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Intelligent Parking Service System Design Based on Digital Twin for Old Residential Areas

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Abstract: Due to the increasing number of vehicles and the limited land supply, old residential areas generally face parking difficulties. An intelligent parking service is a critical study direction to address parking difficulty since it can achieve the automatic management of parking processes and planning of parking spaces. However, the existing intelligent parking service systems have shortcomings such as low information quality, low management efficiency, and single service mode. To address the shortcomings, in this paper, we conduct a systematic study on utilizing digital twin (DT) technology to improve the intelligent parking service system. The main contributions are threefold: (1) We analyze the function requirements of the intelligent parking service for old residential areas, such as visual monitoring, refined management, and simulation optimization. (2) We design a DT-based intelligent parking service system by collecting data on physical parking space, constructing the corresponding virtual parking space, and building the user interaction platform. An old residential area in Guangzhou, China is used as a use case to show that the designed parking service system can meet the function requirements. (3) Through mathematical modeling and simulation evaluation, we utilize two typical intelligent parking services including dynamic parking planning and driving safety assessment to demonstrate the effectiveness of the proposed system. This study provides innovative solutions for parking management in old residential areas, utilizing DT technology to not only improve information quality and management efficiency, but also provide a theoretical basis and practical reference for the intelligent transformation of urban parking services.

Keywords: digital twin; intelligent parking service system; old residential area

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1. Introduction

Due to the increasing number of vehicles and the limited land supply, parking difficulty has become a common problem, especially in old residential areas. With the rapid development of technologies such as big data, the Internet of Things, and artificial intelligence, an intelligent parking service is a critical study direction to address parking difficulty [1]. Various intelligent parking service systems have been proposed to automatically manage parking services including vehicle entry and exit, parking billing and payment, parking space sharing, and security monitoring [2–4].

However, due to the outdated parking facilities and lack of early space planning in old residential areas, it may not be practical to deploy existing intelligent parking service systems directly. First, the existing systems' collected information has low quality and difficulty reflecting the complex situation of old residential areas. The existing intelligent systems only provide collection and backend management of vehicle entry and exit information, lacking effective information integration and comprehensive digital characterization of physical parking facilities, real-time parking space usage, and road traffic status [5]. The low-quality information makes it hard for managers to provide service responses

quickly. Second, the existing systems have low management efficiency. The systems rely on static models and traditional management methods, and cannot adapt to dynamically changing parking demands [6]. Due to lacking intelligent analysis tools, managers rely heavily on empirical decision making, which can easily lead to judgment errors. Third, the parking service mode is single and lacks specificity, making it difficult to cope with diverse parking scenarios and different emergencies. Due to the changing parking demand and occupancy of parking spaces over time [7], and the possibility of sudden peak congestion, it may lead to chaotic parking space scheduling without reasonable parking planning. It is necessary to design differentiated parking services for these scenarios and emergencies, and optimize them through virtual simulation to improve service quality effectively. Here we take Maofang community, a typical old residential area in Guangzhou, China, as the research object. The intelligent parking service system it adopts has the abovementioned issues and needs a novel system to provide efficient parking management and meet dynamic parking needs.

The key to designing an intelligent parking service system suitable for old residential areas is to realize the interactive integration between the intelligent system and the complex physical parking environment, and digital twin (DT) technology provides an effective solution. DT is the process of presenting physical entities in digital form, creating corresponding virtual models, simulating their behavior in the real world, and assisting in the construction and operation of physical entities through real-time data fusion, virtual–real interaction, optimization iteration, and other means [8,9]. At present, DT is widely applied in multiple fields. In the manufacturing industry, the real-time monitoring of production equipment through DT technology improves efficiency and product quality [10]. In the aerospace field, DT technology is used to monitor aircraft performance and predict faults [11]. In urban management, DT technology is used to integrate urban data and optimize resource allocation [12]. In intelligent transportation, DT technology can be used to monitor traffic flow and reduce congestion [13]. In building management, DT technology is utilized to track the structural health of buildings in real time [14]. In the field of healthcare, DT technology can be used to simulate the physiological state of patients and provide personalized treatment [15]. In energy management, DT technology is utilized to monitor and optimize energy production and consumption, improve energy efficiency, and support sustainable development [16].

In this paper, we use DT as an important foundation to design an intelligent parking service system in which the virtual parking environment has dynamic real-time interaction, integration, coordination, and optimization with the physical parking environment of old residential areas. The main contributions of this paper are summarized as follows.

- We analyze the function requirements of the intelligent parking service such as visual monitoring, refined management, and simulation optimization. The required functions make the designed intelligent system suitable for the complex situation of old residential areas.
- We design an intelligent parking service system based on DT. The system can be established by collecting data on physical parking space, constructing the corresponding virtual parking space, and building the user interaction platform. An old residential area in Guangzhou, China is used as a use case to show the designed intelligent parking service system with modules such as comprehensive overview, operational control, resource management, and simulation optimization, which can meet the function requirements.
- We demonstrate the application of the DT-based system in complex scenarios of old residential areas through two typical intelligent parking services, i.e., dynamic parking planning and driving safety assessment. The simulation results verify the effectiveness.

The rest of the paper is organized as follows. In Section 2, the function requirement analysis and DT-based system design are introduced. Section 3 describes the system implementation. Section 4 describes the principle and the simulation of the dynamic

parking planning service. Section 5 provides the details and simulations of the driving safety assessment service. Finally, Section 6 gives the conclusion.

2. Function Requirement and System Design

In this section, we analyze the demand for intelligent parking services in old residential areas and design an intelligent parking service system based on DT technology to meet the function requirements.

2.1. Functional Requirement Analysis

In order to overcome the shortcomings of low information quality, low management efficiency, and single service mode in existing intelligent parking service systems, the designed intelligent parking service system needs to meet the following three functional requirements.

Visual monitoring function: Existing intelligent systems collect information with limited dimensions and lack visualization, making it difficult to timely reflect on the complex situation of old residential areas. It is necessary to establish a comprehensive visual monitor for parking services. The collected information should contain multiple dimensions such as vehicle entry and exit information, parking space usage, and basic traffic flow data. Multiple visualization methods can be used to enhance the effectiveness of information display, including the real-time display of parking space status and graphical representation of the real-time usage of each parking space; 3D model visualization, which displays the layout and structure of the parking lot through 3D models, in order to provide managers with a more intuitive understanding of the parking environment; a historical data trend chart, displaying the trend of historical parking data, helping to identify patterns and peak periods; and heat map analysis, displaying the distribution of parking demand and guiding the formulation of management strategies. The status statistics dashboard combines the requirements of managers to conduct global and local statistical analysis of monitoring data, and visually displays the calculation results of specific indicators. Specific requirements include real-time parking status monitoring, peak hour analysis, historical data comparison, regional performance evaluation, etc. Through visual monitoring, managers can capture the overall information and detailed changes in parking spaces of old residential areas, thus making correct management decisions.

Refined management function: Existing parking service management of intelligent systems overly relies on manual labor and is inefficient. It is necessary to achieve high-precision monitoring data collection, parking information management, and parking situation prediction through the virtual–real interaction of digital twins. By using a visual interface to manage parking services such as parking data statistics and analysis, revenue management, user information management, parking resource management, and violation alarm, managers can be separated from complex manual operations, and handle information and events more conveniently and quickly.

