Optimization of Operating Parameters of Tig Welding of Incoloy (800ht) through Response Surface Methodology

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Abstract: In the present study, Response Surface Methodology (RSM) is implemented to determine optimum process variables of TIG welding of Incoly-800HT sheets. Voltage, Welding current and speed of welding are considered as factors. Ultimate tensile strength at room temperature, yield strength at room temperature, ultimate tensile strength at 750^{0}C, yield strength at 750^{0}C and toughness are considered as responses. The Design of Experiment based on central composite response surface design, experimenting is formulated using the Design Expert 12 software. Grey Relational Analysis (GRA) carried on the responses and grey relational coefficients are calculated. The grey relational coefficients are subjected to Principal Component Analysis (PCA) using PAST 3.26 software that transforms the five responses into a single response. The optimization of parameters is carried by Response Surface Methodology and contribution by each input parameter is estimated by ANOVA (Analysis of Variance).

Key words: TIG welding, Design of Experiment, GRA, PCA, RSM and ANOVA.

I. INTRODUCTION

Incoloy 800HT is a nickel –iron – chromium alloy which exhibits strength and good resistance to oxidation, carburization and other type of corrosion at elevated temperatures.

Table1: Chemical Composition (%wt) of base metal

Ni	Cr	Fe	C	Al	Ti	Al+Ti	ASTM grain Size
30-35	19-23	39.5 min	0.06-0.1	0.25-0.6	0.25-0.6	0.85-1.2	5 or coarser

A. Rahmel et.al.(1998) mentioned that Incoloy 800HT has superior creep strength combined with resistance to corrosion at high temperature, makes this alloy suitable for applications involving long time exposure to high temperatures in corrosive atmosphere. The applications of Incoloy 800HT are furnace components and equipment, hydrocarbon reforming, heat treating furnaces, heat exchanger tubes in nuclear reactors [1]. TIG welding is best suited joining process for precipitation hardening alloys because it provides excellent protection against oxidation by providing a shield gas.

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To weld Incoloy 800HT sheet of 4 mm by butt joint, inert gas argon isused to protect the molten weld pool and melting filler wire from oxidation and contaminants. Direct Current (DC) with TIG electrode connected to the negative (-) polarity is employed. P. Kumar et.al. (2011) stated that the TIG welding is a multi response and multi factor fabrication process. TIG welding suits for joining common metals like steel, magnesium, nickel, aluminium and their alloys of thickness up to 6mm in any position [2]. S Datta et.al. (2008) established that the input parameters affect the mechanical properties, weld bead geometry, and metallurgical properties of the welded joint. The overall quality of the weldments is certainly being affected by the input process parameters [3]. F Kolhan et.al. (2011) stated that obtaining required weld quality in the TIG welding by controlling input process parameters is a complicated process. A scientific approach is required to decide the combination of input parameters to optimize the overall weld quality [4]. S Subramaniam et.al. (1999) listed the usual procedure to select the input process parameters to get the desired weld quality. The skilled operator or engineer select the input process parameters based on the trail and error method and each time the weldment is tested for the required output variables [5]. S V Sapakal et.al. (2012) mentioned the application of techniques like design of experiment (DoE), computational network and evolutionary algorithms are used to develop mathematical models for weld quality in terms of welding process input parameters of the weld joint. The mathematical model is analysed to get input parameters that result in getting the desired weld quality. S V Sapkal et.al. (2012) optimised the input process parameters welding current, voltage and welding speed using Taguchi method to obtain maximum depth of penetration in the mild steel specimen [6]. Arun Kumar Srirangan et.al. (2016) used Taguchi grey relational analysis to optimize the output variables such as ultimate tensile strength, yield strength and impact toughness. A combination of current, voltage and welding speed was found for the maximum grey relational grade for quality weld joints [7]. Mohan K Pradhan et.al. (2011) solved the problem to obtain a set of input parameters to optimize the contrasting responses problem i.e. to maximize productivity and to minimize the reduced surface roughness of the Electro Discharge Machined product [8]. A. Tamilarasan et.al. (2014) presented the optimization of the responses work piece surface temperature, cutting forces and sound pressure level in hard milling of the material 100MnCrW4 tool steel with

Table2: Chemical Composition (%wt) of filler metal

Grade	Ni	Cr	Fe	Nb	Ti	C	Mn	Si	S	P	Cu
ERNiCr-3	Min 67	18.0-22.0	Max 3.0	2.0-3.0	Max 0.75	Max 0.05	2.5-3.5	Max 0.5	Max 0.015	Max 0.015	Max 0.5

TiN+TiAlN coated WC inserts. A hybrid technique response surface methodology based box-behnken design along with grey relational analysis was used for statistical optimization [9]. Manish Gangil et.al. (2018) proposed a integrated approach of grey relational analysis coupled with principal component analysis for the optimisation of the machining parameters of electro discharge machining. Design of experiment was carried according to the response surface and principal component analysis was carried on the responses to find weightage [10]. S Dewangan et.al. (2014) carried the work to optimize the multiple responses – surface roughness, material removal rate and the surface crack density in the electo discharge maching. They used the integrated approach of coupling principal component analysis with grey relational analysis [11]. Ning Li et.al. (2019) considered the nonlinearity between the different responses. Grey relational analysis was employed to convert the responses into grey relational coefficients, and then kernel principal component analysis was used to find the kernel principal components. The weights calculated from the principal components showed the relative importance. Finally kernel grey relational grade was used as the optimization criterion to identify the optimal set of input parameters [12]. Suman Chatterjee et.al. (2014) applied weighted principal component analysis along with response surface method. Principal component analysis was applied to find the weightage of the responses so that their relative importance can be evaluated. Weighted principal component analysis was used to remove correlation between responses and convert the correlated responses to non correlated principal components. Later these principal components were aggregated to calculate the multi-response performance index. The integrated study response surface methodology coupled with weighted principal component analysis is applied to estimate the optimal parametric setting [13].

