

Research on Coordinated Control Strategy of Electric Vehicle Pile Group Load based on Virtual Aggregation

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Abstract

In an effort to lessen the impact of cities on the environment, more and more electric vehicles are entering the market as a viable substitute for fossil fuels. But advancements in electric car technology have been slowed by the wrong positioning of charging sites. This study presents an index method for assessing the position of electric car charging heaps. It is based on sixteen parameters chosen from four categories: economy, environment, cost, as well as service quality. This study develops a set coverage concept and uses a greedy heuristic approach to determine the best places to put charge piles based on the assessment. In this research, we build a model for managing household electric car charging piles using a deep reinforcement learning method. The report suggested a novel method of controlling the conventional plug-and-play charging method in homes, which reduced the negative effects of unauthorized charging of EVs on the power grid. This control method suggests a charging pile group control model using a deep reinforcement learning algorithm, taking into account the time-sharing pricing of electric car charging as well as the safe and economical functioning of the transmission network. Delay in dispatching depending on the power grid's load change rate, reference load dispatching, and dispatching load increments are the primary components of this control method. The district distribution network can run more smoothly, charging pile operators can make more money, and electric vehicle users can pay less to charge their vehicles. Lastly, the report uses an analysis of the current placement of electric car charging heaps to confirm the model's reasonableness and viability. The evaluation-based set coverage model is a novel approach to determining the best locations for electric car charging heaps across the United States, and this research intends to lay the theoretical groundwork for the growth of this emerging energy sector.

Keywords: Electric Vehicles, Charging Pile Groups, Virtual Aggregation, Coordinate Control, DRL-SAC, Best Charging Station Selection and ACO

1. INTRODUCTION

There has been a recent uptick in interest in electric cars due to concerns about the environment and the depletion of conventional fossil fuels. But range anxiety about EVs is a major problem that slows their growth since there aren't enough charging stations [1]. Charging stations, supporting charging technologies, and companies related to electric vehicles have all seen significant growth and transformation with the electric car sector. Still, issues such as a lack of charging pile usage, trouble earning a profit for running businesses, and trouble locating heaps for electric car users persist [2]. The use of electric car charging stations has been on the rise in recent years, paralleling the growth in the market share of clean energy vehicles. Consequently, it is crucial to check the charging pile before exiting the manufacturer. There has to be an upgrade to the existing testing technique for the human-machine interface functionality since it is inefficient, prone to errors, expensive, and poses the risk of electric shock [3].

The government and public have shown great support for innovative concepts like electric cars, power grids, and traffic as a means to address energy shortages with air pollution, thanks to the ongoing advancements in urban intelligence. The charging pile has the usual traits of an Internet of Things terminal and is an important node for data exchange. Unfortunately, there is a lack of standardization in the guidelines for electric car grid connections, which will in turn compromise the reliability and safety of the power grid [4]. The market for EVs has been growing at a fast pace in the last few years. A growth of 59.25% from 2020 will bring the overall number of new energy cars in the nation to 7.84 million by the end of 2021, making them 2.60% of the total vehicles. The electrical system will be unaffected by a few of electric automobiles. The electrification of every type of passenger automobiles, however, will eventually lead to the emergence of large-scale electric vehicles [5]. Charging stations and other infrastructure for electric vehicles are expanding at a similar rate as the electric car sector in China. The DC charging pile is like the gas station's fuel dispenser: it connects new energy electric cars to the grid and charges them. The quantity of electric cars should be proportional to the size of the charging pile system, which is the infrastructure for supplying electricity to electric vehicles [6].

The charging pile helps the charging station and the EVs that use it by acting as a go-between for the electric energy that flows among the power grid with the EVs. A big number of charging piles' intricate energy trading behavior with the power grid and the EV group is challenging to examine correctly [7]. Using a charger that is installed on the vehicle to charge the power battery, the AC charging pile is the primary energy supply facility for residential electric cars. The existing standard from the State Grid Corporation of China specifies the AC charging pile's operation without considering the power grid's response to harmonics from vehicle-mounted chargers [8]. As ecological and environmental issues become more severe and fossil fuels become scarce, new energy production will become the dominating force in China's energy system. One example of this is the country's strong push to promote electric cars, which rely on new energy. A lot of people are interested in studying charging stacks these days, therefore researchers are trying to figure out how to make testing instruments that are portable, accurate, and useful [9].

There will be a greater and greater likelihood of employing charging heaps as the number of electric cars in China increases. A mobile payment platform may facilitate the flow of information between users and charge piles, as well as provide charging-related services to users, all against the backdrop of the fast growth of mobile Internet technology [10]. More and more people are opting to drive electric vehicles as a result of the growing awareness of energy and environmental concerns throughout the globe. Nevertheless, the power grid's instability will worsen due to EV charging chaos, which in turn causes "peak-on-peak" of residential load, which in turn necessitates more capacity from power supply equipment, which in turn causes its utilization rate to drop, which is bad for the grid's economic and stable operation [11]. The design and development of DC charging heaps and fast charging stations is moving at a breakneck pace to keep up with the demands of various electric car kinds. A lot of people are interested in studying the standardized DC charging pile. Because the characteristics of every section in the charging pile are different, the current that each module assumes while working in parallel could vary, which might shorten the life of the charging pile and cause damage to certain modules before their time [12].

The overarching goal of this research is to suggest the best time to charge electric vehicles. Our field's principal research and development foci are the total charging time of an electric vehicle with the total distance it must travel from its origin to its destination. There are three main challenges to consider when planning electric car charging schedules:

- Distribution of Space Subject to Arbitration. Since the locations of the electric vehicles are entirely up to chance in our scenario, the paths taken by the charging schedule are subject to vary. This is different from when the EVs charge at certain locations and times.
- The fee structure is not uniform. Our main concern is that there are two possible charging speeds for electric vehicles: slow and speedy. Whilst in slow charging mode, the battery power is low. A long period of time is required to charge an electric car. Due to the slow charging rate, this approach requires a long parking duration. When several electric cars try to use the quick charging pile at once, it becomes a bottleneck. Power interruptions and congestion around fast charging stations might result from such measures.
- Our capabilities are limited. Because of the limited amount of juice left in the battery, electric cars can't access all charging stations. Consequently, not every charging stations will be available since there is an ultimate distance that booked EVs may travel.

To test how well our system works, we do out experiments here. In this research, we first detail the dataset that was used. The findings of the experiment are then reported.

