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ORIGINAL RESEARCH

Optimizing the electrical vehicle parking and charging assignments: a balanced approach using mathematical modeling

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Abstract
This study introduces a mathematical modeling framework specifically designed for electric vehicles (EVs) to tackle intricate challenges in real-world transportation scenarios, focusing on two critical areas: parking optimization and vehicle scheduling. The first component centers on developing a mathematical model for optimizing vehicle placement within parking lots to minimize maneuvering costs that significantly impact parking efficiency. This model enhances the overall effectiveness of parking space utilization by strategically determining vehicle positioning. The second aspect addresses idle time minimization for charging electric vehicles through the idle time minimization for electric vehicle charging scheduling model. This mathematical model efficiently schedules multiple EVs by dynamically assigning charging slots based on arrival and departure times and the charging station's capacity, thereby reducing waiting time and improving the charging infrastructure's efficiency. The real-time vehicle scheduling optimization model also focuses on the dynamic management of vehicle scheduling, assigning vehicles to service tasks while considering vehicle availability, time constraints, and energy levels. Numerical examples are provided to substantiate the proposed models, illustrating their practical applications and validating their reliability and effectiveness in optimizing vehicle management systems. The study concludes by examining the spatial distribution of vehicles and ideal assignments, demonstrating how these mathematical models facilitate informed decision-making in real-time, ultimately contributing to enhanced operational efficiency in vehicle management systems.

Keywords Electric vehicles · Charging scheduling · Mathematical modeling · Optimization · Mathematical programming

1 Introduction

Parking lot optimization is critical in urban planning and transportation management, particularly in densely populated areas with limited parking space and high demand (Parmar et al. 2020; Dudaklı and Baykasoğlu 2024). Efficient parking space utilization enhances drivers' convenience and reduces traffic congestion, environmental pollution, and urban sprawl (Litman 2020). However, traditional parking lot design and management methods often need to improve to maximize the efficiency of available space. The scope of this study centers around optimizing parking lot management by developing a mathematical model that addresses both vehicle placement and EV charging schedules (Selvik et al. 2022; Abdelmoumene et al. 2024). These mathematical models are designed to minimize various cost functions, including maneuvering costs, idle time, and fuel consumption, while also integrating real-time dynamic management for effective parking space utilization.

In recent years, there has been growing interest in applying mathematical modeling techniques to address the challenges of parking lot optimization (Shen et al. 2019; Zhang et al. 2023). By employing mathematical models, researchers and practitioners can analyze various factors influencing parking lot efficiency, such as vehicle placement, traffic flow, and user behavior (Shen et al. 2019; Łach and Svyetlichnyy 2024). Moreover, these models enable the formulation of

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optimization algorithms aimed at minimizing different cost functions, including travel time, congestion, fuel consumption, and environmental impact. In the landscape of modern urban development, the management of parking facilities is a pivotal challenge, influencing the flow of vehicular traffic and the overall efficiency and sustainability of transportation networks (Louati et al. 2024). With the proliferation of vehicles in urban areas, the demand for parking spaces has surged, exacerbating issues such as congestion, emissions, and inefficient resource allocation (Kong et al. 2023). In response to these pressing challenges, optimizing vehicle placement within parking lots has emerged as a critical area of focus for researchers, policymakers, and urban planners alike (Kirschner and Lanzendorf 2020; Fadhel et al. 2024). This research embarks on a journey to explore the intricacies of parking lot management through the lens of mathematical modeling, with a primary objective of minimizing various cost functions associated with this domain.

For instance, Zhao et al. (2024) proposed a real-time EV charging scheduling model using ordinal optimization to manage charging flexibility efficiently. Similarly, Beermann (2024) introduced a war strategy optimization algorithm to optimize EV charging operations, focusing on minimizing delays and costs. Zhao and Liang (2023) developed a smart grid-based framework incorporating reinforcement learning to address dynamic EV charging and discharging schedules. Moreover, Salam et al. (2024) emphasized the importance of integrating real-time traffic data with charging schedules to enhance operational efficiency. These studies highlight the growing recognition of dynamic management in EV-related optimization while underscoring the need for comprehensive models that integrate real-time factors effectively (Veza et al. 2024; Sumitkumar and Al-Sumaiti 2024).

The primary focus is on creating a comprehensive framework that improves the efficiency of traditional parking lot systems and enhances the operational performance of EV infrastructure. The study aims to optimize static parking allocation and dynamic, real-time vehicle scheduling in urban environments. This research holds significant practical implications for urban planners, transportation authorities, and policymakers (Orieno et al. 2024; Choudhary et al. 2024). By improving space utilization and reducing inefficiencies, the study alleviates traffic congestion, lowers emissions, and promotes more sustainable urban transportation networks (Jamadar et al. 2022; Lv and Shang 2023; Adnan et al. 2024). Moreover, integrating EV charging management aligns with the global push toward greener cities. As cities grow and evolve, the need for effective strategies to optimize parking resources becomes increasingly urgent (Singh 2023). Real-time data in parking management allows for dynamic adjustments based on vehicle flow and demand, further enhancing system adaptability (Jamadar et al. 2023a, b). The model also provides a scalable solution, making it applicable to various urban settings and adaptable to evolving technologies, such as autonomous vehicles.

By delving into mathematical modeling, we aim to harness the power of quantitative analysis to unravel the complexities inherent in parking lot management. The mathematical modeling offers a systematic and rigorous framework for understanding the dynamics of parking facilities, enabling us to formulate optimization problems that address key factors such as space utilization, traffic flow, and environmental impact (Lee et al. 2023). At the heart of this research lies the recognition that traditional approaches to parking lot management often need to be revised to address the multifaceted challenges urban centers face. The conventional methods based on heuristic rules or intuitive decision-making need more precision and scalability to optimize parking resources in a rapidly changing urban environment (Feng et al. 2022). By contrast, mathematical modeling provides a principled approach to problem-solving, allowing us to formulate and solve optimization problems with clear objectives and constraints (Tian et al. 2024). We propose a mathematical model for vehicle placement to minimize maneuvering costs, applied to two mathematical models: optimizing electric vehicle charging schedules to reduce idle time and dynamically managing vehicle assignments in real time. Our results demonstrate significant improvements in EV charging efficiency and real-time vehicle scheduling, highlighting the model's practical applicability and effectiveness. Figure 1 illustrates a parking layout consisting of three rows of parking spaces, with four stacks allocated to each row. This configuration provides a visual representation of the spatial arrangement that will be analyzed and optimized in the context of the proposed mathematical modeling approach for parking lot optimization.

Through this study, we seek to advance state-of-the-art parking lot management by developing mathematical models that minimize different cost functions relevant to various optimization domains. By optimizing vehicle placement within parking lots to minimize these costs, we aim to enhance urban transportation networks' overall efficiency, sustainability, and user experience (Alho et al. 2018; Jamadar et al. 2023a, b). Although extensive research has been conducted on parking lot optimization, a significant gap remains in integrating EV charging schedules with real-time dynamic vehicle management. Previous studies have focused mainly on static optimization for traditional vehicles, neglecting the complexities introduced by EVs and real-time scheduling demands.

