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Multi-Objective Ant Lion Optimizer for Solving Environmental/Economic Dispatch

Abstract*. In this paper, a new meta-heuristic algorithm, called multi-objective ant lion optimizer (MOALO) is presented to solve environmental economic dispatch (EED) problem considering transmission losses. MOALO is inspired by the hunting mechanism of ant lions in nature. It has fast convergence speed due to the use of roulette wheel selection technique. The effectiveness of the proposed algorithm has been tested on the standard IEEE 30-bus test system and the results were compared with other methods reported in recent literature. The simulation results show that the proposed algorithm outperforms previous optimization methods.*

Streszczenie. *Przedstawiono nowy meta-heurystyczny algorytm MOALO do rozwiązywania problemu ekonomicznego rozsyłu energii z uwzględnieniem warunków środowiskowych. Algorytm jest inspirowany mechanizmem polowania. Daje on szybkie rozwiązanie z wykorzystaniem zasady koła w ruletce. Algorytm sprawdzono wykorzystując system testowy IEEE-30-bus. (Wieloobiektowy algorytm mrowkolwowaty do rozwiązywania problemu ekonomicznego rozsyłu energii z uwzględnieniem środowiska)*

Keywords: multi-objective ant lion optimizer, economic dispatch, emission dispatch, combined economic emission dispatch.
Słowa kluczowe: ekonomiczny rozsył energii, owady mrówkolwaowate, emisja zanieczyszczeń.

Introduction

Optimization of the modern power system plays a major role in thermal power plants energy production. The challenges of the engineers are to optimize the real power of the generating units and to minimize the fuel cost of the power plant. Economic dispatch (ED) is one of the most fundamental issues in operation and control of power systems to allocate generations among the committed units. The main goal of the ED problem is to determine the amount of real power contributed by online thermal generators satisfying load demand at any time subject to unit and system constraints so as the total generation cost is minimized. Therefore, it is very important to solve the problem as quickly and precisely as possible [1, 2]. Therefore, recently most of the researchers made studies for finding the most suitable power values produced by the generators depending on fuel costs. In these studies, they produced successful results by using various optimization algorithms [3-5]. Despite the fact that the traditional ED can optimize generator fuel costs, it still cannot produce a solution for environmental pollution due to the excessive emission of fossil fuels.

Currently, a large part of energy production is done with thermal sources. Thermal power plant is one of the most important sources of carbon dioxide (CO_2), sulfur dioxide (SO_2) and nitrogen oxides (NO_x) which create atmospheric pollution [6]. Emission control has received increasing attention owing to increased concern over environmental pollution caused by fossil based generating units and the enforcement of environmental regulations in recent years [7]. Numerous studies have emphasized the importance of controlling pollution in electrical power systems [8].

Combined economic and emission dispatch (CEED) has been proposed in the field of power generation dispatch, which simultaneously minimizes both fuel cost and pollutant emissions. When the emission is minimized the fuel cost may be unacceptably high or when the fuel cost is minimized the emission may be high. A number of methods have been presented to solve CEED problems such as multi-objective differential evolution algorithm [9], genetic algorithm [10-12], simulated annealing [13], biogeography-based optimization [14], modified bacterial foraging algorithm [15], particle swarm optimization [16-18], artificial bee colony algorithm [19-21], gravitational search algorithm [22], moth swarm algorithm [23], and adaptive wind driven optimization [24].

In this paper, MOALO algorithm has been used to solve the CEED problem considering transmission loss. Combined economic emission dispatch (CEED) solution which was performed using MOALO algorithm was tested on the standard IEEE 30-bus 6-generator test system. The results were compared to those reported in the literature.

Problem Formulations

The CEED problem targets to find the optimal combination of load dispatch of generating units and minimizes both fuel cost and emission while satisfying the total power demand. Therefore, CEED consists of two objective functions, which are economic and emission dispatches. Then these two functions are combined to solve the problem. The CEED problem can be formulated as follows [11]:

$$F_T = Min\ f(FC, EC) \tag{1}$$

where F_T is the total generation cost of the system, FC is the total fuel cost of generators and EC is the total emission of generators.

