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GRID INTEGRATED ELECTRIC CAR CHARGING OPTIMIZATION USING TOPSIS AND GREY WOLF OPTIMIZATION

Sucharita Ghorui[1], Bidrohi Bhattacharjee[2], Arijit Chakrabarti[2], Pradip Kumar Sadhu[2]

[1]Seacom Engineering College, Howrah, West Bengal. India
[2]Department of Electrical Engineering, Indian Institute of Technology (Indian School of Mines), Dhanbad, Jharkhand-826004, India

ORCID iDs:		
	Sucharita Ghorui	https://orcid.org/0009-0006-6737-5546
	Bidrohi Bhattacharjee	https://orcid.org/0000-0001-7622-8034
	Arijit Chakrabarti	https://orcid.org/0000-0002-0115-7478
	Pradip Kumar Sadhu	https://orcid.org/0000-0001-8104-5232

Abstract. *Electric cars are becoming popular these days and the adoption is on the rise. It is crucial to figure out a smart way to schedule when they can charge and discharge. This scheduling should consider the technical limitations of power grids while meeting the economic and environmental goals. For improving the management of power usage of electric cars, a new approach has been proposed in this paper. The proposed approach includes a charging plan that incorporates a vehicle-to-grid (V2G) method with an objective to reduce the variation in power usage and to cut down the cost of charging for electric cars in the residential areas. TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) has been used to address the complex scheduling problem and Grey Wolf Optimization (GWO) has been applied for optimizing the schedules. This paper compares the suggested strategy with both single and multi-objective scheduling, focusing on factors like energy losses, peak load on transformers, and the load on power lines. To test the effectiveness of this approach, the authors have applied it to a 38-node distribution feeder in an experiment. The results show that the solutions obtained using TOPSIS are very helpful for smoothing out peaks in power demand and reducing costs. In simpler terms, this approach would help make electric car charging more efficient and economical while also benefiting the power grid. Integrating EV charging stations with the power grid presents challenges like managing changing demand, balancing the load, and keeping energy costs low. To solve these problems, this paper introduces an innovative approach that combines the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) with Grey Wolf Optimization (GWO). Our method uses the strengths of both techniques to find the best charging strategies based on several factors,*

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Corresponding author: Bidrohi Bhattacharjee
Department of Electrical Engineering, Indian Institute of Technology (Indian School of Mines), Dhanbad, Jharkhand-826004, India
E-mail: onlybidrohi@gmail.com

such as cost, grid stability, and user convenience. The GWO algorithm imitates the hunting strategy of grey wolves to search for optimal solutions, while TOPSIS ranks these solutions by their closeness to the ideal outcome. This combination provides a more effective and flexible way to manage complex charging scenarios than traditional methods. By improving the efficiency of the charging process and minimizing its impact on the grid, this approach supports a smarter, greener future where EVs can be charged more intelligently and affordably.

Key words: *Advanced metering infrastructure, distribution system operator, mixed-integer linear programming, TOPSIS, valley filling model.*

1. INTRODUCTION

In modern days, more people are using Electric Vehicles (EVs) for transportation in order to tackle the environmental issues globally. However, this growing popularity of EVs has been raising concerns about how they are charged and it might lead to potential problems for the power grids. If the EV charging is not coordinated properly, it could result in issues like overloading transformers and power lines, exceeding voltage limits, and causing more power losses. This, in turn, might require expensive upgrades to the power network, especially during peak usage times. Apart from the technical challenges of integrating EVs into the existing infrastructure, the other big problem is that many people are hesitant to switch to electric transportation. To encourage people to adopt EVs, it is essential to make it economically attractive for them. Coordinated charging is a solution to these challenges. By actively managing EV charging in a coordinated way, the power grid capacity and available resources can be utilized properly. People would be encouraged to support the coordinated EV charging when it aligns with their economic interests. Some research has happened in the area of Electric Vehicle charging considering balancing environmental concerns, technical challenges, and economic factors [17]. In [17], the main goal was to cut down on CO2 emissions from both the power grid and the vehicles themselves. Another study [10] has suggested a step-by-step approach towards charging EVs, with the aim of minimizing changes in power usage, differences between peak and low periods, and the overall cost of the charging. The comparison of different strategies for charging EVs, considering the views of various parties involved, has been discussed in [4]. In [4], the focus has been minimizing both fuel and electricity costs, as well as the wear and tear on the EV batteries. The authors have put an emphasis on the health of the battery in the optimization process as the battery contributes significantly to the overall cost of EVs and it tends to wear out over time. However, such studies [17] have not looked into how the charging strategies would affect the power grid itself. The study mentioned in [5], has suggested a plan to give people incentives for using electricity during off-peak hours, when not many people are using it. The idea has been to reduce the loss of money and the ups and downs in the power supply. Particle swarm optimization (PSO) has been used to figure out the best way to solve the problem with multiple goals. However, in those studies, it has been assumed that all electric vehicles (EVs) have been showing up and leaving at the same time. The study in [11] has come up with a smart way for EVs to work together to spend less money on electricity and reduce power losses. A technique called weighted sum aggregation factors has been used to tackle the problem with many goals with an assumption that all EVs are starting with the same amount of charge. However, the vehicle-to-grid (V2G) mode has not been studied in that research work. In [2], a plan has been created to make micro grids work better, involving Electric Vehicles (EVs), the power grid, and distributed power sources. The method called ε-constrained has been used to figure out the best way to balance different goals. But, the uncertainties related to EVs have not been studied. In [10], a way to optimize multiple things at once, like reducing variations in power use and cutting down on costs has been suggested. A method that combines weighted sums and fuzzy logic has been used for this optimization. Another study [11] has focused on coordinating EVs in the best way to save money and reduce emissions. The ε-constrained optimization method has been used considering Vehicle-to-Grid (V2G) mode, but none of these studies have consider the cost of wear and tear on the EV batteries. Few studies [9, 3] have included the analysis on how charging Electric Vehicles (EVs) with a Vehicle-to-Grid (V2G) method affects both the technical and economic aspects. Another study [9] has used a weighted approach. The weighted approach depends a lot on the chosen weights, while the ε-constraints [3] have treated one goal as the main one and the others as secondary. To put it simply, these studies have explored different ways to make electric vehicles work well with the power grid, considering factors like costs, emissions, and wear on the EV batteries. Various methods have been used to find the best solutions, but each approach has its own strengths and limitations.

TOPSIS is a helpful method for solving problems with multiple goals, ensuring that the different solutions are spread out evenly and are computationally efficient. It is widely used in various engineering fields [6] and has more recently been applied to solve issues related to planning for multiple objectives in distributed energy resources (DER) [6,1]. Another study [6] has provided a balanced solution for goals like reducing power loss, deviations in node voltage, voltage stability index, and voltage constancy margin. Additionally, TOPSIS has been combined with a metaheuristic technique for solving multi-objective problems [1].

This research work has looked into a way to arrange the charging of Electric Vehicles with multiple goals. The aim is to propose the best charging plan that can minimize both

(1) Changes in power usage

(2) The overall cost of charging and discharging.