The paper is organized as follows. Section 2 explains the literature review of the proposed problem. Section 3 developed a mathematical model and its numerical illustration. Section 4 discussed the methodology part of the proposed study. Section 5 shows the case of the mathematical model and its numerical illustrations, while Sect. 6 discuss the

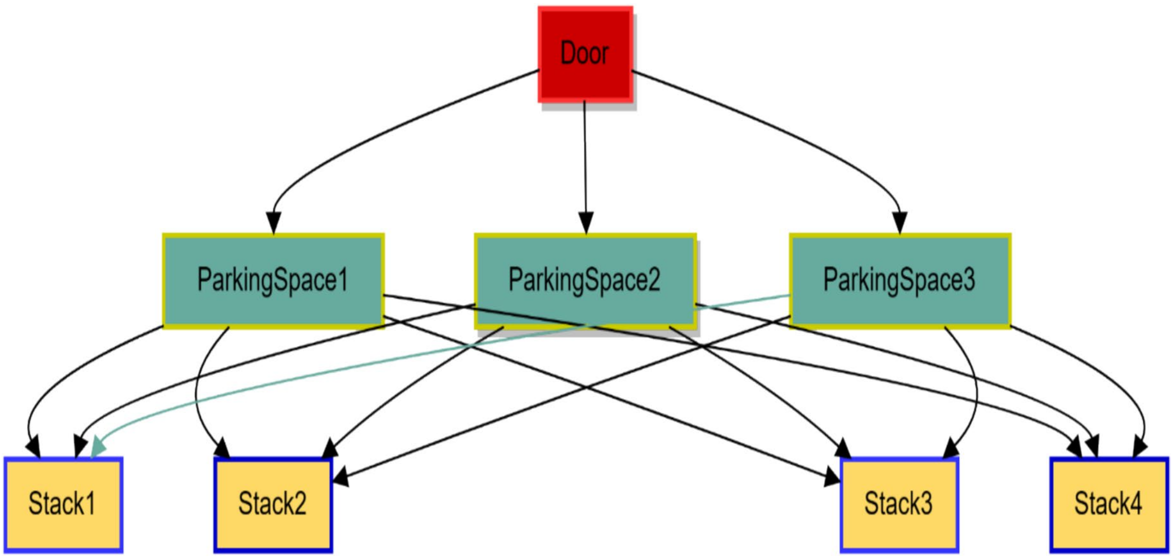

Fig. 1 Parking layout with three spaces and four stacks each

managerial and practical implications. Finally, Sect. 7 discusses the conclusion, discussion and future direction.

2 Literature review

The literature review is divided into two sections to comprehensively understand different aspects of the proposed problem. Each subsection focuses on a specific topic relevant to the research, namely the role of EVs in the transportation sector and efficient parking methods, and energy management systems in transportation.

2.1 Role of EVs in the transportation sector and efficient parking methods

EVs are increasingly pivotal in revolutionizing the transportation sector (Patil 2021). As society seeks to reduce greenhouse gas emissions and combat climate change, EVs offer a promising solution by providing a cleaner alternative to traditional internal combustion engine vehicles (Rossi and Bianchi 2024). Improvements in battery technology have led to longer driving ranges and quicker charging periods for EVs, making them more feasible for daily usage (Ghosh 2020; Aijaz and Ahmad 2022). Additionally, governments everywhere are putting policies into place to encourage the adoption of EVs, such as infrastructure expenditures in charging stations, tax reductions, and subsidies (Qadir et al. 2024).

According to Kouhi and Moradi (2024) and Aldhanhani et al. (2024), a new method was proposed to efficiently park multiple vehicles, focusing on space optimization and safety. The method utilizes connected fifth-degree polynomials and genetic algorithms to plan the optimal vehicle paths, ensuring smooth and collision-free movements within parking lots. The mathematical model accounts for vehicle dynamics, predicting real-time movements to avoid collisions while reducing parking time. By framing the problem as an optimization task, the researchers successfully minimized vehicle maneuvering time and maximized the efficiency of parking spaces. In addition, the model incorporated real-world constraints such as vehicle speed and turning radii, making it more applicable to practical scenarios. On a similar note, Mirzaei and Kazemi (2020) and Squalli (2024) developed a model for planning EV parking lots, considering electrical constraints like current flow and voltage limits at different locations. Their approach ensures optimal parking and energy efficiency, preventing potential overloads on the grid, which is crucial for large-scale EV adoption. These studies highlight the importance of integrating parking infrastructure with energy management systems to achieve sustainable and efficient operations.

Beyond the above consideration, the pivotal research established by Hadian et al. (2020) developed a planning model for EV charging stations that balances electricity demand. They used a combination of optimization algorithms and simulation to schedule EV charging and discharging efficiently. Liu et al. (2020) proposed a new method for effectively managing intelligent parking lots that use hydrogen storage, particularly in uncertain environments where power prices fluctuate. Hossain et al. (2023) and Niri et al. (2024) examined the approaches of various groups involved in the EV battery industry, including government agencies, mining companies, and vehicle and battery manufacturers, to address the challenge of reducing carbon emissions from transportation while meeting sustainability goals. Zeb et al. (2020) and Carey (2023) demonstrated the effective use of all three EV chargers to handle EV charging needs while reducing costs, power losses, and strain on distribution transformers. They developed a model that predicts hourly EV charging demand by considering vehicle arrival and departure times and distances traveled. Sun et al. (2023) and Zahoor et al. (2023) investigated the interconnections between factors such as EV usage, economic growth, urban development, renewable energy consumption, population size, and carbon dioxide emissions in five major countries: the USA, China, France, Germany, and Norway.

A new method for determining the optimal size of energy storage systems for EV parking lots and DGs in modern distribution networks was created by Abo-Elyousr et al. (2022). In these types of problems, various advanced optimization algorithms were used to optimize the different objectives subject to the constraint. Ahmad et al. (2022) investigated different methods proposed by researchers to identify optimal locations for EV charging stations. They evaluated these solutions using various techniques, including Chance constraint programming, GA, and NSGA-2. Shareef et al. (2016) conducted a comprehensive review of EV charging technologies and their impact on society. They discussed the optimal placement and size of EV charging stations in different environments. Chen et al. (2013) analyzed data from over 30,000 personal trips to determine the locations and durations of public parking. Using mathematical programming and data analysis, they created mathematical equations to predict parking demand and optimally assigned locations for EV charging stations. The aim was to reduce the expenses for EV users to access charging stations while ensuring sufficient charging demand.

2.2 Energy management systems in transportation

Energy management systems in transportation play a crucial role in optimizing the utilization of energy resources and enhancing the efficiency of various transportation modes, particularly in the context of EVs and microgrids (Sami et al. 2021; Khan et al. 2024). These systems encompass a range of technologies and methodologies aimed at managing energy consumption in transportation networks. Integrating renewable energy sources, advanced control optimization algorithms, and energy management systems enables the effective management of EV charging infrastructure, balancing supply and demand while minimizing costs and environmental impact (Li et al. 2020; Kumar et al. 2023).

