

A Novel Weighted Ebola Vector Optimization Based Charging Scheduling of Electric Vehicle Integrated with PV Charging Stations

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Abstract

Electric vehicle (EV) charging scheduling integrated with photovoltaic (PV)-based charging stations is an important aspect of smart energy management. This paper presents an optimal EV charging scheduling framework considering solar-powered charging infrastructure and bidirectional vehicle-to-grid (V2G) and grid-to-vehicle (G2V) power transfer. A hybrid weighted ebola vector algorithm is proposed to improve charging coordination and minimize operational cost. In addition, photovoltaic power generation is forecasted using an artificial neural network (ANN) for accurate 24-hour solar energy prediction. The objective function considers peak shaving, valley filling, power loss, charging coordination, and charging cost minimization under varying load conditions. The proposed method is evaluated using a 24-hour load duration curve with forecasted PV power and power loss is compared with the Ebola Optimization Search Algorithm and Weighted Mean Vector Optimization (WMVO) technique under Normal, High EV plug-in, Low Solar power availability, and Peak Hour scenarios. Simulation results demonstrate that the proposed algorithm achieves superior performance in convergence speed, scheduling accuracy, and power loss reduction. The proposed method reduces charging cost by 28%, whereas the Ebola and WMVO methods achieve reductions of 17.7% and 8.8%, respectively. The results confirm the effectiveness of the proposed optimization approach for smart EV charging management with renewable energy integration.

Keywords: Electric vehicle, Vehicle to grid, Grid to vehicle, Optimal scheduling, Photovoltaic

1. Introduction

The usage of electric vehicle (EV) is increasing, due to its eco-friendly benefits; the support to the system is also high. The initiatives in geo marine engineering such as offshore mining, transport, and manufacturing process have been taken for the use of EVs due to decarbonisation, mining in coastal areas, and operational efficiency of electric marine ship, transports and equipment's. However, the major challenges are charging infrastructure, safe use of battery, battery range and effective utilization of energy. Many countries support the production of EV as because of its advantage over gasoline based vehicles [1–3]. Further, EV has been integrated with renewable energy system so that operating cost is reduced, having independent power supply in rural or remote areas. Thus, the EVs are mostly charged with microgrid based charging station with distributed generators such as PV, wind, and diesel generators etc. However, the major challenge to manage available uncertain power with effective utilization of energy and maintaining the other constraints such as load management and battery safety [4–6].

Since, multiple loads such as residential and industrial loads are connected in distribution system [7],[8]. With the rapid development of bidirectional converter, vehicle to grid technology becomes feasible and EVs act as a generator in distribution system [9–13]. But, the energy of EVs are supplied to grid through several constraints such as load shifting, valley filling, peak clipping, and load shaping [14],[15]. On the other hand, to maintain the state of charge (SOC) of battery for availability and safety of battery for vehicle purpose, an

optimal energy management system is essential for charging and discharging scheduling of EVs [16].

The optimal energy scheduling is not only focus on SOC of battery however power loss but the pricing of electricity must be also reduced [17]. To cope with this objective, optimum EV charging scheduling algorithms have been reported with genetic, particle swarm optimization and etc., [18–21]. These research studies are even not considered renewable energy. Further, the research has been carried out with renewable energy integration of EVs charging infrastructure [22–25]. In all these study, optimum energy management of renewable energy sources have been demonstrated using optimization algorithm and cost has been reduced. In most of the above research, uncertainties of EVs, its SOC and price-based inclusion have been considered. Few researchers have paid attention to optimal charging scheduling of EVs in V2G and G2V mode integrated with PV energy. But, in this, only Homer Grid-based case studies have been presented [26]. However, the problem of power loss and cost of energy is not yet reduced with vehicle to grid technology. Hence, more adequate investigations are required in this study. So, the appropriate mathematical modelling of objective functions has been formulated with these considerations and optimum solutions have been found with the proposed hybrid weighted Ebola vector optimization.

Hence this proposal has provided a solution to state its need. The major contributions of this work are as follows:

- A hybrid optimization algorithm is proposed having faster and more stable convergence

characteristics with comparison to ebola and WMVO methods.

- To schedule charging and discharging of EVs integrated with PV based micro grid and grid with low power loss under different scenario.
- To design an optimal energy scheduling algorithm for vehicle to grid and grid to vehicle.
- To reduce the cost of electricity usage through optimum scheduling of EVs.

