Type of contribution:
Editorial
▶ Research Paper
Case Study
Review Paper
Scientific Data
Report of Tech. Application

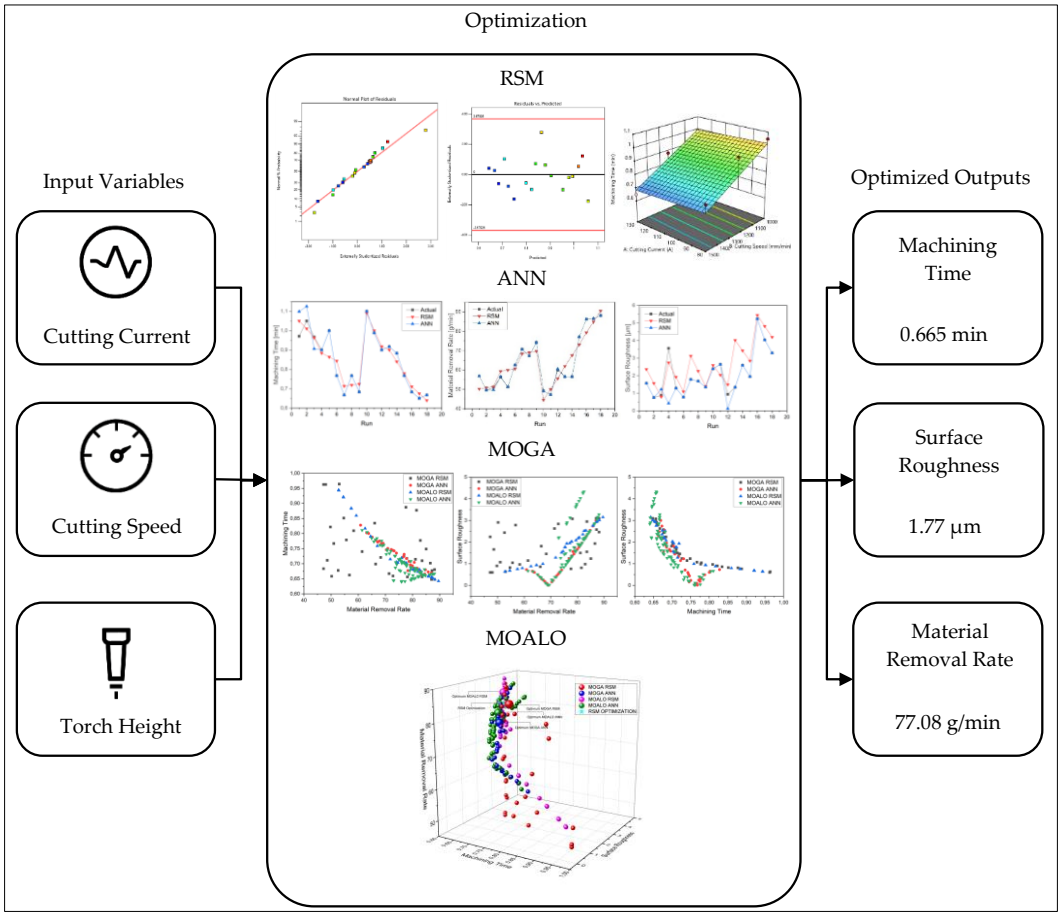
e-issn. 2798-5245

Mechanical Engineering for Society and Industry
Vol. 5, No. 2 (2025) pp 560-575
https://doi.org/10.31603/mesi.11646

Multi-objective optimization of SS 410 CNC plasma cutting using RSM, ANN, MOGA, and MOALO

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Article info
Submitted: 2024-06-26
Revised: 2025-01-07
Accepted: 2025-08-28

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Publisher
Universitas Muhammadiyah Magelang

Highlights:

- The integration of RSM, ANN, MOGA, and MOALO provides an effective optimization framework for CNC plasma cutting of SS 410 alloy.
- Cutting speed mainly affects machining time and material removal rate, while cutting current and torch height influence surface roughness.
- Optimal parameters of 85.31 A, 1500 mm/min, and 5 mm yielded minimal machining time (0.665 min), low surface roughness (1.77 µm), high material removal rate (77.08 g/min), and the highest desirability (0.874).

Abstract

This study focuses on optimizing the CNC plasma cutting process for Stainless Steel 410 alloy, a type of martensitic stainless steel known for its high strength, hardness, and good corrosion resistance, using Response Surface Methodology (RSM) combined with advanced optimization methods. Key input variables, including cutting current, speed, and torch height, were

systematically analyzed to enhance cutting efficiency by minimizing machining time and surface roughness while maximizing material removal rate. The experimental approach utilized a Central Composite Design (CCD) with 18 trials and Analysis of Variance (ANOVA) to validate linear models as optimal predictors for response variables. Results indicate that cutting speed significantly influences machining time and material removal rate, while cutting current and torch height also influence surface roughness. To improve prediction accuracy and explore the parameter space beyond experimental trials, Artificial Neural Networks (ANN) were implemented, demonstrating superior predictive capabilities compared to RSM alone. Moreover, Multi-Objective Genetic Algorithm (MOGA) and Multi-Objective Ant Lion Optimizer (MOALO) were employed to refine optimization outcomes, addressing trade-offs between conflicting objectives. The optimal configuration, identified as a cutting current of 85.31 A, a speed of 1500 mm/min, and a torch height of 5 mm, achieved a machining time of 0.665 minutes, a surface roughness of 1.77 µm, and a material removal rate of 77.08 g/min. These findings underscore the effectiveness of integrating statistical methods with machine learning and advanced optimization algorithms for precision manufacturing. The study offers a comprehensive framework for improving process efficiency and quality in CNC plasma cutting, catering to the growing demand for high-performance cutting techniques in the steel industry.

Keywords: Plasma arc cutting; SS 410 alloy; Response surface methodology; Artificial neural network; Multi-objective genetic algorithm; Multi-objective ant lion optimizer; Process optimization

1. Introduction

The cutting of steel plates is a crucial step in industrial manufacturing, starting from the creation and precise cutting of patterns on base materials. Traditional manual plate cutting methods take into account factors such as cost, design complexity, welding requirements, and optimal cutting positions [1]. However, this conventional approach has shown reduced productivity over time because it relies heavily on skilled labor and is time-consuming. The high likelihood of human error further complicates the process, leading to inefficiencies and inconsistencies [2]. To address these issues, advancements in technology have led to the adoption of specialized cutting machines, including CNC Plasma Cutting Machines, which are designed to improve accuracy and efficiency [3]. These automated systems minimize human error and significantly enhance productivity, making them highly valuable in the steel fabrication industry.

Plasma arc cutting (PAC) has become one of the most versatile and effective thermal-based cutting technologies. By using a restricted plasma arc transferred to the workpiece, this method rapidly heats and melts the material, allowing for fast and precise cuts in various conductive metals [4], [5]. Different variations are available, such as using auxiliary gases, water injection to improve cut quality, underwater cutting, and marking applications [6]. Its benefits include high cutting speeds, minimal slag production, and excellent precision, making it suitable for fabrication, automotive repair, construction, and salvage operations [7]. Despite its advantages, PAC does have drawbacks such as limited cutting depth, noise, fume generation, and ongoing costs related to consumables like electrodes [8], [9], [10]. Optimizing cutting parameters is therefore essential to fully leverage the benefits of this technology while reducing its limitations, ultimately improving performance, efficiency, and cost-effectiveness in industrial applications [11], [12].

