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Analysis of resistance spot welding using multi-objective Taguchi method and RSM

Punita Kumari, Debasish Majhi, Bidyuta Ranjan Rout, Md Saif Ahmed
Department of Mechanical Engineering, NM Institute of Engineering and Technology,Bhubaneswar , Odisha
Department of Mechanical Engineering, Raajdhani Engineering College,Bhubaneswar,Odisha
Department of Mechanical Engineering,Aryan Institute of Engineering and Technology Bhubnaeswar , Odisha
Department of Mechanical Engineering,Capital Engineering College,Bhubaneswar,Odisha

ABSTRACT: *In the present research, the effect of parameters in Resis-tance Spot Welding (RSW) on the weld zone development was first investigated using Taguchi Method. Further, the RSW parameters were to be optimized based on multiple quality features, focusing on weld nugget and Heat Affected Zone using multi-objective Taguchi Method (MTM). The optimum welding parameter for MTM was obtained using Multi Signal to Noise Ratio and the significant level was fur-ther analyzed using Analysis of Variance. Lastly, Response Surface Methodology was employed to develop the math-ematical model for predicting the weld zone development. The experimental study was conducted under varied weld-ing current, weld time and hold time. To validate the pre-dicted model, experimental confirmation test was conducted for plate thickness of 1 and 1.5 mm. Based on the results, the developed model can be effectively used to predict the size of weld zone which can improve the welding quality and performance in RSW.*

Keywords *Multi-objective Taguchi Method (MTM). Resistance Spot Welding (RSW) · Design of Experiment (DoE) · Optimization · · Analysis of Variance (ANOVA) · Response Surface Methodology (RSM)*

I. INTRODUCTION

The use of Design of Experiment (DoE) in different appli-cations has grown recently (Ghoreishi and Atkinson 2002; Ghoreishi et al. 2002; Benyounis et al. 2008; Ghoreishi 2006). DoE is a scientific method for identifying the param-eters associated with a process and thereby determining the optimal settings for the process parameters for enhanced per-formance and capability. To predict the welding parameters accurately without consuming time, materials and labour effort, there are various methods of obtaining the desired output variables through models development. Using appro-priate statistical technique such as Taguchi Method (TM), the number of necessary experiments can be reduced and the statistical significance of parameters can be safely identified.

In general, optimization is the process of estimating the potential minimum value of machining performance at the optimal point of process parameters. Some researchers car-ried out investigations dealing with machining parameters modeling and optimization to determine the optimal values of the process. An intelligent approach for process modeling and optimization of Electric Discharge Machining (EDM) was reported by Joshi and Pande (2011). Process model-ing using Finite Element Method has been integrated with soft computing technique and Genetic Algorithm (GA) to improve prediction of the model. The proposed integrated approach was found efficient and robust as the suggested optimum process parameters can give the expected optimum performance of the EDM process. Another work using com-bined modeling function of fuzzy inference with the learning ability of Artificial Neural Network (ANN) for modeling the flank wear of cryogenically treated AISI M2 high speed steel tool was presented by Gill et al. (2012). It was determined that the prediction showed a good agreement with the experi-mental data. Another approach is using Simulated Annealing and GA techniques to estimate optimal process parameters of machining performance which was investigated by Mohd Zain et al. (2011). The authors found out that the proposed integration systems were managed to estimate the optimal process parameters, leading to the minimum value machin-ing performance when compared to the experimental data.

In welding process, literature reports that work has been done on various aspects of modeling and optimization in order to determine the welding input parameters that lead to the desired weld quality. TM approach has been applied by Anawa and Olabi (2008) to optimize the laser welding process of dissimilar material with the same thickness. The experimental results indicated that the process could be opti-mized using TM in order to obtain superior welded joints. Response Surface Methodology (RSM) was applied by Kol-eva (2005) to establish the relationship between performance characteristics and their influencing factors. A new statisti-cal approach was proposed to choose the focus position at a condition of maximum thermal efficiency and welding depth. Application of RSM for predicting weld bead quality in sub-merged arc welding of pipes was investigated by Gunaraj and Murugan (1999). The authors found out that the pro-posed method are useful for predicting the weld bead quality and selecting optimum process parameters for achieving the desired quality and process optimization. A mathematical model has been developed to predict the tensile strength of friction stir welded AA6061 aluminum alloy joint by incor-porating welding parameters and tool profiles using RSM and this was presented by Elangovan et al. (2009). The devel-oped mathematical model can be effectively used to predict the tensile strength of Friction Stir Welding (FSW) joints at 95 % confidence level. The used of TM and regression anal-ysis in order to optimize Nd-YAG laser welding parameter to seal an iodine-125 radioisotope seed into a titanium capsule was studied by Thakur et al. (2010). The confirmation exper-iments were conducted at the optimal welding conditions, the results showed that the titanium tube ends were sealed perfectly. A modified TM to analyze the effect of welding process parameter on the weld pool geometry and then to determine the TIG welding process parameters combination associated with the optimal weld pool geometry was adopted by Juang and Tarng (2002). The authors reported that the quality characteristics were greatly improved by using this approach.

