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An Efficient Modified HPSO-TVAC-Based Dynamic Economic Dispatch of Generating Units

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CONTENTS

Abstract—This paper proposes a novel particle swarm optimization (PSO) algorithm with population reduction, which is called modified new self-organizing hierarchical PSO with jumping time-varying acceleration coefficients (MNHPSO-JTVAC). The proposed method is used for solving well-known benchmark functions, as well as non-convex and non-smooth dynamic economic dispatch (DED) problems for a 24 h time interval in two different test systems. Operational constraints including the prohibited operating zones (POZs), the transmission losses, the ramp-rate limits and the valve-point effects are considered in solving the DED problem. The obtained numerical results show that the MNHPSO-JTVAC algorithm is very suitable and competitive compared to other algorithms and have the capacity to obtain better optimal solutions in solving the non-convex and non-smooth DED problems compared to the other variants of PSO and the state of the art optimization algorithms proposed in recent literature. The source codes of the HPSO-TVAC algorithms and supplementary data for this paper are publicly available at https://github.com/ebrahimakbary/MNHPSO-JTVAC.

Keywords: dynamic economic dispatch, jumping time-varying acceleration coefficients, population reduction, self-organizing hierarchical PSO
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1. INTRODUCTION

Electric power systems are considered as one of the most important energy infrastructures, where with the ever increasing growth of energy consumption, the complexity of main grids has also increased. In integrated power systems, thermal plants generate the main portions of the required power. Nowadays, one of the critical problems in power system operations is load distribution between energy generation units as such that it leads to the minimum cost for power plants. Supplying the required electrical energy demands with the minimum cost is among the most essential problems in power systems. Considering nonlinear constraints and a non-flat cost function, the problem is very complicated and should be solved by an optimization method with the features of simple implementation and high quality and reliability. Due to the non-convexity of the problem, using mathematical methods for solving this problem is complex and has a high computational burden. Today there is an effort to reduce the costs through using optimization and artificial intelligence methods [1–4]. In this regard, many various mathematical or artificial intelligence methods have been applied for solving the economic load dispatch (ELD) problem, including Lambda step method [5], gradient method [6], common coefficients [7], and optimum point method [8]. These methods are mostly repetitive mathematical methods which despite achieving a relatively accurate solution for the considered problem, they are limited in most of the actual applications; for instance, the heat increase rate characteristics of the units must be continuous.

Alternatively, regarding the optimization methods based on intelligent algorithms, in addition to avoidance from encountering the mentioned limitations, the time and dimensions of the problem solution are almost linearly increased with the number of power system units, making these algorithms apropos and suitable candidates for solving the actual economic load dispatch problems [9–12].

In the recent years, a wide variety of meta-heuristic-based optimization algorithms and their improved or hybrid versions have been applied to solve different ED and DED problems, such as symbiotic organisms search (SOS) algorithm [13], artificial bee colony (ABC) [14], artificial immune system (AIS) [15], hybridization of AIS and sequential quadratic programing (AIS-SQP) [16], hybridization of AIS and GA (HIGA) [17], ant colony optimization algorithm (MACO) [18], a hybrid GA and bacterial foraging (BF) algorithm (HGABF) [19], evolutionary programing (EP) [20], modified hybrid EP and sequential quadratic programing (MHEP-SQP) [21, 22], simulated annealing (SA) [11], enhanced bee swarm optimization (EBSO) [23], imperialist competitive algorithm (ICA) [24], PSO and its improved versions [25–33], firefly algorithms (FFA) [34, 35], differential evolution (DE) and the improved DE algorithms [36–43], a hybrid of DE and PSO [44], teaching learning algorithm (TLA) and modified TLA (MTLA) [45–47], a modified crow search algorithm (MCSA) [48], Coulomb-Franklin algorithm (CFA) [49], seeker optimization algorithm (SOA) [50], harmony search (HS) [51], crisscross optimization algorithm (CSO) [52], enhanced cross-entropy (ECE) method [53], etc.

Despite numerous successes obtained by HPSO-TVAC algorithm [54] in different fields of optimizations such as [30], there is still a need for increasing its local and global search abilities. So, a new and powerful type of HPSO-TVAC, known as NHPSO-JTVAC [55], is investigated in this paper for solving DED problems and its best control parameters for DED problems are presented. Furthermore, to increase its local and global search abilities, the population reduction theory is used in NHPSO-JTVAC algorithm to remove the ineffective population in the optimization process during the iterations. Thereby more time and iterations are assigned to the most effective population in the rest of the optimization process. In this paper, load supply during 24-hours is considered as a real optimization problem, where technical constraints such as ramp up/down rate of production, limitations of inlet valves of forbidden zones in the power plants, and maximum and minimum power generations of the units are taken into account. The results show that the proposed algorithm is very powerful and accurate for various types of small and large test systems.

The rest of this paper is structured as follows: The dynamic economic dispatch problem formulation is introduced in Section 2. A review of PSO and NHPSO-JTVAC algorithms is presented in Section 3. Also, the proposed MNHPSO-JTVAC algorithm is introduced in this section. The simulation results and investigations of NHPSO-JTVAC and MNHPSO-JTVAC algorithms are presented in Section 4. MNHPSO-JTVAC is applied to two real test power systems involving 10-unit and 30-unit test power systems. Finally, Section 5 concludes the paper.

2. DYNAMIC ECONOMIC DISPATCH PROBLEM

2.1. DED Optimization Model

Economic Load dispatch determines the economical operating condition of a power system through appropriate distribution of energy generation resources for the system's load supply. Its primary goal is to minimize the total generation cost on account of utilizing the generation resources. The ELD problem specifies the generation amount of the plants to minimize the total costs. It is formulized as an optimization problem to minimize the total fuel costs of all plants that supply the load and losses. Therefore, the economic load dispatch problem can be written as follows by optimizing the below objective function [56–58]:

$$\min \sum_{t=1}^{24} \left(\sum_{i=1}^{N} F_{i,t}(P_{i,t}) + \lambda \left(\sum_{i=1}^{N} P_{i,t} - P_{D,t} - P_{loss,t} \right)^2 \right) \tag{1}$$

where $F_{i,t}$ is the fuel cost of the i-th plant at time t, N represents the number of operating generators of the power system, $P_{i,t}$ is the output power of the i-th generator at time t; $P_{D,t}$ expresses the electrical load demand or power consumption at time t, and $P_{loss,t}$ is the active power transmission losses of the electrical power transmission system at time t; and λ is the penalty factor for violating the power balance constraint between the plants and the consumption loads and transmission losses. $F_{i,t}$ $(P_{i,t})$ is often presented by a second-order polynomial equation [56–58]:

$$F_{i,t}(P_{i,t}) = \alpha_i + b_i P_{i,t} + c_i P_{i,t}^2 \tag{2}$$

where a_i, b_i, and c_i are the cost coefficients of the i-th generator. To consider the effects of the valve positions, the sinusoidal functions are added to the fuel cost function as follows [56–58]:

$$F_{i,t}(P_{i,t}) = \alpha_i + b_i P_{i,t} + c_i P_{i,t}^2 + \left| e_i \sin\left(f_i \left(P_{i,t}^{\min} - P_{i,t} \right) \right) \right| \tag{3}$$

