

Solution of Economic and Environmental Dispatch with Valve Point Effect Using Moth Swarm Algorithm

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Abstract — In this paper, a new bio inspired optimization technique called Moth Swarm Algorithm (MSA) is developed to find the optimal solution for Combined Economic and Environmental dispatch (CEED) problems. Its aim to minimize both the operating fuel cost and emission levels simultaneously while satisfying load demand and operational constraints. The CEED problem is formulated as multi-objective function by considering the fuel cost and environmental pollutant impact with satisfying load demand and operational constraints. The developed algorithm is carried on two different test cases having valve point effect. The simulated result is compared with those obtained by other algorithms in the literature to confirm its effectiveness. Results show that the MSA gives best fuel cost and minimum emission than the other reported algorithms.

Keywords— Moth Swarm algorithm optimization; Combined Economic and Environmental dispatch; Valve Point Effect.

I. INTRODUCTION

During the last decades, the increasing in industrial application day after day requires electric energy. The great percentage of electrical energy is produced from fossil fuel in thermal power plants. Economic load dispatch (ELD) problem has become crucial task in operation and planning of power system [1, 2]. This operation is to schedule the committed generating units output to meet the load demand for the purpose of minimizing the total fuel cost while satisfying a series of equality and inequality constraints. As result the combined economic and emission dispatch (CEED) is the modification on the traditional (ELD) to meet the need of reducing atmospheric pollution. CEED problem is a multi-objective function which have two objective function, minimization the total fuel cost and reduction the emission pollution.

Recently, several optimization techniques have been proposed to solve CEED problems such as Genetic Algorithm (GA) [3], Particle Swarm Optimization (PSO) [4], Ant Colony Optimization (ACO) [5], Differential Evolution (DE) [6], Evolutionary Strategy (ES) [7], Evolutionary Programming (EP) [8], [9], Pareto Differential Evolution PDE [10], Strength Pareto Evolutionary Algorithm-2 SPEA-2 [10], Gravitational Search Algorithm (GSA) [11], Multi-Objective Differential Evolution MODE [10], Enhanced Multi-Objective Cultural Algorithm EMOCA [13], Artificial Bee Colony and Personal

best-oriented ABC_PSO [12], Flower Pollination Algorithm FPA [15], Non dominated Sorting Genetic Algorithm-II NSGAII [10], Modified Artificial Bee Colony with Disruptive Logistic map MABC/D/Log [14], Modified Artificial Bee Colony with Disruptive Cat MABC/D/Cat [14],

Moth Swarm algorithm (MSA) is a novel optimization technique that has been presented by Al-Attar A. et al. [16]. MSA simulates the oriented motion of moth flame insects around the moonlight and artificial lights. In MSA the exploration and exploitation capabilities are enhanced by applying a Lévy-mutation and learning mechanism with immediate memory.

In this paper, MSA is used for solving ELD and CEED problems considering series of constraint, such as the upper and lower limit of each generators and valve point effect (VPE). The main purpose of CEED problems are minimization the total fuel cost and reducing the emission level simultaneously. A price penalty factor approach is proposed to convert the CEED problem into a single objective function. The proposed algorithm is tested on 10 and 40 thermal generation units and the results are compared with those obtained by other techniques.

The rest of paper is arranged as follows: Section II describes the problem formulation of ELD and CEED problems. Section III explains the concept of MSA and its implementation procedures for solving the CEED problem. Section IV shows the numerical results. Finally, the conclusions of this work are presented in Section V.

II. PROBLEM FORMULATION

The main purpose of solving the CEED problem is minimizing the fuel cost and emission of generation units' simultaneously with considering the system constraints. CEED problem can be described as follows:

2.1. Economic load dispatch (ELD)

ELD problem is defined as minimizing the total fuel cost of the thermal generation units. Thereby, ELD problem can be defined as follows:

$$F_t = \sum_{i=1}^d F_i(P_i) = \sum_{i=1}^d a_i P_i^2 + b_i P_i + c_i \quad \$ \quad (1)$$

where, F_t is the total fuel cost. a_i , b_i and c_i are the cost coefficients of i^{th} generator in $\$/\text{MW}^2$, $\$/\text{MW}$ and $\$$ respectively. d is number of generators.

