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Cost-Effective Unit Commitment of Thermal Units Considering Plug-in Electric Vehicles and Renewable Energy Sources using Chromatic Seahorse Optimizer

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Abstract

This study proposes a novel and cost-effective approach to solving the Unit Commitment Problem (UCP) of thermal power systems by employing the Chromatic Seahorse Optimizer (CSHO) algorithm. The primary objective is to minimize the total operating cost while ensuring optimal scheduling of thermal generating units under dynamic smart grid scenarios. The rapid integration of Plug-in Electric Vehicles (PEVs)andRenewable Energy Sources (RES)**,** particularly wind energy, adds uncertainty and complexity to power system operations, necessitating advanced optimization strategies.

The CSHO algorithmis a newly developed metaheuristic inspired by the spiral reproductive behavior of seahorses, enhanced through chromatic adaptation strategies to balance exploration and exploitation more effectively. This hybrid nature makes CSHO highly suitable for handling the nonlinear, constrained, and combinatorial characteristics of the UCP. The algorithm is implemented in MATLAB 2021, and simulations are conducted on the IEEE-39 bus system, modified to include equivalent PEVs and wind generation units.Results show that CSHO consistently achieves lower total operating costs across all scenarios compared to several state-of-the-art soft computing methods. The algorithm also demonstrates superior performance in terms of convergence speed and solution stability.

Keywords: Unit Commitment, Plug-in Electric Vehicles,Renewable Energy Sources, Cost minimization, Chromatic Seahorse Optimizer.

1. Introduction

The growing global demand for sustainable and intelligent energy systems has led to significant transformations in power system planning and operation. One of the most critical operational tasks in power systems is the Unit Commitment Problem (UCP), which involves determining the optimal scheduling of generating units to meet forecasted electricity demand at the minimum operational cost while satisfying various technical and operational constraints. The problem becomes increasingly complex with the integration of Plug-in

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Electric Vehicles (PEVs) and Renewable Energy Sources (RES) such as wind energy, due to their stochastic and dynamic nature [1-2].

Plug-in Electric Vehicles are emerging as flexible and controllable energy resources. Their charging and discharging capabilities offer unique opportunities for demand-side management and grid support through vehicle-to-grid (V2G) operations. Simultaneously, renewable energy, particularly wind, is becoming a major contributor to modern power systems. However, its variability and intermittency pose new challenges in ensuring system reliability and economic efficiency [3]. The UCis a classical optimization problem in power system operations, involving the optimal scheduling of generation units to minimize operational costs while satisfying various system and unit constraints. The complexity of the UC has increased substantially in recent years due to the integration of PEVs and RES into modern power grids, necessitating more advanced and adaptive optimization methods.Traditional approaches such as Dynamic Programming, Lagrangian Relaxation and Mixed-Integer Linear Programming have been extensively used to solve UCP. While these methods can provide optimal solutions, their performance degrades significantly with increasing problem size, non-linearity, and the presence of uncertainty [4-5].

To overcome these limitations, researchers have explored metaheuristic algorithms such as Genetic Algorithm [6], Particle Swarm Optimization [7], Ant Colony Optimization [8], Differential Evolution [9] and Artificial Bee Colony [10]. These algorithms offer flexibility and scalability and have shown promising results in solving large-scale and complex UCPs. However, issues such as premature convergence and poor exploration-exploitation balance still persist. The inclusion of PEVs in the unit commitment framework introduces a new dimension of flexibility and complexity. Charging and discharging of PEVs, especially under Vehicle-to-Grid (V2G) schemes, can significantly impact the load profile and reserve margins. Researchers have modelled PEVs as controllable loads or distributed storage to enhance grid stability and reduce operational costs. For example, [11] demonstrated cost savings and peak load shaving by incorporating V2G into the UCP using PSO.However, the integration of PEVs also introduces uncertainties in user behaviour, charging patterns, and mobility, which require adaptive and intelligent optimization strategies capable of handling stochastic variables.