In the literature cited above, most of the works applied either GRA or GRA coupled with PCA to optimize the input process parameters to obtain required quality weldments. It is also observed that few works had been carried out in optimization of Incoloy 800HT welding process parameters. Applying grey relational analysis alone implies that we are assuming that equal weights of responses, which is cannot be considered as objective. Some authors integrated PCA and GRA to assign weights to the responses based on the PCA analysis. PCA analysis transforms several responses into a single response in dynamic multi-response problem. This single response, PCA score is optimised by RSM and significance of each process parameter is estimated by ANOVA.

II. PROPOSED METHODOLOGY

The limits for process parameter values are to be decided by trial and error method. After fixing limits for the process parameters, the design of experiment based on central composite design will be carried using Design Expert 12 software. The experiment will be conducted as per the design of experiment and the welded specimens will be tested for the selected output parameters. Gray Relational Analysis (GRA) will be applied on the obtained output parameters and the Gray Relational Coefficients are calculated. With the Gray Relational Coefficients as input the Principal Component Analysis (PCA) will be conducted using the PAST 3.26 software and scores will be obtained. With the overall PCA score and process parameters the ANOVA and RSM will be conducted for optimization using Design Expert 12 software.

The frame work for the proposed integrated methodology is presented below.

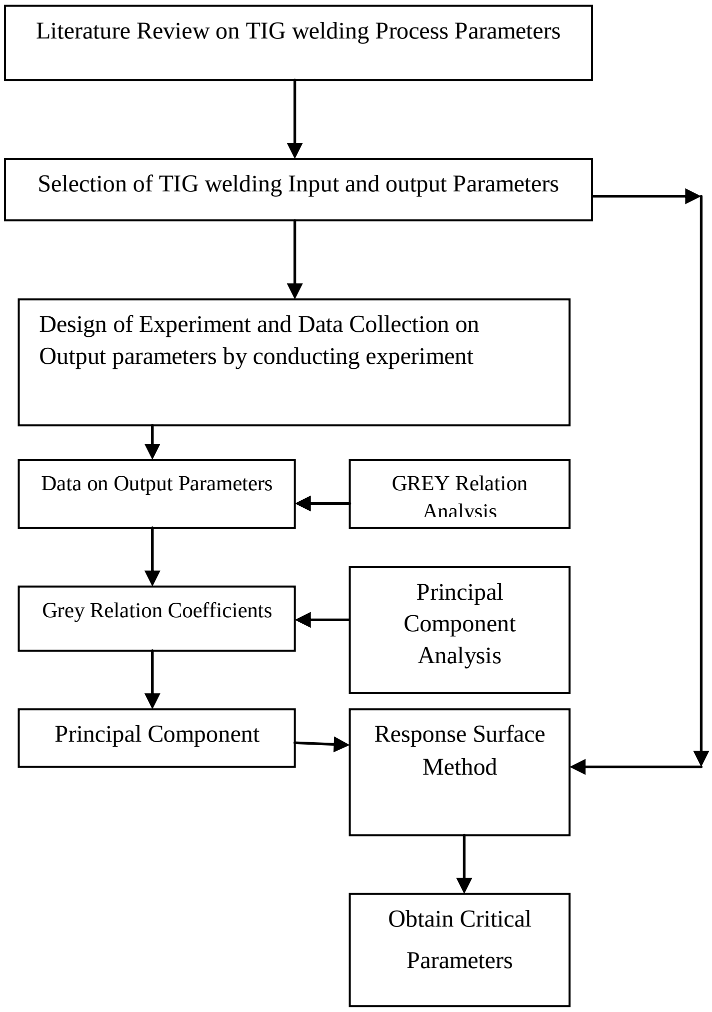

Fig.1. Frame work for the proposed integrated methodology

A. Grey Relational Analisis

Grey relational analysis is a decision making technique to determine the relational uncertainty among all the attributes.

For systems with incomplete description, relatively fewer data available and for which standard statistical assumptions are not applicable grey analysis is required. Grey relational analysis defines the ideal target sequence and establishes the relational grade after comparing with the objective sequence (measured data). Grey relational analysis analyses the relational grade for discrete sequences.

In this paper, GRA method is proposed to find the grey relation coefficients which are used to determine principle components of the TIG welding response variables. The proposed GRA methodology is presented below.

Step 1: *Obtaining the data on response variables.*

The data on the response variables of the TIG welding is collected.

Step 2: *Standardizing the data on the response variables*

To overcome the difficulty to compare the different response variables exerting different influence, the standardization of these factors must be done. The following formulae is used to standardize the data based on the following types of factors

Benefit type:

$$xs_i(j) = \frac{|x_i(j) - \min x_i(j)|}{\max x_i(j) - \min x(j)} \qquad \ldots(2.1)$$

Cost type:

$$xs_i(j) = \frac{\max x_i(j) - x_i(j)}{\max x_i(j) - \min x_i(j)} \qquad \ldots(2.2)$$

Nominal type:

$$xs_i(i) = 1 - \frac{|x_i(j) - x(j)|}{\max(\max x_i(j) - x(j), x(j) - \min x_i(j))} \qquad \ldots(2.3)$$

Where $x_i(j)$ is the reference value of j^{th} enabler of i^{th} alternative

Where $x\ (j)$ is the objective value of j^{th} enabler

Step 3: *Determining the absolute differences and maximum and minimum values of them.*

The absolute difference in the compared series and the referential series is to be obtained by

$$\Delta x_i(j) = |x_0(j) - xs_i(j)| \qquad \ldots(2.4)$$

x_0(j)= reference value of j th enabler of i^{th} bank

The maximum and the minimum absolute differences are to be found from the absolute difference of the compared series and the referential series.

