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Modified moth swarm algorithm for optimal economic load dispatch problem

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ABSTRACT

In this study, optimal economic load dispatch problem (OELD) is resolved by a novel improved algorithm. The proposed modified moth swarm algorithm (MMSA), is developed by proposing two modifications on the classical moth swarm algorithm (MSA). The first modification applies an effective formula to replace an ineffective formula of the mutation technique. The second modification is to cancel the crossover technique. For proving the efficient improvements of the proposed method, different systems with discontinuous objective functions as well as complicated constraints are used. Experiment results on the investigated cases show that the proposed method can get less cost and achieve stable search ability than MSA. As compared to other previous methods, MMSA can archive equal or better results. From this view, it can give a conclusion that MMSA method can be valued as a useful method for OELD problem.

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Nomenclature

B_{tn}, B_{0t}, B_{00}	Coefficients of B-matrix for transmission power loss
Cp	The number of randomly selected control variables among *Dim* variables
D_s	Total system demand
Dim	The number of control variables of each solution
$\varepsilon_1, \varepsilon_2$, r_1, r_2, r_3	Random numbers distributed uniformly within the interval [0,1]
j	The *jth* variable of the *pth* new solutions
L_{p1}, L_{p2}	Two Lévy flight distributions
m_t, n_t, o_t	Fuel cost function coefficients of the *tth* thermal generator
m_{tS}, n_{tS}, o_{tS}	Fuel cost function coefficients for the *S* fuel type of the *tth* thermal generator
n_1, n_2, n_3	The number of solutions in group 1, group 2 and group 3
$P_{tS,\min}, P_{tS,\max}$	The minimum and maximum power output of the *tth* thermal generator corresponding to the fuel cost source *S*
P_t	Power output of the *tth* thermal generator

$P_{t,\min}, P_{t,\max}$	The minimum and maximum power output of the *tth* thermal generator
P^{l}_{tj-1}, P^{u}_{tj}	The lower and upper limits of the *jth* prohibited operating zone of the *tth* generation unit
t, T	The current iteration and the maximum iteration
$V_{r1}, V_{r2}, V_{r3}, V_{r4}, V_{r5}, V_{rA}$	Randomly selected solutions from solutions
V_{best}, V_{Gbest}	The best solution in group 1, group 2 and all groups

1. INTRODUCTION

In a power system, electric energy is produced by thermal plants, hydropower plants and renewable power plants. The fuel cost of renewable power plants such as solar thermal plants, photovoltaic power plants and wind turbines is approximately equal to zero; however, the sources are unstable and changeable during a small interval. On the contrary, the fuel cost for power generation of thermal plants is very expensive owing to fossil fuel. In the future, the fossil fuel including gas coal, and oil becomes exhausted. So, the fuel cost of thermal plants is the main objective during the operation of the power systems. So far, a solution for dealing with the fuel cost of thermal plants can be implemented by an optimal economic load dispatch problem (OELD). The work in OELD problem is to determine the best effective strategy for allocating the power output of all available thermal plants so that total fuel cost of plants can be decreased at least level [1]. In this paper, we concentrate to study three systems that are employed to test the powerful ability of optimization tools. The first system with 6 units considers single fuel, prohibited zones and power loss. The second system with 10 units considers multiple fuels. The last system with 20 units considers power losses in the line transmission. For the first system, a huge number of methods consisting of modified particle swarm optimization (MPSO) [1], hybrid bacterial foraging algorithm and Nelder Mead algorithm (HBFNM) [2], differential evolution (DE) algorithm [3], multiple tabu search algorithm (MTS) [4], self-organizing hierarchical particle swarm optimization (SOH_PSO) [5], new adaptive particle swarm optimization (NAPSO) [6], krill herd algorithm (KHA) [7], chaotic bat method (CBM) [8], exchange market method (EMM) [9], adaptive charged system search method (ACSS) [10], opposition based krill herd method (OKHM) [11], and improved social spider optimization algorithm (ISSO) [12] have been satisfactorily applied. In this method group, MPSO [1] is a version of particle swarm optimization developed in 2007 while ISSO [12] is a variant of social spider optimization algorithm (SSO) proposed in 2019. ISSO was improved based on the classical SSO by proposing three improvements.

