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Abstract

The superiority and profile of the weld obtained through Gas Metal Arc Welding (GMAW) are not only depends on the chemical configuration of the flux, but also on the choice of welding parameters. Since variety of process parameters influence the results, a proper empathetic of process performance and identification of suitable welding conditions (i.e. optimum setting of process parameters) are indeed essential to enhance quality. The present work highlights the application and comparison of single-response optimization using Response Surface Methodology (RSM) with Meta Heuristic Optimization techniques namely Particle Swarm Optimization (PSO) and Firefly Algorithm (FA). The experimental analysis is conducted by optimizing the input parameters like Current Rating (Amp), Feed Rate (m/min), Welding Speed (mm/sec) and Gas Flow (l/m). An attempt has been made in the present research work by taking AISI: 430 stainless steel specimens to compare and analyse the performance in terms of weld bead geometry (Bead Width (mm), Bead Height (mm) and Depth of Penetration (mm)), Hardness (VHN) and Tensile Strength (N/mm²) using IRB 1410 Industrial manipulator. The effect of process parameters on ferritic stainless steel of series 400 (AISI: 430) grade has been analysed using Response Surface Methodology (RSM) method. Further, Meta Heuristic Optimization techniques namely Particle Swarm Optimization (PSO) and Firefly Algorithm (FA) have been developed further to minimize the bead width, bead height and maximize the depth of penetration. While fairly similar results were achieved with the implementation of Particle Swarm Optimization (PSO) and Firefly Algorithm (FA) were computationally efficient. Experimental validation of the single-objective as well as multi-objective optimization results indicates that the empirical models for the quality prediction with proposed optimization results are better for the GMAW process by IRB 1410 Industrial manipulator.

Key Words: GMAW Process, AISI: 430 Stainless Steel, IRB 1410 Industrial Manipulator, RSM Methodology, Meta Heuristic Optimization Techniques

1. INTRODUCTION

Nowadays, a non hardenable AISI: 430 Stainless Steel which belongs to ferritic group of steels is widely developed for its good resistance and formability, and also for its good mechanical properties. Highly stress corrosion resistance and relatively low production cost are the main reasons for the increasing applications of AISI 430 ferritic stainless steels [1]. AISI: 430 stainless steels are essentially used in automotive systems, structural frames, body paneling of buses and coaches, and home appliances [2]. Among the other welding process GMAW is a versatile process extensively used in manufacturing of ferrous and non-ferrous materials as it greatly improves the weldment quality characteristics. Gas Metal Arc Welding (GMAW) is an arc welding process in which the heat source is an arc formed between the consumable metal electrode and the work piece with an external supplied inert gas such as argon or helium [3].

The production of high quality weld joint is mainly depends on the features of the bead geometry, mechanical metallurgical characteristics of the weld as on the various aspects of weld chemistry, and these features are highly influenced by the variables such as Weld Bead Geometry (Bead Height (BH), Depth of Penetration (DOP) and Bead Width (BW)), Hardness (HD) test and Tensile (TS) test and the different input parameters such as Welding Current, Feed Rate, Welding Speed and Gas Flow [4-9]. The international engineering and welding communities like European Federation for Welding, Joining and Cutting (EWF) is strongly interested in investing in research and development geared towards finding optimized methods for obtaining weldments of acceptable quality [10]. Numerous expert methods such as artificial neural network, fuzzy logic, finite element, genetic algorithm etc. have been applied for optimizing process parameters, since it has been found that applying the most appropriate process parameters has a huge impact on the eventual quality of each weldment [11-15].

In order to assure the quality of the weldments, welding parameters are preferably optimized using conventional optimization technique like Response Surface Methodology (RSM) and Taguchi Method. Compare with Taguchi, RSM is wished for achieving the desired quality and process optimization [16] because it will be used to determine the cause and effect relationship between true mean response and input control variables for the selection of optimum process parameters. In recent days, various Meta heuristic algorithm like PSO (Particle Swarm Optimization), GA (Genetic Algorithm), ANN (Artificial Neural Network) and BPNN (Back Propagation Neural Network) have also been applied to find desired process parameters. Currently robotic welding systems are becoming increasingly popular and tend to substitute more and more mechanized and automated welding [17-25]. Robotic welding equipment can be programmed for different weldments. In this paper an attempt has been directed towards the development of a Meta Heuristic Optimization Techniques to optimize the welding parameters for the material Ferritic Stainless Steel 430 using IRB 1410 Arc Welding Robot.

2. MATERIALS AND METHODS

2.1. EXPERIMENTAL DESIGN

In the present work, IRB 1410 Arc Welding Robot is utilised to perform the experimental investigations. The experimental Setup of IRB 1410 Arc Welding Robot is shown in Figure 1 and its specification are given in Table 1. This industrial manipulator is designed to offer the high-quality welds with minimum downtime and provides operators with intelligent controls to manage the welding process parameters. The new intelligent welding power source (special type of electrical power is required to make an arc welding) provides the enhanced control of welding process, allowing the operators to specify the process parameters such as voltage, current and gas flow. During the arc welding process, an arc welding gun or torch is used to transmit current from welding cable to electrode. If the nozzle of the torch become close to the arc, spatter will be gradually deposited on the specimen. To avoid that, a torch cleaner is often used in the process to remove the spatters. Wire feeder is also used to feed the consumable electrode during the arc welding process to ensure the continuous flow. Wire feeder coil is fixed with the guide tube over the roller as shown in the figure. At the end of the torch, wire liner should be visible to confirm the wire feeder coil is aligned accurately with the guide tube. Nozzle hole of 0.8 mm meter is adapted in the torch end and pushed the wire liner manually for a few lengths to start the feeding. If any hit occurred on the wire liner, there may be misalignment with the wire liner. The wire feeder coil is driven by friction between the wire feed drive roller and the wire.

Figure 1. IRB 1410Arc Welding Robot

Table 1. IRB 1410 Arc Welding Robot specifications

Parameters	Value
Handling Capacity	5 kg
Number of axes	6
Accuracy	0.05 mm
Weight	225 kg
Wire Feeder Diameter	1.2 mm

Figure 2. Cause and effect schematic of GMAW process

Cause and effect analysis technique is implemented to identify the most probable causes affecting a welding process. It can help to analyze cause and effect relationships associated with input and output parameters for better performance and accuracy. It visually depicts a clear picture of the possible causes of a particular parameter impact on the output responses. The welding effect is placed in a box on the right and a long process line is drawn pointing to the box as shown in Figure 2. Usually the major categories of welding causes are implying that it relies mainly on the Machine (Equipment), Method and Material. Each of these welding causes can be viewed as an affect in its own right with its own process. Based on the inferences, the following fixture design, base material and gas selections are carried out to optimize the process with better accuracy.

