International Journal of Integrated Engineering, Vol. 8 No. 3 (2016) p. 21-32

Optimization of Submerged Arc Welding process Parameters Using PCA-Based Taguchi Approach.

P.Sreeraj*

* Department of Mechanical Engineering, Younus College of Engineering and Technology, Kollam, 691010, INDIA.

Received 28 October 2016; accepted 8 December 2016, available online 8 December 2016

Abstract: The present study highlights optimization of submerged arc welding (SAW) process parameters in order to obtain optimal parametric combination to yield favorable weld bead geometry in mild steel plates IS 2062. Taguchi's L_{25} orthogonal array (OA) design and signal- to- noise ratio (S/N ratio) have been used in this study. Penetration (P), bead width (W), reinforcement (R) and Percentage dilution (D) are selected as objective functions. The principal component analysis coupled with Taguchi method has been applied to solve this multi response optimization problem. Carried out to meet basic assumption of Taguchi method, individual response correlations have been eliminated first by means of principal component analysis (PCA).The correlated responses then transformed into uncorrelated or independent 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 using Taguchi method. Developed model has been checked for adequacy and significance based on ANOVA test. Accuracy of optimization was confirmed by conducting confirmation tests. The study highlights effectiveness of the proposed method for solving multi-objective optimization of submerged arc weld.

Keywords: SAW, Taguchi's concept, orthogonal array, bead geometry, PCA

1. Introduction

Submerged arc welding is a multi-factor, multi-objective manufacturing process. Because of easy control of process variables, high quality, deep penetration and smooth finish, it is widely preferred in ship building industry. In the present work, the effect of voltage, current, nozzle to plate distance and welding speed on bead geometry have been studied. Mechanical and chemical properties of good weld depend on bead geometry. Bead geometry has a direct effect on process parameters. Because of this, it is necessary to study the relationship between process parameters and weld bead geometry.

Fig 1 shows weld bead geometry. Mechanical strength of weld metal is highly influenced by the composition of metal but also by weld bead shape. This is an indication of bead geometry. It mainly depends on welding current; welding speed, arc voltage etc [1]. This paper highlights the study carried out to develop mathematical models to optimize weld bead geometry, on bead on plate welding by submerged arc welding SAW.

In this study Taguchi method coupled principal component analysis (PCA) is used for solving the multi optimization problem. This method utilizes a well balanced experimental design with limited number of experimental runs called orthogonal array (OA) and signal to noise ratio (S/N ratio) which serve the objective function to be optimized, within experimental domain. The traditional Taguchi method cannot solve multi-objective optimization problems.

The original Taguchi method is designed and utilized to optimize a single quality characteristic or response. Furthermore, optimization of multiple objectives or responses is much more difficult than optimization of a single objective. Improving one particular quality characteristic would likely cause deliberate degradation of the other critical quality characteristics. It leads to increment of uncertainty at the time of decision-making process. In order to overcome this difficulty, the Taguchi method coupled with principal component analysis used to solve the optimization problem in this study.

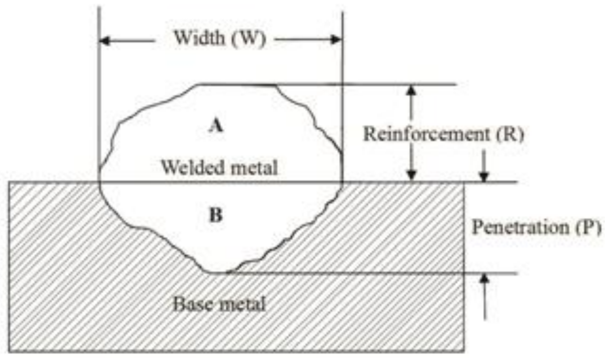

Fig 1 weld bead geometry

2. Taguchi Method

Taguchi method uses a special type of design of orthogonal arrays (OA) to study the entire parameter space with smaller number of experiments. The

*Corresponding author: pathiyasseril@yahoo.com

experimental results are then transferred to signal- to-noise (S/N) ratio. This ratio can be used to measure the quality characteristics deviating from desired values. Usually there are three categories of in the analysis of the signal-to-noise ratio that is the lower- the- better (LB), higher- the- better (HB) and nominal- the- best (NB) [2]. Regardless of category of quality characteristics larger signal –to-noise ratio corresponds to the better quality characteristics. The optimal process parameters are the levels with highest signal–to-noise ratio. Once the experimental data is normalized using NB/LB/HB criteria; normalized value lies between zero and one. Zero represented worst quality and one represented most satisfactory quality. Since S/N ratio is expressed as mean (signal) to the noise (deviation from the target); maximizing S/N ratio ensures minimum deviation and hence it is (S/N ratio) to be maximized.