In the above equation, e_i and f_i are coefficients for the valve positions of the i-th generator. As it is seen, Eq. (1) is converted to a non-convex and non-smooth combinational function. It should be mentioned that the power losses can be calculated by using loss coefficients B.

2.2. Constraint of Output Power of Generators

The output power of generators must be within a specified range that is vital for sustained operation of generator boilers. So, the power output of generators should satisfy the following equation:

$$P_{i,t}^{\min} \le P_{i,t} \le P_{i,t}^{\max} \tag{4}$$

2.3. Ramp Up/Down Rates of Thermal Plants

Due to technical reasons, thermal plants are not able to immediately increase or decrease their output power and this is accompanied by a specific rate. Simply put, every plant has its own limitations for ramping up/down the output power, whose violation will lead to a damage to the rotor and increase the operation cost. The limitations are modeled through the following constraints [56–58]:

$$\begin{aligned} &\max\left(P_{i,t-1} - RDR_{i,t}, P_{i,t}^{\min} \right) \le P_{i,t}(t) \ \text{ and} \\ &P_{i,t}(t) \le \min\left(P_{i,t-1} + RUR_{i,t}, P_{i,t}^{\max} \right) \end{aligned} \tag{5}$$

where, RDR_i and RUR_i are the ramping down and up of the i-th thermal generator in the plant.

2.4. Prohibited Operating Zones (POZ) of Power Generation

Power plants are not capable of producing power in some zones between the minimum and maximum power generation limits. There areas are so-called POZ and specified as:

$$P_{i,t} \in \begin{cases} P_{i,t}^{\min} \le P_{i,t} \le P_{i,t,1}^{l} \\ P_{i,t,k-1}^{u} \le P_{i,t} \le P_{i,t,k}^{l}; k = 2, \ldots, n_i; \quad \forall i \in \Omega \\ P_{i,t,n_i}^{u} \le P_{i,t} \le P_{i,t}^{\max} \end{cases} \tag{6}$$

where n_i is the number of POZ for the i-th generating unit in the system.

3. THE MODIFIED NHPSO-JTVAC (MNHPSO-JTVAC) ALGORITHM USING POPULATION REDUCTION

3.1. Classic PSO

PSO is a social search algorithm inspired from the social behavior of bird flocks and fish swarms while moving here and there. The algorithm has been first used for discovering the patterns ruling the simultaneous fly of birds and the sudden change of path and so shape-change of the bird flock. A set of particles is assumed at the first step. Each particle has a position and a velocity vector and tends to move to the optimal points according to their velocity. In this method, a position vector, P and a velocity vector, V is considered for each particle. If the dimension of the problem is D, then these two vectors are calculated through Eqs. (7) and (8) in each iteration [59, 60]:

$$\begin{aligned} v_{i,j}^{Iter+1} &= v_{i,j}^{Iter} + c_1^{Iter} \times r_{1,j} \times (p_{i,j}^{Iter} - x_{i,j}^{Iter}) + c_2^{Iter} \\ &\quad \times r_{2,j} \times (p_{g,j}^{Iter} - x_{i,j}^{Iter}) \end{aligned} \tag{7}$$

$$X_i^{Iter+1} = V_i^{Iter+1} + X_i^{Iter} \tag{8}$$

c_1 and c_2 are the learning (acceleration) coefficients, where c_1 is the cognitive parameter and c_2 is the social parameter. P_i shows the best historical position of the i-th particle and P_g is the best historical position of all particles of the population up to iteration $Iter$. The index j shows the problem dimension. One of the main drawbacks of the algorithm is immature convergence to the local optimal solutions.

3.2. Self-Organizing Hierarchical PSO with Time-Varying Acceleration Coefficients (HPSO-TVAC)

HPSO-TVAC [54] is one of efficient improved versions of original PSO. The difference between HPSO-TVAC and original PSO is that in the former, the acceleration coefficients c_1^{Iter} and c_2^{Iter} are updated iteratively, using the following equations [54]:

$$c_1^{Iter} = (c_{1f} - c_{1i}) * \frac{Iter}{Iter_{\max}} + c_{1i} \tag{9}$$

$$c_2^{Iter} = (c_{2f} - c_{2i}) * \frac{Iter}{Iter_{\max}} + c_{2i} \tag{10}$$

where c_{1i}, c_{1f}, c_{2i} and c_{2f} are selected as proposed by [54]: starting value of c_1^{Iter} is $c_1^1 = c_{1i} = 2.5$ and its final value is $c_1^{Iter_{\max}} = c_{1f} = 0.5$; Also, starting and final values of c_2^{Iter} are $c_2^1 = c_{2i} = 0.5$ and $c_2^{Iter_{\max}} = c_{2f} = 2.5$, respectively.

3.3. The New Self-Organizing Hierarchical PSO With Jumping Time-Varying Acceleration Coefficients (NHPSO-JTVAC)

The HPSO-TVAC is one of important versions of PSO which is being widely used in numerous optimization problems for optimization and comparison goals. An improved version of HPSO-TVAC was proposed in [55], namely NHPSO-JTVAC, for increasing quality of the solutions, convergence speed and ability to avoid pre-mature convergence. There are two simple differences between NHPSO-JTVAC and its ancestor algorithm.