As a result, optimal solutions found by ISSO were better than MPSO and other methods. For 10-unit system, many methods as DE [3], antlion optimization algorithm (ALO) [13], artificial immune system (AIS) method [14], enhanced augmented Lagrange Hopfield network (EALHN) [15], enhanced lagrangian artificial neural network (ELANN) [16], improved quantum-behaved particle swarm optimization (IQPSO) [17], modified firefly algorithm (MFA) [18] and modified stochastic fractal search algorithm (MSFS) [19] have been successfully employed with the impressive results. Among these methods, MSFS is the latest tool that has been formed by proposing three modifications based on the structure of stochastic fractal search (SFS). By applying these modifications, the search ability of MSFS has been significantly improved when compared to SFS in term of solution quality, convergence speed and stabilization. For the last system, several methods are used for OELD problem. They include MFA [18], MSFS [19], Hopfield model (HM) [20], biogeography-based optimization (BBO) algorithm [21], general algebraic modeling system (GAMS) [22], improved group search optimizer (IGSO) [23], backtracking search algorithm (BSA) [24] and improved cuckoo search algorithm (ICSA) [25]. The contribution of the above algorithms is worthy of recognition in dealing with such OELD problem because these algorithms supply different solutions in aim to the most economical and stable power system operation.

Moth Swarm Algorithm (MSA) was a population-based method that proposed in 2017 [26]. Although MSA has used three phases including reconnaissance phase, transverse orientation phase and celestial navigation phase for producing new solution, it only has produced a number of new solutions equaling to population. The disadvantage of MSA is low solution quality, many calculation processes and variation searches by owning many formulas. In this study, a modified moth swarm algorithm (MMSA) is proposed pursuant to the traditional MSA by canceling ineffective formulas and using effective one to deal with drawbacks of MSA. Via three test systems, the results found by the proposed method are compared to other ones for solving OELD problem. Consequently, the key work considered as contributions in the study can be presented as follows:

- Point out disadvantages of MSA
- Suggest highly effective improvements on MSA
- MMSA has a faster simulation time and reaches a high performance and enhances stable search ability

2. MODEL OF ECONOMIC LOAD DISPATCH
2.1. Objective function

Reducing total fuel cost (*TC*) of all units available in the plant is the most momentous mission of OELD problem [27]. Its mathematical model is expressed by:

$$Reducing\ TC = \sum_{t=1}^{NG} TG_t \quad (1)$$

where TG_t is a cost function of the *tth* thermal unit and Its variable is a power output of the unit *t*. TG_t is established by two forms corresponding to two cases of using single fuel or multi fuel sources as given in (2) and (3) [28].

$$TG_t = m_t + n_t P_t + o_t P_t^2\ ,\ t=1, NG \quad (2)$$

$$TG_t = \begin{cases} m_{t1} + n_{t1}P_t + o_{t1}P_t^2, & \text{fuel 1, } P_{t1,\min} \le P_t \le P_{t1,\max} \\ \vdots & \\ m_{tS} + n_{tS}P_t + o_{tS}P_t^2, & \text{fuel 1, } P_{tS,\min} \le P_t \le P_{tS,\max} \end{cases} \quad (3)$$

2.2. Constraints of OELD problem

The solutions of the objective function of OELD problem must be constrained as follows:

- Balance between supply side and demand side: The entirety of system demand (D_s) and power losses in transmission lines (P_{Loss}) has a relationship with the power generation of units as the (4) [29].

$$D_s + P_{Loss} = \sum_{t=1}^{NG} P_t \quad (4)$$

In (4), the total power losses in transmission lines P_{Loss} is calculated by

$$P_{Loss} = \sum_{t=1}^{NG}\sum_{n=1}^{NG} P_t B_{tn} P_n + \sum_{t=1}^{NG} B_{0t} P_t + B_{00} \quad (5)$$