Among various optimization approaches, Response Surface Methodology (RSM) is widely recognized as a robust and effective option. First introduced by Box and Wilson in the 1950s [38], RSM provides a structured statistical framework to model and analyze problems where multiple variables affect a response of interest. It uses polynomial regression models to establish the relationships between input parameters and output results, helping researchers understand the influence of each factor [13]. RSM also supports sensitivity analyses, which help clarify how variations in parameters impact outcomes. This capability is especially critical when optimizing PAC processes [14], [15], [16]. Using experimental designs such as Central Composite Design (CCD), RSM enables precise tuning of parameters like cutting current, speed, and torch height to achieve better surface quality, reduced kerf width, and minimized heat-affected zones [17], [18], [19], [20], [21].

To address complex and nonlinear relationships that RSM alone may not fully capture, Artificial Neural Networks (ANN) provide a complementary solution. Inspired by the structure of the human brain, ANN models consist of interconnected layers of neurons that learn patterns in data through iterative training processes [22], [23]. ANN has been shown to be highly effective in

modeling PAC processes, accurately representing the interactions between parameters such as cutting speed, gas pressure, and current. ANN can optimize outcomes like kerf width, surface roughness, and material removal rate more effectively than traditional methods [24], [25], [26], [27]. For instance, some ANN models have achieved R^2 values up to 0.96 in predicting kerf width, clearly demonstrating superior prediction accuracy compared to statistical approaches [24]. Carefully designed ANN architectures, with optimized hyperparameters and training strategies, allow manufacturers to achieve higher precision and improved operational efficiency [22], [27], [28].

As optimization needs become more advanced, the Multi-Objective Genetic Algorithm (MOGA) offers a powerful tool to manage multiple conflicting objectives. Based on natural selection principles, MOGA explores a range of solutions and evolves them to find the most balanced parameter settings. This helps manufacturers achieve the best trade-offs among surface roughness, machining time, and material removal rate [28], [29]. When combined with RSM and ANN, MOGA creates a hybrid approach that benefits from the strengths of each method. This combined strategy has been shown to significantly improve both precision and efficiency in manufacturing processes such as PAC, enhancing surface quality and increasing material removal rates [30], [31], [32], [33], [34].

Another advanced method, the Multi-objective Ant Lion Optimization Algorithm (MOALO), has been developed to further refine optimization. Inspired by the hunting strategy of ant lions, this algorithm effectively balances exploration of new solutions and fine-tuning of existing ones. MOALO is especially useful when integrated with RSM and ANN, as it helps avoid local minima and enhances global search capabilities. By refining solutions from MOGA and ANN, MOALO contributes to greater accuracy and process consistency [35], [36], [37], [38].

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) supports decision-making by ranking alternatives based on their closeness to the ideal and farthest solutions. Through objective weighting and normalization, TOPSIS provides a straightforward way to evaluate different parameter sets and select configurations that offer the best balance between productivity and quality [39], [40]. When used together with RSM, ANN, MOGA, and MOALO, TOPSIS helps identify the most effective parameter combinations to achieve high material removal rates with minimal surface roughness and optimal machining time [41].

In this study, a comprehensive approach combining RSM, ANN, MOGA, MOALO, and TOPSIS was used to optimize plasma arc cutting of SS 410 alloy plates. By systematically analyzing and tuning key factors such as cutting current, cutting speed, and torch height, this research aims to reduce machining time and surface roughness while maximizing material removal rate. The overall objective is to create a highly efficient and precise cutting process that meets modern industry demands for quality and productivity.

2. Methodology

This study adopts an integrated approach combining Response Surface Methodology (RSM), Artificial Neural Networks (ANN), and Multi-Objective Genetic Algorithm (MOGA) to optimize the plasma arc cutting process of SS 410 alloy plates. The material used is SS 410 alloy, a martensitic stainless steel that offers high strength, hardness, and good corrosion resistance. It consists of 11.5% Chromium, 1% Manganese, 1% Silicon, 0.75% Nickel, 0.04% Phosphorus, 0.03% Sulfur, 0.15% Carbon, and the balance is Iron [42].

The raw plate material used for experiments had a thickness of 10 mm and an initial dimension of 500 mm × 300 mm, consistent with the study by Pothur *et al*. [42]. During and after the cutting process, no significant warping was observed, which indicates that the thermal deformation was minimal and well-controlled. This condition was monitored visually and through flatness measurements.

For specimen preparation, the plasma cutting machine was programmed to cut dumbbell-shaped profiles and linear segments with a final specimen size of approximately 100 mm × 30 mm for each test piece, as shown in the reference design [42]. Each experimental configuration was repeated three times to ensure reliability and reproducibility of the results, thus providing a robust statistical basis for analysis. The experiments were performed using a CNC Plasma Arc Machine (Multi Therm Eco) manufactured by Messer Cutting Systems, configured with a supply voltage of 3 × 400 V at 50 Hz, a rated power of 30 kW, a primary fuse of 16 A, and an open-circuit voltage of 230 V. Argon gas was used as the plasma gas due to its stability and effectiveness in producing high-quality cuts.

Three process parameters were chosen as input factors: cutting current (ranging from 80 to 130 A), cutting speed (1000, 1250, and 1500 mm/min), and torch height (3, 4, and 5 mm) as folloeing **Table 1**. The experimental design was structured using a face-centered Central Composite Design (CCD), which included 18 trials combining factorial, axial, and center points to enable building a quadratic model and capture interaction effects among variables as listed in **Table 2**.

The objective of this optimization was to minimize machining time and surface roughness while maximizing material removal rate (MRR). Each test specimen's machining time, surface roughness, and MRR were measured. Surface roughness was measured using a Mitutoyo Surftest SJ-210 tester, while MRR was calculated based on Eq. (1).

$$MRR = \frac{W\,RW}{T} \tag{1}$$

where WRW is the workpiece removal weight (grams), and T is machining time (minutes) [42]. Detailed parameters and corresponding output results for each trial are presented in **Table 2**. This table includes cutting current, cutting speed, torch height, machining time, surface roughness, and MRR values for all 18 experiments, providing a comprehensive overview of the process variations and performance outcomes.

The data from RSM experiments were modeled using Design-Expert® software to identify significant factor effects and generate predictive equations. Statistical analysis was carried out through Analysis of Variance (ANOVA) to verify the model's significance and identify contributions of each parameter.

To further improve predictive capability, ANN models were developed using feed-forward architecture trained via backpropagation algorithms [43]. The input variables (cutting current, cutting speed, torch height) and output responses (machining time, surface roughness, MRR) were normalized before training. The ANN structure and hyperparameters were optimized using the Taguchi method [44], [45], and model performance was evaluated using Mean Squared Error (MSE) and R^2 metrics.