The increasing penetration of wind energy has brought considerable challenges to unit commitment due to its intermittent and non-dispatch able nature. Various approaches have been proposed to address the variability of wind power, including stochastic modelling [12], probabilistic forecasting, and robust optimization [13]. These methods often rely on historical data and scenario-based techniques, which can be computationally intensive and lack generalizability.Metaheuristic algorithms have also been used to handle wind-integrated UCPs, often in hybrid or multi-objective frameworks. For instance, [14] applied a hybrid GA-

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PSO model to optimize the scheduling of thermal and wind units. However, these methods often suffer from trade-offs between accuracy and computational time, especially in high-dimensional search spaces.

The integration of RES and EVs into UC models has gained significant attention due to their potential to enhance power system flexibility and sustainability. Dhawale et al. [15] proposed a chaotic slime mould optimizer (CSMO) to solve the UC problem in systems incorporating wind power and EVs with vehicle-to-grid (V2G) capabilities, demonstrating reduced operational costs. Egbue et al. [16] developed a UC model specifically focused on optimizing V2G operations, highlighting the impact of EVs on system reliability and load balancing. Salman et al. [17] addressed day-ahead unit commitment in scenarios with high penetration of RES and EV charging stations, emphasizing the challenges posed by dynamic and uncertain load profiles. Abdelhakeem et al. [18] introduced modified arithmetic optimization algorithms to address uncertainties in intermittent RES and EV integration, improving solution robustness across various operational scenarios.

Kamboj and Malik [19] applied a chaotic zebra optimization algorithm (CZOA) to optimize UC and generation scheduling in an integrated power system with plug-in EVs and renewable, achieving notable cost efficiency and scalability. Pan and Liu [20] incorporated interval uncertainty modeling to account for seasonal variations in RES output and EV behavior, and evaluated different EV charging/discharging pricing schemes, underlining the role of economic incentives in UC decisions. Collectively, these studies highlight the importance of advanced optimization methods and uncertainty modeling in achieving cost-effective and reliable power system operation with high levels of RES and EV integrationDespite the promising results achieved using existing metaheuristic approaches, most algorithms still face challenges such as premature convergence, lack of diversity, and slow convergencerate in highly constrained and uncertain environments like wind- and PEV-integrated systems.

To address these limitations, this paper proposes a novel Chromatic Seahorse Optimizer (CSHO)-a metaheuristic inspired by the spiral reproductive behaviour of seahorses and enhanced with chromatic learning mechanisms. The proposed method is designed to balance exploration and exploitation effectively, adapt to diverse search landscapes, and robustly solve the UCP under four real-world scenarios involving thermal units, PEVs, V2G, and wind integration.

2. Problem Representation

2.1 Objective Function

The generation schedule is planned in advance to ensure reliable power supply meeting forecasted demand. Renewable sources improve efficiency and reliability [10]. The total fuel

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cost (FT) is calculated by summing the generation cost of all units over the scheduled time period $F_T = \sum_{i=1}^{H}\left[\sum_{i=1}^{N}\left(a_i P_{i,h}^2 + b_i P_{i,h} + c_i\right)U_{i,h} + ST_{c(i)}\left(1-U_{i(h-1)}\right)U_{i,h}\right]$ $/hr (1)

where a_i, b_i and c_i are the fuel cost function expressed in \$/h, \$/MWh, and \$/MWh^2, respectively.

Mathematically, start-up cost $ST_{c(i)}$ can be expressed as the sum of cold start-up (CSch(i)) and hot start-up cost (HSch) of ith unit, respectively.

Mathematically, the start-up cost $ST_{c(i)}$ of ith generating unit can be represented as the sum of its cold start costCSch(i)) and hot start cost (HSch) depending on the unit's downtime

$$ST_{c(i)} = \begin{cases} HSch(i); MDt(i) \le T_{hi}^{OFF} \le \left(MDt(i) + CSh(i)\right) \\ CSch(i); \quad T_{hi}^{OFF} > \left(MDt(i) + CSh(i)\right) \end{cases} \quad \left(i \in N; h = 1,2,3,\ldots\ldots,H\right) \tag{2}$$