The research work has used TOPSIS method to create a model for scheduling EVs with multiple objectives (MOM). This approach has been compared with a simpler model that focuses on just one goal, and it has been tested with different levels of EV usage. This scheduling plan has been applied to a 38-node distribution system and the results have been thoroughly evaluated through simulations. The paper has been organized into sections covering the modelling of EV power demand, stating the goals, using the TOPSIS method, setting up the optimization plan, and summarizing the outcomes from the simulations.

2. Literature Review

Optimizing transportation and logistics efficiency focuses on improving vehicle routes to reduce costs and minimize environmental impacts. This review examines various methods and algorithms used to optimize vehicle paths, highlighting the need for innovative approaches in response to growing global demand for effective network. As electric vehicles (EVs) gain popularity due to environmental concerns and energy shortages, a major challenge remains the lack of charging infrastructure. Some researcher proposes a real-time, IoT-based system to enhance the existing EV charging network by forecasting demand and recommending charging stations based on cost and time. Similarly, one of researcher use mobile data and genetic algorithms to optimize charging station locations, reducing energy waste and excess driving in urban environments like Boston. Some researcher focus on strategically placing EV charging stations in urban areas to minimize energy loss, stabilize voltage, and reduce land costs, using differential evolution and Harris Hawks Optimization methods. Some researcher suggests a fast-charging station model incorporating renewable energy and storage systems, which enhances profitability and resilience. Some researcher proposes a two-stage method for identifying optimal charging station locations in Hungary, using a comprehensive assessment of EV potential. Some researcher introduces an agent-based simulation framework to evaluate charging infrastructure scenarios in a small Swiss town, emphasizing the impact of pricing on charging behavior and infrastructure viability. Some researcher uses fuzzy logic and analytic hierarchy processes to select optimal sites for charging stations, while a researcher develops a model for strategic placement of public charging stations based on driver behavior in Beijing. Some researcher employs a hierarchical probabilistic forecasting method to predict EV loads across different regions, and some researcher analyses the challenges of expanding EV infrastructure in multi-unit residential buildings in British Columbia, proposing policy interventions. Overall, the review highlights that optimizing vehicle paths is a complex field requiring advanced algorithms and technologies. Future research should focus on real-time data integration, sustainability, and ranger collaboration between academia and industry to drive innovation in vehicle route optimization.

Table 1 Comparison list of literature review on EV charging stations optimization

Reference	Focus Area	Method Used	Key Contributions
[21]	IoT used for EV Charging	PHP, IoT sensors, Cloud Computing, Linux	Improves charging efficiency and reduces waiting times.
[22]	Finding Best Locations for EV Stations	mobile data tracking, Genetic algorithm	Cuts down on driving distance, energy waste, and station numbers.
[23]	EV Charging Station Design	Estimation methods, Evolutionary Algorithms	Optimizes energy use, voltage stability, and land costs.
[24]	Designing Fast-Charging Stations	Simulations, Genetic Algorithm	Boosts profitability and reliability with renewable energy.
[25]	Strategic EV Station Placement	Multi-criteria Analysis, Hexagonal Evaluation	Finds the best locations for stations in cities.
[26]	EV Charging Simulation	Spatial Data, Agent-based Modelling	Evaluates cost-effectiveness and power grid impacts.
[27]	Choosing EV Station Sites	Fuzzy Logic, Decision-Making Tools	Chooses sites based on sustainability and other factors.
[28]	Planning Public EV Charging Stations	Deterministic Models, Location Planning	Plans station placement to reduce driver stress and range anxiety.
[29]	Forecasting EV Load	Stochastic Models, Data Aggregation	Improves accuracy of load predictions by up to 9.5%.
[30]	EV Charging in Urban Areas	Causal Loop Diagrams (CLD)	Helps create policies for urban EV charging.
Proposed	Optimizing EV Routes	Grid Integrated Electric Car Charging Optimization	TOPSIS and GREY WOLF OPTIMIZATION

3. Assumptions for EV Charging Optimization

Here are some simplified assumptions for optimizing electric vehicle (EV) charging:

- Charging Stations: Charging stations are well-placed in the best possible locations, and the number and locations of these stations are already known.
- Charging Demand: The need for charging depends on how far an EV drives, and the likelihood of different travel distances follows a specific pattern (Rayleigh distribution).
- EVs: Each EV operates independently, has some level of smart technology, and can communicate with other EVs.
- Users: Drivers of EVs will manage their energy use, choose the most suitable charging station, and know their charging needs, destination, and how much charge they have left.
- Charging Process: Charging can be either fast or slow, with a fixed rate, and each EV typically charges for 15 minutes.
- Uncertainties: Unexpected events or uncertainties are not taken into account.
- Traffic: Real-time traffic information is available and can be used to optimize charging decisions.

When optimizing EV charging stations for long-term profit, we need to consider several important factors, especially related to scalability and battery health:

a) Scalability:

Expanding Infrastructure: As more people use EVs, charging stations must expand efficiently. This means carefully planning where to add new charging points, upgrading existing ones, and making sure they are well distributed to meet future demand. Keeping Up with Technology: Charging stations need to be ready for new technologies like ultra-fast or wireless chargers and compatible with future EVs. Planning for these changes helps avoid outdated technology.

Smart Grid Integration: Charging stations should be integrated with the electric grid to balance electricity use. Smart charging can adjust rates based on grid capacity, electricity prices, and demand, reducing costs and increasing profit.

b) Battery Health

Managing Charging Speed: Fast charging is convenient but can wear out batteries faster, affecting both EV performance and customer satisfaction. Offering different charging speeds and educating users on best practices can help maintain battery life.

Smart Charging Algorithms: Using intelligent algorithms that adjust charging based on the battery's health can help prolong battery life. This involves tracking the battery condition and adjusting charging speeds accordingly.

Educating Users and Providing Incentives: Encouraging users to opt for slower charging when possible or charge during off-peak times can help preserve battery health and reduce the burden on the grid.

c) Long-Term Economic and Environmental Impact

Analyzing Costs and Benefits: While slower charging and better battery management might lower immediate profits, they can lead to long-term benefits like happier customers, fewer battery replacements, and increased loyalty.

Sustainability and Regulations: Promoting practices that protect battery health also aligns with environmental goals and regulatory requirements, which can affect the long-term profitability of charging stations.

d) Stochastic Optimization to Handle Uncertainty

Including Battery Health in Optimization Models: The optimization approach can be extended to include battery health as a key factor in deciding charging rates, energy buying strategies, and pricing.

Simulating Different Scenarios: Running simulations with different scenarios, such as the rate of EV adoption, advancements in battery technology, and changes in energy markets, can help plan for future scalability and battery management.

4. COMPARISON WITH OTHER OPTIMIZATION ALGORITHMS

Genetic Algorithm (GA): GA is good at searching through large sets of possible solutions but tends to be slower and needs more computational power. It can also get stuck on suboptimal solutions because it sometimes converges too quickly.

