**Prediction of Weld Metal Tensile Strength of Mild Steel Weldments Using Response Surface Methodology Based on Simulation Software**

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**Abstract:** Estimating weld metal tensile strength in the arc welding process is crucial for ensuring the quality and integrity of the welded joints. The weld metal tensile strength in the arc welding process plays a crucial role in determining the quality and efficiency of the weld. This study uses three input process parameters: welding current, welding voltage, and welding speed. Were utilized in order to predict the weld metal tensile strength using response surface methodology (RSM). It was observed that the RSM prediction model gave a mean absolute percentage error MAPE of 0.1 %, and Nash Sutcliffe efficiency (NSE) gave 99%. Indicate that the RSM model is an accurate prediction model. Therefore, the RSM is recommended for predicting the weld metal tensile strength of the arc welding process.

**Keywords:** Tensile strength, Simulation software, RSM, and JWES

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1. **INTRODUCTION**

Welding is the process of joining two metallic components at their faying surfaces, which are the areas in direct contact or close proximity with each other. While welding is commonly used to connect pieces made from the same type of metal, it can also be effective for bonding dissimilar metals. The American Welding Society has cataloged around 50 different welding operations, each employing various forms or combinations of energy to achieve the necessary heat. Welding processes are primarily categorized into two main groups: fusion welding and solid-state welding. Fusion welding techniques involve melting the base metals, often with the addition of filler metal to the molten pool, which enhances the process and provides greater mass and strength to the welded joint. Conversely, an autogenous weld is a fusion welding method that does not use filler metal. The most prevalent welding techniques are classified under the fusion category, which can be subdivided into several broad types (with their respective acronyms from the American Welding Society): Arc Welding (AW): This category includes various welding techniques in which metals are heated by an electric arc. Some arc welding methods may also apply pressure during the process, and most utilize filler metal. Resistance welding (RW): Resistance welding achieves coalescence using heat from electrical resistance to the flow of current passing between the faying surfaces of two parts held together under pressure. Oxyfuel gas welding (OFW): These joining processes use an oxyfuel gas, such as a mixture of oxygen and acetylene, to produce a hot flame for melting the base metal and filler metal, if one is used. Other fusion-welding processes. Other welding processes that produce fusion of the metals joined include electron beam welding and laser beam welding. In the chemical, nuclear power, and oil and gas industries, the welding process has long been regarded as a crucial step in the manufacturing process [1]. Girth welding of steel pipes is a widely employed technique in various industries for the creation and connection of pipeline networks. However, it is well-recognized that welding introduces a significant level of residual stress. Such residual stresses can adversely affect structural efficiency by impairing fatigue strength, leading to brittle fractures, or inducing stress corrosion cracking (SCC), particularly in the longitudinal direction of the pipe. Consequently, accurate prediction of residual stress behavior and thorough structural stress analysis are essential to ensure the integrity of welded structures. One effective approach for estimating the magnitude and distribution of residual stresses in welded systems is numerical modeling [2]. While selecting welding process parameters is frequently done based on professional opinion or recommendations from welding manuals, it does not ensure the best or nearly the best weld bead profile for that specific welding environment. A weld's mechanical qualities and decreased post-weld flaws are two elements that affect its quality; the chemical makeup and metallurgical traits of the weld metal influence both. The bead geometry determines a weld's mechanical and metallurgical qualities, which are closely linked to the welding process. It is important to remember that post-weld flaws, such as cracks, are created on the weld line when the weld product is bent or shock-tested. Poor mechanical qualities of the weldment are often caused by metallurgical anomalies associated with fusion welding techniques, such as solidification cracking, segregation, porosity present, and grain growth in the heat-affected area. An arc is created between the non-consumable tungsten electrode and the workpiece during tungsten inert gas (TIG) welding. Usually, argon, an inert gas, protects the arc, electrode, and molten pool from contamination. Where the metal structure is dilated, and there is a strong triaxial tensile stress, hydrogen is likely to be drawn to those regions. It is, therefore, drawn to these regions in front of stressed fractures or notches [3]. The main applications of welding include: (1) construction, such as buildings and bridges; (2) piping, pressure vessels, boilers, and storage tanks; (3) shipbuilding; (4) aircraft and aerospace; and (5) automotive and railroad industries. Welding is utilized in a wide range of locations and sectors. Due to its versatility as an assembly technique for commercial products, many welding operations take place in factories. However, several traditional processes, like arc welding and oxyfuel gas welding, use equipment that can be easily moved, allowing these operations to occur outside of factory settings as well. In this paper a model has been developed using response surface methodology (RSM) in order to predict weld metal tensile strength.