The remaining of this paper is organised as follows: Section 2 explains the proposed method system architecture, with constraints. In section 3, proposed hybrid weighted ebola vector optimization method and details of proposed algorithm for EVs charging scheduling has been demonstrated. Simulation results and comparison with EOSA and WMVO optimization are explained in section 4 and the conclusion of this method is in section 5.

2. System Description

The block diagram of proposed novel hybrid optimization-based EV charging scheduling has been depicted in **Figure 1**. The data flow among the EVs users, grid, and PV through proposed hybrid weighted ebola vector optimization has been demonstrated. The EVs user having bidirectional features that they can support the grid by transferring power during the plug in at charging station. The proposed algorithm is designed in such a way that this can reduce the charging cost, reduce the peak load, and support the grid while at same time maintain the energy demand of the users with the support of PV. In spite of several constraints such as random arrival of vehicles, battery charging rate, and battery safety, the proposed optimization has to ensure maximum utilization of PV power. In this system converter efficiency is also considered for more feasible for real world scenario. Thus the proposed optimal scheduling algorithm is the central processing unit for charging station, EVs user, and power supplier. In addition to that the PV power demand for charging the vehicle is estimated using the ANN approach for more penetration of renewable energy and makes the system more economical.

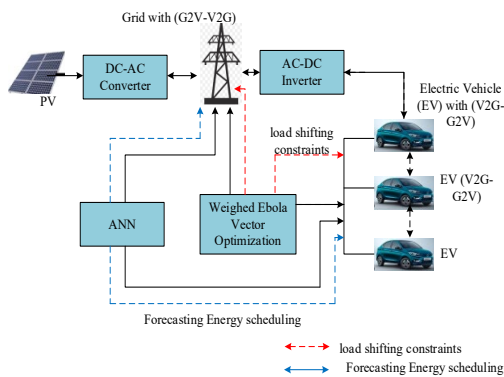


Figure 1 Block Diagram of Optimal Energy Scheduling of G2V and V2G

2.1 Objective function and its constraints

The objective function is formulated firstly on the basis of load duration curve, available solar power, and random arrived EVs with its initial SOC value. To make the load duration curve flat at different target load, valley filling and peak shaving operation occurs. During valley filling, power is supplied to grid by available solar power and available plugin vehicle with sufficient SOC. On the other hand, power is supplied to EVs from available solar power and grid during the peak shaving. The objective function and its constraints of this operation has formulated mathematically in ref. [27] and summarized here as follows:

Grid load variation: The difference between the actual load and the desired load is known as the grid load variation and formulated as given in Eq. (1):

$$f_1(\Delta P) = \frac{P_{TL}(t)}{N} - \frac{P_{AL}(t)}{N} - P_{EV}(t) \quad (1)$$

where, $P_{EV}(t) = \sum_{i=1}^N P_{ev}(t)$, N =number of EV, P_{ev} is charging/ discharging power of individual EV, P_{PV} is the available solar power supply, P_{AL} depicts the actual load in 24 h load duration curve. The N represent to the total number of EV connected to the grid correspondingly satisfies the SoC limit.

Cost reduction function: The objective function is to minimize the charging cost. The charging cost of each EV is calculated using below Eq. (2);

$$f_2(C) = R_p \times E_c(t) \quad (2)$$

where The required power R_p to charge the EV and $E_c(t)$ denotes electricity price at time t .

Total power loss: In V2G and G2V operation, total power loss is mainly caused due to charging and discharging efficiency of the battery depends on battery parameter and converter associated with it. Thus the power loss is calculated in this study using charging and discharging conversion coefficient of battery of EVs [28],[29]. The Eq. (3) describes the loss calculation as follows:

$$f_3(TPL) = P_{V2G}(1 - \eta_{discharge}) + P_{G2V}(1 - \eta_{charge}) \quad (3)$$

Where, P_{G2V} and P_{V2G} are power transferred from grid to vehicle and vehicle to grid during charging and discharging of EV's battery η_{charge} and $\eta_{discharge}$ are the charging and discharging coefficient of battery.

