International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Journal Européen des Systèmes Automatisés
Vol. 58, No. 1, January, 2025, pp. 39-45
Journal homepage: http://iieta.org/journals/jesa

A Hybrid Moth Flam Algorithm Based on Particle Swarm Optimization for Unit Commitment Problem Solving

Shatha S. Abdulla Al-Kubragyi, Inaam Ibrahim Ali*

Department of Electrical Engineering, University of Technology, Baghdad 10001, Iraq

Corresponding Author Email: inaam.i.ali@uotechnology.edu.iq

https://doi.org/10.18280/jesa.580105

Received: 31 July 2024
Revised: 29 September 2024
Accepted: 10 October 2024
Available online: 31 January 2025

Keywords:
moth flam algorithm, particle swarm optimization, unit commitment (UC)

ABSTRACT

Unit commitment (UC) is the most important optimization task for power system operation. It is categorized as a large combinatorial, nonlinear, high-dimensional, mixed-integer optimization problem to schedule the best generation units during each distinct operating period to meet the demands of the system load and spinning reserve capacity. This study proposed a new hybrid paradigm by combining the Moth Flame Optimizer algorithm and particle swarm optimization (MPO-PSO) to determine the optimal solution to the unit commitment problem. The approach logically combines the ideas of MFO and PSO to overcome their shortcomings and improve their ability to search globally the MFO-PSO approach is better able to handle challenging, confined and unknown search space problems. Additionally, it is a simple methodology and requires a limited number of parameters. The MFO-PSO approach is evaluated against other evolutionary heuristic algorithms such as (EE, M-FA, PSO, AMFA, PSO-GWO, MPSO-EO, and MFO) on 26 bus-test system to manage the UC problem. It is evident from the statistical results, that the proposed algorithm can offer competitive and highly promising results. Regarding cost improvement and execution time the outcomes show that the suggested hybrid approach performs better than certain other heuristic algorithms and original MFO. The influence of the MFO-PSO approach on the accuracy and convergence rate for dealing the UC issue is shown by the simulation results section. It can be observed from the obtained results that, in comparison to the original MFO technique, the algorithm demonstrated improved accuracy, fast convergence, and good performance. Because of these details, the estimation showed increased accuracy and convergence. The interesting thing to note of it is that the PSO is added to improve the MFO's accuracy, which is already rather high. Furthermore, the study also shows the algorithm's efficacy in resolving difficult issues with constrained and unknown search spaces.

1. INTRODUCTION

In the modern energy system technology, the greatest interesting and a challenging aspect of the power system process is deciding the prober electrical generating units should operate at each time in order to meet a fluctuating electricity demand [1]. These estimations and actions cover under the subject of the unit commitment (UC). Unit commitment is the issue of identifying the ideal set of power production units in service for a daily to weekly time in order to accomplish a specific goal subject to a wide range of operating restrictions. The committed units must meet the system's predicted demand and spinning reserve requirement at the lowest possible operating cost [2]. Thus, the UC problem is highly challenging because of its intrinsic high-dimensionality, non-convexity, discreteness, and non-linearity. The initial solution needs to meet the constraints on the start-up and shut-down of the scheduled units during each planning period, as well as the requirements for system capacity and unit generation limit. The final solution must locate the best scheduling of the generation units during each distinct operating period to meet the demands of the system load and spinning reserve capacity [2, 3].

Numerous approaches had been presented to address the UC topic. Some of classical methodologies such as dynamic programming (DP) [4], Lagrangian relaxation (LR) [5], Tabu Search and Interior Point Optimization [6] introduced to find a satisfactory solution or near optimum solution of the UC problem However, these methods necessitate a significant amount of work to establish inference rules for vast systems with an excessive number of units and a wide range of limitations. As a result, a long execution time is required. Recently, simulated annealing (SA) and genetic algorithms (GA) which simulate natural processes were being used more often to solve optimization problems in scientific and engineering fields. The UC problem was managed effectively by using adaptive SA method but the hill-climbing inspection is quick and it only chooses the best solution due to the sub-optimization search [7]. The implementation of GA to resolve the unit commitment issue had been covered [8]. The GA achieved a good solution in UC problem along with the constraints. However, GA requires a number of steps for resolving the unit commitment issue, for achieving satisfactory response and an accuracy solution, the fitness function, parameter coding, and genetic operations such as mutation, convergence, and crossover criteria were chosen based on the characteristics of the UC situation.