The following are reviews of some works that have been carried out for modeling and optimization in the Resistance Spot Welding (RSW) process. The investigation on the opti-mization and the effect of welding parameters on the tensile shear strength of spot welded galvanized steel sheet was pre-sented by Thakur and Nandedkar (2010). The authors found that it is possible to increase tensile shear strength signifi-cantly using the proposed statistical technique. Investigation on the optimization and effect of welding parameters on the tensile shear strength of spot welded SAE 1010 steel sheet using Taguchi method was reported by Esme (2009). The author concluded that TM can be effectively used for opti-mization of spot welding parameters. A mathematical model for predicting the nugget diameter and tensile shear strength of galvanized steel was developed by Luo et al. (2011) using nonlinear multiple regression analysis and ANN approach. According to the prediction models, the prediction systems of welding process parameters were formulated in order to obtain the desired welding quality. A systematic approach to determine the effect of process parameters on tensile shear strength of resistance weld joint of austenitic stainless steel AISI 3040 using Taguchi Method was studied by Thakur and Nandedkar (2010). The confirmation test was conducted and the result shows it was within 95 % confidence interval of predicted optimal value of selected parameters. The use of Taguchi's loss function analysis to a spot welding process in order to discover the key process parameters which influ-ence the tensile strength of welded joints was investigated by Rowlands and Antony (2003).The purpose of this research was to illustrate an application of DoE to a spot welding process.

Various techniques have been developed for solving mul-tiple objective optimization problems. One of the techniques is the weighted additive utility function (Malakooti 2000, 2010, 2011). In this approach, the objective values of differ-ent objectives are combined to form a single objective func-tion that represents the utility of each alternative. Multiple objective optimization deals with identifying a compromis-ing solution that simultaneously satisfies multiple objectives (Li et al. 2012; Berrichi et al. 2009). Another technique for multi-objective optimization is using Taguchi Quality Loss function which was presented by Aslan (2008). The results show considerable improvement in both the quality charac-teristics, as compared to the initial value. The MTM approach is also reported by Dubey and Yadava (2008a) for the opti-mization of laser beam cutting process. The authors found that the quality characteristics were improved considerably.

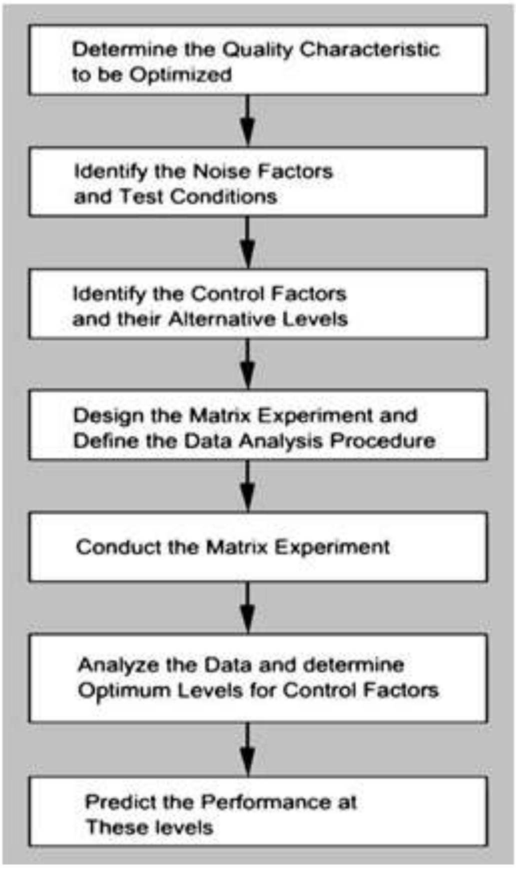
The design of experiment based studies on RSW process so far have been mainly aimed at the optimization of the single quality characteristic at a time. As the main objective of manufacturing process is always to improve the overall quality of a product, it is necessary to optimize multiple qual-ity characteristics simultaneously. RSW is one of the most important manufacturing processes in automotive industry for assembling bodies. Quality and strength of the welds are defined by the quality of the weld nuggets (Eisazadeh et al. 2010). The quality is best judged by the nugget size, Heat Affected Zone (HAZ) and joint strength (Thakur et al. 2010). Therefore, it is of important to select the welding process parameters for obtaining optimal size of the weld nugget. Simultaneous consideration of multiple responses approach has yet not been explored in the study of RSW process using

