Springer

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Journal of Mechanical Science and Technology 31 (5) (2017) 2513~2522
www.springerlink.com/content/1738-494x(Print)/1976-3824(Online)
DOI 10.1007/s12206-017-0449-x

Optimization of submerged arc welding process parameters using quasi-oppositional based Jaya algorithm†

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(Manuscript Received September 11, 2016; Revised December 27, 2016; Accepted January 26, 2017)

Abstract

Submerged arc welding (SAW) is characterized as a multi-input process. Selection of optimum combination of process parameters of SAW process is a vital task in order to achieve high quality of weld and productivity. The objective of this work is to optimize the SAW process parameters using a simple optimization algorithm, which is fast, robust and convenient. Therefore, in this work a very recently proposed optimization algorithm named Jaya algorithm is applied to solve the optimization problems in SAW process. In addition, a modified version of Jaya algorithm with oppositional based learning, named "Quasi-oppositional based Jaya algorithm" (QO-Jaya) is proposed in order to improve the performance of the Jaya algorithm. Three optimization case studies are considered and the results obtained by Jaya algorithm and QO-Jaya algorithm are compared with the results obtained by well-known optimization algorithms such as Genetic algorithm (GA), Particle swarm optimization (PSO), Imperialist competitive algorithm (ICA) and Teaching learning based optimization (TLBO).

Keywords: Submerged arc welding; Optimization; Jaya algorithm; Quasi-opposition based learning

1. Introduction

Submerged arc welding (SAW) is a process of joining metals by coalescence. The heat required for coalescence is provided by an arc generated between consumable electrode and work-piece. The process is widely used in heavy welding industry for fabrication of pipelines, gas cylinders, ship building, mining and mineral processing equipment, etc.

A common problem encountered by the manufacturers in the case of SAW process is setting the process parameters to achieve best performance of the process. This is mainly because the SAW process is characterized by multiple input parameters such as wire feed rate, electrode stickout, traverse speed, welding current, arc voltage, contact tip-to-plate distance, etc. These input parameters significantly influence the responses such as weld bead geometry, tensile strength, hardness, impact value, deposition rate, penetration of weld, etc.

Traditionally, manufacturers choose a process parameter setting either by time consuming trial and error method, or based on the judgment of machine operator or from the machine handbook. However, a process parameter setting determined in this manner is usually far from optimum. Therefore, an urge to achieve more ideal values of output parameters has steered the researchers towards the use of optimization techniques for selection of input process parameters of SAW.

Researchers and practitioners have made several attempts for prediction and optimization of process parameters to achieve good quality of weld in SAW process. Benyounis and Olabi [1] provided a comprehensive review on the use of statistical techniques, evolutionary algorithms and computational networks used by previous researchers for prediction and optimization of welding process parameters. Datta et al. [2] applied Taguchi method for optimization of bead geometry, Heat affected zone (HAZ) and depth of penetration in SAW process. Kiran et al. [3] studied the influence of welding current on weld geometry and mechanical properties of weld in two wire tandem SAW process. Dhas and Kumanan [4] studied the influence of process parameters such as welding current, arc voltage, welding speed and electrode stickout on bead width and developed mathematical models. Further, Particle swarm optimization (PSO) algorithm was applied to minimize the weld bead width. Narang et al. [5] used Response surface methodology (RSM) to develop empirical models for depth of penetration, bead height, depth of HAZ, bead width and HAZ width in SAW process.

Kiran et al. [6] studied the effect of process variables on weld bead quality in two wire tandem submerged arc welding of HSLA steel using RSM. Lan et al. [7] analyzed the microstructural variation and mechanical behaviors in submerged

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arc welded joint of high strength low carbon bainitic steel. Li and Lu [8] developed a hybrid heat source model for tandem submerged arc welding process using artificial neural network algorithm and support vector machine algorithm. Lee and Song [9] used Taguchi method and fuzzy logic for optimization of process parameters of SAW process. Rao and Kalyankar [10] developed mathematical models for bead width, reinforcement, penetration, hardness and tensile strength of weldment. These mathematical models were used to formulate objective functions for Teaching-learning-based optimization (TLBO) algorithm in order to optimize the SAW process.

Roy et al. [11] applied fuzzy based multiobjective threshold acceptance algorithm for optimization of micro structure and mechanical properties of submerged arc welded joints. Singh et al. [12] applied desirability function approach to optimize the penetration, reinforcement and bead width. Sarkar et al. [13] applied grey-fuzzy based Taguchi method to maximize tensile strength and toughness and minimize hardness of weldments in SAW process. Sudnik et al. [14] developed mathematical model of submerged arc welding process and the phenomena of arc cavity was investigated. Lafdani et al. [15] developed empirical models for penetration depth, weld reinforcement form factor and penetration shape factor in SAW process and the same were optimized using desirability function approach.

Aghakhani et al. [16] applied fuzzy logic to optimize weld bead penetration of submerged arc welding process. Lu et al. [17] developed predictive control based double electrode submerged arc welding to minimize the energy consumption of the process by reducing the required heat input to achieve the same deposition rate. Podder et al. [18] developed regression equations which were used to determine the double ellipsoidal heat source for SAW of low carbon, mild steel plates.