The first difference is that NHPSO-JTVAC uses (11)–(13) to calculate the acceleration coefficients c_1 and c_2.

$$c^{Iter} = (c_f - c_i) * \frac{Iter}{Iter_{\max}} + c_i \tag{11}$$

$$c_1^{Iter} = |w|^{\left(c^{Iter} * w\right)} \tag{12}$$

$$c_2^{Iter} = |1 - w|^{\left(\frac{c^{Iter}}{1-w}\right)} \tag{13}$$

where w is a standard normal random number, and c^{Iter} changes from $c^1 = c_i = 0.5$ to $c^{Iter_{\max}} = c_f = 0.0$.

As it seen from these equations, both acceleration coefficients are formulated as exponential values. This way, the algorithm will experience sudden jumps which help with escaping from local optima and also its search areas are increased.

Another suggestion of [55] for improving HPSO-TVAC is to use $(P_g^{Iter} + P_r^{Iter}) - 2 * X_i^{Iter}$ instead of $P_g^{Iter} - X_i^{Iter}$ in (7), where P_r^{Iter} is the best personal value of a randomly chosen particle (like rth particle). This proposal on one hand, is based on the fact that using $P_g^{Iter} - X_i^{Iter}$ makes the algorithm more prone to being trapped in local optima [61], and on the other hand it was shown that if simply $P_r^{Iter} - X_i^{Iter}$ is used, the basic rules and structure of HPSO-TVAC are neglected and convergence speed and efficiency are decreased. By implementing the proposal, suitable and acceptable convergence is achieved while escaping from pre-mature convergence to the local optima and improving the quality of final solution. The new search equation will be as:

$$v_{i,j}^{Iter+1} = c_1^{Iter} \times r_{1,j} \times (p_{i,j}^{Iter} - x_{i,j}^{Iter}) + c_2^{Iter} \times r_{2,j} \times \left(\left(p_{g,j}^{Iter} + p_{r,j}^{Iter} \right) - 2 * x_{i,j}^{Iter} \right) \tag{14}$$

Real-parameter unimodal test functions:
F_1: Shifted Sphere
F_2: Shifted Schwefel's Problem 1.2
F_3: Shifted Rotated High Conditioned Elliptic
F_4: Shifted Schwefel's Problem 1.2 with Noise in Fitness
F_5: Schwefel's Problem 2.6 with Global Optimum on Bounds
Real-parameter multimodal test functions:
F_6: Shifted Rosenbrock's
F_7: Shifted Rotated Griewank's without Bounds
F_8: Shifted Rotated Ackley's with Global Optimum on Bounds
F_9: Shifted Rastrigin's
F_{10}: Shifted Rotated Rastrigin's
F_{11}: Shifted Rotated Weierstrass
F_{12}: Schwefel's Problem 2.1
Real-parameter expanded test functions:
F_{13}: Shifted Expanded Griewank's plus Rosenbrock's Function
F_{14}: Shifted Rotated Expanded Scaffer's f_6 Function

TABLE 1. Summary of the 14 selected 30-D benchmark optimization functions for comparative study with $F_{\min}$=0 based on the information provided by P.N. Suganthan, et al, 2005 and J.J. Liang, et al, 2013.

3.4. NHPSO-JTVAC with Dynamic Population Reduction

In the performed simulations of NHPSO-JTVAC algorithm for different test functions, if the number of population is increased, for some test functions the solution becomes better while for some other test functions it becomes worse. In the same manner, when the number of population is decreased, then the same event occurs. These all depend on the nature of the test functions; because in the real world we deal with various problems of different features. Moreover, in case the number of iterations is increased in the same conditions, then it is possible to increase the escaping ability of the algorithm from getting trapped in the local solutions; so a better solution will be obtained. To approach this objective, in the proposed MNHPSO-JTVAC, first we initiate the optimization process of NHPSO-JTVAC algorithm with a proper population, $Np^{initial}$. Then, during the algorithm iterations for optimization, the weaker population is eliminated from the

Function		Standard HPSO-TVAC Mean Std. Dev Rank	NHPSO-JTVAC with c^1 $(=c_i)\rightarrow c^{Iter_{\max}}(=c_f)$ **0.5→0** Mean Std. Dev Rank	1→0 Mean Std. Dev Rank	1→0.5 Mean Std. Dev Rank	2→0.0 Mean Std. Dev Rank
Unimodal functions	F_1	4.24E − 25	**1.60E − 25**	2.86E − 25	4.10E − 18	1.30E − 24
		4.03E − 26	**3.11E − 26**	8.09E − 26	3.15E − 18	4.00E − 25
		3	**1**	2	5	4
	F_2	1.84E − 11	**9.82E − 12**	9.05E − 07	6.12E − 03	1.39E − 03
		2.17E − 11	**1.25E − 11**	8.68E − 07	4.23E − 03	1.08E − 03
		2	**1**	3	5	4
	F_3	1.25E + 06	**6.14E + 05**	6.25E + 05	1.19E + 06	1.22E + 06
		5.58E + 05	**2.98E + 05**	3.52E + 05	4.89E + 05	8.72E + 05
		5	**1**	2	3	4
	F_4	4.65E + 04	3.86E + 02	**3.28E + 02**	7.09E + 02	5.33E + 02
		8.69E + 03	2.26E + 02	**2.50E + 02**	3.16E + 02	2.62E + 02
		5	2	**1**	4	3
	F_5	1.02E + 04	4.95E + 03	**4.27E + 03**	4.47E + 03	4.43E + 03
		3.23E + 03	1.18E + 03	**9.50E + 02**	1.24E + 03	8.27E + 02
		5	4	**1**	3	2
Multimodal functions	F_6	3.86E + 01	**2.05E + 01**	3.60E + 01	5.14E + 01	6.13E + 01
		4.75E + 01	**3.36E + 01**	5.66E + 01	5.53E + 01	6.04E + 01
		3	**1**	2	4	5
	F_7	1.65E − 02	1.31E − 02	2.95E − 02	**1.10E − 02**	1.98E − 02
		1.29E − 02	1.72E − 02	2.02E − 02	**7.52E − 03**	1.47E − 03
		3	2	5	**1**	4
	F_8	2.14E + 01	**2.09E + 01**	**2.09E + 01**	**2.09E + 01**	**2.09E + 01**
		6.51E − 02	**4.75E − 02**	**4.89E − 02**	**4.68E − 02**	**7.69E − 02**
		2	**1**	**1**	**1**	**1**
	F_9	**7.30E − 01**	9.75E + 00	1.03E + 01	9.85E + 00	1.76E + 01
		7.95E − 02	1.11E + 01	5.00E + 00	4.15E + 00	1.99E + 01
		1	2	4	3	5
	F_{10}	5.84E + 02	5.63E + 01	**4.72E + 01**	6.16E + 01	7.91E + 01
		9.12E + 01	2.00E + 01	**1.27E + 01**	4.47E + 01	5.49E + 01
		5	2	**1**	3	4
	F_{11}	5.09E + 01	**2.21E + 01**	2.33E + 01	2.31E + 01	2.24E + 01
		1.89E + 00	**3.00E + 00**	4.47E + 00	3.08E + 00	5.27E + 00
		5	**1**	4	3	2
	F_{12}	2.98E + 06	**4.80E + 04**	4.90E + 04	4.96E + 04	4.84E + 04
		3.09E + 05	**4.29E + 04**	6.09E + 04	7.57E + 04	4.77E + 04
		5	**1**	3	4	2
Expanded functions	F_{13}	4.34E + 00	**2.04E + 00**	6.78E + 00	8.21E + 00	6.88E + 00
		1.70E + 00	**1.48E − 01**	4.80E + 00	4.92E + 00	4.66E + 00
		2	**1**	3	5	4
	F_{14}	1.44E + 01	**1.25E + 01**	1.28E + 01	1.26E + 01	1.26E + 01
		8.13E − 01	**5.36E − 01**	3.11E − 01	3.36E − 01	4.83E − 01
		4	**1**	3	2	2
Total mean time (sec)		39.20	39.15	39.14	39.73	39.48
Nb/Nw/Mr		1/7/3.57	**9/0/1.5**	4/1/2.5	2/3/3.36	1/2/3.49

