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An Adaptive Scheduling Framework for EV Charging: Integrating Preemption and Multi-Objective Optimization

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Abstract**—*This study develops an adaptive scheduling model for electric vehicle (EV) charging that integrates linear programming with a heuristic algorithm to address dynamic demand and spatial constraints. The proposed model considers vehicle priority, benefit-to-cost ratio, geographic distance, station capacity, and charging power limits. A key innovation is the implementation of a dynamic order insertion mechanism, allowing newly arrived vehicles to preempt part of the charging allocation from existing vehicles when necessary. Simulation experiments demonstrate the model's effectiveness in balancing scheduling efficiency and fairness. Comparative analyses across different priority allocation strategies reveal that a moderate constraint—such as the Equal_Min_Ratio approach—achieves the highest total benefit while ensuring equitable resource distribution across all priority levels. The results provide actionable insights for EV infrastructure planning and real-time charging management. This research offers both a rigorous multi-objective formulation and a deployable scheduling solution to support the development of sustainable and responsive EV charging systems.*

Keywords**—** *Electric vehicle charging, dynamic scheduling, resource allocation, heuristic algorithm, Preemption.*

I. INTRODUCTION

With the popularity of EVs, user behavior and its psychological factors become important factors affecting the acceptance of EVs. Wang et al. [13] explored the range anxiety problem, which refers to the user's concern about the driving distance of EVs, a situation that significantly hinders the widespread adoption of EVs. Caperello and Dowd [9] highlighted the need for a deeper understanding of user behavior, since Caperello and Dowd [9] emphasized the need for a deeper understanding of user behavior, as user acceptance and usage habits have a direct impact on the market performance of EVs, and Hsu et al. [1] investigated the dynamic routing problem considering time-dependent charging demand, and pointed out that the routing strategy of EVs needs to be adjusted in real time to enhance user charging experience and satisfaction in the event of changes in charging demand. The rational planning of charging infrastructure is crucial to promote the popularity of EVs. Zhang et al. [2] present a review of charging station location selection, pointing out that the number and location of charging stations directly affects the user's charging convenience, and thus the acceptance of EVs. Răboacă et al. [8] pay attention to the optimization of the temporary location of the mobile charging stations, especially during the peak demand period, when the fixed charging stations may not be able to satisfy all the users. charging stations may not be able to satisfy all users' needs, so flexible configuration of mobile charging stations becomes an important research direction. Liu et al. [12] analyzed the optimal location of EV charging stations in urban environments using a mixed integer planning model, aiming to improve the efficiency of charging station usage to support the widespread application of EVs. In studying the EV charging and routing problem, scholars have adopted various mathematical models and optimization methods. Chen et al. [11] reviewed the routing strategy under charging station configuration, emphasized its complexity, and proposed corresponding solutions. Kwan et al. [6] established an optimization framework aiming to resolve the conflict between charging and driving. Zhang et al. [3] proposed a multi-objective optimization model to solve the EV routing problem considering a time window, emphasizing the necessity of finding an optimal solution under time constraints. In addition, Li et al. [4] investigated optimal charging scheduling in a smart grid environment, emphasizing the importance of grid load balancing.

Although the government has begun to increase the number of charging stations, parking remains a significant transportation issue in larger cities. Drivers will take advantage of the charging time to leave their cars and do other things (e.g., leisure activities, eating), which will likely affect other drivers who need to charge their vehicles. Therefore, there is a need for a mechanism to adjust the EV charging problem. In this study, a pre-emption mechanism is proposed, in which when a driver with charging needs wants to enter a charging station for charging service, the EV that has been charged to a level that allows for subsequent driving needs to release the resources of the charging station, to maximize the charging station's efficiency, and at the same time, reduce the customer's anxiety about the charging of the EVs.

Finally, the remainder of the paper is structured as follows:

Section 2 explains the studies on the problem of the proposed scheduling and allocation system. for the EVs. Section 3 describes the key elements involved in the implementation of the heuristic algorithm and the proposed methodology. Section 4 discusses numerical experiments and the results of the implemented method. Section 5 concludes the findings of this research.

