Gravitational Search Algorithm for Solving Combined Economic and Emission Dispatch

Jordan Radosavljević
Faculty of Technical Sciences, University of Priština in Kosovska Mitrovica
Kosovska Mitrovica, Serbia
jordan.radosavljevic@pr.ac.rs

Abstract — **This paper presents a gravitational search algorithm (GSA) for solving the combined economic and emission dispatch (CEED) problem in power systems. Numerical results for the standard IEEE 30-bus six-generator test system have been presented to illustrate the performance and applicability of the proposed approach. The results obtained are compared to those reported in the recent literature. Those results show that the proposed algorithm provides effective and robust high-quality solution of the CEED problem.**

Key words- economic dispatch; emission; gravitational search algorithm;

I. INTRODUCTION

Economic dispatch (ED) problem has a significant importance in the power system's operation, economic scheduling and security. The ED problem solution aims to minimize the cost of generation of electric power though optimal adjustment of the committed generating unit outputs, while at the same time satisfying all unit and system constraints. It is a large-scale non-linear constrained optimization problem. With the increased public awareness of the environmental pollution, the traditional ED, which ignores the pollutant emissions of the fossil fuels used by the thermal plants, no longer satisfies the needs [1]. When the environmental concerns are combined with the ED then the problem becomes CEED problem. This problem considers two objectives such as minimization of the fuel cost and emission from the thermal power plants with both equality and inequality constraints. So, the CEED problem is a multi-objective mathematical problem in which conflicting objectives are optimized simultaneously.

Environmental aspect adds complexity to the solution of the economic dispatch problem due to the nonlinear characteristics of the mathematical models used to represent emissions. In addition, the CEED problem can be complicated even further if non-smooth and non-convex fuel cost functions are used to model generators, such as valve point loading effects. All these considerations make the CEED problem a highly nonlinear and a multimodal optimization problem [2].

Generally, three approaches to handle the CEED problem have been reported in [3]. In the first approach, the emission is treats as a constraint with a permissible limit. However, this formulation has a severe difficulty in getting the trade-off relations between cost and emission. The second approach treats the emission as another objective in addition to the cost objective. In this case, the CEED problem is converted into a single objective optimization problem either by linear combination of both objectives or by considering one objective at a time for optimization. In the third approach, simultaneously conflicting objectives are evaluated together in the solution of the CEED problem. Both the fuel cost and the emission are minimized together.

In practice, the economic dispatch problem has been solved by using deterministic (classical) and population-based optimization methods. In the past few decades, many classical optimization methods such as gradient method, Newton's method, linear programming, non-linear programming, dynamic programming, goal programming technique and Lagrangian relaxation algorithm, have been applied to various ED problems. However, most of them have difficulties to solve ED problems due to non-linearity and non-convexity fuel cost and emission characteristics. The conventional optimization methods are highly sensitive to the starting point and frequently converge to local optimum solution. Moreover, these methods are not able to find a solution with a significant computational time for medium or large-scale CEED problem [2].

Recently, many population-based methods have been used to solve complex constrained optimization problems. Generally, achieving optimal or near optimal solution for a specific problem will require multiple trials as well as appropriate tuning of associated parameters [4]. A wide variety of population-based techniques such as artificial bee colony algorithm (ABC) [1], spiral optimization algorithm (SOA) [2], genetic algorithm (GA), non-dominated sorting genetic algorithm (NSGA), niched Pareto genetic algorithm (NPGA) [5], non-dominated sorting genetic algorithm (NSGA II) [6,7], differential evolution (DE) [8,9], multi objective differential evolution (MODE) [10], particle swarm optimization (PSO) [11], multi-objective particle swarm optimization (MOPSO) [3], modified bacterial foraging algorithm (MBFA) [12], etc., have been applied in solving the non-linear CEED problems with different objective functions.

This paper proposes a GSA algorithm to solve the CEED problem. The performance of the proposed algorithm is tested on the standard IEEE 30-bus six-generator test system. Numerical results obtained by the proposed approach were compared with other optimization results reported in the literature recently.