TABLE 2. The results of standard HPSO-TVAC and NHPSO-JTVAC algorithms on 30-D real-parameter functions.

algorithm populations and Np number of better populations reach the next iteration. Finally, in the last iteration, the number of algorithm population reaches Np^{final}, where the equation for describing this population decreasing rate is given in (15). Thereby a tradeoff between the algorithm population and the number of performed iterations is created which improves the performance of the algorithm and the quality of the final solution for various test functions.

$$Np = \text{round}\left(Np^{initial} - \left((Np^{initial} - Np^{final}) * \left(\frac{FEs}{FEs_{\max}}\right)\right)\right) \tag{15}$$

4. SIMULATION RESULTS

4.1. Comparison of HPSO-TVAC Algorithms for Solving Real Parameter Test Functions

In this section, 14 well-known benchmark functions [62, 63] were optimized, aimed at deeply understanding the performance of the HPSO-TVAC algorithms and assessing the effectiveness of the sets of control parameters and the population reduction in HPSO-TVAC. The 14 well-known benchmark functions are listed in Table 1 [62, 63]. The value of the dimension of searching space, D, was set to 30 for all test functions. For each HPSO-TVAC algorithm and each real parameter test function, 30 independent runs were conducted with 300,000 function evaluations (FES) as the termination criterion. It should be noted that the global optimums of all 14 real parameter test functions are $F_{\min}=0$.

4.1.1. Effectiveness of the Control Parameter Setting (Test 1). In this section, first the best control parameters are set and tested for c_1 or c_i and $c^{Iter_{\max}}$ or c_f. The control parameters of HPSO-TVAC are set according to the obtained best parameters in [54] and shown in the previous section. In the first test, the population of all algorithms is the same and equal to 40. The best results of the algorithms including the average value, standard deviations, and the algorithm rank among all given algorithms for different parameter sets are listed in Table 2. As seen, in general, NHPSO-JTVAC has better results compared to the original HPSO-TVAC algorithm. $c_i = 0.5$ and $c_f = 0$ lead to the best results among all parameter sets, where between 14 benchmark functions, it has 9 best values ($Nb = 9$) and never gives the worst result ($Nw = 0$). Also, it has the best average value ($Mr = 1.5$) between the algorithms. For instance, the convergence characteristics curve of the algorithms for different parameters' setting and for the third test function is shown in Fig. 1.

4.1.2. Effectiveness of the Dynamic Population Reduction (Test 2). In this section, the best parameter sets of the algorithm are selected from the previous test (i.e. $c^1=0.5 \rightarrow c^{Iter_{\max}} = 0$), and the effect of population reduction method on NHPSO-JTVAC algorithm is tested based on Eq. (15) with different populations. A summary of the obtained

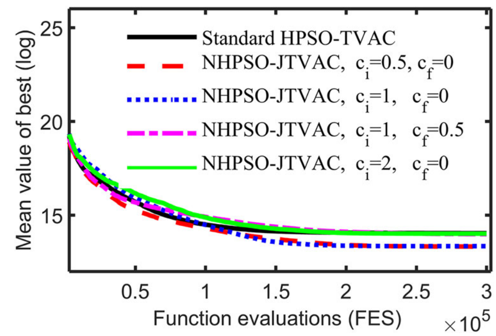

FIGURE 1. Convergence characteristics for standard HPSO-TVAC and NHPSO-JTVAC algorithms for F_3 and test 1.

results for the mentioned algorithm with different populations and the population reduction method have been given in Table 3. As one can observe from the table, in case it is possible to make a balance between the number of algorithm iterations and algorithm population in a fixed function evaluation (FES), then it is likely to obtain acceptable high quality solutions for different test functions. Here we succeeded in achieving this objective through a population set with values of $Np^{final} = 20$ and $Np^{initial} = 40$, and increased the algorithm ability. In case we intended to run the algorithm with a large or small fixed population size, then different results would be achieved for different test functions. Additionally, as an example, the convergence characteristics curves of the test algorithms are plotted in Fig. 2 for the third test function to show the effects of the dynamic population reduction method.

4.2. MNHPSO-JTVAC Algorithm to DED Considering Constraints

In this section, the test power systems for DED problems are introduced and the related information is presented. The under-study systems are a standard 10-unit system [24] and a 30-unit system [52]. The data of the test systems, including the load demands during a 24-hour period, loss matrix coefficients, cost function coefficients and the limitation ranges were extracted from [24] and [52].

The steps of the proposed MNHPSO-JTVAC for solving optimal DED problems is presented in Fig. 3; which are as follows:

Step 1: Set the initial parameters of MNHPSO-JTVAC through the parameters of the under-study test system.

