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ORIGINAL RESEARCH

Modelling autonomous vehicle parking: An agent-based simulation approach

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Abstract

Autonomous vehicles (AVs) present a paradigm shift in addressing conventional parking challenges. Unlike human-driven vehicles, AVs can strategically park or cruise until summoned by users. Utilizing utility theory, the parking decision-making processes of AVs users are explored, taking into account constraints related to both cost and time. An agent-based simulation approach is adopted to construct an AV parking model, reflecting the complex dynamics of the parking decision process in the real world, where each user's choice has a ripple effect on traffic conditions, consequently affecting the feasible options for other users. The simulation experiments indicate that 11.50% of AVs gravitate towards parking lots near their destinations, while over 50% of AVs avoid public parking amenities altogether. This trend towards minimizing individual parking costs prompts AVs to undertake extended empty cruising, resulting in a significant increase of 48.18% in total vehicle mileage. Moreover, the pricing structure across various parking facilities and management dictates the parking preferences of AVs, establishing a nuanced trade-off between parking expenses and proximity for these vehicles.

1 | INTRODUCTION

In recent years, countries around the world have been investing significant human and material resources in researching autonomous driving technology, leading to continuous development and improvement in autonomous vehicles (AVs) [1]. With the deep integration of emerging technologies such as 5G communication technology and artificial intelligence, AVs are gradually maturing and showing a practical trend in the 21st century, becoming a part of people's daily lives [2]. Compared to traditional Human-driven Vehicles (HVs), the automated parking function offered by AVs provides a completely different travel experience for travellers. Travellers can simply get in or out of the AV at their final destination, eliminating the burden of searching for parking spaces in parking lots [3]. AVs access parking information, such as parking availability and fees, through cloud data, and autonomously make parking decisions and reserve parking spaces. Utilizing on-board sensors, cameras, and other technologies, AVs can automatically detect and identify parking spaces, precisely control their parking positions, and independently carry out parking tasks without the need for human intervention.

The emergence of AVs presents new opportunities and challenges for addressing parking issues in the transportation system. On the one hand, the automated parking feature avoids the need for drivers to cruise around searching for parking spaces near their destinations, improving parking convenience and avoiding human errors during parking operations. Moreover, AVs are not limited by walking distances, enabling them to utilize parking resources in suburban and residential areas. They can even cruise throughout the entire activity duration [4], thus saving parking costs and mitigating parking supply-demand conflicts. Additionally, since AVs do not require driver operating space, they can park in tightly arranged parking spaces, making efficient use of land resources [5]. On the other hand, AVs may choose to search and navigate to low-cost or even free parking spaces, inevitably leading to empty cruising miles, where vehicles operate without passengers. This can result in additional traffic volume, wastage of road resources, and exacerbation of traffic congestion and delays, posing a significant challenge to the transportation system [6].

The future implementation of AV parking in real-world scenarios, and the challenge of effectively describing these processes at a micro-level, have not yet been satisfactorily answered. This study proposes an agent-based model to evaluate the parking choices of private AVs in the downtown area and investigates how these choices impact the traffic network. Specifically, we consider a downtown area where users of private AVs engage in activities during different periods. The AVs then select various parking modes based on their users' activity schedules, to minimize their total parking costs. The primary contribution of this work is the microsimulation of AVs parking behaviour. This model is developed within a formalized environment, providing a simple yet powerful framework to represent all parking considerations or preferences of AVs, capturing their interactions, and revealing various consequences of AVs' parking choices. It establishes a foundation for research and optimization of parking policies in the era of AVs. The framework is highly flexible and can be extended to more complex scenarios.

The rest of this paper is structured as follows. The current literature and the research gap are presented in Section 2. The model formulation and simulation characteristics are presented in Section 3. The simulation findings are presented in Section 4 for a real-world example. Section 5 concludes this paper.

2 | LITERATURE REVIEW

The acceleration of urbanization has brought increased attention to parking research and the influence of parking policies [7]. Numerous studies have endeavoured to model the effects of cruise parking (cruising to find a parking spot), user preferences when selecting parking spaces, and the impact of diverse parking policies and management strategies on congestion [8–10]. Naturally, these models take HVs into account. Recently, researchers have also delved into investigating the implications of AVs on parking. Table 1 provides a summary of relevant studies. In the early foundational literature, a few studies are particularly notable. Firstly, Levin and Boyles [11] utilized the traditional four-step method to explore the potential impact of AVs parking on traffic networks. Subsequently, Childress et al. [12] investigated the primary factors influencing AVs parking behaviour using an activity-based model. Furthermore, Zakharenko [13] discussed the equilibrium issues concerning AVs parking. It is important to note that while these studies considered the impact of AV parking to some extent, however, their primary focus was not exclusively on the parking issues of AVs. Following the pioneering works, Harper et al. [14] delved deeper into the complexities of parking behaviour associated with AVs. They examined the broader implications on the economy, environment, and individual mobility patterns. However, their research primarily focused on traditional parking lot scenarios. Expanding upon this groundwork, Zhang et al. [15] introduced the "Home parking" paradigm, offering a more comprehensive perspective that intertwined AVs parking decisions with route choice.

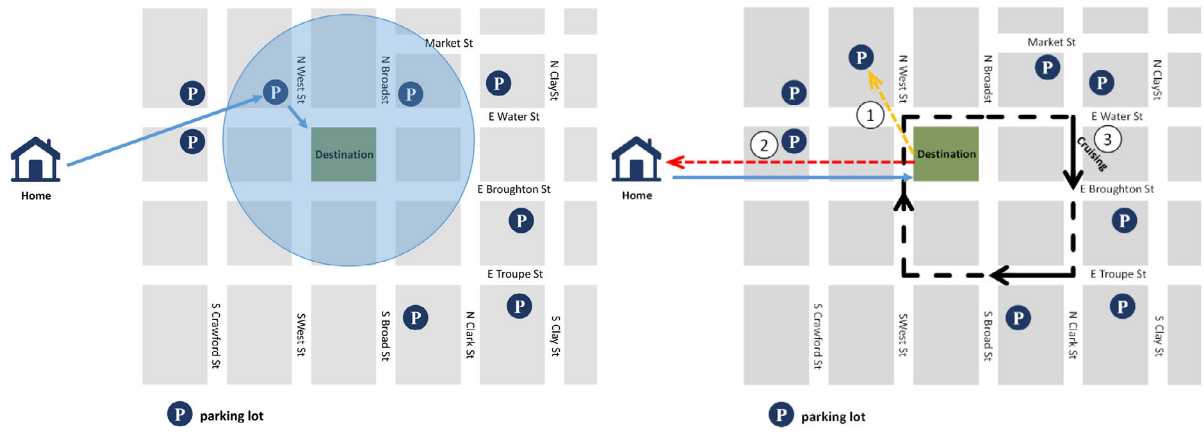
However, the above model only considers long-duration trips, leading to its neglect of short-duration trips. For short-duration trips, continuous empty cruising can become an alternative to parking. In other words, vehicles remain in an empty cruising state instead of utilizing any parking space until the travellers finish their activities. As a result, some researchers have begun to focus on this particular parking pattern and investigate its impact on congestion and social welfare. Bischoff et al. [16], employing MATSim as their simulation tool, delved into three distinct parking modalities: conventional parking lots, AV-specific parking slots, and continuous empty cruising. Their findings suggest that travellers might avoid continuous cruising in lieu of parking due to congestion concerns. Conversely, Millard-Ball [17] posited that AVs might adopt slower cruising speeds as a cost-controlling measure. They further hypothesized that these vehicles, given their capacity for inter-vehicular collaboration, could opt for more congested cruising routes intentionally to induce traffic jams, thereby mitigating cruising costs. This strategic congestion might lead to a higher propensity for AVs to favor continuous cruising over parking. Building on this, Bahrami et al. [3] introduced an equilibrium model for parking selection, aimed at investigating parking preferences of travellers in city centres across varying activity durations. Their empirical results underscored the possibility that, in the absence of congestion pricing, AVs might lean towards cruising instead of parking, potentially exacerbating traffic congestion.

The above studies present interesting results and findings on the parking choice behaviour of AVs. A common theme among these investigations is their emphasis on the intricate relationship between AVs, parking behaviour, and travel distances. Different studies often operate under their unique assumptions and employ distinct modelling methods, making it difficult to compare their results directly. The existing research on the parking choice behaviour of AVs mainly reveals the following gaps: (1) There is a strong reliance on assumptions about AV behaviour, with a tendency to use equilibrium models to explain their parking actions; (2) most studies are based on hypothetical networks or synthetic travel data, overlooking the dynamic interactions between real road networks and the diverse parking choices of AVs.

To fill the research gap, this paper employs real-world network data to construct an agent-based parking simulation system tailored for autonomous driving scenarios. The contributions of this paper include: (1) Describing the micro-behaviour of AV parking choices through utility theory and simulating the real-world parking process of AVs with a multi-agent design; (2) systematically examining the impact of traveller personal attributes, travel costs, and differentiated parking pricing strategies on the parking choice behaviour of AVs, and quantitatively assessing the specific impact of AV parking behaviour on the overall traffic conditions of road networks; (3) discussing the constraints imposed by empty cruising charges on AV behaviour, and the network impacts, in response to the additional trips generated by AVs that negatively affect the road network.

TABLE 1 Literature overview.

Literature	Key aspects of AVs parking research	Parking mode	Research method	Key finding
Levin and Boyles [11]	Exploring the impact of AV parking on traffic networks	Parking lots/ Home parking	Four-stage method	AVs increase vehicle miles travelled due to empty cruising caused by seeking low-cost parking
Childress et al. [12]	Examining the determinants of AVs' parking decisions	AVs parking only	Activity-based model	Increasing road capacity, reducing travel time for travellers, and increasing parking fees have led to an increase in AVs' driving mileage
Zakharenko [13]	Investigating the effects of AVs' parking on typical urban forms	Parking lots /AVs parking only / Home parking	Network equilibrium	AVs can indeed potentially reduce the parking demand in city centres and contribute to the expansion of urban areas
Harper et al. [14]	Assessing the economic, environmental, and travel effects of AV-induced parking choices	Parking lots	Agent-based simulation	AVs tend to park in economically distant parking Spaces, which increases mileage
Zhang et al. [15]	Formulating a traffic network equilibrium model incorporating AV parking behaviours	Parking lots / Home parking	Network equilibrium	As AVs travel empty, traffic congestion due to parking searches is increased
Bischoff et al. [16]	Evaluating parking efficiency: a comparison between AVs and HVs	Parking lots / AVs parking only / Empty cruise	Agent-based simulation	Compared to HVs, AVs increase mileage, and induced road congestion causes an increase in return time
Millard-Ball [17]	Investigating AV parking strategies through microsimulation data from San Francisco	Suburban parking (free) / Home parking / Empty cruise	Game theory	AVs can work together to cause traffic jams, reducing cruise costs
Su and Wang [18]	Exploring the influence of parking lot costs on AV parking locations	Downtown parking / Home parking / Shared parking	Network equilibrium	Overall queue congestion can be significantly reduced through reasonable parking pricing
Bahrami et al. [3]	Analyzing AV parking preferences in downtown areas across different activity times	Suburban parking (free) / Home parking / Empty cruise	Network equilibrium	AVs in the absence of congestion charging may choose to cruise rather than stop, exacerbating traffic congestion
Kang et al. [19]	Delving into route, mode, and parking lot choice in the AV equilibrium context	Downtown parking / Suburban parking	Network equilibrium	The AVs scenario will increase the average travel time by approximately 50%, and some areas currently used as parking spaces can be reprogrammed
Zhao et al. [20]	Congestion insights for AVs using centralized parking dispatch	Parking lots	Macroscopic fundamental diagram	Centralized scheduling can optimize parking search time and ease traffic congestion
Bahk et al. [21]	Observing mileage variations in an AV-centric environment	Parking lots	Multinomial logit model	The notable surge in the mileage covered by AVs necessitates the formulation of strategic measures by planners to curtail the occurrence of unoccupied miles travelled by AVs in close proximity to event venues
Mondal et al. [22]	Advancing traffic demand forecasting techniques in the realm of AVs	Home parking / Parking lots	Four-stage method	Empty trips are a contributing factor to the escalation of vehicle miles travelled, resulting in a notable effect on vehicle hours of operation and the exacerbation of traffic congestion
Tang et al. [23]	Studying AV parking mode choice at different AV penetration rates	Home parking / Parking lots / Empty cruise	Agent-based simulation	AVs can reduce the overall parking costs and enhance the parking convenience for both AVs and HVs



(a) HV (b) AV

FIGURE 1 Schematic of parking choices of Autonomous Vehicles (AVs) and Human-Driven Vehicles (HVs).

