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Original Article

Scheduling Strategy for Charging and Discharging of Electric Vehicles to Reduce the Cost based on Hybrid Local Optimum and Global Optimum Scheme

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Abstract *- The growing usage of EVs has led to considerable progress in eco-friendly transportation. However, the effective administration of EV charging and discharging continues to be a vital challenge for personal vehicle owners and the stability of the larger electrical grid. This document introduces an innovative scheduling approach that utilizes quadratic programming to enhance the charging and discharging of electric vehicles, aiming primarily at reducing costs. The various factors involved in this scheduling technique are stations, EVs, city infrastructure, and the EV coverage area. The main aim of this research is to minimize the cost and make it most effective so that it can reduce the problem that occurs during a quadratic programming optimization task; the approaches that are utilized for this process are hybrid local and global optimum approaches. The properties of this scheduling approach are that it ensures that EVs can get changed at the time of off-peak hours so that it can optimize energy consumption because the electricity prices are lower at the time of off-peak hours. The experimental demonstration of the proposed scheduling strategy is performed in MATLAB/Simulink, and the efficiency of the proposed scheduling strategy is validated for the EVs.*

Keywords *- Electric Vehicles (EVs), Global optimum scheme, Scheduling strategy, Energy consumption, Cost reduction.*

1. Introduction

EV technology is one of the trending technologies that play a huge part in the transformation of the transportation sector when compared with traditional fuel-based vehicles (Patil & Kalkhambkar, 2020) [1] (Tan et al., 2017) [2]. Battery management is one of the critical bottlenecks in EVs, and the charging process and charging scheduling increase the challenges for EV adoption (Mao et al., 2019) [3] (Qureshi et al., 2021) [4] (Wu & Chen, 2021) [5]. Battery management and charge scheduling are extremely important, especially for improving the performance and life cycle of the battery.

Traditional methods of EV charging are often static, lacking adaptability to varying conditions, availability of energy sources for charging (such as grid stations), and user preferences. Consequently, this results in suboptimal energy utilization, vehicle congestion during peak hours, and increased operational costs for both EV owners and utilities (Mukherjee & Gupta, 2014) [6] (Morsalin et al., 2016) [7]. By optimizing the charging schedule of EVs based on the vehicle range and driving modes, the cost of energy consumption can be reduced, thereby enhancing the overall efficiency of the EV and its model structure, which is illustrated in Figure 1 [8].

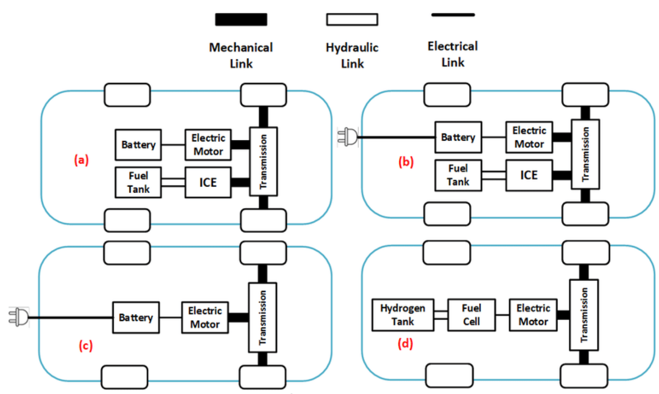

Fig. 1 Structure of Electric Vehicles (EVs) [8]

In most cases, some regions do not sufficiently incorporate EV distribution and charging. Therefore, a bottom-up and top-down power at the micro-level cannot be set up yet. An effective micro-scale EV charging station prediction technique must be further investigated using suitable simulated or actual data. In general, it is essential to understand EV charging patterns because these infrastructures attract new EV buyers as an administrative strategy. If an EV is used in the urban environment, then the driver will be informed about the need for recharging based on the daily EV user profile (Luo et al., 2020) [9]

(Devendiran et al., 2021) [10]. In this case, the charging process can be slow. If the vehicle is operated over longer distances outside of the urban environment, then the most efficient solution (from the point of view of user comfort) is using a fast-charging station. However, designing an appropriate charging schedule is challenging considering the varying charging patterns, dynamic EV range, etc. The addressed major problems are slow charging for the EVs, charging infrastructure limitations, Demand creation due to mass creations of EVs, and cost and accessibility. This document aims to tackle the limitation by implementing an innovative scheduling approach that utilizes quadratic programming capabilities to improve EVs' efficiency and minimize charging expenses. The proposed quadratic programming approach is based on a Hybrid Local Optimum and Global Optimum Scheme for minimizing the energy cost.