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II. Literature Review

A. User Behavior and System Efficiency

User behavior has a direct impact on the efficiency of EV charging systems, and research in this area focuses on understanding user charging behavior and its impact on system performance. Caperello and Dowd [9] analyzed the impact of user behavior on EV adoption and proposed suggestions to improve user experience in order to promote the popularity of EVs. Gifford et al. [10] reviewed the literature on EV charging behavior, explored various factors affecting charging efficiency, and pointed out the need to strengthen the charging infrastructure to improve the overall system operational efficiency. Kwan's [7] study, on the other hand, focused on the impacts of charging infrastructure on EV adoption, and put forward corresponding policy recommendations, emphasizing the interactions between system efficiency and user behavior. interactions between system efficiency and user behavior.

B. EV Routing and Charging Strategies

The EV routing problem is closely related to charging strategies, and research in this area has focused on how to optimize the travel paths considering user behavior and charging demand. Chen et al. [11] reviewed the charging station considerations in EV routing, and proposed a variety of solutions to address challenges in different contexts. Conversely, he suggested a framework for improving EV charging and routing that takes into account the effects of user behavior. Range anxiety is an important factor affecting EV users' routing choices, and Wang et al. [13] conducted an in-depth study on this to investigate how to reduce users' anxiety to promote EV usage. In addition, Hsu et al. [1] investigated the dynamic routing problem of EVs considering time-dependent charging demand and proposed a corresponding optimization strategy, while Zhang et al. [14] proposed a multi-objective optimization model aiming to improve the routing efficiency of EVs, which together provide theoretical support to enhance the operational efficiency and user satisfaction of EVs.

C. Charging Infrastructure and Planning

The planning of charging infrastructure is an important component of EV development, which involves the location and quantity allocation of charging stations. Studies have shown that optimizing charging station locations using demand forecasting and geographic information systems (GIS) can significantly improve charging convenience, e.g., Zhang et al. [15] summarized a variety of charging station siting methods in their paper, emphasizing user demand-based planning strategies. In addition, Răboacă et al. [8] proposed a temporary location optimization model for mobile charging stations that considers user demand and geographic characteristics in order to provide better services during peak demand periods, while Liu et al. [12] analyzed the optimal location of EV charging stations in an urban environment using a mixed-integer planning model, which further confirmed the importance of rational planning for enhancing system efficiency. The study also emphasizes how crucial it is to plan well in order to improve the system's effectiveness. Finally, Sullman et. al [5] explored the issue of routing optimization for EV service systems, emphasizing the consideration of charging demand.

III. Mathematical Model of This Study

A. Symbols

In this section, a mathematical model is developed to address the problem under investigation. It defined the symbols, assumed the hypothesis, and developed a heuristic algorithm to solve the problem. Table I shows the symbol definitions of the developed model

TABLE I. the variables used in the developed model

Parameter Definitions
• Set of vehicles: $V = \{1, 2, ..., N\}$ • Set of charging stations: $S = \{1, 2, ..., M\}$ • Set of time slots: $T = \{0, 1, ..., T_{max}-1\}$ For each vehicle $v \in V$, define parameters: • Priority: $p_v \in \{1, 2, 3\}$ • Cost: $c_v > 0$ • Benefit: $b_v > 0$ • Location coordinates: $loc_v = (x_v, y_v) \in \mathbb{R}^2$ • Arrival time: $a_v \in T$ • Charging demand: $d_v > 0$ • Vehicle type: $type_v$ • Power demand: $P_v > 0$ For each charging station $s \in S$, define parameters: • Location coordinates: $loc_s = (x_s, y_s) \in \mathbb{R}^2$ • Capacity (max simultaneous vehicles): $C_s > 0$ • Max charging power limit (per time slot): $M_s > 0$ For each charging station $s \in S$, define parameters: • Location coordinates: $loc_s = (x_s, y_s) \in \mathbb{R}^2$ • Capacity (max simultaneous vehicles): $C_s > 0$ • Max charging power limit (per time slot): $M_s > 0$
Decision Variables
• Charging allocation ratio: $x[v,s,t] \in [0,1],\ \forall v \in V, s \in S, t \in T$ Represents the charging allocation ratio of vehicle v at station s during time slot t. • Station selection: $y[s] \in \{0,1\},\ \forall s \in S$ Indicates whether charging station s is selected.
Auxiliary Function
$dist(v,s) = \sqrt{(x_v - x_s)^2 + (y_v - y_s)^2}$

B. Hypothesis

Several constraints are defined to ensure a feasible schedule.