The optimized ANN predictions were integrated into the MOGA framework to handle multi-objective optimization. MOGA was initialized with a random population representing various cutting parameter combinations, and each solution (chromosome) was evaluated based on fitness functions derived from the RSM and ANN models [46], [47]. The algorithm employed selection mechanisms, crossover, and mutation to evolve the solutions over generations. Elitism was applied to retain the best solutions, while Pareto fronts visualized the trade-offs among objectives such as minimizing surface roughness and maximizing MRR. The combination of RSM, ANN, and MOGA offered a hybrid optimization strategy that balances machining efficiency and product quality. This integrated methodology allowed the study to build on the foundation laid by Pothur *et al*. [42], expanding it with advanced predictive and optimization techniques validated through rigorous experimentation.

Table 1. Input variable and factor value

Input Factor	Factor Value
Cutting Current	80 ≤ A ≤ 130
Cutting Speed	1000 ≤ B ≤ 1500
Torch Height	3 ≤ C ≤ 5

Table 2. Parameters and values [42]

Trial	Input			Output		
	Cutting Current [A]	Cutting Speed [mm/min]	Torch Height [mm]	Machining Time [min]	Surface Roughness [µm]	Material Removal Rate [g/min]
1	80	1000	3	0.971	1.566	56.823
2	80	1000	4	1.05	0.75	49.514
3	80	1000	5	0.967	0.881	50.936
4	80	1250	3	0.9	3.559	56.267
5	80	1250	4	1	1.287	51.19
6	80	1250	5	0.767	0.773	62.528
7	80	1500	3	0.667	1.786	70.631
8	80	1500	4	0.767	1.685	67.223
9	80	1500	5	0.683	1.349	74.111
10	130	1000	3	1.1	2.387	49.136
11	130	1000	4	0.988	2.643	47.202
12	130	1000	5	0.9	0.935	59.944
13	130	1250	3	0.917	1.337	56.507
14	130	1250	4	0.883	2.592	56.493
15	130	1250	5	0.767	1.945	77.084
16	130	1500	3	0.683	5.238	86.199
17	130	1500	4	0.65	4.036	86.462
18	130	1500	5	0.667	3.291	88.121

3. Results and Discussion

3.1. Validation of the Response Surface Methodology Approach

The RSM modeling has been carried out in the previous section and uses the data in **Table 2** with 18 sample data which then produces optimized data from the response factor which consists of machining time, surface roughness, and material removal rate. Where the results of the RSM analysis obtain the recommended mathematical modeling is linear mode for all response factors. In Response Surface Methodology (RSM), the linear model serves to estimate coefficients that depict the impact of each factor on the response variable [48]. Employing a least squares approach, the model minimizes the sum of squared errors between observed and predicted responses, providing a robust estimation method. With the results of the machining response time being the best results in the form of a linear model among the other models with ANOVA results which can be seen in **Table 3**, also the results obtain that sum of squares suggested model is Linear vs Mean.

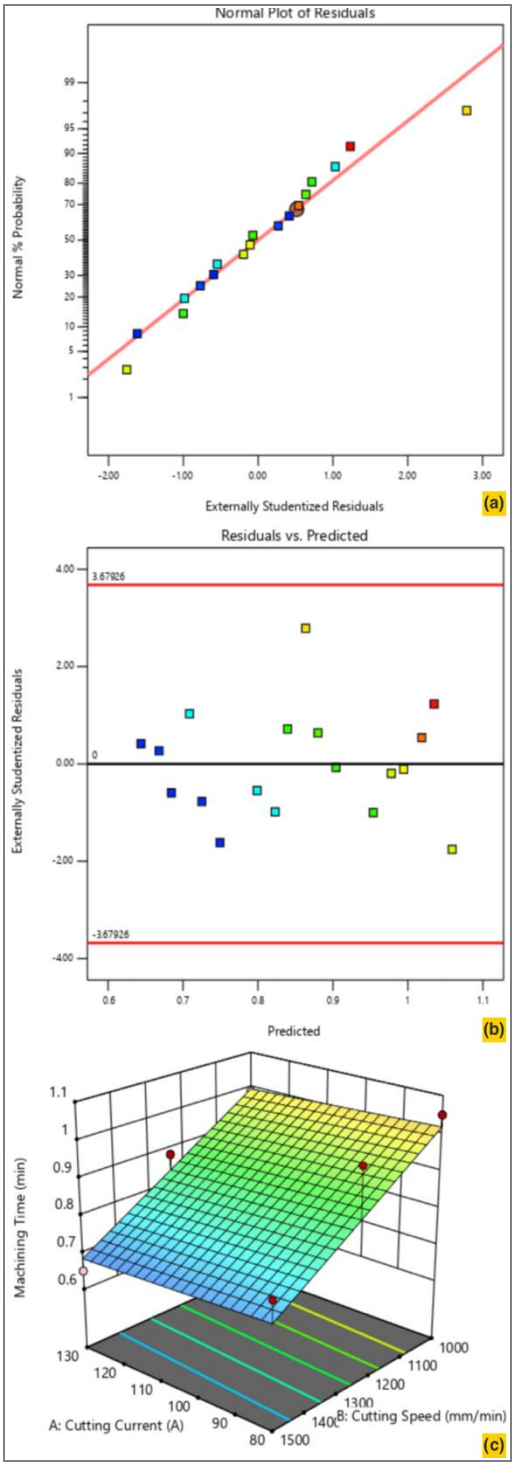


Figure 1.
(a) Normal plot of residuals;
(b) Residual vs predicted;
(c) Relations graphs between machining time variables

In the **Table 3** shows that the F-value is 25.99, indicating that a significant model only has a 0.01% chance of experiencing noise and a p-value of less than 0.05 can indicate that the model is significant, while a value of more than 0.10 indicates that the model is less significant. The obtained results also clearly demonstrate that cutting speed has the most dominant effect on machining time, consistent with the findings of Pothur *et al*. [42] where cutting speed contributed more than 77% to the machining time variation. This confirms that higher cutting speed reduces the machining time significantly, supporting higher productivity in industrial applications. The integration with ANN further validated the model, achieving R-values close to 1, indicating high predictive accuracy and robust generalization.

Based on the results shown in the best fit statistics test, namely at machining time with a mean value of 0.8515, then a standard deviation value is 0.0632 and an R^2 value is 0.8472, which means that the model is acceptable with close to the actual value. The model's predicted R^2 of 0.7551 and adjusted R^2 of 0.8145 demonstrate a harmonious alignment, with the discrepancy between the two being less than 0.2. This congruence underscores the reliability and robustness of the model in capturing the variance within the data. Furthermore, the adequate precision, which gauges the signal-to-noise ratio, reveals a favorable ratio of 13.928, well above the desirable threshold of 4. This signifies a robust signal amidst the noise, bolstering the model's efficacy and reliability. With such promising metrics, the model stands poised as a valuable tool for traversing the intricate design space, offering insights and guidance essential for informed decision-making and optimization efforts with the equation model of machining time, which can be seen from Eq. (2). So then this equation can produce planning or diagnosis results which can be seen in **Figure 1a** and **Figure 1b**, as well as the relationship of input variables to machining time in **Figure 1c.**

Machining Time = + 0.8515 - 0.01121A - 0.1549B - 0.0406C - 0.0097AB - 0.0204AC + 0.0255BC (2)

Table 3. ANOVA results for linear model on machining time

Source	Sum of Squares	df	Mean Square	F-value	p-value	Remark
Model	0.3104	3	0.1035	25.99	< 0.0001	Significant
A-Cutting Current	0.0026	1	0.0026	0.6544	0.4321	-
B-Cutting Speed	0.2880	1	0.2880	72.04	< 0.0001	-
C-Torch Height	0.0198	1	0.0198	4.94	0.0432	-
Residual	0.0560	14	0.0040	-	-	-
Cor Total	0.3663	17	-	-	-	-

