Multi-Criteria Modeling for Smart Parking and Parking Reservation

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Abstract

In the realm of smart cities, issues related to vehicle parking have increasingly contributed to traffic congestion, primarily due to drivers searching for vacant spots and the inefficient management by parking operators. Therefore, smart parking systems must continuously be enhanced with real-time models that can reflect the availability of parking spaces and improve the utilization of parking capacity, thereby addressing part of these challenges. This paper proposes a two-stage hybrid approach aimed at optimizing parking space reservations in smart parking systems. The model enables drivers to locate the most time-efficient parking spot within these systems. In the first stage, the parking space is evaluated within an environment defined by fixed capacity. In the second stage, the most suitable parking spot is made available through a hierarchical parking management system using a search-based method. The approach is grounded in Markov Chain modeling, which is employed to accurately estimate the number of vehicles requiring reservations. Underestimation of this figure results in insufficient demand adjustments, whereas overestimation leads to additional operational costs. Therefore, the proposed system uses Markov Chains for capacity forecasting and mathematical models to simulate the temporal movement of vehicles within the parking facility to determine the proportion of reserved versus regular parking spaces. This temporal analysis improves reservation predictions and yields an average occupancy rate of approximately 0.032, with 15 successful reservations recorded over a 24-hour period.

Keywords: *Smart Parking, Parking Capacity, Parking Reservation, Markov Chain.*

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1. Introduction

In the contemporary urban landscape, the rapid rise in vehicle ownership coupled with limited land availability has intensified the pressure on city infrastructure to provide efficient parking solutions. Traffic congestion, fuel wastage, and increased carbon emissions are often exacerbated by drivers searching for vacant parking spots, a challenge that has necessitated the evolution of smart parking systems as a crucial element of smart cities [1]. These systems aim to optimize space utilization, reduce traffic load, and improve overall commuter satisfaction by integrating real-time monitoring, reservation, and allocation functionalities. However, the complexity of dynamic urban environments requires sophisticated models that account for space availability, user preferences, arrival time variability, and predictive demand estimation.

Recent advancements in artificial intelligence, machine learning, Internet of Things (IoT), and blockchain technologies have led to the emergence of intelligent parking solutions that are adaptive, autonomous, and user-centric [2]. For instance, smart sensors and real-time data analytics have been employed to monitor occupancy and guide vehicles toward available spaces efficiently, while blockchain-based frameworks offer secure, decentralized platforms for managing transactions and access control [3, 4]. Nevertheless, despite these innovations, a persistent challenge remains in accurately predicting availability and allocating spaces in a manner that minimizes user inconvenience and system-wide inefficiencies.

To address these concerns, researchers have proposed reservation-based parking systems that allow users to book spaces in advance, thereby reducing the uncertainty associated with parking availability [5]. A two-stage reservation and allocation model, as demonstrated in recent studies, incorporates factors such as parking unpunctuality and prioritizes allocation based on both time-efficiency and spatial proximity to the user's destination [5]. Such models benefit significantly from predictive mechanisms like Markov chains, which can estimate time-varying parking demand and vehicle movement dynamics [6, 7]. These tools provide a foundation for real-time simulations that dynamically adapt to incoming data and behavioral variations in user patterns.

Parking space reservation is not merely a logistical improvement but also a matter of environmental and social significance. Eco-friendly parking models that prioritize sustainability metrics—such as reduced vehicle idle time, emission minimization, and energy efficiency—are receiving increased attention in urban mobility strategies [8]. These systems integrate environmental goals into their operational logic, thereby aligning with broader global sustainability agendas. Moreover, advanced detection algorithms such as Hybrid DenseNet and deep learning-based frameworks have demonstrated high accuracy in identifying available parking spots in real-time, thereby enhancing the reliability of the reservation system [9, 10].

The evolution from static to dynamic, sensor-driven, and learning-enabled parking systems has also ushered in new paradigms in user interaction and decision-making. The incorporation of Monte Carlo simulation techniques, for example, enables planners to assess and optimize space distribution under uncertainty, offering robust insights into usage patterns and service delivery optimization [11]. Similarly, the application of multi-agent systems in parking allocation introduces a decentralized intelligence that adapts to localized constraints and preferences, promoting scalability and autonomy [12].

Simulation-based models play a critical role in the evaluation and validation of these smart parking systems before their deployment. Through comprehensive modeling environments like MATLAB or similar platforms, variables such as entry rates, reservation durations, user priorities, and system constraints can be systematically tested [13]. Time-step controlled simulations provide the granularity needed to capture dynamic fluctuations in demand and supply, while visual outputs help identify high-demand blocks and bottlenecks in real-time. These insights not only support design optimization but also improve user satisfaction through data-informed space management.

Moreover, the integration of social welfare considerations in parking space allocation adds another layer of strategic importance. Systems designed with the objective of maximizing collective utility—rather than individual benefit alone—can contribute to fairer and more equitable urban transport environments [14]. Such models evaluate trade-offs between individual user convenience and overall system efficiency, a perspective especially relevant in shared public spaces.

From a systems engineering standpoint, the implementation of deep learning classifiers such as Extreme Learning Machines (ELMs) in smart occupancy detection has shown promising outcomes in terms of speed and precision [15]. These classifiers facilitate rapid identification of empty slots, enabling faster decision-making and enhancing the responsiveness of the reservation system. In parallel, Markov-based queueing models have been adopted to estimate wait times, predict congestion scenarios, and manage vehicular inflows more effectively [7]. These models account for stochasticity in arrival and departure times, providing a more realistic and adaptive decision framework.

With urban populations projected to grow significantly in the coming decades, the role of parking infrastructure in sustainable city planning cannot be understated. Integrating smart parking within the broader smart city ecosystem not only improves urban livability but also contributes to economic productivity and environmental health [16]. As demonstrated in literature reviews and empirical case studies, the successful implementation of smart parking systems requires an interdisciplinary approach, involving collaboration among software engineers, urban planners, transportation authorities, and end users [17, 18].

Despite the progress made, several operational and ethical considerations remain. Ensuring data privacy, addressing user mistrust in automated systems, and maintaining system availability during peak hours are challenges that necessitate robust design and regulatory oversight. Additionally, redundancy mechanisms must be embedded to prevent system failures due to inaccurate predictions or sensor malfunctions. The effectiveness of smart parking technologies will ultimately hinge on their ability to offer reliable, equitable, and user-centered solutions that scale with urban growth and technological advancement.

In this study, we propose a simulation-driven, multi-criteria modeling framework for smart parking reservation and allocation. The model utilizes a hybrid approach combining real-time decision-making algorithms, predictive analytics based on Markov chains, and optimization strategies that account for space availability, user preferences, and environmental considerations. By leveraging the latest innovations in artificial intelligence and urban informatics, this research aims to contribute a scalable and sustainable solution for smart urban parking, aligning technological advancement with social and ecological responsibility.