Simulation optimization function: Based on different parking demands and emergencies, it is necessary to develop and simulate targeted and reasonable parking planning, which can provide a reliable basis for managers' decision making in complex scenarios and emergencies. The digital twin of virtual parking spaces possesses the geometric structure and physical characteristics of physical parking spaces, and can make corresponding behavior consistent with physical entities. Therefore, based on virtual parking spaces, different scenarios and events of parking in old residential areas can be simulated, and event processing such as parking planning can be simulated to achieve a virtual display and an evaluation of emergency plans in real scenarios. This provides data support for emergency plan evaluation, making optimization and verification more intuitive and reasonable.

2.2. Design of Digital Twin System

In order to achieve the abovementioned functional requirements, we propose a DT-based [17] parking service system consisting of the following parts as shown in Figure 1.

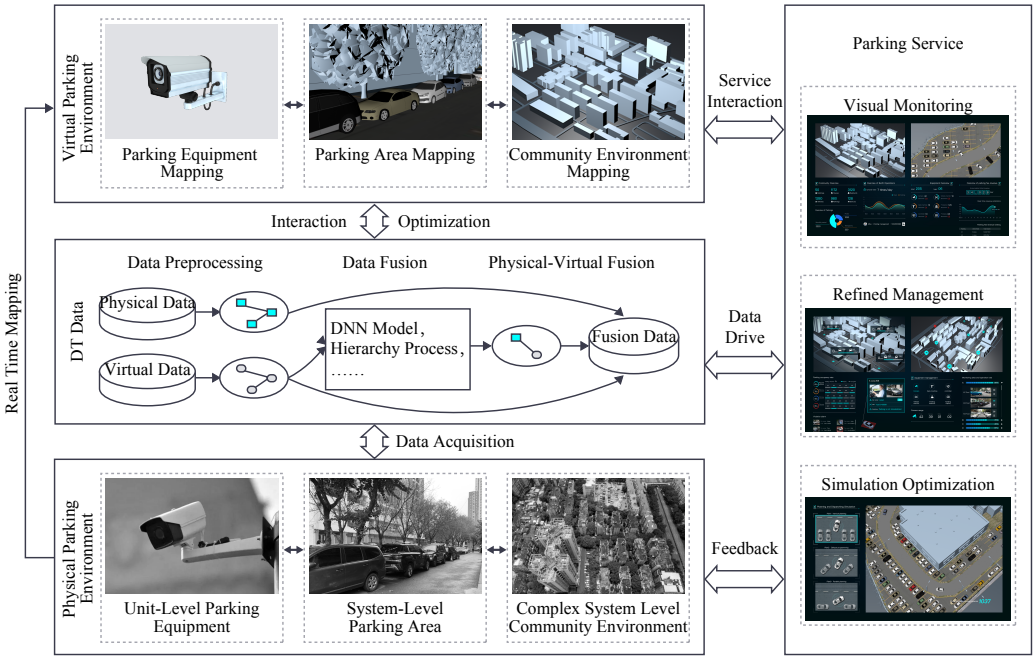


Figure 1. Digital twin-based intelligent parking service system.

- Physical parking environment (PPE): In order to make parking services comprehensive and targeted to old residential areas, the system should achieve refined data collection and management. From the perspective of the entire parking service process, PPE includes physical entities and their attribute information from unit-level parking equipment components, system-level parking areas, and complex system-level community environments. During the parking service process, PPE generates status data such as parking space occupancy and equipment usage, which is the source of data information for the entire system, and is collected and transmitted through sensors.
- Virtual parking environment (VPE): VPE is a real-time and accurate digital mapping of PPE, which establishes a comprehensive digital model by describing all elements such as parking areas and their components in geometric, physical, behavioral, and rule-based dimensions. The digital model can fully express parking information in the virtual world and truly reflect the dynamic operation process of the parking area. At the same time, the digital model can be used for various applications such as analyzing parking space usage and turnover rate, real-time alarm processing for parking violations, etc.
- Parking services (PS): PS is an important way to achieve the intelligent interconnection and interactive integration of the entire process between intelligent parking service systems and physical parking environments in old residential areas. By encapsulating various models and algorithms in a service-oriented manner, the corresponding PS is provided based on the function requirements, including visual monitoring, refined management, and simulation optimization.
- Digital twin data (DTD): As the core element of the intelligent parking service system, DTD integrates all data generated and derived from PPE, VPE, and PS to provide data support for intelligent parking services.
- Connectivity (CN): CN connects PPE, VPE, PS, and DTD as an organic whole. PPE transmits real-time collected parking physical entities and status data to VPE and DTD. The former is used to update the parking area model and achieve virtual real mapping, while the latter forms data management. Through transmission and feedback to PPE, the operation optimization of PPE is achieved; VPE obtains historical data from DTD for model training and performs service analysis driven by real-time data. The analysis results are returned to DTD on the one hand and, on the other hand, in PS, a simulation optimization plan is formed to support decision making;

PS can request analysis services in VPE through an interactive interface, and send control decisions to parking administrators through SMS or App format to achieve the monitoring of the physical parking environment.

3. System Implementation

In this section, we explain how to implement the proposed DT-based intelligent parking service system. The implementation process includes three stages, namely physical data collection, virtual model constitution, and interactive platform building, as shown in Figure 2. We also take the Maofang community, a typical old residential area in Guangzhou, China as the research object and show the built DT-based intelligent parking service system including functional modules.

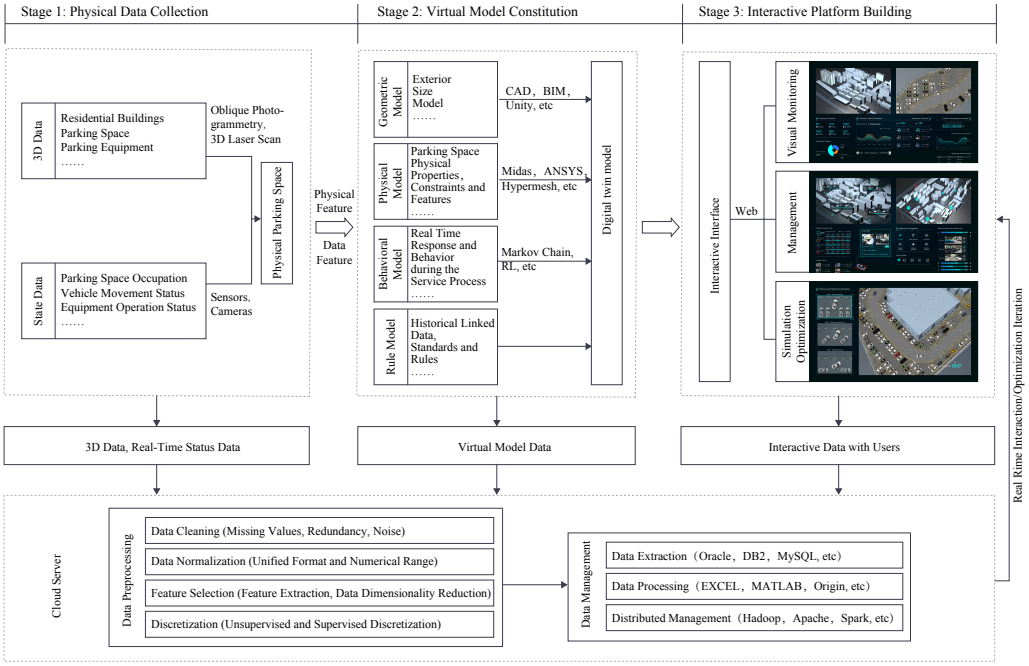


Figure 2. The implementation of the DT-based intelligent parking service system.