3 | METHODOLOGY

3.1 | Modelling parking choice behaviour

3.1.1 | Model assumptions

To facilitate essential ideas without loss of generality, the modelling of AV parking choice behaviour is based on the following basic assumptions:

A1: Assuming each traveller is perfectly rational, they would always choose the option with the lowest parking cost to minimize their overall travel expenses.

A2: Assuming the cost function for calculating the cost of sending their AV back home does not take into account the benefits generated by other household members using the vehicle during that period.

A3: Assuming travellers are myopic in their choices of parking modes and parking lots, their decisions are solely based on the current instantaneous cost and ignore perceptual errors in the information.

A4: Assuming that travellers do not modify their parking decisions during the activity period after making a parking choice.

3.1.2 | Model setting

We examine a city centre where a continuous range of AV users gather to engage in activities of varying durations. We assume that the activity time t for users is distributed continuously within the range of $[0, T]$. Upon arrival, each AV user is faced with a parking decision. Unlike HVs, which require users to choose a parking lot near the destination and then walk, AV users can have their AV drop them off at the destination and then autonomously park. They can choose to park in public parking lots, send their AV back home, or opt for cruising within the area as an alternative to traditional parking, as illustrated in Figure 1 (Figure 1a shows the parking process of HVs, and Figure 1b displays the parking process of AVs). Using utility theory, we then model their parking choice behaviour. Below, we will separately introduce the costs of each parking option.

We start with the cost of parking in public parking lots. The model simulates the process where travellers arrive at their destination and AVs search for public parking lots to complete parking, and then return to the original destination after the travellers finish their activities. The model takes into account whether the travellers have made a prior reservation for the vehicle. If the travellers have made a reservation, their waiting cost will be disregarded. Therefore, the total cost of this model can be quantified as the cost of vehicle usage for the round trip between the destination and the parking lot, the parking fee at the parking lot, and the time cost for the travellers that may arise due to waiting. The cost function for choosing public parking can be represented as follows:

$$
\begin{gathered}
U_{\text{parkinglot}} = \\
\min_{p_i \in P} \left[\min_{k \in \prod^{s,p_i}} \left((1-\lambda_{\text{subs}}) \cdot f_{VOT} \cdot t_k + 2 \cdot d_k \cdot \left(f_e^l + f_m^l \right) + C_{p_i}\left(t_{p_i}\right) \right) \right] \\
s.t. \, Availability(p_i) \geq 1, \forall p_i \in P \\
2 \cdot \mu_t \cdot t_k < h, \forall k \in \prod^{s,p_i}
\end{gathered} \tag{1}
$$

where $U_{\text{parkinglot}}$ represents the total cost for AV users to choose a public parking lot for parking. P represents the set of parking lots, $p_i \in P$. Π^{s,p_i} represents the set of paths between the destination and the parking lot p_i, $k \in \Pi^{s,p_i}$. f_m^l represents the maintenance cost required for the AV to travel one unit distance. f_e^l represents the energy consumption cost required for the AV to travel one unit distance. d_k represents the distance of path k, indicating that the traveller chooses path k to travel between the destination and the parking lot. λ_{subs} represents whether the traveller has made a prior reservation for the AV pick-up. In this case, $\lambda_{\text{subs}} = 1$ indicates a reservation has been made, while $\lambda_{\text{subs}} = 0$ indicates no reservation has been made.

f_{VOT} represents the time cost for the traveller to wait for the AV pick-up. t_k represents the travel time required to take path k. h represents the duration of the traveller's activity. t_{p_i} represents the duration of time that the AV is parked at the parking lot p_i, $t_{p_i} = h - (1 + \lambda_{\text{subs}}) \cdot t_k$. $C_{p_i}(t_{p_i})$ represents the parking fee rate function for the parking lot p_i, which is dependent on the parking duration t_{p_i}. Availability (p_i) represents the available parking spaces at the parking lot p_i. μ_t represents the time reliability, which is a value greater than or equal to 1. A higher value closer to 1 indicates higher reliability. For this study, the default value is assumed to be 1.2. It should be noted that $2 \cdot \mu_t \cdot t_k < h$ is not a hard constraint, but rather our treatment here is to reduce the search cost. Moreover, ensuring the round-trip time is less than the activity time can better serve passengers. The AV can actually choose options where the round-trip time is greater than h. For choices that exceed the activity time, introducing a penalty cost proportional to the extra waiting time can relax the $2 \cdot \mu_t \cdot t_k < h$ constraint, and the utility function becomes:

$$\begin{aligned} U_{\text{parkinglot}} = \min_{p_i \in P} \Bigg[& \min_{k \in \Pi^{s,p_i}} \left((1 - \lambda_{\text{Subs}}) \cdot f_{VOT} \cdot t_k + 2 \cdot d_k \cdot \left(f_e^l + f_m^l \right) \right. \\ & \left. + \ C_{p_i}\left(t_{p_i}\right) \right) + \partial \cdot \max\left(0, 2 \cdot \mu_t \cdot t_k - h\right) \Bigg] \\ & \text{s.t.Availability}\left(p_i\right) \geq 1, \forall p_i \in P \end{aligned} \tag{2}$$

where ∂ is the penalty coefficient for additional waiting time. This translation allows for the possibility that the algorithm can consider longer travel times if they are justified by lower costs in other areas, even if they result in penalties being applied.

AV users also have the option to send their AV back home. Similar to parking in public parking lots, the total cost includes the vehicle usage cost for the AV round trip between the destination and home, as well as the time cost incurred by the travellers waiting for pick-up. The difference is that we assume no parking fee is required at home. Therefore, the cost function for this model can be formulated as follows:

$$\begin{aligned} & U_{\text{home}} = \min_{k \in \Pi^{s,r}} \left(2 \cdot d_k \cdot \left(f_e^l + f_m^l \right) + (1 - \lambda_{\text{Subs}}) \cdot f_{VOT} \cdot t_k \right) \\ & \text{s.t.Availability(home)} \geq 1 \\ & 2 \cdot \mu_t \cdot t_k < h, \forall k \in \Pi^{s,r} \end{aligned} \tag{3}$$

where U_{home} represents the total cost for the AV users to send their AV back home. $\Pi^{s,r}$ represents the set of paths between the destination and their home, $k \in \Pi^{s,r}$. Availability (home) represents the available parking spaces at the traveller's residence. Here, a similar approach can be applied to the constraint $2 \cdot \mu_t \cdot t_k < h$.

Apart from parking, the AV also has the option to remain near the destination and continuously cruise throughout the entire duration of their users' activities. The model simulates the process where the AV, upon reaching the destination, performs empty cruising in the vicinity. The cruising range is restricted within the detection range of the roadside unit to which the destination belongs. The total cost of this model includes the vehicle usage cost generated by continuous empty cruising and the potential waiting cost for the traveller after completing their activity. The cost function can be quantified as follows:

$$\begin{aligned} U_{\text{cruise}} = & \left(f_e^l + f_m^l \right) \cdot \overline{v(t)}_{RSU_l} \cdot h \\ & + (1 - \lambda_{\text{subs}}) \cdot f_{VOT} \cdot \left(\frac{d_{RSU_i}}{\overline{v(t)}_{RSU_l}} \right) \end{aligned} \tag{4}$$

where U_{cruise} represents the total cost of cruising within the area. RSU_i represents the roadside unit to which the destination area belongs. $\overline{v(t)}_{RSU_i}$ represents the average vehicle speed of all roads within RSU_i. d_{RSU_i} represents the detection distance of the roadside unit RSU_i, and for this study, it is assumed to be $d_{RSU_i} = 1$ km.

Finally, travellers will choose the parking method i^* that minimizes the cost function U_i. When making decisions, the cost function for parking choice is estimated based on the instantaneous state. The actual cost, influenced by changes in the network, will be determined at the conclusion of the simulation, using the real parking duration and travel distance for calculation.

$$i^* = \arg\min U_i, i \in \{\text{parkinglot, home, cruise}\} \tag{5}$$

As a comparison, we present the utility function for HVs. We assume that all individuals have the ability to access current information on parking, including details about both space availability and fees. Given that a significant number of parking facilities are now linked with public traveller information systems, this data can be easily obtained via smartphone parking applications. HV drivers will consider the maximum tolerance for parking fees and walking distance to choose a parking lot, as follows:

$$\begin{aligned} & U_{\text{HV}} = \min_{p_i \in P} \left[\min_{k \in \Pi_{\text{walk}}^{s,p_i}} \left(2 \cdot d_k^{\text{walk}} \cdot f_{\text{walk}} + C_{p_i}\left(t_{p_i}\right) \right) \right] \\ & \text{s.t.Availability}\left(p_i\right) \geq 1, \forall p_i \in P \\ & d_k^{\text{walk}} < d_{\max}^{\text{walk}}, \forall k \in \Pi_{\text{walk}}^{s,p_i} \end{aligned} \tag{6}$$

where U_{HV} represents the total cost for HV users parking. d_k^{walk} represents the distance of walk path k, indicating that the traveller chooses walk path k to travel between the destination and the parking lot. $d_{\max}^{\text{walk}}$ represents the maximum acceptable walking distance. $\Pi_{\text{walk}}^{s,p_i}$ represents the set of walk paths between the destination and the parking lot p_i, $k \in \Pi_{\text{walk}}^{s,p_i}$. f_{walk} represents the walking cost, used to penalize walking distance. For HVs, t_{p_i} represents the activity time and the walking time to and from the parking lot., $t_{p_i} = h + 2 \cdot \frac{d_k^{\text{walk}}}{v_{\text{walk}}}$. v_{walk} represents walking speed, valued at 5 km/h. It's noteworthy that when an HV driver arrives at a parking lot and finds no available parking spaces, the driver will directly drive to the nearest available parking lot to the destination to ensure quick parking.

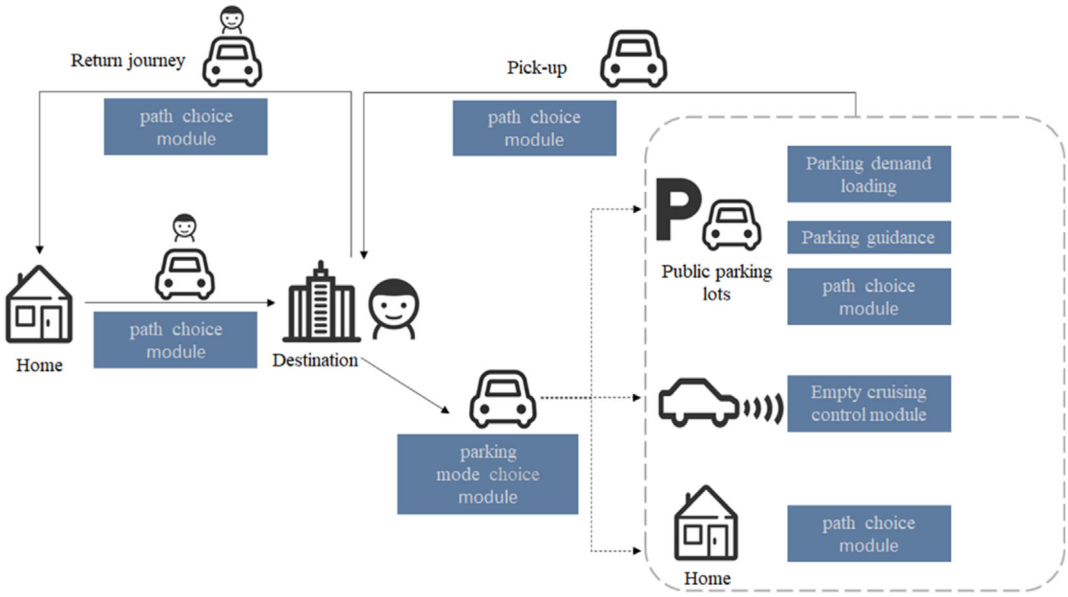


FIGURE 2 Simulation system module design.

