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Multi-Objective Optimization of Submerged Arc Welding Process

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الفاعلية المتعدده الموضوعية لطريقة اللحام الغاطس

سواريف داتا ، سيبا سانكار ماهباترا

الخلاصة: اللحام الغاطس هو تكنلوجيا تصنيع مهمة وخاصة إذا استعملت لربط معادن ذات اسماك كبيرة في مرة واحدة. من اجل الحصول على مفصل كفوء، عدة عوامل للحام الغاطس يجب ان تدرس بدقة لتحسين النوعية. العديد من نظم معادن قد تم إقتراحها في بحوث سابقة للتعامل مع هذا الموضوع. ومع ذلك عدد مهم من الاعمال السابقة كانت تأمل لتفعيل اللحام الغاطس و مفرداتة باستجابة واحدة. في الاوضاع العملية، ليس فقط تاثير مفردات العملية و تاثيراتها المتفاعلة على المخرجات قد تم فحصها بدقة ولكن هناك محاولة لجعلها ذات فاعلية باكثر من استجابة واحده بصورة متزامنة. ومن اجل ذلك فان الدراسة الحالية تاخذ بعين الاعتبار اربعة عمليات لمفردات السيطرة وهي: الفولتية، سرعة تغذية السلك، السرعة الجانبية، بروز الاكترود. نوعية السلك المختار ترتبط بمزايا هندسة الخرز هي عمق النفاذية و التسليح وعرض الخرز. في التقرير الحالي تم اقتراح اسلوب مدمج قابل كل ذو فاعلية متزامنة مع الاستجابة المتعدده النوعيات للحام الغاطس. في الطريقة الفردية بواسطة إختيار الدالة المرغوبة المناسبة. بافتراض اهمية متساوية لكافة الاستجابات، فان هذه القيم الفردية المرغوبة قد جمعت لحساب القيم المرغوبة الشاملة. طريقة السطح الرباعي الاستجابة RSM قد تم تطبيقها لتاسيس نظام رياضي يمثل الرغبة الشاملة كداله تشمل على تاثير خطي رباعي تفاعلي للعملية و المفردات. هذا النموذج قد تم تفعيلة اخيرا خلال الحقل التجريبي باستعمال خوارزميات PSO . فحوصات تأكيدية بينت نتائج مرضية. طريقة مفصلة الى RSM الدالة الرغبة DF وكذلك الفاعلية المعتمدة على اسلوب الفاعلية PSO قد تم تبيانة في البحث.

المفردات المفتاحية : لحام غاطس SAW ، فاعلية متعدده الاهداف، طريقة السطح المستجيب RSM ، دالة الرغبه DF، فاعليه حشد الجزيئات PSO.

Abstract: Submerged arc welding (SAW) is an important metal fabrication technology specially applied to join metals of large thickness in a single pass. In order to obtain an efficient joint, several process parameters of SAW need to be studied and precisely selected to improve weld quality. Many methodologies were proposed in the past research to address this issue. However, a good number of past work seeks to optimize SAW process parameters with a single response only. In practical situations, not only is the influence of process parameters and their interactive effects on output responses are to be critically examined but also an attempt is to be made to optimize more than one response, simultaneously. To this end, the present study considers four process control parameters viz. voltage (OCV), wire feed rate, traverse speed and electrode stick-out. The selected weld quality characteristics related to features of bead geometry are depth of penetration, reinforcement and bead width.

In the present reporting, an integrated approach capable of solving the simultaneous optimization of multi-quality responses in SAW was suggested. In the proposed approach, the responses were transformed into their individual desirability values by selecting appropriate desirability function. Assuming equal importance for all responses, these individual desirability values were aggregated to calculate the overall desirability values. Quadratic Response Surface Methodology (RSM) was applied to establish a mathematical model representing overall desirability as a function involving linear, quadratic and interaction effect of process control parameters. This model was optimized finally within the experimental domain using PSO (Particle Swarm Optimization) algorithm. A confirmatory test showed a satisfactory result. A detailed methodology of RSM, desirability function (DF) and a PSO-based optimization approach was illustrated in the paper.

Keywords: Submerged arc welding (SAW), Multi-objective optimization, Response surface methodology (RSM), Desirability function (DF), Particle swarm optimization (PSO)

1. Introduction

Submerged arc welding (SAW) is a multi-factor, multi-objective metal joining technology in which several process control parameters interact in a complicated manner and influence differently on quality of the prepared

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weld. Weld quality depends on various features of bead geometry, mechanical-metallurgical characteristics of the weld as well as on weld chemistry. Moreover, the cumulative effect of combined aforesaid quality features determines the extent of joint strength that determines functional aspects if the weld is subjected to practical field of application. Therefore, preparation of a satisfactory good quality weld seems to be a challenging job. Complete knowledge regarding the mode of influence of the process control parameters and their interactions are to be exactly known prior to select an optimal process environment capable of producing desired quality weld. However, SAW optimization is a difficult task due to simultaneous fulfillment of multi-quality features which should be close to the desired target value at the optimal setting. In practice, it may happen that an improvement of one response may cause severe loss to another quality feature for a particular parametric combination.