- A vehicle's total allocated charging across all stations and time slots does not exceed its need.
- The number of vehicles charging at a station in a given time slot does not exceed its capacity (only for selected stations).
- The total power demanded by charging vehicles at a station in a given time slot does not exceed its maximum charging power (only for selected stations).

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- Minimum charging ratios are enforced based on vehicle priority.
- A vehicle's total allocation does not exceed 1 (to avoid over-allocation, although this seems redundant with the charge need constraint).
- Charging can only be allocated at selected stations.
- Each vehicle can only be assigned a total allocation of up to 1 at any single station across all time slots.

This study utilizes linear programming to determine the optimal selection and scheduling of charging stations for a set of electric vehicles, considering factors such as priority, cost, benefit, distance, station capacity, and power limits. It also includes a mechanism to handle the dynamic arrival of new vehicles and attempt to fit them into the existing schedule, potentially by preempting (reducing the charge allocated to) other vehicles.

$$\max Z = \sum_{v,s,t} x[v,s,t] \times ((b_v - c_v)/p_v - \alpha \times dist(v,s)) - \beta \sum_s y[s] \quad (1)$$

s.t

$$\sum_{s,t} x[v,s,t] \le d_v,\ \forall v \in V \quad (2)$$

$$t \le C_s \times y[s],\ \forall s \in S,\ t \in T \quad (3)$$

$$\sum_v x[v,s,t] \times P_v \le M_s \times y[s],\ \forall s \in S,\ t \in T \quad (4)$$

$$x[v,s,t] = 0,\ \forall v \in V,\ s \in S,\ t < a_v \quad (5)$$

$$\sum_{s,t} x[v,s,t] \ge r[p_v] \times d_v,\ \forall v \in V \quad (6)$$

$$x[v,s,t] \le y[s],\ \forall v \in V,\ s \in S,\ t \in T \quad (7)$$

$$\sum_{t=0}^{T} x[v,s,t] \le 1,\ \forall v \in V,\ s \in S \quad (8)$$

$$x[v,s,t] \in [0,1],\ y[s] \in \{0,1\} \quad (9)$$

$$s^* = \arg\min_{s:\, y[s]=1} dist(v_{new}, s) \quad (10)$$

$$\text{Number of vehicles charging at } s^* \text{ at anew} < Cs^* \quad (11)$$

$$\sum v\, x[v,s^*,a_{new}] \times Pv + Pnew \le Ms^* \quad (12)$$

$$x[v,s^*,a_{new}] := x[v,s^*,anew] - \delta \quad x[v_{new}, s^*, a_{new}] := \delta \quad (13)$$

$$\text{where } \delta \le \min(x[v,s^*,a_{new}], d_{new}) \text{ to ensure feasibility} \quad (14)$$

This objective function aims to maximize total net benefit, considering the benefits and costs of each vehicle, as well as the distance and priority factors. The first part $\sum_{v,s,t} x[v,s,t] \times ((b_v - c_v)/p_v - \alpha \times dist(v,s))$ represents the net benefit of vehicles during the charging process, considering the benefits minus costs and distance impacts. The second part $-\beta \sum_s y[s]$ represents the cost of selecting charging stations. The constraint (2) ensures that the total allocation of each vehicle does not exceed its charging demand, preventing overcharging or resource waste. By preventing the number of cars charging at any given station at any given time from exceeding its capacity, constraint (3) safeguards the charging station's operational effectiveness. The constraint (4) ensures that the power usage at the charging station does not exceed its maximum power limit during any time slot, preventing overload situations. The constraint (5) ensures that vehicles do not charge before their arrival time, reflecting real-world time management. The constraint (6) ensures that each vehicle's charging ratio meets its priority requirements, where r [1] = 1.0, r [2] = 0.7, and r [3] = 0.5, thereby ensuring that higher-priority vehicles receive adequate charging. The constraint (7) ensures that charging allocations can only occur at selected charging stations, enhancing the model's rationality and operability. The constraint (8) ensures that the total charging ratio at any single station does not exceed 1, preventing excessive charging of any vehicle at the same charging station. The constraint (9) ensures that the charging allocation ratios are within reasonable limits and that station selection is a binary variable for optimization calculations. This formula (10) determines the nearest selected charging station for a new vehicle, facilitating quick insertion into the charging plan. The constraint (11) checks if there is space at the charging station when the new vehicle arrives. The constraint (12) ensures that the power usage at the charging station during the new vehicle's arrival time does not exceed the maximum limit. This strategy (13) ensures that if there is no space at the charging station, the charging ratio δ, δ is preempted from existing vehicles. The constraint (14) ensures that the preempted charging ratio does not exceed the existing vehicle's charging ratio or the new vehicle's demand, ensuring feasibility.