2. RELATED WORK

Improving the load prediction impact of charging piles of electric vehicles determined by time and space constraints in an Internet of Things environment is proposed in [13]. That approach can address the issues of poor power quality and difficult power grid control caused by the spatial and temporal randomness of charging loads. The journey chain is plucked at random after building an electric car charging model, a model of a traffic road network using the Internet of Things, and a model of a travel chain with varying degrees of complexity. The journey route and time are calculated using the Internet of Things traffic road network framework in conjunction using the shortest travel time restriction. Electric car charging locations and times are controlled by the current State of Charge and the final destination. The input to the deep multi-step time-space dynamic neural network is the time-space distribution data for the energy storing electric vehicle charging pile at various times and locations, and the network's output is the charging pile in real-time.

In order to facilitate energy mutual assistance across several electric cars, the authors of [14] suggest a single DC-DC converter that makes use of virtual power oriented model predictive control. One solution that can satisfy high voltage gain and power density demands is the bidirectional full bridge series resonant DC-DC converter, also known as BDB-SRC. At the same time, there are portability benefits to that structure. Variable settings, such as charging load characteristics, are also present across the various electric vehicle models. They suggest VP-MPC for DC-DC converters as a solution to that issue. Lastly, the suggested energy transfer converter that links two electric cars is shown to have great performance based on the findings of both experiments and simulations.

A new EV charging pile that incorporates charging, discharging, while storage is constructed using battery energy storage devices in [15]. For simulating the charge control guidance module, an EV charging model is built using Multisim software. Building on that foundation, new approaches to energy storage charging pile management systems for electric vehicles are investigated via research into cutting-edge technologies including big data, embedded systems, cloud computing, mobile Internet, and the Internet of Things. To further examine the charging pattern, the K-Means clustering analysis approach is used. Power storage, user control, equipment control, transaction control, and large data analysis are all conceivable features of that design. First, the paper's simulations demonstrate that the control guidance circuit is capable of meeting the needs of the energy-storage charging pile; second, the voltage state changes smoothly during the switching process of the charging pile connection state; and third, the output power is sufficient to meet the layout and application requirements of the charging pile. Efficiently reducing the system's operating and maintenance expenses while providing more pleasant and easy charging services is possible with the help of that innovative approach and technological route for electric car charging pile administration design.

Using computer vision as a replacement for human labor, suggests an intelligent interactive testing system for the HMI function of electric car charging heaps in [16]. Interface perception, robotic arm control, and the cloud architecture are the three main components of the system. As part of the interface perception module, that study presents the essential technologies, such as the parallel multi-model text recognition system and the multi-task network that finish the interface positioning along with text detection. In order to ensure that charging heaps are of high quality, twenty devices in the State Grid of China's quality inspection workshop have confirmed the system's functionality. Additional findings from comparisons with various quality assessment techniques are also included in the publication.

The goal of the work in [17] is to provide secure, efficient, and reliable online management services for a huge number of equipment in the ubiquitous power Internet of Things and to realize the worldwide unified identification and management of big terminal equipment based on that technology using blockchain technology. To address the electricity market's shortcomings, that paper examines the potential applications of blockchain technology, proposes a solution based on blockchain technology, and then applies blockchain analytics to the electricity market for renewable energy. Experimental results demonstrate that the blocking time of the new area grows in direct proportion to the length of the blockchain, with only a small drop in overall performance; thus, that scheme can accommodate the real-world demands of an extensive network of multiple access terminals in the pervasive power Internet of Things. It is clear that electric car charging heaps have been much more efficient since blockchain technology founded on the power of the Internet of Things was successfully implemented.

A bidirectional energy flow may be achieved and the device's current stress can be reduced using an ultra-high voltage AC/DC isolated matrix converter, which is suggested in the article [18] and used to V2G electric car charging heaps. The suggested

topology's ultra-high voltage module may also provide many electric car kinds with significant charging power and a broad voltage range. Through the use of simulation, the suggested topology and control approach are confirmed.

In order to accomplish the aim of lowering the price of the charging station, the charging control issue of energy storage charging heaps is suggested in [19], which takes into consideration the degradation of batteries and charging efficiency while considering the charging demand of EVs. Furthermore, by posing the mean field term, they are able to derive the ideal pricing strategy for power trading between charging stations and EVs under the mean field equilibrium condition, as well as model the interaction between the charging stations, power grid, and EVs as a finite-time dynamic game problem. They also develop decentralized energy planning control strategies that enhance charging piles. The authors provide an iterative technique to address the charge control issue, and numerical simulations confirm both the program's efficacy and the problem's logic.

The primary focus of the development of energy routers and controllers in [20] article is to address the need for organized charging. In order to facilitate real-time monitoring while strategy adjustment for orderly charging of electric vehicles, the energy controller is tasked with creating a local control strategy, ensuring that energy routers operate in an organized manner, and uploading and synchronizing data from both the grid and electric vehicle charging stations to the service platform. A new type of smart meters called an energy router gathers data from several new energy-consuming devices, including electric cars, thermal storage electric heating, microgrids, distributed power sources, energy storage, and distributed power sources. Two methods of consumer interaction—through master station and Bluetooth—are supported, and it may network locally and autonomously in regions.

3. Problem Statement

The world's oil reserves are running low. Electric cars have a long range, therefore when it's time to refuel, the user of an EV first considers how far it is to the nearest charging station. The impact of the endurance quality is to blame for this. Another crucial consideration when choosing a charging facility to aim for is the current traffic situation. The charging procedure for electric vehicle users would be severely affected if traffic is often congested. If an electric vehicle (EV) attempts to use the charging station that is geographically nearest to it, it may encounter an overcrowding problem and have to wait a long time to be serviced. If the charging station it chooses is far away, however, the driver will have to put in a lot of time behind the wheel, and the weather and traffic will make the journey much more difficult. The benefits of conserving energy and reduced emissions from fully electric cars are substantial. The amount of charging stations needed and where they should be located in urban areas are decided by the traffic patterns on individual roads. High electrical loads pose a safety risk and can up the cost of locations when allocated irrationally. The management model for charging pile groups based on the power grid's load curve works well for electric vehicle groups, but it won't work so well for residential charging pile groups because their quick transition from peak to low periods causes the load on the grid to fluctuate a lot, which isn't good for the grid's smooth operation.

