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Solving Charging Scheduling Problem in Electric Vehicles Using Optimization Algorithms

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Abstract. This research addresses the problem of scheduling electric vehicle charging times, with the primary objective of minimising total tardiness, defined as the waiting time beyond the specified charging duration. The complexity arises from multiple interacting constraints, making it difficult to produce a feasible schedule that also minimises tardiness. As this problem is NP-hard, this study proposes a metaheuristic approach integrating a cellular processing algorithm with a Greedy Randomised Adaptive Search Procedure (GRASP). This paper provides a detailed implementation and description of the methods, along with a comprehensive calculation of the objective function, addressing areas that require further exploration in the existing literature.

Keywords: minimize, total tardiness, electric vehicles, NP-hard, metaheuristic, cellular processing algorithm, GRASP.

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1 Introduction

The growth of electric vehicles (EVs) has emerged as one of the most significant trends in the automotive industry over the past decade, with global sales reaching 17 million units in 2024 (Energy Agency, 2024). Forecasts indicate that by 2030, more than 50% of new car sales will be electric (Edison Guasumba-Maila et al., 2021), with substantial contributions from Latin American countries (Ramírez et al., 2021). This shift is primarily driven by heightened awareness of climate change and the urgent need for sustainable transportation solutions. The exponential rise in the popularity of EVs can be attributed to several factors, including their operational cost efficiency, substantial reduction in environmental impact, and superior performance compared to fossil fuel-powered vehicles (Arias Pérez & García, n.d.; Dora Morín García Presenta et al., 2015).

Several elements have fueled the growth of EVs, such as government incentives, stringent environmental regulations (Sanz Arnaiz & González Fabre, n.d.), and technological advancements driven by consumer demand. Countries worldwide have adopted policies to promote the uptake of electric vehicles, including subsidies, tax reductions, and other incentives for manufacturers (Plug In America, n.d.; Schmerler Vainstein et al., 2019). For instance, Norway has successfully increased EV adoption to over 54% of total car sales by implementing aggressive tax incentives and exemptions from tolls and parking fees (Figenbaum & Kolbenstvedt, 2016). This model could serve as a blueprint for other nations aiming to enhance their EV market share.

Significant advancements in battery technologies have enabled electric vehicles (EVs) to achieve greater range and reduced charging times, with innovations like solid-state batteries promising further improvements in safety, energy density, and longevity (Chen & Shi, n.d.). These technological advancements have encouraged more automotive manufacturers to enter the EV market, as evidenced by the rapid growth in global EV sales, which reached almost 14 million in 2023 (VIRTA, 2024). However, a critical limitation remains inadequate charging infrastructure, particularly in developing countries (Gorky Reyes-Campaña & Javier Guanuche-Larco, 2021). The International Energy Agency predicts that the number of EVs on the road will reach approximately 230 million by 2030 (Sanz Arnaiz & González Fabre, n.d.), signifying a substantial shift towards cleaner and more sustainable transportation.

While the anticipated growth of EVs is expected to have a profound impact on the automotive industry and the broader economy, driving investments in clean energy and reducing greenhouse gas emissions, it also presents challenges. The surge in EV demand is likely to result in a considerable increase in energy consumption, alongside the existing limitation of charging stations (Gelmanova et al., 2018). According to a 2019 report by the McKinsey Global Institute, the demand for electricity to power EVs could increase by 30% by 2030, leading to potential stress on existing energy infrastructures (Timo Möller et al., 2019). The electric vehicle charging scheduling problem is particularly complex and is classified as NP-hard due to the multitude of constraints and variables involved, including charging times, vehicle arrival patterns, and the physical limitations of charging infrastructure. This complexity necessitates the use of advanced optimization techniques such as heuristic and metaheuristic approaches like genetic algorithms, simulated annealing, local search methods, or particle swarm optimization to find feasible solutions within reasonable computational times. Moreover, the existing charging infrastructure is often inadequate to support the rapid increase in EV adoption. This challenge is exacerbated by the "range anxiety" experienced by potential EV users, a concern driven by the insufficient availability of charging stations (Shrestha et al., 2022). As a result, innovative solutions are urgently needed to optimize the electric vehicle charging scheduling problem, which necessitates strategic planning for charging station utilization and the effective management of energy resources. Efficient scheduling of charging times is essential to minimize waiting times and maximize the effective use of charging infrastructure.