To manage and control a smart parking system, a decision-making mechanism for vehicles and a communication system for monitoring the occupancy of each parking spot and related data are required. The precise mechanisms for sensing, communication, and computation are beyond the scope of this study, as the main focus is solely on developing optimal parking allocation decision-making mechanisms that are compatible with any such infrastructure. For instance, it is assumed that a driver requests a parking location, and the related information is provided upon entry. The system determines the designated spot based on a localization algorithm. Accordingly, the general steps of reserving a spot in a smart parking system can be seen in the following diagram.

2. Parking Management System

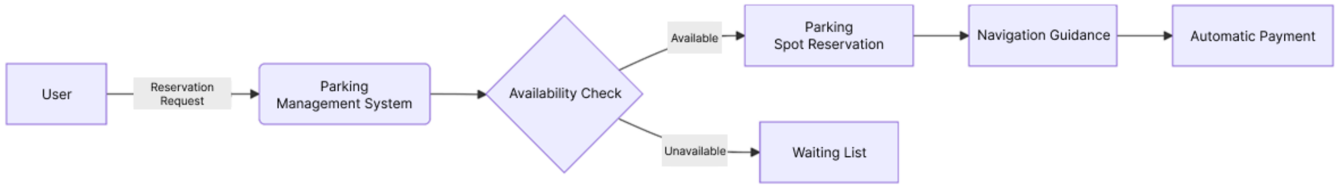


Figure 1. Flowchart and General Overview of Vehicle Reservation in Smart Parking

Based on this, the process steps followed include: (1) user identification, (2) time/location selection, (3) real-time data processing, (4) internal guidance, and (5) automatic settlement. However, challenges exist that require the use of various approaches such as mathematical functions and heuristic procedures for parking space allocation, which are discussed in the following sections.

2.1. Mathematical Modeling in Parking Space Allocation

The aforementioned method, based on certain objective functions, is categorized under optimal parking selection systems. Generally, we define a weighted objective function foundation. Self-operated parking, modeled via the Markov chain approach, can incorporate various configurations. Thus, the allocation of a parking space and the required driving effort to reach a particular spot at a specific time is defined as follows:

$$\min \sum_{i=1}^{n} \sum_{j=1}^{m} C_{ij} * X_{ij}$$

This includes a balancing factor to consider conflicting objectives, meaning when one is emphasized, it can be defined with minimum and maximum associated spaces. The function includes two variables: vehicle and reservable spot. Moreover, since the driving distances vary across parking areas, normalized distances can be used instead of actual distances. A two-stage approach is proposed for reservation and allocation, which—due to space occupancy and the precise localization of drivers—may sometimes fail in reallocating requests. Given these limitations, the following constraints are defined:

Each vehicle can have at most one parking space:

$$\sum_{j=1}^{m} X_{ij} \leq 1 \quad \forall i \in \{1,\dots,n\}$$

Each parking space can be occupied by at most one vehicle:

$$\sum_{i=1}^{n} X_{ij} \leq 1 \quad \forall j \in \{1,\dots,m\}$$

This model considers the greedy selection method for minimizing the distance between the vehicle and the parking location, registering one parking spot per vehicle. Note that random methods can sometimes result in additional costs. On the other hand, in a goal-balanced approach, both options are considered with appropriate weights. Therefore, we aim to analyze the problem based on predictions using the Markov chain.

2.2. Statistical Evaluation of Capacity Prediction

In this section, we use statistical and mathematical models, including the Markov chain, in the proposed system.

We consider an objective function for decision-making in discrete parking location scenarios. The optimization problem can be solved using any exhaustive search algorithm with varying time complexities. Thus, for a parking facility with several hundred to a thousand vehicles, the allocation problem can be solved in a fraction of a second. The Markov chain prioritizes vehicle entry/exit times based on real-time data sets. Utilizing the Markov chain, we can estimate the initial modeling:

$$p(X_{t+1} = j \mid X_t = i) = p_{ij}$$

We then define the transition matrix of different states as follows:

$$[\,[p_{11} \dots p_{1n}], \dots, [p_{m1} \dots p_{mn}]\,]$$

With adjustments, we define adaptive weighted cost functions that include reservation-based parking. Optimal routing to the designated parking spot, which is the target of the objective function, is defined as:

$$f(n) = g(n) + h(n)$$

Where g(n) is the cost from the start to node *n*, and h(n) is the estimated cost to the goal. Additionally, the Poisson distribution for vehicle entries is represented as:

$$p(k) = (\lambda^k * e^{(-\lambda)}) / k!$$

Where λ is the average vehicle arrival rate per hour and k is the number of arriving vehicles. For calculating optimal capacity per location, we use:

$$c = A / (2.5 * 5) * n$$

This is based on approximate dimensions per vehicle and includes a defined zone for each. For average waiting time calculation, assuming a service rate (μ) of 20 vehicles/hour and an arrival rate (λ) of 15 vehicles/hour, we get:

$$w_q = \lambda / (\mu * (\mu - \lambda)) = 15 / (20 * (20 - 15)) = 0.15 \text{ hours} = 9 \text{ minutes}$$

This is computed under a simple example scenario.

3. Reservation Design and Modeling

For the final simulation, a set of essential parameters must be considered, as shown in the table below:

Table 1. Reservation Parameter Specification in Smart Parking

Row	Main Parameters	Sub-parameters	Description
1	Parking Model	Number of spaces	Determine total available parking spots
		Types of spaces	Spaces for disabled, electric vehicle charging
		Space positions	Routing-related aspects for simulation
2	Reservation Requests	Arrival rate	Determine average number of reservation requests per time unit
		Entry time	Exact time of reservation requests
		Reservation duration	Duration the user wishes to reserve a spot
		Reservation request time	Time before the desired entry when the reservation is made
3	Space Allocation Algorithm	First available space	Simplest method: assign first available spot
		Nearest available spot	Allocate space closest to entry or user’s destination
		Random allocation	Random selection of an available space
		Priority-based algorithms	Allocation based on user priority
5	Vehicle Entry/Exit Model	Actual entry time	Actual time of vehicle arrival
		Actual exit time	Actual time of vehicle departure
		No-show probability	Percentage of reservations not resulting in vehicle arrival
6	Evaluation Metrics	Occupancy rate	Percentage of occupied spaces over time
		Reservation acceptance rate	Percentage of successful reservation requests
		Reservation wait time	Time users wait to access reserved spaces
		Space efficiency	Extent of parking space utilization
		User satisfaction	User satisfaction inferred via acceptance and wait times

According to this table, six primary parameters are considered. Based on their significance, the simulation is conducted using MATLAB. Initially, with parameter definition, suitable values for all key elements (number of spaces, arrival rate, reservation time distribution, allocation algorithm, etc.) are established. These values may be based on actual or hypothetical data. The model is implemented in the chosen simulation tool, including the parking structure, reservation request inflow, allocation algorithms, and vehicle entry/exit processes. The simulation is run for a defined period (e.g., several hours, one day, or one week). Data related to evaluation metrics (occupancy rate, acceptance rate, etc.) is collected and analyzed.