2.2. Fuel cost considering valve point effect

Practically, the quadratic fuel costs of some generation units are non-smooth functions due to influences of the steam admission from their control valves which call valve-point loading effect. Steam admission will lead to occurrence of ripples in fuel cost [17] as shown in Fig. 1. The valve-point loading effect is considered by adding a sine term to the fuel cost as follows:

$$F_t = \sum_{i=1}^d F_i(P_i) = \sum_{i=1}^d a_i P_i^2 + b_i P_i + c_i + |f_i \sin(e_i(P_{min} - P_i))| \quad \$ \quad (2)$$

where, e_i and f_i are the i^{th} generator coefficients for the valve point effect in $\$$ and MW^{-1} , respectively.

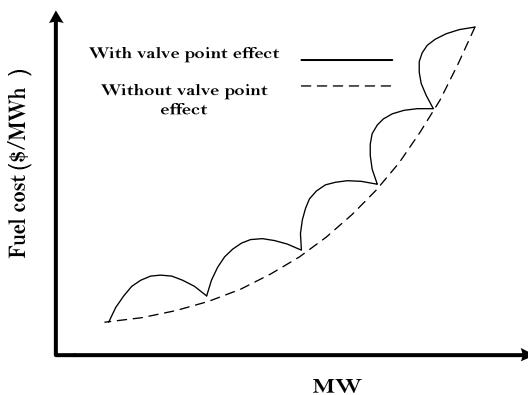


Fig. 1. Cost function with and without valve point effect.

2.3. Emission dispatch problem

Burning fossil fuels of the generation units leads to atmospheric pollutants where Sulphur dioxide and nitrogen oxides are emitted [18]. The emission of each generator is modeled as summation of two terms including quadratic and an exponential function as described in Eq. (3) [19].

$$E_t = \sum_{i=1}^d E_i(P_i) = \sum_{i=1}^d (k_i P_i^2 + l_i P_i + g_i + m_i \times \exp(h_i \times P_i)) \quad (3)$$

where, E_t is the total emission. E_i is the emission of i^{th} generator. g_i , h_i and k_i are the i^{th} generator emission coefficients in kg/MW^2 , kg/MW and kg respectively.

2.4. CEED problem

CEED problem solution target is minimizing two objective function include the total fuel cost and emission simultaneously. The CEED problem is converted from multi-

objective function to a single objective function using price penalty factor method as follows:

$$F = F_t + R \times E_t \quad (4)$$

where, R is the price penalty factor. The procedures for finding the price penalty factor can be arranged as follows:

- (1) Find the price penalty factor for each unit as:

$$R_i = \frac{F_i(P_i^{max})}{E_i(P_i^{max})} \quad \$/\text{kg} \quad (5)$$

- (2) Arrange the value of R_i in ascending order.

- (3) Add the P_i^{max} of each generation unit one at a time, starting from the lowest R_i until

$$P_i^{max} \geq P_D \quad (6)$$

- (4) Find the last value of R_i that achieves the previous condition which represents the price penalty factor.

2.5. Constraints

Minimizing the previous objective function subject, the following constraints:

2.5.1. Quality constraint

The quality constraint represents the power balance in system where the generated active power equals to summation of the total power demand and the power loss as follows:

$$\sum_{i=1}^d P_i = P_D + P_L \quad (7)$$

where, P_D is the load power demand and P_L is the system power loss which can be calculated using Kron's loss formula as follows:

$$P_L = \sum_{i=1}^d \sum_{j=1}^d (P_i B_{ij} P_j) + \sum_{i=1}^d B_{oi} P_i + B_{oo} \quad (8)$$

where, B_{ij} , B_{oi} and B_{oo} are the loss coefficients. P_i and P_j are the output powers of i^{th} generator and j^{th} generator, respectively.

2.5.2. inequality constraint

Inequality constraint includes the generator output power limits as:

$$P_i^{max} \geq P_i \geq P_i^{min} \quad (9)$$

where, P_i^{max} and P_i^{min} the maximum and the minimum limits of generated power, respectively.