The next analysis is regarding the response of surface roughness which can be seen in **Table 4** with a suggested model in the form of a linear model, so that the adjusted R^2 value is 0.5085 and the F-value is 6.86 which is still categorized as a significant model with a 4.5% chance of experiencing noise and p-value less than 0.05 may indicate the model is still significant. In the other side, the surface roughness estimation formula is on Eq. (3) that based on the suggested linear model. From **Table 4**, it can be interpreted that both cutting current and speed significantly influence surface roughness, which is also confirmed by Pothur *et al*. [42] where cutting current was found critical in affecting the thermal energy input and thus the surface texture. The positive coefficient of cutting current indicates that higher currents tend to increase roughness due to higher heat input. Meanwhile, an optimal torch height ensures minimized surface defects. Such results are critical since a smoother surface reduces post-processing time and cost.

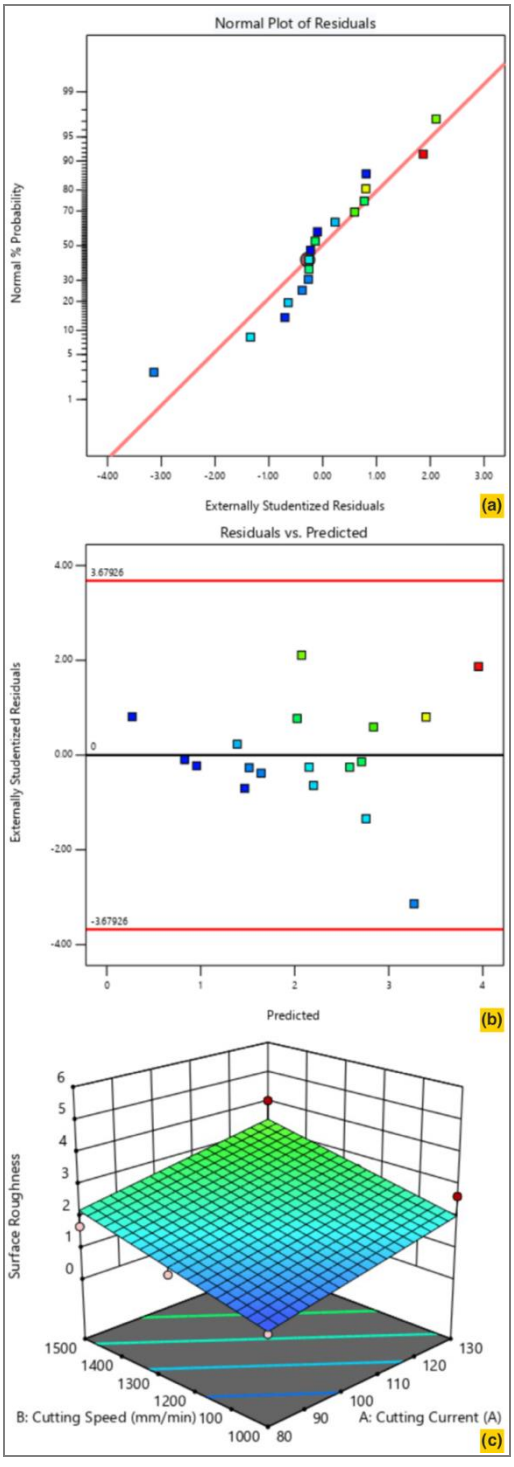


Figure 2. (a) Normal plot of residuals; (b) Residual vs predicted; (c) Relations graphs between surface roughness variables

Apart from that, graphs of the normal plot and residual vs prediction are also obtained in **Figure 2a** and **Figure 2b** which depict scatter plot patterns that are close to the normal line and do not cross the boundaries of the maximum and minimum predicted values, so the results of the model are considered usable. The correlation between design variables and surface roughness is additionally illustrated in **Figure 2c**.

The final analysis before carrying out the optimization process is carrying out an ANOVA analysis on the material removal rate. Just like the previous response variable, the recommended model for material removal rate is a linear model. This linear model produces an adjusted R^2 value that is greater than the surface roughness variable, namely 0.7294 with an F-value of 16.27 which can be categorized as a significant model because it only has 0.01% experimental noise and a p-value smaller than 0.05, so the significant model is close to the actual. It is worth noting that the cutting speed again plays a major role, as supported by Pothur *et al*. [42], who emphasized cutting speed's dominant contribution of nearly 70% to MRR variation. The higher MRR implies better material throughput and higher productivity, though it needs to be carefully balanced with surface roughness and machining time. The integration of RSM with ANN and evolutionary

algorithms in this study offers superior capability to explore such trade-offs, which is not extensively discussed in previous works, making this research more comprehensive and robust.

Surface Roughness = + 0.2.11 + 0.5982A + 0.6853B - 0.5583C + 0.4148AB + 0.0931AC - 0.0309BC (3)

Table 4. ANOVA results for linear model on surface roughness

Source	Sum of Squares	df	Mean Square	F-value	p-value	Remark
Model	15.82	3	5.27	6.86	0.0045	Significant
A-Cutting Current	6.44	1	6.44	8.38	0.0117	-
B-Cutting Speed	5.63	1	5.63	7.33	0.0170	-
C-Torch Height	3.74	1	3.74	4.87	0.0446	-
Residual	10.76	14	0.7683	-	-	-
Cor Total	26.57	17	-	-	-	-

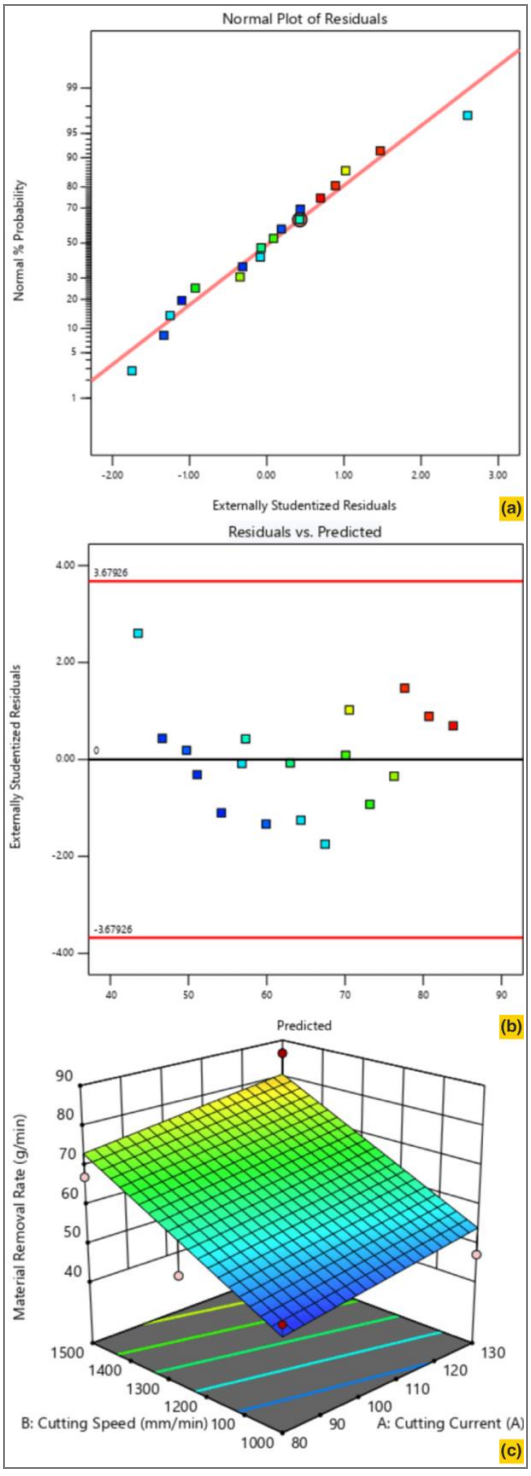


Figure 3. (a) Normal plot of residuals; (b) Residual vs predicted; (c) Relations graphs between material removal rate variables

