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Application of Regression Models in Multi-Objective Optimization of FCAW Process Variables on Volume of Austenitic Stainless-Steel Clad Layers

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Keywords: Cladding, Stainless steel. Volume of reinforcement. Volume of penetration, Optimization, Genetic algorithm, Response surface methodology

ABSTRACT

Metal cladding is a process of depositing a thick layer of material over another material using a suitable welding process to preserve the material from corrosion problems. Cost estimation for producing the cladding with desired quality is essential in fabrication industries, which includes the cost of consumable filler material. Analysis on volume of metal deposited during cladding process could provide necessary knowledge about consumption of filler wire and thereby the cost of consumables. In this work, an attempt was made to perform multi-criteria optimization for depositing a heat resistant layer over a material used in boiler construction. Therefore, low thermal conductivity 316L grade of austenitic stainless steel was surfaced over IS:2062 structural steel plates using FCAW process. Rotatable central composite design for five factors and five levels was used to perform the experiments. Mathematical models were developed for the prediction of volume of reinforcement and volume of penetration and tested for adequacy with the help of ANOVA technique. Multi-objective constrained optimization was carried out using RSM and genetic algorithm tool to yield best optimum set of process variables for the responses of interest. Optimum settings and developed models were validated by good agreement shown during conformity test experiments. The findings have wide industrial applications in the field of surfacing.

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INTRODUCTION

Weld metal cladding is a process to enhance chemical, mechanical and metallurgical properties of material surfaces. Numerous fields viz. chemical plants, fertilizer plants, nuclear power plants, pressure vessels, railways and even aircraft and missile components are started making use of this technique to enhance the properties and/or repair of the worn-out components at their surfaces with feasible cost instead of replacing them completely (Murugan and Parmar, 1994). Various welding processes such as Gas Metal Arc Welding (GMAW), Gas Tungsten Arc Welding (GTAW), Shielded Metal Arc Welding (SMAW), Plasma Arc Welding (PAW), Submerged Arc Welding (SAW), Flux Cored Arc Welding (FCAW), Oxy-Acetylene Welding (OAW), Electroslag Welding (ESW), explosive welding and laser welding are imperative processes frequently employed for clad surfacing in fabrication industries (Palani and Murugan, 2006, 2007; Kannan and Yoganandh, 2010; Balan et al., 2018; Benyounis and Olabi, 2008; Senthilkumar et al., 2014; Gomes et al., 2012; Gao et al., 2016). Effective selection and control of FCA welding process parameters are very much essential in producing quality claddings (Kannan and Yoganandh, 2010). Quality of cladding is assessed based on bead geometry. Basic clad bead geometry includes clad bead reinforcement height, clad bead width and depth of penetration (Sowrirajan et al., 2018). Figure 1 shows the basic bead geometry factors of a cladding process.

Pressure vessels involved in heat transfer through wall sections. Reduction in heat loss is possible, if the clad layer is formed using low thermal conductivity material as shown in Figure 2. Especially, Heat loss is possibly reduced with increase in clad bead height as it helps to increase the clad layer thickness. Temperature drop across a composite layer is depends on thermal conductivity (k_1 & k_2) of layer materials and thermal contact resistance at the interface. Fig. 2 shows the concept of temperature drop across the composite layers made by cladding process

(Sowrirajan et al., 2018). Stainless steel cladding is a trendy option to fabricate corrosion resistance surfaces on low carbon steel. Austenitic stainless steels possess low thermal conductivity than other grades, so that, it has the ability to reduce heat loss and better weldablity property of this grade made suitable for welding (Sowrirajan et al., 2018; Cengel, 2008; Kothandaraman and Subramanyan, 2014). Also, these alloy steels are effective to control wear problems as well. Usually, composite clad layer sections are formed in pressure vessels to improve surface properties of base material (Sowrirajan et al., 2018; Kannan et al., 2014). Regularly, a definite quantity of heat energy is continuously transferred to the atmosphere through the walls of the pressure vessels. Reducing this conduction heat loss up to a possible extend will increase the efficiency of thermal equipment up to a considerable level. This requires an effective study on cladding process.