Ghaderi et al. [19] applied Genetic algorithm (GA) and Imperialist competitive algorithm (ICA) to maximize the deposition rate of SAW process. Moradpour et al. [20] applied Nondominated sorting genetic algorithm (NSGA) to optimize penetration, bead width and bead height of weld in SAW process. Mitra et al. [21] developed mathematical formulation for estimation of residual stresses in submerged arc weldments using finite element analysis. Kazemi et al. [22] optimized the depth of penetration in SAW process using response surface methodology.

The performance of SAW process is measured in terms of bead geometry, mechanical and microstructural properties of the weld, productivity, energy consumption and sustainability of the process. Therefore, selection of these process parameters has a great influence the quality of the weldment. For this purpose researchers have applied various statistical optimization techniques such as grey relational analysis, Taguchi method, desirability function approach, etc [1]. Although, statistical optimization techniques are widely used by researchers to solve number of engineering optimization problems, the solutions provided by statistical techniques are often discrete combination of predetermined levels of process parameters and therefore, there is a possibility that the solution provided by statistical techniques may not be optimum, especially in the case of complex optimization problems. Metaheuristic optimization algorithms are very effective in solving optimization problems. However, the use metaheuristic algorithms for optimization of SAW process requires, mathematical models of the process which can precisely map the relationship between input and output parameters for formulation of objective function. Researchers have widely studied the influence of important control parameters of SAW process such as current, voltage, wire feed, welding speed, wire diameter, contact tip to workpiece distance, polarity, wire extension, etc. on the performance measures and mathematical models have been developed. These mathematical models can be used as objective functions metaheuristic optimization algorithms in order to determine the best combination of control parameters for improving the performance of the SAW process. It is revealed from the literature review that the researchers have already developed regression models for SAW process and the same had been used as objectives function for algorithms such as GA, PSO, ICA, TLBO, etc.

However, it has been observed that in addition to tuning of common control parameters such as population size and number of generations, the metaheuristic algorithms require tuning of algorithm-specific parameters which further enhances the user effort. For instance, GA requires tuning of cross-over probability, mutation probability, and selection operator; PSO requires inertia weight and learning factors [4]; ICA requires initial imperialist countries, revolution rate, assimilation coefficient and assimilation angle [19]. Although, TLBO algorithm does not require tuning of any algorithm specific parameters [10], in the TLBO algorithm a solution is updated in two phases (i.e. teacher phase and learner phase) which may increase its complexity. Furthermore, in TLBO algorithm the importance is given only to the best solution and the effect of the worst solution which may have a good potential to explore the search space is not considered.

Recently, Rao [23] proposed a new metaheuristic algorithm named Jaya algorithm which does not require tuning of any algorithm specific parameters. The algorithm is simple in application, solutions are updated using a single equation, and importance is given to the best as well as the worst solution in the current population. Jaya algorithm has a good exploration and exploitation ability. Jaya algorithm has already proved its effectiveness in solving a number of constrained and unconstrained engineering optimization problems [23-25]. In order to further enhance the convergence speed of Jaya algorithm the concept of oppositional based learning is introduced into Jaya algorithm.

In this paper three optimization case studies related to SAW process are presented and the same are solved using Jaya and QO-Jaya algorithms. The results of Jaya and QO-Jaya algorithms are compared with the results of well-known optimization algorithms such as TLBO, PSO, GA and ICA in terms of the objective function value and convergence rate.

The Jaya algorithm and Quasi-opposition based Jaya algorithm (QO-Jaya) are described in the following sections.

2. The Jaya algorithm

In Jaya algorithm an initial population (P) is randomly generated obeying the upper and lower bounds of the process variables. Thereafter, each variable of every candidate solution in P is stochastically updated using Eq. (1)

$$V^{new}_{i,j,k} = V^{old}_{i,j,k} + r1_{i,j,k}\left(V_{i,best,k} - abs\left(V^{old}_{i,j,k}\right)\right) - r2_{i,j,k}\left(V_{i,worst,k} - abs\left(V^{old}_{i,j,k}\right)\right) \quad (1)$$
$$i=1,2,3,....,g \ ; \ j=1,2,3,....,P \ ; \ k=1,2,3,....,d$$

where i is the iteration number and j represents a candidate solution in the current population. $V^{old}_{i,j,k}$ is the old value of k^{th} variable of j^{th} candidate solution; $V^{new}_{i,j,k}$ is the updated value of k^{th} variable of j^{th} candidate solution. Similarly, $V_{i,best,k}$ is the k^{th} variable of the best candidate solution found in the i^{th} iteration; $V_{i,worst,k}$ is the k^{th} variable of the worst candidate solution in the i^{th} iteration; $r1$ and $r2$ are random numbers in the range of [0, 1]; g is the maximum number of generations; P is the population size and d is the number of variables. The random numbers $r1$ and $r2$ act as scaling factors and ensure good exploration of the search space. The absolute value of the of a variable of a candidate solution ($abs\left(V^{old}_{i,j,k}\right)$) considered in Eq. (1) further enhance the exploration ability of the algorithm.