**II Literature Review**

The increasing occurrence of mechanical component failures, partly due to subpar weld joints, has prompted research into optimizing weld joint strength. The appropriate combination of input process parameters, crucial across all welding methods, heavily influences weld quality. To attain the desired weld quality, researchers examined weld features such as bead geometry and mechanical properties of input parameters. The study employed Response Surface Methodology (RSM) to forecast and optimize the strength properties (tensile strength and hardness) of a 10mm thick mild steel plate welded using Gas Tungsten Arc Welding. Model adequacy was verified through analysis of variance (ANOVA) and deemed sufficient. ANOVA results indicated that current and gas flow rate significantly impacted tensile strength, while gas flow rate and filler rod diameter had the most notable effect on hardness. The model's significance was demonstrated by an F-value of 12.69 at a P value of 0.0001 for tensile strength and an F-value of 8.51 at a P value of 0.0001 for hardness. Optimal conditions were observed at a current of 170.12 amp, voltage of 19.84 volts, gas flow rate of 23.92 l/min, and filler rod diameter of 2.4mm, resulting in tensile strength of 497.555N/mm 2 and hardness of 192.556BHN. Keywords: welding, gas tungsten arc welding, tensile strength, hardness, response surface methodology [4]. The significance of welding quality in metal production is paramount, as it enhances the durability, toughness, and strength of engineering structures. The evaluation of weld quality encompasses various parameters. Conventional methods, including welder expertise, charts, and handbooks, have been employed to determine optimal welding parameters, offering simplicity and cost-effectiveness. However, relying exclusively on these methods does not ensure satisfactory welding outcomes, particularly in novel welding processes. This study aims to utilize artificial intelligence models for parameter optimization to address this challenge. Mild steel plate was selected as the research material due to its availability. An optimal experimental design was conducted using design software. Gas tungsten arc welding was employed to create weld samples, with input factors including gas flow rate, voltage, and current. The desired outputs were the weld strength factor, weld factor of safety, and weld quality index. The response surface methodology (RSM) and artificial neural network (ANN) models were utilized to generate optimal solutions for controlling and predicting experimental responses. The RSM model was developed, tested, and validated, demonstrating high strength and accuracy in maximizing weld strength, quality index, and weld factor of safety. Similarly, the ANN model provided close correlations with experimental results, enhancing prediction capabilities [5]. The study used the response surface method (RSM) to optimize the welding input variables and its mechanical response parameters when using the tungsten inert gas (TIG) welding process to mild steel metal materials. The study has reviewed numerous research studies and study-related material. It also showed that, as far as the researchers know, no mechanical properties of the particular mild steel weld bead geometry under study had been investigated. Because IS 2062 is the subject of the investigation, the response surface optimization method was used for the analysis. The outcome displays the ideal solutions for the response parameters and input factors. Hardness strength (344.628 MPa), yield strength (331.042 MPa), percentage elongation (25.272%), ultimate tensile strength (452.780), shear stress (409.484 MPa), and impact energy response (118.00 J) are the outcomes of optimization for the response parameters. 78.41% of the models created to get the best results are desirable. Industrialization and mild steel firms will be built on the findings. Additionally, engineering and industrialization decision-making will be based on the research [6].

**III METHODOLOGY**

* 1. **Material selection**

Two mild steel specimens, each measuring 150 mm by 100 mm by 6 mm, served as the workpiece for this project. The V-shaped groove used to manufacture these specimens had the following dimensions: 30° for the groove angle, 3 mm for the root face, and 0.75 mm for the root gap. A surface grinder was then used to polish the faces of 24 pairs of these specimens with uniform groove angles and root faces. Two plates with a constant root spacing of 0.75 mm were attached at both ends along the width to create a butt joint. Following welding, each plate was chopped to the proper shape to determine the penetration depth using a power hacksaw. A portable gas-cutting machine held the welding flame with a fixed arm that may move at various recognized speeds. The experiment's electrode was a 1.2 mm diameter mild steel wire coated in copper. A roller drive system supplied the wire through the welding gun. CO2 was utilized as the shielding gas and delivered under control at a steady pressure and flow rate. Table 1 and Table 2 give, respectively, the chemical compositions of the base metals and their mechanical properties. The welding process uses a shielding gas to protect the weld specimen from atmospheric interaction. For this study, 100% pure Argon gas was used. The weld samples were made from a 10mm thick mild steel plate; the plate was cut to size with the power hacksaw. The edges were ground, the surface was polished with emery paper, and the joints were welded. After that, the response (preheat temperature) was then measured and recorded [7].

