

On Enhancing Electric Vehicle Ecosystem in Urban Scenario

Tanish Nagrani¹, Shivam Pandey¹, Naveen Kumar¹, Manish Chaturvedi²

1- Indian Institute of Information Technology Vadodara, Gujarat, India

2-Institute of Infrastructure, Technology, Research And Management, Gujarat, India

Abstract—This paper addresses the critical issue of air pollution caused by fossil fuel-powered vehicles by proposing a comprehensive solution centered on Electric Vehicles (EVs) and advanced charging infrastructure. While EVs present a viable alternative, challenges such as inefficient charging infrastructure and scheduling algorithms hinder their widespread adoption. To tackle these issues, our study introduces a series of models aimed at optimizing EV scheduling at charging stations, reducing overall charging time, minimizing queuing, and boosting revenue for charging facilities. The first model takes a straightforward approach, directing EVs to the nearest charging station based solely on commute time. Building on this, the second model incorporates waiting time, reducing overall delays and improving charging efficiency. In the final model, historical data on waiting times is used to calculate average delays, enabling a more informed and proactive scheduling strategy. Through extensive simulations and data analysis, we assess the effectiveness of these algorithms. Our findings show substantial improvements in charging efficiency, shorter wait times, and better resource utilization at charging stations. By offering practical solutions to EV charging challenges, this research contributes to the development of sustainable transportation infrastructure, reduces the transportation sector's reliance on non-renewable resources, and supports global efforts to combat air pollution.

Index Terms—Electric Vehicle, Charging Station, Waiting Time, Historic Time, Infrastructure, Simulation

I. INTRODUCTION

With approximately 25% of global greenhouse gas emissions originating from the transportation sector, the adoption of low-carbon solutions is highly desirable [1], [2]. One notable effort, EV30@30, strives to achieve a 30% adoption of electric vehicles (EVs) in the vehicle market by 2030, with participation from countries like the USA and India [3], [4]. To support EV adoption, countries like India have greenlit Phase II of the Faster Adoption and Manufacturing of Hybrid and Electric Vehicles Scheme (FAME).

Despite these efforts, the adoption of EVs in developing countries like India and Bangladesh has been hampered by challenges such as high initial costs, limited charging infrastructure, and underdeveloped road networks. To address these issues, the Ministry of Power in India has implemented proactive measures to promote the establishment of EV charging infrastructure, offering incentives for both charging station operators and EV owners.

However, the high setup costs of charging stations remain a significant hurdle, compounded by the need to streamline the charging process to reduce waiting times and minimize

strain on the electric grid. Several studies have investigated the impact of EVs on the electrical system. For instance, Muratori [5] examines the effects of EV charging on residential distribution grids and underscores the importance of smart charging strategies to prevent grid overloads [6]. Similarly, Zhang et al. [7] explore the potential of demand response programs in optimizing EV charging and mitigating its impact on the grid [8].

Further research by Amini et al. [9] highlights the benefits of integrating EVs with renewable energy sources, showing how coordinated charging can reduce peak demand and enhance grid stability [5]. Optimized charging strategies were found to significantly lower operational costs and environmental impact. Similarly, Wang et al. [10] explored the feasibility of using second-life EV batteries for grid storage, demonstrating how this can extend battery life and provide ancillary services to the grid [7]. Amini et al. [9] also analyzed user charging behavior, revealing that preferences for charging location and time significantly impact the effectiveness of charging stations. Understanding these patterns helps policymakers and businesses better plan and deploy stations. These studies underscore the need for intelligent charging infrastructures that can adapt to varying demand and supply conditions.

This paper studies a series of models aimed at optimizing overall charging times (including both charging and waiting times at charging stations) for EVs, enhancing the efficient utilization of charging infrastructure, and alleviating the burden on the electric grid. The main contributions of this paper are summarized as follows:

- We propose a series of EV scheduling algorithms for existing charging infrastructure, optimizing overall vehicle charging time, charging station utilization, and the final state of charge of the vehicle.
- The algorithms are simulated, compared and analyzed.

The paper is structured as follows: Section II outlines the system architecture and the assumptions made in this work; Section III elaborates on the proposed charge scheduling models; Section IV details the results of the numerical simulations used to evaluate the proposal; and Section V presents the conclusions drawn from this study and directions for future research.

II. SYSTEM ARCHITECTURE AND ASSUMPTIONS

This section aims to introduce the proposed system model and the assumptions underlying this work.