Minimization of Fuel Cost

The ED problem can be formulated in a quadratic form as follows [11]:

$$FC = \sum_{i=1}^{N} \left(a_i P_i^2 + b_i P_i + c_i \right) \tag{2}$$

where P_i is the power generation of the ith unit; a_i, b_i, and c_i are fuel cost coefficients of the ith generating unit and N is the number of generating units.

Minimization of Emission

The classical ED problem can be obtained by the amount of active power to be generated by the generating units at minimum fuel cost, but it is not considered as the amount of emissions released from the burning of fossil fuels. Total amount of emissions such as SO_2 or NO_X depends on the amount of power generated by until and it can be defined as the sum of quadratic and exponential functions and can be stated as [11]:

$$EC = \sum_{i=1}^{N} \left(\alpha_i P_i^2 + \beta_i P_i + \gamma_i + \eta_i \exp(\delta_i P_i) \right) \tag{3}$$

where α_i, β_i, γ_i, η_i and δ_i are emission coefficients of the ith generating unit.

Combined Environmental Economic Dispatch (CEED)

CEED is a multi-objective problem, which is a combination of both economic and environmental dispatches that individually make up different single problems. At this point, this multi-objective problem needs to be converted into single-objective form in order to fulfill optimization. The conversion process can be done by using the price penalty factor [11]. However, the single-objective CEED can be formulated as shown in equation (4):

(4) $$F_T = (w * FC + (1-w) * h * EC)$$

under the following condition,

(5) $$0 \le w \le 1$$

where *w* is weighting factor: *w*=1 (fuel cost minimization), *w*=0 (NOx emission minimization), and *w*=0.5 (CEED minimization) and *h* is the price penalty factor.

Problem Constraints

There are two constraints in the EED problem which are power balance constraint and maximum and minimum limits of power generation output constraint.

Active power balance equation

For power balance, an equality constraint should be satisfied. The total generated power should be the same as total load demand plus the total line loss.

(6) $$P_D = \sum_{i=1}^{N} P_i - P_{Loss}$$

where P_D is the total load demand and P_{Loss} is total transmission losses. The transmission losses P_{Loss} can be calculated by using *B* matrix technique and is defined by (7) as,

(7) $$P_{Loss} = \sum_{i=1}^{N}\sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{0i} P_i + B_{00}$$

where B_{ij} is coefficient of transmission losses and the B_{0i} and B_{00} is matrix for loss in transmission which are constant under certain assumed conditions.

Minimum and maximum power limits

Generation output of each generator should lie between minimum and maximum limits. The corresponding inequality constraint for each generator is

(8) $$P_i^{\min} \le P_i \le P_i^{\max} \text{ for } i = 1,2,\cdots,N$$

where $P_i^{\min}$ and $P_i^{\max}$ are the minimum and maximum outputs of the *i*th generator, respectively.

Multi-Objective Ant Lion Optimization (MOALO)

In order to propose the multi-objective models of Ant Lion Optimizer (ALO) algorithm [25], the fundamentals of this algorithm should be discussed first. An algorithm should follow the same search behaviour to be considered as an extended version of the same algorithm. The ALO algorithm mimics the hunting mechanism of antlions and the interaction of their favourite prey, ants, with them.

Similarly to other population-based algorithm, ALO approximates the optimal solutions for optimization problems with employing a set of random solutions. This set is improved based on the principles inspired from the interaction between antlions and ants. There are two populations in the ALO algorithm; set of ants and set of antlions. The general step of ALO to change these two sets and eventually estimate the global optimum for a given optimization problem are as follows [26]:

a) The ant set is initialized with random values and are the main search agents in the ALO.
b) The fitness value of each ant is evaluated using an objective function in each iteration.
c) Ants move over the search space using random walks around the antlions.
d) The population of antlions is never evaluated. In fact, antlions assumed to be on the location of ants in the first iteration and relocate to the new positions of ants in the rest of iterations if the ants become better.
e) There is one antlion assigned to each ant and updates its position if the ant becomes fitter.
f) There is also an elite antlion which impacts the movement of ants regardless of their distance.
g) If any antlion becomes better then the elite, it will be replaced with the elite.
h) Step b to g are repeatedly executed until the satisfaction of an end criterion.
i) The position and fitness value of the elite antlion are returned as the best estimation for the global optimum.