**Table 1.** Chemical Composition of EN-3A[8]

|  |  |  |
| --- | --- | --- |
|  |  | Elements (wt.%) |
| Steel | ASTM | Cr | Ni | Mn | Mo | Si | N | C | P | S | Fe |
| Mild steel | EN-3A | - | - | 0.78 | 0.76 | 0.22 | - | 0.15 | 0.029 | 0.021 | Bal |

**Table 2.** Mechanical Properties of EN-3A

|  |  |  |  |
| --- | --- | --- | --- |
| Base metal | Tensile strength (MPa) | Yield strength (MPa) | Percentage Elongation(%)  |
| EN-3A | 724 | 289 | 24 |

* 1. **Selection Welding Process Parameters**

The study considers key input process parameters such as welding current, welding voltage, and welding speed, while the response or measured variable weld metal tensile strength. The three input process parameters specified in Table 3, with their upper (+1) and lower (-1) levels, as well as an appropriate design matrix, have all been investigated [8]. The output variable is specified in Table 4.

**Table 3.** Input Process Parameters [8]

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| No.S. | Factors | Notation | Unit |  |  | Level |  |
|  |  |  |  |  | -1 | 0 | +1 |
| 1 | welding Current | C | (A) |  | 140 | 160 | 180 |
| 2 | welding Voltage | V | (V) |  | 24 | 26 | 28 |
| 3 | welding Speed | S | (mm/min) |  | 16.5 | 19.3 | 22 |

**Table 4.** The Response Selected for These Experiments

|  |  |  |  |
| --- | --- | --- | --- |
| No.S. | Response | Notation | Unit |
| 1 | Weld metal tensile strength  | TS  | MPa |

* 1. **Simulation and Prediction Models Approaches (JWES)**

The balanced chemical composition content is found using an artificial neural network (ANN) model offered by the Japan welding engineering society (JWES) on its website. The JWES ANN model allows one to manipulate 16 elements of the WM compositions, each within a specified range, and seek a predictive weld metal tensile strength and the HAZ maximum hardness depending on input process parameters [9]. The Japan welding engineering society (JWES) is a commonly recognized professional association specializing in developing welding in Japan. The JWES was established to promote advancements in welding engineering and its applications, and it plays a crucial role in bringing together researchers, engineers, and academics in the welding community. Furthermore, JWES actively supports the development of quality standards in the welding sector, guaranteeing the superior caliber of goods produced in Japan.

* 1. **Design of Experiments (DOE)**

Factorial designs are frequently employed when conducting studies with multiple factors and needing to examine the combined impact of the factors on a response variable. The main effects and interactions are usually defined when discussing joint factor effects. The fact that each k element of interest has just two levels is a highly significant specific case of the factorial design. These designs are sometimes referred to as 2k factorial designs since every copy of such a design has precisely 2k experimental trials or runs [10].

* + 1. **Factorial Design**

Many experiments involve the study of the effects of two or more factors. In general, factorial designs are most efficient for this type of experiment. By a factorial design, we mean that in each complete trial or replication of the experiment, all possible combinations of the levels of the factors are investigated. For example, if there are levels of factor A and b levels of factor B, each replicate contains all ab treatment combinations. When factors are arranged in a factorial design, they are often said to be crossed. The effect of a factor is defined as the change in response produced by a change in the level of the factor. This is frequently called a main effect because it refers to the primary factors of interest in the experiment [10]. Using the range and levels of the independent variables presented in Table 5, statistical design of experiment (DOE) using factorial design method was done. The total number of experimental runs that can be generated using the factorial design method.