S/N ratio for Nominal- the- best (NB)

$$\eta = 10 \ln_{10} \frac{1}{n} \sum_{i=1}^{n} \frac{\mu^2}{\sigma^2} \quad (1)$$

S/N ratio for Lower- the- better (LB)

$$\eta = -10 \ln_{10} \frac{1}{n} \sum_{i=1}^{n} Y_i^2 \quad (2)$$

S/N ratio for Higher- the- better (HB)

$$\eta = -10 \ln_{10} \frac{1}{n} \sum_{i=1}^{n} \frac{1}{Y_i^2} \quad (3)$$

Y_i = value of the quality characteristic at i^{th} setting.

N= Total number of trial runs at i^{th} setting.

σ = standard deviation.

μ = Mean.

3. Principal Component Analysis (PCA)

PCA is a way of identifying patterns in the correlated data, and expressing the data in such a way so as to highlight the similarities and differences. The main advantage of PCA is that once the patterns in data have been identified, the data can be compressed, i.e., by reducing the number of dimensions, without much loss of information. The entire work is based on the assumption that there is no interaction effect of the process parameters involved. The methods involved in PCA are given below [3]:

1. Getting the data
2. Normalization of data.
3. Calculation of covariance matrix.
4. Interpretation of covariance matrix.

The normalized data have been utilized to construct a variance –covariance matrix *M.*, which is illustrated as below:

$$M = \begin{bmatrix} N_{1,1} & N_{1,2} & \cdots & N_{1,\mu} \\ N_{2,1} & N_{2,2} & \cdots & N_{2,p} \\ . & . & \cdots & . \\ . & . & \cdots & . \\ N_{q,1} & N_{q,2} & \cdots & N_{q,p} \end{bmatrix} \quad (4)$$

Where

$$N_{k,l} = \frac{Cov\left(Y^*_{i,k}, Y^*_{i,l}\right)}{\sqrt{Var\left(Y^*_{i,k}\right), Var\left(Y^*_{i,l}\right)}} \quad . (5)$$

In which u stands for the number of quality characteristics and P stands for the number of experimental runs. Then eigenvectors and Eigen values of matrix M can be computed which can be denoted by $\overline{V}_j$ and λ_j respectively.

In PCA the eigenvector $\overline{V}_j$ represents the weighing factor of j number of quality characteristic of the j^{th} principal component. For example Q_j represents j^{th} quality characteristic, the j^{th} principal component ψ_j can be computed as quality vector with required quality characteristics.

$$\psi_j = V_{1j}Q_1 + V_{2j}Q_2 + \cdots\cdots\cdots + V_{jj}Q_j = \overline{V}_j\overline{Q} \quad (6)$$

It is to be noted that every principal component j ψ represents a certain degree of explanation of the variation of quality characteristics, namely the accountability proportion (AP). When several principal components are accumulated, it increases the accountability proportion of quality characteristics. This is denoted as cumulative accountability proportion (CAP).

If a quality characteristic j Q strongly dominates in the j^{th} principal component, this principal component becomes the major indicator of such a quality characteristic. It should be noted that one quality indicator may often represent all the multi-quality characteristics. Selection of individual principal components (j ψ), those to be included in the composite quality indicator ψ, depends on their individual accountability proportion. But the case where to deal with more than two principal components in which accountability proportion of all principal component bear remarkable values those cannot be neglected; the problem of computing composite principal component arises There are various formulas on aggregation of individual principal components as reported in literature to compute a (MPI) multi-response performance index(composite principal component). There is no strong mathematical background to compute this MPI. Therefore, it depends on the discretion of decision makers. In this study MPI is converted to quality loss indicator which is a comparison to ideal that is to be minimized to get optimized result.

4. Experimentation

The experiment was designed based on Taguchi's method. The experiment was conducted as per L_{25} orthogonal array using COLTON submerged arc welding equipment (SAW). Bead on plate welding was carried on IS 2062 grade carbon steel. Test plates of size 300 x 200 x 10 mm were cut from steel plate of and one of the surfaces are cleaned to remove oxide and dirt before welding with EH 14 wire of 4 mm diameter in the form of coil. ASK74S granular flux is baked for two hours and tip of the welding wire, arc and the welding joint in the work piece are covered by this heated flux before welding. No Inert gas is used for welding. Two transverse specimens were cut from each weldment and standard metallographic procedures were adopted. Bead profiles were drawn using a reflective type profile projector [4]. Chemical composition of base metal and filler wire is shown in Table 1.