2.2. FIXTURE DESIGN

A fixture is a supportive element essentially required in most of the automation manufacturing systems, inspections, and assembly operations. Fixture supports to securely locate the workpiece in a required position or orientation with respect to any component like cutting tool or measuring device as for instance in assembly or welding. The robotic welding operation requires specialized fixtures to accurately hold the weld piece during welding operation. The fixture is fabricated for the size 600mm x 600mm x 20mm to provide a supporting structure with greater capabilities to hold the workpieces. Toggle clamps are also used to clamp the workpiece in the fixture as shown in the Figure 3.

Figure 3. Fixture design taken for the present work

Toggle clamps used in this fixture helps to hold the workpiece in the immobility state. The clamps are operated manually through a lever system. If the lever actuated, the clamp moves against the work piece and holds the specimen rigidly. Toggle clamps will firmly hold the work piece until the operator move the lever to release the toggle. In between the work piece and fixture, rubber wiper is placed which acts as securing element.

2.3. BASE MATERIAL SELECTION

The material AISI: 430 is a non-hardenable steel contains 16 to 18 % straight chromium and belongs to the ferritic group of steels. This material is well known for its good corrosion resistance and formability coupled with better mechanical properties. Ferritic stainless steel is magnetic and better resistance to high temperature corrosion than the martensitic types. This material is widely used in functional applications where the cost is major factor e.g. automotive exhaust systems, catalytic convertor, radiator caps, and chimney liners. This steel is routinely joined by all fusion and resistance welding processes with the consideration of two important factors of weld joints such as solidification cracking and preservation of corrosion resistance in the heat affected zone. The chemical composition of the base material and the filler wire are given in Table 2 and Table 3. The chemical composition is measured by Optical Emission Spectrometer (BRIRD- DV6). The test plate dimensions are 100mm x 83 mm x 5.8 mm. The electrode used is 430 flux core wire (CF- 8C) with the diameter of 0.8mm.

Table 2 Chemical composition of base material

Material	C	Mn	P	S	Si	Cr
AISI 430	0.019	0.383	0.026	0.003	0.470	16-18

Table 3 Chemical composition of wire feed coil

Material	C	Mn	P	S	Si	Cr
AISI 430	0.019	0.383	0.026	0.003	0.470	16-18

2.4. Gas Selection

The general gases used for MIG welding process are Argon, Carbon dioxide (CO₂), Oxygen (O₂) and Helium. The most commonly used mixtures of gases for stainless steel are 2% Carbon dioxide and 98% Argon to protect the weld part from atmosphere gases and water vapour. Argon gases supports to ensure the quality of the weld compare to the other gases. Argon gas flow can be controlled by flow regulator in the Argon cylinder. In this experimentation, torch maintains the wire feeder and gas flow will be in stable condition during welding operation. The diameter of the welding wire depends upon the base material thickness. According to the base material thickness as 5.8mm, the wire feeder wire is selected as 0.8mm throughout the welding operation.

3. EXPERIMENTATION DESIGN AND PROCEDURE

In all the welding processes, the quality of welded joints greatly influenced by the values of process parameters. Moreover, joint edge preparation has often necessary when plates with more than 5mm thickness. This edge modification concentrates due to the heat in melted area and reduces the arc power which was necessary for penetration. This result in lowering the heat input rate and reduces the risk of unforeseen distortions or metallurgical structure alterations. The joint edge geometry will be specified by groove angle, root face and root opening as shown in Figure 4.

Figure 4. Joint edge specifications for GMAW of plates

60° Groove Angle without gap

60° Groove Angle with 1mm gap

Groove Angle 70°

Figure 5. V- groove angles of the joints taken for experimentation trials

For the specimens in this proposed research work, joint edge geometries are prepared by milling process in the form of V-bevelled based on ANSI/AWS D 1.1 standard. Single V preparation with broad root face is welded with 60° Groove angle, 60° Groove angle with 1mm gap and 70° Groove angle. The penetration is not good in 60° Groove angle with 1mm gap and 70° Groove angle as shown in Figure 5. Henceforth, V-groove angle is maintained at 60° with zero mm root opening gap.

3.1. DESIGN OF EXPERIMENTS USING RESPONSE SURFACE METHODOLOGY (RSM)

The design of the experiment is an obvious approach particularly dealing with a fairly novel process as it reduces the number of experimental trials to be taken to establish the process as well as to distinguish the influence of process parameters on resultant quality. Response Surface Methodology (RSM) is a type of effective method to optimize the process conditions and to find the optimum value of the process input parameters. RSM is an inexpensive response surface model approximating the relationship between input variables and desired responses. This methodology concerns with a set of mathematical and statistical tools that can be used to predict the response influenced by the considered input variables, to optimize the response. By using RSM, it is possible to define the relationships between the responses and the main controllable input factors as well as it is a powerful technique, when all independent variables can be measurable, controllable and continuous along the experiment (with negligible error). The expression for the response surface can be

$$y = f(x_1, x_2, \dots, x_k) \quad (1)$$

If the response is well modeled by a linear function of the independent variables, the approximating function is the first-order model

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \epsilon \quad (2)$$

The mathematical model of quadratic surface is described as Second Order Model

$$y = \beta_0 + \sum_{i=1}^k \beta_i x_i + \sum_{i=1}^k \beta_{ii} x_i^2 + \sum_{i < j} \beta_{ij} x_i x_j + \epsilon \quad (3)$$

The Design of Experiment (DOE) is carried out by RSM technique using Minitab- 17 statistical software by considering four factors and five levels of problem. The design matrix is chosen to conduct 32 experiments with 2 replications. Total number of experiments is 64. Two level factorials with half fraction consists of thirty-two cube points with twelve centre points and twenty axial points are taken into analysis. The Table 4 depicts the levels and factors of the DOE required to optimize the values of welding input parameters using single response optimization to predict the quality of weld characteristics.