Tay and Butler (1996) proposed an application of an integrated method using experimental designs and neural network technologies for modeling and optimizing a metal inert gas (MIG) welding process. Correia *et al*. (2004) used Genetic Algorithm (GA) to decide near-optimal settings of a GMAW welding process. Dongcheol et al. (2002) suggested the use of Genetic Algorithm and Response Surface Methodology (RSM) for determining optimal welding conditions. Hsien-Yu Tseng (2006) proposed an integrated approach to address the welding economic design problem. The integrated approach applied general regression neural network (NN) to approximate the relationship between welding parameters (welding current, electrode force, welding time, and sheet thickness) and the failure load. An analytical formula was generated from the trained general regression neural network, and the mathematical model for the economic welding design was constructed. GA was then applied to resolve the mathematical model and to select the optimum welding parameters. These parameters were recommended for use to obtain the preferred welding quality at the least possible cost.

Zhao et al. (2006) focused on the performance -predicting problems in the spot welding of the body-galvanized steel sheets. Artificial Neural Networks (ANNs) were used to describe the mapping relationship between welding parameters and welding quality. After analyzing the limitation that existed in standard back propagation (BP) networks, the original model was optimized based on a lots of experiments. A lot of experimental data about welding parameters and corresponding spot-weld quality were provided to the ANN for study. The results showed that the improved BP model can predict the influence of welding currents on nugget diameters, weld indentation and the shear loads ratio of spot welds. The forecasting precision was quite high satisfying the practical application value. Pasandideh and Niaki (2006) presented a new methodology for solving multi-response statistical optimization problems. This methodology integrates desirability function and simulation approach with a genetic algorithm. The desirability function was used for modeling the multi-response statistical problem whereas the simulation approach generated required input data and finally the genetic algorithm was implemented to optimize the model.

Praga-Alejo *et al*. (2008) highlighted that the Neural Network (NN) with GA as a complement are good optimization tools. The authors compared its performance with the RSM that is generally used in the optimization of the process, particularly in welding.

Many designed experiments require the simultaneous optimization of multiple responses. The common trend to tackle such an optimization problem is to develop mathematical models of the responses. These indicate the entire process behavior. The effect of process parameters on different responses can be analyzed from the developed models. Multiple linear regression and Response Surface Methodology are two common tools available for developing the mathematical models of the responses as a function of process parameters. Depending on the requirement, each quality features/responses are optimized (maximized or minimized) to determine the optimal setting of the parameters. However, this method is applicable for the optimization of a single objective function. In a multi-objective case, it is essential to convert these multiple objectives to an equivalent single objective function which has to be optimized finally.

A common approach is to use a desirability function combined with an optimization algorithm to find the most desirable settings. In the desirability function approach, individual response desirability values are calculated depending on the target as well as prescribed tolerance limit of the response variables. Individual desirability values are then aggregated to calculate the overall desirability value. The optimal setting is one which can maximize the overall desirability. In doing so, a mathematical model is required for overall desirability. The model is then optimized finally. However, as the number of factors that affect the complexity of a multiple response problem increases, conventional optimization algorithms can fail to find the global optimum. For these situations, a common approach is to implement a heuristic search procedure like the GA and ANN or other optimization algorithms like Controlled Random Search (CRS) Price, W. L. (1977). However, it has been found that GA was adapted many times by previous researchers; less effort was made on application of CRS and even PSO in optimizing features of submerged arc weld. In consideration of the above, the present study aims at evaluating a near optimal parameter setting for the optimization of bead geometry parameters of a submerged arc weld. The study proposes integrating RSM-based desirability function approach and a PSO algorithm for multi-response optimization of SAW. Bead geometry parameters of submerged arc weld on mild steel were selected as multi-objective responses and they were optimized to select the optimal process environment. Finally, the study concludes the effectiveness and application feasibility of the proposed integrated approach.

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2. Desirability Function (DF) Approach

Individual desirability values related to each of the quality parameters are calculated using the formula proposed by Derringer and Suich in1980.

There are three types of desirability function: Lower-the-Better (LB), Higher-the-Better (HB) and Nominal-the-Best (NB). In the present investigation, for reinforcement and bead width LB criteria; and for penetration depth HB criteria have been selected. This is because, the objective of the work was to minimize reinforcement and bead width (to reduce weld metal consumption) and to maximize penetration depth as strength of the welded joint directly depends on penetration depth. The NB criterion is generally selected in cases where responses have their fixed target value.

An individual desirability value using the Lower-the-better (LB) criterion is shown in Fig. 1. The value of $\hat{y}$ is expected to be the lower the better. When $\hat{y}$ is less than a particular criteria value, a desirability value d_i equal to 1; if $\hat{y}$ exceeds a particular criteria value, the desirability value equals to 0. d_i varies within the range 0 to 1. The desirability function of the Lower-the-better (LB) criterion can be written as below (Eqs. 1 to 3). Here, $y_{\min}$ denotes the lower tolerance limit of $\hat{y}$, the $y_{\max}$ represents the upper tolerance limit of $\hat{y}$ and r represents the desirability function index, which is to be assigned previously according to the consideration of the optimization solver. If the corresponding response is expected to be closer to the target, the index can be set to the larger value, otherwise a smaller value.

