

Identification of optimum laser beam welding process parameters for dissimilar steels butt joint based on AI Algorithms SA, GA and WOA

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ABSTRACT

KEYWORDS

Artificial Intelligence,
Laser Beam Welding,
Genetic Algorithm,
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Algorithm,
Whale Optimization
Algorithm.

In the 4th Industrial Revolution is implemented with the help of advances in Artificial Intelligence (AI). The effect of the AI has automatized the mechanical engineering with the smart machines and robots. The technology used these days in the machines is to aid the solutions in the direction of the real-world and complex problems. In the Industrial Revolution, manufacturing the better quality product with the high speed and accuracy is possible with advanced manufacturing by using laser beam. Laser is used to weld the similar/dissimilar with optimum strength and Heat Affected Zone. AI is used to find the better manufacturing process parameters of the Laser beam welding process. In this research paper, the laser beam welding is used to weld the AISI 316 and AISI 4130 steel metals and identified the optimal combination with the AI algorithms Genetic Algorithms, Simulated Annealing, and Whales Optimization Algorithm.

1. Introduction

Artificial Intelligence (AI) has laid a better impact over these donkey's years in the manufacturing industry and has progressed smart systems that are a better aid to the human life and has also widened the horizons for the researchers with respect to future developments. In the 4th Industrial Revolution is implemented with the help of AI in advanced manufacturing (Bijivemula et al., 2022).

In order to solve complex issues in manufacturing applications where conventional methodologies and approaches are not feasible or efficient, Artificial Intelligence (AI) is a set of computational methodologies and approaches that are inspired by nature (Bijivemula et al., 2020). AI techniques and methods, evolutionary computation, including neural networks, and fuzzy logic systems, have rapidly evolved over the last decades (Reddy et al., 2017). Recently researchers have paid special attention to the AI algorithms, which are also been successfully used to solving engineering-related issues in manufacturing. However, for this type

of large and complex problems in manufacturing, the AI algorithms require a significant amount of calculation time due to stochastic nature of the search approaches. As a result, it may be necessary to create effective algorithms to identify solutions in practical tenders with limited time, money and resources (Wang, 2019).

Simultaneously, Laser Beam welding using to join dissimilar metals has become necessary with growth of Engineering and Technology so as to meet the latest manufacturing requirements of goods / products. Laser beam is used to weld the metals with high speed, more strength and minimum heat affected zone. Further, it's possible to join the dissimilar metals by using laser at optimal combinations. The optimal combination of process parameters are identified by using AI Algorithms (Bakhtiyari et al., 2021).

2. Literature Review

The implementation of AI in the manufacturing process of Laser Beam Welding related Literature Review discussed in the following.

Welding of dissimilar metals has become necessary with growth of Engineering and Technology so as to meet the latest manufacturing requirements

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of goods / products. Materials other than standard and advanced high strength steels found to have significant usage in the thin - fenced structures of the car - body, aircraft, rockets, satellite vehicles, trains followed by the safety improvement, mass reduction and improved corrosion resistance (Evin et al., 2016). Dissimilar metals welding at present stands as a major scientific and technical challenges for the Engineering and Technical experts. Emerging new technologies with greater flexibility require dissimilar metals particularly in the joining of AISI steels. Among them, the AISI4130 steel, which is a Low Alloy Steel containing of Cr, Mo and Mn is said to be in forefront. It is used in oil industry and electricity plants, because of its identical better strength at high heats area developed in heat exchangers and generators (Baddoo, 2008).

AISI316 Steel is the next greatest commonly used steel after AISI304. The marine grade AISI 316 ASS usually contains Cr, Mo and Ni. AISI316 is used in various industries such as lubricant, gas, petrochemical, pharmaceutical, food process industries, etc., for manufacturing of sheets and pipes but it is more costlier in comparison to AISI 304 steel (Tash, 2015).

The UTS and impact strength beside with the weld-operating charges of Laser joints made of AISI304 are experimental study based on Laser power, speed and focal position (Benyounis et al., 2008). Design-expert software is used to establish the design matrix and analyze the experimental data for the relationship between butt weld joint and operating costs. Then, the software is used to develop mathematical models to investigate the optimal joining conditions in order to productivity increase and reduce the total operating cost.

The influence of Laser beam power, welding speed and focal point position on weld joint of low carbon steel and AISI 316 steel mechanical properties and operating cost are investigated (Olabi et al., 2013). The investigational plan is based on Box–Behnken design, whereas non-linear equations are developed for forecasting the mechanical properties.