3.1. Physical Data Collection Stage

At this stage, the modeling of the physical parking environment is performed by collecting 3D and state data of physical entities, providing a data source for achieving the digital twin of parking services. Since the physical parking space is the foundation of the entire system, accurate collection and analysis of the physical parking space are vital for establishing the system. The physical parking space contains 3D data and state data of physical entities such as residential buildings, roads, parking spaces, and parking management equipment. Three-dimensional data such as the appearance, size, and model of physical entities can be obtained by combining various sensing techniques such as oblique photogrammetry and 3D laser scanning [18]. At the same time, various low-cost sensors and cameras such as pressure sensors, radar, and infrared can be deployed to obtain real-time status data, such as parking space occupancy, vehicle and pedestrian movement status, and equipment operation. Through wireless gateways and wired connections, the perceived state data are uploaded to the cloud server for storage.

3.2. Virtual Model Constitution Stage

At this stage, the virtual parking environment is constructed in the cloud server to recover the real situation of the physical parking environment based on the imported 3D and state data of physical entities. The construction of a virtual parking environment includes geometric models, physical models, behavioral models, and rule models. The geometric

model is a 3D model that reflects the geometric spatial structure of the physical entity in the parking environment. Based on imported 3D data, CAD 2022 is used to generate 3D models of physical entities such as residential buildings, parking spaces, and vehicles. Unity is used to integrate these models with real-time data to build a dynamic virtual parking environment that is synchronized with real physical entities [19]. The physical model is the physical features, constraints, and attributes assigned to the established virtual entity. By using software such as Midas 2021 and ANSYS 16.0, physical properties such as gravity, collision, and fluid are added to the virtual entities [20]. For example, if a vehicle collides with an obstacle, it can cause structural damage. The behavior model simulates the behavior reactions of physical entities in the real world based on external environments. By using dynamic learning methods such as Markov chains and reinforcement learning, virtual entities can learn the behavioral responses of physical entities [21]. For example, on rainy days, there may be water accumulation on roads and outdoor parking spaces, resulting in slippery roads. Virtual entities also exhibit the same behavior. Rule models are intelligent representations of virtual entities, which can be trained and learned through deep learning models or by developing relevant functions based on relevant rules and standards in the field. They endow virtual entities with the ability to evaluate, judge, predict, and optimize changes in environmental rules, breaking the current situation where traditional parking service systems require managers to make judgments themselves, and achieving intelligent monitoring and management. For example, through deep learning models in the cloud server, the systems can predict the changes in parking demand and provide the corresponding parking services.

3.3. Interactive Platform Building Stage

At this stage, the interactive platform is built on the cloud server to achieve the interaction between users and the system. The cloud server first performs preprocess operations (e.g., cleaning, normalization, and feature selection) on the collected data, and uses database software such as Hadoop 2.7 and Apache Spark 2.4.0 to store and manage all the data including 3D and state data of the physical parking environment, DT data of the constructed virtual parking environment, and interaction data with users [22]. Then, the cloud server mines the internal rules of the data through deep learning models, designs different optimization strategies for parking service based on the mined rules, and evaluates the strategies through simulations in the virtual parking environment. Finally, a web interface is developed using the Java language, allowing users to connect to the cloud server through simple operations, achieving the intelligent management of various data and visual control of virtual entities.

3.4. Functional Modules

We take the Maofang community, a typical old residential area in Guangzhou, China as the research object to show the DT-based intelligent parking service system. As shown in Figures 3–6, the DT-based intelligent parking service system contains the following four functional modules. The functional modules meet the aforementioned function requirements, effectively alleviating the parking difficulties in the old residential area.

Comprehensive overview: As shown in Figure 3, the comprehensive overview module provides comprehensive digital recording and visualization for parking services in old residential areas. Specifically, the 3D display of the overall parking environment and spatial structure of the old residential area are provided. The module also performs comprehensive monitoring of macro indicators such as community overview, parking space overview, equipment overview, and financial overview, and presents them in an intuitive digital form. This assists the managers in fully controlling the comprehensive situation in the old residential area. The managers can visually see each zone's information such as parking space occupancy, road traffic, and equipment operation, which provides a reliable decision-making basis for parking service planning and scheduling between zones.

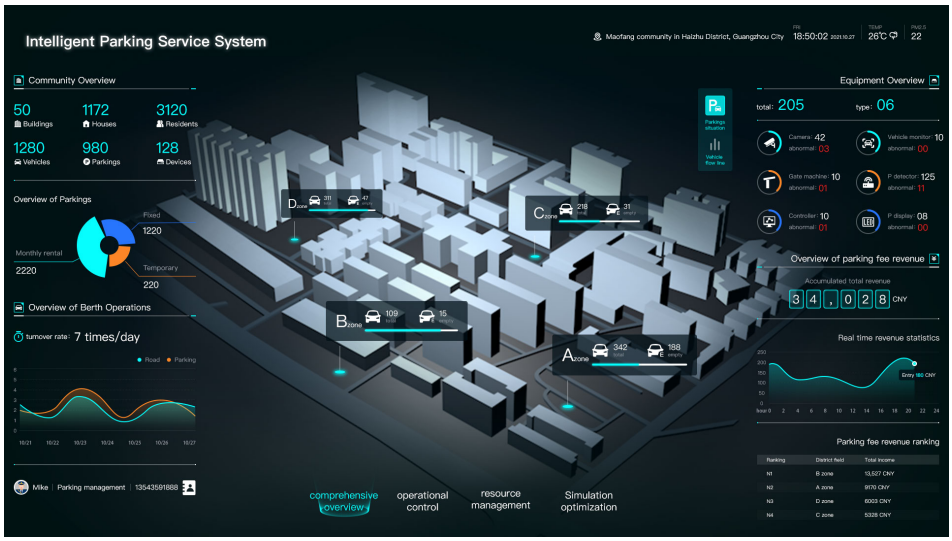


Figure 3. The interface of the comprehensive overview module.

Operational control: As shown in Figure 4, the operational control module provides visualization and intelligent management of the operational details of parking services in the old residential area. By using a DT model mapping the parking environment of the old residential area in real time, the real situation of traffic flow and parking spaces is presented. Combining the DT model and the on-site images captured by monitoring cameras, the system can judge the movement and parking status of vehicles, recognize parking violations and sudden accidents, and provide reminders and reference solutions for managers. The module also supports the analysis and statistics of the number of idle parking spaces, number of parked cars, and operation situation in specific zones by time period, and presents them in a graphical format. In this way, the managers can grasp real-time parking details and perform remote operations, improving the efficiency of intelligent parking management.