The antlions maintain the best position obtained by the ants and guide the search of ants towards the promising regions of the search space. In order to solve optimization problems, the ALO algorithm mimics random walk of ants, entrapment in an antlion pit, cunstructing a pit, sliding ant towards antlions, catching prey and re-constructing the pit, and elitism.

To model such interactions, ants are required to move over the search space and antlions are allowed to hunt them and become fitter using traps. Since ants move stochastically in nature when searching for food, a random walk is chosen for modeling ants' movement as follows:

(9) $$X(t) = [0, cums(2r(t_1)-1, cums(2r(t_2)-1, \ldots, cums(2r(t_n)-1]$$

where *cums* calculates the cumulative sum and *r(t)* is defined as follows:

(10) $$r(t) = \left\{ \begin{Bmatrix} 1, & if \;\; rand > 0.5 \\ 0, & if \;\; rand \le 0.5 \end{Bmatrix} \right.$$

is a stochastic function where *t* shows the step of random walk and *rand* is a random number generated with uniform distribution in the interval of [0,1].

In order to keep the random walk in the boundaries of the search space and prevent the ants from avershooting, the random walks should be nomalized using the following equation:

(11) $$X_i^t = \frac{(X_i^t - a_i)\times(d_i - c_i^t)}{(d_i^t - a_i)} + c_i$$

where a_i is minimum random walk of *i*-th variable, d_i indicates the maximum random walk of *i*-th variable, c_i^t is minimum of *i*-th variable at *t*-th iteration, and d_i^t is the maximum of *i*-th variable at *t*-th iteration.

ALO simulates the entrapment of ants in antlions pit by changing the random walks around antlions. The following equations have been proposed in this regard:

(12) $$c_i^t = Antlion_j^t + c^t$$

(13) $$d_i^t = Antlion_j^t + d^t$$

where c^t is the minimum of all variables at *t*-th iteration, d^t indicates the vector including the maximum of all variables at *t*-th iteration, c_i^t is the minimum of all variables for *i*-th ant, d_i^t is the maximum of all variables for *i*-th ant, and $Antlion_j^t$ shows the position of selected *j*-th antlion at *t*-th iteration.

In nature, bigger antlions construct bigger pit to increase their chance of survival. In order to simulate this, ALO utilizes a roulette wheel operator that selects antlions based on their fitness value. The roulete wheel assists fitter antlion to attact more ants.

For mimicking the sliding ants towards antlions, the boundaries of random walks should be decreased adaptively as follows:

$$c^t = \frac{c^t}{I} \quad (14)$$

$$d^t = \frac{d^t}{I} \quad (15)$$

where I is a ratio, c^t is the minimum vector of all variables at *t*-th iteration, and d^t indicates the vector including the maximum of all variables at *t*-th iteration.

The second to last step in ALO is catching the ant and re-constructing the pit. The following equation simulates this:

$$Antlion_j^t = Ant_i^t,\ if \quad f(Ant_i^t) > f(Antlion_j^t) \quad (16)$$

where *t* shows the current iteration, $Antlion_j^t$ shows the position of selected *j*-th antlion at *t*-th iteration, and Ant_i^t indicates the position of *i*-th ant for *t*-th iteration.