3.2 | Analytical framework

Our model operates within an agent-based simulation framework, with the system's module design illustrated in Figure 2. The model replicates all car trips within a city. It allocates the origin–destination (OD) demand matrix for traffic zones to the road network based on departure time interval slices using dynamic user assignment (DUA), which converges to a dynamic user equilibrium (DUE) state. Once a user reaches their destination, the model evaluates various parking possibilities considering the current simulation time step (current simulation network state) and the user's activity duration. Subsequently, each user selects the parking option with the lowest instantaneous cost and follows the most efficient route between the destination and the chosen parking location. Although a user cannot modify their parking decision after being dropped off, the vehicle can adapt its route to the parking location by re-evaluating travel costs and adjusting en-route. The model endogenously captures the impact of each user's decision on congestion and the subsequent decisions of other users who make parking decisions, by allowing for an adaptive response to evolving traffic and parking conditions.

Expanding on this framework, the AVs parking simulation system in this paper consists of four types of intelligent agents: AVs, parking lots, road-side units (RSUs), and traffic management centres (TMC). Agent-based modelling (ABM) allows for the modelling of individual agents' independent behaviour within a complex system while considering their interactions with each other (Helbing, 2012). Within this system, each agent can communicate in real-time, assess the environment through ongoing interactions, and make decisions accordingly. Agents are capable of continuously adjusting their states and behaviours based on environmental conditions, planning their actions, and ultimately achieving their objectives. The functionalities and attributes of each type of agent are summarized in Table 2. AVs serve as the system's mobile units, executing fundamental behaviours such as following, lane changing, and making parking decisions. Parking lots allocate parking spaces to AVs and manage reservation information. RSUs, acting as critical nodes for information dissemination, are capable of acquiring real-time data within their coverage area and exchanging data with the TMC. Additionally, RSUs can receive cruising demands from AVs and allocate cruising paths. The TMC, functioning as the brain of the entire system, is responsible for processing global information and providing comprehensive path guidance to AVs. Figure 3 presents a general review of how the AVs parking simulation system works using a UML sequence diagram.

3.3 | Algorithm design

This section presents the algorithmic implementations of the main modules in the simulation system, including the path choice algorithm, the empty-cruising control algorithm and the parking decision algorithm.

3.3.1 | Dynamic network and route choice

The framework for routing within a dynamic road network employs the A* algorithm [24] to navigate the directed weighted graph $G = (V, E, L, W)$, where V is the set of nodes corresponding to intersections, E is the set of directed edges, representing the connections between nodes, L is the length of the edge and W is the weight of each edge during the

TABLE 2 Intelligent agent attribute configuration.

Intelligent agents	Functionality	Attributes
AVs	Implementation of vehicle micro-level driving, path choice, and parking behaviour choice	Speed, acceleration, vehicle type, activity duration, path choice rules, parking decision rules
Parking lots	Dynamic updating of parking resources, parking space reservations, and parking space allocation	Parking lot capacity, number of available parking spaces, parking reservation information, parking prices, parking lot location
RSUs	Implementation of road state recognition and vehicle cruise control	Static information (speed limits, number of lanes, link lengths) and dynamic information (vehicle count, average vehicle speed, travel time)
TMC	Updating and integrating road resources, parking resources, and handling requests from AVs	Vehicle information, road condition information, parking lot information

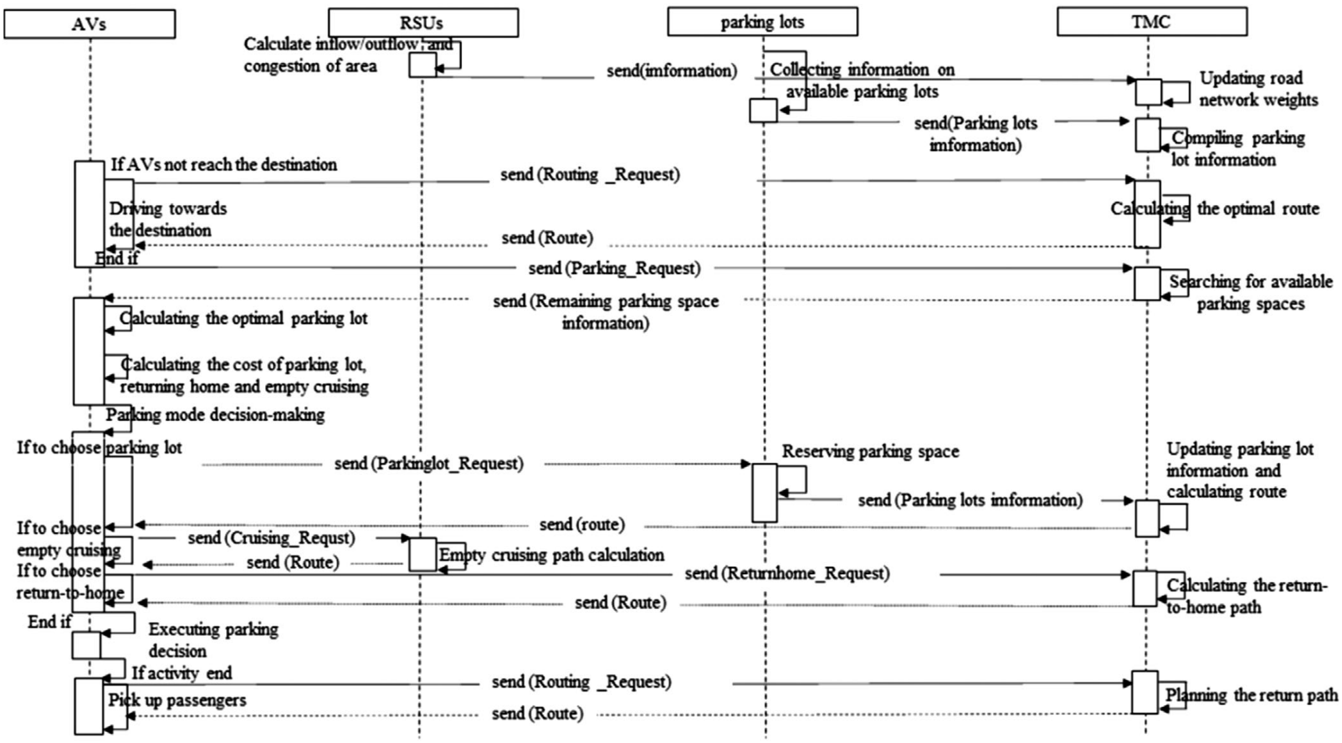


FIGURE 3 The simulation running logic for the parking process of AVs using a UML sequence diagram.

time interval t. This weight, pivotal for reflecting real-time traffic conditions, adjusts dynamically, and serves as a basis for route choice by integrating both current and historical traffic data. Distinctively, the system differentiates between passenger-carrying and empty vehicles by employing separate impedance functions for each, focusing on efficiency and minimal congestion for the former, and prioritizing the influence of cruising distance and activity duration for the latter. For passenger-carrying vehicles, the determination of the shortest path involves calculating the travel time for each link. This is accomplished by dividing the length of the road by either the current average speed of all vehicles on the road or by the road's speed limit if no vehicles are present. The formula can be expressed as follows:

$$w_{PAX}(t, e_i) = \begin{cases} \dfrac{l_{e_i}}{V_{e_i}^{\max}}, & t = t_0 \\ w(t - \Delta t, e_i) \cdot \eta + \dfrac{l_{e_i}}{V_{e_i}^{avg}(t)} \cdot (1 - \eta), & t \neq t_0 \end{cases} \tag{7}$$

where $w_{PAX}(t, e_i)$ is the weight of a link e_i at time t. $w(t - \Delta t, e_i)$ is the weight of a link e_i in the previous period. $V_{e_i}^{avg}(t)$ is the average speed of a link e_i at time t. $V_{e_i}^{\max}$ is the maximum speed limit of e_i. η is the remembering factor, we consider η equal to 0.5.

For empty vehicles, the impedance function comprises two parts: the vehicle usage cost and the traveller wait time cost, which is linked to the choice of parking mode. Additionally, the calculation takes into account only the travel time on the road, excluding the time spent accessing and parking in a space. The formula can be expressed as follows:

$$w_{MT}(t, e_i) = \begin{cases} 2 \cdot l_{e_i} \cdot \left(f_e^l + f_m^l\right) + (1 - \lambda_{\text{Subs}}) \cdot f_{VOT} \cdot \dfrac{l_{e_i}}{V_{e_i}^{\max}}, & t = t_0 \\ 2 \cdot l_{e_i} \cdot \left(f_e^l + f_m^l\right) + (1 - \lambda_{\text{Subs}}) \cdot f_{VOT} \cdot \dfrac{l_{e_i}}{V_{e_i}^{avg}(t)}, & t \neq t_0 \end{cases} \tag{8}$$

Algorithm 1 outlines the primary process for vehicle routing, which we transform into a dynamic graph search problem.

ALGORITHM 1 Path guidance algorithm.

```
Input: vehicleCollection
Output: vehicleroute
for vehicle in vehicleCollection do
    start, destination ← vehicle.currentPosition, vehicle.destination
  if start = destination then
  continue
  end if
    openList, closedList ← [start], []
    start.g, start.f ← 0, heuristic(start, destination)
  while openList do
      current ← min(openList, key = λnode: node.f)
  if current = destination then
  vehicle.path ← constructPath(current)
  break
  end if
      openList.remove(current)
      closedList.append(current)
  for neighbor in getNeighbors(current) do
  if neighbor ∈ closedList then
  continue
  end if
        tentativeG ← current.g + distance(current, neighbor)
  if neighbor ∉ openList or tentativeG < neighbor.g then
  neighbor.parent, neighbor.g, neighbor.f ← current, tentativeG,
  tentativeG + heuristic(neighbor, destination)
  if neighbor ∉ openList then
          openList.append(neighbor)
  end if
  end if
  end for
  end while
  if not openList then
  vehicle.path ← []
  end if
end for
```

3.3.2 | Empty cruising control algorithm

Considering the empty cruising of AVs is a challenging task as it requires balancing the economic efficiency of the movement while minimizing the impact on regional traffic. However, the core focus of this paper is not on the specific decision-making process for empty cruising paths. Instead, we generally measure the average utility of cruising paths. In this context, we adopt a random walk model to describe the movement of AVs within the cruising area. In the random walk model, vehicles have a probability of moving in a specific direction at each time step, making it analogous to a Markov chain model [25, 26]. Let's assume that we have N states, which represent intersections or links in G. This allows us to construct an $N \times N$ transition probability matrix P, where $p(i, j)$ represents the transition probability from state i to state j. Consequently, given the vehicle's current state as i, it will transition to state j in the next time step with a probability of $p(i, j)$. Since each state can only transition to other states or remain in the current state, the sum of all elements in each row of the transition probability matrix must equal 1. Mathematically, this can be expressed as $\sum_j p(i, j) = 1$. In this specific model, the transition probabilities are determined based on the simplest assumption that individuals have no memory, goals, or knowledge of the network beyond the street segments immediately visible at an intersection. Therefore, the transition probabilities depend solely on the visible street segments at each intersection. The model assumes that individuals randomly choose one of the visible street segments to move to in the next time step, with equal probabilities assigned to each visible street segment. This implies that the transition probabilities follow a uniform distribution among the available options. Algorithm 2 illustrates the control flow for continuous empty cruising, with the cruising range limited to the destination's corresponding RSU and the depth of the cruising path controlled based on the duration of activity.