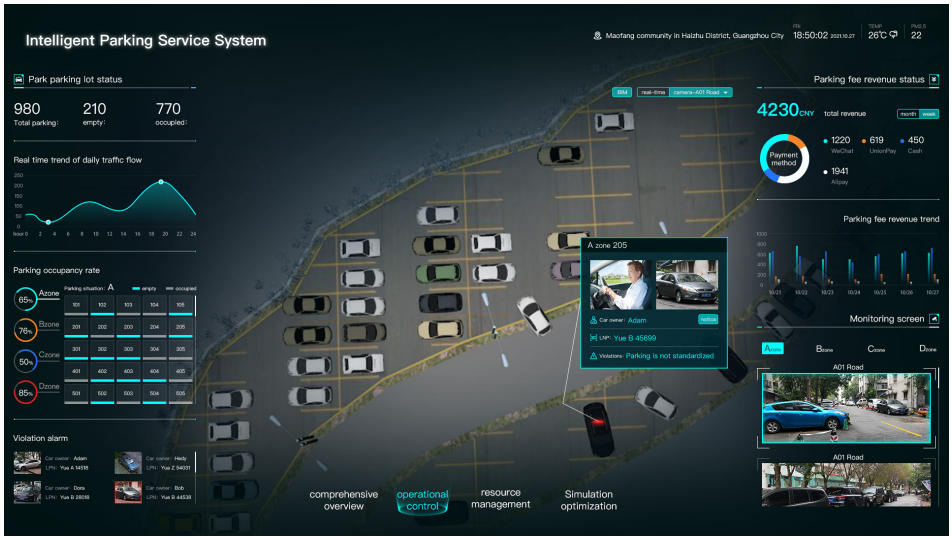


Figure 4. The interface of the operational control module.

Resource management: As shown in Figure 5, the resource management module provides intelligent digital management of physical resources such as parking equipment and vehicles. In the 3D space of the virtual parking environment, the module provides visualization of positioning and distribution information for parking equipment such as cameras and gate machines, as well as all vehicles entering the community. At the same time, statistical data of various physical resources is displayed in a graphical manner.

Managers can track specific information about physical resources in the 3D space of the virtual parking environment. For example, clicking on a 3D model of parking equipment can view information such as its usage status and degree of damage. Click on the 3D model of a certain car can view its parking status and real-time monitoring screen.

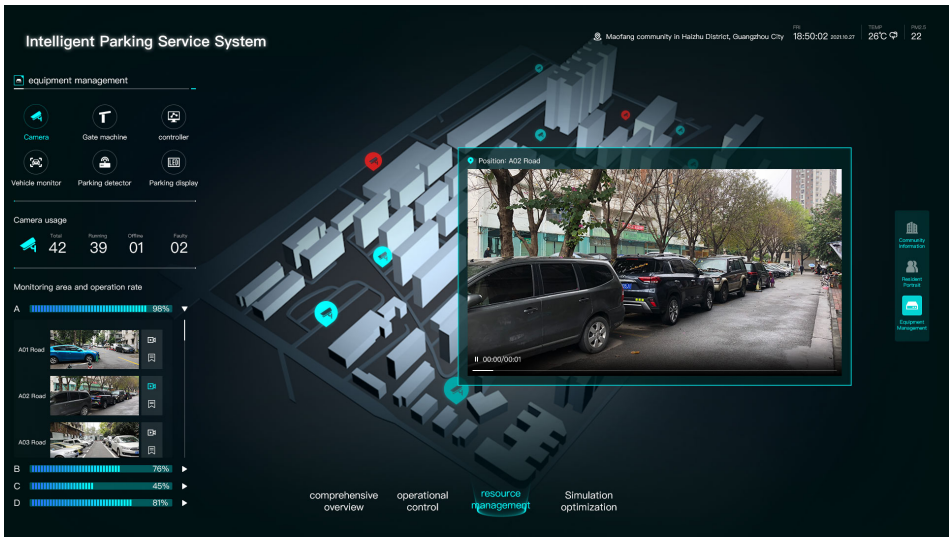


Figure 5. The interface of the resource management module.

Simulation optimization: As shown in Figure 6, the simulation optimization module simulates different situations in the virtual parking environment of the DT model according to historical and real-time data. In this way, the system can conduct simulation tests on the designed parking planning, and conduct multi-dimensional comparisons to select the optimal plan for pre-deployment. Take parking demands as an example. The system predicts future parking demands by training a deep neural network through historical parking data, and visualizes the prediction in the virtual parking environment by simulation. According to changes in parking demands, different planning schemes are designed and selected for simulation tests. For example, during peak parking demand, vertical planning can be chosen to obtain more parking spaces, while, during low peak parking demand, parallel planning can be chosen to provide more road space. The simulation of contingency plans helps to develop corresponding management mechanisms for emergencies, avoiding road congestion and resource waste.

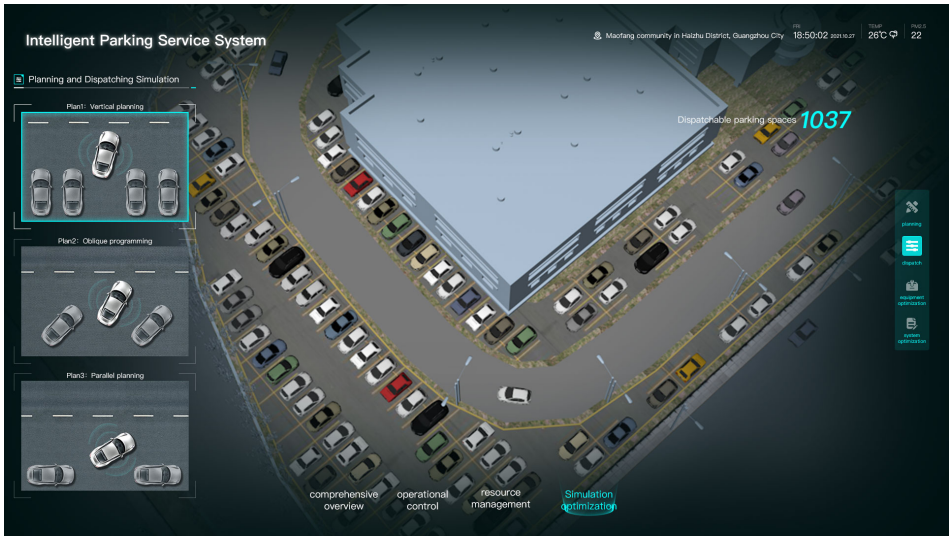


Figure 6. The interface of the simulation optimization module.

