MSc project thesis

Parking Space Allocation Strategy Optimization during Planned Special Events

Yunyun Wang

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Thesis Committee
Dr. ir. M. Rinaldi (Main supervisor)
Dr. V.L. Knoop (Chairman)
Dr.ir. G. Correia
Ir. Elif Arslan (Daily Supervisor)

Abstract

This project aims to relieve traffic pressure and enhance the parking experience for attendees during planned special events (PSEs). The objective is to develop an optimal strategy for efficiently allocating parking spaces during PSEs in parking lots.

PSEs, such as football games or large concerts, typically result in concentrated vehicle arrivals within a limited time period, leading to increased traffic flow, potential disruptions, elevated emissions, and safety concerns in nearby areas. By optimizing parking space allocation strategies in the parking lot, this project seeks to improve overall traffic management and relieve these challenges.

To achieve this, a linear programming (LP) algorithm and a simulation-based genetic algorithm (GA) are employed to search for the optimal solution. While the LP model offers computational efficiency, it has limitations in incorporating different route conditions. To address this, an agent-based simulation is constructed to depict the interaction and movement of vehicles within the parking lot. The simulation-based GA utilizes objective values derived from the simulation, providing a more comprehensive basis for finding the optimal solution. The allocation process considers factors such as parking lot layout, vehicle entry time step, and specific parking rules including road directions within the parking lot.

Results demonstrate that the optimal strategy obtained from the simulation-based GA outperforms comparison groups. The simulation-based GA showcases its ability to converge on the optimal solution within a large solution area. The optimal strategy saving time for all vehicles, particularly during periods of high demand. Effective parking is achieved by allocating parking spaces according to the arrival order and positioning vehicles on the left or right based on their arrival order and parking space location.

By employing these methods, this project offers a valuable contribution to the field of parking space allocation in the parking lot during PSEs, enhancing the overall parking experience for event attendees.

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Contents

List of Figures

List of Tables

1 Introduction

1.1 Background

Special events are recognized as one of the causes of traffic congestion listed by the Federal Highway Administration (FHWA) (Mcgurrin et al., 2012). On regular days, traffic demand can be considered as a repeated stochastic process with similar dynamic patterns within a day. However, during special events, traffic management needs to accommodate unusually high traffic demands (Ruan et al., 2016). Among special events, planned special events (PSEs), such as football games, and concerts, are an important factor in urban congestion.

PSEs bring substantial traffic in a short period, creating high traffic pressure in a concentrated area (Kwoczek et al., 2014; Zheng et al., 2023). The vehicles cruising in search of parking spaces exert considerable pressure on the surrounding road network and parking facilities. PSEs contribute significantly to traffic congestion by generating high traffic volumes in a relatively small area within a limited time frame (Fernando, 2019).

Efficient parking strategies become crucial during PSEs to mitigate the impact of traffic congestion. The successful implementation of effective parking space allocation strategies during PSEs relies on considering the perspectives and interests of various stakeholders involved. These stakeholders encompass event organizers, venue managers, transportation agencies, and event attendees (Lin and Chen, 2017; Tempelmeier et al., 2020; Pulugurtha et al., 2020; Hang et al., 2019). Event organizers primarily prioritize providing a positive attendee experience, which includes efficient parking operations to minimize delays and congestion. Transportation agencies aim to optimize traffic flow and alleviate overall traffic pressure during PSEs. Event attendees seek a convenient and seamless parking experience, minimizing the time spent searching for parking spaces.

While PSEs occur infrequently, they place significant demands on traffic infrastructure, including parking facilities. Meeting this demand entails considerable financial costs. Unfortunately, parking space shortages are a common occurrence, particularly during peak hours (Xie et al., 2022). Cruising for parking spaces contributes to increased traffic pressure, with cruising activities accounting for up to 30% of congestion in urban areas (Nawaz et al., 2013). Additionally, the time spent searching for parking spaces contributes to traffic congestion (Zhao et al., 2021a). Even though many cities provide a significant number of parking spaces on streets or in parking lots, drivers often spend a long time cruising or get stuck in congestion due to poor organization. While some cities offer information about available parking spots in certain areas, dynamic traffic conditions may render these spaces unavailable upon arrival, or drivers may spend excessive time searching for a spot within the parking lot.

Traffic congestion resulting from special events has adverse effects on both societal and personal benefits. These include long travel times, increased travel costs for travelers and shipping companies, air and noise pollution, high energy consumption, and greenhouse gas emissions (Wang et al., 2019). Additionally, traffic congestion can lead to driver frustration and reduce the effectiveness of the traffic system (Xie et al., 2019; Afrin and Yodo, 2020). It poses challenges to the sustainability and resilience of the traffic system (Afrin and Yodo, 2020; Poumanyvong et al., 2012). Frequent braking during the congestion results in insufficient combustion of fuels and harmful emission gas (Su et al., 2020; Lu et al., 2021; Rajé et al., 2018). Viard and Fu (2015) highlight that traffic congestion contributes to air pollution through drivers' delays and tailpipe emissions. Additionally, it negatively affects economic growth by impacting labor costs, working hours, and delivery times (Rahman et al., 2022a). The delays and costs associated with traffic congestion are particularly significant in densely populated areas (Afrin and Yodo, 2020).

Constructing additional parking facilities to meet the high parking demand during PSEs is not a cost-effective solution. Therefore, efficient parking operations become essential to maximize the utilization of existing parking lots. Efficient operations enable vehicles to quickly find parking spaces, reducing cruising and waiting times, and optimizing the utilization of parking facilities.

Large parking lots that serve events like football games or concerts are critical parking supporting facilities. However, the complex and dynamic nature of traffic within these parking lots often leads to congestion in the absence of efficient management strategies (Shao et al., 2008; Zhang et al., 2021). Optimizing the operation of these parking facilities is one way to mitigate this burden, allowing vehicles to be parked quickly instead of waiting outside the parking lot or cruising on the road.

Various research efforts have focused on developing smart parking facilities through the use of sensors, GPS technology, mathematical algorithms to monitor parking space availability (Bock et al., 2020), smart guidance (Shin and Jun, 2014), dynamic parking allocation (Mladenović et al., 2021), parking recommendation (Horng, 2014). Automation technology, such as automated valet parking (AVP), has also been implemented within parking lots to enhance efficiency and save human effort (Zhao et al., 2021a; Zhang et al., 2021). Parking allocation strategies have been proposed to address parking pressure in public areas, maximize parking lot profitability, and increase the chances of vehicles being accepted into parking lots. Researchers have explored parking lot allocation strategies to help optimize the performance of parking lots to achieve the effective utilization of the parking lot and address parking pressure (Nakazato et al., 2022a; Errousso et al., 2022; Duan et al., 2020a; Cai et al., 2019; Babic et al., 2018).

Developing an effective parking space allocation strategy for parking lots that enhances safety and reliability can help reduce the time wasted in traffic cruising, alleviate traffic pressure, and maximize the utilization of parking infrastructure during planned special events. Such strategies can reduce the risk of driver distractions and potential collisions during parking (Bock et al., 2020). Besides, organizing the parking process more effectively also leads to higher driver satisfaction (Bock et al., 2020). Furthermore, environmental concerns, such as energy consumption, emissions, and noise, can be addressed by reducing unnecessary time spent searching for parking spaces (Shin and Jun, 2014; Mladenović et al., 2021), contributing to energy savings and emission reduction in line with climate goals.

1.2 Research Objective and Questions

Based on the background, the efficient organization of parking facilities can alleviate parking pressure, enhance driver experience, and reduce negative environmental impacts. The objective of this research is to develop an optimal parking space allocation strategy during PSEs to ensure efficient parking lot performance.

Based on the research objective, the main research question is:

How to determine an effective strategy for allocating vehicles in a parking lot during PSEs?

To address this main research question, the following sub-questions are proposed:

1. How can the realistic movement of vehicles inside the parking lot be simulated?
   - How do vehicles interact with other vehicles and parking lot infrastructure?
   - What types of interference and congestion occur within the parking lot?
2. How should the algorithm be designed to incorporate the complex situation within the parking lot and search for the optimal solution?
3. How does the demand level impact the efficiency of the allocation strategy?
4. How does the parking lot layout influence the allocation strategy?
5. How should the optimal strategy be interpreted and understood?

By addressing these research questions, the study aims to contribute to the development of an optimal parking space allocation strategy in a parking lot during PSEs.

1.3 Research Structure

This chapter serves as an introduction to the project, providing the research background, objectives, and structure. The following chapters are organized as follows:

- Chapter 2: Literature Review

  Conduct a review of existing literature on parking lot management during PSEs, parking space allocation strategies, and relevant traffic models.

- Chapter 3: Methodology

  Develop a linear programming and simulation-based genetic algorithm designed to search for the optimal parking space allocation solution. Construct a simulation model that serves two purposes: testing the proposed strategy and serving as a basis for searching for optimal solutions.

- Chapter 4: Experimentation

  Apply the developed algorithms and test their performance and effectiveness.

  Analyze and evaluate the experiment results to assess the feasibility and efficiency of the proposed approach.

- Chapter 5: Conclusion and Discussion

  Provide a conclusion for the research and engage in further discussion about the application and future work related to the developed parking space allocation strategy.

2 Literature Review

2.1 Parking Management During Planned Special Events

Planned special events (PSEs) include sports events, concerts, etc (Lin and Chen, 2017), have distinct characteristics that deviate from the normal traffic distribution (Ruan et al., 2016). These events are scheduled, occur at specific locations, and can vary in duration depending on the event type (Lin and Chen, 2017). The problem occurs within the temporal proximity to the event and spatial proximity to the event venue. So it is easier to organize and control than unexpected accidents. These events can cause severe traffic congestion and require effective traffic management strategies (Lin and Chen, 2017).

Researchers have proposed various studies to address parking management during PSEs. Lin and Chen (2017) proposed a mesoscopic simulation model to evaluate traffic impacts generated by PSEs and assess mitigation measures reduced by traffic control plans. They employed a dynamic traffic assignment (DTA) model to capture the temporal effects of congestion and the impacts of time-varying demands and supplies during the PSEs. Tempelmeier et al. (2020) employed a supervised machine learning approach to predict the traffic impact of PSEs, and came up with an algorithm to identify subgraphs of transportation graphs that are typically affected by PSEs. Ruan et al. (2016) formulated a linear integer model to optimize the scale and location of parking lots associated with mega-event sites. The objective was to maximize the number of travelers who could complete their journeys within a reasonable travel time. Henao and Marshall (2013) conducted a study on parking at a sports event stadium in Denver, Colorado and discovered that while there was an adequate parking supply, the provision of parking was not efficient. They emphasized the importance of considering the relationship between parking utilization and parking supply as part of an overall parking plan.

2.2 Parking Strategies in Urban Areas

Efficient parking strategies in urban areas aim to reduce the time spent searching for parking spaces, alleviate traffic congestion, and enhance the overall parking experience. Researchers have developed various solutions for smart parking systems to optimize the parking facilities' performance. Promy and Islam (2019) introduced an Android-based navigation system that assists drivers in finding nearby parking spaces. Nakazato et al. (2022b) proposed a smart parking system with a reservation system and a dynamic parking fee design. To address the issue of traffic congestion caused by vehicles searching for parking in urban areas, Geng and Cassandras (2013) introduced a smart parking system to allocate and reserve the optimal parking spaces for drivers using a mixed-integer linear programming (MILP) problem. Wu et al. (2022) proposed ParkHop, a mobile crowdsensing system that aggregates the availability of parking spaces both on the street and in the parking lot through sensorless sensing and disseminates this information with up-to-date prices to drivers. Rahman et al. (2022b) utilized mobile deep learning techniques to predict parking occupancy, reducing drivers' search time for parking spaces.

Researchers have also focused on developing dynamic parking distribution algorithms to maximize the utilization of parking resources in the city. Zhao et al. (2020) developed a dynamic parking distribution algorithm considering shared and non-shared modes to maximize parking resource utilization in the city. Xie et al. (2021) created a parking allocation model that balances the utilization of surrounding parking resources and reduces dynamic traffic pressure by considering the ability of dynamic and static traffic conversion. Enhanced autonomy of the traffic system can also contribute to parking efficiency. Sayarshad (2023) designed an intelligent public parking allocation system for autonomous vehicles, allowing them to move from crowded city centers to less congested areas for parking, and a dynamic optimization formulation is proposed considering drivers' preferences including rent bid, parking lot searching time, and travel costs.

Emerging technologies have provided smart solutions for urban parking space allocation. Arellano-Verdejo et al. (2019) developed a mathematical model and evolutionary algorithm to optimize the allocation of public parking spots in a smart city. Wireless Sensor Networks have been used to create parking lot guidance systems, enabling drivers to find nearby parking spaces through mobile apps. GPS traces and sensors have been utilized to sense on-street parking space availability, improving traffic efficiency. Shin et al. (2018) came up with a smart parking guidance algorithm for city transportation management, considering factors like the driving distance, walking distance, and traffic congestion. Anusha and Pushpalatha (2022) proposed a smart parking guidance algorithm that considers driving and walking distances, as well as traffic congestion. Sangeetha et al. (2022) utilized Internet of Things (IoT) technology to assist parking systems to address traffic congestion, parking spaces lack, and safety issues.

2.3 Parking Strategies Within Parking Lots

The advancement of smart technologies and algorithms has enabled the implementation of intelligent parking systems within parking lots. These systems utilize controllers, sensors, computer vision, and IoT technology and so on to optimize vehicle allocation and enhance the overall parking experience.

Smart parking systems incorporate various technologies to assist drivers in finding parking spaces. Asaduzzaman et al. (2015) proposed a smart parking system for heavy traffic environments that can hold multi-floor buildings and send messages to vehicles about the status of parking spaces. Besides, IoT technology enables accessibility to things from a remote location. Mahendra et al. (2017) implemented IoT-based sensors in the parking system to help drivers reserve parking spaces from a remote location. Huang et al. (2018) integrated parking reservations into automated valet parking (AVP) system, in which a privacy-preserving reservation scheme was proposed. Patil et al. (2018) demonstrated a centralized parking system for drivers to reach the free parking slots through the fastest route. The development of computer vision also helped in smart parking systems. Prabagar et al. (2021) used computer vision to monitor the availability of spots and the entry and exits of the vehicles. Bibi et al. (2017) presented an automatic smart parking system based on computer vision to assist drivers to find a suitable parking space and to reserve it. Athira et al. (2019) used optical character recognition to identify the availability of parking spaces. Dogaroglu et al. (2021) tested an Intelligent Parking Guidance System (IPGS) model with Conventional System (CS) where drivers prefer the closest parking utility with regard to capacity utilization, and IPGS has higher efficiency.

