MULTI OBJECTIVE OPTIMIZATION OF TIG WELDING PROCESS PARAMETERS USING FUZZY BASED TAGUCHI METHODOLOGY

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الملخص

في هذه الورقة تم تطبيق اسلوب المنطق الغامض المستند على منهجية تاغوتشي مع خصائص الاداء المتعدد وذلك لغرض تحسين جودة عملية اللحام باستخدام غاز التنغستن. تم استخدام مؤشر الاداء متعدد الاستجابة (MRPI) لحل المشاكل المتعلقة بخصائص الاداء المتعدد في مجال عملية اللحام باستخدام غاز التنغستن. هذا الاسلوب يقوم بتحويل الاهداف المتعددة والمعقدة (مخرجات عملية اللحام) الى قيمة فردية واحدة لمؤشر الاداء المتعدد الاستجابة (MRPI) وبناء على القيمة المتحصل عليها من المؤشر (MRPI) يتم تحديد المستويات المثلى للمتغيرات المؤثرة والداخلة في عملية اللحام والمتمثلة في (تيار اللحام وسرعة اللحام ومعدل تدفق الغاز). تم اجراء هذه التجارب باستخدام تصميم تاغوتشي المؤلف من ثلاثة مستويات وثلاثة متغيرات (L9) كمفهوم لتصميم التجربة. وتم ايضا دراسة مقاومة الشد وقيمة الصلادة الدقيقة لشفة اللحام المؤثرين في جودة اللحام (خصائص الجودة) كمخرجات للدراسة. هذه المخرجات تم استخدامها بعد ذلك كمدخلات فردية الى نظام الية الاستنتاج الغموضية (Fuzzy Inference) ومؤشر الاداء المتعدد الاستجابة (MRPI) كمخرج فردي للنظام. كما تم استخدام تحليل التباين (ANOVA) لتقييم مدى تأثير وفعالية كل متغير من المتغيرات الداخلة في عملية اللحام على مخرجات الدراسة. من خلال الدراسة تبين لنا أن المتغير الخاص بسرعة اللحام هو المتغير الاكثر تأثيراً وأهمية في عملية اللحام ووفقا لأكبر قيمة لمؤشر الاداء المتعدد الاستجابة (MRPI) المتحصل عليها عند أقصى مقاومة للشد وأقصى قيمة صلادة لشفة اللحام. الاسلوب المقترح في هذه الدراسة يعتبر من الطرق الجديدة والفعَّالة في عملية تحسين خصائص الأداء المتعدد في مجال اللحام باستخدام غاز التنغستن.

ABSTRACT

In this paper, the application of fuzzy logic technique-based Taguchi methodology approach for optimizing the TIG welding process with multiple performance characteristics is reported. A multi-response performance index is used to solve the correlated multiple performance characteristic problems in the field of TIG welding process. This approach converts the complex multiple objectives into a single multi-response performance index (MRPI). Based on MRPI, optimum levels of input parameters (welding current, welding speed, and gas flow rate) were identified. Experiments were conducted based on Taguchi L9 orthogonal array design. Ultimate tensile strength and weld bead micro-hardness are selected as response parameters (quality characteristics) and fed as input to fuzzy inference system and MRPI is obtained as output. Analysis of variance (ANOVA) was employed to estimate the significant contributions of input parameters. Confirmation test is conducted and reported. It is found that the welding speed parameter is the most significant control factor affecting in the process according to the weighted multi-response performance index of the maximum ultimate tensile strength and maximum weld bead micro-hardness. The proposed approach developed in this study was used as a novel and efficient technique in improving multiple performance characteristics in the field of TIG welding process.

KEYWORDS: TIG; Fuzzy Logic; Taguchi Method; ANOVA; Ultimate Tensile Strength; Weld Bead Micro-Hardness.

INTRODUCTION

Generally, the target of any welding processes is to obtain a weld joints meet the required specifications. Welding input parameters play a very significant role in determining the quality of a weld joint. the quality of a weld joint is directly influenced by the welding input parameters during the welding process. The desired welding input parameters are determined based on experience or from a handbook value. However, this does not ensure whether this input parameters meet the specifications required or not. Traditionally, it has been necessary to determine the optimum level of welding input parameters for every new welding product to obtain a welded joint with the required specifications. This is a common problem that has faced the manufactures in industry today to control the input process parameters that get the best quality for welded joints. To overcome this problem, various optimization methods have emerged to define the desired output variables through developing mathematical models to establish the relationship between the input parameters and output variables [1].

Genichi Taguchi has developed a powerful tool in the design of experiment methods. The developed method of Taguchi can optimize performance characteristics through the settings of process parameters and reduce the sensitivity of the system performance to source of variation. However, most published Taguchi applications to date have been concerned with the optimization of a single performance characteristic. Handling the more demanding for multiple performance characteristics is still an interesting research problem [2].

In this study, the use of fuzzy logic technique to perform fuzzy reasoning of multiple performance characteristics has been studied. It is shown that optimization of multiple performance characteristics can be transformed into optimization of a single multi-response performance index (MRPI). The integration of fuzzy logic with the Taguchi method can be used as approach to solve the optimization of the multiple performance characteristics.

Y.S. Tarng et al. [3] used of fuzzy logic in the Taguchi method to optimize the submerged arc welding process with multiple performance characteristics for mild steel plate. An orthogonal array, the signal-to-noise ratio, multi-response performance index, and analysis of variance were employed to study the performance characteristics in SAW process. The process parameters namely, arc current, arc voltage, welding speed, electrode protrusion, and preheat temperature were optimized with considerations of the performance characteristics, including deposition rate and dilution. Experimental results were provided to confirm the effectiveness of this approach.