**Table 5.** Experimental Result using Factorial Design

|  |  |  |  |
| --- | --- | --- | --- |
| Run | Current(A) | Voltage(V) | Speed(mm/min) |
| 1 | 160 | 28 | 22 |
| 2 | 140 | 24 | 16.5 |
| 3 | 140 | 28 | 22 |
| 4 | 160 | 24 | 22 |
| 5 | 180 | 28 | 22 |
| 6 | 180 | 26 | 19.3 |
| 7 | 140 | 24 | 22 |
| 8 | 140 | 24 | 19.3 |
| 9 | 160 | 26 | 19.3 |
| 2 | 180 | 26 | 22 |
| 11 | 180 | 24 | 22 |
| 12 | 180 | 28 | 16.5 |
| 13 | 180 | 28 | 19.3 |
| 14 | 160 | 26 | 22 |
| 15 | 160 | 24 | 19.3 |
| 16 | 160 | 24 | 16.5 |
| 17 | 180 | 24 | 19.3 |
| 18 | 180 | 24 | 16.5 |
| 19 | 160 | 28 | 19.3 |
| 20 | 140 | 28 | 16.5 |
| 21 | 140 | 26 | 22 |
| 22 | 140 | 28 | 19.3 |
| 23 | 180 | 26 | 16.5 |
| 24 | 160 | 28 | 16.5 |
| 25 | 140 | 26 | 19.3 |
| 26 | 160 | 26 | 16.5 |
| 27 | 140 | 26 | 16.5 |

* 1. **Regression Models**

Creating an approximation model for the actual response surface is necessary to implement response surface methodology (RSM) practically. Usually, an unexplained physical process drives the actual reaction surface underlying. The approximation model is an empirical model based on observed data from the system or process. A group of statistical methods called multiple regression effectively develops the empirical models needed for RSM. For example, we want to create an empirical model that relates the cutting tool's practical life to the tool's angle and cutting speed—a response surface model of the first order that could explain this relationship [10].

* 1. **Response Surface Methodology Approach**

This study developed a model using response surface methodology (RSM) via Minitab software to predict variables of the weld metal tensile strength. The design of the experiment (DOE) method is a statistical method for studying a process with a limited number of tests. Response surface methodology (RSM) is a common and powerful regression-based modeling approach that uses a mathematical model to determine the relationship between multiple complicated factors and process responses. It also has significant uses in developing, formulating, and designing new items, as well as improving designs for existing ones [11]. The manufacturing industry is where RSM is most commonly utilized, significantly when multiple input factors can affect measurements of a product's performance process or characteristics. The response refers to these characteristics of quality or performance indicators. While sensory reactions, ranks, and attribute responses are not uncommon, they are usually measured on a continuous scale. The majority of RSM practical uses will require multiple responses. When used in a test or experiment, the input variables—also referred to as independent variables—are within the engineer's or scientist's control [10].

1. **Results and Discussion**

**4.1 Discussion based on RSM**

The effects of the three input process parameters welding current, input 1 (C (A)), input 2 (welding Voltage (V), and input 3 (welding Speed (mm/min)) and their effects on the response Weld metal tensile strength TS (MPa) is analyzed and studied using the experimental values. The JWES is implemented to calculate the weld metal tensile strength (MPa) for each run. values of the weld metal tensile strength (MPa) are also presented in Table 6.

**Table 6.** Results of The Calculated Weld Metal Tensile Strength as Actual Values By JWES

|  |  |  |
| --- | --- | --- |
| Run | Inputs | Output |
| Current(A) | Voltage(V) | Velocity(mm/min) | Weld Metal Tensile Strength (MPa) |
| 1 | 160 | 28 | 22 | 772.4 |
| 2 | 140 | 24 | 16.5 | 772.1 |
| 3 | 140 | 28 | 22 | 804.5 |
| 4 | 160 | 24 | 22 | 809.1 |
| 5 | 180 | 28 | 22 | 748.1 |
| 6 | 180 | 26 | 19.3 | 736.6 |
| 7 | 140 | 24 | 22 | 843.9 |
| 8 | 140 | 24 | 19.3 | 809.1 |
| 9 | 160 | 26 | 19.3 | 760.7 |
| 2 | 180 | 26 | 22 | 764.5 |
| 11 | 180 | 24 | 22 | 782.6 |
| 12 | 180 | 28 | 16.5 | 692.9 |
| 13 | 180 | 28 | 19.3 | 721.8 |
| 14 | 160 | 26 | 22 | 790.8 |
| 15 | 160 | 24 | 19.3 | 778.6 |
| 16 | 160 | 24 | 16.5 | 743.6 |
| 17 | 180 | 24 | 19.3 | 752.2 |
| 18 | 180 | 24 | 16.5 | 722 |
| 19 | 160 | 28 | 19.3 | 746.9 |
| 20 | 140 | 28 | 16.5 | 740.3 |
| 21 | 140 | 26 | 22 | 820.1 |
| 22 | 140 | 28 | 19.3 | 772.1 |
| 23 | 180 | 26 | 16.5 | 706.3 |
| 24 | 160 | 28 | 16.5 | 714.9 |
| 25 | 140 | 26 | 19.3 | 790.8 |
| 26 | 160 | 26 | 16.5 | 727 |
| 27 | 140 | 26 | 16.5 | 755.1 |