The developed technologies have also facilitated the implementation of dynamic control and planning methods within parking lots, given the dynamic nature of parking space availability. Real-time GPS data helps in dynamic parking allocation. Mladenović et al. (2021) established a dynamic parking allocation scenario using GPS data to guide the vehicle to the designated parking lot, solving a binary programming model. Duan et al. (2020b) also employed a binary programming model for parking lot allocation optimization. Shin et al. (2018) developed a dynamic control of intelligent parking guidance using neural network predictive control to operate an intelligent parking guidance system, which is for assessing and selecting the best parking lot in a real-time environment. Yang et al. (2021) analyzed parking space utilization and developed a dynamic model for parking space allocation to improve driver satisfaction and occupancy balance. Xie et al. (2022) employed a system-side Deep Reinforcement Learning (DRL)-based cooperative approach with a global objective for parking space allocation, considering immediate and future effects. Zhang et al. (2021) developed an online parking assignment strategy in an environment with partially connected vehicles using a multi-agent deep reinforcement learning approach.

The use of automated guided vehicles (AGVs) within parking lots has gained attention for enhancing efficiency and reducing congestion. Zhang et al. (2021) proposed a cooperative approach for multi-AGV systems inspired by hierarchical traffic control, solving parking space allocation using deep reinforcement learning. Cooperative driving is also implemented at the lower level to avoid congestion and collisions (Digani et al., 2014). Fransen et al. (2020) conducted research on real-time path planning for large, dense grid-based AGV systems using a dynamic approach.

2.4 Traffic Models for Parking Analysis

A reliable traffic model is crucial for understanding and effectively parking management. Choice behaviors play a significant role in model formulation, for example in agent-based models, as each vehicle makes decisions such as route selection, parking space search, stay duration, and exit strategy (Vo et al., 2016). Vo et al. (2016) divided parking movement into 2 steps: route choice for parking strip and route choice for parking space, which are highly affected by choice behaviors. Factors like travel time to the parking space, walking time to the destination, and guidance signs affect drivers' choice of parking space. The empirical analysis is commonly used to construct parking choice behavior and statistical models for arrival and departure. Attributes like travel time, walking distance, and parking probability are used to study drivers' preferences. Xu and Sun (2022) investigated the ”arrival priority” and ”reservation priority” in parking management and developed an ”ant colony-genetic” algorithm to find the optimal strategy to minimize the total parking cost. Mei et al. (2020) formulated an agent-based model to describe parking and traffic conditions and optimize the strategy based on the performance from the simulation using a genetic algorithm. Zhao et al. (2021b) proposed a simulation-based optimization model using a genetic algorithm to solve the system design of station location and vehicle deployment. To optimize parking space management, hierarchical architecture models have been constructed, such as bi-level simulation optimization systems to reach different level objectives (Zhang et al., 2021; Vo et al., 2016; Duan et al., 2020b). For example, aiming to find the optimal solution for parking space management, a bi-level simulation optimization system is constructed, and found out that different parking time limitations help to enhance the parking lot efficiency (Vo et al., 2016). The upper level is an optimization model aimed at maximizing the social benefit, including driving time, searching time, and walking time. The operation management policies are simulated in the lower level, which is a multi-agent-based simulation.

In the context of multi-region urban road networks, macroscopic modeling for autonomous vehicles (AVs) with dynamic control (Zhao et al., 2021a) has been applied to reduce cruising-for-parking time. A centralized parking dispatch approach optimizes the distribution of floating AVs and provides route guidance.

Microscopic models are utilized for traffic simulation within parking lots. During the 2008 Beijing Olympic Games at the National Stadium in China, a complex evacuation problem with a large audience was addressed using microscopic simulation in VISSIM, demonstrating high accuracy for validating the evacuation plan (Shao et al., 2008). Microscopic simulation offers advantages such as a more precise representation compared to macroscopic simulation, considering factors like passenger diversity, vehicle features, driving skills, highway network, and organizing efforts (Shao et al., 2008). Makarova et al. (2022) utilized microscopic simulation to evaluate the efficiency and additional effects of urban parking organization. However, it also lacks the extensive data required and the need for advanced computer resources (Naghawi and Wolshon, 2012).

2.5 Research Gap

The identified research gap revolves around the specific challenges associated with efficiently allocating parking spaces in a parking lot during PSEs such as football games or large concerts. While existing literature addresses parking space allocation in urban areas and single parking lots, there is a lack of studies that specifically focus on the unique requirements and complexities of allocating parking spaces efficiently in a parking lot during PSEs.

The challenges in parking space allocation during PSEs arise from the sudden increase in vehicle volume and the need to accommodate a large number of attendees within a limited time-frame. These events demand strategies capable of handling high parking demand, optimizing parking space utilization, ensuring smooth traffic flow, and minimizing congestion in the specific context of a single parking lot.

While some existing approaches in the literature can be extended to address parking space allocation challenges, a more adaptive and tailored method is needed to the unique requirements of PSEs and the characteristics of a single parking lot. The existing approaches often lack a comprehensive focus on the specific challenges posed by high traffic volumes and time-constrained parking requirements during PSEs in a single parking lot setting.

Therefore, the primary contribution of this research lies in the development of an approach that specifically addresses the challenges of efficient parking space allocation during PSEs in a single parking lot. This research takes into account the distinctive context of PSEs, considering factors such as high parking demand, time constraints, traffic flow management, and attendee arrivals.

By focusing on the efficient allocation of parking spaces in the parking lot during PSEs, this research aims to enhance the overall traffic management, reduce cruising time, and improve the parking experience for event attendees. The proposed algorithmic approach offers a tailored solution that accounts for the unique requirements and constraints of PSEs in a single parking lot setting, thereby providing a valuable contribution to the field.

The proposed research seeks to assist drivers in swiftly locating parking spaces in the parking lot, thereby enhancing their parking experience and reducing cruising time outside the venue. By effectively utilizing the parking lot, the study aims to alleviate traffic pressure near the event location, providing a practical solution without the need for additional time-consuming and costly construction of parking facilities.

Through the development of an algorithmic approach, this research contributes to the field by offering a solution to optimize parking space allocation strategies in the parking lot under the untypically high parking demands during PSEs.

3 Methodology

3.1 Introduction

The methodology adopted is to identify the most effective parking space allocation strategy for mitigating traffic congestion during PSEs. By minimizing the overall time taken by vehicles to the allocated parking space, the aim is to alleviate traffic pressure in the vicinity of the venue. To address this objective, two distinct methods have been developed.

Linear programming (LP) is a commonly used approach for optimization tasks, including similar parking optimization problems (Ruan et al., 2016; Geng and Cassandras, 2013). There exist powerful and mature solvers such as Gurobi developed to solve optimization problems including LP, providing computation efficiency (Roth and Yih, 2004). However, in the later experiments (See Section 4.1.1 with solution shown in Figure 4.1), since the lack of consideration of the dynamic traffic in the parking lot, it showed limitations in approximating different traffic situations for different routes.

To address its limitations, a simulation-based optimization approach is proposed. The simulation-based optimization is also used in parking-related problems (Mei et al., 2020; Zhao et al., 2021b). In this approach, an agent-based simulation is constructed in NetLogo to model the intricate dynamics of the parking process. By considering factors such as vehicle movement, parking lot layout, and parking space availability, the simulation provides a more detailed approximation of the real-world complexities involved in parking lots. This agent-based simulation serves as a foundation for generating data to inform the subsequent optimization process and further experimentation.

To search for the optimal solution using the simulation data, we employ the simulation-based genetic algorithm (GA). GA is known for its relatively faster convergence speed among heuristic algorithms and its ability to efficiently yield near-optimum solutions (Zhao et al., 2021b). By integrating the agent-based simulation with the GA, this simulation-based optimization approach provides a robust and comprehensive framework for addressing parking space allocation. This approach not only overcomes the limitations of LP formulations but also leverages the strengths of simulation and optimization techniques to deliver more practical solutions. Through this methodology, we aim to contribute to the development of effective parking allocation strategies that account for real-world complexities.

3.2 Optimization Objective and Assumptions

In the context of PSEs with a high demand for parking spaces, the parking lot consists of N parking spaces, accommodating a maximum of N vehicles.

The optimization objective aims to find the optimal allocation strategy that reduces the overall travel time for drivers. By minimizing the total travel time TTT that drivers spend in the parking lot, the goal is to save time for drivers and optimize the utilization of parking spaces.

The objective function is shown as Formula 3.1:

$$Min \quad TTT = \sum_{i=1}^{N} TT_{ij} \quad (i, j \in \{1, 2, 3, ..., N\}) \tag{3.1}$$

TT_{ij}, travel time for vehicle i to its assigned parking space j

To formulate the LP model, certain assumptions have been made to simplify the modeling and analysis process, allowing for a focused examination of specific aspects of the allocation strategy. These assumptions are as follows:

- During PSEs, it is assumed that the parking demand is high, resulting in all parking spaces being occupied. This assumption allows for studying the strategy in a scenario where parking resources are limited.
- Due to the nature of PSEs, vehicles are assumed to arrive in a concentrated time period. It is assumed that the next vehicle arrives and enters the parking lot as soon as the entrance is available until the total number of vehicles N is present in the parking lot.
- All vehicles are assumed to be identical, obeying the same rules and exhibiting the same behavior. This simplification enables the focus to be on the impact of the allocation strategy rather than individual vehicle characteristics.
- Only the time spent inside the parking lot is considered in the model. Factors outside the parking lot are disregarded to allow for a more specific analysis of the allocation strategy within the parking lot.
- The driving speed is assumed to be consistent for all vehicles. This assumption helps maintain simplicity in the model and allows for a more straightforward analysis of the allocation strategy.
- Delay occurs when a leading vehicle is parking and blocking the road, resulting in waiting time for the following vehicle. It is assumed that only one vehicle ahead will affect the following vehicle. This assumption simplifies the delay process and provides a basis to analyze the impact of such delays on the allocation strategy.
- Vehicles are assumed to only park in the parking spaces on the right-hand side. This simplifies the allocation process and allows for a more focused analysis of the strategy within the given constraints.
- The time required for a vehicle to complete the parking maneuver (denoted as γ) is assumed to be the same for every vehicle. This assumption helps maintain simplicity in the model and facilitates the analysis of the allocation strategy.

These assumptions help streamline the model and focus on the important characteristics of the allocation strategy. They allow for studying the strategy in a scenario where parking resources are limited and provide a clear sequence of vehicle entry. Additionally, the simplification of vehicle characteristics, driving speed, and parking rules enables a more focused analysis of the impact of the allocation strategy.

However, it is noted that deviation from these assumptions could require more comprehensive modeling techniques and may lead to different allocation strategies. Varying arrival patterns and rates, different vehicle characteristics, and driver behaviors would introduce additional dynamics and complexities, requiring a more tailored strategy. Furthermore, considering factors outside the parking lot and more complex route choices would introduce additional decision-making factors and increase the complexity of the problem.

3.3 Linear Programming (LP)

In this section, we formulate a Linear Programming (LP) model to address the parking space allocation problem in a parking lot. We provide two simple examples: one with only one route (See Section 3.3.1) and another with several routes (See Section 3.3.2).

3.3.1 One-route Case

To illustrate the linear programming algorithm, we start with the layout $Single - Route\ Layout$, which consists of only one route where vehicles drive along the arrows (Figure 3.1).

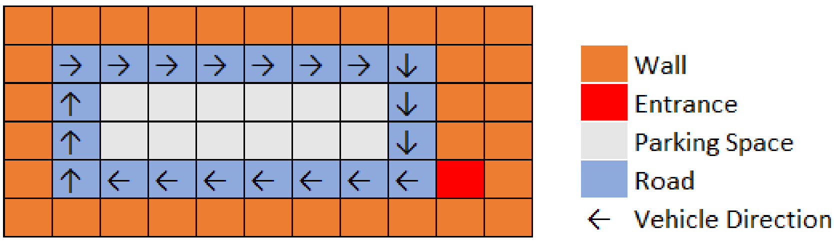


Figure 3.1: Single-Route Layout

The objective function Formula 3.1 aims to minimize the total travel time spent (TTT) for all vehicles inside the parking lot. Considering both driving time t_{ij} and waiting time w_{ij} in congestion, TT_{ij} can be divided into 2 parts:

$$TT_{ij} = t_{ij} + w_{ij} \tag{3.2}$$

t_{ij}, time spent by vehicle i from the entrance to parking space j in the parking lot when it is driving

w_{ij}, time spent by the vehicle i driving to parking space j in the parking lot when it stopped and waiting, occurring when it is blocked by the leading vehicle.

For t_{ij}, it is calculated:

$$t_{ij} = l_{ij} / \bar{v}_i \tag{3.3}$$

l_{ij} , the driving distance for vehicle i to parking space j

$\bar{v}_i$, the average speed

The distance for vehicles to drive from the entrance to the assigned parking spaces inside the parking lot, referred to as the route length, is independent of the vehicles and only depends on the location of the parking spaces:

$$l_{ij} = d_j \tag{3.4}$$

The order of parking spaces is sorted in descending:

$$d_1 \geq d_2 \geq \cdots \geq d_N \tag{3.5}$$

It is important to note that the sum of travel distances for all vehicles remains constant since all the parking spaces are occupied:

$$\sum_{j=1}^{N} d_j = \alpha \tag{3.6}$$

α, a positive constant

The speeds of each vehicle is $\bar{v}$ during driving, resulting in the equation:

$$\sum_{i=1}^{N} t_{ij} = \sum_{j=1}^{N} d_j/\bar{v} = \alpha/\bar{v} = \beta \tag{3.7}$$

β, a constant

Consequently, the objective function can be expressed as:

$$min \quad TTT = \beta + \sum_{i=1}^{N} w_i \tag{3.8}$$

As a result, minimizing the objective function is equal to minimize the sum of w_{ij}, we define it as W:

$$min \quad W = \sum_{i=1}^{N} w_{ij},\ j \in 1,2,3,...N \tag{3.9}$$

To approximate the waiting time for each vehicle, a binary variable matrix $X = (x_{ij})_{1\leq i\leq N, 1\leq j\leq N}$ is defined:

$$x_{ij} = \begin{cases} 1 & \text{if vehicle } i \text{ is assigned to parking space } j \\ 0 & \text{else} \end{cases} \tag{3.10}$$

For each vehicle, it can only be assigned 1 parking space, and each parking space can only accommodate 1 vehicle.

$$\sum_{j=1}^{N} x_{ij} = 1 \quad (i \in 1,2,3,...,N) \tag{3.11}$$

$$\sum_{i=1}^{N} x_{ij} = 1 \quad (j \in 1, 2, 3, ..., N) \tag{3.12}$$

In this case, vehicles enter the parking lot one by one in a sequence. To further illustrate the interaction between vehicles, 3 consecutive vehicles 0, 1, 2 are taken for an example Figure 3.2:

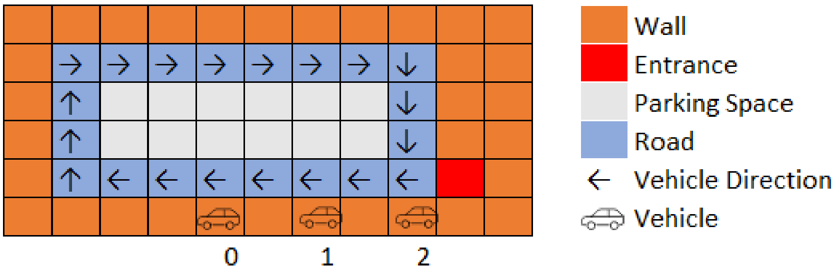


Figure 3.2: Consecutive Vehicles in the Parking Lot

For vehicle 1, only vehicle 0 has chance to block it, and vehicle 2 has nothing with it since it enters later and follows the vehicle 1.