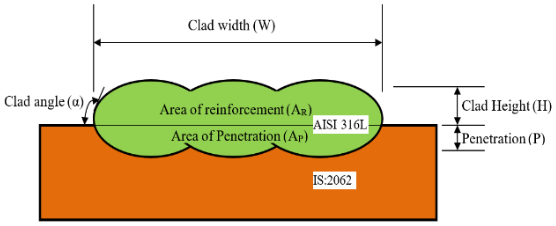

Fig. 1. Basic bead geometry

Engineers often search for optimum selection of controllable process parameters to produce desired bead geometry with cost and time benefits. Mathematical models in terms of controllable process parameters are capable for the prediction of weld bead dimensions and for the optimization the process variables. In present days, the traditional optimization techniques used for the optimization purpose is greatly reduced due to lack of robustness and non-conventional more intellectual techniques are on the working platform popularly with the accessibility and affordability of modernized computers. The Genetic Algorithm (GA) is a trendy intelligent optimization technique that was employed for the present work to avail optimal set of process parameters (Kannan et al., 2013; Sathiya et al., 2013; Senthilkumar et al., 2017).

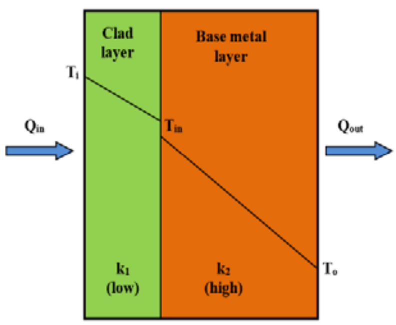

Fig. 2. Concept of temperature drop across a composite layer

Lot of research works were carried out already for achieving desired bead geometry dimensions with best quality and productivity. Preparation of budget for any engineering process is essential to take decision on feasibility. Consumption of filler wire is important in arriving total cost of cladding. Volume of filler metal deposited is required to calculate the cost of the filler wire. But, a separate analysis on volume of reinforcement and volume of penetration could be helpful in controlling the quality of cladding effectively. Lack of previous works in this view is an evident to study the volume of reinforcement and volume of penetration. Hence, this work aims to produce the clad layer for reducing heat loss and to optimize the welding process parameters for producing required volume of filler metal deposition with best quality using genetic algorithm.

EXPERIMENTAL WORK

To investigate the heat transfer characteristics of the structural steel plates with the austentitic stainless steel-clad layer, the base structural steel specimens were prepared for the dimensions of 100×50×20 mm. Austenitic Stainless-steel clad layers were deposited using 316L flux cored filler wire of 1.2 mm diameter. Weld bead geometry dimensions and thermal properties are highly influenced by the parameters such as open circuit voltage (V), wire feed rate (F), welding speed (S), nozzle-to-plate distance (D) and electrode angle (E) were selected based on the previous studies (Sowrirajan et al., 2018). The limits of each variables were determined based on the trail runs and the levels were identified using suitable formula (Kannan et al., 2013). Table 1 indicates the selected variables and their levels for conducting the experimental studies. The edges of the specimen were prepared to ensure the good quality weld joints (Sathiya et al., 2013) through the pre-processes like grinding and cleaning on the steel plates. Based on central composite design, 32 experiments were carried out using Esseti-Unimacro 501C welding machine. In all the experiments, the three clad layers were made with the overlapping of 40% to ensure the dilution in the acceptable limit (Murugan and Parmar, 1994; Siddaiah et al., 2016). In order to prevent the undesirable reactions, a mixture of CO_2 (95%) and Argon (5%) was used as shielding gas and the flow rate was set as 18 litres per minute. After the surfacing of clad layers, they were allowed to cool naturally. The cladded specimen surfaces are well prepared using emery paper and nital solution (etching) for metallurgical studies. All clad specimens obtained from experimental runs are shown in Figure 3.