The last operator in ALO is elitism, in which the fittest antlion formed during optimization is stored. The fittest ant lion should be able to affect the movements of all ants during iterations. It is assumed that every random walks of ants around a chosen antlion by the roulette wheel and the elite instantaneously as follows:

$$Ant_i^t = \frac{R_A^t + R_E^t}{2} \quad (17)$$

where R_A^t is random walk around antlion selected by roulette wheel at *t*-th iteration, R_E^t is the random walk around the elite at *t*-th iteration, and Ant_i^t indicates the position of *i*-th ant for *t*-th iteration.

As mentioned in the literature review, there are different approaches for finding and storing Pareto optimal solutions using heuristic algorithms. In this work, we employ an archive to store Pareto optimal solutions. Obviously, the convergence of the MOALO algorithm inherits from the ALO algorithm. If we pick one solution from the archive, the ALO algorithm will be able to improve its quality. However, finding the Pareto optimal solutions set with a high diversity is challenging.

To overcome this challenge, we have inspired from the MOPSO algorithm and utilized the leader selection and archve maintenance. For measuring the distribution of the solutions in the archive, we use niching. In this approach, the vicinity of each solution is investigated considering a pre-defined radius. The number of solutions in the vicinity is then counted and considered as the measure of distribution. To improve the distribution of the solutions in the archive, we considered two mechanism similarly to those in MOPSO. Firstly, the antlions areselected from the solutions with the least populated neighbourhood. The following equation is used in this regard that defines the probability of choosing a solution in the archive:

$$P_i = \frac{c}{N_i} \quad (18)$$

where *c* is a constant and should be greater than 1 and N_i is the number of solutions in the vicinity of the *i*-th solution.

Secondly, when the archive is full, the solutions with most populated neighbourhood are removed from the archive to accommodate new solutions. The following equation is used in this regard that defines the probability of removing a solution from the archive:

$$P_i = \frac{N_i}{c} \quad (19)$$

where *c* is a constant and should be greater than 1 and N_i is the number of solutions in the vicinity of the *i*-th solution.

In order to require ALO to solve multi-objective problem, (16) should be modified due to the nature of multiobjective problems.

$$Antlion_j^t = Ant_i^t,\ if \quad f(Ant_i^t) < f(Antlion_j^t) \quad (20)$$

where *t* shows the current iteration, $Antlion_j^t$ shows the position of selected *j*-th antlion at *t*-th iteration, and Ant_i^t indicates the position of *i*-th ant for *t*-th iteration.

Another modification is for the selection of random antlions and elite in (17). We utilize a roulette wheel and (17) to select a non-dominated solution from the archive. The rest of the operator in MOALO are identical to those in ALO. After all, the pseudocodes of the MOALO algorithm are shown in Table 1.

Table 1. Pseudocodes of MOALO

```
Multi-Objective Ant Lion Optimization (MOALO)
while the end condition is not met
  for every ant
      Select a random antlion from the archive
      Select the elite using Roulette wheel from the archive
      Update c and d using equations (14) & (15)
      Create a random walk and normalize it using equations (9) &
      (11)
      Update the position of ant using equation (17)
  end for
  Calculate the fitness of all ants
  Update the archive
  if the archive is full
      Delete some solutions using Roulette wheel and (19) from the
archive
      to accommodate new solutions.
  end
end while
Return archive
Update elite if an ant lion become fitter than the elite
end while
Return elite
```

Simulation Results and Discussion

The proposed MOALO algorithm is tested on the standard IEEE 30-bus power system with six-generating units in order to investigate its effectiveness. The single-line diagram of the IEEE 30-bus test system is shown in Figure 1 and the detailed data are given in [21, 22]. The parameters of all thermal units (generation limits, fuel cost and NO_x emission coefficients) are presented in Table 2, followed by *B*-loss coefficients are presented in Table 3. The load demand of the system is 283.4 MW. The values of MOALO algorithm for solving CEED problem in this paper are designated as follow: the number of population size, NP = 30; and the number of iterations, maxIter = 200.

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

Case A: In this case, we take IEEE 30-bus test system with considering transmission losses.

Case B: In this case with neglecting transmission losses.