Step 2: Generate the initial population based on the number of populations and the minimum and maximum

Function		Np=40 Mean Std. Dev Rank	Np=20 Mean Std. Dev Rank	Np=60 Mean Std. Dev Rank	**$Np^{initial}$=40 Np^{final}=20** Mean Std. Dev Rank	$Np^{initial}$=60 Np^{final}=20 Mean Std. Dev Rank
Uni-modal functions	F_1	1.60E − 25 3.11E − 26 4	2.87E − 25 9.10E − 26 5	**1.32E − 25** **2.99E − 26** **1**	1.51E − 25 3.29E − 26 2	1.56E − 25 5.21E − 26 3
	F_2	9.82E − 12 1.25E − 11 3	**2.66E − 14** **3.85E − 14** **1**	2.15E − 08 1.82E − 08 5	4.04E − 12 3.41E − 12 2	2.51E − 11 1.98E − 11 4
	F_3	6.14E + 05 2.98E + 05 5	5.25E + 05 2.92E + 05 2	5.69E + 05 2.54E + 05 4	**5.01E + 05** **1.88E + 05 1**	5.40E + 05 2.33E + 05 3
	F_4	3.86E + 02 2.26E + 02 4	5.10E + 02 3.09E + 02 5	**2.36E + 02** **2.10E + 02** **1**	3.61E + 02 3.18E + 02 3	3.45E + 02 2.14E + 02 2
	F_5	4.95E + 03 1.18E + 03 3	6.64E + 03 1.62E + 03 5	5.00E + 03 1.14E + 03 4	4.44E + 03 1.33E + 03 2	**4.48E + 03** **1.16E + 03 1**
Multi-modal functions	F_6	2.05E + 01 3.36E + 01 3	2.01E + 01 3.39E + 01 2	3.73E + 01 4.36E + 01 5	**5.05E + 00** **6.21E + 00 1**	2.09E + 01 2.72E + 01 4
	F_7	**1.31E − 02** **1.72E − 02** **1**	1.48E − 02 1.17E − 02 2	1.85E − 02 1.25E − 02 4	1.84E − 02 1.25E − 02 3	2.31E − 02 2.08E − 03 5
	F_8	**2.09E + 01** **4.75E − 02** **1**	**2.09E + 01** **4.38E − 02** **1**	**2.09E + 01** **4.56E − 02** **1**	**2.09E + 01** **7.84E − 02** **1**	**2.09E + 01** **4.56E − 02** **1**
	F_9	9.75E + 00 1.11E + 01 3	7.50E + 00 7.27E + 00 2	1.07E + 01 3.25E + 00 5	**7.10E + 00** **3.09E + 00 1**	1.09E + 01 5.85E + 00 4
	F_{10}	5.63E + 01 2.00E + 01 2	6.41E + 01 1.74E + 01 4	7.33E + 01 3.81E + 01 5	**4.98E + 01** **1.28E + 01 1**	5.65E + 01 1.96E + 01 3
	F_{11}	**2.21E + 01** **3.00E + 00** **1**	2.68E + 01 4.29E + 00 4	2.34E + 01 4.61E + 00 2	2.53E + 01 6.37E + 00 3	2.53E + 01 6.60E + 00 3
	F_{12}	4.80E + 04 4.29E + 04 3	9.92E + 04 9.83E + 04 5	**3.48E + 04** **7.54E + 04** **1**	**3.37E + 04** **9.97E + 04 1**	7.21E + 04 6.50E + 04 4
Expanded functions	F_{13}	2.04E + 00 1.48E − 01 2	**1.83E + 00** **8.49E − 01** **1**	6.38E + 00 4.78E + 00 5	4.27E + 00 4.59E + 00 3	4.81E + 00 3.55E + 00 4
	F_{14}	1.25E + 01 5.36E − 01 2	1.27E + 01 3.16E − 01 3	1.27E + 01 3.06E − 01 3	**1.23E + 01** **2.79E − 01** **1**	1.28E + 01 2.54E − 01 4
Total mean time (sec)		39.15	42.75	38.10	40.92	40.49
Nb/Nw/Mr		3/1/2.64	3/5/2.93	4/5/3.29	**7/0/1.79**	2/2/3.21

TABLE 3. The results of NHPSO-JTVAC ($c^1 = \mathbf{0.5} \rightarrow c^{Iter_{\max}} = \mathbf{0}$) algorithms with dynamic population reduction on 30-D real-parameter functions.

values of the control variables, the system limitations, and optimal DED problem limitations.

Step 3: Apply the system and optimal DED problem limitations, calculate the objective function (1) of the initially produced solutions and store them as the initial solutions. The Algorithm 1 is shown the constraint-handling procedure of non-differentiable and non-convex DED problem.

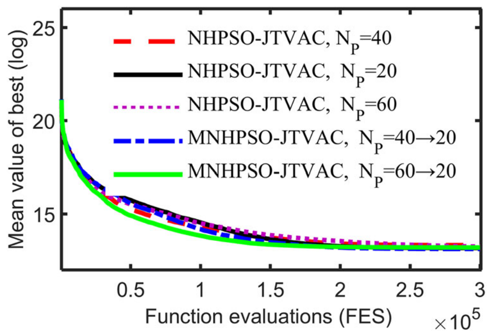

FIGURE 2. Convergence characteristics for standard HPSO-TVAC and NHPSO-JTVAC algorithms for F_3 and test 2.

Algorithm 1: The constraint-handling procedure of non-differentiable and non-convex DED problems for the algorithm solutions (population).

for $j=1$ to Np **do**

for $i=1$ to N_g **do**

calculate the power losses equation $P_{loss,t}$ by using loss coefficients B as follows:

$$P_{loss,t}=\sum_{i=1}^{N_g}\sum_{k=1}^{N_g}P_{i,t}B_{ij}P_{k,t}+\sum_{i=1}^{N_g}B_{0i}P_{i,t}+B_{00}$$

calculate equation $P^{j}_{Iter,I}$ by: $P^{j}_{Iter,I}=P_D+P_{loss,t}-\sum_{g=1,g\neq I}^{N_g}P^{j}_{Iter,g,t}$;

{** The generating power output constraint limitations of system thermal units **}

if $P^{j}_{Iter,I}$ out of its range ($P^{j}_{Iter,I}< P^{L}_{I,t}$ or $P^{j}_{Iter,I}> P^{U}_{I,t}$)