II. PROBLEM FORMULATION

The solution of the combined economic and emission dispatch problem is achieved by minimizing the objective function (OF) combined with the weighted sum method under the system constraints [1].

$$\text{OF} = \text{Min}\left\{ w \sum_{n \in N_G} F_n\left(P_{G,n}\right) + (1-w)\gamma \sum_{n \in N_G} E_n\left(P_{G,n}\right) \right\} \quad (1)$$

In Eq. (1), the fuel cost rate ($/h) is shown with $F_n\left(P_{G,n}\right)$ and emission rate (ton/h) with $E_n\left(P_{G,n}\right)$. Scaling factor, weight factor and the set of all the thermal generation units are denoted as γ, w $\left(0 \le w \le 1\right)$ and N_G respectively. $w = 1$ corresponds to the minimization of total fuel cost only, likewise, $w = 0$ corresponds to the minimization of total emission only.

A. Fuel cost function

Fuel cost function of each generator in the system may be represented as a quadratic function of real power generation:

$$F_n\left(P_{G,n}\right) = a_n + b_n P_{G,n} + c_n P_{G,n}^2 \quad (\$/\text{h}) \quad (2)$$

where a_n, b_n and c_n are the cost coefficients.

B. Emission function

Fossil-fueled thermal units cause atmospheric waste emission composed of gases and particles such as carbon dioxide (CO_2), sulfur dioxide (SO_2), nitrogen oxide (NO_x). Different mathematical models were proposed to represent the emission function of thermal generating units [16]. In this paper, the emission function of each thermal unit is defined as the sum of a quadratic function and an exponential function [1]:

$$E_n\left(P_{G,n}\right) = \alpha_n + \beta_n P_{G,n} + \eta_n P_{G,n}^2 + \xi_n \exp\left(\lambda_n P_{G,n}\right) \quad (\text{ton/h}) \quad (3)$$

where α_n, β_n, η_n, ξ_n and λ_n are coefficients of the n*th* generator emission characteristics. In the Eqs. (2)-(3), the $P_{G,n}$ is in MW.

C. Constraints

During the minimization process, some equality and inequality constraints must be satisfied. In this process, an equality constraint is called a power balance and an inequality constraint is called a generation capacity constraint.

C1. Power balance constraint

The total power generation must cover the total load demand P_{load} and the real power loss in transmission lines P_{loss}. Accordingly, the power balance constraint can be represented as follows:

$$\sum_{n \in N_G} P_{G,n} - P_{load} - P_{loss} = 0 \quad (4)$$

The transmission losses of the system are represented by loss coefficients (B_{nj}), normally referred to as B-loss matrices. The B-loss matrices approximate the system losses as a quadratic function of the generator real powers:

$$P_{loss} = \sum_{n \in N_G} \sum_{j \in N_G} P_{G,n} B_{nj} P_{G,j} + \sum_{n \in N_G} B_{0n} P_{G,n} + B_{00} \quad (5)$$

where B_{nj}, B_{0n} and B_{00} are the coefficients of the B-loss matrices.

C2. Generation capacity constraint

For stable operation, real power output of each generator is restricted by minimum $P_{G,n}^{\min}$ and maximum $P_{G,n}^{\max}$ power limits as follows:

$$P_{G,n}^{\min} \le P_{G,n} \le P_{G,n}^{\max} \qquad \left(n \in N_G\right) \quad (6)$$

C3. Slack generator calculation

To enforce active power balance constraint given in Eq. (4), a dependent generator (slack generator) should be selected. As the slack generator, the generator which indexed with N_G is adopted. The value of generation power, P_{G,N_G}^{old}, is calculated by using Eq. (7) where the initial value of power loss is set to zero $\left(P_{loss}^{old} = P_{loss}^{first} = 0\right)$ [1].

$$P_{G,N_G}^{old} = P_{load} - \sum_{n=1}^{N_G - 1} P_{G,n} \quad (7)$$

After obtaining P_{G,N_G}^{old}, new power loss, P_{loss}^{new}, is determined from Eq. (5). According to this, P_{G,N_G}^{new} is calculated using the following equation:

$$P_{G,N_G}^{new} = P_{load} + P_{loss}^{new} - \sum_{n=1}^{N_G - 1} P_{G,n} \quad (8)$$

The result of this equation is controlled in Eq. (9) and if the error value (ε) is below error tolerance value, TOL_ε (e.g. TOL_ε=10^{-6}), the equation satisfies the power balance constraint.

$$\varepsilon = \left| P_{loss}^{new} - P_{loss}^{old} \right|, \qquad \varepsilon \le TOL_\varepsilon \quad (9)$$