In the first case, the best solutions for power outputs, fuel cost and NO_x emission obtained by using MOALO for *w*=1, *w*=0, and *w*=0.5 are given in Table 4. The results obtained by MOALO for the test system along with corresponding data from the literature are summarized in Table 5. As can be seen in Table 5, the MOALO provided better values for the minimum fuel cost and NO_x emission in regard to the values obtained by the algorithms proposed in [9, 14, 16, 22, 23, 24]. Figure 2 shows the convergence characteristic of fuel cost optimization with MOALO. Figure 3 shows the Pareto optimal solution when fuel cost and emission optimized simultaneously.

In the second case, the best solutions for power outputs, fuel cost and NO_x emission obtained by using MOALO for w=1, w=0, and w=0.5 are given in Table 6. The results obtained by MOALO for the test system along with corresponding data from the literature are summarized in Table 7. As can be seen in Table 7, the MOALO provided better values for the minimum fuel cost and NO_x emission in regard to the values obtained by the algorithms proposed in [14, 16, 22, 23].

Table 2. Generation limits, fuel cost and NO_x emission coefficients for IEEE 30-bus test system [21]

Unit	P_i^{min}	P_i^{max}	a_i	b_i	c_i	α_i	β_i	γ_i	η_i	δ_i
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 3. Transmission loss coefficients [21]

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

$$B_{0i} = \left[-0.0107 \;\; 0.0060 \;\; -0.0017 \;\; 0.0009 \;\; 0.0002 \;\; 0.0030\right]$$

$$B_{00} = 0.00098573$$

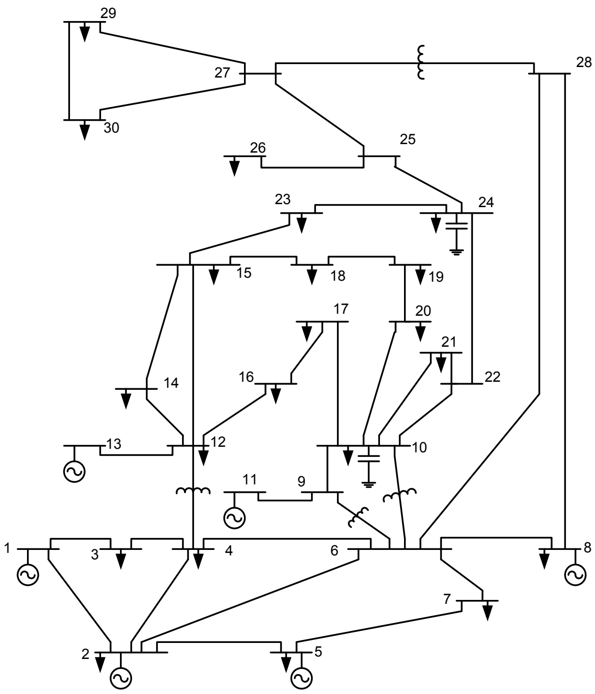

Fig. 1. Single-line diagram of IEEE 30-bus test system [20]

Table 4. The best solutions obtained by using MOALO (Case A)

w	Generation (MW)						Fuel Cost ($/h)	NO_x Emission (ton/h)	P_{Loss} (MW)
	P_1	P_2	P_3	P_4	P_5	P_6			
1	12.0969	28.6312	58.3557	99.2854	52.3970	35.1899	605.99837	0.20453	2.55619
0	37.3419	50.1791	51.2265	46.6136	51.2815	50.1836	639.75214	0.18672	3.42623
0.5	23.2164	37.2784	54.3552	77.2134	52.4097	41.5729	612.02569	0.19264	2.64599

