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A Comparative Study of Metaheuristic Optimization Approaches to Optimize Laser Welding Process Parameter with Pre-Set Weld Size Magnitude for AISI 416 and AISI 440 FSe Stainless Steels

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1. Introduction

In recent years, the boom of laser technology has gradually replaced traditional technologies. With advantages such as flexible adjustment of energy intensity, high accuracy, fast processing speed, non-pollution, etc., the applications of the laser are preferred and widely used in modern industries, including the automotive and aviation industry, electronics industry, and medical equipment manufacturing industry [1, 2]. In particular, laser welding has many outstanding features such as a small and precise heat input source, fast welding speed, small heat-affected zone, small weld width & high penetration, and small residual stress & deformation, so this welding method is widely used in industry [2, 3]. In general, the mechanical properties or quality of the weld depend on the geometry of the weld [4]. Therefore, the selected welding process parameters, such as laser power (*LP*), welding speed (*WS*), fiber diameter (*FD*), welding position, and shielding gas, are essential. These parameters have to be well controlled during the welding process. Besides, the accuracy of these parameters depends on the skill and experience of engineers or operators. That is an important challenge for today's manufacturers. Recently, many studies have been done on different aspects of laser welding technology. Benyounis et al. [5] performed optimization of input parameters (*LP*, focal position - *FP*, and *WS*) to effectively control tensile strength (*TS*), toughness, and operating costs of laser butt welds for stainless AISI 304 steel through statistical probability and the response surface methodology (RSM). The combination of graphical analysis and ANOVA allowed the identification of the most important process factors contributing to the optimal response. The authors showed that graphic optimization techniques could be used to quickly obtain the optimal welding parameter set and reduce the cost considerably. Anawa and Olabi [6] built the L25 matrix using Taguchi for input parameters (*LP*, *FP*, and *WS*) and output parameters (*TS* & signal-to-noise ratio) for laser welds for AISI 304 and low carbon steels. Their results showed that the *LP* had the strongest influence, followed by the *WS*, but the *FP* did not have an effect within the applied parameters. Khan et al. [7] optimized the laser welding process parameters for AISI 416 and AISI 440 FSe stainless steels with a thickness of 0.55 mm. The full factorial design of experiments (DOE) was set up with Design-Expert V7 software, including 18 experiments with three *LP* & *WS* levels and two fiber diameter (*FD*) levels. The ANOVA was used to determine the process parameters. The results showed that the *LP* and *WS* were the two most important parameters affecting weld bead geometry and shear forces. Zhao et al. [8] evaluated the effect of the *LP*, *WS*, *FP*, and gap parameters of the laser-welded butt joint for SAE1004 steel with a thickness of 0.4 mm on the geometry weld, and using the RSM to build the mathematical model for response parameters. The *LP* and *WS* influence all output parameters. The RSM has given the optimal input parameter values: *WS* is 34.7 mm/s, prescribed gap is 0.12 mm, *FP* is -0.12 mm, and *LP* is 628 W. Reisgen et al. [9] presented the quality of CO2 laser weld for the Dual-phase/Transformation induced plasticity steel, which is mentioned in this study. The mathematical model shows the relationship between process parameters: *FP*, *LP*, & *WS*, and response parameters: heat input, weld bead width & penetration, *TS*, and dome height, which were developed by the RSM on Box-Behnken design. The results show that welding quality and cost reduction could be obtained with optimal welded conditions. With the goals achieved through numerical methods and graphical optimization methods, it is shown that the cost of making welds decreases by 11.7% and the productivity increases when the welding speed reaches the maximum. Zhang et al. [10] researched the laser welding for the AISI 304 stainless steel with a thickness of 12 mm with the deep penetration assessed through the set of process parameters: focus len & size, *LP*, *WS*, shielding gases (3 different types: Ar, N_2, and He) and output parameters: top & bottom weld width and weld penetration. After implementing industry standards, the welding samples are cut by EDM, the microstructure is examined using the optical microscope, and the horizontal *TS* and fractured surfaces are examined by SEM. The results showed that weld speed and focal position are directly related to each other, and with *FP*, respectively, the penetration is not full in the case of thickness plates, and reaches the maximum when using He gas, followed by N_2 gas, and finally Ar gas. Sokolov and Salminen [11] prepared laser welding of S355 steel, 20 mm thick with four butt joint settings, using waterjet cutting to chamfer the weld edges and shot blasting to achieve the required surface roughness. After welding, the study evaluated the effects of *WS*, *PW*, and *FD* on the penetration and HV5 hardness of the weld. Ahn et al. [12] studied the weld for Ti-6Al-4V alloy by