If vehicle 0 is allocated with a parking space ahead of vehicle 1 along the route, it will not block vehicle 1. However, if vehicle 0 is allocated a parking space behind vehicle 1, it will block vehicle 1, causing it to wait.

Since we only consider that only one vehicle ahead will affect the following vehicle, which means if there is a following vehicle assigned a parking space further along the route than the leading vehicle, it will be blocked, and it will have to wait until the leading vehicle completes its parking process. The Expression 3.13 is used to calculate waiting time.

w_{ij} is a binary variable, either a positive constant γ or 0, where $1 \leq i \leq N-1, 1 \leq j \leq N$:

$$w_{ij} = \begin{cases} \gamma & x_{ij} + x_{i+1,d} = 2,\ 1 \leq d \leq j \\ 0 & \text{else} \end{cases} \tag{3.13}$$

It can be written in terms of inequality, where $1 \leq i \leq N-1, 1 \leq j \leq N, 1 \leq d \leq j$

$$w_{ij} \geq \gamma \times (x_{ij} + x_{i+1,d} - 1) \tag{3.14}$$

$$w_{ij} \leq \gamma \times x_{ij} \tag{3.15}$$

$$w_{ij} \leq \gamma \times x_{i+1,d} \tag{3.16}$$

3.3.2 Multi-route Case

To extend the linear optimization algorithm to a more complex layout with several routes, the parking lot layout and the routes are defined as depicted in Figure 3.3, the parking spaces are classified into 3 zones according to the route:

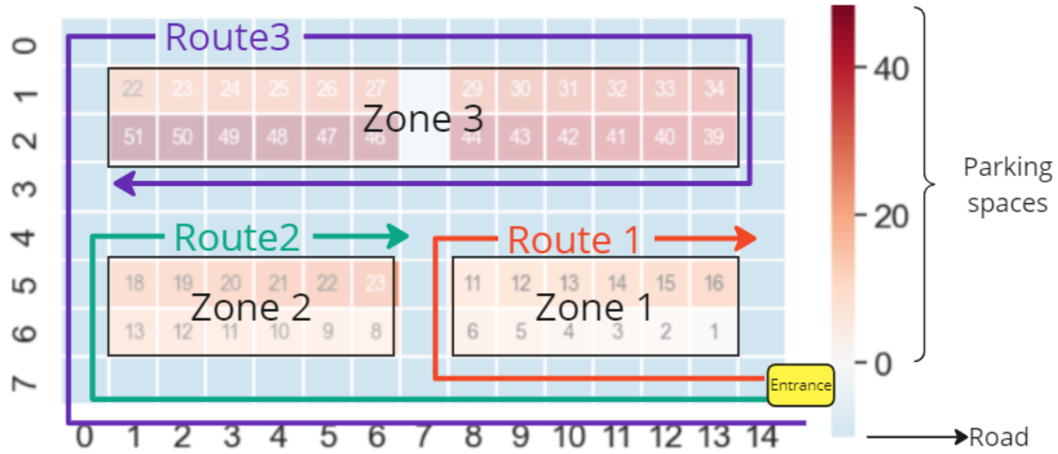


Figure 3.3: Routes and Zones in *Layout*1

We maintain the same assumptions as defined in Section 3.3.1. However, in this case, the parking spaces are not situated along a single route. Instead, there are three routes, and there are overlapping sections between them. The distance to each parking space is approximated by the patch number along the respective route. The color gradient in the heatmap Figure 3.4 indicates these distances, with darker colors representing longer routes. The numerical values displayed on the parking spaces indicate the corresponding distances starting from the entrance along the route.

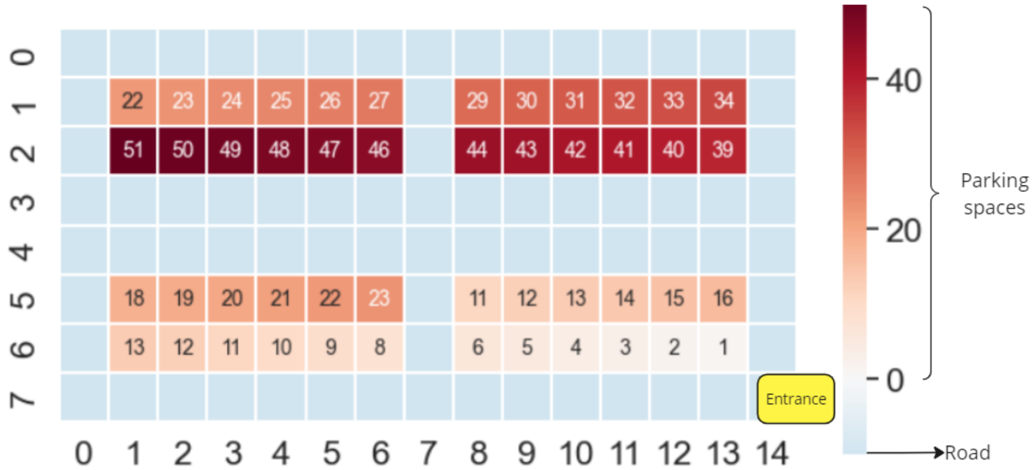


Figure 3.4: Parking Space Distance Heatmap: $Layout1$

In the extended formulation, we retain the same variables and objective function as in Formulas 3.1 - 3.12. The objective is also to minimize W. However, there are some modifications to account for the presence of multiple routes and the impact of blocking only between vehicles assigned to parking spaces along the same route. It should be noticed that there are overlapping between each route, so that parking spaces can belong to 1 or more routes. In this case, there are 3 routes and 48 parking spaces, so $N = 48$ and routes number $L = 3$. To represent the relationship between parking spaces and routes, a binary parameter matrix $Y = (y_{km})_{1 \leq k \leq N, 1 \leq m \leq L}$ is introduced:

$$y_{km} = \begin{cases} 1 & \text{if parking space k is along the route m} \\ 0 & \text{else} \end{cases}$$

For each route m, subset X_m is defined:

$$X_m = \{x_{ij} | x_{ij} \in X \ \wedge \ y_{jm} = 1, 1 \leq m \leq L\} \tag{3.17}$$

When two vehicles are allocated with parking spaces in the same subset, the leading vehicle could block the following vehicle. The formula 3.13, 3.14, 3.15, 3.16 can be extended in this multi-route case to calculate the waiting time w_{ij} with:

$$1 \leq i \leq N - 1$$
$$1 \leq j \leq N$$
$$1 \leq d \leq j$$
$$i, j, d \in \mathbb{Z}$$
$$(x_{ij} \in X_1 \ \wedge x_{i+1,d} \in X_1) \vee \ (x_{ij} \in X_2 \ \wedge x_{i+1,d} \in X_2) \vee ... \vee (x_{ij} \in X_L \ \wedge x_{i+1,d} \in X_L)$$

The problem is solved in Section 4.1.1. From the optimal solution found by LP, it seems not to integrate the dynamic traffic situation along each route. To integrate the dynamic in the parking lot, the following Section 3.4 and Section 3.5 introduced a simulation-based optimization algorithm.

3.4 Agent-based Simulation

3.4.1 Introduction

Agent-based modeling, also known as multi-agent-based modeling, is commonly used to simulate travel behaviors, including parking behaviors (Vo et al., 2016; Zhao et al., 2018). It is suitable to model the activities of agents in the transport system and replicate the driver's behavior (Ni and Sun, 2017; Chen et al., 2016; Ni and Sun, 2017; Vo et al., 2016). It allows for the explicit modeling of individual drivers' behavior and their interactions, providing insights into their movement patterns.

NetLogo is an open-source software for multi-agent-based modeling simulation showing advantages for behavioral simulation (Vo et al., 2016), which can be used to simulate travel behavior for a large number of agents and allow inputs like non-homogeneous environment and personal preferences (Zhao et al., 2021a). It has its own programming language that facilitates efficient learning and utilization. Users can create their own models in NetLogo with the simple scripting language and user-friendly interface. NetLogo allows researchers not only to look into the microscopic level considering individual behaviors of drivers but also the macroscopic level coming from their interactions (Vo et al., 2016).

In this section, an agent-based simulation is constructed to simulate the parking process of vehicles within the parking lot using NetLogo. This simulation environment captures the interactions between vehicles and the environment. The implementation in NetLogo allows for a microscopic analysis of individual driver behaviors. By simulating the behavior of each driver agent, insights can be gained into the parking process at both the individual and collective levels, providing a relatively realistic representation of the parking lot dynamics. Each vehicle in the parking lot can act as an agent to obey some simple rules. The simulation shows the entering and parking of the vehicles. The exiting process is not considered here.

3.4.2 Parking Lot Layouts

In the simulation, some basic visual settings for patches and agents are like the following:

- Patch colors

  Green for entrance. Cyan for the road. Grey for parking spaces.

- Agent shape

  All Agents are the same vehicle shape.

- Size

  The size for patches and agents setting is described in section 3.4.4.

Two parking lot layouts are constructed for the simulation. A simpler *Layout*1 aligns with Section 3.3.2 and a more complex and realistic *Layout*2.

Both layouts only include the entrance, parking spaces, and lanes of the parking lot and exclude other infrastructures. The simulation specifically focuses on the entering behavior of vehicles and does not consider the exiting process.

The layout *Layout*1 (Figure 3.5) has more simplification and constraints, is suitable for a clear understanding of vehicle movement and basic illustration and testing. In this *Layout*1, vehicles can only be parked on the right side, with less number of parking spaces and providing fewer routes inside the parking lot. Additionally, some roads in *Layout*1 have only one lane to simplify the movement dynamics.

By simplifying and imposing more constraints on *Layout*1, specific aspects of the parking lot such as the parking space distance, can be isolated and studied, which allows for easier analysis and interpretation of the results. By having some roads with only one lane, vehicle movement dynamics can be affected to provide more insight into congestion and interference that occur due to restricted lanes. Besides, with fewer parking spaces and restricted routes, it allows for the exploration of the effects of limited availability and potential congestion in a simplified setting.

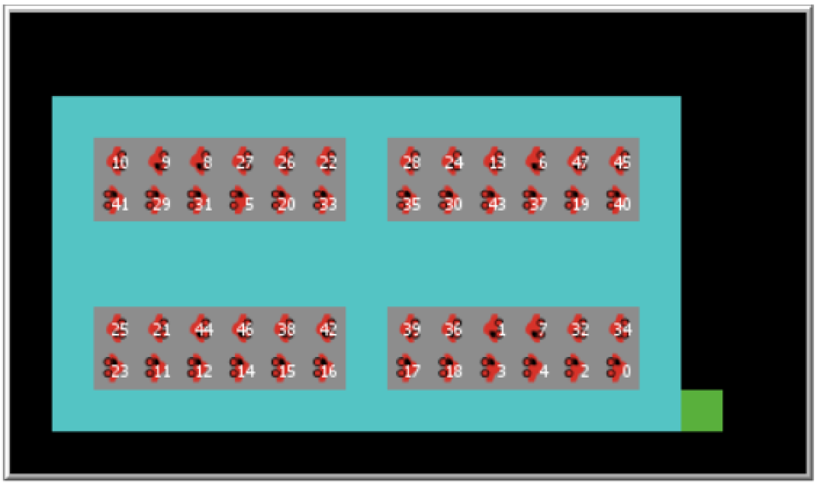


Figure 3.5: Simulation: *Layout*1 - Occupied Parking Lot Visualization

Figure 3.6 illustrates the directions of lanes in *Layout*1, showing the flow of traffic.

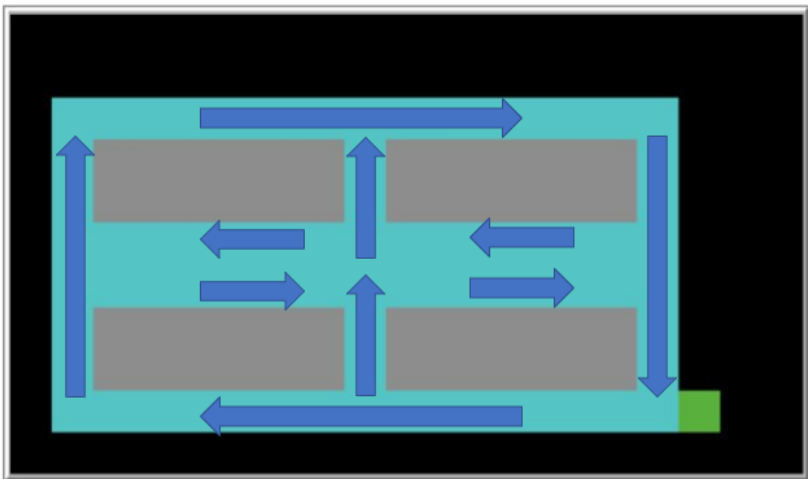


Figure 3.6: Simulation: *Layout*1 - Road Direction

To introduce more dynamics, vehicles in *Layout*2 have the option to park on either the right or left side. Since vehicles drive on the right side of the road, if they want to park on the left side, they have to change lanes. *Layout*2 is shown in Figure 3.7 which is derived from a layout in a microscopic simulation for a real parking lot in Eindhoven ensuring a realistic representation of the parking environment, which was also used in an agent-based simulation before by Vo et al.. Compared to *Layout*1, *Layout*2 has more complex interaction rules that allow vehicles to choose parking spaces on either the right or left side. It also features a more complex environment with a greater number of parking spaces and more complex routes.

*Layout*2 enables the study of lane change dynamics and their influence on the allocation strategy. Besides, deriving this layout from a real parking lot ensures a more accurate representation of the parking environment, allowing for insights that can be applied to real-world parking scenarios.

The direction for the road is shown in Figure 3.8.