To tackle this challenge, this research focuses on developing innovative optimization algorithms specifically aimed at addressing electric vehicle charging scheduling problems. By enhancing the efficiency of charging station utilization and optimizing the allocation of resources, the study aims to contribute significantly to the sustainable management of electric vehicle infrastructures. The proposed algorithms will not only improve the operational performance of charging stations but also facilitate a more effective integration of EVs into the existing power grid. This work seeks to provide practical solutions that align with the growing demand for electric vehicles while ensuring reliable and efficient energy consumption.

In conclusion, while the rise of electric vehicles represents a critical step toward a more sustainable future, it is accompanied by significant challenges that must be addressed. The development of robust charging infrastructures and innovative scheduling algorithms will be pivotal in unlocking the full potential of EVs as a viable alternative to traditional vehicles, thus contributing to a cleaner environment and a more sustainable energy landscape.

2 Methodology

This research addresses the electric vehicle (EV) charging scheduling problem, which is classified as NP-hard due to its complexity and the multitude of constraints involved. To find feasible and near-optimal solutions within reasonable computational times, the use of optimization algorithms is proposed, specifically a Greedy Randomized Adaptive Search Procedure (GRASP) and a Cellular Processing Algorithm (CPA) that incorporates GRASP within each processing cell (PCell).

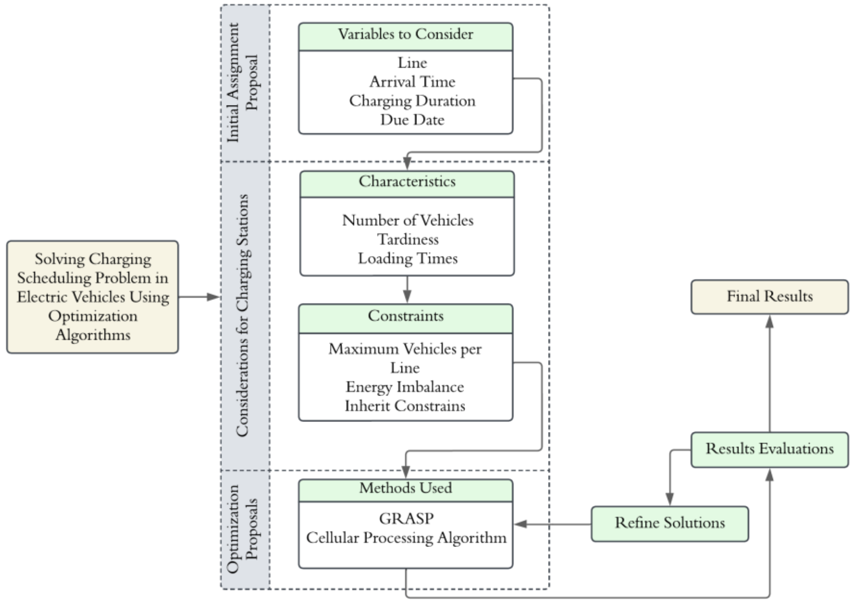

Fig. 1. Methodology flowchart for solving the EV charging scheduling problem using optimization algorithms.

Figure 1 illustrates the overall methodology employed in this study. The process begins with an initial assignment proposal, considering essential variables such as line assignment, arrival time, charging duration, and due date. Specific characteristics of the charging stations are then incorporated, including the number of vehicles, tardiness, and loading times. Various constraints are also considered, such as the maximum number of vehicles per line, energy imbalance, and inherent problem constraints. Based on these considerations, optimization methods GRASP and CPA are applied to generate and refine solutions, ultimately aiming to minimize total tardiness in the EV charging schedule.

The primary objective is to minimize total tardiness, defined as the waiting time beyond the specific charging time for each vehicle. The problem involves scheduling n vehicles across m charging lines, considering variables such as arrival time (ti), charging duration (pi), due date (di), and the characteristics of the charging stations. Constraints include a maximum number of vehicles per line, energy balance across lines, and the condition that vehicles cannot depart before their charging is complete. Given the NP-hard nature of the problem, heuristic and metaheuristic algorithms are suitable for obtaining high-quality solutions.

A GRASP algorithm is first implemented to generate initial solutions. GRASP is an iterative process combining a greedy randomized construction phase and a local search procedure to refine solutions. In the version with Due Date Reordering (Algorithm 1), vehicles are reordered based on their due dates to prioritize those with earlier deadlines.