Particle Swarm Optimization (PSO): PSO, like GWO, is inspired by social behavior. However, it might not always strike a good balance between searching for new solutions and refining existing ones, which can lead to getting stuck on suboptimal solutions.

Simulated Annealing (SA): SA is effective at avoiding suboptimal solutions, but it can take a long time to find the best solution, especially when dealing with complex problems.

Differential Evolution (DE): DE works well for certain types of optimization problems but often requires careful tuning of parameters and can be more computationally expensive.

Ant Colony Optimization (ACO): ACO is great for solving problems where the goal is to find the best combination of options, but it can be complicated to set up and often needs more iterations to find a solution, making it less efficient for problems requiring continuous optimization.

5. THE SUPERIORITY OF THIS WORK OVER OTHER OPTIMIZATION ALGORITHMS

To explain why the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and Grey Wolf Optimization (GWO) are better than other optimization methods, we should compare them based on key features like efficiency, speed of finding solutions, handling multiple goals, and robustness.

Table 2 Comparison list of TOPSIS and GWO to Other Methods

Factor	TOPSIS	Grey Wolf Optimization (GWO)	Other Algorithms
Simplicity and Ease of Use.	Easy to use and understand; involves basic calculations.	Simple setup; easy to program and apply.	Many traditional algorithms are more complicated.
Convergence Speed	Fast for ranking tasks; not specifically for optimization.	Quickly finds good solutions by effectively searching the solution space.	Varies; some algorithms are slower.
Multi-Objective Handling	Great for handling multiple criteria or objectives.	Good at solving problems with multiple goals.	Many require special modifications.
Exploration vs. Exploitation	N/A (doesn't search like optimization algorithms).	Balances searching for new solutions and refining known good ones.	Many algorithms struggle to balance this.
Robustness and Flexibility	Works well in many decision-making situations.	Strong against getting stuck on poor solutions; adaptable to different types of problems.	Often less flexible or need tuning.
Scalability	Scales easily with different numbers of criteria.	Can handle large and complex problems.	Depends on the specific algorithm.
Computational Cost	Low cost; involves simple matrix operations.	Low to moderate, depending on problem size.	Some algorithms can be very costly.

6. ENERGY REQUISITE MODELING OF EVS

This research work has looked into how to plan the charging of Electric Vehicles when they are parked in a housing parking lot. The assumption is that all the cars become accessible in the late afternoon after people come back from work till the next day when they head out again. A charging coordinator (CC) is in charge of managing the schedule, making sure the EVs get charged optimally. When an EV arrives at the parking lot, the owner tells the CC details like how much charge is remaining in the battery, information about the EVs battery like capacity, how far it can drive on a full charge (AER or All-Electric Range), and when it needs to leave. With this information, the CC can plan the charging schedule to meet the energy needs of all the EVs.

To figure out how Electric Vehicles (EVs) are typically used, the authors have used a simulation that considers a probability density function. It takes into account things like when the EV shows up and leaves, as well as how far it travels each day. It has also been assumed that the owners of Plug-in Electric Vehicles prefer to have a fully charged battery before they head out. It has helped calculate how much charging is needed based on the total distance the EV would cover during the day, the initial charge level (State of Charge or SOC), and the charge level at the time to leave. The work mentioned in [7] has provided this info about how EVs are typically used.

Here, SOC (State of Charge) means how much energy is still there in the EV battery when it arrives at the parking lot. To make sure that the battery lasts for a long time, a minimum SOC of 20% has been set. The initial SOC has been figured out based on how far the EV has travelled. If an EV has covered a distance represented as D and has an AER (All-Electric Range) of D_r, the initial SOC when it arrives, called SOC_a arrival, is calculated like this:

$$SOCa = 1 - \frac{D}{D_r} \tag{1}$$

To make sure an Electric Vehicle (EV) gets the right amount of charge, the owner has to tell the charging coordinator (CC) about the initial SOC, just like people with regular fuel-based cars share details about their fuel needs. It has been assumed that the EV needs to have a full charge, so the required exit SOC is cent percent. The energy needed to charge the EV battery depends on how much charge is remaining when it arrives. This energy has come from the utility, and it can be expressed as:

$$E_r = \frac{(1 - SOCa)B_c}{\eta} \tag{2}$$

Here, E_r represents the energy needed for a full battery charge, B_c is the battery capacity, and η is the charging efficiency of the EV. In the charging mode of EV, the efficiency is $1/\eta_c$ & in discharging state, the efficiency is η_d.

7. SYSTEM DESIGN

In the created model, the DSO (Distribution System Operator) takes on the job of planning and organizing resources in the local power distribution network. Fig. 1 shows how the DSO interacts with its overseer upstream and the different players and parts downstream in the system [20].

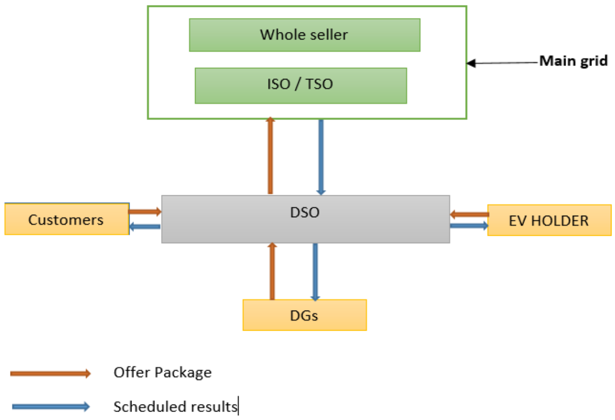


Fig. 1 Connections among participants & DSO

7.1. Advanced Metering Infrastructure

The Advanced Metering Infrastructure (AMI) is a present system for keeping track of & managing how much energy has been used. It includes smart meters, communication networks and systems for handling data, making it possible for utility providers and consumers to talk to each other. AMI allows to exchange data in real-time, giving more detailed information about how we use energy. This technology makes things work more efficiently, helps with programs that respond to changes in energy demand, and gives consumers the power to make smart choices about how they use energy.

7.1.1. Power Line Carrier Communication Smart Meters

These meters are connected at customers' homes, and they are of two types, one for single-phase and another for three-phase systems. The smart meters used by average and big customers can connect straight to the efficacy by using GPRS. Besides measuring the electricity used by individual customers, these smart meters also measure electrical parameters for every feeder in the key substation and distribution substation transformers of subordinate section rated (63/20 kV) & (20/0.4 kV). Collecting all this data makes it easy to calculate how much energy is lost in every line in both the Medium Voltage & Low Voltage networks [20].

7.1.2. Data Concentrators (DC)

These devices are strategically positioned close to the substation rate 20 kV/ 400 V distribution transformers. Their job is to keep an eye on all the combined data coming from smart meters in the Low Voltage (LV) network installations. These concentrators use

Power Line Carrier Communication (PLCC) to talk to smart meters, making it easy to exchange data and create communication links with central systems that manage meter data.

7.1.3. The Meter Data Management System

The Meter Data Management or Repository systems work like a central hub. They gather and handle raw information from all meters, making sure to provide cleaned-up data to the Distribution System Operator and other application systems.