4. Proposed Work

4.1 System Model

How far it is to go from your starting point to the charging station is the EV charging distance. The path to a charging station could vary across EVs. It is predicated that a charging station is located along the shortest route, as determined by the Dijkstra algorithm, from the point of departure, in order to measure the distance among EVs and these stations. Here we have a real-world traffic network that uses the shortest path method; let's pretend that the shortest route from the starting point to EV_i to a charging pile CP_j located near a charging station includes parts of z-road that are d_{ij1} , d_{ij2} , ..., and d_{ijz} , respectively. Then, the distance d_{ij} for EV_i using Eq. (1) to determine the distance to travel from its starting point to the charging pile CP_j .

$$d_{ij} = d_{ij1} + d_{ij2} + \dots + d_{ijz} \quad (1)$$

The average speed on each road section may be obtained using the real-time traffic situation. This work uses Eq. (2) to determine the amount of time it takes for an electric vehicle to obtain to a charging station based on the average velocity, which is reflective of real-life conditions.

$$t_{ij} = \frac{d_{ij1}}{v_{ij1}} + \frac{d_{ij2}}{v_{ij2}} + \dots + \frac{d_{ijz}}{v_{ijz}} \quad (2)$$

Where t_{ij} is the total journey time for EV_i to get to the charging pile CP_j ; $d_{ij1}, d_{ij2}, \dots$, and d_{ijz} are the length of the z road divisions, and $v_{ij1}, v_{ij2}, \dots$, and v_{ijz} are the typical speeds at which cars travel along these sections of road. Under the assumptions made in this research, every charging station is equipped with various charging piles, and every EV logically selects the one with the least amount of waiting time. Electric vehicle charging follows the DRL regulation. An electric vehicle may be charged instantly upon arriving at a station that has an idle pile. Therefore, in this instance, waiting is not required. When there are more electric vehicles parked at a charging station than heaps, cars that arrive later must wait in lines that correspond to various piles. The time it takes to charge the electric vehicles in the line before the one being considered, t_{iw} , determines how long it will take for EV_i to wait. The quantity of energy that has to be charged along with the charging power of the pile determine how long it takes for an electric vehicle to go from the moment it arrives at the charging station to the moment it is finished charging. Keep in mind that the quantity of power that needs charging is directly proportional to the disparity between the electric vehicle's remaining power and the capacity of its battery. It is believed that the quantity of power an EV uses is continuously changing during its journey. How much power an electric vehicle has left in its battery when it gets to the charging station is dependent on both its starting power and how much power it used while on the road.

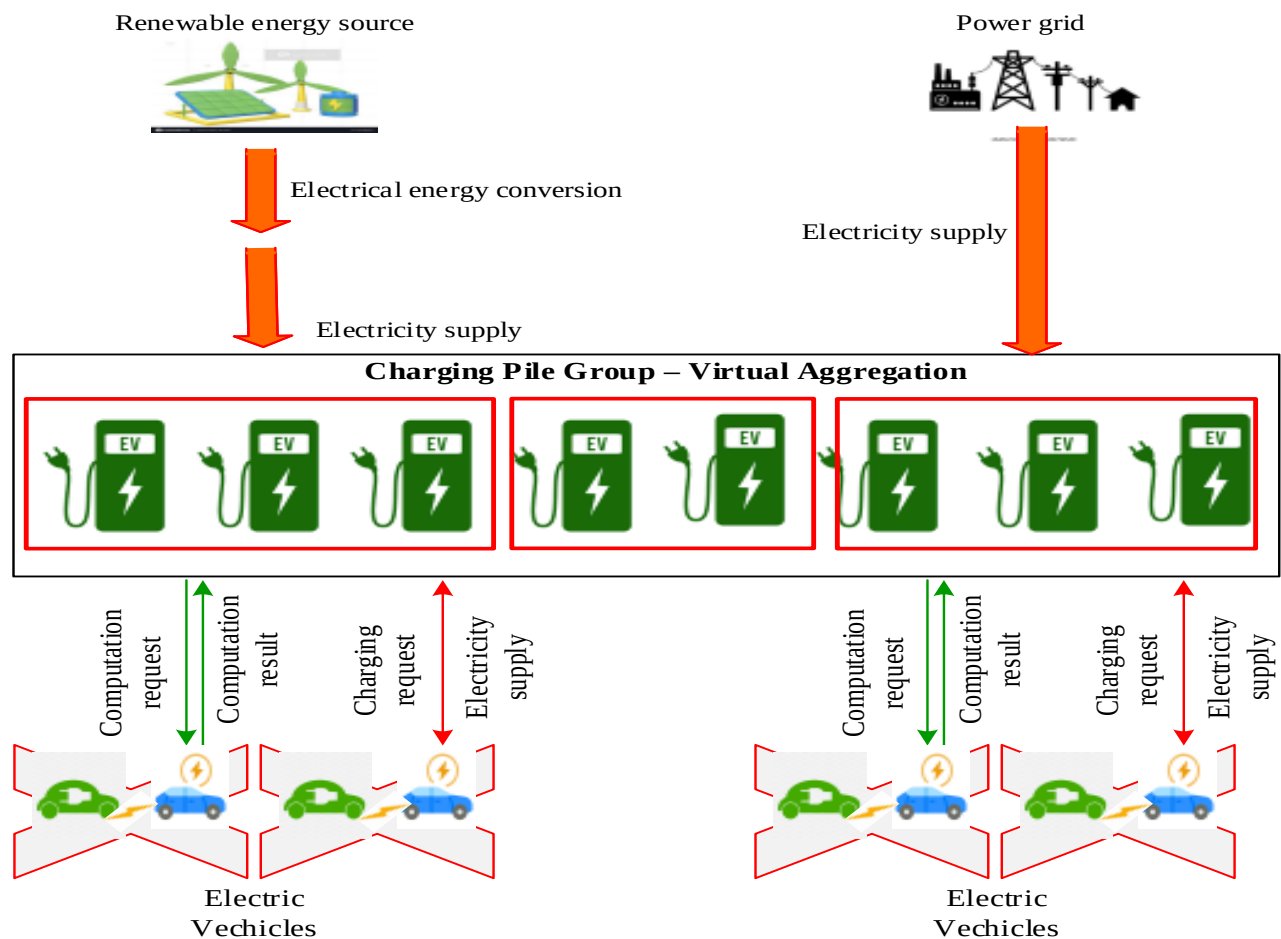


Fig.1. Typical EV Model in Charging Pile Groups

The following are the stages of delay control that are dependent on the power grid's load change rate:

- Step 1: Find out the electrical grid's current load change rate, denoted as MP;
- Step 2: Find out whether v_p is below zero. Step 3 is carried out if all the requirements are satisfied; else, step 6 is carried out;
- Step 3: Consider this rate of change and determine the waiting time T_{im} of a single charging pile;

Step 4: Find out whether there's a charging pile that's linked to the grid during Tim's waiting time. In such case, the following steps are carried out: if not, step 1 is followed;

Step 5: After Tim's waiting period ends, the power grid is linked to the next charging pile. Repeat the first step;

Step 6: The total amount of charging piles linked to the grid will be decreased by one if the vp exceeds a certain limit value. Unless otherwise specified, no action is taken. Repeat the first step.