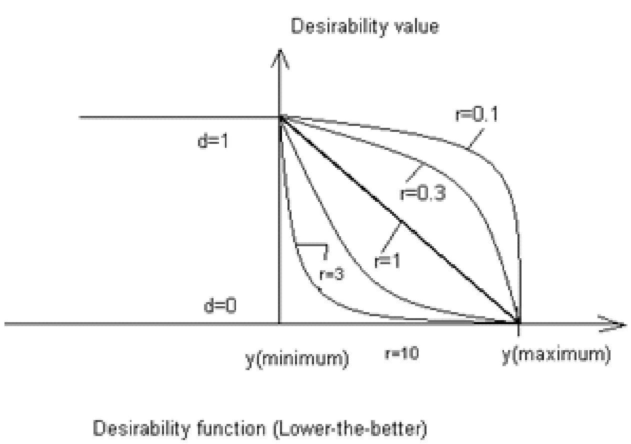

Figure 1. Desirability Function (LB)

$$\text{If } \hat{y} \le y_{\min},\ d_i = 1 \tag{1}$$

$$\text{If } y_{\min} \le \hat{y} \le y_{\max},\ d_i = \left(\frac{\hat{y} - y_{\max}}{y_{\min} - y_{\max}} \right)^r \tag{2}$$

$$\text{If } \hat{y} \ge y_{\max},\ d_i = 0 \tag{3}$$

An individual desirability value using the Higher-the-better (HB) criterion is shown in Fig. 2. The value of $\hat{y}$ is expected to be the higher the better. When $\hat{y}$ is exceeds a particular criterion value, according to the requirement, the desirability value d_i is equals to 1; if $\hat{y}$ is less than a particular criteria value, *ie*. less than the acceptable limit, the desirability value is equals to 0. The desirability function of the Higher-the-better (HB) criterion can be written as below (Eqs. 4 to 5). Here, $y_{\min}$ denotes the lower tolerance limit of $\hat{y}$, the $y_{\max}$ represents the upper tolerance limit of $\hat{y}$ and r represents the desirability function index, which must have been previously according to the consideration of the optimization solver. If the corresponding response is expected to be closer to the target, the index can be set to the larger value, otherwise to a smaller value.

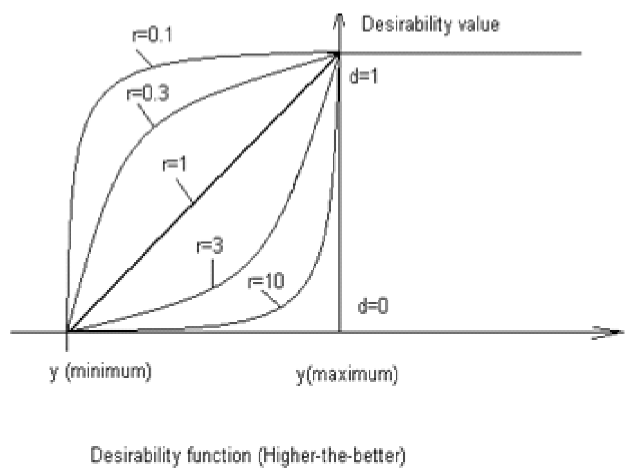

Figure 2. Desirability Function (HB)

$$\text{If } \hat{y} \le y_{\min},\ d_i = 0 \tag{4}$$

$$\text{If } y_{\min} \le \hat{y} \le y_{\max},\ d_i = \left(\frac{\hat{y} - y_{\min}}{y_{\max} - y_{\min}} \right)^r \tag{5}$$

$$\text{If } \hat{y} \ge y_{\max},\ d_i = 1 \tag{6}$$

The individual response desirability values were accumulated to calculate the overall desirability, using the following Eq. (7). Here, D is the overall desirability value, d_i is the individual desirability value of ith quality characteristic and n is the total number of responses. w_i, is the individual response weightage.

$$D = (d_1^{w_1} d_2^{w_2} \ldots\ldots\ldots\ldots d_n^{w_n})^{\frac{1}{\sum w}} \tag{7}$$

3. Response Surface Methodology (RSM)

The response function that represents any of the output features of the weldment can be expressed as

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$$Y = f(V, Wf, Tr, N) \quad (8)$$

Here, Y is the response. V = voltage (OCV), Wf = Wire feed rate, Tr = Traverse Speed and N = electrode stick-out.

The selected relationship is a second-degree response surface, which is expressed as follows: -

$$\begin{aligned} Y = \beta_0 &+ b_1 V + b_2 Wf + b_3 Tr + b_4 N + b_{11} V^2 \\ &+ b_{22} Wf^2 + b_{33} Tr^2 + b_{44} N^2 \\ &+ b_{12} V.Wf + b_{13} V.Tr + b_{14} V.N \\ &+ b_{23} Wf.Tr + b_{24} Wf.N + b_{34} Tr.N \end{aligned} \quad (9)$$

$\beta_0, b_i\big|_{i=1}^{4}$, $b_{ii}\big|_{i=1}^{4}$ and all b_{ij} (interaction term coefficients) are constant. The dimensions (units) of the constants should be such that they must take care of the dimensional similarity on both sides of Eq. (9).