C. Decision of the Heuristic Algorithm

Since the allocation, scheduling, and route planning problems have been proven to be NP-hard problems, the study established an algorithm to obtain an approximate optimization of the problem. The code of this study implements a dynamic electric vehicle charging scheduling and station selection model using the pulp library for linear programming. Here's a breakdown of the key components.

1. Vehicle Class: Represents an electric vehicle with attributes like name, priority, cost, benefit, current location, arrival time, charge need, vehicle type, and power demand. It also stores the charging allocation result.
2. Station Class: Represents a charging station with attributes like name, location, capacity (number of vehicles it can serve simultaneously), maximum charging power per time slot, and a flag indicating if the station is selected for use in the schedule.
3. Scheduler Class: This is the core class that manages vehicles and stations and performs the scheduling optimization.
   o__init__: Initializes the scheduler with a time horizon number of time slots).
   - add_vehicle: Adds a Vehicle object to the scheduler.
   - add_station: Adds a Station object to the scheduler.
   - distance: Calculates the Euclidean distance between two locations.
   - schedule: This is the main optimization function.
   - It creates a linear programming problem using pulp.
   - Decision Variables:
   - allocation: A continuous variable representing the proportion of a vehicle's charging need allocated to a specific station within a particular time slot.
   - station_selection: A binary variable indicating whether

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a station is selected (1) or not (0).

- Objective Function: Maximizes the total net benefit (benefit minus cost, adjusted by priority) from charging allocations, while penalizing distance to stations and the cost of selecting stations.
- It updates the is_selected attribute for each station and the allocation attribute for each vehicle based on the optimization results.