2.2 Systems and unit Constraints

a. Operating limits constraints

Each generating unit operates within specific minimum and maximum power limits to ensure safe and economical performance. Power generation below the minimum limit is technically inefficient, while generation beyond the maximum limit may cause equipment stress or operational instability. These limits are determined based on the unit's heat rate characteristics and fuel cost coefficients.

$$P_{g\min(i)} \le P_{g(i)} \le P_{g\max(i)} \quad \left(i \in 1,2,\ldots.,N; \quad h \in 1,2,\ldots.,H\right) \tag{3}$$

b. Load balance constraints

The load demand varies continuously throughout the scheduling period rather than remaining constant. To maintain system stability and reliability, the total power produced by all committed generating units at any given hour must match the required load demand. Hence, at every time interval, the combined output from thermal units and the available wind power generation must be equal to the total power demand

$$\sum_{i=1}^{N} P_{g(i)} U_{i,h} + P_g^w = D_L \quad \left(i = 1,2,\ldots\ldots,N\right) \tag{4}$$

Case-1: During charging of vehicle (grid to vehicle)

$$\sum_{i=1}^{N} P_{g(i)} U_{i,h} + P_g^w = D_L + D_h^V \quad \left(i = 1,2,\ldots\ldots,N\right) \tag{5}$$

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Case-2: During discharging (vehicle to grid)

$$\sum_{i=1}^{N} P_{g(i)} U_{i,h} + P_g^w + D_h^V = D_L \qquad (i = 1,2,.....,N) \tag{6}$$

The power outputs of all generating units during a specific time period must collectively meet the forecasted load demand. For the given power outputs *Phi*, (i=1, 2, NG), the power output of the Rthreference unit is determined using the power balance equation to ensure total generation equals the system demand

$$P_{Rh} = D_L - \sum_{i=1}^{NG} P_{g(i)} U_{i,h} + P_g^w \qquad (i = 1,2,.....,N) \tag{7}$$

Case-1: During charging of vehicle

$$P_{Rh} = \left(D_L - \sum_{i=1}^{N} \left(P_{g(i)} U_{i,h} + P_g^w \right) - D_h^V \right) \qquad (i = 1,2,.....,N) \tag{8}$$

Case-2: During discharging

$$P_{Rh} = \left(D_L - \sum_{i=1}^{N} \left(P_{g(i)} U_{i,h} + P_g^w \right) - D_h^V \right) \qquad (i = 1,2,.....,N) \tag{9}$$

c. Vehicle-to-Grid (V2G) constraint

Vehicle-to-Grid technology allows a specified number of registered EVs to actively participate in the Unit Commitment process. During off-peak hours, these vehicles are charged either from the utility grid or renewable energy sources. The charging and discharging periods depend on the battery capacity and the available charging infrastructure. It is also assumed that all EVs are charged through standalone systems installed at designated parking locations

$$\sum_{t=1}^{H} N_{V2G(t)} = N_{V2G}^{Max}(t) \tag{10}$$

d. Spinning reserve constraints

Unexpected events such as sudden load fluctuations or generator outages require extra generation capacity to ensure system reliability. This additional available capacity is referred to as the spinning reserve**.** To maintain a sufficient reserve margin while meeting load demand, generation scheduling must be planned in advance. The integration of wind energy provides supplementary power, which helps support total generation and reduces the burden on thermal units. Mathematically, the spinning reserve can be expressed as:

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$$\sum_{i=1}^{N} P_{g\max(i)} U_{i,h} + P_{g(h)}^{w} \geq D_{L(h)} + SP_{R(h)} \qquad (h = 1,2,\ldots\ldots,N) \tag{11}$$

Grid to vehicle

$$\sum_{i=1}^{N} P_{g\max(i)} U_{i,h} + P_{g(h)}^{w} \geq D_{L(h)} + SP_{R(h)} + D_{h}^{V} \qquad (h = 1,2,\ldots\ldots,N) \tag{12}$$