With the advancement in evolutionary heuristic algorithms some literatures had used evolutionary-based metaheuristic optimization algorithms to study the UC problem. In general, "shuffled frog leaping algorithm (SFLA) [9], artificial bee colony (ABC) [10], bat-inspired algorithm (BA) [11], gray wolf optimization (GWO) [12], firefly approach [13] and particle swarm optimization (PSO) [14]" build algorithmic logic from everyday occurrences in the natural world. These approaches can be effectively solving multi-objectives nonlinear optimization problems with continuous and discrete variables, doesn't require useless computation time in addition, effective in exploiting the solutions. However, the algorithms face challenges such as the method's exploitation of the possible solution is unacceptable and the global optimal solution becomes less efficient and requires more computing time if the parameters are not set correctly. Ananthan et al. [14, 15] proposed PSO algorithm based on the UC problem. PSO is initialized by particles which is represented the set of possible solutions. The evolutionary process has few adjustable factors and is very simple. "Combinatorial, multimodal, multi-objective, and nonlinear problems" could all be solved with it successfully. Nevertheless, this algorithm has limitations including parameters adjusting, the selection of a proper swarm size and penalty functions that depend on the problem. Later, to increase the level of performance, several hybrid algorithms had been used in the literature to tackle the UC problem. Rastgou and Bahramara [16] proposed an adjusted firefly method to deal the unit commitment issue more effectively. SA method was combined with "Modified Sub-gradient Method (MSG)" [17]. A hybrid PSO-GWO approach for the unit commitment problem was presented [18, 19]. Moreover, a hybrid method known as MPSO-EO [20] proposed that combines the modified particle swarm optimization (MPSO) with the equilibrium optimizer (EO).

In the course of time, the Moth Flame Optimization (MFO) technique is a recently offered as intelligence technique [21]. The MFO approach was applied to solve the UC issue [22]. It is characterized by a minimal number of parameters and a straightforward construct. Furthermore, MFO is simple to use, reliable, and effective. However, although MFO can find the global optimal solution in some cases with less computational values, it finds a difficult to find the optimal solution in some extremely difficult optimization cases. On the other hand, despite PSO has comparatively fast response level, PSO's early convergence to the near-optimal and inefficiency in exploring the whole search space are its main drawbacks. So, Yang et al. [23] suggested combining MFO and PSO to improve the search for diversification in extremely difficult optimization subjects. As it is pointed out, Shaikh et al. [24] suggest a hybrid approach integrating MFO with PSO (MFOPSO) to improve MFO efficiency for calculating transmission line parameters optimally.

This study proposed the hybrid MFO-PSO algorithm to determine the optimal solution of unit commitment problem as efficiently as possible. It is compared with a various optimization technique to address the UC problem and assess the accuracy of the proposed approach.

The paper's main contributions summarize as follows:

1. The motivation of this study, suggest a new approach with inspiration from nature for resolving the UC difficulty and to compete with other existing techniques to solve another power system issues.

2. Compared to other established methods, MFO-PSO approach is better able to handle challenging confined and unknown search space problems. Additionally, it is simple methodology and requires a limited number of parameters. Thus, MFO-PSO has been used to address a real complex power system issue.

3. As far as the authors are aware. The MFO-PSO approach which was motivated by the nocturnal navigation strategy of moths around light sources has never before been applied to the UC problem.

The remainder of the work is divided as below: Section 2 presents the formulation of the unit commitment problem. Then, the MFO-PSO approach is detailed in Section 3 in addition to a thorough explanation of the steps involved the using MFO-PSO approach to resolve the UC task. The outcomes and numerical results of the simulation provides in Section 4. The final section of the paper is concluded in Section 5.

2. MATHEMATICAL MODELLING OF UNIT COMMITMENT

The main focus of unit commitment is the generating unit's ON and OFF states at various internal times. It also needs to maintain estimated load levels and spinning reserve requirements while satisfying all generating unit constraints. Additionally, optimal power flow is used to reduce fuel consumption [25]. Therefore, when combined, the unit commitment and optimal power flow study provide a cost-saving methodology for power generating units [8].