Analysis of variance (ANOVA) was calculated to check whether or not the model is significant and also to was evaluated to check the significant contributions of the input variables towards each response. It uses the F-value which is the variance of the group means and P-value which is the probability of obtaining a result at least as extreme as the one that was actually observed. A large F-value along with a low P-value (0.05% and below) signifies the absence of external influence on the variance as well as confirms that the model is significant. Table 7, which shows the analysis of variance for the weld metal tensile strength (MPa), represented a Model F-value of 3949.73 along with a p-value of 0.000, which implies the model is significant. The values of "P-value" are less than 0.05 which indicate that, the model terms are significant as stated earlier. The "P-value" of the input parameters namely, current velocity, and voltage, indicates that, these parameters had the most significant effects on the response.

**Table 7**. Analysis of variance for the weld metal tensile strength (MPa)

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Source | DF | Adj SS | Adj MS | F-Value | P-value |
| Model | 9 | 35543.7 | 3949.3 | 3949.73 | 0.000 | Significant |
| Linear  | 3 | 35344 | 11781.3 | 11781.3 | 0.000 | Significant |
| Current  | 1 | 12839.6 | 12839.6 | 12839.6 | 0.000 | Significant |
| Voltage  | 1 | 4970.1 | 4970.1 | 4970.1 | 0.000 | Significant |
| Velocity  | 1 | 17534.4 | 17534.4 | 17534.4 | 0.000 | Significant |
| Square  | 3 | 56.4 | 18.8 | 18.8 | 0.000 | Significant |
| Current\*Current | 1 | 40.9 | 40.9 | 40.9 | 0.000 | Significant |
| Voltage\*Voltage | 1 | 10.1 | 10.1 | 10.1 | 0.000 | Significant |
| Velocity\*Velocity | 1 | 5.5 | 5.5 | 5.5 | 0.000 | Significant |
| 2-Way Interaction | 3 | 114.3 | 38.1 | 38.1 | 0.000 | Significant |
| Current\*Voltage  | 1 | 16.8 | 16.8 | 16.8 | 0.001 | Significant |
|  Current\*Velocity | 1 | 60.8 | 60.8 | 60.8 | 0.000 | Significant |
|  Voltage\*Velocity  | 1 | 36.7 | 36.7 | 36.7 | 0.000 | Significant |
| Error | 17 | 16.8 | 1.0 |  |  |  |
| Total  | 26 | 35560.5 |  |  |  |  |
| Model Summary |
|  | S | R-sq | R-sq(adj) | R-sq(pred) |  |  |
|  | 0.994920 | 99.95% | 99.93% | 99.88% |  |  |

Table 8 shows the estimated regression coefficient for weld metal tensile strength (MPa), representing the p-values determining whether the effects are significant or insignificant.

**Table 8.** The estimated regression coefficient for Weld Metal Tensile Strength (MPa)

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Source | Effect | Coef | SE Coef | T-Value | P-value |  |
| constant |  | 760.029 | 0.507 | 1500.02 | 0.000 | Significant |
| Current  | -53.417 | -26.709 | 0.235 | -113.89 | 0.000 | Significant |
| Voltage  | -33.234 | -16.617 | 0.325 | -70.86 | 0.000 | Significant |
| Velocity  | 62.422 | 31.211 | 0.235 | 133.09 | 0.000 | Significant |
| Current\*Current | 5.222 | 2.611 | 0.406 | 6.43 | 0.000 | Significant |
| Voltage\*Voltage | 2.589 | 1.294 | 0.406 | 3.19 | 0.000 | Significant |
| Velocity\*Velocity | -1.910 | -0.955 | 0.406 | -2.35 | 0.000 | Significant |
| Current\*Voltage  | 2.367 | 1.183 | 0.287 | 4.12 | 0.000 | Significant |
|  Current\*Velocity | -4.503 | -2.251 | 0.287 | -7.84 | 0.000 | Significant |
|  Voltage\*Velocity  | -3.498 | -1.749 | 0.287 | -6.09 | 0.000 | Significant |