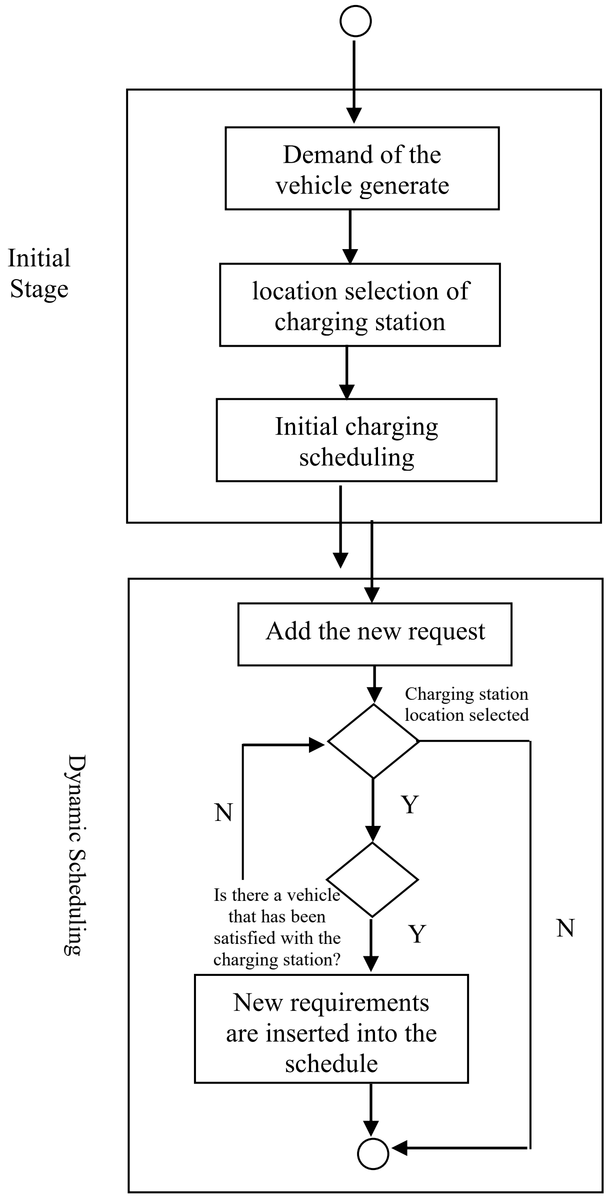


Fig. 1. The process of the heuristic algorithm in this study.

4. insert_vehicle_with_preemption Function: This function demonstrates how to handle the arrival of a new vehicle and attempt to insert it into the existing schedule.
   - It finds the nearest selected station to the new vehicle.
   - It checks if there is space (capacity and power) at that station during the new vehicle's arrival time.
   - If there is space, the new vehicle is directly assigned.
   - If there is no space, it attempts to "preempt" (reduce the allocation of) existing vehicles at that station and time slot to make space for the new vehicle, prioritizing vehicles with higher existing allocations.
   - It adds the new vehicle to the scheduler and prints the result of the insertion attempt.
5. generate_random_vehicle Function: A helper function to create Vehicle objects with random attributes for simulation purposes.

IV. THE RESULT OF THE STYDY

In Section 3, this study proposes a mathematical model to obtain the maximum profit for Electric Vehicles (EVs) and applies Colab programming to develop a heuristic algorithm. In this section, datasets from past studies are cited to support the calculations presented in this study. The result of this study would provide a solution for EVs. In the initial stage of this study, three charging stations and five electric vehicles (EVs) with charging demands are generated, and the relevant parameters and demands of the EVs are randomly generated. Then, based on the demand of these five electric vehicles, it is determined which charging station the vehicle will be charged at. In the dynamic scheduling phase, the parameters and demands of a new EV are randomly generated and inserted into the existing schedule, and the impact of the addition of the latest EV on the EV schedule is analyzed, and the significance of the new EV is explored.

A. Charging Station Allocation

In the simulation scenario of this study, there are three candidate charging station locations: StaA: coordinate (0, 0), StaB: coordinate (5, 0), and StaC: coordinate (3, 4). Based on the randomly generated demand of the vehicle and through the results of the scheduling algorithm of this study, the final site selection is shown in Table 2. The station selection results reflect the fact that under limited resources and space constraints, the algorithm prioritizes sites that can effectively serve a large number of vehicles and that have spatial coverage and demand response capabilities

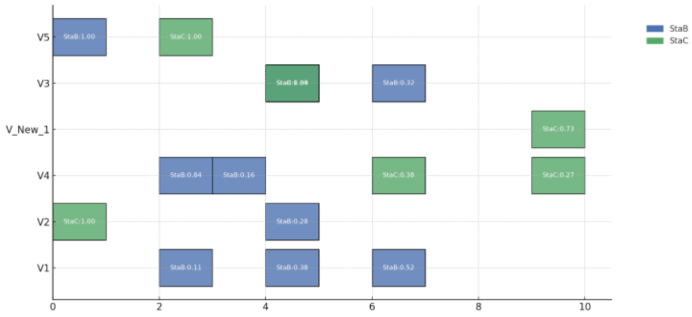
TABLE II. Charging Station Allocation.

Station	location	The station was select or not
StaA	(0, 0)	No
StaB	(5, 0)	Yes
StaC	(3, 4)	Yes

B. The Gantt Chart Analysis of Vehicle Charging Scheduling

Figure 2 shows the Gantt Chart of the vehicle charging schedule generated from the simulation results of this study. This graph plots the vehicle as the vertical axis and the time period as the horizontal axis, using different colors to indicate the charging time period and the proportion of corresponding electricity consumption for each vehicle at various charging stations (e.g., StaB and StaC). This graph helps visualize the time distribution of vehicle charging and assess whether the scheduling is efficient and feasible.

