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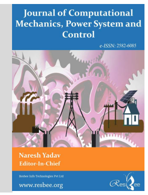

Hybrid Optimization based Electric Vehicle Charging- Discharging Scheduling with Renewable Energy Resources

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Abstract: The increasing adoption of EVs and the integration of RES present both opportunities and challenges for modern power systems. To schedule EV charging and discharging in conjunction with renewable energy sources like solar and wind, this article suggests a hybrid optimization-based method. The objective is to enhance energy efficiency, minimize dependency on fossil fuels, and ensure grid stability. Furthermore, the rising demand for electric vehicles (EVs) necessitates more innovative strategies to balance charging loads with fluctuating renewable energy availability. Various system configurations, including PV systems, fuel cells, and battery energy storage, are reviewed and analyzed for their technical and economic viability. A comprehensive assessment of the integration of EVs with renewable energy also addresses the potential for demand-side management techniques to optimize grid operations. The proposed scheduling method, AO-GW, optimizes the energy management efficiently under dynamic conditions, accounts for the intermittent nature of RES and the dynamic charging demands of EVs, optimizing energy flows between vehicles, storage units, and the grid. Simulation results demonstrate that hybrid optimization strategies improve system reliability, reduce energy costs, and support the effective integration of renewable energy into EV infrastructure, contributing to sustainable and resilient energy ecosystems. These advancements further pave the way for enhancing the overall sustainability of the transportation and energy sectors.

Keywords: Electric Vehicle, Photovoltaics, Charging-Discharging Scheduling, Renewable Energy Resources, Battery Energy Storage Systems.

Nomenclature

Abbreviation	Description
HEV	Hybrid Electric Vehicle
C-DS	Charging-Discharging Scheduling
RES	Renewable Energy Resources
PHEV	Plug-In Hybrid Electric Vehicles
PV	Photovoltaic
BESS	Battery Energy Storage Systems
ICE	Internal Combustion Engine
GWO	Grey Wolf Optimization
WOA	Whale Optimization Algorithm
IDS	Intrusion Detection System
SHT	Sequential Hypothesis Testing
AMI	Advanced Metering Infrastructures
FC	Fuel Cell
EV	Electric Vehicle
FCEV	Fuel Cell Electric Vehicle
ER-EV	Extended-Range Electric Vehicle
AO	Aquila Optimizer

1. Introduction

EVs have been created and embraced as a greener substitute to lower greenhouse gas emissions and reliance on fossil fuels [6]. A controller that gets power from renewable energy sources or the utility grid charges the battery of an electric vehicle. The main categories of EVs include HEV, FCEV, ER-EV, PHEV, and BEV. The efficiency of an HEV's powertrain largely depends on driving behavior and the performance of key components such as converters, switches, and motor drives [7]. In addition to advancements in physical components, substantial progress is being made in HEV software to enhance overall system efficiency. Typically, a HEV combines an ICE with an electric motor for propulsion.

With growing global concern over environmental sustainability, automakers are increasingly prioritizing HEV development. This increased focus on sustainability is driving significant investment in research and development to further optimize EV technology for greater environmental benefits. Hydrogen has also emerged as a clean fuel alternative aimed at reducing emissions, and FCs are being explored as a viable replacement for conventional gasoline-powered vehicles [2]. This is attributed to the low emissions, reduced dependence on crude oil, and improved fuel efficiency offered by FC systems, which collectively enhance air quality, energy security, and efforts to combat climate change. Leveraging the strengths of both FC technology and renewable energy, integrating PV cells into electric vehicles can increase onboard energy availability, even while driving. PV energy, being abundant, free, and renewable, is among the most valuable clean energy sources [12,13].

To manage the intermittent nature of renewable energy, BES are commonly employed. The integration of BES into the EV charging infrastructure can provide critical support in balancing energy loads and reducing grid stress, especially during periods of high demand. Integrating EV chargers with BES helps minimize negative impacts on the power grid. Additionally, the battery's characteristics and charging process significantly affect its lifespan, energy efficiency, and charging duration [11]. Efficient battery management systems (BMS) are also being developed to optimize charging rates and prevent overcharging, which can extend the lifespan of EV batteries and enhance overall efficiency. EV battery charging still largely relies on traditional fossil fuels, contributing to environmental pollution. To address this, researchers and companies are increasingly promoting the use of renewable energy sources, such as solar, wind, and biogas, for EV charging. Instead of depending on the conventional power grid, wind energy and other renewables offer cleaner alternatives. When managed effectively, the charging and discharging of HEV batteries can allow them to function as dispatchable energy storage systems. This helps balance energy supply and demand while enhancing grid flexibility and reliability. HEVs also support the integration of renewables into the power grid by mitigating the variability inherent in sources like wind and solar.