The equation from Table 4.4, which shows of estimated regression coefficients for weld metal tensile strength (MPa) of the first and the second order, represents the individual effects and combined interactions of the selected variables against the measured response weld metal tensile strength (MPa) this equation presented in equation 1.

Weld Metal Tensile Strength (MPa) = 1148.2 - 3.406 Current - 23.75 Voltage + 31.03 Velocity+ 0.00653 Current\*Current+ 0.324 Voltage\*Voltage- 0.1263 Velocity\*Velocity+ 0.02958 Current\*Voltage- 0.04093 Current\*Velocity- 0.3180 Voltage\*Velocity

 (1)

Fig. 1 shows the probability plots for weld metal tensile strength. This figure is introduced to check the normality of the results. The Normal probability plot has some points that do not lie along the line in the upper and lower region. This may indicate potential outliers in data. It can be seen from the probability plots, that the normal distribution is the best one, since all data fall within the 95% confidence interval.



**Figure 1.** Probability Plots for Weld Metal Tensile Strength (MPa)

It's also observed that, the coefficient of determination (R-Squared) is 99.95% which indicates that the ability of the mathematical model ability to predict the values of the weld metal tensile strength (MPa). The value of the adjusted coefficient of determination (Adj. R-Squared) is 99.93% which indicates the accuracy of the model based on the significant parameters and their interactions. Fig. 2 shows the actual versus the predicted values of the weld metal tensile strength.



**Figure 2.** The Actual Versus the Predicted Values for Weld Metal Tensile Strength(MPa)

The goal is to predict a response (output variable) that is impacted by a number of independent variables (input process parameters) through accurate experiment design in Table 9. The response data were considered as the actual values using the JWES. Subsequently, the data were inputted into a Minitab software. Then, the predicted values, using the devolved mathematical model, of the weld metal tensile strength (MPa) were also given in Table 9.

**Table 9.** The actual and the predicted values of the weld metal tensile strength (MPA) using JWES and RSM, respectively

|  |  |  |
| --- | --- | --- |
| Run | Inputs | Output |
| Actual | Predicted |
| Current(A) | Voltage(V) | Velocity(mm/min) | Weld Metal Tensile Strength (MPa) | Weld Metal Tensile Strength (MPa) |
| 1 | 160 | 28 | 22 | 772.4 | 773.2 |
| 2 | 140 | 24 | 16.5 | 772.1 | 772.3 |
| 3 | 140 | 28 | 22 | 804.5 | 803.6 |
| 4 | 160 | 24 | 22 | 809.1 | 809.9 |
| 5 | 180 | 28 | 22 | 748.1 | 748.0 |
| 6 | 180 | 26 | 19.3 | 736.6 | 736.5 |
| 7 | 140 | 24 | 22 | 843.9 | 842.7 |
| 8 | 140 | 24 | 19.3 | 809.1 | 809.1 |
| 9 | 160 | 26 | 19.3 | 760.7 | 760.6 |
| 2 | 180 | 26 | 22 | 764.5 | 763.9 |
| 11 | 180 | 24 | 22 | 782.6 | 782.4 |
| 12 | 180 | 28 | 16.5 | 692.9 | 693.6 |
| 13 | 180 | 28 | 19.3 | 721.8 | 722.3 |
| 14 | 160 | 26 | 22 | 790.8 | 790.3 |
| 15 | 160 | 24 | 19.3 | 778.6 | 778.5 |
| 16 | 160 | 24 | 16.5 | 743.6 | 744.0 |
| 17 | 180 | 24 | 19.3 | 752.2 | 753.2 |
| 18 | 180 | 24 | 16.5 | 722 | 721.0 |
| 19 | 160 | 28 | 19.3 | 746.9 | 745.2 |
| 20 | 140 | 28 | 16.5 | 740.3 | 740.2 |
| 21 | 140 | 26 | 22 | 820.1 | 821.9 |
| 22 | 140 | 28 | 19.3 | 772.1 | 773.4 |
| 23 | 180 | 26 | 16.5 | 706.3 | 706.0 |
| 24 | 160 | 28 | 16.5 | 714.9 | 714.3 |
| 25 | 140 | 26 | 19.3 | 790.8 | 790.0 |
| 26 | 160 | 26 | 16.5 | 727 | 727.9 |
| 27 | 140 | 26 | 16.5 | 755.1 | 754.9 |