The Response Surface Methodology (RSM) is an efficient tool, which is widely applied for modeling the output response(s) of a process in terms of the important controllable variables and then finding the operating conditions that optimize the response. The Eq. (9) can be written as a multiple linear regression model as follows: -

$$\begin{aligned} Y = \beta_0 &+ \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 \\ &+ \beta_6 x_6 + \beta_7 x_7 + \beta_8 x_8 + \beta_9 x_9 \\ &+ \beta_{10} x_{10} + \beta_{11} x_{11} + \beta_{12} x_{12} + \beta_{13} x_{13} + \beta_{14} x_{14} \end{aligned} \quad (10)$$

Here, $Y = f(x_i\big|_{i=1}^{14})$ and

$$\begin{aligned} &\beta_1 = b_1, \beta_2 = b_2, \beta_3 = b_3, \beta_4 = b_4, \beta_5 \\ &\quad = b_{11}, \beta_6 = b_{22}, \beta_7 = b_{33}, \\ &\beta_8 = b_{44}, \ \beta_9 = b_{12}, \beta_{10} = b_{13}, \beta_{11} \\ &\quad = b_{14}, \beta_{12} = b_{23}, \ \beta_{13} = b_{24}, \beta_{14} = b_{34} \\ &x_1 = V, x_2 = Wf, x_3 = Tr, x_4 = N, x_5 \\ &\quad = V^2, x_6 = Wf^2, x_7 = Tr^2, \\ &x_8 = N^2, \ x_9 = V.Wf, x_{10} = V.Tr, x_{11} \\ &\quad = V.N, x_{12} = Wf.Tr, x_{13} = Wf.N, \ x_{14} = Tr.N \end{aligned}$$

The method of least squares can be used to estimate the regression coefficients in Eq. (10). In this study regression coefficients were computed by statistical software package MINITAB (Release 14).

4. Particle Swarm Optimization (PSO) Algorithm

Particle swarm optimization (PSO) is a population-based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995, inspired by the social behavior of bird-flocking or fish-schooling.

PSO shares many similarities with evolutionary computation techniques such as Genetic Algorithms (GA). The system is initialized with a population of random solutions and searches for optima by updating generations. However, unlike GA, PSO has no evolution operators such as crossover and mutation. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles.

Each particle keeps track of its coordinates in the problem space which is associated with the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called *pbest*. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the neighbors of the particle. This location is called *lbest*. When a particle takes all the population as its topological neighbors, the best value is a global best and is called *gbest*.

The particle swarm optimization concept consists of, at each time step, changing the velocity of (accelerating) each particle toward its p*best* and *lbest* locations (local version of PSO). Acceleration is weighted by a random term, with separate random numbers being generated for acceleration toward *pbest* and *lbest* locations.

In the past several years, PSO has been successfully applied in many research and application areas. It has been demonstrated that PSO gets better results in a faster, cheaper way than other methods.

Another reason that PSO is attractive is that there are few parameters to adjust. One version, with slight variations, works well in a wide variety of applications. Particle swarm optimization was used for approaches that can be used across a wide range of applications, as well as for specific applications focused on a specific requirement.

5. Experimentation

Bead-on-plate submerged arc welding (on mild steel plates of thickness 10 mm) was carried out following 34 full factorial design which consists of 81 combinations of voltage (OCV), wire-feed rate, traverse speed and electrode stick-out. Each process control parameters was varied in three different levels during experiments. Interaction effects of process parameters were assumed negligible in the present study. Three responses related to features of bead geometry viz. bead width, reinforcement and depth of penetration were selected in the present study. A copper coated electrode wire of diameter 3.16 mm (AWS A/S 5.17:EH14) was used during the experiments. Welding was performed with flux (AWS A5.17/SFA 5.17) with grain size 0.2 to 1.6 mm with basicity index 1.6 (Al_2O3+MnO_2 35%, CaO+MgO 25% and SiO_2+TiO_2 20% and CaF_2 15%). The experiments were performed on a Submerged Arc Welding Machine-INDARC AUTOWELD MAJOR (Maker: IOL Ltd., India). While the weld was being made, the specimens were prepared for metallographic test. Features of bead geometry (macrostructure) were observed in Optical Trinocular Metallurgical Microscope (Make: Leica, GER-

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Table 1. Process control parameters and their limits

Parameters	Units	Notation	Level -1	Level 0	Level +1
Voltage (OCV)	Volts	V	27	28	29
Wire feed rate	cm/min	Wf	655	970	1285
Traverse speed	cm/min	Tr	72	98	124
Stick-out	mm	N	27	29	31

