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Optimal design of flux for submerged arc weld properties based on RSM coupled with GRA and PCA

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Abstract: This paper presents an effective approach for the selection of flux for optimised mechanical properties of low carbon steel welds. The weld is mainly characterised by impact strength, ultimate tensile strength, percentage elongation and hardness. Since the mechanical performance is measured by multiple performance characteristics, the grey relational analysis is used to determine the optimal combination of flux for mechanical properties. Moreover, principal component analysis has been used to evaluate the weighting values for various performance characteristics so that their relative importance can be properly considered. Fluxes were designed using RSM and have been developed through agglomeration technique. By analysing the grey relational grade, it is found that both the impact strength and ultimate tensile strength have the same weightage. The results of confirmation test obtained using this approach show that the GRA coupled with PCA can be effectively used for optimisation of flux for mechanical performance characteristics.

Keywords: submerged arc welding; GRA; response surface method; PCA; tensile strength; elongation.

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1 Introduction

Submerged arc welding (SAW) is widely used because of its inherent quality of good finish, high deposition rate, double protection from the atmospheric contamination and easy control on process variables (Houldcroft, 1989). This welding process differs from the other welding processes in that the arc is submerged and invisible. Both AC and DC current can be used. The welds made by the SAW process have high strength and ductility with low hydrogen and nitrogen content. This welding process is used for low alloy steels, mild steels, low carbon steels as well as nickel-based alloys, stainless steels and other non-ferrous metals. It has been confirmed that the flux composition affects the weld metal chemistry (Indacochea et al., 1985; Blander and Olson, 1984). Although, the equilibrium is not attained in the chemical reactions that take place during submerged arc welding because of very high temperature and fast cooling rate. However, the attempts have been made by researchers to develop the theoretical models for elements transfer considering the equilibrium conditions between the slag and weld metal (Chai and Eager, 1981; Mitra and Eager, 1984).

Various researchers have studied the effect of flux composition on weld metal chemistry, microstructure and mechanical properties. However, the optimisation of flux composition for mechanical performance characteristics, chemical composition, and microstructure is much less reported. Kanjilal et al. (2006) discussed the combined effect of flux and welding variables on the chemical composition and mechanical properties. The study revealed that the welding parameters had a profound effect on the chemical composition. The binary flux ingredients and interaction between the flux ingredients and welding parameters are more important than the individual flux ingredients. Bang et al. (2009) investigated the effect of wire-flux combination on chemical composition, tensile strength and impact strength of the welds and the responses were interpreted in terms of elements transfer. It was found by the researchers that C and Mn both were transferred to the slag from the weld. Prashad and Dwiedi (2008) studied the effect of welding current and heat input on the microstructure, hardness and toughness of the weld. The study revealed that that low heat input produced weld metal free from columnar grains. The increase in heat input coarsened the grain structure and produced columnar dendrite in the weld metal. The toughness of the weld was also dependent on the current and travel speed.

Jindal (2013) used the XVERTD design to develop the fluxes for HSLA steel and proposed the optimum composition of flux for elements transfer study in SAW. The researchers suggested the optimum combination of additives CaO 11.61%, Al_2O_3 12.32%, CaF_2 15% and MgO 39%. Adeyeye and Oyawale (2009) used a mathematical programming optimisation technique integrated with the statistical design of mixture experiments. The researchers optimised the weld metal properties for the given flux ingredients. The researchers concluded that the optimised values for various weld properties are: acicular ferrite 51.2%, Charpy impact toughness 29 joules, silicon transfer 0.23% and weld oxygen content 249 ppm. Majetich (1985) investigated the effects of SAW parameters on hard facing weld metal characteristics. The research revealed that the optimisation of hard facing welding conditions can both result in improved properties and reduce the cost of manufacture. Akkas et al. (2013) developed the models correlating the welding process parameters with the bead geometry of the welds. To correlate the above, ANN and neuro-fuzzy system approachs were used. From the developed models, it was also revealed that the appropriate values of welding parameters may be selected for controlling the bead geometry.

Ampiboon et al. (2015) studied the effect of welding process parameters on ultimate tensile strength of the structural steel ST37-2 by metal active gas welding. The developed model showed that the wire feed rate had the greatest effect on UTS and flow rate of gas had the least. Kumar et al. (2015) proposed the fuzzy logic model and optimum levels of NiO, MnO and MgO were obtained by using a single MRPI for impact strength and hardness for SiO_2 base fluxes. Roy et al. (2013) used grey-based genetic algorithm for optimisation of mechanical properties of the welds. The optimal process parameters used were wire feed rate, stick out and travel speed.