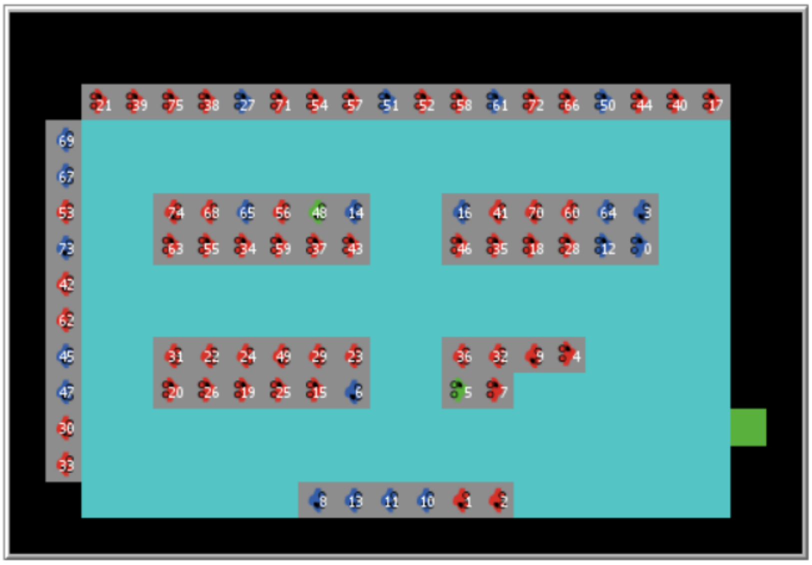


Figure 3.7: Simulation: *Layout*2 - Occupied Parking Lot Visualization

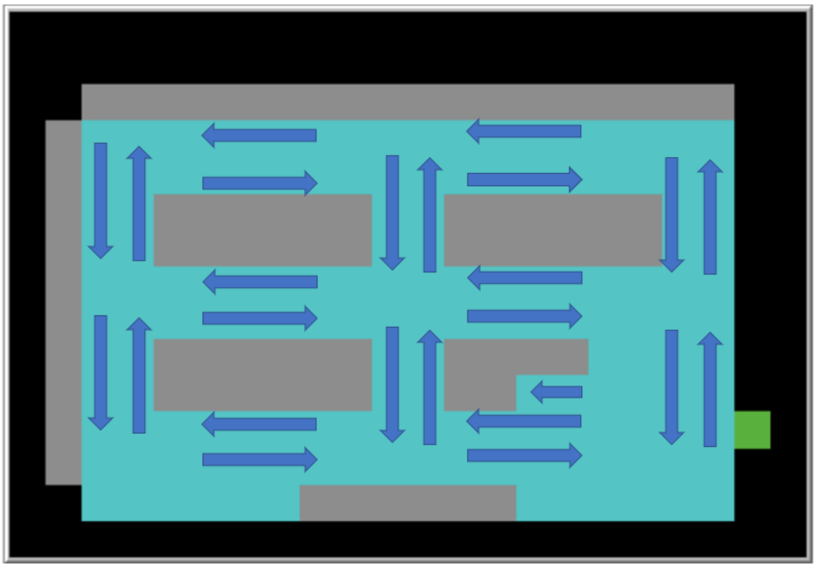


Figure 3.8: Simulation: *Layout*2 - Road Direction

3.4.3 Agent Interaction Rules

In agent-based modeling, rules are essential for defining the behavior and decision-making processes of individual agents within a system. These rules are necessary for successful simulation and analysis. By specifying interaction rules, the model becomes more representative of the complexity and dynamics of the system. In this case, the agents are vehicles.

Similarly like the assumptions in Section 3.3, to simplify the simulation, focus on specific aspects of the allocation strategy, and provide a controlled environment for evaluating the strategy's performance, in this simulation the following assumptions are made before the interaction rules:

- All vehicles are identical and follow the same rules. This simplification allows for a uniform analysis of the allocation strategy without considering individual vehicle characteristics or behaviors.
- All parking spaces in the simulation are assumed to be identical. The time required to complete the parking maneuver is assumed to be the same for all spaces, regardless of the availability of other spaces nearby. This assumption helps streamline the simulation and allows for a more focused analysis of the allocation strategy.
- Vehicles enter the parking lot one by one in a sequential manner. Given the high parking demand, the following vehicle arrives and enters the parking lot as soon as the entrance becomes available. This assumption ensures a consistent flow of vehicles and allows for the analysis of the allocation strategy under high demand conditions.
- Lane changes are only allowed when the left side of the vehicle is empty. This assumption imposes a constraint on vehicle movements and helps maintain a structured environment within the parking lot simulation.

The interaction rules are further classified into two categories: car-to-car interaction rules and car-to-environment interaction rules.

Car-to-car Interaction Rules

When vehicles are on straight lanes, Newell's Car-Following Model is used (Newell, 2002). Newell's car-following model is commonly used in discrete simulation due to its simplicity and ability to capture essential dynamics of vehicle movement. It offers computational efficiency and realistic vehicle behavior by considering maintaining safe headway and adjusting speed based on the leading vehicle's velocity (Ahn et al., 2004; Newell, 2002; Chen et al., 2012). While Newell's car-following model has its limitations, such as its reliance on a single optimal velocity function, it remains a widely used choice for discrete simulation due to its simplicity, computational efficiency, and reasonable approximation of real-world traffic behavior.

The leading vehicle and the following vehicle are shown in Figure 3.9:

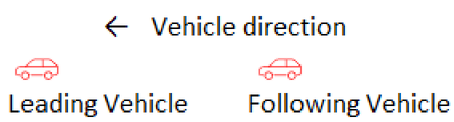


Figure 3.9: Leading Vehicle and Following Vehicle

The speed function for the following vehicle, based on Newell's car-following model, is given by:

$$v(t+T) = max[0, min(v_0, (s - s_0/T))] \tag{3.18}$$

where:

$v(t)$, speed function for the following vehicle at time t

T, time step

v_0, maximum speed

s, distance gap between the following vehicle and the leading vehicle

s_0 minimum distance gap between the following vehicle and the leading vehicle

The distance gap s is the gross headway (including the vehicle length) minus the vehicle length itself:

$$s = h - l_v \tag{3.19}$$

h, gross headway, from the head to the leading vehicle to the head of the following vehicle

l_v , vehicle length

It is extended to the speed calculation when there are no leading vehicles but only walls in front of the vehicle. The distance gap s is measured by the perpendicular distance between the vehicle and the wall in front of the vehicle.

Car-to-Environment Interaction Rules

Car-to-environment rules should capture the realistic interactions between vehicles and their surrounding environment within the parking lot. These rules consider factors such as entering the parking lot, parking in parking spaces, and making turns. The following rules are applied:

- Entering the parking lot

  Each vehicle will enter the parking lot when both the patch representing the entrance and the patch in front of it is empty. The entering process continues until the vehicle number inside the parking lot reaches the demand level. The maximum demand level is equal to the capacity of the parking lot (the number of parking spaces).

- Parking into the parking spaces

  Routes to each parking space are predetermined, eliminating the freedom for vehicles to choose their routes. Vehicles cannot enter the parking spaces as soon as they arrive at their allocated spaces. Each vehicle takes a predetermined time t_{park} to complete the parking process after reaching its allocated space.

- Making turns at crossings

  When vehicles are about to change their directions at the crossings or corners, they change their directions without any speed loss. After changing direction, they continue driving along the lane center.

The simulation continues until all vehicles are parked, at which point the simulation stops.

The flowchart for vehicles driving in the parking lot is depicted in Figure 3.10:

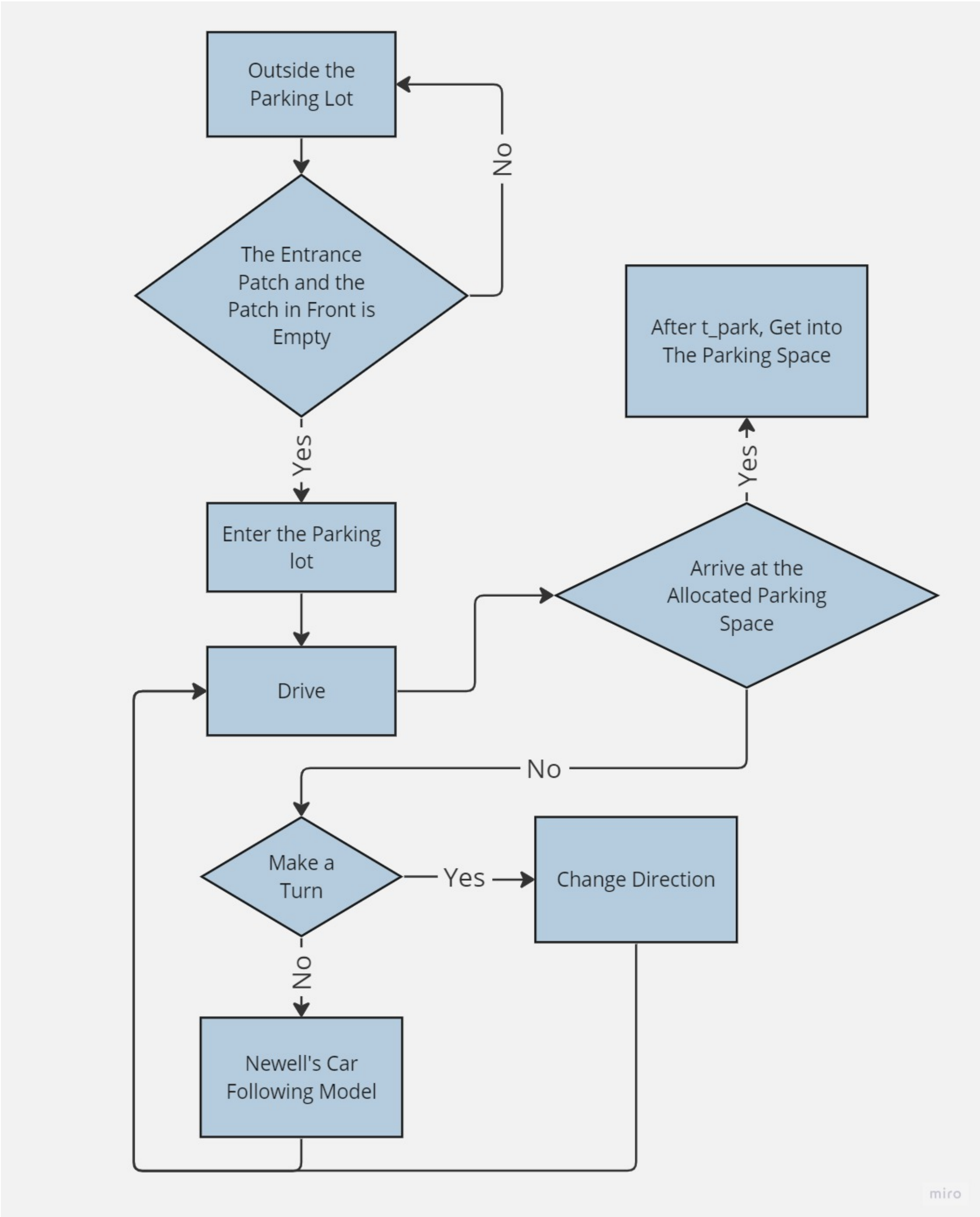


Figure 3.10: Vehicle Driving Flowchart

3.4.4 Basic Parameters Setting

Setting parameters in an agent-based model for car movement in a parking lot is crucial for capturing and representing the key characteristics and behaviors of the system accurately. Setting these parameters such as speed, and headway based on valid references helps create a more realistic representation of how vehicles interact within the parking lot. Realism and accuracy in modeling are essential for capturing the dynamics of the parking lot and deriving meaningful insights from the simulation. Besides, by clearly defining the values and ranges of parameters, the simulation experiments are ensured reproducible.

In the simulation, the world is composed of patches, which are squares in NetLogo (Tisue and Wilensky, 2004; Gooding, 2019). Each patch corresponds to a 5.5 m by 5.5 m square parking space, aligning with the recommendation of the Urban Plan Institute (Zhao et al., 2018; Vo et al., 2016). The time step is tuned to guarantee a smooth simulation performance. The following parameters used for vehicle movement are set for vehicle movement in the simulation shown in Table 3.1.

Table 3.1: Parameters Setting

Parameters	Description	Value
v_0	Speed limit	30 km/h (Zhao et al., 2018)
s_0	Expected distance gap	4.0 m (Sui et al., 2022)
l_v	Length of vehicle	3.72 m (Kumar and Mudgal, 2023)
t_{park}	Time for parking maneuver	30 s(Vo et al., 2016)
T	Time step	0.6 s

Parameters were set through the scroll bar at the simulation interface. The interface for the simulation constructed in NetLogo is shown in Figure 3.11.

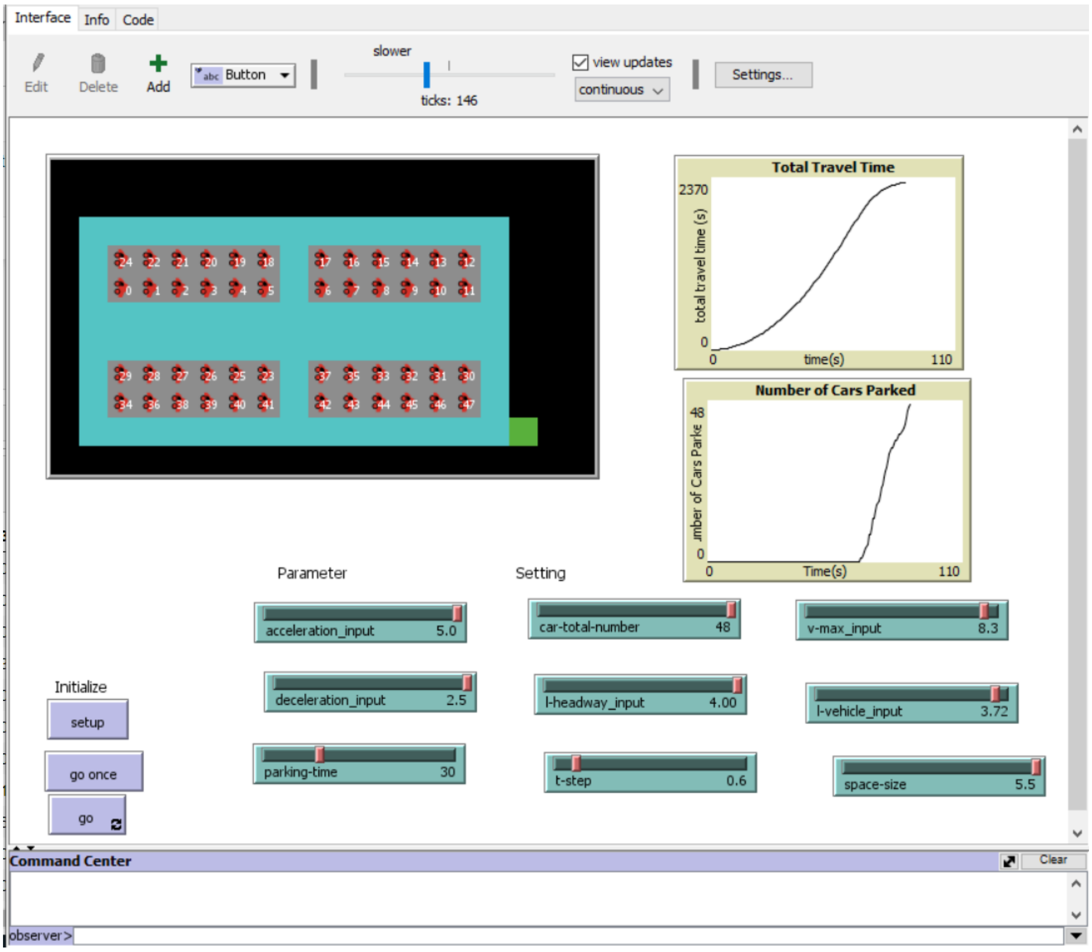


Figure 3.11: Simulation Interface

3.5 Genetic Algorithm (GA)

The Genetic Algorithm (GA) is an optimization algorithm inspired by natural selection and genetics. It can be well applied for the simulation-based optimization (Mei et al., 2020; Zhao et al., 2021b).

