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Optimization and modeling of spot welding parameters with simultaneous multiple response consideration using multi-objective Taguchi method and RSM[†]

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Abstract

This paper presents an alternative method to optimize process parameters of resistance spot welding (RSW) towards weld zone development. The optimization approach attempts to consider simultaneously the multiple quality characteristics, namely weld nugget and heat affected zone (HAZ), using multi-objective Taguchi method (MTM). The experimental study was conducted for plate thickness of 1.5 mm under different welding current, weld time and hold time. The optimum welding parameters were investigated using the Taguchi method with L_9 orthogonal array. The optimum value was analyzed by means of MTM, which involved the calculation of total normalized quality loss (TNQL) and multi signal to noise ratio (MSNR). A significant level of the welding parameters was further obtained by using analysis of variance (ANOVA). Furthermore, the first order model for predicting the weld zone development is derived by using response surface methodology (RSM). Based on the experimental confirmation test, the proposed method can be effectively applied to estimate the size of weld zone, which can be used to enhance and optimized the welding performance in RSW or other application.

Keywords: Multi objective taguchi method; Multi signal to noise ratio; Resistance spot welding; Response surface methodology

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1. Introduction

The design of experiment (DoE) is widely used in technical as well nontechnical research fields to develop a mathematical relationship between the process input parameters and the output variables in order to optimize the input parameters that lead to the desired quality. In most resistance spot welding (RSW) research, the weld quality is best judged by nugget size and joint strength [1]. Therefore, it is important to select the welding process parameters for obtaining optimal size of weld nugget. Usually, the desired welding process parameters are determined based on experience or from the handbook. However, this does not ensure that the selected welding process parameters can produce the optimal weld nugget for that particular welding machine and environment.

To overcome this problem, various optimization methods can be applied to define the desired output variables through developing mathematical models to specify the relationship between the input parameters and output variables. Some works have been done on various aspects of modeling and process optimization in the RSW process. Ugur Esme [2] reported an investigation on the optimization and effect of welding parameters on the tensile shear strength of spot welded SAE 1010 steel sheet using Taguchi method. Thakur and Nandedkar [1] presented a systematic approach to determine the effect of process parameters on tensile shear strength of RSW of austenitic stainless steel AISI 3040 using Taguchi method. Darwish and Al-Dekhial [3] proposed response surface methodology (RSM) for the influence of spot welding parameters on the strength of spot welded aluminum sheets. Rowlands and Antony [4] investigated the use of Taguchi's loss function analysis and RSM to a spot welding process in order to discover the key process parameters which influence the tensile strength of welded joints.

Taguchi methods have proved to be successful over the last fifteen years for the improvement of product quality and process performance. Based on the review of past researches, most of the investigations focused on modeling and optimizing single quality characteristic which may deteriorate other characteristics. As the main objective of the manufacturing process is always to improve the overall quality of a product, it is necessary to optimize multiple quality characteristics simultaneously. Anthony [5] has demonstrated a Taguchi quality loss function based multi-objective optimization technique for

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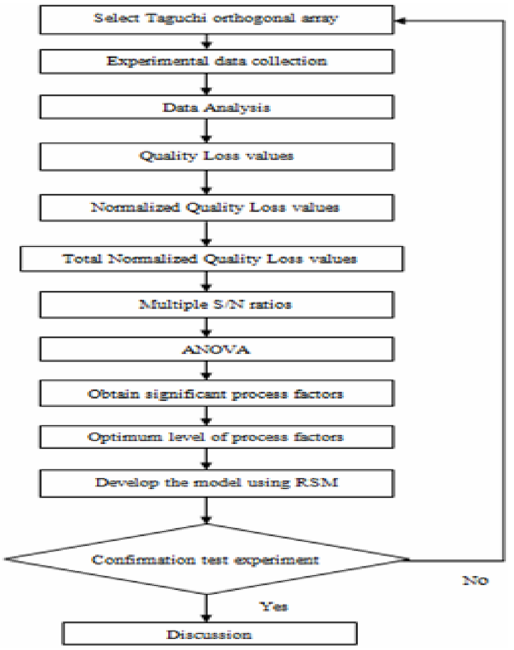

Fig. 1. Flow chart of the research methodology.

manufacturing processes taking an example of electronic assembly problem. He found considerable improvement in multiple quality characteristics, in comparison to single quality characteristics. Multi-objective Taguchi method (MTM) approach has been used for the optimization of the laser beam cutting process by Dubey and Yadava [6, 7]. The authors found that quality characteristics were improved considerably. Simultaneous consideration of multiple responses approach has yet not been explored in the study of RSW process using MTM and response surface methodology (RSM).