This article offers the following key contributions:

- Proposed a hybrid optimization framework integrating AO-GW for efficient EV charging–discharging scheduling.
- Enhances grid stability and energy cost-efficiency by leveraging renewable energy sources in EV scheduling.
- Demonstrates superior performance of the hybrid AO-GW algorithm compared to standalone metaheuristics in terms of convergence and energy utilization.

The structure of the paper is about charging and discharging scheduling EVs, which is covered in Section 2. Problem Definition of the existing methods is given in Section 3. The application of the metaheuristic algorithms for scheduling process optimization is described in depth in Section 4. Section 5 presents various case studies and simulation results that showcase the advantages of the proposed method in real-world scenarios, particularly during peak demand periods. A thorough explanation of the simulation's outcomes and performance assessment is provided in Section 5. Section 6 wraps up the study and suggests possible avenues for further investigation in this area.

2. Related Works

A HEV charging station with a small-scale solar system and battery energy storage was proposed by Andrija Petrusic et al. [1] in 2021. Through the computation of the renewable energy share obtained from the battery storage, this approach seeks to lessen the adverse effects of uncontrolled EV charging. Multi-attribute utility theory serves as the foundation for the methods used to optimize the battery's charging/discharging schedule and EV charging levels. Reducing battery degradation, optimizing renewable energy consumption (from the solar system and the battery), and limiting charging expenses are the main goals of the optimization criteria. A genetic algorithm designed for the multicriteria optimization function is used to tackle the problem. This approach highlights the importance of integrating renewable energy and energy storage to optimize EV charging while minimizing negative environmental impacts.

A Power Management and Control system for a HEV that uses photovoltaic, fuel cell, and battery energy sources was presented by Naoui Mohamed et al. [2] in 2021. Two converters connected the fuel cell and photovoltaic systems in parallel, providing electricity to the main traction motor or a bank of lithium batteries. A hybrid recharging system was produced by this configuration. The entire recharging system was mathematically modeled by the study, taking into account variables including vehicle load, stepwise component modeling, and a thorough examination of the required electrical equipment. After that, a streamlined power management loop was created and put into use. The integration of fuel cells and photovoltaics highlights the growing trend of combining various renewable sources to maximize energy availability for EVs.

In 2021, using an energy storage technology and renewable energy, Desheng Li et al. [3] created an energy management plan for a sizable EV charging station. The energy requirements for charging EV batteries are satisfied by the grid-connected storage system. As customer energy needs vary, scheduling charging and discharging for grid-to-vehicle and vehicle-to-grid operations is challenging. A 400 kWp solar system, a 100kW/500kWh energy storage system, and a charging station with up to 500 charging stations were all subjected to a power scheduling algorithm based on chance-constrained programming. Despite the unpredictability of PV generation, this strategy maximizes power distribution, which benefits EV users as well as the charging station. To ensure that energy consumption stays within the contract's capacity restrictions, the system incorporates time-of-use adjustments, taking into account charging/discharging priorities and electricity pricing. The use of chance-constrained programming emphasizes the need for advanced optimization techniques to manage the uncertainties associated with renewable energy generation.

A hybrid machine learning-based energy management policy for renewable-powered microgrids was proposed by Ming Lei et al. [4] in 2021, taking into account the need for HEV charging. Their strategy reduces grid operating expenses by leveraging the WOA. They also developed an IDS based on the SHT technique to detect identity-based cyberattacks on wireless AMI, including masquerade and Sybil assaults. RSS levels are used by the suggested IDS to distinguish between signal sources and identify possible cyberattacks. This work introduces the intersection of machine learning and cybersecurity in renewable energy systems, which is increasingly critical for protecting the integrity of grid-connected EV infrastructure.