- Generation restriction**:** For each unit *t*, its power output generated is limited by [30]

$$P_{t,\min} \le P_t \le P_{t,\max} \quad (6)$$

- Violated working zone restriction: As the drawback of some equipment of unit, prohibited operating zones are existing. In these zones, thermal units do not operate. The typical restriction can be seen in the following form [7],

$$P_t \in \begin{cases} P_{t,\min} \le P_t \le P_{t1}^{l} \\ P_{tj-1}^{u} \le P_t \le P_{tj}^{l} \\ \vdots \\ P_{tN_k}^{u} \le P_t \le P_{t,\max} \end{cases} \quad (7)$$

3. METHOD
3.1. Moth swarm algorithm

MSA [26] was also based on the population to find the best solution. The initial population with *n* solutions is divided into three groups with n_1, n_2 and n_3 solutions corresponding to three phases of producing new solutions. The detail of these phases is presented below:

- Reconnaissance Phase: Firstly, the mutation technique is used for creating new solutions as the following model

$$S_p = V_{r1} + L_{p1}.\left(V_{r2} - V_{r3}\right) + L_{p2}.\left(V_{r4} - V_{r5}\right); p \in \{1, 2, \ldots, n_1\} \quad (8)$$

Secondly, adaptive crossover technique is used in aim to create the mixed solutions $Y_{p,j}$ as shown in (9)

$$Y_{p,j} = \begin{cases} V_{p,j} & \text{if } j \in Cp \\ S_{p,j} & \text{if } j \notin Cp \end{cases}; j = (1,2,...,Dim) \tag{9}$$

Thirdly, selection technique is applied to compare between old solutions and mixed solutions based on their fitness function to keep better ones as depicted in (10)

$$V_p = \begin{cases} V_p & \text{if } Fitness(Y_p) \geq Fitness(V_p) \\ Y_p & \text{if } Fitness(Y_p) < Fitness(V_p) \end{cases} \tag{10}$$

For the next phase, V_{Lights} containing n solutions is chosen, in which each solution is formed by randomly selecting the kept solutions in group 1.

- Transverse orientation phase: In the second phase, solutions are updated by using the (11),

$$V_i = \left|V_i - V_{Lights,i}\right|.e^{\theta}.\cos 2\pi\theta + V_i \ ; \ i \in \{n_1 + 1, n_1 + 2, \ldots, n_1 + n_2\} \tag{11}$$

where θ is a random number within the interval [-1-(t/T),1] [26]; n_2 is obtained by:

$$n_2 = round\left((n - n_1) \times \left(1 - \frac{t}{T}\right)\right) \tag{12}$$

- Celestial navigation phase: In the last phase, n_3 solutions are divided in two groups and newly updated by:

$$V_k = V_k + V_{rA} + \left[\varepsilon_1.V_{best} - \varepsilon_2.V_k\right]; \ \forall k \in \{n_2 + n_1 + 1, ..., n\} \tag{13}$$

$$V_k = V_k + r_1.V_{rA} + \left(1 - \frac{t}{T}\right) \cdot r_2 \cdot \left(V_{ligth,k} - V_k\right) + \left(\frac{2t}{T}\right) \cdot r_3 \cdot \left(V_{best} - V_k\right); \forall k \in \{n_2 + n_1 + 1, ..., n\} \tag{14}$$

3.2. The modified moth swarm algorithm

As seen from (8), new solutions via the mutation technique are updated by employing a random solution with two step sizes and two Lévy Flight distributions. Clearly, the newly produced solutions are always updated around random solutions. This work shows that a possibility of randomly selected one solution can be exploited many times for updating new different solutions while promising solutions could not be used. In addition, the exploitation space of Lévy Flight distribution is very large. So, if such distribution is used two times, some effective search zone can be eliminated. To cover the drawbacks, we propose new formula to replace with (8) as presented in (15).

$$V_p = V_p + L_{p1}.\left(V_p - V_{Gbest}\right); p \in \{1, 2, \ldots, n_1\} \tag{15}$$

As seen from (9), the adaptive crossover technique is applied to mix solutions. Obviously, this process does not ensure the quality of mixed solutions better than that of old solutions. By experiment, we saw that this technique should be ignored. It means that all new solutions updated by using (8) are compared to old solutions to keep better ones

4. NUMERICAL RESULTS

To appraise the performance of the proposed MMSA, 6-unit system considering single fuel source with prohibited zones and power loss constraints [3], 10-unit system relating to multiple fuel sources [15], and 20-unit system concerning single fuel source and power loss constraint [25] have been used. The detailed information and control parameters are abridged in Table 1. One hundred independent trial runs have been implemented for MSA and MMSA on a PC with processor Core i5 – 2.2 GHz and 4GB of RAM.