The overall process includes the following steps:

1. At each time unit, the probability of a new reservation request is evaluated.

2. If a new reservation is made and a vacant space is available, it is assigned, and the reservation details are recorded.
3. Expired reservations are reviewed, and corresponding spaces are released.
4. At the end of each time unit, the current occupancy rate and total number of reservations are stored in their respective arrays.
5. The average occupancy rate and total number of reservations are computed and displayed at the end.

In the figure below, the parking area is divided into approximately 30 blocks, which are used in the context of the number of reservations made within a parking space. These reservations are also tracked based on time. Upon a successful reservation, its information is stored in the reservation structure, and the reservation number is recorded in the parking space array. This array is then examined, and if a space is occupied (non-zero value), the value 1 is entered into the reservation location matrix for that space and that specific time.

4. Simulation Models for the Reservation System

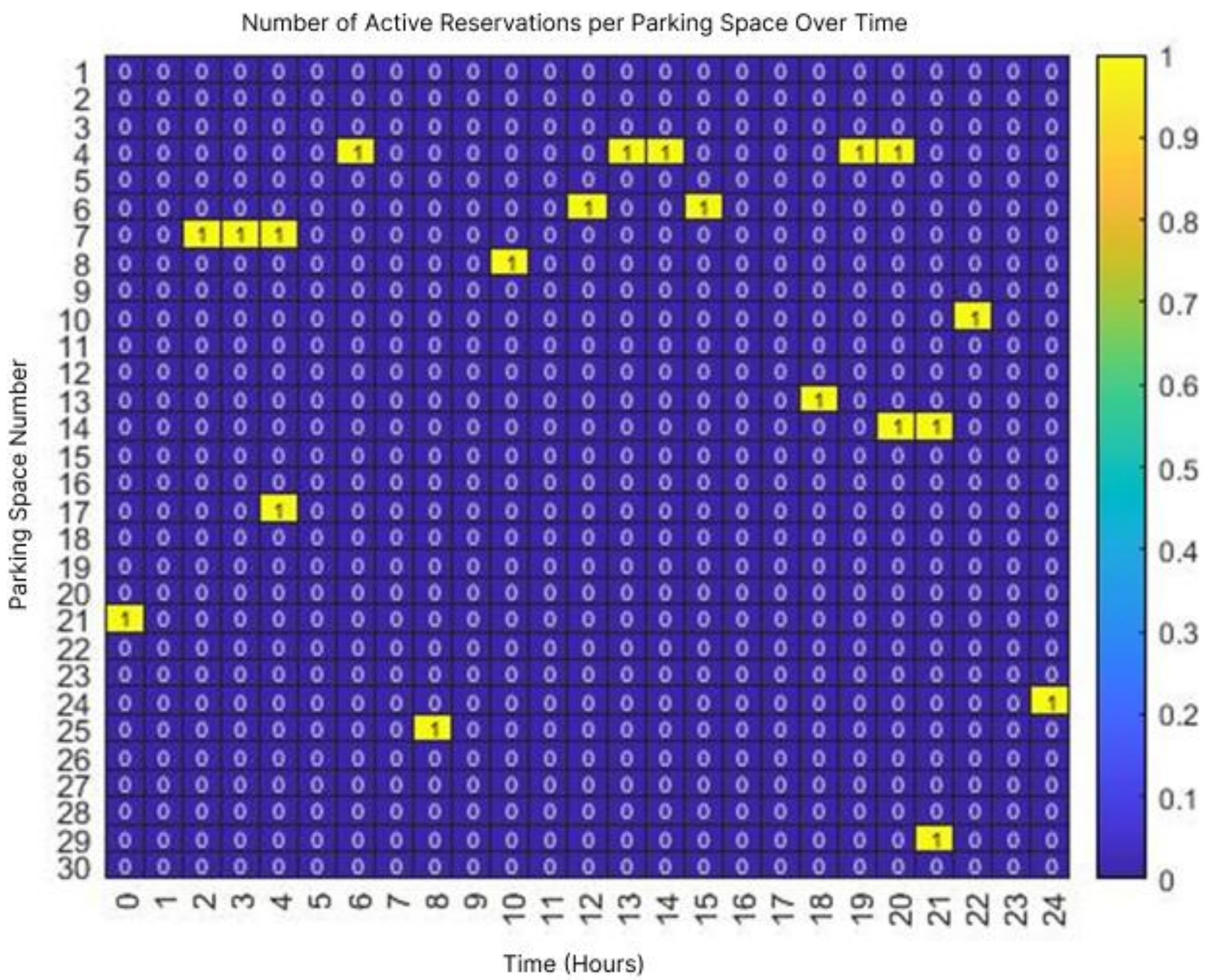


Figure 2. Reservation Location Based on Time

A graph is generated to display the total number of reservations for each parking space over the entire simulation period. This graph illustrates which parking spaces were most in demand. In the figure below, the total number of reservations for each block is also shown. Based on the evaluation period, it can be observed that Block 1 had the highest number of reservations. Simulation parameters such as the number of spaces, reservation arrival rate, average reservation duration, and total simulation time were defined, along with a time_step variable to control temporal resolution. The storage arrays included: (1) simulation timestamps, (2) parking occupancy rate at each time interval, and (3) cumulative number of reservations made by each time segment.