4.2 DRL-SAC

The charging unit is seen as the intermediary that communicates with both the electric vehicle and the electrical grid in the scheduling challenge of charging and discharging EVs. The EV's state of charge (SOC) and historical power costs are part of the environmental condition. We use the most recent 24 hours' worth of power prices as our input state in this article. Consequently, the term "state" is expanded to mean $s = (SOC_t, P_{t-23}, \dots, P_t)$. This research views the EV user as a price-taker whose charging and discharging actions do not affect energy pricing due to the modest capacity of EVs. The charging or discharging rate is an ongoing parameter that defines the operations performed by the charging gadget at each time step $\in [-e_{dis}^{max}, e_{ch}^{max}]$. Noted that at this point the $e_{dis}^{max}, e_{ch}^{max}$ serve as the upper limit for charging power and maximum discharge power, correspondingly. The EV is discharged when the discharging power is negative. Recalling from before, the likelihood of the transition $\Pr(s_{t+1} | s_t, a_t)$ is affected by the present state of charge, power rates, and pricing. We pretend the transition frequency is random in order to mimic the actual situation. We disregard the power loss when charging and discharging for the sake of conciseness in the notation. Additionally, the EV's battery dynamics are shown as $SOC_{t+1} = SOC_t + a_t$.

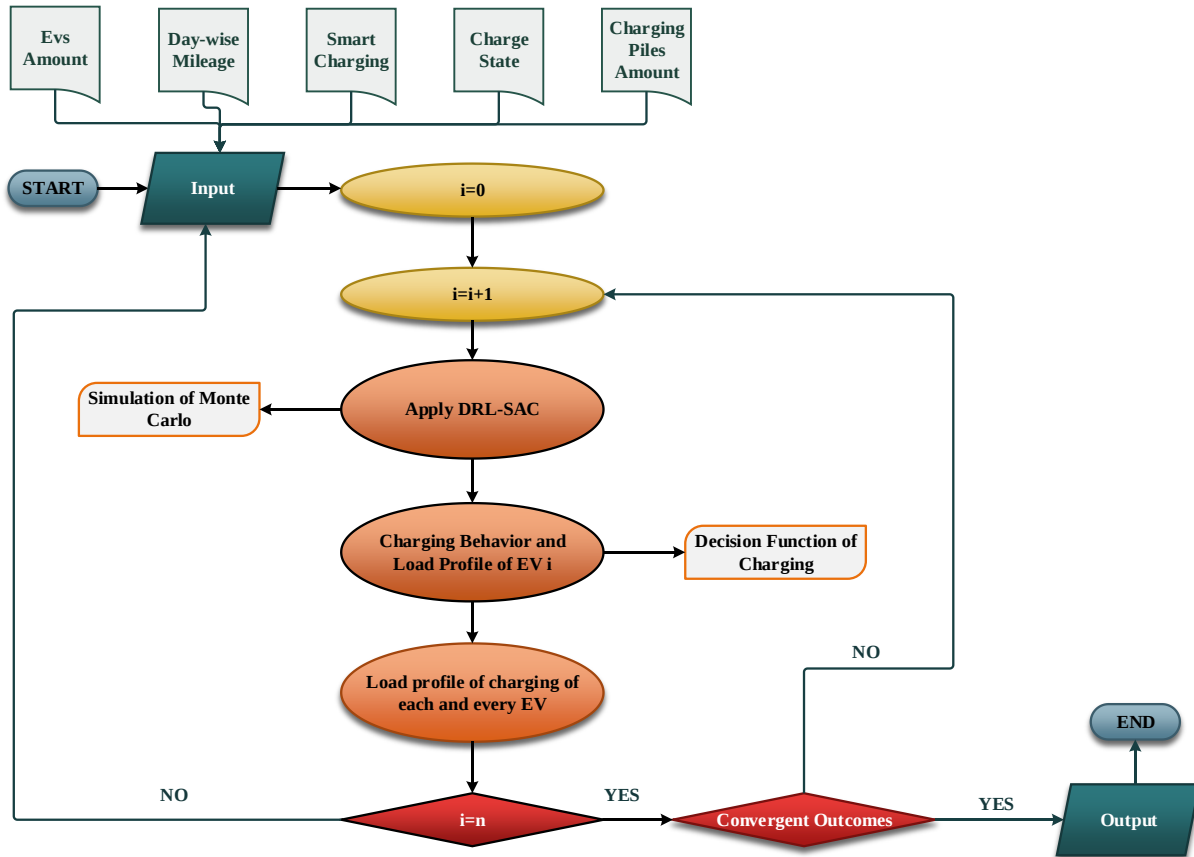


Fig.2. DRL based EV Model with Virtual Aggregation

The charging agent's primary objective is to keep the charging cost as low as possible in relation to the dynamic power pricing. Therefore, the negative of the charging cost might be defined as the reward function R_t :

$$R_t = R(s_t, a_t, s_{t+1}) = -a_t * P_t \quad (3)$$

Staying within the recommended range of the SOC will ensure that the EV is completely charged before leaving and prevent over-discharging. In this case, the cost function is defined as the gap between the actual and desired state of cleanliness (SOC), or the minimal SOC requirement:

$$R_t^c = \begin{cases} |SOC_t - S_{SOC_{target}}|, & \text{if } t = T \\ SOC_{min} - SOC_t, & \text{if } t < T \text{ and } SOC_{min} > SOC_t \end{cases} \quad (4)$$

at departure time T, the first line indicates the extent of the SOC's deviation from its target SOC. Below the minimal threshold value, the second line shows the quantity of energy S_{OC} .