The effect of green Laser welding input parameters - power, pulse duration and pressured air flow on copper joint is studied for its penetration by varying the force (Altarazi et al., 2016). Design and analyses for responses are studied by using response surface methodology, ANOVA, and

then overlaid outline plots are drawn based on the output results. The results have specified that the Laser power and pulse duration have the most significance on the significant force and penetration depth. The Design of Experiments based on ANN and GA modelling are carried-out by considering four process parameter (Liu et al., 2020) based on Taguchi L_{16} only.

From the literature survey, GA is widely applied due to its versatility and global optimization capability. SA is effective for local search based and simple implementation of efficient in small or noisy datasets. WOA is Nature-inspired exploration–exploitation balance and favorable convergence behavior. It is relatively new in welding optimization, shows promising results in achieving superior weld quality and minimizing process defects.

Hence, to fill research gap, the present work is taken up to study the multi-response optimization (AI algorithms: GA, SA, WOA of more than four process parameters and there by leading to the effective utilization of joining AISI 4130 and AISI 316 steel metals used in the modern manufacturing field.

3. Experimental Process

Experimental process consists of Metals selection and preparation, CO2 LBW using to join and after that testing of weld joint quality.

In this work, alloy steel plates of AISI 4130 with 2 mm and also the stainless steels plate of AISI 316 considered as base metals. EDM machine is using to cut into 130×80 mm size, for better closer fitness (zero gap) of base metals. CO2 LBW machine is using for joining of dissimilar metals. CO2 Laser Beam is using to fusion the base metal according to the L25 experimental combinations. An L25 experimental combination is considered according to DOE Taguchi five process parameters and five levels. The experimental combination of process parameters are shown in the Table 1.

After completion of joining dissimilar metals, the quality of weld joint is measuring by strength and geometry. Weld joint strength is tested based on Micro hardness and bead width is measuring for geometry of weld joint. Micro hardness and Bead width is measured at cross-section of the weld joint as per ASTM standees. The testing specimens are shown in the Fig. 1 and crosssection of the weld joint is also shown in Fig. 2.

Table 1

Tested weld joints results of AISI 316 and AISI 4130 steels.

Ex. Trial	Process parameters					Output results	
	LP (W)	WS (m/min)	BA (Deg.)	FPP (mm)	FL (mm)	MH (HV1)	WB (mm)
1	1400	1.2	88	-0.2	16	450	1.2816
2	1400	1.4	89	-0.1	17	320	1.1504
3	1400	1.6	90	0.0	18	370	1.1125
4	1400	1.8	91	0.1	19	465	1.0090
5	1400	2.0	92	0.2	20	515	1.1883
6	1600	1.2	89	0.0	19	489	1.1089
7	1600	1.4	90	0.1	20	522	1.1029
8	1600	1.6	91	0.2	16	520	1.1210
9	1600	1.8	92	-0.2	17	510	1.1059
10	1600	2.0	88	-0.1	18	400	1.1805
11	1800	1.2	90	0.2	17	520	1.2194
12	1800	1.4	91	-0.2	18	525	1.3856
13	1800	1.6	92	-0.1	19	515	1.1986
14	1800	1.8	88	0.0	20	533	1.1259
15	1800	2.0	89	0.1	16	525	1.2894
16	2000	1.2	91	-0.1	20	517	1.3158
17	2000	1.4	92	0.0	16	527	1.3506
18	2000	1.6	88	0.1	17	539	1.3546
19	2000	1.8	89	0.2	18	487	1.2884
20	2000	2.0	90	-0.2	19	510	1.3594
21	2200	1.2	92	0.1	18	478	1.3982
22	2200	1.4	88	0.2	19	492	1.3775
23	2200	1.6	89	-0.2	20	490	1.3561
24	2200	1.8	90	-0.1	16	323	1.1849
25	2200	2.0	91	0.0	17	400	1.3054

The Micro hardness and Bead width is measured at cross-section of the weld joint and the Hot Mounting specimens are prepared as shown in fig. 1. The different steel weld joint was studied throughout the mid thickness of the weldment by using a hardness tester with a load

of 1 kgf. The captured the weldments by the microscope and macrographs are captured at 20X magnification using Struers welding expert system measuring the Weld geometry of bead width. the measured Micro hardness and Bead width values are presented in Table 1.

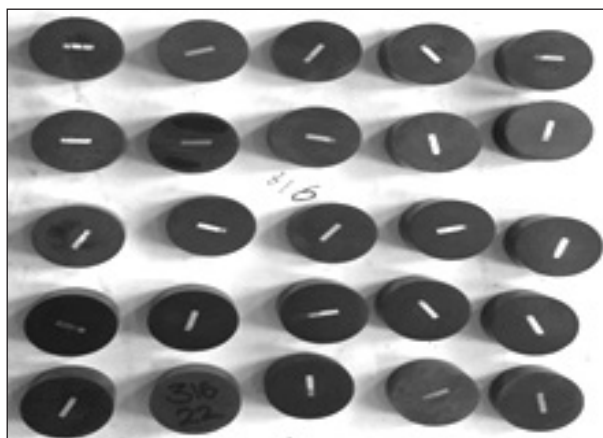


Fig. 1. Hot mounting specimens.