Step 4: *Determining the grey relational coefficient*

Grey relational coefficient ξ can be determined using the equation shown below

$$\xi_i(j) = \frac{\Delta\min + p\Delta\max}{\Delta x_i(j) + p\Delta\max} \qquad \ldots(2.5)$$

p is the distinguishing coefficient or identification coefficient and it is generally taken as 0.5.

B. Principal Component Analysis

Principal Component Analysis (PCA) is an adaptive data analysis technique for reducing dimensionality of large datasets, to increase interpretability without losing information. It is done by creating new uncorrelated variables known as principal components, those maximize the variance.

Principal Component Analysis explains the correlation structure explained by the correlated number of p variables with the uncorrelated number of k variables which the linear combinations of the original variables provide (p > k). Eigen values and Eigen vectors of the covariance or correlation matrices are used to find the linear combinations of the p variables in the X data matrix. Let Let λ_1>= λ_2>= λ_3>= λ_p the Eigen values and, l_1 l_2 , , ... ,l_p be the orthogonal Eigen vectors of the correlation matrix. Linear combinations of the variables can be calculated as $PC_i = l_i^1 * X$, (i =1, 2. . . p) . The explanation ratio of total variance of k principal component is described as $\frac{\lambda_k}{\lambda_1 + \lambda_2 + \ldots\lambda_p}$. The main steps are discussed below.

Step1: *Collecting the data*

Original matrix is formed by collecting the data on the variables for the given number of samples. In this paper, the grey correlation coefficient matrix is considered as standardized decision matrix.

Step 2: *Determining the eigen values and eigen vectors*

Eigen values and eigen vectors are determined for the grey correlation coefficient matrix using principal component analysis.

Step 3: *Identifing the principal components*

There are two criteria to identify the principal components. First one to identify the principal component is 'the Eigen value one criterion, also known as the Kaiser criterion, in which the principal components with eigen value more than one are retained. The second one is the scree test in which a graph is drawn between eigen values and components and identify a "break" between the components with relatively large eigen values and those with small eigen values. The components that appear before the break are assumed to be meaningful and only those components are retained.

Step 4: *Determining the t-values*

Weigthed principal component values (t- values) are determined using the equation.

$t = \sum_{k=1}^{m} w_k PC_k$ Where w_k is the weight of the 'kth' principal component.

Determination of weights: if $\lambda_1 + \lambda_2 + \ldots\lambda_p$ are eigen values of the principle components, 1,2,…n are the principal components having eigen value more than one, then explanation ratio is given by the following relation.

$$\lambda_1 / (\lambda_1 + \lambda_2 + \ldots\lambda_n)$$
$$\lambda_2 / (\lambda_1 + \lambda_2 + \ldots\lambda_n)$$
$$.$$
$$.$$
$$\lambda_n / (\lambda_1 + \lambda_2 + \ldots\lambda_n)$$

For determining the sign of w_k s, signs of the components of the PC_k are considered. If the majority of the components are negative, then the weight is negative , and if the majority of the components are positive, then the weight is positive.

Step 5: Determining the principal component scores

The principal component scores are obtained from the equation

$$PC_{score} = D_z t$$ (Where D_z = standardized decision matrix)

C. Response Surface Methodology

Response surface methodology is a mathematical and statistical tool used to develop, analyse and optimise the multi variable problems. RSM develops the mathematical relationship between measured responses and input parameters. The response variables are replaced with the principal scores, which explains the maximum variance in the data. The scores of the selected principal components are optimized with the help RSM.

***Step1:** Obtaining the data on factors*

In this paper, input parameters like voltage, current, and welding speed are considered as factors.

***Step 2:** Determining the Critical parameters*

Critical parameters that affect the output parameters are determined by knowing the significance of model terms (input parameters) on principal component scores based on output parameters of the samples is evaluated by the F–test using ANOVA.

III. RESULT ANALYSIS

Response Surface Methodology is a statistical method to analyse and optimize the response in interest, which is under the influence of many input variables. The TIG welding of Incoloy 800HT specimens was performed according to the central composite response surface design. The input parameters according to the design of experiment and the responses obtained from the various tests are furnished in the table 3.

Table 3: Experimental design with results

Factor	Name	Units	Type	Min	Max	Coded Low	Coded High	Mean	Std. Dev.
A	Voltage	V	Numeric	8.60	15.40	-1 ↔ 8.60	+1 ↔ 15.40	12.00	1.70
B	Current	A	Numeric	76.00	144.00	-1 ↔ 76.00	+1 ↔ 144.00	110.00	17.03
C	Welding Speed	mm/s	Numeric	1.0000	2.00	-1 ↔ 1.20	+1 ↔ 2.00	1.50	0.2534

Experiment No.	Welding Current (Amp)	Voltage (V)	Welding Speed (mm/s)	UTS (R.T) (Mpa)	YS (R.T) (Mpa)	UTS (750^{0}C) (Mpa)	YS (750^{0}C) (Mpa)	Toughness (J)
1	12.0	110	1.5	600.78	406.94	575.93	377.88	55.7
2	14.0	130	1.8	578.31	400.33	561.06	357.55	53.3
3	12.0	110	1.5	601.75	404.79	575.28	377.55	55.7
4	8.6	110	1.5	612.50	409.22	585.37	391.35	55.6
5	10.0	90	1.8	617.43	426.45	594.70	400.19	57.6
6	14.0	130	1.2	584.13	387.43	557.16	355.57	53.6
7	12.0	110	1.5	600.78	406.94	575.93	377.88	55.6
8	12.0	110	1.5	599.81	409.09	576.58	378.21	55.6
9	10.0	130	1.2	598.09	390.15	568.40	371.61	53.7
10	15.4	110	1.5	589.05	404.65	566.49	364.40	55.6
11	12.0	76	1.5	621.95	426.63	594.78	400.26	59.3
12	12.0	144	1.5	579.62	387.26	557.09	355.51	52.0
13	10.0	90	1.2	623.25	413.55	590.80	398.21	58.0
14	14.0	90	1.8	603.47	423.73	583.46	384.15	57.6
15	12.0	110	1.5	598.84	411.24	577.23	378.54	55.5
16	12.0	110	1.5	602.72	402.64	574.63	377.22	55.8
17	12.0	110	2.0	595.93	417.69	579.18	379.53	55.4
18	12.0	110	1.0	605.72	395.97	572.61	376.19	55.9
19	14.0	90	1.2	609.29	410.83	579.56	382.17	57.9
20	10.0	130	1.8	592.27	403.05	572.30	373.59	53.3