Table 1 Chemical Composition of Base Metal and Filler Wire

	Elements, Weight %								
Materials	C	Si	Mn	P	S	Al	Cr	Mo	Ni
IS 2062	0.150	0.160	0.870	0.015	0.016	0.031	-	-	-
EH 14	0.12	0.1	0.172	0.03	0.03	-	-	-	-

5. Plan of Investigation

The research work was carried out through following steps [5]:

1. Identifying the quality characteristics and process parameters to be evaluated.
2. Determining number of levels for the process parameters and possible interactions between process parameters.
3. Select appropriate orthogonal array and assign process parameters to the orthogonal array.
4. Conduct experiment as per arrangement of orthogonal array.
5. Analyse the experiments through PCA based Taguchi approach.
6. Select the optimum level of process parameters.
7. Conducting confirmation experiment.

5.1 Development of orthogonal array

Welding parameters and their levels are shown in Table 2. The experimental design based on an orthogonal array (OA). It allows the effect of each welding process parameters at different levels to be separated out. The selection of appropriate orthogonal array is based on total degree of freedom (dof). The degrees of freedom are defined as the number of comparisons between process parameters that must be able to determine which level is better and specifically how much better is [6]. The degrees of freedom for the orthogonal array should be greater than or at least equal to, those for the process parameters. In this study L_{25} orthogonal array with 8 columns and 18 rows was used. This is shown in Table 3.

Table 2 Welding Parameters and their Levels

Parameters	**Unit**	**Notation**	**1**	**2**	**3**	**4**	**5**
Welding Current	A	I	350	420	500	580	650
Welding Speed	mm/min	S	30	40	50	60	70
Voltage	v	V	24	26	28	30	32
Nozzle to plate distance	mm	T	30	32.5	35	37.5	40

5.1 Development of orthogonal array

Welding parameters and their levels are shown in Table 2. The experimental design based on an orthogonal array (OA). It allows the effect of each welding process parameters at different levels to be separated out. The selection of appropriate orthogonal array is based on total degree of freedom (dof). The degrees of freedom are defined as the number of comparisons between process parameters that must be able to determine which level is better and specifically how much better is [6]. The degrees of freedom for the orthogonal array should be greater than or at least equal to, those for the process parameters. In this study L_{25} orthogonal array with 8 columns and 18 rows was used. This is shown in Table 3.

Table 3 Orthogonal array

Trial Number	Design Matrix			
	I	**S**	**V**	**T**
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

5.2 Conducting experiments as per orthogonal array

In this work Twenty five experimental runs were allowed as per the orthogonal array for the estimation of parameters on bead geometry as shown Table 3 at random. At each run settings for all parameters were disturbed and reset for next deposit [7]. This is very essential to introduce variability caused by errors in experimental set up. A large sheet of steel w is used to carry experiments. This is to achieve required parametric combination in each set up.

5.3 Recording of Responses

For measuring the weld bead geometry, the transverse section of each weld overlays was cut using band saw from mid length. Position of the weld and end faces were machined and grinded. The specimen and faces were polished and etched using a 5% nital solution to display bead dimensions. The weld bead profiles were traced using a reflective type optical profile projector. Then the bead dimension such as depth of penetration height of reinforcement and weld bead width were measured using tool maker's microscope [8]. The bead profiles traced using AUTO CAD software in order to measure percentage of dilution ,which is the area of penetration (B) divided by total area of wed (A+B)as shown in Fig 1. The measured weld bead dimensions and percentage of dilution is shown in Table 4.