4.1. Investigating the improved level of the proposed method

In this section, the improvement level of the proposed method over MSA has been examined. Results obtained by the two methods are shown in Figures 1-6. Fitness under 100 runs for three cases are displayed in Figures 1, 3 and 5 while the best cost (*Min.FC*), the average cost (*Aver.FC*), and the worst cost (*Max.FC*) are presented in Figures 2, 4 and 6. Figures 1, 3 and 5 indicate that variations of the best cost and the worst cost values of MMSA are always smaller than those of MSA. Especially, in Figure 3 for 10-unit system with load demand of 2400 MW, 2500 MW, and 2700 MW and Figure 5 for 20-unit system, almost all runs of MMSA are approximately distributed on line. Furthermore, standard deviation of the proposed method and MSA is also reckoned under 100 runs. Figures 2, 4 and 6 point out that the costs of MMSA are better than those of MSA. Thus, the proposed method is capable of obtaining good results in three cases.

Table 1. Information of three used standard systems and the selected control parameters

Case	Test system	Type of fuel cost function	Constraints	*N*	*T*
1	6-unit	Fuel single	- Active power output - Balance between demand side and supply side - Prohibited zones	20	50
2	10-unit	Multi-fuel	- Active power output - Balance between demand side and supply side	40	200
3	20-unit	Fuel single	- Active power output - Balance between demand side and supply side	40	300

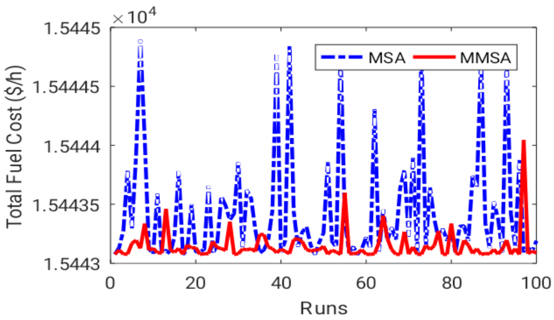

Figure 1. The fitness function given by MSA and MMSA methods over 100 runs for case 1