3.5. System Scalability

The effectiveness of the DT-based intelligent parking service system in Guangzhou provides a good foundation for the expansion to other cities. The differences in infrastructure, parking demand, and user behavior among different cities require flexibility and adjustability in system design. Firstly, in terms of scalability, other cities can leverage the core advantages of DT technology to optimize parking management through data collection and virtual model construction. For example, in emerging cities such as Shenzhen or Hangzhou, more advanced IoT technology and mobile applications can be utilized to quickly collect parking data and update the parking space status in real time. In some old cities, such as Beijing or Nanjing, the system needs to consider the compatibility of existing infrastructure and may require certain modifications in physical facilities to integrate intelligent sensors and monitoring equipment. Secondly, for different infrastructures, the functional modules of the system also need to be adjusted accordingly. In areas with more modern infrastructure, the system can focus on advanced features such as dynamic pricing, intelligent navigation, and user feedback integration to enhance the user experience and resource utilization. In areas with relatively underdeveloped infrastructure, the system may focus more on basic data collection and information integration to ensure that managers can obtain timely and accurate information to respond to changes in parking demand. Finally, to adapt to the policies and user habits of different cities, the system design should take into account factors such as local government regulations, residents' parking behavior, and community culture. By establishing a flexible system architecture, targeted optimization can be achieved to enable the intelligent parking service system to operate efficiently in different urban environments, effectively alleviating parking difficulties.

4. Dynamic Parking Planning

In this section, we take the dynamic parking planning service to demonstrate the application of the DT-based system's refined management and simulation optimization functions in intelligent parking services. Using a specific parking zone in the old residential area as the research object, a deep neural network is trained using historical parking data to predict parking demand for the next day. By simulating different parking planning schemes in the intelligent parking service system, we compare the satisfaction effects of different schemes on parking demands, providing a basis for managers to choose the optimal parking planning scheme. As shown in Figure 7, the simulation process is divided into two parts, namely parking demand simulation and parking scheme simulation.

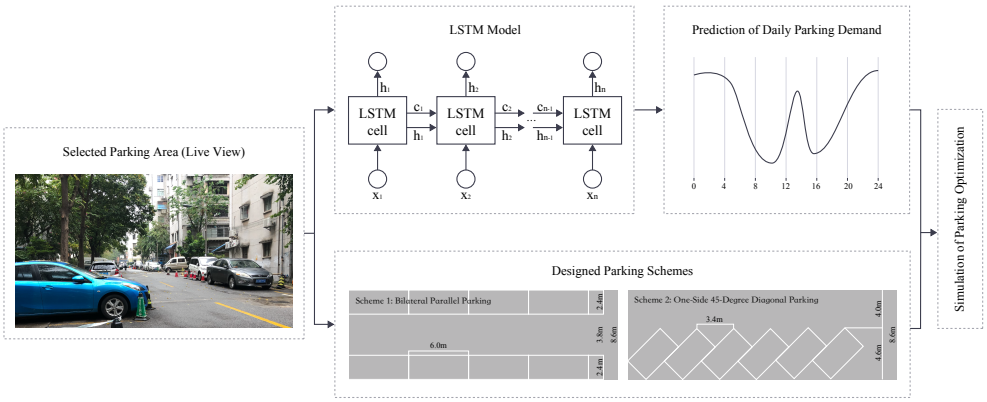


Figure 7. Simulation of different parking planning schemes.

For parking demand simulation, we use parking volume data collected from the past half month in the zone as input, train a Long Short-Term Memory (LSTM) network, and learn the changes in parking volume data over time. Compared to other deep neural networks, LSTM networks have the characteristics of memory and forgetting in time series through the forget gate, input gate, and output gate in the structure [23]. Specifically,

the sliding time window method is used to extract time series $X = \{x_1, x_2, \ldots, x_n\}$ from the parking volume data. When the dataset contains y time points with the time window width z, the sample size of the time series is $n = y - z + 1$. The LSTM network represents short-term memory through hidden states $H = \{h_1, h_2, \ldots, h_n\}$ and long-term memory through cell states $C = \{c_1, c_2, \ldots, c_n\}$. At the time point t, based on the hidden state of the previous time point h_{t-1} and the data input at the current time point x_t, the values of the forgetting gate F_t, input gate I_t, and output gate O_t are calculated using the Sigmoid function, and the candidate cell $\tilde{c}_t$ at the current time point is calculated using the Tanh function. The forget gate can control the degree the cell at the previous time point needs to forget, while the input gate can control the degree the candidate cell needs to retain. The two gates are combined to update the cell at the current time point, which is given as follows:

$$c_t = F_t \odot c_{t-1} + I_t \odot \tilde{c}_t, \tag{1}$$

where $\odot$ is the element multiplication of vectors. The cell output can be controlled to the hidden state through the output gate, which is represented as follows:

$$h_t = O_t \odot \tanh(c_t). \tag{2}$$

By utilizing the long-term and short-term memory characteristics of LSTM networks, it can accurately estimate the changes in parking demand over time. Figure 8 shows the predicted parking demand and actual parking volume for the new day, with a simulation prediction error of only 2%.

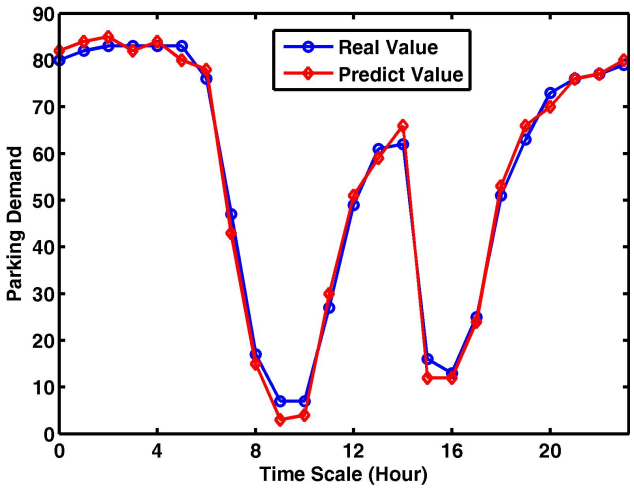


Figure 8. Performance of prediction on parking demands.

For the simulation of parking schemes, we consider three parking planning schemes: a bilateral parallel parking scheme, a single-side 45-degree diagonal parking scheme, and a dynamic parking scheme. The dynamic parking plan is to dynamically choose between the two parking planning schemes based on the predicted parking demand, in order to fully utilize the limited parking space and provide sufficient driving space. The ratio of parking demand to the provision of parking spaces is chosen as the indicator for testing, and the optimal indicator is close to 1. If the indicator is too low, it indicates excessive waste of parking space. If the indicator is too high, it indicates that the supply of parking spaces cannot meet the parking demand. Figure 9 shows the simulation results of the parking planning schemes. Compared to the other two parking schemes, the dynamic parking scheme can continuously maintain close to the optimal indicator.

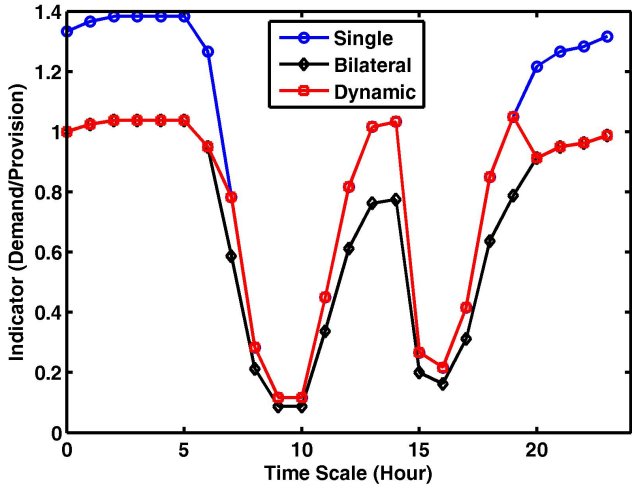


Figure 9. Performance comparison of different parking planning schemes.