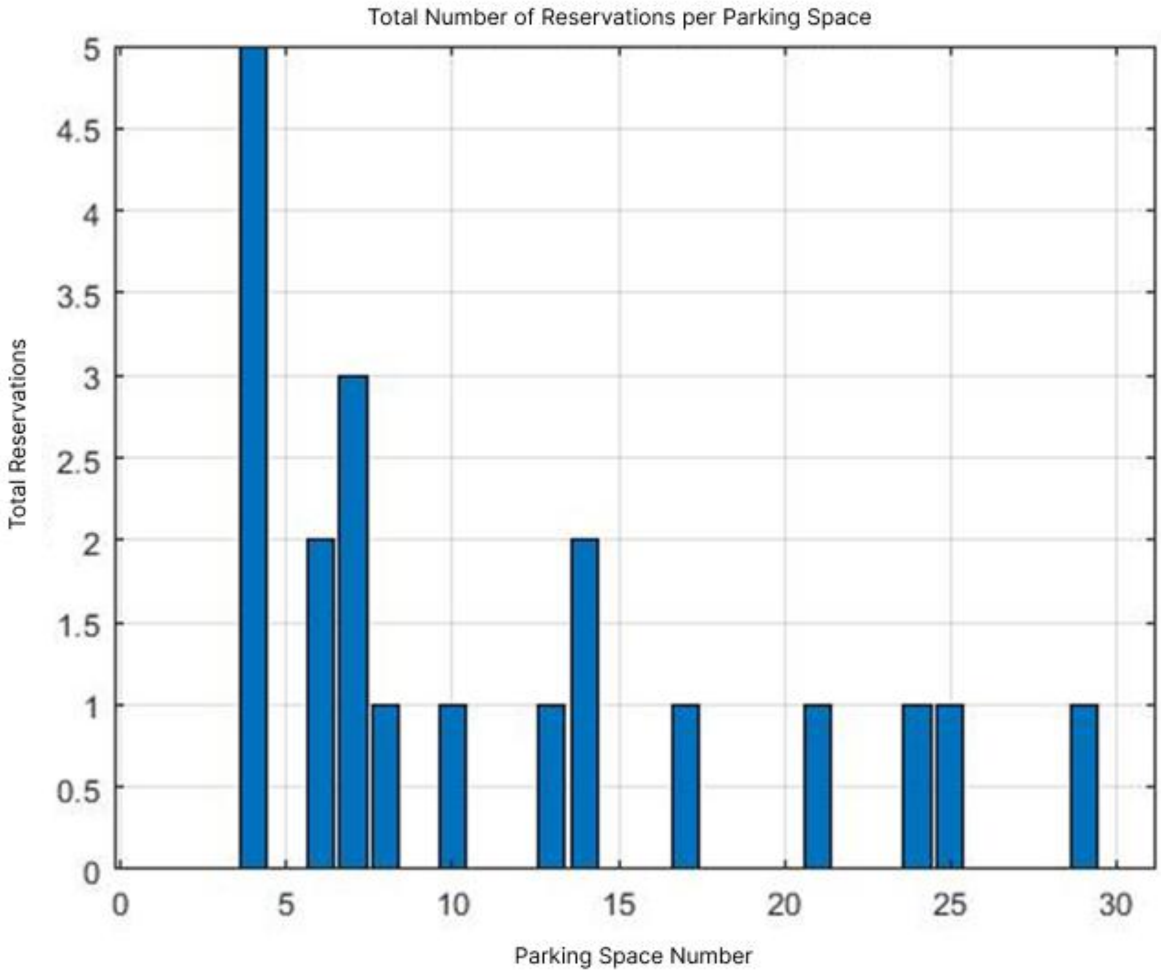


Figure 3. Number of Reservations per Parking Block

This graph shows how many times each parking space was reserved during the entire simulation. Taller bars indicate spaces with higher demand. The data presents the number and location of reservations over time, helping to understand usage patterns and identify which areas are more likely to be reserved. The overall parking occupancy rate over time is also illustrated in the figure below. It is observed that peak congestion occurs in the early morning and late evening. These fluctuations are also considered cyclically and may vary in other simulations.

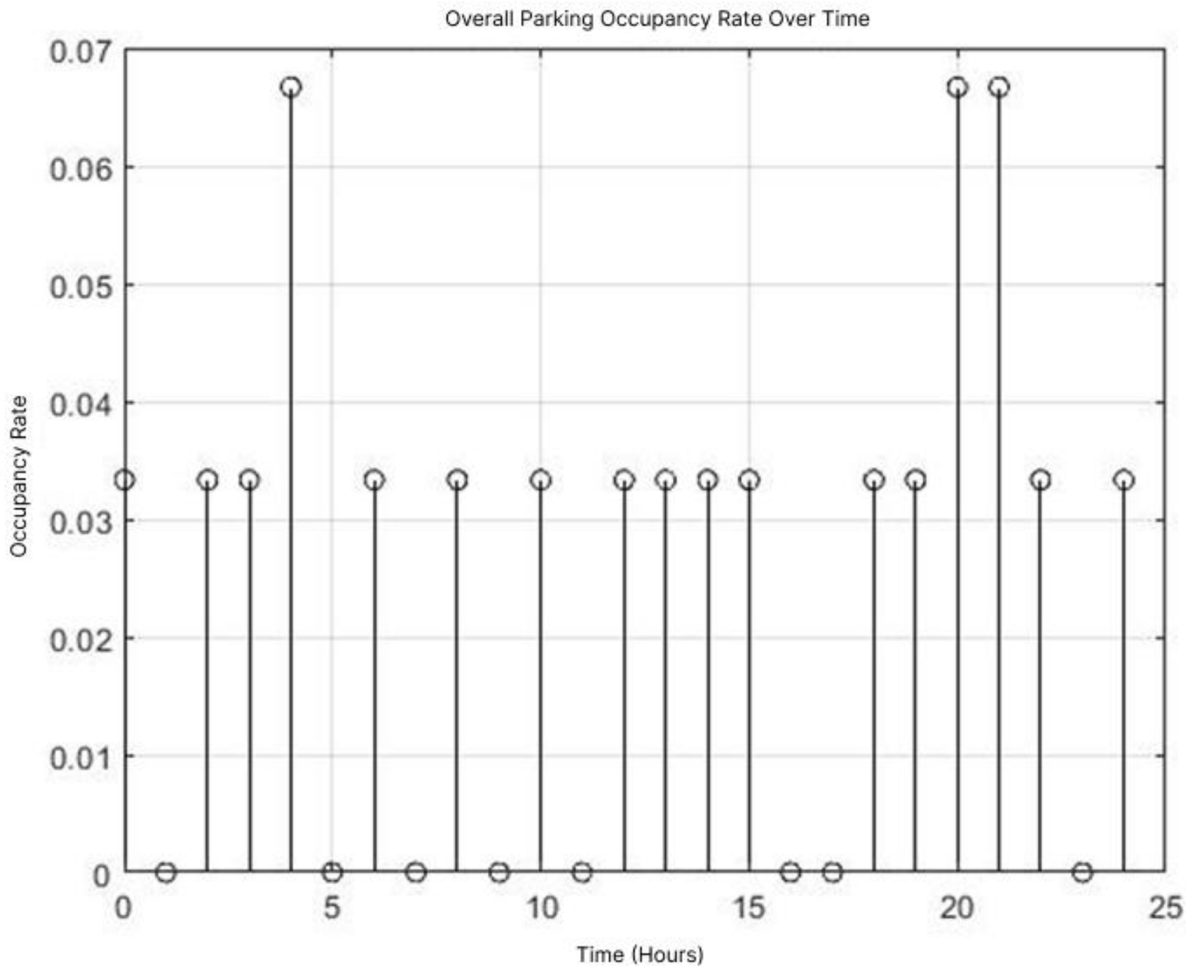


Figure 4. Parking Lot Occupancy Over Time

In the following figure, the vehicle entry and exit times are analyzed. The traffic pattern was examined within a 24-hour period, showing variations by hour. The average number of reservation requests per time unit—such as one-hour intervals—can be either constant or vary according to probabilistic distributions, particularly the Poisson distribution.