Table 2. Design of experiment and data related to bead geometry parameters

Sl. No.	Design of experiment (Factorial combination)				Response data (Bead geometry)		
	V	Wf	Tr	N	P	R	W
1	-1	-1	-1	-1	3.849	1.761	10.061
2	-1	-1	-1	0	3.748	1.725	10.520
3	-1	-1	-1	1	3.627	1.709	11.219
4	-1	-1	0	-1	3.472	1.374	9.151
5	-1	-1	0	0	3.451	1.368	9.320
6	-1	-1	0	1	3.410	1.382	9.729
7	-1	-1	1	-1	3.155	1.287	8.821
8	-1	-1	1	0	3.214	1.311	8.700
9	-1	-1	1	1	3.253	1.355	8.819
10	-1	0	-1	-1	4.149	1.836	10.980
11	-1	0	-1	0	4.038	1.780	11.530
12	-1	0	-1	1	3.907	1.744	12.320
13	-1	0	0	-1	3.762	1.446	9.720
14	-1	0	0	0	3.731	1.420	9.980
15	-1	0	0	1	3.680	1.414	10.480
16	-1	0	1	-1	3.435	1.356	9.040
17	-1	0	1	0	3.484	1.360	9.010
18	-1	0	1	1	3.513	1.384	9.220
19	-1	1	-1	-1	4.649	2.067	11.559
20	-1	1	-1	0	4.528	1.991	12.200
21	-1	1	-1	1	4.387	1.935	13.081
22	-1	1	0	-1	4.252	1.674	9.949
23	-1	1	0	0	4.211	1.628	10.300
24	-1	1	0	1	4.150	1.602	10.891
25	-1	1	1	-1	3.915	1.581	8.919
26	-1	1	1	0	3.954	1.565	8.980
27	-1	1	1	1	3.973	1.569	9.281
28	0	-1	-1	-1	3.638	1.565	11.671
29	0	-1	-1	0	3.577	1.515	11.980
30	0	-1	-1	1	3.496	1.485	12.529
31	0	-1	0	-1	3.321	1.208	10.121
32	0	-1	0	0	3.340	1.188	10.140
33	0	-1	0	1	3.339	1.188	10.399
34	0	-1	1	-1	3.064	1.151	9.151
35	0	-1	1	0	3.163	1.161	8.880
36	0	-1	1	1	3.242	1.191	8.849
37	0	0	-1	-1	3.888	1.670	12.550
38	0	0	-1	0	3.817	1.600	12.950
39	0	0	-1	1	3.726	1.550	13.590
40	0	0	0	-1	3.561	1.310	10.650
41	0	0	0	0	3.570	1.270	10.760
42	0	0	0	1	3.559	1.250	11.110
43	0	0	1	-1	3.294	1.250	9.330
44	0	0	1	0	3.383	1.240	9.150
45	0	0	1	1	3.452	1.250	9.210

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46	0	1	-1	-1	4.338	1.931	13.089
47	0	1	-1	0	4.257	1.841	13.580
48	0	1	-1	1	4.156	1.771	14.311
49	0	1	0	-1	4.001	1.568	10.839
50	0	1	0	0	4.000	1.508	11.040
51	0	1	0	1	3.979	1.468	11.481
52	0	1	1	-1	3.724	1.505	9.169
53	0	1	1	0	3.803	1.475	9.080
54	0	1	1	1	3.862	1.465	9.231
55	1	-1	-1	-1	3.523	1.509	14.101
56	1	-1	-1	0	3.502	1.445	14.260
57	1	-1	-1	1	3.461	1.401	14.659
58	1	-1	0	-1	3.266	1.182	11.911
59	1	-1	0	0	3.325	1.148	11.780
60	1	-1	0	1	3.364	1.134	11.889
61	1	-1	1	-1	3.069	1.155	10.301
62	1	-1	1	0	3.208	1.151	9.880
63	1	-1	1	1	3.327	1.167	9.699
64	1	0	-1	-1	3.723	1.644	14.940
65	1	0	-1	0	3.692	1.560	15.190
66	1	0	-1	1	3.641	1.496	15.680
67	1	0	0	-1	3.456	1.314	12.400
68	1	0	0	0	3.505	1.260	12.360
69	1	0	0	1	3.534	1.226	12.560
70	1	0	1	-1	3.249	1.284	10.440
71	1	0	1	0	3.378	1.260	10.110
72	1	0	1	1	3.487	1.256	10.020
73	1	1	-1	-1	4.123	1.935	15.439
74	1	1	-1	0	4.082	1.831	15.780
75	1	1	-1	1	4.021	1.747	16.361
76	1	1	0	-1	3.846	1.602	12.549
77	1	1	0	0	3.885	1.528	12.600
78	1	1	0	1	3.904	1.474	12.891
79	1	1	1	-1	3.629	1.569	10.239
80	1	1	1	0	3.748	1.525	10.000
81	1	1	1	1	3.847	1.501	10.001

P (Penetration), R (Reinforacement) and W (bead width)

MANY, Model No. DMLM, S6D & DFC320 and Q win Software). The domain of the experiment is shown in Appendix (Table 1). The design of experiment (DOE) and collected experimental data, related to individual quality indicators of bead geometry are listed in Appendix (Table 2). These data were utilized in proposed integrated optimization approach, to be discussed later.

6. Results and Discussions of Proposed Optimization Approach

6.1 Calculation of Individual Desirability Values and Overall Desirability Function

The flow chart of the approach is furnished below in Appendix (Fig. 3). Response data were transformed to their individual desirability values using a desirability function approach (Fuller, D. and Scherer, W., 1998). These are shown in Table 3. For depth of penetration HB (Higher-the-better) and for reinforcement as well as bead width LB (Lower-the-better) criteria were selected. The index of desirability function was the selected one. In this computation the minimum and maximum values of each response (Table 2) were denoted as y_{min} and y_{max} respectively. Individual desirability values of the responses were clustered to calculate the overall desirability value (Table 3). It was assumed that all responses are equally important. The same weight was assigned to all responses.