The other power loss is the battery degradation cost that depends on charging and discharging rate, depth of discharge, battery cycles and etc. however, and this is calculated for battery life span and techno economics analysis for monetary cost for long time span. Thus, here for this analysis, this factor is not considered.

The overall objective function can be expressed by Eq. (4) as:

$$F_{obj} = w_1 f_1(\Delta P) + w_2 f_2(C) + w_3 f_3(TPL) \quad (4)$$

where, w_1 , w_2 , and w_3 are weighting coefficient satisfying following Eq. (5):

$$w_1 + w_2 + w_3 = 1, \text{ and } 0 \leq w_i \leq 1 \quad (5)$$

Constraints: The power balance equation, minimum and maximum SOC, charging rate of charging station and PV power availability are the major constraints considered here for EV charging scheduling and can be represented by following Eqs. (6)–(10):

$$P_{grid}(t) = P_{AL}(t) \pm P_{EV}(t) - P_{PV}(t) \quad (6)$$

Allow discharging only if

$$SOC > SOC_{min} \quad (7)$$

Allow charging only if

$$SOC < SOC_{max} \quad (8)$$

$$P_{ev,charging} \leq P_{ev,max} \quad (9)$$

$$P_{ev,discharging} \leq -P_{ev,max} \quad (10)$$

These are the various restrictions on both the EV and the grid sides that prevent the best potential solution to the optimization problem from being achieved. And in order to be effective, the algorithm must adhere to all of these restrictions.

3. Proposed Hybrid Weighted Ebola Vector Optimization Algorithm

In this proposed method, the two optimizations are combined, one is Ebola optimization search algorithm (EOSA) and weighted mean of vectors optimization (INFO) is also called weighted mean vector optimization (WMVO) as shown in **Figure 2**. The proposed hybridization approach used the exploration capability of EOSA and local exploitation capability of WMVO. Thus, the fast convergence and accuracy of the optimization will be enhanced. Therefore, the proposed hybrid optimization is used to schedule and allow charge discharge from the battery charger to filling the valley load condition of grid and EV. The proposed hybrid optimization is used with following steps:

The EOSA optimization method is based on a nature inspired by the effectiveness in propagating the disease through the ebola virus.

3.1 Ebola Optimization Search Algorithm (EOSA)

Ebola optimization search algorithm (EOSA) is a new nature inspired meta-heuristic algorithm for global optimization problems. The population is prone to being arbitrarily moved around by the Ebola virus and the disease as susceptible (S), infected (I), quarantined (Q), hospitalised (H), recovered (R), and dead (D) sub-populations [30]. A new population based and bio inspired optimization algorithm is

motivated by the effectiveness in propagating the disease through the virus. To update the positions of each exposed individual, Eq. (11) applies,

$$X_i^{t+1} = X_i^t + \alpha r_1 (X_{best}^t - X_i^t) + \beta r_2 (X_r^t - X_i^t) \quad (11)$$

where, X_r is randomly selected infected individual, X_i is position of individual i at iteration t , α and β are control parameters, X_{best} is global best and $(r_1, r_2) \sim U(0, 1)$.

The mutation/ recovery phase and transmission mechanisms/ infection phase help maintain diversity in the population, reducing the risk of early stagnation. This balance improves convergence toward optimal solutions. Because infected individuals (solutions) spread promising traits quickly through the population, good solutions propagate rapidly, leading to faster convergence and efficient performance compared to traditional algorithms.

The EOSA having easy mathematical modelling and few control parameters are required as compared to algorithms like Genetic Algorithm and lower computational complexity in comparison to some swarm-based methods. [30],[31]. Instead of random movement, new candidate solutions are generated using weighted mean of vectors algorithm.

3.2 Weighted Mean of Vector Optimization (WMVO)

The weighted mean of vectors algorithm is a population based optimization algorithm that calculates the weighted mean for a set of vectors in the search space. The optimization algorithm introduced in this method is based on a weighted mean, which demonstrates a unique location in an object or system [32].

Thus weight mean is calculated for fitness function for top k solutions using Eq. (12):

$$w_j = \frac{1/f(x_j^t)}{\sum_{m=1}^k 1/f(x_m^t)} \quad (12)$$

where, w_j is the weight of j^{th} best individual, k is number of top individuals for weighted mean, x_j^t is selected top solutions.