7.1.4. Electric Vehicle Charging Points

Charging points for EV at homes or workplaces, also known as charging plugs, have an electric plug for each system that comes with a Power Line Carrier Communication (PLCC) modem. This modem sends information about the electric vehicle (EV) to a smart meter. To make this system even better, there is a proposed identification chip that can be installed in electric vehicles. When an Electric Vehicle (EV) is connected to a charging point, a special chip in the EV drives the signal to the smart meter. As soon as the smart meter detects that an EV is plugged in, it promptly shares details about the charging and discharging activities with the Meter Data Management and Repository. Fig. 2 indicates the Advanced Metering Infrastructure.

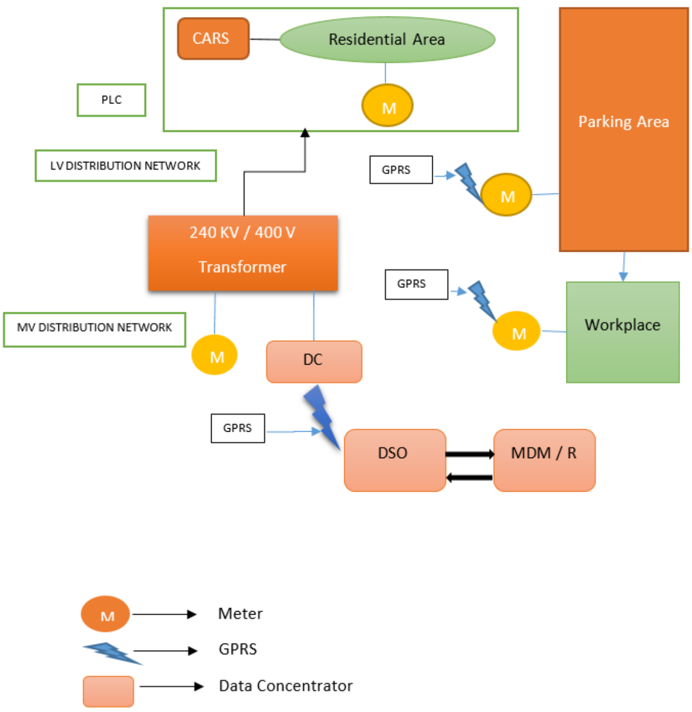


Fig. 2 Advanced Metering Infrastructure

7.2. System for the Management of Electric Vehicles

When Electric Vehicles (EVs) are brought into the distribution network, a system is set up inside the Distribution Management System (DMS). This system is called the Electric Vehicles Management System and it is like a small part that works within the larger DMS. The main job of EVMS is to plan and control when EVs charge and discharge their batteries in a smart distribution network. To do this, EVMS gets information about the EV owners from the MDM system. It also gets data about charging-discharging from the MDM system and uses the Geographical Information System (GIS) to give details about where things are on the network and where EV resources are located. The EVMS keeps a database that has information about the EV resources, their features, and what they have done in the past. If people with EVs want to take part in charging or discharging events, they can sign up through a mobile app or a website. It is a straightforward process, as shown in Fig. 3.

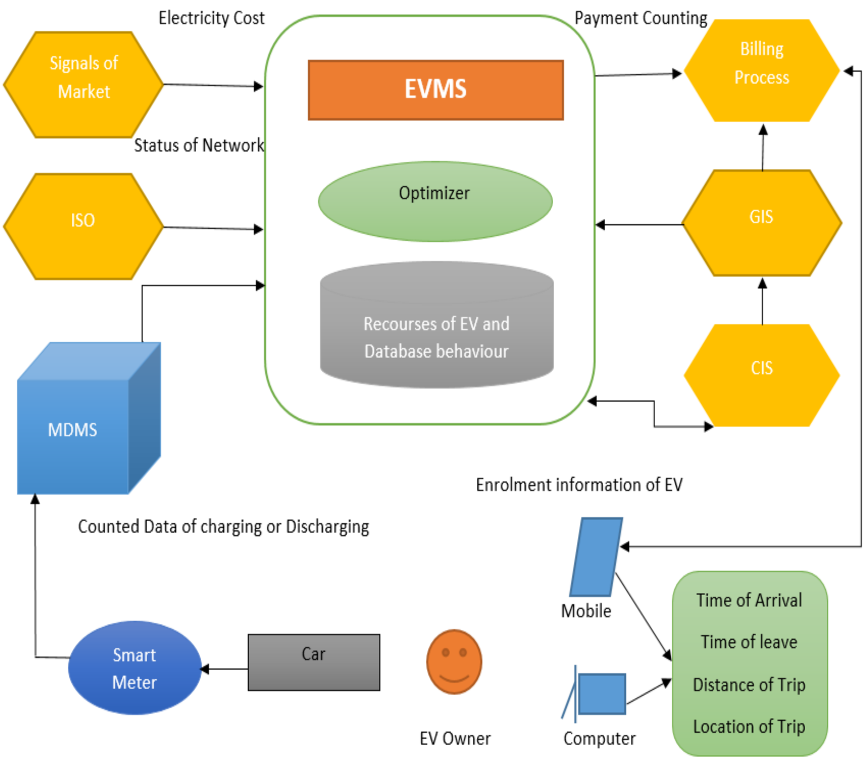


Fig. 3 Illustration of EV management system

8. Problem Formulation of Multiobjective Function

This section explains the objective function, the limitations or constraints, and setting up the plan with multiple goals using the TOPSIS method in the new preparation policy.

8.1. Objective Functions and Restraints

8.1.1. The Valley Filling Model (VFM)

This is a plan used to manage when electric vehicles (EVs) charge or discharge in smart grids. The focus here is on making the most of times when electricity demand is low, often called valleys, in the overall electricity usage pattern. By smartly adjusting when EVs charge or discharge during these periods, the VFM (Valley Filling Model) aims to improve how the grid is balanced, to make the most efficient use of resources, and possibly to lower the overall energy costs. This approach will help EVs fit in smoothly with the larger energy system supporting sustainability and keeping the grid stable. In other words, it is about reducing the gap between how much electricity is used at a particular moment and the average amount used, which is called load variations [19].
Where,

$$f_1 = \sum_{t=1}^{24} (S_{sys}^t - S_{sys}^t)^2 \tag{3}$$

$$S_{sys}^t = \sqrt{(L_{sys}^t)^2 + (Q_{res}^t)^2} \tag{4}$$

$$L_{sys}^t = L_{res}^t + \sum_{i=1}^{N_V} L_{i,EV}^t \Delta t \tag{5}$$

In this situation, where N_v stands for the total number of vehicles and S_{avg} is the normal apparent load of the system, Eqn. (4) signifies the whole actual system power, called S^t_{sys}. Eqn. (5) shows that the entire active power demand (L^t_{sys}), which is the sum of domestic load (L^t_{res}) and the total electric vehicle (EV) load ($L^t_{i,EV}$) at any given time t. In this study, one-hour interval has been considered and is denoted by t.