Adjust the value $P^{j}_{Iter,I}$ its range (i.e. $P^{L}_{g,t}\leq P_{g,t}\leq P^{U}_{g,t}$);

end if

{** The POZ constraint limitations (when $P^{j}_{Iter,I}$ in its n_ith POZ) **}

calculate equation $P_I^{\text{bound}_j}$ using: $P_I^{\text{bound}_j}=\frac{(P^{l}_{g,t,z}+P^{u}_{g,t,n_i})}{2}$; $z=2,\dots,n_i;\forall g\in\Omega$;

if $P^{j}_{Iter,I}$ bigger of $P_I^{\text{bound}_j}$ ($P_I^{\text{bound}_j}<P^{j}_{Iter,I}$)

Set $P^{j}_{Iter,I}=P^{u}_{g,t,n_i}$;

else if $P^{j}_{Iter,I}\leq P_I^{\text{bound}_j}$

Set $P^{j}_{Iter,I}=P^{l}_{g,t,z}$;

end if

end for

end for

Step 4: Enhance the previous step solutions based on (8) and (14), apply the system and optimal DED problem limitations and the constraint-handling procedure using

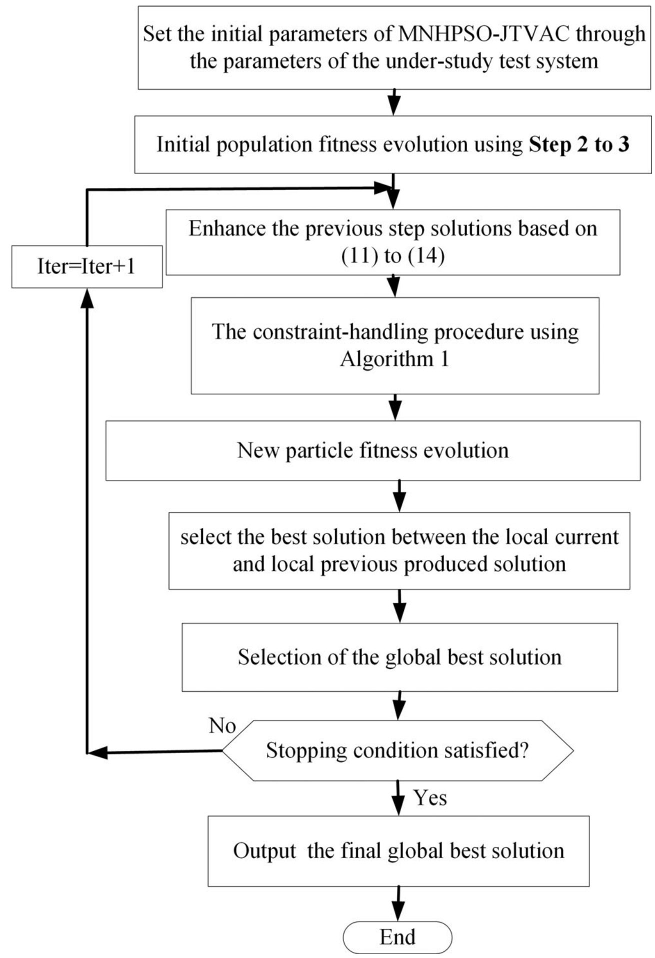

FIGURE 3. Steps of the proposed algorithm.

Algorithm 1, and calculate their objective function (1). Then for the next iteration, select the best solution between the current and the previous solutions.

Step 5: Compare the best particle solution with the best global solution of the previous step. If the best particle solution is better than the previous global optimal solution, then the former replaces the latter, otherwise the previous best global solution is retained in the algorithm memory.

Step 6: Is the algorithm termination criterion completed? If yes, then finish the program and print the best global solution as the best solution, otherwise go to Step 4 and continue the optimization process.

It should be mentioned that because of the population reduction strategy of MNHPSO-JTVAC, the maximum iteration number is not a fair termination criterion for different algorithms and so the maximum function evaluations (FES) is selected as the termination criterion.

Method	Total generation cost ($)				
	Minimum	Average	Maximum	Std. Dev	Rank
AIS-SQP [16]	1,029,900	N/A	N/A	N/A	30
ABC [14]	1,021,576	1,022,686	1,024,316	N/A	23
CDBCO [64]	1,021,500	1,024,300	N/A	N/A	22
CSDE/best/1 [36]	1,019,536	1,022,883	N/A	N/A	14
IDE [42]	1,026,269	N/A	N/A	N/A	27
CDE [37]	1,019,123	1,020,870	1,023,115	1310.70	13
DE1 [39]	1,019,786	N/A	N/A	N/A	15
MDE [38]	1,031,612	1,033,630	N/A	N/A	33
AHDE [58]	1,020,082	1,022,476	N/A	N/A	18
HDE [1]	1,031,077	N/A	N/A	N/A	31
AIS [15]	1,021,980	1,023,156	N/A	N/A	24
HIGA [17]	1,018,473	1,019,328	1,022,284	N/A	7
ECE [53]	1,022,271	1,023,334	N/A	N/A	25
SOA-SQP [50]	1,021,460	1,023,840	1,026,852	N/A	21
CSO [52]	1,017,660	1,018,120	1,019,286	302.3103	2
ICA [24]	1,018,467	1,019,291	1,021,796	693.487	6
SOS [13]	1,020,894	1,021,073	1,021,195	N/A	19
HHS [51]	1,019,091	N/A	N/A	N/A	11
TLA [46]	1,019,925	1,020,411	1,021,118	N/A	17
MACO [18]	1,019,093	1,019,254	1,024,311	348.03	12
TVAC-IPSO [30]	1,018,217	1,018,965	1,020,417	N/A	5
DGPSO [65]	1,028,835	1,030,183	N/A	N/A	29
EAPSO [25]	1,018,510	1,018,710	1,019,302	N/A	8
BBPSO [66]	1,018,159	1,019,850	1,021,813	826.94	4
FAPSO [29]	1,019,851	1,020,522	1,021,463	N/A	16
IPSO [31]	1,023,807	1,026,863	N/A	1569.80	26
CSAPSO [28]	1,018,767	1,019,874	N/A	N/A	9
HQPSO [67]	1,031,559	1,033,837	1,036,681	N/A	32
ICPSO [27]	1,019,072	1,020,027	N/A	493.21	10
PSO-SQP(C) [68]	1,027,334	1,028,546	1,033,983	N/A	28
Standard HPSO-TVAC	1,020,895	1,023,892	1,026,699	833.67	20
NHPSO-JTVAC	1,018,018	1,019,115	1,021,235	528.10	3
MNHPSO-JTVAC	**1,017,639**	**1,017,705**	**1,018,538**	**224.74**	**1**

TABLE 4. Statistical optimal results obtained by different optimization algorithms for Case 1.