Algorithm 1

```
Sol←∅
best←∅
LoadVehicles()
InitializeParameters()
ReorderVehiclesByDueDate()
for i←1 to MaxIter do
Sol←AssignVehicles()
totalTardiness←CalculateTardiness(Sol)
if totalTardiness<tardiness(best) then
 best←Sol
 end if
 end for
 Output: best
```

In the version without DDR (Algorithm 2), vehicles are not reordered, the algorithm processes them in their original sequence.

Algorithm 2

```
Sol←∅
best←∅
LoadVehicles()
InitializeParameters()
for i←1 to MaxIter do
Sol←AssignVehicles()
totalTardiness←CalculateTardiness(Sol)
if totalTardiness<tardiness(best) then
best←Sol
end if
end for
Output: best
```

To enhance solution quality, a Cellular Processing Algorithm (CPA) is incorporated, where each PCell applies the GRASP algorithm (Algorithm 3). The CPA allows for parallel processing and information sharing between cells, potentially leading to better solutions.

Algorithm 3

```
Input: Number of PCells n
Output: Optimized results
Initialize PCells n
for each PCell i from 1 to n do
Initialize parameters for PCell[i]
end for
repeat
for each PCell i from 1 to n do
Apply GRASP:
Initialize candidate solution
repeat
Select component from candidates based on greedy criteria
Add component to candidate solution
until stopping criteria for construction are met
Local Search(candidate solution)
end for
Check for Stagnation:
if stagnation is detected then
Print "Stagnation detected, terminating process."
break
end if
Preference Communication Process for Roulette Selection Parameter Adjustment
until termination criteria are met
Output: finish
```

The algorithms were implemented using C++, and the code structure follows the pseudo-codes presented. Key components include Data Structures, which comprise custom data constructs designed to efficiently handle vehicle and scheduling information. Sorting Mechanisms are applied to organize vehicles by due dates or other prioritized criteria, supporting a streamlined greedy selection process. Constraint Handling involves algorithmic checks for operational constraints, such as the maximum number of vehicles per production line and adherence to energy balance requirements, before assigning vehicles to slots. Performance Metrics focus on total tardiness, providing a quantitative measure for evaluating solution quality. The scheduling model for vehicle charging management considers various essential variables and constraints, each representing specific aspects of the assignment process to ensure operational efficiency.

Line Assignment (Li): The charging line to which vehicle i is assigned.
Arrival Time (ti): The time at which vehicle i arrives at the charging station.
Charging Duration (pi): The time required to fully charge vehicle i.
Due Date (di): The latest time by which vehicle i should be charged and ready for departure.
Number of Vehicles (n): Total vehicles to be scheduled.
Tardiness (Ti): The delay beyond the due date for vehicle i.
Loading Times (Ci): The actual time when vehicle i starts charging.
Maximum Vehicles per Line: Each charging line can accommodate a limited number of vehicles simultaneously.
Energy Imbalance: The difference in the number of vehicles or total charging time across lines should not exceed a specified threshold to maintain energy balance.
Inherent Constraints: Vehicles cannot be removed from the charging line before their charging is complete.

The optimization process involves applying the GRASP algorithm to generate initial solutions and then refining them using the CPA. The GRASP algorithm constructs solutions by iteratively selecting components based on a greedy function and randomization to explore diverse regions of the solution space. The CPA enhances this process by allowing multiple PCells to process solutions in parallel, sharing information to avoid local optima and improve overall solution quality.
After generating initial solutions, they are evaluated based on total tardiness and other performance metrics. If necessary, solutions are refined using local search procedures within the GRASP algorithm or by adjusting parameters in the CPA to escape stagnation and explore new solutions. The optimized schedules aim to minimize total tardiness while satisfying all constraints. The methodologies employed provide a balance between solution quality and computational efficiency, making them suitable for practical applications in EV charging station management.

3 Results

In this section, the comparative results of the proposed methods for scheduling electric vehicle (EV) charging are presented, the standard Greedy Randomized Adaptive Search Procedure (GRASP), an enhanced version incorporating Dynamic Demand Response (GRASP DDR), and the Cellular Processing Algorithm (PCEL). The objective is to minimize the total tardiness in EV charging schedules across various instances, ensuring efficient utilization of charging infrastructure and adherence to user requirements.