A. Grey Relational Analysis (GRA)

The experimental data was normalized and standardised as discussed in the section II(A). In this study all the responses were "Higher- the – Better" or "Benefit" type. The minimum and maximum difference in the sequence for each response was sorted out from the calculated absolute differences. The Grey Relation Coefficients were calculated taking the distinguishing coefficient as 0.5 and the values are shown in the table 5.

Table 4: Normalised values and Deviational sequence

	Normalised values					Deviational sequence				
Experiment No.	UTS (R.T)	YS (R.T)	UTS (750^{0}C)	YS (750^{0}C)	Toughness	UTS (R.T)	YS (R.T)	UTS (750^{0}C)	YS (750^{0}C)	Toughness
1	0.5	0.4998	0.4998	0.4998	0.5068	0.5	0.5001	0.5001	0.5001	0.4931
2	0	0.3319	0.1053	0.0455	0.178	1	0.668	0.8946	0.9544	0.8219
3	0.5215	0.4452	0.4826	0.4925	0.5068	0.4784	0.5547	0.5173	0.5074	0.4931

4	0.7607	0.5577	0.7503	0.8008	0.4931	0.2392	0.4422	0.2496	0.1991	0.5068
5	0.8704	0.9954	0.9978	0.9984	0.7671	0.1295	0.0045	0.0021	0.0015	0.2328
6	0.1295	0.0043	0.0018	0.0013	0.2191	0.8704	0.9956	0.9981	0.9986	0.7808
7	0.5	0.4998	0.4998	0.4998	0.4931	0.5	0.5001	0.5001	0.5001	0.5068
8	0.4784	0.5544	0.5171	0.5072	0.4931	0.5215	0.4455	0.4828	0.4927	0.5068
9	0.4401	0.0734	0.3	0.3597	0.2328	0.5598	0.9265	0.6999	0.6402	0.7671
10	0.2389	0.4417	0.2494	0.1986	0.4931	0.761	0.5582	0.7505	0.8013	0.5068
11	0.971	1	1	1	1	0.0289	0	0	0	0
12	0.0291	0	0	0	0	0.9708	1	1	1	1
13	1	0.6677	0.8944	0.9541	0.8219	0	0.3322	0.1055	0.0458	0.1780
14	0.5598	0.9263	0.6996	0.64	0.7671	0.4401	0.0736	0.3003	0.36	0.2328
15	0.4568	0.609	0.5343	0.5146	0.4794	0.5431	0.3909	0.4656	0.4853	0.5205
16	0.5431	0.3906	0.4653	0.4851	0.5205	0.4568	0.6093	0.5346	0.5148	0.4794
17	0.392	0.7729	0.586	0.5367	0.4657	0.6079	0.227	0.4139	0.4632	0.5342
18	0.6099	0.2212	0.4117	0.4621	0.5342	0.39	0.7787	0.5882	0.5378	0.4657
19	0.6893	0.5986	0.5961	0.5957	0.8082	0.3106	0.4013	0.4038	0.4042	0.1917
20	0.3106	0.401	0.4035	0.404	0.178	0.6893	0.5989	0.5964	0.5959	0.8219

Table 5: Grey Relational Coefficients

Experiment No.	UTS (R.T) (Mpa)	YS (R.T) (Mpa)	UTS(750^0 C) (Mpa)	YS(750^0 C) (Mpa)	Toughness (J)
1	0.5	0.49993651	0.499933678	0.49994414	0.503448276
2	0.333333333	0.42807437	0.358508513	0.343781209	0.378238342
3	0.511030248	0.47405178	0.491459121	0.496284795	0.503448276
4	0.676399759	0.53066451	0.6669616	0.715198977	0.496598639
5	0.794273595	0.99093884	0.995772787	0.996881265	0.682242991
6	0.364831953	0.33429566	0.333746569	0.333631551	0.390374332
7	0.5	0.49993651	0.499933678	0.49994414	0.496598639
8	0.489435853	0.52881128	0.508705628	0.50365785	0.496598639
9	0.471761495	0.35048518	0.416694306	0.438510534	0.394594595
10	0.396506088	0.4724589	0.399809059	0.384219112	0.496598639
11	0.945309213	1	1	1	1
12	0.339939486	0.33333333	0.333333333	0.333333333	0.333333333
13	1	0.60079353	0.825629792	0.916069601	0.737373737
14	0.53183432	0.87159619	0.624730648	0.581395349	0.682242991
15	0.479308874	0.56122594	0.517790905	0.507427146	0.489932886
16	0.52255814	0.45071551	0.483267086	0.49267863	0.51048951
17	0.451295441	0.68768559	0.547104079	0.519081313	0.483443709
18	0.56175	0.39100209	0.459466049	0.481752611	0.517730496
19	0.616799341	0.55474144	0.553207104	0.552946991	0.722772277
20	0.420392891	0.45498671	0.456019359	0.456213681	0.378238342

B. Principal Component Analysis (PCA)

The principal component analysis reduces the number of correlated variables into smaller number of independent artificial variables known as principal components (PCs). In this study five variables (grey relation coefficients of responses presented in the table 5) were analysed, hence five principal components were extracted. Two principal components were identified as significant as the Eigen Values of these two principal components together accounted for 95.77% of the total variance. The Eigen values and the explained variation for the retained principal components are furnished in the table 6.