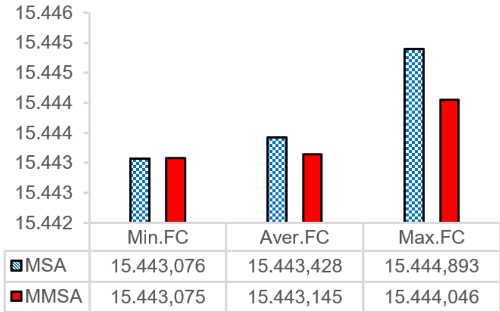

Figure 2. The costs from MSA and MMSA methods for case 1

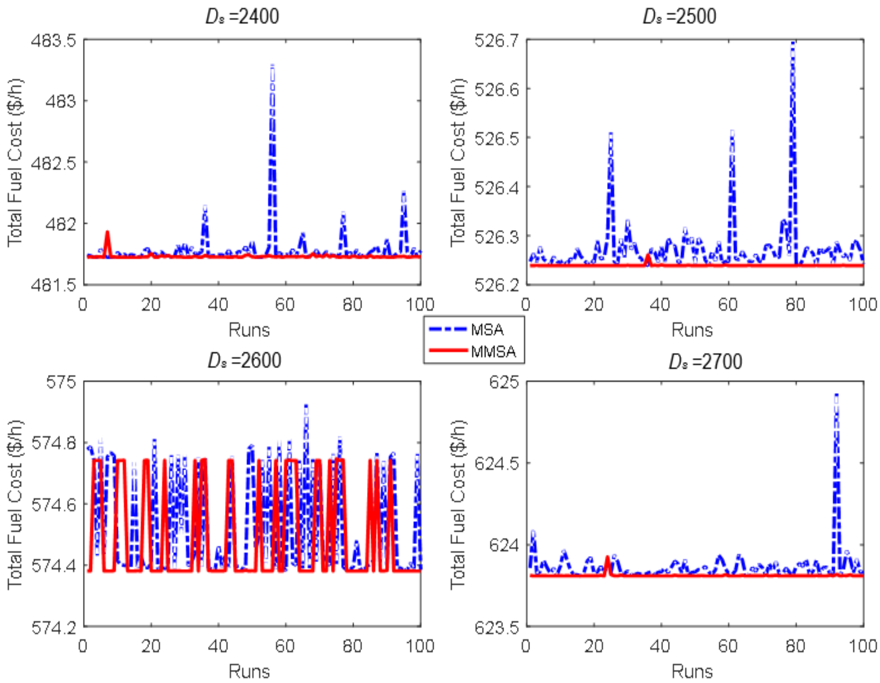

Figure 3. The fitness function given by MSA and MMSA methods over 100 runs for case 2 with different load demands

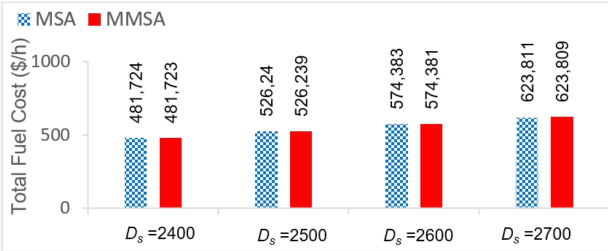

Figure 4. The minimum and standard deviation cost from MSA and MMSA methods for case 2

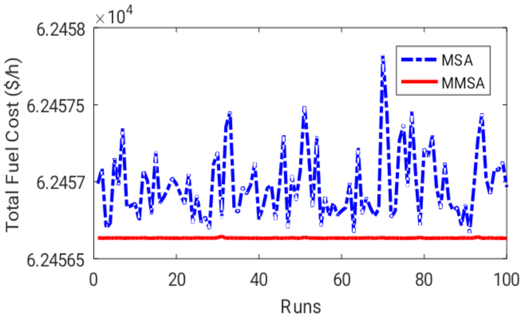

Figure 5. The fitness function given by MSA and MMSA methods over 100 runs for case 3

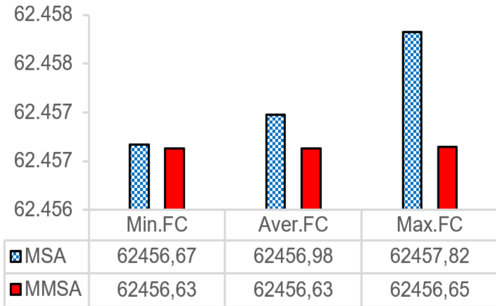

Figure 6. The costs from MSA and MMSA methods among 100 runs for case 3

4.2. Comparison of results on three systems

In OELD problem, the best cost is applied to be a main criterion for comparing the feasibility of MMSA on searching solutions to other previous reported techniques. In the case 1, the results from Figure 7 show that MMSA, KHA [7], EMM [9], OKHM [11], and ISSO [12] have a similar cost value of 15.443,075 ($/h) that is considered as the optimal result of this case. CBA [8] is the worst one with result of 15.450,238 ($/h). For case 2, from Table 2 the five smallest results are from MMSA, DE [3], ALO [13], EALHN [15], and MSFS [19] amongst the nine considered methods for different load demands. The best costs corresponding to four levels of load demand are 481.723 ($/h), 526. 239 ($/h), 574.381 ($/h), and 623.809 ($/h), in turns. ELANN [16] has bigger costs than nine compared methods while IQPSO [17] does not report cost value for load demand of 2700 (MW). The best cost of 62,456. 633 ($/h) is the smallest value for case 3 as shown in Figure 8. The figure shows that MMSA, MSFS [19], GAMS [22], IGSO [23], and ICSA [25] attain the same value and are put at the top group. The rest group has a presence of MFA [18], HM [20], BBO [21], and BSA [24] with the reported results of 62,456.638, 62,456. 634, 62,456.793, 62,456.6933 ($/h), respectively. After discussing the compared results of different methods for all cases, it can be seen that the optimization results of MMSA were equal or better than those from other algorithms.