The target function of UC is to minimize the total cost over a period of time, considering the costs associated with operating, starting and shutting down each unit under the related constraints as stated mathematically in Eq. (1) [3, 16]:

$$F(P_i^t, U_i^t) = \sum_{t=1}^{T}\sum_{i=1}^{N}[F_i(P_i^t) + SC_i^t(1 - U_i^{t-1})]U_i^t + \sum_{t=1}^{T}\sum_{i=1}^{N} SD_i^t \times (1 - U_i^t)U_i^{t-1} \quad (1)$$

where, $F_i(P_i^t)$ represents the fuel cost of the *i-th* number of generators units at the t of hours, and it can be stated mathematically as:

$$F_i(P_i^t) = \alpha_{i_i}(P_i^t)^2 + \beta_i P_i^t + \gamma_i \quad (2)$$

where, α_{i_i}, β_i and γ_i are the fuel cost constant of the *i-th* unit. T is time, N is the total number of generators, P_i^t represents output power of *i-th* unit at time *t*, U_i^t is status of unit *i* at hour *t* (*ON*=1, *OFF*=0).

SC_i^t represents the startup cost of *i-th* unit at hour *t*, and is defined with following mathematical formula:

$$SC_i^t = \begin{Bmatrix} HS_{cost}\ if\ T_{i,down} \le T_{i,off}^t \le T_i^{down} + T_i^{cold} \\ CS_{cost}\ if\ T_{i,off}^t \ge T_i^{down} + T_i^{cold} \end{Bmatrix} \quad (3)$$

SD_i^t represents the shutdown cost of *i-th* unit at hour *t*, which it is assigned as a constant value for every generator unit.

Subject to the following system constraints:

System power balance:

The load demand must be met by the total power produced in each time [22].

$$\sum_{i=1}^{N} U_i^t P_i^t = P_d^t \tag{4}$$

P_d^t: Power loading on the system at hour *t*.

Units capacity limitation:

It's important to satisfy the minimum and maximum power limitations of units.

$$P_i^{min} U_i^t \leq P_i^t \leq P_i^{Max} U_i^t, i = 1,2, \dots . N \tag{5}$$

P_i^{min}, P_i^{Max}: the lower and upper output power limits of *i-th* unit.

Minimum up/down time limitations:

The operating unit needs to be on for a specific amount of time. It's called minimum up time during this period. However, there is a minimum amount of time that must pass after a unit is de-committed before it can be recommitted. This period is called the time of minimum downtime. These limitations can be shown as [10]:

$$T_i^{on} \geq MUT_i \tag{6}$$

$$T_i^{off} \geq MDT_i \tag{7}$$

T_i^{on}: Minimum time that the unit *i-th* has been online constantly.

T_i^{off}: Minimum time that the unit *i-th* has been unavailable (offline)

MUT_i and MDT_i: The minimum up/down time of the *i-th* unit.

UC solution is not convex issue because it involves structure binary variables. These variables make solving the UC extremely challenging and problematic. The coupling constraint for the UC problem is load balance. The unit coupling constraints are designed so that, in the event that the coupling constraints are satisfied, the behavior of one unit influences that of other units.

3. PROPOSED METHOD

Moth-flame optimization: MFO is based on the moth's nocturnal transverse navigation strategy around light sources by maintaining a constant angle with the sky. The moth population acts as the candidate search solutions flying throughout the area using the specified strategy. Whereas, the flame population displays the best locations for the moths that have been found thus far. Moths are capable of flying in multi-dimensions or hyper-dimensional space by manipulating their position vectors. The proposed algorithm ensures convergence, and it is simple to use, reliable, and effective [23, 24].

With N moths in a D-dimensional search area, at the *k-th* iteration, assume M_i^k and F_j^k represent the location of the *i-th* moth and the *j-th* flame consequently. Later, a flame updates each moth's position using a mathematical model that is created using the equation:

$$M_i^{k+1} = D_i^k * e^{bv} * \cos(2\pi v) + F_j^k \tag{8}$$

where, v is a vector consisting of D random values uniformly distributed on [-1, 1], the factor b is predetermined which determines the form of the logarithmic spiral, and D_i^k refers to the distance of the *i-th* moth from the *j-th* flame, which has the following definition:

$$D_i^k = \left| F_j^k - M_i^k \right| \tag{9}$$

The population size of moths is predetermined, whereas the number of the flame population is adaptively determined based on the search iteration, which is computed using the following formula:

$$flame\_no^k = round\ (N - k * \frac{N-1}{KMax}) \tag{10}$$

where, *KMax* is the upper limit of search iterations. The number of flames appears to gradually decrease, and only in the last stages of iterations, the moths adjust their location in relation to the best flame.