where y_i (mean) and σ (standard deviation) denote the observe data at i th trial and n is the number of trials. From the S/N ratio, the effective parameters having influence on pro-cess results can be obtained and the optimal sets of process parameters can be determined.

For simultaneous optimization of more than one qual-ity characteristic, it is necessary to compute the Normalized Quality Loss because each quality characteristics has differ-ent units of measurement. The Normalized Quality Loss can be computed as (Antony 2001):

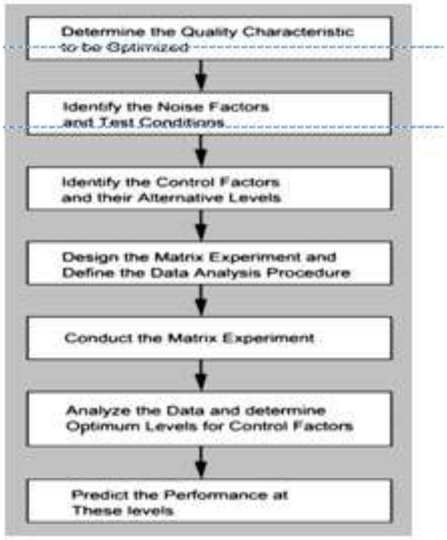
Methodology for multi-objective optimization

For optimizing multiple weld quality characteristics (nomi-nal weld nugget and smaller HAZ size) simultaneously, the TM is applied in this study. This section gives a brief idea on the TM and RSM approach.



Taguchi method for parameter design

In the TM, the optimum level of input process parameters or control factors are decided on the basis of statistical analysis of experimental results that makes the process insensitive to the effect of variations due to uncontrollable or noise fac-tors such as environmental temperature, humidity and vibra-tion. In this method, the experiments are performed as per standard Orthogonal Array (OA) (Ross 1996; Phadke 1989). With such an arrangement, completely randomized experi-ments can be conducted (Kwak 2005). An advantage of the TM is that it emphasizes a mean performance characteristic value close to the target value rather than a value within cer-tain specification limits, thus improving the product quality. It can be used to quickly narrow the scope of a research pro-ject or to identify problems in a manufacturing process from data already in existence (Fraley et al. 2006). The selection of appropriate OA is based on total Degree of Freedom (DoF) which is computed as (Dubey and Yadava 2008a,b):



$$y_{ij} = \frac{L_{ij}}{L_{i*}} \qquad (5)$$

where y_{ij} is the Normalised Quality Loss associated with the i th quality characteristic at the j th trial condition, and it varies from a minimum of zero to a maximum of 1. L_{ij} is the quality loss or MSD for the ith quality characteristic at the j th trial, and L_{i*} is the maximum quality loss for the i th quality characteristic among the experimental runs.

After the Normalized Quality Loss values for each charac-teristic have been determined, the next step is to compute the Total Normalized Quality Loss (Y_j) corresponding to each trial condition. It can be computed using (Ross 1996):

$$Y_j = \sum_{i=1}^{k} w_i y_{ij} \qquad (6)$$

$$\text{DoF} = \{(\text{number of levels} - 1) \text{ for each factor}\}$$
$$+ \{(\text{number of levels for A} - 1)$$
$$\times (\text{number of levels for B} - 1) \text{ for each interaction} + 1\} \qquad (1)$$

where w_i represents the weighting factor for the i th quality characteristic, k is the total number of quality characteristics. A single overall S/N ratio for all quality characteristics is computed in place of separate S/N ratios for each of the quality characteristic in multi-objective optimization. This overall S/N ratio is known as Multiple S/N Ratio (MSNR). The MSNR for j th trial (η^e_j) is computed as (Antony 2001):

where A and B are the interacting control factors.

