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Bead geometry optimization of Submerged Arc Weld: Exploration of Weighted Principal Component Analysis (WPCA)

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Abstract— **The present work attempts to overcome underlying assumptions in traditional Taguchi based optimization techniques highlighted in literature. Taguchi method alone fails to solve multi-response optimization problems. In order to overcome this limitation, exploration of grey relation theory, desirability function approach, utility theory etc. have been found amply applied in literature in combination with Taguchi method. But aforesaid approaches relies on the assumption that individual response features are uncorrelated i.e. independent of each other which are really impossible to happen in practice. The study takes into account this response correlation and proposes an integrated methodology in a case study on optimization of multiple bead geometry parameters of submerged arc weldment. Weighted Principal Component Analysis (WPCA) has been applied to eliminate response correlation and to convert correlated responses into equal or less number of uncorrelated quality indices called principal components. Based on individual principal components a Multi-response Performance Index (MPI) has been introduced to derive an equivalent single objective function which has been optimized (maximized) using Taguchi method. Experiments have been conducted based on Taguchi's L_{25} Orthogonal Array design with combinations of process control parameters: voltage, wire feed, welding speed and electrode stick-out. Different bead geometry parameters: bead width, bead height, penetration depth and HAZ dimensions have been optimized. Optimal result has been verified by confirmatory test. The study highlights effectiveness of the proposed method for solving multi-objective optimization of submerged arc weld.**

Keywords-submerged arc weld; Taguchi method; Weighted Principal Component Analysis (WPCA); Multi-response Performance Index (MPI)

I. INTRODUCTION AND PRIOR STATR OF ART

The Submerged Arc Welding (SAW) process is mainly characterized by multiple process parameters influencing multiple performance outputs such as deposition rate, percent dilution, features of bead geometry, mechanical-metallurgical characteristics of weldment as well as the heat affected zone (HAZ), which subsequently affect overall weld quality. Proper selection and control of process parameters can achieve satisfactory quality weld. However, SAW optimization is very difficult due to existence of multiple quality indices which may be contradicting in nature depending on the requirements. Moreover, direct and interactive effects of process parameters also influence extent of weld quality. It is therefore, indeed require selecting the best suited process environment i.e. optimal parametric combination to produce desired quality weld. Literature has been found rich enough in investigations on modeling, simulation as well as optimization of welding phenomena.

Tsai et al. [1] optimized submerged arc welding process parameters in hardfacing. Tarng and Yang [2] applied Taguchi method to the optimization of the submerged arc welding process. Taguchi method was used to formulate the experimental layout, to analyze the effect of each welding parameter on welding performance, and to predict the optimal setting for each welding parameter. Gunaraj and Murugan [3] applied Response Surface Methodology (RSM) for prediction and optimization of weld bead quality in submerged arc welding of pipes by establishing mathematical models. Tarng et al. [4] applied grey based Taguchi method for optimization submerged arc welding process parameters in hardfacing. Datta et al. [5] developed statistical models for predicting bead volume of submerged arc butt-weld. Patnaik et al. [6] studied the effect of process parameters on output features of submerged arc weld by using Taguchi method. The relationship between control factors and performance outputs was established by means of nonlinear regression analysis, resulting in a valid mathematical model. Finally, Genetic Algorithm (GA) was employed to optimize the welding process with multiple objectives. Datta et al. [7]] applied Taguchi philosophy for parametric optimization of bead geometry and HAZ width in submerged arc weld. In another paper Datta et al. [8] used grey relational analysis in combination with Taguchi method to optimize features of bead geometry of submerged arc weld. Muruganath [9] used Non-dominated Sorting Genetic Algorithms (NSGA) to optimize the contradicting combination of strength and toughness of steel welds.

