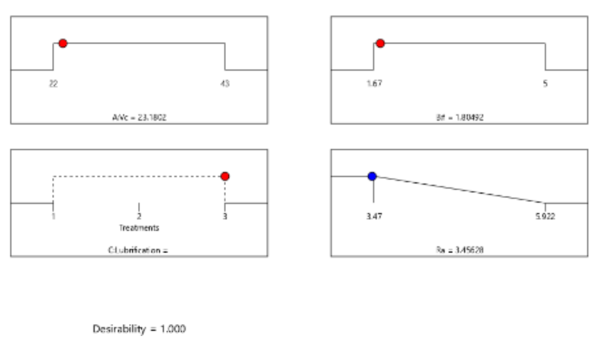


Fig. 5 – Optimization Diagram of Surface Roughness (*Ra*)

4. CONCLUSION

The experimental research in this study aims to model the performance factor of metallic surfaces (surface roughness *Ra*) and optimize cutting conditions (rotation speed, feed, and lubrication type) during boring of holes in an alloy steel ($50CrNi_3Mn$) using a car-bide reamer. The obtained results have led to the following conclusions:

The results of ANOVA for surface roughness (*Ra*) at a 95% confidence level show that the type of lubrication (oil) is the most significant factor affecting Ra, with a contribution of 96.76 %. This is followed by cutting speed (V_c) with a contribution of 4.66 %, and feed rate (f) with a contribution of 1.59 %.

The mathematical models based on Response Sur-face Methodology (RSM) for surface roughness and the rate of chip removal, having R^2 values of 98.01 % and 99.76 % respectively, demonstrate good agreement with experimental data.

The contour plots determined in this study enable visualization of the response surface. They also assist in establishing the values of responses and desirable operating conditions.

The multi-objective optimization conducted in this study is based on the Desirability Function (DF) approach. The optimal conditions obtained according to the three chosen criteria are as follows: (Minimized surface roughness (Ra)) $V_c = 22.261$, $f = 1.796$ (mm/sec) with oil lubrication. The optimized surface roughness is $Ra = 3.463$ μm with a desirability of 1.

Enhancing the surface quality of metals is pivotal in optimizing their physical properties, including corrosion resistance, wear, and fatigue. By managing cleanliness, roughness, and surface appearance, we can also influence properties such as electrical and thermal conductivity, reflectivity, and the aesthetic appeal of metals.

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Оптимізація умов різання для металевих поверхонь легованої сталі 50CrNi3Mn за допомогою дизайну Box-Behnken, ANOVA та функції бажаності (Box-ANOVA-DF)

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Робота спрямована на моделювання коефіцієнта ефективності металевих поверхонь (шорсткість поверхні *Ra*) та оптимізацію умов різання (швидкість обертання *N*, швидкість подачі *f* і тип змащення) під час розточування отворів у легованій сталі (50CrNi3Mn) за допомогою твердосплавної розгортки. Поєднання дизайну Box-Behnken і ANOVA було застосовано з 15 експериментами на основі ортогонального плану L15 з використанням таких факторів: швидкість обертання (22 (м/хв) і 43 (м/хв)), швидкість подачі *f* (1,67, 3,33 і 5 мм/с) і тип змащення (сухе, повітря та масло). Статистичний аналіз результатів був проведений на основі дисперсійного аналізу для визначення найбільш значущих параметрів, що впливають на експериментальні результати. Для пошуку оптимальних факторів для мінімізації *Ra* було встановлено підхід функції бажаності. Оптимальні умови, отримані відповідно до трьох вибраних критеріїв, такі: $V_c = 22.261$, $f = 1.796$ (мм/с) при масляному змащуванні. Оптимізована шорсткість поверхні становить $Ra = 3.463$ мкм.

Ключові слова: Металеві поверхні, Шорсткість, Оптимізація, ANOVA, Box-Behnken, Функція бажаності.