In the context of parking space allocation, where the objective is to find the optimal assignment of available parking spaces to vehicles, the search space can be complex, especially in larger parking lots with numerous spaces and roads. GA excels at exploring large and complex solution spaces, efficiently evaluating different allocation possibilities, and identifying optimal solutions.

A simulation-based GA allows for the integration of simulation and can utilize the data generated from the simulation. It takes into account the complex interactions between vehicles and the environment. The simulation serves as a platform to evaluate the efficiency of different allocation strategies based on objective values, and the GA selects solutions with higher fitness based on their performance in the simulation.

The basic workflow for GA used in this research is illustrated in Figure 3.12:

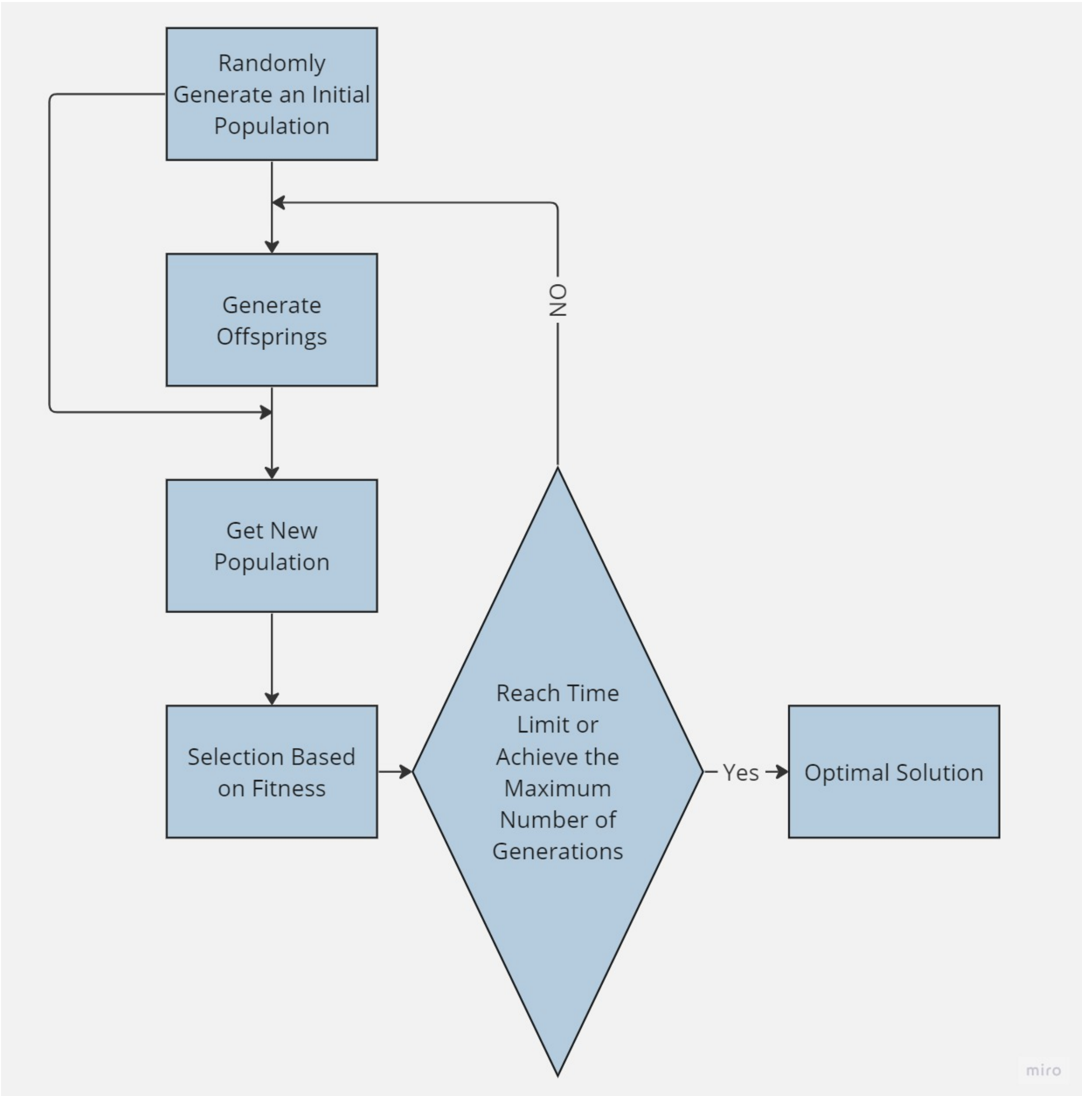


Figure 3.12: GA Flowchart

In this algorithm, candidate solutions also known as chromosomes, are represented as arrays. As the algorithm iterates through generations, solutions with higher fitness are retained as parents for the subsequent generation, while lower fitness solutions are discarded. The process of generating offspring involves recombination through crossover and introducing random variations through mutation. Additionally, a reparation process is applied to ensure the generated solutions comply with problem-specific constraints.

3.5.1 Chromosome Coding

In cases where route choice is not available, and the order of vehicles is followed, each vehicle is assigned a parking space. The allocation solution can be represented as a chromosome, where each gene represents a parking space with a vehicle allocated. As shown in Figure 3.13, *chromosome*1 means that the first parking space is assigned to vehicle 3, the second is assigned to vehicle 5, and so on.

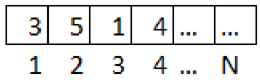


Figure 3.13: *Chromosome*1 Genetic Coding for Optimal Parking Space Allocation

In situations where vehicles have the option to choose between parking on the left or right, an additional chromosome *chromosome*2 is defined to represent the direction in which the vehicle will drive to the assigned parking space. As shown in Figure 3.14, 1 indicates that the assigned parking space is on the right of the vehicle, while 0 represents that it is on the left.

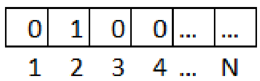


Figure 3.14: *Chromosome*2 Genetic Coding for Optimal Parking Space Allocation

3.5.2 Crossover

Crossover is a genetic operator in GA that mimics the natural process of genetic recombination. The purpose of crossover is to explore new regions of the search space by combining favorable characteristics of different individuals. By exchanging genetic material, the crossover operator promotes diversity in the population and helps to maintain a balance between exploration and exploitation of the search space.

The crossover process involves generating new offspring by recombining the genes of two parents. Two parents are randomly selected from the parent population, and gene exchange occurs at designated crossover locations. This combination allows the offspring to inherit favorable traits from both parents and promotes diversity in the offspring population. In this case, allocation strategies in different areas of the parking lot can be combined through the crossover.

The process is: two cross locations are randomly chosen on *Parent*1. The section between to cross locations is replaced with the corresponding section on *Parent*2, as shown in Figure 3.15.

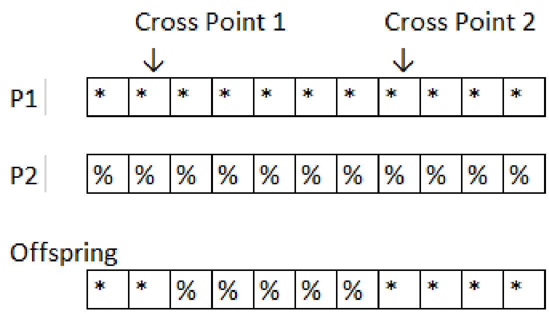


Figure 3.15: Crossover

3.5.3 Mutation

Mutation is another genetic operator that introduces random changes in the chromosomes of the population. It allows for exploration of the search space beyond the limitations imposed by crossover alone. Mutation adds diversity by introducing random variations to individual chromosomes, which can potentially lead to the discovery of new and better solutions. It helps prevent premature convergence and allows the GA to escape local optima by providing occasional random exploration. Genes have a mutation rate, allowing them to mutate into another randomly chosen gene. Figure 3.16 depicts this mutation process. With a mutation rate, the gene mutates to a different gene. In this case, for example, it means that a parking space assigned to a vehicle is changed to be assigned to another vehicle.

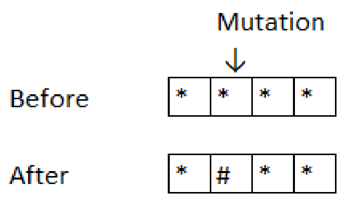


Figure 3.16: Mutation

3.5.4 Reparation

Reparation is a process that ensures the generated solutions comply with problem-specific constraints or requirements. Considering the constraints in the parking spaces allocation, *chromosome*1 requires all genes to be unique since each vehicle can only be allocated to one parking space. After the crossover and mutation operations, every gene is examined. If a gene is found to be non-unique within the chromosome, it is replaced by another randomly available gene which doesn't show in the chromosome. The process is shown in Figure 3.17.

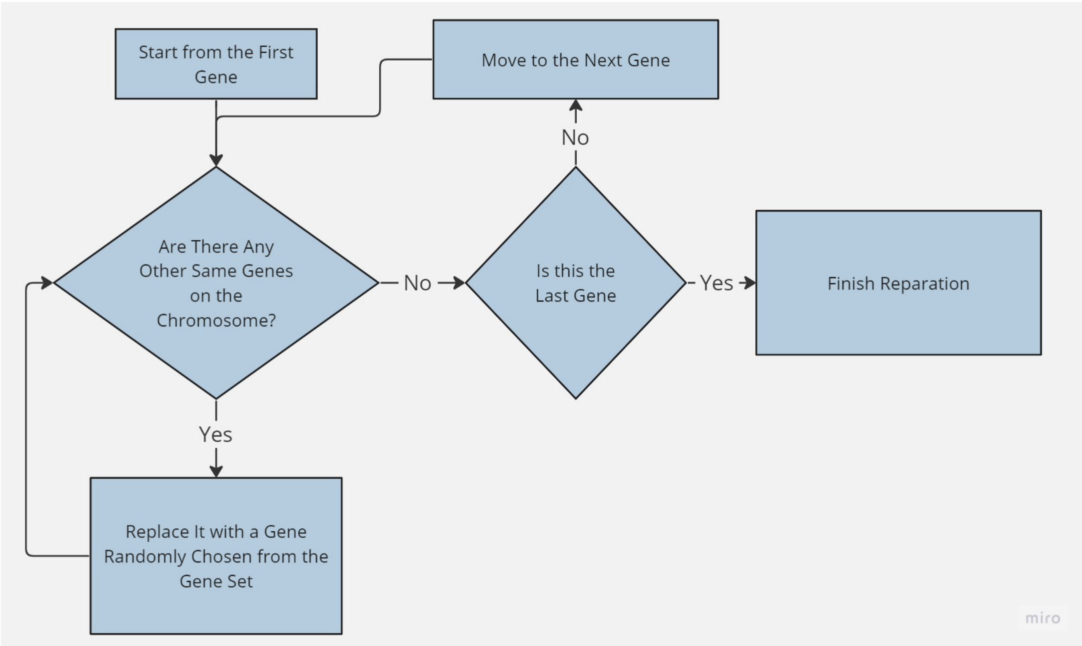


Figure 3.17: Reparation Flowchart

It is important to note that while the reparation approach guarantees the uniqueness of genes within the chromosome, it does not guarantee the optimality of the solution. The process of selection and further iterations in the GA contribute to the evolution of the population and the generation of optimal solutions. Therefore, the reparation process serves as a necessary step to ensure the fulfillment of constraints, while the subsequent iterations help refine and improve the solutions over time.

3.5.5 Selection Strategy

Individuals with higher fitness are selected as the parents of the next generation. The fitness is scaled with the value of the objective value TTT. Since the objective is to minimize TTT, the individuals with lower TTT have higher fitness.

The value of fitness is calculated like the following:

- For the population, calculate the objective value TTT for each individual. Then the maximum TTT_{max} among the population is determined.
- The fitness function f for each individual is a defined as a function of TTT, solutions with lower travel time are with higher fitness:

$$f(z) = TTT_{max} - TTT \tag{3.20}$$

By calculating fitness as the difference between the maximum TTT across the generation and the TTT for a particular solution, the selection strategy aims to maximize improvement. Individuals with lower TTT will have higher fitness values, making them more likely to be selected for reproduction and survive into subsequent generations.

After the calculation for fitness, individuals with fitness in the top 50% are selected as parents for generating the offspring. The number of offspring equals the number of parents, and these parents and offspring form the population for the next generation. In this way, the best individual is always kept in the population. This selection process promotes convergence towards better solutions over generations by favoring individuals with lower total travel times.

3.5.6 Hyperparameters

When employing the GA for searching for the optimal solution, several important hyperparameters impact the performance and effectiveness of the algorithm.

- *population_size*

  The number of individuals in the population. A larger population size allows for more exploration of the search space by maintaining a diverse set of solutions. This can be beneficial in the early stages of optimization when a wide exploration is desired. It may speed up the convergence process as it increases the chances of finding high-quality solutions. However, it also comes with higher computational costs.

  On the other hand, a smaller population size promotes exploitation by focusing on a more refined set of solutions that have the potential for further improvement. Smaller population sizes may converge slower but could be computationally more efficient.

- *num_generations*

  The number of iterations or generations of the algorithm. The number of generations determines how many iterations the GA will run. Increasing the number of generations allows for more iterations, potentially leading to a better convergence towards the optimal solution. However, setting too many generations can result in unnecessary computational costs if the convergence has already been achieved. If time is limited, a lower number of generations can still produce acceptable results, while a higher number of generations can be employed for more precise and refined solutions.

- *mutation_rate*

  The probability for mutation during the algorithm. The mutation rate determines the probability of introducing random changes in the chromosomes. A higher mutation rate encourages exploration by introducing more diverse genetic material into the population. This can be beneficial in preventing premature convergence and escaping local optima.

  However, a very high mutation rate can lead to excessive exploration, hindering the convergence process. A lower mutation rate promotes exploitation by focusing on the existing genetic material, allowing the GA to refine and improve the already discovered solutions.

4 Experimentation

In this chapter, experiments are conducted on two layouts: $Layout1$, which represents a simpler layout, and $Layout2$, which is more complex. The performance of the strategies found by both the LP model and the simulation-based GA algorithm is tested on Layout1 to compare their effectiveness. Subsequently, the simulation-based GA algorithm is applied to $Layout2$ to study optimal strategies under different demand levels.

4.1 Experiment on $Layout1$

In this section, both LP and simulation-based GA are applied on $Layout1$ in search of the optimal solution.

4.1.1 Experiment Setup

LP

The LP is solved using a Python extension module called "gurobipy" from Gurobi (Gurobi Optimization, 2021; Pedroso, 2011). Gurobi is a widely used optimization solver which is suitable for linear optimization, with high reliability and performance.