In the Jaya algorithm, a candidate solution moves closer to the best solution in every generation, but at the same time a candidate solution moves away from the worst solution. Thereby, a good exploration and exploitation of the search space is achieved. Fig. 1 shows the flowchart of Jaya algorithm. Readers may refer the following website https://sites.google.com/site/Jayaalgorithm/ for details.

3. The quasi-oppositional based Jaya algorithm

In order to further diversify the population and improve the convergence rate of Jaya algorithm, in this paper the concept of opposition based learning [25] is introduced in the Jaya algorithm. To achieve better approximation, a population opposite to the current population is generated and both are considered at the same time. However, in order to maintain the stochastic nature of Jaya algorithm quasi-opposite population is generated. A quasi-opposite value of a variable of a candidate solution is not a mirror point of the variable; rather it is a value which is randomly chosen between the center of the search space and the mirror point of the variable. The quasi-opposite population is generated using Eqs. (2)-(4).

$$V^{q}_{i,j,k} = rand(a,b) \quad (2)$$

$$a = \frac{V^{L}_{k} + V^{U}_{k}}{2} \quad (3)$$

$$b = V^{L}_{k} + V^{U}_{k} - V_{i,j,k} \quad (4)$$
$$i=1,2,3,....,g \ ; \ j=1,2,3,....,P \ ; \ k=1,2,3,....,d$$

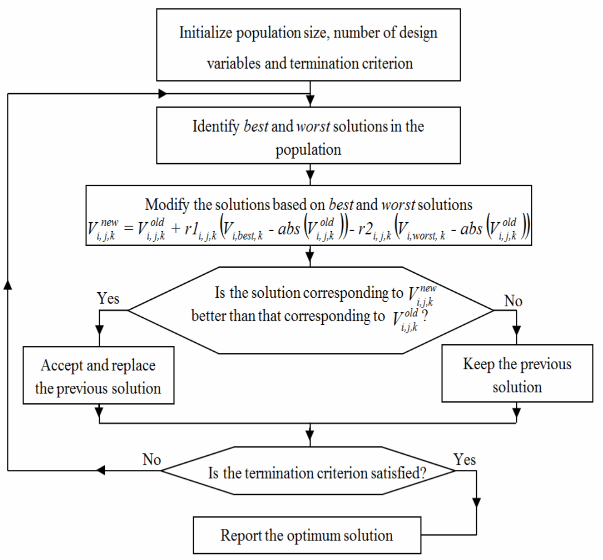


Fig. 1. Flow chart for Jaya algorithm.

where V^{L}_{k} and V^{U}_{k} are the lower and upper bound values of the k^{th} variable; $V^{q}_{i,j,k}$ is the quasi- opposite value of $V_{i,j,k}$. Fig. 2 gives the flowchart for QO-Jaya algorithm.

The computer programs for Jaya and QO-Jaya algorithm are developed in MATLAB R2009a. A computer system with a 2.93 GHz processor and 4 GB random access memory is used for execution of the program.

The next section describes three SAW optimization case studies and the same are attempted using Jaya and QO-Jaya algorithms.

4. Optimization of submerged arc welding process

4.1 Case study 1

The optimization problem formulated in this case study is based on the empirical models developed by Rao and Kalyankar [10] for bead width 'BW' (mm), weld reinforcement 'R' (mm), weld penetration 'P' (mm), tensile strength 'TS' (MPa) and weld hardness 'H' (Rc). Welding current 'I' (Amp), voltage 'V' (volts), welding speed 'S' (cm/min) and wire feed 'F' (cm/min) were considered as process parameters. The empirical models developed by Rao and Kalyankar [10] are used as it is to formulate the objective function in this case study.

4.1.1 Objective functions

The regression models developed by Rao and Kalyankar [10] are considered as objective functions in this case study and the same are expressed by Eqs. (5)-(9) in terms of uncoded values of process variables.

$$\text{minimize } BW = 475.425 - 0.9814I - 15.0015V + 2.4805S - 0.351F + 0.001179I^2 + 0.25575V^2 - 0.109781S^2 + 0.000773F^2 \quad (5)$$

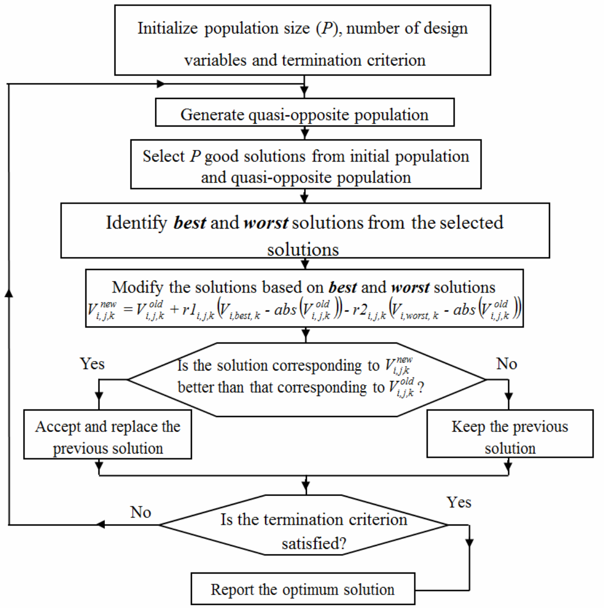


Fig. 2. Flow chart for QO-Jaya algorithm.