The literature survey on submerged arc welding shows that no scientific criterion is available for predicting the weld metal chemistry and mechanical properties of the welds for a given flux, wire-base plate combination. For understanding this, a sound scientific approach for the design of fluxes, manufacturing of fluxes, characterisation of physical and chemical properties and sound experimentation is required. The optimisation of flux composition has not been reported for various mechanical properties. So an attempt has been made to optimise the flux composition. The optimised data may be utilised by the fabricators and the welding consumables can be selected accordingly. Mild steel has got the good weldability with moderate strength and it is the most widely used steel in fabrication and structural applications. For critical applications, the steel should be able to withstand higher stresses and these should have a low weight. In high carbon steels, the strength may be high but the chances of brittle fracture are also high. So, because of general, critical and versatile applications, mild steel was selected for this study. These steels should also maintain their impact strength at low-temperature applications, like offshore oil platforms, bridges and heavy structures. So the aim should be to improve the strength of welded structure and it should be safe against brittle fracture. The mechanical properties of the welds are decided by the flux, welding consumables, microstructure formed, elements transferred to the weld and cooling rate. So a combination of response surface methodology based on grey relational analysis coupled to a principal component analysis has been used to select the optimal flux composition for high impact strength and ultimate tensile strength.

2 Experimental procedure

In this study, 20 fluxes were designed by using central composite design, using response surface methodology. The base fluxes CaO-SiO$_2$-Al$_2$O$_3$ were designed based on binary and ternary phase diagrams. The design matrices in coded and actual percentage forms are given in Table 1. The base fluxes were prepared in the ratio of 7:10:2. CaF$_2$, FeMn and NiO were added in the range of (2% to 8%) to the base fluxes to study the effect of C, Si, Mn, S, and Ni transfer on the weld metal properties such as impact strength, UTS and elongation. The fluxes were made by agglomeration technique. For making fluxes, all the constituents were mixed in a container and potassium silicate was added as binder. Potassium silicate was heated in a container and it was added to the powder, drop by drop. After addition of binder, the green pellets were made. These pellets were of various sizes, so these pellets were crushed in to smaller size balls and finally the grain size was measured from a sheave. These green pellets were dried for almost 24 hours and then were baked in a furnace maintained at 400°C for 5 to 6 hours, in order to remove the moisture. The agglomerated fluxes weighing each 1.5 kg were kept in air-tight jars. For this study, 20 beads on plate welds were made from the different 20 fluxes. The welding parameters were decided on the basis of a pilot experiment and these were made as constant. The various SAW parameters were identified by making trial runs to carry out the investigations. The welding parameters such as voltage, current, travel speed, nozzle to plate distance and wire feed rate were decided by laying beads on plates with varying amount of voltage, current and travel speed. After judging the bead appearance, geometry and slag detachability, the above parameters were identified. The selected parameters were kept as follows: voltage of 30 volt, current of 475 A and travel speed of 20 cm/minute.

Figure 1 Preparation of fluxes (see online version for colours)

The complete flux composition design matrix is given in Table 2. The measured mechanical properties of the welds are given in Table 3. Figure 1 represents the pictorial view of flux preparation and Figure 2 shows the tested samples of impact strength and tensile tests.

Table 1 Design matrix in coded form

No. of experiment	*wt% in coded form*			*wt% (grams)*		
	CaF_2 (A)	*FeMn (B)*	*NiO (C)*	*CaF_2 (A)*	*FeMn (B)*	*NiO (C)*
1	+1	–1	–1	8	2	2
2	0	+1	0	5	8	5
3	+1	–1	+1	8	2	8
4	–1	–1	–1	2	2	2
5	0	0	0	5	5	5
6	0	0	0	5	5	5
7	+1	+1	+1	8	8	8
8	0	0	0	5	5	5
9	0	–1	0	5	2	5
10	+1	0	0	8	5	5
11	0	0	+1	5	5	8
12	–1	–1	+1	2	2	8
13	0	0	0	5	5	5
14	0	0	0	5	5	5
15	+1	+1	–1	8	8	2
16	–1	0	0	2	5	5
17	0	0	0	5	5	5
18	0	0	–1	5	5	2
19	–1	+1	+1	2	8	8
20	–1	+1	–1	2	8	2

Figure 2 Tested samples for impact and tensile strength (see online version for colours)