Reinforcement volume (VR) and penetration volume (VP) were considered as output responses. Measurements were made using profile projector for clad height (H), clad width (W), depth of penetration (P), area of reinforcement (A_R) and area of penetration

(A_P). Reinforcement volume and penetration volume values were calculated using the formulas, $VR=A_R$*Length of plate, $VP=A_P$* Length of plate and presented in the Table 2 (Gunaraj and Murugan, 2000).

Table 1. Details of FCAW process parameters

Parameters with notations	**Units**	**Levels**				
		-2	**-1**	**0**	**+1**	**+2**
Open circuit voltage (V)	Volts	30	32	34	36	38
Wire feed rate (F)	m/min	9	11	13	15	17
Welding speed (S)	m/min	0.18	0.26	0.34	0.42	0.5
Nozzle-to-plate distance (D)	mm	17	19	21	23	25
Electrode angle (E)	degree	5	10	15	20	25

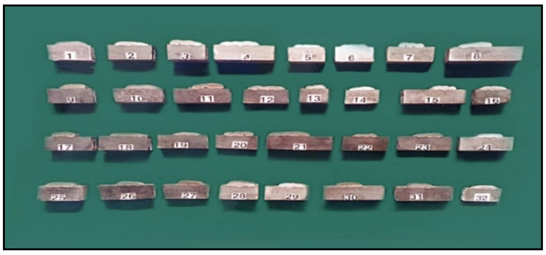

Fig. 3. Clad specimens during experimental runs

Table 2. Design matrix with response values

Runs	Process parameters (Coded)					Responses	
	V	F	S	D	E	Volume of Reinforcement, VR (cm^3)	Volume of penetration, VP (cm^3)
1	-1	-1	-1	-1	+1	11.0	1.03
2	+1	-1	-1	-1	-1	9.5	0.98
3	-1	+1	-1	-1	-1	13.1	1.24
4	+1	+1	-1	-1	+1	13.3	2.38
5	-1	-1	1	-1	-1	6.0	1.60
6	+1	-1	+1	-1	+1	6.2	1.91
7	-1	+1	+1	-1	+1	9.2	1.43
8	+1	+1	+1	-1	-1	12.3	1.31
9	-1	-1	-1	+1	-1	10.2	0.78
10	+1	-1	-1	+1	+1	10.5	1.56
11	-1	+1	-1	+1	+1	14.3	0.98
12	+1	+1	-1	+1	-1	13.1	1.54
13	-1	-1	+1	+1	+1	6.2	0.80
14	+1	-1	+1	+1	-1	7.2	0.93
15	-1	+1	+1	+1	-1	7.9	1.06
16	+1	+1	+1	+1	+1	8.3	1.45
17	-2	0	0	0	0	9.3	0.84
18	+2	0	0	0	0	9.7	1.69
19	0	-2	0	0	0	6.6	1.46
20	0	+2	0	0	0	12.8	1.54
21	0	0	-2	0	0	18.0	1.47
22	0	0	+2	0	0	6.0	1.60
23	0	0	0	-2	0	9.3	1.83
24	0	0	0	+2	0	9.35	1.20
25	0	0	0	0	-2	9.15	1.22
26	0	0	0	0	+2	9.15	1.32
27	0	0	0	0	0	8.8	1.25
28	0	0	0	0	0	9.5	1.60
29	0	0	0	0	0	9.0	1.50
30	0	0	0	0	0	9.5	1.40
31	0	0	0	0	0	9.3	1.26
32	0	0	0	0	0	8.7	1.56