Instead of random movement, new candidate solutions are generated using Eq. (13)

$$X_{wm}^t = \sum_{j=1}^k w_j x_j^t \quad (13)$$

Now combine exploration (ESO) and exploitation (WMVO) as shown in **Figure 2**. The combined mathematical formulation is described in Eq. (14) given as follows:

$$X_i^{t+1} = \begin{cases} X_i^t + \alpha r_1 (X_{best}^t - X_i^t) + \beta r_2 (X_r^t - X_i^t) & r < p(t) \\ X_i^t + \gamma r_3 (X_{wm}^t - X_i^t) & r \geq p(t) \end{cases} \quad (14)$$

Where, γ is exploitation factor and t decreases over iterations: $p(t) = 1 - \frac{t}{T}$ where, T is the maximum iterations.

Hence, the combined hybrid WEVO is formulated using Eq. (15):

$$X_i^{t+1} = X_i^t + \delta(t)[\alpha r_1(X_{best}^t - X_i^t) + \beta r_2(X_r^t - X_i^t)] + (1 - \delta(t))[\gamma r_3(X_{wm}^t - X_i^t)] \quad (15)$$

where $\delta(t) = \begin{cases} 1, & r < p(t) \\ 0, & otherwise \end{cases}$

With adaptive scaling of coefficients over time, final expression of proposed hybrid optimization is given by Eq. (16):

$$X_i^{t+1} = X_i^t + \alpha r_1(X_{best}^t - X_i^t) + \beta r_2(X_r^t - X_i^t) + \gamma r_3(X_{wm}^t - X_i^t) \quad (16)$$

Proposed hybrid algorithm Structure

Step 1: Initialization

Generate population randomly.

Step 2: EOSA Phase (Exploration)

- Classify into S, I, Q, H, R, D groups.
- Spread infection (generate new solutions).
- Maintain diversity.

Step 3: WMVO Phase (Exploitation)

- Select top k best solutions.
- Compute weighted mean.
- Update weaker individuals toward weighted centre.

Step 4: Adaptive Switching

Use:

- Iteration threshold

OR

- Diversity metric
- to switch between ESO and WMVO.

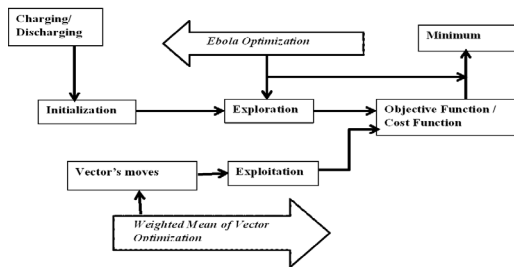


Figure 2 Block Diagram of proposed hybrid Weighted Ebola Vector Optimization for EV charging Scheduling

3.3 Proposed Algorithm for Optimum EV Charging Scheduling

Step 1: input parameters: forecasted PV power, load duration curve, plug in EVs, battery capacity, charging rate, SOC limits.

Step 2: initiate the first loop: $i = \frac{\text{Sample of load data during 24 hr.}}{\text{No. of sample}}$

Step 3: compare the Target load P_{TL} and P_{AL} , and action to be taken

ACTION:

- V2G operation, if $P_{AL} < P_{TL}$
- G2V operation, if $P_{AL} > P_{TL}$

No action $P_{AL} = P_{TL}$

Step 4: $\Delta P = P_{AL} - P_{TL}$ is calculated

ACTION:

if $\Delta P \leq P_{PV}$, charging is done by PV supply;

Otherwise: if $\Delta P > P_{PV}$, charging is done by Grid.

Step 5: update the number of plugin EVs (N), and check the SOC limits

Step 6: initiate the second iteration $j = \text{number of plugin EVs (N)}$

Step 7: check the SOC limits and allow the charging and discharging as per Eqs. (7)–(8) and moves to next steps, otherwise if there is no transfer of power with the vehicles, jump to step 14.

Step 8: calculate the power shared among the EVs by computing the objective function represented in Eq. (4) using proposed hybrid weighted vector ebola optimization.

Step 9: initiate the iterations of proposed optimization by defining the inputs i.e., populations, lower bound and upper bound, no of iterations, convergence criteria.