With the ANOVA result that can be seen on **Table 5**, the formula of material removal rate can obtained on Eq. (4). Additionally, **Figure 3a** and **Figure 3b** showcase normal plot and residual vs prediction graphs, illustrating scatter plot patterns closely aligned with the normal line and avoiding crossing the boundaries of maximum and minimum predicted values, hence affirming the model's reliability. Furthermore, **Figure 3c** elucidates the relationship between design variables with material removal rate.

Then the overall results of the statistical analysis are plotted into the provided histograms juxtapose actual and predicted values for machining time, surface roughness, and material removal that can be seen on **Figure 4a**, **Figure 4b**, and **Figure 4c** rate across 18 run orders. Machining time predictions are closely aligned with actual values, suggesting an effective prediction model. Surface roughness shows greater discrepancies, indicating potential complexities in the prediction model. Material removal rates are generally well-predicted, with a few exceptions signaling room for model improvement. Overall, the visual layout of the histograms is clear and facilitates direct comparison between actual and predicted figures.

After obtaining all the results of the ANOVA analysis on the response or output variables that have been determined, the optimization process begins by setting each optimization criterion for the input and output variables as can be seen in **Figure 4**. The input variables consist of cutting current, cutting speed, and torch height. The input variables are set in a range except the cutting speed variable which is set to maximum, because the cutting speed can affect the efficiency of the cutting process time which is considered linear to the machining time. Meanwhile, the output or response variables are set to a minimum except for the material removal rate, because the higher the cutting removal rate, the more

Material Removal Rate = + 63.69 + 3.77A + 13.27B + 3.10C + 4.15AB + 2.45AC + 0.0601BC (4)

Table 5. ANOVA results for linear model on material removal rate

Source	Sum of Squares	df	Mean Square	F-value	p-value	Remark
Model	2483.24	3	827.75	16.27	< 0.0001	Significant
A-Cutting Current	256.32	1	256.32	5.04	0.0415	-
B-Cutting Speed	2111.84	1	2111.84	41.52	< 0.0001	-
C-Torch Height	115.08	1	115.08	2.26	0.1548	-
Residual	712.09	14	50.86	-	-	-
Cor Total	3195.33	17	-	-	-	-

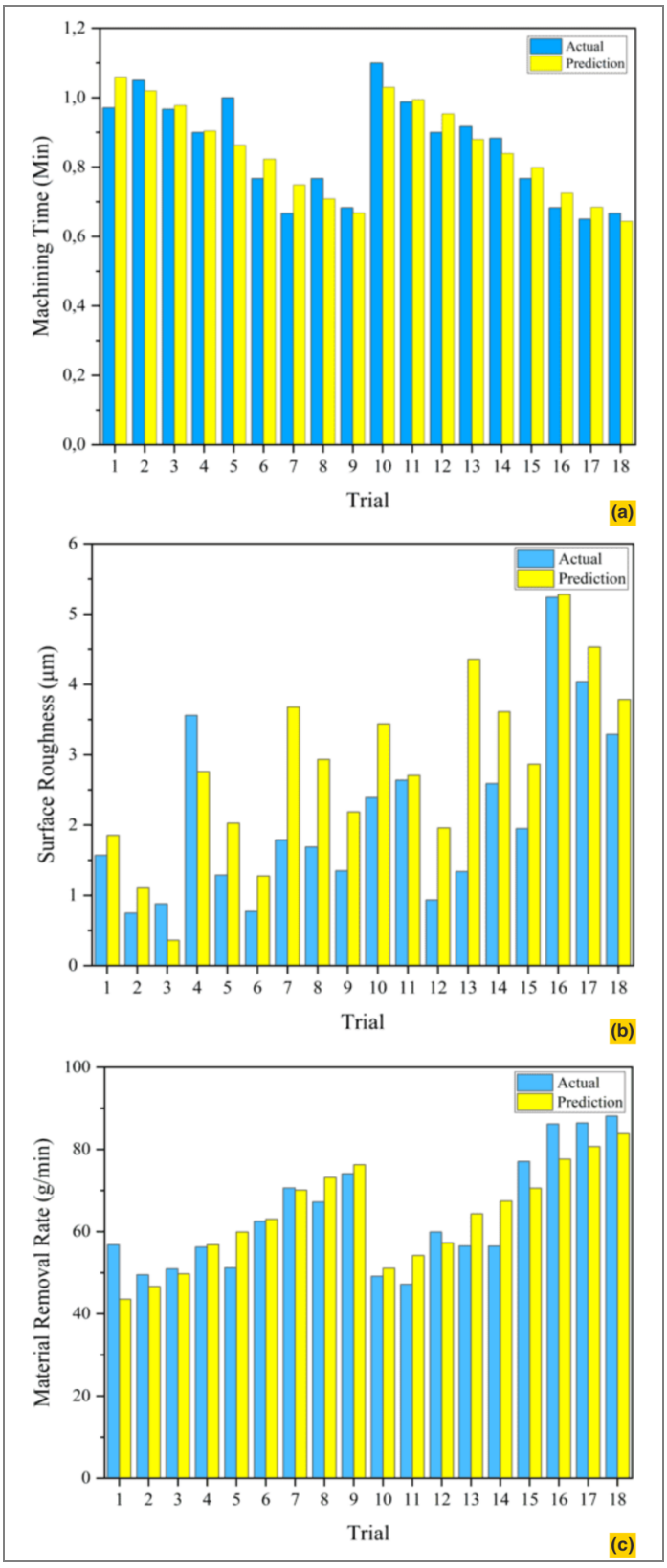


Figure 4. (a) Machining time actual vs predicted; (b) Surface roughness actual vs predicted; (c) Material removal rate actual vs predicted

efficient the cutting process will be, which in turn can result in higher productivity in plasma cutting applications.

The results obtained based on the RSM optimization process with the constraints determined above can be seen in **Figure 5**. The most optimal value of cutting current is 85.3073 A with a cutting speed of 1500 mm/min and a torch height of 5 mm. The results of optimizing the input variable values produce the highest desirability value of 0.874 when compared with the values of 90 other solutions as shown in **Figure 6**. So that the most optimal results were obtained from the values of machining time, surface roughness, and material removal rate with respectively 0.665496 min, 1.76911 µm, and 77.0775 g/min. When compared to the work by Pothur *et al*. [42], this study achieves improved surface roughness (1.77 µm vs. up to 5.2 µm) while maintaining a high MRR and low machining time, showcasing a significant advancement. The ANN models built in this study further confirm predictive accuracy beyond linear statistical models, achieving near-perfect R-values and minimal errors. Moreover, the multi-objective optimization using MOGA and MOALO introduced here enables flexible selection of parameter combinations depending on priority in productivity or quality which enhances the practical applicability of the findings.