1.1. The Main Contributions of this Work

This research proposes the design of a quadratic programming-based approach to enhance the efficiency of EVs by optimizing the cost of charging, and it can also increase the charging speed of the vehicles. The suggested charging scheduling method seeks to lower the expenses of EV operation by purposefully planning charging during periods of low electricity demand due to the mass production of EVs. The charging and discharging mechanism of the battery is analyzed for the load demand and different operating models. In addition, this paper analyzes the possible operating modes of EVs and achieves stable, desirable performance.

The rest of the paper is structured as follows: Section II discusses the review of existing literary works related to charge scheduling of EVs and cost optimization. Section III provides a brief description of the proposed methodology for reducing EV costs. Section IV discusses the MATLAB/SIMULINK-based performance analysis, and Section V concludes the paper.

2. Literature Review

In [11] (Salah & Oulamara, 2014), this research addresses the Electric Vehicle Scheduling and Optimal Charging Problem (EVSCP) in a commercial context, aiming to optimize the use of EVs and CVs. It employs a mixed-integer linear programming model to enhance scheduling while considering operational constraints. The project supports fleet managers transitioning to sustainable EV fleets, focusing on costs, emissions, and battery health. In [12] (Yao et al., 2020), a methodology for the Electric Vehicle Scheduling Problem with Multiple Vehicle Types (MVT-E-VSP) in public transportation. It optimizes schedules by simulating driving range, recharging duration, and energy usage to cut annual costs by 15. 93% compared to traditional methods, offering insights on charger placement and recharging strategies. In (Sassi & Oulamara 2017) [13], the EVSCP for fleets combines EVs and Combustion Vehicles (CVs). It asserts that EVSCP is NP-hard and utilizes mixed-integer linear programming, solved with CPLEX for smaller instances. It presents two heuristics for larger cases: the Sequential Heuristic (SH) and the Global Heuristic (GH), proving effective for up to 200 EVs and 320 tours. In [14] (Wan et al., 2018), an optimal charging strategy for Electric Vehicles (EVs) using demand response programs and real-time pricing to reduce costs. It frames the challenge as a Markov Decision Process (MDP) with unknown transition probabilities. A model-free deep reinforcement learning method is proposed, incorporating a representation network and Q-network, demonstrating effectiveness through experiments. In [15] (Cai et al., 2018), how EV charging influences load-generation balance in a microgrid with distributed generators, energy storage systems, and control units. A statistical model accounts for the uncertainty in EV battery state of charge, establishing an optimization problem for economic microgrid operation through day-ahead scheduling using serial quadratic programming.

In [16] (Rahman et al., 2020), analyzes PHEV charging/discharging timing in a Vehicle-to-Grid system, comparing deterministic and probabilistic methods. It highlights quadratic programming for efficient schedules and Monte Carlo simulations for TOU planning, demonstrating V2G's effectiveness in load leveling and cost reduction through a case study in [17] (Yin et al., 2023), in large-scale disordered EV charging, such as voltage drops and increased network losses. It proposes a dynamic pricing strategy to optimize grid operations, balancing wind power, EV needs, and network safety. A case study validates this multi-objective optimization approach, benefiting both stakeholders. In [18] (Wu & Pang, 2023), an optimal scheduling strategy for EVs within microgrids addresses uncertainties in charging and discharging patterns through fuzzy theory and dynamic pricing. The method reduces total operating costs and peak-valley load differences by influencing EV owners with pricing incentives. A case study reveals significant cost reductions and load differences, validating the model’s effectiveness.

In [19] (Ren et al., 2023), an LSTM-ILP framework aimed at optimizing EV charging through Vehicle-to-Grid participation. It considers demand, discharge capability, and preferences to reduce charging costs and grid load fluctuations. In [20], grid security issues from unregulated EV access using a reinforcement learning method with the SAC framework, optimizing charging schedules while reducing costs and preventing transformer overload. In [21], metaheuristic algorithms enhance EV charging schedules with V2G technology, reducing costs and managing energy demand. Among the four algorithms, WOA showed superior performance, improving user satisfaction. In [22], an enhanced hybrid PSO-GSA algorithm reduces grid load fluctuations and charging costs by effectively balancing exploration and exploitation, leading to improved convergence and user benefits.