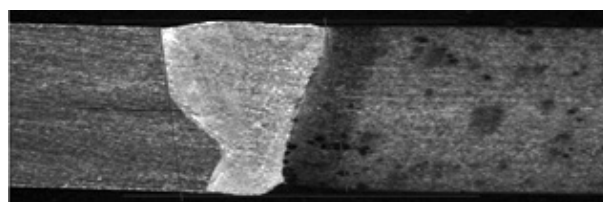


Fig. 2. Weld geometry measuring macrograph.

4. Optimisation of Process Parameters

To determine the method that obtains the optimal values in terms of result and speed of evaluation, and gives the fastest result. AI Optimisation Algorithms GA, SA and WOA are applied for optimisation of welding process parameters for obtaining better MH and Bead Width. When the result obtained from the comparison is evaluated, the best calculation time of the calculations for all functions is done with GA, the best results are obtained with WOA for Rastrigin. The optimization process required objective function and boundary conditions. The boundary conditions are shown in Table 2.

The multi-objective non-linear regression equations are developed to find the optimal process parameters in joining of dissimilar metals by LBW so that the maximum Micro Hardness are obtained with minimum Bead Width.

Regression Model is using developed second order regression equations are developed using Regression analysis in MINITAB. The MINITAB using developed regression equations are (1) & (2).

$$\begin{aligned} \text{MH} = & 37592 + (9.56 \times \text{LP}) - (2312 \times \text{WS}) - (1052 \times \text{BA}) - \\ & (47 \times \text{FPP}) + (311 \times \text{FL}) - (0.000686 \times \text{LP}^2) + (324 \times \text{WS}^2) + (7 \\ & .52 \times \text{BA}^2) - (73.6 \times \text{FPP}^2) + (1.02 \times \text{FL}^2) + (0.190 \times \text{LP} \times \text{WS}) - \\ & (0.0968 \times \text{LP} \times \text{BA}) - (0.0338 \times \text{LP} \times \text{FPP}) + (0.0775 \times \text{LP} \times \text{FL}) \\ & + (51.6 \times \text{WS} \times \text{FPP}) + (47.4 \times \text{WS} \times \text{FL}) + (0.7 \times \text{BA} \times \text{FPP}) - \\ & (6.24 \times \text{BA} \times \text{FL}) + (5.8 \times \text{FPP} \times \text{FL}) \end{aligned} \quad \text{.....(1)}$$

Table 2

Boundaries of process parameters.

Process Parameters	Symbols	Lower & Upper Bound
Laser power (W)	LP	(1400, 2200)
Welding speed (m/min)	WS	(1.2, 2.0)
Beam angle (Degrees)	BA	(88, 92)
Focal point position (mm)	FPP	(-0.2, 0.2)
Focal length (mm)	FL	(16, 20)

$$\begin{aligned} \text{BW} = & -209 + (0.0275 \times \text{LP}) - (4.96 \times \text{WS}) + (4.43 \times \text{BA}) - \\ & (47.6 \times \text{FPP}) - (1.27 \times \text{FL}) - (0.000002 \times \text{LP}^2) + \\ & (0.075 \times \text{WS}^2) - (0.0231 \times \text{BA}^2) - (5.86 \times \text{FPP}^2) - \\ & (0.0097 \times \text{FL}^2) - (0.000834 \times \text{LP} \times \text{WS}) - (0.000256 \times \text{LP} \times \\ & \text{BA}) + (0.00293 \times \text{LP} \times \text{FPP}) + (0.000254 \times \text{LP} \times \text{FL}) \\ & + (0.033 \times \text{WS} \times \text{BA}) + (0.448 \times \text{WS} \times \text{FPP}) + (0.1836 \times \\ & \text{WS} \times \text{FL}) + (0.412 \times \text{BA} \times \text{FPP}) + (0.00921 \times \text{BA} \times \text{FL}) + \\ & (0.225 \times \text{FPP} \times \text{FL}) \end{aligned} \quad \text{.....(2)}$$

$$Z = (0.5 \times \text{MH}) + (0.5 \times \text{BW}) \quad \text{.....(3)}$$

4.1 Multi objective function

The multi-objective equation is generated by using weighted method. The multi-objective regression model for MH and BW are shown in the form of equation (3).