3.3.3 | Parking decision algorithm

To address how AVs select parking modes, we design the corresponding parking decision algorithm (Algorithm 3). This algorithm starts by collecting the necessary constraints from the AVs that have initiated parking requests. These constraints include information such as vehicle type, current location, activity duration of the passenger, and availability of parking space at the passenger's residence. Next, dynamically retrieving external information, including the road network and static information of parking lots (such as parking locations, charging rules, and

ALGORITHM 2 Empty cruising control algorithm.

```
Input: currentTime, vehicleList
Output: Empty cruising path
for each vehicle in vehicleList do
    rsuInfo ← queryRSUInfo(vehicle)
    cruiseArea ← getArea(rsuInfo)
    destination ← queryDestination(vehicle)
    activityDuration ← queryActivityDuration(vehicle)
    activityStartTime ← queryActivityStartTime(vehicle)
    currentLocation ← queryCurrentLocation(vehicle)
      if currentTime ≥ activityEndTime − travelTime then
    navigateToDestination(vehicle, destination)
    updateVehicleInfo(vehicle)
      else
    nextLocation ← None
        while nextLocation is None or currentLocation = nextLocation do
    nextLocation ← calculateNextLocation(cruiseArea)
          if currentLocation = nextLocation then
    nextLocation ← None
          end if
        end while
    navigateToNextLocation(vehicle, nextLocation)
      end if
end for
```

ALGORITHM 3 Parking decision algorithm.

```
Input: park_demand_vehicles
Output: parking_mode
for each vehicle in park_demand_vehicles do
    min_cost_parkinglot ← ∞
    for each parking_lot in parking_lots_information do
        if query_capacity() ≠ 0 then
            paths ← collect_sorted_paths()
            for each path in paths do
                if 2 × travel_time × time_reliability_factor < activity_time then
                    Parkinglot_cost ← update_parkinglot_cost()
                    break
                end if
            end for
            if parkinglot_cost < min_cost_parkinglot then
                min_cost_parkinglot ← parkinglot_cost
            end if
        end if
    end for
    if household_parking_capacity_utility > 0 then
        paths ← collect_sorted_paths()
        for each path in paths do
            if 2 × travel_time × time_reliability_factor < activity_time then
                household_parking_utility ← update_household_parking_utility()
                break
            end if
        end for
        empty_cruise_utility ← calculate_empty_cruise_utility()
        if parking_mode[vehicle] = parking_lot then
            update_parking_lots_information(optimal parking lot)
        end if
    end if
    parking_mode[vehicle] ← compare_utility()
end for
return parking_mode
```

real-time parking space availability). Based on the gathered constraints, we filter out feasible parking lots and available parking spaces from the parking lots, aiming for the optimal public parking lot as the one with the lowest total cost. Simultaneously, alternative options are tracked, evaluating the home parking cost if it is feasible, as well as the cost of continuous empty cruising. Eventually, the optimal parking mode is determined and the parking path is re-planned accordingly. If the returned parking mode involves parking at a parking lot, the reservation information for the corresponding parking space is updated. It is worth noting that the algorithm sets rules that prevent AVs from competing for the same parking space and limit the number heading to a parking lot to the available spaces.

4 | EMPIRICAL ILLUSTRATION

4.1 | Simulation setup

The impacts of AVs within a real-world network in Nanning, China are examined. The scope of this study encompasses the downtown area of Nanning, which can fully represent the characteristics and trends of urban population movement (see Figure 4). We utilize OpenStreetMap (OSM) to obtain road network data, conduct topological repairs on the network structure, adjust the lane layout and connection order at intersections, set up U-turn lanes, and optimize the phase sequence of traffic lights at some intersections. Additionally, use the Amap interface to acquire on-street parking spaces and public parking lots within the designated study area. The parking system establishes visibility by providing information about the occupancy rate of the parking lot prior to the vehicle's arrival.

The 2021 Nanning residents travel survey (1.14% sampling, 36,800 households) provides information on trips that include both travel and parking needs. This data set provides detailed records of the daily activity chains of citizens, including information on households, family members, vehicles, and travel details. The resident travel information is presented as shown in Table 3. The family number, member number, and trip number are used to obtain the traveller's activity chain. The duration of an activity is calculated as the time difference between

TABLE 3 Resident travel information.

Family number	Member number	Trip number	Departure time	Departure location	Arrival time	Arrival location	Trip purpose	Transportation mode
771010110001	2	1	23-12-2021 07:30 AM	(108.37067, 22.84634)	23-12-2021 08:00 AM	(108.31599, 22.82697)	Work commuting 1	Private car
771010110001	2	2	23-12-2021 07:00 PM	(108.31599, 22.82697)	23-12-2021 07:30 PM	(108.37067, 22.84634)	Work commuting 2	Private car
771010204045	1	1	23-12-2021 07:15 AM	(108.32920, 22.83444)	23-12-2021 07:35 AM	(108.23687, 22.81324)	School commuting 1	Private car
771010204045	1	2	23-12-2021 07:35 AM	(108.23687, 22.81324)	23-12-2021 08:30 AM	(108.31899, 22.77263)	Work commuting 1	Private car
771010304045	1	1	23-12-2021 10:00 Am	(108.343555, 22.827416)	23-12-2021 11:00:00	(108.397215, 22.815108)	Business trip 1	Private car
771010305023	1	1	23-12-2021 09:09 AM	(108.28966, 22.84087)	23-12-2021 09:30 AM	(108.32650, 22.86733)	Leisure trip 1	Private car
…	…	…	…	…	…	…	…	…

Note: In 'Trip Purpose', 1 represents the outward journey, and 2 represents the return journey.

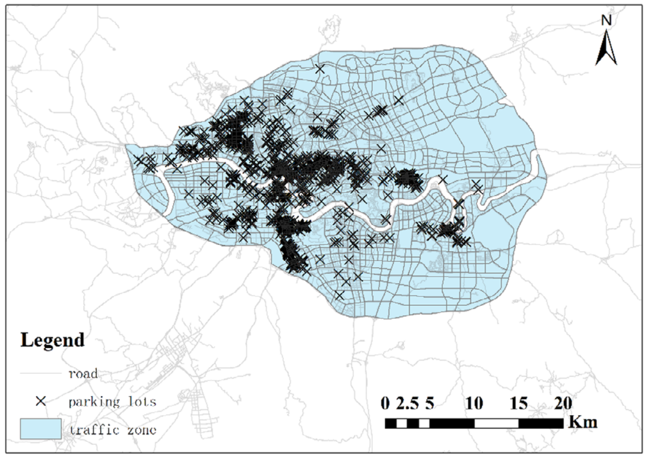
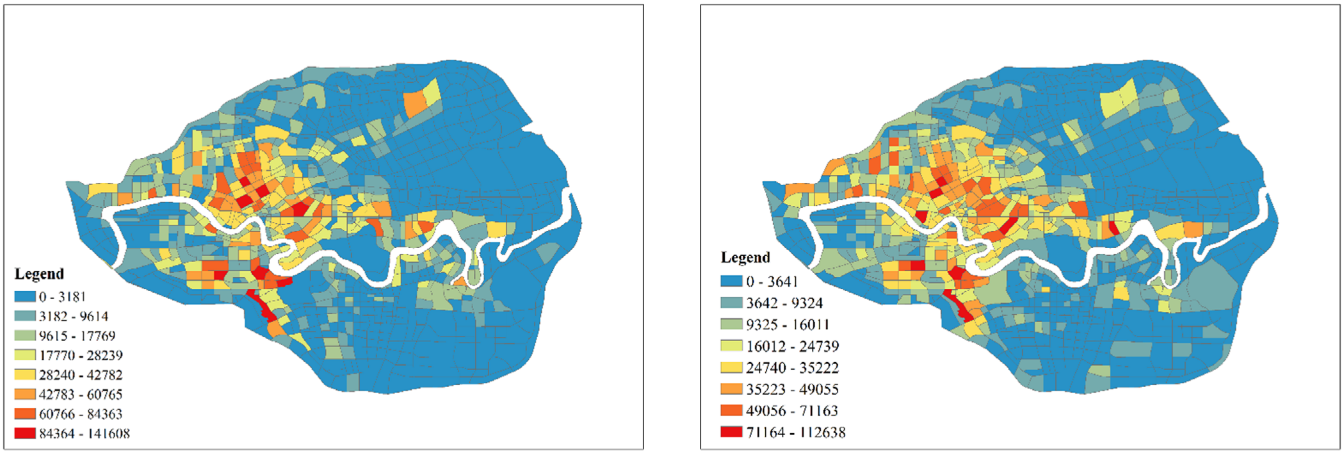


FIGURE 4 Study area.

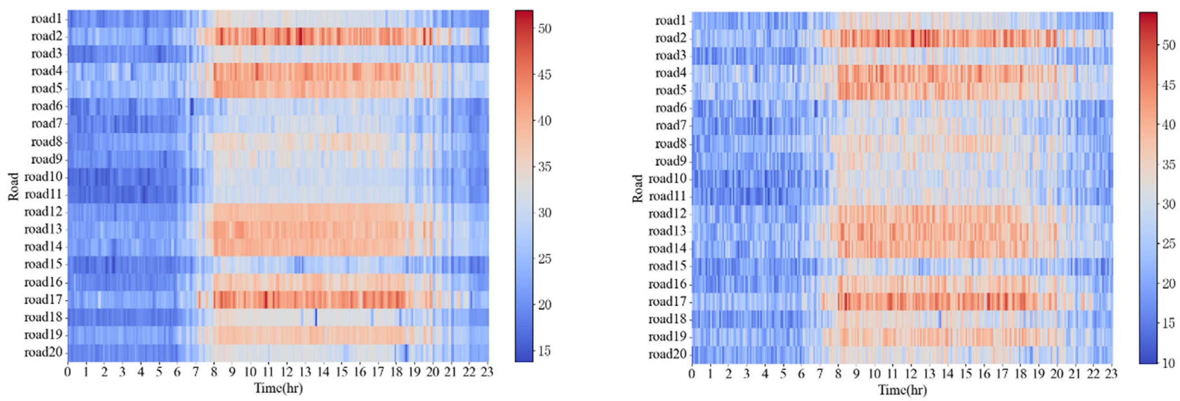
someone's arrival at a location and their departure from that location to undertake their next trip. We exclude trips where both the origin and destination are outside the study area, and for trips that originate from outside and arrive at the study area, the home parking option is not considered. This study only considers samples of private car and uses synthetic population generation method to expand the sample size. The expanded daily traffic demand is shown in Figure 5. Additionally, parking demand is generated based on the arrival time, location, and duration of each activity of the travellers. Due to the heavy transit traffic and many public transportations, such as taxis and buses, still being unknown, the alignment of the network traffic status for simulating the real travel environment is achieved through traffic condition data obtained from Amap. The comparison between the calibrated model and the actual road speeds is shown in Figure 6. The simulation time is 24 h a day, with an interval of 5 min. Based on the distribution of departure time intervals of trips, the daily OD matrix is sliced. In each iteration, AVs perform actions according to their current state, as illustrated in Figure 3. Once the journey of an AV ends, it exits the simulation and both its driving and parking processes are recorded. The entire simulation process is shown in Figure 7.

We employ the open-source traffic simulation software SUMO, along with traffic control interface (TraCI), for conducting the simulations. SUMO is a highly effective microsimulation tool used for modelling, analyzing, and assessing the performance of urban traffic networks [27]. TraCI, on the other hand, serves as an application programming interface (API) that establishes a connection between the road traffic network simulation and external applications (e.g. Python). It offers real-time information about the road network and simulated objects during the simulation runtime. The AVs are classified as passenger vehicles with a prescribed length of 5 meters, encompassing two types: fuel-powered vehicles and electric vehicles. Considering the overall market scale, the proportion of these two types stands at 70% for fuel-powered vehicles and 30% for electric vehicles [28]. The movement of the vehicle adheres to the Krauss car-following model and SL2015 lane-changing model. We have endowed AVs with superior performance compared



(a) traffic generation (b) traffic attraction

FIGURE 5 Daily traffic demand generation. (a) Traffic generation, (b) traffic attraction.