Vehicle to

$$\sum_{i=1}^{N} P_{g\max(i)} U_{i,h} + P_{g(h)}^{w} \geq D_{L(h)} + SP_{R(h)} - D_{h}^{V} \qquad (h = 1,2,\ldots\ldots,N) \tag{13}$$

3. Solution Methodology

3.1 Seahorse Optimizer (SHO)

The SHO is the nature-inspired population based optimization methodology developed by Zhao, S*et. al* in the year 2023 [25-26]. The SHO is based on the natural life cycle of a sea horse searching for prey, movement and breeding behavior in the sea. Natural behavior of Seahorse Optimizer is shown in Fig. 1. The solution of the optimization problem is mainly based on the four behaviors of SHO, such as

- Movement Behaviour
- Foraging Behaviour and
- Breeding Behaviour

The performance of SHO is evaluated on 23 well-known functions and CEC2014 benchmark functions compared with six state-of-the-art meta-heuristic algorithms. Finally, five real-world engineering problems are utilized to test the effectiveness of SHO. The mathematical modeling of the initialization function, creating of populations, current positions, updating of search agents and representation of searching agents, are clearly described in the following sections.

Fig. 1 Natural behavior of Seahorse Optimizer

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The initial population of the SHO algorithm is mathematically represented as follows:

$$\mathrm{Sh}=\begin{bmatrix} x1,i & \dots & x1,Dim-1 & x1,\mathrm{Dim} \\ x2,i & \dots & \dots & x2,\mathrm{Dim} \\ \vdots & \vdots & \vdots & \vdots \\ xN & \dots & xN,Dim-1 & xN,\mathrm{Dim} \end{bmatrix} \tag{14}$$

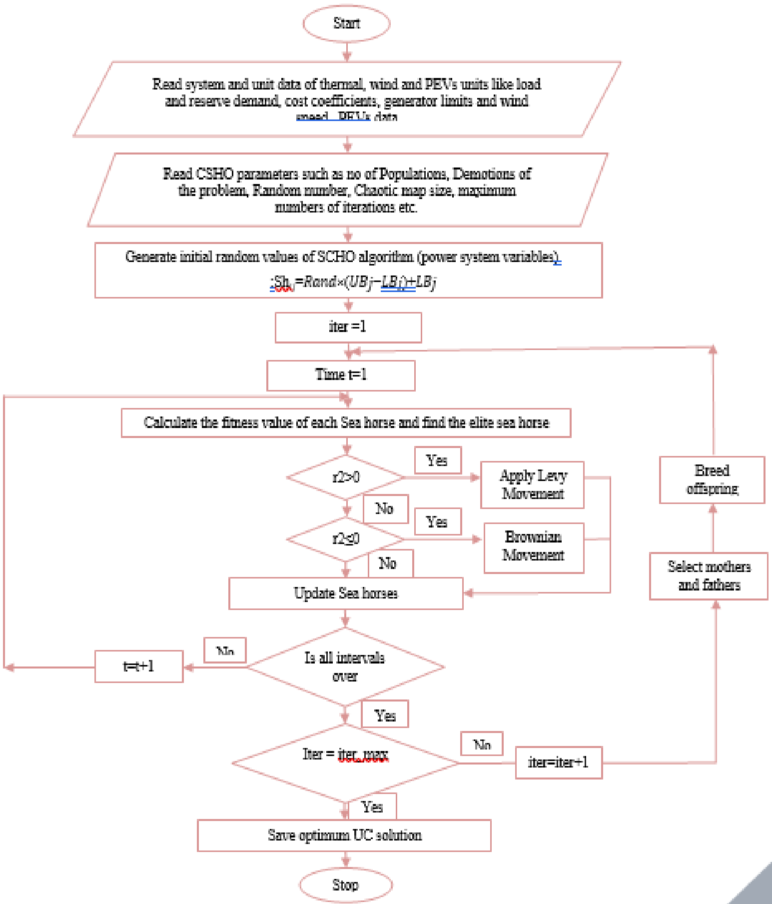

Fig. 2 Flow chart for RES and PEVs constrained UC problem using CSHO

$\mathrm{Sh}_{ij}=Rand\times(UBj-LBj)+LBj$(20)

$$\mathrm{Sh}_{elite}=(f(X_i)) \tag{15}$$

The mathematical representations of Movement Behavior, Foraging Behavior and Breeding Behavior are clearly represented [21-22]. The flow diagram of SHO is presented in Fig.