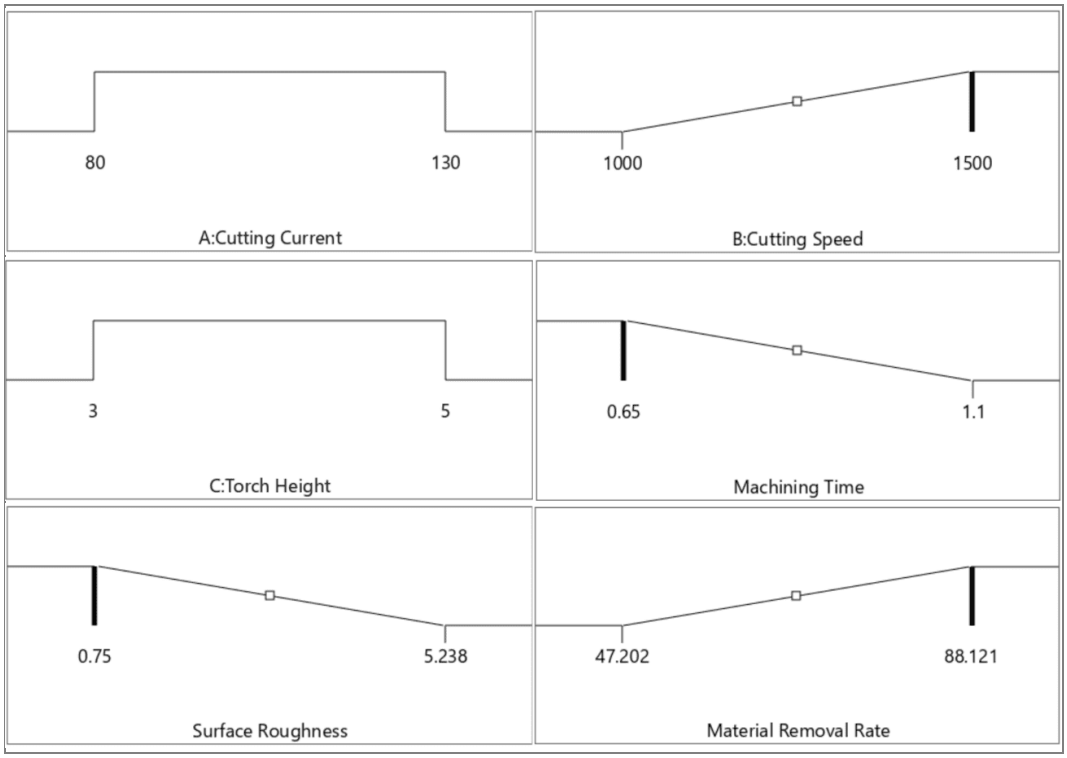


Figure 5. Optimization setting process of machining time, surface roughness, and material removal rate

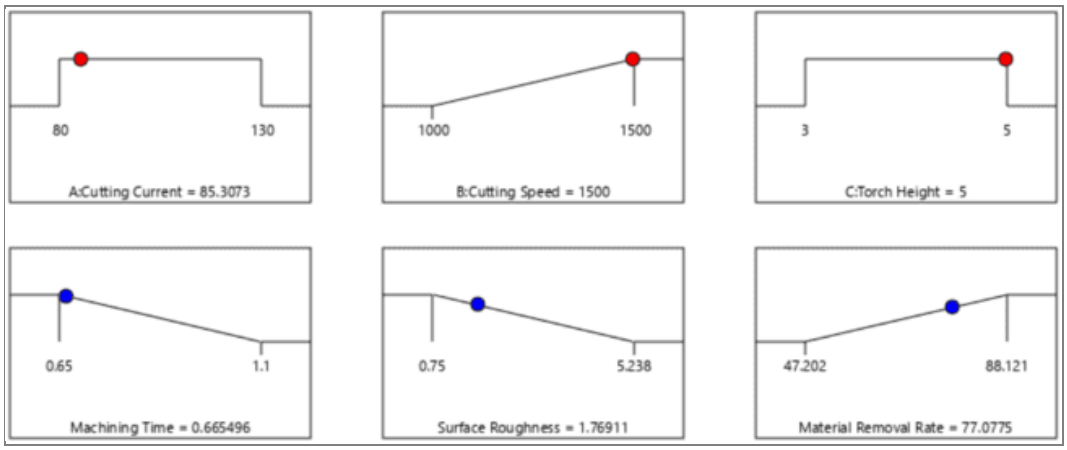


Figure 6. Optimization results of machining time, surface roughness, and material removal rate

3.2. Artificial Neural Network-Based Modelling

The Artificial Neural Network (ANN) model was used to predict machining time, surface roughness, and material removal rate based on input factors such as cutting current, cutting speed, and torch height. The results, alongside comparisons of actual values with predictions from both Response Surface Methodology (RSM) and ANN, are presented in **Figure 7** and **Figure 8**. **Figure 7a** highlights the ANN model's excellent predictive capability, with correlation coefficients (R-values) of 1, 0.99719, and 0.99945 for the training, testing, and combined datasets, respectively, demonstrating a near-perfect match between predicted and actual outcomes. **Figure 7b** illustrates the training state of the ANN model over 1000 epochs, showing the gradient steadily reducing to 6.7514e-06 and the learning rate stabilizing at 5. Importantly, no validation checks occurred during training, confirming the absence of overfitting. **Figure 7c** tracks the reduction in mean squared error (MSE) throughout the training process, with the best performance achieved at epoch 998, reaching an impressively low MSE of 7.7324e-14. Meanwhile, **Figure 7d** provides an error histogram, showing most errors clustered around zero, reinforcing the ANN model's accuracy and reliability.

The comparisons in **Figure 8** further highlight the strengths of ANN over RSM in predicting key parameters. In **Figure 8a**, both RSM and ANN closely follow the actual machining time values, but ANN predictions align more precisely. Similarly, **Figure 8b** shows the predicted and actual values for material removal rate, where ANN demonstrates a slightly better fit, particularly for higher rates, reflecting its superior handling of variability. For surface roughness, depicted in **Figure 8c**, the ANN model again shows closer alignment with actual values compared to RSM, emphasizing its ability

to capture complex relationships. Together, these results underscore the ANN model's superior performance across all output variables, with high accuracy, minimal error, and robust predictive capabilities. This makes ANN a powerful tool for optimizing machining processes, offering precise insights into the plasma arc cutting parameters and their outcomes.