(a) real (b) simulation

FIGURE 6 Comparison of speeds between real and simulated environments (random sampling of 20 roads). (a) Real, (b) simulation.

to HVs, primarily through enhanced car-following and lane-changing model coefficients. Different users may have different valuations of time, depending on a variety of factors such as the nature of their activities, their personal preferences, or even the urgency of their schedules. The variation in behaviour among AVs can be enhanced by implementing varying proportions of pick-up reservation for distinct travel purposes. However, by using annual average income and work hours to create a standardized measure of time value that varies with each user and activity, the calculations within the utility function become more direct. Table 4 presents the default values that were employed in the simulation. The calculations pertaining to these values are available in the appendix.

4.2 | Results and discussion

The simulation experiment is comprehensively analyzed from five perspectives: (1) Exploring the preferences of AVs parking modes choice, (2) examining in detail how distance factors affect AV parking decisions, (3) assessing the responsiveness of AVs to different parking lot fee structures, (4) investigating the broader implications of AVs on traffic network efficiency and flow, and (5) discussing pricing strategies for AV empty cruising.

4.2.1 | AV parking mode choice

The characteristics of different parking modes of AVs are shown in Table 5. The simulation results indicate distinct differences in travel behaviour characteristics across various parking modes. The choice of parking mode is closely linked to cost. While the average parking cost for the continuous cruising mode is the lowest, its cost per hour is the highest, making it most suitable for short trips. Conversely, for longer trips, the economic benefits of parking in a parking lot or at home become more apparent. Although the average cost of parking in a parking lot is approximately 5 CNY higher than parking

TABLE 4 Parameters and their default values in the simulation.

Parameters for the car-following model and the lane-changing model			
		HVs	**AVs**
accel	acceleration (m/s^2)	2.6	3.8
decel	deceleration (m/s^2)	3.5	4.5
emergencyDecel	emergency deceleration (m/s^2)	9	9
sigma	driving tolerance	0.5	0
minGap	minimum clearance (m)	2.5	1.5
Tau	expected headway (s)	1	0.6

Parameters for the parking fee		
C_1	parking cost per unit time in the first category area (¥/h)	10
C_2	parking cost per unit time in the second category area (¥/h)	5
C_3	parking cost per unit time in the third category area (¥/h)	3

Parameters for reservation mode		
Activity purpose	**Percentage of non-appointments ($\lambda_{\text{subs}} = 0$)**	**Percentage of appointments ($\lambda_{\text{subs}} = 1$)**
Work commuting	30%	70%
Business trip	50%	50%
Leisure trip	50%	50%
School commuting	100%	0
Others	100%	0

Other parameters		
f^{Fuel}	cost per mile for fuel-powered AVs (¥/km)	0.85
f^{Electric}	cost per mile for electric AVs (¥/km)	0.52
f_{VOT}	Value of time (¥/h)	49

TABLE 5 Characteristics of parking choice behaviour in AVs.

Parking mode	**Parking lot**	**Home parking**	**Empty cruising**	**Average**	**HV (Average)**
proportion	45.69%	54.01%	0.30%	–	–
Total Cost (¥)	22.22	17.03	10.91	19.38	25.4
Average activity time (h)	5.92	9.19	0.40	7.67	7.73
Unit hourly cost (¥/ h)	3.75	1.85	27.28	2.53	3.29
Average empty cruising distance (km)	6.55	18.20	24.52	12.90	–
Average home distance (km)	15.99	8.62	10.20	11.99	12.01

at home, the selection of a parking mode is also influenced by travel distance and activity duration. When the destination is far from home and the activity duration is relatively short, parking in a parking lot emerges as the optimal choice. Conversely, when the destination is closer to home and the activity duration is longer, AVs tend to choose home parking. Additionally, compared to HVs, the average total cost for AVs decreases from 25.4 CNY to 19.38 CNY, representing a 24% reduction. AVs indeed offers the potential to make parking more comfortable and affordable by altering parking strategies. However, on average, each autonomous vehicle will generate 12.90 km of empty cruising distance, presenting significant challenges for future urban traffic.

Parking choice behaviour at different times of the day also have significant differences. Figures 8a and 8b show the percentage of different parking choice behaviours of AVs throughout the day and at different time periods, respectively. The day is divided into three main periods: morning peak hour, evening peak hour, and off-peak hours. During the morning peak hour on weekdays, which is defined as 07:00–09:00 AM, over 70% of vehicles choose to park at home. This is likely because the primary purpose of travel during this period is to commute

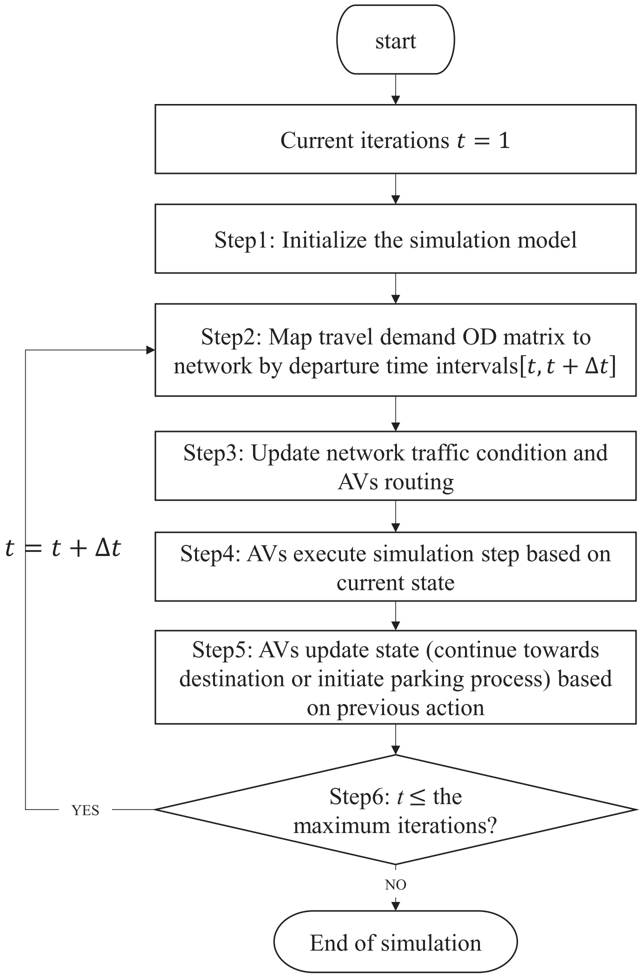


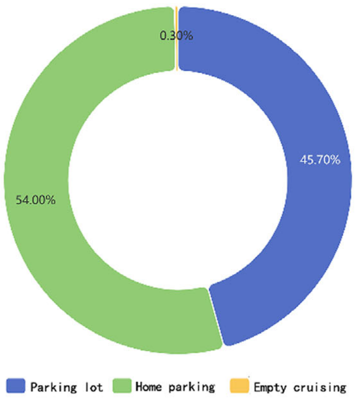
FIGURE 7 Simulation process.

to work, which typically involves a relatively long duration of activity. Therefore, the home parking mode, which allows for extended parking time, is preferred. In contrast, the parking demand during the evening peak hour (from 5:00 PM to 7:00 PM) and off-peak hours is characterized by a higher proportion of vehicles choosing to park in parking lots. This shift in behaviour can be attributed to the nature of trips during these periods, which are mostly non-work-related and thus tend to have a shorter duration of activity. Parking in parking lots, which can be more convenient for shorter durations, becomes the more popular choice. The cruise parking mode sees less popularity throughout all times of the day, with its higher cost and longer average duration of travel during workdays rendering it less attractive and leading to a lower selection ratio. Notably, compared to off-peak hours, cruising is chosen more frequently during the morning and evening peak hours when the traffic network is particularly congested. In these peak periods, the cruising time for autonomous vehicles directly aligns with the activity time of travellers, and the slower road speeds lead to fewer kilometres being driven, potentially reducing energy costs. However, this practice of cruising instead of parking can contribute to worsening the traffic conditions, as it increases the number of vehicles on the road during already busy times.

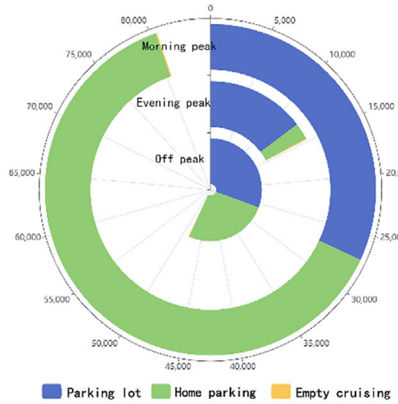
Figures 8c further analyze the distribution of AV choices over time. If a traveller's activity time exceeds 60 min, they will not choose the continuous cruising mode as a substitute for parking. As the duration of the traveller's activities at the destination increases, the proportion of those choosing to park at home gradually increases. We observe a low adoption of the cruising choice by AVs. In estimating the costs associated with cruising, we used the regional average speed multiplied by the activity time, which may not accurately reflect real-world scenarios. In reality, due to traffic congestion, route changes, or other unforeseen factors, the actual cost might be lower than our estimate. This discrepancy is vital in explaining why the usage rate of the empty cruising strategy is lower than anticipated. Additionally, our choice of cruising routes somewhat overlooks the possibility of AVs proactively entering congested areas to reduce travel costs, which could inevitably increase the likelihood of AV cruising.

Figure 8d,e reveals how energy type shapes parking mode choice behaviours. The simulation results indeed highlight the energy type as a pivotal factor significantly influencing parking mode choices. Initially, travellers using fuel-powered vehicles are more inclined to opt for parking lot parking, accounting for 52% of all trips with such vehicles. In contrast, those using electric vehicles tend to prefer parking at home, making up 69% of all electric vehicle trips. This preference isn't solely due to the lower operating costs of electric vehicles but might also be associated with the convenience of home charging. Further analysis indicates that electric vehicles exhibit longer distances in cruising without passengers in the simulation. This suggests that as vehicle operating costs decrease, cruising becomes more economical, potentially promoting this behaviour. This trend provides insight into future travel patterns: as operating costs reduce, a larger number of gasoline vehicle users might transition to electric vehicles, lured by their greater cost efficiency and flexibility. In summary, the type of energy not only affects parking choices but might also further shape future travel and parking habits.

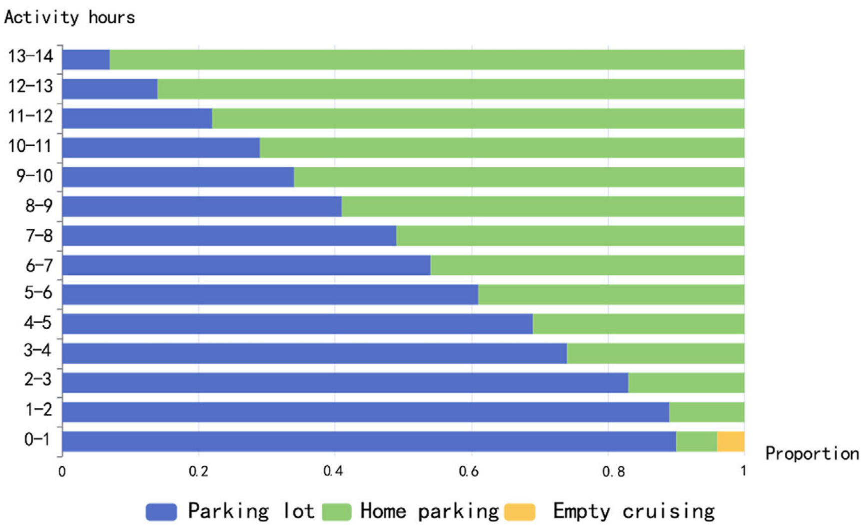
The percentage of AVs in the traffic network is likely to impact parking behaviour. Therefore, we explore variations in AV parking mode at different AV penetration rates, as shown in Figure 9. In our simulation, we assume that AV and HV parking space selection is based on equal competition and a first-come, first-served basis. Regarding demand initialization, whether a vehicle is an AV or HV is determined through random sampling, consistent with the AV penetration rate. The overall trend indicates that as the AV penetration rate increases, the proportion of parking in parking lots gradually rises (from 27.46% to 45.69%), while the proportion of parking at home (from 66.74% to 54.01%) and empty cruising as a parking alternative (from 5.8% to 0.3%) declines. The reason for the low proportion of parking lot usage in scenarios with low AV penetration rates may be due to the competitive disadvantage with HVs for parking lot spaces, leading to increased parking costs at parking lots, and thus a shift towards home parking and empty cruising. Due to the free nature of home parking, there is a significant preference for it across different penetration rates.