J. Edwin and S. Kumanan [4] have developed an intelligent predictive technique's artificial neural network (ANN) and fuzzy logic models for weld residual stress prediction. The authors were developed the models using Matlab toolbox functions. Data set required to train the models were obtained through finite element simulation.

Results from the fuzzy model were compared with the developed artificial neural network model, and these models were also validated.

J. Edwin and M. Satheesh [5] have applied grey based fuzzy logic method to solve correlated multiple response optimization problems in the field of submerged arc welding. The authors were used this approach to convert the complex multiple objectives into a single grey-fuzzy reasoning grade. Based on grey-fuzzy reasoning grade, optimum levels of parameters (welding current, arc voltage, and welding speed) were identified. Also, they were performed nine experiments based on an orthogonal array of Taguchi method. Weld bead hardness and material deposition rate were selected as the quality targets. The authors were found that the welding current is the most significant controlled factor for the process according to the weighted some grade of the maximum weld bead hardness and material deposition rate. The proposed technique provides manufactures to develop intelligent manufacturing system to achieve the highest level of automation.

M. Satheesh and J. Edwin [6] have applied an efficient technique, fuzzy based desirability method to solve correlated multiple response optimization problems, in the field of flux cored arc welding (FCAW). The authors were used this approach to convert the complex multiple objectives into a single fuzzy reasoning grade. Based on fuzzy reasoning grade, optimum levels of parameters (Welding current, arc voltage, and electrode stickout) were identified. Experiments were performed based on Taguchi method. Weld bead hardness and material deposition rate were selected as quality targets. Significant contributions of parameters were estimated using analysis of variance (ANOVA). From experimental results, it was found that the electrode stickout is the most significant controlled factor for the process according to the weighted fuzzy reasoning grade of the maximum weld bead hardness and material deposition rate. The proposed technique allows manufactures to develop intelligent manufacturing system to achieve the highest level of automation.

A. Kumar et al. [7] have proposed a fuzzy logic model to investigate the effect of three different proportions of flux alloying element using submerged arc welding process. The authors were used Taguchi orthogonal array, L9 SiO_2 based agglomerated fluxes were prepared and tested for mechanical properties of weld metal (Vickers hardness and impact strength). Multi-objective optimization was done using fuzzy logic model for Vickers hardness and impact strength of weld metal. From a fuzzy logic model proposed, optimal levels of fluxes were obtained using a single multi-response performance index (MRPI).

Lin et al. [2] have applied the hybrid Taguchi with fuzzy logic method for optimization of electrical discharge machining process parameter. The authors were selected the machining parameters for optimization (the workpiece polarity, pulse-on time, duty factor, open discharge voltage, discharge current and dielectric fluid) with considerations of the multiple performance characteristics (electrode wear ratio and material removal rate). From experimental results, they concluded that the optimization methodology developed in the study was useful in improving multiple performance characteristics in the electrical discharge machining operation.

Fuzzy Based Taguchi Methodology

The proposed approach combines the fuzzy logic with Taguchi method in order to determine the process parameters with optimal performance characteristics.

Taguchi Method

Genichi Taguchi has developed a method based on "Orthogonal Array" to study the control parameters with a small number of experiments. The experimental results are then transformed into a signal-to-noise (S/N) ratio. The S/N ratio can be used to measure the deviation of the performance characteristics from the desired values. Usually, there are three categories of performance characteristics in the analysis of the *S/N* ratio: the lower-the-better, the higher-the-better, and the nominal-the-better. Regardless of the category of the performance characteristic, a larger *S/N* ratio corresponds to better performance characteristic. Therefore, the optimal level of the process parameters is the level with the highest *S/N* ratio. Furthermore, a statistical analysis of variance (ANOVA) is performed to identify the process parameters that are statistically significant. The optimal combination of the process parameters can then be predicted based on selected S/N ratio category for analysis. Finally, a confirmation experiment is conducted to verify the optimal process parameters obtained from the parameter design [8].

Fuzzy Logic

The fuzzy logic is special expert system that can be used to optimize desired values from the set of input and output variables. The set of values that are determined from experimental results. A general fuzzy controller consists of four modules, fuzzification, fuzzy rule base, fuzzy inference engine, and defuzzification. Figure (1) provides a brief overview of structure of a fuzzy expert system model. The details of these steps are briefly described in the following sections [9]:

Step 1: Fuzzification model.

In fuzzification model step, measured input (S/N) ratio of crisp value converted into appropriate fuzzy sets (linguistic variables) low, medium, high. These fuzzy sets are expressed in the forms of fuzzy membership values based on various membership functions (MFs).

Step 2: Fuzzy rules Knowledge base model.

In this step, a fuzzy rules knowledge base model step, a fuzzy model uses fuzzy rules, which are linguistic IF-THEN statements involving fuzzy sets and fuzzy inference. Fuzzy rules play key role in representing expert modeling knowledge and experience and in linking the input variables of fuzzy models to output variables. The most type used of fuzzy rules is known as Mamdani fuzzy rules. Rule base in linguistic form are formulated on the basis of experimental observations.

Step 3: Fuzzy inference engine model.

In fuzzy inference engine model step, fuzzy inference is sometimes called fuzzy reasoning. It is used in a fuzzy rule to determine the rule output from the given rule input information. Fuzzy rules represent modeling knowledge or experience. The output fuzzy sets represent classification of MRPI into low, medium, and high values.