Development of mathematical models and conformity tests

Mathematical models for the prediction of reinforcement volume and penetration volume were developed using the coefficients obtained from Minitab 14 software package by performing response surface analysis of experimental results. The output function for an output response can be represented as Y = f (V, F, S, D, E). The following second order polynomial equation was selected to represent response surface of responses for five variables, in which coefficient b_0 is the constant term; coefficients b_1, b_2, b_3, b_4 and b_5 are linear terms; coefficients b_{11}, b_{22}, b_{33}, b_{44} and b_{55} are square terms; coefficients b_{12}, b_{13}, b_{14}, b_{15}, b_{23}, b_{24}, b_{25}, b_{34}, b_{35} and b_{45} are interaction terms (Sowrirajan et al., 2018).

$$Y = b_0 + b_1V + b_2F + b_3S + b_4D + b_5E + b_{11}V^2 + b_{22}F^2 + b_{33}S^2 + b_{44}D^2 + b_{55}E^2 + b_{12}VF + b_{13}VS + b_{14}VD + b_{15}VE + b_{23}FS + b_{24}FD + b_{25}FE + b_{34}SD + b_{35}SE + b_{45}DE \quad (1)$$

The detailed regression analysis, clearly indicates their influencing levels on the cladding process and the insignificant coefficients are identified through the p-values (<0.05). It is a fact that the regression equations are usually simplified by neglecting the insignificant coefficients without compromising the accuracy level of the equation. Though, the final mathematical models for the present study were developed with the consideration of all significant and insignificant coefficients considering the genetic algorithm optimization. F-tests and t-tests were incorporated for checking the importance of coefficients and variables (Palani and Murugan, 2007). The developed models were involved to test their adequacy by using ANOVA technique. Moreover, the coefficient of determination (R^2) was taken as furthermore deciding factor. Based on the evaluation of R^2 values, it was found that the developed models are quite adequate. Table 3 depicts the ANOVA data of the present work. Final mathematical models developed in coded form for the responses are given in Equations (2) & (3).

Reinforcement volume

$$VR = 9.17727 + 0.1375V + 1.54583F\text{-}2.32083S\text{-}0.11667D\text{-}0.0125E + 0.04773V^2 + 0.09773F^2 + 0.67273S^2 + 0.00398D^2\text{-}0.03977E^2 + 0.15625VF + 0.43125VS\text{-}0.09375VD\text{-}0.45625VE\text{-}0.03125FS\text{-}0.35625FD\text{-}0.14375F\ldots 0.13125DE$$

$$VR = 9.17727 + 0.1375V + 1.54583F - 2.32083S - 0.11667D - 0.0125E + 0.04773V^2 + 0.09773F^2 + 0.67273S^2 + 0.00398D^2 - 0.03977E^2 + 0.15625VF + 0.43125VS - 0.09375VD - 0.45625VE - 0.03125FS - 0.35625FD - 0.14375FE - 0.33125SD - 0.41875SE + 0.13125DE \quad (2)$$

Penetration volume

$$\mathrm{VP} = 1.44705 + 0.20167\mathrm{V} + 0.08167\mathrm{F} + 0.01083\mathrm{S} - 0.16833\mathrm{D} + 0.09583\mathrm{E} - 0.05955\mathrm{V}^2 - 0.0008\mathrm{F}^2 + 0.00795\mathrm{S}^2 + 0.00295\mathrm{D}^2 - 0.0583\mathrm{E}^2 + 0.05\mathrm{VF} - 0.1075\mathrm{VS} + 0.03625\mathrm{VD} + 0.18625\mathrm{VE} - 0.11125\mathrm{FS} + 0.0075\mathrm{FD} + 0.005\mathrm{FE} - 0.0775\mathrm{SD} - 0.045\mathrm{SE} - 0.07125\mathrm{DE} \quad (3)$$

Table 3. Analysis of variance table

Response	Sum of Squares (SS)		Degrees of freedom (DF)		Mean Square value (MS)		F-Value	p-value (Prob> F)	R^2 (%)	Adj. R^2 (%)
	Reg.	Res.	Reg.	Res.	Reg.	Res.				
Reinforcemet volume (VR)	215.144	6.623	20	11	10.7572	0.6021	17.87	0.000	97.0	91.6
Penetration volume (VP)	3.4508	0.2734	20	11	0.17254	0.02485	6.94	0.001	92.7	79.3