Table 4 Orthogonal array and Observed Values of weld Bead Geometry

Trial No.	Design Matrix				Bead Parameters			
	I	S	V	T	W (mm)	P (mm)	R (mm)	D (%)
1	1	1	1	1	18.567	3.202	4.817	42.161
2	1	2	2	2	16.664	3.625	4.929	40.193
3	1	3	3	3	13.532	4.360	5.231	49.012
4	1	4	4	4	12.583	4.341	5.256	37.345
5	1	5	5	5	12.743	4.306	5.102	50.432
6	2	1	2	3	15.649	2.529	4.513	40.340
7	2	2	3	4	15.792	3.532	4.304	44.152
8	2	3	4	5	14.641	2.530	4.912	40.548
9	2	4	5	1	12.781	3.821	4.786	41.177
10	2	5	1	2	23.684	4.234	8.112	34.340
11	3	1	3	5	12.912	3.015	3.534	47.761
12	3	2	4	1	13.743	3.267	3.098	46.666
13	3	3	5	2	12.861	3.561	4.120	46.056
14	3	4	1	3	21.543	4.812	7.386	35.712
15	3	5	2	4	22.612	3.712	7.814	37.093
16	4	1	4	2	12.012	2.531	3.253	48.388
17	4	2	5	3	12.631	2.501	3.746	40.327
18	4	3	1	4	22.902	3.561	5.910	40.405
19	4	4	2	5	21.231	3.505	6.265	39.213
20	4	5	3	1	18.236	3.587	7.545	34.780
21	5	1	5	4	10.438	2.419	2.698	46.912
22	5	2	1	5	23.760	3.619	5.210	40.223
23	5	3	2	1	21.194	3.921	5.634	38.461
24	5	4	3	2	19.523	3.525	6.021	40.102
25	5	5	4	3	17.091	3.501	5.204	46.391

6. Optimization of SAW Process

Assuming, the number of experimental runs in Taguchi's OA design is *m*, and the number of quality characteristics is *n*. The experimental results can be expressed by the following series [9]:

$$X_1, X_2, X_3, \ldots\ldots, X_i, \ldots\ldots\ldots, X_m$$

Here,

$$X_1 = \{X_i(1),\ X_i(2),\ X_i(3), \ldots\ldots\ X_i(k) \ldots\ldots\ X_i(n)\}$$

.
.
.

$$X_i = \{X_i(1),\ X_i(2),\ X_i(3), \ldots\ldots\ X_i(k) \ldots\ldots\ X_i(n)\}$$

.
.
.

$$X_m = \{X_m(1),\ X_m(2),\ X_m(3), \ldots\ldots\ X_m(k) \ldots\ldots\ X_m(n)\}$$

Here X_i represents i^{th} experimental results and is called the comparative sequence in grey relational analysis.

Let be X_0 be the reference sequence:
.Let,

$$X_0 = \{X_0(1),\ X_0(2),\ X_0(3), \ldots\ldots\ X_0(k) \ldots\ldots\ X_0(n)\}$$

The value of the elements in the reference sequence means the optimal value of the corresponding quality characteristics. X_0 and X_i both includes n elements and $X_0(k)$ and $X_i(k)$,represent the numeric value of k^{th} element in the reference sequence and the comparative sequence., respectively ,k= 1,2,3,.............n.

6.1 Normalization of responses.

When the range of the series is too large or the optimal value of quality characteristics is too enormous, it will cause influence of some factors to be ignored. The original experimental data must be normalized to eliminate such effect [10]. There are three different type of normalisation such as lower- -the- better, higher- the-better and nominal- the -best; which is shown by equations (7), (8) and (9).

LB (lower-the-better):

$$X_i^*(k) = \frac{\min X_i(k)}{X_i(k)} \tag{7}$$

HB (higher-the –better):

$$X_i^*(k) = \frac{X_i(k)}{\max X_i(k)} \tag{8}$$

.

NB (nominal-the –best):

$$X_i^*(k) = \frac{\min\{X_i(k), X_{ob}(k)\}}{\max\{X_i(k), X_{ob}(k)\}} \tag{9}$$

Here,
I = 1, 2, 3,.........................., m;

k=1, 2, 3,........................., n

$X_i^*(k)$ = normalized value data of the k^{th} element in the i^{th} sequence.

$X_{ob}(k)$ = desired 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.............,m can be viewed as the comparative sequence used in the grey relational analysis.

6.2 Checking correlation between two quality characteristics.

$$Q_i = \{X_0^*(i), X_1^*(i), X_2^*(i) \ldots\ldots\ldots\ldots\ldots\ldots X_i^*(i)\}$$

Where,

i=1, 2, 3... ...., .n.