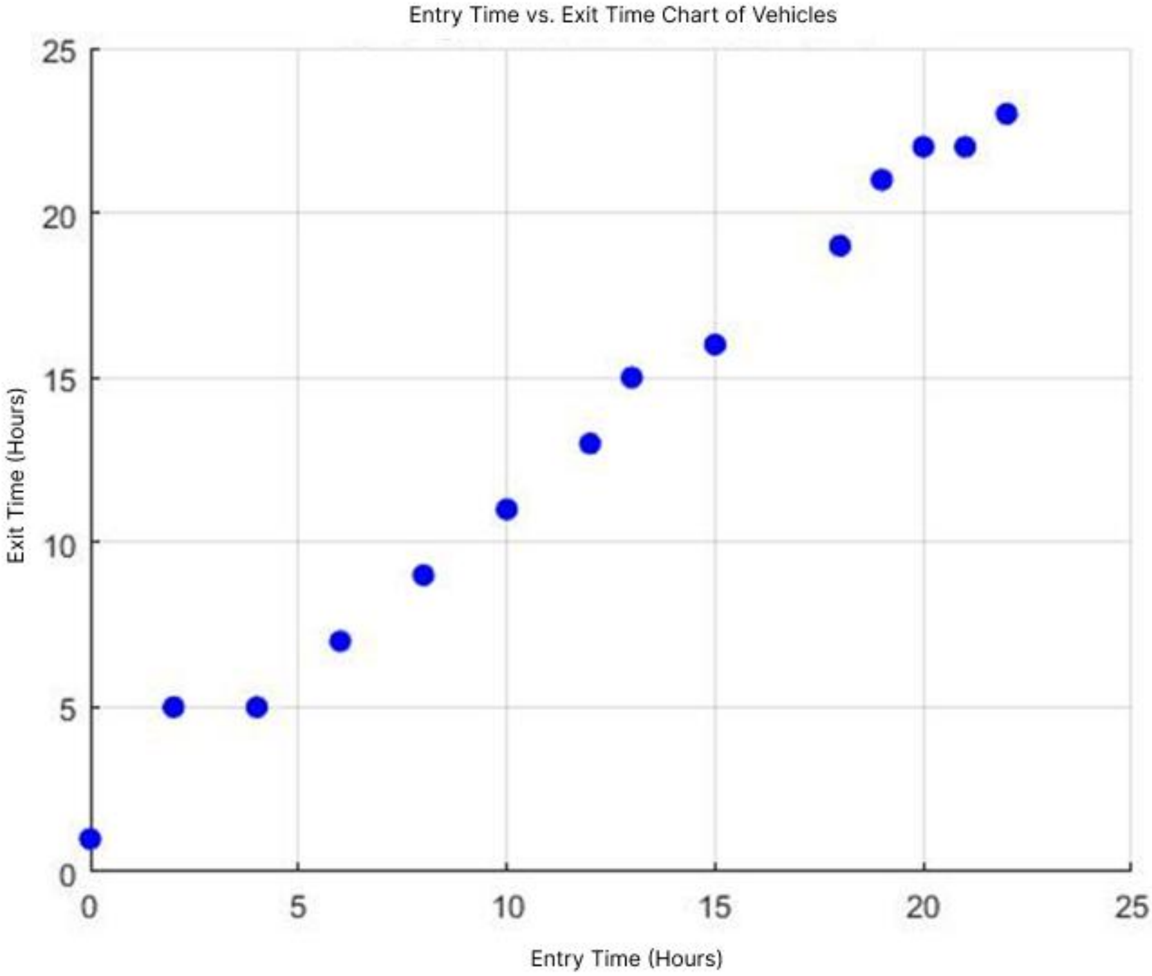


Figure 5. Entry/Exit Chart of the Parking Lot

Based on the data modeling in MATLAB, scenarios were considered in which reservations were made at different times of the day. As the reservation and occupancy capacity progresses over time, the occupied capacity increases while available capacity decreases. When the available capacity approaches zero, it indicates the parking lot is full. The graph on the number of reservation attempts and successful reservations shows how many users attempted to reserve a spot and how many of those were successful due to space availability. The difference between these two lines may represent unmet demand.