Literature depicts two diverse directions on the research of weld optimization. In one trend attempt has been made to model the welding process behavior. In this case, mathematical models are developed to represent process responses as a function of input parameters. If the problem deals with only one objective function; it can easily be optimized by an optimization algorithm. But when more than one response comes under consideration and the system is subjected to a number of constraints it is very difficult to tackle the problem. Evolutionary algorithms like Simulated Annealing, Genetic Algorithm, Neural Network (NN) and Particle Swarm (PSO) optimization can provide an approximate solution in the experimental domain. If these algorithms follow continuous search ideology then the optimal solution may be infeasible to achieve in practice. The reason behind that, the setup usually has the provision of controlling parameters at some discrete levels. This problem can be avoided if these algorithms are modified to follow continuous search to discrete search in the parametric domain. This may add complexity to the problem and requires in depth knowledge of computer programming.

The second trend in solving optimization problem highlights application feasibility of Taguchi's philosophy of robust design. Taguchi method is very popular as it requires a well balanced experimental design (limited number of experiments) which saves time as well as cost. Not only this, Taguchi approach finds optimal at discrete levels of the process parameters. But this method fails to solve multi-objective optimization problems. In order to overcome this, previous researchers applied desirability function approach [10], grey relation theory [8], utility theory [11, 12], VIKOR method [13] in combination with Taguchi method. The purpose is to aggregate multiple responses (objective functions) into an equivalent quality index (single objective function) which can easily be optimized using Taguchi method. But aforesaid approaches are based on the assumption that response features i.e. quality indices are uncorrelated i.e. independent which seems to be totally infeasible in practical case. To overcome this shortcoming, in the present work, Principal Component Analysis (PCA) has been explored to eliminate correlation that exists between the responses and to evaluate independent i.e. uncorrelated quality indices which are denoted as Principal Components. These individual principal components have been aggregated further to compute a multi-response performance index (MPI). MPI has been optimized (maximized) finally by Taguchi method. Optimal result was verified through confirmatory test. This indicates application feasibility of the aforesaid methodology proposed for multi-response optimization and off-line control of correlated multi-quality weld bead characteristics in submerged arc welding.

II. EXPERIMENTS AND DATA COLLECTION

Experiments of submerged arc welding on mild steel plates of thickness 15.50 mm [SAIL Steel, IS 2062, Grade A], have been carried out as per Taguchi's L_{25} orthogonal array (OA) design [14], with twenty five combinations of voltage (OCV), wire feed rate, traverse speed and electrode stick-out. The selected process control parameters and corresponding parametric values at different levels have been furnished in Table I. Design of experiment has been given in Table II. In order to form bead-on-plate submerged arc welds on the samples [$100 \times 50 \times 15.50$], copper coated electrode wire of 3.15 mm diameter has been used with type AUTOMELT EL8 (AWS A 5.17/5.23 EL8, IS 7280: AS-1) of ADOR WELDING LIMITED, INDIA. Chemical composition of the wire: C- 0.04%, Mn- 0.4%, Si- 0.05%. AUTOMELT A55 flux [Make: ADOR WELDING LIMITED, INDIA] has been used with the following compositions.

SiO_2 + TiO_2= 30%
CaO + MgO= 10%
Al_2O_3 + MnO= 45%
CaF_2= 15%
Grain Size = 0.25 - 2.00 mm
Basicity Index = 0.6

Welding has been performed on the SAW setup [Make: ADOR WELDING LIMITED, INDIA] Model- MAESTRO 1200(F). After removing the solidified slag, the weld samples have been cooled in the room atmospheric condition. Cross section of the samples of about 15-20 mm of thickness has been cut by hydraulic power saw with normal water as coolant. The section faces of each sample have been machined by shaper to get parallel plane as well as semi finished surface. Then the samples (sections) have been filed with smooth flat file followed by finishing with emery papers of grade 150, 600, 2000 consecutively to get almost mirror finish. The faces of the samples have been polished by self fabricated polisher using leather buffer to achieve the mirror finished surface. The finished surfaces have been etched with natal solution i.e. 10% nitric acid solution in distilled water in room atmospheric condition. The weld bead geometry: bead width, penetration depth, reinforcement and HAZ dimension has been observed (tabulated Table III) under Optical Trinocular Metallurgical Microscope (Make: Leica, GERMANY, Model No. DMLM, S6D & DFC320 and Q win Software).