Step 10: verify if the new solutions are within the limits using Eqs. (9)–(10). If not, force them within limits and proceeds to the next step

Step 11: find the global best solutions using Eq. (16) i.e., the power is shared by all the plugin vehicles

Step 12: update the SOC of the entire plug in vehicles

Step 13: verify, all vehicles are considered for next interval. If no, update the no of plugin vehicles and return to step 7. If yes, moves to the next step.

Step 14: calculate the new load i.e., $P_{NL} = P_L + \sum_0^N P_{EV}$

Step 15: check if the first iteration end then find the valley filling, peak shaving, optimum cost and power loss are computed using Eqs. (1)–(3); if no, then increment the iteration and returns to step 2.

Based on the proposed algorithm, brief results are demonstrated and results are analysed in next section.

4. Result and Discussion

This section examines the effectiveness of the proposed method for the specified target load and various average SOC, taking into account the 24-hour load duration and random vehicle arrival. Bidirectional power transmission from V2G and G2V, respectively, demonstrates the potential of valley filling and peak shaving. To confirm the efficacy of the scheduling algorithm, loss minimization is computed using the proposed optimal scheduling. Both the cost-saving analysis and the convergence curve of the proposed optimal algorithm are depicted in this section. These results are simulated in MATLAB Simulink with the proposed algorithm.

4.1 Load Curve

24 hr. load duration curve has been depicted in **Figure 3** and considered for further investigation of valley filling and peak shaving during V2G and G2V operation using proposed EVs charging scheduling algorithm.

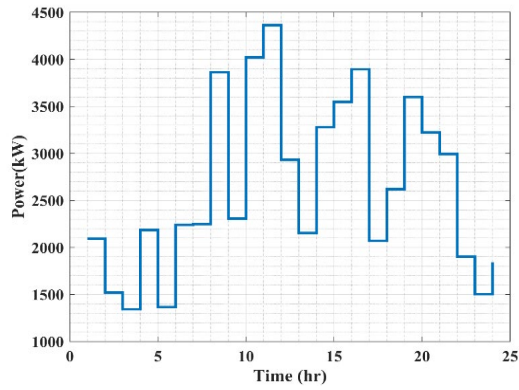


Figure 3 Load Curve

4.2 EV availability

Since, EVs arrival at charging station is random in real world scenario. However, in numerous research studies practical driving pattern is used but in this paper random arrival of EVs are simulated in Mat Lab using random function for more close to real world scenario and shown in **Figure 4**. These random EVs with their random initial SOC_i are plug in to charging station. However, there minimum and maximum SOC has been considered as constraints in demonstrated in subsequent section.

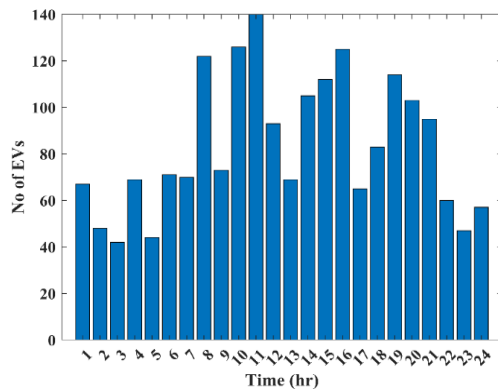


Figure 4 Numbers of EVs

The accurate PV power is predicted using the widely used ANN approach [33] discussed in section 2.1 and depicts in **Figure 5**. The accuracy of ANN approach is clearly visible in **Figure 5** and used for further analysis. This available solar renewable energy power is optimally used using the proposed algorithm for valley filling and peak shaving using V2G and G2V operation.

The inputs from **Figures 3–5** are used to simulate the effectiveness of proposed optimum approach. In this case, target load is considered as 2776 kW and three different average initial SOC_i are considered as 40%, 60%, and 80%. The effectiveness of proposed optimal algorithm for valley filling and peak shaving has been demonstrated by comparing the actual load and optimized load and depicts in **Figure 6(a)–(c)**, respectively. It can be observed that peak shaving is attained at 97.36%, 99.34%, and 99.5% for average

initial SOC_i of 40%, 60%, and 80%, respectively, whereas valley filling is 100% at all average initial SOC_i.