3.2 Chaotic Sea- Horse Optimizer (CSHO)

Chaotic maps are very important for optimization problems. Avoid local optima, Improve convergence, Speed up convergence and Improvethe searching behaviour of SHO [27].In this

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article, the logistic type chaotic map is used to replace the $rand$in SHO algorithm. The mathematical equation of the logistic type chaotic map is as follows:

$$(i+1)=a\times(i)(1-ylog(i)) \quad (16)$$

Where $a$is 4.So, the chaotic map variable with range [0,1] is obtained. So, the movement of SHO is represented as follows.

$$\theta=ylog\times 2 \quad (17)$$

4. Results and Discussion

The proposed Chromatic Seahorse Optimizer has been applied to the IEEE 39-bus system with 10 thermal units over a 24-hour scheduling horizon. Integration of wind units and Plug-in Electric Vehicles further improved system flexibility and cost-efficiency. Wind energy, predominantly available during night hours, helped reduce thermal generation, while PEVs charged during off-peak and discharged (via V2G) during peak hours, flattening demand peaks. The simulation has been implemented in MATLAB 2021a on a high-performance system equipped with an Intel i7 processor and 8 GB RAM.

Table 1 Unit data for Standard Ten unit test system

Quantities	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5
P_{max} (MW)	455	455	130	130	162
P_{min} (MW)	150	150	20	20	25
a ($/h)	1000	970	700	680	450
b ($/MWh)	16.19	17.26	16.60	16.50	19.70
c ($/MW^{2}h)	0.00048	0.00031	0.00200	0.00211	0.00398
Min up time (h)	8	8	5	5	6
Min down time (h)	8	8	5	5	6
Startup cost ($)	4500	5000	550	560	900
Initial status (h)	8	8	-5	-5	-6

Quantities	Unit 6	Unit 7	Unit 8	Unit 9	Unit 10
P_{max} (MW)	80	85	55	55	55
P_{min} (MW)	20	25	10	10	10
a ($/h)	370	480	660	665	670
b ($/MWh)	22.26	27.74	25.92	27.27	27.79

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c ($/MW^{2}h)	0.00712	0.00079	0.00413	0.00222	0.00173
Min up time (h)	3	3	1	1	1
Min down time (h)	3	3	1	1	1
Startup cost ($)	170	260	30	30	30
Initial status (h)	-3	-3	-1	-1	-1

Table 2 Forecasted load demand, Reserve demand and Market price for Standard Ten unit test system

Hour (h)	Forecasted Demand (MW)	Forecasted Reserve (MW)
1	700	70
2	750	75
3	850	85
4	950	95
5	1000	100
6	1100	110
7	1150	115
8	1200	120
9	1300	130
10	1400	140
11	1450	145
12	1500	150
13	1400	140
14	1300	130
15	1200	120
16	1050	105
17	1000	100
18	1100	110
19	1200	120
20	1400	140
21	1300	130
22	1100	110