Step 4: Defuzzification model.

In Defuzzification of the output values step, there is a mathematical process used to convert a fuzzy set or fuzzy sets to a real number (a crisp MRPI) for each run of experiment to be used for optimization.

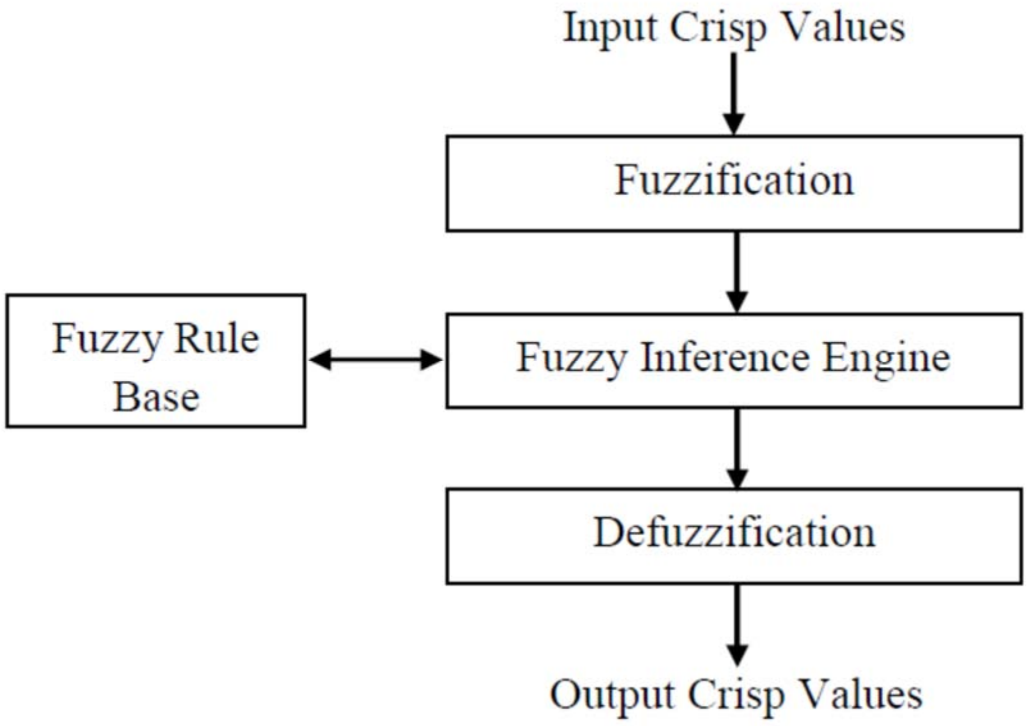

Figure 1: Structure of a fuzzy expert system model [10]

Proposed Approach Methodology

Figure (2) shows a brief overview of the implementation procedures of the fuzzy based Taguchi method. The steps of applying the fuzzy-based Taguchi method to optimize the proposed approach will be described as in follows:

Step 1: Design an appropriate orthogonal array to plan the experimental design and determining the level of parameters.

Step 2: Conduct the experiment based on the orthogonal array.

Step 3: Compute the (S/N) ratios for responses using the higher-the-better category of the performance characteristics.

Step 4: Design of the fuzzy logic unit based on two-input-one-output fuzzy logic unit to combine these two performance characteristics into a single performance index.

Step 5: Establishing triangular membership function and fuzzy rule to fuzzify the (S/N) ratio for each response.

Step 6: Obtaining the optimal solution through Taguchi approach by select the optimal level setting of process parameters which has greatest MRPI value among all possible combinations of the process parameters.

Step 7: Analyze the data results with ANOVA.

Step 8: verify the optimal process parameters through confirmation tests.

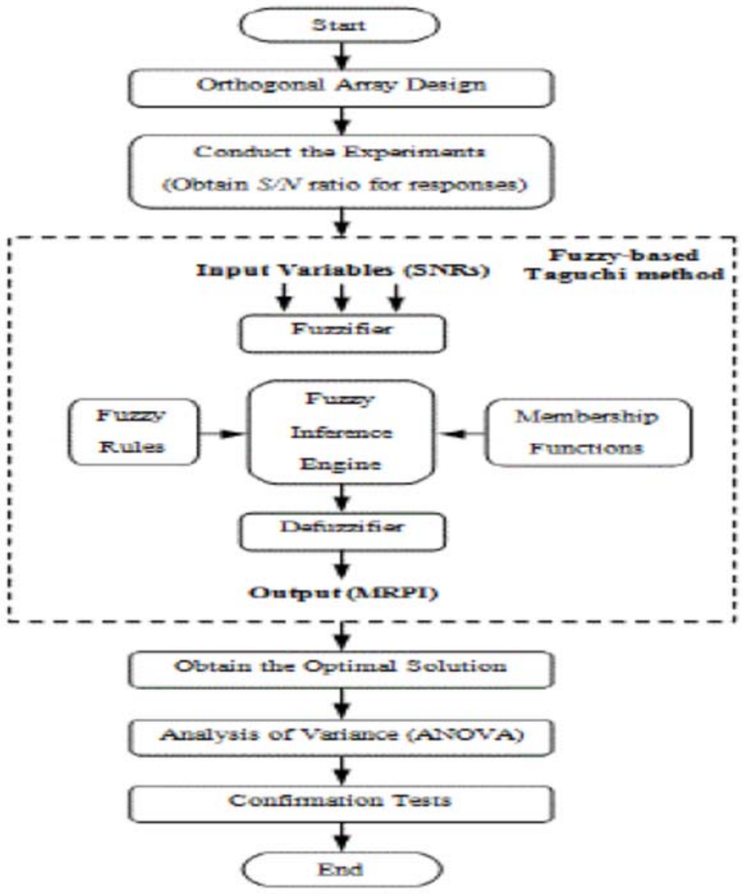

Figure 2: Implementation procedures of the fuzzy-based Taguchi method. [11]

EXPERIMENTAL METHODOLOGY

In the present study, TIG welding process has been done for studying the effect of process parameters on ultimate tensile strength (UTS) and weld bead micro-hardness for autogenous single pass square butt-welded joints of AISI304L austenitic stainless steel.