Table 1 displays the total tardiness obtained by each method across 30 Type 1 instances. Each instance represents a specific set of vehicles and scheduling constraints. The total tardiness is calculated as the sum of delays beyond the desired completion times for all scheduled vehicles. Lower tardiness values indicate better scheduling performance. The results in Table 1 show that the standard GRASP method outperforms GRASP DDR and PCEL in the majority of instances. Specifically, GRASP achieves lower total tardiness in 17 out of 30 instances. This suggests that GRASP provides more efficient scheduling in terms of minimizing delays. However, GRASP DDR outperforms GRASP and PCEL in 7 instances, and PCEL outperforms both GRASP and GRASP DDR in 6 instances, indicating that each algorithm can be more effective under certain conditions. These results suggest that while GRASP is generally superior, GRASP DDR and PCEL have potential advantages in specific scenarios. For example, GRASP DDR excels in dynamic environments with variable resource availability, and PCEL proves particularly effective in highly congested situations.

Table 1. Tardiness in hours for Type 1 Instances GRASP DDR vs GRASP vs PCEL

Type 1 Instances	GRASP DDR	GRASP	PCEL
Instance 1	305.2	**271.6**	388.8
Instance 2	**153.1**	159.6	315.5
Instance 3	113.3	**98.3**	141.7
Instance 4	147.3	**78.4**	153.8
Instance 5	**112.3**	114.5	191.3
Instance 6	153.2	**36.4**	174.1
Instance 7	672.3	599.2	**354.7**
Instance 8	**97.8**	132.3	148.5
Instance 9	261.4	246.6	**160.9**
Instance 10	138.2	**90.7**	144.3
Instance 11	249.0	**200.5**	295.9
Instance 12	125.9	**118.9**	198.3
Instance 13	110.4	**83.4**	176.2
Instance 14	532.2	395.1	**141.2**
Instance 15	324.6	**144.7**	222.4
Instance 16	**92.5**	107.4	208.8
Instance 17	**88.2**	94.0	257.2
Instance 18	**163.9**	204.5	292.5
Instance 19	**180.6**	200.1	243.9
Instance 20	198.8	**194.7**	233.9
Instance 21	129.5	**75.1**	82.5
Instance 22	74.3	**70.2**	192.2
Instance 23	111.8	**96.3**	391.0
Instance 24	290.8	254.3	**205.9**
Instance 25	322.6	218.6	**206.1**
Instance 26	145.4	**113.7**	168.1
Instance 27	113.6	118.2	**79.15**
Instance 28	257.6	**180.5**	221.3
Instance 29	325.9	**296.8**	410.8
Instance 30	294.3	**151.0**	179.3

To further evaluate the proposed methods, results were compared with those obtained by other authors in the literature. Table 2 presents this comparison, including results from a Genetic Algorithm (GA) (García-Álvarez et al., 2015), a GRASP method, and a Memetic Algorithm (MA) (García-Álvarez et al., 2018).

Table 2. Methods Comparison for Type 1 Instances

N	Δ	GA	GRASP	MA	GRASP DDR*	GRASP*	PCEL*
20	0.2	5442.3	5348.3	5210.8	6285.8	**5145.3**	6580

In Table 2, N represents the number of vehicles, and Δ is a parameter related to the balance constraint. The GRASP method developed in this study achieves the lowest total tardiness among all compared algorithms, demonstrating superior performance in minimizing delays in EV charging schedules under the given constraints. Although GRASP DDR and PCEL do not outperform the GRASP implementation in terms of total tardiness, they remain competitive when compared to the GA, the GRASP, and the MA. This indicates that GRASP DDR and PCEL have potential benefits that may be realized in specific scenarios. Specifically, GRASP DDR shows advantages in scenarios with moderate congestion or variability in charging times or due dates, while PCEL demonstrates strengths in highly challenging conditions, such as high congestion, tight deadlines, or limited charging infrastructure. To gain deeper insights into the scheduling patterns of the employed methods, the visual representations generated by the algorithms were analyzed.