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23	900	90
24	800	80

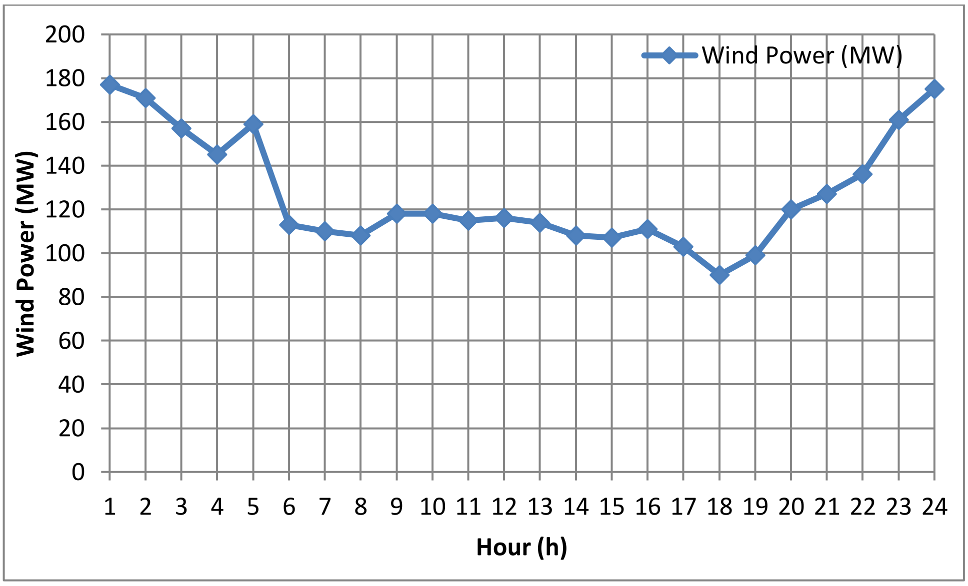

Fig. 3 Wind power generation proposed test system

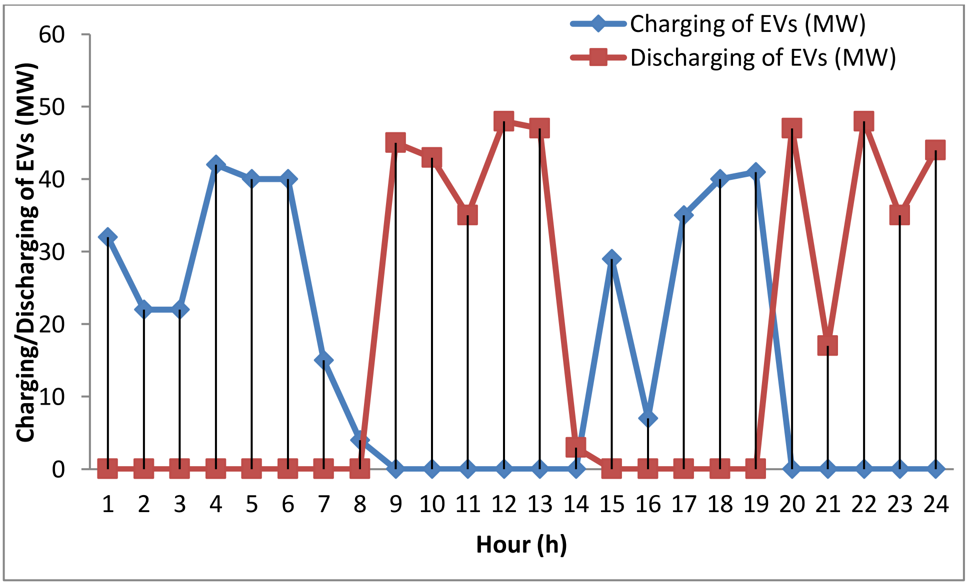

Fig. 4 Charging and Discharging power of EVs

The Proposed test system integrating PEVs and wind generation into the thermal unit commitment problem improves grid flexibility and efficiency. Wind power is variable and uncertain, while PEVs can act as mobile energy storage. The unit data and load data are taken from reference [12] and presented in Table 1 and Table 2, respectively. By strategically

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charging when wind power is high and discharging during peak demand, PEVs help balance supply and demand, reduce the operational burden on thermal units, lower costs, and enhance renewable energy utilization

Wind power generation by a turbine is highly dependent on wind speed, which fluctuates continuously, resulting in variable power output. Various methods have been developed to predict the uncertainties associated with wind energy. In this study, the Weibull distribution [16] is employed to model wind speed variability and assess associated uncertainties. Fig.3 illustrates the proposed wind power generation**,** where wind energy is integrated with thermal units and PEVs. This configuration allows the system to utilize renewable energy more effectively while reducing dependency on thermal generation.