Table 4. Levels and Factors of the DOE

Factors	Level 1(-2)	Level 2 (-1)	Level 3(0)	Level 4(+1)	Level 5(+2)
Current (Amp)	240	260	280	300	320
Feed Rate (m/min)	5	6	7	8	9
Welding Speed (mm/sec)	10	12.5	15	17.5	20
Gas Flow(l/m)	12.5	15	17.5	20	22.5

Central Composite designs (CCD) approach of RSM is undertaken to be the better technique for five-level factorial designs which follows a class of approximately rotatable second order. It follows an independent quadratic design by requiring fewer experimental trials. The behaviour coordination is at the midpoints of edges on the process space in conjunction with the centre. In the present research, CCD technique has been instigated and experimental design matrix is expressed as shown in Table 5. The experimental tests were conducted as similar to the same design matrix. During the experimentation, it is necessary to eliminate the factors like environment factor, welding electrode variances, etc. that might affect the final results by adding unaccounted error. Further, in order to evaluate the robustness and suitability of the developed model with analysis of variance (ANOVA) study was carried out. The detailed analysis was implemented exclusively for the five designated response characteristics, namely Bead Width (mm), Bead Height (mm), Depth of Penetration (mm), Hardness (VHN) and Tensile Strength. Hence, from the characteristic correlations individual mathematical models were created for each response parameters.

Table 5. Design matrix of DOE

Sl.No	Design Matrix				Current	Feed rate	Welding speed	Gas Flow
1	0	0	0	0	280	7	15	17.5
2	0	0	0	0	280	7	15	17.5
3	2	0	0	0	320	7	15	17.5
4	1	1	-1	1	300	8	12.5	20
5	0	0	0	0	280	7	15	17.5
6	-1	1	-1	1	260	8	12.5	20
7	-1	1	-1	1	260	8	12.5	20
8	-1	-1	1	-1	260	6	17.5	15
9	-1	1	1	-1	260	8	17.5	15

10	0	-2	0	0	280	5	15	17.5
11	0	0	0	0	280	7	15	17.5
12	-2	0	0	0	240	7	15	17.5
13	1	-1	-1	1	300	6	12.5	20
14	-1	-1	1	-1	260	6	17.5	15
15	0	0	0	0	280	7	15	17.5
16	0	0	0	0	280	7	15	17.5
17	0	2	0	2	280	9	15	17.5
18	-1	-1	-1	-1	260	6	12.5	15
19	1	1	-1	1	300	8	12.5	15
20	0	0	-2	0	280	7	10	17.5
21	-1	-1	-1	1	260	6	12.5	20
22	-2	0	0	0	240	7	15	17.5
23	1	-1	-1	1	300	6	12.5	20
24	0	0	0	-2	280	7	15	12.5
25	-1	-1	-1	1	260	6	12.5	20
26	1	1	-1	-1	300	8	12.5	15
27	-1	1	-1	-1	260	8	12.5	15
28	-1	-1	0	1	260	6	17.5	20
29	1	1	1	-1	300	8	17.5	15
30	0	0	0	0	280	7	15	17.5
31	0	0	-2	0	280	7	10	17.5
32	1	1	1	1	300	8	17.5	20
33	0	0	0	-2	280	7	15	12.5
34	-1	1	-1	-1	260	8	12.5	15
35	0	0	0	0	280	7	15	17.5
36	1	1	1	1	300	8	17.5	20
37	0	0	0	0	280	7	15	17.5
38	-1	1	1	1	260	8	17.5	20
39	1	-1	1	-1	300	6	17.5	15
40	-1	1	1	1	260	8	17.5	20
41	2	0	0	0	320	7	15	17.5
42	0	0	2	0	280	7	20	17.5
43	0	0	0	0	280	7	15	17.5
44	0	0	0	0	280	7	15	17.5

45	-1	-1	1	1	260	6	17.5	20
46	-1	-1	-1	-1	260	6	12.5	15
47	0	0	0	0	280	7	15	17.5
48	-1	1	1	-1	260	8	17.5	15
49	0	0	0	2	280	7	15	22.5
50	1	-1	1	1	300	6	17.5	20
51	1	1	1	-1	300	8	17.5	15
52	1	1	-1	1	300	8	12.5	20
53	1	-1	1	1	300	6	17.5	20
54	0	0	0	0	280	7	15	17.5
55	1	-1	-1	-1	300	6	12.5	15
56	1	-1	-1	-1	300	6	12.5	15
57	0	0	0	0	280	7	15	17.5
58	1	-1	1	-1	300	6	17.5	15
59	0	2	0	0	280	9	15	17.5
60	0	-2	0	0	280	5	15	17.5
61	0	0	0	2	280	7	15	22.5
62	0	0	2	0	280	7	20	17.5

4. EXPERIMENTAL METHODOLOGY AND ANALYSIS

In the current research, GMAW welding technique has been investigated on a 200mm x 20mm dimension specimen of on ferritic stainless steel of series 400 (AISI: 430) grade and methodical experimentation procedure has been executed to optimize the multiple process parameters. The specimens are welded using the IRB1410 arc welding robot by changing the parameters such as Current Rating (Amp), Feed Rate (m/min), Welding Speed (mm/sec) and Gas Flow (l/m). The welded specimens are cut into the required testing dimensions of 200mm x 20mm. The bead profiles of welded specimen such as Bead width (BW), Depth of penetration (DP), Bead Height (BH) are analyzed using profile projector. The micro vickers hardness (VHN) tests are performed on the etched transverse cross section of the welded zone using a load of 500 g, which is applied for duration of 10 seconds. Three measurements in each welded zone are taken at regular intervals and the average hardness values are noted. The weld zones have higher hardness than the base metal zone. The variation of hardness across the weld metal is related to micro structural variation. The hardness values are higher in the weld metal area due to high dislocation density in the weld metal.

Figure 6. Tensile Standard dimensions

Figure 7. Dumb-bell shape

Figure 8. Universal Testing machine

The plates of AISI:430 stainless steel plates are welded by using industrial manipulator. The experiments are conducted as per the design factors. The values of Weld Bead Geometry (BH, DOP and BW) are noted for the corresponding input process parameters. The hardness value is identified for each specimen by using Vickers hardness tester and also the tensile strength is predicted for each specimen by using universal testing machine. Tensile test is conducted to study about the ultimate tensile strength of the weld joint. To achieve this, the maximum load can be applied to the welded specimen. For this test, the specimens are cut into dumbbell shape of standard dimensions as per the ANSI/AWS D1.1 standard as shown in Figure 7 which is made using L MILL 55 CNC machine as shown in Figure 8. The results obtained from Weld Bead Geometry (BH, DOP, and BW), Hardness (HD) test and Tensile (TS) test are tabulated in the Table 6. These experimental data are used to find the fitness function for designing optimization techniques.