laser with deep penetration through input parameters: *LP*, laser speed, and beam *FP*, and output parameters: microstructure, HAZ, weld zone, and failure. In this study, the traditional method used with two process variables is considered constant. The results show that the weld width increases with increasing laser power and focal length, reducing welding speed. Gao et al. [13] studied the optimization of arc laser welding geometry for stainless steel AISI 316L. The L25 matrix Taguchi method was used to design a 5-level 4-factor experiment to investigate process parameters. The Kriging model is selected to establish a relationship between process parameters (welding current, *LP*, travel speed, and distance between laser and arc) and response parameters (bead width, penetration depth, and bead reinforcement). The author performs optimization using the Genetic Algorithm (GA). The results show that *LP*, welding current, and *WS* strongly affect bead width and penetration depth. The optimization results show that the microstructure is more uniform and the microhardness gradually increases from the welding zone to the base metal zone. Shrivastava et al. [14] studied the optimization of laser welding for P92 (creep strength enhanced ferritic - CSEF) steel. The Taguchi-based GRA (gray relational analysis) model was used to set up the mathematical model with input parameters: *LP*, *WS* & *FP*, and output parameters: weld width, penetration, and HAZ width. The ANOVA analysis results show that *WS* affects 74.39 %, *FP* 14.63 %, and focal length 10.97 %, with optimal values respectively 3kW, 1 m/min, and 4 mm for the used material. Vijayan et al. [15] presented results in optimizing the parameters of a diffusion-cooled CO_2 laser for low-carbon steel. The RSM and the GA were used for comparison. The mathematical model shows two output parameters (weld bead geometry and heat-affected zone) set up according to the three input parameters (*LP*, *WS*, and *FP*). Yang et al. [16] integrated the Kriging model with the Non-Sorting Genetic Algorithm-II (NSGA-II) to optimize process parameters of laser and magnetic welds to reduce defects and increase penetration and weld quality. Before establishing the relationship between input parameters (magnetic flux density, *LP*, and *WS*) and welding a seam profile of the welding process with the Kriging meta-model, a five-level three-factor experiment using Taguchi L25 orthogonal array is deployed. After optimizing the multi-objective process parameters by NSGA-II and Pareto solutions, the output parameters are validated through macro, micro testing, and microhardness. The results show that the integration has been highly effective. The research shows that to improve weld quality for different materials and thicknesses, reduce defects, and increase productivity, the application of process parameters optimization algorithms is necessary. The main studied input parameters are *LP*, *WS*, *FP* & *FD*, and the response parameters. The weld joint of base metals is determined by two closely related parameters: LP and WS. The welding area size, thermal influence area, and weld penetration depend on focal position and fiber diameter. Musrrat Ali et al. [17] proposed the MDE algorithm for engineering problems. The study shows a typical difference between the MDE algorithm and the basic DE algorithm: Basic DE uses one type of mutation, but MDE combines two mutations to create the mutation vector. The experiments that were conducted show that the proposed algorithm outperforms the basic DE algorithm in all benchmark problems and real-world applications. Nguyen Ngoc Son [18] surveyed and studied the factors affecting the convergence quality of the DE algorithm and proposed an improved differential evolution optimization algorithm, HDE and MDE: 1. neural network weights, MLP trained to achieve a globally optimal solution & improve convergence speed during network training, and 2. NNARX prediction model weights to identify nonlinear systems. Tran Thien Huan [19] used the MDE algorithm - Modified Differential Evolution: 1. optimizes gait parameters to help bipedal robots walk stably for bipedal robots with high speed. Accurate leg lifting & simulation, and experimental results on a small-sized bipedal robot (HUBOT-5) are compared with the GA - Genetic Algorithm algorithm and the PSO - Particle Swarm Optimization algorithm. swarm math) and (2) optimize the four parameters of the pose generator (*WPG*) using the AENM model - Adaptive Evolutionary Neural Model (adaptive evolutionary neural network) in a large-sized bipedal robot model, small HUBOT-5. Akararungruangkul and Kaewman [20] used the MDE algorithm to solve the specific situation of the location routing problem: 1. modify the mutation formula of the DE algorithm & 2. new rules in finding the search for lumps. From the calculation results, in some cases, the author shows that MDE produces 13.82 % better than the basic DE algorithm. Srichok et al. [21] combined the surface response method and the MDE algorithm to optimize friction stir welding parameters: stir speed, welding velocity, axial force, stir pin profile, and pin material. stirred. The optimal parameters are 1417.68 rpm, 60.21 mm/min, 8.44 kN, and the hexagonal stirring pin profile & JIS SKD11 steel as stirring pin material. The *TS* achieved from this set of parameters is 294.84 MPa, 1.48% better than the response surface method.