The obtained P_{G,N_G} is checked whether it satisfies the constraint defined in Eq. (6) or not. Consequently, the variable $P_{G,N_G}^{\lim}$ is defined as:

$$P_{G,N_G}^{\lim} = \begin{cases} P_{G,N_G}^{\max} & \text{if} \quad P_{G,N_G} > P_{G,N_G}^{\max} \\ P_{G,N_G}^{\min} & \text{if} \quad P_{G,N_G} < P_{G,N_G}^{\min} \\ P_{G,N_G} & \text{if} \quad P_{G,N_G}^{\min} \le P_{G,N_G} \le P_{G,N_G}^{\max} \end{cases} \tag{10}$$

Inequality constraint of the dependent variable, that is P_{G,N_G}, is added to the objective function as a quadratic penalty terms. The new expanded objective function to be minimized becomes:

$$\mathrm{OF}_p = \mathrm{OF} + \lambda_p \left(P_{G,N_G} - P_{G,N_G}^{\lim}\right)^2 \tag{11}$$

where λ_p is the penalty factor.

III. Overview of GSA

The gravitational search algorithm (GSA) is a newly stochastic search algorithm developed by Rashedi et al. [13]. In this algorithm, agents are considered as objects and their performances are measured by their masses. The GSA could be considered as an isolated system of masses. It is like a small artificial world of masses obeying the Newtonian laws of gravitation and motion. By lapse of time, the masses will be attracted by the heaviest mass which it represents an optimum solution in the search space. GSA has been verified as having high-quality performance in solving different optimization problems [17-20].

In a system with N agents (masses), the position of the ith agent is defined by:

$$X_i = \left[x_i^1, \ldots, x_i^k, \ldots, x_i^n\right] \quad \text{for} \quad i = 1,2,\ldots,N \tag{12}$$

where n is the search spase dimension of the problem, i.e. the number of control variables, and x_i^k defines the position of the ith agent in the kth dimension.

After evaluating the current population fitness, the mass of each agent is calculated as follows:

$$M_i(t) = m_i(t) \Big/ \sum_{j=1}^{N} m_j(t) \tag{13}$$

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \tag{14}$$

where $fit_i(t)$ represent the fitness value of the agent i at time (iteration) t. $best(t)$ and $worst(t)$ is the best and worst fitness of all agents, respectively and defined as follows (for a minimization problem):

$$best(t) = \min_{j \in \{1,\ldots,N\}} fit_j(t) \tag{15}$$

$$worst(t) = \max_{j \in \{1,\ldots,N\}} fit_j(t) \tag{16}$$

According to Newton gravitation theory, the total force that acts on the ith agent in the kth dimension at t time is specified as follows:

$$F_i^k(t) = \sum_{j \in Kbest, j \ne i} r_j G(t) \frac{M_j(t) M_i(t)}{R_{i,j}(t) + \varepsilon} \left(x_j^k(t) - x_i^k(t)\right) \tag{17}$$

where r_j is a random number in the interval [0, 1], $G(t)$ is gravitational constant at time t, $M_i(t)$ and $M_j(t)$ are masses of agents i and j, ε is a small constant and $R_{ij}(t)$ is the Euclidian distance between the two agents i and j given by the following equation:

$$R_{ij}(t) = \left\| X_i(t), X_j(t) \right\|_2 \tag{18}$$

Kbest is the set of first K agents with the best fitness value and biggest mass, which is a function of time, initialized to K_0 at the beginning and decreased with time. In such a way, at the beginning, all agents apply the force, and as time passes, *Kbest* is decreased linearly and at the end there will be just one agent applying force to the others. By the law of motion, the acceleration of the ith agent, at t time in the kth dimension is given by following equation:

$$a_i^k(t) = F_i^k(t) / M_i(t) \tag{19}$$

The searching strategy on this notion can be defined to find the next velocity and next position of an agent. Next velocity of an agent is defined as a function of its current velocity added to its current acceleration. Hence, the next position and next velocity of an agent can be computed as follows:

$$v_i^k(t+1) = r_i v_i^k(t) + a_i^k(t) \tag{20}$$

$$x_i^k(t+1) = x_i^k(t) + v_i^k(t+1) \tag{21}$$

where r_i is a uniform random variable in the interval [0, 1]. This random number is utilized to give a randomized characteristic to the search. x_i^k represents the position of agent i in dimension k, v_i^k is the velocity and a_i^k is the acceleration.