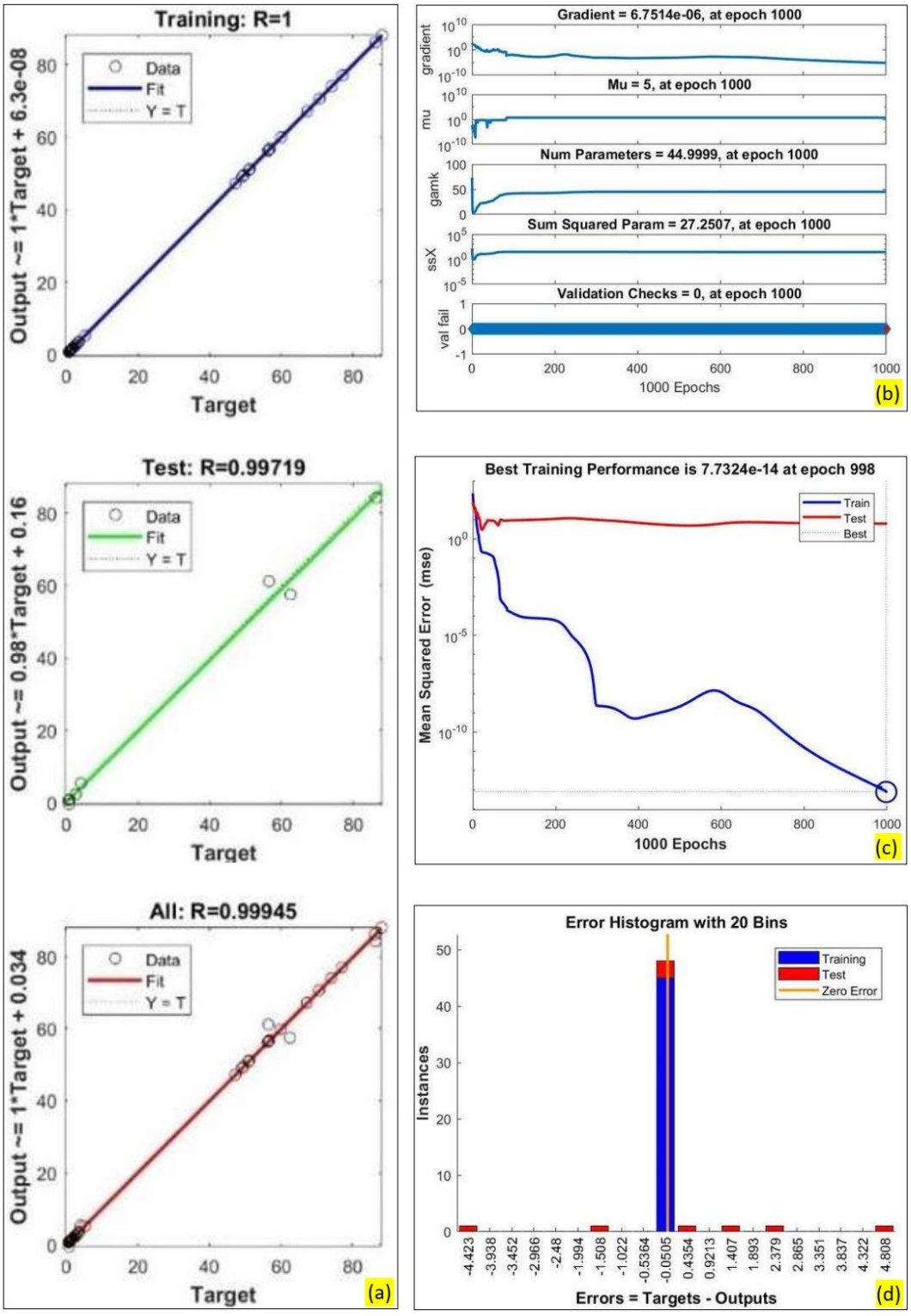


Figure 7.
(a) Regression data;
(b) Training state;
(c) Validation training performance;
(d) Error histogram

3.3. Multi-Objective Evolutionary Algorithm Moga and Moalo Optimization

This section presents the optimization results of plasma arc cutting (PAC) using the Multi-Objective Genetic Algorithm (MOGA) and the Multi-Objective Ant Lion Optimizer (MOALO), in combination with Response Surface Methodology (RSM) and Artificial Neural Networks (ANN).

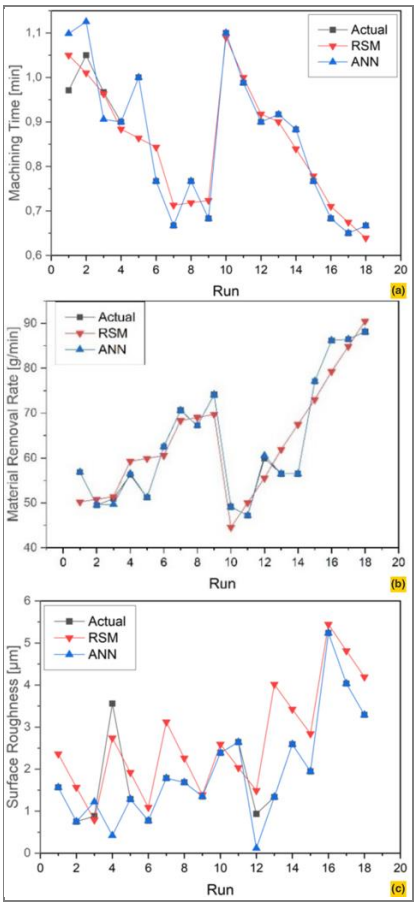


Figure 8. Comparison between actual values and correlation values: (a) Machining time; (b) Material removal rate; (c) Surface roughness

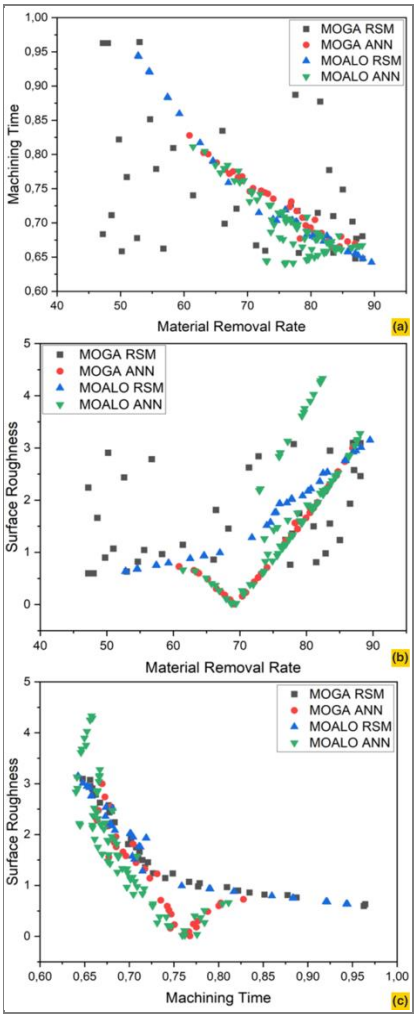


Figure 9. Comparison of PAC using MOGA RSM, MOGA ANN, MOALO RSM, and MOALO ANN for: (a) Machining time vs material removal rate; (b) Surface roughness vs material removal rate; (c) Surface roughness vs machining time

These methods were evaluated to achieve multiple objectives, including minimizing machining time and surface roughness while maximizing material removal rate. **Figure 9** and **Figure 10**, along with **Table 6**, provide a detailed comparison of the outcomes achieved by each method.