III. OVERVIEW OF MOTH SWARM ALGORITHM OPTIMIZATION

Moth Swarm Algorithm (MSA) is a new bio-inspired optimization technique that is conceptualized from motion of a moth swarm towards moonlight. Moth positions represent the candidate solution in optimization problem. Every position is

considered a source light and the objective function value represents its luminescence intensity. Three groups of moths determine the aspects of MSA technique which are pathfinders group, Prospectors group and onlookers group. The main task of pathfinders group is guiding the swarm to the best positions (light sources). Prospectors group is a small group employed to find a new area around the pathfinders by navigation randomly in spiral path. Onlookers are the third group where the moths go directly to the global position directly. The procedures of MSA are organized as follows:

- (1) Initialization:** the moth positions are created randomly within the upper and lower limits of control variables as follows:

$$X(n, d) = \text{rand} * (Up(n, d) - Lp(n, d)) + Lp(n, d) \quad (10)$$

where, Up and Lp are the upper limit and the lower limit of the control variables, respectively. n is number of moths and d is number of variables (dimension).

- (2) Selection:** the objective functions are calculated for all moths and determine the best moths in term of the objective function then select the first best moths as light sources or (pathfinders) and the second best are selects as prospectors while the worst moths are selected as onlookers.

- (3) Discovering:** to avoid algorithm stagnation or enhancing its exploration phase the pathfinder moths try to find new areas or update their locations by interact together (crossover operations) by applying a crossover with lévy-mutation. The crossover point are determined based on solutions diversity where the normalized dispersal degree σ_j^t of the population at t iteration is assigned as:

where,

$$\bar{x}_j^t = \frac{1}{n_p} \sum_{i=1}^{n_p} x_{ij}^t \quad (11)$$

$$\sigma_j^t = \sqrt{\frac{\frac{1}{n_p} \sum_{i=1}^{n_p} (x_{ij}^t - \bar{x}_j^t)^2}{\bar{x}_j^t}} \quad (12)$$

where, n_p is number of pathfinders. Hence, the relative dispersion is founded as:

$$\mu^t = \frac{1}{d} \sum_{j=1}^d \sigma_j^t \quad (13)$$

If the pathfinder moths have a low dispersal degree, they will be taken in the group of crossover points C_p , as follows:

$$j \in c_p \quad \text{if} \quad \sigma_j^t \leq \mu^t \quad (14)$$

Pathfinder variables will update their position by crossover process hence the solution will be updated by integrated the modified of the sub-trail solution into the analogical variables. The full trial solution S_{pj} may be defined as:

$$S_{pj}^t = \begin{cases} S_{pj}^t & \text{if } j \in c_p \\ x_{pj}^t & \text{if } j \notin c_p \end{cases} \quad (15)$$

The best obtained solutions are captured to continue for the next iteration as follows:

$$\overrightarrow{x_p^{t+1}} = \begin{cases} \overrightarrow{x_p^t} & \text{if } f(\overrightarrow{S_p^t}) \geq f(\overrightarrow{x_p^t}) \\ \overrightarrow{s_p^t} & \text{if } f(\overrightarrow{S_p^t}) < f(\overrightarrow{x_p^t}) \end{cases} \quad (16)$$

The probability Pr_p depends upon the fitness function (f_p) value or the luminescence (fit_p) intensity which can be found as follows:

$$Pr_p = \frac{fit_p}{\sum_{p=1}^{n_p} fit_p} \quad (17)$$

$$fit_p = \begin{cases} \frac{1}{1 + f_p} & \text{for } f_p \geq 0 \\ 1 + |f_p| & \text{for } f_p < 0 \end{cases} \quad (18)$$

- (4) Spiral transferring:** prospector moths update their positions in spiral path around the pathfinder moths as follows:

$$x_i^{t+1} = |x_i^t - x_p^t| \cdot e^\theta \cdot \cos 2\pi\theta + x_p^t \quad (19)$$

where, x_p^t is the pathfinder position which is selected based on its probability P_p and x_i^t is the. $\theta \in [r, 1]$ is a random value to define the spiral shape and $r = -1 - t/T_{max}$. T_{max} is maximum number of iterations.