It must be pointed out that the gravitational constant $G(t)$ is important in determining the performance of GSA. It is initialized at the beginning and will be reduced with time to control the search accuracy. In other words, the gravitational constant is a function of the initial value G_0 and time t:

$$G(t) = G_0 \exp(-\alpha\, t/T) \tag{22}$$

where α is a user specified constant, t the current iteration and T is the maximum iteration number. The parameters of maximum iteration T, population size N, initial gravitational constant G_0 and constant α control the performance of GSA.

A. GSA implementation

Proposed GSA approach has been applied to solve the CEED problem. The control variables of the CEED problem constitute the individual position of several agents that represent a complete solution set. In a system with N agents, the position of the ith agent is defined by:

$$X_i = \left[x_i^1, ..., x_i^k, ..., x_i^n\right] \quad \text{for} \quad i = 1,2,...,N \quad \text{and} \quad n = N_G - 1 \qquad (23)$$

The elements of agent X_i are real power outputs of all generation units, except the slack generator. Different steps to solve the CEED problem using GSA are listed as follow:

Step 1 Search space identification. Initialize GSA parameters like: N, T, G_0, and α.

Step 2 Initialization: generate random population of N agents. The initial positions of each agent are randomly selected between minimum and maximum values of the control variables (i.e. real power outputs of the generation units).

Step 3 Calculate the real power output of slack generator for each agent in current population.

Step 4 Calculate the fitness value for each agent using (1).

Step 5 Update the $G(t)$ (22), *best*(t) (15), *worst*(t) (16) and $M_i(t)$ (13) for i=1,2,...,N.

Step 6 Calculation of the total force in different directions using (17).

Step 7 Calculation of acceleration of each agent using (19).

Step 8 Calculation of velocity of all agents using (20).

Step 9 Update each agent's position using (21).

Step 10 Repeat Steps 3-9 until the stop criteria is reached. That is a predefined number of iteration, T.

Step 11 Return best solution. Stop.

IV. SIMULATION RESULTS

The proposed GSA algorithm is tested on the standard IEEE 30-bus six-generator test system for P_{load} = 283.4 MW. This test system is widely used as benchmark in the power system field for solving the CEED problem [2]. The fuel cost coefficients and the NO_x emission coefficients, including the limits of generation for the generators of the test system are listed in Table I. In this study, the scaling factor in (1) is taken as $\gamma_{NO_x} = 1000$ (\$/ton) and the error tolerance value in (9) is $TOL_\varepsilon = 10^{-6}$ MW. The B-loss matrix values are shown as follows:

$$B = \begin{bmatrix} 0.1382 & -0.0299 & 0.0044 & -0.0022 & -0.0010 & -0.0008 \\ -0.0299 & 0.0487 & -0.0025 & 0.0004 & 0.0016 & 0.0041 \\ 0.0044 & -0.0025 & 0.0182 & -0.0070 & -0.0066 & -0.0066 \\ -0.0022 & 0.0004 & -0.0070 & 0.0137 & 0.0050 & 0.0033 \\ -0.0010 & 0.0016 & -0.0066 & 0.0050 & 0.0109 & 0.0005 \\ -0.0008 & 0.0041 & -0.0066 & 0.0033 & 0.0005 & 0.0244 \end{bmatrix}$$

$$B_0 = \left[-0.0107 \quad 0.0060 \quad -0.0017 \quad 0.0009 \quad 0.0002 \quad 0.0030\right]$$

$$B_{00} = \left[0.00098573\right]$$

The algorithm have been implemented in MATLAB 2011b computing environment and run on a 2.20 GHz, PC with 3.0 GB RAM. Twenty consecutive test runs have been performed for each case examined. The results shown are the best values obtained over these 20 runs. The GSA parameters used for the simulation are adopted as follow: α is set to 10 and G_0 is set to 1. The population size N and maximum iteration number T are set to 50 and 200, respectively, for all case studies.

For the purpose of comparison with the reported results, the test system is considered for two cases as follows:

Case A: With considering P_{loss} ; **Case B**: With neglecting P_{loss}. Table II shows the optimum solution values of GSA for the weight factor: w = 1 (fuel cost minimization), w = 0 (NO_x emission minimization), and w = 0.5 (combined fuel cost and NO_x emission minimization – CEED minimization).