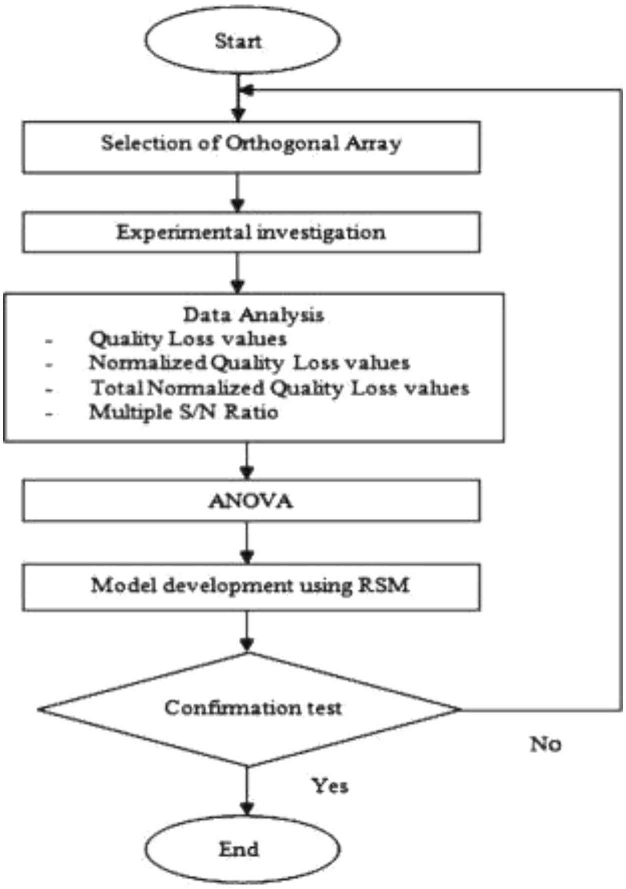
In TM, Signal to Noise Ratio (η) represents the quality characteristic for the response and mathematically it can be computed as (Phadke 1989):

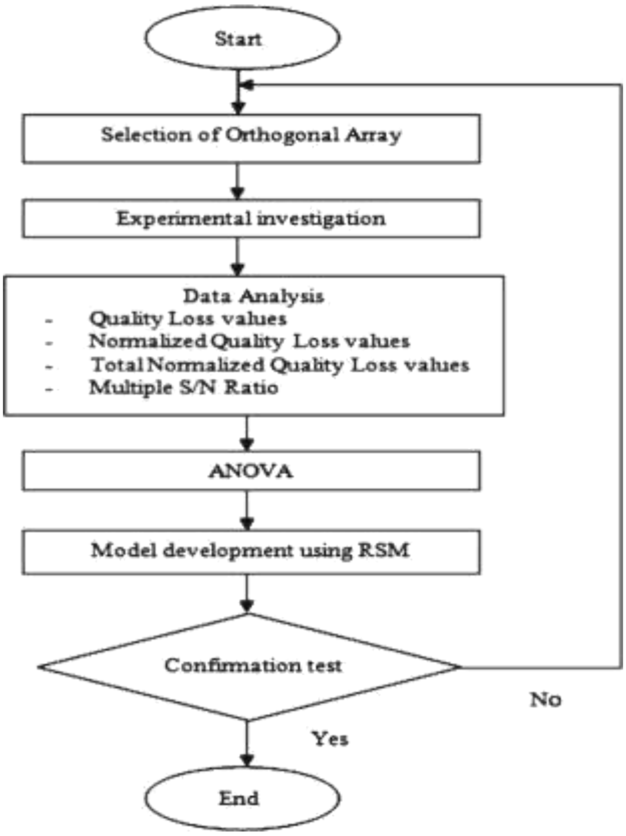
$$\eta = -10 \log [\text{MSD}] \qquad (2)$$

where MSD is Mean Square Deviation from the desired value and commonly known as Quality Loss Function. Usually, there are three categories of quality characteris-tics in the analysis of the S/N ratio which are smaller-is-better, higher-is-better and nominal-is best. In the present case for the radius of weld nugget and width of HAZ the nominal-is-best and the smaller-is-better were chosen respectively using the following equations:

$$\eta^e_j = -10 \log_{10}(Y_j) \qquad (7)$$

In addition to the MSNR, a statistical Analysis of Variance (ANOVA) can be employed to estimate quantitatively the relative significance factors on quality characteristics (Juang and Tarng 2002; Son et al. 2007). If the probability value (p value) is less than the significance level (α), the factor is then regarded to be statistically significant (Rowlands and Antony 2003). The relative significance of factors is often represented in terms of F-ratio or in percentage contribution. The greater the F-ratio indicates that the variation of the pro-cess parameter makes a big change on the performance, or if p ratio is less than 0.05 the more significant will be the factor. The step applied in this study is presented in Fig. 1.