A. Proposed system architecture

To address the goals of maximizing EV owners' State of Charge (SoC) while minimizing charging time and cost, enhancing charging stations' service rate and revenue, and optimizing load management on the electricity grid, this paper proposes a centralized server-based architecture. Fig 1 presents the system architecture, which consists of charging stations, a centralized server, EVs, and the electric grid, along with the communication infrastructure that enables real-time interaction among these components to achieve efficient scheduling and grid stability.

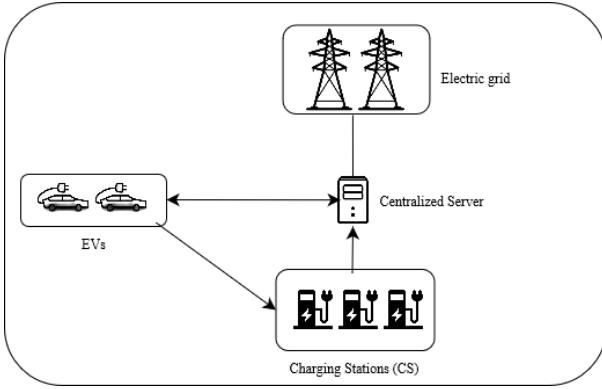


Fig. 1. System Model

- **Charging Station (CS):** The charging station (CS) is responsible for providing best-effort charge delivery to the requesting EVs. We assume that each CS is equipped with the necessary communication modules to monitor and report its current waiting time to the centralized server at regular intervals.
- **Electric Vehicle (EV):** The EV continuously monitors its battery level, remaining range, and current location. Whenever charging is needed, it sends this status information to the central server and waits for recommendations on the optimal charging strategy.
- **Centralized Server:** It functions as a central entity that collects updated waiting time data from the connected charging stations (CSs) and stores it in a local database. Upon receiving a request from an EV, it processes the request using the EV's data, advanced algorithms, and the locally stored information to generate a recommended list of CSs. This recommendation list is then sent to the EV, helping the driver make the optimal decision.
- **Electricity grid:** It manages the electricity supply to the connected charging stations.
- **Communication Infrastructure:** The communication infrastructure enables real-time data exchange among EVs, CSs, the centralized server, and the electricity grid. This is achieved using an MQTT-based publish-subscribe messaging protocol, which ensures efficient, low-latency communication. The infrastructure supports the timely delivery of updates such as EV charging requests, CS waiting times, and grid load information. Each entity

acts as either a publisher, subscriber, or both, allowing for scalable and efficient coordination among all system components.

B. Problem statement and assumptions

This work addresses the scheduling problem for EVs using existing charging stations, aiming to ensure that EVs can recharge as quickly as possible and return to their original positions with a high state of charge. The scheduling algorithm optimizes the total charging time, which includes the time taken for the EV to reach the charging station, waiting time, actual charging time, and return time to the original position. Simultaneously, the goal is to distribute EVs evenly across available charging stations to prevent overcrowding at any specific station.

We assume that the requesting EV is stationary while searching for a suitable charging station and has sufficient charge to reach at least one charging station. The EV travels to the charging point at a constant average speed throughout the journey. After charging, the EV returns to its initial position. Additionally, the EV has a constant rate of battery consumption and a constant charging rate. The return path is the same as the initial route to the charging station. Traffic congestion scenarios are not considered in this work.

A local scenario where an EV needs charging is illustrated in Fig 2. In the figure, the circular periphery around the EV represents an imaginary area that the EV can reach with its current SoC. It is assumed that the detailed road network is known to the central server. The reachable paths are routes that the EV can take to reach the charging stations within its periphery. Upon receiving a request from the EV, the central server identifies the reachable charging stations, computes their servicing times, and suggests an optimal list of charging stations to the EV, aiming to minimize travel distance, waiting time, and overall charging cost.

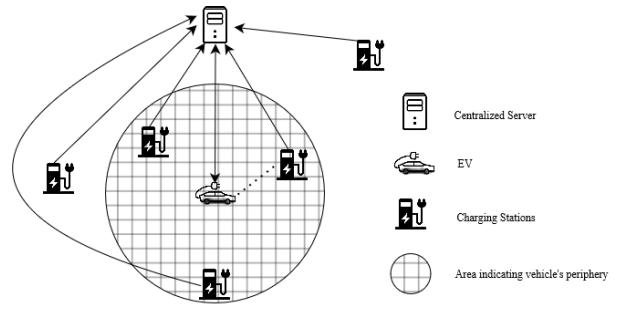


Fig. 2. Example scenario - interaction among system elements to serve an EV in need of charging

In the following sections, we present detailed proposal for various charge scheduling approaches.