Table 6: Eigen values and explained variation

Principal Component	Eigen Values	Explained Variation
First	4.42637	88.527%
Second	0.362109	7.2422%

Weighted principal component values (t-values) were determined as discussed in the section II(B). The t-values for the retained principal components were calculated after obtaining loadings for the responses from the software PAST3.26. The t-values were calculated by considering the weights of the two principal components as 0.9243 and 0.0756 and the values are furnished in the table 7.

Table 7: Component matrix of principal components

Component Matrix			
	PC 1	PC 2	t-VALUES
UTS(RT)	0.44358	-0.58978	0.365413626
YS(RT)	0.41862	0.77874	0.44580321
UTS 750^0C	0.46921	0.009192	0.434385726
YS 750^0C	0.4644	-0.20494	0.413751456
TOUGHNESS	0.43837	0.060407	0.40975216

The single response for optimization PCA SCORE, was calculated by matrix multiplication of weighted principal component values matrix and principal scores matrix and the obtained values are furnished in the table 8.

Table 8: Principal component scores and the overall PCA score

	Scores					
	PC 1	**PC 2**	**PC 3**	**PC 4**	**PC 5**	**PCA SCORE**
1	-0.54516	-0.01622	0.04208	-0.028132	-0.0047661	-0.201753445
2	-2.1538	0.34033	-0.07162	0.0038078	0.0086863	-0.661283654
3	-0.6028	-0.15115	0.083724	-0.021843	-0.0068903	-0.263146867
4	0.83391	-0.67647	-0.67728	-0.030167	0.021846	-0.294581379
5	4.0671	0.56945	-1.0789	-0.096089	-0.0021728	1.230730364
6	-2.3279	-0.11949	0.12563	-0.043715	0.0066508	-0.864705492
7	-0.56406	-0.01882	0.0055009	-0.016092	-0.0081408	-0.222111296
8	-0.49807	0.12642	-0.038636	-0.014757	-0.0065744	-0.151225655
9	-1.5779	-0.50102	-0.18317	0.014917	-0.0034489	-0.874750182
10	-1.3852	0.31867	0.39615	-0.038007	0.017245	-0.200684216
11	5.3467	0.23652	0.63411	-0.1155	-0.0030823	2.28559547
12	-2.5494	-0.06449	-0.1829	-0.0321	0.0044412	-1.051246573
13	3.2833	-1.5464	-0.023562	0.18207	0.0044514	0.577293176
14	1.3109	1.3468	0.38349	0.19263	0.010211	1.32989599
15	-0.44096	0.28173	-0.12126	0.0070255	-0.008733	-0.088881822
16	-0.63355	-0.27493	0.16081	-0.021161	-0.0061995	-0.295514564
17	-0.15849	0.86081	-0.32001	0.11779	-0.0095072	0.231669868
18	-0.72934	-0.62541	0.31104	0.043161	-0.016212	-0.398994199
19	0.71239	-0.14318	1.0097	-0.081216	0.0049404	0.603507278
20	-1.3876	0.056782	-0.45488	-0.02263	-0.0027455	-0.689815899

In this work, PCA is employed to obtain a single output variable by aggregating the multiple variables. The PCA SCORE represents the overall quality of welding and now onwards will be called as Overall Weld Quality.

C. Response Surface Methodology: Development of model

In this work, RSM is used to find the critical input parameters of TIG welding that affect the overall weld quality aggregated from the five output parameters. The input parameters were considered as factors and PCA SCORE that represent the overall weld quality was considered as response and RSM on the selected response through Design Expert 12 software was implemented.

A mathematical model for the Overall Weld Quality was developed by carrying regression analysis and the model is presented below by the equation 3.1. The regression model presented below is in terms of actual factors with the original units of factors.

$$\text{Overall Weld Quality} = +8.80078+0.136915\text{Voltage}-0.164358\text{Current} + 1.49265\text{Welding Speed} - 0.000271\text{Voltage} * \text{Current} + 0.019050\text{Voltage} * \text{Welding Speed} - 0.020656\text{Current} * \text{Welding Speed} - 0.005163\text{Voltage}^2 + 0.000696\text{Current}^2 + 0.414714\text{Welding Speed}^2 \quad ...(3.1)$$

Experimental values and the predicted values of Overall Weld Quality obtained from the developed mathematical model are shown in the figure 2 and table 9.