The main objective of this article is to control weld size, which should be achieved through two approaches. The first is to use the mathematical model of Khan et al. [7] to estimate two response parameters: the Width of the Weld Zone (*WWZ*) and the Penetration Depth of the Weld (*PDW*). Next, the meta-heuristic optimization algorithm will be used to solve the problem of optimizing three input parameters of the laser welding process: *LP* (Laser Power) & *WS* (Welding Speed), and *FD* (Fiber Diameter).

2. Problem Formulation About the Parameters of the Laser System to Achieve the Desired Size for the Weld

Fig. 1 shows the algorithm diagram that optimizes the parameters of the laser system to obtain the desired size for the weld. The mode of laser welding is described in subsection 2.1.

The meta-heuristic optimization algorithms are used to find three input parameters: *LP* (Laser Power), *WS*

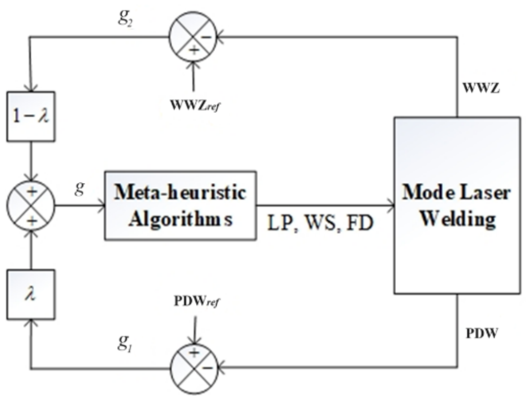

Fig. 1. Diagram of the optimization algorithm

(Welding Speed), and *FD* (Fiber Diameter) of the laser welding process and calculate two response parameters: the Width of the Weld Zone (*WWZ*) and the Penetration Depth of the Weld (*PDW*) of the weld bead size.

The optimal target function of the meta-heuristic optimization algorithm is mentioned in subsection 2.2.

2.1. Mode laser welding

Fig. 2 shows the laser welding mode using the continuous wave Nd:YAG laser (Rofin DY011).

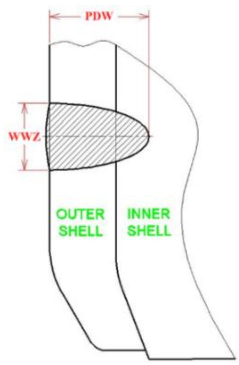

Fig. 2 The diagram shows two-dimension parameters of overlap weld [7]

The optimization problem formulated in this study is based on the analysis given by Khan et al. [7] on the laser welding in a constrained overlap combination for the AISI 416 and AISI 440Fse steels (types of martensite stainless steels) as shown in Fig. 2. The thickness of the outer shell is 0.55 mm. The process parameters considered for this model are the same as those considered by Khan et al. [7], and these are LP (W), WS (m/min), and FD (m) while WWZ (m) and PDW (m) are considered performance measures. The coded factors are extracted from Design-Expert software shown in Eqs. (1) and (2):

$$WWZ = (1265000 \times FD + 21185000 \times WS + \\ +264820 \times LP - 221789170) \times 10^{-6} \quad , \tag{1}$$

$$PDW = (3097 \times WS \times FD - 2694 \times LP \times FD - \\ -7375 \times LP \times WS - 9361 \times FD - \\ -25069 \times WS + 21306 \times LP + 89194) \times 10^{-6} \, . \tag{2}$$