III. PROPOSED CHARGE SCHEDULING APPROACHES

This work proposes several charge-scheduling algorithms aimed at improving the total charging time for electric vehicles

while maximizing the service rate of charging stations and managing the load on the electricity grid. The algorithms are developed sequentially into three versions: the Nearest Charging Station (*NCS*) approach, the Charging Station with Least Waiting Time (*LWT*) approach, and the Charging Station with Least Historic Waiting Time (*LHWT*) approach.

In the *NCS* approach, the process is straightforward, with the EV focusing on minimizing total commute time and achieving maximum State of Charge (SoC) upon return to its original location.

The *LWT* approach introduces more realistic parameters, such as waiting times at charging stations, while the *LHWT* approach incorporates average historical waiting times to optimally predict waiting times. The goal is to achieve optimal EV distribution and improve charging efficiency. Table I summarizes the symbols and notations used in subsequent sections. Each version is described in detail in the following sections.

Symbol	Description
r	Rate of consumption of charge
R	Rate of charging
i	i^{th} electric vehicle
j	j^{th} charging station
$t(i, j)$	Time taken by the i^{th} EV to reach the j^{th} charging station
SoC_m	The maximum state of charge of an EV
SoC_s	The initial state of charge of an EV
$\text{SoC}_e(i, j)$	The state of charge of the i^{th} EV battery when it reaches the j^{th} charging station
$\text{SoC}_f(i, j)$	The final state of charge of the i^{th} EV battery after it reaches back to its original position from the j^{th} charging station
$c(i, j)$	Charging time for the i^{th} EV at the j^{th} charging station
w_j	Waiting time at the j^{th} charging station
n	Number of charging stations in the EV's periphery

TABLE I
LIST OF ABBREVIATIONS AND SYMBOLS

A. Nearest Charging Station (*NCS*) Approach

This version of the EV charge scheduling algorithm prioritizes the nearest charging station to minimize commute time for EVs needing a recharge and to avoid battery depletion. The EV sends a charging request to the central server, which computes the road distances from the EV to the charging stations and returns a list of the nearest charging stations. In this approach, the EV is directed to the closest available charging station, ensuring that it can achieve maximum State of Charge (SoC) upon returning to its original location.

The algorithm defines the total charging time $T(i, j, \text{SoC}_s)$ of i^{th} EV at j^{th} charging station with current charge status SoC_s as follows:

$$T(i, j, \text{SoC}_s) = 2 \times t(i, j) + \frac{\text{SoC}_m - (\text{SoC}_s - (t(i, j) \times r))}{R}$$

Here, j represents the nearest charging station to the EV. $t(i, j)$ denotes the time taken by the EV to reach the j^{th} charging station. We assume that the return time is the same as the time to reach the charging station, given that the same

path is taken both ways. Thus, the travel time to the charging station is minimized. The total charging time is the sum of the round-trip travel time ($2 \times t(i, j)$) and the actual charging time at the charging station. This accounts for the decrease in State of Charge (SoC) during travel. Since we consider the least travel time to the charging station, this version defines the optimal charging time T_{\min} as follows:

$$T_{\min}(i, \text{SoC}_s) = T(i, j, \text{SoC}_s)$$

The final *SoC* after reaching the original location will be

$$\text{SoC}_f(i, j) = \text{SoC}_m - ((t(i, j) \times r))$$

This approach aims to maximize the final State of Charge (SoC_f) upon the vehicle's return to its original location by selecting the station with the lowest commute time. This algorithm is simple and straightforward to implement. However, a drawback is that it does not account for waiting times at the nearest station. Typically, EVs are unevenly distributed across a geographical area, leading to an uneven allocation of EVs to charging stations. As a result, some stations become highly utilized while others remain underused, increasing total charging time due to longer waiting periods. To address this issue, we propose a new algorithm in the next approach, which considers waiting times for a more realistic charging scenario. This leads to a better distribution of EVs across charging stations and improves the total charging time.