Apart from this, Ghadikolaei et al. (2024) developed a new MOPSO-HS system to manage energy in a microgrid under an uncertain environment. The system considers renewable energy sources, parking lots, and variations in energy demand. MOPSO-HS is an algorithm that combines two existing algorithms, mutant multi-objective particle swarm optimization, and harmony search, to manage energy in the microgrid. They developed a method to efficiently manage energy in a small-scale power grid, even when there is uncertainty regarding factors such as renewable energy availability and fluctuating energy demand. Zanvettor et al. (2022) investigated the energy pricing in parking lots for EVs, mainly when the number of vehicles and their charging times are uncertain. They proposed a novel pricing strategy that guarantees a daily profit for the parking lot with a high level of confidence. Betkier et al. (2021) and Trinko et al. (2023) proposed a new mathematical model for transporting vehicles carrying hazardous, oversized, or valuable cargo within a transportation network. The method was implemented into a computer program using the Neo4j graph database, enabling the analysis and assessment of these routes.

However, on the other hand, Park and Choi (2021) proposed a new control method for electric four-wheel drive vehicles using model predictive control. The method considers vehicle constraints, predicts future movement, and provides stable control inputs for path tracking. Additionally, they developed a more efficient algorithm for linear programming and optimized torque distribution for improved performance. Mozaffari et al. (2020) developed an algorithm to predict EV behavior and estimate the number of EVs at charging stations. They formulated a model to optimize the placement of charging stations and upgrade the power grid, considering various stakeholders' needs. They also developed a simplified energy consumption model for EVs at charging stations, aiding future infrastructure planning. Abapour et al. (2019) proposed a strategic and forward-looking approach for planning distributed generation systems and EV parking facilities while considering demand response (DR) programs. They used Stackelberg game theory to model the interaction between the distribution company and customers participating in DR initiatives. Mortaz et al. (2019) developed a mathematical model to decide where and how large vehicle-to-grid (V2G) facilities should be in a microgrid. They proposed a novel approach for identifying the most suitable location and size of parking facilities that integrate V2G technology into a microgrid connected to the primary power grid. Shafie-Khah et al. (2017) proposed a model for EV parking lot operators to participate in energy markets while considering uncertainties in EV owner behavior. Yi and Bauer (2016) addressed the challenge of identifying optimal locations for charging stations in urban areas. They focused on two primary objectives: maximizing the accessibility of charging stations to households and minimizing energy costs associated with electric transportation. Furthermore, they also proposed a decision-making framework that considers factors related to energy efficiency and household accessibility to enhance overall electric transportation infrastructure planning.

Given this importance, the potential research study of Bagula et al. (2015) and Sirbiladze et al. (2022) proposed a method for determining the optimal locations of nodes in wireless sensor networks, specifically for intelligent parking systems. They proposed a precise solution method based on integer linear programming to address this issue effectively. Fazelpour et al. (2014) studied the optimal design and placement of a distributed generation (DG) system in an electrical grid to enhance voltage stability and reduce power loss. They examined selecting a hybrid renewable energy system that connects to the grid to meet the DG system's requirements. Ko and Jang (2013) examined the potential of the online electric vehicle (OLEV) system as a future public transportation option in South Korea. They proposed a mathematical model and optimization approach to determine the optimal placement of power transmitters and battery size for the OLEV-based mass transit system. Su and Chow (2011) proposed an efficient method for controlling multiple plugin hybrid EVs charging at a municipal parking station. The method considers factors such as energy cost, the current charge level of each vehicle, and the remaining charging time.

Although considerable advancements have been made in optimizing EV parking and charging infrastructure, significant gaps remain. Existing models primarily focus on static optimization, often overlooking the dynamic and real-time complexities of vehicle scheduling and charging management (Tan et al. 2022; Elghanam et al. 2024). Moreover, many studies must fully account for integrating vehicle parking optimization and energy management in scenarios where real-time decision-making is crucial (Jamadar et al. 2023a, b; Abdelmoumene et al. 2024). Additionally, the optimization methods in these studies often fail to address the idle time during charging, which can significantly affect the overall efficiency of EV charging stations. This research contributes by addressing these gaps by developing two novel mathematical models. The ITMEVCS model aims to minimize idle time in charging schedules, dynamically optimizing charging slot assignments based on EV arrival and departure times. The RTVSO model, on the other hand, focuses on real-time vehicle scheduling, optimizing vehicle assignments to service requests by considering vehicle availability, energy levels, and time constraints. These models, validated through numerical illustrations, offer practical solutions for real-world EV management challenges, ensuring efficient parking and charging while reducing operational costs and improving decision-making in dynamic environments.

3 Formulation of the mathematical model

3.1 Mathematical model 1

In the initial part of this section, the notations are outlined and presented in Table 1. Following this, mathematical modeling is introduced and elaborated.

$$Z_1 = \sum_{i\in I}\sum_{j\in I}\sum_{k\in K}\sum_{l\in L} d_{ij}.x_{ijkl} \tag{1}$$

Equation (1) calculates and minimizes the total maneuvering cost of the proposed mathematical model.

$$\sum_{j\in I}\sum_{k\in K}\sum_{l\in L} x_{ijkl} = 1\, for\; i \in I \tag{2}$$

Constraint (2) indicates that each vehicle must be parked exactly once. No vehicle can be parked in multiple positions, and each must be assigned to a parking position.

$$\sum_{i\in I} x_{ijkl} \le 1\, for\, j \in J, k \in K, l \in L \tag{3}$$

Constraint (3) indicates that each parking space in the proposed model can accommodate at most one vehicle in a given position. There are no overlaps or conflicts in vehicle positions within the parking area.

$$\sum_{k\in K}\sum_{l\in L} d_{ij}.x_{ijkl} \le \sum_{k\in K}\sum_{l\in L} d_{i(j+1)}.x_{i(j+1)kl}\, for\; i \in I, j \in J \tag{4}$$

Constraint (4) indicates that vehicles can only be removed in the order they are parked, preventing the situation where a vehicle parked behind another must be removed first.

Table 1 Notations of mathematical model 1

Sets	
I	Set of vehicles, $i = 1,2,\ldots..,\|I\|$
J	Set of stacks, $j = 1,2,\ldots..,\|I\|$
K	Set of positions in each stack, $k = 1,2,\ldots..,\|K\|$
L	Set of parking spaces, $l = 1,2,\ldots..,\|L\|$
Decision variables	
x_{ijkl}	Binary variable indicating whether vehicle i is parked in stack j, position k, parking space l
Parameters	
d_{ij}	Distance or maneuvering cost to remove vehicle i from stack j

$$x_{ijkl} \in \{0,1\}\, for\, i \in I, j \in J, k \in K, l \in L \tag{5}$$

Equation (5) represents the binary constraints of the mathematical model.

This generalized model can be customized by providing specific values for the maneuvering cost (d_{ij}) based on the layout and characteristics of the parking lot. The objective is to determine the optimal placement of vehicles that minimizes the overall maneuvering cost.