2.2. Target function

For the weld size to follow the **pre-set** weld size (WWZ_{ref}, PDW_{ref}), the difference between the magnitude of the weld size and the pre-set weld size (WWZ_{ref}, PDW_{ref}) represents the two objective functions as below:

$$\begin{cases} g_1 = \left| WWZ_{ref} - WWZ \right| \\ g_2 = \left| PDW_{ref} - PDW \right| \end{cases} . \tag{3}$$

Thus, to achieve the desired weld size, it is necessary to find the minimum value of the two objective functions g_1 and g_2 or the integration objective function according to Eq. 4:

$$\begin{cases} g = \lambda \times \left| WWZ_{ref} - WWZ \right| + (1-\lambda) \times \left| PDW_{ref} - PDW \right| \\ WWZ_{min} \le WWZ \le WWZ_{max}; \ PDW_{min} \le PDW \le PDW_{max} \end{cases} . \tag{4}$$

In which, (WWZ_{min}, WWZ_{max}) and (PDW_{min}, PDW_{max}) are limit of the weld size, $\lambda (0 < \lambda \le 1)$ is optimally selected to prioritize between the variance with the desired Width of the Weld Zone magnitude (λ increase) and the variance with the desired Penetration Depth of the Weld magnitude (λ decreased).

In this study, each method was performed 200 times to evaluate the reproducibility of the results obtained. From the results obtained after 10 runs, the statistical parameters (mean value, standard deviation, etc.) are calculated and compared overall. The comprehensive flowchart of the overall procedure is presented in Fig. 3. The parameters in the implementation include the population size (*NP*) of the three methods, *NP* = 30, and the number of identical variables, *D* = 3. The optimally selected parametric values for each method are as follows:

- The mutation and Crossover rates of the GA are 0.2 and 0.7, respectively.
- The JAYA: No.
- The MDE: The mutation value (*F*) is random [0.4; 1.0], and the Crossover Probability (*CR*) is random [0.7; 1.0].

The performance of the three algorithms is evaluated with "the standard values" mentioned above.

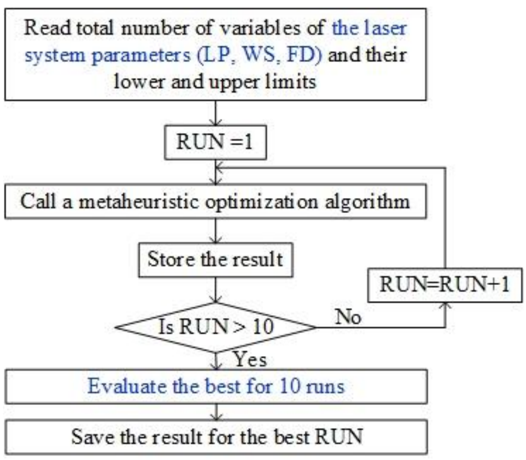

Fig. 3 Flowchart of the basic procedure

3. Results and Discussion

This study implements three meta-heuristic optimization techniques using MATLAB version 2014b software on a computer with an Intel Core i5 3210 m, 2.5 GHz, and 8 GB RAM configuration.

Materials: AISI 416 and AISI 440Fse steels, types of martensitic stainless steels.

The desired size of the weld is WWZ_{ref} = 570 µm, PDW_{ref} = 840 µm, respectively (based on experimental results I of Khan et al. [7]).

To start the experimental process of comparing the three algorithms: GA, JAYA, and MDE with each other, the λ value in Eq. (4) is chosen to be 0.5.

The lower and upper bound values of *LP* are 800 W and 1000 W, *WS* are 4.5 m/min and 7.0 m/min, and *FD* are 300 µm and 400 µm, respectively.

The results after 10 runs of the three optimal parameter values and the best value of the objective function of the three algorithms: GA, JAYA, and MDE, are presented in Table 1, respectively.