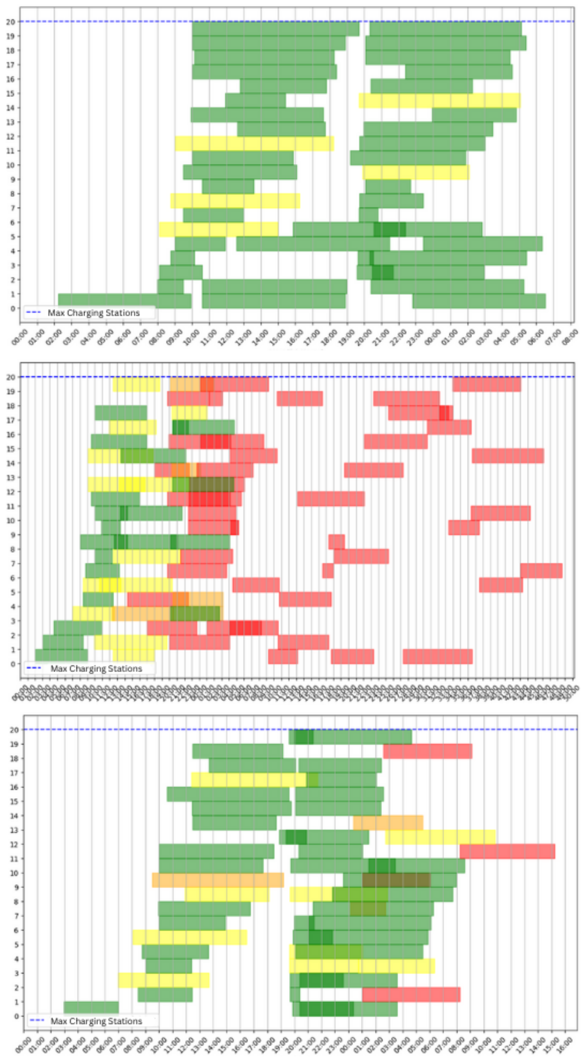

Fig. 2. Scheduling Vehicles Over Time at Charging Stations using GRASP DDR.

In the Gantt charts, the X-axis represents time, while the Y-axis corresponds to individual charging stations, with a dotted blue line indicating the maximum capacity constraint. Each colored bar represents an EV charging session. When a session exceeds its predetermined due time, meaning the finish time is later than the set deadline, the excess time is computed as its tardiness.

Sessions that finish exactly on time without tardiness are colored green. For sessions with tardiness, a continuous color gradient is used, yellow indicates slight delays, orange signals moderate delays, and red represents severe delays. Rather than assigning fixed numerical thresholds to these colors, the tardiness values are normalized relative to the maximum tardiness observed in the instance. This approach transparently converts any delay beyond the due time into a quantifiable measure of tardiness while maintaining an adaptable visual representation.

Figure 2 presents the vehicle schedule over time for the three lines under a Type 1 instance (instance 7) with N = 20 and Δ = 0.2, as generated by the GRASP DDR algorithm. Although the figure primarily illustrates the temporal distribution of tardiness, the analysis reveals an overall tardiness of 672.3 hours.

Fig. 3. Scheduling Vehicles Over Time at Charging Stations using GRASP.

Figure 3 illustrates the vehicle scheduling over time across the three lines for the same Type 1 instance (instance 7) with N = 20 and Δ = 0.2, as obtained using the GRASP algorithm. The underlying analysis indicates a total tardiness of 599.1 hours.

Fig. 4. Scheduling Vehicles Over Time at Charging Stations using CPA.

In contrast, Figure 4 presents the schedule for the same instance and parameters, but obtained using the Cellular Processing Algorithm (CPA). The graphical distribution of tardiness over time corresponds to a markedly lower cumulative delay of 354.7 hours, highlighting the enhanced performance of the CPA approach in minimizing delays under these conditions.

Analyzing Figures 2, 3, and 4 reveals that the CPA achieves more efficient vehicle-to-charging-station scheduling, resulting in fewer vehicles experiencing significant tardiness. In contrast, the GRASP and GRASP DDR methods display charging session distributions that, in certain cases, lead to increased delays, particularly during peak demand periods. These observations corroborate that each algorithm exhibits specific advantages depending on the scenario.