B. Least Weighting Time (*LWT*) Approach

The algorithm in this version takes waiting times at charging stations into account. The central server receives the current location of the EV, computes the distance between the EV and every charging station within its periphery, retrieves the corresponding waiting time from locally stored data for each station, and then communicates a list of optimal charging stations to the EV. The total charging time $T(i, j, \text{SoC}_s)$ for an i^{th} EV at a charging station j with current State of Charge (SoC_s) is now computed as follows:

$$T(i, j, \text{SoC}_s) = 2 \times t(i, j) + w_j + \frac{\text{SoC}_m - (\text{SoC}_s - (t(i, j) \times r))}{R}$$

where w_j represents the waiting time at charging station j . The optimal total charging time $T_{\min}(i, \text{SoC}_s)$ for i^{th} EV with current state of charge SoC_s is now determined iteratively from the total charging times of all the reachable charging stations (in the periphery), as follows:

$$T_{\min}(i, \text{SoC}_s) = \min_{1 \leq j \leq n} (T(i, j, \text{SoC}_s))$$

where, n is the number of charging stations in the EV's periphery.

The *NCS* approach does not account for the unequal distribution of EVs among charging stations, which can lead to increased total charging time. While it ensures the maximum final State of Charge (SoC) by selecting the closest charging station, it does not address the issue of uneven EV distribution.

In contrast, the *LWT* approach improves total charging time by distributing EVs more evenly, using a minimum waiting time strategy. However, this approach does not guarantee the maximum final SoC. In the worst case, the maximum loss of SoC while returning to the original location will be nearly equivalent to the charge consumed traveling to the charging station.

In reality, EV charging requests vary based on factors such as time of day (lower during off-peak hours and higher during peak hours), working days versus weekends, the rise in new EVs in a location, and the expansion of charging infrastructure. Waiting times at charging stations are therefore highly dynamic.

Although the *LWT* approach offers better distribution of EVs across charging stations, it is likely that waiting times will suddenly increase when an EV arrives at its assigned station. This sudden increase in waiting time can lead to longer total charging times. To address this more realistic and dynamic scenario, we propose a new version that considers both waiting times and historical EV charging data.

C. Least Historic Weighting Time (*LHWT*) approach

This version introduces the concept of historical waiting times. The waiting time is calculated using historical data, which provides the average waiting time for a specific station at a particular time. This approach accounts for real-time changes or patterns in waiting times at various charging stations. To address the current waiting time at a charging station, the algorithm incorporates a weighted average of both historical waiting time and the current actual waiting time.

By integrating historical waiting time data, the algorithm can more intelligently route EVs to less congested stations and predict optimal charging times based on past patterns. This reduces the likelihood of sudden long wait times, provides better estimates of waiting times, and leads to more efficient charging times for EVs. The total charging time is now computed as follows.

$$T(i, j, SoC_s) = 2 \times t(i, j) + w_j + \frac{SoC_m - (SoC_s - (t(i, j) \times r))}{R}$$

where w_j is computed as :

$$w_j = \beta \times w_c + (1 - \beta) \times w_h$$

Here, w_c is the updated waiting time stored on the central server at the time of total charging time computation, and w_h is the weighted average of historical waiting times for similar time durations. β is the parameter used to assign weights to w_c and w_h . In this work, β is set to 0.7, giving slightly more weight to the current waiting time compared to historical waiting times.

Now, the optimal charging time for EV i with a current state of charge SoC_s among n charging stations is computed as follows:

$$T_{\min}(i, SoC_s) = \min_{1 \leq j \leq n} T(i, j, SoC_s)$$

This version integrates historical weighted waiting time data to predict future waiting times. By placing greater emphasis on current waiting times while also factoring in historical waiting times, the *LHWT* approach aims to offer a balanced method for forecasting optimal waiting times at charging stations. Optimizing waiting times contributes to achieving optimal total charging time. In the worst case, the final State of Charge (SoC) remains the same as in the *LWT* approach, meaning the loss of charge while returning from the chosen charging station is nearly equivalent to the charge consumed traveling to the station.

A high-level comparison of the three approaches based on charging station selection criteria, vehicle distribution, and charging station evaluation criteria is provided in Table II. The following sections will discuss the simulation details of these approaches and analyze their performance.