In the present paper, MTM was applied to optimize the welding parameters under simultaneous consideration of multiple weld quality characteristic (nominal weld nugget and smaller HAZ size). The optimization approach starts with the calculation of total normalized quality loss (TNQL) under simultaneous consideration of response weighting factor and followed by the observation of multi signal to noise ratio (MSNR). The significant level of the welding parameters was further obtained by using analysis of variance (ANOVA). Furthermore, the first order response was developed using RSM. Using the response model, one can predict the development of weld nugget and HAZ size. Experimental confirmation test was also conducted to validate the predicted model. The step applied in this research is shown in Fig. 1.

2. Principle of experimental planning method

2.1 Taguchi & multi-objective Taguchi method

The Taguchi design method is a simple and robust technique for optimizing the process parameters. In this method, main parameters which are assumed to have influence on process results are located at different rows in a designed orthogonal array (OA). With such an arrangement, completely randomized experiments can be conducted [8]. An advantage of the Taguchi method is that it emphasizes a mean performance characteristic value close to the target value rather than a value within certain specification limits, thus improving the product quality. It can be used to quickly narrow the scope of a research project or to identify problems in a manufacturing process from data already in existence [9].

In this method, main process parameters or control factors which influence process results are taken as input parameters and the experiment is performed as per specifically designed OA. The selection of appropriate OA is based on total degree of freedom (dof) which is computed as [6, 7]:

$$\begin{aligned} \text{dof} = \ & \{(\text{number of levels} - 1) \text{ for each factor}\} + \\ & \{(\text{number of levels} - 1) \text{ x}(\text{number of levels} - 1) \\ & \text{for each inter action} + 1\}. \end{aligned} \quad (1)$$

In general, signal to noise (S/N) ratio (η, dB) represents quality characteristics for the observed data in the Taguchi design of experiments (DoE) and mathematically can be computed as [6, 7]:

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

where MSD is mean square deviation from the desired value and commonly known as quality loss function.

Usually, there are three categories of the quality characteristic in the analysis of the S/N ratio: smaller-is-better, higher-is-better and nominal-is-best. In this research for the radius of weld nugget and width of HAZ the nominal-is-best and the smaller-is-better was chosen, respectively, with following equations:

$$\text{Nominal-is-best} = \eta = -10 \log 10\ \sigma 2 \quad (3)$$

$$\text{Smaller-is-better} = \ \eta = -10 \log \left[\frac{1}{n} \sum_{i=1}^{n} y_i^2 \right] \quad (4)$$

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

The Taguchi method also provides a better feel for the relative effect of the different parameters/factors that can be analyzed by the analysis of the variance (ANOVA). It is a statistical method to estimate quantitatively the relative significance factors on quality characteristics [10, 11]. If the p-value is less than the significance level (α), the factor is then regarded to be statistically significant [4, 12]. The relative significance of factors is often represented in terms of F-ratio or in percentage contribution. Greater the F-ratio indicates that the variation of the process parameter makes a big change on the performance, or for p-ratio less than 0.05 the more significant will be the factor.

In multi-objective optimization, 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. This overall S/N ratio is known as multiple S/N ratio (MSNR). The MSNR for *j*th trial (η_j^e)is computed as [5]:

$$\eta_j^e = -10\log_{10}\left(Y_j\right) \tag{5}$$

$$Y_j = \sum_{i=1}^{k} w_i y_{ij} \tag{6}$$

$$y_{ij} = \frac{L_{ij}}{L_{i*}} \tag{7}$$

where *Yj* is the total normalized quality loss in *j*th trial, *wi* represents the weighting factor for the *i*th quality characteristic, *k* is the total number of quality characteristics and *yij* is the normalized 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. *Lij* is the quality loss or MSD for the *i*th quality characteristic at the *j*th trial, and *Li** is the maximum quality loss for the *i*th quality characteristic among all the experimental runs.

2.2 Response surface methodology (RSM)

Response surface methodology is a collection of statistical and mathematical methods that are useful for the modeling and analyzing engineering problems. The main objective is to optimize the response surface that is influenced by various process parameters. Response surface methodology also quantifies the relationship between the controllable input parameters and the obtained response surfaces [6, 13]. The goal is to optimize the response variable; 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 functional relationship between independent variables and the response surface.