The moths that have been sorted based on their fitness value form the flame population in the initial iteration. The optimal moth in the first location of the flame population will be designated and the remaining moths will be arranged similarly. Subsequently, the flame population will comprise the better $flame\_no^k$ individuals chosen from the set of the previous iteration's flame population and the current iteration's moth population [23].

Particle swarm optimization: The process of the PSO algorithm consists of a random collection of particles in a certain trajectory traveling in the direction of the best solution. Particles are driven depending on their former best location, their neighboring locations, and the best position among total particles. Each particle moves towards the optimal solution based on its previous best position given by P_best, position of other particles and the optimum solution attained out of all the other particles given by g_best. let v_i^k and x_i^k are the velocity and position, respectively [15, 24]. Typically, the adjusted values for the location and velocity of the *i-th* particle are determined by analyzing Eqs. (11) and (12).

$$v_i^{k+1} = \omega * v_i^k + c_1 r_1 (p\_best_i^k - x_i^k) + c_2 r_2 (g\_best^k - x_i^k) \tag{11}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{12}$$

Proposed hybrid MFO-PSO: Early convergence is a general disadvantage for both MFO and PSO. The PSO iteration results in the search center of the total swarm convergent to one point, the best global location, and a negligible decrease in the particle's speed as it leaves local optima in the next iterations. The situation in MFO is noticeably worse. since the search center index has adjusted to one at last iterations of the program [23].

To deal the premature convergence point and enhance their capacity for global search, a hybrid algorithm logically incorporates the ideas of the MFO position-adjusting process of moths about a flame and the PSO local attractor. To ensure that the PSO algorithm converges, that every particle must be close to its local attractor Q_i^k [26]. The local attractor is known as below:

$$Q_i^k = \emptyset * p\_best_i^k + (1-\emptyset) * g\_best^k \qquad (13)$$

where, $\emptyset$ is "a vector with uniformly distributed multi-dimension random numbers on [0, 1]". In this approach assume there are no defined $pbest$ and $gbest$ in MFO, the flame with the same sequence number for every moth is considered the pbest, and the best flame in the flame population is considered the gbest in our approach [23, 24]. This leads to the following modification of each moth's position update equation:

$$M_i^{k+1} = D_i^k * e^{bv} * \cos(2\pi v) + Q_i^k \qquad (14)$$

Hence, the distance is computed by following formula:

$$D_i^k = \left|Q_i^k - M_i^k\right| \qquad (15)$$

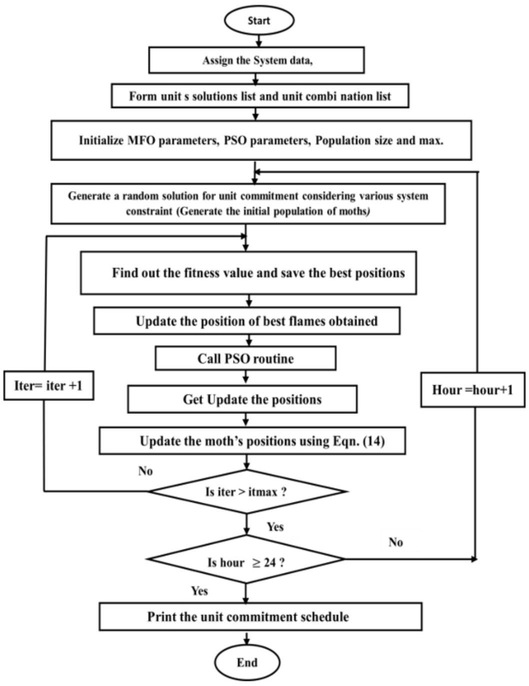

Figure 1. Flowchart of the proposed HMFOPSO

Figure 1 displays the flowchart for the suggested MFO-PSO approach for solving UC problem.