Parameter	NCS	LWT	LHWT
CS selection criteria	Nearest CS	CS with least current waiting time	CS with least historic waiting time
Vehicle distribution to CSs	Unevenly distributed	Evenly distributed	Evenly distributed
CS evaluation criteria	Commute time + Charging time	Commute time + Charging time + waiting time	Commute time + Charging time + weighted average waiting time

TABLE II
COMPARISON OF NCS, LWT AND LHWT

IV. SIMULATION

This section provides simulation details including setup, parameters utilized, processes, results, and performance analysis of NCS, LWP, LHWT approaches discussed above.

A. Simulation Setup and Assumptions

The simulation uses the following input parameters:

- The simulation is carried out over 10 days.
- The symmetric 30kmX30km grid is considered as a road network.
- There are 20 charging stations distributed across the grid.
- Each charging station has 3 charging points.
- The charging stations are strategically positioned at 3 kms intervals, originating from the center of the grid at coordinates (0,0).
- The EV dispatch coordinates from where the EVs leave for charging are specified as follows:

$$\{\{9, 9\}, \{9, 12\}, \{12, 9\}, \{12, 12\}\}.$$

- We have categorized the EV dispatch rate based on general traffic hours as seen in Table III. This categorization allows for optimized dispatching of EVs based on varying traffic conditions throughout the day.
- Average speed of each EV is 40 kilometers/hour.

Traffic hours	Time period	EV dispatch rate(hourly)
Peak hours	8 am - 11 am, 6 pm - 9 pm	20 - 40
Moderate hours	6 am - 8 am, 11 am - 1 pm, 4 pm - 6 pm	15 - 30
Off-peak hours	1 pm - 4 pm, 9 pm - 12 am	10 - 20
Night hours	12 am - 6 am	5 - 10

TABLE III
DISPATCH RATE OF EVS AT DIFFERENT TIMES OF DAY

To create a realistic and manageable simulation model, several key assumptions have been established. These assumptions are designed to streamline the simulation process, ensuring consistency and clarity while reflecting plausible real-world conditions. A few of the assumptions are already mentioned in section II-B, the rest are as follows:

- Constant rate of charging (R) is assumed to be 100 kW.
- To maintain uniformity, the rate of battery consumption ' r ' is expressed in milliwatts (mW) by equating it to $R/1000$.

The simulations were performed on a personal computer equipped with an Intel Core i7 processor and Intel Iris Xe Graphics. The system has 4 cores, 8 threads, and 16 GB of DDR4 RAM. Java was selected as the primary programming language for implementation, and MS Visual Studio 2022 served as the integrated development environment.

For dispatching EVs at different times of the day, we created a `requestTimes` text file containing the times when EVs should leave for charging. The number of EVs departing at different times follows the pattern shown in Table III. The simulation runs for 10 days, with 295 EVs dispatched for charging each day, totaling 2,950 EVs charged by the end of day 10. For the simulation of the *LHWT* approach, which incorporates historical waiting times, we initially ran a simulation for 70 days to obtain average historical waiting times per station based on the *LWT* settings. This historical data was then used in the *LHWT* approach for a subsequent 10-day simulation. Other parameters used in the simulation are detailed in Section IV-A.

Waiting Time (in minutes)	NCS	LWT	LHWT
Maximum	1094.88	175.32	131.02
Minimum	0	87.77	41.51
Average	184.105	161.32	119.91

TABLE IV
COMPARISON OF EV WAITING TIMES (NCS, LWT, LHWT)

B. Analysis of simulation results

The simulation results are shown in Figures 3 and 4. Fig 3 illustrates the distribution of EVs across given 20 charging stations for NCS, LWT and LHWT. Fig 4 shows the distribution of waiting times at these 20 charging stations for each version.

The simulation results shown in Fig 3 reveals that in NCS, where EVs are sent to the nearest station for charging, all the EVs cluster at only three out of the 20 available charging

stations. This occurs because, when calculating the manhattan distance between the EV dispatch coordinates and charging stations coordinates, the majority of EVs end up being routed to these three stations.