Reg.- Regression, Res. -Residual

The validities of regression models were tested by plotting scatter charts. Typical scatter plots are presented in Figures 4 and 5 to show the perfection of fit between observed and predicted responses. The scattered chart shows that the both responses are scattered very nearer to 45° straight line, evident a perfect fit for the responses (Palani and Murugan, 2007). Also, an experimental run was performed checking the ability of models in predicting the responses using different values of process variables other than the values used in the design matrix. The results show good agreement comparing to the experimental values towards the developed models. The results of conformity test run are presented in Table 6.

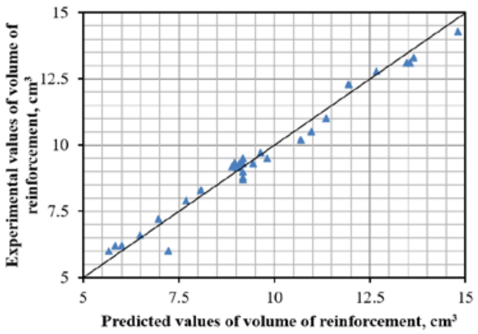

Fig. 4. Scatter chart for VR

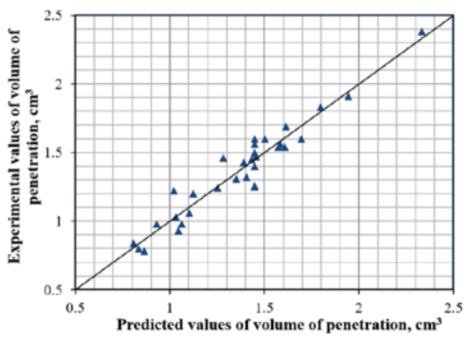

Fig. 5. Scatter chart for VP

MULTI-OBJECTIVE OPTIMIZATION

A solution arrived for an individual single objective may not be suitable because of the reason that a solution set of input decision variables obtained for an optimum level may affect the remaining response variables accordingly. There is a possibility to produce unacceptable results for the output variables other than the objective (Sowrirajan et al., 2018). Multi objective optimization is an appropriate process to be carried out for the problems with multi-responses. Therefore, multi-response optimization was carried out since the successful metal deposition by FCAW process is completely a multi-response process. The foremost objective was set to enhance volume of reinforcement (VR) so that to increase the clad height. However, the other objective was to decrease volume of penetration (VP) in order to achieve quality benefits.

Optimization using RSM

The multi objective optimization was carried out using response optimizer in MINITAB 14 software with the suitable lower and upper values of the responses (Sowrirajan et al., 2018). The main objective of the work is to reduce the heat loss across the clad layer. Hence, the goal of the optimization process was set as maximizing the volume of reinforcement and minimizing the volume of penetration. The minimum value of volume of reinforcement in the response table has been set as lower limit and the maximum response as target values. Similarly, for the volume of penetration the target value has been as the lowest value in the response. Weight and importance values of the two objectives were set as unity. The optimum set of process variables were explored using response optimizer. Numbers of local solutions were obtained for the best solutions through the various starting points. Finally, a global solution which provides the best possible set of process parameters that satisfying the goals of the optimization was attained. These set of values were taken as near optimal values for genetic algorithm optimization.

Optimization using GA

The multi objective optimization solver (gamultiobj) available under optimization tools in MATLAB R2013a was used to carry out multi objective optimization (Konak et al., 2006; Goldberg, 2000; Katherasan et al., 2014; Sathiya et al., 2012). The objectives were to maximize volume of reinforcement and to minimize volume of penetration. The regression models developed for the prediction of responses (eqns. (2) & (3)) were used to formulate objective functions. As GA always minimizing the objectives, fitness functions were written such that to meet the objectives of responses i.e. negative sign was included in order to maximize the reinforcement volume and given in equations (4) & (5). A separate Matlab code file was generated to assign fitness functions for performing multi objective optimization. Constraints on five controllable FCAW process variables such as open circuit voltage, wire feed rate, welding speed, nozzle-to-plate distance and electrode angle were applied based on the lower and upper levels followed during experimental work.