$$\text{minimize}\, R = 931.851 - 2.45118 I - 30.4892 V - 2.44028 S + 0.111489 F + 0.0778514 I V + 0.00841464 I S - 0.0171696 V S \quad (6)$$

$$\text{maximize}\, P = -668.516 + 0.094333 I + 43.0883 V + 0.47667 S + 0.064944 F - 0.000092 I^2 - 0.7175 V^2 - 0.018515 S^2 - 0.000134 F^2 \quad (7)$$

$$\text{maximize}\, TS = -1148.73 - 0.1934 I + 20.1667 V + 9.5 S + 9.774 F + 0.001467 I^2 - 0.0834 V^2 - 0.4037 S^2 - 0.01885 F^2 \quad (8)$$

$$\text{maximize}\, H = 772.444 - 1.45667 I - 30 V - 0.04167 S + 0.00556 F + 0.0018 I^2 + 0.5 V^2 . \quad (9)$$

4.1.2 Process parameter bounds

The parameter bounds considered in this work are same as those considered by Rao and Kalyankar [10] expressed by Eqs. (10)-(13)

$$350 \le I \le 450 \quad (10)$$

$$28 \le V \le 32 \quad (11)$$

$$4 \le S \le 20 \quad (12)$$

$$190 \le F \le 310 . \quad (13)$$

The five objectives considered in this work i.e. weld bead width, weld reinforcement, weld penetration, tensile strength and weld hardness are mutually conflicting in nature. Therefore, in order to find an optimum combination of process parameters which satisfies all the objectives simultaneously a combined objective function is formulated by using the weighted sum method, assigning equal weightage to all the objectives. The combined objective function is expressed by Eq. (14).

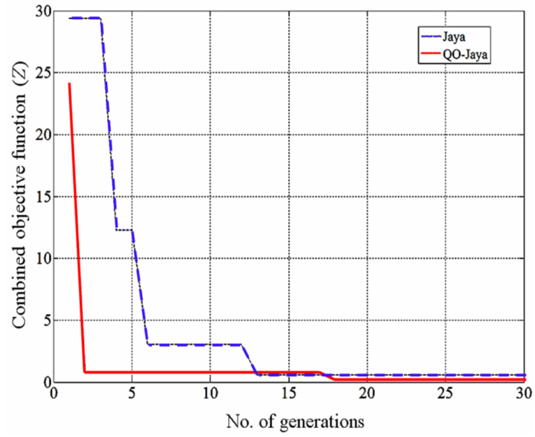


Fig. 3. Convergence graphs of Jaya and QO-Jaya algorithms for case study 1.

$$\text{minimize}\, Z = w_1\left(\frac{BW}{BW^*}\right) + w_2\left(\frac{R}{R^*}\right) - w_3\left(\frac{P}{P^*}\right) - w_4\left(\frac{TS}{TS^*}\right) - w_5\left(\frac{H}{H^*}\right) \quad (14)$$

where BW* and R* are the minimum values of weld bead width and weld reinforcement, respectively, obtained by solving Eqs. (5) and (6), separately. Similarly, P*, TS* and H* are maximum values of weld penetration, tensile strength and weld hardness, respectively, obtained by solving Eqs. (7)-(9), separately. All five objectives are assigned equal weights (i.e. $w_1 = w_2 = w_3 = w_4 = w_5 = 0.2$). In this work, only for the purpose of demonstration equal weights are assigned to the objectives. However, in actual practice, the decision maker may assign his own set of weights based on his order of importance of objectives.

4.1.3 Constraints

The weld reinforcement should be at least up to the upper edge of the joint, which causes joining of filler material with the base metal up to the face of the weld joint [10]. Similarly, the penetration exceeding the root gap up to 0.5 mm is allowable as it can be easily removed by grinding operation. However, weld penetration exceeding the root gap beyond 0.5 mm is undesirable from economic point of view [10]. Therefore, in order to fulfill the above conditions appropriate constraints are introduced in the optimization problem.