Simulation-Based GA

Considering the computation efficiency and the exploration ability mentioned in Section 3.5.6, the hyperparameters have been tuned within following range: $population\_size$ [10,50], $num\_generations$ [50,200], $mutation\_rate$ [0.01,0.1].

The chosen hyperparameters for the experiment on $Layout1$ are shown in Table 4.1.

Table 4.1: Hyperparameters $Layout1$

$population\_size$	20
$num\_generations$	100
$mutation\_rate$	0.05

4.1.2 Experiment Results *Layout*1

In this section, the experiment results for LP and simulation-based GA are shown and the optimal strategies are tested in simulation.

To visually represent distinct allocation strategies, heatmaps are utilized. Each parking space is assigned a specific label corresponding to the entry sequence of vehicles. For instance, the number '3' on a parking space indicates that it is allocated to the vehicle labeled as '3'. The heatmaps use color-coded grids, where the color intensity of each parking space indicates the entry sequence, with darker shades representing vehicles that entered later. This visual representation provides a clear distinction between vehicles based on their entry order and enables efficient analysis of the allocation strategies.

LP

The optimal strategy of LP for parking spaces allocation is shown in Figure 4.1, where the label on the parking spaces indicates the order of the vehicles:

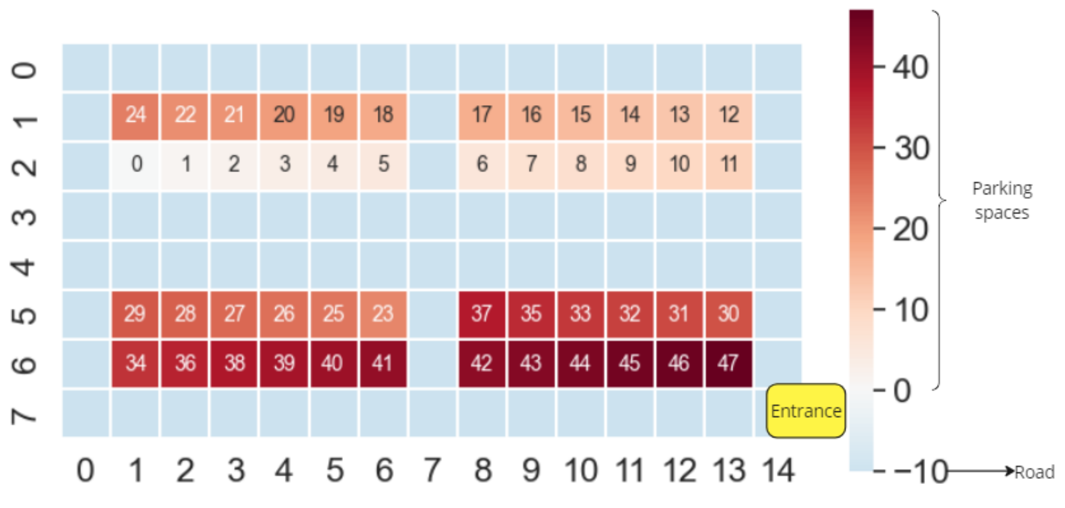


Figure 4.1: LP Optimal Parking Space Allocation Heatmap: *Layout*1

With this solution, the objective value is:

$$TTT = \beta + W = \beta + 0 = \beta \tag{4.1}$$

According to the settings in Section 3.4.4, the patch width is 5.5m, the speed is 30 km/h, and the TTT is calculated with a value of 768.24s.

It means that there is no blocking in the parking lot. Comparing Figure 4.1 and Figure 3.4, it can be observed that essentially allocates vehicles according to travel distance from the furthest to the nearest, ensuring that no vehicle blocks the following vehicles.

Simulation-Based GA

The objective values across generations are shown in Figure 4.2.

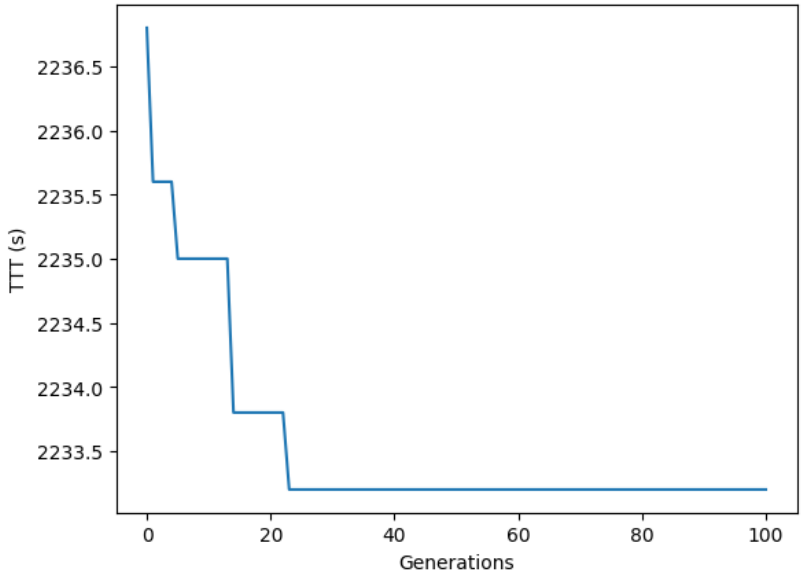


Figure 4.2: TTT across Generations

The strategy converges within the first 25 generations, with an objective value of 2233s. The strategy allocation is shown in Figure 4.3:

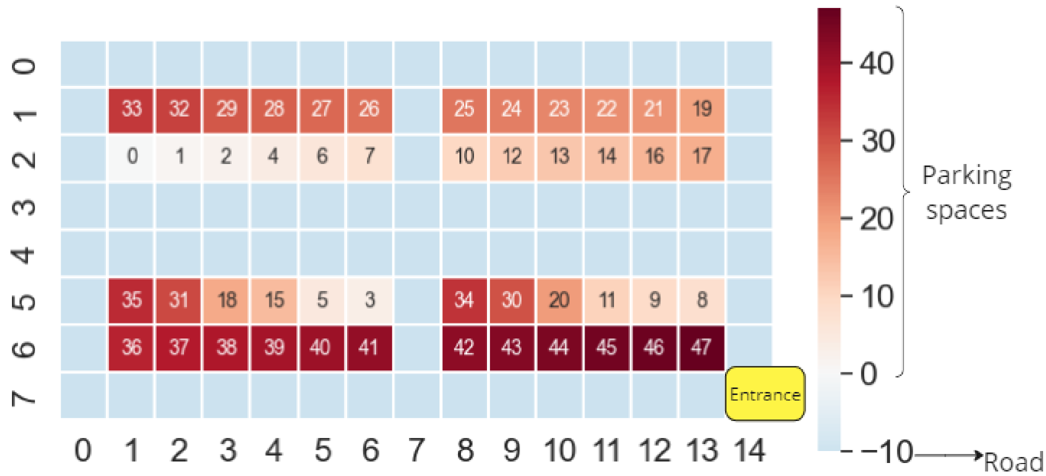


Figure 4.3: Optimal Parking Space Allocation Heatmap: $Layout1$

Comparison in Simulation

To test the efficiency of both optimal strategies found by LP and simulation-based GA, they are tested in the simulation.

Three strategies are compared:

- *S_GA*: the strategy got from the simulation-based GA.
- *S_LP*: the strategy got from the LP. It allocates vehicles from the furthest to the nearest.
- *S_Near_Far*: the comparison group, as allocates vehicles from the nearest to the furthest.

The performance of the *S_LP* is analyzed first.

For *S_LP*, a situation is shown in Figure 4.4. It reveals that parking spaces in the red rectangle are utilized later compared to those in the yellow rectangle, even though they could have been used earlier without disrupting the flow in another route. Vehicles driving at a speed lower than the free flow speed are shown in green. Vehicles slow down at the corner to avoid hitting the wall, and the following vehicles have to adjust their speed to maintain a safe distance. Vehicles move slower on the left part of the parking lot. It can be observed as the magenta arrows indicated that if a vehicle makes a turn instead of going straight, it can avoid congestion in the front.

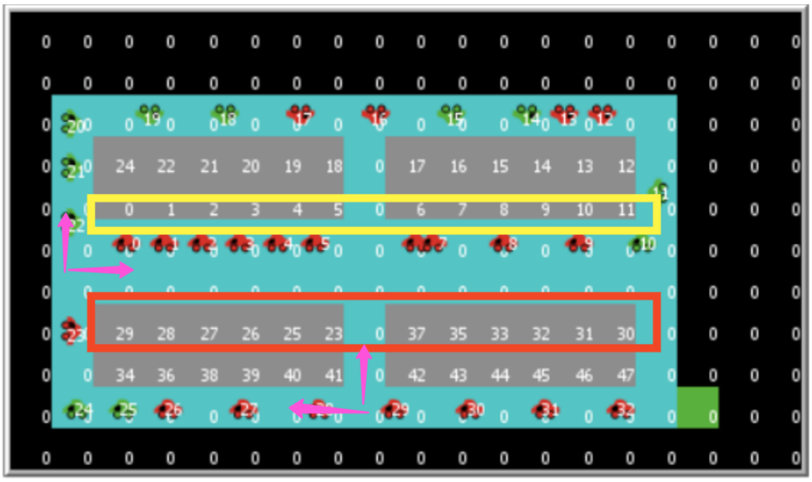


Figure 4.4: *S_LP* Simulation *Layout*1

However, it is noticed that the objective value *TTT* got from the simulation of *S_LP*, 2340.53s, is actually higher than that calculated in Section 4.1.2, 768.24s. This discrepancy arises due to the strategy used by the LP model, which allocates parking spaces with shorter distances to vehicles that enter later to avoid blocking for subsequent vehicles. However, this strategy does not consider the dynamic route situation, where some routes may have congestion while others allow vehicles to move more freely. The oversimplified delay formulation in the LP model underestimates the actual delay in the parking lot.

Figure 4.5 shows clear differences in S_GA parking space allocation compared to Figure 4.1. There is a clear inconsistency in the allocation of parking spaces within the red rectangles, where the parking spaces in the blue rectangles are occupied earlier than the rest. The parking spaces in the blue rectangles are located at the end of each route.

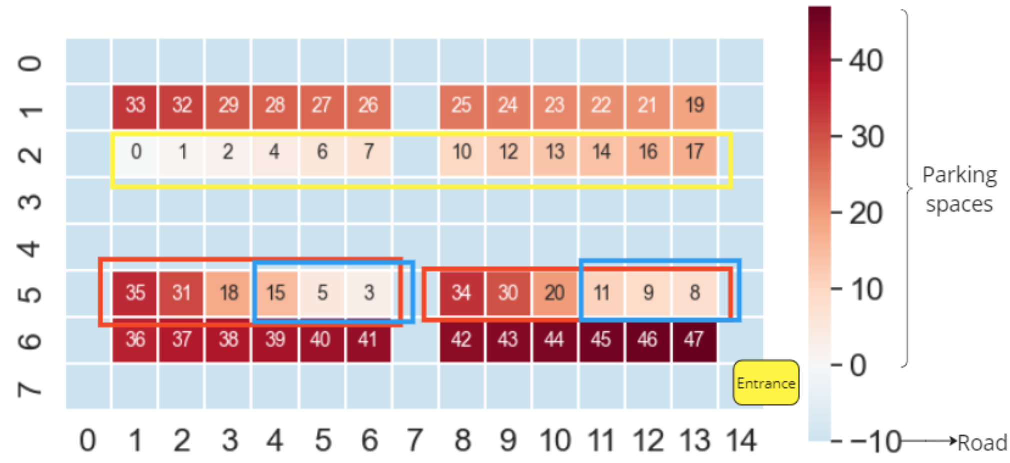


Figure 4.5: S_GA $Layout1$ Heatmap

Through the simulation, it can be observed that parking spaces along each route are filled during an overlapping period. Vehicles along Route 1 and Route 2 (routes are defined in Figure 3.3) be allocated earlier to help vehicles avoid congestion along Route 3. This can be clearly seen in the simulation (Figure 4.6), where vehicles are ready to park in both the yellow and red rectangles at the same time, unlike S_LP shown in Figure 4.4.

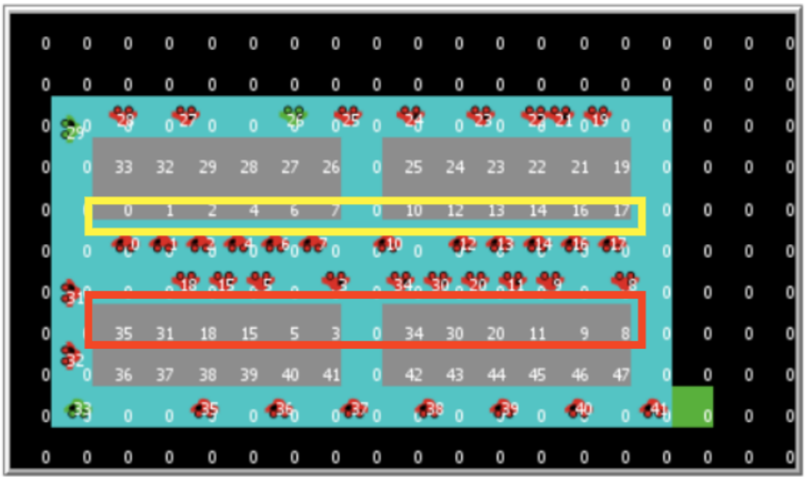


Figure 4.6: S_GA $Layout1$

To further evaluate S_GA and S_LP, S_Near_Far is defined. In this strategy, the parking lot is filled along routes from the nearest to the furthest, and vehicles can only select the parking space on the right, shown in Figure 4.7. This strategy is the reverse process of S_LP.