4.2 GA optimization

Genetic Algorithm (GA) is based on the ideas of natural selection and genetics. It is ability to identify better or almost better optimal value for challenging issues that would otherwise take a lifetime to resolve with good-enough and fast-enough. This makes genetic algorithms attractive for use in solving optimization problems by Evolutionary, population-based, stochastic types. The Methodology of GA is start with initialize population (N) and Genetic operators are Selection, Crossover, Mutation, Evaluation and Survivor Selection. At every evolutionary step, known as a generation, the individuals in the current population are decoded and evaluated according to some predefined quality generation), individuals are selected according to their fitness.

As per the above GA methodology process based on identified the optimal combination of

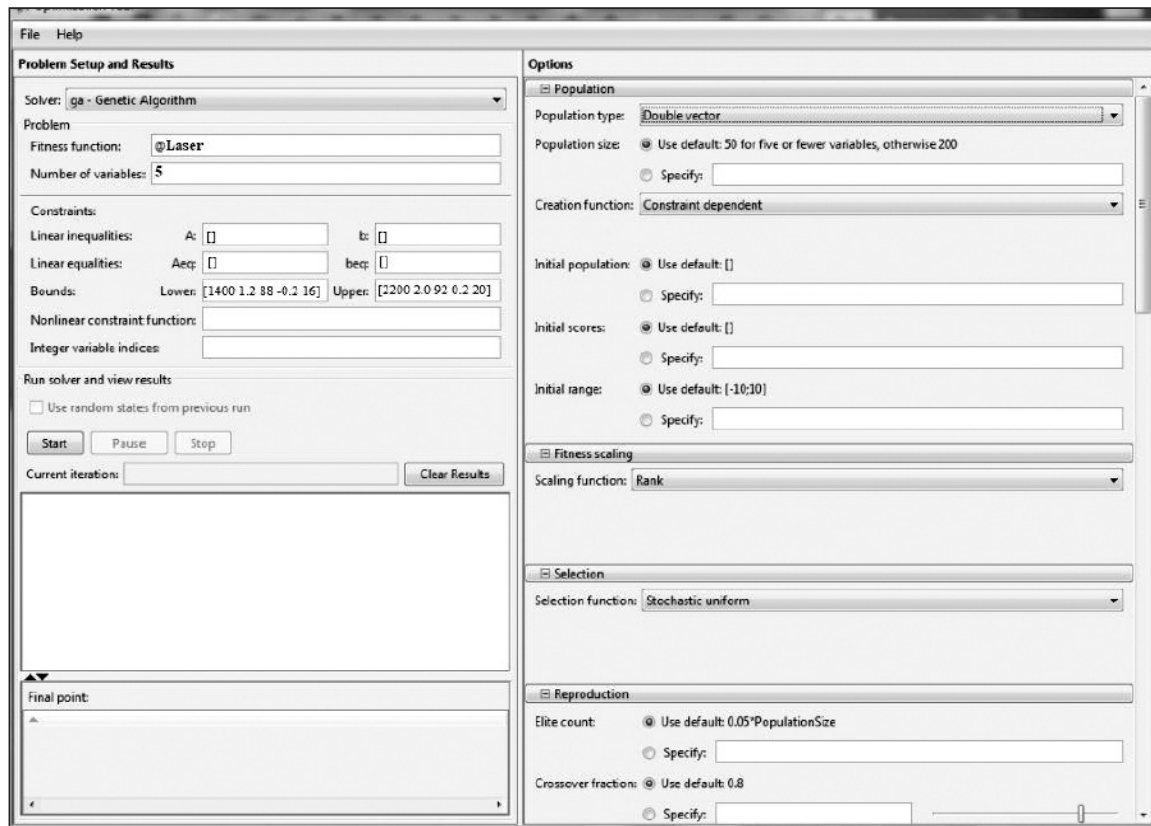


Fig. 3. GA tool input of GUI in MATLAB.

Table 3

GA using identified optimal combinations.

Process parameters					Output results		Error
LP (W)	WS (m/min)	BA (Deg)	FPP (mm)	FL (mm)	MH (HV1)	WB (mm)	
2066.03	1.99	88.0	0.19	19.99	520	1.1546	9.25 &10.5
2066	2.0	88.0	0.19	20.0	525	1.25	

process parameters and optimal value of the objective function solved by using MATLAB Global Optimization Toolbox of GA shown in the fig. 3.

The optimisation search starts from lower limit of process parameters and the curve varies with respect to process parameters. The screenprint taken during the running of the program is shown in Fig. 4. The curve variation at the initial stage is due to the search for an optimum solution of 208 iterations till study state condition is reached. The study state of curve will be stated after 50 iterations and optimal combination obtained at 208 iterations with less time. A set of output results showing optimal parametric values for AISI 4130 weld joint consisting of a run of 208 iterations are shown in Table 3.