3. 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 1.5 mm + 1.5 mm of low carbon steel. The chemical composition of the workpiece is listed in Table 1. Three welding parameters such as welding current, weld time and hold time were selected for experimentation with three levels of each factor. The value of the welding process parameter at the different levels is tabulated in Table 2. Experimental process was conducted using L_9 orthogonal array in Taguchi method which has nine rows corresponding 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.

Symbol	Factors	Unit	Level 1	Level 2	Level 3
A	Weld 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 OA.

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

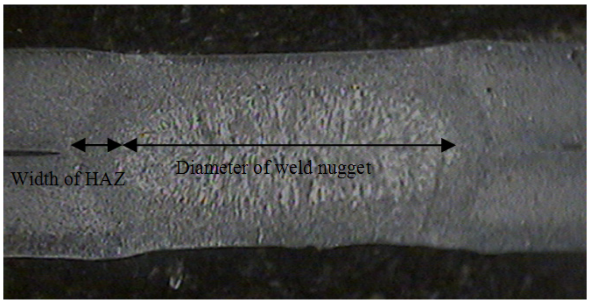

Fig. 2. Macrograph of weld zone.

To measure the outputs which are the radius of weld nugget and witdth of HAZ, the welded plates were 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 the weld zone was captured using a metallurgical microscope interfaced with an image analysis system as shown in Fig. 2.

4. Results and discussion

The values of the observed data for radius of weld nugget and width of HAZ are shown in Table 4. Two or more experimental data are needed because the quality characteristic for radius of weld nugget is nominal-is-best and its S/N ratio is based on standard deviation.

Table 4. Experimental results.

Experiment number	Radius weld nugget 1 (mm)	Radius weld nugget 2 (mm)	Width of HAZ 1 (mm)	Width of HAZ 2 (mm)
1	1.5765	1.2460	1.2115	1.5505
2	1.5255	1.7290	1.5000	1.2880
3	1.6780	1.8050	1.1950	1.3135
4	1.9660	1.8475	1.3560	1.2540
5	1.9070	2.0085	1.1610	1.0425
6	1.9490	2.0425	1.1950	0.9745
7	2.3985	2.3135	0.9915	0.9240
8	2.3815	2.3050	1.0590	1.0510
9	2.4570	2.4070	0.9655	0.9830

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

Experiment number	A	B	C	Quality loss values (dB)	
				Radius weld nugget	Width of HAZ
1	1	1	1	0.0546	1.9071
2	1	2	2	0.0207	1.9432
3	1	3	3	0.0080	1.5731
4	2	1	2	0.0070	1.7030
5	2	2	3	0.0051	1.2138
6	2	3	1	0.0043	1.1766
7	3	1	3	0.0036	0.9172
8	3	2	1	0.0029	1.1130
9	3	3	2	0.0012	0.9491

4.1 Multi-objective optimization results

From Table 4, quality loss values for different quality characteristics (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 experimental run have been calculated using Eq. (7) 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 (5), respectively. These results are shown in Table 7.

In calculating total normalized quality loss values, two unequal weights, $w_1 = 0.8$ for radius of weld nugget and $w_2= 0.2$ for width of HAZ were used. Higher weighting factor was assigned to the weld nugget because it is more important compared to HAZ in order to achieve a good quality of weld in resistance spot welding 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 are weld current at level 3 (6.0kA), weld time at level 3 (14 cycles) and hold time at level 3 (4 cycles).

Table 6. Normalized quality loss values.

Experiment number	A	B	C	Normalized quality loss values	
				Radius weld nugget	Width of HAZ
1	1	1	1	1.0000	0.9814
2	1	2	2	0.3790	1.0000
3	1	3	3	0.1476	0.8095
4	2	1	2	0.1285	0.8763
5	2	2	3	0.0943	0.6246
6	2	3	1	0.0800	0.6055
7	3	1	3	0.0661	0.4720
8	3	2	1	0.0535	0.5727
9	3	3	2	0.0233	0.4884

Table 7. Total normalized quality loss values (TNQL) and Multiple S/N ratios (MSNR).