6.2 Development of Response Surface Model of Overall Desirability

RSM was applied to derive a mathematical model of overall desirability. Overall desirability was expressed as a function of four process control parameters. The model consists of linear, square (quadratic) and interaction terms of the process parameters affecting the overall desirability value. The constant term and coefficients of the

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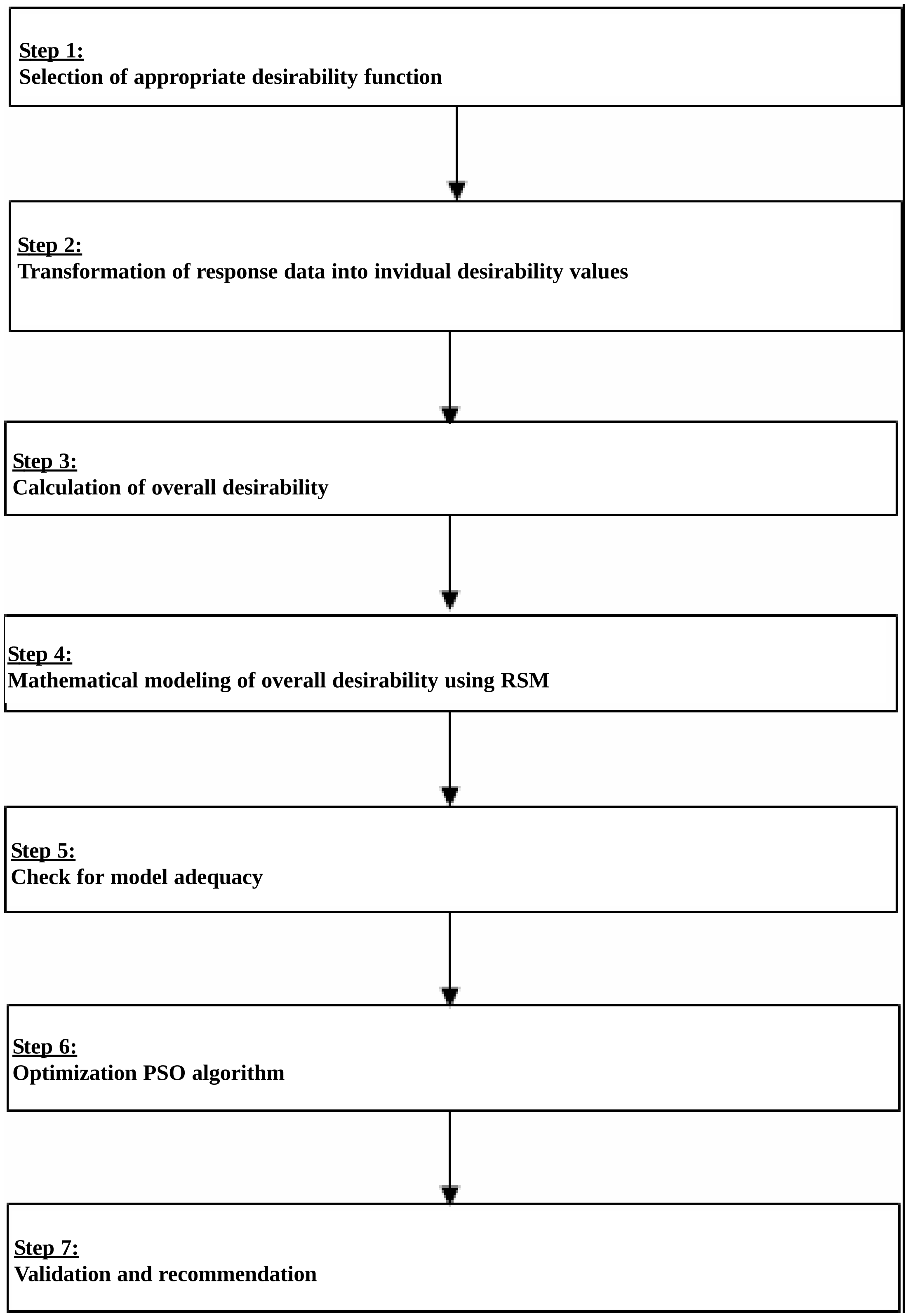

Figure 3. Proposed optimization approach

factors/interaction of factors were evaluated with the statistical-software package Minitab (Release 14). Minitab's multiple linear regression approach was used to derive this model (Eq. 11).

$$\begin{aligned} D = {} & 0.625 - 0.0505V + 0.0317\,Wf + 0.0677\,Tr \\ & + 0.0244N - 0.0343V^2 - 0.0445\,Wf^2 - 0.112\,Tr^2 \\ & - 0.0315N^2 - 0.0003V.Wf + 0.0166\,V.Tr \\ & + 0.0049V.N + 0.114Wf.Tr - 0.0131Wf.N \\ & + 0.0411Tr.N \end{aligned} \tag{11}$$

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Table 3. Individual desirability values and calculated overall desirability