The proposed approach considers different aspects of EV charging, such as charging demand, discharging potential, price of electricity, and demands of users and EV aggregators. Initially, the cost of charging and discharging in EVs is reduced, and the PVLD of the utility grid is reduced. In the next step, the dynamic price of electric energy is determined using the LSTM model, and ILP is employed to solve the optimization problem related to the charging and discharging of EVs. Lastly, an optimal cost of the electric energy and an optimal charging and discharging schedule is obtained. Results of the simulation analysis show that the strategy based on LSTM-ILP effectively reduces the charging cost of EVs and achieves an appropriate Peak and valley trimming of the grid load. As observed from the results, the charging cost of the EVs was minimized by 42.1 % and 22 % compared to conventional unordered charging and ordered charging, respectively. It can be inferred from existing works that the conventional control strategies lack the desired robustness and do not consider the uncertainty of EVs.

3. Research Methodology

This segment will examine the suggested Scheduling Strategy for the Charging and Discharging of EVs using a hybrid optimal method based on quadratic programming. The algorithms and techniques used will be described in detail. Battery management strategies are important to ensure proper operation of EVs. This includes an optimal charging and discharging scheduling which is critical to minimize the cost of charging in EVs. Optimal scheduling refers to the process of strategically planning and controlling the charging and discharging mechanism of EV batteries to achieve specific objectives efficiently. The primary goal of optimal scheduling is typically to minimize operational costs and enhance energy efficiency in EVs. This research uses a quadratic programming approach to design the scheduling strategy based on the Hybrid Local Optimum and Global Optimum Scheme. The stages involved in the proposed approach are discussed in the below sub-sections, and it is illustrated in Figure 2.

3.1. Data Collection and Description of System Components

The data of 500 EVs is assumed (by random generation) wherein the information related to EVs, such as percentage of battery, charging time (hrs), charging efficiency, and start point and end point (destination point) of EVs, is randomly generated. The expressions for determining this information are given as follows:

Battery percentage = batt_crit + randi (100 - batt_crit);

Charge time = (100-battery percentage) * (25 + randi (10)) / (10* (94 + randi (6)));

Start position X = random number of size x; size x = 500;

Start Position Y = random number of size y; size y=500;

Destination Y = random number of size y;