4.3 SA optimization

SA introduced Kirkpatrick et al. (1983) by inspiring the hardening procedure of annealing operation. Annealing operation states the best (optimal) arrangements of molecular in everyplace metal particles potential energy of the mass is minimized and denotes refers to the progressive cooling of metals that have been exposed to extreme heat. Simple improvement based local search strategies try to gain improvements in solution quality as fast as possible. Hence we can interpret this behavior as "quenching" in the sense of thermodynamics. The local optimum we reach by this way of proceeding corresponds to a high energy state with inferior crystalline structure. An interesting property of cooling processes in

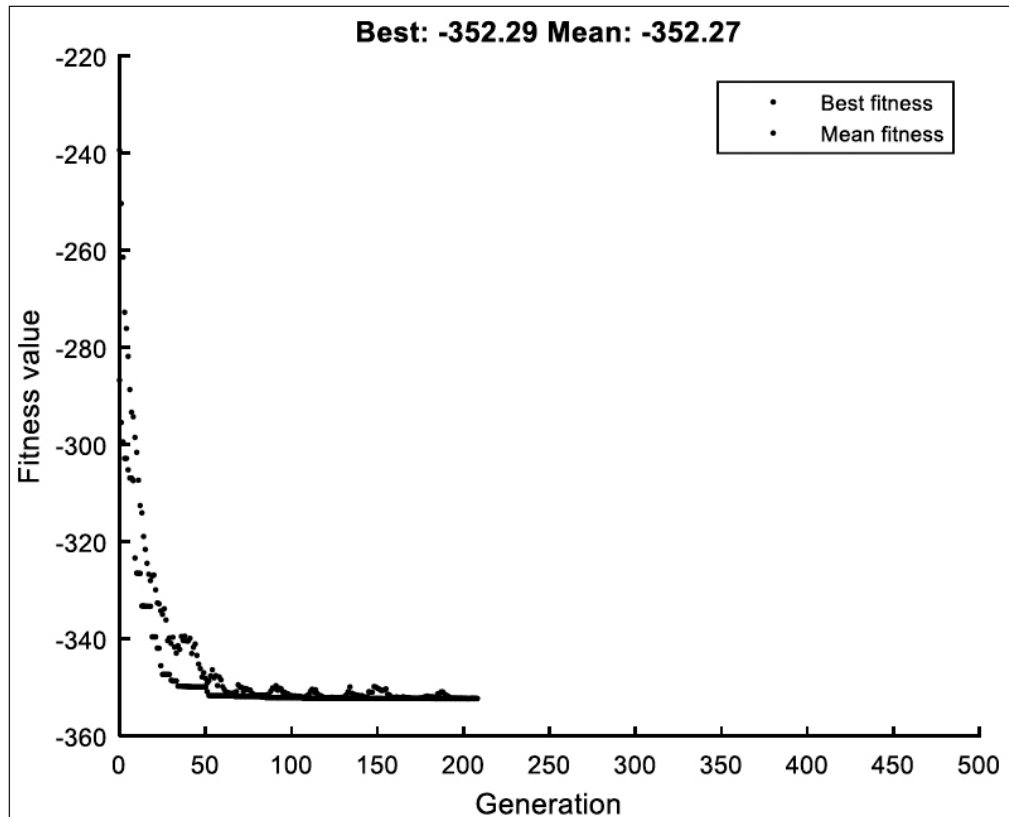


Fig. 4. The curve varies with respect to process parameters in GA.