$$y(1) = -(9.17727 + 0.1375 * x(1) + 1.54583 * x(2) - 2.32083 * x(3) - 0.11667 * x(4) - 0.0125 * x(5) + 0.04773 * x(1) * x(1) + 0.09773 * x(2) * x(2) + 0.67273 * x(3) * x(3) + 0.00398 * x(4) * x(4) - 0.03977 * x(5) * x(5) + 0.15625 * x(1) * x(2) + 0.43125 * x(1) * x(3) - 0.09375 * x(1) * x(4) - 0.45625 * x(1) * x(5) - 0.03125 * x(2) * x(3) - 0.35625 * x(2) * x(4) - 0.14375 * x(2) * x(5) - 0.33125 * x(3) * x(4) - 0.41875 * x(3) * x(5) + 0.13125 * x(4) * x(5)) \quad (4)$$

$$y(2) = 2.44705 + 0.20167 * x(1) + 0.08167 * x(2) + 0.01083 * x(3) - 0.16833 * x(4) + 0.09583 * x(5) - 0.05955 * x(1) * x(1) - 0.0008 * x(2) * x(2) + 0.00795 * x(3) * x(3) + 0.00295 * x(4) * x(4) - 0.0583 * x(5) * x(5) + 0.05 * x(1) * x(2) - 0.1075 * x(1) * x(3) + 0.03625 * x(1) * x(4) + 0.18625 * x(1) * x(5) - 0.11125 * x(2) * x(3) + 0.0075 * x(2) * x(4) + 0.005 * x(2) * x(5) - 0.0775 * x(3) * x(4) - 0.045 * x(3) * x(5) - 0.07125 * x(4) * x(5) \quad (5)$$

Table 4. Optimal solutions arrived for best fitness values in GA

S.No	V	F	S	D	E	Reinforcement volume, VR (cm^3)	Penetration volume, VP (cm^3)
1	-2.0	+0.5	-2.0	+2.0	+2.0	-23.61	0.45
2	-2.0	-0.1	-2.0	+2.0	+2.0	-23.42	0.32
3	-2.0	+1.8	-2.0	+2.0	+2.0	-24.30	0.75
4	-2.0	+1.3	-2.0	+2.0	+2.0	-23.97	0.64
5	-2.0	+0.8	-2.0	+2.0	+2.0	-23.72	0.51
6	-2.0	-0.2	-2.0	+2.0	+2.0	-23.37	0.28
7	-2.0	-2.0	-2.0	+2.0	+2.0	-23.27	-0.13
8	-2.0	-0.5	-2.0	+2.0	+2.0	-23.35	0.22
9	-2.0	+1.9	-2.0	+2.0	+2.0	-24.39	0.77
10	-2.0	+2.0	-2.0	+2.0	+2.0	-24.46	0.79
11	-2.0	+1.7	-2.0	+2.0	+2.0	-24.14	0.71
12	-2.0	+1.2	-2.0	+2.0	+2.0	-23.92	0.61
13	-2.0	+0.9	-2.0	+2.0	+2.0	-23.83	0.54
14	-2.0	+0.4	-2.0	+2.0	+2.0	-23.49	0.42
15	-2.0	+1.0	-2.0	+2.0	+2.0	-23.87	0.56
16	-2.0	-2.0	-2.0	+2.0	+2.0	-23.27	-0.13
17	-2.0	+0.9	-2.0	+2.0	+2.0	-23.79	0.54
18	-2.0	+0.9	-2.0	+2.0	+2.0	-23.76	0.53
19	-2.0	+2.0	-2.0	+2.0	+2.0	-24.42	0.79
20	-2.0	+1.0	-2.0	+2.0	+2.0	-23.83	0.56
21	-2.0	+0.7	-2.0	+2.0	+2.0	-23.72	0.49
22	-2.0	+1.4	-2.0	+2.0	+2.0	-24.09	0.66
23	-2.0	-0.1	-2.0	+2.0	+2.0	-23.46	0.32
24	-2.0	+1.7	-2.0	+2.0	+2.0	-24.27	0.73
25	-2.0	-0.2	-2.0	+2.0	+2.0	-23.42	0.29
26	-2.0	-0.5	-2.0	+2.0	+2.0	-23.35	0.22
27	-2.0	+1.1	-2.0	+2.0	+2.0	-23.91	0.58
28	-2.0	+0.8	-2.0	+2.0	+2.0	-23.76	0.51
29	-2.0	+0.4	-2.0	+2.0	+2.0	-23.60	0.42
30	-2.0	+2.0	-2.0	+2.0	+2.0	-24.46	0.79
31	-2.0	+1.4	-2.0	+2.0	+2.0	-24.09	0.66
32	-2.0	+1.2	-2.0	+2.0	+2.0	-23.97	0.61
33	-2.0	+1.9	-2.0	+2.0	+2.0	-24.39	0.77
34	-2.0	+0.5	-2.0	+2.0	+2.0	-23.65	0.45
35	-2.0	+0.6	-2.0	+2.0	+2.0	-23.69	0.47