Under the same system data, control variable limits and constraints, the results for Cases A and B obtained using the GSA approach are compared to some other algorithms reported in the literature as shown in Tables III and IV, respectively. From these tables, it can be seen that the proposed approach outperforms many techniques used to solve CEED problems because the results obtained using GSA are either better or comparable to those obtained using other techniques. This highlights its ability to find better quality solution.

Figs. 1-3 illustrates the convergence characteristics of GSA for the fuel cost, NO_x emission and combined fuel cost and NO_x emission minimization, respectively. As can been seen, the proposed GSA algorithm is converge to its global optimal solution in very small number of iteration for all cases.

TABLE I. GENERATION LIMITS, FUEL COST AND EMISSION COEFFICIENTS OF THE TEST SYSTEM.

Unit	$P_{G,n}^{\min}$	$P_{G,n}^{\max}$	a_n	b_n	c_n	α_n	β_n	η_n	ξ_n	λ_n
1	5	150	10	200	100	4.091e-2	-5.554e-2	6.940e-2	2.0e-4	2.857
2	5	150	10	150	120	2.543e-2	-6.047e-2	5.638e-2	5.0e-4	3.333
3	5	150	20	180	40	4.258e-2	-5.094e-2	4.586e-2	1.0e-6	8.0
4	5	150	10	100	60	5.326e-2	-3.550e-2	3.380e-2	2.0e-3	2.0
5	5	150	20	180	40	4.258e-2	-5.094e-2	4.586e-2	1.0e-6	8.0
6	5	150	10	150	100	6.131e-2	-5.555e-2	5.151e-2	1.0e-5	6.667

TABLE II. THE BEST SOLUTION FOR FUEL COST AND NO_x EMISSION.

	w	Generation (MW)						Fuel cost ($/h)	NO_x emission (ton/h)	P_{loss} (MW)
		$P_{G,1}$	$P_{G,2}$	$P_{G,3}$	$P_{G,4}$	$P_{G,5}$	$P_{G,6}$			
Case A	1	12.09691	28.63121	58.35574	99.28540	52.39700	35.18993	605.99837	0.220729	2.55619
	0	41.09251	46.36678	54.44194	39.03737	54.44590	51.54849	646.20699	0.194179	3.53300
	0.5	22.55425	35.45564	57.00526	74.53983	54.82119	41.55654	612.25279	0.203570	2.53270
Case B	1	10.97194	29.97662	52.42982	101.61988	52.42982	35.97193	600.11141	0.222145	-
	0	40.60738	45.90691	53.79387	38.29530	53.79384	51.00270	638.27344	0.194203	-
	0.5	23.22984	36.03388	53.88180	74.57677	53.88179	41.79592	606.79829	0.203289	-

TABLE III. COMPARISON OF BEST SOLUTION FOR CASE A.

Methods	Fuel cost minimization (w=1)		NO_x emission minimization (w=0)		CEED minimization (w=0.5)	
	Fuel cost ($/h)	NO_x emission (ton/h)	Fuel cost ($/h)	NO_x emission (ton/h)	Fuel cost ($/h)	NO_x emission (ton/h)
ABC [1]	605.4258	0.2210	646.0455	0.1942	612.195	0.2035
MOPSO [3]	607.7900	0.2193	644.7400	0.1942	615.000	0.2021
GA [5]	607.7800	0.2199	645.2200	0.1942	-	-
NSGA [5]	607.9800	0.2191	638.9800	0.1947	617.8000	0.2002
NPGA [5]	608.0600	0.2207	644.2300	0.1943	617.7900	0.2004
NSGA II [6]	607.8010	0.2189	644.1330	0.1942	-	-
NSGA II [7]	613.6759	0.2223	648.7090	0.1942	-	-
DE [8]	608.0658	0.2193	645.0850	0.1942	-	-
DE [9]	606.0000	0.2217	645.5900	0.1942	-	-
MODE [10]	606.4160	0.2221	643.5190	0.1942	614.170	0.2043
PSO [11]	607.8400	0.2192	642.9000	0.1942	-	-
MBFA [12]	607.6700	0.2198	644.4300	0.1942	616.496	0.2002
MODE/PSO [14]	606.0073	0.2209	646.0243	0.1942	-	-
MA θ-PSO [15]	605.9984	0.2206	649.2070	0.1942	-	-
GSA	**605.99837**	**0.220729**	**646.20699**	**0.194179**	**612.25279**	**0.203570**

TABLE IV. COMPARISON OF BEST SOLUTION FOR CASE B.

