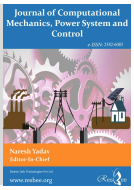
Vol.8 Issue 3 July 2025

Journal of Computational Mechanics, Power System and Control

Received 26 May, Revised 9 June, Accepted 18 June



Electric Vehicle Charging and Discharging Scheduling Approach Using Hybrid Optimization Algorithm

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Abstract: Mostly, Electric vehicles (EVs) experience power losses during the discharging and charging period and are connected to the building systems that supply the vehicle. These losses not only affect energy efficiency but also increase operational costs and stress on both the battery and the power grid. In order to ensure trip demand, user discharge and charge costs, and increase the precision of load demand curve prediction, this study proposes a dynamic charge and discharge optimization method that employs the charge and discharge control coefficient in each response period as the control object. By considering user behavior, state of charge, and grid demand simultaneously, the model ensures a balanced interaction between EVs and the power system. In contrast, the distribution network will suffer significantly from the chaotic charging and discharging of large numbers of EVs; however, EVs can be grouped and directed to charge and discharge in a systematic way, which will help delay distribution network investment. Therefore, this model suggested a new hybrid optimization algorithm, with the combination of Whale Optimization Algorithm (WOA) and Particle Swarm Optimization Algorithm (PSOA), to increase the utilization of renewable energy, reduce costs, and enhance grid stability. The hybridization leverages the global search ability of WOA and the fast convergence of PSOA, thereby overcoming the limitations of using each algorithm independently. In comparison to the present models, the proposed approach produced an accurate value of 0.97 for the EV discharging and the charging model. In MATLAB, the proposed framework is verified. The outcomes show that the suggested approach outperforms the conventional techniques for scheduling EV charges and discharges.

Keywords: Electric vehicle; Particle Swarm Optimization Algorithm; Whale Optimization Algorithm; Hybrid Optimization Algorithm.

Nomenclature

Abbreviation	Description
QPSO	Quantum Particle Swarm Optimization
EV	Electric Vehicle
V2G	Vehicle To-Grid
PSOA	Particle Swarm Optimization Algorithm
SW-OBLCSO	Backward Learning Competitive PSOA Based on Local Search Optimization
BESS	Battery Energy Storage System
CO_2	Carbon Dioxide
WOA	Whale Optimization Algorithm
V2G	Vehicle-to-Grid
DR	Demand Response
PICEAg-EV	Preference-Inspired Co-Evolutionary Algorithm for Electric Vehicle
BSS	Battery Storage System
MGSAPSO	Modified Gravitational Search Algorithm and Particle Swarm Optimization Algorithm
GSA	Gravitational Search Algorithm
HPWOA	Hybrid Particle Swarm Optimization - Whale Optimization Algorithm

1. Introduction

A number of countries globally have implemented Electric Vehicle (EV) technology, and a wide range of vehicles, including trucks, buses, taxis, and private automobiles, have switched to electric power [6]. Nowadays, EVs are being increasingly employed for environmental protection and greenhouse gas emission reduction in addition to lowering the usage of fossil fuels. This global transition reflects both policy-driven initiatives and consumer demand for sustainable mobility solutions. Nonetheless, the primary obstacle to the advancement of EV technology continues to be battery limitations [7]. First off, assuming its initial cost of acquisitions and battery life, the battery is considered a costly element of an EV. Furthermore, the interaction of the battery mostly determines the travel range per charge. With a range of 320 to 480 kilometers between charges, the lithium-ion battery is the most widely utilized battery in EVs. Although lithium-ion technology dominates, research continues into solid-state and alternative chemistries to address safety, density, and longevity challenges. The prolonged charging process and high infrastructure costs were addressed in [8] by designing a sophisticated battery information management system. The plan was to charge the exchanged batteries in a management center and then use an efficient

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supply chain to transport them to a switching station. However, a large number of battery loads would emerge from the model's assumption that all battery charging occurs entirely at the center [9]. Delivering the substantial EV battery pack is a challenge for the model, and there is a chance that it could become damaged in transit. A wind-powered BSS can be economical, due to the results of an economic dispatch model that was developed for an EV battery swapping station.