Based on the mean absolute percentage error (MAPE) value as given by equation 2, a comparison between the actual values and the anticipated values of weld metal tensile strength (MPa) is used to validate the RSM model. It was determined that (MAPE) was 0.1%. Additionally, Figure 3 shows that weld metal tensile strength (MPa) predicted values relative to their actual values in the RSM model. Indicate accurately represents the RSM model's actual weld metal tensile strength (MPa) values.

MAPE= $\frac{1}{n} \sum\_{i=1}^{n}\left|\frac{A-P}{A} \right|$ ☒ 100% (2)

**Where**;

A: The actual value for weld metal tensile strength (MPa

P: The predicted value for weld metal tensile strength (Mpa)

n: Number of Experiments

**Figure. 3** Comparison Between Actual and Predicted of Weld Metal Tensile Strength (MPa) By RSM

Based on the Nash-Sutcliffe Efficiency (NSE) value as given by equation 3, a comparison between the actual values and the anticipated values of weld metal tensile strength (MPa) is used to validate the RSM model. It was determined that (NSE) was 99%. Indicate accurately represents the RSM model's actual weld metal tensile strength (MPa) values. The Nash-Sutcliffe Efficiency (NSE) was also calculated to evaluate the model's efficiency by equation 3 [11].

NSE =$ \frac{\sum\_{}^{}\left(A-P\right)^{2} }{\sum\_{}^{}\left(A-\overline{A}\right)^{2} }$ (3)

Where;

A: Actual value for weld metal tensile strength (MPa).

$\overline{A}$: Average actual value for weld metal tensile strength (MPa).

P: Predict a value for weld metal tensile strength (MPa).

**IV Conclusions**

This study examined three input process parameters: welding current (A), welding voltage (V), and welding speed (mm/min). It utilized Response Surface Methodology (RSM) to predict the tensile strength of the weld metal (MPa). The RSM prediction model demonstrated a Mean Absolute Percentage Error (MAPE) of 0.1% and a Nash-Sutcliffe Efficiency (NSE) of 99%, indicating that the RSM model is highly accurate. Therefore, RSM is recommended for predicting the tensile strength of weld metal in the arc welding process (MPa).

5. **References**

[1] M. P. Groover, Fundamentals of modern manufacturing: materials, processes and systems, 4th ed., United States of America: John Wiley & Sons, 2010.

[2] N. Moslemi, "novel systematic numerical approach on determination of heat source parameters in welding process," j o u r n a l of ma t e r i a l s r e s e a r c h and technology , pp. 4427-4444, 2022.

[3] P. Pondi, "Prediction of tungsten inert gas welding process parameter using design of experiment and fuzzy logic," Journal of Advances in Science and Engineering, pp. 86-97, 2021.

[4] S. O. Sada\*, "OPTIMIZATION OF WELD STRENGTH PROPERTIES OF TUNGSTEN INERT GAS MILD STEEL WELDS USING THE RESPONSE SURFACE METHODOLOGY," Nigerian Journal of Technology (NIJOTECH), vol. 37, pp. 407-415, 2018.

[5] 1. T.A, "Application of Response Surface Methodology and Artificial Neural Network Analytical methods in modelling Shock Resistance of Pipeline Weldments," Global Journal of Environmental Science and Technology, vol. 12(2), pp. 62-70, 2024.

[6] C. E. Chuka, "Parametric Prediction and Optimization of Mild Steel Geometry Composition Using TIG Welding Methods," Journal of Engineering Research and Reports, vol. 23, no. 12, pp. 10-23, 2022.

[7] P. Pondi, "Performance of RSM and ANN in Optimizing and Predicting Heat Input needed to Eliminate Crack Formation in Mild Steel Weldment," International Journal of Advances in Engineering and Management (IJAEM), pp. 686-699, 2021.