Sl. No.	DP	DR	DW	D
1	0.4953	0.3280	0.8223	0.5112
2	0.4315	0.3666	0.7624	0.4941
3	0.3552	0.3837	0.6712	0.4506
4	0.2574	0.7428	0.9411	0.5646
5	0.2442	0.7492	0.9191	0.5519
6	0.2183	0.7342	0.8657	0.5177
7	0.0574	0.8360	0.9842	0.3615
8	0.0946	0.8103	1.0000	0.4248
9	0.1192	0.7631	0.9845	0.4474
10	0.6845	0.2476	0.7024	0.4919
11	0.6145	0.3076	0.6306	0.4921
12	0.5319	0.3462	0.5275	0.4597
13	0.4404	0.6656	0.8669	0.6334
14	0.4208	0.6935	0.8329	0.6241
15	0.3886	0.6999	0.7677	0.5933
16	0.2341	0.7621	0.9556	0.5545
17	0.2650	0.7578	0.9595	0.5776
18	0.2833	0.7320	0.9321	0.5782
19	1.0000	0.0000	0.6268	0.0000
20	0.9237	0.0815	0.5431	0.3444
21	0.8347	0.1415	0.4281	0.3698
22	0.7495	0.4212	0.8370	0.6417
23	0.7237	0.4705	0.7911	0.6458
24	0.6852	0.4984	0.7140	0.6247
25	0.5369	0.5209	0.9714	0.6477
26	0.5615	0.5380	0.9635	0.6627
27	0.5735	0.5338	0.9242	0.6565
28	0.3621	0.5380	0.6122	0.4923
29	0.3237	0.5916	0.5719	0.4784
30	0.2726	0.6238	0.5002	0.4398
31	0.1621	0.9207	0.8145	0.4954
32	0.1741	0.9421	0.8120	0.5107
33	0.1735	0.9421	0.7782	0.5029
34	0.0000	0.9818	0.9411	0.0000
35	0.0625	0.9711	0.9765	0.3898
36	0.1123	0.9389	0.9806	0.4693
37	0.5199	0.4255	0.4975	0.4792
38	0.4751	0.5005	0.4452	0.4731
39	0.4177	0.5541	0.3617	0.4375
40	0.3136	0.8114	0.7455	0.5745
41	0.3192	0.8542	0.7311	0.5842
42	0.3123	0.8757	0.6854	0.5723
43	0.1451	0.8757	0.9178	0.4886
44	0.2013	0.8864	0.9413	0.5517
45	0.2448	0.8757	0.9334	0.5849
46	0.8038	0.1458	0.4271	0.3685
47	0.7527	0.2422	0.3630	0.4045
48	0.6890	0.3173	0.2676	0.3882
49	0.5912	0.5348	0.7208	0.6108
50	0.5905	0.5991	0.6946	0.6264
51	0.5773	0.6420	0.6370	0.6181
52	0.4164	0.6024	0.9388	0.6175

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53	0.4662	0.6345	0.9504	0.6551
54	0.5035	0.6452	0.9307	0.6712
55	0.2896	0.5981	0.2950	0.3711
56	0.2763	0.6667	0.2742	0.3697
57	0.2505	0.7138	0.2222	0.3412
58	0.1274	0.9486	0.5809	0.4126
59	0.1647	0.9850	0.5980	0.4595
60	0.1893	1.0000	0.5837	0.4798
61	0.0032	0.9775	0.7910	0.1346
62	0.0909	0.9818	0.8460	0.4226
63	0.1659	0.9646	0.8696	0.5182
64	0.4158	0.4534	0.1855	0.3270
65	0.3962	0.5434	0.1529	0.3205
66	0.3640	0.6120	0.0889	0.2706
67	0.2473	0.8071	0.5170	0.4691
68	0.2782	0.8650	0.5223	0.5009
69	0.2965	0.9014	0.4961	0.5100
70	0.1167	0.8392	0.7729	0.4230
71	0.1981	0.8650	0.8160	0.5190
72	0.2669	0.8692	0.8277	0.5769
73	0.6681	0.1415	0.1203	0.2249
74	0.6423	0.2529	0.0758	0.2310
75	0.6038	0.3430	0.0000	0.0000
76	0.4934	0.4984	0.4976	0.4964
77	0.5180	0.5777	0.4909	0.5277
78	0.5300	0.6356	0.4529	0.5343
79	0.3565	0.5338	0.7991	0.5337
80	0.4315	0.5809	0.8303	0.5926
81	0.4940	0.6066	0.8302	0.6289

DP (Desirability of penetration), DR (Desirability of reinforcement), DW (Desirability of bead width), OD (Overall desirability)

Table 4. Check for significance of the constant and coefficients in the model

Predictor	Coefficient	P-value	Comment
Constant	0.6250	0.000	Significant
V	-0.0505	0.000	Significant
Wf	0.0317	0.003	Significant
Tr	0.0677	0.000	Significant
N	0.0244	0.019	Significant
V2	-0.0343	0.054	Insignificant
Wf*Wf	-0.0445	0.013	Significant
Tr*Tr	-0.1120	0.000	Significant
N*N	-0.0315	0.076	Insignificant
V*Wf	-0.0003	0.983	Insignificant
V*Tr	0.0166	0.185	Insignificant
V*N	0.0049	0.694	Insignificant
Wf*Tr	0.1140	0.000	Significant
Wf*N	-0.0131	0.292	Insignificant
Tr*N	0.0411	0.001	Significant