Start
Selection of Orthogonal Array
Experimental investigation
Data Analysis
- Quality Loss values
- Normalized Quality Loss values
- Total Normalized Quality Loss values
- Multiple S/N Ratio
ANOVA
Model development using RSM
Confirmation test
No
Yes
End


Start
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Experimental investigation
Data Analysis
- Quality Loss values
- Normalized Quality Loss values
- Total Normalized Quality Loss values
- Multiple S/N Ratio
ANOVA
Model development using RSM
Confirmation test
No
Yes
End

Fig. 1 Flow chart of experimental procedures

Response surface methodology (RSM)

The RSM, developed by Box and Wilson in the early 1950s, is a collection of statistical and mathematical techniques that are used to model and analyze engineering applications. In these engineering applications, a response of interest is usu-ally influenced by several variables and the objective of the engineering applications is to find the variables that can opti-mize the response (Hou et al. 2007; Raissi and Eslami Farsani 2009; Abbasi and Mahlooji 2012). The design procedure of RSM consists of the following steps (Myers et al. 2009):

i. Designing of a series of experiments for adequate and reliable measurement of the response of interest.
ii. Developing a mathematical model of the second order response surface with the best fittings.
iii. Finding the optimal set of experimental parameters that produce a maximum or minimum value of response.
iv. Representing the direct and interactive effects of pro-cess parameters through two and three dimensional plots.

If all variables are assumed to be measurable, the response surface can be expressed as follows:

$$y = f(x_1, x_2, \ldots x_k) \quad (8)$$

The goal is to optimize the response variable y, it is assumed that the independent variables are continuous and controllable by experiments with negligible errors. It is required to find a suitable approximation for the true func-tional relationship between independent variables and the response surface.

Experimental process set-up and procedures

In this study, the electrode size, electrode force and squeezing cycle were set to be constant throughout the investigation on welding two layers (1 mm + 1 mm) and (1.5 mm + 1.5 mm) of low carbon steel. The chemical composition of the work-piece is listed in Table 1. Three welding parameters such as welding current, weld time and hold time were selected for experimentation with three levels for each factor. The value of the welding process parameter at different levels is tabulated in Table 2. Experimental process was conducted using L_9 orthogonal array in Taguchi Method which has nine rows cor-responding to the number of experiments as shown in Table 3.

Table 1 Chemical composition of workpiece

Percent composition (%)	C	Mn	Si	S	P	Cr	Ni
	0.186	0.146	0.011	0.0011	0.001	0.035	0.032

Table 2 Control factors and their levels used in OA design matrix

Thickness (mm)	Symbol	Factors	Unit	Level 1	Level 2	Level 3
1.0 + 1.0	A	Welding current	kA	4	5	6
	B	Weld time	cycle	8	10	12
	C	Hold time	cycle	1	2	3
1.5 + 1.5	A	Welding current	kA	4	5	6
	B	Weld time	cycle	10	12	14
	C	Hold time	cycle	2	3	4

Thickness (mm)	Symbol	Factors	Unit	Level 1	Level 2	Level 3
1.0 + 1.0	A	Welding current	kA	4	5	6
	B	Weld time	cycle	8	10	12
	C	Hold time	cycle	1	2	3
1.5 + 1.5	A	Welding current	kA	4	5	6
	B	Weld time	cycle	10	12	14
	C	Hold time	cycle	2	3	4

Table 3 Experimental layout using L_9 orthogonal array

Experiment number	Levels of factors		
	A	B	C
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

To measure the outputs which are the radius of weld nug-get and witdth of HAZ, the welded plates was cut transversely from the middle position using a common cutting machine. These specimens were prepared by the usual metallurgical polishing methods and etched with 2 % nital solution and weld zone was captured using a metallurgical microscope interfaced with an image analysis system. A schematic illus-tration of the weld zone is shown in Fig. 2.