The technological and financial viability of PV-powered EV charging stations in Vietnam was investigated by Phap Vu Minh et al. [5] in 2021, taking into account different solar irradiation conditions. EV renewable energy infrastructure expansion may contribute to lower greenhouse gas emissions and better urban air quality. Emissions from EVs charged by PV systems are lower than those from utility grid-powered EVs. Therefore, integrating solar energy with EV charging stations presents a viable strategy for attaining sustainability in the expanding EV market. Although the number of EVs in Vietnamese cities has grown quickly, there is still a lack of adequate charging infrastructure, with the majority of stations still using electricity from the grid. This study emphasizes the growing importance of localized renewable energy solutions in emerging markets, where the infrastructure for EVs is rapidly developing.

3. Problem Definition

An overview of techniques for charging and discharging scheduling with RES is included in this section. A hybrid EV charging station that incorporates battery energy storage and a small-scale photovoltaic system was suggested in [1]. Though it did not measure the battery's renewable energy contribution, this hybrid design showed that it was possible to assess how various parameters affect the best possible outcome. However, the challenge lies in optimizing the charging schedules while accounting for the fluctuating nature of renewable energy generation, such as the intermittency of solar power. A hybrid EV powered by PV, fuel cells, and batteries was given a power management and control system in [2]. Significant stationary charging benefits were made possible by the technology without the need to connect to the grid, which was particularly advantageous in regions with strong solar radiation. However, the power output of the battery drops when a fuel cell is installed in addition to the PV system. This creates an imbalance in the energy flow, where the integration of multiple energy sources needs to be carefully optimized to maximize system efficiency and ensure a stable power supply. An energy management plan for a large-scale EV charging station that makes use of RES and energy storage was the main topic of study [3]. Despite the uncertainties in PV generation, it is shown that power dispatch might be advantageous to both the station and EV users. However, grid demands could not be met by the PV and energy storage system alone. This highlights the need for dynamic scheduling algorithms that can manage energy from both renewable sources and the grid to meet fluctuating demand while minimizing reliance on fossil-fuel-based energy. In [4], a hybrid machine learning-based energy policy that took into consideration the needs of HEV charging was implemented in microgrids that were based on renewable energy. This method increased performance and viability, but it was pointed out that unexpected requests for charging could strain the grid and interfere with regular operations. The introduction of intelligent scheduling systems capable of forecasting demand patterns and optimizing grid interactions is essential to avoid system overloads and ensure reliable EV charging services. Lastly, a technical and financial evaluation of PV-powered EV charging stations in Vietnam under various solar irradiance conditions was carried out by [5]. The analysis made clear that a viable route to sustainable growth is the integration of solar energy with

EV charging infrastructure. However, when there is no sunlight, the system's efficiency decreases since solar arrays are unable to produce enough electricity to meet charging demands. To mitigate this, integrating energy storage solutions and forecasting techniques to predict solar energy availability could enhance system efficiency and reliability during non-sunny periods.

4. Proposed Methodology

4.1. Electric Vehicle Charging- Discharging Scheduling

As electric vehicles (EVs) proliferate, controlling their charging and discharging poses difficulties for both users and the electrical infrastructure. This section discusses the necessity of effectively scheduling these tasks using a profitable V2G approach that is advantageous to grid operators as well as EV owners. By maximizing charging and discharging when cars are parked, the goal is to lower users' daily energy expenses and contribute to balancing grid demand. The V2G concept enables bi-directional energy flow between EVs and the grid, where EVs can act as mobile energy storage systems that discharge stored energy back to the grid during peak demand periods, while charging during off-peak hours when energy costs are lower. Important elements, including EV battery limits, user travel habits, fluctuating electricity costs, grid demand patterns, and battery wear, must all be taken into account in the solution. The efficiency of this approach relies on accurately predicting these variables to ensure that charging and discharging schedules are optimized for both economic and technical benefits. By adjusting schedules to reflect daily price swings, the ultimate goal is to reduce the net cost and the difference between charging expenses and discharging revenue [8,9]. This methodology not only helps to lower electricity costs for EV owners but also provides grid operators with a valuable tool for managing peak demand and maintaining grid stability. Through intelligent scheduling, EV owners can be incentivized to participate in demand response programs, thereby contributing to a more resilient and suitable power grid.