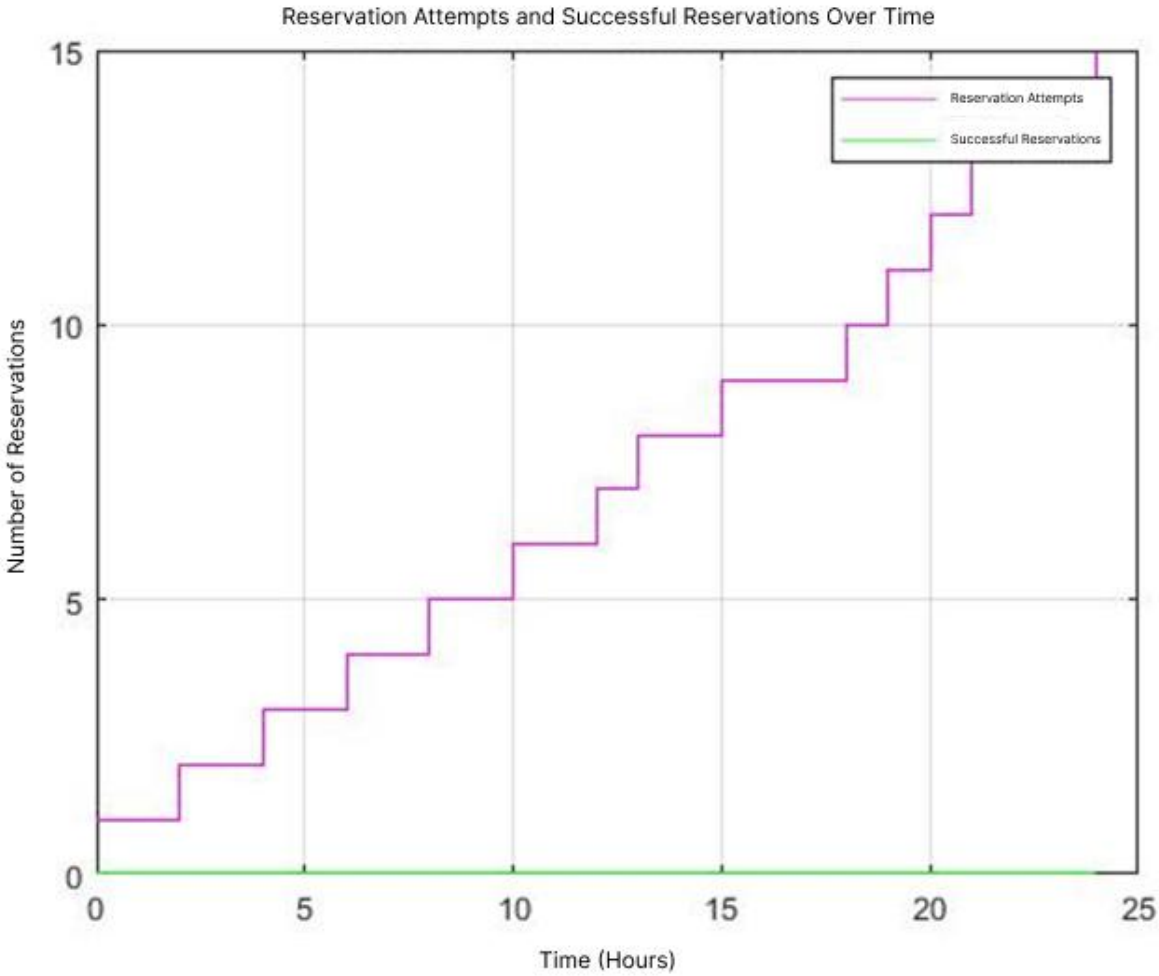


Figure 6. Reservation Activity in a Single Day

Throughout one full day, it is observed that 15 individuals attempted to reserve a parking space. This outcome is directly linked to the earlier graphs, especially entry and exit hours, where intelligent systems identified and made available empty spaces for reservation. Another important point is that capacities must be updated in accordance with vehicle departures, which is critical for system performance. For example, if a vehicle exits and its departure is not recorded on time, its spot will not be available for subsequent reservations, which becomes a significant flaw in smart parking system management. Therefore, real-time recording and storage of occupancy and availability status is essential, as illustrated graphically below.

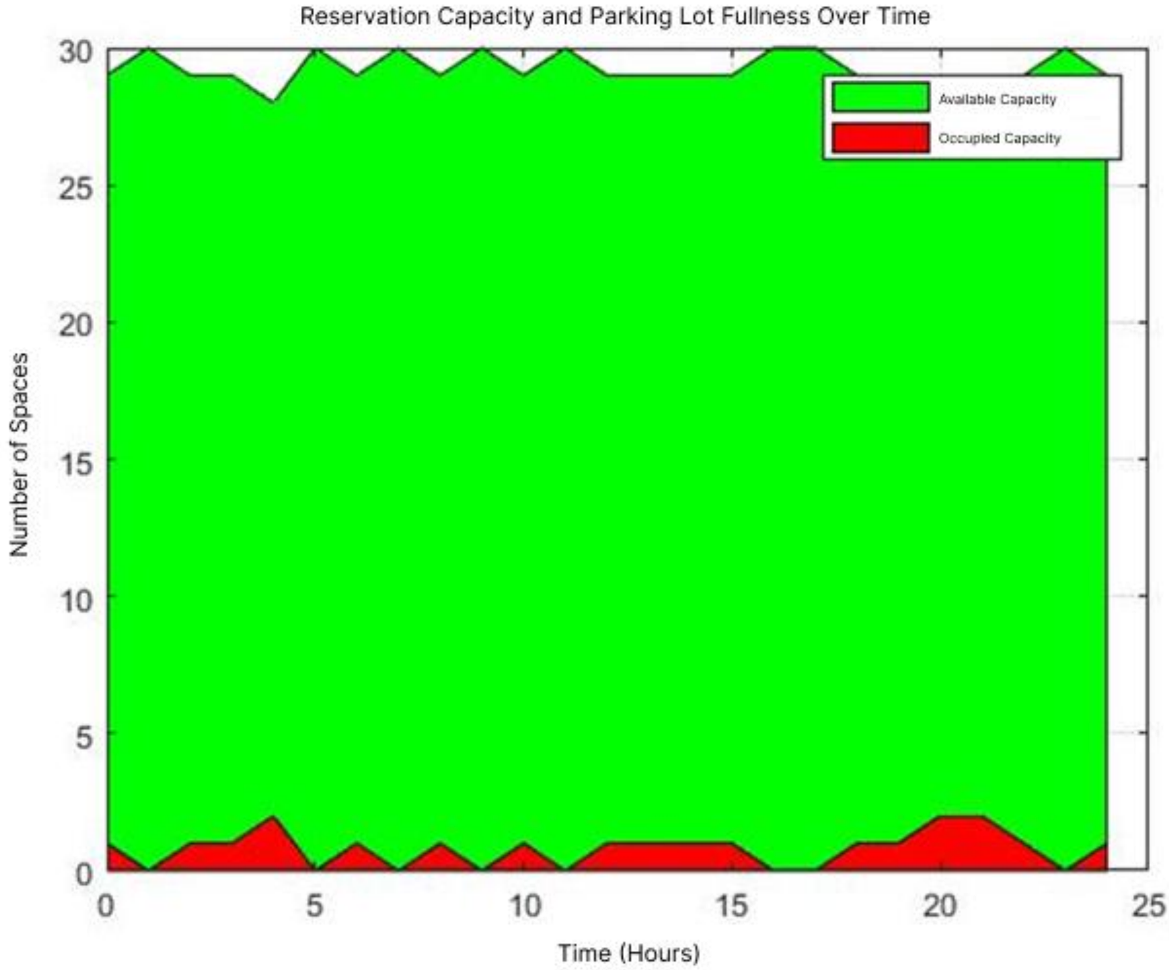
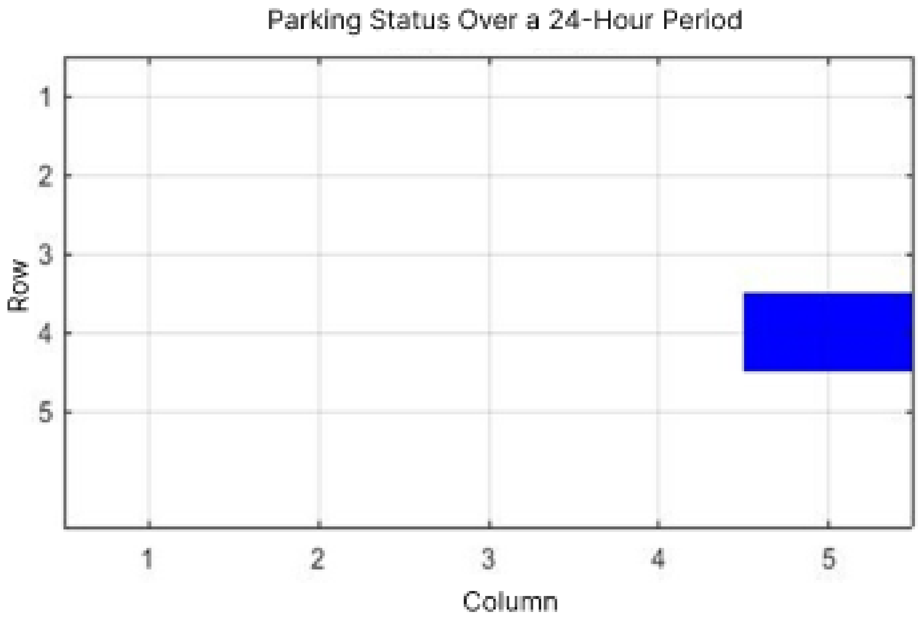


Figure 7. Graphical Representation of Parking Space Occupancy Status

In smart parking systems, routing strategies and vehicle detection techniques within a pervasive computing environment must operate in real-time. The task of finding parking spaces becomes non-trivial and requires specialized evaluation. At this stage, we compared the overall parking status across various time intervals. As shown over a 24-hour cycle, capacities fluctuate, and the status of each block may vary, indicating whether it is full or empty.