Methods	Fuel cost minimization (w=1)		NO_x emission minimization (w=0)		CEED minimization (w=0.5)	
	Fuel cost ($/h)	NO_x emission (ton/h)	Fuel cost ($/h)	NO_x emission (ton/h)	Fuel cost ($/h)	NO_x emission (ton/h)
SOA [2]	600.986	0.20889	640.749	0.18729	624.604	0.18708
MOPSO [3]	600.12	0.2216	637.42	0.1942	608.65	0.2017
GA [5]	600.11	0.2221	638.26	0.1942	-	-
NSGA [5]	600.34	0.2241	633.83	0.1946	606.03	0.2041
NPGA [5]	600.31	0.2238	636.04	0.1943	608.90	0.2015
NSGA II [6]	600.155	0.22188	638.269	0.19420	-	-
NSGA II [7]	600.7422	0.2204	636.7316	0.1942	-	-
DE [8]	600.1114	0.2221	638.2907	0.1942	-	-
DE [9]	600.11	0.2231	638.860	0.1952	-	-
PSO [11]	600.13	0.2199	636.62	0.1943	-	-
MBFA [12]	600.17	0.2200	636.73	0.1942	610.906	0.2000
MODE/PSO [14]	600.115	0.22201	638.270	0.194203	-	-
MA θ-PSO [15]	600.1114	0.2221	638.2734	0.1942	-	-
GSA	**600.11141**	**0.222145**	**638.27344**	**0.194203**	**606.79829**	**0.203289**

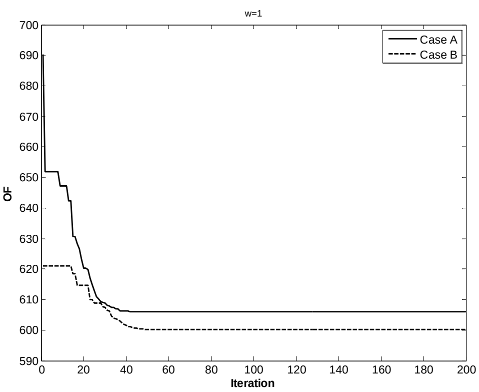

Fig. 1. Convergence characteristics of GSA in case fuel cost min. (w=1).

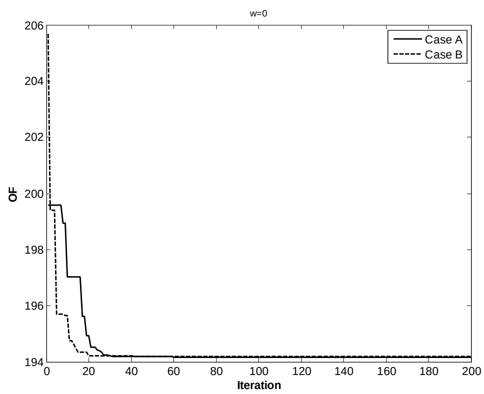

Fig. 2. Convergence characteristics of GSA in case NO_x emission min. (w=0).

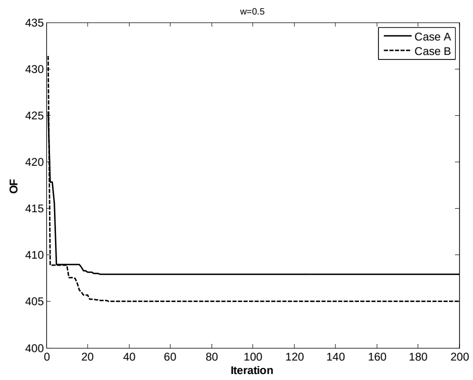

Fig. 3. Convergence characteristics of GSA in in case combine fuel cost and NO_x emission minimization - CEED (w=0.5).

V. Conclusion

In this paper, a GSA optimization algorithm has been proposed and successfully applied to solve the CEED problem. Simulation results show that the GSA approach provides effective and robust high-quality solution. Moreover, the results obtained using GSA are either better or comparable to those obtained using other techniques reported in the literature.

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