Table 6. Experimental results holding bead geometry by varying input parameters

Sl.No	Current Rating (Amp)	Feed Rate (m/min)	Welding Speed (mm/sec)	Gas Flow (l/m)	BH	DOP	BW	HD	TS
1	280	7	15	17.5	1.023	5.182	4.235	282.95	198.103
2	280	7	15	17.5	1.023	5.188	4.234	287.45	258.649
3	320	7	15	17.5	1.012	5.207	4.185	305.55	114.4828
4	300	8	12.5	20	0.998	5.226	4.227	301.05	209.278
5	280	7	15	17.5	1.025	5.189	4.239	289.45	306.897
6	260	8	12.5	20	1.08	5.224	4.281	315.15	285.7241
7	260	8	12.5	20	1.083	5.234	4.286	319.05	286.8966
8	260	6	17.5	15	0.959	5.187	4.192	221.25	337.348
9	260	8	17.5	15	0.996	5.149	4.218	219.65	316.5517
10	280	5	15	17.5	0.99	5.219	4.246	293.55	332.6217
11	280	7	15	17.5	1.023	5.185	4.235	290.95	265.518
12	240	7	15	17.5	1.021	5.181	4.178	261.7	312.579
13	300	6	12.5	20	0.983	5.208	4.223	299.15	223.4483
14	260	6	17.5	15	0.958	5.112	4.194	224.95	338.096
15	280	7	15	17.5	1.028	5.182	4.239	270.55	280
16	280	7	15	17.5	1.022	5.189	4.233	292.5	275.482
17	280	9	15	17.5	1.045	5.261	4.267	290.95	243.4483
18	260	6	12.5	15	1.036	5.205	4.124	252.75	303.4483
19	300	8	12.5	15	1.016	5.258	4.205	317.9	245.546
20	280	7	10	17.5	1.078	5.239	4.175	307.05	385.845
21	260	6	12.5	20	1.072	5.261	4.174	312.35	346.255
22	240	7	15	17.5	1.029	5.184	4.179	264.3	314.828
23	300	6	12.5	20	0.988	5.207	4.227	297.7	224.1765

24	280	7	15	12.5	0.994	5.139	4.219	228.7	297.416
25	260	6	12.5	20	1.072	5.268	4.176	309	344.379
26	300	8	12.5	15	1.018	5.249	4.205	314.25	211.0345
27	260	8	12.5	15	1.029	5.239	4.199	283.6	224.828
28	260	6	17.5	20	0.998	5.207	4.152	240.05	424.5412
29	300	8	17.5	15	1.087	5.221	4.171	254.35	347.241
30	280	7	15	17.5	1.025	5.181	4.231	276.05	288.241
31	280	7	10	17.5	1.079	5.229	4.171	315.95	377.278
32	300	8	17.5	20	1.065	5.229	4.108	253.7	251.6581
33	280	7	15	12.5	0.992	5.134	4.213	224	280.201
34	260	8	12.5	15	1.029	5.235	4.191	280.9	227.8431
35	280	7	15	17.5	1.025	5.182	4.231	289.45	251.385
36	300	8	17.5	20	1.061	5.228	4.109	235.45	258.7562
37	280	7	15	17.5	1.029	5.182	4.23	274.3	250.3448
38	260	8	17.5	20	1.049	5.162	4.215	240.65	408.1681
39	300	6	17.5	15	1.039	5.139	4.273	256.45	289.5419
40	260	8	17.5	20	1.044	5.168	4.211	237.65	403.793
41	320	7	15	17.5	1.018	5.209	4.18	308.3	154.6412
42	280	7	20	17.5	1.064	5.157	4.124	238.95	459.358
43	280	7	15	17.5	1.028	5.182	4.231	273.45	301.207
44	280	7	15	17.5	1.025	5.179	4.237	283.05	270.3119
45	260	6	17.5	20	0.991	5.203	4.15	240.45	426.2069
46	260	6	12.5	15	1.031	5.209	4.129	253.95	310.1831
47	280	7	15	17.5	1.023	5.182	4.229	281.15	273.1034
48	260	8	17.5	15	0.993	5.149	4.217	218.5	319.3581
49	280	7	15	22.5	1.016	5.202	4.193	226.3	253.916
50	300	6	17.5	20	0.998	5.209	4.151	261.45	279.278
51	300	8	17.5	15	1.085	5.221	4.177	255.65	316.748
52	300	8	12.5	20	0.991	5.228	4.221	297.25	211.586
53	300	6	17.5	20	0.996	5.208	4.15	258.45	282.981
54	280	7	15	17.5	0.992	5.182	4.238	269.3	294.0586
55	300	6	12.5	15	1.016	5.163	4.258	268.9	284.8276
56	300	6	12.5	15	1.011	5.167	4.25	266.75	276.0861
57	280	7	15	17.5	1.029	5.189	4.23	272.55	255.6824

58	300	6	17.5	15	1.031	5.137	4.269	250.95	295.1864
59	280	9	15	17.5	1.048	5.263	4.241	287.6	240.6161
60	280	5	15	17.5	0.991	5.213	4.245	294.6	328.9655
61	280	7	15	22.5	1.019	5.206	4.199	228.95	248.348
62	280	7	20	17.5	1.069	5.159	4.129	232.45	464.828

4.1. MATHEMATICAL MODEL: REGRESSION ANALYSIS

In this section, single response optimization using RSM technique statistical results are used for the analysis of bead height (BH), depth of penetration (DOP), bead width (BW), hardness (HD) and tensile strength (TS). The response function for BH is expressed as:

$$\text{Bead Height} = 1.904 + 0.00004 A - 0.0859 B - 0.22784 C + 0.12313 D - 0.000003 A^*A - 0.001751 B^*B + 0.001880 C^*C - 0.000810 D^*D + 0.000114 A^*B + 0.000491 A^*C - 0.000363 A^*D + 0.004688 B^*C + 0.001262 B^*D \quad (4)$$

By taking Equation 4 established by regression analysis for bead height, analysis of variance results for the response surface cubic model is given in Table 7. The Model F-value of 124.27 indicates that the model is significant. In fact, it is chance of about 0.01% to get large F-Value mostly could occur due to noise. The obtained model terms are significant due to the “Prob > F” values smaller than 0.05. In this case A, B, D, C, D, AA, BB, CC, DD, AB, AC, AD, BC, BD are significant model terms. Values greater than 0.1 indicate the model terms are not significant. If there are many insignificant model terms, model reduction may improve the model. The “Lack of Fit F-value” of 0.88 shows that lack of fit is not significant relative to the pure error. There is a 56.4% chance that large F – value of lack of fit could occur due to noise. Non-significant lack of fit is good. From Table 7, the “Pred. R-squared” of 0.9592 is in sensible agreement with the ‘Adj. R-squared’ of 0.9633. The corresponding residual plot for the bead height is given in Figure 9.