Table 1

The optimal parameter values and the best value of the objective function

Run	**Algo-ritm**	**Parameter value**			**Best fitness value** g, µm
		LP, W	*WS*, m/min	*FD*, µm	
1	GA	844.14	5.08	364.15	*0.2919*
	JAYA	930.97	6.19	327.12	0.0817
	MDE	881.92	5.61	347.23	5.91e-05
2	GA	902.20	5.86	338.69	0.1026
	JAYA	943.31	6.33	322.35	0.0585
	MDE	870.42	5.45	352.30	0.0002
3	GA	968.21	6.56	313.28	0.0339
	JAYA	1005.80	6.87	300.31	0.1841
	MDE	825.25	4.74	373.61	0.0002
4	GA	889.65	5.71	343.86	0.0814
	JAYA	1007.24	6.86	300	0.0882
	MDE	856.85	5.25	358.46	9.34e-06
5	GA	867.79	5.40	353.78	0.3083
	JAYA	956.56	6.47	317.44	0.2135
	MDE	***988.92***	***6.73***	***306.05***	***3.07e-06***
6	GA	894.23	5.74	342.18	0.3919
	JAYA	971.01	6.58	312.31	0.0682
	MDE	913.82	6.01	333.87	0.0004
7	GA	864.75	5.37	354.57	0.5660
	JAYA	810.89	4.50	380.83	0.0841
	MDE	901.90	5.87	338.75	0.0005
8	GA	893.07	5.74	342.88	0.4838
	JAYA	839.47	4.99	366.59	0.0872
	MDE	965.77	6.54	314.13	0.0001
9	***GA***	***919.62***	***6.08***	***331.55***	***0.0118***
	JAYA	***843.65***	***5.05***	***364.62***	***0.0350***
	MDE	991.82	6.76	305.05	0.0180
10	GA	884.84	5.64	346.11	0.1871
	JAYA	847.98	5.14	362.49	0.1944
	MDE	837.43	4.95	367.63	4.57e-05

Fig. 4 shows the average value of the objective function for each algorithm: GA (green color), JAYA (blue color), and MDE (red color).

Based on the results in Table 1, the mean value of the best fitness value g to find the optimal solution of the GA, JAYA, and MDE algorithms are 0.2459108 µm, 0.109538035 µm, and 0.001985485 µm, respectively. At the same time, Fig. 4 also shows that the convergence rate gradually accelerates from GA to JAYA, then to MDE: the MDE algorithm provides superior results because the MDE algorithm can escape from local extrema and has an earlier convergence speed than GA and JAYA.

Table 2 shows the set of optimal three main parameters to achieve the desired size of the weld with the smallest g value.

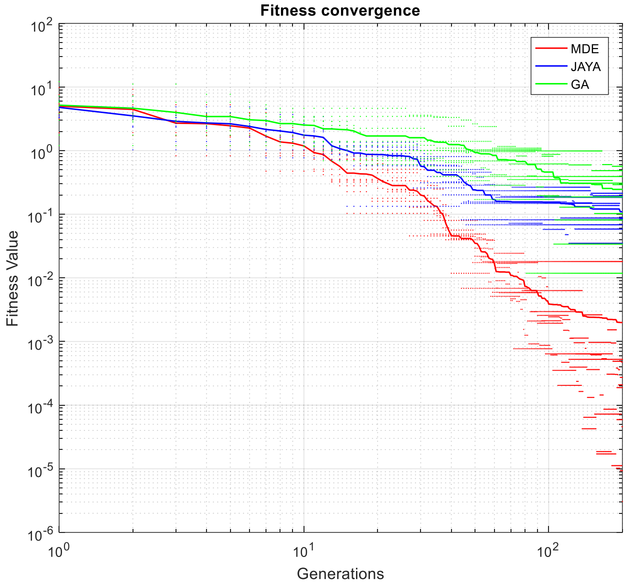

Fig. 4 The convergence of the GA, JAYA, and MDE algorithms

Table 2

The optimal parameter value with the smallest g value

Algo-rithm	**Parameter value**			**The smallest value of the best fitness value** g, µm
	LP, W	*WS*, m/min	*FD*, µm	
GA	919.62	6.08	331.55	0.0118
JAYA	843.65	5.05	364.62	0.0350
MDE	988.92	6.73	306.05	3.07e-06

Table 3

The errors of the optimal *LP*, *WS*, and *FD* parameters with the examined experiment I results of Khan et al. [7]

WWZ_{ref}=570 µm and PDW_{ref}=840 µm				
		LP, W	*WS*, m/min	*FD*, µm
The examined experiment I results of Khan et al. [7]		1000	7	300
Errors, %	GA	-8.03	-13.14	10.51
	JAYA	-15.7	-27.8	21.54
	MDE	**- 1.1**	**-3.85**	**2.01**

The errors of the optimal *LP*, *WS*, and *FD* parameters in this study with the examined experiment I results of Khan et al. [7] are shown in Table 3.