Table 2 Base constituents and additives of the flux

Flux	*CaF_2 (gm)*	*FeMn (gm)*	*NiO (gm)*	*CaO (gm)*	*SiO_2 (gm)*	*Al_2O_3 (gm)*
1	120	30	30	486	695	139
2	75	120	75	453	647	130
3	120	30	120	453	647	130
4	30	30	30	519	742	148
5	75	75	75	470	671	134
6	75	75	75	470	671	134
7	120	120	120	420	600	120
8	75	75	75	470	671	134
9	75	30	75	486	695	139
10	120	75	75	453	647	130
11	75	75	120	453	647	130
12	30	30	120	486	695	139
13	75	75	75	470	671	134
14	75	75	75	470	671	134
15	120	120	30	453	647	130
16	30	75	75	486	695	139
17	75	75	75	470	671	134
18	75	75	30	486	695	139
19	30	120	120	453	647	130
20	30	120	30	486	695	139

Table 3 Measured responses of the weldment

Flux	*Impact strength (joule)*	*Hardness (HRB)*	*UTS (MPa)*	*Elongation%*
1	58	64	270.0	19.76
2	55	68	318.0	13.20
3	64	67	320.2	26.16
4	20	66	189.8	7.00
5	12	64	300.0	10.00
6	14	66	320.0	9.80
7	56	66	190.7	8.86
8	23	64	284.7	10.33
9	60	66	280.1	11.41
10	46	65	292.6	21.03
11	12	64	240	6.90
12	14	65	175.7	5.82
13	14	65	330.9	10.10
14	40	64	326.5	16.2
15	56	65	351.0	9.20
16	36	63	152.3	15.65
17	14	64	319.5	15.60
18	12	63	351	7.87
19	58	65	128.8	13.25
20	60	66	319.5	13.68

3 Analysis methods

Response surface methodology explores the relationship between the various variables and one or more responses. The objective is to optimise a response, which is influenced by several input variables. A central composite design has been used for this study. It is a fractional factorial design with centre points and the distance of these centre points from the centre of the design represents the curvature. This curvature depends upon the certain properties desired for the design and on the number of factors involved.

3.1 Grey relational analysis

GRA is a decision-making process which is based on the grey theory. This theory was developed by Deng (1989). In this theory, it is assumed that two types of data exist. These data are known as black and white. The black data represents the unknown information while white data represents the known information. Besides the above two systems, there may be another situation in which part of the information is known and part of the information is unknown. This incomplete information is known as a grey system. In this study, three responses, UTS, impact strength and percentage elongation, were considered for maximisation while one response, hardness, was considered for a specific value. As the units and the ranges of various input and output factors may differ, so the original data must be normalised in order to make this data comparable. The first step in GRA is to normalise the data. The procedure for applying GRA is as follows (Vijayan and Rao, 2014):

1 Normalisation of the data.

2 After normalisation, the grey relational coefficients for the various experiments are calculated.

3 Calculation of grey relational grade.

To make the original sequences into a comparable sequence, data pre-processing is done (Pradhan, 2012). After normalisation, each response is designated between 0 and 1. To normalise the data the following equation (1) is used for maximising the responses (Vijayan and Rao, 2014).

$$x_i^*(k) = \frac{x_i^0(k) - \min x_i^0(k)}{\max x_i^0(k) - \min x_i^0(k)} \tag{1}$$

To achieve the nominal value normalisation will be done as given below in equation (2).

$$x_i^*(k) = 1 - \frac{\left|x_i^0(k) - x^0\right|}{\max x_i^0(k) - x^0} \tag{2}$$

where $x_i^0(k)$ is the original sequence, $\min x_i^0(k)$ is the minimum $x_i^0(k)$ value, max $x_i^0(k)$ is the largest $x_i^0(k)$ value and x^0 is the desired value. To achieve lower the better, the normalisation will be done as follows in equation (3)

$$x_i^*(k) = \frac{\max x_i^0(k) - x_i^0(k)}{\max x_i^0(k) - \min x_i^0(k)} \tag{3}$$

The next step is to calculate the grey relational coefficient. The grey relational coefficients are calculated to express the relationship between the idle and the actual experimental result. This is generally represented by $\xi(k)$ and can be calculated from the below-given relation (4).

$$\xi(k) = \frac{\Delta_{\min} + \xi\Delta_{\max}}{\Delta_{oi}(k) + \xi\Delta_{\max}} \tag{4}$$

where ξ is the distinguishing coefficient. It is generally taken as 0.5. After calculating grey relational coefficient, the grey relational grade is calculated as follows in equation (5).