3.2 Numerical illustration and analysis

An organization in a bustling city center grapples with inefficiencies in its parking lot. With limited space and a constant stream of vehicles, the parking manager faces a significant challenge in optimizing the placement of cars to minimize maneuvering efforts during vehicle removal. The parking lot comprises three spaces (X, Y, and Z) and three stacks (A, B, and C). Eight vehicles arriving at a different time must be strategically placed to avoid unnecessary maneuvers during departure. An optimization model is proposed to identify the optimal vehicle configuration within a parking lot to minimize the total maneuvering cost.

Let, Sets: $I = \{1,2,3,4,5,6,7,8\}$, J = {A, B, C}, L = {X, Y, Z}, Maneuvering Costs: Let us assume the maneuvering costs d_{ij} for removing vehicle i from stack j are as follows:

$d_{1A} = 1,\ d_{2A} = 2,\ d_{3A} = 3,\ d_{4A} = 4,\ d_{5A} = 5,\ d_{6A} = 6,\ d_{7A} = 7, d_{8A} = 8$

$d_{1B} = 2,\ d_{2B} = 3,\ d_{3B} = 4,\ d_{4B} = 5,\ d_{5B} = 6,\ d_{6B} = 7,\ d_{7B} = 8, d_{8B} = 9$

$d_{1C} = 3,\ d_{2C} = 4,\ d_{3C} = 5,\ d_{4C} = 6,\ d_{5C} = 7,\ d_{6C} = 8,\ d_{7C} = 9, d_{8C} = 10$

$$Z = \sum_{i=1}^{8} \sum_{j\in\{A,B,C\}} \sum\nolimits_{K=1}^{4} \sum_{l\in\{X,Y,Z\}} d_{ij}.x_{ijkl} \tag{6}$$

Equation (6) calculates the minimization of the total maneuvering cost of the proposed mathematical model 1.

$$\sum_{j\in\{A,B,C\}} \sum\nolimits_{k=1}^{4} \sum_{l\in\{X,Y,Z\}} x_{ijkl} = 1\, for\, i \in \{1,2,..,8\} \tag{7}$$

Constraint (7) states that each vehicle must be parked exactly once.

$$\sum\nolimits_{i=1}^{8} x_{ijkl} \le 1\ for\, j \in \{A,B,C\}, k \in \{1,2,3,4\}, l \in \{X,Y,Z\} \tag{8}$$

Constraint (8) represents each parking space that can accommodate at most one vehicle at a given position.

$$\sum_{K=1}^{4} \sum_{l\in\{X,Y,Z\}} d_{ij}.x_{ijkl} \le \sum_{K=1}^{4} \sum_{l\in\{X,Y,Z\}} d_{i(j+1)}.x_{i(j+1)kl}$$
$$for\, i \in \{1,2,..,7\}\, j \in \{A,B,C\} \tag{9}$$

Constraint (9) indicates that vehicles can only be removed in the order they are parked.

$$x_{ijkl} \in \{0,1\}\, for\, i \in \{1,2,..,8\},\ j \in \{A,B,C\}, k \in \{1,2,3,4\}, l \in \{X,Y,Z\} \tag{10}$$

Equation (10) shows the binary constraints of the proposed mathematical model 1.

In this proposed numerical example, Table 2 shows the optimal solutions for vehicle placement in the parking lot using the Pulp optimization library in Python.

The optimization model successfully achieved optimal vehicle placement in the parking lot, resulting in total maneuvering costs 36.0. The solution status was deemed optimal. The configuration indicates that Vehicle 1 is parked in Stacks A, Position 1, and Space Y, followed by strategically arranged placements for Vehicles 2 to 8. This optimal arrangement streamlines the parking process and minimizes the overall maneuvering efforts required for vehicle removal. These results offer valuable insights for the parking manager, enhancing the efficiency of the parking system and exemplifying the effectiveness of mathematical optimization in addressing real-world challenges. Figure 2 illustrates the optimal placement of the eight EVs in the parking lot, ensuring efficient use of space and accessibility to charging stations. The arrangement maximizes the parking lot's capacity while facilitating smooth entry and exit for each vehicle based on arrival and departure times.

4 Proposed methodology

In this study, we tackled several challenges in parking lot management and real-time vehicle scheduling optimization by developing three distinct mathematical models. Leveraging the Pulp optimization library in Python, each model was formulated and solved to address specific objectives.

Table 2 Optimal solution for vehicle placement in the parking lot

Vehicle	Stacks	Position	Space
1	A	1	Y
2	A	3	X
3	A	2	X
4	A	4	Y
5	A	2	Z
5	A	4	Z
7	A	3	Z
8	A	4	X

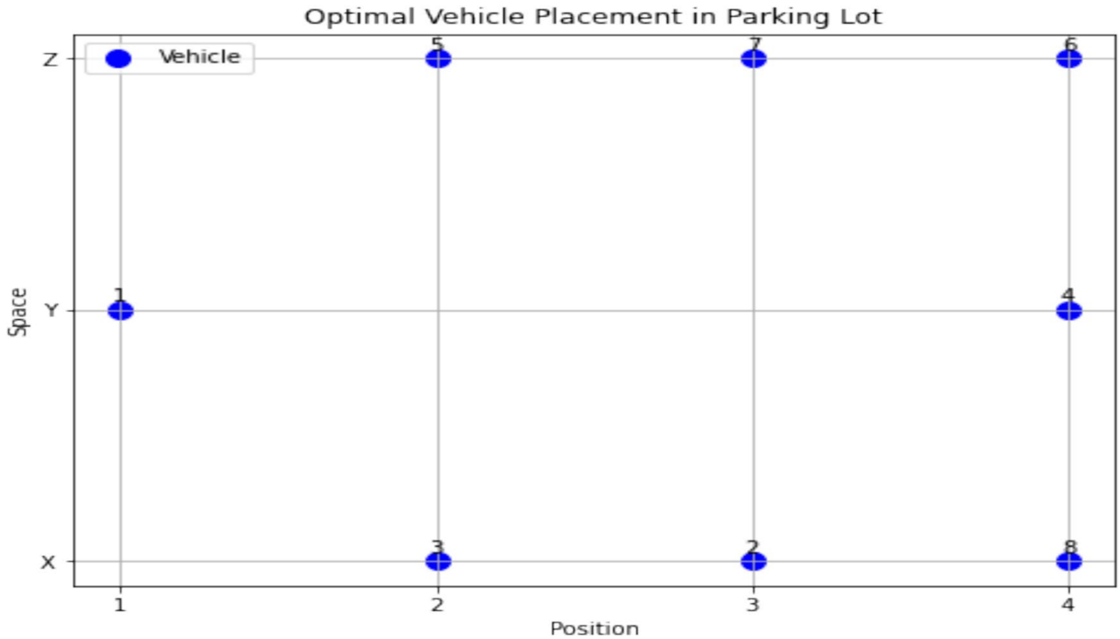

Fig. 2 Depicts the optimal vehicle placement in the parking lot

Firstly, we addressed the issue of optimizing vehicle placement in a parking lot with three spaces and four stacks to minimize inefficiencies associated with vehicle removal. Formulating a mathematical model using linear programming, we defined decision variables for vehicle placement and considered constraints on parking space capacities and sequential removal order. By implementing the model with Pulp, we obtained the optimal configuration of vehicles, significantly reducing the overall maneuvering efforts required for vehicle removal. Next, we focused on minimizing idle time for electric vehicle charging scheduling (ITMEVCS). Formulating a mathematical optimization model, we dynamically allocated charging slots while considering arrival and departure times, charging station capacities, and idle time minimization. Implementing the model with Pulp allowed us to optimize the charging schedule, significantly reducing idle time and enhancing charging infrastructure efficiency.