It is the normalized series of the i^{th} quality characteristic .The correlation coefficient between quality characteristic is given by;

$$\rho_{jk} = \frac{Cov(Q_j, Q_k)}{\sigma_{q_j} \times \sigma_{q_k}} \tag{10}$$

J=1, 2, 3.....,n
K=1, 2, 3......,n
$j \neq k$

Here ρ_{jk} is the correlation coefficient between quality characteristics j and quality characteristic k; $Cov\left(Q_j, Q_k\right)$ is the covariance of quality characteristic *j* and *k;* σq_j *and* σq_k are the standard deviation of quality characteristic *j* and quality characteristic *k*, respectively.
The correlation coefficient is checked by testing following Hypothesis:

$$\begin{cases} H_0 : \rho_{jk} = 0 (There \quad is \quad no \quad correlation) \\ H_1 : \rho_{jk} \neq 0 (There \quad is \quad correlation) \end{cases}$$

6.3 Calculation of principal component score

1. Calculate the Eigen value λ_k and corresponding Eigen vector β_k (k=1, 2, 3 ....) from the correlation matrix formed by all quality characteristics.

2. Calculate principal component scores of the normalized reference sequence and comparative sequence using the following equation.
   i^{th}, i=0,1,2,......m; k=1,2,3.....,n.
   $Y_i(k)$ is the principal component score of the k^{th} element in i^{th} series.

$X_i^*(j)$ is the normalized value of the j^{th} element in the i^{th} sequence, and is β_{kj} the j^{th} element of eigenvector β_k .

3. Accountability proportion of individual principal components has been treated as individual priority weights. Finally, multi-response performance index (MPI) is calculated. The quality loss $\Delta_{0,j}$(k) ,compared to that of ideal index is calculated by following equation.

$$\Delta_{0,i}(k) = \begin{cases} \left| X_o^*(k) - X_i^*(k) \right|, (no \quad significant \quad correlation) \\ \left| Y_0(k) - Y_i(k) \right|, (significant \quad correlation) \end{cases}$$

Optimal setting is then evaluated by minimizing this $\Delta_{0,i}(k)$ quality loss estimate) by using Taguchi method

7. Data Analysis and Evaluation of Optimal Setting

Experimental data in Table 4 has been normalized using equation (7), (8) and (9). For dilution and penetration higher –the –better (HB), for bead width and reinforcement lower the better (LB) criterion have been selected. The normalized value is shown in Table 5.

Table 5 Normalized data

SL No	**W**	**P**	**R**	**D**
Ideal solution	1	1	1	1
1	0.9021	0.9021	0.5133	0.7405
2	0.8948	0.8948	0.5288	1
3	0.5255	0.5255	0.5978	0.7998
4	0.7339	0.7339	0.6268	0.8754
5	0.5257	0.5257	0.5492	0.8040
6	0.7940	0.7940	0.5637	0.8164
7	0.8798	0.8798	0.3325	0.6809
8	0.6265	0.6265	0.7634	0.9470
9	0.6789	0.6789	0.8708	0.9253
10	0.7400	0.7400	0.6548	0.9132
11	1	1	0.365286	0.708122

12	0.7714	0.7714	0.3452	0.7355
13	0.5259	0.5259	0.8293	0.9594
14	0.5197	0.5197	0.7202	0.7996
15	0.7400	0.7400	0.4565	0.8011
16	0.7283	0.7283	0.4306	0.7775
17	0.7454	0.7454	0.3575	0.6896
18	0.5027	0.5027	1	0.9302
19	0.7520	0.7520	0.5178	0.7975
20	0.8148	0.8148	0.4788	0.7626
21	0.7325	0.7325	0.4480	0.7951
22	0.7275	0.7275	0.5184	0.9198
23	0.9021	0.9021	0.5133	0.7405
24	0.8948	0.8948	0.5288	1
25	0.5255	0.5255	0.5978	0.7998