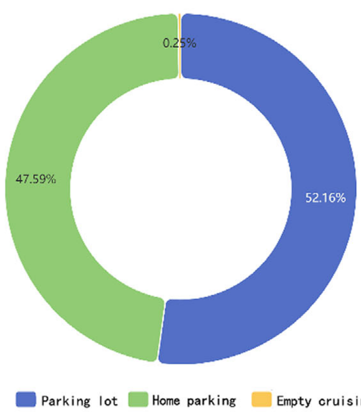
(a) Distribution of all-day parking mode choice



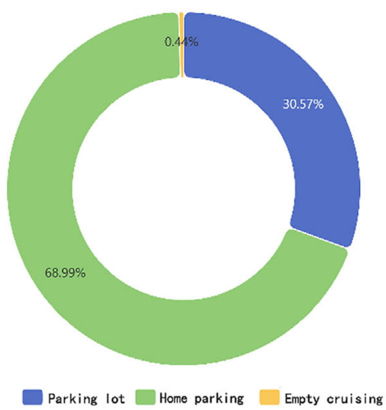
(b) Distribution of parking mode choice during morning peak, evening peak, and off-peak



(c) Proportion of parking mode choices by activity duration



(d) fuel-powered AV parking mode choices



(e) electric AV parking mode choices

FIGURE 8 Distribution of parking mode choice. (a) Distribution of all-day parking mode choice, (b) distribution of parking mode choice during morning peak, evening peak, and off-peak, (c) proportion of parking mode choices by activity duration, (d) fuel-powered AV parking mode choices, and (e) electric AV parking mode choices.

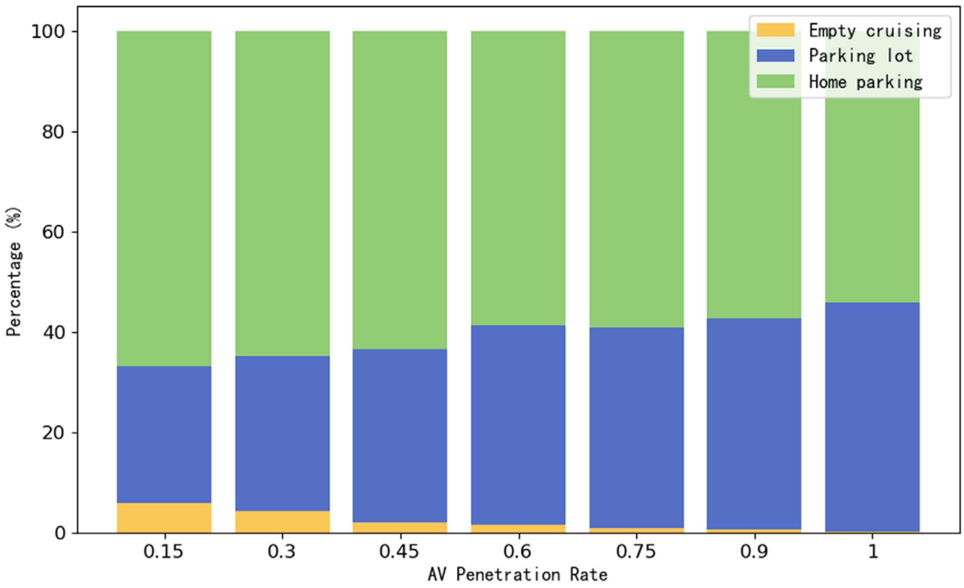


FIGURE 9 Variations in AV parking mode at different AV penetration rates.

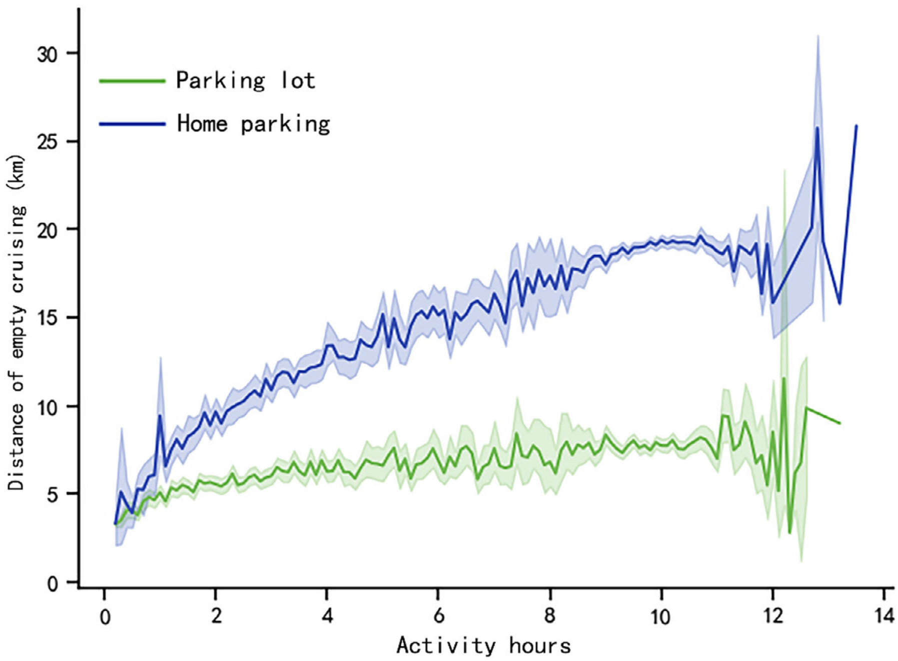


FIGURE 10 Relationship between travellers' activity time and empty cruising distance.

4.2.2 | Distance analysis in AV parking strategies

AV parking mode is shaped by a range of distance-related factors, such as the OD distance and the empty cruising distance. This section delves into how these distances influence parking mode. Additionally, it is observed that during the parking phase, the cruising alternative to parking often employs a random walk approach, which leads to stochastic variations in distance. Given this, our analysis places a particular emphasis on the comparison between parking lot usage and residential parking.

Figure 10 reveals the relationship between the empty cruising distance and activity time. For the parking behaviour of AVs, there is a significant positive correlation between the empty cruising distance and the duration of activities. The long duration of an activity offers AVs a sufficient time window to economically justify choosing distant parking spots, as longer activities accumulate higher parking fees, encouraging AVs to seek out cheaper or free parking options further away, or even to return home as a strategy to save on costs. If the passenger's activity time is short, but the parking distance is far, it may lead

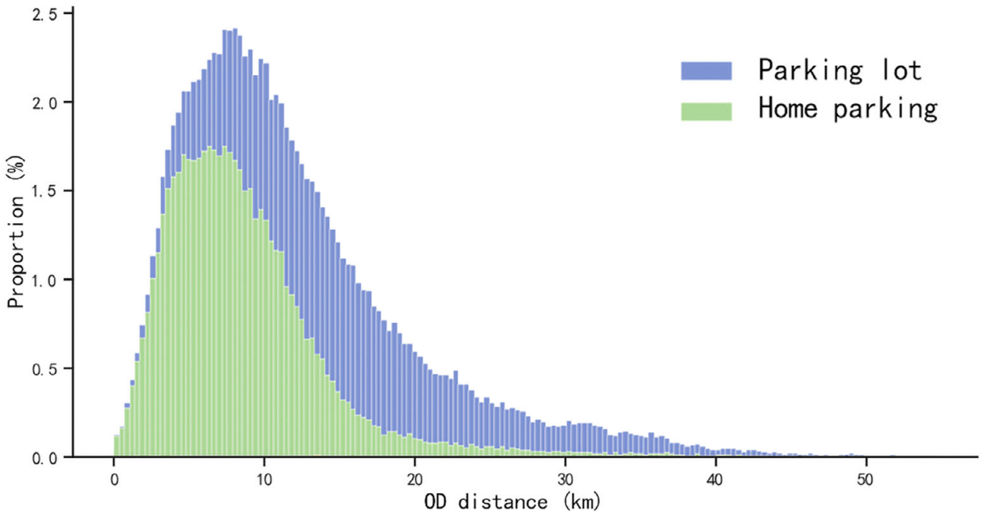


FIGURE 11 Distribution of travellers' parking mode choice and distance from home.

to additional waiting penalties. This pattern suggests that as the activity time of travellers increases, the vehicle driving cost is more effectively shared, thereby reducing the parking cost per unit time. Moreover, it's worth noting that when the activity duration exceeds 12 h, the data variance increases. This might be due to the small sample size. To better understand and predict parking behaviour, a larger sample size and more data may be needed.

Figure 11 elucidates the substantial impact of geographic distance between a traveller's residence and the intended activity location on the selection of parking strategies. The analysis indicates that when the spatial separation from a traveller's domicile to the activity site is confined within a radius of 9 km, a substantial majority, exceeding 80%, prefer the convenience of home-based parking. Nevertheless, this tendency exhibits a marked decrease as the geographic distance broadens. For distances spanning from 9 to 20 km, the proportion of individuals opting for residential parking plunges to approximately 46%. This trend intensifies for greater distances; when the spatial separation transcends the 20-km threshold, the preference for home-based parking contracts further, with a mere 16% adhering to this strategy. Contrastingly, the proclivity for parking lot usage exhibits an inverse correlation with distance. Specifically, once the distance breaches the 12-km mark, the balance tilts in favour of parking lots, with the proportion of individuals opting for this strategy exceeding 50%. Interestingly, the strategy of continuous cruising demonstrates a relative immunity to the influences of distance from home. Its prevalence maintains a steady distribution across all measured distances, suggesting that it is less contingent on the geographic proximity of the traveller's residence.

We also explore whether there are differences in the choice of parking lot under automatic driving. Figure 12 presents the distribution of distances between destinations and parking lots for both AVs and HVs choosing to park in parking lots. Simulation results indicate a distinct behavioural pattern for AVs compared to traditional ones. For trips involving AVs that opt for parking lot parking, approximately 43% choose lots located less than 1 km from their destination. This preference declines as the distance increases, with virtually no travellers opting for parking areas beyond an 8-km radius. This observed trend suggests that while the lower parking costs in suburban areas might incentivize travellers to park further from their destinations, there's a trade-off between the savings from parking costs and the convenience of proximity. In contrast, for HVs, the walking distance post-parking is a significant constraint. These drivers tend to prioritize parking close to their destination, with less emphasis on parking cost considerations, thereby adhering to a "the closer, the better" mentality. Taking a broader perspective, only 25.2% of AVs choose to park in lots near their destination (within 1 km). This accounts for just 11.5% of all trips. Thus, it's projected that the future will see a substantial shift in parking behaviour, with 88.5% of trips potentially leveraging the automated parking feature of AVs, underscoring the transformative impact of autonomous technology on urban mobility and parking landscapes.

4.2.3 | AV parking lot fee sensitivity

This subsection aims to investigate the impact of different parking charging scenarios on parking behaviour choice. We present two scenarios beyond the base scenario (Scenario A) to account for the heterogeneity of parking charging schemes. In Scenario A, parking is charged per hour. Based on the hourly charge in Scenario A, Scenario B sets the daily maximum charge, which is three times the hourly rate per parking lot (see Table 6). In Scenario C, the parking fee is paid by employers. In many countries, employers provide free parking or reimburse parking costs. This paper assumes that 80% of employees do not need to pay parking fees to the parking lot when commuting.