EVs play a major role in grid management and Carbon Dioxide (CO_2) decrease through Demand Response (DR) plans. Their insignificant battery capacity implies aggregator participation is necessary for successful participation, even though their integration into Vehicle-to-Grid (V2G) systems improves efficient energy transmission. Aggregators also make it simpler to regulate energy flow and participate in the market, which helps EV owners maximize their profits and optimize prices [10]. Thus, EVs are not only transportation assets but also potential grid stabilizers when properly coordinated. However, legislative changes are necessary to facilitate V2G interactions due to regulatory and technical problems, such as the requirement for sophisticated bidirectional charging systems. The resource allocation-based Preference-Inspired Co-Evolutionary Algorithm for EVs (PICEAg-EV) is proposed to address the multi-objective optimum control problem while considering user trips. In order to minimize the cost of charging for consumers, Reference [11] suggests an optimal control method for charge scheduling and establishes the load elasticity coefficient based on the regional power grid load. Reference [12] defines the capacity margin index and charge priority index and suggests a coordinated charge strategy using a valley filling strategy to choose the target time slot with enough residual power in the power grid for charge scheduling and to identify the charge priority of each EV in each time slot. These approaches highlight the importance of integrating user behavior and grid conditions into optimization frameworks for practical scheduling.

The charging station's location, size, and method were determined using a heuristic optimization technique, taking into account the fixed demand of electric vehicles. A simplified genetic algorithm was suggested by [13] to find the best way to figure out the airport buses' charging schedule. For the scheduling problem, [14] suggested a direct forecast approach that is faster than the general solution. However, this study merely created the fundamental program for resolving a specific issue utilizing optimization algorithms. Also, when they used several algorithms to solve their difficulties, they did not compare the results. In addition to the operating model and optimization techniques, the suggested Battery Energy Storage System (BESS) model largely depends on the characteristics of EV batteries [15]. Similar issues affect the current scheduling methods for EV charging and discharging, such as expensive infrastructure costs, unstable grids, and user-specific issues, including charging preferences and range anxiety. Another major challenge is the stochastic nature of EV arrivals and departures, which introduces uncertainty into scheduling models and complicates prediction accuracy. It also suffered problems with power demands, owner behavior, and EV arrival time uncertainty, which made it more difficult to develop efficient scheduling plans. Therefore, the model suggested a new hybrid optimization strategy that combines the PSO and WOA techniques for scheduling EV charging and discharging to save costs, maximize grid stability, and optimize load demand. The synergy of PSO's fast convergence and WOA's global search ability makes the hybrid approach particularly suitable for nonlinear, multi-objective scheduling problems. By utilizing the advantages of both algorithms, this method offers a V2G strategy that is both economical and grid-supportive.

The contribution of the paper is specified below,

- To develop an EV charging and discharging scheduling method to balance user preferences and battery health while minimizing costs and variations in grid load. It is especially utilized for optimizing the EV's load demand.
- To introduce a hybrid optimization technique to attain more effective and efficient solutions. This method is used to cut down on computing time, increase the utilization of renewable energy, improve grid stability, and decrease expenses.

The organization of the paper is mentioned as follows: Section 2 represents the literature survey and problem statement of the existing approach-based charging and discharging schedules of EVs. Section 3 gives the proposed methodology of the EV charging and discharging schedules. Result and Discussion of the proposed approach is presented in Section 4. Finally, Section 5 concluded the suggested optimization-based EV charging and discharging scheduling model.

2. Literature Survey

2.1 Related Work

The related existing work for the suggested EV charging and discharging model is given below,

In 2022, Haihong*et al.* [1] suggested a dynamic charge and discharge optimization approach that uses the control object to be the charge and discharge control coefficient for each response period. The suggested

method takes into consideration of the interests of users and the peak shaving demand of the power grid. The models can trip the time-space distribution of EV users, sort each response period according to the starting time from small to large, and use Quantum Particle Swarm Optimization (QPSO) to solve the multi-objective optimization of the charge and discharge control coefficient for the sorted response period. The findings show that, while guaranteeing trip demand and revenues for EV owners, the suggested approach may effectively decrease the load demand curve's peak valley disparity and variance. However, the QPSO-based model has limitations in scalability when the number of EVs grows significantly, as the optimization process becomes computationally intensive.