8.1.2. Minimum Charging or Discharging Cost Model (MCM)

The charging cost and discharging cover all the money spent by the Charging Controller (CC). This overall cost includes what it takes to charge, the money earned from discharging, and the costs linked to the wear and tear on the battery. The charging and discharging cost is expressed as:

$$C_{charge} = \sum_{i=1}^{N_V} \sum_{t=1}^{t_{i,p}} \lambda^t \cdot x \tag{6}$$

Here, λ_t represents the electricity cost at time t, and x represents the rate of charging / discharging at time t. The cost associated with battery degradation is expressed as:

$$C_{deg} = \sum_{i=1}^{N_V} \frac{C_{bat} \cdot B_{c,i} + C_l}{B_l \cdot B_{c,i} \cdot DOD} \cdot E_{dis}^{\Delta t} \tag{7}$$

Here, C_{bat} represents the battery cost, $B_{c,i}$ denotes the capacity of battery of the electric vehicle, C_l is the labour cost for replacement the battery, and DOD refers to the discharge depth . In this research, C_{bat} = 300$ / kWh, C_l = 240$, B_l = 5000 at eighty percent discharge. Consequently, the total cost of charging/ discharging acquired by the Charging Controller (CC) can be stated as:

$$f_2 = C_{charge} + C_{deg} \tag{8}$$

8.1.3. Multi Objective Model

The purpose of objective in this structure is crafted to concurrently enhance both load variance and the whole cost acquired by the Charging Controller (CC). Thus, the function of objective is expressed as:

$$f_3 = \min(f_1 + f_2) \tag{9}$$

8.2. Multi-objective formulation

The Multi-Objective Formulation Using Technique for Order of Preference by Similarity to Ideal Solution TOPSIS is a method for solving problems with multiple conflicting goals. It looks at various criteria all at once, aiming to find the best solution considering these criteria. TOPSIS involves comparing different solutions to both an ideal solution (where all criteria are maximized) and a nadir solution (where all criteria are minimized). Solutions are then ranked based on how close they are to the ideal solution and how far they are from the nadir solution.

In the case of optimizing the charging and discharging model mentioned earlier, TOPSIS has been used to find a set of solutions that balances minimizing load variance and reducing the total cost for the Charging Controller (CC). This method allows decision-makers to choose a solution from the Pareto front that best suits their preferences and goals.

9. KEY ADVANTAGES OF TOPSIS AND GWO OVER OTHER ALGORITHMS

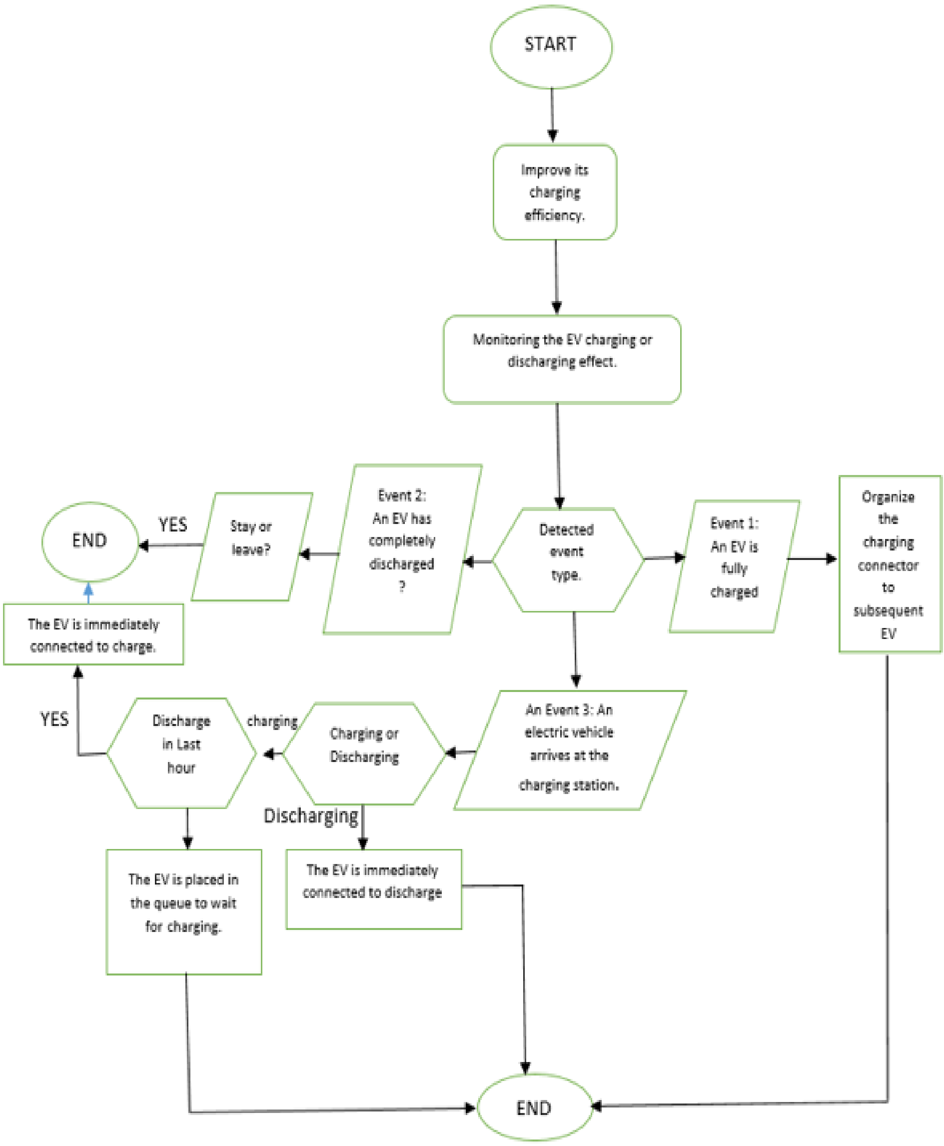
9.1. TOPSIS Advantages:

- Simple and Clear: Provides an easy way to rank options by comparing them to the best and worst outcomes, making it straightforward for decision-making.
- Good for Multiple Criteria: Designed to handle decisions with many criteria, especially when there are conflicting objectives.
- Efficient to Compute: Requires less computing power than many other methods, using mainly simple calculations.

9.2. Grey Wolf Optimization (GWO) Advantages:

- Balanced Search: Effectively balances finding new solutions and improving existing ones, reducing the chance of getting stuck in suboptimal solutions.
- Quick Convergence: Finds solutions quickly by mimicking the grey wolves' hunting strategy.
- Flexible and Reliable: Works well for various types of optimization problems and is less likely to get trapped in local optima.
- Easy to Use: Simpler to implement than many other complex algorithms.