Rao and Kalyankar [10] solved this problem by using TLBO algorithm considering a population size of 20 and maximum number of generations equal to 30 thus making the number of function evaluations 1200. It may be noted that in TLBO algorithm the number of function evaluations = 2 × population size × no. of generations. Therefore, for fair comparison of results the same number of function evaluations are used in the present work with the population size of 20 and maximum number of generations equal to 60 for Jaya and QO-Jaya algorithms. The optimum parameters setting for

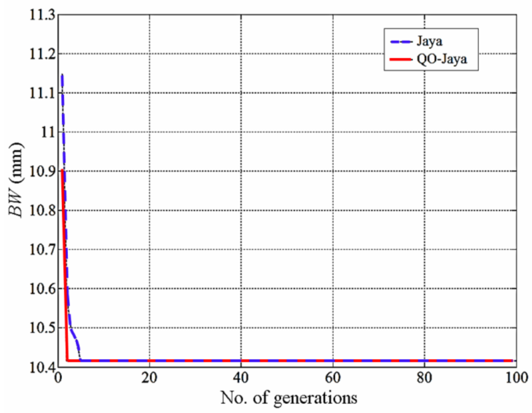


Fig. 4. Convergence graphs of Jaya and QO-Jaya algorithms for case study 2.

individual responses obtained using TLBO, Jaya and QO-Jaya algorithms are reported in Table 1. The optimum parameters setting for the combined objective function obtained using TLBO algorithm and Jaya algorithm are reported in Table 2. The convergence graph of Jaya and QO-Jaya algorithms is shown in Fig. 4.

4.2 Case study 2

The optimization problem formulated in this work is based on the empirical models for weld bead width developed by Dhas and Kumanan [4]. Welding current 'I' (Amp), arc voltage 'V' (volts), welding speed 'S' (mm/min) and electrode stickout 'E' (mm) are considered as process parameters. In this work the regression models developed by Dhas and Kumanan [4] is considered as it is to formulate the objective function.

4.2.1 Objective function

The objective is to improve the quality of weld by minimizing the weld bead width expressed by Eq. (15)

$$\begin{aligned} \text{minimize}\, BW = {} & 118 + 0.0056I - 1.3167V - 0.1708S \\ & - 6.33E + 0.0028IE + 0.0667VE \\ & + 0.0083SE. \end{aligned} \tag{15}$$

4.2.2 Process parameter bounds

The process parameter bounds considered in this work are same as those considered by Dhas and Kumanan [4] expressed by Eqs. (16)-(19).

$$360 \le \mathrm{I} \le 390 \tag{16}$$
$$25 \le \mathrm{V} \le 30 \tag{17}$$
$$400 \le \mathrm{S} \le 420 \tag{18}$$
$$19 \le \mathrm{E} \le 25\,. \tag{19}$$

Dhas and Kumanan [4] used GA and PSO algorithms to minimize the weld bead width using a population size of 20 and maximum number of generations equal to 100 (i.e maximum number of function evaluations equal to 2000). Now the same problem is solved using Jaya and QO-Jaya algorithms in order to see whether any improvement in weld bead width can be achieved. For the purpose of fair comparison of results, the maximum number of function evaluations for Jaya and QO-Jaya algorithms are maintained 2000. Therefore, a population size of 20 and maximum number of generations equal to 100 are chosen for Jaya and QO-Jaya algorithms. Table 3 shows the comparison between the results obtained using Jaya, QO-Jaya, GA and PSO algorithms. Fig. 4 shows the convergence graphs for Jaya and QO-Jaya algorithms.

4.3 Case study 3

The optimization problem formulated in this work is based on the empirical models developed by Ghaderi et al. [19] for deposition rate 'DR' in submerged arc welding process. Welding current 'I' (Amp), arc voltage 'V' (Volt), welding speed 'S' (mm/min), conducting tip-to-plate distance 'C' (mm) and thickness of TiO_2 nano-particles 'F' are considered as process parameters. In this work the regression model developed by Ghaderi et al. [19] is considered as it is to formulate the objective function.

4.3.1 Objective function

In this case study the maximization of deposition rate is considered as objective. In this case study, the regression model developed by Ghaderi et al. [19] for deposition rate 'DR' (Kg/h) is used as objective function and is expressed in terms of coded values of process variables by Eq. (20). The ranges of input parameters are taken from Ghaderi et al. [19] and are coded in the range of -2 to 2.

$$\begin{aligned} \text{maximize}\; DR = {} & 8.25 - 0.143V + 1.44I + 0.497C + 0.523F \\ & - 0.210VS + 0.186VC + 0.424IS - 0.231SC \\ & + 0.393CF - 0.227V^2 + 0.268I^2 \\ & + 0.0917S^2 + 0.100C^2. \end{aligned} \tag{20}$$

4.3.2 Process parameter bounds

The process parameter bounds considered in this work are expressed by Eqs. (21)-(25).

$$500 \le \mathrm{I} \le 700 \tag{21}$$
$$24 \le \mathrm{V} \le 32 \tag{22}$$
$$30 \le \mathrm{C} \le 40 \tag{23}$$
$$300 \le \mathrm{S} \le 500 \tag{24}$$
$$0 \le \mathrm{F} \le 1\,. \tag{25}$$

Ghaderi et al. [19] solved the optimization problem using GA and ICA. A population size of 20 and maximum number of generations equal to 50 were considered for GA (i.e. maximum number of function evaluations equal to 1000). Therefore, in order to maintain the same number of function evaluations as used by GA, a population size of 20 and maximum number of generations equal to 50 are considered for Jaya and QO-Jaya algorithms. For ICA, Ghaderi et al. [19] considered a total number of countries equal to 80 and maximum number of epochs equal to 15 (i.e. maximum number of function evaluations equal to 1200). Therefore, for the purpose of fair comparison of results, a same number of function evaluations are used in the present work for Jaya and QO-Jaya algorithms. Thus, a population size of 20 and maximum number of generations equal to 60 are chosen for Jaya and QO-Jaya algorithms. Table 5 shows the comparison of results obtained by ICA, Jaya and QO-Jaya algorithms. Figs. 5(a) and (b) show the convergence graphs for Jaya and QO-Jaya algorithms.