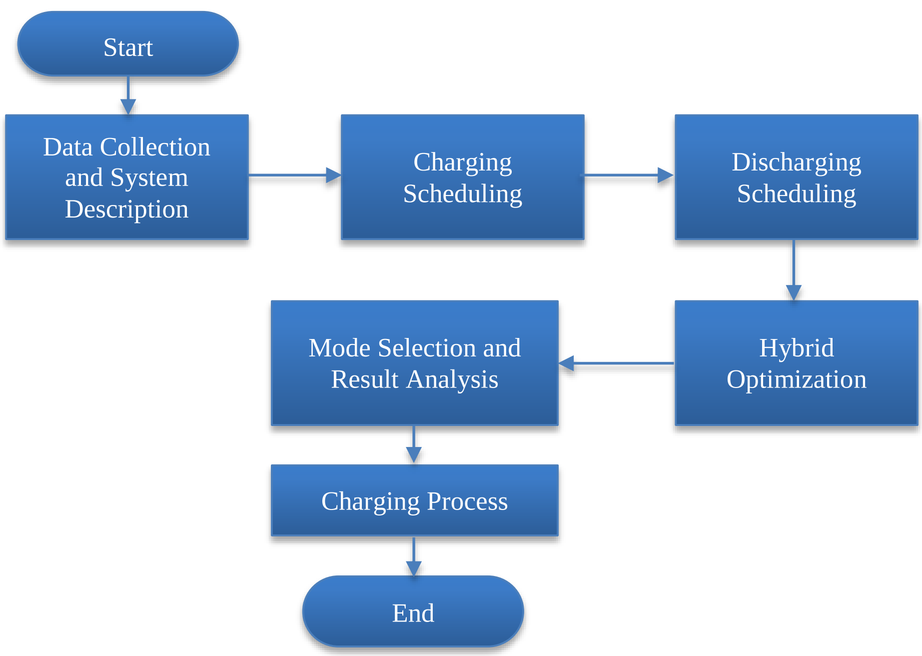

Fig. 2 Proposed approach

In this research, each EV is considered to have a fixed threshold of the SoC value of the battery. Suppose the difference between the present energy levels and maximum energy levels in the battery is less than the threshold value. In that case, the EV attempts to find an appropriate charging station for charging based on the optimal solution generated by the quadratic programming method. In addition, the EV also selects the nearest or closest Charging Station (CS) based on the available electrical energy, which is decided by the quadratic programming technique. The CS is located at a specific location and consists of multiple slots for charging EVs in parallel. Details of CS, such as the number of EVs already present in the CS and the time required for charging, are determined by the optimal quadratic programming approach. This approach is considered a centralized architecture for charging the 'n' number of EVs. While selecting nearby CS, EVs access details and make reservations.

In this approach, certain assumptions are made wherein it is assumed that the CSs are present in the urban areas and that the quadratic programming method can manage the charging processes for all EVs present in the network. It is presumed that all EVs are equipped with wireless communication devices that allow the vehicles to interact with CS to request or reserve charging slots. As mentioned previously, CS is assumed to have multiple charging slots to enable parallel charging of EVs.

The sequence of EVs charging is determined on a first come first serve basis, and EVs at a low charging stage must proceed to the chosen CS (determined by the quadratic programming technique) for charging. Other vehicles go to the CS based on their respective charging state. If an EV arrives before the scheduled time, then its priority will be changed, and if the CS is full, i.e., if all charging slots are occupied, then EVs must wait till the slots become free. Especially each EV has its time slot for parking at the CS; hence, in certain cases, EVs might leave the CS without getting charged.

3.2. Problem Formulation

This research considers a smart charging scheduling mechanism wherein the peak energy demand is determined based on the load profile. In this approach, the critical state vehicle is charged in the CS during peak load times, and the EV battery is charged during off-peak times. This is achieved by analyzing the load profile of the CS. The batteries are charged during low load demand, and this is mathematically expressed as follows:

$$\text{Minimize } (Ecs)2 \tag{1}$$

$$ECS = El + Ec \tag{2}$$

Where Ecs is the output power of the charging station, El is the load profile of the CS, and Ec is the charging power of the EV. In Equation (2), El is an important constraint, and Ec is optimized to reduce Ecs.

The problem in this research is formulated for analyzing two cases: (1) when the batteries of EVs should charge and (2) when the batteries of EVs should discharge. The optimization section addresses the optimization process of the formulated problem.

3.3. Hybrid Optimization Algorithm (Local Optimal Scheme and Global Optimal Scheme)

Quadratic programming represents a mathematical optimization method employed to address issues in which both the objective function and constraints are quadratic. In this study, specifically for examining the charging scheduling of EVs, quadratic programming is utilized to enhance the charging and discharging schedules of EVs with the main aim of reducing the costs linked to their operation. It considers various cost factors, constraints, and decision variables to find the most cost-effective and efficient charging strategy for EVs, ultimately benefiting vehicle owners, grid operators, and the environment. The steps involved in the hybrid optimization algorithm are illustrated in Figure 3.

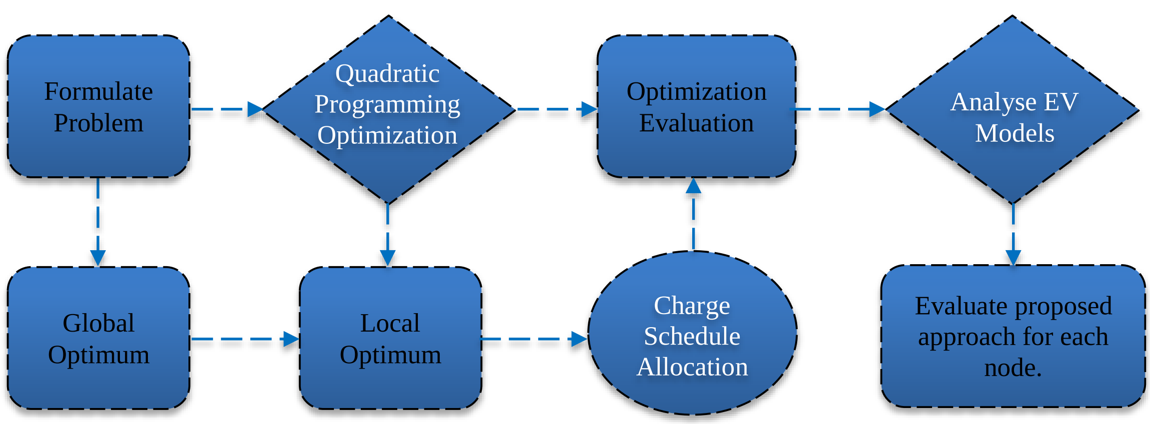

Fig. 3 Hybrid optimization algorithm

EVs scheduling process includes certain variables such as vehicle power level analysis, duration analysis, and System on Chip (SoC) for various time intervals at the time of the charging and discharging process.