Experimental procedure

Experiments were conducted using Handy TIG 180 SW welding machine by using direct current electrode negative (DCEN) polarity. The welding conditions which have been kept constant in this experiment are shown in Table (1). AISI304L austenitic stainless steel has been selected as the base material with dimension 150mm × 150mm × 3mm. The experiment set-up used consists of speed-controlled tractor (to control welding speed) with a table for supporting the specimens. The welding torch is held to the travel tractor to make sure the torch is fixed at a set-up angle and setting the required electrode to plate distance. Autogenous single pass with square butt joints are performed on the weld plates at different levels of welding current, welding speed, and gas flow rate as shown in Table (2). Based on Taguchi's (L9) orthogonal array design of experiments, combination a series of joining processes is performed in welding machine. The photograph of the experimental set-up for TIG welding is shown below in Figure (3).

Table 1: Fixed welding conditions.

Polarity	DCEN (Direct Current Electrode Negative)
Power Supply	230 V
Shielding Gas	Argon (99.99%)
Electrode Diameter	1.6 mm
Tungsten Electrode Characteristics	2% Throated, Red color code
Torch Nozzle Material	Ceramic
Nozzle Size	4
Torch Position (Gun Angle)	Vertical (zero deg.)
Electrode to plate distance (Arc gap)	3 mm

Table 2: Welding parameters and their levels

Process Parameters	Level 1	Level 2	Level 3
A: Welding Current (Amp.)	**130**	**135**	**140**
	1	2	3
B: Welding Speed (mm/min)	**180**	**190**	**200**
	1	2	3
C: Gas Flow Rate (Liter/min)	**4**	**6**	**8**
	1	2	3

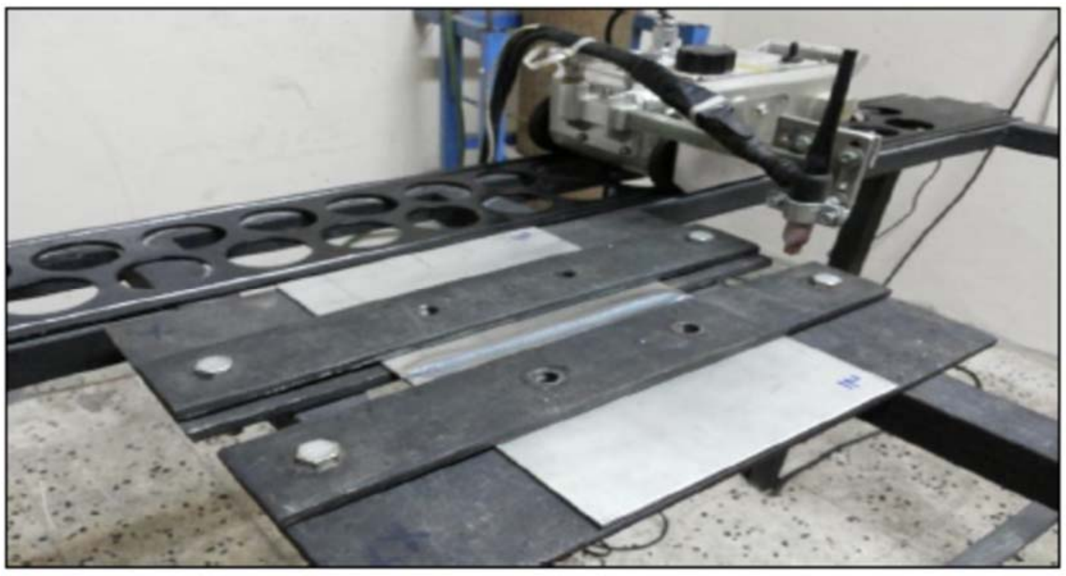

Figure 3: Experimental set-up for TIG welding.

Orthogonal array experiment

To select an appropriate orthogonal array for experiments, the total degrees of freedom must be computed. In the present study, the interaction between the welding parameters is neglected. Therefore, degree of freedom due to the three sets and three levels of welding process parameters are analyzed. The degree of freedom for the orthogonal array should be greater than or at least equal to those for the process parameters. In this study, an L9 orthogonal array with three columns and nine rows was used. This array has eight degrees of freedom and it can handle three levels of process parameters. Each welding parameter is assigned to a column and nine welding parameter combinations are available. Therefore, only nine experiments are required to study the entire welding parameter space using the L9 orthogonal array design. The experimental combination of the process parameters with coded values using L9 orthogonal array is presented in Table (3).

Table 3: Experimental design matrix using L9 orthogonal array.

No.	A: Welding Current	B: Welding Speed	C: Gas Flow Rate
1	1	1	1
2	1	2	2
3	1	3	3
4	2	1	2
5	2	2	3
6	2	3	1
7	3	1	3
8	3	2	1
9	3	3	2

Welding performance evaluation

Welding performance is evaluated by UTS and weld bead micro-hardness and considered as objectives. UTS test was performed on Zwick universal tester machine. Tensile test specimens prepared according to ASTM standards (E8M). While the weld bead micro-hardness test was carried out on Vickers micro-hardness testing machine (MVK-E) which having diamond indenter by applying a load of 200g with X400 magnification.