In 2021, Wan-Jun *et al.* [2] proposed a Backward Learning Competitive Particle Swarm Optimization (PSO) technique, known as SW-OBLCSO, which was developed using the standard IEEE-33 node distribution system as the study object. The SW-OBLCSO algorithm uses techniques for both competitive and reverse learning. The experimental findings demonstrated the outstanding convergence speed and global search capability of the suggested algorithm. Minimum operation costs, system grid loss, load peak-valley difference, environmental pollution, node voltage offset rate, and lowest charge cost were the optimization goals. According to the findings, the proposed plan could shift the charging load in both space and time, which would stabilize load fluctuations in the distribution grid, enhance the quality of power grid operation, reduce user charging prices, and accomplish the anticipated study objectives. Nevertheless, the algorithm is sensitive to parameter tuning and risks falling into local optima under highly dynamic EV arrival conditions.

In 2022, Xizheng*et al.* [3] established the Particle Swarm Optimization (PSO) Algorithm's global memory capacity into the Gravitational Search Algorithm (GSA). Designing an adjustable inertia vector, and chaotic starting population, learning factor simultaneously enhanced the hybrid algorithm. The optimization results indicated that the ordered charging-discharging strategy can improve grid economy and safety while reducing 78.77% of the microgrid load variance and 13.38% of the overall cost under the same weight factor. Furthermore, the load variance might be reduced by 22.36% and the overall cost by 14.06% with sensible scheduling of the distributed power output. Also, by examining the effects of varying numbers of EVs and charging models, the efficacy of the suggested plan was demonstrated. Despite its strong performance, MGSA-PSO involves high computational complexity, which reduces its practicality for real-time grid applications.

In 2021, Ning *et al.* [4] proposed a multi-energy scheduling model that incorporates the photovoltaic system and is based on the ordered charging and discharging of EVs in typical urban residences. The minimum variance of the total power demand and the minimum scheduling cost were chosen as the model's optimization objectives to improve models with a single objective in earlier research. The multi-objective particle swarm optimization approach was then utilized to address the problem. The findings demonstrate that: 1) the overall power load in the region using the scheduling algorithm was substantially lower than that of the region with disordered charging, where the expansion rate of peak electricity consumption can be lowered by as much as 127.2%; 2) the system's profitability increases significantly as the number of EVs taking part in the scheduling increases. The profit from dispatching 70 EVs can be up to 150% greater than that from sending 10 EVs. Although promising, the model tends to oversimplify user heterogeneity and may restrict flexibility in individual charging preferences.

In 2022, Mengjiao*et al.* [5] suggested a distribution transformer capacity allocation model as the optimization target constraint and an optimal dispatch model for electric vehicles that takes distribution network safety into account. While meeting regional distribution transformer needs and preserving distribution network security, this model could successfully reduce needless investment when compared to the majority of optimized dispatch models used to maximize aggregator revenues and minimize peak-to-valley differences and load fluctuations in distribution networks. The findings demonstrated that the presented optimal scheduling approach could successfully limit distribution network load fluctuations, maintain the voltage offset within the permitted voltage deviation range, and successfully defer distribution network investment. However, the reliance on advanced infrastructure and strict coordination mechanisms may pose challenges for large-scale deployment.

2.2 Problem Statement

In this section, the problem definition of the existing models used for the EV charging and discharging schedules is presented. The high charging demand for electric taxis was one of Paper [1]'s disadvantages, but it also had the benefit of guaranteeing trip demand, user charge and discharge costs, and improving the accuracy of load demand curve prediction. Still, its inability to scale efficiently across diverse EV categories highlights the need for more adaptive algorithms. While a SW-OBLCSO is suggested in [2] and offers the advantages of a low operating cost, low environmental pollution, a low peak-valley load difference, a low node voltage offset rate, a low system grid loss, and a low charge cost, it also poses difficulties in determining the global optimum and accepting a range of user behavior. This limitation

reduces its robustness in heterogeneous and highly dynamic EV populations. In [3], a hybrid MGSA-PSO method is proposed. It can optimize load dispatch, preserve operating costs, and increase grid stability. However, it also has a variable and stochastic period of EV driving for different owners in different areas. A multi-energy scheduling model [4] has the benefit of minimizing scheduling costs and power load fluctuation, but it also has the disadvantage of potentially eliminating the user from the scheduling process. This exclusion of user behavior limits its practicality in consumer-centric EV ecosystems. The benefits of an optimal dispatch model in [5] include maximizing aggregator income, minimizing load variations and peak-to-valley variances in distribution networks, and preserving distribution network security. Significant disadvantages also include the potential for higher infrastructure investment to handle peak loads and the expense of having advanced control systems in place, willing to take part in aggregation regulation under various compensation price incentives.