5. Driving Safety Assessment

In this section, we take a driving safety assessment service to demonstrate the application of the DT-based system's refined management and simulation optimization functions in intelligent parking services. Due to the narrow roads in the old community, driving safety and risk assessment are particularly important. Specifically, we construct the mathematical model of driving vehicles and analyze their safety decision for driving. The model of vehicles is constructed based on the full velocity difference model (FVDM) [24], which is expressed as

$$\dot{v}_i(t) = \alpha(V(d_i(t-\tau)) - v_i(t-\tau)) + k(v_{i-1}(t-\tau) - v_i(t-\tau)), \tag{3}$$

where $v_i(t)$ and $d_i(t)$ are the speed and spacing of the i-th vehicle at time t, $i \in \{1, 2, \ldots, n\}$. The drivers' response sensitivity and headway sensitivity coefficient are expressed as α and k. The driver's response delay is defined as τ. The velocity optimization function $V(d_i(t))$ is empirically given by

$$V(d_i(t)) = 16.8(tanh(0.0860(d_i(t) - 25)) + 0.913). \tag{4}$$

To simplify the analysis, this paper takes three vehicles as an example to build a vehicle model and analyze it. Let $u_i(t) = v_{i-1}(t) - v_i(t)$ denote the relative velocity between the $(i-1))$-th and i-th vehicles $(i = 1, 2)$, respectively. The lead vehicle speed is expressed as v_0. Specifically, the DT system is described by the following ordinary differential equations (ODEs) [25]:

$$\begin{aligned}
&\dot{d_1}(t) = u_1(t),\\
&\dot{u}_1(t) = -\alpha V(d_1(t-\tau)) - (\alpha + k)u_1(t-\tau) + \alpha v_0(t),\\
&\dot{d_2}(t) = u_2(t),\\
&\dot{u}_2(t) = \alpha(V(d_1(t-\tau) - V(d_2(t-\tau))) - (\alpha + k)u_2(t-\tau) + ku_1(t-\tau).
\end{aligned} \tag{5}$$

We ensure driving safety based on the risk assessment that the first condition is the stability of the vehicle system. Because of the system's instability, the speed and distance state will be dispersed, resulting in vehicle collisions. Equation (5) is a nonlinear system. The stability analysis method of nonlinear system dynamics is to linearize the system near its fixed point [26]. We investigate the stability of the corresponding nonlinear system by studying the change in the characteristic equation root of the linearized system [27]. Therefore, we linearize the DT system at the fixed point. We have provided the detailed steps in Appendix A.

Combining Equations (A3) and (A11), we obtain

$$v_0^{*'} = 16.8(\sqrt{\frac{1.4448 - \frac{\sqrt{\omega^4-(k+\alpha)^2\omega^2}}{\alpha}}{1.4448}} + 0.913). \tag{6}$$

To determine the stability region of the system, we calculate the derivative of λ over v_0 and obtain its real part at $v_0 = v_0^{*'}$ as follows:

$$\mathbf{Re}(\frac{\mathrm{d}\lambda}{\mathrm{d}v_0})\Big|_{v_0=v_0^{*'}} = \frac{\frac{\alpha*P}{8.4}(\cos(\omega\tau)*M - N*\sin(\omega\tau))}{M^2+N^2} \neq 0, \tag{7}$$

where P, M, and N are provided in Appendix A.

Next, we evaluate driving risks using time to collision (TTC) and distance-related average crash (DRAC) to ensure driving safety. TTC, DRAC, margin to collision (MTC), and time headway (TH) are common methods using peak over threshold models [28,29]. In this paper, we select TTC and DRAC to assess the crash risk.

TTC refers to the duration before the collision occurs between two vehicles traveling at constant speeds, where the speed of the following vehicle is higher than that of the leading vehicle. TTC is expressed as

$$\mathrm{TTC} = \begin{cases} \frac{d_i(t)-l_{i-1}}{v_i(t)-v_{i-1}(t)} & v_i(t) > v_{i-1}(t), \\ \infty & v_i(t) < v_{i-1}(t), \end{cases} \tag{8}$$

where l_{i-1} is the length of the $(i-1)$-th vehicle. In this paper, we consider the three cases to evaluate the crash risk. First, when TTC > 5.5 s, the gap between vehicles is safe for driving. When 3 s < TTC $\leq$ 5.5 s, the gap between vehicles is conflicting, and, when TTC < 3 s, the gap between vehicles has a crash risk.

DRAC represents the maximum deceleration required for a vehicle to avoid a collision. A higher DRAC value indicates a higher collision risk. DRAC is expressed below:

$$\mathrm{DRAC} = \frac{(v_i(t) - v_{i-1}(t))^2}{d_i(t) - l_{i-1}}. \tag{9}$$

The gap between vehicles is safe for driving when DRAC $\leq$ 3.35 or, else, the gap between vehicles is a crash risk.

Validation of Safety Decision

We make driving safety decisions based on the system's stability range. When the system is stable, vehicles can maintain a safe distance. When the system is in a chaotic state, it leads to traffic congestion and increases the risk of collisions between vehicles. We set the parameters of the experiments in Table 1.

Table 1. Parameters set for the experiment.

Vehicle	Variable	Symbol	Value	Unit
All	Initial speed	$v_i(0)$	4	m/s
	Initial spacing	$d_i(0)$	10	m
	Equilibrium speed	v*	15	m/s
	Equilibrium spacing	s*	15	m
	Speed limit	v_{max}	30	m/s
	Vehicle length	L	5.5	m
Lead HV	Driver's response sensitivity	α	-	1/s
	Driver's headway sensitivity coefficient	k	-	1/s
	Driver's response delay	τ	1.0	s
Following HV	Driver's response sensitivity	α	-	1/s
	Driver's headway sensitivity coefficient	k	-	1/s
	Driver's response delay	τ	1.0	s

Figure 10a shows the relationship between speed v_0 and amplitude ω of the imaginary part of the characteristic root and driver's response sensitivity α. Figure 10b shows the relationship between speed v_0 and amplitude ω of the imaginary part of the characteristic root. Below the curve indicates system stability, while above indicates system instability. We can adjust the speed v_0 of the lead vehicle to maintain the stability of the platoon system, ensuring the safe driving of the vehicles. Figure 10 shows the relationship between speed v_0 and driver's response sensitivity α. The speed curve v_0 keeps constancy in $\alpha \in [0, 1.71]$, i.e., v_0 = 15 m/s. At $\alpha = 1.71$, the speed curve rises sharply, then it rises slowly, continuing until $\alpha = 6$. When $\alpha = 6$, the speed curve v_0 reaches a steady state, i.e., v_0 = 35 m/s.