Table 7. ANOVA table for bead height

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	13	0.0564	0.004	124.27	0
Linear	4	0.011	0.0027	79.06	0
A	1	0.0001	0.0001	3.53	0.067
B	1	0.0093	0.0093	266.76	0
C	1	0.0004	0.0004	13.59	0.001
D	1	0.0011	0.0011	32.36	0
Square	4	0.0107	0.0026	76.73	0
A*A	1	0.0001	0.0001	3.10	0.085
B*B	1	0.0001	0.0001	5.02	0.03
C*C	1	0.0078	0.0078	225.87	0
D*D	1	0.0014	0.0014	41.85	0
2-Way Interaction	5	0.0347	0.0057	198.47	0
A*B	1	0.0001	0.0001	4.76	0.035
A*C	1	0.0192	0.0192	550.93	0
A*D		0.0105	0.0105	301.79	0

B*C	1	0.0043	0.0043	125.72	0
B*D	1	0.0003	0.0003	9.12	0.004
Error	48	0.0016	0.00003		
Lack of fit	11	0.0003	0.00003	0.88	0.564
Pure Error	37	0.0013	0.00003		
Total	61	0.0581			
Model Summary					
S		R-sq	R-sq(adj)	R-sq(pred)	
0.00593		97.11%	96.33%	95.92%

Figure 9. Obtained residual plot for the bead height parameter

By taking other parameter like depth of penetration, the regression equation is given as:

$$\text{Penetration} = 8.507 - 0.01416 A - 0.2962 B - 0.1071 C + 0.05067 D + 0.000009 A^2 + 0.01434 B^2 + 0.000574 C^2 - 0.000456 D^2 + 0.000803 A^2 B + 0.000265 A^2 C - 0.001000 B^2 C - 0.005925 B^2 D + 0.000840 C^2 D \quad (5)$$

Based on the Equation 5 for weld penetration, analysis of variance results for the response surface cubic model is given in Table 8. The Model F-value of 60.47 indicates that the model is significant. In fact, it is chance of about 0.01% to get large F-Value mostly could occur due to noise. The obtained model terms are significant due to the “Prob > F” values smaller than 0.05. In this case A, B, C, D, AA, BB, CC, DD, AB, BC, BD, CD are significant model terms. Values greater than 0.1 indicate the model terms are not significant. If there are many insignificant model terms, model reduction may improve the model. The “Lack of Fit F-value” of 0.88 shows that lack of fit is not significant relative to the pure error. There is a 36.1% chance that large F – value of lack of fit could occur due to noise. Non-significant lack of fit is good. From Table 8, the “Pred. R-squared” of 0.8953 is in sensible agreement with the ‘Adj. R-squared’ of 0.9269. The corresponding residual plot for the penetration is given in Figure 10.

Table 8. ANOVA table for depth of penetration

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	13	0.071	0.005	60.47	0
Linear	4	0.0354	0.0088	98.31	0

A	1	0.0007	0.0007	8.16	0.006
B	1	0.0055	0.0055	60.99	0
C	1	0.019	0.019	210.98	0
D	1	0.0102	0.0102	113.12	0
Square	4	0.0134	0.0033	37.34	0
A*A	1	0.0006	0.0006	7.33	0.009
B*B	1	0.0117	0.0117	130.28	0
C*C	1	0.0007	0.0007	8.16	0.006
D*D	1	0.0004	0.0004	5.15	0.028
2-Way Interaction	6	0.022	0.0036	48.71	0
A*B	1	0.0082	0.0082	91.48	0
A*C	1	0.0056	0.0056	62.25	0
A*D		0	0	1.01	0.32
B*C	1	0.0002	0.0002	2.22	0.143
B*D	1	0.007	0.007	77.80	0
C*D	1	0.0008	0.0008	9.77	0.003
Error	48	0.0042	0.00009		
Lack of fit	10	0.001	0.0001	1.14	0.361
Pure Error	37	0.0032	0.00008		
Total	61	0.075			
Model Summary					
S		R-sq	R-sq(adj)	R-sq(pred)	
0.0094		94.25%	92.69%	89.53%

Figure 10. Residual plots of Depth of penetration

By following, depth of penetration, the bead height mathematical expression is given as

$$\text{Bead Width} = -5.57261 + 0.0383208A + 0.3287B + 0.258390C + 0.157675D - 0.000032673A^2 + 0.0042433B^2 - 0.00332107C^2 - 0.00107107D^2 - 0.00141406AB - 0.000248125AC - 0.000358125AD - 0.00448750BC + 0.00451250BD - 0.00359500CD \quad (6)$$

The bead width with regression model representation of Equation 6, respective analysis of variance results for the response surface cubic model is given in Table 9. The Model F-value of 359.32 indicates that the model is significant. In fact, it is chance of about 0.01% to get large F-Value mostly could occur due to noise. The obtained model terms are significant due to the “Prob > F” values smaller than 0.05. In this case A, B, C, D, A², B², C², AB, AC, AD, BC, BD, CD are significant model terms. Values greater than 0.1 indicate the model terms are not significant. If there are many insignificant model terms, model reduction may improve the model. The “Lack of Fit F-value” of 0.88 shows that lack of fit is not significant relative to the pure error. There is a 0.016% chance that large F – value of lack of fit could occur due to noise. Non-significant lack of fit is good. From Table 9, the “Pred. R-squared” of 0.9827 is in sensible agreement with the ‘Adj. R-squared’ of 0.9880. The corresponding residual plot for the penetration is given in Figure 11.

Table 9. ANOVA table for bead width

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	14	0.1112	0.0079	359.32	0
Linear	4	0.0104	0.0002	118.11	0
A	1	0.0003	0.0003	16.17	0
B	1	0.0006	0.0006	31.56	0
C	1	0.0076	0.0007	344.92	0
D	1	0.0017	0.0017	79.8	0
Square	4	0.0357	0.0089	404.08	0
A*A	1	0.0097	0.0097	441.86	0
B*B	1	0.001	0.001	46.58	0
C*C	1	0.0246	0.0246	1114.56	0
D*D	1	0.0025	0.0025	115.93	0
2-Way Interaction	6	0.065	0.01	490.29	0
A*B	1	0.0255	0.0255	1157.72	0
A*C	1	0.0049	0.0049	222.79	0
A*D		0.0102	0.0102	464.1	0
B*C	1	0.004	0.004	182.18	0
B*D	1	0.004	0.004	184.21	0
C*D	1	0.0161	0.0161	730.74	0
Error	47	0.001	0.00002		
Lack of fit	10	0.0003	0.00003	1.6	0.145
Pure Error	37	0.0007	0.00002		
Total	61	0.1122			
Model Summary					
S		R-sq	R-sq(adj)	R-sq(pred)	
0.0047		99.07%	98.80%	98.27%