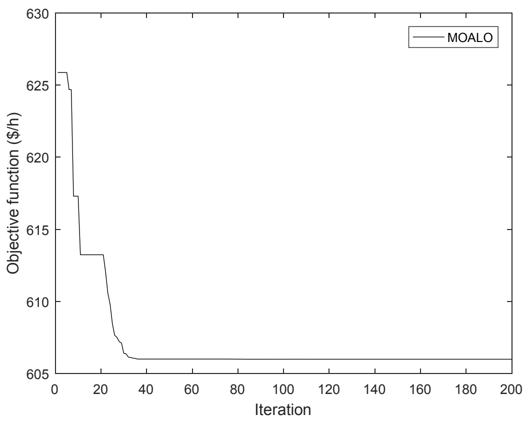

Fig. 2. Fuel cost optimization with MOALO (Case A)

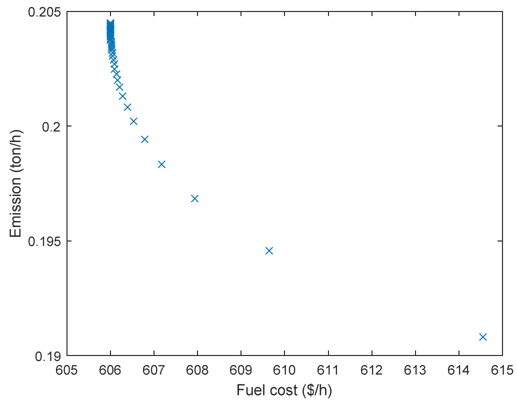

Fig. 3. Fuel cost and emission optimization with MOALO (Case A)

Table 5. Comparison of best solution (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)
MODE [9]	606.41060	0.2221	643.5190	0.1942	614.1700	0.2043
MBFA [14]	607.6700	0.2198	644.4300	0.1942	616.4960	0.2002
MOPSO [16]	607.7900	0.2193	644.7400	0.1942	615.0000	0.2021
GSA [22]	605.9984	0.2207	646.2070	0.1942	612.2530	0.2036
MSA [23]	605.9984	0.2207	646.2049	0.1942	612.2519	0.2038
AWDO [24]	605.9984	0.2207	646.2070	0.1942	612.2528	0.2036
MOALO	605.99837	0.20453	639.75214	0.18672	612.02569	0.19264

Table 6. The best solutions obtained by using MOALO (Case B)

w	Generation (MW)						Fuel Cost ($/h)	NO_x Emission (ton/h)	P_{Loss} (MW)
	P_1	P_2	P_3	P_4	P_5	P_6			
1	10.9719	29.9766	52.4299	101.6199	52.4298	35.9720	600.11141	0.20523	-
0	36.8275	49.6415	50.7287	45.8475	50.7287	49.6261	631.98790	0.18686	-
0.5	23.7145	37.8025	51.4852	77.1837	51.4853	41.7288	606.39137	0.19250	-

Table 7. Comparison of best solution (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)
MBFA [14]	600.17	0.2200	636.73	0.1942	610.906	0.2000
MOPSO [16]	600.12	0.2216	637.42	0.1942	608.65	0.2017
GSA [22]	600.11141	0.222145	638.27344	0.194203	606.79829	0.203289
MSA [23]	600.11141	0.22215	638.27583	0.194203	606.80105	0.20329
FFA [23]	600.11141	0.22214	638.27398	0.194203	606.79835	0.20329
PSOGSA[23]	600.11141	0.22215	638.27452	0.194203	606.79841	0.20329
MOALO	600.11141	0.20523	631.98790	0.18686	606.39137	0.19250

Conclusion

In this paper, a new approach based on multi-objective ant lion optimizer (MOALO) algorithm has been presented and successfully applied to solve the combined economic emission dispatch problem considering transmission losses. The problem has been formulated as multiobjective optimization problem with competing fuel cost and environmental impact objectives. The effectiveness of proposed algorithm is demonstrated on the standard IEEE 30-bus test system with six generating units. The comparison of the results obtained with other methods reported in the literature shows the superiority of the proposed algorithm and its potential for solving the combined economic emission dispatch problems in large-scale power systems. The results obtained from the test systems have indicated that the proposed technique has better performance in terms of minimum fuel costs and NO_x emissions than other optimization methods reported in the literature.

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