Finally, we developed a real-time vehicle scheduling optimization (RTVSO) model to manage vehicles dynamically based on operational conditions and diverse requirements. We formulated an optimization approach to optimally assign vehicles to service requests over discrete time intervals, considering vehicle availability, location constraints, and energy levels. By implementing and solving the model with Pulp, we achieved an optimized real-time vehicle scheduling solution that minimized idle time, efficient resource allocation, and response times. The Pulp optimization library enabled us to implement and solve each mathematical model efficiently, providing practical solutions to complex optimization problems in parking lot management and real-time vehicle scheduling.

5 Application of mathematical models

5.1 Idle-time minimization for electric vehicle charging scheduling (ITMEVCS)

The mathematical model of the ITMEVCS is designed to address the complex challenges associated with scheduling EVs for charging, emphasizing the reduction of idle time and efficient utilization of charging resources. The primary objective of the ITMEVCS is to dynamically allocate charging slots for EVs while considering their arrival and departure times, charging station capacity, and the need to minimize idle periods when an EV is stationed at the charging station but not actively charging. The model employs binary decision variables to determine the optimal charging schedule for each EV, considering constraints such as the station capacity, individual EV charging power, and temporal limitations. By minimizing idle time, the ITMEVCS aims to enhance the charging infrastructure's overall efficiency, contributing to EV's effective integration into the energy grid.

5.1.1 Mathematical model 2

Decision variable: Let x_{it} be a binary decision variable that equals one if EV i is scheduled to charge at time slot t, and 0 otherwise.

Parameters: A_i is the arrival time of EV I, D_i is the departure time of EV I, C_t is the charging capacity at time slot t, P_i is the charging power of EV I, and n represents the number of EVs.

$$\text{Minimize} Z_2 = \sum_{i=1}^{n} \sum_{t=A_i}^{D_i - 1} 1 - x_{it} \quad \forall t \tag{11}$$

Constraint (11) minimizes the total idle time, where idle time is the time when an EV is at the charging station but not charging.

Subject to the constraints

$$\sum_{t=A_i}^{D_i - 1} x_{it} = 1 \quad \forall i \tag{12}$$

Constraint (12) shows that each EV must be charged during its time at the station.

$$\sum_{i=1}^{n} P_i x_{it} \le C_t \quad \forall t \tag{13}$$

Equation (13) shows the charging station capacity constraint.

$$x_{it} \in \{0,1\} \quad \forall i, t \tag{14}$$

Equation (14) represents the binary decision variable constraints.

$$x_{it} = 0 t < A_i \, or \, t \ge D_i \tag{15}$$

Equation (15) represents the time slot constraints of the proposed mathematical model.

This mathematical model aims to minimize idle time while ensuring that each EV is charged during its scheduled time at the station and respecting the capacity constraints of the charging station. Binary variables x_{it} indicates the EV i is scheduled to charge at time t. The objective function reflects the total idle time we seek to minimize.

5.1.2 Numerical illustration and analysis

In this case, the primary objective is to minimize idle time for a fleet of eight EVs, each with distinct arrival and departure times, charging power requirements, and a shared charging station with fixed capacities at different hourly time slots.

Let Sets: i : Set of EVs ($i = 1,2,\ldots,8$), t : Set of hourly time slots ($t = 1,2,\ldots,10$)

Decision variable: Let x_{it} be a binary decision variable that equals one if EV i is scheduled to charge at time slot t, and 0 otherwise.

Parameters: $n = 8$ (number of EVs), Time slots = 10 (number of hourly time slots), Charging capacity = [1,1,1,1,1,1,1,1,1,1] (charging capacity at each time slot), Arrival and departure times for each EV, Charging power for each EVs.

Table 3 presents the charging schedule for eight EVs, detailing their arrival and departure times and respective charging power requirements. Each EV is assigned specific time slots for charging, ensuring the station's capacity constraints are respected.

$$\text{Minimize} Z = \sum_{i=1}^{8} \sum_{t=A_i}^{D_i - 1} 1 - x_{it} \quad \forall t \tag{16}$$

Constraint (16) is designed to minimize the total idle time in the proposed numerical illustration.

Subject to the constraints

$$\sum_{t=A_i}^{D_i - 1} x_{it} = 1 \quad \forall i \tag{17}$$

Constraint (17) shows that each EV must be charged during its time at the station.

Table 3 Electric vehicles charging schedule

EVs	Arrival time	Values	Departure times	Values	Charging power	Values
EV1	A1	2	D1	7	P1	2
EV2	A2	4	D2	9	P2	1
EV3	A3	1	D3	6	P3	3
EV4	A4	3	D4	8	P4	2
EV5	A5	2	D5	5	P5	1
EV6	A6	5	D6	10	P6	2
EV7	A7	1	D7	4	P7	1
EV8	A8	3	D8	7	P8	2

$$\sum_{i=1}^{8} P_i x_{it} \leq C_t \quad \forall t \tag{18}$$

Equation (18) represents the charging station capacity constraint.

$$x_{it} \in \{0,1\} \quad \forall i, t \tag{19}$$

Equation (19) represents the binary decision variable constraints.

$$x_{it} = 0 \text{ for } t < A_i \, or \, t \geq D_i \tag{20}$$

Equation (20) represents the time slot constraints.

This numerical illustration captures the essence of the hour or day-ahead scheduling problem for 8 EVs, considering their arrival and departure times, charging capacities, and the need to minimize idle time while respecting constraints.

The eight EVs' hour- or day-ahead scheduling problem was successfully addressed using the Pulp library in Python. The optimization model efficiently allocates charging schedules, minimizing idle time while adhering to individual arrival and departure constraints and charging station capacity limitations. The optimal schedule indicates the specific time slots for each EV to charge, demonstrating the effectiveness of mathematical optimization and the Pulp library in finding resource-efficient solutions for complex scheduling problems. The optimal charging schedule for eight EVs was determined through a mathematical model that minimizes idle time while considering individual arrival and departure times and charging station capacity constraints. The schedule reveals that EV 1 charges during time slots 3 and 4, EV 2 charges at time slot 9, EV 3 charges at time slot 2, EV 4 charges at time slot 5, EV 5 charges at time slot 3, and EV 8 charges at time slot 7. This result optimally allocates charging resources to each EV, ensuring efficient utilization and adherence to specific operational constraints. Figure 3 illustrates the optimal charging schedule for the eight EVs, ensuring that each EV is charged within its specified time window while minimizing idle time. The schedule adheres to the charging station's capacity constraints, effectively distributing charging times across the available hourly slots.