Table 6 Principal component scores and the composite welding quality index

SL No	(1st PC) Ψ_1	(2nd PC) Ψ_2	(3rdPC) Ψ_3	MPI	Δ_{0i}(MPI)	S/N ratio
Ideal solution	-1.9740	1.8650	0.6630	-0.1937	0.0000	-15.3790
1	-1.8123	0.1649	-0.6520	-1.7476	1.5539	-14.6183
2	-0.7478	2.2257	-0.2553	0.4684	0.6621	-10.0089
3	1.5291	-1.2833	0.0505	0.8170	1.0107	-8.9955
4	0.3177	0.5255	-0.5063	0.5784	0.7721	-9.7018
5	1.3912	-1.3396	0.2559	0.6599	0.8536	-9.4670
6	-0.5535	0.2686	0.1743	-0.3933	0.1996	-12.1003
7	-2.4283	-0.7702	-0.0148	-2.8414	2.6477	-16.225
8	1.8244	0.7579	0.7618	2.2741	2.4678	-2.6700
9	1.6820	1.0738	-0.0126	2.2646	2.4583	-2.7304
10	0.4992	0.9124	0.5175	1.0274	1.2211	-8.3213
11	-3.1371	0.1713	-0.3816	-3.0476	2.8539	-16.4977
12	-1.3633	-0.9098	-0.0609	-1.8611	1.6674	-14.799
13	2.8397	0.4244	0.3054	3.0758	3.2695	5.0654
14	1.9544	-1.0895	-0.31650	1.3271	1.5208	-7.2603
15	-0.5348	-0.3516	-0.3386	-0.7441	0.5504	-12.8259
16	-0.6147	-0.6528	-0.1401	-0.9789	0.7852	-13.279
17	-1.2976	-1.3966	0.8399	-2.0153	1.8216	-15.0400

18	3.4405	0.3798	0.0267	3.6340	3.8277	80.9151
19	-0.4481	-0.1996	0.2183	-0.5441	0.3504	-12.4197
20	-1.1755	-0.2045	-0.3436	-1.3009	1.1072	-13.8656
21	-0.52656	-0.4566	-0.7273	-0.8147	0.621	-12.9648
22	0.1926	0.6426	0.7533	0.5864	0.7801	-9.6790
23	-1.8123	0.1649	-0.6520	-1.7476	1.5539	-14.6183
24	-0.7478	2.2257	-0.2553	0.4684	0.6621	-10.0089
25	1.5291	-1.2833	-0.6520	0.7791	0.9728	-9.1117

Table 7 Correlation check (# significant correlation)

Sl No	Correlation between responses	Pearson's correlation coefficient	Comments	P-value
1	Bead width and penetration	0.3876	Both are correlated	0.0556
2	Bead width and reinforcement	0.7754	Both are correlated	0.0000#
3	Bead width and dilution	-0.6649	Both are correlated	0.0003#
4	Penetration and reinforcement	0.6276	Both are correlated	0.0008#
5	Penetration and dilution	-0.2683	Both are correlated	0.1998
6	Reinforcement and dilution	-0.7407	Both are correlated	0.0000#

After normalization, a check has been mode to verify whether the responses i.e., quality indices are correlated or not. The correlation coefficient between penetration and dilution becomes -0.2683(p value =0.1998), which indicates that the responses are highly correlated .The coefficient of correlation, between two responses has been calculated using equation (10)). Table 6 represents the values of these independent principal components for 25 experimental runs. Table 7 represents Pearson's coefficient between the responses. In all cases non-zero value of correlation coefficient indicates that all response features are correlated to each other Table 8 shows correlation matrix and Eigen values.

Table 8 Analysis of correlation matrix, Eigen vectors, Eigen values, accountability proportion (AP), cumulative accountability portion (CAP) computed under four major quality indicators.

	Ψ_1	Ψ_2	Ψ_3	Ψ_4
Eigen value	**2.7782**	**1.0052**	**0.2166**	**0.0000**
Eigen vector	$\begin{bmatrix} -0.547 \\ -0.547 \\ -0.525 \\ -0.355 \end{bmatrix}$	$\begin{bmatrix} 0.398 \\ 0.398 \\ 0.313 \\ 0.756 \end{bmatrix}$	$\begin{bmatrix} 0.205 \\ 0.205 \\ 0.791 \\ -0.538 \end{bmatrix}$	$\begin{bmatrix} -0.707 \\ -0.707 \\ 0.000 \\ 0.000 \end{bmatrix}$
Proportion (AP)	**0.695**	**0.251**	**0.054**	**0.000**
Cumulative (CAP)	**0.695**	**0.946**	**1.000**	**1.000**

In order to eliminate response correlations, PCA analysis has been applied to derive multi response index (MPI) using the following equation (11). The analysis of correlation matrix is shown in Table 7.

$$MPI = \psi_1 \times 0.695 + \psi_2 \times 0.251 + \psi_3 \times 0.054 \quad (11)$$

MPI has been treated as a single objective function and quality loss is calculated, which is to be minimized which is shown in Table 6.

Taguchi's Lowe the better (LB) criterion has been used to minimize the quality loss .Fig 2 shows S/N ratio plot from with optimal factorial combination. The optimal setting is I_4 S_3 V_1 T_4 .S/N ratios are shown in Table 6.The result has been verified through confirmatory experiment, which showed satisfactory results. The maximum possible number of principal component to be computed is equal to the number of responses. In this study four responses selected.