4. RESULT AND DISCUSSION

To evaluate the proposed MPO-PSO approach, ten units and a 24-hour period are considered as the bench-test system. Table 1 displays the generators input data for the system [22]. The daily load demand of this case study is shown in Figure 2, which shows that the maximum system's demand is at the 11th and 12th hours, and its minimum system's demand is at the first hour. Table 2 lists the parameters setting for MFO-PSO, MFO, and PSO that are utilized in this issue. The setting parameters of the suggested hybrid MFO-PSO algorithm and original MFO method are identical. The suggested MFO-PSO algorithm's parameters for the simulation analysis are the same as those of the MFO method with population size of 20 and maximum number of iterations is 100. The commitment and generation schedule optimization results are displayed in Tables 3 and 4, respectively. Each line shows the unit's output power. The total cost is displayed in the final row of Table 4. Because the methods used in the simulation analysis are stochastic optimization approaches, the algorithm is executed with 20 trials using different search agents (random initial population) over a 24-hour period to assess the robustness of the MFO-PSO approach for solving unit commitment problem. The MFO-PSO algorithm's outcomes for the unit's output power for varied load demands are shown in Tables 4 and 5. From the Table 5, it evident that the values of the cost function and execution time that MFO-PSO obtained are outperform or close to the MFO, PSO, and other algorithms. It demonstrates the MFO-PSO algorithm's robustness in handling unit commitment problems. Table 5 shows the outcomes of using 7 various approaches on the 10-unit test system and compares them with the findings of the proposed method (MPO-PSO) for cost and implementation time. For the aforementioned 10-unit system, the obtained cost is 553552$. It is clear from Table 5 that the hierarchical proposed approach outperforms some other heuristic algorithms like (EE [3], M-FA [13], PSO [15], AMFA [16], PSO-GWO [18], MPSO-EO [20], and MFO [22]) in terms of reported cost improvement and execution time. Figure 3 depicts the convergence characteristics of fuel cost comparison of 10 generating unit test system according to the number of iterations. A comparison is made between the original MFO and the proposed method (MPO-PSO) performance. It is obvious that MFO-PSO has superior convergence than MFO.

Table 1. The input figures of ten generating unit system [22]

Unit	γ ($/h)	β ($/MWh)	α ($/MW^{2}h)	P_{imax} (MW)	P_{imin} (MW)	HS_{cost} ($)	CS_{cost} ($)	MUTi (h)	MDTi (h)	T_i Cold (h)	Initial State (h)
P1	1000	16.19	0.00048	455	150	4500	9000	8	8	5	8
P2	970	17.26	0.00031	455	150	5000	10000	8	8	5	8
P3	700	16.6	0.002	130	20	550	1100	5	5	4	-5
P4	680	16.5	0.00211	130	20	560	1120	5	5	4	-5
P5	450	19.7	0.00398	162	25	900	1800	6	6	4	-6
P6	370	22.26	0.00712	80	20	170	340	3	3	2	-3
P7	480	27.74	0.00079	85	25	260	520	3	3	2	-3
P8	660	25.92	0.00413	55	10	30	60	1	1	0	-1
P9	665	27.27	0.00222	55	10	30	60	1	1	0	-1
P10	670	27.79	0.00173	55	10	30	60	1	1	0	-1

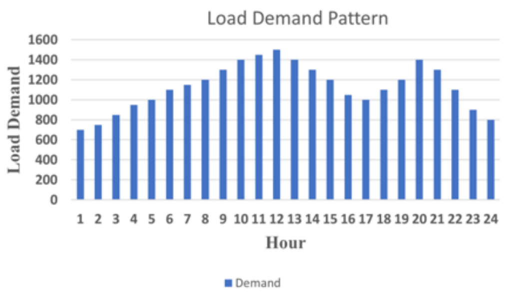

Figure 2. Load demand pattern for 24 h for 10-unit system

Table 2. The parameters setting for MFO-PSO, MFO, and PSO

Parameters of PSO	
inertia weight ω	0.85
c_1 and c_2	2
random values of numbers r_1 and r_2	0, 1
Parameters of MFO	
v is a vector consisting of random values	[-1, 1]
factor b	1

Table 3. Commitment schedule for ten generating unit system using proposed method (HMFOPSO)