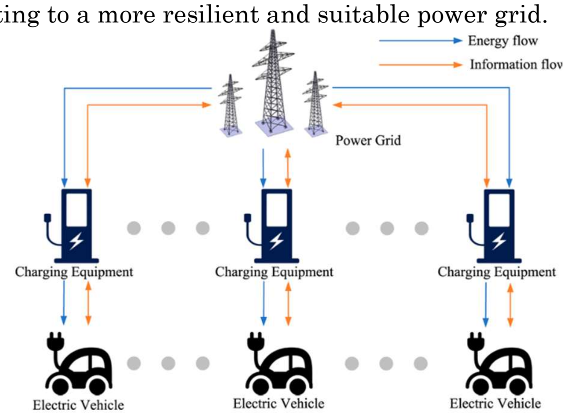


Fig. 1. Electric Vehicle Charging- Discharging Scheduling

4.2. Aquila Optimizer (AO)

The AO is a metaheuristic optimization method that draws inspiration from the unique hunting habits of the Aquila bird [15]. The Aquila Optimizer algorithm incorporates an "expanded exploration" phase, denoted as $u1$, which mirrors the high-altitude soaring and rapid descent hunting behavior of Aquila birds. This strategy enables a comprehensive examination of the search space from a great height, facilitating the identification of potential prey and the selection of the most promising hunting ground. The mathematical formulation of this expanded exploration tactic is detailed and presented in Equation (1).

$$v_1^{(h+1)} = v_{best}^{(j)} \times \left(1 - \frac{j}{J}\right) + \left(v_N^{(j)} - rand \times v_{best}^{(j)}\right) \tag{1}$$

In this method, J represents the maximum number of iterations, while j indicates the current iteration. The best result obtained up to the j^{th} iteration is represented by $v_{best}^{(j)}$. The initial exploration within the candidate solution population (v_1) leads to the solution for the subsequent iteration, denoted as $v_1^{(j+1)}$. Additionally, N signifies the population size, and D represents the dimension size. This exploration phase emphasises diversification to escape local optima, allowing the optimizer to perform global searches in complex landscapes. The average value of jth the positions of connected existing solutions at the iteration is calculated using Equation (2) and is denoted as $v_N^{(j)}$. To dynamically adjust the depth of the search space, a count of iterations is incorporated through the expression $\left(1-\frac{j}{J}\right)$.

$$v_N^{(j)} = \frac{1}{M}\sum_{i=1}^{N} v_i(j), \textit{for all } k = 1,2,...,G \tag{2}$$

4.2.1. Narrowed Exploration

The AO algorithm's narrowed exploration strategy (v_2) mirrors the hunting behavior of Aquila birds. To capture their prey, these birds employ a contour-like flight pattern with rapid gliding strikes concentrated in a focused search area. This method, mathematically represented in Equation (3), aims to determine the solution $v_2^{(j+1)}$ for subsequent iterations, where h denotes the current iteration.

$v_2^{(j+1)} = v_{best}^{(j)} \times Levy(G) + v_S^{(j)} + (u-v)\times rand$ (3)

In the Aquila Optimization method, the Lévy flight distribution in a D-dimensional space is denoted as $Lévy(G)$. The Lévy flight mechanism enhances the optimizer's ability to jump across regions of the search space, promoting both intensification and diversification. During the j^{th} iteration, a random solution $u_R^{(h)}$ is identified within the range [1, N], where N represents the population size. A fixed constant s , typically set to 0.01, is used to define the Lévy flight distribution in conjunction with two randomly selected parameters, v and u both of which range between 0 and 1. The mathematical formulation of this process is presented in Equation (4).

$$Levy(G) = r\times \frac{v\times\sigma}{|u|^{\frac{1}{\alpha}}} \tag{4}$$

Equation (5) calculates the value r , using a constant parameter α set to 1.5.

$$\sigma = \left(\frac{\gamma(1+b)\times sin\left(\frac{\pi b}{2}\right)}{\gamma\left(\frac{(1+b)}{2}\right)\times b\times 2^{\left(\frac{b-1}{2}\right)}}\right) \tag{5}$$

The spiral shapes within the search range, designated by u and v respectively, are represented by Equations (6) and (7). These spiral forms are defined in Equation (3).

$$u = s_1 + UG_1cos\left(-\omega G_1 + \left(\frac{3\pi}{2}\right)\right) \tag{6}$$

$$v = s_1 + UG_1sin\left(-\omega G_1 + \left(\frac{3\pi}{2}\right)\right) \tag{7}$$

These spiral paths enable the optimizer to converge toward the most promising solutions by mimicking the fine-tuned motion of Aquila birds during prey targeting. Over a predetermined number of search iterations, the variable s_1 takes values in the range (1, 20). The parameters w and U have fixed values of 0.005 and 0.00565, respectively. $G_1 \in Z$ in ranges from 1 to the dimension G of the search space. This multi-phase strategy alternating between expanded and narrowed exploration ensures a balance between exploration and exploitation, which is crucial for solving high-dimensional optimization problems.