The entire work is based on two assumptions:

(a) Bead quality depends on features of bead geometry only.
(b) There is no interaction effect of the process parameters involved.

III. PROPOSED METHODOLOGY

Traditional Taguchi approach fails solve a multi-response optimization problem. It is felt necessary to combine these multiple objectives (criteria or response attributes) into an equivalent single objective function which is going to be treated as the representative overall quality index for multi-quality characteristics. In this context application of Principal Component Analysis (PCA) deserves mention [15]. The method is helpful to eliminate response correlation, if it exists. This approach converts correlated responses into an equal or less number of uncorrelated quality indices which are called individual principal components. The principal component which has the maximum accountability proportion (AP) is generally treated as overall performance index. But when more than one principal component has considerable value of accountability proportion which cannot be ignored; the problem of computing composite principal component arises. Literature indicates that different researchers suggested different approaches to calculate this composite principal component [15, 16, 17]. But those approaches are not reliable always and at the same time there is no physical interpretation of the said composite principal component. It is just a mathematical tool to facilitate the solution of optimization problems.

In consideration of the above Weighted Principal Component Analysis (WPCA) was suggested by Liao [18]. The study provided scientific means for computation of composite principal component. Values of individual principal components multiplied by their priority weight were added to calculate the composite principal component defined as Multi-response Performance Index (MPI). MPI was optimized (maximized) using Taguchi method.

IV. ANALYSIS RESULTS AND DISCUSSIONS

Experimental data (Table III) has been normalized first. The objective is to minimize bead width, reinforcement, depth of HAZ and to maximize depth of penetration. For this purpose (Lower-the-Better) LB criteria has been selected for bead width, reinforcement as well as depth of HAZ. Penetration depth follows Higher-the-Better (HB) criteria. Data has been normalized using the equations shown below.

(a) (Lower-the-Better) criteria:

$$X_i^*(k) = \frac{\min X_i(k)}{X_i(k)} \tag{4}$$

Here, $i = 1, 2, \ldots\ldots, m;$ $k = 1, 2, \ldots\ldots\ldots, n$

(b) HB (Higher-the-Better)

$$X_i^*(k) = \frac{X_i(k)}{\max X_i(k)} \tag{5}$$

Here, $i = 1, 2, \ldots\ldots, m;$ $k = 1, 2, \ldots\ldots\ldots, n$

Assuming, the number of experimental runs in Taguchi's OA design is m, and the number of quality characteristics is n.

$X_i^*(k)$ is the normalized data of the $k\,th$ element in the $i\,th$ sequence.

$X_{0b}(k)$ is the desired value of the $k\,th$ quality characteristic. After data normalization, the value of $X_i^*(k)$ will be between 0 and 1. The series $X_i^*, i = 1, 2, 3, \ldots\ldots, m.$ can be viewed as the comparative sequence used in the present case.

After data normalization a check has to be made whether responses are correlated or not. Table IV represents Pearson's correlation coefficient between the responses. In all cases non-zero value of correlation coefficient indicates that all response features are correlated to each other. In order to eliminate response correlation Principal Component Analysis has been applied. Table V represents results of PCA (Eigen value, Eigen vector, accountability proportion AP and cumulative accountability proportion CAP).

Next, correlated responses have been converted into uncorrelated quality indices called principal components (ψ_1 , ψ_2 , ψ_3 and ψ_4). These individual principal components have been furnished in Table VI. Accountability proportion of individual principal components has been treated as individual priority weights [18]. Finally, multi-response performance index (MPI) has been computed using the following equation (Table VI).

$$MPI = \psi_1 \times 0.509 + \psi_2 \times 0.342 + \psi_3 \times 0.082 + 0.067 \times \psi_4 \tag{5}$$

MPI has been treated as single objective function for optimization in order to maximize it. The factorial combination that maximized MPI can be treated as optimal parametric combination/ most favorable process environment ensuring high surface quality. This has been performed using Taguchi method. Figure 1 represents S/N ratio plot of MPI; S/N ratio has been calculated using Higher-the-Better (HB) criteria. Optimal setting has been evaluated from this plot. Predicted optimal combination becomes: V1 F1 S5 N4. Optimal result has been verified through confirmatory test. According to Taguchi' prediction [19] predicted value of S/N ratio for MPI becomes 0.320465 (higher than all entries in Table 9) whereas in confirmatory experiment it is obtained a value of 0.4892. So quality has improved using the optimal setting.