EVs' charging and discharging process is performed using a quadratic equation to optimize the objective function. The quadratic programming consists of certain constraints, which are given below.

3.3.1. Battery Capacity Constraints

The battery power of the EVs is properly monitored using SoC, which is maintained within a limit until the end of the scheduling process.

3.3.2. Energy Balance Constraints

To maintain the performance of EVs, it is very essential to reduce their energy consumption. So that the power utilized by the EVs remains equal to the power supplied to the grid.

3.3.3. CS Related Constraints

Closed Charging Stations (CCS) mainly concentrate on the EV load and demand applied to the charging slots.

Following the formulation of the objective function and constraints, cost minimization is concentrated by finding an optimal decision variable, and for that purpose, the quadratic programming solvers are utilized. Certain mathematical analysis is required to perform such finding of an optimal decision variable, which is achieved using the optimization algorithms.

The characteristics of the quadratic programming are very adjustable to perform effective charging and discharging schedules for EVs by analysing their power level and battery condition. This process is directly dynamically reflected in cost minimization.

The optimization technique used for this process is a quadratic program-based optimization strategy, which is the most effective model for the process of cost minimization at the time of charging and discharging of EVs. In this model, the global optimum solution is applied to find the maximum or minimum value of the objective function where the global minimum is represented as x_global used to reduce the charging cost where the analysis is discussed below.

If x > x_global, then optimize f (x) for all values of x.

An extreme (highest or minimum) point of the objective function for a specific area of the input space is known as a local optimum. Formally, x_local is a local minimum of the objective function f for the minimization situation if and only if:

If f (x) equals f (x_local)

For every value of ‘x’, it must be ensured that the value is within the interval and that the amount of power needed to charge the EV battery is calculated, as shown in Equation (3).

Power required = (Battery capacity) - (Power remaining in the battery) (3)

The amount of time needed to charge an electric vehicle battery depends on the charger's rated output power. Thus, the charging time can be determined using the formula shown in Equation (4).

R = (Battery capacity - Power remaining in the battery) / (Rated output of the charge (4)

Where R is the charging time in hours. Correspondingly, the cost of charging a single EV can be determined using (5), which is given as follows:

Charging Cost of an EV = Power necessary * Ecost (t) (5)

Where Ecost (t) is the cost of energy at a specific hour, the cost of all the vehicles' charging can be minimized using the most effective method of scheduling, known as globally optimal scheduling. The locally optimal scheduling scheme is the ideal response to the local scheduling optimization issue. Optimized Charge schedule is allocated based on the maximum price and minimum price. Based on that, the objective function has been implemented, and the charging rate is determined using a locally optimal scheduling approach. Mathematically, it is represented as shown in Equation (6).

Charging rate matrix = number of EVs * number of charging slots (6)

Further, the charging status of all EVs is verified, and it is checked whether all EVs are fully charged. The charging level of EVs is checked at each interval, and the required energy level for each EV is determined. Furthermore, the nearby CS is located, and the charging status is updated for each EV. The best solution obtained through quadratic programming is updated to find the global optimal value. Further, the cost is minimized, and slots allotted by both local and global controllers are used to determine the status of EV charging.

Lastly, the quadratic programming strategy checks whether the EV requires charging or not based on the modes of the vehicle. If charging is required, then the closest CS is located, and the slots are booked. In this research, four modes are considered for the analysis i.e., (a) Normal mode, (b) Echo mode, (c) Traffic mode, and (d) Terrain mode. The results of the proposed approach for all these modes are discussed in the next section.

4. Results and Discussions

This section discusses the experimental validation of the proposed approach, which is simulated using the MATLAB/SIMULINK platform. Initially, the decision variables for the simulation are declared, such as the number of stations, number of EVs, dimension of city, and EV range. The considered values are tabulated in Table 1.