Experiment number	A	B	C	TNQL	MSNR (dB)
1	1	1	1	0.9962	0.0164
2	1	2	2	0.5032	2.9819
3	1	3	3	0.2800	5.5279
4	2	1	2	0.2781	5.5578
5	2	2	3	0.2003	6.9814
6	2	3	1	0.1851	7.3252
7	3	1	3	0.1473	8.3173
8	3	2	1	0.1574	8.0296
9	3	3	2	0.1163	9.3415
Mean of MSNR of all experimental runs					6.0088

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

Symbol	Factors	Mean of multiple S/N ratio (dB)		
		Level 1	Level 2	Level 3
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 level

ANOVA technique has been employed to detect significant factors in multi-objective optimization for radius of weld nugget and width of HAZ. The result of ANOVA for the welding outputs is presented in Table 9. This analysis shows that weld current was statistically significant since its p-value is less than 0.05. Furthermore, 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 variation will have a great influence on the performance [2]. The percentage contribution of different control factors on multiple quality characteristics (radius of weld nugget and width of HAZ) shows that welding current was the major factor (73.91%); it is followed by weld time (16.72%) and hold time (7.14%). In resistance spot welding, welding current

Table 9. ANOVA result.

Factors	Welding current	Weld time	Hold time	Error	Total
DoF	2	2	2	2	8
Sum of square	50.780	11.491	4.971	1.463	68.705
Mean of square	25.3897	5.7454	2.4854	0.7316	
F	34.71	7.85	3.40		
P	0.028	0.113	0.227		
Contribution %	73.91	16.72	7.14		

Table 10. Result of the confirmation experiment.

	Initial parameter setting	Optimal process parameters		Error (%)
		Prediction	Experiment	
Level	$A_2B_2C_3$	$A_3B_3C_2$	$A_3B_3C_3$	
Radius of weld nugget (mm)	1.958	2.499	2.492	0.34
Width of HAZ (mm)	1.102	0.9042	0.8875	1.89
Multiple S/N ratio (dB)	6.9814	10.885	11.16	
Improvement in multiple S/N ratio = 4.179 dB				

and contact surface have the greatest effect on the growth of weld nugget [3, 14, 15].

4.2 Response surface modeling

The first order response surface model for radius of weld nugget and width of HAZ was developed from the experimental response values obtained using OA experimental matrix. These equations were developed using RSM in MINITAB software.

$$\text{Radius of weld nugget} = -0.63251 + 0.39188\,A + 0.04127\,B + 0.05083C \quad (8)$$

$$\text{Width of HAZ} = 2.47007 - 0.17371\,A - 0.02754\,B - 0.03450\,C \quad (9)$$

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 not, the values 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 0.0457859 and width of HAZ is 0.0664677, which are smaller and R^2 value for both response (radius of weld nugget and width of HAZ) are 98.94% and 90.33%, respectively. These are moderately high; therefore the data for each response are well-fitted in the developed models.

4.3 Confirmation tests

The final step is verification experiments to validate that 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 previously evaluated. After determining the optimum conditions, a new experiment was conducted with the optimum levels of the welding parameters ($A_3B_3C_3$). Then the predicted value of MSNR (η_{opt}) at the optimum parameter levels was calculated by using the following equation [6, 16]:

$$\eta_{opt} = \bar{\eta} + \sum_{i=1}^{p}\left(\eta_{mi} - \bar{\eta}\right) \quad (10)$$

where $\bar{\eta}$ is the mean MSNR of all experimental runs, p is the number of main welding parameters that significantly affect the performance and η_{mi} is the average MSNR at the optimal level.

The predicted value of MSNR and that confirmation experiment is shown in Table 10. The improvement in multiple S/N ratio from initial parameter which is $A_2B_2C_3$ setting to the optimal parameters ($A_3B_3C_3$) is found to be 4.179 dB. The results show considerable improvement in both the quality characteristics (radius of weld nugget and width of HAZ) with the multi-response optimization used, as compared the initial value of radius weld nugget and width of HAZ.

Confirmation experimental results are also compared with Eqs. (8) and (9). Results of confirmation test compared to predicted value for radius of weld nugget and width of HAZ using the developed model and also the percentage error are also shown in Table 10. 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 result.

5. Conclusions

A multi-objective optimization has been applied with simultaneous consideration of multiple response (radius of weld nugget and width of HAZ) using Taguchi method to optimize the multiple quality characteristics in RSW process. Based on the modeling and optimization results, the following conclusions can be drawn:

(1) Multiple characteristics such as radius of weld nugget and width of HAZ can be simultaneously considered using multi-objective Taguchi method.

(2) The contribution of different control factors is welding current (73.91%), weld time (16.72%) and hold time (7.14%). The highly effective parameter for the development of radius weld nugget and width of HAZ is the welding current.

(3) The optimum parameters for nominal weld nugget and smaller HAZ size are: welding current at level 3 (6.0 kA), weld time at level 3 (14 cycles) and hold time at level 3 (4 cycles).

(4) The developed linear response surface model for prediction radius of weld nugget and width of HAZ has been found well fitted.

(5) The confirmation test 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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