TABLE I. PROCESS PARAMETERS

Parameters	***Units***	***Level values***				
		Level 1	***Level 2***	***Level 3***	***Level 4***	***Level 5***
Voltage (OCV) V	V	32.5	35	37	39	41
Wire feed F	Knob setting	2	3	4	5	6
Traverse speed S	m/min	0.30	0.45	0.60	0.75	0.90
Stick-out N	mm	25	27	29	31	33

TABLE II. DESIGN OF EXPERIMENT

Sl. No.	***Design of experiment: Levels of factors (Factorial combinations)***			
	V	***F***	***S***	***N***
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	1	4	4	4
5	1	5	5	5
6	2	1	2	3
7	2	2	3	4
8	2	3	4	5
9	2	4	5	1
10	2	5	1	2
11	3	1	3	5
12	3	2	4	1
13	3	3	5	2
14	3	4	1	3
15	3	5	2	4
16	4	1	4	2
17	4	2	5	3
18	4	3	1	4
19	4	4	2	5
20	4	5	3	1
21	5	1	5	4
22	5	2	1	5
23	5	3	2	1
24	5	4	3	2
25	5	5	4	3

TABLE III. EXPERIMENTAL DATA

Sample No.	***Penetration (mm)***	***Reinforcement (mm)***	***Bead width (mm)***	***Width of HAZ (mm)***
01	1.61	2.14	15.41	1.17
02	3.27	2.19	15.25	1.39
03	4.93	3.38	12.68	1.13
04	5.30	3.69	9.80	0.75
05	5.17	3.71	9.73	0.60
06	1.39	1.81	13.99	1.47
07	2.27	2.16	12.65	1.08
08	4.17	2.43	13.20	1.00
09	4.99	3.16	12.19	0.71
10	8.76	**5.77**	18.13	**3.11**
11	1.51	1.59	11.15	0.97
12	2.47	2.07	13.35	0.97
13	4.78	2.64	10.01	0.61
14	7.34	5.58	17.00	2.01
15	8.21	4.85	11.59	1.03
16	1.70	1.45	10.01	1.06
17	2.76	1.63	11.97	0.74
18	6.82	3.92	20.53	1.53
19	6.99	4.35	16.06	1.20
20	8.62	3.94	13.89	1.23
21	1.45	1.53	8.57	1.83
22	3.35	2.74	21.37	2.59
23	6.30	3.09	18.14	1.15
24	8.81	2.54	15.77	0.71
25	7.26	4.57	13.16	0.70

TABLE IV. CORRELATION CHECK (#SIGNIFICANT CORRELATION)

Sl. No.	***Correlation between responses***	***Pearson's correlation coefficient***	***Comment***	***P-value***
1	Penetration and reinforcement	-0.647	Both are correlated	0.000#
2	Penetration and bead width	-0.204	Both are correlated	0.316
3	Penetration and HAZ width	+0.145	Both are correlated	0.481
4	Reinforcement and bead width	+0.501	Both are correlated	0.009#
5	Reinforcement and HAZ width	+0.143	Both are correlated	0.484
6	Bead width and HAZ width	+0.585	Both are correlated	0.002#

TABLE V. EIGENVALUES, EIGENVECTORS, ACCOUNTABILITY PROPORTION (AP) AND CUMULATIVE ACCOUNTABILITY PROPORTION (CAP) COMPUTED FOR THE FIVE MAJOR QUALITY INDICATORS