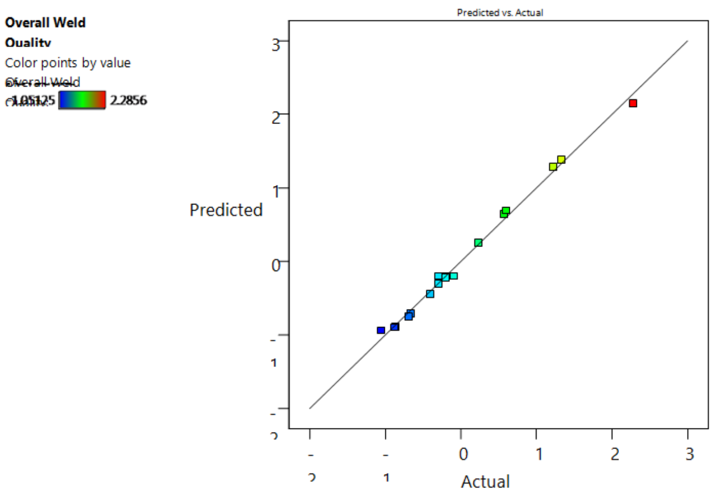

Fig. 2. Experimental and predicted values of PCA Score

Table 9: Predicted values and experimental values of Overall Weld Quality

Run Order	Actual Value	Predicted Value	Error	Square of Error	
1	-0.2018	-0.203	0.0012	1.44E-06	Mean Squared Error (MSE) = 0.004606117
2	-0.6613	-0.7071	0.0458	0.002098	
3	-0.2631	-0.203	-0.0601	0.003612	
4	-0.2946	-0.3026	0.008	6.4E-05	
5	1.23	1.29	-0.06	0.0036	
6	-0.8647	-0.898	0.0333	0.001109	
7	-0.2221	-0.203	-0.0191	0.000365	
8	-0.1512	-0.203	0.0518	0.002683	
9	-0.8748	-0.9004	0.0256	0.000655	
10	-0.2007	-0.2228	0.0221	0.000488	
11	2.29	2.14	0.15	0.0225	
12	-1.05	-0.9406	-0.1094	0.011968	
13	0.5773	0.6449	-0.0676	0.00457	
14	1.33	1.38	-0.05	0.0025	
15	-0.0889	-0.203	0.1141	0.013019	
16	-0.2955	-0.203	-0.0925	0.008556	
17	0.2317	0.2473	-0.0156	0.000243	
18	-0.399	-0.446	0.047	0.002209	
19	0.6035	0.6907	-0.0872	0.007604	
20	-0.6898	-0.7552	0.0654	0.004277	

The comparison of predicted values of overall weld quality from the mathematical model and experimental values shows that the predicted values are close to the experimental values. The Mean Squared Error (MSE) of as low as 0.0046 indicates that the model fits well can be used for the further purpose.

D. ANOVA for the model developed

The significance of each input factor on the performance characteristic is investigated by the statistical procedure ANOVA. ANOVA results for the proposed quadratic mathematical model are shown in the table 10. The accuracy of the model is evaluated by the F-value, p-value and the fit statistics.

Table 10: ANOVA results

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	13.26	9	1.47	165.70	< 0.0001	significant
A-Voltage	0.0086	1	0.0086	0.9686	0.3482	
B-Current	10.41	1	10.41	1170.57	< 0.0001	
C-Welding Speed	0.5137	1	0.5137	57.76	< 0.0001	
AB	0.0009	1	0.0009	0.1059	0.7516	
AC	0.0010	1	0.0010	0.1175	0.7389	
BC	0.1229	1	0.1229	13.82	0.0040	
A^2	0.0064	1	0.0064	0.7149	0.4176	
B^2	1.16	1	1.16	130.10	< 0.0001	
C^2	0.0195	1	0.0195	2.19	0.1697	
Residual	0.0889	10	0.0089			
Lack of Fit	0.0607	5	0.0121	2.15	0.2105	not significant
Pure Error	0.0282	5	0.0056			
Cor Total	13.35	19				

The F-value of 165.70 implies the model was significant. The probability of getting this large F-value due to noise is only 0.01%. The significant model terms can be identified by p-values (the terms with p-values less than 0.05 are significant and the terms with p-value greater than 0.1 are insignificant). In this case B, C, BC, B^2 were significant model terms. The Lack of Fit F-value of 2.15 implies the Lack of Fit was not significant. The probability of getting this large Lack of Fit F-value due to noise is 21.05%.

Table 11: Fit Statistics for the model

Std. Dev.	0.0943	**R^2**	0.9933
Mean	-1.548E-07	**Adjusted R^2**	0.9873
C.V. %	6.092E+07	**Predicted R^2**	0.9620
		Adequate Precision	46.2659

The Predicted R^2 of 0.9620 is in reasonable agreement with the Adjusted R^2 of 0.9873; i.e. the difference is less than 0.2. Adequate Precision measures the signal to noise ratio. A ratio greater than 4 is desirable. The ratio of 46.266 indicates an adequate signal. This model can be used to navigate the design space.

E. Effect of Combination of Input Parameters on Overall Weld Quality

To evaluate the combined effect of input parameters on response, the 3-D surface plots are used. The figures 2, 3 and 4 shows 3-D response surface plots obtained from RSM numerical optimization analysis. They show the effect of combination of input parameters on the Overall Weld Quality. The Overall Weld Quality rapidly decreases as the current increases and after 130amp Overall Weld Quality remains constant, where as voltage has no effect on the Overall Weld Quality. The Overall Weld Quality increases slightly with increase in welding speed.

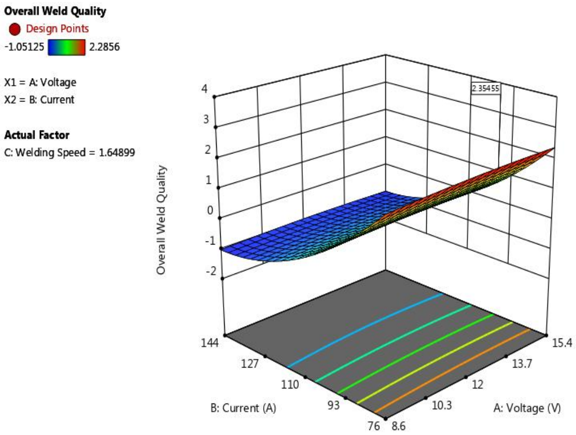

Fig. 3. Surface plot for Overall Weld Quality for varying Current and Voltage at Welding Speed 1.64899 mm/min

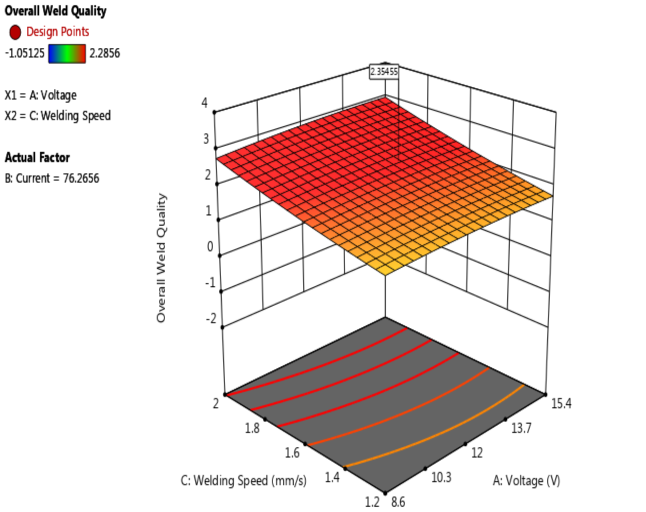

Fig. 4. Surface plot for Overall Weld Quality for varying Welding Speed and Voltage at Current 76.2656 amp