10. FLOWCHART



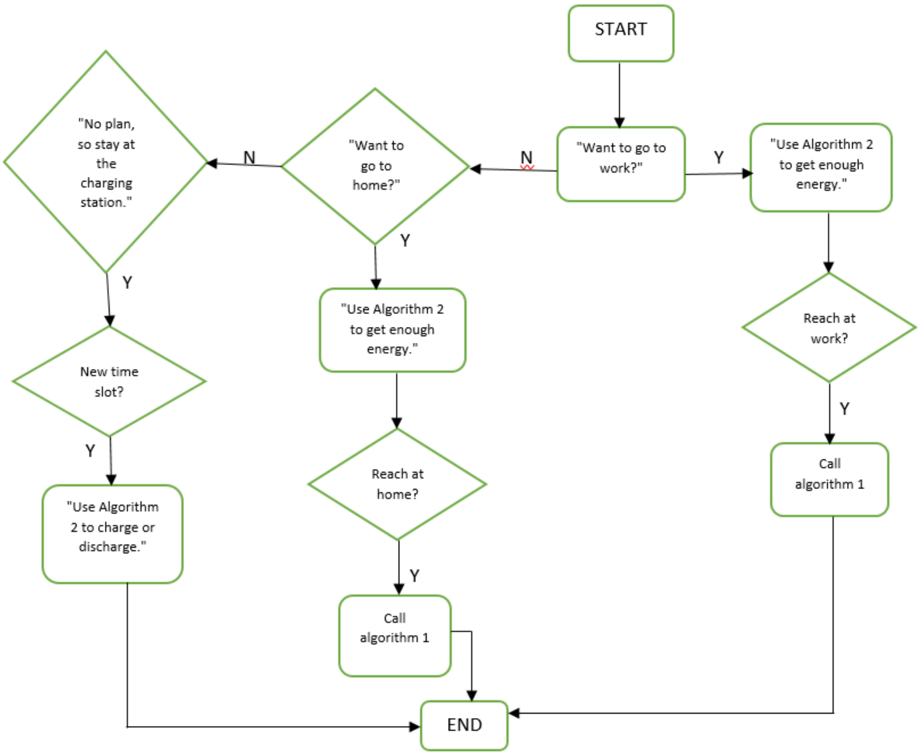


Fig 4 Flow Chart of Private EV

11. Optimization Structure

All optimizations in this study have used GWO, which is a metaheuristic algorithm motivated by how grey wolves hunt [14]. In the grey wolves hunting process, leaders alpha (α), beta (β), and delta (δ) exchange information about each other's positions.

$$\vec{X}(k+1) = \vec{X}_p(k) - \vec{A}\,.\,\vec{D} \quad (10)$$

$$\vec{D} = \left|\vec{C}\ .\ \vec{X}_p(k) - \vec{X}\,k\right| \quad (11)$$

K stands for the current iteration, $\vec{X}$ stands for the position of grey wolf, $\vec{X}_p$ stands for the position of prey, and $\vec{D}$ stands for prey distance. The formula of vectors $\vec{A}$ and $\vec{C}$ are as follows:

$$\vec{A} = 2a.\vec{r}_1 - a \quad (12)$$

$$C = 2.\vec{r}_2 \quad (13)$$

Where r_1 and r_2 are random vectors. Its range is [0, 1], and the value of a linearly decreases from 2 – 0 of iterations. The location of every wolf is simplified as follows:

$$\vec{X}(k+1) = \frac{1}{length(p)} \sum_{i \in p} X_p(+1), p[\alpha, \beta, \delta] \tag{14}$$

12. Simulation Results and Discussion

In this section, the study has looked into how to best include Electric Vehicles (EVs) in a 38-node bus system, presented in Figure 4. The focus is on the residential area, where EVs are only supposed to be present. The details about the 38-node system and residential electricity usage are taken from a source [20]. The power factor for homes is assumed to be 0.9, and a 1000 KVA transformer supplies power to the residential area. A 3-tier pricing system has been considered as well as 5 types of EVs, along with a domestic charger that can handle 3.33 kW for charging and discharging of EVs. Assuming that households use a maximum of 4 kW, there are 230 houses on the residential side [3]. With an average of 2.12 vehicles per house, it can be found that there are a total of 488 vehicles in the residential area [15]. It has been assumed that these EVs are spread out evenly across the residential nodes [7]. The driving patterns for these vehicles are taken from a particular source.

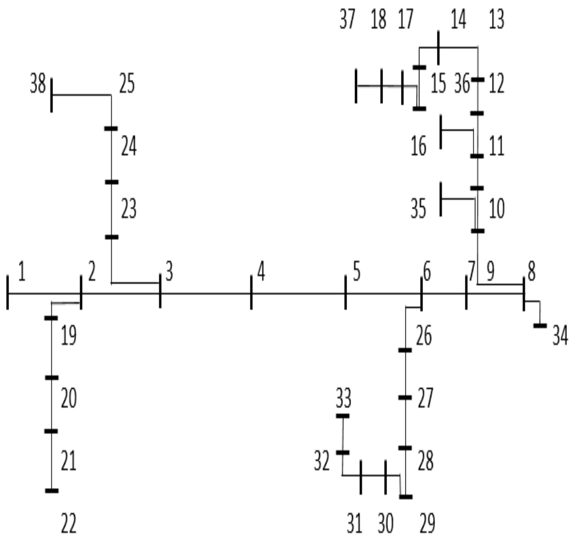


Fig. 5 38-node bus distribution system

In this study, it has been figured out when and how Electric Vehicles (EVs) should charge using a method called TOPSIS. To show that TOPSIS works well, its results have been compared with two other methods, VFM and MCM. Different levels of EVs in the residential area have been considered, which is the EV penetration (20%, 40%, 60%, 80%). EV penetration [31] is about how many EVs are there. The aim is to find the most

EVs that can be there without causing problems for the power system, like overloading transformers or lines or messing with the voltage. The limits for that are mentioned Table 3 [9].

Table 3 Range of Voltage, Transformer and Line Loading

Range of Voltage	Range of Transformer Loading	Range of Line Loading
1 p.u. (Upper Limit)	1000 KVA	Line no. 14 (6 to 26) 1.5 p.u.
0.93 (Lower Limit)	1000 KVA	Line no. 19 (30 to 31) 0.5 p.u.

Table 4 illustrates how different strategies and Electric Vehicle (EV) numbers impact power lines, peak power demand, and energy losses. VFM can easily handle 80% EVs, while MCM copes well with 40%. MOM accommodates 60% EVs without infrastructure issues. VFM keeps peak demand below 952.17 kVA, whereas MCM surpasses this when EVs reach 60%. Network losses rise with more EVs; MOM losses fall between VFM and MCM, with MCM losses increasing notably as EVs rise.

In Figure 5, the graph shows how Electric Vehicle (EV) scheduling impacts [32] the transformer load profiles with different strategies and EV numbers. For Voltage and Frequency Management (VFM), scheduling helps smooth out peaks and valleys, resulting in a more consistent load profile at all penetration levels. With Mixed-Integer Linear Programming (MCM), EVs assist in filling valleys and shaving peaks at low EV penetration. However, at higher penetration (60% and 80%), MCM introduces a new peak due to its objective of minimizing charging/ discharging costs. The MOM scheduling from the TOPSIS approach achieves a balance between the objectives of VFM and MCM, falling the dissimilarities between peak and valley loads while ensuring the morning peak stays below 1000 kVA transformer limit.