Table 3Simulation results of EVs and wind integrated UC problem

Hour (h)	Total Generation	Fuel Cost ($)	Start Up Cost ($)	Total cost ($)
1	555	11202	1450	12652
2	601	11965	0	11965
3	715	13944	170	14114
4	847	16757	560	17317
5	881	17352	60	17412
6	1002	20055	0	20055
7	1044	20791	0	20791
8	1095	22300	60	22360
9	1137	23034	750	23784
10	1239	25349	30	25379
11	1300	27214	60	27274
12	1336	27954	0	27954
13	1239	25566	0	25566
14	1189	23946	0	23946
15	1122	22772	60	22832
16	946	19702	260	19962
17	932	19459	170	19629
18	1050	21514	0	21514

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19	1142	23122	60	23182
20	1233	25559	0	25559
21	1156	23367	0	23367
22	916	17965	0	17965
23	704	13753	0	13753
24	581	11633	0	11633
Total		**486275**	**3690**	**489965**

Electric Vehicles operate using stored electrical energy in onboard batteries and are typically considered as additional loads on the power system [17-18]. EVs can be broadly categorized into battery electric vehicles (BEVs), plug-in electric vehicles (PEVs), and hybrid electric vehicles (HEVs). With ongoing advancements in battery technology, a wide range of EV models are now being produced at scale. Various types of electrochemical batteries commonly used in EVs are listed in [10]. In [19], a structured vehicle-to-grid planning approach is presented, focusing on cost minimization strategies. Moreover, the increasing availability of charging infrastructureboth en route and at parking locationshas significantly boosted consumer interest in EV adoption. A representative charging and discharging profile for EVs is illustrated in Fig.4.

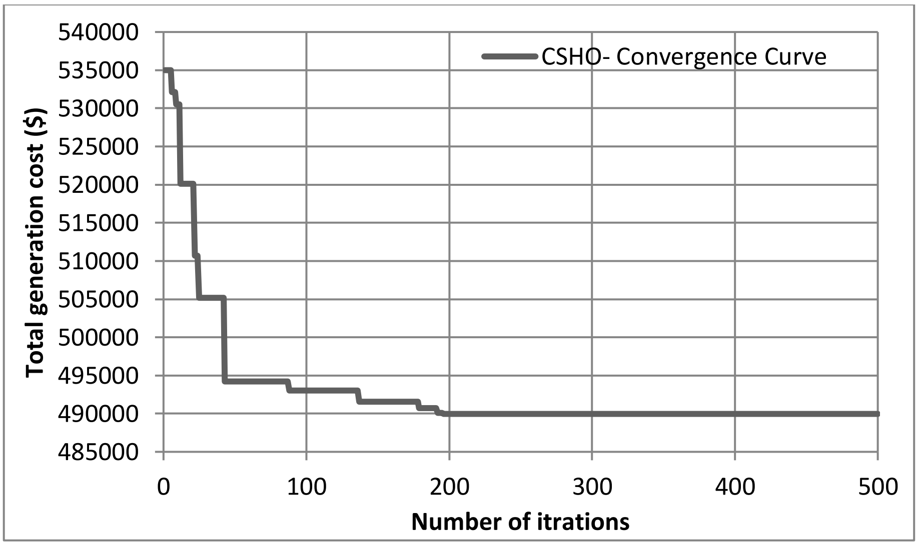

Fig. 5 Convergence curve of proposed CSHO method

Table 3 shows the simulation results of the UC problem for a system with thermal generation, EVs and wind energy. It lists the total generation, fuel costs, start-up costs, and total costs for various generation levels, illustrating how the algorithm optimizes energy production and

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minimizes costs. The total cost for the entire simulation period is $ 489,965,with a fuel cost of $ 486,275and a start-up cost of $ 3,690. This demonstrates the algorithm's ability to efficiently manage the system and reduce operational costs while integrating renewable energy sources and EVs.The convergence curve of the proposed CSHO for thermal units integrated with EVs and wind generation is presented in Fig. 5. It can be observed that approximately 180 to 200 iterations are sufficient to achieve the minimum total operating cost of the proposed test system.