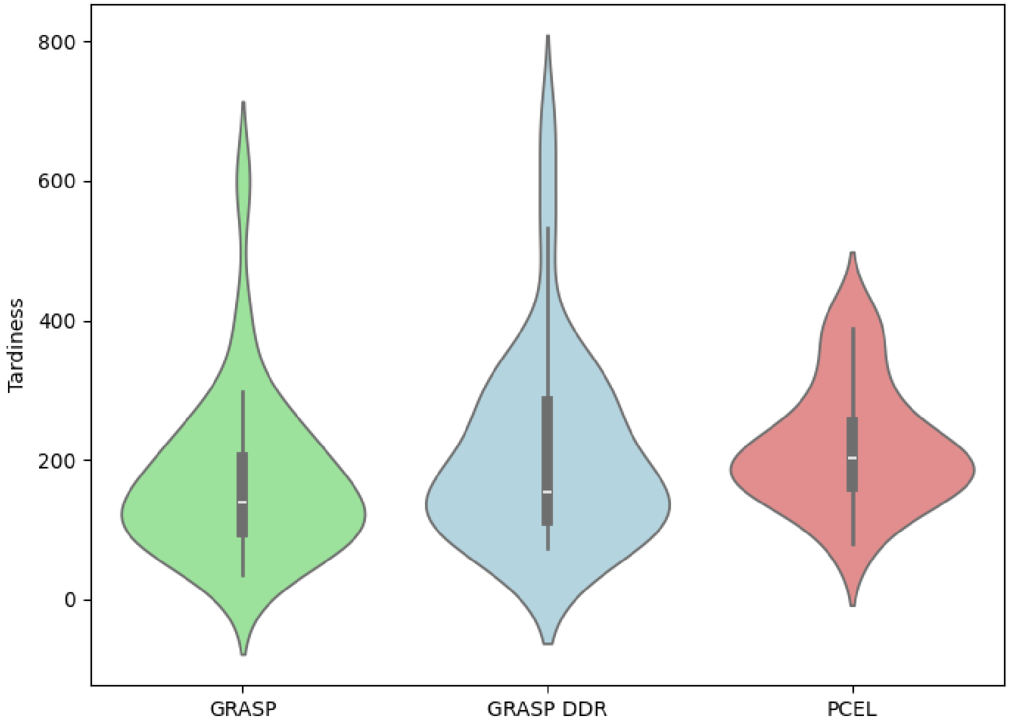

Fig. 5. Tardiness Distribution for GRASP, GRASP DDR and PCEL Models.

The violin plot in Figure 5 shows the distributions of tardiness values for each model, highlighting the density and variability of the data. It reveals that all models have right-skewed distributions, with GRASP and GRASP DDR showing more pronounced tails due to high maximum tardiness values compared to their medians. This indicates that while GRASP performs best on average, it may struggle with certain instances, leading to higher variability. PCEL, despite higher average tardiness, offers more stability, which could be crucial in applications requiring predictable outcomes.

4 Conclusions and future work

The comparative analysis of GRASP, GRASP DDR, and CPA for electric vehicle charging scheduling demonstrates that the standard GRASP algorithm provides superior solutions, achieving the lowest total tardiness across the evaluated instances and constraints. GRASP consistently outperforms GRASP DDR and CPA, as well as other algorithms from the literature, such as Genetic and Memetic Algorithms, highlighting its effectiveness in optimizing EV charging schedules and reducing delays. This underscores the robustness of the GRASP approach in contributing to more efficient management of charging infrastructure.

The GRASP method developed in this study also surpasses other algorithms from the literature, such as the Genetic Algorithm and Memetic Algorithm, under the instances and constraints considered. This highlights the effectiveness of the approach in optimizing EV charging schedules and reducing delays.

While GRASP DDR and CPA do not outperform GRASP overall, their competitive performance in certain instances suggests that they may be more suitable under specific conditions. Further investigation is needed to identify these conditions and fully exploit the potential of GRASP DDR and CPA.

The analysis of the scheduling visualizations provides valuable insights into how each method allocates charging sessions over time. The graphical representations help to identify congestion periods and capacity constraints that affect scheduling efficiency; these tools are key to understanding and improving scheduling algorithms. In summary, this study demonstrates that the proposed algorithms are effective tools for scheduling EV charging, improving upon previous methods and contributing to more efficient management of charging infrastructure.

As outlined in the methodology, future work will focus on the improvement of the Cellular Processing Algorithm (CPA) for EV charging scheduling. It is anticipated that the CPA, with its ability to model complex interactions and dynamic behaviors within the system, will outperform the current algorithms. The CPA's inherent parallelism and adaptability make it a promising approach for handling the increasing complexity and scale of EV charging networks.

Future work will involve implementing and testing the CPA in various scenarios, comparing its performance against GRASP and GRASP DDR. It is expected that the CPA will provide improved scheduling efficiency, reduced tardiness, and enhanced scalability. Additionally, the aim is to investigate the integration of machine learning techniques to further optimize scheduling decisions based on real-time data and predictive analytics.

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