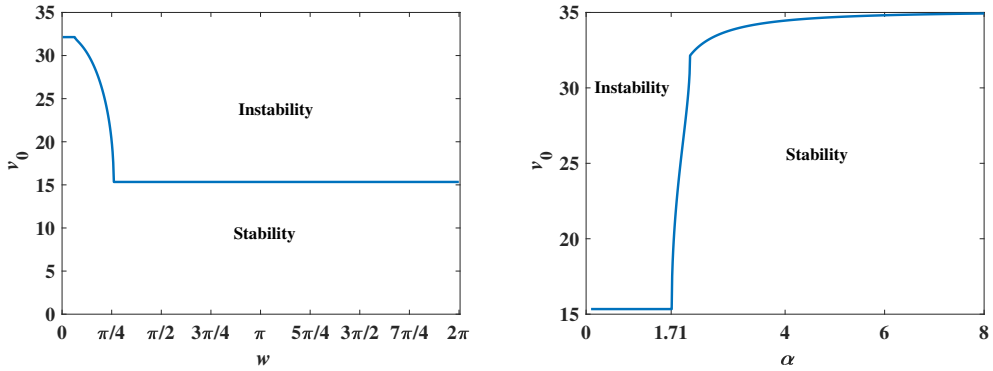


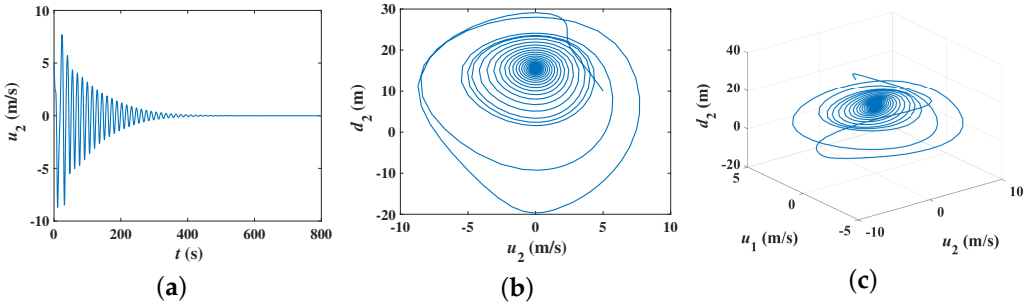
Figure 10. Relationship between speed v_0 and amplitude ω of the imaginary part of the characteristic root and driver's response sensitivity α. (**a**) Relationship between speed v_0 and amplitude ω of the imaginary part of the characteristic root. (**b**) Relationship between speed v_0 and driver's response sensitivity α.

Figures 11–13 show the vehicle trajectories under different system states. Figure 11a shows that, in the relative velocity is stable for the vehicle platoon; the curve initially exhibits large amplitude oscillations and eventually converges to zero. This indicates that the speeds of the vehicles are the same. They are in a safe driving state with a certain spacing between the vehicles. In Figure 11b, as the relative speed tends towards zero, the spacing tends towards a fixed point. We obtain that the phase space trajectory has the same result in Figure 11c. Figure 12a shows that the relative velocity in the boundary is stable for the vehicle platoon. The curve exhibits oscillations of constant amplitude. The phase plane trajectory forms a limit cycle. As the trajectory diverges outward, it is always attracted to move along the cycle, as shown in Figure 12b. The same conclusion can also be drawn from the phase space trajectory, as shown in Figure 12c. Figure 13a shows the relative velocity in the chaotic characteristics of the vehicle platoon. The curve fluctuates with varying amplitudes. From Figure 13b, we can see from the phase plane that the trajectory diverges outward, then becomes attracted and spirals inward. The trajectory repeats in sequence. This is the characteristic of a chaotic attractor. The phase space representation is more intuitive, appearing to have no pattern yet exhibiting a certain order, as shown in Figure 13c. Due to the chaotic nature, the spacing and relative fluctuations between vehicles are significant, which can easily lead to traffic congestion and rear-end collision risks.

Based on the experimental results above, it is evident that the necessary condition for driving safety control is to keep the platoon in a stable state. We adjust the leading vehicle speed v_0 according to the platoon stability condition to ensure the safe driving of the platoon.

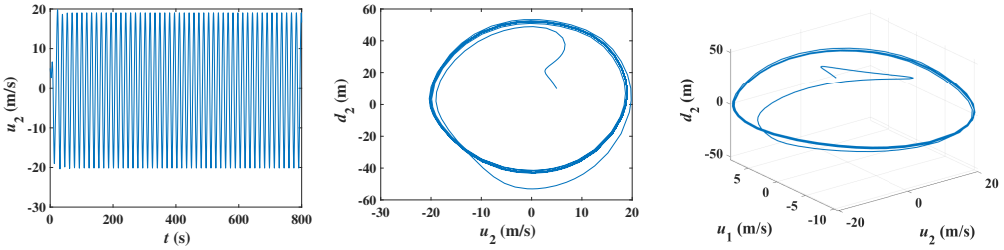
We utilized the TTC and DRAC risk metrics to evaluate the risk of the stability-based driving safety decision that has been designed in Figure 14. To demonstrate the experimental results, we use 1/TTC for the experiments. 1/TTC also represents TTC. From Figure 14a, we can observe that all 1/TTC values are less than 0.182 ($1/\mathrm{TTC}_{\min}$ = 0.182). This indicates that there is no collision between the leading vehicle and the following vehicle,

and they are in a safe driving state. Figure 14b shows that all DRAC values are less than 3.35. This indicates that there is no crash risk between the leading vehicle and the following vehicle, and the driving is safe. The assessment results of TTC and DRAC on driving risk reveal the feasibility and reliability of the safety driving decision proposed in this paper.



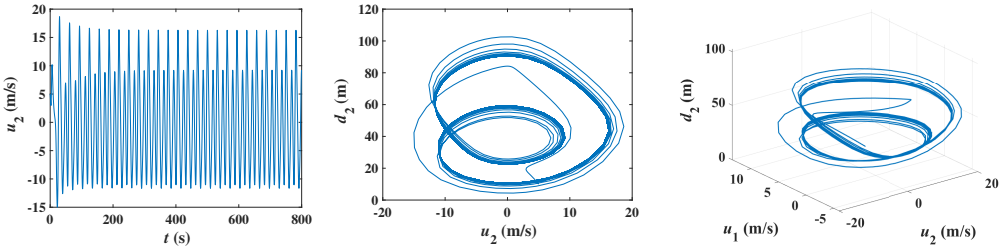
(**a**) (**b**) (**c**)

Figure 11. Stability of vehicle platoon. (**a**) Relative velocity. (**b**) Phase plane. (**c**) Phase space.



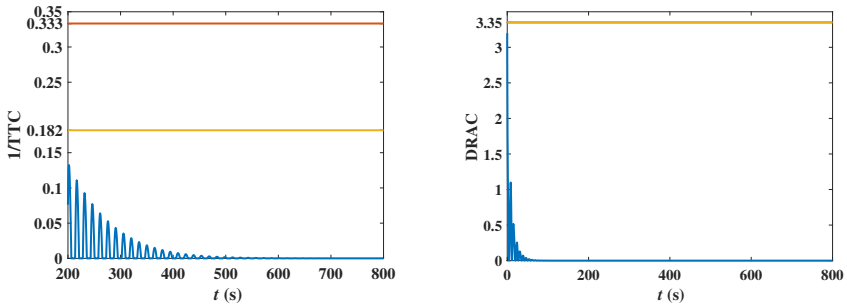
(**a**) (**b**) (**c**)

Figure 12. Boundary stability of vehicle platoon. (**a**) Relative velocity. (**b**) Phase plane. (**c**) Phase space.