Figure 11. Residual plots of Bead Width

Now, hardness estimation is conducted with the representation of the regression equation is expressed as

$$\text{Hardness} = -1464 + 1.655A + 45.5B + 6.4C + 147.6D + 0.0017527 + 2.3B^2 - 0.354C^2 - 2.219D^2 + 0.0919AC - 0.1499AD - 2.58750BC - 2.09375BD - 0.728000CD \quad (7)$$

From the regression analysis given by Equation 7, respective analysis of variance results for the response surface cubic model is given in Table 10. The Model F-value of 51.89 indicates that the model is significant. In fact, it is chance of about 0.01% to get large F-Value mostly could occur due to noise. The obtained model terms are significant due to the “Prob > F” values smaller than 0.05. In this case A, B, C, D, A², B², C², D², AC, AD, BC, BD, CD are significant model terms. Values greater than 0.1 indicate the model terms are not significant. If there are many insignificant model terms, model reduction may improve the model. The “Lack of Fit F-value” of 0.068 shows that lack of fit is not significant relative to the pure error. There is a 0.041% chance that large F – value of lack of fit could occur due to noise. Non-significant lack of fit is good. From Table 10, the “Pred. R-squared” of 0.8776 is in sensible agreement with the ‘Adj. R-squared’ of 0.9092. The corresponding residual plot for the penetration is given in Figure 12.

Table 10. ANOVA table for Hardness

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	12	48798.1	4066.5	51.89	0
Linear	4	31465.4	7866.4	100.38	0
A	1	3253.8	3253.8	41.52	0
B	1	256.7	256.7	3.28	0.076
C	1	26287.6	26287.6	335.45	0
D	1	1667.3	1667.3	21.28	0
Square	3	11981.3	3993.8	50.96	0
B*B	1	307.2	307.2	3.92	0.053
C*C	1	283.6	283.6	3.62	0.063
D*D	1	11123.8	11123.8	141.95	0
2-Way Interaction	5	5351.5	1070.3	13.66	0
A*C	1	676.2	676.2	8.63	0.005
A*D	1	1797.0	1797.0	22.93	0

B*C	1	1339.0	1339.0	17.09	0
B*D	1	876.8	876.8	11.19	0.002
C*D	1	662.5	662.5	8.45	0.005
Error	49	3839.9	78.4		
Lack of fit	12	2649.8	220.8	6.87	0.000
Pure Error	37	1190	32.2		
Total	61	52638			
Model Summary					
S		R-sq	R-sq(adj)	R-sq(pred)	
8.85237		92.71%	90.92%	87.76%

Figure 12. Residual plots of Hardness

Finally, the tensile strength evaluation is followed by the regression equation is

$$\text{Tensile strength} = -2282 + 23.87A - 195.3B - 162.0C + 153.4D - 0.03039A^2 + 5.963C^2 + 0.396AB - 0.1307AC - 0.545848AD + 4.48953BC \quad (8)$$

By following Equation 8, its corresponding analysis of variance results for the response surface cubic model is given in Table 11. The Model F-value of 52.06 indicates that the model is significant. In fact, it is chance of about 0.023% to get large F-Value mostly could occur due to noise. The obtained model terms are significant due to the “Prob > F” values smaller than 0.05. In this case A, B, C, D, A^2 , AB, AC, AD, BC are significant model terms. Values greater than 0.1 indicate the model terms are not significant. If there are many insignificant model terms, model reduction may improve the model. The “Lack of Fit F-value” of 0.027 shows that lack of fit is not significant relative to the pure error. There is a 0.041% chance that large F – value of lack of fit could occur due to noise. Non-significant lack of fit

is good. From Table 11, the “Pred. R-squared” of 0.8751 is in sensible agreement with the ‘Adj. R-squared’ of 0.8943. The corresponding residual plot for the penetration is given in Figure 13.

Table 11. ANOVA table for Tensile Strength

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	10	249736	24973.6	52.60	0
Linear	4	123399	30849.8	64.98	0
A	1	68464	68464.4	144.20	0
B	1	13873	13872.6	29.22	0
C	1	40952	40952.4	86.26	0
D	1	110	109.7	0.23	0.633
Square	2	95093	47546.6	100.14	0
A*A	1	8626	8626.2	18.17	0
C*C	1	81095	81095.1	170.81	0
2-Way Interaction	4	31244	7810.9	16.45	0
A*B	1	2010	2010.0	4.23	0.045
A*C	1	1366	1366.3	2.88	0.096
A*D	1	23836	23836.0	50.20	0
B*C	1	4031	4031.2	8.49	0.005
Error	51	24214	474.8		
Lack of fit	14	12350	882.2	2.75	0.007
Pure Error	37	11863	320.6		
Total	61	273949			
Model Summary					
S		R-sq	R-sq(adj)	R-sq(pred)	
21.7894		91.16%	89.43%	87.51%

Figure 13. Residual plots of Tensile Strength

The suitability of established models has been verified by using analysis of variance technique (ANOVA). On accordance with the ANOVA method, if the evaluated F-ratio of the regression model is less than the value of F-ratio

from F-statistics over the confidence level of 95%, then the established model is well fit. Tables 7-11 provides the ANOVA results for bead height (BH), bead width (BW), depth of penetration (DP), hardness (HS) and tensile strength (TS) respectively. From the table, it is inferred that the created regression model for every parameter is found to best fit with respect to the 95% confidence level. Also, by holding P-value less than 0.05 indicates that the model terms are significant for model building.

4.2. CONFIRMATION TEST FOR SINGLE RESPONSE OPTIMIZATION

The optimized parameters have been confirmed by accompanying three confirmatory tests. The obtained optimum value through desirability function in RSM is given in Table 12. For confirmatory test, new set of process parameters are considered for welding technique execution. When the welding run is performed its corresponding bead profile geometry, hardness and tensile strength are measured.