Here, we create a new kind of limited deep reinforcement learning algorithm called augmented Lagrangian soft actor-critic (DRL-SAC) that is based on the augmented Lagrangian technique. The chosen reinforcement learning algorithm has to be efficient with samples and meet certain restrictions in order to resolve the issue under investigation. In order to train DRL algorithms, the agent must often interact with the environment in order to gather enough samples, which might be a burden on sampling efficiency. But it's not practical to continually gather a large quantity of operational data for the EV charging schedule challenge in the real world. It is possible to repurpose past operational experiences with the off-policy DRL method because the learnt control policy (goal policy) with the policy that produces immediate control action (the conduct policy) are distinct. Both the sample efficiency and the applicability of off-policy DRL algorithms to the issue under study are much higher than those of on-policy ones.

Traditional RL approaches have neglected to take safe exploration into account while considering constraints compliance. It is not ethical to provide RL agents unlimited freedom since certain of their exploratory actions might cause bodily harm. Over discharging, in the context of an electric vehicle charging control issue, may cause serious state-of-charge violations, which might harm the battery or make the driver unhappy. This highlights the critical nature of creating an RL algorithm that consistently achieves near-satisfaction of constraints.

The SAC algorithm overcomes the less-than-ideal by including entropy into the value operation, which improves the exploration-exploitation tradeoff. With respect to state s_t , the entropy of a probabilistic strategy is described as $(\pi(\cdot | s_t)) = -\sum_a \pi(a | s_t) \log \pi(a | s_t)$. Afterwards, SAC's state-action value function is shown as:

$$Q^\pi(s_t, a_t) = E_{a_{t+1} \sim \pi_{s_{t+1}} \sim Pr} [R_t + \gamma(Q^\pi(s_{t+1}, a_{t+1}) + \alpha H(\pi(\cdot | s_{t+1})))] \quad (5)$$

We may define the policy function as a distribution of probabilities $\pi(\cdot | s_t)$ in a stochastic manner as:

$$\pi(\cdot | s_{t+1}) = \frac{e^{\frac{Q^\pi(s_t)}{\alpha}}}{\sum_a e^{\frac{Q^\pi(s,a)}{\alpha}}} \quad (6)$$

Unfortunately, the SAC is limited to solving MDPs, despite its outstanding performance on many difficult control problems. Reworking the reward function to include penalties for infeasible control over constraints is a widely used method for solving CMDPs using DRL algorithms. But an unrealistic or too sequential control strategy will result from only multiplying the reward function by the product of the fixed punishment coefficient and constraint violation. Not to mention how inefficient and time-consuming trial-and-error is while trying to determine the punishment coefficient. Here, we provide DRL-SAC, an extension of the SAC algorithm that we believe would better meet the operational restrictions of CMDPs. Here is one way to construct the ideal scheduling issue for electric vehicle charging and discharging:

$$\max_{\pi} J(\pi) = \mathbb{E}_{\tau \sim \rho_{\phi}} [\sum_{t=0}^T \gamma^t R_t] \quad (7)$$

s.t.

$$\begin{aligned} \underline{a} &\leq a \leq \bar{a} \\ \mathbb{E}_{(s_t, a_t) \sim \rho_\pi} [-\log(\pi_i(a_t | s_t))] &\geq \mathcal{H} \\ \mathcal{J}^c(\pi) = \mathbb{E}_{\tau \sim \rho_\phi} [\sum_{t=0}^T \gamma^t R_t^c] &\leq \bar{\mathcal{J}}_c \end{aligned} \quad (8)$$

Which maximizes the negative of charged cost is the goal function. The action limit is indicated by the first line of constraints, where $\underline{a}$ and $\bar{a}$ signify the lower and upper bounds, respectively. The second set of limitations represents the minimum allowable entropy, while the third sets the maximum allowable SOC deviation. It has been observed that the definition of the action space already includes the action bound. Our approach involves using the augmented Lagrangian technique to transform the initial limited optimization problem into an unconstrained problem formulation.

$$\max_{\pi} \min_{\alpha, \lambda} \mathcal{J}(\pi) + \alpha \left(-\mathcal{H} - \log(\pi_i(a_t | s_t)) \right) + \lambda (\bar{\mathcal{J}}_c - \mathcal{J}^c(\pi)) + \frac{\delta_\lambda}{2} (\bar{\mathcal{J}}_c - \mathcal{J}^c(\pi))^2 \quad (9)$$

Where α, λ entropy constraint as well as price constraint are multiplied by, correspondingly. In this case, the augmented Lagrangian equation uses the δ_λ , which stands for the updated step size of λ , as the penalty coefficient. on each optimization issue, the entropy threshold and upper limit on SOC deviations are found. The SOC deviance is immediately punished in the reward function of classic RL-based techniques. To put it otherwise, they see the variables α as well as λ as penalty coefficients. But it's not easy to guarantee the correct values for the penalty coefficients; they can be overly cautious or just not practicable. In order to get out of this jam, we solve the optimization issue using the augmented Lagrangian approach, which ensures that the primal as well as dual variables both get to their best possible values, and therefore that the constraints are satisfied.

In order to quantify the policies, the state-action value functions $Q^\pi(s, a)$ is defined as Eq.(9). In the Lagrangian function, the $Q^\pi(s, a)$ represents the expected discounted reward and the corresponding entropy multiplier product after taking action a under state s with policy π . Noted that we store the tuple $\{s_t, a_t, R_t, R_t^c, s_{t+1}\}$ in the experience replay buffer $\mathcal{D}$ in each timestep and use these data for training.

We estimate the action-value function using two sets of neural networks $Q^\phi(s_t, a_t)$ inside timestep t . By using the Bellman equation and anticipating every potential future state and action with π , we may roughly determine the present state-activity value. That is:

$$\begin{aligned} Q^\phi(s_t, a_t) &\approx \mathbb{E}_{s, a, r, s_{t+1}} [y_t] \\ y_t &= R_t + \gamma * Q^{\hat{\phi}}(s_{t+1}, a_{t+1}) \end{aligned} \quad (10)$$

where the $\hat{\phi}$ may a soft update be applied to the target network?: $\hat{\phi} = \eta\phi + (1 - \eta)\hat{\phi}$. The update rate is represented by the symbol. Therefore, the goal of training ϕ is to reduce the MSE as much as possible.

$$\mathcal{L}(\phi) = \mathbb{E}_{s, a, r, s_{t+1}} \left[(Q^\phi(s_t, a_t) - y_t)^2 \right] \quad (11)$$

In a similar vein, the cost's action-state value function is constructed. For the purpose of approximating the cost value function, we use both sets of networks $Q_c^\phi(s_t, a_t)$. In a similar vein, one may roughly estimate the present cost worth as:

$$\begin{aligned} Q_c^\phi(s_t, a_t) &\approx \mathbb{E}_{s, a, r, s_{t+1}} [y_t^c] \\ y_t^c &= R_t^c + \gamma * Q_c^{\hat{\phi}}(s_{t+1}, a_{t+1}) \end{aligned} \quad (12)$$

Where $\hat{\phi}$ We minimize loss to update the parameters of ϕ in the desired network for the cost value function.

$$\mathcal{L}_c(\phi) = \mathbb{E}_{s, a, r, s_{t+1}} \left[(Q_c^\phi(s_t, a_t) - y_t^c)^2 \right] \quad (13)$$

Similar to how reward function networks use soft updates, cost value unit networks do the same.