Analysis of the signal-to-noise ratio

In the Taguchi method, a loss function is defined to calculate the deviation between the experimental value and the desired value. There are three categories of performance characteristic in the analysis of the signal-to-noise ratio, that is, the lower-the-better, the higher-the-better, and the nominal-the-better. In this study, the higher-the-better performance characteristic is selected to obtain maximum UTS and weld bead micro-hardness. The loss function of the higher-the better performance characteristic can be expressed as [2]:

$$L_{ij} = \frac{1}{n}\sum_{k=1}^{n}\frac{1}{y_{ijk}^2} \quad (1)$$

where L_{ij} is the loss function of the ith performance characteristic in the jth experiment, n is the number of tests, and y_{ijk} is the experimental value of the ith performance characteristic in the jth experiment at the kth test. The loss function is further transformed into a signal-to-noise ratio. In the Taguchi method, the S/N ratio is used to determine the performance characteristic deviating from the desired value. The signal-to-noise ratio η_{ij} for the *i*th performance characteristic in the *j*th experiment can be expressed as [2]:

$$\eta_{ij} = -10 \log (L_{ij}) \tag{2}$$

Table (4) shows the experimental results for the objectives (UTS and weld bead micro-hardness) with its signal-to-noise ratios based on the experimental design matrix as mentioned in Table (3).

Now S/N ratio suitably divided into three categories: low (L), medium (M), and high (H) according to the range of S/N values as shown in Table (5).

Table 4: Experimental results and S/N ratios for UTS and weld bead micro-hardness.

Sample number	Ultimate tensile strength (MPa)	S/N Ratio of UTS (dB)	Micro-hardness (HVN)	S/N Ratio of Micro-hardness (dB)
1	630.00	55.9868	186.5	45.4136
2	581.67	55.2935	172.5	44.7358
3	436.00	52.7897	169.0	44.5577
4	581.00	55.2835	180.0	45.1055
5	636.67	56.0782	190.5	45.5979
6	524.00	54.3866	177.0	44.9595
7	529.00	54.4691	176.0	44.9103
8	641.67	56.1462	202.5	46.1285
9	454.67	53.1539	174.5	44.8359

Table 5: Signal to noise ratios for response variables.

Sample number	S/N Ratio of UTS (dB)	S/N Ratio of Micro-hardness (dB)	Classifying S/N ratios	
			S/N (UTS)	S/N (micro-hardness)
1	55.9868	45.4136	High	Mid
2	55.2935	44.7358	Mid	Low
3	52.7897	44.5577	Low	Low
4	55.2835	45.1055	Mid	Mid
5	56.0782	45.5979	High	High
6	54.3866	44.9595	Mid	Mid
7	54.4691	44.9103	Mid	Mid
8	56.1462	46.1285	High	High
9	53.1539	44.8359	Low	Low

Fuzzy logic unit

In this study, the use of fuzzy logic to deal with the optimization of a process with multiple performance characteristics is used. Using a procedure originated by Ibrahim Mamdani in the late 70s, four steps are taken [10]:

- Fuzzification (using membership functions to graphically describe a situation).
- Rule evaluation (application of fuzzy rules).
- Fuzzy inference engine (fuzzy reasoning).
- Defuzzification (obtaining the actual results).

The Schematic diagram for the two inputs into one output fuzzy logic system is shown in Figure (4).

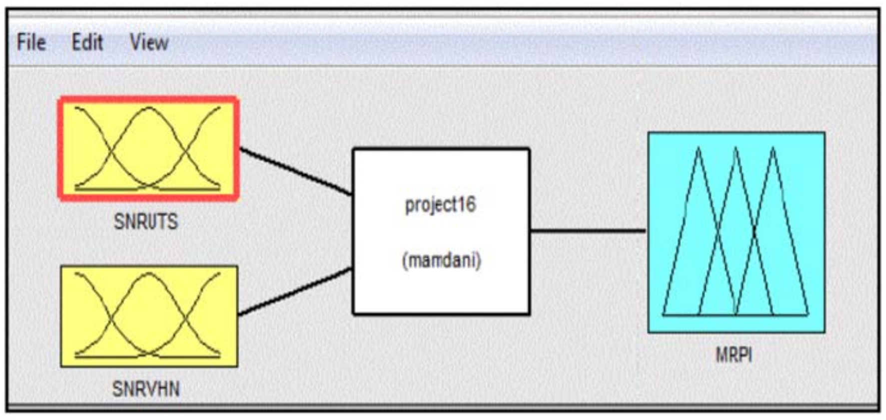

Figure 4: Schematic diagram of Mamdani model for MRPI.

Several fuzzy rules are derived based on the performance requirement of the process. The loss functions corresponding to each performance characteristic is fuzzified and then a single MRPI is obtained through fuzzy reasoning on the fuzzy roles. The MRPI can be used to optimize the process based on the Taguchi approach. MRPIs were calculated by using MATLAB (fuzzy logic toolbox) for calculating the single-value MRPI [12]. The first step is to define the membership functions for UTS and weld bead micro-hardness. In this study, a triangular membership function is used for all input and output variables. Low, medium, and high values were defined for each membership functions according to the range determined in Table (5). These memberships function are shown in Figures (5 and 6) respectively.