4.3. Grey Wolf Optimizer

The social structure and hunting habits of grey wolves, apex predators at the top of the food chain, served as the model for the GWO, a population-based metaheuristic algorithm [14]. The pack's hierarchy is organized as follows:

- The α wolves are the leaders of the pack. They make decisions, and their commands are followed by the rest of the wolves.
- β wolves serve as subordinates to the alpha. They assist in decision-making and are the most likely candidates to become the next alpha.
- Δ Wolves submit to both the alpha and beta wolves but maintain authority over the omega wolves.
- δ wolves occupy the lowest rank in the pack. They act as scapegoats, hold the least influence, and are the last to feed. This hierarchical structure is emulated in the optimizer to coordinate agents and balance exploration and exploitation within the search space.

4.3.1. Encircling the Prey

When the prey's location is identified, grey wolves initiate the encircling process. This involves estimating the distance between each wolf and the prey using Equation (8), followed by updating their positions based on Equation (9).

$$\vec{C} = \left|\vec{D} \cdot v_p(j) - v(j)\right| \tag{8}$$

$$v(j+1) = v_p(j) - \vec{B} \cdot \vec{C} \tag{9}$$

Here, j represents the current iteration. The difference vector $\vec{D}$, defined using $\vec{C}$, determines whether the wolf moves toward the vicinity of the prey or in the opposite direction. Vectors $\vec{B}\, and\, \vec{D}$ are coefficient vectors, while v_p denotes the best solution position vector identified by the prey so far, and v represents the position vector of a grey wolf. Both $\vec{B}\, and\, \vec{D}$ are updated throughout iterations as follows:

$$\vec{C} = 2\vec{s_2} \tag{10}$$

$$\vec{B} = 2\vec{b} \cdot \vec{s_1} - \vec{a} \tag{11}$$

Here $\vec{s_1}\, and\, \vec{s}_2$ are randomly generated stochastic vectors within the interval [0, 1]. The coefficients $\vec{C}$ and $\vec{B}$ are calculated using Equations (10) and (11), respectively. The components of vector $\vec{a}$ a decrease linearly from 2 to 0 for the iterations, as defined by Equation (12).

$$b = 2 - 2 \times \frac{j}{J} \tag{12}$$

Here, j represents the current iteration, while J denotes the total number of iterations. This linear decrement in coefficient plays a critical role in gradually shifting the algorithm's behaviour from exploration to exploitation as iterations progress.

4.3.2. Hunting the Prey

The top three solutions represented by the $\alpha, \beta\, and\, \Delta$ wolves are thought to be the ones that are closest to the optimal value in GWO, where the global optima of a problem are unknown. Equations (13)– (15) direct the wolves towards superior solutions within the search space bounds, and are used to simulate this process.

$$\begin{aligned} \vec{C}_\alpha &= \left|\vec{D_1} \cdot v\alpha(j) - v(j)\right| \\ \vec{C}_\beta &= \left|\vec{D}_1 \cdot v_\beta(j) - v(j)\right| \\ \vec{C}_\delta &= \left|\vec{D}_1 \cdot v_\delta(j) - v(j)\right| \end{aligned} \tag{13}$$

$$\begin{aligned} v_1 &= v_\alpha - \vec{B}_1 \cdot \left(\vec{C}_\alpha\right) \\ v_2 &= v_\beta - \vec{B}_2 \cdot \left(\vec{C}_\beta\right) \\ v_3 &= v_\delta - \vec{B}_3 \cdot \left(\vec{C}_\delta\right) \end{aligned} \tag{14}$$

$$v(j+1) = \frac{v_1 + v_2 + v_3}{3} \tag{15}$$

Where $\vec{C}_\alpha, \vec{C}_\beta,\, and\, \vec{C}_\delta$ represents the distances between the search agents and the three best solutions found so far. The vectors $\vec{B}_1, \vec{B}_2,\, and\, \vec{B}_3$ are randomly generated. By considering multiple leaders (α, β, and δ), the GWO avoids premature convergence and ensures better diversity in solution exploration.