Optimization was started initially with default settings of optimization toolbox. Further, the parameters were varied by changing one parameter at a time while keeping other parameters as set earlier. Number of trials was allowed on monitoring the solutions. Finally, 35 set of process parameters were arrived to yield best solutions after 203 iterations. These set of values with corresponding objective values are shown in Table 4. The settings of genetic algorithm toolbox for the input decision variables corresponding to the best fitness values of objectives are shown in Table 5.

Table 5. GA parameter settings for the best fitness values of objectives

Parameters	**Method/Value**
Number of variables	5
Lower bounds	[-2 -2 -2 -2 -2]
Upper bounds	[+2 +2 +2 +2 +2]
Population type	Double vector
Population size	100
Creation function	Feasible
Initial range	[-2;+2]
Selection function	Tournament
Tournament size	2
Reproduction cross over fraction	0.7
Mutation	Constraint dependent
Cross over function	Scattered
Migration	Forward
Migration fraction	0.1
Distance measure function	Default
Stopping criteria generation	250
Stall generation	200

RESULTS AND DISCUSSION

The results obtained for the multi-response optimization using RSM for achieving maximum value volume of reinforcement (VR) and minimum value of volume of penetration (VP) of stainless-steel claddings are shown in Figure 6. The global solution for the optimization was arrived based on the consideration of effects of process variables on the responses by RSM. Best global solution suggested after went through a number of local solutions and optimum set of process parameter values are presented in the Table 6. Composite desirability values for all three responses were almost unity. Hence, this combination of process parameters is believed to be the best optimized settings of FCAW process parameters suggested by RSM to obtain the desired values of responses simultaneously.

The genetic algorithm was also allowed to search for a best set of process parameters. In support to this, the relationship between average spread and generations obtained are shown in Figure 7. It is seen that, the spread was wider at the start and later the spread converges to a narrow range with respect to the increase in generations and therefore, no contravention noted. Also, the relationship between volume of reinforcement and volume of penetration is represented in the pareto front optimal points shown in Figure 8. These optimal points are supportive to choose a set of alternative process parameters for producing claddings with productivity and quality benefits. Optimization results obtained from RSM is shown in Figure 6 and compared with GA in Table 6 for comparison purpose. It could be seen that GA results are better than RSM results to yield best set of optimum process variables of FCAW process, though, the difference in values between RSM and GA results was almost negligible.