Hour	Generation Schedule for 10 Generating Unit System									
	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
1	1	1	0	0	0	0	0	0	0	0
2	1	1	0	0	0	0	0	0	0	0
3	1	1	0	0	0	0	0	0	0	0
4	1	1	0	0	1	0	0	0	0	0
5	1	1	0	0	1	0	0	0	0	0
6	1	1	0	1	1	0	0	0	0	0
7	1	1	1	1	1	0	0	0	0	0
8	1	1	1	1	1	0	0	0	0	0
9	1	1	1	1	1	1	0	0	0	0
10	1	1	1	1	1	1	1	0	0	0
11	1	1	1	1	1	1	1	1	0	0
12	1	1	1	1	1	1	1	1	1	0
13	1	1	1	1	1	1	1	0	0	0
14	1	1	1	1	1	1	0	0	0	0
15	1	1	1	1	1	0	0	0	0	0
16	1	1	1	1	1	0	0	0	0	0
17	1	1	1	1	1	0	0	0	0	0
18	1	1	1	1	1	0	0	0	0	0
19	1	1	1	1	1	0	0	0	0	0
20	1	1	1	1	1	1	1	0	0	0
21	1	1	0	1	1	1	1	0	0	0
22	1	1	0	0	1	1	1	0	0	0
23	1	1	0	0	0	1	0	0	0	0
24	1	1	0	0	0	0	0	0	0	0

Table 4. Generation schedule for 10 generating unit system using proposed method (HMFOPSO)

Hour	Generation Schedule for 10 Generating Unit System										P_D
	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	
1	455	245	0	0	0	0	0	0	0	0	700
2	455	295	0	0	0	0	0	0	0	0	750
3	455	395	0	0	0	0	0	0	0	0	850
4	455	455	0	0	40	0	0	0	0	0	950
5	455	455	0	0	90	0	0	0	0	0	1000
6	455	455	0	130	60	0	0	0	0	0	1100
7	455	410.071	130	130	25	0	0	0	0	0	1150
8	455	455	130	130	29.999	0	0	0	0	0	1200
9	455	455	130	130	110	20	0	0	0	0	1300
10	455	455	130	130	162	43	25	0	0	0	1400
11	455	455	130	130	162	80	25	13	0	0	1450
12	455	455	130	130	162	80	25	53	10		1500
13	455	455	130	130	162	43	25	0	0	0	1400
14	455	455	130	130	110	20	0	0	0	0	1300
15	455	455	130	130	30	0	0	0	0	0	1200
16	455	310	130	130	25	0	0	0	0	0	1050
17	455	260	130	130	25	0	0	0	0	0	1000
18	455	360	130	130	25	0	0	0	0	0	1100
19	455	455	130	130	30	0	0	0	0	0	1200
20	455	455	130	130	162	43	25	0	0	0	1400
21	455	455	0	130	162	73	25	0	0	0	1300
22	455	455	0	0	145	20	25	0	0	0	1100
23	455	425.001	0	0	0	20	0	0	0	0	900
24	455	345	0	0	0	0	0	0	0	0	800
Total cost											553552$

Table 5. Overall cost ($) and implementation time (s.) comparison of various methods

Method	Overall Cost ($)	Implementation Time (s.)
EE [3]	563978.9812	----
M-FA [13]	557873	0.117938
PSO [15]	567330.56	----
AMFA [16]	563865	2.62
PSO-GWO [18]	565210	----
MPSO-EO [20]	563977.0122	----
MFO [22]	564810	20.4563
HMFOPSO (proposed)	553552	0.135