Table 1. Decision variables for simulation

Parameters	Values
Number of Stations	10 (Max 1 station per sq km)
X- Dimension of city	500 Km
Y- Dimension of city	500 Km
Total Number of EVs (EV num)	500
Critical Battery Percentage (batt_crit)	20 %
Range of EV (evrange)	207 km (Maximum distance covered at full charge

The tow count (number of vehicles that need to be towed due to non-availability of sufficient charge in the vehicle battery) is considered initially to be 0. In the next step, the charging station is allocated for each EV along with the charging station number, charge time of EV, slot book for the EV vehicle, and location.

Here, the coordinates of the CS are generated randomly, and the number of CS allotted to each EV is 10 (maximum). As mentioned previously, if the vehicle is at its lowest level of charging, then the EV finds the closest charging station and books the slot. For further experimentation, other parameters such as the base load and predicted base load, the basic price of the grid, length of charging time, EV battery capacity, charging rate, number of Charge EVs, and vehicle to the grid are considered.

4.1. Base Load and Predicted Base Load

The outcomes illustrating the examination of the actual base load and forecasted base load are presented in Figure 4. In general, the factor of real base load in EVs defines the utility of the charging process at each instant of time.

Similarly, the predicted base load defines the estimated utility of the charging process in the EVs at each period, and the prediction can be performed according to the past and current charging processes. From Figure 4, it is understood that the predicted base load value is higher than the predicted real base load value.

The graph above shows that the load (KW) profile is examined over 24 hours, illustrating the contrast between the actual base load and the forecasted base load. The graph shows that both real and predicted base load decreases from 0 to 10 hours, and the peak load is from 15 to 20 hours.

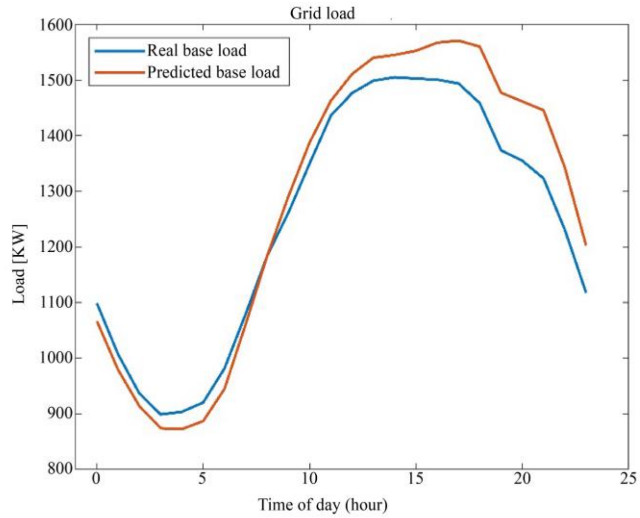

Fig. 4 Analysis of real base load and predicted base load

4.2. Load with Optimal Charging of EVs

The process is mainly developed to increase the efficiency of the EVs and as well to reduce the cost. In general, here the term load defines the demand of the charging process. The load with optimal EV charging is shown in Figure 5. This ideal charging is utilized in several processes, such as baseload without EV charging, overall load with globally optimal EV charging, locally optimal EV charging, native EV charging, and hybrid processes. For the performed load analysis, this calculation is carried out up to 24 hours, showing variation in the presented charging processes. A comparison of pricing for different charging stations based on the time of day is presented in Figure 5.

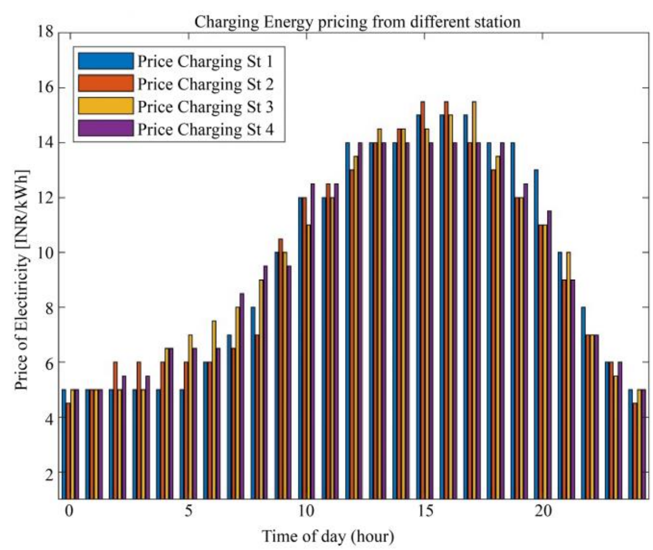

Fig. 5 Charging energy pricing comparison

Based on graphs, it can be said that the cost of charging in EVs maximum between 15 to 20 hours. The remaining time it charges, during this time cost is low and with load considerations. The cost of charging for different stages is illustrated in Figure 5, and the pricing comparison for different charging stations is presented in Figure 5.