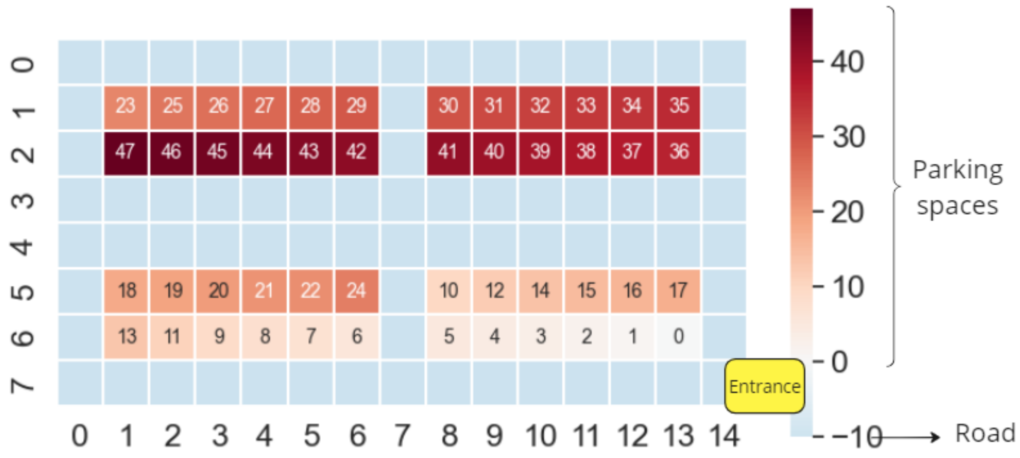


Figure 4.7: S_Near_Far $Layout1$ Heatmap

Data are acquired from the NetLogo simulation. Strategies are compared through 2 aspects: the number of parked vehicles at the same time (Figure 4.8) and the TTT with the number of parked vehicles (Figure 4.9):

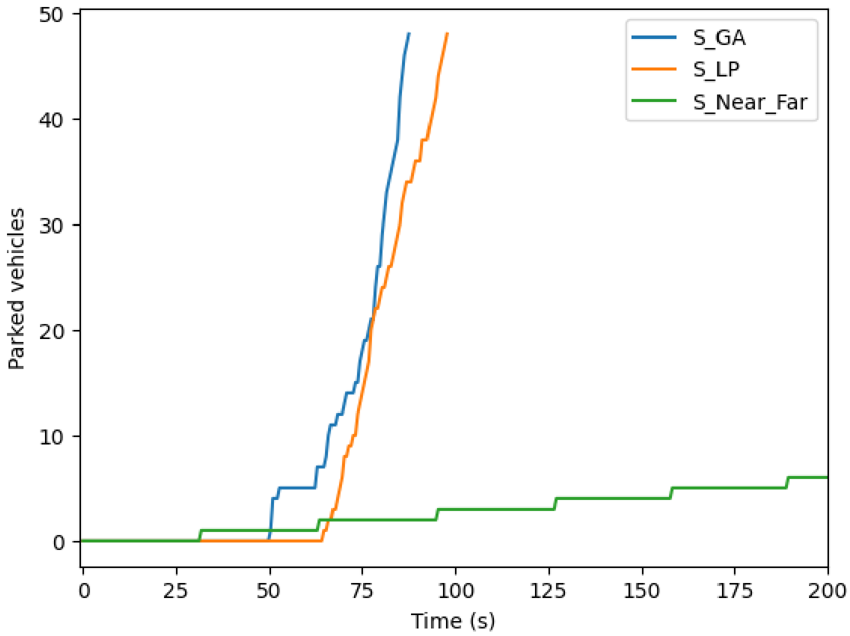


Figure 4.8: Parked Vehicles-Time *Layout*1

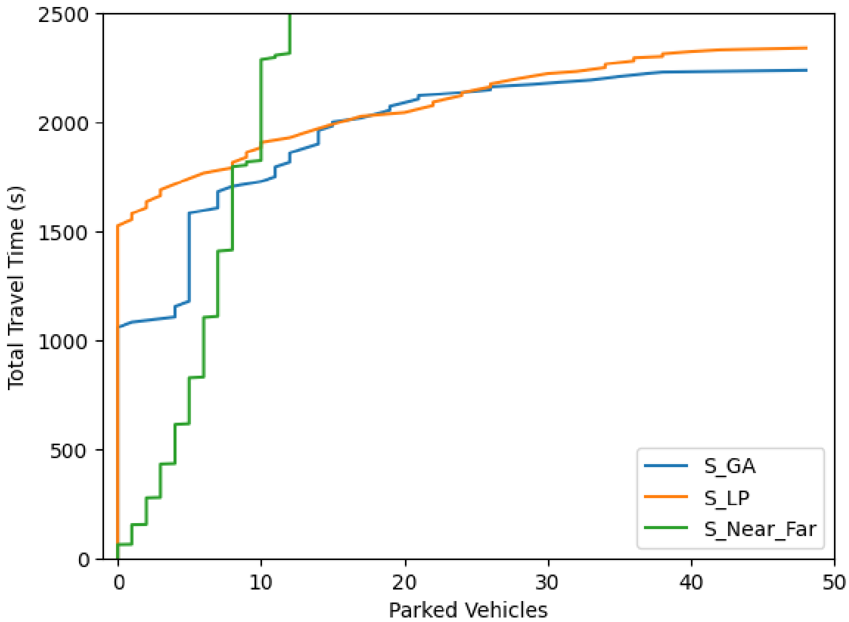


Figure 4.9: Total Travel Time - Parked Vehicles *Layout*1

It can be seen from Figure 4.8 that S_GA has all the vehicles parked earlier than S_LP. Although the parking speed is slower at the beginning, S_GA allocates all the vehicles in a shorter time. For the first half of the total vehicles, the time cost is almost the same for both S_GA and S_LP. However, S_GA is faster in parking the second half of the total vehicles.

From Figure 4.9, it can be seen S_LP takes a long time before the first vehicle is parked, and after that, vehicles are parked at a relatively even speed. In contrast, S_GA has a clear gap, with some vehicles being parked earlier. This indicates that some vehicles along routes 1 and 2 are parked first, followed by the rest of the vehicles. The advantage of S_GA is more apparent when it is time for vehicles that enter relatively late parking. For S_LP, the line is smoother, reflecting that the parking spaces are allocated one by one based on the distance order.

However, S_Near_Far, which allocates parking spaces from the nearest to the furthest, performs the worst. Vehicles entering later are blocked by the vehicles entering earlier. Even though the vehicles entering earlier can park earlier, the vehicles entering later experience much longer travel time, which is detrimental to the objective. Vehicles entering later have more delays, resulting in a longer TTT.

Based on these results, the strategy obtained through simulation-based GA exhibits better performance and aligns more sensibly with the parking situation than the one obtained from LP in this case. The simulation-based GA algorithm is capable of incorporating complex interactions among vehicles in the parking lot, making it a better choice for finding the optimal solution for the more complex $Layout2$ in the next section.

4.2 Experiment on $Layout2$

Building upon the findings from the experiment on $Layout1$, the simulation-based GA algorithm is now applied to $Layout2$, which has more complex routes and rules. The objective is to search for the optimal allocation strategy under different demand levels. Several comparison groups are defined to benchmark the efficiency of the optimal strategy (Section 4.2.1).

4.2.1 Experiment Setup

The experiment setup involves a predefined set of control group strategies, which are compared against the optimal strategy obtained from the simulation-based GA algorithm applied to $Layout2$ (referred to as S_GA_2).

There are 4 comparison strategies defined. The allocation strategies for comparison groups and heatmaps are shown in the following:

- $S\_Near\_Far\_Right$: The parking lot is filled along routes from the nearest to the furthest, and vehicles can only select the parking space on the right.

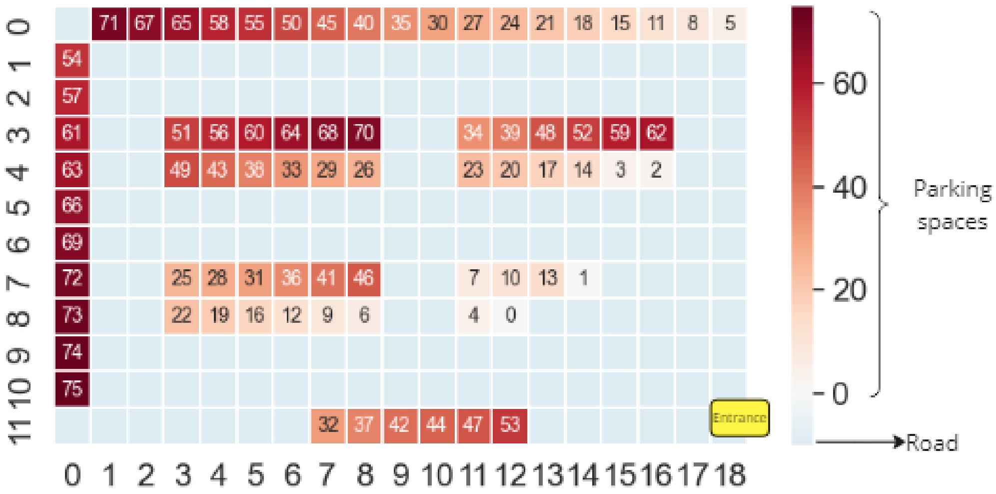


Figure 4.10: *S_Near_Far_Right* Heatmap *Layout*2

- *S_Far_Near_Right*: The parking lot is filled from the furthest to the nearest, and vehicles can only select the parking space on the right, which is the reverse allocation to *S_Near_Far_Right*.
- *S_Near_Far_Left*: The parking lot is filled from the nearest to the furthest, and vehicles can only select the parking space on the left/

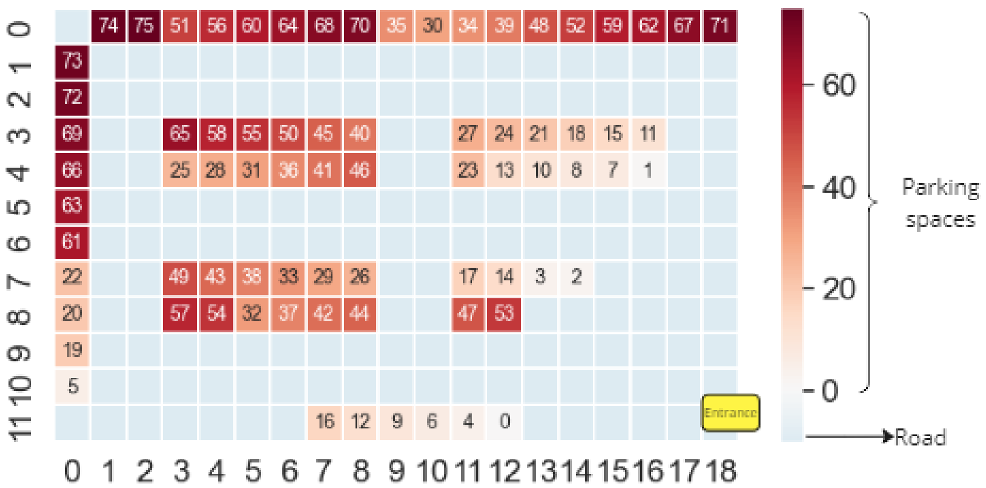


Figure 4.11: *S_Near_Far_Left* Heatmap *Layout*2

- *S_Far_Near_Left*: The parking lot is filled from the furthest to the nearest, and vehicles can only select the parking space on the left, which is the reverse allocation to $S\_Near\_Far\_Left$.

The experiment is conducted by simulation under different demand levels, representing 39% (30 vehicles), 59% (45 vehicles), 79% (60 vehicles), and 100% (76 vehicles) of the parking lot's capacity. Considering the computation efficiency and exploration ability, the hyperparameters settings are as follows:

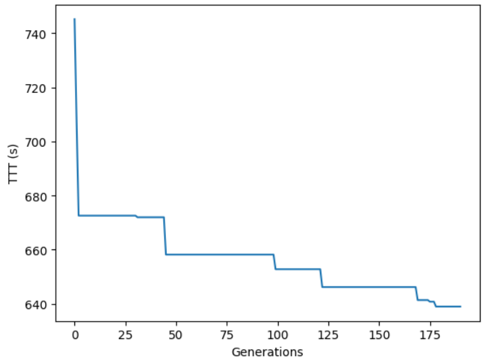
Table 4.2: Hyperparameters $Layout2$

$population\_size$	100
$num\_generations$	0.1
$mutation\_rate$	Constrained by computation time

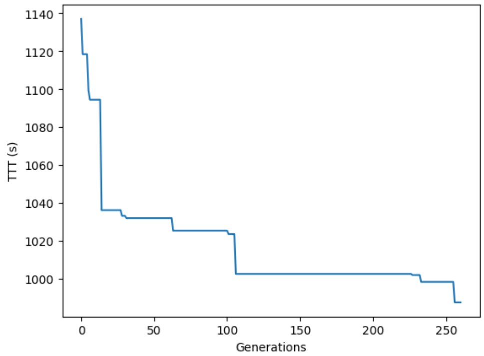
The computation is automatically stop running in 24 hours in a virtual environment with 5 CPUs and memory for each CPU is 10 GB.

4.2.2 Experiment Results $Layout2$

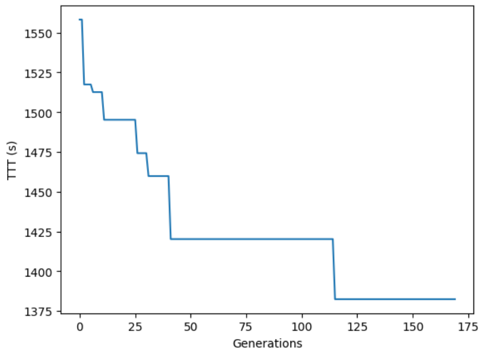
The objective values, i.e., TTT, across the generations for different demand levels are depicted in the following:



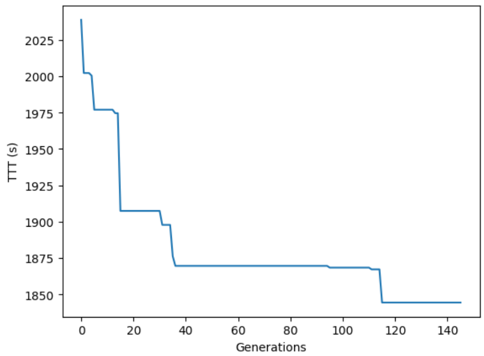
(a) Demand = 39% Capacity



(b) Demand = 59% Capacity



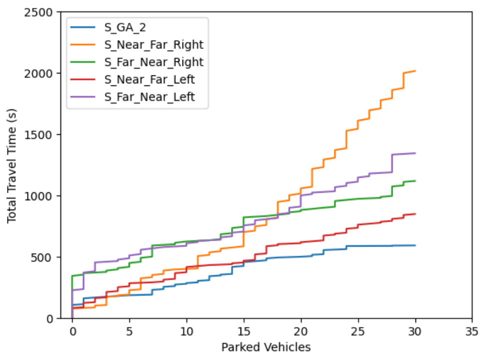
(c) Demand = 79% Capacity



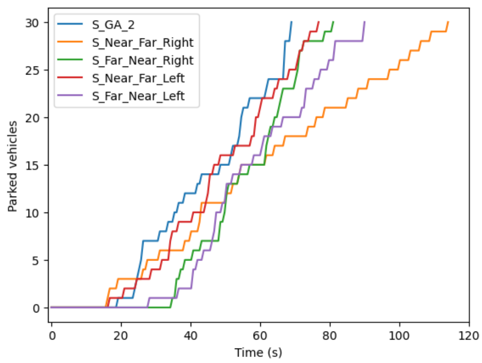
(d) Demand = 100% Capacity

Figure 4.12: TTT across Generations under Different Demand Levels

It can be observed that the objective value shows a decreasing trend across generations, which means that it is searching for better strategies. The strategies under different demands are compared based on the number of parked vehicles at the same time and the TTT with the number of parked vehicles:

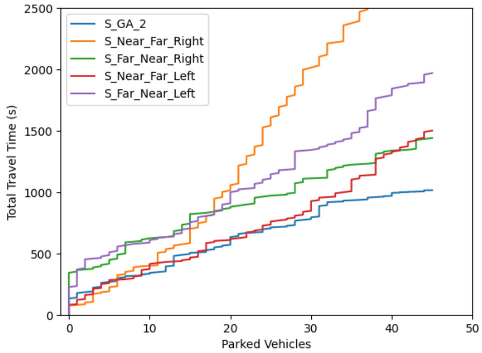


(a) TTT - Parked Vehicles

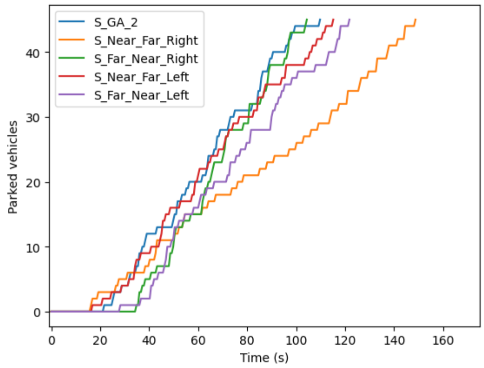


(b) Parked Vehicles - Time

Figure 4.13: 39% Demand

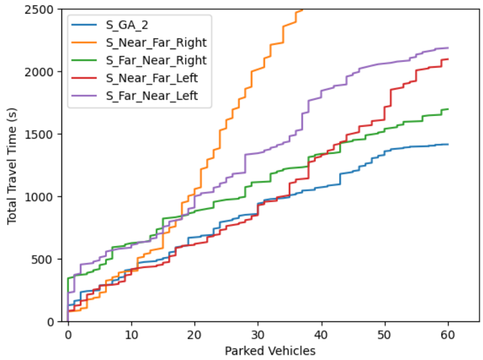


(a) TTT - Parked Vehicles

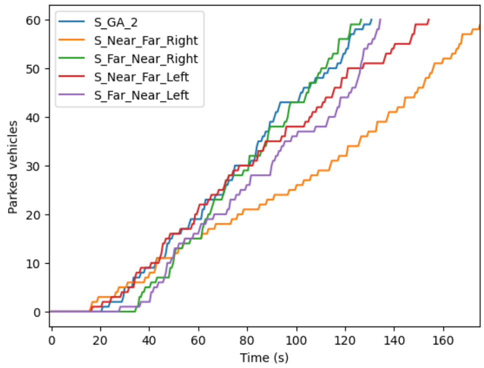


(b) Parked Vehicles - Time

Figure 4.14: 59% Demand

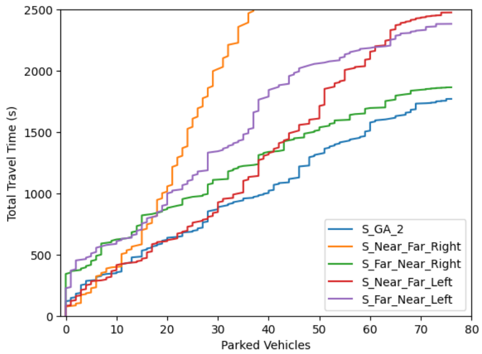


(a) TTT - Parked Vehicles

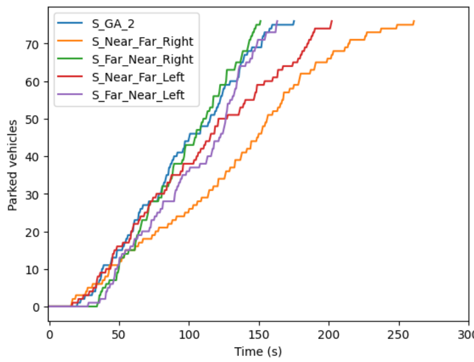


(b) Parked Vehicles - Time

Figure 4.15: 79% Demand



(a) TTT - Parked Vehicles



(b) Parked Vehicles - Time

Figure 4.16: 100% Demand

It can be observed that for different demand levels, the optimal strategy implemented using the GA leads to a clear decrease in TTT compared to the comparison groups. This indicates that even for lower demand levels, applying an effective allocation strategy can save drivers time. For higher demand levels, it can save more time considering TTT values. The advantages of the optimal strategy become more apparent compared to other strategies when almost half of all vehicles are parked.

Additionally, the time period spent in the parking lot for the optimal strategy is close to the lowest among these strategies, even though it is not the objective to optimize it. Besides, for strategies allocating vehicles from the nearest to the furthest, $S\_Near\_Far\_Left$ and $S\_Near\_Far\_Right$, they always perform the worst among these strategies, which indicates that the vehicles allocated earlier block the following vehicles.

Since our scenario is during PSEs, the demand is assumed as 100% capacity. The strategy for vehicle allocation in $Layout2$ is shown in Figure 4.17 where the red vehicles chose parking spaces on the right side and the blue vehicles chose the parking spaces on the left side.

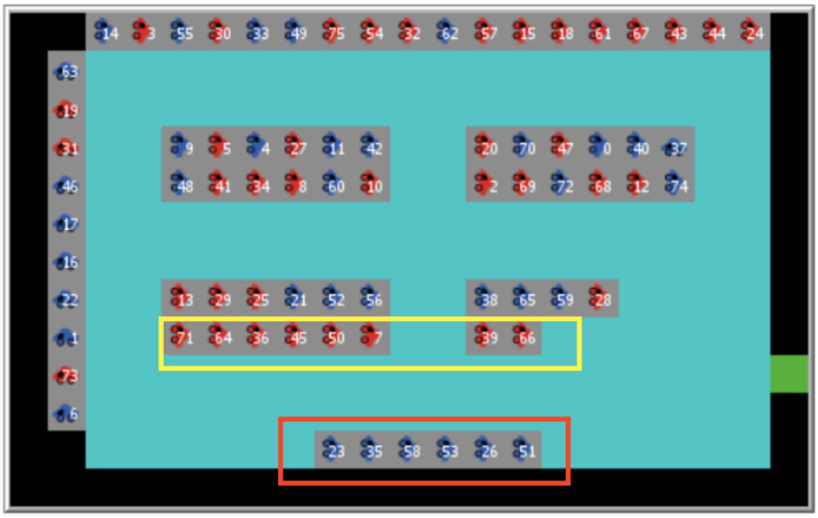


Figure 4.17: Simulation: Optimal Allocation Strategy $Layout2$

It can be observed that vehicles are more likely to be assigned parking spaces on either the right or left side in certain areas. Vehicles drive to specific areas and park when the parking spaces are on the designated side. For example, in the yellow rectangle area, vehicles are directed to park on the right side, while in the red rectangle area, they are instructed to park on the left side. The decision to assign parking spaces on a particular side and instruct vehicles to park on that side is made when vehicles enter to optimize the flow in the parking lot.

The heatmap for this strategy is shown in Figure 4.18:

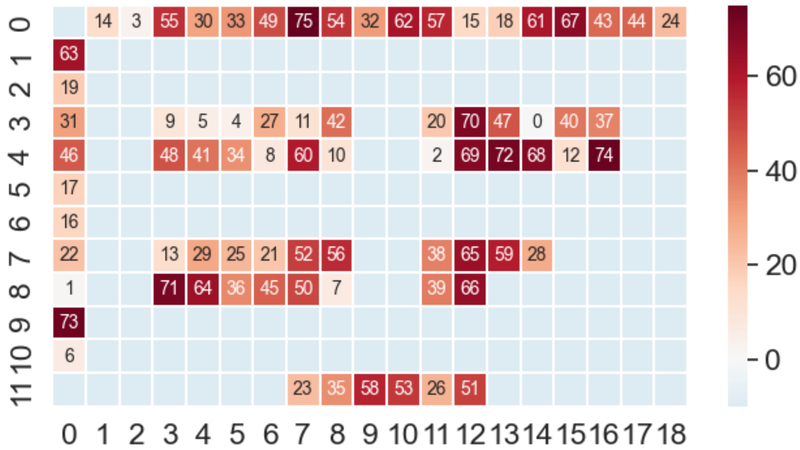


Figure 4.18: Heatmap: Optimal Allocation Strategy *Layout*2

It can be observed from Figure 4.18 that the area in the upper left, which is relatively far away from the entrance, is clearly with the lighter colors, which means that it was allocated to vehicles entering early. This allocation helps avoid congestion near the entrance and prevents blocking vehicles entering later.

Overall, the results from the experiment on *Layout*2 demonstrate that the simulation-based GA algorithm can effectively find an optimal allocation strategy under different demand levels. The optimal strategy consistently outperforms the control group strategies in terms of reducing the objective value TTT.

5 Conclusion and Discussion

Overall, the research has provided insights into how to find an optimal strategy for efficiently allocating vehicles in a parking lot during PSEs. This chapter concludes the research and provides a discussion of the research.

5.1 Conclusion

The main research question addressed in this research is '**How to determine an effective strategy for allocating vehicles in a parking lot during PSEs?**' To answer the main research question, the following sub-questions are explored:

- How can vehicle movement inside the parking lot be realistically simulated?

  The use of agent-based modeling in the NetLogo software allowed for a realistic simulation of vehicle movement within the parking lot. The simulation captured the complex interactions between vehicles, including car-following behaviors and specific rules for crossing and parking movements. This simulation provides a solid foundation for evaluating the effectiveness of allocation strategies.

  In the parking lot, the sudden change in the leading vehicle speed has a clear effect on the following vehicles. From the simulation, it can be observed that when a vehicle is ready to park or it decelerates at the corner to avoid hitting the wall, the following vehicle may also need to decelerate or even stop to keep a safe distance. This phenomenon can propagate backward to influence several vehicles following, which causes congestion on the road.

- How does the demand level impact the efficiency of the allocation strategy?

  The efficiency of the allocation strategy is influenced by the demand level. During high-demand periods, effective allocation becomes crucial to optimize parking space utilization and reduce cruising time. The performance difference among strategies becomes more significant under high-demand scenarios, highlighting the importance of implementing an effective strategy to accommodate increased traffic.

- How does the parking lot layout influence the allocation strategy?

  The layout of the parking lot, including the arrangement of parking spaces and entrances, as well as the overall traffic flow, significantly impacts the effectiveness of the allocation strategy. Wider space near the entrance and allocating vehicles far from the entrance first can help let vehicles enter the parking lot faster. Well-planned routes and an efficient allocation strategy can minimize congestion and conflicts, resulting in improved traffic flow. Dynamic traffic conditions within the parking lot also affect the strategy's performance, as congestion can lower the efficiency of the allocation strategy.

- How should the algorithm be designed to incorporate the complex situation in the parking lot and search for the optimal solution?

  The algorithm designed for this research aimed to minimize the total travel time within the parking lot for all vehicles, considering the global benefit. Constraints based on the parking lot's capacity were taken into account. A simulation-based Genetic Algorithm (GA) was chosen as the optimization method due to its ability to incorporate dynamic traffic conditions and converge at an optimal solution. The efficiency of the solution was evaluated using objective values obtained from the agent-based simulation.

- How should the optimal strategy be interpreted and understood?

  The optimal allocation strategy significantly enhances the overall operational efficiency of the parking lot, effectively mitigating congestion issues. By prioritizing global optimization over individual preferences, the strategy allocates parking spaces and provides route instructions to vehicles based on a comprehensive assessment of the entire system. This approach may involve assigning vehicles that enter the lot early to more distant locations, strategically optimizing the traffic flow, and improving overall performance.

Based on the answers to these sub-questions, the overall answers for the main research question are summarized in the following:

An effective allocation strategy is crucial in optimizing the utilization of parking spaces, and its impact becomes more significant under high demand. The spatial arrangement of parking spaces, entrances, and overall traffic flow also plays a crucial role in the effectiveness of the allocation strategy.

To achieve more realistic details and meaningful results, the integration of realistic simulations using agent-based modeling proved beneficial. The simulation-based GA demonstrated its advantage in converging towards an optimal strategy by considering objective values obtained from the simulation.

The optimal allocation strategy identified in this research improves the overall efficiency of the parking lot. It was observed that prioritizing global optimization over individual preferences, such as allocating vehicles entering early to further locations, leads to better overall traffic flow. Balancing individual and global objectives can be crucial when designing an effective strategy.

5.2 Discussion

5.2.1 Stakeholder Relevance and Feasibility of Practical Applications

The success of the implementation of the parking space allocation strategy during PSEs relies on the perspectives and interests of various stakeholders involved. The stakeholders could include event organizers, venue managers, transportation agencies, event attendees, etc.

Event organizers are primarily concerned with providing a positive attendee experience, which includes efficient parking operations to reduce delays and congestion. Transportation agencies aim to optimize traffic flow and attendees seek to a convenient and smooth parking experience.

This research addresses the concerns of these stakeholders. By creating a simulation-based optimization, it can find the optimal parking space allocation strategy to improve the overall experience for event attendees by minimizing their time to get parked. Besides, it helps the traffic agencies and venue managers to relieve the traffic pressure by reducing the vehicle cruising time outside the venue. It can also reduce the corresponding environmental impact and the potential cost of the additional parking facilities construction.

Practical implementation of the proposed strategy could involve several considerations. The implementation process could be: when a vehicle arrives, it gets a parking space allocated and then drives along the pre-defined route to the allocated parking space. To achieve that, first, real-time information about parking space availability and traffic conditions should be collocated ensuring up-to-date decision-making. It can be done through sensors, cameras, or mobile applications. Besides that, the navigation system is crucial for the attendees to conduct the allocation strategy. It can be done by visible signs or mobile apps to provide routes or turn-by-turn directions.

5.2.2 Future Work

Several areas of future research can further enhance parking space allocation strategies during PSEs:

- Algorithm Hyperparameter Optimization

  Fine-tuning the hyperparameters of the genetic algorithm, such as population size, number of generations, and mutation rate, may lead to even more optimal results. Exploring different parameter settings can help improve the efficiency and convergence speed of the algorithm.

- Parameter Sensitive Analysis

  Conducting an analysis to determine the factors that have a significant influence on the strategy design, such as speed limit settings, road width, and driver characteristics (e.g., age, driving experience), can provide insights into optimizing the parking lot allocation strategy.

- Real-world Validation

  Conducting real-world experiments and validations of the proposed strategy and algorithm can provide more concrete evidence of its effectiveness. Implementing the strategy in actual parking lots during high-demand periods and comparing the results with existing allocation methods would be beneficial.

- Generalizability

  While the research has focused on a specific parking lot layout, further investigation can explore the generalizability of the proposed methodology and strategy across different parking lot configurations. Testing the methodology and strategy efficiency in various layouts and assessing its performance can provide insights into its adaptability and robustness.

- Integration with Smart Technologies

  Investigating the integration of the proposed strategy with smart technologies, such as sensors, data analytics, and automated systems, can enhance the overall efficiency of parking lots. This can involve developing intelligent algorithms that dynamically adjust the parking allocation based on real-time data and optimize traffic flow within the parking lot.

By addressing these areas of future research, parking lot allocation during PSEs can be further improved, resulting in more efficient and convenient parking experiences for drivers. Additionally, the optimization of parking operations can contribute to reducing congestion, minimizing environmental impact, and potentially reducing the need for additional parking facilities construction.

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