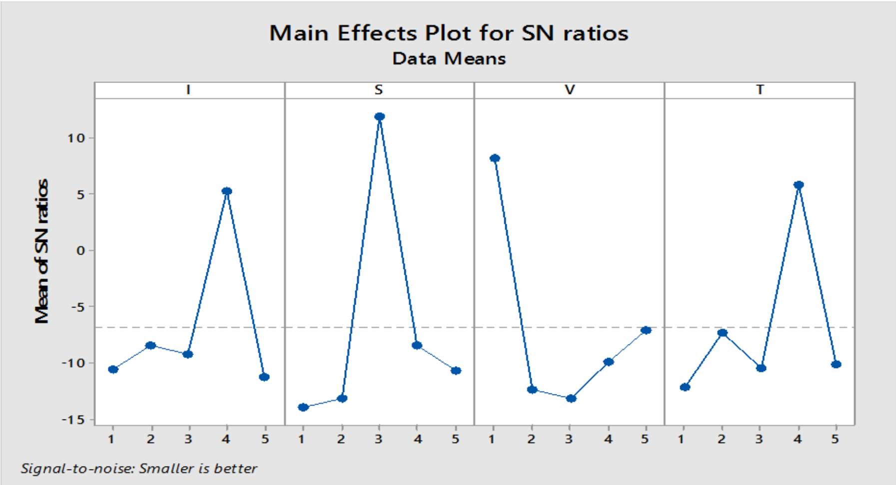

Fig 2 Main plot for S/N ratios.

Table 9. Response Table for Signal to Noise Ratios

Level	I	S	V	T
1	-10.558	-13.892	8.207	-12.126
2	-8.409	-13.151	-12.395	-7.311
3	-9.264	11.939	-13.119	-10.502
4	5.262	-8.424	-9.913	5.839
5	-11.277	-10.718	-7.027	-10.147
Delta	16.539	25.832	21.326	17.966
Rank	4	1	2	3

8. Analysis of Variance (ANOVA)

Analysis of variance (ANOVA) technique was used to test the adequacy of the model. This method is very useful to reveal the level of significance of influence of factors or interaction factors on particular response. It separates the total variability of responses into contributions rendered by each of parameter and error.

$$SS_T = SS_F + SS_e \quad (12)$$

Where

$$SS_T = \sum_{j=1}^{p} \left(\gamma_j - \gamma_m\right)^2$$

SS_T =Total sum of squared deviations about the mean

SS_F = Sum of squared deviations due to each other

SS_e =Sum of squared deviations due to error

γ_j =Mean response for j^{th} experiment

γ_m = Grand mean of responses

Depending on F-value, P- value (probability of significance is calculated If P value is 95% confidence level then factors are significant.

*Corresponding author: pathiyasseril@yahoo.com

penerbit.uthm.edu.my/ojs/index.php/ijie

Table 10 Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	4	13.315	3.329	1.10	0.384
I	1	0.857	0.857	0.28	0.601
S	1	12.068	12.068	3.98	0.060
V	1	0.003	0.003	0.00	0.972
T	1	0.386	0.386	0.13	0.725
Error	20	60.610	3.030		
Total	24	73.926			

9. Validation of Models

The predicted quality loss $\bar{\gamma}$ using the optimal level of design parameters can be calculated as:

$$\bar{\gamma} = \gamma_m + \sum_{i=0}^{p} \overline{\gamma_j} - \gamma_m \qquad (13)$$

Where γ_m is the total mean quality loss and $\bar{\gamma}$ is the mean quality loss at the optimal level and p is the number of the main design parameters that affect the quality characteristics. Table 10 represents the comparison of the predicted bead geometry parameters with that of actual by using optimal welding conditions; good agreement between the two has been observed and improvement of overall S/N ratio is the result. This proves the utility of the proposed approach in relation to process optimization, where more than one objective has to be fulfilled simultaneously.