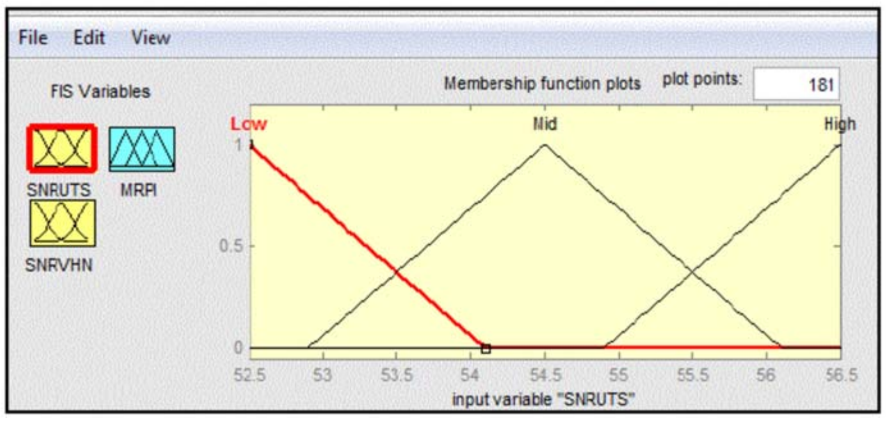

Figure 5: Membership function for UTS (S/N).

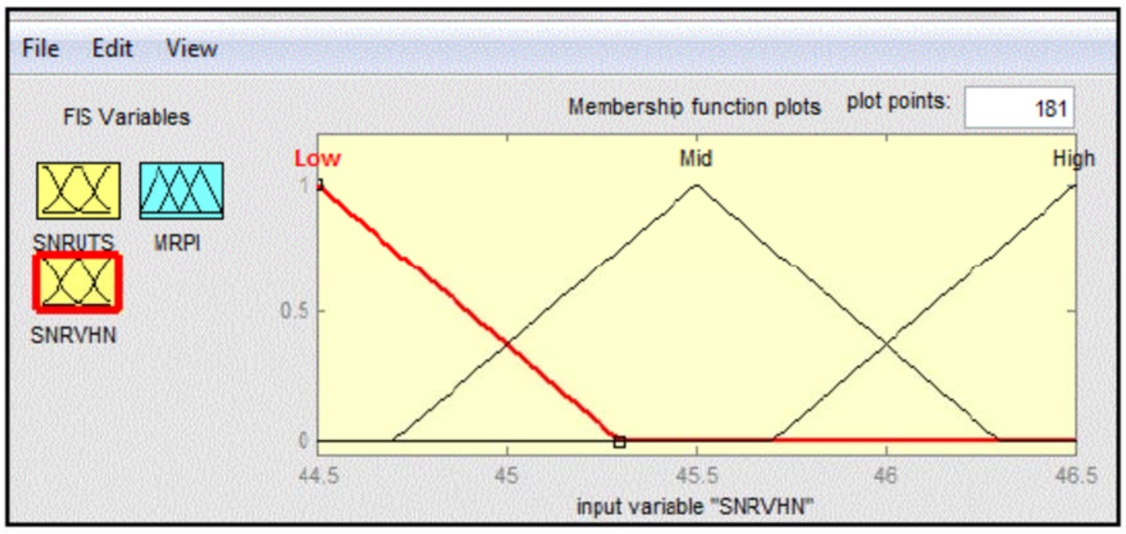

Figure 6: Membership function for micro-hardness (S/N).

Output membership function for the output, i.e. MRPI was defined. According to the input S/N values, it was decided on having three levels for the output function: low, medium, and high as shown in Figure (7)

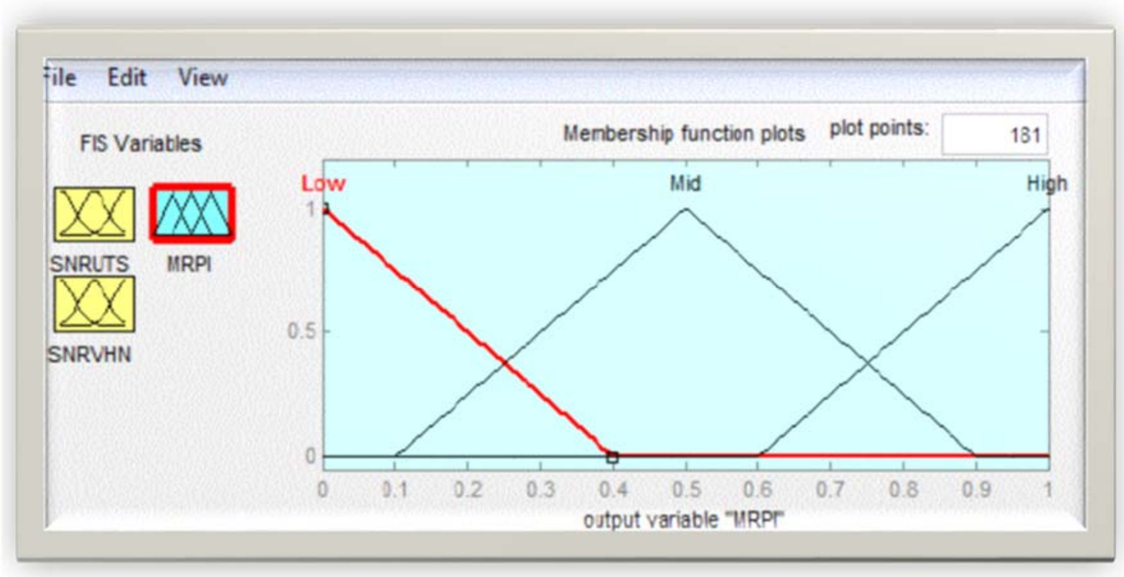

Figure 7: Output membership function for MRPI.