Figure 9a, **Figure 9b** and **Figure 9c** offers two-dimensional insights into the trade-offs between machining time, surface roughness, and material removal rate. In **Figure 9a**, the relationship between machining time and material removal rate highlights the superior performance of MOALO ANN, which achieves shorter machining times and higher material removal rates compared to other models. MOGA ANN also performs competitively but slightly lags behind MOALO ANN in achieving optimal trade-offs. **Figure 9b** shows the comparison of surface roughness and material removal rate, where MOALO ANN demonstrates the most favorable outcomes by minimizing surface roughness while maintaining high material removal rates. Then the **Figure 9c** illustrates the relationship between surface roughness and machining time, with MOALO ANN consistently achieving better results, delivering low surface roughness values at reduced machining times.

Figure 10 extends the comparison into three dimensions, providing a comprehensive visualization of machining time, surface roughness, and material removal rate for each optimization method. The clustering of points for MOALO ANN around the most desirable trade-offs reinforces its robustness in handling complex multi-objective relationships. MOGA ANN also exhibits strong performance, while the RSM-based models, including MOGA RSM and MOALO RSM, show more scattered distributions, reflecting less optimal results.

The optimal values achieved by MOALO ANN offers the best balance, achieving a machining time of 0.68598 minutes, a surface roughness of 1.81333 µm, and a material removal rate of 80.89614 g/min. MOGA RSM achieves the shortest machining time at 0.74874 minutes and the lowest surface roughness of 1.23531 µm, alongside a high material removal rate of 85.03034 g/min, making it highly effective for productivity. However, MOALO RSM achieves the highest material removal rate at 85.78177 g/min with a machining time of 0.65792 minutes, but at the cost of a higher surface roughness of 2.75472 µm. MOGA ANN provides a balanced outcome, with a machining time of 0.67711 minutes and a surface roughness of 1.56114 µm, though it sacrifices material removal rate (78.27714 g/min). RSM Optimization offers moderate performance across all objectives, serving as a baseline for comparison.

Table 6 summarizes the optimal values obtained using the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to determine the most effective configurations for PAC optimization. The RSM method achieves the shortest machining time of 0.665 minutes and a surface roughness of 1.76911 µm, with a material removal rate of 77.0775 g/min, offering a balanced baseline for comparison. MOGA RSM achieves the best

surface roughness of 1.235 µm and a high material removal rate of 85.030 g/min, though with a slightly longer machining time of 0.749 minutes. MOGA ANN improves machining time (0.708 minutes) and maintains a moderate surface roughness (1.445 µm), but its material removal rate is slightly lower at 78.664 g/min. MOALO RSM demonstrates the highest material removal rate of 85.781 g/min and a machining time of 0.658 minutes but suffers from a significantly higher surface roughness of 2.755 µm. Finally, MOALO ANN strikes the best balance, achieving a machining time of 0.686 minutes, a surface roughness of 1.813 µm, and a material removal rate of 80.896 g/min, making it the most well-rounded and effective method for multi-objective optimization.

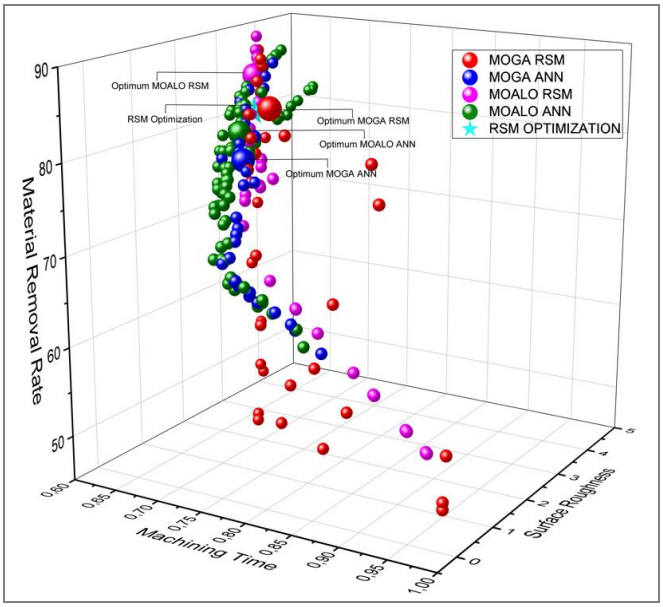


Figure 10. (3D Graph Comparison Optimization of RSM, MOGA RSM, MOGA ANN, MOALO RSM, and MOALO ANN

Table 6. Summary of optimal value comparisons for each model

Method	Cutting Current [A]	Cutting Speed [mm/min]	Torch Height [mm]	Machining Time [min]	Surface Roughness [µm]	Material Removal Rate [g/min]
RSM	85.307	1500	5	0.665	1.76911	77.0775
MOGA RSM	86.015	1427.288	4.991	0.749	1.235	85.030
MOGA ANN	108.098	1407.692	4.998	0.708	1.445	78.664
MOALO RSM	118.697	1500	5	0.658	2.755	85.781
MOALO ANN	107.311	1448.035	5	0.686	1.813	80.896

4. Conclusion

This study successfully developed a robust predictive and optimization model for the CNC plasma cutting process of SS 410 alloy, leveraging the Response Surface Methodology (RSM) and Artificial Neural Networks (ANN). The research revealed that cutting speed is the most critical factor influencing machining time and material removal rate, while cutting current and torch height also significantly affect surface roughness. By employing multi-objective optimization techniques, such as the Multi-Objective Genetic Algorithm (MOGA) and Multi-Objective Ant Lion Optimizer (MOALO), the study effectively balanced competing objectives, achieving optimal trade-offs between productivity and quality. The optimal parameters were identified as a cutting current of 85.31 amperes, a cutting speed of 1500 millimeters per minute, and a torch height of 5 millimeters. Under these conditions, the CNC plasma cutting process demonstrated superior performance. The machining time was minimized to 0.665 minutes, the surface roughness was reduced to 1.77 micrometers, and the material removal rate increased to 77.08 grams per minute. These findings validate the integration of statistical and machine learning methods as powerful tools for optimizing complex manufacturing processes. The contributions of this study extend beyond immediate parameter optimization. The predictive models and optimization techniques provide a scalable framework applicable to other materials and cutting processes, addressing the increasing demand for precision, efficiency, and cost-effectiveness in modern manufacturing. Ultimately, this research supports advancements in CNC plasma cutting technology, enhancing its role in achieving high-quality results in industrial applications while minimizing resource consumption and production costs.

Acknowledgements

The authors would like to thank Prof. Dr-ing. Nasruddin as a lecturer in the Design of Experiment (DoE) and colleagues Masters in Mechanical Engineering, Faculty of Engineering, University of Indonesia, who have taken the time to provide useful opinions and knowledge so that the writing of this article can be completed.

Authors' Declaration

Authors' contributions and responsibilities - W.R.S.: conceptualization, methodology, formal analysis, writing—original draft, validation. B.A.S.: writing—review and editing, validation. G.; supervision, resources, project administration. D.A.F.; supervision, resources, project administration. All authors have read and agreed to the published version of the manuscript.

Funding – This research was funded by The Indonesia Endowment Funds for Education (LPDP) Ministry of Finance with the contract number: 0000559/TRP/M/19/lpdp2023.

Availability of data and materials - All data is available from the authors.

Competing interests - The authors declare no competing interests.

Additional information – No additional information from the authors.

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