4.3. Energy Evaluation Analysis

Overall Energy evolution of EVs is from 16 to 20 hours for discharging at a high cost and charging at less cost, shown in Figure 5. In the proposed hybrid method, the average energy utilized by the grid is higher, and the peak level is also lower compared to other methods. In this research, 10 EVs are considered for the analysis. Using the local optimal scheme, the energy grid utilized to 3500 kWh is illustrated in Figure 6.

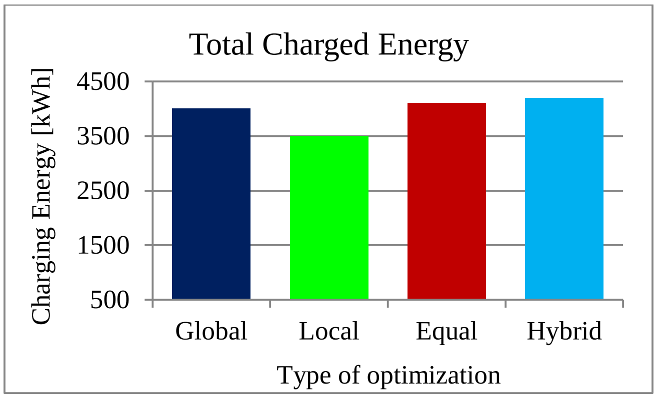

Fig. 6 Energy evolution for EV

In the equal allocation scheme, the energy grid utilized more than 4100 kWh, and in the global allocation scheme, the energy grid utilized 4000 kWh, slightly more than the earlier method. In the hybrid allocation scheme, the energy utilized is about 4200 kWh. The evolution of the energy in the proposed approach is illustrated in Figure 6. The output graphs for different modes of EV operation (normal mode, eco mode, traffic mode, and terrain mode) are shown in Figure 7.

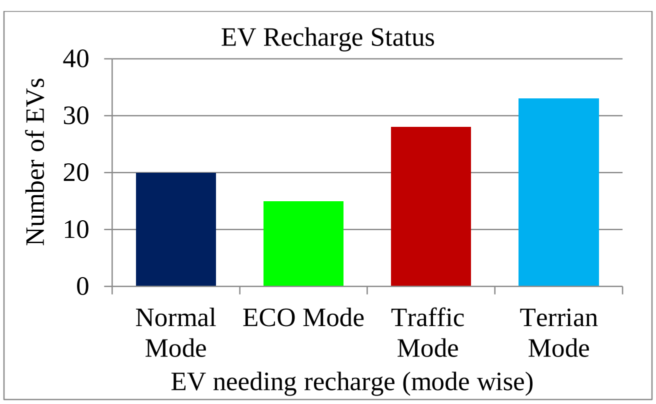

Fig. 7 Model-based charge status

As per the output graph shown in Figure 7, If an EV is running in normal mode, then the battery discharges in a regular manner before reaching the charging station, and in this case, the tow count is at 20.

If an EV is running in Echo mode, then the battery discharges slowly compared to other EVs whose battery discharges quickly before reaching the charging station, and in this case, the tow count is at 15. If an EV is running in traffic mode, then the battery discharges faster than normal and eco modes before reaching the charging station, and here, the tow count is at 28.

As a result, the count has increased. Lastly, if the EV is running in terrain mode, then it discharges very Fast compared to other methods, and in this case, the tow count is at 33, and thereby, the count is further increased.

4.4. Comparative Analysis

The methods that are utilized for the comparative analysis are DRLCDS [20], MAOCDS [21] and IGPOCDS [22]. Figures 8, 9, and 10 discuss the proposed hybrid scheduling technique for EV charging, which employs a quadratic programming method combining local and global optimization to enhance efficiency.