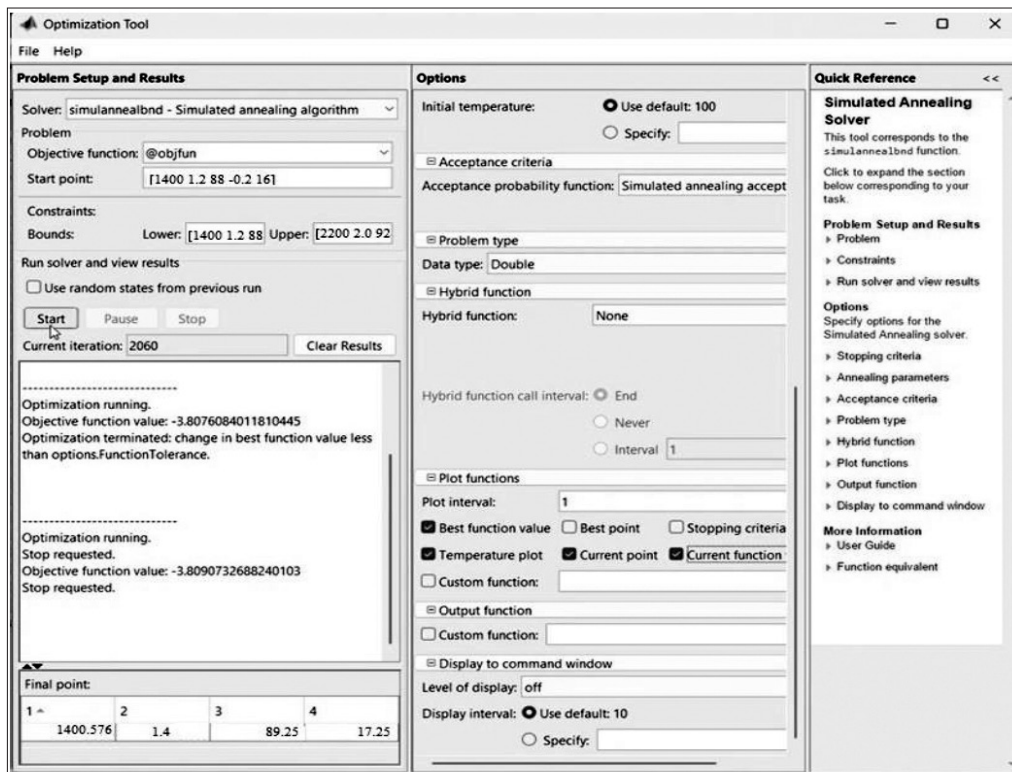


Fig. 5. SA Tool input of GUI in MATLAB.

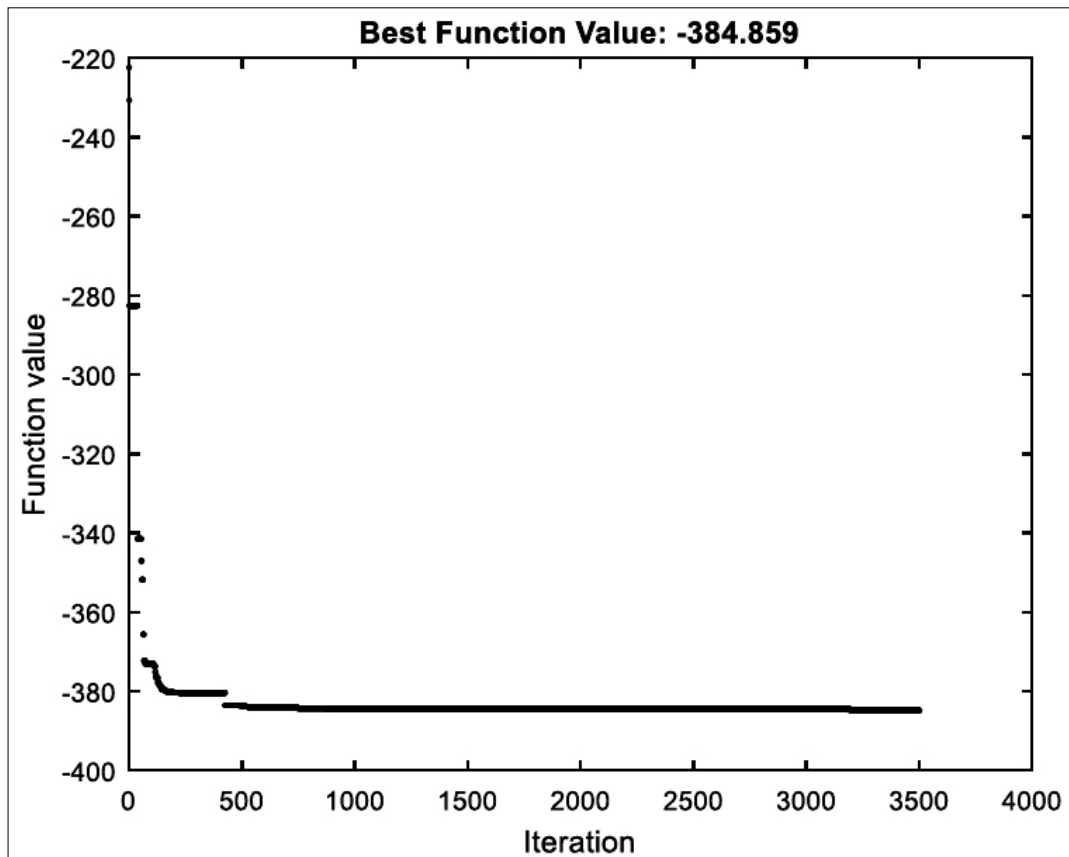


Fig. 6. The curve varies with respect to process parameters in SA.

nature is the chance of occurrence of high energy states even at late stages of such a process.

The following algorithm is using to solve the NP type of problem.