Table 4 Effect of different ideas under various penetration

Charging Strategy	Level of Presentation	Capacity of Line		Peak Load in KVA	Losses in MW
		Line no. 14	Line no. 19		
Base case	0	64.70%	67.90%	952.18	1.84
VFM	20%	57.91%	62.01%	854.54	1.85
	40%	54.61%	67.89%	806.01	1.88
	60%	54.71%	52.61%	809.47	1.93
	80%	57.61%	67.41%	849.7	1.97
MCM	20%	61.41%	66.41%	910.63	1.86
	40%	62.91%	66.01%	927.18	1.9
	60%	70.01%	112.01%	1032.01	1.98
	80%	88.01%	141.21%	1294.71	2.06
MOM	20%	61.11%	64.21%	901.39	1.86
	40%	61.11%	64.21%	901.39	1.89
	60%	62.41%	94.61%	923.33	1.96
	80%	66.91%	102.61%	989.85	1.99

Table 5 presents a comparison of several scheduling methods according to load variance and charging/discharging expenses. At whatever degree of EV penetration, VFM exhibits superior load variance over MCM. To maximise benefits, the VFM strategy is to charge when costs are low and discharge when costs are high. However, MOM optimizes EVs to minimize charging costs while still achieving a flat load profile. For a given EV penetration, MOM achieves a trade-off between better load variance over MCM and cheaper charging/ discharging costs over VFM. With the TOPSIS approach, solutions obtained are favorable for both smoothing out load variations and minimizing charging costs. This means achieving a substantial EV presence while maintaining an advantage in load variance and charging expenses.

Table 5 Comparison List of Various Objectives

Level of Penetration	Charging Plan	Total cost of daily charging	Load Difference
20%	VFM	58.59	3.054×10^5
	MCM	37.87	4.47×10^5
	MOM	45.51	4.01×10^5
40%	VFM	144.08	6.72×10^4
	MCM	99.29	2.78×10^5
	MOM	131.66	2.01×10^5
60%	VFM	285.56	6.44×10^4
	MCM	163.86	5.01×10^5
	MOM	239.1	1.91×10^5
80%	VFM	434.27	9.23×10^4
	MCM	207.26	1.01×10^6
	MOM	346.53	2.85×10^5

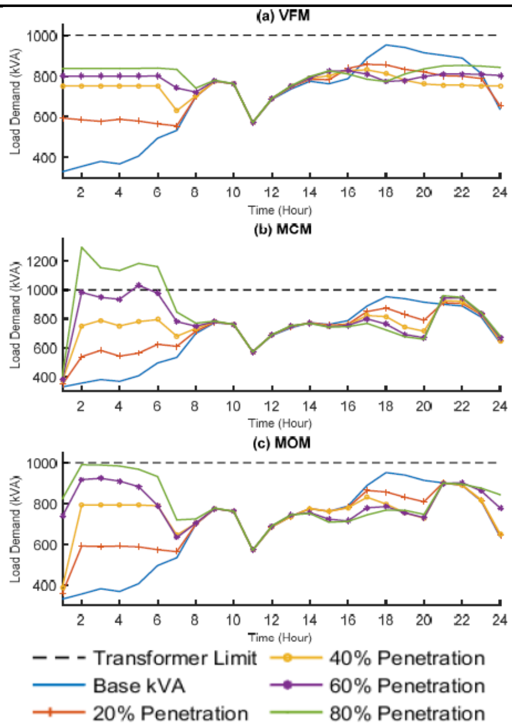


Fig. 6 Different changing models of load profiles

Thus, the study has suggested that by using MOM with the TOPSIS approach, a significant number of EVs into the system can be introduced while maintaining a stable electricity load and keeping charging costs [33] in check.

13. CONCLUSION

This paper has analyzed a multi-objective optimization framework for effectively employing the TOPSIS method for scheduling Electric Vehicles (EVs). GWO has been used to manage the optimization. The research work has compared the effectiveness of multi-objective scheduling against a single-objective optimization approach. The findings have revealed that Voltage and Frequency Management (VFM) excels at reduced load variance, while Mixed-Integer Linear Programming (MCM) performs better in terms of charging/ discharging costs. However, the TOPSIS approach provides balanced results, combining the advantages of both objectives. This approach can strike a balance, guaranteeing significant EV integration with positive results for both the goals. The efficiency of the proposed strategy has demonstrated by applying this technique to a test case.

TOPSIS is useful for decision-making problems that involve multiple criteria, as it allows for quick and efficient ranking of different options. Grey Wolf Optimization (GWO) is very effective for finding the best solutions in optimization problems because it balances searching for new solutions and refining known ones, converges quickly, is reliable, and easy to implement. When used together, TOPSIS and GWO create a strong approach for solving complex optimization problems, combining simplicity, efficiency, and flexibility in a way that many traditional algorithms do not. To ensure the long-term success of EV charging stations, a comprehensive approach is needed that balances scalability and battery health. This means planning for growth while keeping customers satisfied and operations sustainable by considering long-term effects on profitability and battery life.

REFERENCES

[1] M. Sharif and H. Seker, "Smart EV Charging with Context-Awareness: Enhancing Resource Utilization via Deep Reinforcement Learning", *IEEE Access*, vol. 12, pp. 7009-7027, 2024.

[2] M. Sharif, G. Lückemeyer and H. Seker, "Context Aware-Resource Optimality in Electric Vehicle Smart2Charge Application: A Deep Reinforcement Learning-Based Approach", *IEEE Access*, vol. 11, pp. 88583–88596, 2023.

[3] D. M. Doe, D. Chen, K. Han, Y. Dai, J. Xie, and Z. Han, "Real-Time Search-Driven Content Delivery in Vehicular Networks for AR/VR-Enabled Autonomous Vehicles", In Proceedings of the 2023 IEEE/CIC International Conference on Communications in China (ICCC), 2023, pp. 1-6.

[4] U. Demir, G. Akgun, M. C. Akuner, M. Pourkarimi, O. Akgun and T. C. Akinci, "An Innovative Approach to Electrical Motor Geometry Generation Using Machine Learning and Image Processing Techniques", *IEEE Access*, vol. 11, pp. 48651-48666, 2023.

[5] F. Giordano, C. Diaz-Londono and G. Gruosso, "Comprehensive Aggregator Methodology for EVs in V2G Operations and Electricity Markets", *IEEE Open J. Veh. Technol.*, vol. 4, pp. 809-819, 2023.

[6] M. A. Beyazit, A. K. Erenoğlu and A. Taşcıkaraoğlu, "Scheduling of Mobile Charging Stations for Fair Electric Vehicle Charging", In Proceedings of the 2023 International Conference on Smart Energy Systems and Technologies (SEST), 2023, pp. 1-6.

[7] F. J. Y. Zou, X. Zhang and B. Zhang, "Online Optimal Dispatch Based on Combined Robust and Stochastic Model Predictive Control for a Microgrid Including EV Charging Station", *Energy*, vol. 247, p. 123220, 2022.