For enhancing the convergence characteristics of MSA, the prospectors number n_f is decreased with iterations as follows:

$$n_f = \text{round}\left((n - n_p) \times \left(1 - \frac{t}{T_{max}}\right)\right) \quad (20)$$

- (5) Navigation around global solution:** the main purpose of this procedure is enhancing the convergence characteristics. Decreasing of prospectors number will lead to increase the onlookers number $n_o = n - n_f - n_p$. The onlookers are forced to search at the most promising area and to achieve this onlooker are split into the following two parts:

(a) Gaussian walks: in this part, the onlookers navigate and focus on the promising places by using Gaussian stochastic distribution. The size of onlookers in this part is $n_G = \text{round}(n_o/2)$. The found new onlookers by Gaussian stochastic distribution are given as follows:

$$x_i^{t+1} = x_i^t + \varepsilon_1 + [\varepsilon_2 \times \text{best}_g^t - \varepsilon_3 \times x_i^t] \quad \forall i \in \{1, 2, \dots, n_G\} \quad (21)$$

$$\varepsilon_1 \sim random(size(d))$$

$$\oplus N \left(best_g^t, \frac{\log t}{t} \times (x_i^t - best_g^t) \right) \quad (22)$$

where, $best_g^t$ is the best obtained solution. ε_1 is a random samples taken from Gaussian stochastic distribution ε_2 and ε_3 are random numbers within the rang [0,1].

(b) Learning mechanism with immediate memory. The size of these onlookers equal to $n_A = n_o - n_G$. The new founded onlookers are based on learning operators with an instantaneous memory which can be found as follows:

$$x_i^{t+1} = x_i^t + 0.001 \cdot T_{\max} [x_i^{\min}, x_i^{\max} - x_i^t] \\ + (1 - t/T_{\max}) \cdot r_1 \\ \cdot (best_p^t - x_i^t) + 2t/T_{\max} \cdot r_2 \\ \cdot (best_g^t - x_i^t) \quad (23)$$

where, $best_g^t$ is the best obtained solution. r_1 and r_2 are random numbers within the rang [0,1].

Implementation of MSA for economic and emission dispatch

Step 1 : Read the system data including the generators parameters.

Step 2 : Define the parameters of MSA includes number of search agents, number of Pathfinders, maximum number of iterations, upper and lower limits of generated powers and the system constraints.

Step 3 : Initialize the first population of moths (generated powers), randomly as depicted in (15). Find the Price penalty factor and calculate the objective function of each search agents

$$X = \begin{bmatrix} P_{g1,1} & P_{g1,2} & \dots & P_{1d} \\ P_{g2,1} & P_{g2,2} & \dots & P_{g2,1} \\ \vdots & \vdots & \ddots & \vdots \\ P_{gn,1} & P_{gn,2} & \dots & P_{gn,d} \end{bmatrix} \quad (24)$$

Step 4 : Select the first best moths as pathfinders and the second best are selected as prospectors while the worst moths are selected as onlookers in term of the objective function.

Step 5 : Find the new moths as follows:

- Update the pathfinders according to (11) – (16).
- Update the prospectors according to (19).
- Update the onlookers according to (12) to (14).

Step 6 : Calculate the objective function of the updated moths.

Step 7 : Repeat steps from (21) to (23) until the stopping criteria are achieved.

Step 8 : obtain the best pathfinder (the optimal generators output) and its corresponding objective function.

IV. RESULT AND DISCUSSION

To verify the effectiveness of MSA for solving CEED problem, it has been applied on two test systems and the obtained results are compared with other optimization techniques. The software program code was written in the commercial MATLAB software program computing environment using M-File program. It is applied on a 2.20 GHz i5 personal computer with 4.00 GB-RAM and using MATLAB R2014a. for all studied cases the search agents number and maximum number of iteration are set to be 50 and 200, respectively.

4.1) Test case 1

The first test system consists of ten thermal generators with non-smooth fuel cost and emission functions and its load demand is 2000MW. The system data including the cost coefficients, emission coefficients, and the transmission loss are given in [13]. The simulation results for solving the CEED problem that obtained by MSA and other meta-heuristic optimization techniques including the generated active power, total fuel costs and emissions are listed in Table I. the founded fuel cost considering the valve point effect equals to $1.1335*10^5$ \$ while emission equals to 4102.4 Ib, thereby the obtained fuel cost is less by 113539 \$, 113510 \$, 113490 \$, 113484 \$, 113445 \$, 113420 \$ compared to NSGAII [10], PDE [10], SPEA-2 [10], GSA [11], MODE [10], EMOCA [13], ABC_PSO [12], respectively. also the obtained emission is less by compared to NSGAII [10], PDE [10], SPEA-2 [10], GSA [11], MODE [10], EMOCA [13], ABC_PSO [12]. Thus the MSA proposed algorithm succeed achieving the best CEED solution with minimum time.