5.2 Real-time vehicle scheduling optimization (RTVSO)

The RTVSO represents a comprehensive mathematical model designed to dynamically and efficiently make real-time vehicle management decisions based on current operational conditions and diverse requirements. This model considers vehicle availability, time constraints, location constraints, and optimization objectives to formulate an

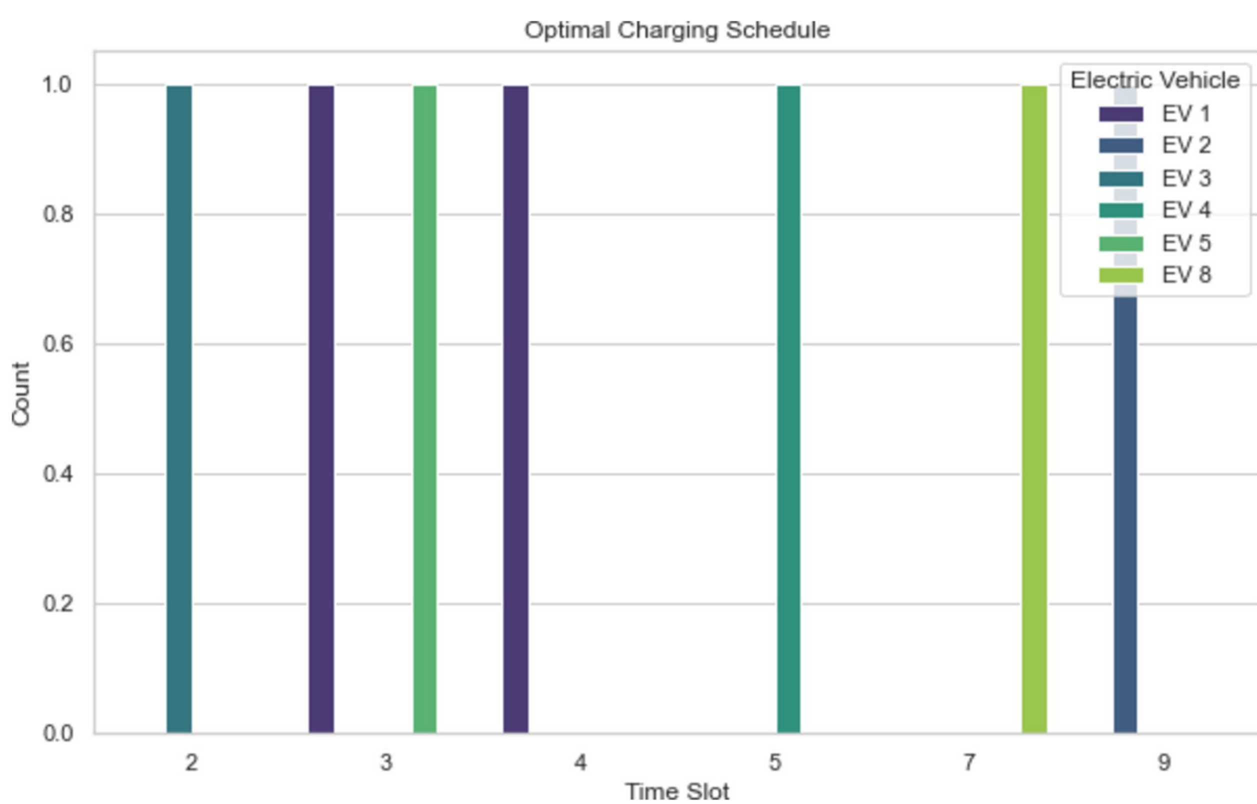

Fig. 3 Depicts the optimal scheduling charge of EVs

approach that optimally assigns vehicles to service requests over discrete time intervals. RTVSO minimizes the total assignment cost associated with assigning vehicles to requests at specific times. The model ensures that each vehicle is precisely located at a single location at any given time and that each request is assigned to a single vehicle. Additionally, energy constraints are incorporated, accounting for the energy levels of the vehicles and the distances traveled. By addressing these complexities in real-time scheduling, the RTVSO aims to enhance the efficiency and effectiveness of vehicle management systems in dynamic environments.

5.2.1 Mathematical model 3

Table 4 outlines the essential notations for the RTVSO model, including sets, parameters, and decision variables, such as the assignment of vehicles to locations and requests over time.

$$\text{Minimize } Z_3 = \sum_{v \in V} \sum_{r \in R} \sum_{t} C_{vrt}.x_{vrl}(t) \tag{21}$$

Constraint (21) minimizes the total assignment of vehicles to requests overtime cost, where C_{vrt} is the cost associated with assigning vehicle v to request r at time t.

Subject to the constraint

$$\sum_{l \in L} x_{vrl}(t) = 1 \quad \forall v \in V, \forall t \tag{22}$$

Constraint (22) represents that each vehicle must be at exactly one location at any given time.

$$\sum_{v \in V} x_{vrl}(t) \le 1 \quad \forall l \in V, \forall t \tag{23}$$

Constraint (23) represents that each location must have at most one vehicle at any given time.

$$\sum_{v \in V} y_{vr}(t) = 1 \quad \forall r \in R, \forall t \tag{24}$$

Constraint (24) represents that each request must be assigned to precisely one vehicle at any given time.

$$y_{vr}(t) \le x_{vrl}(t) \quad \forall v \in V, r \in R, \forall t \tag{25}$$

Constraint (25) computes that a vehicle can only be assigned to a request if it is at the pickup location at the requested time.

$$y_{vr}(t) = y_{vr}(t+1) \quad \forall v \in V, \forall r \in R, \forall t \tag{26}$$

Constraint (26) computes that once a vehicle is assigned to a request, it must stay assigned until completion.

$$e_v - \sum_{l \in L} d_{vl}(t).x_{vrl}(t) \ge 0 \quad \forall v \in V, \forall t \tag{27}$$

Equation (27) shows the energy constraints for each vehicle.

5.2.2 Numerical illustration and analysis

In this numerical example, there are eight vehicles (V), eight locations (L), and four service requests (R). The distance matrix (d_{vl}) represents the travel distance between vehicles and locations. The energy levels (e_v) indicate the initial energy level of each vehicle. Requests are associated with pickup (p_r) and destination (d_r) locations. The objective is to minimize the total assignment cost (Z_3) for real-time vehicle scheduling, where the $C_{vrt} = 1, \forall v, rt$ cost is assumed to be 1 for each assignment. The mathematical model includes constraints that ensure that each vehicle is at exactly one location at any given time, each location has at most one vehicle, each request is assigned to precisely one vehicle, and vehicles can only be assigned to a request if they are at the pickup location at the requested time. The

Table 4 Notations of mathematical model 3

Sets	
V	The set of vehicles, where $v \in V$
R	The set of requests for service, where $r \in R$
Parameters	
t	The time index representing discrete time intervals
L	The set of locations where $l \in L$
$d_{vl}(t)$	The distance between vehicle v and location l at time t
p_r	The pickup location of the request r
d_r	The destination location of the request r
e_v	The energy level of vehicle v
Decision variables	
$x_{vrl}(t)$	A binary variable indicating whether vehicle v is at location l at time t
$y_{vr}(t)$	A binary variable indicating whether vehicle v is assigned to request r at time t

Table 5 Distance matrix d_{vl}

S. no.	A	B	C	D	E	F	G	H
1	10	5	15	20	8	12	18	25
2	12	8	14	10	15	7	20	22
3	15	10	18	22	10	8	25	30
4	8	6	12	16	5	10	15	18
5	14	12	20	25	8	6	22	28
6	18	15	25	30	12	8	28	35
7	22	20	30	35	15	12	35	40
8	25	22	35	40	18	14	40	45

Table 6 Pickup locations p_r and destination locations d_r

r	(p_r, d_r)
a	(A, B)
b	(C, D)
c	(E, F)
d	(G, H)

Table 7 Energy levels e_v

Entity	Energy levels
e_1	30
e_2	40
e_3	35
e_4	25
e_5	30
e_6	45
e_7	40
e_8	50

energy constraints were also considered for each vehicle. The solution to this optimization problem was implemented in Python using the Pulp library, a linear programming tool, allowing for efficient real-time vehicle scheduling based on current operational conditions and diverse requirements.