Table 11 Results of conformity experiment

Parameters	Initial factor setting	Prediction	Experiment
Level of factors	$I_1 S_1 V_1 T_1$	$I_4 S_3 V_1 T_4$	$I_4 S_3 V_1 T_4$
Bead width	18.567	16.134	17.225
Reinforcement	4.817	3.982	3.347
Penetration	2.202	2.125	2.985
D (%)	42.161	40.131	40.643
Overall S/N ratio	-14.618	-7.822	-7.639
Improvement in S/N ratio	8.660		

10. Results and Discussions

In this study Taguchi's Lower-the better criteria has been used to minimize the quality loss. Fig 2 shows S/N ratio with optimal parameter combination as $I_4 S_3 V_1 T_4$ .This has been verified through confirmatory tests conducted. The maximum possible number of principal components computed is equal to the number of responses however in this case the fourth components accountability is zero hence it is neglected. This study deals with three principal components composite element. Then quality loss is calculated. Results of ANOVA in Table 10 indicate that voltage with high p value of 0.972 is the most effective parameter in this multi criteria optimization. Table 9 shows response table for signal to noise ratios. Table 11 shows conformity tests conducted as per optimization results. According to Taguchi' prediction formula predicted value of S/N ratio for MPI becomes -7.820 whereas in confirmatory experiment it is obtained a value of -7.632. So quality has improved using the optimal setting. We can see that there is improvement in overall S/N ratio.

11. Conclusions

In this study, a detailed methodology of PCA based hybrid Taguchi optimization technique has been presented for evaluating the bead geometry and parametric combinations in submerged arc welding process. The study proposes an integrated optimization approach using Principal Component Analysis (PCA) 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 submerged arc welding.

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 response variables for optimization.
2. Based on accountability proportion (AP) and cumulative accountability proportion (CAP), PCA analysis can reduce the number of response variables to be taken under consideration for optimization.
3. Based on accountability proportion (AP); treated as individual response weights, this method 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 has to be optimized simultaneously.
4. The said approach can be recommended for continuous quality improvement and off-line quality control of a process/product

Acknowledgement

The authors sincerely acknowledge the help and facilities extended to them by the department of mechanical engineering YOUNUS college of Engineering and technology, Kollam, India.

References

[1] Kannan,T.; Murugan, N;.Effect of flux cored arc welding process parameters on duplex stainless steel clad quality ,journal of Material Processing Technology vol.176,(2016), pp 230-239.

[2] Ugur Esme ;Melih Bayramoglu;Yugut Kazanancoglu; Sueda Ozgun ;Optimization of weld bead geometry in TIG welding process using Grey relational analysis and Taguchi method, Materials and technology Vol.43,(2009), pp 143-149.

[3] Jagannatha,N.; Hiremath, S.S; Sadashivappa, K ;.Analysis and parametric optimization of abrasive hot air jet machining for glass using Taguchi method and utility concept, International Journal of Mechanical and materials engineering. Vol. 7, (2012), pp. 9 – 15, No.1.9.15.

[4] Norasiah Muhammed; Yupiter HP Manurung; Muhammed Hafidzi , Optimization and modelling of spot welding parameters with simultaneous response consideration using multi objective Taguchi method and utility concept. Journal of Mechanical science and Technology. Vol.26 (8),(2012), pp. 2365 - 2370.

[5] Thakur, A.G; Nandedkar, V.M, Application of Taguchi method to determine resistece spot welding conditions of austenitic stainless steel AISI 304,journal of scientific and industrial research .Vol- 69,(2010),pp 680-683.

[6] Tarng,Y.S; Yang;W.H ; Optimization of weld bead geometry in gas tungsten arc welding by the Taguchi method , International Journal of Advanced Manufacturing Technology. Vol-14,(1998), pp 549-554.

[7] Saurav Datta; Ashish Bandyopadhyay; Pradip Kumar Pal;. Grey based Taguchi method for optimization of bead geometry in submerged arc bead on plate welding, International Journal of Advanced Manufacturing Technology. Vol-39, (2008), pp 1136-1143.

[8] Gunaraj, V.; Murugan, N; Prediction and comparison of the area of the heat effected zone for the bead on plate and bead on joint in SAW of pipes, Journal of Material processing Technology. Vol. 95,(2009), pp. 246 - 261.

[9] Katherasan,D; Madana Sashikant; P; Sathiya, P ;.Flux cored arc welding parameter optimization of AISI 316L (N) austenitic stainless steel, World academy of science, Engineering and Technology Vol.6,(2012), pp.635-642

[10] Sanji Moshat; Saurav Datta;Ashish Bandyopadhyay, Pradeep Kumar Pal; Optimisation of CNC end milling process parameters using PCA-based Taguchi method, International Journal of Engineering Science and Technology, Vol (2),(2010),pp 92-102.