The valley filling and peak shaving operation using V2G and G2V occurs even very low average SOC_i i.e., 40%. The load curve does not meet fully the target load at this low average SOC_i due to its constraint that vehicle is not allowed to discharge below 50% for the safe operation of battery. The proposed algorithm is not only to take care of target load but also the safe operation battery of EVs. Further, this can be observed from **Figure 6(b)** and **Figure 6(c)**, the valley filling and peak saving operation are achieved using bidirectional power flow with proposed algorithm. Thus, the proposed algorithm operates more accurately when plug in EVs having higher average initial SOC_i. These facts can be utilized by aggregator for improving the process for valley filling and peak shaving.

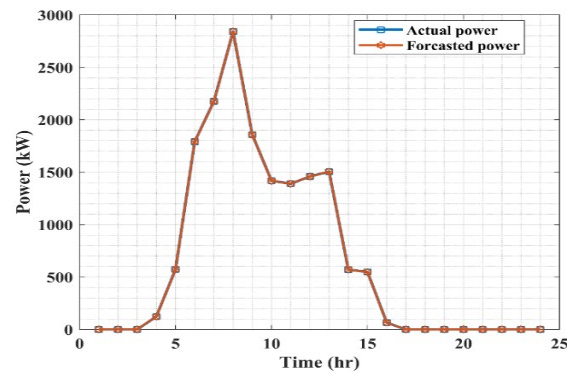
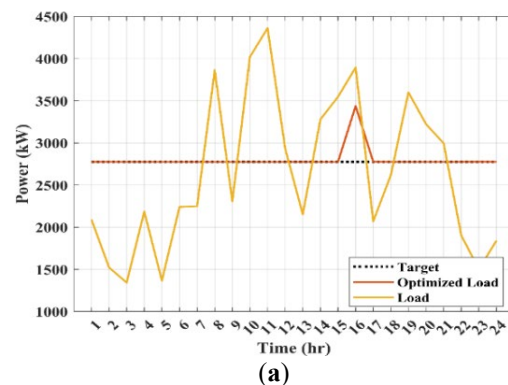
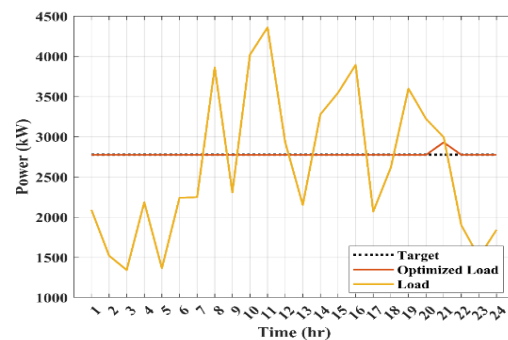


Figure 5: Performance of Forecasted PV power using ANN method



(a)



(b)

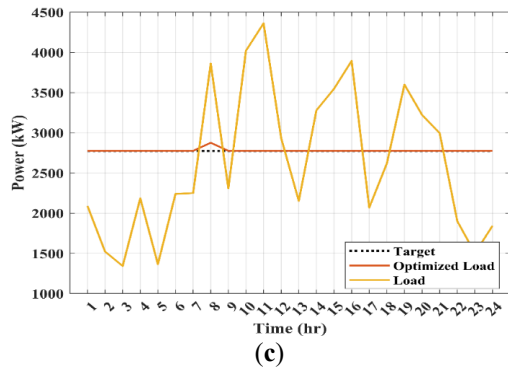


Figure 6 Optimized load curve with 2776 kW, target load and average SOC_i of (a) 40%, (b) 60%, (c) 80%

This is clearly visible from **Figure 7(a)**, the power transfer from vehicle to grid is less due to low average initial SOC i.e., 40% whereas, the power transfer during V2G is more when average initial SOC is comparatively high i.e., 60% and 80% depicted in **Figure 7 (b)** and **(c)**, respectively. On the other hand, the power transfer from G2V is more at low average initial SOC i.e., 40% whereas, the power transfer during G2V is less when average initial SOC is comparatively high i.e., 60% and 80% depicted in **Figure 7(b)** and **Figure 7(c)**, respectively. This validates the operation of valley filling and peak shaving using bidirectional power flow by proposed optimal scheduling algorithm.