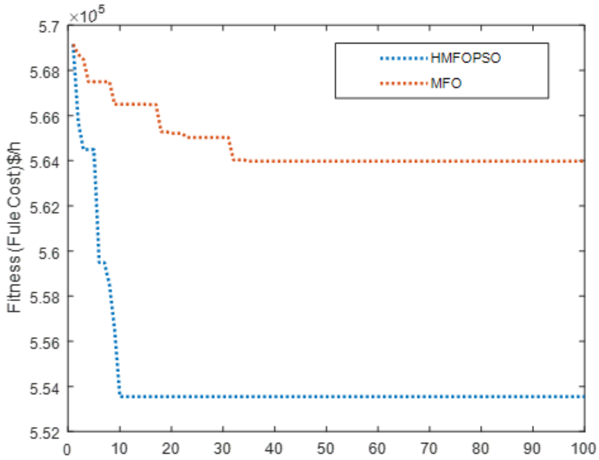

Figure 3. The convergence characteristic of fuel cost

5. CONCLUSION

Unit commitment plays a vital role in optimization tasks for power system operation to meet their system level requirements of power quality and demand response capability. It attempts to reschedule the generation units at a specific time in order to achieve an overall reduction in generation costs subject to a wide range of operating restrictions. To resolve the unit commitment issue and to superior of the sub-optimal operation of existing algorithms, a hierarchical hybrid approach by combining the Moth Flame Optimizer algorithm and particle swarm optimization (MPO-PSO) has been presented in this paper. The hierarchical approach plans the generating units for each hour in order to achieve the feasible states while meeting given constraints. It is tested on a benchmark system (10-unit case study), and the estimated cost is 553552 $. A comparison is made between the efficacy of the suggested algorithms and several other evolutionary algorithms. Comparison results confirm that the MFO-PSO approach is better able to handle challenging confined and unknown search space problems. Additionally, it is simple methodology and requires a limited number of parameters. Thus, MFO-PSO has been used to address a real complex power system issue.

REFERENCES

[1] Abed, A.M., Alkhazraji, A.A., Al-Kubragyi, S.S.A. (2023). Modelling and simulation of an on grid 100-kW photovoltaic system. International Journal of Power Electronics and Drive Systems (IJPEDS), 14(3): 1651-1659. https://doi.org/10.11591/ijpeds.v14.i3.pp1651-1659

[2] Gaing, Z.L. (2003). Discrete particle swarm optimization algorithm for unit commitment. In 2003 IEEE Power Engineering Society General Meeting (IEEE Cat. No. 03CH37491), Toronto, ON, Canada, pp. 418-424. https://doi.org/10.1109/PES.2003.1267212

[3] Shahbazitabar, M., Abdi, H. (2017). A solution to the unit commitment problem applying a hierarchical combination algorithm. Journal of Energy Management and Technology, 1(2): 12-19. http://doi.org/10.22109/jemt.2017.92981.1027

[4] Ouyang, Z., Shahidehpour, S.M. (1991). An intelligent dynamic programming for unit commitment application. IEEE Transactions on Power Systems, 6(3): 1203-1209. https://doi.org/10.1109/59.119267

[5] Jiang, Q., Zhou, B., Zhang, M. (2012). Parallel augment Lagrangian relaxation method for transient stability constrained unit commitment. IEEE Transactions on Power Systems, 28(2): 1140-1148. https://doi.org/10.1109/TPWRS.2012.2216553

[6] Borghetti, A., Frangioni, A., Lacalandra, F., Lodi, A., Martello, S., Nucci, C.A., Trebbi, A. (2001). Lagrangian relaxation and tabu search approaches for the unit commitment problem. In 2001 IEEE Porto Power Tech Proceedings (Cat. No. 01EX502), Porto, Portugal, p. 7. https://doi.org/10.1109/PTC.2001.964914

[7] Dudek, G. (2010). Adaptive simulated annealing schedule to the unit commitment problem. Electric Power Systems Research, 80(4): 465-472. https://doi.org/10.1016/j.epsr.2009.10.019

[8] Ozoemena, O.E., Adamu, A. (2022). Optimal unit-commitment generation scheduling using genetic algorithm: A case study of a 10-generator power system network. Nigerian Journal of Technology, 41(2): 302-310. https://doi.org/10.4314/njt.v41i2.12

[9] Anita, M., Raina, R., Raglend, J. (2022). Solution of profit based unit commitment including wind energy using improved shuffled frog leaping algorithm. International Journal of Renewable Energy Research, 12(2): 1097-1104. https://doi.org/10.20508/ijrer.v12i2.12883.g8497

[10] Deka, K., Goswami, B. (2017). Artificial bee colony algorithm for profit based unit commitment using modified pre-prepared power demand table. International Research Journal of Engineering and Technology, 4(5): 620-627.