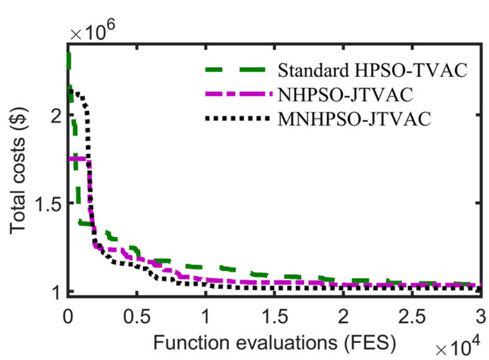

FIGURE 4. Convergence characteristics of HPSO-TVAC algorithms for Case 1.

The proposed algorithm was applied on four different cases as follows and the obtained results were compared with those of the recent presented algorithms. As said before, the main objective of optimal DED problem is to reduce the generation cost of electrical power for the system. The four different cases include:

Case 1: Ten-thermal-generator test system with considering ramp rate constraints and valve-point effects and without considering prohibited operation zones limits (POZs) and system transmission losses, including 24×10 control variables.

Case 2: The test system of Case 1 with considering system transmission losses, including 24×10 control variables.

Case 3: The test system of Case 1 with considering system transmission losses and generators' prohibited operation zones limits (POZs), including 24×10 control variables.

Case 4: Thirty-thermal-generator test system by tripling the test system of Case 1, with 24×30 control variables.

Method	Total generation cost ($) Minimum	Average	Maximum	Loss (MW)	Std. Dev	Rank
HIGA [17]	1,041,088	1,042,980	1,044,927	853.53	N/A	11
ECE [53]	1,043,989	1,044,470	N/A	N/A	N/A	16
CDBCO [64]	1,042,900	1,044,700	N/A	839.31	N/A	14
SOS [13]	1,042,869	1,042,900	1,042,945	N/A	N/A	13
AIS [15]	1,045,715	1,047,050	1,048,431	835.62	N/A	17
ICA [24]	1,040,758	1,041,664	1,043,173	848.797	N/A	8
EBSO [23]	1,038,915	1,039,188	1,039,272	N/A	N/A	4
ABC [14]	1,043,381	1,044,963	1,046,805	817.80	N/A	15
LDISS-2 [69]	1,039,083	1,041,091	1,042,630	812.5324	N/A	6
MIQP [70]	1,038,550	N/A	N/A	N/A	N/A	3
MILP-IPM [71]	1,040,676	N/A	N/A	N/A	N/A	7
MHEP-SQP [22]	1,050,054	1,052,349	N/A	N/A	N/A	20
CSO [52]	1,038,320	1,039,374	1,042,518	802.62	395.6737	2
MACO [18]	1,042,273	1,042,790	1,044,117	142.33		12
TVAC-IPSO [30]	1,041,066	1,042,118	1,043,626	854.033	N/A	9
IPSO [31]	1,046,275	1,048,154	N/A	N/A	N/A	18
DGPSO [65]	1,049,167	1,051,725	N/A	N/A	N/A	19
Standard HPSO-TVAC	1,041,724	1,043,943	1,046,829	848.0065	1698.34	10
NHPSO-JTVAC	1,039,055	1,041,631	1,044,722	845.8647	782.02	5
MNHPSO-JTVAC	**1,038,211**	**1,038,995**	**1,040,618**	**843.7335**	**371.45**	**1**

TABLE 5. Statistical optimal results obtained by different optimization algorithms for Case 2.

Method	Total generation cost ($) Minimum	Average	Maximum	Loss (MW)	Std. Dev	Rank
CDBCO [64]	1.0444E+06	N/A	N/A	N/A	N/A	4
SOS [13]	1,044,431	1,044,438	1,044,458	N/A	N/A	5
Standard HPSO-TVAC	1,043,950	1,044,580	1,046,621	814.8210	985.25	3
NHPSO-JTVAC	1,043,039	1,043,502	1,044,197	805.2476	669.28	2
MNHPSO-JTVAC	**1,042,146**	**1,042,673**	**1,043,548**	**801.0085**	**324.45**	**1**

TABLE 6. Statistical optimal results obtained by different optimization algorithms for Case 3.

4.2.1. Case 1. Table 4 lists optimal results of Case 1 such as the minimum, average, maximum and standard deviations (Std. Dev) of the total cost obtained over 30 runs by the HPSO-TVAC algorithms and the previously developed algorithms such as AIS-SQP [16], ABC [14], CDBCO [64], CSDE/best/1 [36], IDE [42], CDE [37], DE1 [39], MDE [38], AHDE [58], HDE [1], AIS [15], HIGA [17], ECE [53], SOA-SQP [50], CSO [52], ICA [24], SOS [13], HHS [51], TLA [46], MACO [18], TVAC-IPSO [30], DGPSO [65], EAPSO [25], BBPSO [66], FAPSO [29], IPSO [31], CSAPSO [28], HQPSO [67], ICPSO [27] and PSO-SQP(C) [68]. Best results obtained of MNHPSO-JTVAC algorithm for each case are in **bold**. It can be observed that the obtained optimal generator schedule with proposed MNHPSO-JTVAC optimizer is better than that of the previously developed algorithms reported in the literature. Fig. 4 represents convergence characteristics of the HPSO-TVAC algorithms toward obtained optimal solution for Case 1.