From Table 3, the MDE algorithm shows the least error.

The study continues to use the MDE algorithm to optimize three laser system parameters to achieve two different weld sizes: (WWZ_{ref} = 660 µm, PDW_{ref} = 643 µm), (based on experimental results II of Khan et al. [7]) and (WWZ_{ref} = 484 µm, PDW_{ref} = 939 µm) (based on experimental results III of Khan et al. [7]).

Table 4 shows the results and errors of the optimal LP, WS, and FD parameters in this study compared to the examined experiment II and III results of Khan et al. [7].

The comparison results by the MDE algorithm are less than 10% acceptable.

Table 4

The results and the errors of the optimal *LP*, *WS*, and *FD* parameters with the examined experiment II and III results of Khan et al. [7]

		LP, W	*WS*, m/min	*FD*, μm
WWZ_{ref}=660 μm PDW_{ref}=634 μm	The examined experiment II results of Khan et al. [7]	900	6.5	400
	This study (λ = 0.9)	859.05	6.99	399.99
	Errors, %	**-4.5**	**7.5**	**0.0025**
WWZ_{ref}=485 μm PDW_{ref}=939μm	The examined experiment III results of Khan et al. [7]	850	5	300
	This study (λ = 0.9)	875.9	4.501	300.01
	Errors, %	**3.04**	**-9.9**	**3.3e-3**

4. Conclusions

In this article, the Modified Differential Evolution (MDE), Genetic Algorithm (GA), and JAYA algorithm perform inverse optimization of the input parameters of the laser welding for the AISI 416 and AISI 440Fse steels (types of martensite stainless steels) to achieve the size of the weld (the pre-set size of the weld): the Width of the Weld Zone WWZ_{ref} and the Penetration Depth of the Weld PDW_{ref}. Optimization results of input parameters: *LP* (Laser Power), *WS* (Welding Speed), and *FD* (Fiber Diameter) of GA algorithm with weight λ = 0.1 compared with the experimental results measured by Khan et al. [7] with errors of 1.89%, 4.80%, and 2.92%, respectively. Besides, the article also compares optimal results between the three random algorithms mentioned above: The MDE algorithm has superior quality and efficiency compared to the JAYA and GA algorithms because the MDE algorithm can escape the local extremum and has a high convergence speed earlier than GA and JAYA. The optimal results of the MDE algorithm continue to be compared with the experimental results measured by Khan et al. [7] with an error of less than 10%.

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A COMPARATIVE STUDY OF METAHEURISTIC OPTIMIZATION APPROACHES TO OPTIMIZE LASER WELDING PROCESS PARAMETER WITH PRE-SET WELD SIZE MAGNITUDE FOR AISI 416 AND AISI 440 FSE STAINLESS STEELS

S u m m a r y

Optimization methods are used to accurately predict laser welding process parameters, helping to save material, effort, and time in determining the desired output variables. Based on a mathematical model, parameter selection is considered a binding optimization problem. The work involved is closely related to evolutionary optimization algorithms. This article proposes highly effective meta-heuristic methods: the GA (Genetic Algorithm), the JAYA optimization algorithm, and the MDE (Modified Differential Evolution) algorithm, which optimize the parameters of the laser welding to achieve the desired size for the weld. The performance of these three methods is evaluated on laser welds for AISI 416 and AISI 440 FSe stainless steels. With the same initial conditions, the MDE algorithm outperforms the other algorithms, the GA and JAYA algorithms, regarding the best fitness value after ten runs. Thus, the MDE algorithm is used to optimize three parameters: Laser Power (*LP*), Welding Speed (*WS*), and Fiber Diameter (*FD*) to achieve two desired welding dimensions: the Width of the Weld Zone (*WWZ*) and the Penetration Depth of the Weld (*PDW*) for laser welds.

Keywords: AISI 416 and AISI 440 FSe stainless steels, parameters of laser welding, Modified Differential Evolution (MDE) algorithm, JAYA optimization algorithm, Genetic Algorithm (GA).

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