3. Proposed Methodology

Charging and discharging are the essential procedures that allow Electric Vehicles (EVs) to operate properly. With the increasing penetration of EVs in modern power networks, their coordinated charging and discharging have become a critical factor in energy management and demand response. The continuous development of large-scale EVs has provided the power system with a vast number of dispatchable resources. Because of the rise in electricity demand, the power system will be significantly impacted by EVs. Therefore, intelligent scheduling becomes essential for the process of charging and discharging EVs. In this case, the optimization procedure is carried out to control the consumption of energy, save costs, and maintain grid stability.

In the same way, the current scheduling model has several drawbacks, such as the need to enhance charging and discharging instances in order to improve grid stability, lower costs, and lessen difficulty for EV prospects. Additionally, existing models often fail to consider real-time variations in energy prices, dynamic user behavior, and stochastic travel patterns of EV owners, which significantly affect the efficiency of scheduling strategies. In this model, the EV's charge and discharge scheduling mechanism used a novel hybrid optimization technique called Hybrid Particle Swarm Optimization - Whale Optimization Algorithm (HPWOA)for the purpose of optimizing EV charging and discharging patterns in order to reduce costs and enhance grid stability.

According to this model, the main factors influencing battery loss are the charge and discharge rate, capacity, depth of discharge, number of cycles, and state of charge. Accurately modeling these factors ensures that the optimization process not only minimizes operational costs but also prolongs battery life, which is a major concern for EV owners and fleet operators. The battery life and number of cycles are approximately linear, and the battery degradation cost is calculated using Eq. (1):

$$\begin{cases} D_{n,t}^{V2G} = \left|\dfrac{Bn}{100}\right| \dfrac{y_{n,t}}{D_n} D^A \\ y_{n,t} = \max\left\{0, \left(R_{n,t-1} - R_{n,t}\right) D_n\right\} \end{cases} \tag{1}$$

Where $D_{n,t}^{V2G}$ is the expense of the EV's battery degradation over time t. Bn is the linear association coefficient, which is 0.015625 in the current study, between cycle times and battery life, D_n is the electric vehicle's battery capacity, $y_{n,t}$ is the vehicle's periodic capacity for charging and discharging. $R_{n,t}$ and $R_{n,t-1}$ are the vehicle's SOC for the current period t and the prior period. While there is no expense associated with battery loss during charging, there is when the EV responds to V2G discharge in period t .This distinction highlights that V2G participation, while beneficial to the grid, incurs additional costs on EV owners, making optimal scheduling crucial for fair cost-benefit distribution.

As a desired function is provided in Eq. (2), determine the EV's smallest cost for the charge and discharge time after taking into consideration of the battery cycle charge and discharge cost.

$$\begin{cases} \min f_a = \sum_{t=t_{n,in}}^{t_{n,out}} \left(\dfrac{d_{m,t} y_t Q_r}{4} + D_{n,t}^{V2G} \right) \\ z_t \in \left\{ D_{cp,t}, D_{cu,t}, D_{cv,t}, D_{dp,t}, D_{du,t}, D_{dv,t} \right\} \end{cases} \tag{2}$$

When $t_{n,out}$ is the time for EV expected to leave the grid and $t_{n,in}$ represented the charge and discharge scheduling's starting time of the EV's time. f_b is the EV's charge and discharge costs once battery loss is taken into account. Q_r represents the EV's rated power for charging and discharging. The charge prices through peak, normal, and valley periods are as follows $D_{cp,t}$, $D_{cu,t}$, and $D_{cv,t}$. $D_{dp,t}$, $D_{du,t}$, and $D_{dv,t}$ denoted the discharge values during the peak, normal, and valley periods. Incorporating these time-of-use prices

ensures that the scheduling mechanism prioritizes charging during low-cost valley periods and discharging during high-value peak periods, thereby maximizing economic benefits.

The objective is to reduce the load variation for peak-to-valley during the response time, which is represented by Eq. (3), to avoid EVs being widely charged during hours of high-power demand after being connected to the grid, which would result in peak-to-peak superposition.

$$\begin{aligned} &\min f_b = Q_{n,pk} - Q_{n,vl} \\ &\begin{cases} Q_{n,pk} = \max\limits_{t_{n,in} \le t \le t_{n,out}} \left\{ Q_t + Q_{n,t} \right\} \\ P_{n,vl} = \max\limits_{t_{n,in} \le t \le t_{n,out}} \left\{ Q_t + Q_{n,t} \right\} \end{cases} \end{aligned} \tag{3}$$

The trip chain's unpredictability means that each EV might react to V2G scheduling multiple times throughout the day. To address this, the proposed HPWOA algorithm dynamically adapts to each EV's availability window, ensuring flexibility in participation while maintaining overall system stability. As a result, each EV's various V2G reaction times must be examined throughout the day. Similarly, $Q_{n,t}$ is the m-th EV's charge and discharge power during the time t when reacting to a V2G dispatch, respectively. $Q_{n,pk}$ and $Q_{n,vl}$ represent the m-th EV's electric power consumption peak and valley values during the reaction time.