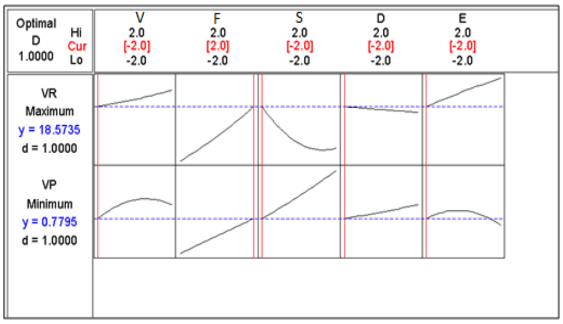

Fig. 6. Optimal set of process parameters and responses using RSM

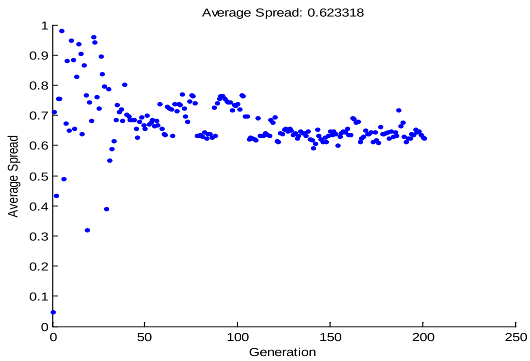

Fig. 7. Average spread for the optimization

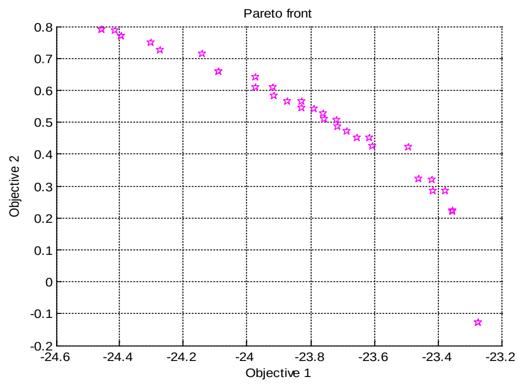

Fig. 8. Pareto front optimal points between reinforcement volume (Objective 1) and penetration volume (Objective 2)

Table 6. Comparison of RSM and GA results

Description	Parameters/Responses	Units	Optimization results (coded)	
			RSM	GA
Process variables (coded)	Open circuit voltage (V)	-	-2	-2
	Wire feed rate (F)	-	+2	+2
	Welding speed (S)	-	-2	-2
	Nozzle-to-plate distance (D)	-	-2	+2
	Electrode angle (E)	-	+2	+2
Cladding Responses	Reinforcement volume (VR)	cm^3	18.57	24.45
	Penetration volume (VP)	cm^3	0.78	0.79
Conformity test results	Reinforcement volume (VR)	cm^3	-	24.22
	Penetration volume (VP)	cm^3	-	0.80

Conformity tests were conducted with the settings suggested by genetic algorithm tool for validating the capability of developed mathematical model and optimization results. A like working conditions established during the experimental runs was developed and followed during this conformity test run also. Results obtained during this experiment are presented in Table 6. The prediction capability of the models and the optimum set of process variables were found to be quite acceptable with good agreements based on the results of conformity tests.

CONCLUSION

Following conclusions were arrived from this investigation.

(i) Response surface methodology was successfully implemented to establish mathematical regression models for stainless steel-clad bead geometry factors (i.e. volume of reinforcement and volume of penetration) and to establish fitness functions for the GA optimization.

(ii) It was revealed that the GA was able to produce the best optimal set of process parameters for the objectives considered though both RSM and GA producing optimal solutions with a negligible difference for multi-objective optimization.

(iii) The genetic algorithm could suggest a number of optimal solutions to support the operator's choice whereas RSM could be employed for availing near optimal solutions such that a reference point to GA.

(iv) Conformity experiments reveal that prediction capability of developed models and optimization results obtained are readily acceptable to produce the claddings with desired goals.

(v) The optimum set of the FCAW process parameters suggested by the GA was able to produce cladding with the volume of reinforcement of 24.22 cm^3 and volume of penetration of 0.80 cm^3 without compromising productivity and quality benefits.

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