4.3.3. Attacking the Prey

In this phase, GW disperses to search for prey and then converges to initiate an attack. The convergence process involves shrinking the encircling mechanism to tighten the search around optimal candidates, enabling finer local search.

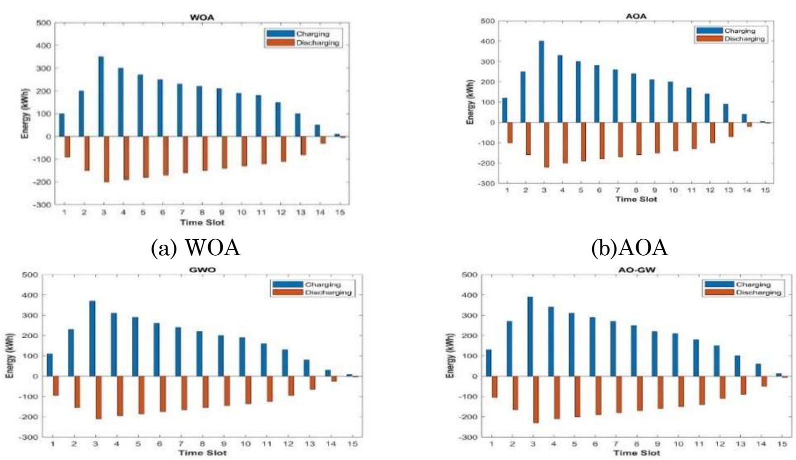
4.3.4. Searching for the Prey

Once the prey ceases movement, the wolves proceed to capture it, completing the hunting process. During the exploration phase, grey wolves search the environment based on the relative positions of the top three candidates, α, β, and δ [10]. This strategy allows the optimizer to perform a wide-ranging search early in the process, helping to discover global optima across complex landscapes.

5. Results and Discussions

The effectiveness of the proposed EV charging and discharging scheduling strategy is evaluated using the results of an extensive simulation conducted using the MATLAB environment. This section explains the simulation setup and offers a comparative analysis of the results, with a focus on three key areas: lowering daily user expenditures, managing grid energy use, and evaluating algorithm performance. With significant advantages for EV owners, the simulation results demonstrate the effectiveness of using metaheuristic methods for scheduling optimization in V2G systems. The main benefit is the minimum cost, which is attained by carefully scheduling EV charging for times when power rates are low and discharging for times when demand is at its highest. This dual strategy significantly reduces overall EV ownership costs and creates revenue opportunities through grid service contributions. In addition to cost savings, these algorithms enhance grid reliability by smoothing demand peaks and integrating renewable energy sources more effectively.

Fig. 2 illustrates the performance of WOA, AOA, GWO, and AO-GW algorithms in minimizing regular user expenses by analyzing the total energy allocated for charging and discharging across all EVs in the individual time slot. Among the algorithms evaluated, WOA demonstrated strong capabilities in reducing charging costs and maximizing discharging revenue, thereby effectively minimizing users' daily financial burden. AOA also performed well, particularly in aligning charging patterns with renewable energy availability, while GWO showed consistent results through its strong exploitation behavior, although with some limitations in dynamic adaptation. The AO-GW method, however, outperformed the standalone methods by combining the global exploration strength of AOA with the local search refinement of GWO, achieving a balanced and superior optimization outcome. This hybridization showcases the power of integrating complementary algorithmic strengths to solve real-world multi-objective optimization problems in smart grid environments.



(a) WOA (b)AOA

(c)GWO (d)AO-GW

Fig. 2. *Total energy assigned for charging or discharging by WOA, AOA, GWO, and AO-GW*

By making sure EVs are adequately charged and accessible when needed, without the need for physical interaction, the optimization procedures are made to reflect user activity patterns and improve user convenience. This user-centric design ensures seamless operation, enhancing the practicality of Vehicle-to-Grid (V2G) systems in real-world applications. Moreover, these strategies improve energy efficiency and foster environmental sustainability by adapting to grid demand and integrating renewable energy sources, contributing to lower carbon emissions. Such adaptability plays a key role in balancing energy loads and supporting clean energy transitions. They also support battery health management by avoiding excessive charging/discharging cycles, thus extending battery lifespan and lowering maintenance costs. Efficient scheduling minimizes stress on battery components, which is essential for preserving performance over long periods of use. Importantly, the proposed framework is adaptable to evolving market conditions, ensuring long-term relevance in the dynamic EV landscape. Its scalability and flexibility make it suitable for integration with future smart grid technologies and policy shifts.