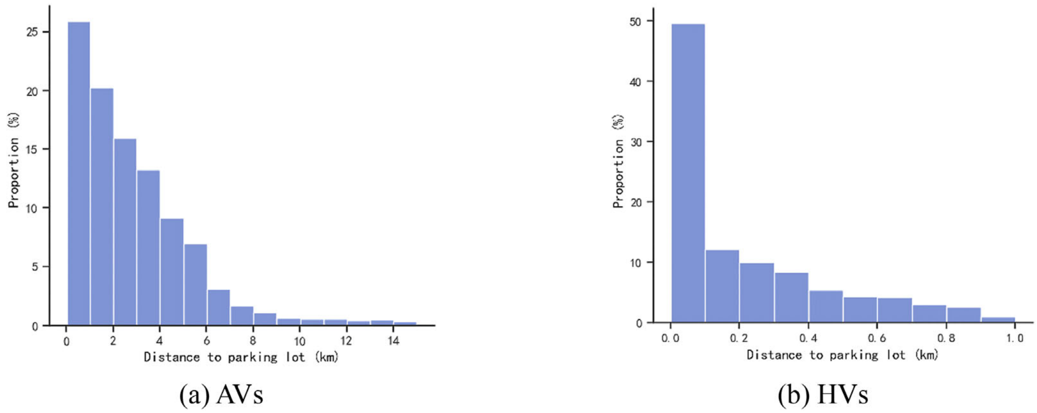


FIGURE 12 Comparison of parking lot distance distributions. (a) AVs, (b) HVs.

TABLE 6 Parking space charging area and fee division in scenario b.

Area	Basic parking charge (¥/h)	Maximum daily parking charge (¥/day)
First category area	10	30
Second category area	5	15
Third category area	3	9

TABLE 7 Characteristics under different parking charging scenarios.

	Scenario A	Scenario B	Scenario C
Proportion of trips parked in parking lots	45.69%	76.32%	85.68%
Average time (h)	5.92	7.84	8.12
Average distance of empty cruising (km)	6.55	1.53	0.94
Average cost (¥)	22.22	10.43	–
The proportion of parking fees	77.78%	83.76%	–

Table 7 shows the simulation results of different parking charging scenarios. The simulation results of scenario a show that for travellers who choose to park in the parking lot, 22.22% of the total parking cost is still the cost of vehicle use and the cost of waiting time. In Scenario B, when the parking time is less than 3 h, there is no difference between the hourly parking rate and the daily maximum parking rate. However, when the parking time is greater than 3 h, the maximum daily parking fee is lower than the hourly parking fee. Therefore, in this scenario, some travellers' parking choices will shift from home parking to parking in the parking lot, especially for long commutes.

Figure 13 shows the heat maps of parking space usage distribution under three scenarios. In scenario A, parking hotspots are not concentrated in the city centre, but are distributed at the boundary of the third category area and the second category area of parking fees, indicating that travellers expect to find a relatively economical parking lot within the shortest possible travel distance. Compared with scenario A, the competitiveness of the second category parking area in scenario b is significantly improved, but the impact on the competitiveness of the first category area is small. This may be due to the small scope of a class of areas, travellers can spend less travel costs to reduce the total cost of parking. It should be noted that in scenario b, even though the total cost has been reduced to 10.4, the return to residence parking mode is still competitive (22.49% of all trips). The heat map of parking space usage distribution in Scenario C shows that the free parking spaces provided by employers greatly improve the utilization rate of parking lots in the city centre and increase the proportion of parking in parking lots. Only when the commuting distance is short, that is, the employee's residence is extremely close to the workspace, the traveller may choose to park at home.

4.2.4 | AVs impact on traffic network

This paper utilizes three indicators to assess the influence of AVs on the traffic network. The first indicator is vehicle miles travelled (VMT), which is calculated by:

$$\mathrm{VMT} = \sum_{e_i}^{G} \mathrm{VMT}_{e_i} = \sum_{e_i}^{G} \left(\mathrm{flow}_{e_i} \cdot \mathrm{length}_{e_i}\right) \tag{9}$$

where G represents the set of links in the study area. VMT_{e_i}, flow_{e_i} and length_{e_i} denote the vehicle mileage, the total traffic flow, and the length of a link e_i, respectively.

The second indicator is total VHT, which is calculated by:

$$\mathrm{VHT} = \sum_{e_i}^{G} \mathrm{V}HT_{e_i} = \sum_{e_i}^{G} \left(\frac{\mathrm{flow}_{e_i} \cdot \mathrm{length}_{e_i}}{\mathrm{speed}_{e_i}}\right) \tag{10}$$

where speed_{e_i} represents the average speed of a link e_i.

The third indicator is total vehicle delay (VD), which is the time lost due to driving below the ideal speed (planned parking

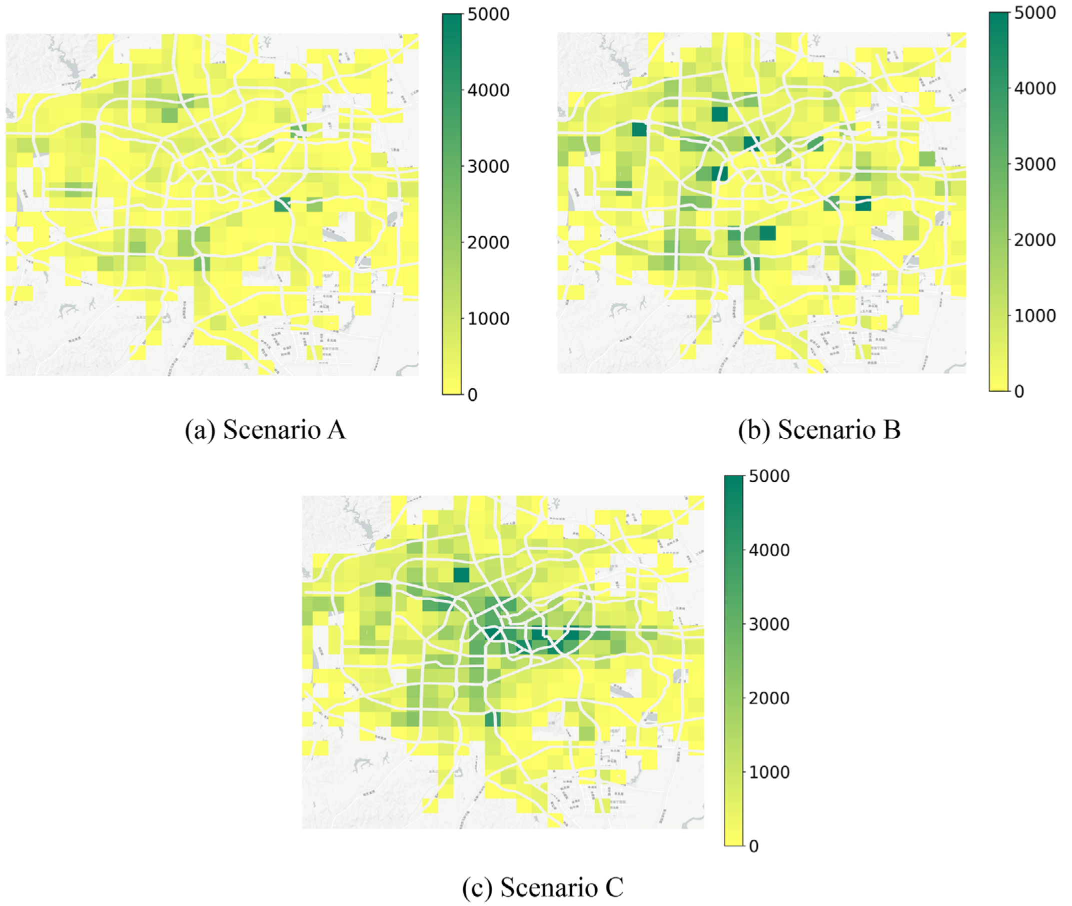


FIGURE 13 Parking space usage distribution. (a) Scenario A, (b) Scenario B, (c) Scenario C.

TABLE 8 Comparison of VMT between HVs and AVs.

VMT	HVs	AVs	Variation
Total VMT (1000 km)	3738.91	5540.28	48.18%
VMT of non-empty cruising (1000 km)	3738.91	3688.00	−1.36%
VMT of empty cruising (1000 km)	–	1852.28	–
Average VMT (km/pcu)	26.02	38.55	48.18%

TABLE 9 Comparison of VHT between HVs and AVs.

VHT	HVs	AVs	Variation
Total VHT (h)	128,772.80	241,427.41	87.48%
VTH of non-empty cruising (h)	128,772.80	154,740.41	20.17%
VTH of empty cruising (h)	–	86,687.10	–
Average VHT (h/pcu)	0.90	1.68	87.48%

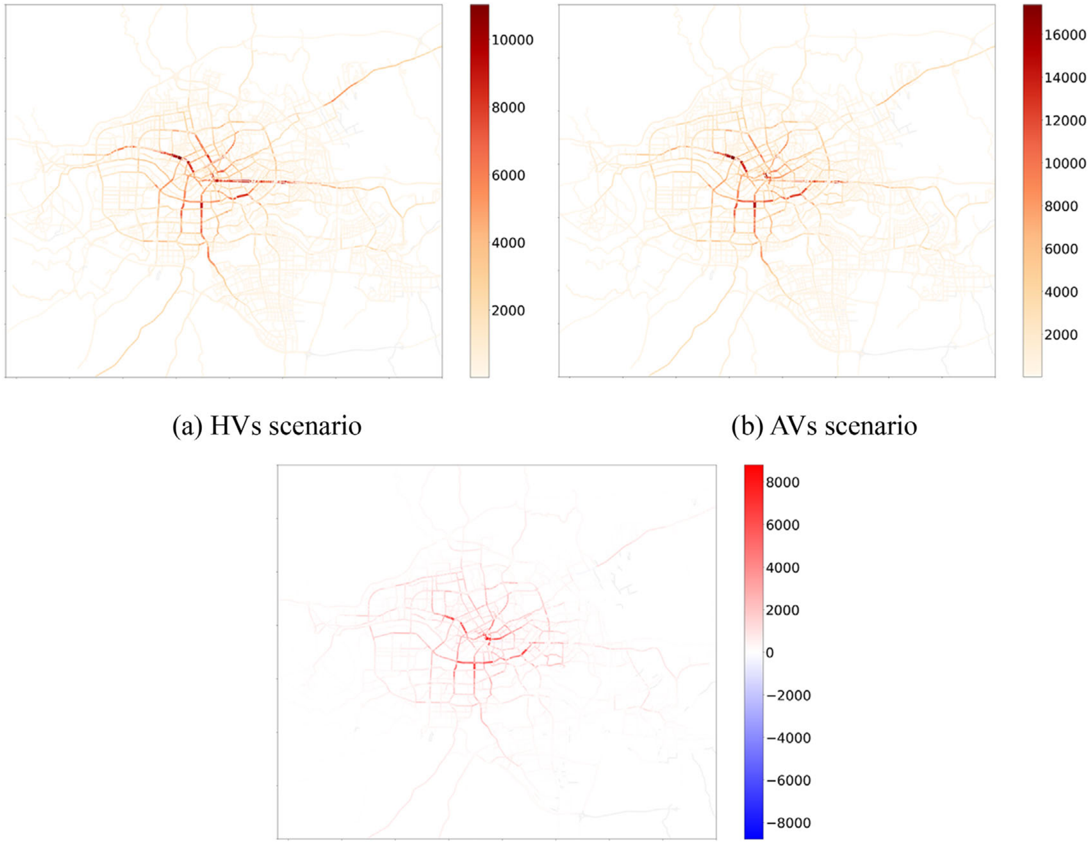
is not counted) and is calculated by:

$$VD = \sum_{e_i}^{G} \mathrm{VD}_{e_i} = \sum_{e_i}^{G} \mathrm{flow}_{e_i} \cdot \left(\frac{\mathrm{length}_{e_i}}{\mathrm{speed}_{e_i}} - \frac{\mathrm{length}_{e_i}}{\mathrm{speed}_{e_i,\max}} \right) \tag{11}$$

where $\mathrm{speed}_{e_i,max}$ is the maximum driving speed of a link e_i and VD_{e_i} represents the delay time for vehicles to cross a link e_i.