	ψ_1	ψ_2	ψ_3	ψ_4
Eigenvalues	2.0349	1.3666	0.3290	0.2695
Eigenvector	$\begin{vmatrix} -0.440 \\ +0.600 \\ +0.572 \\ +0.345 \end{vmatrix}$	$\begin{vmatrix} +0.584 \\ -0.291 \\ +0.349 \\ +0.673 \end{vmatrix}$	$\begin{vmatrix} +0.492 \\ +0.190 \\ +0.562 \\ -0.637 \end{vmatrix}$	$\begin{vmatrix} +0.472 \\ +0.721 \\ -0.484 \\ +0.153 \end{vmatrix}$
AP	0.509	0.342	0.082	0.067
CAP	0.509	0.850	0.933	1.000

TABLE VI. PRINCIPAL COMPONENTS AND CALCULATED MPI

Sample No.	*Penetration*	*Reinforcement*	*Bead width*	*Width of HAZ*	*Calculated MPI*
Ideal Situation	***1.0770***	***1.3150***	***0.6070***	***0.8620***	***1.1055***
01	0.8212	0.4487	0.2045	0.3841	0.6139
02	0.7043	0.5108	0.3493	0.4466	0.5918
03	0.5810	0.7952	0.3984	0.3275	0.6223
04	0.7473	1.0806	0.3525	0.2665	0.7967
05	0.8251	1.2094	0.2210	0.2854	0.8708
06	0.9025	0.3476	0.3141	0.4180	0.6320
07	0.8686	0.5655	0.2812	0.3627	0.6829
08	0.7281	0.7331	0.3289	0.4312	0.6772
09	0.7198	1.0113	0.2226	0.3873	0.7565
10	0.0502	0.8023	0.6797	0.4512	0.3859
11	1.1248	0.5193	0.2955	0.4610	0.8052
12	0.8775	0.6002	0.2378	0.4214	0.6997
13	0.9198	1.1178	0.2259	0.3882	0.8950
14	0.1807	0.7877	0.5524	0.3823	0.4323
15	0.3933	1.1073	0.5598	0.3867	0.6507
16	1.2000	0.5014	0.4055	0.4843	0.8480
17	1.0852	0.7196	0.2091	0.5668	0.8536
18	0.2554	0.7541	0.4359	0.4901	0.4565
19	0.3286	0.8891	0.4351	0.4330	0.5360
20	0.3115	1.0079	0.5873	0.5031	0.5851
21	1.1813	0.3900	0.6142	0.3272	0.8070
22	0.4595	0.3639	0.3654	0.4024	0.4153
23	0.4171	0.7970	0.3742	0.5271	0.5509
24	0.5049	1.1763	0.3675	0.7499	0.7397
25	0.4960	1.1930	0.2857	0.4337	0.7130

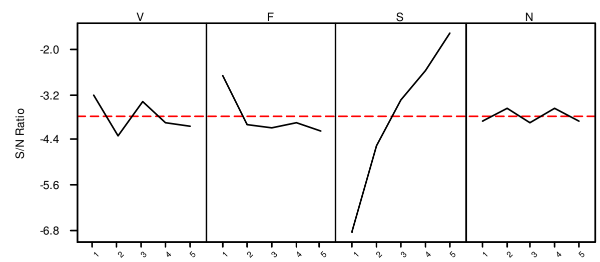

Figure 1. S/N ratio plot of MPI

V. CONCLUSIONS

The foregoing study deals with optimization of multiple bead geometry characteristics of SA weldment in order to determine an optimal parametric combination (favorable process environment) capable of producing desired weld quality. The study proposes an integrated optimization approach using Weighted Principal Component Analysis (WPCA) in combination with Taguchi's robust design methodology. The following conclusions may be drawn from the results of the experiments and analysis of the experimental data in connection with correlated multi-response optimization in SAW.

1) Application of PCA has been recommended to eliminate response correlation by converting correlated responses into uncorrelated quality indices called principal components which have been as treated as independent response variables for optimization.
2) Based on accountability proportion (AP); treated as individual response weights, WPCA can combine individual principal components into a single multi-response performance index MPI to be taken under consideration for optimization. This is really helpful in situations where large number of responses have to be optimized simultaneously.
3) The said approach can be recommended for continuous quality improvement and off-line quality control of a process/product.

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