The second step was to define a rule base for calculating MRPI from the input values of S/N ratios for objectives (there are three levels of input variables and three levels of the output variable), then in third step, the fuzzy inference engine performs fuzzy reasoning based on fuzzy rule base to generate a fuzzy value (MRPI values). How the Rule-base was decided is captured in the Table (6).

Table 6: linguistic variables for the rule base.

Run	S/N (UTS)	S/N (micro-hardness)	MRPI
1	High	Mid	High
2	Mid	Low	Mid
3	Low	Low	Low
4	Mid	Mid	Mid
5	High	High	High
6	Mid	Mid	Mid
7	Mid	Mid	Mid
8	High	High	High
9	Low	Low	Low

After defining the rule base with the fuzzy inference engine, each rule presents in rule base are defuzzified using centroid method. Figure (8) is shown rule editor of Mamdani model in fuzzy logic unit [12]. Finally, the defuzzification step with an aggregation method was used to obtain the MRPI values. The values of MRPI are given in Table (7). These values were obtained by inserting the S/N values for the two input parameters. To determine the optimal welding conditions, it is required to find the greatest MRPI values among all possible combinations of the process parameters. Average MRPI values for a factor at particular level are summarized in Table (8) and presented in Figure (9), from the obtained results, it is obvious that the responses are mainly affected by the welding speed and gas flow rate, while the welding current has the less effect on the responses as shown in Table (8).

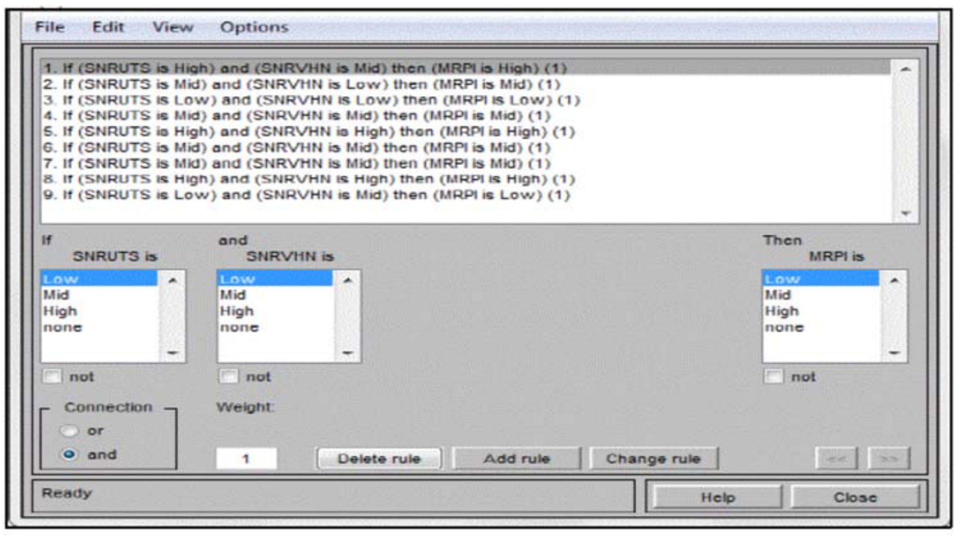

Figure 8: Rule base of Mamdani model in fuzzy logic unit.

Table 7: MRPI values corresponding to all control and response parameters.

Run	Level of Process Parameters			Measured Response Parameters		MRPI
	A	B	C	S/N (UTS)	S/N (micro-hardness)	
1	1	1	1	55.9868	45.4136	0.779
2	1	2	2	55.2935	44.7358	0.507
3	1	3	3	52.7897	44.5577	0.134
4	2	1	2	55.2835	45.1055	0.546
5	2	2	3	56.0782	45.5979	0.845
6	2	3	1	54.3866	44.9595	0.5
7	3	1	3	54.4691	44.9103	0.5
8	3	2	1	56.1462	46.1285	0.85
9	3	3	2	53.1539	44.8359	0.299

Table 8: Average MRPI values for a factor at particular level.

Factor	A	B	C
Level 1	0.4733	0.6083	**0.7097**
Level 2	**0.6303**	**0.7340**	0.4507
Level 3	0.5497	0.3110	0.4930
Max-Min	0.1570	0.4230	0.2590
Rank	3	1	2