[8] B. Das, "INFLUENCE OF PROCESS PARAMETERS ON DEPTH OF PENETRATION OF WELDED JOINT IN MIG WELDING PROCESS," International Journal of Research in Engineering and Technology, vol. 02, no. 10, 2013.

[9] K. Sampath, "High strength steel weld metal properties: metallurgical criteria and computational tools," Welding in the World, vol. 67, pp. 2081-2105, 2023.

[10] R. H. MYERS, Response surface methodology : process and product optimization using designed experiments, United States of America: John Wiley & Sons, 2016.

[11] F. F. ALFazani, "Modeling and Prediction of Angular Distortion in (MIG) Welding Process," in 1st International Conference of Engineering Sciences (ICES2022), sirt, 2022.

[12] Y. Yang, "Development and Application of on-Line Weld Modelling Tool," Welding in the World, Le Soudage Dans Le Monde, vol. 53, p. 1/2, 2009.

[13] Y.-P. Yang, "ONLINE SOFTWARE TOOL FOR PREDICTING WELD RESIDUAL STRESS AND DISTORTION," in American Society of Mechanical Engineers, Pressure Vessels and Piping Division (Publication) PVP, Chicago, Illinois, USA, 2008.

[14] D. C. Montgomery, Design and analysis of experiments, United States: John Wiley & Sons,, 2013.

[15] N. Nazemi, "A FINITE ELEMENT ANALYSIS FOR THERMAL ANALYSIS OF LASER CLADDING OF MILD STEEL WITH P420 STEEL POWDER," in Proceedings of the ASME 2016 International Mechanical Engineering Congress and Exposition IMECE2016, Phoenix, Arizona, USA, 2016.

[16] P. C. Adamczuk, "Methodology for predicting the angular distortion in multipass butt-joint welding," Journal of Materials Processing Technology, vol. 240, pp. 305-313, 2017.

[17] S. Kumar, "Effect of heat input on the microstructure and mechanical properties of gas tungsten arc welded AISI 304 stainless steel joints," Materials & Design, vol. 32, pp. 3617-3623, 2011.

[18] K. G. Kumar, "Characterization of metallurgical and mechanical properties on the multi-pass welding of Inconel 625 and AISI 316L," Journal of Mechanical Science and Technology, vol. 29, pp. 1039-1047, 2015.

[19] I. Hassan, "The application of fuzzy logic techniques to improve decision making in apparel size," World Journal of Advanced Research and Reviews (WJARR), vol. 19, pp. 607-615, 2023.

[20] S. Kumar, "Effect of heat input on the microstructure and mechanical properties of gas tungsten arc welded AISI 304 stainless steel joints," Materials & Design, vol. 32, pp. 3617-3623, 2011.

[21] D. S. Badkar, "Development of RSM- and ANN-based models to predict and analyze the effects of process parameters of laser-hardened commercially pure titanium on heat input and tensile strength," Int J Adv Manuf Technol, pp. 1319-1338, 2012.

[22] O. A. Denali, "Modeling and Prediction of Warpage in Plastic Injection Molded Parts Using Adaptive Neuro-Fuzzy Inference System (ANFIS)," in International Conference on Mechanical and Industrial Engineering, Tripoli-Libya, 2022.

[23] F. Sabzehee, "TEC Regional Modeling and Prediction Using ANN Method and Single Frequency Receivers over IRAN," ANNALS OF GEOPHYSICS, vol. 61, p. 7297, 2018.

[24] F. Alfazani, "Fuzzy Logic Technique and Response Surface Methodology to Predict the Material removal rate of Abrasive Water Jet Process (AWJM) Parameters on Inconel – 188," in First Libyan Conference on Technology and Innovation 2024, Benghazi / Libya, 2024.

[25] F. O. Uwoghiren, "Comparative Analysis of the Combined Effect of Input Parameters on Heat Input and Heat Affected Zone in TIG Welding," Nigerian Journal of Technology (NIJOTECH), vol. 41, pp. 50-54, 2022.

[26] A. L. Dhobale, "REVIEW ON EFFECT OF HEAT INPUT ON TENSILE STRENGTH OF BUTT WELD JOINT USING MIG WELDING," INTERNATIONAL JOURNAL OF INNOVATIONS IN ENGINEERING RESEARCH AND TECHNOLOGY [IJIERT] , vol. 2, no. 9, pp. 2394-3696, 2015.