4.2.2. Case 2. Table 5 lists optimal results of Case 2 such as the minimum, average, maximum and standard deviation of the total cost obtained over 30 runs by the HPSO-TVAC algorithms and the previously developed algorithms such as HIGA [17], ECE [53], CDBCO [64], SOS [13], AIS [15], ICA [24], EBSO [23], ABC [14], LDISS-2 [69], mixed integer quadratic programing (MIQP) [70], hybrid interior point method and mixed-integer linear programing (MILP-IPM) [71], MHEP-SQP [22], CSO [52], MACO [18], TVAC-IPSO [30], IPSO [31] and DGPSO [65]. The minimum cost obtained using proposed MNHPSO-JTVAC algorithm is 1,038,211 $, whereas minimum cost obtained for the case 2 using standard HPSO-TVAC and NHPSO-JTVAC methods are 1,039,055 $and 1,041,724 $,

Method	Total generation cost ($)				
	Minimum	Average	Maximum	Std. Dev	Rank
MACO [18]	3,059,047	3,068,101	3,079,851	3238.99	17
EBSO [23]	3,054,001	3,054,697	3,055,944	N/A	11
DE [37]	3,163,000	3,173,100	N/A	N/A	28
ECE [53]	3,084,649	3,087,847	N/A	N/A	23
HHS [51]	3,057,313	N/A	N/A	N/A	16
CDBCO [64]	3,081,400	3,088,500	N/A	N/A	21
HIGA [17]	3,055,435	3,058,126	3,066,755	N/A	14
CSADHS [40]	3,054,709	3,055,071	3,055,138	N/A	12
EP-SQP [21]	3,159,204	3,169,093	N/A	N/A	27
MHEP-SQP [22]	3,151,445	3,157,738	N/A	N/A	26
CSO [52]	3,051,260	3,053,465	3,054,960	256.2274	10
HGABF [19]	3,050,235	3,051,291	3,053,567	N/A	9
TSMILP [72]	3,047,932	3,047,932	3,047,932	N/A	3
MIQP [70]	3,049,359	3,049,359	3,049,359	N/A	8
EFA [35]	3,048,867	3,050,679	3,051,531	N/A	6
SAMFA [34]	3,048,898	3,050,548	3,051,394	N/A	7
MTLA [46]	3,048,609	3,049,871	3,051,113	N/A	4
EP [20]	3,046,110	3,046,640	3,046,970	227.87	2
IPSO [31]	3,090,570	3,071,588	N/A	N/A	24
EAPSO [25]	3,054,961	3,055,257	3,055,341	N/A	13
ICPSO [27]	3,064,497	3,071,588	N/A	N/A	19
CSAPSO [28]	3,066,907	3,075,023	N/A	N/A	20
BBPSO [66]	3,062,144	3,067,277	N/A	2177.60	18
DGPSO [65]	3,148,992	3,154,438	N/A	N/A	25
FAPSO [29]	3,048,609	3,049,162	3,049,781	N/A	4
Standard HPSO-TVAC	3,084,580	3,116,502	3,154,818	3299.14	22
NHPSO-JTVAC	3,048,661	3,050,195	3,053,428	893.25	5
MNHPSO-JTVAC	**3,045,545**	**3,046,407**	**3,048,006**	**300.83**	**1**

TABLE 7. Statistical optimal results obtained by different optimization algorithms for Case 4.

respectively. Also, it can be seen from Table 5 that the quality of the obtained results by proposed MNHPSO-JTVAC algorithm such as the minimum, mean and maximum cost are better than other algorithms reported in literature.

4.2.3. Case 3. In this case, the practical and operational constraints, such as ramp rate constraints, valve-point effects, prohibited operation zones (POZs) limits and system transmission losses are considered. Table 6 lists optimal results of this case such as the minimum, average, maximum and standard deviation of the total cost obtained over 30 runs by the HPSO-TVAC algorithms and the previously developed algorithms such as CDBCO [64] and SOS [13]. It can be observed that the obtained optimal generator schedule with proposed MNHPSO-JTVAC optimizer is better than that of the CDBCO [64], SOS [13], standard HPSO-TVAC and NHPSO-JTVAC algorithms in terms of the minimum, average, maximum and standard deviation (Std. Dev) of the total generation cost.

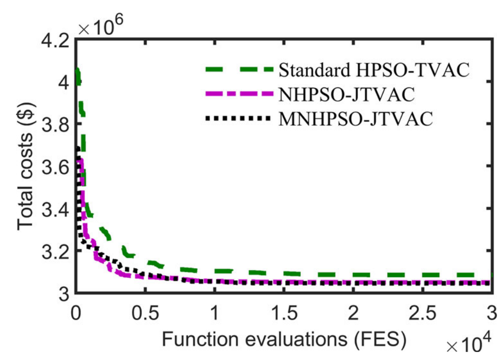

FIGURE 5. Convergence characteristics of the HPSO-TVAC algorithms for Case 4.

4.2.4. Case 4. This case is thirty-thermal-generator test system test system created by tripling the ten-thermal-generator test system of case 1 with considering ramp rate constraints, valve-point effects, and without prohibited operation zones limits (POZs) and system transmission loss. Table 7 lists optimal results this case such as the minimum, average, maximum and standard deviation of the total cost obtained over 30 runs by the HPSO-TVAC algorithms and the previously developed algorithms such as MACO [18], EBSO [23], DE [37], ECE [53], HHS [51], CDBCO [64], HIGA [17], CSADHS [40], EP-SQP [21], MHEP-SQP [22], CSO [52], HGABF [19], deterministic two-stage mixed integer linear programing (TSMILP) [72], MIQP [70], EFA [35], SAMFA [34], MTLA [46], EP [20], IPSO [31], EAPSO [25], ICPSO [27], CSAPSO [28], BBPSO [66], DGPSO [65] and FAPSO [29].

The comparative study of the proposed algorithms and the previously developed algorithms reported in literature shows that the proposed MNHPSO-JTVAC optimizer has effective performance and is a reliable tool in solving large-scale DED problems. Fig. 5 represents convergence characteristics of the HPSO-TVAC algorithms toward obtained optimal solution for Case 4.

5. CONCLUSIONS

This paper proposes a novel PSO algorithm, called MNHPSO-JTVAC, which is an improved version of self-organizing hierarchical PSO with time-varying acceleration coefficients (HPSO-TVAC). In the proposed MNHPSO-JTVAC algorithm, a modification has been made in choosing the control parameters of HPSO-TVAC. In addition, to balance and tradeoff between the number of iterations and the number of population, the dynamic population reduction method was introduced during the algorithm's iterations. At first, the efficiency of the proposed algorithm for 14 well-known benchmark functions was assessed. Then, it is used to solve different dynamic economic dispatch problems with the objective of minimizing the operation cost, taking into account the equality and inequality constraints of the generators and the system. The obtained results show that the proposed MNHPSO-JTVAC algorithm yields better standard deviation and final solutions for the benchmark test functions and dynamic economic dispatch problems in comparison with the recently presented algorithms, which verifies the efficiency and superiority of the proposed method in solving the optimization problems.

DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

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