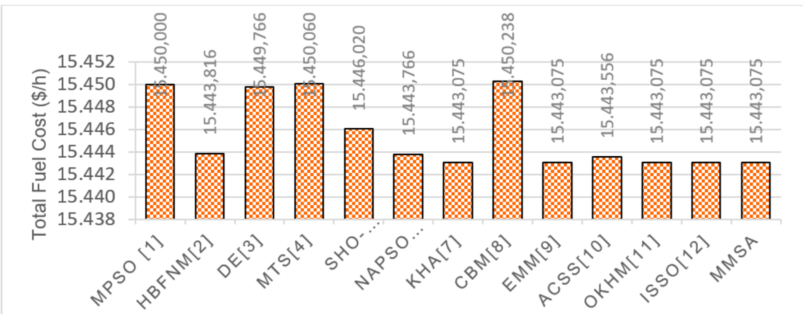

Figure 7. The best cost comparison among different algorithms for 6-unit system

Table 2. The best cost comparison among different algorithms for 10-unit system with various load demands

Methods	*Min. FC* ($/h)			
	D_s = 2400	D_s=2500	D_s= 2600	D_s= 2700
DE [3]	481.723	526.239	574.381	623.809
ALO [13]	481.723	526.239	574.381	623.809
AIS [14]	481.723	526.240	574.381	623.809
EALHN [15]	481.723	526.239	574.381	623.809
ELANN [16]	481.740	526.270	574.410	623.880
IQPSO [17]	481.732	526.245	574.387	-
MFA [18]	481.723	526.240	574.381	623.810
MSFS [19]	481.723	526.239	574.381	623.809
MMSA	481.723	526.238	574.381	623.809

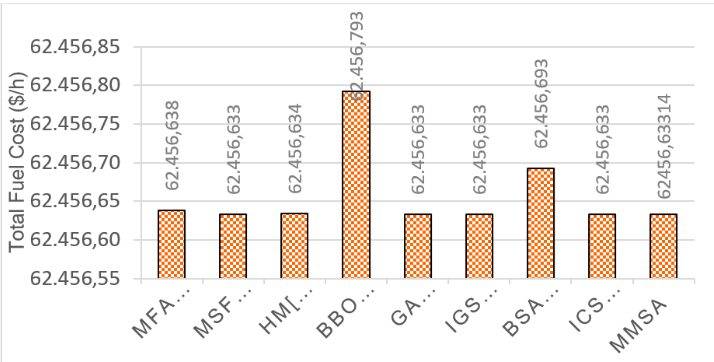

Figure 8. The best cost comparison among different algorithms for 20-unit system

5. CONCLUSION

In this study, the proposed MMSA is suggested for determining optimal solutions for various systems of the OELD problem. MMSA method is built by improving the first phase of MSA for handling the shortcomings of MSA like low solution quality, many calculation processes and variation searches. By applying improvements, the proposed method has better solution quality and smaller variation than MSA via the results obtained from three test systems. In comparisons with other existing methods, it also shows that MMSA reaches the best cost value to be equal or better than other methods for all cases. Additionally, the efficiency of MMSA over other reported algorithms has also been proven by calculating saving cost. Namely, the saving cost can reach to 7.16 ($/h) for case 1, 0.017 ($/h) for case 2 with load demand of 2400 (MW), 0.031 ($/h) for case 2 with load demand of 2500 (MW), 0.029 ($/h) for case 2 with load demand of 2600 (MW), 0.071 ($/h) for case 2 with load demand of 2700 (MW) and 0.16 ($/h) for case 3. As a result, it can deduce that the proposed method could be considered as a promising optimization method for addressing the OELD problem.

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