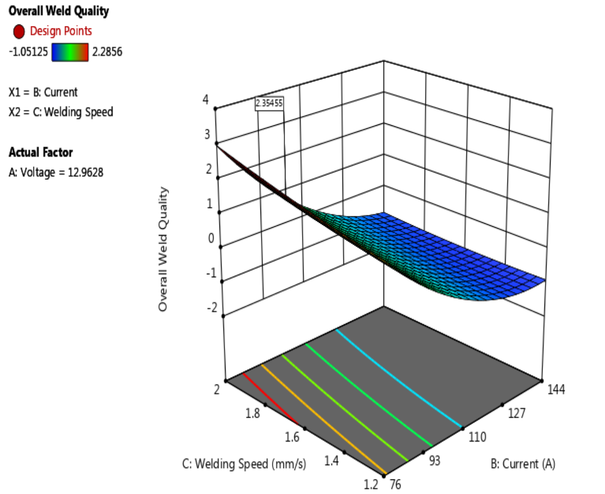

Fig. 5. Surface plot for Overall Weld Quality for varying Current and Welding Speed at Voltage 12.9628 V

F. Optimization of Overall Weld Quality – Ramp Function Graph

The ramp graphs for the input parameters Voltage, Current and Welding Speed between the low and high limits of the input parameters are shown in the figure 5. The desirability for the input parameters varies between 0 and 1. The red dots show the optimum values and the blue dot shows the corresponding maximum value of the response.

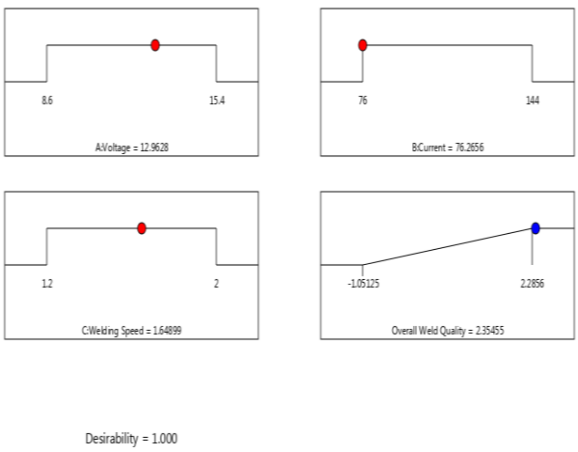

Fig. 6. Ramp graph of optimum parameters and maximum response

G. Validation

Figure 7 shows a three dimensional graph of standard error of a 2-factor face central composite design. The red dots in the plot represent the coordinates of the design points. The coordinates varies between -1 to +1 in coded units of the factors, which allow us to compare on a common scale. The design need to ideally produce a flat error profile (an area of uniform precision) centred in the middle of the design space. For a RSM design this should appear as either a circle or a square, preferably exhibiting symmetry. The present RSM design produced flat bottom in this bowl-shaped surface of standard error, which we can see in the three dimensional graph of standard error of design for the significant parameters Current and Welding Speed.

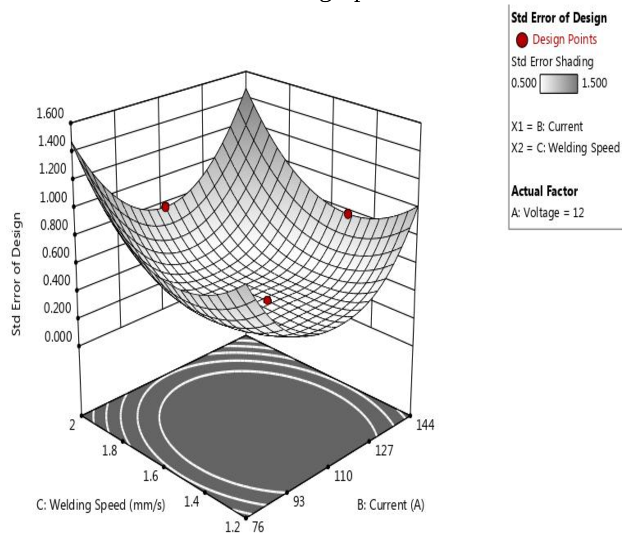

Fig. 7. Graph for Standard Error of Design for varying Current and Welding Speed at 12V Voltage