Table 12. Results of optimal parameters values by RSM

BH	DOP	BW	HD	TS	C	FR	WS	GF
1.082	5.207	4.282	312.02	154.51	320	9	10	12.5

Table 13. Confirmation test results of single response optimization

Sl. No	Parameters	Optimized parameters with predicted values	Experimentally observed Values	% of error
1	Current	320 Amp	320 Amp	-
2	Feed Rate	9 m/min	9 m/min	-
3	Welding Speed	10 mm/sec	10 mm/sec	-
4	Gas flow	12.5 l/min	12.5 l/min	-
5	Bead Height	1.082 mm	1.096 mm	-1.29
6	Depth of Penetration	5.207 mm	5.129 mm	1.497
7	Bead Width	4.282 mm	4.119 mm	3.806
8	Hardness	312.02 VHN	314.56 VHN	-0.814
9	Tensile Strength	154.51 N/mm ²	152.32 N/mm ²	1.417

The confirmation test is carried out using optimal value and average values of three experimented results are tabulated in Table 13. From the Table 13, it is clearly seen that the experimental results of bead profiles have come closer to the predicted values and also the error is negligible. Further, it is confirmed that the percentage error is less than 1.5% i.e. percentage error is within the acceptable range.

5. MULTI-RESPONSE OPTIMIZATION

In addition to the single response optimization, for the synchronized optimization of all the five performance characteristics, a multi-objective optimization technique for the process parameters has also been investigated. For this analysis, PSO (Particle Swarm Optimization) and Firefly algorithm (FA) are considered in which developing optimization function includes all the response characteristics. In this present work, the implementing PSO and Firefly algorithms are employed to identify the fine optimized values of input parameters, weld geometries and material properties.

5.1. PARTICLE SWARM OPTIMIZATION

Particle swarm optimization (PSO) is a population based stochastic optimization technique inspired by social behaviour of bird flocking or fish schooling. The system is initialized with a population of random solutions and searches for optima by updating generations. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles. This concept consists of, a teach time step, changing the velocity of (accelerating) each particle towards its 'pbest (best solution (fitness) achieved so far)' and 'lbest (local best)' locations. Acceleration is weighted by a random term, with separate random numbers being generated for acceleration

toward 'pbest' and 'lbest' locations. Another “best” value that is tracked by the particle swarm optimizer obtained so far by any particle in the population is termed as “gbest (global best)”. Figure 14 shows the flowchart of the PSO algorithm executed in the present work.

Input: f : the function to optimise; s : the swarm size; d : the problem dimension

X_{min} , X_{max} : Lower and upper boundaries for decision variables

V_{min} , V_{max} : Lower and upper boundaries for particles velocities

Output: x^* : the best particle position found (global best); f^* : the best fitness value found;

Initialise: position $x_i = (x_{i1}, \dots, x_{id})$ and velocity $v_i = (v_{i1}, \dots, v_{id})$, for all particles in problem space; evaluate $f(x_i)$ in d variables and get $pbest_i$, ($i = 1, \dots, s$); $gbest \leftarrow \text{best of } pbest_i$; While stopping criteria is false do; Compute inertia weight (ω) if it is not a constant

Repeat for s times

Repeat for d times

update v_i for particle; validate for velocity boundaries

If $v_i^j < v_{min}$; $v_i^j \leftarrow v_{min}$

else if $v_i^j > v_{max}$; $v_i^j \leftarrow v_{max}$

end if

update x_i for particle ; validate for position boundaries

If $x_i^j < x_{min}$; $x_i^j \leftarrow x_{min}$

else if $x_i^j > x_{max}$; $x_i^j \leftarrow x_{max}$

end if

compute $f(x_i)$

End Repeat for d

compute $f(x_i)$; obtain new $pbest_i$

If $f(x_i) < f(pbest_i)$ then $pbest_i \leftarrow x_i$; If $f(x_i) < f(gbest)$ then

$gbest \leftarrow x_i$; $f(gbest) \leftarrow f(x_i)$

end if

End Repeat for s

End while

$x^* \leftarrow gbest$; $f^* \leftarrow f(gbest)$

Figure 14. PSO algorithm execution procedure for the welding parameter optimization

The PSO parameters chosen for optimizing the welding parameters are number of birds (n) are 50, number of iterations (N) is around 100, learning factors (c1 and c2) are usually taken as 2. The fitness function considered for PSO training are minimization of bead width and reinforcement and maximization of the depth of penetration. The weightage for weld bead, reinforcement and depth of penetration are taken as 0.25, 0.25 and 0.5 respectively.

Figure 15. Convergence graph for welding input parameters using PSO algorithm

Figure 15 shows the plot between the input parameters such as current (C), wire feed rate (FR), welding speed (WS) and gas flow (GF) versus number of iterations. The optimized values of input parameters for the desired welding profile are tabulated in Table 14.

Table 14 Optimized input parameters using PSO algorithm

BH	DOP	BW	HD	TS	C	FR	WS	GF
1.0228	5.136	4.258	280.94	307.51	240	5	10	22.5

5.2. FIREFLY ALGORITHM

The flashing characteristics of fireflies can idealize to develop firefly inspired algorithms. For simplicity in describing the Firefly Algorithm (FA), use the following three idealized rules: 1) All fireflies are unisex so that one firefly will be attracted to other fireflies 2) Attractiveness is proportional to their brightness, thus for any two flashing fireflies, the less brighter one will move towards the brighter one. The attractiveness is proportional to the brightness and they both decrease as their distance increases. If there is no brighter one than a particular firefly, it will move randomly. 3) The brightness of a firefly is affected or determined by the landscape of the objective function. For a maximization problem, the brightness can simply be proportional to the value of the objective function. Based on these three rules, the basic steps of the firefly algorithm (FA) can be summarized as the pseudo code as follows

Objective function $f(x)$,

$$x = (x_1, \dots, x_d)^T$$

Generate initial population of fireflies

x_i ($i = 1, 2, \dots, n$) Light intensity I_i at x_i is determined by $f(x_i)$

Define light absorption coefficient γ while ($t < \text{Max Generation}$)

for $i = 1 : n$ all n fireflies

for $j = 1 : i$ all n fireflies

if ($I_j > I_i$), Move firefly i towards j in d -dimension;

end if , Attractiveness varies with distance r via $\exp[-\gamma r]$

Evaluate new solutions and update light

Intensity end for j ;

end for I ;

Rank the fireflies and find the current best end while

Post process results and visualization

For predicting each response, a quadratic model is generated. This empirical model is used to optimize the welding input parameters to achieve minimum bead width and bead height and maximize the depth of penetration. Simulation runs are carried out to optimize the firefly algorithm parameters by varying number of fireflies up to 1000 iterations as shown in Figure 16.