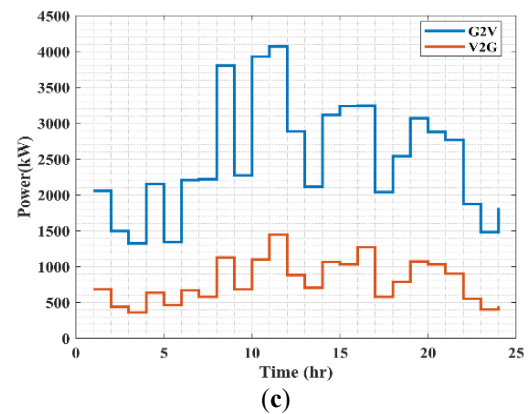
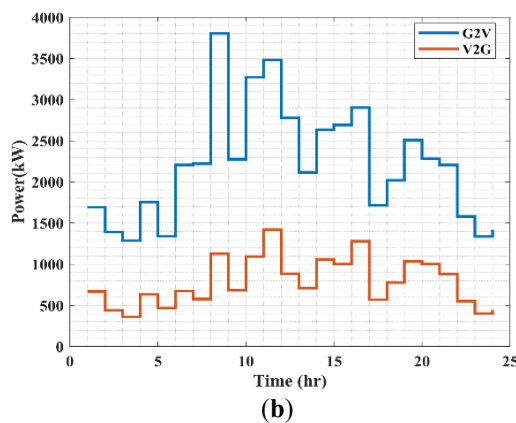
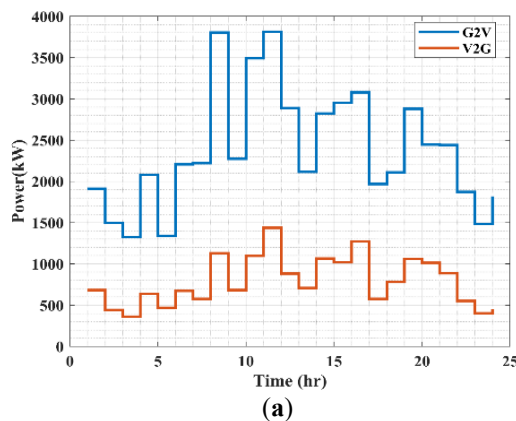


Figure 7 Performance of Power transmission for G2V and V2G (a) SOC 40% (b) SOC 60% (c) SOC 80%

Since the suggested method optimally schedules the charging and discharging, the power loss has been computed using Eq. (3) by taking the charging and discharging coefficient into account, as shown in **Figure 8**. The scenario-based power loss is determined to compare the proposed method's effectiveness to the Ebola Method and WMVO under different operating conditions, such as Normal, High EV, Low Solar, and Peak Hour scenarios. The scenario-based analysis demonstrates the effectiveness of the proposed optimization strategy under various operational conditions. In the normal scenario, the system operates with minimal stress and low power loss. However, in High EV and Peak Hour settings, additional demand greatly increases network loading and power loss. Similarly, decreased renewable generation in the Low Solar scenario increases reliance on conventional power sources, resulting in larger losses. In the normal case, the lowest power loss, 25 kW is obtained, as compared to the Ebola technique (36 kW) and the WMVO (40 kW). However, during peak-hour operation, the proposed approach decreased power loss to 39 kW, while the Ebola Method and WMVO had losses of 55 kW and 60 kW, respectively. The proposed technique consistently produced reduced power loss compared to the Ebola technique and WMVO in all cases, demonstrating its superior optimization capabilities and operational reliability.

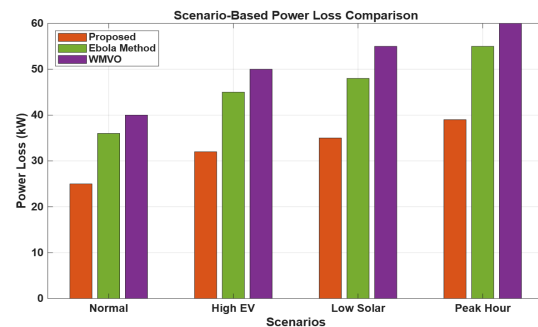


Figure 8 Scenario-based power loss comparison under different operating conditions using proposed, Ebola Method, and WMVO algorithms.

To demonstrate the effectiveness of proposed hybrid weighted Ebola vector optimization algorithms, the convergence curve has been depicted in **Figure 9** and compared with existing WMVO and Ebola optimization. This is clearly illustrated from **Figure 9**, the proposed optimization converges more quickly compares to the other two individual optimization techniques. This result demonstrates the superiority of proposed hybrid algorithm over the other two individual optimization techniques.