[8] R. Guo and W. Shen, "An Enhanced Multi-Constraint State of Power Estimation Algorithm for Lithium-Ion Batteries in Electric Vehicles", *J. Energy Storage*, vol. 50, p. 104628, 2022.
[9] R. R. Kumar, P. Guha and A. Chakraborty, "Comparative Assessment and Selection of Electric Vehicle Diffusion Models: A global outlook", *Energy*, vol. 238, p. 121932, 2022.
[10] A. Kapoor, V. Patel, A. Sharma and A. Mohapatra, "Centralized and Decentralized Pricing Strategies for Optimal Scheduling of Electric Vehicles", *IEEE Trans. Smart Grid*, vol. 13, no. 3, pp. 2234-2244, May 2022.
[11] T. Long, Q.-S. Jia, G. Wang and Y. Yang, "Efficient Real-Time EV Charging Scheduling via Ordinal Optimization", *IEEE Trans. Smart Grid*, vol. 12, no. 5, pp. 4029-4038, Sep. 2021.
[12] J. Liu, G. Lin, S. Huang, Y. Zhou, Y. Li and C. Rehtanz, "Optimal EV Charging Scheduling by Considering the Limited Number of Chargers", *IEEE Trans. Transport. Electrific.*, vol. 7, no. 3, pp. 1112–1122, Sep. 2021.
[13] T. Panayiotou, M. Mavrovouniotis and G. Ellinas, "On the Fair-Efficient Charging Scheduling of Electric Vehicles in Parking Structures", In Proceedings of the 2021 IEEE International Intelligent Transportation Systems Conference (ITSC), Indianapolis, IN, USA, 2021, pp. 1627-1634.
[14] R. Das, Y. Wang, K. Busawon, G. Putrus and M. Neaimeh, "Real-Time Multi-Objective Optimization for Electric Vehicle Charging Management", *J. Cleaner Prod.*, vol. 292, p. 126066, 2021.
[15] W. Yin, Z. Ming and T. Wen, "Scheduling Strategy of Electric Vehicle Charging Considering Different Requirements of Grid and Users", *Energy*, vol. 232, p. 121118, 2021.
[16] S. Woo, S. Bae, and S. J. Moura, "Pareto Optimality in Cost and Service Quality for an Electric Vehicle Charging Facility", *Appl. Energy*, vol. 290, p. 116779, 2021.
[17] M. Jafari, A. Kavousi-Fard, T. Niknam and O. Avatefipour, "Stochastic Synergies of Urban Transportation System and Smart Grid in Smart Cities Considering V2G and V2S Concepts", *Energy*, vol. 215, p. 119054, 2021.
[18] S. Liu, X. Xia, Y. Cao, Q. Ni, X. Zhang and L. Xu, "Reservation-Based EV Charging Recommendation Concerning Charging Urgency Policy", *Sustain. Cities Soc.*, vol. 74, p. 103150, 2021.
[19] M. Rezaeimozafar, M. Eskandari and A. V. Savkin, "A Self-Optimizing Scheduling Model for Large-Scale EV Fleets in Microgrids", *IEEE Trans. Ind. Informat.*, vol. 17, no. 12, pp. 8177-8188, Dec. 2021.
[20] K. Zhou, L. Cheng, X. Lu and L. Wen, "Scheduling Model of Electric Vehicles Charging Considering Inconvenience and Dynamic Electricity Prices", *Appl. Energy*, vol. 276, p. 115455, 2020.
[21] Sun, P., R. Bisschop, H. Niu and X. Huang, "A Review of Battery Fires in Electric Vehicles", *Fire Technol.*, vol. 56, pp. 1361-1410, 2020.
[22] G. F. Savari, V. Krishnasamy, J. Sathik, Z. M. Ali and S. H. Abdel Aleem, "Internet of Things Based Real-Time Electric Vehicle Load Forecasting and Charging Station Recommendation", *ISA Trans.*, vol. 97, pp. 431-447, 2020.
[23] M. M. Vazifeh, H. Zhang, P. Santi and C. Ratti, "Optimizing the Deployment of Electric Vehicle Charging Stations Using Pervasive Mobility Data", *Transp. Res. Part A Policy Pract.*, vol. 121, pp. 75-91, 2019.
[24] A. Pal, A. Bhattacharya and A. K. Chakraborty, "Allocation of Electric Vehicle Charging Station Considering Uncertainties", *Sustain. Energy, Grids Netw.*, vol. 25, p. 100422, 2021.
[25] J. Domínguez-Navarro, R. Dufo-López, J. Yusta-Loyo, J. Artal-Sevil and J. Bernal-Agustín, "Design of an Electric Vehicle Fast-Charging Station with Integration of Renewable Energy and Storage Systems", *Int. J. Electr. Power Energy Syst.*, vol. 105, pp. 46-58, 2019.
[26] C. Csiszár, B. Csonka, D. Földes, E. Wirth and T. Lovas, "Urban Public Charging Station Locating Method for Electric Vehicles Based on Land Use Approach", *J. Transp. Geogr.*, vol. 74, pp. 173-180, 2019.
[27] M. Pagani, W. Korosec, N. Chokani and R. Abhari, "User Behaviour and Electric Vehicle Charging Infrastructure: An Agent-Based Model Assessment", *Appl. Energy*, vol. 254, p. 113680, 2019.
[28] Y. Ju, D. Ju, G. E. D. Santibanez, M. Giannakis and A. Wang, "Study of Site Selection of Electric Vehicle Charging Station Based on Extended GRP Method Under Picture Fuzzy Environment", *Comput. Ind. Eng.*, vol. 135, pp. 1271-1285, 2019.
[29] L. Pan, E. Yao, Y. Yang and R. Zhang, "A Location Model for Electric Vehicle (EV) Public Charging Stations Based on Drivers' Existing Activities", *Sustain. Cities Soc.*, vol. 59, p. 102192, 2020.
[30] L. Buzna et al., "An Ensemble Methodology for Hierarchical Probabilistic Electric Vehicle Load Forecasting at Regular Charging Stations", *Appl. Energy*, vol. 283, p. 116337, 2021.
[31] B. Bhattacharjee, P. K. Sadhu, A. Ganguly and A. K. Naskar, "Using Fuzzy Systems for Optimal Network Reconfiguration of a Distribution System with Electric Vehicle Charging Stations and Renewable generation", *Microsyst. Technol.*, vol. 30, no. 10, pp. 1381-1392, 2024.

[32] B. Bhattacharjee, P. K. Sadhu, A. Ganguly, A. K. Naskar and S. P. Bihari, "Photovoltaic Integrated Optimized Energy Storage Drives for Electric Vehicles", *J. Energy Storage*, vol. 98, p. 113098, 2024.

[33] B. Bhattacharjee, P. K. Sadhu, A. Ganguly, and A. K. Naskar, "Photovoltaic Energy Based Fast Charging Strategy for VRLA Batteries in Small Electric Vehicles for Sustainable Development", *Microsyst. Technol.*, vol. 30, no. 2, pp. 141-153, 2024.