Step 1: Specifying no. of generations 'N'

Step 2: Population generation (random)

Step 3: Generate initial passable populations

Step 4: Initialize the temperature, the ending temperature to stop, the cooling rate and probability of acceptance.

Step 5: Select the next neighbor based on initial conditions

Step 6: This is the current solution. Calculate the $\Delta E = \text{current solution} - \text{best solution}$ and temperature $T = \alpha T$.

Step 7: If $\Delta E > 0$. Calculate probability of acceptance.

Step 8: If $\Delta E < 0$. Change the best position

Step 9: Best position = Current Position

Step 10: Accept the corresponding position

Step 11: If the probability of acceptance lies within

the given range accept them as probably accepted position.

Step 12: Repeat all these steps until the initial temperature reaches the specified ending temperature.

In general, The SA algorithm typically adopts a repetitive movement based on a varying temperature parameter that mimics the metals' annealing process. The Matlab developed above SA algorithm toolbox using to solved. The MatLab tool box user interface is shown in the fig. 5.

The optimisation search starts from lower limit of process parameters and the curve varies with respect to process parameters. The screenshot taken during the running of the program is shown in Fig. 6. The curve variation at the initial stage is due to the search for an optimum solution of 3501 iterations till study state condition is reached. The study state of curve will be stated after 400 iterations and optimal combination obtained at 3501 iterations with less time. A set of output results showing optimal parametric values for AISI 4130 weld joint consisting of a run of 3501 iterations are shown in Table - IV.

Table 4

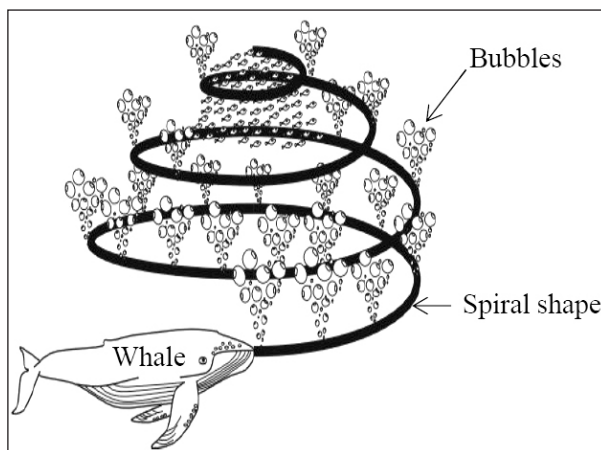
SA using identified optimal combinations.

Process parameters					Output results		Error
LP (W)	WS (m/min)	BA (Deg.)	FPP (mm)	FL (mm)	MH (HV1)	WB (mm)	
1469.47	1.2	91.99	0.1993	16.00	520	1.1210	10.25 & 9.89
1470	1.2	92	0.2	16.00	504	1.028	

4.4 WOA optimization

WOA is a new meta-heuristic optimization algorithm that mimics humpback whales' intelligent bubble net hunting techniques. WOA is a simple with robust and swarm based stochastic optimization approach (Reddy et al., 2021).

The model consists of three stages: (i) Encircling prey, (ii) Spiral bubble net feeding and (iii) Search for prey



(i) Encircling prey

Humpback whale can discover the region of prey and encircle them. The WOA algorithm considers current best search agent position which is the goal prey or optimum point,

(ii) Spiral Updating Position

In this approach, a spiral equation is created between the position of whale and prey to simulate the helix-shaped movement of humpback whales as described

(iii) Search for prey

Almost all meta-heuristic algorithms explore the optimum using random selection. In the bubble-net method, position of the optimal design is not known and hence humpback whales search for prey randomly. In contrast to the exploitation phase within interval $[-1,1]$

The optimisation search starts from lower limit of process parameters and the curve varies with respect to process parameters. The screenprint taken during the running of the program is shown in Fig. 7. The curve variation at the initial stage is due to the search for an optimum solution of 3500 iterations till study state condition is reached. The study state of curve will be stated after 100 iterations and optimal combination obtained at 200 iterations with less time. A set of output results showing optimal parametric values for AISI 4130 weld joint consisting of a run of 3500 iterations are shown in Table 5.

5. Comparison and Selection of the Best Optimization Approach

Optimal combination of process parameters are identified by using GA, SA, WOA optimal values based on that identified the better optimization technique. The optimal combination of process parameters and optimum values of GA, SA and WOA are presented In the Table 6.

From the table 6, the GA using to obtained the MH= 520 HV1 & WB = 1.1546 mm. similarly, SA using to optioned the MH= 520 HV1 & WB = 1.1210 mm and WOA is using to optioned the MH= 526 HV1 & WB = 1.158.