Taking vehicle V1 as an example, its charging behavior covers the 2nd, 4th, and 6th time slots of StaB station. It allocates a charging ratio of 0.73 to the 9th time slot of StaC before inserting the order. This graph identifies whether each vehicle has charging behaviors across stations or time slots, and also helps to observe whether there is resource competition among vehicles. Additionally, the length and position of the color blocks can be used to assess whether the overall scheduling achieves the goal of load balancing.

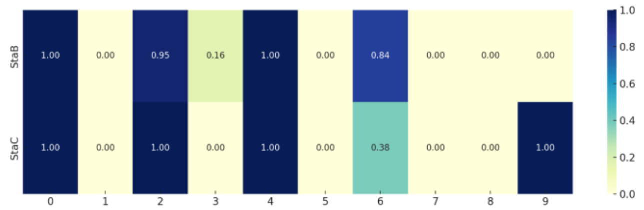


Time slot

Fig. 2. Gantt Chart of the study

C. *Heat map analysis of charging station usage rate during different time periods*

Figure 3 shows the heatmap of the total utilization of the charging stations in each time period, the vertical axis is the charging stations (StaB and StaC), and the horizontal axis is the time period from 0 to 9, the color shades represent the degree of resource utilization in that time period, and the values represent the total amount of electricity. This map can be used to analyze the loading situation at each station during different administrative periods and to identify potential congestion bottlenecks and uneven resource allocation within the system.



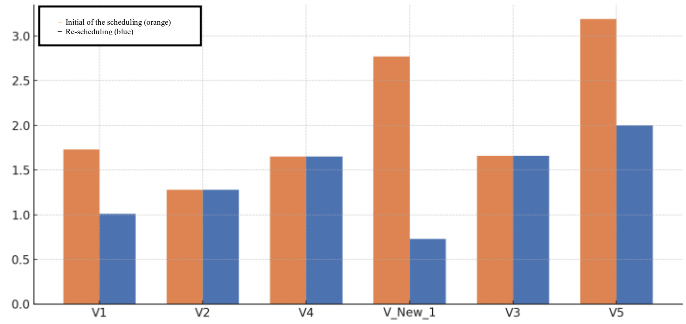
Time slot

Fig. 3. Heatmap of the study

From the Fig. 3, it can see that StaB has a higher utilization rate in time periods 4 and 6, which indicates that these two periods are the areas where multiple vehicles are competing for resources, while StaC has a significant peak in time period 9, which is the resource used by the subsequent insertion of the single-vehicle V_New_1. Overall, the heatmap can effectively help system designers identify high-load periods and reallocate resources accordingly or delay non-essential charging as a response.

D. *Comparison of vehicle charging demand and actual allocation*

Figure 4 shows a comparison between the charging demand and the actual allocation for each vehicle. The orange bars represent the original demand of the vehicles, while the blue bars represent the total amount of charging they receive after scheduling. This figure is used to evaluate the performance of the scheduling algorithm in terms of resource satisfaction, as well as a measure of fairness and completeness of resource allocation,



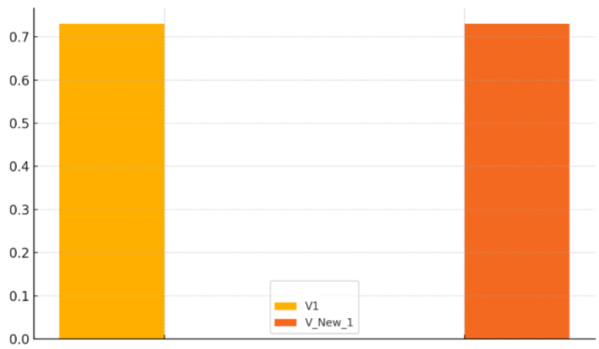
the vehicles

Fig. 4. the actual allocation for each vehicle

The results showed that most of the vehicles (e.g., V1, V2, V4) were able to satisfy the demand almost wholly or entirely. However, the newly inserted vehicle, V_New_1, only receives 0.73 units of resources, which is insufficient compared to its demand of 2.77, indicating that under limited resources, the later vehicles may not be able to satisfy the demand completely. The result of this figure further demonstrates the impact of the insertion mechanism on the overall resource allocation and emphasizes the importance of demand prioritization and resource reservation strategy.