EV SOC: It is stated as a proportion and is intended to protect the battery life from harm. Eq. (4) requires that the battery's energy be restricted.

$$SOC_{\min} \le SOC \le SOC_{\max} \tag{4}$$

where $SOC_{\min}$ is the minimum SOC and $SOC_{\max}$ is the maximum SOC. Maintaining the SOC within these bounds prevents overcharging and deep discharging, which are known to cause significant battery degradation.

The model uses a 20% $SOC_{\min}$. The battery's lifespan could be reduced, and damage could also occur below this threshold. Furthermore, it is advised to cease charging at 80% of ($SOC_{\max}$) rather than 100% of SOC because higher voltage and heat from full charging may damage the EV's battery material. This approach not only safeguards the battery's electrochemical properties but also improves the long-term economic value of EV ownership by reducing replacement costs.

The primary limitation with regard to the charging scheduling issue is the charging time. The charging time preferences of an EV driver should be taken into account. User-specific flexibility windows ensure that the optimization process aligns with real-world user needs while still contributing to grid objectives. If an EV driver wants to charge in the morning, for instance, a limit on the available charging periods is taken into consideration to give convenient charging at the appropriate time slots. The availability of the charging station can enhance the EV driver's charging experience by giving an indicator of the waiting time based on load demand.

3.1 Implemented a hybrid optimization algorithm technique for EV charging and discharging schedules

A model suggested new hybrid optimization strategies that combine two algorithms, PSOA and WOA, respectively, to decrease operating costs, maximize battery health, besides enhance grid stability and efficiency. The integration of these algorithms leverages PSO's global exploration capability and WOA's exploitation ability, resulting in a more robust search process for optimal solutions. To identify best response, PSO requires a specific quantity of initial solutions and then iterations. The particle must update two quantities throughout each iteration and update: the population ideal position and the individual optimal position.

Here, k the total number of iterations is the definition of the particle swarm $\left\{ Y_1^k, Y_2^k, ..., Y_N^k \right\}$. The particle updates its position and speed by Eq. (5) after determining the two quantities of individual ideal position Q_{best}^k and population optimal position H_{best}^k:

$$\begin{cases} U_1^{k+1} = \delta U_i^k + d_1 r_1 (Q_{best}^k - Y_i^k) + d_2 r_2 (H_{best}^k - Y_i^k) \\ Y_i^{k+1} = Y_i^k + U_i^{k+1}, \end{cases} \tag{5}$$

Where δ is the weight of inertia, which is typically 0.9, r_1 and r_2 are random values with a uniform distribution from 0 to 1, similarly, d_1 and d_2 referred to as learning factors or acceleration factors. The inertia weight helps maintain a balance between exploration of the global search space and exploitation of the best solutions found so far.

In the subsequent stage, there will be slow convergence if the velocity of the particle is excessively different. A simplified PSO method has been presented in the literature to address this issue (Lin et al.,

2020). This modification avoids premature stagnation in suboptimal regions by allowing the algorithm to adaptively refine the search direction. The implemented technique eliminates the velocity time and uses only a position term to regulate the evolutionary direction of particles; Eq. (6) in the conventional PSO is reduced as

$$Y_i^{k+1} = \delta Y_i^k + d_1 r_1 \left(Q_{best}^k - Y_i^k \right) + d_2 r_2 \left(H_{best}^k - Y_i^k \right) \tag{6}$$

Using traditional optimization algorithms like linear programming to handle the non-linear, multi-constrained,multi-variable, and high-dimensional EV optimization problem is challenging (Liu et al., 2020). This study uses the WOA with the PSO method for optimization because the regular PSO algorithm is prone to local optimum. By combining WOA, the algorithm gains an enhanced capability to escape local minima and improve convergence toward global optima.