5.1 Analysis on Computational Time

The computational efficiency of the evaluated algorithms is analyzed in Table 1. The WOA recorded the highest computational time at 1255 seconds. In comparison, the AOA and the GWO demonstrated improved efficiency, requiring 903 seconds and 923 seconds, respectively. The proposed hybrid AO-GW approach achieved the best performance, completing the task in 813 seconds, indicating its superior computational efficiency among the tested methods. This improvement is attributed to the synergy between AOA's broad exploration capabilities and GWO's refined exploitation mechanism, which leads to faster convergence. Faster computational times are particularly beneficial in real-time applications, where rapid decision-making is essential for dynamic energy management.

Table 1. *Computational Time*

Methods	Computational time
WOA	1255 sec
AOA	903 sec
GWO	923 sec
Proposed AO-GW	813 sec

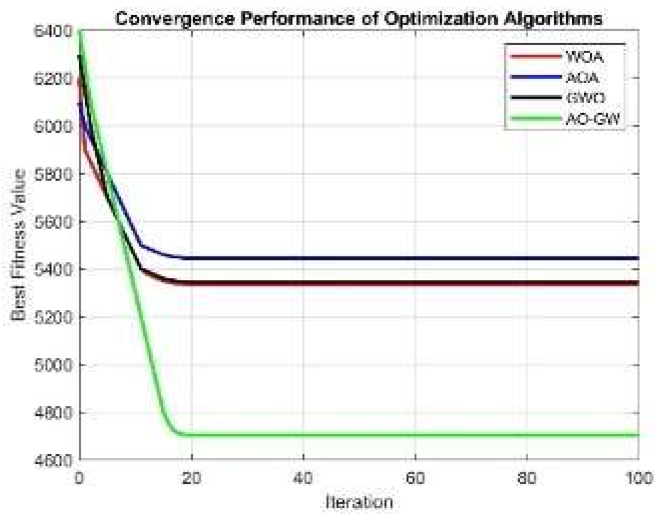


Fig. 3. *Convergence Analysis*

Fig. 3 illustrates how the Best Fitness Value changes over iterations for four different optimization algorithms, such as WOA, AOA, GWO, and the proposed approach called AO-GW. These algorithms aim to find the least possible value (the best fitness value) for a given problem, and the graph shows how quickly and effectively they achieve this as the number of iterations increases. The AO-GW hybrid procedure exhibits the best convergence performance, achieving the lowest fitness value and converging rapidly. This superior convergence behavior reflects the algorithm's ability to efficiently escape local optima and accelerate progress toward global solutions, which is critical in time-sensitive smart grid applications. The rapid decline in fitness value during early iterations indicates a strong exploration phase, while the steady improvement in later stages highlights effective exploitation.

6. Conclusion

In this study, a comprehensive analysis of metaheuristic algorithms, such as WOA, AOA, GWO, and the proposed hybrid AO-GW approach, was conducted to optimize EV charging and discharging schedules within smart grids powered by renewable energy resources. The results demonstrate that all algorithms contribute effectively to reducing operational costs and enhancing grid interaction through intelligent scheduling. Among them, the AO-GW hybrid model consistently outperforms the others by combining AOA's strong global search capability with GWO's refined local optimization, leading to improved energy efficiency, greater alignment with user behavior, and maximized utilization of renewable energy. This hybrid synergy allows the algorithm to maintain a balance between exploration and exploitation, ensuring robust performance across diverse operational scenarios. Furthermore, the optimized scheduling not only reduces electricity expenses for EV users but also supports environmental goals by minimizing carbon emissions and prolonging battery life. By adapting charging and discharging to real-time grid conditions, the proposed method enhances the sustainability and reliability of smart energy ecosystems. The adaptability and robustness of the hybrid approach make it a promising solution for future large-scale V2G systems, particularly in dynamically evolving energy markets. Its scalability and compatibility with renewable energy integration position it as a viable tool for supporting long-term decarbonization strategies and smart grid evolution.

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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