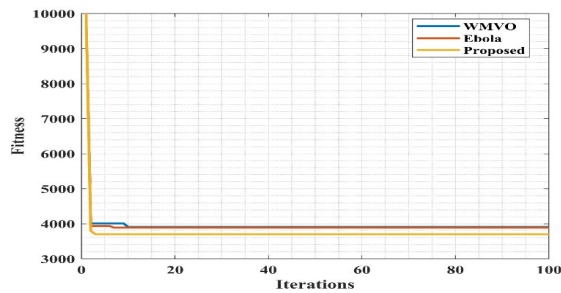


Figure 9 Comparison of Fitness for proposed method with other optimization techniques

To demonstrate the significance of proposed novel optimum charging scheduling algorithm, the cost for charging the EVs is calculated using the Eq. (2), and depicted in **Figure 10**. Further, the effectiveness of the validation of proposed algorithm has been done by comparing the cost for charging of EVs is compared with WMVO and Ebola optimization techniques. Thus, this is clearly visible that, the average operational cost obtained using the proposed technique is approximately Rs. 262,500, whereas Ebola method and WMVO produced average costs of Rs. 300,000 and Rs. 332,500, respectively. Thus, the charging cost is reduced by 28% using the proposed hybrid optimization techniques whereas; the charging cost is reduced by 17.7% and 8.8% by Ebola and WMVO respectively and clearly depicted in **Figure 11**. This validates the facts that the proposed method not only effective for peak shaving and valley filling using V2G and G2V operation, but also this provides the economic feasibility for the users.

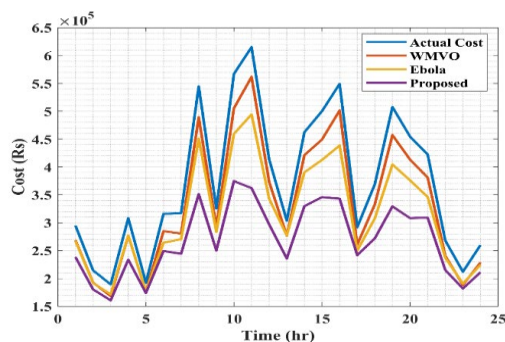


Figure 10 Comparison of Cost (Rs) for proposed method with Existing method

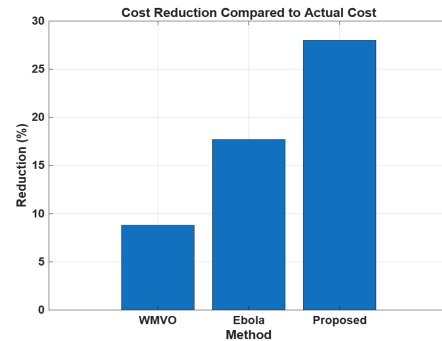


Figure 11 Comparison of Cost reduction (%) for proposed method with Existing method

5. Conclusion

This paper presented an intelligent EV charging scheduling framework integrated with a photovoltaic (PV) based charging station for smart grid applications. A hybrid algorithm was developed to optimize EV charging coordination while considering bidirectional V2G and G2V power transfer. In addition, an ANN was employed for accurate 24-hour photovoltaic power forecasting, enabling effective utilization of renewable energy during the scheduling process. The proposed optimization framework successfully addressed key smart grid objectives, including peak shaving, valley filling, charging cost minimization, and power loss reduction under different operating conditions. Simulation results demonstrated that the proposed algorithm outperformed the Ebola Optimization Search Algorithm and Weighted Mean Vector Optimization (WMVO) technique in terms of convergence speed, scheduling accuracy, and overall system performance. The proposed method achieved a charging cost reduction of 28%, compared with 17.7% and 8.8% obtained using the Ebola and WMVO methods, respectively. Furthermore, scenario-based analysis under Normal, High EV penetration, Low Solar availability, and Peak Hour conditions verified the robustness and adaptability of the proposed approach. The faster and more stable convergence characteristics of the proposed algorithm confirm its suitability for real-time EV charging management in renewable energy-integrated smart grid environments.

6. Acknowledgments

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