The WOA was modeled after the hunting strategies of humpback whales, is an effective optimization method with a shown search capability. In this way, these whales move toward the surface while creating bubbles and encircling their prey with a bubble net. The WOA has copied this technique, which is unique to these species. This biologically inspired approach allows the algorithm to dynamically switch between global search (exploration) and local search (exploitation), improving optimization robustness.

At the first stage, the distance between the prey and the whale in the place is calculated using this spiral updating position method. After that, a spiral condition is added between the prey and the humpback whale's position to imitate the behavior described in Eq. (7):

$$\overline{Y}_{t+1} = \overline{Y}_t + \overline{D} e^{bl} . \cos(2\pi l) \tag{7}$$

It is observed that $\overline{D} = \left| \overline{Y}(t) - \overline{Y(t)} \right|$ indicates the separation between the prey and the whale. Furthermore, it displays a constant to simulate the logarithmic winding condition and an arbitrary number between [-1, 1]. This spiral mechanism ensures that solutions move closer to the optimal point while maintaining sufficient diversity to avoid premature convergence.

Humpback whales circle their prey in a spiral motion as they approach the surface. Therefore, as illustrated below, this work uses a 50% chance of diminishing encircling and spiral movement to renew whale locations, which is an arbitrary value in the interval [0,1]:

$$\vec{x}_{t+1} = \begin{cases} \vec{Y}_t - \vec{A}.\vec{D} & If\ Q < 0.5 \\ D.e^{bl} . \cos(2\pi l) + \vec{Y}_t & If\ Q < 0.5 \end{cases} \tag{8}$$

This probabilistic mechanism enables the algorithm to balance exploration and exploitation adaptively, ensuring that both early-stage global search and late-stage fine-tuning are effectively handled.

4. Result and Discussion

The dual hybrid optimization-based EV model's performance is calculated with the use of MATLAB 2021b to produce data from the Simulink model. Moreover, the accuracy of the suggested approach for charging and discharging power, as well as load demand, with varying optimization weight for the test sample, is established. The simulation environment replicates real-world grid scenarios, enabling accurate assessment of the proposed optimization algorithm under different operational conditions. A comparison of the discharge and charge power, an original load demand curve, and the optimized load demand curve has been used to assess the effectiveness of the findings' performance. Such comparative evaluation ensures that improvements in grid stability, cost reduction, and user satisfaction are quantitatively demonstrated. These analyses validated the efficacy of the model.

4.1. Optimization Outcomes: Below Various Optimization Weights in The Similar Response Time

The EV charging data for the same response period, assuming 100% user responsiveness, is as follows: P_r = 10, $S_{m,in}$ = 0.8162, $S_{m,tg}$ = 0.95, $t_{m,in}$ = 30, $t_{m,es}$ = 19, C_m = 20, $t_{m,rout}$ = 50. With optimization weights of $\lambda_1 : \lambda_2 : \lambda_3 : \lambda_4 : \lambda_5$ = 0:2:0.2:0.2:0.2:0.2, $\lambda_1 : \lambda_2 : \lambda_3 : \lambda_4 : \lambda_5$ = 0:1:0.2:0.3:0.3:0.1, and $\lambda_1 : \lambda_2 : \lambda_3 : \lambda_4 : \lambda_5$ = 0:1:0.3:0.3:0.2:0.1, the discharge and charge optimization results are examined when the user reacts to V2G. These weight configurations represent different prioritization strategies between minimizing grid fluctuations, reducing battery degradation costs, and maximizing economic returns. Fig. 1-3 displays the load demand curve as well as charge and discharge power distribution under various weights.

In the response period, the proposed hybrid optimization algorithm-based model can lower the power grid's load demand and raise it during the response period's valley, as shown in Fig. 1-3, under the three optimization weights. This demonstrates the algorithm's ability to smoothen demand peaks while increasing off-peak utilization, a key requirement for efficient grid management.