4.2) Test case 2

In this case, forty generating units with non-smooth fuel cost and emission functions. Unit data for 40-generators test case system and loss coefficients are given in [20] which has a total power demand 10500 MW. It should highlight that the power losses in this case is neglected thus the summation of generated powers equal to total power demand [20]. Table II summarizes the result obtains from MSA and compared with NSGA-II, MODE, GSA [11], PDE, SPEA-2[10], MABC/D/Cat [14] and MABC/D/Log [14]. The obtained fuel cost and emission by MSA for this are $1.2405*10^5$ \$ and $2.1541*10^5$ ton, respectively. From Table II, it is clear that the result of the proposed algorithm has better results with lowest fuel cost and emission compared with other meta-heuristic optimization techniques. Moreover, the average CPU time is less than other algorithms.

Table.I RESULTS OF 10- GENERATING UNITS COMPARING WITH OTHER ALGORITHM.

Outputs	NSGAII [10]	PDE [10]	GSA [11]	EMOCA [13]	SPEA-2 [10]	MODE [10]	ABC_PSO [12]	MSA
P1 (MW)	51.9515	54.9853	54.9992	55	52.9761	54.9487	55	54.9250
P2 (MW)	67.2584	79.3803	79.9586	80	72.813	74.5821	80	78.6747
P3 (MW)	73.6879	83.9842	79.4341	83.5594	78.1128	79.4294	81.14	90.8276
P4 (MW)	91.3554	86.5942	85.0000	84.6031	83.6088	80.6875	84.216	85.2798
P5 (MW)	134.0522	144.4386	142.1063	146.5632	137.2432	136.8551	138.3377	149.6373
P6 (MW)	174.9504	165.7756	166.5670	169.2481	172.9188	172.6393	167.5086	160.7688
P7 (MW)	289.4350	283.2122	292.8749	300	287.2023	283.8233	296.8338	297.5672
P8 (MW)	314.0556	312.7709	313.2387	317.3496	326.4023	316.3407	311.5824	310.0808
P9 (MW)	455.6978	440.1135	441.1775	412.9183	448.8814	448.5923	420.3363	426.6177
P10 (MW)	431.8054	432.6783	428.6306	434.3133	423.9025	436.4287	449.1598	429.1621
Fuel cost*10 ⁵ (\$)	1.13539	1.1351	1.1349	1.13445	1.1352	1.13484	1.1342	1.1335
Emission (Ib)	4130.2	4111.4	4111.4	4113.98	4109.1	4124.9	4120.1	4102.4
Losses (MW)	84.25	83.9	83.9869	83.56	84.1	84.33	84.1736	83.6187
CPU(S)	6.02	4.23	NA	2.90	7.53	3.82	NA	3.223747

Table.II RESULTS OF DIFFERENT ALGORITHMS FOR 40-GENERATORS POWER SYSTEM WITH VALVE POINT EFFECT.