Table 8 lists the VMT generated by vehicles under the two travel modes. The total VMT of AVs is 48% higher than that of to HVs. The empty cruising of AVs accounted for 32% of the total travel distance, and the average VMT is 12.9 km. This is because if the traveller chooses to park at home, his empty cruising miles will be the miles travelled from home to work and from work to home, and thus more travel distance will be generated. In other words, the more travellers choose the parking behaviour of home parking and continuous empty cruising, the more VMT is generated. The simulation results show that in the automatic driving environment, the new parking behaviour causes a significant increase in road network load, and the use intensity of the AVs is higher than that of the HVs under the same travel scale.

A similar pattern is observed in VHT, as shown in Table 9, which lists the VHT generated by vehicles in two scenarios: one with HVs and the other with AVs. The total VHT of AVs increased by a significant 87% compared to HVs. Notably, the empty cruising of AVs accounted for 35.9% of the total VHT. This implies that, in the AVs scenario, while it positively impacts



(a) HVs scenario

(b) AVs scenario

(c) The difference in traffic volume distribution between HVs and AVs scenarios

FIGURE 14 Traffic volume and its difference distribution in HVs and AVs scenarios. (a) HVs scenario, (b) AVs scenario, (c) the difference in traffic volume distribution between HVs and AVs scenarios.

road capacity, the additional VHT caused by empty cruising cannot be fully offset. In addition, the empty cruising of AVs is influenced by various factors such as the AV routing algorithm and passenger demand patterns, which may lead to varying degrees of impact. Despite the advantages of AVs in increasing road capacity and reducing traffic congestion, there is still room for improvement in optimizing the utilization of AVs during empty cruising. Developing more sophisticated autonomous driving routing and scheduling algorithms, as well as incentivizing carpooling and ride-sharing, can help minimize the negative impact of empty cruising on overall VHT.

Figures 14a and 12b show the daily road traffic generated by manually driven vehicles and AVs in the whole process of travel, respectively, and Figure 14c shows the difference between the two. As the chart shows, the increase in road traffic is mainly concentrated in the city centre. That said, the new parking modes of AVs put more pressure on the traffic carrying capacity of the city centre. Further, according to the Highway label in OSM, the road types in the simulation scenario have been calibrated. The changes in VMT, VHT, and VD under different road types during peak hours are summarized in Table 10. The results indicate that the VHT of all road types decreased to varying degrees. Notably, residential roads experienced the largest increase in VMT (68.6%). Additionally, for Motorways, trunk roads, and secondary roads, while they account for a relatively low proportion of empty cruising VMT, the decrease in VHT and increase in VD are much more significant compared to other road types. This is mainly because congestion has already been observed on these roads in the scenario with HVs. Thus, the increase in empty cruising adds to the existing problem of serious delays caused by congestion on these road types. In general, despite significant improvements in the performance of AVs, the empty cruising behaviour of AVs may

TABLE 10 Changes in VMT, speed, and delay by road type for HVs and AVs.

Road type	OSM label	VMT	VHT	VD
Motorway	highway. motorway	41.54%	−1.31%	35.68%
Trunk road	highway. trunk	40.86%	−3.91%	202.92%
Primary road	highway. primary	41.75%	−4.84%	95.22%
Secondary road	highway. secondary	50.96%	−4.62%	82.42%
Tertiary road	highway. tertiary	52.39%	−2.33%	42.54%
Residential road	highway. residential	68.59%	−3.60%	75.37%

TABLE 11 Characteristics of parking choice behaviour in empty cruising charge.

Parking mode	Parking lot	Home parking	Empty cruising	Average
proportion	62.00%	37.80%	0.20%	–
Total Cost (¥)	25.61	19.72	10.60	23.35
Average activity time (h)	6.70	9.30	0.37	7.67
Unit hourly cost (¥/ h)	3.82	2.12	28.65	3.04
Average home distance (km)	14.69	7.54	17.32	11.99

still negatively impact the operating efficiency of the road network. Therefore, further research and planning are needed to ensure the effective application of autonomous driving technology, reduce traffic congestion, and optimize the operation of urban transportation systems.

4.2.5 | Strategizing empty cruise charges

The advancement of autonomous driving technology has blurred the lines between vehicular traffic management and parking management. As observed in the simulation results of the previous section, empty cruising traffic flow of AVs exerts a negative impact on the transportation network. Consequently, this section investigates the implementation of a cruising charge management mechanism. This is aimed at influencing the parking choice behaviour of AVs and thereby curtailing the extent of their empty cruising mileage.

This study employs a static charging strategy based on the distance of empty cruising trips. A fixed unit charge for empty cruising is applied to the distance travelled without passengers, and this cost is incorporated into the parking mode selection cost function. The unit charge for empty cruising is priced using the traffic delay cost method, with the charge serving to compensate for the congestion delays caused by empty cruising. Charging sub-zones are delineated according to variations in traffic demand, and the unit costs calculated for these zones are 1.98 CNY/km within the Nanning city express loop, and 0.61 CNY/km for the area outside the express loop but inside the ring road. For a detailed calculation process, please refer to the Supporting Information attached.

Table 11 describes the changes in AV parking selection after the implementation of empty cruising charges. The proportion of home parking dropped to 37.8%, a significant decrease from the 54.01% observed in the no-charge scenario. The empty cruising charge led to a substantial shift in parking demand towards parking lots, with the proportion of parking lot usage rising to 62%. There is a slight decrease in the number of AVs opting for cruising as an alternative to parking, as the unit cost of cruising substitution is already relatively high, which makes the impact of the additional empty cruising charge less significant.

Figures 15 and 16 further depict the distribution of empty cruising distance and time for AVs under both empty cruising charge and no-charge conditions. In the no-charge scenario, AVs are often observed to cruise extensively and for long periods in search of suitable parking spots. The introduction of an empty cruising charge strategy notably reduces both cruising distance and time. Specifically, in the no-charge scenario, the average empty cruising distance for AVs is 12.9 km, with an average cruising time of 36.3 min. In contrast, with the charge strategy in place, the average empty cruising distance drops to 10.3 km, a reduction of 20.16%, and the cruising time decreases to 23.8 min, down by 38.84%. Figure 17 also indicates that compared to the no-charge scenario, traffic volume in the city centre has somewhat diminished. Additionally, while the total cost in the charging scenario has increased, this rise is still below the total cost in the HV scenario. This suggests that implementing an empty cruising charge policy can effectively balance individual and collective benefits by further constraining AV behaviour.

5 | CONCLUSION

Here, we investigate the impact of AVs on parking strategies, given the novel capabilities of their autonomous parking functionalities. These pioneering features afford users the luxury of commanding their vehicles to engage in empty cruising or revert to their domiciles, obviating the traditional reliance on standard parking facilities. Leveraging an agent-based model, we simulated the parking behaviour of AVs within an authentic network setting. An underlying assumption governing our study is the rational behaviour of each traveller, geared towards minimizing parking expenditures while being tethered by time constraints. Our model is multifaceted, integrating determinants such as parking availability, associated costs, proximity to end destinations, and prevailing traffic conditions.

Our simulation experiments shed light on the transformative parking demand landscape sculpted by the proliferation of AVs and the resultant potential challenges. The data intimates a decline in parking demand within urban cores but forecasts a marked surge within residential precincts. The widespread embracement of AVs might also catalyze a surge in empty cruising, escalating the aggregate vehicle mileage, thereby exacerbating traffic congestion and environmental perturbations. It's salient to highlight that our simulations did not account for potential congestion repercussions stemming from passenger ingress and egress activities, nor the complex dynamics introduced by a heterogeneous mix of autonomous and conventional

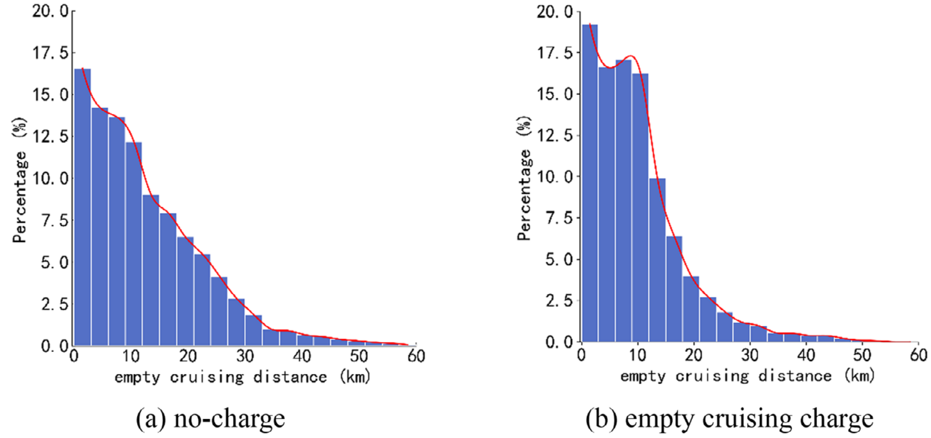


FIGURE 15 Changes in empty cruising distance under empty cruising charging policy. (a) No-charge, (b) empty cruising charge.

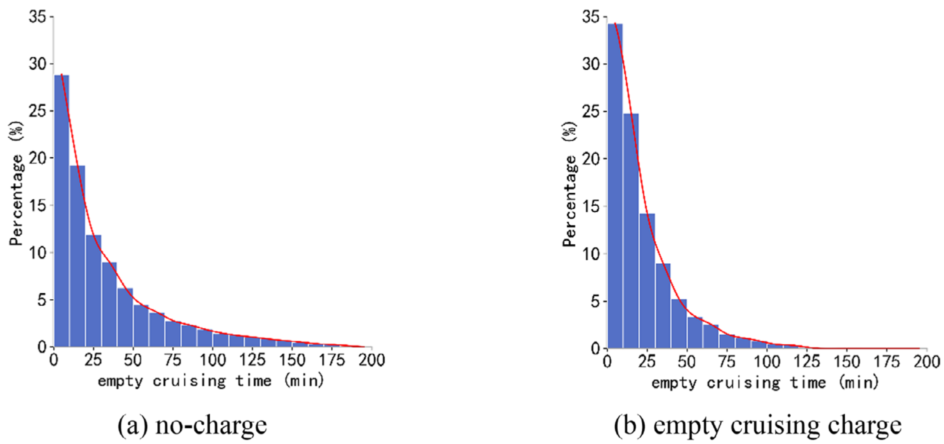


FIGURE 16 Changes in empty cruising time under empty cruising charging policy. (a) No-charge, (b) empty cruising charge.

FIGURE 17 Traffic volume changes under an empty cruising charge compared to a no-charge scenario.

vehicles. Consequently, our findings might offer a conservative estimation of the congestion induced by AV proliferation. The future enhancements can be approached from the following perspectives: (1) In designing strategies for cruising as an alternative to parking, the profit-seeking behaviour of AVs, which aims to reduce costs by increasing congestion, might lead to additional traffic congestion. (2) Considering the coexistence of AVs and HVs in parking scenarios, it's important to explore how they interact in terms of competition and cooperation.

The advent of autonomous mobility promises to cast a profound, transformative shadow over global transport paradigms and urban morphology. In the wake of advancing autonomous technologies, it becomes imperative to recalibrate traffic governance frameworks. The objective is twofold: harnessing the inherent benefits of this nascent technology whilst tempering its inadvertent detriments, all in the pursuit of fostering sustainable urban transit systems. There exists an emergent need to refine land-use doctrines governing both nascent and existing parking infrastructures across commercial and residential landscapes and to revamp policies overseeing the transit demands of empty cruising vehicles. Such proactive stratagems, including the implementation of an unoccupied cruising charge, are quintessential in pre-emptively addressing the societal challenges that might arise from the surge in vehicle travel due to AV-induced empty cruising.

AUTHOR CONTRIBUTIONS

The authors confirm their contribution to the paper as follows: Study conception and design: Wenhao Li and Yanjie Ji. Programming and interpretation of results: Wenhao Li and Yewen Jia. Draft manuscript preparation: Wenhao Li, Phil Blythe, and Shuo Li. All authors reviewed the results and approved the final version of the manuscript.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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