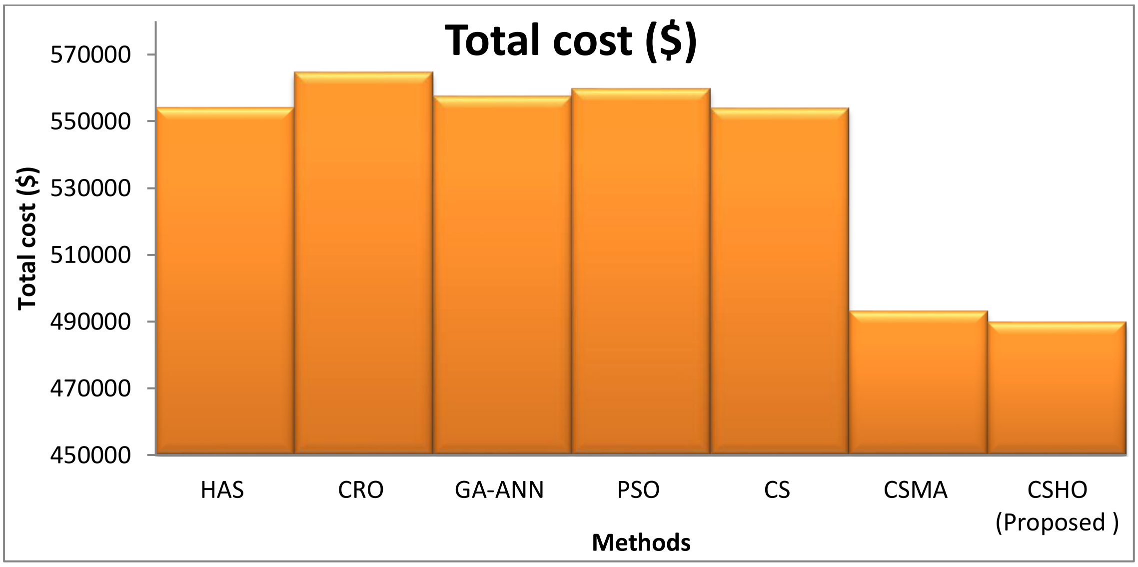

Fig. 6 Comparison of total cost of proposed with existing methods

Acomparativestudyevaluates the total costs of the CSHO algorithm against other optimization methods for two cases: Case-1 (thermal units only)andCase-2 (thermal units integrated with EVs and wind generation)**.** InCase-1**,** CSHO achieves a total cost of $ 560,685**,** outperforming other techniques. In Case-2, which includes the integration of EVs and wind power, CSHO delivers the lowest cost of $489,965better than methods like CSMAand HAS**.**The comparison of the total operating cost of the proposed method with existing approaches for thermal units integrated with EVs and wind generation is shown in Fig. 6.FromTable 3and Fig6, it is evident that the proposed CSHO algorithm effectively minimizes the total operating cost in both traditional and hybrid energy systems. The novelty of the proposed CSHO lies in its enhanced exploration and exploitation balance, which enables faster convergence and improved solution accuracy compared to conventional optimization methods

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5. Conclusion

From the obtained results and analysis, it is evident that the proposed CSHO algorithm exhibits superior performance in solving the UC problem for both conventional thermal systems and hybrid configurations integrating wind generation and PEVs.The algorithm effectively minimizes total operating costs while satisfying all operational and system constraints. In Case-1, involving only thermal units, the CSHO achieved an optimal cost of $560,685, while in Case-2, with the integration of EVs and wind energy, the total cost was significantly reduced to $489,965. The integration of renewable sources and EVs not only enhanced system flexibility but also reduced dependency on thermal generation during peak hours. The convergence characteristics further confirm that the CSHO achieves optimal solutions efficiently within a limited number of iterations (180–200), reflecting its strong convergence capability. The integration of EVs and wind generation in Case 2 reduces the total operating cost by approximately 12.61 %compared to the conventional thermal-only system in Case 1. Overall, the proposed CSHO exhibits a balanced exploration–exploitation mechanism, improved solution accuracy, and faster convergence compared to existing methods, making it a promising approach for cost-effective and sustainable power system scheduling.

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