Outputs	NSGAII [10]	SPEA-2 [10]	GSA [11]	MABC/D/Log [14]	MODE [10]	PDE [10]	MABC/D/Cat [14]	MSA
P ₁ (MW)	113.8685	113.9694	113.9989	110.7998	113.5295	112.1549	110.7998	110.634
P ₂ (MW)	113.6381	114	113.9896	110.7998	114	113.9431	110.7998	109.776
P ₃ (MW)	120	119.8719	119.9995	97.3999	120	120	97.3999	117.451
P ₄ (MW)	180.7887	179.9284	179.7857	174.5486	179.8015	180.2647	174.5504	135.169
P ₅ (MW)	97	97	97	97	96.7716	97	87.7999	95.8187
P ₆ (MW)	140	139.2721	139.0128	105.3999	139.2760	140	105.3999	137.920
P ₇ (MW)	300	300	299.9885	259.5996	300	299.8829	259.5996	297.231
P ₈ (MW)	299.0084	298.2706	300	284.5996	298.9193	300	284.5996	290.192
P ₉ (MW)	288.8890	290.5228	296.2025	284.5996	290.7737	289.8915	284.5996	294.778
P ₁₀ (MW)	131.6132	131.4832	130.3850	130	130.9025	130.5725	130	239.700
P ₁₁ (MW)	246.5128	244.6704	245.4775	318.2129	244.7349	244.1003	318.1921	315.086
P ₁₂ (MW)	318.8748	317.2003	318.2101	243.5996	317.8218	318.2840	243.5996	244.023
P ₁₃ (MW)	395.7224	394.7357	394.6257	394.2793	395.3846	394.7833	394.2793	306.577
P ₁₄ (MW)	394.1369	394.6223	395.2016	394.2793	394.4692	394.2187	394.2793	449.454
P ₁₅ (MW)	305.5781	304.7271	306.0014	394.2793	305.8104	305.9616	394.2793	470.642
P ₁₆ (MW)	394.6968	394.7289	395.1005	394.2793	394.8229	394.1321	394.2793	394.379
P ₁₇ (MW)	489.4234	487.9857	489.2569	399.5195	487.9872	489.3040	399.5195	479.705
P ₁₈ (MW)	488.2701	488.5321	488.7598	399.5195	489.1751	489.6419	399.5195	486.886
P ₁₉ (MW)	500.8	501.1683	499.2320	506.1716	500.5265	499.9835	506.1985	421.430
P ₂₀ (MW)	455.2006	456.4324	455.2821	506.2206	457.0072	455.4160	506.1985	484.854
P ₂₁ (MW)	434.6639	434.7887	433.4520	514.1105	434.6068	435.2845	514.1472	433.453
P ₂₂ (MW)	434.15	434.3937	433.8125	514.1472	434.5310	433.7311	514.1455	442.387
P ₂₃ (MW)	445.8385	445.0772	445.5136	514.5664	444.6732	446.2496	514.5237	481.271
P ₂₄ (MW)	450.7509	451.8970	452.0547	514.4868	452.0332	451.8828	514.5386	435.029
P ₂₅ (MW)	491.2745	492.3946	492.8864	433.5195	492.7831	493.2259	433.5196	441.081
P ₂₆ (MW)	436.3418	436.9926	433.3695	433.5196	436.3347	434.7492	433.5195	434.769
P ₂₇ (MW)	11.2457	10.7784	10.0026	10	10	11.8064	10	12.6220
P ₂₈ (MW)	10	10.2955	10.0246	10	10.3901	10.7536	10	15.6951
P ₂₉ (MW)	12.0714	13.7018	10.0125	10	12.3149	10.3053	10	15.7430
P ₃₀ (MW)	97	96.2431	96.9125	87.8042	96.9050	97	97	88.8972
P ₃₁ (MW)	189.4826	190.0000	189.9689	159.733	189.7727	190.0000	159.733	173.964
P ₃₂ (MW)	174.7971	174.2163	175	159.7331	174.2324	175.3065	159.733	178.781
P ₃₃ (MW)	189.2845	190	189.0181	159.733	190	190	159.733	161.424
P ₃₄ (MW)	200	200	200	200	199.6506	200	200	199.400
P ₃₅ (MW)	199.9138	200	200	200	199.8662	200	200	178.377
P ₃₆ (MW)	199.5066	200	199.9978	200	200	200	200	199.988
P ₃₇ (MW)	108.3061	110	109.9969	89.1141	110	109.9412	89.1141	101.710
P ₃₈ (MW)	110	109.6912	109.0126	89.1141	109.9454	109.8823	89.1141	107.275
P ₃₉ (MW)	109.7899	108.5560	109.4560	89.1141	108.1786	108.9686	89.1141	89.9452
P ₄₀ (MW)	421.5609	421.8521	421.9987	506.1951	422.0628	421.3778	506.1879	426.454
Total cost*10 ⁵ (\$)	1.2583	1.2581	1.2578	1.24491161	1.2579	1.2573	1.24490903	1.2405
Emission *10 ⁵ (ton)	2.1095	2.1110	2.1093	2.56560267	2.1119	2.1177	2.56560267	2.1541
CPU (S)	7.32	8.57	NA	NA	5.39	6.15	NA	5.22021

V. CONCLUSION

In this paper, the moth swarm optimization (MSA) algorithm has been developed in order to solve the combined economic and environmental dispatch (CEED) problems. The developed MSA has been compared with different optimization techniques. The obtained results have proved the superiority of MSA for solving CEED problems in term of the convergence characteristics and minimum objective functions for small and large scale power systems. Moreover, valve point effect, environmental emissions, and transmission line losses are included in the CEED analysis. Consequentially, MSA optimization technique can be considered a raising technique for solving CEED problems in power systems. The obtained results verified the effectiveness and superiority of MSA compared to other meta-heuristic optimization techniques.

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