5.3 Ant Colony Optimization for Optimum Charging Station Selection

In the ACO metaheuristic, a group of ant colonies repeatedly produces answers to the issue at hand by following pheromone trails that are linked to heuristic information and correctly specified solution components. Algorithm 1 presents the ACO metaheuristic's framework. In order to improve the algorithm's performance, ants adjust the pheromone trails while the algorithm runs. In this research, we tackle the scheduling issue of the charging station using Ant Colony System (ACS), which is very effective in decreasing overall tardiness for various scheduling problems.

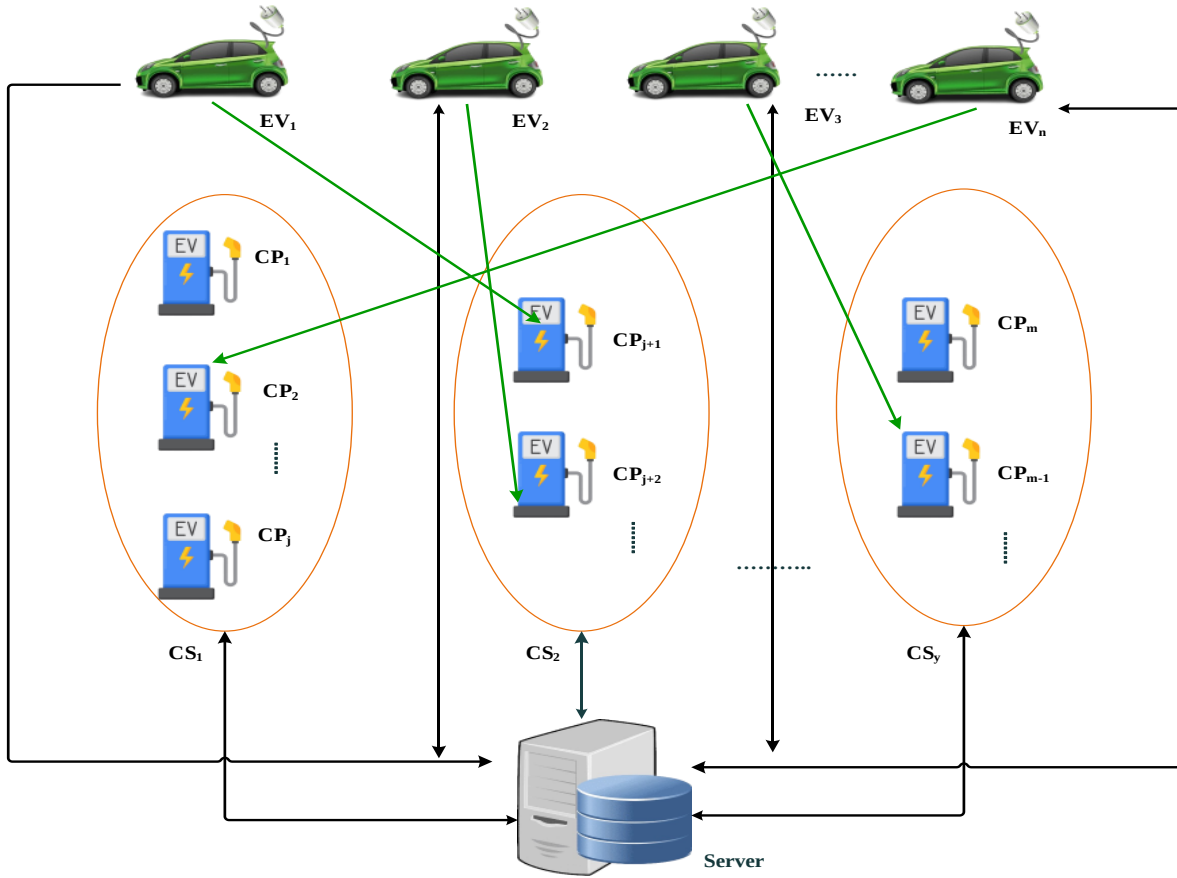


Fig.3. EV Model with Charging Pile Groups Optimum Selection

A. Constructing Solutions

When using ACS, every ant begins with a blank slate of assigned EVs and adds unscheduled EVs one at a time until every EV is scheduled. In its most basic form, a built solution is just a series of EVs, or a different combination of EV indices. Keep in mind that, similar to the scheduler technique suggested in, a charging plan is constructed depending on the permutation order of the EVs. To be more precise, to schedule all of the EVs in the permutation in a sequential fashion, giving each EV the earliest feasible start time, but still satisfying all restrictions in relation to the EVs that came before. Using the following choice rule, Ant k chooses the unscheduled EV j to be added to the permutation at position i :

$$j = \begin{cases} \arg \max_{l \in S^k} [\tau_{il}]^\alpha [\eta_{il}]^\beta, & \text{if } q \leq q_0 \\ \mathcal{J}, & \text{otherwise} \end{cases} \quad (14)$$

where τ_{il} is the pheromone trail linked to the assignment of EV l at position i and η_{il} is the intuition behind assigning EV l in position i , S^k where q is a uniformly distributed random variable, α regulates the effect of the pheromone trails, β controls the influence of

the heuristic information, and is the partial set of planned EVs. $Q \in [0,1]$, $q_0 (q_0 \in [0,1])$ is a parameter that regulates the decision rule's exploration, as well as j is a random variable that represents an EV index and is chosen using the following distribution:

$$p_{ij}^k = \frac{[\tau_{ij}]^\alpha [\eta_{ij}]^\beta}{\sum_{l \notin S^k} [\tau_{il}]^\alpha [\eta_{il}]^\beta}, \text{ if } j \notin S^k \quad (15)$$

To rephrase, an ant's optimal decision-making is suggested by pheromone trails and heuristic information (exploitation) with probability q_0 , but an ant's decision-making is influenced by these same factors with probability $(1-q_0)$.