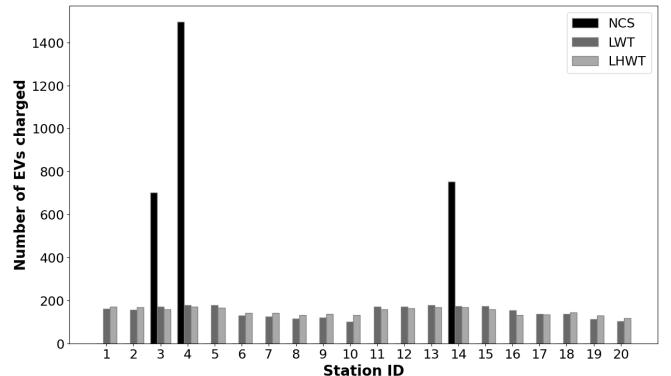


Fig. 3. Total number of EVs charged at each station (NCS, LWT, LHWT)

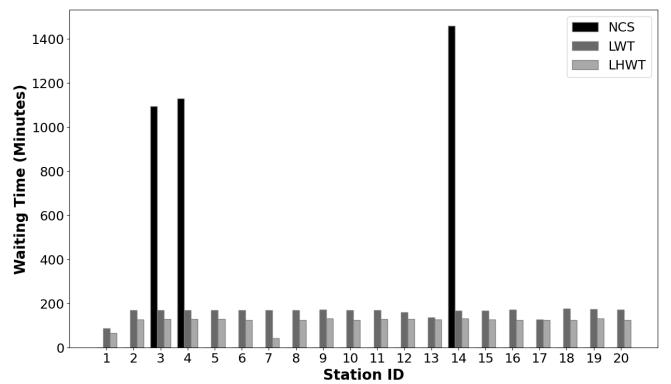


Fig. 4. Average Waiting time of EVs at each station (NCS, LWT, LHWT)

The LWT approach shows an increase in the total number of EVs charging per station compared to NCS. The distribution of EVs is more uniform due to the introduction of the waiting time parameter, which causes EVs to travel a bit further to stations with lower waiting times, as shown in Table IV. This results in better utilization of charging stations. The LHWT approach, which incorporates historical waiting time data, further improves the variance in charging station utilization compared to LWT, as evidenced in Figure 3.

Our goal was to reduce waiting times with the introduction of new versions. In the NCS approach, where EVs cluster at only three stations, the average waiting time was significantly high at 184.105 minutes. The average waiting time over the three utilized stations was 1,227.36 minutes. In the LWT approach, the distribution of EVs became more uniform, resulting in a more balanced waiting time, with each EV experiencing an average of 161.32 minutes. The LHWT approach, incorporating historical waiting times, achieved the lowest average waiting time of 119.91 minutes. This represents a significant improvement over both NCS and LWT. Additionally, by distributing EVs more evenly across stations,

the newer versions alleviated stress on the grid, preventing overload at specific stations and ensuring more efficient energy usage across the network.

V. DISCUSSION

This study focuses on a flat-surfaced road network under normal traffic conditions and assumes that EVs charge fully until reaching 100% State of Charge (SoC). In practice, traffic conditions vary, and during peak congestion hours, enhancing the efficiency of EV charging services becomes critical. One proposed solution, as mentioned in [11], is to charge EVs only until a SoC threshold (typically 85 – 90%) is reached. Since charging speed decreases exponentially after this point, limiting charging to this threshold can reduce overall charging time and increase the service rate. This approach also benefits the revenue model of charging stations.

Another alternative to the LWT approach is implementing an advanced booking system for charging slots, as discussed in [12]. Instead of relying on historical data to estimate waiting times, drivers could reserve specific time slots in advance. This system could streamline the charging process, reduce waiting times, and ensure efficient use of charging infrastructure. By allowing drivers to schedule their charging sessions, stations can better manage demand, particularly during peak hours, providing a more reliable and convenient service.

However, this approach has several challenges. Cancellations can lead to underutilization of charging stations if reserved slots are not promptly reallocated. Late arrivals might disrupt the schedule, causing delays and impacting subsequent reservations, while early arrivals could lead to congestion if drivers attempt to charge before their reserved time, straining the station's capacity.

To address cancellations, overbooking could be employed, similar to practices in the airline industry. However, this introduces the risk of overloading the system, leading to increased wait times if too many vehicles arrive simultaneously. Managing unexpected demand spikes can challenge service rates and overall station utilization. While advanced booking can improve efficiency, it requires careful management to maintain the reliability and effectiveness of the charging infrastructure.

VI. CONCLUSION

This paper presents a series of charge scheduling models designed to optimize EV waiting times at charging stations. By progressively incorporating more complex parameters, these models demonstrate significant improvements in total charging time and waiting times.

Future work will aim to refine these models further by integrating dynamic data from real-time traffic and weather conditions. Additionally, the exploration of renewable energy sources and smart grid technologies will be pursued to enhance the sustainability and efficiency of EV charging infrastructure.