(**a**) (**b**) (**c**)

Figure 13. Chaotic characteristics of vehicle platoon. (**a**) Relative velocity. (**b**) Phase plane. (**c**) Phase space.



(**a**) (**b**)

Figure 14. Risk evaluation between head and following vehicle by TTC (**a**) and DRAC (**b**).

6. Conclusions

In this paper, we proposed an intelligent parking service system for old residential areas based on DT technology. The proposed system utilizes the virtual–real interaction of DT to digitally characterize the complex parking environment in old residential areas. A use case is provided to demonstrate the system's function modules including comprehensive overview, operational control, resource management, and simulation optimization. The simulation results verified the system can assist in optimizing parking planning and driving safety to improve the decision making in parking services. The application of this system will help alleviate the increasingly serious parking problem and enhance the travel experience of community residents. Although this study demonstrates the potential of DT technology in intelligent parking systems, there are still limitations. For example, the initial implementation of the system is mainly based on specific cases, which may lack broad adaptability to other types of residential environments. In addition, the study did not fully consider users' acceptance of new technologies and the complexity of practical operations. Future research will focus on expanding the system to various residential environments outside of Guangzhou, analyzing the differences in parking demand between new and old residential areas, and customizing and adjusting system functions. At the same time, cross-regional data integration and sharing will be explored, and a unified platform will be designed to achieve real-time updates and interoperability of parking information. In addition, more intelligent algorithms and machine learning technologies will be introduced to achieve personalized and precise parking management services, and strategies will be dynamically adjusted using historical data.

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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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Appendix A

Let the right-hand side of Equation (5) equal 0; we obtain the fixed point $(d_1^*, u_1^*, d_2^*, u_2^*) = (d_1^*, 0, d_2^*, 0)$. $d_1^* = d_2^*$, and d_1^* is expressed as

$$d_1^* = \frac{artanh(\frac{v_0}{16.8} - 0.913)}{0.0860} + 25. \tag{A1}$$

We linearize the nonlinear system Equation (5) at a fixed point $(d_1^*, u_1^*, d_2^*, u_2^*)$, linearizing the system as

$$\begin{aligned} \dot{d_1}(t) &= u_1(t), \\ \dot{u_1}(t) &= -\alpha V'(d_1^*) d_1(t-\tau) - (\alpha + k) u_1(t-\tau), \\ \dot{d_2}(t) &= u_2(t), \\ \dot{u_2}(t) &= \alpha V'(d_1^*) d_1(t-\tau) - \alpha V'(d_2^*) d_2(t-\tau) - (\alpha + k) u_2(t-\tau) + k u_1(t-\tau), \end{aligned} \tag{A2}$$

where $V'(d_1^*)$ and $V'(d_2^*)$ are expressed as

$$V'(d_1^*) = V'(d_2^*) = 1.4448 - 1.4448(\frac{v_0}{16.8} - 0.913)^2. \tag{A3}$$

We take the characteristic equation and rewrite Equation (A2) as follows:

$$\dot{X}(t) = \mathbf{A}X(t) + \mathbf{B}X(t-\tau) \tag{A4}$$

where $X(t) = [d_1(t), u_1(t), d_2(t), u_2(t)]^T$. Matrices **A** and **B** are denoted as

$$\mathbf{A} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix}, \quad \mathbf{B} = \begin{bmatrix} 0 & 0 & 0 & 0 \\ -\alpha V'(d_1^*) & -(\alpha+k) & 0 & 0 \\ 0 & 0 & 0 & 0 \\ \alpha V'(d_1^*) & k & -\alpha V'(d_2^*) & -(\alpha+k) \end{bmatrix}.$$

Therefore, the eigenvalue equation of Equation (A4) is

$$\begin{aligned} p(\lambda,\tau) &= \det(\lambda I - A - Be^{-\lambda\tau}) \\ &= \begin{vmatrix} \lambda & -1 & 0 & 0 \\ \alpha V'(d_1^*)e^{-\lambda\tau} & \lambda + (\alpha+k)e^{-\lambda\tau} & 0 & 0 \\ 0 & 0 & \lambda & -1 \\ -\alpha V'(d_1^*)e^{-\lambda\tau} & -ke^{-\lambda\tau} & \alpha V'(d_2^*)e^{-\lambda\tau} & \lambda + (\alpha+k)e^{-\lambda\tau} \end{vmatrix} \\ &= (\lambda(\lambda + (\alpha+k)e^{-\lambda\tau}) + \alpha V'(d_1^*))(\lambda(\lambda + (\alpha+k)e^{-\lambda\tau}) + \alpha V'(d_2^*)e^{-\lambda\tau}) \\ &= (\lambda(\lambda + (\alpha+k)e^{-\lambda\tau}) + \alpha V'(d_1^*)e^{-\lambda\tau})^2 = 0, \end{aligned} \tag{A5}$$

i.e.,

$$\lambda(\lambda + (\alpha+k)e^{-\lambda\tau}) + \alpha V'(d_1^*)e^{-\lambda\tau} = 0 \tag{A6}$$

The stability of the DT system $p(i\omega,\tau) = 0$, i.e.,

$$\forall\, \omega > 0, \alpha > 0, K > 0, \tau > 0, s.t., \;\; p(\pm i\omega,\tau) = 0, \tag{A7}$$

Substituting $\lambda = i\omega$ into Equation (A5) yields

$$-\omega^2 + (k+\alpha)\omega\sin(\omega\tau) + \alpha V'(d_1^*)\cos(\omega\tau) = 0, \tag{A8}$$

$$(k+\alpha)\omega\cos(\omega\tau) - \alpha V'(d_1^*)\sin(\omega\tau) = 0. \tag{A9}$$

Squaring and adding Equations (A8) and (A9), we can obtain

$$\omega^4 - (k+\alpha)^2\omega^2 - (\alpha V'(d_1^*))^2 = 0, \tag{A10}$$

Obtain the only positive real root by solving for Equation (A10).

$$V'(d_1^*) = \frac{\sqrt{\omega^4 - (k+\alpha)^2\omega^2}}{\alpha}. \tag{A11}$$

P, M, and N are denoted as

$$M = (\alpha+k)\cos(\omega\tau) - \tau\omega(\alpha+k)\sin(\omega\tau) - \tau\alpha V'(d_1^*)\cos(\omega\tau), \tag{A12}$$

$$N = \omega - (\alpha+k)\sin(\omega\tau) + \omega - \omega\tau(\alpha+k)\cos(\omega\tau) + \tau\sin(\omega\tau)\alpha V'(d_1^*), \tag{A13}$$

$$P = \sqrt{\frac{1.4448 - \sqrt{\omega^4 - (k+\alpha)^2\omega^2}}{\alpha}}. \tag{A14}$$

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