$$x_i = \frac{1}{n}\sum_{k=1}^{n} \xi_i(k) \tag{5}$$

3.2 Principal component analysis

PCA was developed by Pearson (1901) and Hotelling (1933). This approach explains the variance and covariance structure of a set of defined variables by way of the linear combinations. The various steps for applying PCA are as follows (Siddiquee et al., 2010):

1 Normalisation of the given set of variables.

2 The normalised data are used to make a variance-covariance matrix as follows:

$$S = \begin{matrix} x_{1,1} & x_{1,2} & \cdots & x_{1,n} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m,1} & x_{m,2} & \cdots & x_{m,n} \end{matrix}$$

Here, n is the number of weldment properties and m is the number of experiments.

3 Correlation coefficient array.

The correlation coefficient array is calculates as follow in equation (6).

$$R_{jl} = \frac{\left(\operatorname{cov}\left(x_i(J), x_i(l)\right)\right)}{\sigma_{xi}(j)\sigma_{xi}(l)}; \; j = 1, 2, ..., n; \; i = 1, 2, ..., n. \tag{6}$$

The eigenvalues and eigenvectors are calculated from the correlation coefficient array given by equation (7).

$$\left(R - \lambda_K I_m\right)V_{ik} = 0 \tag{7}$$

where λ_K shows eigenvalues, $\sum_{k=1}^{k=n} \lambda_k = n,\ k = 1, 2, \cdots, n$ and

$V_{ik} = [a_{ki}, a_{k2X_1}, ..., a_{km}]^T$, shows the eigen vectors corresponding to eigenvalues.

4 Principal component: It can be calculated as follows in equation (8).

$$Y_{mk} = \sum_{i=1}^{n} X_m(i) V_{ik} \tag{8}$$

where y_{m1} is the first principal component, y_{m2} is called the second principal component and so on the other values may be calculated.

4 Analysis and discussion

In this study, the multi-objective optimisation has been used for impact strength and ultimate tensile strength. The percentage elongation and hardness have not been considered for optimisation because the elongation and impact strength are proportional to each other (Modi et al., 2001) and hardness is supposed to have a targeted value. The maximum UTS occur for weld no. 15 and minimum for weld no. 19. The eigenvalues and values for principal components are given in Tables 4 and 5, respectively. Table 6 shows the normalised value, deviation, grey relational coefficients for impact strength as well as tensile strength with the grey relational grades and the ranking for all designed fluxes. Ranking depicts that the flux no. 3 is optimum for high values of UTS as well as impact strength. The suggested composition of the flux contains CaF_2 8%, FeMn 2% and NiO as 8%. The corresponding impact strength and UTS are 64 joules and 320.2 N/mm^2.

Table 7 shows the ANOVA analysis for response surface reduced quadratic model for GRG. The regression equation for GRG in terms of flux constituents has also been developed and is shown in equation 9. The quadratic model is significant with a p-value < 0.0001. The R^2 value for the developed model is 0.86 and the adjusted R^2 is in close agreement with the pred. R^2. The lack of fit is also insignificant for the model. The ANOVA results also indicate that CaF_2 is the most significant factor in deciding the GRG.