II. RESULTS AND DISCUSSION

The values of the observed data for the radius of weld nugget and width of HAZ are shown in Table 4. Two or more exper- imental data are needed because the quality characteristics for radius of weld nugget is nominal-is-best and it's S/N ratio is based on standard devition.

Multi-objective optimization results using Taguchi approach From Table 4, Quality Loss values for different quality char-acteristics (nominal-is-best for radius of weld nugget and smaller-is-better for width of HAZ) in each experimental run are calculated using Eqs. (3) and (4). These Quality Loss values are shown in Table 5. The Normalized Quality Loss values for both quality characteristics in each experimen-tal run have been calculated using Eq. (5) that is shown in Table 6. The Total Normalized Quality Loss values (TNQL) and MSNR for multiple quality characteristics for radius of weld nugget and width of HAZ have been calculated using Eqs. (6) and (7) respectively. These results are shown in Table 7. In calculating TNQL, two unequal weights which are w_1 = 0.8 for radius of weld nugget and w_2 = 0.2 for width of HAZ are used. Higher weighting factor has been assigned to the weld nugget because it is more important as compared to the HAZ in order to achieve a good quality of weld in RSW process.

The effect of different control factors on MSNR is shown in Table 8. The optimum levels of different control factors for nominal radius of weld nugget and minimum width of HAZ obtained for sheet thickness (1.0 + 1.0) mm are weld current at level 3 (6.0 kA), weld time at level 3 (12 cycles) and hold time at level 2 (2 cycles). For sheet thickness (1.5 +

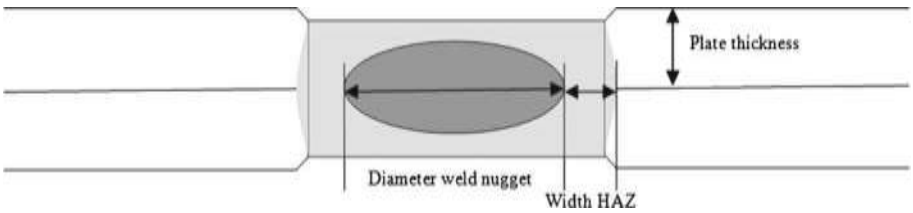

Fig. 2 Macrograph of weld zone

Table 4 Experimental results for radius of weld nugget and width of HAZ

Experiment number	(1.0 + 1.0) mm				(1.5 + 1.5) mm			
	[redacted]				[redacted]			
	Radius weld nugget 1	Radius weld nugget 2	Width of HAZ 1	Width of HAZ 2	Radius weld nugget 1	Radius weld nugget 2	Width of HAZ 1	Width of HAZ 2
1	1.6525	1.8900	1.0425	1.2370	1.5765	1.2460	1.2115	1.5505
2	1.6355	1.8475	0.9405	0.9745	1.5255	1.7290	1.5000	1.2880
3	1.6780	1.8390	1.0255	1.0510	1.6780	1.8050	1.1950	1.3135
4	1.8135	1.9405	0.9240	0.8900	1.9660	1.8475	1.3560	1.2540
5	1.9830	2.1015	0.8050	1.0340	1.9070	2.0085	1.1610	1.0425
6	1.9070	2.0085	1.0510	0.8350	1.9490	2.0425	1.1950	0.9745
7	2.3305	2.4235	0.9830	0.8140	2.3985	2.3135	0.9915	0.9240
8	2.4150	2.4915	0.9910	0.7850	2.3815	2.3050	1.0590	1.0510
9	2.5595	2.6120	0.8050	0.8475	2.4570	2.4070	0.9655	0.9830

Table 5 Quality loss values for radius of weld nugget and width of HAZ

Experiment number	Quality Loss values (dB)			
	(1.0 + 1.0) mm		(1.5 + 1.5) mm	
	Radius of weld nugget	Width of HAZ	Radius of weld nugget	Width of HAZ
1	0.0282	1.2990	0.0546	1.9071
2	0.0224	0.9168	0.0207	1.9432
3	0.0129	1.0779	0.0080	1.5731
4	0.0081	0.8226	0.0070	1.7030
5	0.0070	0.8454	0.0051	1.2138
6	0.0052	0.8892	0.0043	1.1766
7	0.0043	0.8073	0.0036	0.9172
8	0.0029	0.7916	0.0029	1.1130
9	0.0014	0.7310	0.0012	0.9491

dB decibel

Table 6 Normalized quality loss values for radius of weld nugget and width of HAZ