Therefore, the GA tool using to identified the optimum valve with less time, comparatively SA and WOA. The better optimum value obtained in the WOA. The better optimum value obtained in the WOA, but it takes long running time.

6. Conclusions

Based on the joining of AISI 4130 and AISI 316 by using CO₂ LBW experimental work, the following conclusions are drawn.

- Non-linear regression equations are generated with better reliability and model coefficient.
- The non-linear and multi-objective regression equation is using identified the better

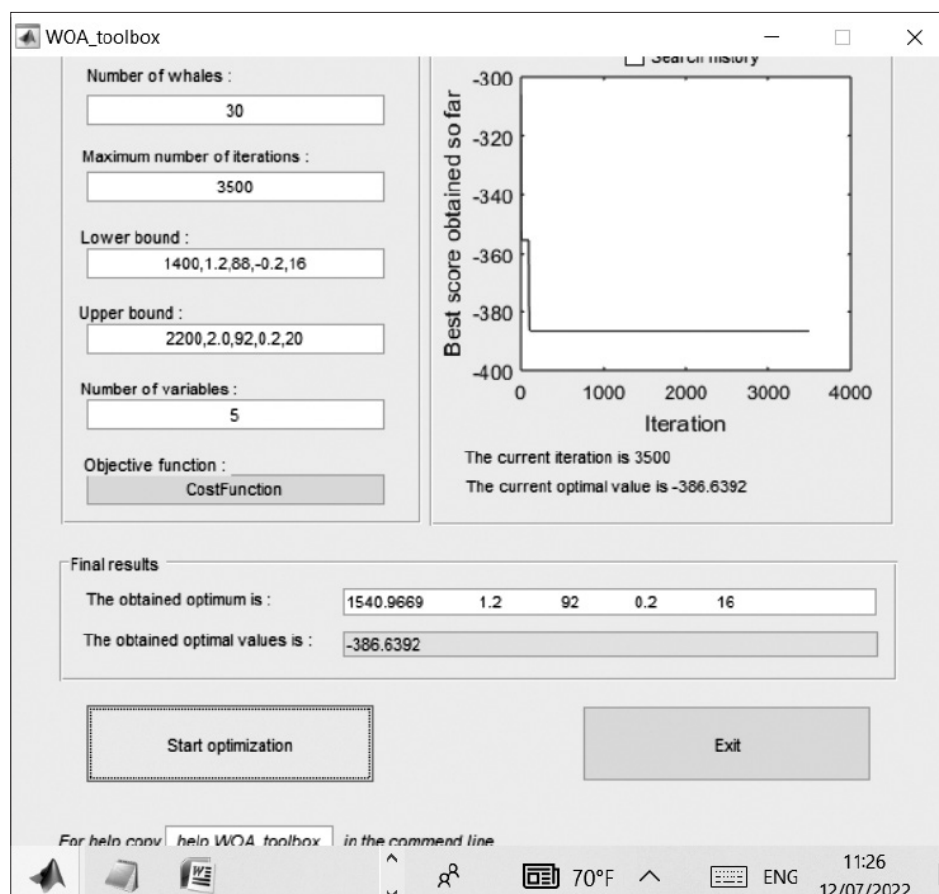


Fig. 7. The curve varies with respect to process parameters in WOA.

Table 5

WOA using identified optimal combinations.

Process parameters					Output results		Error
LP (W)	WS (m/min)	BA (Deg.)	FPP (mm)	FL (mm)	MH (HV1)	WB (mm)	
1469.47	1.2	91.99	19	16.00	526	1.158	9.09 & 7.58
1470	1.2	92	20	16.00	514	1.2	

Table 6

Comparison of optimal combinations (GA, SA and WOA).

Optimization Technique	Process parameters					Output results		Error
	LP (W)	WS (m/min)	BA (Deg)	FPP (mm)	FL (mm)	MH (HV1)	WB (mm)	
GA	2066.03	1.99	88.0	0.19	19.99	520	1.1546	9.25 & 10.5
	2066	2.0	88.0	0.19	20.0	525	1.25	
SA	1469.47	1.2	91.99	0.1993	16.00	520	1.1210	10.25 & 9.89
	1470	1.2	92	0.2	16.00	504	1.028	
WOA	1469.47	1.2	91.99	19	16.00	526	1.158	9.09 & 7.58
	1470	1.2	92	20	16.00	514	1.2	

optimum value with optimal combination of process parameters by using AI tools: GA, SA and WOA.

- Conformation test is conducted as per the optimal combination of GA, SA and WOA and the errors are within the limit.
- Optimum value is obtained at less time in GA and WOA is used to obtain better optimal value and WOA evaluation process is simple with robust and swarm based stochastic optimization approach.

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