Parking Status Over Time: 24 Hours
Row
1
2
3
4
5
Column
1
2
3
4
5


Parking Status Over a 24-Hour Period
Row
1
2
3
4
5
Column
1
2
3
4
5

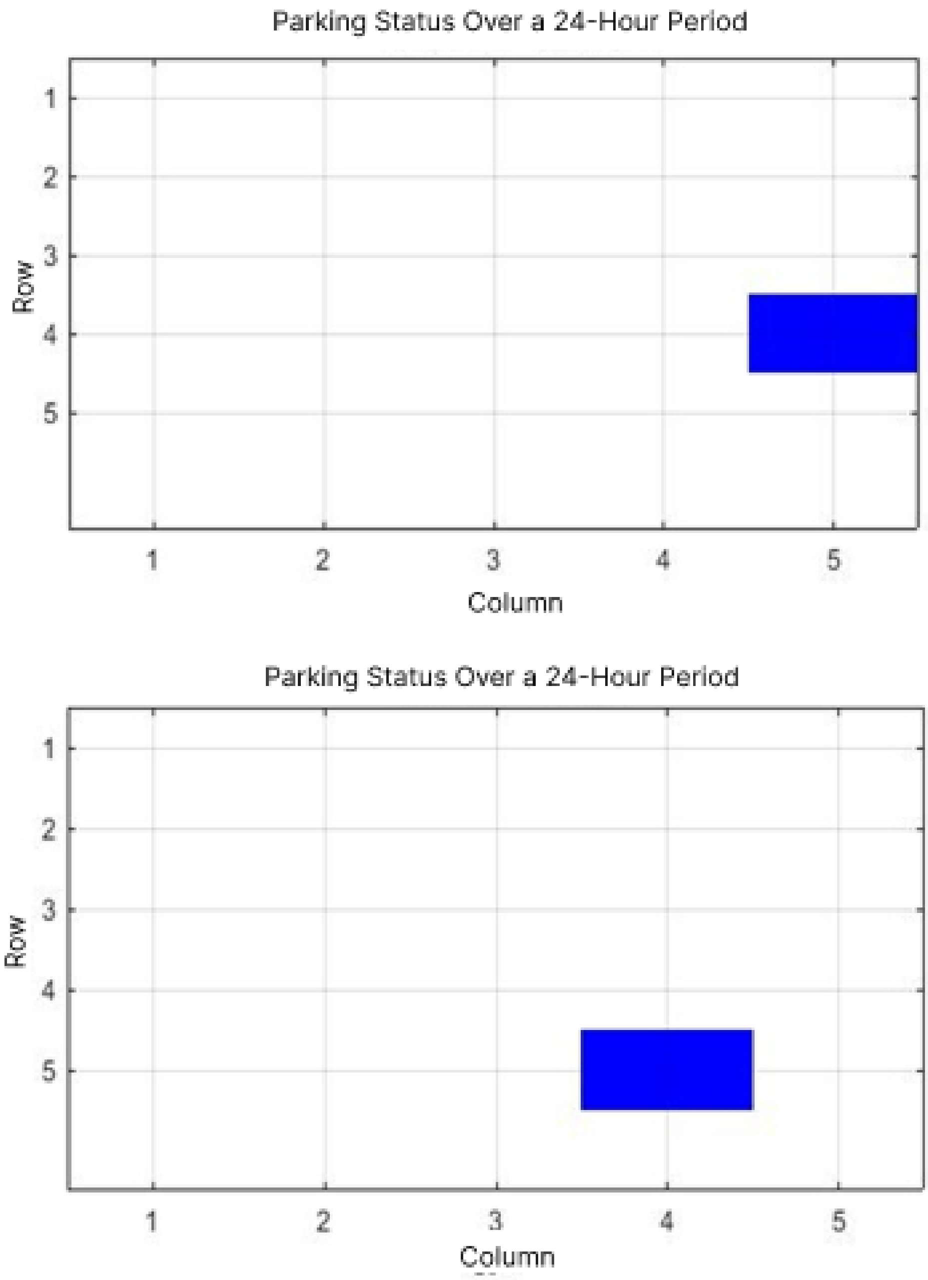


Figure 8. Overall Parking Lot Status at Different Times

With advancements in technology, various parking space allocation mechanisms—such as entry priority and reservation priority—are developed. Therefore, accurate recording of vehicle entry and exit times is necessary, as shown in the figure below. This precise and automated recording can significantly enhance and improve the performance of smart parking systems. For this purpose, arrays have even been defined for storing data related to forecasting and prediction errors. In this simulation, an average occupancy rate of approximately 0.032 was observed, with a total of 15 successful reservations. We considered predicted values, actual occupied capacity, and forecast error (actual value – predicted value).

ArrivalTime	DepartureTime	SpaceNumber
0	60	21
120	300	7
240	300	17
360	420	4
480	540	25
600	660	8
720	780	6
780	900	4
900	960	6
1080	1140	13
1140	1260	4
1200	1320	14
1260	1320	29
1320	1380	10

Figure 9. Vehicle Entry and Exit Chart at Specific Times

Forecasting and error calculations are performed in a loop after a designated delay and sufficient data collection. Occupied capacity is estimated for the average prediction window, and error is calculated at each time step. A prediction accuracy chart is also plotted using actual and predicted occupancy capacities over time. Note that this forecast accuracy may be limited depending on average traffic. For a more precise evaluation of a predictive model's performance, it is usually necessary to conduct multiple simulations and compute statistical error metrics over the entire simulation period or a separate testing segment. Evaluating appropriate parking management policies maximizes social welfare. Statistically, three latent variables—users' attitudes toward parking, perceived risks of on-street versus off-street parking—significantly influence policy segmentation for appropriate parking strategy evaluations, as demonstrated in this article.

5. Discussion and Conclusion

The results of this study present a robust simulation-based framework for smart parking reservation and space allocation, which demonstrates high potential in optimizing urban parking efficiency. The proposed model effectively integrates multi-criteria decision-making and Markov-based forecasting to enhance the reliability and responsiveness of parking management. During a 24-hour simulation cycle, the model recorded 15 successful parking reservations with an average occupancy rate of 0.032, reflecting an overall low idle capacity and efficient space turnover. The division of the parking environment into 30 discrete spatial blocks enabled precise tracking of reservation frequency and real-time occupancy, allowing for dynamic adaptation to usage fluctuations throughout the day. Notably, the highest volume of reservations occurred during early morning and late evening hours, consistent with typical urban commuting patterns.