Experiment number	Normalized quality loss values

	(1.0 + 1.0) mm		(1.5 + 1.5) mm	
	Radius of weld nugget	Width of HAZ	Radius of weld nugget	Width of HAZ
1	1.0000	1.0000	1.0000	0.9814
2	0.7968	0.7057	0.3790	1.0000
3	0.4595	0.8298	0.1476	0.8095
4	0.2859	0.6332	0.1285	0.8763
5	0.2489	0.6508	0.0943	0.6246
6	0.1826	0.6845	0.0800	0.6055
7	0.1533	0.6214	0.0661	0.4720
8	0.1037	0.6094	0.0535	0.5727
9	0.0488	0.5627	0.0233	0.4884

1.5) mm, the optimum levels obtained are weld current at level 3 (6.0 kA), weld time at level 3 (14 cycles) and hold time at level 3 (4 cycles).

ANOVA technique has been employed to detect signifi-cant factors in multi-objective optimization for radius of weld nugget and width of HAZ. The result of ANOVA for the welding outputs are presented in Tables 9 and 10 for 1 and 1.5 mm, respectively. According to this analysis, it shows that weld current was statistically significant since its p-value is less than 0.05 for both (1.0 + 1.0) and (1.5 + 1.5) mm. Fur-thermore, it also shows the percentage contribution which indicates the relative power of a factor to reduce variation. For a factor with a high percentage contribution, a small var-iation will have a great influence on the performance (Esme 2009). The percentage contribution of different control fac-tors on multiple quality characteristics (radius of weld nugget

Table 7 Total normalized quality loss values (TNQL) and multiple S/N ratios (MNSR)

Experiment number	(1.0 + 1.0) mm		(1.5 + 1.5) mm	
	TNQL	MSNR (dB)	TNQL	MSNR (dB)
1	1.0000	0.0000	0.9962	0.0164
2	0.7786	1.0865	0.5032	2.9819
3	0.5336	2.7275	0.2800	5.5279
4	0.3554	4.4923	0.2781	5.5578
5	0.3293	4.8233	0.2003	6.9814
6	0.2830	5.4815	0.1851	7.3252
7	0.2469	6.0734	0.1473	8.3173
8	0.2048	6.8846	0.1574	8.0296
9	0.1516	8.1919	0.1163	9.3415
Mean of MSNR of all experimental runs		4.4179		6.0088

Table 8 Multiple S/N response (average factor effect at different level)

Thickness (mm)	Symbol	Factors	Mean of multiple S/N ratios (dB)		
			Level 1	Level 2	Level 3

1.0 + 1.0	A	Welding current	1.271	4.932	7.050*
	B	Weld time	3.522	4.265	5.467*
	C	Hold time	4.122	4.590*	4.541
1.5 + 1.5	A	Welding current	2.842	6.622	8.563*
	B	Weld time	4.631	5.998	7.398*
	C	Hold time	5.124	5.960	6.942*

* Optimum leveland width of HAZ) shows that welding current was the major factor (88.65 % for 1 mm and 73.91 % for 1.5 mm), followed by weld time (9.99 % for 1 mm and 16.72 % for 1.5 mm) and hold time (0.687 % for 1 mm and 7.14 % for 1.5 mm). In RSW, welding current and contact surface have the greatest effect on the growth of weld nugget (Darwish and Al-Dekhial 1999; Manurung et al. 2010; Hamedi and Pashazadeh 2008).

Response surface modelling After obtaining the optimum parameters for the response, the final equation for radius of weld nugget and width of HAZ was defined using RSM. These equations were generated by the software after the transformation had been carried out.

i. For (1.0 + 1.0) mm sheet thickness:

$$\text{Radius of weld nugget} = 0.046278 + 0.357458\,A + 0.023063\,B - 0.000750\,C \quad (8)$$

$$\text{Width of HAZ} = 1.4896 - 0.08204\,A - 0.00908\,B - 0.01937\,C \quad (9)$$

Table 9 Result of ANOVA for (1.0 + 1.0) mm sheet thickness

Factors	Degrees of freedom (DOF)	Sum of squares	Mean of squares	F	P	Contribution (%)
Weld current	2	51.2807	25.6403	133.13	0.007	88.65
Weld time	2	5.7801	2.8900	15.01	0.062	9.99
Hold time	2	0.3975	0.1988	1.03	0.492	0.687
Error	2	0.3852	0.1926			
Total	8	57.8435				