S = 0.0742512 R-Sq = 78.4% R-Sq (adj) = 73.8%

P - value (probability of significance), S, R-sq (determine to what extent the model can predict well)

The extent of the significance of presence of factors (and interaction of factors) within the model was checked with the Analysis of Variance method (ANOVA) (Table 4). Based on the calculated P-value (probability of significance) of the terms (from Table 4) under considerations, insignificant terms (P-value less than 0.05) were excluded and the final reduced model consisting of significant terms was derived (Eq. 12). This model was optimized (maximized) finally using PSO a algorithm.

$$D = 0.581 - 0.0505V + 0.0317\,Wf + 0.0677\,Tr + 0.0244N - 0.0445Wf^2 - 0.112\,Tr^2 + 0.114Wf.Tr + 0.0411Tr.N \quad (12)$$

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6.3 Particle Swarm Optimization (PSO)

In the present study, the reduced mathematical model for overall desirability (Eq. 12) was optimized using a PSO algorithm. It is a constrained optimization problem since the experimental domain was defined by the bounds on the process variables (V, Wf, Tr and N). The objective is to maximize (Eq. 12) subject to the bounds on the process variables. The values of the parameters of the PSO algorithm used here as follows:

Population size= 50, Range of Velocity Variation v_{max} = +4, v_{min} = -4, Maximum number of iteration = 100, Weighting factor = 0.8, Decrement factor (alpha) = 0.9 and Social parameters C1 = 2.0 and C2 = 2.0. By trial and error the values of the aforesaid parameters were chosen so as to improve an objective function value (overall desirability) at the optimal setting.

After optimization the optimal setting becomes:

$$\begin{bmatrix} V \\ Wf \\ Tr \\ N \end{bmatrix} = \begin{bmatrix} -0.384 \\ 0.916 \\ 0.982 \\ 0.936 \end{bmatrix}$$

(Optimal value of overall desirability becomes 0.707). Figure 4 shows the convergence curve in PSO. Due to non-availability of optimal factors value within equipment's provision, a compromise has to be made. The optimal setting should be modified and set to:

$$\begin{bmatrix} V \\ Wf \\ Tr \\ N \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \\ 1 \\ 1 \end{bmatrix}$$

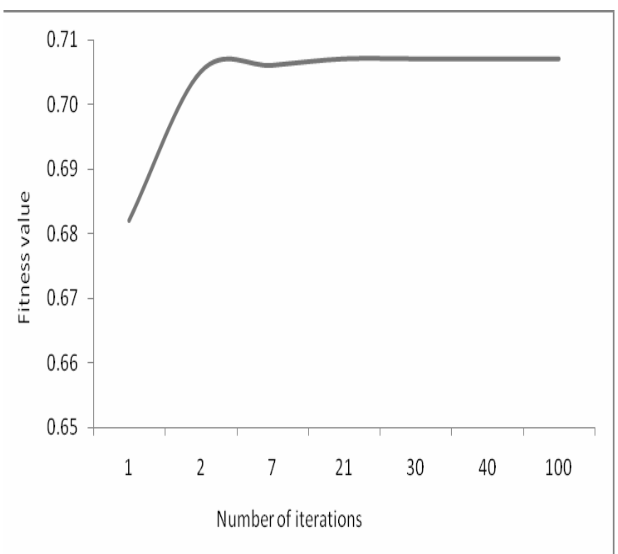

Figure 4. PSO convergence curve

After evaluating the optimal parameter settings, the next step is to predict and verify the enhancement of quality characteristics using the optimal parametric combination. Table 5 reflects the satisfactory result of confirmatory experiment. It indicates that the quality of the weld has improved.

Table 5. Results of confirmatory experiment

	Optimal setting	
	Prediction	Experiment
Level of factors	$V_0 Wf_1 Tr_1 N_1$	$V_0 Wf_1 Tr_1 N_1$
Overall desirability	0.769	0.789

N.B. Subscripts on factors notation represents factor levels

7. Conclusions

Weld quality in SAW depends on features of bead geometry, mechanical-metallurgical characteristics of the weld as well as on weld chemistry. The weld quality improvement is treated as a multi-factor, multi-objective optimization problem. The practical application of SAW requires efficient optimization methodology because process parameters are expected to interact in a complex manner. Therefore, any optimization algorithm must seek to identify interaction effects of input factors and be incorporated in the course of an optimization procedure in a convenient way for developing an efficient methodology. The developed methodology based on RSM, desirability function and PSO algorithm can be applied in practice for continuous quality improvement and off-line quality control. The desirability Function approach converts each of the responses (objectives) into their individual desirability value. Corresponding to each objective, these individual desirability values are then accumulated to compute the overall/composite desirability function, which is to be optimized (maximized) finally. RSM has been applied to derive a mathematical model of overall desirability represented as a function of process control parameters. This mathematical model has been optimized within an experimental domain. Although the paper considers SAW, the procedure is quite generic and can be applied to any process where complex relations among input and output parameters are difficult to predict.

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