The rule that calculates the heuristic information η_{il} for allocating EV j to slot i in the schedule is the one that is most recent. The electric vehicles are sorted according to their specified departure times (d_j) in this dispatching rule.

Algorithm 1 ACO Metaheuristic Outline

```

Set parameters
Initialize pheromone trails
Initialize heuristic information
while (termination condition not satisfied) do
    ConstructSolutions
    PheromoneUpdate
end while
OUTPUT: the best-so-far solution
    
```

Hence, in our case $\eta_{ij} = 1/d_j$. That is to say, the heuristic data will provide an advantage to the EVs that have an earlier departure time need. Section V's investigations go more into the effects to apply this heuristic data.

B. Updating Pheromones

A global update and a local update are the two levels of pheromone updates used in ACS. Only the best-so-far ant $\wedge 1$ is permitted to contribute pheromone to its solution components in the global pheromone trail update that occurs after each algorithmic iteration. Specifically, the following is an update to the pheromone trails linked to the solution elements represented through the best-so-far ant:

$$\tau_{ij} \leftarrow (1 - \rho)\tau_{ij} + \rho\Delta\tau_{ij}^{bs} \quad (16)$$

where $\rho (\rho \in (0,1])$ is the pheromone evaporation proportion and $\Delta\tau_{ij}^{bs} = 1/C^{bs}$, where C^{bs} is the sum of all the solutions' tardiness values. Importantly, ACS ends when the cumulative delay of the best-so-far solutions equals zero, the minimal value determined by Eq. (4). Hence, it is always forbidden to divide by zero.

Quickly after the addition of a new solution component (such as an EV j at position i), ACS implements a step-by-step pheromone updating rule in the current pheromone trail update. For example, here is an update to the pheromone trails linked to those solution components:

$$\tau_{ij} \leftarrow (1 - \xi)\tau_{ij} + \xi\tau_0 \quad (17)$$

where $\xi (\xi \in (0,1])$ serves as a control parameter for the impact of the local pheromone update, with τ_0 being the starting pheromone value. Keep in mind that the optimal value for τ_0 was determined to be $1/rC^{edd}$, where r is the total number of EVs and C^{edd} amounts to the overall tardiness value of the answer generated through the earliest due date rule. At the beginning of the execution, everything pheromone trails are evenly initialized. The local upgrading rule discourages ants from favoring the assignment of EV j

to position i , making them more likely to favor alternative EV assignments to that location. This manner, the search may be explored more thoroughly. Both the local and global pheromone update types are explored in further depth in the experiments.

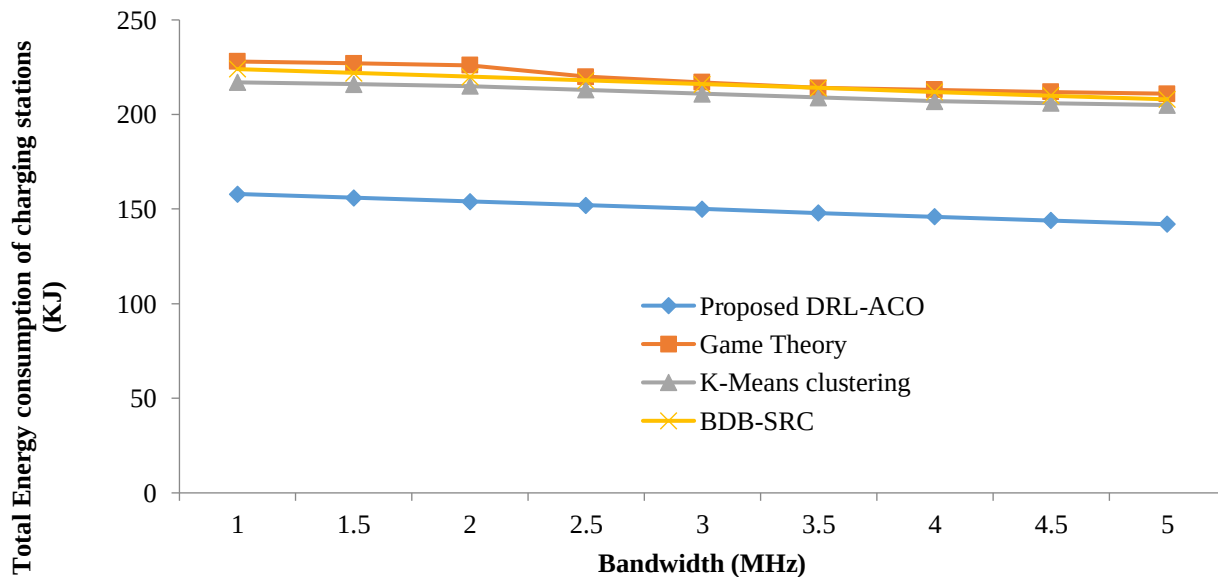
5. Results & Discussion

5.1 Experiment Description

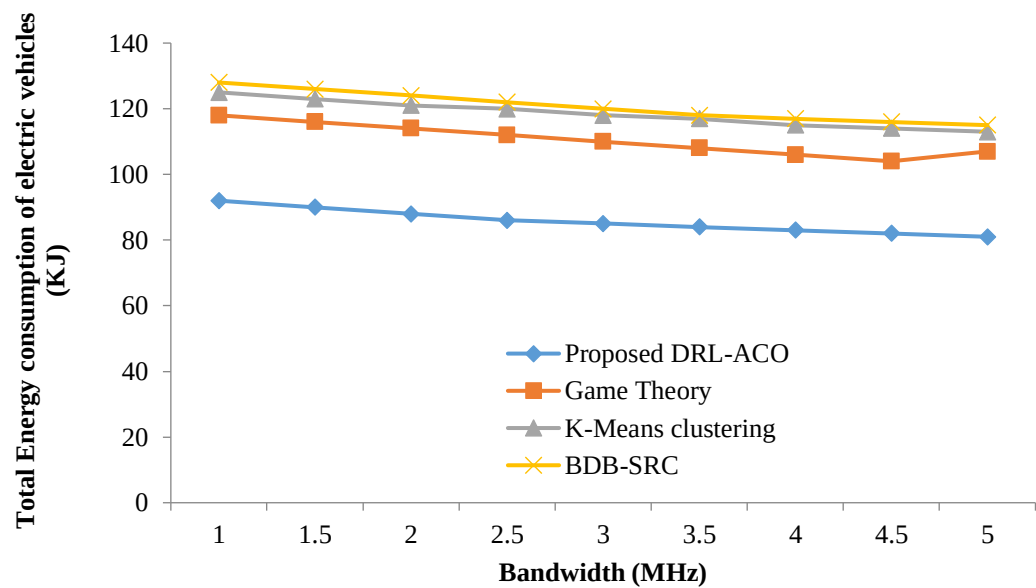
1) Simulation model: To cut down on the amount of training rounds, this experiment sets up 12 charging piles with a combined rated power of 37.5 KW and a battery capacity of 60 Kwh, simulating a community home charging station. The charging piles are then left to run nonstop for 24 hours. Each training round begins with an initialization of the charging stakes' battery power, which is then adjusted at the beginning of each charging time step to account for the uncertainties in the noise simulations real charging scenario. The charging duties is continued until the end of the day's 288 time steps, and the charging stakes' battery power gets started when one of them finishes the task.