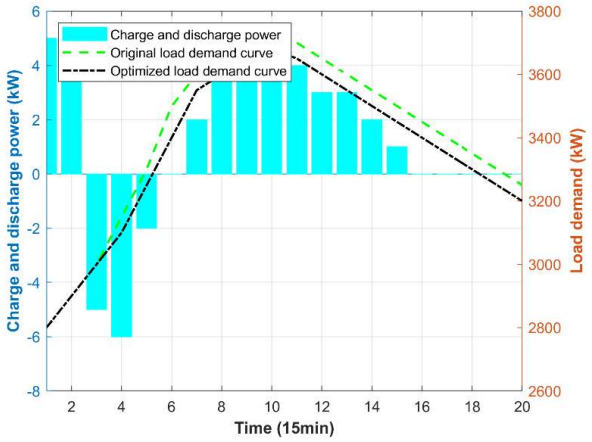

Fig. 1. *Power and load demand curve for charge and dischargewhile the optimization weight is* $\lambda_1 : \lambda_2 : \lambda_3 : \lambda_4 : \lambda_5 =$ *0:2:0.2:0.2:0.2:0.2*

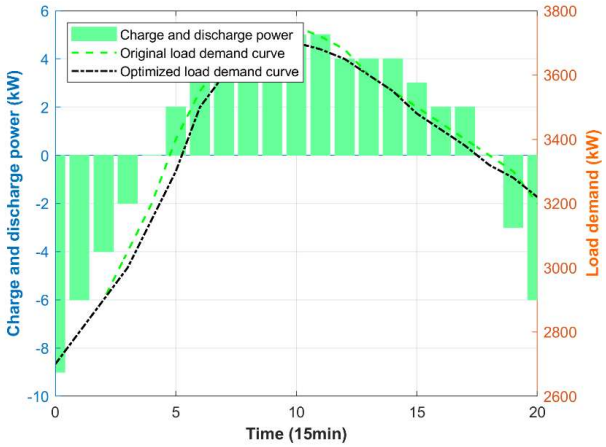

Fig. 2. *Power and load demand curve for charge and discharge while the optimization weight* $\lambda_1 : \lambda_2 : \lambda_3 : \lambda_4 : \lambda_5 =$ *0:1:0.2:0.3:0.3:0.1*

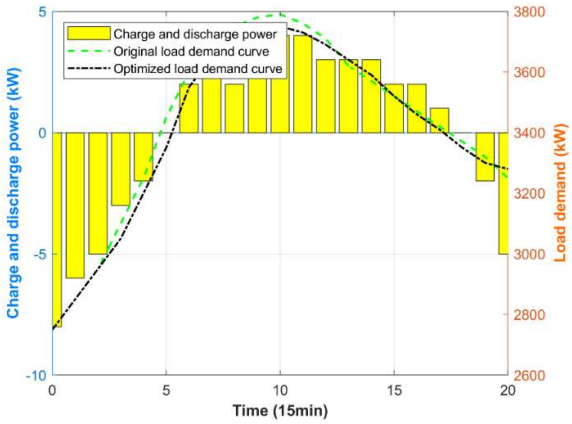

Fig. 3. *Power and load demand curve for charge and discharge while the optimization weight* $\lambda_1 : \lambda_2 : \lambda_3 : \lambda_4 : \lambda_5 =$ *0:1:0.3:0.3:0.2:0.1*

The HPWOA-based optimization procedure for orderly charge and discharge with varying optimization weights is depicted in Fig. 4. The optimum is reached for various optimization techniques in 500 iterations, and the fastest convergence occurs when the optimization weight ratio is $\lambda_1 : \lambda_2 : \lambda_3 : \lambda_4 : \lambda_5 = 0:1:0.3:0.3:0.2:0.1$. This rapid convergence indicates that the hybrid approach effectively balances exploration and exploitation, outperforming traditional single-method optimizers.