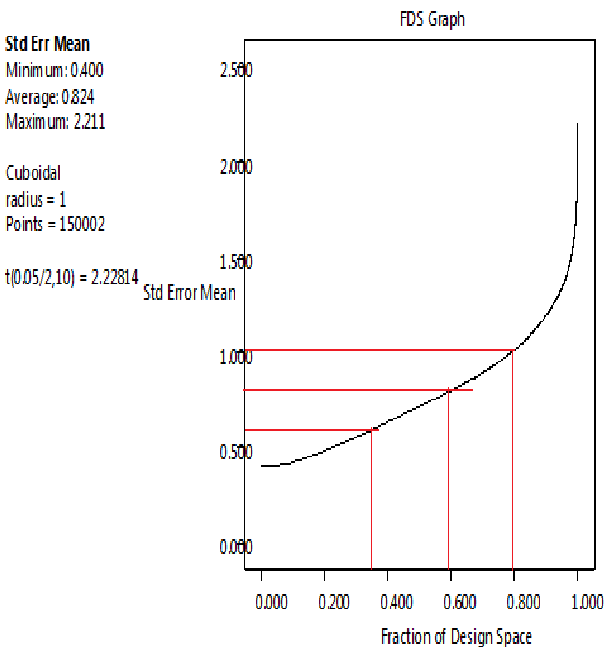

Fig. 8. Fraction of Design Space plot for the developed model

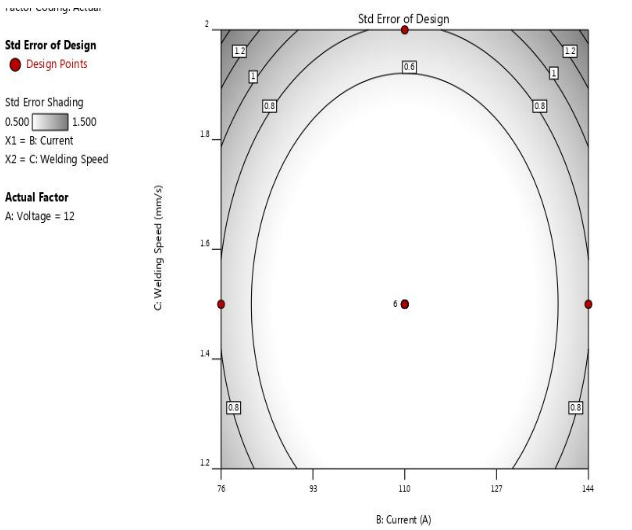

Fig. 9. Contour graph for Standard Error of Design for varying Current and Welding Speed at 12V Voltage

Figure 9 shows the contour graph of the standard error of design. It is observed that three contours (0.6, 0.8 and 1.0) enclose 35%, 59% and 80% of the design space. These values are obtained from the fraction of design space graph as shown in the figure 8. It means 35%,59% and 80% of design space has a relative standard error less than 0.6, 0.8 and 1.0 respectively.

IV.CONCLUSIONS

In the present study the multi objective problem was reduced to equivalent single objective problem using GRA and PCA. The RSM technique was used to optimize the above said single objective-the Overall Weld Quality. This hybrid technique, RSM coupled with GRA and PCA successfully developed statistically valid regression mathematical model. The ANOVA analysis leads to the conclusion that the current was the most influential input parameter, which explains 77.98% of total variation. The next important contribution on the response comes from the welding speed and the significance of voltage was relatively low. The optimum set of process parameters that maximized the response were obtained as: Voltage 12.96 V, Current 76.26 amp and Welding speed 1.65 mm/min.

REFERENCES

1. A. Rahmel, H.J. Grabke, W. Steinkusch,(1994), " Carburization – introductory survey" Mater. Corros, Vol 49, P.P. 221–225.
2. P. Kumar, K.P. Kolhe, S.J. Morey, C.K. Datta (2011) " Process parameters optimization of an aluminium alloy with pulsed gas tungsten arc welding (GTAW) using gas mixtures", Mater. Sci. Appl, Vol 2, P.P. 251–257.
3. S. Datta, A. Bandyopadhyay, P.K. Pal (2008), Int. J. Adv. Manuf. Technol., Vol 39, P.P. 1136–1143.
4. F. Kolahan, M. Heidari (2011), :A new approach for predicting and optimizing weld bead geometry in GMAW", Int. J. Aerosp. Mech. Eng., Vol 5 (2) P.P. 138–142.
5. S. Subramaniam, D.R. White, J.E. Jones, D.W. Lyons (1999), "Experimental approach to selection of pulsing parameters in pulsed GMAW", Weld. Res. Suppl., P.P. 66–172.
6. S.V. Sapakal, M.T. Telsang (2012), "Parametric optimization of MIG welding using Taguchi design method", Int. J. Adv. Eng. Res. Study, Vol 1, P.P. 28–30.
7. Arun Kumar Srirangan, Sathiya Paulraj (2016), "Multi-response optimization of process parameters for TIG welding of Incoloy 800HT by Taguchi grey relational analysis", Engineering Science and Technology, an International Journal, Vol 19, P.P. 811–817.
8. Mohan K Pradhan (2011), " Modelling and Optimisation of Electrical Discharge Machining variables using RSM coupled with GRA and PCA", AICTE Sponsored National Conference on Emerging Trend & its Application in Engineering (NCETAE 2011).
9. A. Tamilarasan, K. Marimuthu (Dec 2013 – Jan 2014), "Multi-response optimization of hard milling process: RSM coupled with grey relational analysis", International Journal of Engineering and Technology (IJET), ISSN: 0975-4024 , Vol 5 No 6 P.P. 4913.
10. Manish Gangil, M. K. Pradhan (2018), " Optimization of machining parameters of EDM for performance characteristics using RSM and GRA", Journal of Mechanical Engineering and Biomechanics, Volume 2, Issue 4, Page 27-33, 2018 ISSN-2456-219X.
11. S. Dewangan, C. K. Biswas, S. Gangopadhyay (December 12th–14th 2014), "Optimization of the quality and productivity characteristics of AISI P20 tool steel in EDM process using PCA-based grey relation analysis", 5th International & 26th All India Manufacturing Technology, Design and Research Conference (AIMTDR 2014), 2014, IIT Guwahati, Assam, India.
12. Ning Li, Yong-Jie Chen, Dong-Dong Kong (2019), "Multi-response optimization of Ti-6Al-4V turning operations using Taguchi-based grey relational analysis coupled with kernel principal component analysis", Adv. Manuf., Vol 7:142–154.
13. Suman Chatterjee, Arpan Kumar Mondal, SibaSankar Mahapatra (December 12th–14th, 2014), "COMBINED APPROACH FOR STUDYING THE PARAMETRIC EFFECTS ON QUALITY OF HOLES USING RSM AND PCA IN DRILLING OF AISI-304 STAINLESS STEEL", 5th International & 26th All India Manufacturing Technology, Design and Research Conference (AIMTDR 2014), IIT Guwahati, Assam, India.

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