E. *Comparative analysis of scheduling and re-scheduling*

Figure 5 compares the schedules of V1 and V_New_1, the horizontal axis is the time period, and the vertical axis is the charging ratio, which clearly shows the resource changes of the two vehicles in each time period before and after the insertion of the order. It can be seen that before the insertion of the order, V1 originally had 0.73 resources in StaC time slot 9. In contrast, after the order was inserted, the time slot was allocated to V_New_1, resulting in a noticeable shift in the scheduling.



the vehicles

Fig. 5. Example of a figure caption.

Figure 5 illustrates how the order insertion mechanism impacts the scheduling configuration of existing vehicles. Although V1 ultimately maintains most of its schedules at the

StaB site, the resource transfer may result in a delay in its overall charging completion time. This result suggests that during real-time scheduling, the priority of the new vehicle, the distance cost, and the degree of disruption to the original schedule should be evaluated to avoid overly sacrificing the performance of the existing vehicle to meet the new demand.

F. *Total Benefit under Different Priority Min Ratio*

To investigate the impact of different priority_min_ratio settings on scheduling efficiency and equity, a sensitivity analysis was conducted using four scenarios: Default, No_Min_Ratio, High_Priority_Only, and Equal_Min_Ratio.

In the Default configuration, priority levels 1, 2, and 3 were assigned minimum allocation ratios of 1.0, 0.7, and 0.5, respectively. This ensured fair allocation across all priority groups, with each achieving a full 100% allocation rate. However, only one station was selected, and the total benefit was relatively low at 482.61. Under the No_Min_Ratio setting, no minimum ratios were imposed. This allowed the model to prioritize high-benefit vehicles (e.g., V1 and V2), leading to a higher total benefit of 555.82. Nevertheless, this resulted in significant imbalance, with lower-priority vehicles (such as V5) receiving no allocation, and average allocation ratios dropping to 0.5 for priority 2 and 0.73 for priority 3. The High_Priority_Only scenario enforced a minimum ratio solely for priority 1 (1.0), disregarding lower tiers. This configuration allowed for the selection of two stations and increased the total benefit to 682.78. However, priority 2 vehicles received no allocation at all, highlighting the trade-off between efficiency and fairness. Finally, the Equal_Min_Ratio strategy applied a balanced approach, setting a uniform minimum ratio of 0.5 across all priority levels. As a result, the system selected two stations, fully met all vehicle demands, achieved perfect allocation ratios (1.0) across the board, and yielded the highest total benefit of 1734.45.

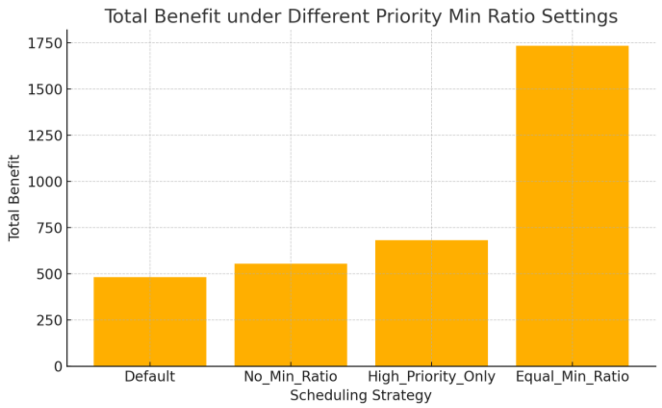


Fig. 6. Example of a figure caption.

As illustrated in Figure 6, this strategy outperformed others in both equity and efficiency, indicating that moderate constraints on minimum priority allocations can lead to optimal overall system performance.

G. *The Average Allocation Ratio under Different Priority*

Figure 7 illustrates the average allocation ratio achieved for each priority level under the four tested scheduling strategies.