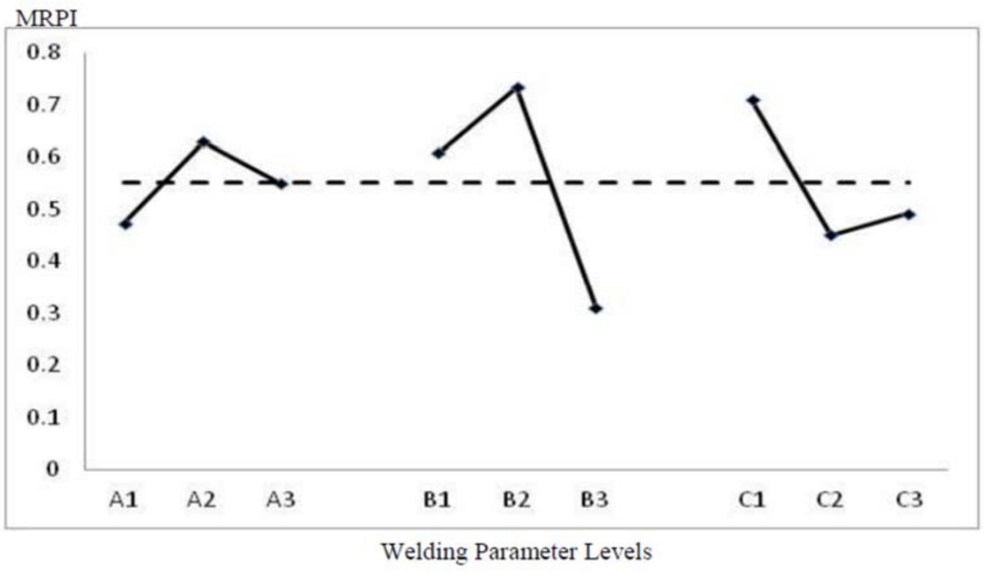

Figure 9: Response graph for MRPI.

In the given model optimum value of MRPI is obtained under: A2B2C1, welding current = 135 Amp., welding speed = 190 mm/min, and gas flow rate = 4 l/min. The highest MRPI value for each column of factors in Table 8 indicates the best level for each factor. Control factors with large range of MRPI values among their levels have more significant influence in the TIG welding process. It is clear that control parameter B (welding speed) has the strongest effect on the quality of welded joints, followed by parameters C (gas flow rate) and A (welding current). The relative effect among the control factors for the MRPIs can be verified by using the ANOVA.

Analysis of variance (ANOVA)

The purpose of the analysis of variance (ANOVA) is to investigate which process parameters significantly affect the performance characteristic. An ANOVA table consists of sums of squares (Seq. SS), corresponding degrees of freedom (df), adjusted mean squares (Adj. MS), the F-ratio corresponding to the ratios of two mean squares. and the contribution proportions from each of the control factors. These contribution proportions are used to assess the importance of each factor for the interested multiple performance characteristic. The results of ANOVA as shown in Table (9) shows that welding speed with a contribution proportion of 59.95% is the most significant control factor on the welding performance characteristic followed by gas flow rate with a contribution proportion of 24.50% and welding current with a contribution proportion of 7.85%.

Table 9: Results of the analysis of variance (ANOVA).

Source	df	Seq. SS	Adj. MS	F	Contribution (%)
A: W. Current	2	0.03698	0.01849	1.01	7.85
B: W. Speed	2	0.28313	0.14156	7.77	59.95
C: Gas Flow Rate	2	0.11582	0.05791	3.18	24.50
Residual Error	2	0.03645	0.01822	-	7.70
Total	8	1.9431	**0.23618**	-	-

Confirmation tests

Once the optimal level of the process parameters is selected, the final step is to predict and verify the improvement of the performance characteristic using the optimal level of the process parameters. The estimated signal-to-noise ratio $\hat{\eta}$ using the optimal level of the process parameters can be calculated as [2]:

$$\hat{\eta} = \eta_m + \sum_{i=1}^{q}(\overline{\eta}_i - \eta_m) \quad (3)$$

where η_m is the total mean of the multiple-response performance index, $\overline{\eta}_i$ is the mean of the multiple-response performance index at the optimal level, and q is the number of the process parameters that significantly affect the multiple performance characteristics.

In this study, η_m= 0.551 for the total mean of the multiple-response performance index, calculated from Table 8 for all control factors among their levels, $\overline{\eta}_i$ = 0.7340 for the mean of MRPI for control factor B at level 2 (welding speed parameter) which has the highest value, q = 1 for control factor B that has the highest effect on the multiple performance characteristics.

Based on Equation (3), the estimated multiple-response performance index using the optimal welding parameters can then be obtained as in following:

$\hat{\eta} = 0.551 + \sum_{i=1}^{1}(0.7340 - 0.551) = 0.734$

Table (10) shows the results of the confirmation experiment using the optimal welding parameters. The ultimate tensile strength is increased from 581.67 MPa to 610 MPa and the weld bead micro-hardness is increased from 172.5 HVN to 195.3 HVN through this study.

Table 10: Results of the confirmation experiment.

	Initial welding parameters	Optimal welding parameters	
		Prediction	Experiment
Level	A1B2C2	A2B2C1	A2B2C1
Ultimate tensile strength (MPa)	55.2935 (581.67)		55.7065 (610)
Micro-hardness (VHN)	44.7358 (172.5)		45.8140 (195.3)
MRPI	0.507	0.734	0.648
Improvement MRPI = 0.141			

CONCLUSION

In this study, the application of fuzzy logic-based Taguchi methodology approach has been introduced to optimize the multiple performance characteristics for TIG welding process. Fuzzy logic is used to perform a fuzzy reasoning of the multiple performance characteristics. While Taguchi method helped in reducing the number of experiments to be performed. From the experimental results, the performance characteristics such as ultimate tensile strength and weld bead micro-hardness can be improved through this approach. It is found that the welding speed parameter is the most significant control factor affecting in the process according to the weighted multi-response performance index of the maximum ultimate tensile strength and maximum weld bead micro-hardness. The best performance characteristics are obtained with an optimum parameter setting of A2B2C1, welding current = 135 Amp., welding speed = 190 mm/min, and gas flow rate = 4 l/min. Confirmation test was conducted to confirm this approach. Finally, the proposed approach employed in this study is a novel and efficient approach for quality optimization of manufacturing systems with multiple performance characteristics consideration and can be use in resolve a complex parameter design problem with multiple responses.

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