5. Results and discussion

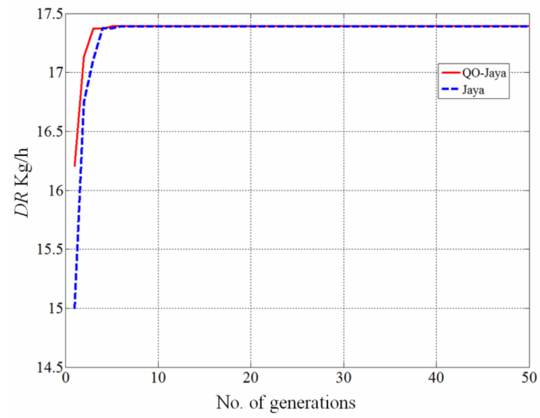
5.1 Case study 1

In the case of individual objective functions the results obtained by Jaya and QO-Jaya algorithms are better than the results obtained by TLBO algorithm. Further, the QO-Jaya algorithm could achieve a lower value of weld reinforcement as compared to Jaya algorithm. In the case of all objective functions considered in the first case study, QO-Jaya algorithm required less number of generations to converge as compared to Jaya and TLBO algorithms (refer Table 1).

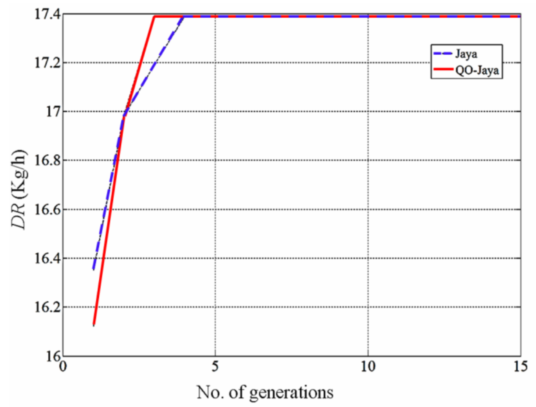
In the case of combined objective function, the Jaya algorithm required only 13 generations and the QO-Jaya algorithm required only 18 generations to achieve convergence. Although, the number of generations required by QO-Jaya algorithm is slightly higher than the number of generations required by Jaya algorithm, the value of combined objective function obtained by QO-Jaya algorithm (i.e. 0.1933) is 65.75 % better than the value of combined objective function obtained by Jaya algorithm (i.e. 0.5644). The robustness of Jaya and QO-Jaya algorithms is tested by running the two algorithms 30 times independently with the same value of population size and the same maximum number of generations, with random initial population in each run.

Jaya and QO-Jaya algorithms achieved the same solution for all the 30 runs with standard deviation equal to zero. Thus, Jaya and QO-Jaya algorithms have demonstrated an ability to operate without deviation with a random initial population each time.

Table 2 shows solutions obtained by Jaya and QO-Jaya algorithms which provide a trade-off between weld bead width, weld penetration, weld reinforcement, tensile strength and hardness. For the purpose of comparison of results, a solution obtained by TLBO algorithm is also reproduced from Ref. [10] in Table 2. It is observed that the value of hardness obtained by TLBO algorithm is higher than the value of hardness obtained by Jaya and QO-Jaya algorithms. This is mainly because the Jaya algorithm has compromised on hardness to achieve a 22.77 % improvement in weld bead width, 28.02 % improvement weld reinforcement, 20.06 % improvement in weld penetration and 1.2 % improvement in tensile strength as compared to the TLBO algorithm.



(a) Convergence graphs for a population size of 20 and maximum number of function evaluations equal to 1000



(b) Convergence graphs for a population size of 80 and maximum number of function evaluations equal to 1200

Fig. 5. Convergence graphs of Jaya and QO-Jaya algorithms for case study 3.

Similarly, the QO-Jaya algorithm has compromised on hardness to achieve a 28.02 % improvement in weld bead width, 99.24 % improvement in weld reinforcement and 11.15 % improvement in weld penetration as compared to TLBO algorithm. The Jaya algorithm obtained a better value of penetration and tensile strength but has compromised on weld bead width and weld reinforcement as compared to QO-Jaya algorithm.

5.2 Case study 2

In the second case study, minimization of weld bead width is considered as objective. The value of weld bead width obtained by Jaya and QO-Jaya algorithms are 18.75 % and 18.30 % lower than the value of weld bead width obtained by GA and PSO algorithms, respectively (refer Table 3). The Jaya and QO-Jaya algorithms are executed 30 times independently with the same population size and the same maximum number of generations with randomly generated initial

Table 1. Comparison of results obtained using TLBO, Jaya and QO-Jaya algorithms for individual responses in case study 1.