2) Data Generation: In this section, we create a random set of GPS coordinates for EVs in the Beijing region. For the purpose of e-vehicle positioning simulation, we next need to transfer the GPS coordinates into the appropriate road segments. In a metropolis, where EVs are often located throughout the road network, the randomly produced GPS data might be anywhere. Using a global map matching algorithm, this stage connects the GPS coordinates of each electric vehicle to the closest relevant segments in road networks. To make sure that the EVs don't end up in the wrong place on the map, we choose a POI (Point of Interest) within a specific range of the EVs to use as their destination. Restaurants, hospitals, Schools, banks, supermarkets, and other POI entities stand for places that are intrinsically linked to people's daily lives, which is why we've decided to use them as our destination. While we're at it, we'll make sure that every electric vehicle can get to a charging station.

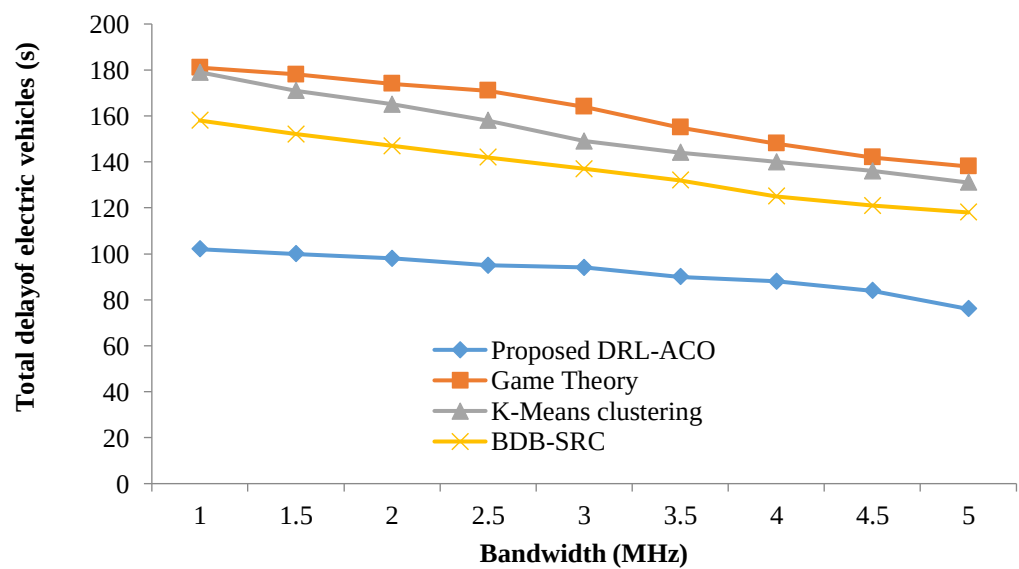
3) Travel Distance Assessment: The shortest navigational distance between electric vehicles and recharge stations in the Open Street Map (OSM) road network is used to determine the EVs' trip distance. By applying the Dijkstra algorithm to the Open Street Map (OSM) road network, we determine the shortest navigational distance. The distance between electric vehicles and each charging pile at the same station is assumed to remain constant here. Hence, we just consider the journey distance as the distance among EVs and the charging station.



(a) CS Energy consumption



(b) EV Energy consumption



(c) System delay

Fig.4(a). Charging Station Energy Consumption, (b). EV Energy Consumption, and (c). System Delay

Fig.4 shows the analysis of Charging Station Energy Consumption, EV Energy Consumption, and System Delay with respect to the existing approaches. When it comes to charging electric cars, this management strategy is quite flexible. A more equitable distribution of charging time may be achieved by using the reference load, which is based on the electric car group's charging demand. To enhance

the average usage rate, the charging pile group can react better alongside the addition of load increment. This adaptation should be tuned according to traffic flows and real demand utilizing the Ant Colony Optimization technique. Without precise knowledge about the departure time, remaining energy, EV's arrival time, as well as real-time power pricing, a model-free safe DRL algorithm is suggested to optimize the real-time charging and discharging schedules. We define the optimum EV charging scheduling issue while considering the uncertainties in the actual world in order to fulfill the EV charging requirement limitations. We have included the augmented Lagrangian technique into the soft actor-critic, which allows DRL approaches to handle limited optimization problems effectively and improve training robustness. This new approach allows us to build the restricted reinforcement learning method. When compared to the benchmark approaches, the DRL-SAC achieves better results in terms of solution optimality and compliance with constraints, according to the numerical findings.

6. Conclusion

Many national governments have passed legislation and instituted policies in response to the alarming rate of carbon emissions growth. Many countries, China included, have set the target of "carbon neutrality" as their long-term objective. A large chunk of the world's greenhouse gas emissions come from the automobile industry, thus they need to start working on alternative fuel cars right once. Concerns over electric vehicle range and long charging periods are only two of the many practical challenges that have arisen as a result of the extensive promotion of EVs. So, academics have been focusing a lot of energy on the synchronized charging problem for EVs. This research suggests the SAC method—based on real-time traffic information as well as the shortest route management algorithm—to optimize charging time and distribute the loads across the charging stations. Automated vehicle charging schedules are generated by the model. Our method beats the standard selection approach, according to the results of the experiments, by making charging stations more efficient and greatly improving EV charging times. For more efficient scheduling of electric car charging on a broad scale, the PEVCS method is also recommended. Depending on the results of the experimental investigation, the program could improve the charging efficiency of the system for a larger number of EVs that are planned to charge.

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