Let Vehicles: V = {1, 2, 3, 4, 5, 6, 7, 8}, Locations: L = {A, B, C, D, E, F, G, H}, Requests: R = {a, b, c, d}.

Table 5 presents the distance matrix d_{vl}, showing the travel distances between each vehicle and the eight possible locations.

Table 6 lists the pickup and destination locations for the four service requests. For example, request a requires a pickup from Location A and a drop-off at Location B, while request d involves moving from Location G to Location H.

Table 7 specifies the energy levels of the vehicles, which influence how far each vehicle can travel.

The optimization model successfully produced a real-time scheduling solution with an objective value of 4.0. they are using the Pulp optimization library in Python. The vehicle locations resulting from the optimization model show an adequate distribution of vehicles across various locations in real-time. Specifically, Vehicle 1 is stationed at Location B, Vehicle 2 at Location G, Vehicle 3 at Location A, Vehicle 4 at Location C, Vehicle 5 at Location D, Vehicle 6 at Location H, Vehicle 7 at Location E, and Vehicle 8 at location F. Furthermore, the model has made optimal real-time assignments, ensuring that each vehicle is assigned to a specific request. It is encouraging to observe that the idle time has been minimized. Specifically, Vehicle 2 was assigned to request d, Vehicle 3 to request a, Vehicle 4 to request b, and Vehicle 7 to request c. This spatial arrangement indicates a well-organized deployment of vehicles, optimizing their positioning to respond efficiently to incoming requests and dynamic changes in the operational environment. This allocation reflects the model's successful real-time decision-making capabilities, contributing to the overall effectiveness of the vehicle management system. The distribution of vehicles across different locations is vital for minimizing response times and ensuring prompt and reliable service.

In Figs. 4 and 5, the vehicle location heatmap and vehicle assignments heatmap illustrate the effectiveness of the real-time vehicle scheduling optimization model by visually representing vehicle distribution and assignments within the parking lot management. These figures highlight optimal vehicle placements and efficient assignment strategies.

The idle-time minimization for electric vehicle charging scheduling and the real-time vehicle scheduling optimization models both focus on optimizing scheduling processes in distinct contexts. The mathematical model of ITMEVCS addresses the challenge of scheduling EVs for charging, with the primary objective of minimizing idle time at charging stations while considering constraints like station capacity, EV charging power, and arrival and departure times. In contrast, the RTVSO model tackles real-time vehicle assignment to service requests, aiming to minimize the total assignment cost while adhering to constraints like vehicle availability, location, time, and energy levels. While ITMEVCS is concerned with the efficient allocation of charging slots for EVs, RTVSO dynamically manages vehicle assignments to service requests in real