Objective	Units	Algorithm	*I* (Amp)	*V* (volts)	*S* (cm/min)	*F* (cm/min)	Optimum result	Required no. generations
*BW**	mm	TLBO[10]	412	29	20	228	17.11	NA
		Jaya	416.20	29.327	20	227.043	**17.062**	25
		QO-Jaya	416.20	29.327	20	227.043	**17.062**	**17**
*R**	mm	TLBO[10]	378	31	18	214	0.0086	NA
		Jaya	375.8213	30.925	7.1382	233.7626	0.00355	15
		QO-Jaya	350	30.8981	4.9221	236.2409	**0.0027**	**12**
*P**	mm	TLBO[10]	444	29	5	241	11.16	NA
		Jaya	450	30.1887	4	277.1496	**11.50**	24
		QO-Jaya	450	30.1887	4	277.1496	**11.50**	**15**
*TS**	MPa	TLBO[10]	448	32	11	253	940.90	NA
		Jaya	450	32	11.766	259.2569	**944.12**	20
		QO-Jaya	450	32	11.766	259.2569	**944.12**	**9**
*H**	Rc	TLBO[10]	350	28	4	307	36.65	NA
		Jaya	350	28	4	310	**36.66**	3
		QO-Jaya	350	28	4	310	**36.66**	**2**

Values in bold indicate better performance of an algorithm as compared to other algorithms.

Table 2. Comparison of results obtained using TLBO, Jaya and QO-Jaya algorithms for combined objective function in case study 1.

Algorithm	Process parameter				Objectives					
	I	*V*	*S*	*F*	*BW*	*R*	*P*	*TS*	*H*	min *Z*
TLBO[10]	445	32	7	193	27.05	0.826	9.32	846.6	**33.45**	19.00
Jaya	423.1719	29.8221	4	267.0907	20.89	0.0152	**11.19**	**856.75**	29.69	0.5644
QO-Jaya	382.41	29.416	20	190	**19.47**	**0.0062**	10.36	717.99	29.02	**0.1933**
% improvement achieved by Jaya algorithm as compared to TLBO algorithm					22.77 %	28.02 %	20.06 %	1.2 %	-	
% improvement achieved by QO-Jaya algorithm as compared to TLBO algorithm					28.02 %	99.24 %	11.15 %	-	-	

Values in bold indicate better performance of an algorithm as compared to other algorithms.

Table 3. Comparison of results obtained using GA, PSO, Jaya and QO-Jaya algorithms in case study 2.

Algorithm	Process parameters				Objective	Required no. of generations
	I (Amps)	*V* (volts)	*S* (mm/min)	*E* (mm)	*BW* (mm)	
GA [4]	364.857	29.7828	419.144	19.67	12.82	NA
PSO [4]	361.0714	26.2714	419.238	19	12.75	81
Jaya	360	25	400	25	**10.416**	**5**
QO-Jaya	360	25	400	25	**10.416**	**2**

Values in bold indicate better performance of an algorithm as compared to other algorithms.

Table 4. Comparison of results obtained using GA, Jaya and QO-Jaya algorithms in case study 3.

Algorithm	Process parameters					Objective	Required no. of generations
	I (Amps)	*V* (volts)	*C* (mm)	*S* (mm/min)	*F* (mm)	max *DR*	
GA [19]	NA	NA	NA	NA	NA	17.29	50
Jaya	700	27.17	40	500	1	**17.393**	7
QO-Jaya	700	27.17	40	500	1	**17.393**	**5**

population each time. It is observed that the Jaya and QO-Jaya algorithms achieved the same minimum value of weld bead width in all the 30 independent runs without deviation.

The Jaya and QO-Jaya algorithms have shown a higher convergence rate as compared to PSO. The PSO algorithm required 81 generations [4] to achieve convergence. On the other hand, Jaya and QO-Jaya algorithms required only 5 and 2 generations, respectively, to achieve minimum value of weld bead width (refer Fig. 4).

5.3 Case study 3

In the third case study, maximization of deposition rate is considered as objective. The Jaya and QO-Jaya algorithms

Table 5. Comparison of results obtained using ICA, Jaya and QO-Jaya algorithms in case study 3.

Algorithm	Process parameters					Objective	Required no. of generations
	I (Amps)	*V* (volts)	*C* (mm)	*S* (mm/min)	*F* (mm)	max *DR*	
ICA [19]	700	27	40	500	1	17.39	7
Jaya	700	27.17	40	500	1	**17.393**	4
QO-Jaya	700	27.17	40	500	1	**17.393**	**3**

Values in bold indicate better performance of an algorithm as compared to other algorithms.

Table 6. Summary of performance of Jaya and QO-Jaya algorithms on three SAW optimization case studies.