Table 4 Eigenvalues table

Eigenvalue	1.0436	0.9564
Proportion	0.522	0.478
Cumulative	0.522	1.00

Table 5 Principle component of variables

Variable	*PC1*	*PC2*
Impact strength	0.707	0.707
UTS	0.707	0.707

Table 6 GRA analysis and GRG ranking

Exp. no.	*Impact strength*				*Ultimate tensile strength*				*GRG*	*Ranking*
	Impact	*Normalised*	*Deviation*	*GRC*	*UTS*	*Normalised*	*Deviation*	*GRC*		
1	58	0.8846	0.1154	0.813	270	0.6355	0.3645	0.5783	0.6954	6
2	55	0.8269	0.1731	0.743	318	0.8515	0.1485	0.7710	0.7569	4
3	64	1.0000	0.0000	1.000	320.2	0.8614	0.1386	0.7829	0.8915	1
4	20	0.1538	0.8462	0.371	189.8	0.2745	0.7255	0.4080	0.3897	19
5	12	0.0000	1.0000	0.333	300	0.7705	0.2295	0.6854	0.5094	15
6	14	0.0385	0.9615	0.342	320	0.8605	0.1395	0.7818	0.5620	13
7	56	0.8462	0.1538	0.765	190.7	0.2786	0.7214	0.4094	0.5870	11
8	23	0.2115	0.7885	0.388	284.7	0.7016	0.2984	0.6263	0.5072	16
9	60	0.9231	0.0769	0.867	280.1	0.6809	0.3191	0.6104	0.7386	5
10	46	0.6538	0.3462	0.591	292.6	0.7372	0.2628	0.6555	0.6232	9
11	12	0.0000	1.0000	0.333	240	0.5005	0.4995	0.5002	0.4168	18
12	14	0.0385	0.9615	0.342	175.7	0.2111	0.7889	0.3879	0.3650	20
13	14	0.0385	0.9615	0.342	330.9	0.9095	0.0905	0.8468	0.5945	10
14	40	0.5385	0.4615	0.520	326.5	0.8897	0.1103	0.8193	0.6697	7
15	56	0.8462	0.1538	0.765	351	1.0000	0.0000	1.0000	0.8824	2
16	36	0.4615	0.5385	0.481	152.3	0.1058	0.8942	0.3586	0.4200	17
17	14	0.0385	0.9615	0.342	319.5	0.8582	0.1418	0.7791	0.5606	14
18	12	0.0000	1.0000	0.333	351	1.0000	0.0000	1.0000	0.6667	8
19	58	0.8846	0.1154	0.813	128.8	0.0000	1.0000	0.3333	0.5729	12
20	60	0.9231	0.0769	0.867	319.5	0.8582	0.1418	0.7791	0.8229	3

Table 7 ANOVA for response surface reduced quadratic model for GRG

Source	*Sum of squares*	*df*	*Mean square*	*F-value*	*p-value Prob > F*	
Model	0.396	6	0.066	13.31	< 0.0001	Significant
CaF_2	0.123	1	0.123	24.79	0.0003	Significant
FeMn	0.029	1	0.029	5.92	0.0302	Significant
NiO	0.039	1	0.039	7.85	0.015	Significant
CaF_2-FeMn	0.072	1	0.072	14.50	0.0022	Significant
FeMn-NiO	0.064	1	0.064	12.94	0.0032	Significant
FeMn	0.069	1	0.069	13.85	0.0026	Significant
Residual	0.065	13	0.005			
Lack of fit	0.046	8	0.006	1.58	0.3181	Not significant
Pure error	0.018	5	0.004			
Cor total	0.461	19				
R-squared	0.860		Adj R-squared	0.795	Pred R-squared	0.527

Final equation in terms of actual factors:

$$\begin{aligned} \text{GRG} = {} & 0.19516 + 0.089647 * \text{CaF}_2 - 0.0097 * \text{FeMn} + 0.028981 * \text{NiO} \\ & -0.010536 * \text{CaF}_2 * \text{FeMn} - 0.0099 * \text{FeMn} * \text{NiO} + 0.013024 * \text{FeMn}^2 \end{aligned} \tag{9}$$

4.1 Confirmatory test

After obtaining the optimal flux combination, the next step is to verify the improvement in mechanical performance characteristics using this optimal flux combination. Table 8 represents the results of the confirmation experiments using this optimal flux combination proposed by the GRA and PCA approach and those of an initial flux composition. The results reveal that that the impact strength is increased from 23 Joules to 64 joules and the ultimate strength is increased from 280 MPa to 320.2 MPa for the optimised flux over the initial composition of the flux constituents.

Table 8 Confirmatory experimental results

Test condition	*CaF_2 (%)*	*FeMn (%)*	*NiO (%)*	*Impact strength (J)*	*UTS (MPa)*
Initial	5%	5%	5%	23.0	280
Optimised	8%	2%	8%	64.0	320.2
Increase (%)	-	-	-	178.26	14.36

5 Conclusions

This study presents an application of grey relational analysis coupled with principal component analysis for optimising mechanical properties of low carbon steel welds. From this study, the following conclusions can be drawn:

1 The principal component analysis has successfully reflected the relative weightage of impact strength and tensile strength of the weldments.

2 The quadratic model for the GRG in terms of actual flux constituents has been proposed using response surface methodology. Based on the results of the ANOVA analyses for GRG, the most significant factor is CaF_2 followed by NiO and then FeMn.

3 The results of impact strength have shown an improvement of 178.26% while using optimised flux composition over the initial values and similarly an increase of 14.36% is observed in tensile strength of the welds.

4 The proposed approach of grey relational analysis coupled with principal component analysis can be successfully applied to the optimisation of mechanical properties of the welds.

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