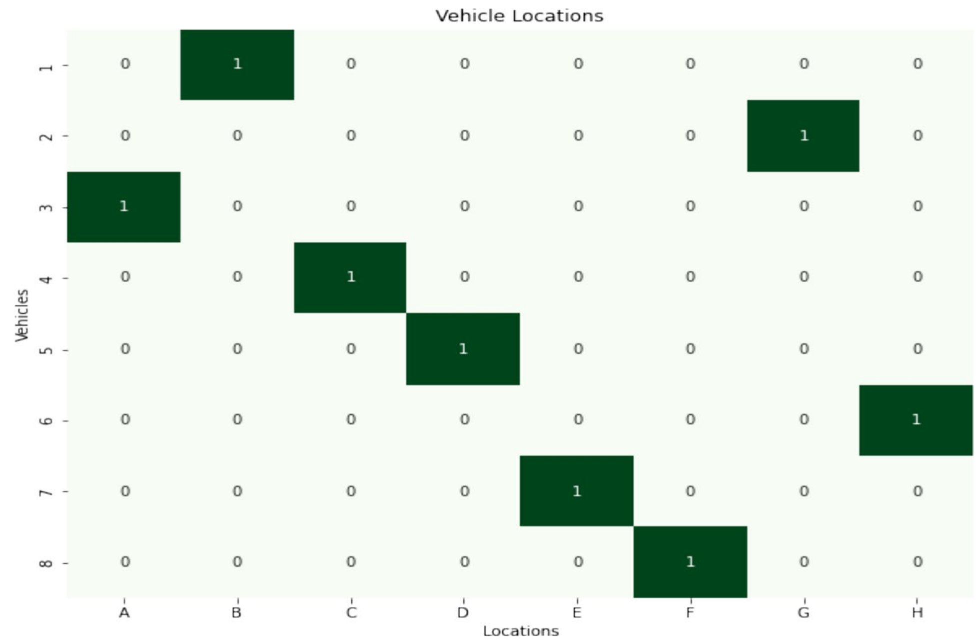

Fig. 4 Shows the vehicle locations' heatmap

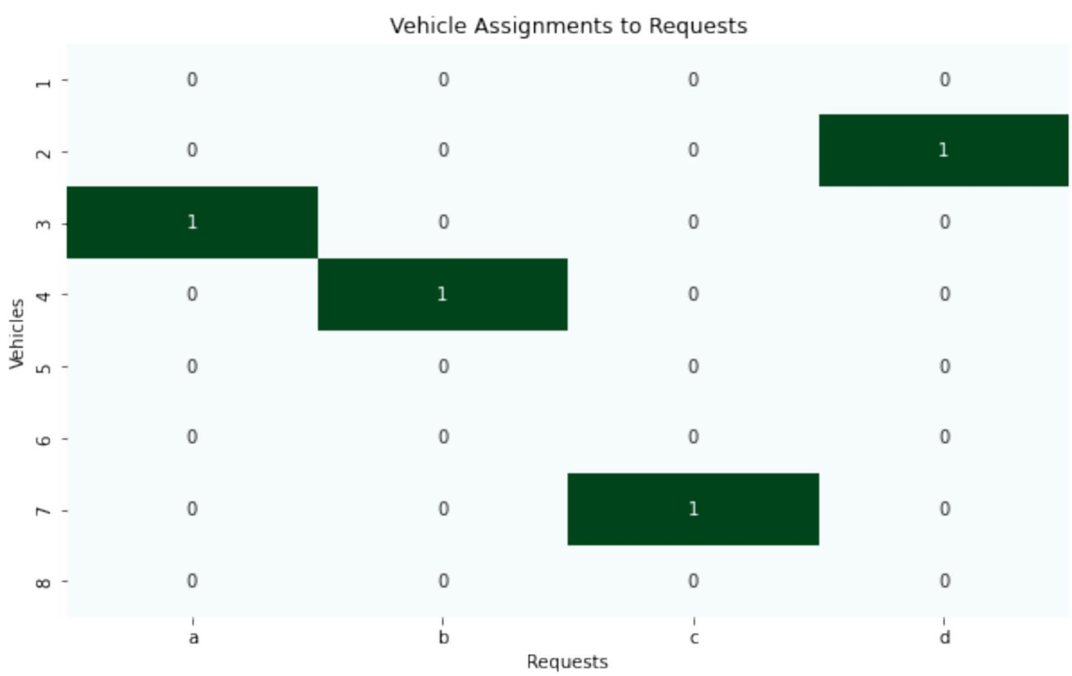

Fig. 5 Shows the vehicle assignments heatmap

time, considering operational factors like travel distances and energy consumption. Both models leverage optimization techniques to enhance resource efficiency in their respective domains.

6 Managerial and practical implications

The mathematical models developed in this study carry significant managerial and practical implications for stakeholders in the transportation and urban planning sectors. First, optimizing vehicle placement in parking lots can reduce operational costs by minimizing maneuvering times and improving space utilization. Managers responsible for parking facilities can leverage these insights to make data-driven decisions that enhance overall efficiency, leading to higher customer satisfaction and increased revenue (Lukic Vujadinovic et al. 2024). Moreover, the idle-time minimization for electric vehicle charging scheduling can optimize the use of charging infrastructure, addressing the growing demand for EVs. It is particularly relevant for charging station managers, who can implement these models to streamline operations, reduce wait times for users, and ultimately promote the adoption of EVs, aligning with broader sustainability goals.

Furthermore, the real-time vehicle scheduling optimization model equips fleet managers with the tools to respond dynamically to operational challenges. Managers can enhance service delivery and operational reliability by enabling more efficient resource allocation and quicker response times to service requests, which is crucial in competitive markets (Yuvaraj et al. 2024; Kahlen et al. 2024). Integrating these models within intelligent city initiatives can facilitate a collaborative approach among stakeholders, including local governments, transportation authorities, and private sector partners (Wolniak et al. 2024). This collaboration can lead to better urban mobility solutions, reduced congestion, and a lower environmental footprint, aligning with city-wide sustainability objectives (Alamoudi et al. 2024). Finally, implementing these mathematical models offers a pathway for organizations to improve their operational frameworks and contribute to developing more intelligent, sustainable urban environments. By embracing these optimization strategies, managers can play a pivotal role in shaping the future of urban transportation, driving innovation, and enhancing the quality of life for city residents.

7 Conclusion

In this study, we have presented three comprehensive mathematical models to address complex challenges in parking lot management and real-time vehicle scheduling optimization. These models leverage mathematical optimization techniques to allocate resources and efficiently make informed decisions in dynamic environments. The first mathematical model, focused on optimizing vehicle placement in parking lots, demonstrated the effectiveness of mathematical modeling in minimizing maneuvering costs. The model successfully determined optimal vehicle placements by formulating binary decision variables and constraints to represent parking configurations and vehicle movements, thereby enhancing parking lot efficiency and reducing maneuvering efforts. The second mathematical model, dedicated to ITMEVCS, showcased the application of mathematical optimization in enhancing the efficiency of charging infrastructure. By dynamically allocating charging slots for EVs while considering arrival and departure times, charging station capacities, and minimizing idle periods, the model contributed to the effective integration of EVs into the energy grid. The numerical result of this model showed a significant reduction in idle time, optimizing the charging schedule and enhancing overall charging infrastructure efficiency.

Finally, the third mathematical model of RTVSO addressed the challenges of dynamically managing vehicles based on current operational situations and requirements. By formulating an optimization approach that optimally assigns vehicles to service requests over discrete time intervals while considering factors such as vehicle availability, location constraints, and energy levels, the model demonstrated the capability to enhance the efficiency and effectiveness of vehicle management systems in dynamic environments. The numerical result of this model showed an optimized real-time vehicle scheduling solution with minimized idle time, efficient resource allocation, and minimized response times. Numerical illustrations accompanying each model provided practical insights into their applications, showcasing their efficacy in real-world scenarios. By integrating these models, our study showcases the synergistic benefits of using mathematical optimization to enhance vehicle placement, EV charging efficiency, and real-time vehicle scheduling, providing a cohesive framework for improved decision-making in vehicle management systems.

Moreover, integrating these mathematical models provides a holistic framework for enhancing transportation systems' overall efficiency and sustainability. By addressing various aspects of vehicle management—from optimizing parking lot configurations to minimizing idle times in EV charging and facilitating real-time scheduling—this study highlights the importance of mathematical optimization in responding to the increasing demands of urban mobility. The findings emphasize the potential for these models to improve operational efficiency and contribute to reducing environmental impacts associated with vehicle emissions and energy consumption. As urban areas continue to grow and the adoption of EVs increases, implementing such optimization strategies will be crucial for creating more innovative, more efficient transportation ecosystems. Future research can explore further refinements to these models, incorporating advanced algorithms and real-time data analytics to enhance their adaptability and performance in ever-changing urban environments.

7.1 Discussion and future directions

The mathematical models presented in this study offer practical solutions to complex challenges in parking lot management and real-time vehicle scheduling optimization. By leveraging mathematical optimization techniques, these models enable decision-makers to make informed decisions, enhance resource allocation efficiency, and improve overall system performance (Yan et al. 2021; Shariatzadeh et al. 2024; Choudhary et al. 2024). Moving forward, integrating these models with innovative city initiatives could further enhance urban mobility and sustainability by optimizing vehicle placement in parking lots and dynamically managing vehicle scheduling in real-time, contributing to reduced congestion and environmental impact (Abdelmoumene et al. 2024; Tian et al. 2024). Additionally, future research could focus on enhancing the scalability and adaptability of the models to accommodate larger parking lots, vehicle fleets, and more complex operational environments.

Incorporating machine learning algorithms and data analytics techniques could improve predictive capabilities, allowing for preemptive resource allocation and better adaptation to changing conditions. Furthermore, exploring evolutionary algorithms, NSGA-2 and 3, multi-objective optimization approaches could balance competing objectives such as minimizing maneuvering costs, reducing idle time, and optimizing energy consumption. Real-world implementation and validation of the models in collaboration with industry partners and local authorities would provide valuable insights into their practical applicability and performance. Lastly, involving stakeholders in the design process and fostering stakeholder engagement can ensure that the models meet their specific needs and address practical challenges effectively, fostering greater acceptance and adoption in real-world settings. These mathematical approaches can contribute to more efficient, sustainable, and resilient urban transportation systems through ongoing innovation and refinement.

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Declarations

Conflict of interest We want to declare that we have no conflicts of interest that could potentially influence the publication of this research work.

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