Table 10 Result of ANOVA for (1.5 + 1.5) mm sheet thickness

Factors	Degrees of freedom (DOF)	Sum of squares	Mean of squares	F	P	Contribution (%)
Weld current	2	50.780	25.3898	34.71	0.028	73.91
Weld time	2	11.491	5.7454	7.85	0.113	16.72
Hold time	2	4.971	2.4854	3.40	0.227	7.14
Error	2	1.463	0.7316			
Total	8	68.705				

ii. For (1.5 + 1.5) mm sheet thickness:

$$\text{Radius of weld nugget} = -0.63251 + 0.39188\,A$$

Table 11 Results of the confirmation experiment

Thickness	Optimal process parameter	Error (%)

$$+0.04127\ B + 0.05083C \quad (10)$$

$$\text{Width of HAZ} = 2.47007 - 0.17371\ A - 0.02754\ B - 0.03450\ C \quad (11)$$

where A, B and C are welding current, weld time and hold time respectively.

To test whether the data are well fitted in the model or otherwise, the value of S and R^2 are observed. In general, the more appropriate regression model is the higher the values of R^2 (R is correlation coefficient) and the smaller the values of S (standard errors of samples). From the developed models, calculated S value of the regression analysis on radius of weld nugget is (0.120029 for 1 mm and 0.0457859 for 1.5 mm) and width of HAZ is (0.0589357 for 1 mm and 0.0664677 for 1.5 mm), which are considered small and R^2 value for both responses (radius of weld nugget and width of HAZ) are (91.54, 71.98 % for 1 mm and 98.94, 90.33 % for 1.5 mm) respectively, these are moderately high. Therefore, the data for each response are considerably well-fitted in the developed models.

Confirmation tests

The final step is a verification experiment to validate the optimum conditions suggested by the matrix experiment do indeed give the projected improvement. The confirmation experiment is performed by conducting a test with a specific combination of the factors and levels as previously evaluated.

After determining the optimum conditions, a new experiment was conducted with the optimum levels of the welding parameters ($A_3B_3C_2$) for 1 mm and ($A_3B_3C_3$) for 1.5 mm.

s

	Prediction	Experiment	
(1.0 + 1.0) mm			
Level	$A_3B_3C_2$	$A_3B_3C_2$	
Radius of weld nugget (mm)	2.466	2.586	4.64
Width of HAZ (mm)	0.8496	0.7675	10.70
(1.5 + 1.5) mm			
Level	$A_3B_3C_3$	$A_3B_3C_3$	
Radius of weld nugget (mm)	2.499	2.492	0.34
Width of HAZ (mm)	0.9042	0.8875	1.89

Confirmation experimental results will be then compared using Eqs. (8)–(11).

Results of confirmation test as compared to the predicted values for radius of weld nugget and width of HAZ and also the percentage error are shown in Table 11. For sheet thickness (1.0 + 1.0) mm, the percentage error between confirmation experiment and prediction is 4.64 and 10.70 % for radius of weld nugget and width of HAZ respectively. While for sheet thickness (1.5 + 1.5) mm the percentage error for radius of weld nugget and width of HAZ is 0.34 and 1.89 % respectively. The percentage errors are within the acceptable range. It shows that the model equation presents good agreement with experimental results.

Conclusions

A Multi-objective Taguchi Method has been applied with simultaneous consideration of multiple response (radius of weld nugget and width of HAZ) to optimize the multiple quality features in RSW process. Based on the modeling and optimization results, it can be concluded that:

i. For both sheet thickness (1.0+1.0) and (1.5+1.5) mm, the highly effective parameter for the development of radius weld nugget and width of HAZ is the welding current.
ii. The developed linear response surface model for pre-diction radius of weld nugget and width of HAZ has been found well fitted.
iii. The optimum parameter for sheet thickness (1.0 + 1.0) mm has been found to be as follow: welding cur-rent at level 3 (6.0 kA), weld time at level 3 (12 cycles) and hold time at level 2 (2 cycles). For sheet thickness (1.5+1.5) mm, the optimum parameter is welding cur-rent at level 3 (6.0 kA), weld time at level 3 (14 cycles) and hold time at level 3 (4 cycles).
iv. The confirmation tests validated the use of Multi-objective Taguchi Method for enhancing the welding performance and optimizing the welding parameters in RSW process.

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