Case study	Objective	Algorithm	Optimum value	No. of generations	Computational time (sec)
1	min *Z*	TLBO [10]	19	30	NA
		Jaya	0.5644	13	**0.2**
		QO-Jaya	**0.1933**	18	1.09
2	min *BW*	GA [4]	12.82	90	NA
		PSO [4]	12.75	81	NA
		Jaya	**10.416**	5	**0.157**
		QO-Jaya	**10.416**	2	0.308
3	max *DR*	GA [19]	17.29	50	NA
		ICA [19]	17.39	7	NA
		Jaya	**17.393**	4	**0.12**
		QO-Jaya	**17.393**	3	0.38

Values in bold indicate better performance of an algorithm as compared to other algorithms; NA: Data not available in the literature.

could achieve higher deposition rate as compared to GA in only 7 and 5 generations, respectively (refer Fig. 6(a)). Jaya and QO-Jaya algorithms achieved the same value of deposition rate as that of ICA, but in considerably less number of generations as compared to ICA (refer Table 5).

Besides, ICA requires tuning of algorithm specific parameters such as number of imperialist countries, revolution rate, assimilation coefficient and assimilation angle which is required to be done meticulously to avoid slow convergence and entrapment into local optima. On the other hand, in the case of Jaya and QO-Jaya algorithms, unlike ICA the user does not require to tune any algorithm-specific parameters. Jaya and QO-Jaya algorithms achieved the same value of deposition rate for 30 independent runs, demonstrating complete robustness and consistency.

Table 6 summarizes the performance of Jaya and QO-Jaya algorithms in the three optimization case studies considered in this paper. The performance of Jaya algorithm and QO-Jaya algorithm are found to be better than GA, PSO and TLBO algorithms in solving optimization problems of SAW process. The performance of Jaya algorithm and QO-Jaya algorithm are competitive with ICA. However, the Jaya and QO-Jaya algorithms required comparatively less number of generations to converge at the optimum solution as compared to ICA without the need of tuning any algorithm specific parameters.

All the optimization case studies formulated in this work are based on the regression models developed by the previous researchers [4, 10, 19]. These regression models were developed by the researchers by conducting actual welding experiments. Furthermore, it may be mentioned that, in case study 1 the regression models used as objective functions given by Eqs. (5)-(9) were developed by the first author of this paper by conducting actual experimentation on SAW process and validation tests were also conducted.

The main reasons for applying Jaya and QO-Jaya algorithms for solving optimization case studies in this work are that, both Jaya and QO-Jaya algorithms are algorithm-specific parameter-less algorithms, are robust and are simpler in implementation. In order to demonstrate the effectiveness of Jaya and QO-Jaya algorithms in solving the optimization problems of SAW process the results of Jaya and QO-Jaya algorithms are compared with the results of other algorithms such as GA, PSO, ICA and TLBO. The Jaya and QO-Jaya algorithms found superior results as compared to the other algorithms with a very high convergence speed.

The results provided by Jaya and QO-Jaya algorithms are significant and have successfully improved the performance of SAW process. This is mainly because the process parameters combination suggested by Jaya and QO-Jaya algorithms are new and have provided better objective function values as compared to the other algorithms. The process parameter combinations suggested by Jaya and QO-Jaya algorithms are more rational and analogous with the experimental observations of the previous researchers as compared to the process parameter combinations suggested by GA, PSO, ICA and TLBO algorithms.

6. Conclusions

In this work optimization problems of SAW process are solved using Jaya and QO-Jaya algorithms. Three optimization case studies are considered separately and the results obtained using Jaya and QO-Jaya algorithms are compared with those obtained by other well-known optimization algorithms such as GA, PSO, ICA and TLBO.

- The results obtained by Jaya and QO-Jaya algorithms are better as compared to other optimization algorithms such as TLBO in the first case study and GA and PSO in the second case study. In the third case study, the results obtained by Jaya and QO-Jaya algorithms are better than GA. However, the Jaya and QO-Jaya algorithms achieved the same result as achieved by ICA but in relatively less number of generations.
- Both Jaya and QO-Jaya algorithms have shown faster convergence speed in all the three case studies considered in this work, requiring comparatively less number of generations to achieve the optimum solution as compared to other optimization algorithms such as GA, PSO, ICA and TLBO.
- The QO-Jaya algorithm has shown a higher convergence speed as compared to Jaya algorithm owing to the use of quasi-oppositional based concept. However, the computational time required by QO-Jaya algorithm is slightly higher than the Jaya algorithm.
- The robustness of Jaya and QO-Jaya algorithms is tested in all the three case studies by running the algorithms 30 times independently and it is observed that these algrithms possessed complete robustness while solving the three case studies.
- The proposed approach for SAW process parameter selection using Jaya and QO-Jaya algorithms will be very much useful for industrial applications. The Jaya and QO-Jaya algorithms are simple and free from algorithm specific parameters. These are fast, robust and convenient algorithms for solving optimization problems of submerged arc welding process. The Jaya and QO-Jaya algorithms may also be applied to solve the optimization problems of other joining processes such as tungsten inert gas welding, gas metal arc welding, laser welding, etc.

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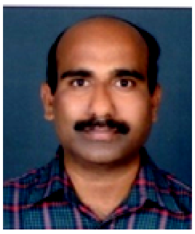

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