[11] Weng, S., Chen, L., Odendaal, K. (2016). Application of bat evolutionary algorithm in optimization of economic dispatch for unit-commitment problem with large uncertainties and high efficiency. MPRA Paper 72528.

[12] Reddy, S., Panwar, L.K., Panigrahi, B.K., Kumar, R., Alsumaiti, A. (2019). Binary grey wolf optimizer models for profit based unit commitment of price-taking GENCO in electricity market. Swarm and Evolutionary Computation, 44: 957-971. https://doi.org/10.1016/j.swevo.2018.10.008

[13] Hussein, B.M., Jaber, A.S. (2020). Unit commitment based on modified firefly algorithm. Measurement and Control, 53(3-4): 320-327. https://doi.org/10.1177/0020294019890630

[14] Ananthan, D., Nishanthinivalli, S. (2014). Unit commitment solution using particle swarm optimisation

(PSO). IOSR Journal of Engineering, 4(3): 1-9.
[15] Kumar, S., Singh, H.D. (2017). Optitimization of unit commitment problem using classical soft computing technique (PSO). International Research Journal of Engineering and Technology, 4(11): 814-820.
[16] Rastgou, A., Bahramara, S. (2021). An adaptive modified firefly algorithm to unit commitment problem for large-scale power systems. Journal of Operation and Automation in Power Engineering, 9(1): 68-79. https://doi.org/10.22098/joape.2021.6423.1483
[17] Başaran Filik, Ü., Kurban, M. (2010). Solving unit commitment problem using modified subgradient method combined with simulated annealing algorithm. Mathematical Problems in Engineering, 2010(1): 295645. https://doi.org/10.1155/2010/295645
[18] Kamboj, V.K. (2016). A novel hybrid PSO–GWO approach for unit commitment problem. Neural Computing and Applications, 27: 1643-1655. https://doi.org/10.1007/s00521-015-1962-4
[19] Al-kubragyi, S., Abdulla, S., Ali, I.I., Alwazni, H., Mohsen, S. (2024). Solving the multi-objective economic-emission load dispatch optimization problem using hybrid GWO-PSO algorithm. International Journal of Intelligent Engineering & Systems, 17(4): 738-750. https://doi.org/10.22266/ijies2024.0831.56
[20] Sayed, A., Ebeed, M., Ali, Z.M., Abdel-Rahman, A.B., Ahmed, M., Abdel Aleem, S.H., El-Shahat, A., Rihan, M. (2021). A hybrid optimization algorithm for solving of the unit commitment problem considering uncertainty of the load demand. Energies, 14(23): 8014. https://doi.org/10.3390/en14238014
[21] Mirjalili, S. (2015). Moth-flame optimization algorithm: A novel nature-inspired heuristic paradigm. Knowledge-Based Systems, 89: 228-249. https://doi.org/10.1016/j.knosys.2015.07.006
[22] Bhadoria, A., Marwaha, S. (2020). Moth flame optimizer-based solution approach for unit commitment and generation scheduling problem of electric power system. Journal of Computational Design and Engineering, 7(5): 668-683. https://doi.org/10.1093/jcde/qwaa050
[23] Yang, Z., Shi, K., Wu, A., Qiu, M., Hu, Y. (2019). A hybird method based on particle swarm optimization and moth-flame optimization. In 2019 11th International Conference on Intelligent Human-Machine Systems and Cybernetics (IHMSC), Hangzhou, China, pp. 207-210. https://doi.org/10.1109/IHMSC.2019.10144
[24] Shaikh, M.S., Raj, S., Babu, R., Kumar, S., Sagrolikar, K. (2023). A hybrid moth-flame algorithm with particle swarm optimization with application in power transmission and distribution. Decision Analytics Journal, 6: 100182. https://doi.org/10.1016/j.dajour.2023.100182
[25] Shafeeq, A.F., Ali, I.I. (2022). Simple strategy for finding optimal location and size of distributed generators and SVC devices in radial distribution systems. International Journal of Intelligent Engineering & Systems, 15(5): 261-272. https://doi.org/10.22266/ijies2022.1031.24
[26] Clerc, M., Kennedy, J. (2002). The particle swarm-explosion, stability, and convergence in a multidimensional complex space. IEEE Transactions on Evolutionary Computation, 6(1): 58-73. https://doi.org/10.1109/4235.985692