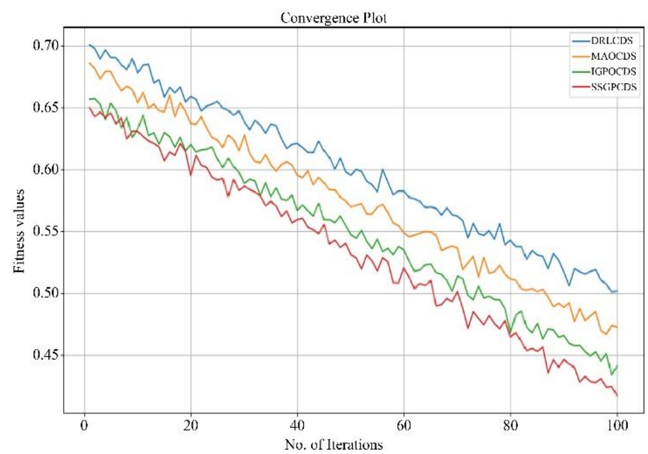

Fig. 8 Convergence plot

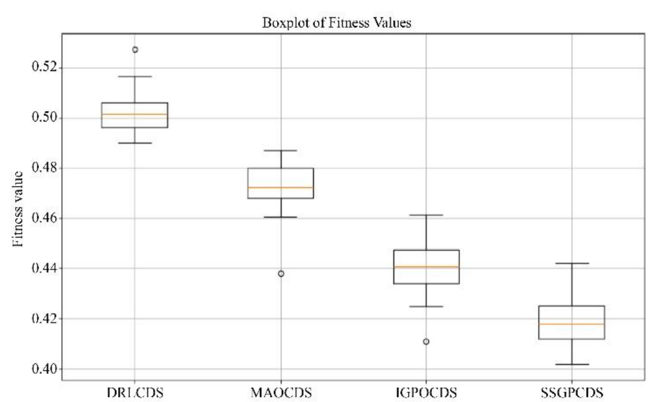

Fig. 9 Boxplot of fitness values

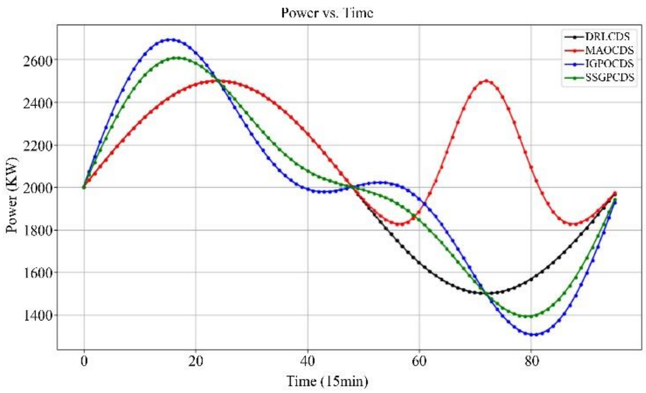

Fig. 10 Power Vs Time calculation

The Convergence Plot shows iterative improvements in fitness value, indicating faster convergence and greater accuracy than traditional methods. The Boxplot of Fitness Values highlights robust performance across various runs, ensuring dependable EV charging and discharging schedules. The Power vs. Time graph highlights the variations in power demand over 24 hours, showcasing the effectiveness of a proposed hybrid scheduling method for EV charging and discharging. It uses the base load as a benchmark to plan EV charging during non-peak, cost-effective times while discharging during peak times, alleviating grid strain. This dynamic coordination minimizes the peak-to-average load ratio, promotes energy efficiency, and ensures grid stability through Vehicle-to-Grid technology, demonstrating the hybrid method's superiority

5. Conclusion

The major concentration of this paper is on the implementation of an optimal scheduling strategy to improve the charging and discharging process of EVs on a real-time basis and it mainly focuses on the reduction of cost. It can also be inferred that a realistic range determination system considering real-time inputs, compared to other average power consumption-based systems, provided better estimation for range prediction. To attain sustainable mobility, this model focuses on quadratic programming to find an optimal solution for cost reduction. The major factors that are considered for this analysis are power level, battery level, and SoC, which are directly reflected in the maximization of efficiency of the charging and discharging processes of EVs. The simulation based on assumptions highlights that a hybrid approach towards charging of EV using a combination of local and global optimization results in better utilization of the power grid as compared to currently used and experimented methods such as stand-alone local optimization or equal allocation-based method. In the future, the extended research concentrates on advanced Artificial Intelligence (AI) optimization models for the further improvement of charging and discharging schedules based on real-time data.

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