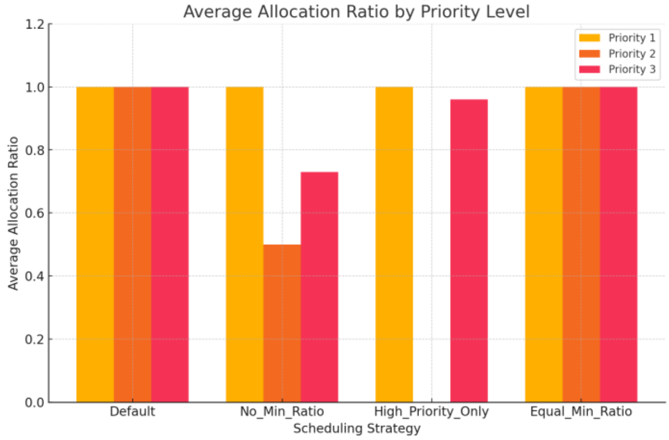


Fig. 7. Example of a figure caption.

As expected, the Default and Equal_Min_Ratio settings ensured full allocation (ratio = 1.0) across all priority levels, reflecting their built-in constraints for minimum guaranteed allocation. In contrast, the No_Min_Ratio setting, which imposes no allocation constraints, led to significant disparities: while Priority 1 still achieved a full allocation, Priority 2 dropped to 0.5, and Priority 3 to 0.73. This indicates a strong bias toward high-priority or high-benefit vehicles, at the expense of lower-priority demands. Similarly, the High_Priority_Only strategy focused entirely on Priority 1, achieving a perfect allocation (1.0), but entirely neglecting Priority 2 (0.0) and nearly satisfying Priority 3 (0.96), likely due to station capacity overflow or cost-effectiveness in allocating leftover resources. The Equal_Min_Ratio approach again stands out as the most balanced, achieving perfect allocation for all priorities while maximizing total benefit. This demonstrates that modest fairness constraints do not compromise performance—in fact, they enhance it by ensuring broader access to charging resources across vehicle types.

V. Conclusion

This study proposes a comprehensive scheduling framework for electric vehicle (EV) charging that integrates linear programming with a heuristic algorithm to optimize the dynamic allocation of charging resources. Rooted in a multi-objective optimization model, the framework accounts for factors such as vehicle priority, cost-benefit ratios, spatial distance, station capacity, and power limitations. One of the key innovations is the introduction of a dynamic preemption mechanism, allowing newly arriving vehicles to be inserted into existing schedules by reallocating portions of charging resources from currently served vehicles. This flexible approach responds to the growing complexity of EV charging systems where unpredictable arrival patterns and varied user behaviors challenge traditional static planning models.

The theoretical formulation in this study ensures not only efficiency but also fairness through priority-based minimum allocation constraints. For example, the inclusion of customizable priority_min_ratio settings enable the system to guarantee minimum service levels for different user classes while maximizing overall net benefit. In addition, the mathematical constraints are carefully designed to preserve feasibility across charging demand, arrival times, spatial limits, and technical boundaries of each station.

From a computational standpoint, the study demonstrates that despite the NP-hard nature of the underlying scheduling problem, an effective heuristic algorithm implemented in Python (via the Pulp library) can generate feasible and near-optimal solutions in a reasonable time. The simulation results—including Gantt charts for time-slot visualization, heatmaps of station utilization, and comparative benefit analyses—offer concrete evidence of the model's performance. Particularly, the Equal_Min_Ratio configuration yielded the highest total benefit (1734.45) and full allocation across all priority levels, showcasing the value of equitable constraint design in balancing efficiency with fairness.In practical application, the proposed model has strong implications for real-time EV charging management. It offers a scalable solution for smart cities, enabling dynamic and preemptive charging schedules that adapt to evolving demand profiles. The simulation tools and visualization outputs provide planners with intuitive, data-driven insights for siting decisions and operational adjustments.

In conclusion, this study contributes not only a novel hybrid model for EV resource allocation but also a practical algorithmic toolset for real-world deployment. By integrating user behavior, operational constraints, and priority-based fairness into one unified scheduling framework, the research bridges theoretical optimization with implementation-ready strategies. As EV adoption accelerates globally, this model offers timely and actionable guidance for sustainable transportation planning and energy-efficient infrastructure design.

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