Figure 16. Convergence graph for optimizing number of fireflies

The optimized firefly parameters are Number of fireflies (n) as 40, Number of iterations (N) as 1000, Randomization parameter (α) as 0.5, Attractiveness (β_{min}) as 0.2, and Light absorption coefficient (γ) as 1. The value of “ α ” is chosen as 0.5 to reduce randomness and to increase the convergence. “ β_{min} ” is *chosen* as 0.2, which varies with the absorption coefficient and source distance, which is the attractiveness of fireflies. Light absorption coefficient “ γ ” is the absorption coefficient, which varies between 0 to ∞ , which depends mainly on the light intensity of fireflies. With the obtained firefly parameters, the input parameters are optimized and shown in Figure 16.

Figure 16. Convergence graph for welding input parameters using Firefly algorithm

The obtained results reveal that initially the value of current, wire feed rate, welding speed and gas flow starts at a random value. But when the iteration progress, it gets settled to the optimized value by increasing number of iterations. Table 15 shows the optimized values of welding input parameters and it is similar to the results of PSO algorithm.

Table 15. Optimized input parameters using Firefly algorithm

BH	DOP	BW	HD	TS	C	FR	WS	GF
1.0228	5.136	4.258	280.94	307.51	240	5	10	22.5

On comparing the optimized results obtained through PSO and firefly algorithms, it is confirmed that parametric coordination for all above-mentioned characteristics are similar; however, PSO algorithm reached the better optimal values in very fewer iterations as compared to firefly algorithm. As a final analysis, the PSO algorithm is computationally more efficient on comparing with firefly algorithm.

5.3. CONFIRMATORY TEST FOR MULTI-RESPONSE OPTIMIZATION

The confirmation test is carried out by considering the new set of process parameters using the optimized input parameters obtained from PSO and Firefly algorithm. The welding run is performed and bead profile geometry Hardness and Tensile strength is measured and average values of three experimented results are presented in Table 16.

Table 16. Confirmation test results of multi-response optimization

Sl.No	Parameters	Optimized parameters with predicted values	Experimentally observed Values	% of error
1	Current	240 Amp	240 Amp	-
2	Feed Rate	5 m/min	5 m/min	-
3	Welding Speed	10 mm/sec	10 mm/sec	-
4	Gas flow	22.5 l/min	22.5 l/min	-
5	Bead Height	1.0228 mm	1.0113 mm	1.124
6	Depth of Penetration	5.236 mm	5.028 mm	3.972
7	Bead Width	4.258 mm	4.196 mm	1.456
8	Hardness	280.94 VHN	281.87 VHN	-0.331
9	Tensile Strength	307.51 N/mm ²	307.03 N/mm ²	0.156

From the Table 16, it is clearly seen that the experimental results of bead profiles have come closer to the predicted values and also the error is negligible. Further, it is confirmed that the percentage error is less than 4% i.e. percentage error is within the acceptable range.

5.4. SEM OBSERVATION OF THE TENSILE FRACTURES

The tensile fractures of the welded joint are examined by Scanning Electron Microscopic (SEM) as shown in Figure 17. The fracture width along the horizontal direction for both joints is noticeably small and the fracture size along the direction perpendicular to the plate surface for both joints is reasonably seems to be large. The fracture of the butt joint consists of large quantities of dimples. A large quantity of columnar grain boundaries distributed along the direction perpendicular to the tensile loading direction in the welding joint.

Figure 17. SEM observations of the tensile fractures of the welded joint

Investigation of the tensile fracture surfaces of the base and AISI: 430 stainless steel specimens is finished at low magnification mainly to identify the side of the welding to analyse the advancing or retreating level where the fracture mainly oriented. The fracture surfaces of tensile weld joints are normally categorized by a bimodal distribution of large voids, associated with the particle reinforcement as shown in Figure 17 (A&B) and large dimples associated with the ductile failure of the ferrite stainless steel material as shown in Figure 17 (C&D). Further, no indication of transformation in the particle–matrix metal interaction induced by the GMAW process is inferred from these SEM analyses.

6. CONCLUSIONS

The welding parameters for the material Ferritic Stainless Steel 430 using IRB 1410 ARC welding Robot is optimized using Response Surface Methodology. In the present work, around 31 experiments are acknowledged using RSM method with 2 replicates. The following results are inferred from both single and multi-response optimization techniques evaluations:

- The optimum welding input parameters obtained by RSM are current (320 Amps), wire feed rate (9 m/min), Welding speed (10 mm/sec) and gas flow (12.5 l/m). For these values, the optimal output parameters obtained by single response optimization are minimum bead height (1.802 mm), minimum bead width (4.287 mm) and maximum depth of penetration (5.207 mm).

- Similarly, the optimum welding input parameters obtained by PSO and FA are current (240 Amps), wire feed rate (5 m/min), welding speed (10 mm/sec) and gas flow (22.5 l/m). For these values, the multi response optimization techniques provide the minimum bead height as 1.0228 mm, minimum bead width as 4.258 mm and maximum depth of penetration as 5.236 mm.
- On comparing the result of RSM and metaheuristic algorithms, the result obtained through the meta heuristic algorithm is better. Although the optimized output values obtained from the PSO and FA algorithm are similar, the PSO converges quicker than FA with minimum number of iterations. Hence the PSO is more computationally efficient than FA and RSM.
- To validate the predicted results with optimized process parameters, confirmation test for both single and multi-response optimization reveal that the computed errors are found to be less than 5% (i.e. more sufficient).
- By the current work on combined experimental and optimization research, it has been understood that both PSO and Firefly algorithms have the capability to perform single as well as multi-objective optimization, particularly for Gas metal arc welding process. Hence, the proposed RSM and meta heuristic optimization algorithm by integrating into the empirical model shows that the implemented optimization framework seems to be reliable and robust.

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Figures

Figure 1

IRB 1410Arc Welding Robot

Figure 2

Cause and effect schematic of GMAW process

Figure 3

Fixture design taken for the present work

Figure 4

Joint edge specifications for GMAW of plates

60° Groove Angle without gap

60° Groove Angle with 1mm gap

Groove Angle 70°

Figure 5

V-groove angles of the joints taken for experimentation trials

Figure 6

Tensile Standard dimensions

Figure 7

Dumb-bell shape

Figure 8

Universal Testing machine

Figure 9

Obtained residual plot for the bead height parameter

Figure 10

Residual plots of Depth of penetration

Figure 11

Residual plots of Bead Width

Residual Plots for hS

Figure 12

Residual plots of Hardness

Figure 13

Residual plots of Tensile Strength

Figure 14

PSO algorithm execution procedure for the welding parameter optimization

Figure 15

Convergence graph for welding input parameters using PSO algorithm

Figure 16

Convergence graph for optimizing number of fireflies

Figure 17

Convergence graph for welding input parameters using Firefly algorithm

Figure 18

SEM observations of the tensile fractures of the welded joint