The effectiveness of the system was reinforced by its ability to adapt to temporal demand variability using a Markov Chain-based capacity prediction method. This enabled the system to anticipate space saturation points and optimize allocation based on both reservation requests and observed occupancy. Moreover, the dynamic matrix logging of real-time entry and exit points allowed for accurate identification of underutilized spaces and automated reallocation in the event of cancellations or no-shows. The simulated routing strategies further contributed to improved user satisfaction by minimizing walking distance and access time. These outcomes align with findings from [5], who demonstrated that a two-stage reservation and allocation model significantly reduces parking uncertainty and congestion, especially during peak hours.

The capacity forecasting element, derived from probabilistic models such as the Poisson distribution and enhanced through adaptive time-step controls, provided a statistically grounded mechanism for real-time space availability estimation. This dynamic calibration allowed for predictive adjustment of reservation limits, enhancing overall system resilience. Studies such as those by [6] and

[7] have similarly emphasized the value of time-varying Markov Chains and queueing theory in modeling vehicle flow and parking capacity. Their findings corroborate the current study's conclusion that predictive modeling significantly reduces user wait times and maximizes occupancy efficiency.

Another critical outcome of the simulation was the visualization of high-demand zones within the parking facility, offering valuable insights into spatial usage patterns. The model's ability to record, analyze, and display reservation densities across blocks enabled the identification of consistently oversubscribed zones. This feature reflects the spatial optimization goals described in [11], who employed Monte Carlo simulations to pinpoint and alleviate congestion in university parking areas. Similarly, the spatial clustering of high-demand zones supports the spatial-temporal optimization approaches advocated in [13], who highlighted that environmental and operational benefits are achieved when parking systems dynamically respond to user behavior and emissions goals.

The simulation also revealed the importance of reservation timing and pre-arrival behavior in optimizing overall system utilization. The integration of behavioral prediction into the allocation algorithm allowed the model to dynamically prioritize early and consistent users, contributing to higher reservation success rates. The benefit of this approach is echoed in [14], who explored how maximizing social welfare through behavioral modeling in parking systems can lead to a more equitable distribution of resources. Likewise, the current findings validate the design philosophy outlined by [12], whose multi-agent parking allocation model prioritized decentralized adaptability in response to real-time user interactions.

In the context of system architecture, the study's implementation of deep learning and detection algorithms, particularly in assigning and verifying available spots, proved vital in enhancing accuracy. By avoiding reliance on manual entry or user error, the model significantly reduced misallocation. This confirms the findings of [10] and [9], both of whom highlighted the critical role of hybrid deep learning models in achieving near real-time detection of parking availability with high accuracy. Furthermore, the application of the Extreme Learning Machine (ELM) paradigm [15] in parking detection shows potential for reducing false positives in occupancy sensing, a factor that contributes to more effective reservation strategies.

From an ecological standpoint, the smart reservation system developed in this study also contributes to environmental efficiency. By reducing idle engine time during search for parking, the model promotes lower fuel consumption and carbon emissions—findings that align with those of [8], who emphasized the sustainability advantages of integrating eco-friendly smart parking management systems into urban infrastructure. These benefits also extend to economic sustainability, where improved space turnover translates into better revenue potential for parking providers without the need for physical expansion. This perspective complements the comprehensive review by [16], who noted that effective smart parking systems must consider environmental, technical, and economic dimensions to achieve real-world impact.

Security and data integrity were implicitly addressed through the simulation's architecture, which could be enhanced through blockchain integration as discussed by [3, 4]. Their blockchain-enabled frameworks offer a secure and decentralized mechanism for transaction logging, identity verification, and system trustworthiness. Such enhancements are particularly vital in systems that rely on user-generated inputs and remote interactions. The decentralized structure advocated by [18] also provides a model for fault-tolerant system design, which can safeguard against server failure or centralized mismanagement.

Overall, the simulation demonstrates that intelligent reservation systems, when combined with predictive analytics, real-time monitoring, and dynamic decision-making, can offer highly effective solutions to the pressing urban parking challenges. The success of this model validates the direction of recent smart city research, where mobility optimization intersects with sustainability and technological innovation. While the model has shown promising results in simulation, real-world deployment would require additional considerations such as user interface design, mobile integration, legal regulations, and adaptive pricing.

Despite its strengths, the current study has several limitations. First, the simulation was conducted in a controlled virtual environment, which does not fully replicate the complexities of real-world scenarios such as human behavioral deviations, technical failures, or unexpected traffic disruptions. The model also assumes that users consistently follow reservation rules and that sensors operate flawlessly—conditions that may not hold in physical settings. Moreover, external variables such as weather conditions, emergency access requirements, and security concerns were not incorporated into the simulation framework, potentially limiting its practical application.

Second, while the Markov Chain-based prediction model proved effective for time-dependent vehicle behavior, it does not account for longer-term spatial trends or seasonal variability in demand. The model is also constrained by a fixed number of parking blocks, which might not scale optimally in large metropolitan environments with thousands of spaces. Furthermore, the data input was synthetic, and the absence of real-world calibration data may limit the generalizability of the findings. Lastly, integration with other urban mobility platforms (such as public transit apps or ride-sharing systems) was not addressed, which could have enhanced the system's interoperability and user convenience.

Future research should explore real-world pilot implementations of the proposed model to evaluate its effectiveness under actual urban conditions. Incorporating real-time user feedback into system refinement would allow for adaptive learning and continuous optimization. Furthermore, integration with edge computing and 5G technologies could significantly enhance response times and reduce reliance on central servers. It is also recommended that future models incorporate user psychology and behavior modeling to anticipate no-shows, early departures, or last-minute cancellations more accurately.

Another promising direction lies in integrating the reservation system with dynamic pricing models that adjust fees based on demand, duration, and spatial popularity. This would not only incentivize off-peak usage but also increase revenue potential for operators. Additionally, ethical considerations such as privacy protection and data security must be embedded into the system architecture from the design phase. Finally, interdisciplinary collaboration between engineers, urban planners, and behavioral scientists will be essential to ensure holistic development and policy alignment of smart parking solutions.

Parking authorities and city planners should consider adopting smart reservation systems as a core component of urban mobility strategies. Emphasis should be placed on modular system design to allow scalability and future technological upgrades. Continuous monitoring of occupancy and usage trends can guide the redistribution of space or reconfiguration of parking layouts to match actual demand. Operational staff should be trained in both technical maintenance and user assistance, ensuring system reliability and customer satisfaction.

Furthermore, public awareness campaigns are essential to promote user adoption and educate the public on the benefits of smart parking systems. Incentives such as reduced fees for early reservations or eco-friendly vehicles can further align system usage with sustainability goals. Finally, partnerships with private sector technology providers can accelerate innovation, reduce implementation costs, and ensure that systems remain at the cutting edge of urban mobility development.

Authors' Contributions

Authors equally contributed to this article.

Acknowledgments

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

All procedures performed in this study were under the ethical standards.

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