Further research could also investigate the impact of variations in travel time due to uneven road networks and fluctuating congestion levels.

REFERENCES

- [1] Xiaoli Sun, Zhenguo Li, Xiaolin Wang, and Chengjiang Li. Technology development of electric vehicles: A review. *Energies*, 13(1):90, 2019.
- [2] Maen Al Rashdan, Mohammad Al Zubi, and Mohamad Al Okour. Effect of using new technology vehicles on the world's environment and petroleum resources. *Journal of Ecological Engineering*, 20(1):16–24, 2019.
- [3] Nikita O Kapustin and Dmitry A Grushevenko. Long-term electric vehicles outlook and their potential impact on electric grid. *Energy Policy*, 137:111103, 2020.
- [4] Dolf Gielen, Ricardo Gorini, Nicholas Wagner, Rodrigo Leme, Laura Gutierrez, Gayathri Prakash, Elisa Asmelaš, Luis Janeiro, Giacomo Gallina, Giulia Vale, et al. Global energy transformation: a roadmap to 2050. 2019.
- [5] Matteo Muratori. Impact of uncoordinated plug-in electric vehicle charging on residential power demand. *Nature Energy*, 3(3):193–201, 2018.
- [6] Kristien Clement-Nyns, Edwin Haesen, and Johan Driesen. The impact of charging plug-in hybrid electric vehicles on a residential distribution grid. *IEEE Transactions on power systems*, 25(1):371–380, 2009.
- [7] Hao Zhang, Zhaoguang Hu, Zhen Xu, and Yonghua Song. Optimal planning of pev charging station with single output multiple cables charging spots. *IEEE Transactions on Smart Grid*, 7(3):1635–1643, 2016.
- [8] Qiuming Gong, Shawn Midlam-Mohler, Vincenzo Marano, and Giorgio Rizzoni. Study of pev charging on residential distribution transformer life. *IEEE Transactions on Smart Grid*, 3(1):404–412, 2011.
- [9] M. Hadi Amini, Javad Mohammadi, and Ozan Karabasoglu. A comprehensive review of the integration of evs into power grids. *IEEE Systems Journal*, 10(2):708–721, 2016.
- [10] Yifei Wang, Zhiwei Wang, and Haoran Zhang. Second-life ev battery for building energy storage and grid support. *Energy Procedia*, 143:837–842, 2017.
- [11] Pushkar Patel, Harsh Kakani, Manish Chaturvedi, and Naveen Kumar. On pricing models for electric vehicle charging. In *2022 IEEE 25th International Conference on Intelligent Transportation Systems (ITSC)*, pages 158–163. IEEE, 2022.
- [12] Syed Muhammad Danish, Kaiwen Zhang, Hans-Arno Jacobsen, Nouman Ashraf, and Hassan Khaliq Qureshi. Blockev: Efficient and secure charging station selection for electric vehicles. *IEEE Transactions on Intelligent Transportation Systems*, 22(7):4194–4211, 2021.
- [13] FAME India scheme Phase II. Online. Available: <https://fame2.heavyindustry.gov.in/>.
- [14] Revised Consolidated Guidelines Standards for Charging Infrastructure for Electric Vehicles (EV) Promulgated by Ministry of Power. Online. Available: <https://pib.gov.in/PressReleasePage.aspx?PRID=1790136>.
- [15] A. K. Shukla, K. Sudhakar, and Prashant Baredar. Renewable energy resources in south asian countries: Challenges, policy and recommendations. *Resource-Efficient Technologies*, 3(3):342–346, 2018.
- [16] Eric Sortomme and Mohamed A El-Sharkawi. Optimal charging strategies for unidirectional vehicle-to-grid. *IEEE Transactions on Smart Grid*, 2(1):131–138, 2010.
- [17] Nastaran Sadeghianpourhamami, Nima Refa, Matthias Strobbe, and Chris Develder. Quantitative analysis of electric vehicle flexibility: A data-driven approach. *Applied Energy*, 212:1527–1538, 2018.
- [18] Khalid Mohammed Almatar. Increasing electric vehicles infrastructure in urban areas for efficiently employing renewable energy. *Environment, Development and Sustainability*, pages 1–22, 2023.
- [19] Phillip K Agbesi, Rico Ruffino, and Marko Hakovirta. The development of sustainable electric vehicle business ecosystems. *SN Business & Economics*, 3(8):143, 2023.