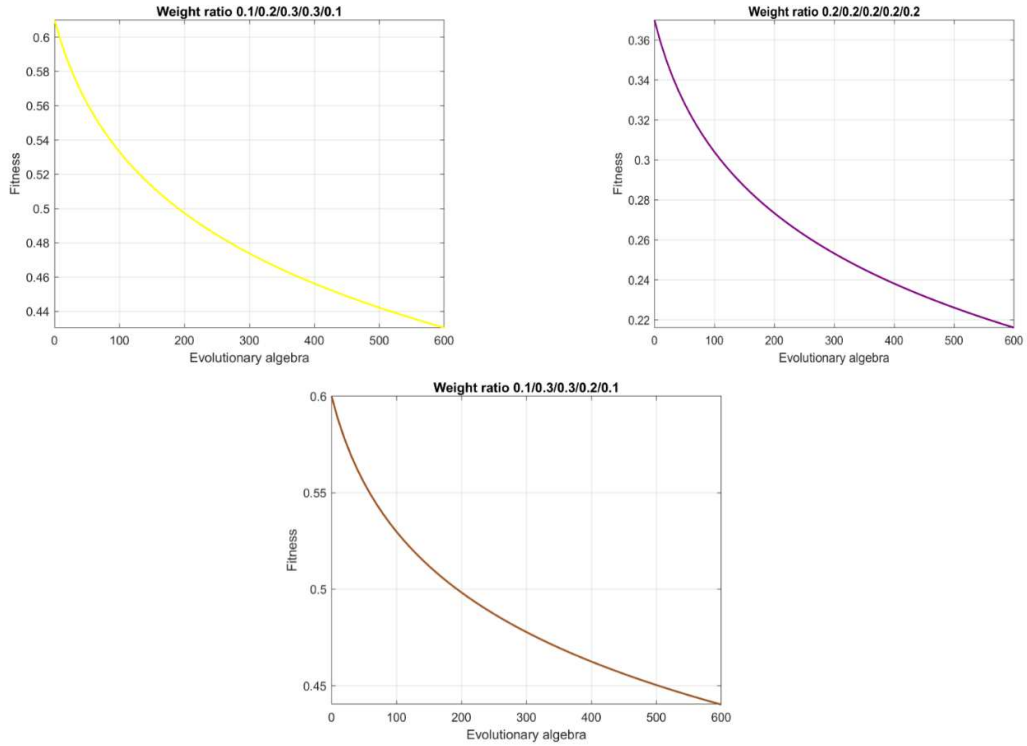

Fig. 4. *Fitness values of the proposed model with various optimization weights*

Table 1. *Optimization outcomes of EV's charge and discharge schedule at a response of 40%*

$\lambda_1:\lambda_2:\lambda_3:\lambda_4:\lambda_5$	Average income of orderly charge and discharge (yuan)	Average SOC satisfaction	Average charge and discharge conversion times	Average optimal fitness value	Peak valley difference (kW)	Peak valley difference (kW)
0.2:0.2:0.2:0.2: 0.2	0.348	0.819	7.180	0.392	2.3912E+03	3.1658E+07
0.1:0.2:0.3:0.3: 0.1	0.381	0.829	6.981	0.609	2.3015E+03	3.1411E+07
0.1:0.3:0.3:0.2: 0.1	0.478	0.845	7.123	0.602	2.2987E+03	3.0772E+07

The EV's charge and discharge optimization outcomes using the suggested HPWOA technique are displayed in Table 1. Each index performs volatily when the optimization weight is $\lambda_1:\lambda_2:\lambda_3:\lambda_4:\lambda_5=$ 0:2:0.2:0.2:0.2:0.2:0.2. Overall, performance across a range of measures improves with increased response. Specifically, a higher degree of user responsiveness enables better load distribution, minimizes peak-to-valley gaps, and enhances grid reliability. The regularity in responsiveness is not represented by the advantages and disadvantages of various metrics under different optimization weights. This variability suggests that while certain optimization weight combinations yield superior grid-level benefits, they may impose higher costs on EV owners, underscoring the need for adaptive weight tuning in real-world applications.

A higher valley load and a smaller peak load are characteristics of the optimized load demand when the charge and discharge optimization strategy recommended in this study is put into practice. This confirms that the proposed HPWOA-based approach not only achieves load leveling but also improves energy utilization efficiency, making it a promising solution for future smart grid systems with high EV penetration.

5. Conclusion

This work introduced a novel hybrid optimization technique for charge and discharge scheduling in EVs to optimize discharging and charging schedules, though including various objectives such as cost, grid stability, and user preferences. The proposed approach demonstrated that combining PSO and WOA can effectively address the multi-objective nature of EV scheduling problems, outperforming conventional methods in both convergence speed and solution quality. Similarly, this scheduling of the EV model was performed. As a result, changing requirements of EVs and easily accessible charging stations were discovered. Subsequently, the EV was scheduled utilizing the charge and discharge scheduling algorithm,

which was previously modelled using HPWOA technology. In this case, a multi-objective fitness function was created with a number of parameters, such as the distance, charging cost, user choice, and remaining power. This comprehensive fitness formulation ensured a balanced trade-off between user convenience, operational efficiency, and grid stability. The EVs were assigned to the charging and discharging station based on the scheduling technique. The efficiency of the approach was then revealed by updating the EV charging and discharging scheduling model features. With the lowest charging cost, lowest fitness, and maximum power, respectively, the suggested HPWOA performed better than the competition. Future studies should investigate the possibilities of V2G technology and focus on creating integrated algorithms that take into account the requirements of many users.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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