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Resilience towarded Digital Twins to improve the adaptability of transportation systems

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ABSTRACT

This work aims to investigate the role of the resilience of Digital Twins on the applicability of the transportation system. A literature study is conducted to review the current status of research on transportation systems and Digital Twins. It is found that the current research on Digital Twins technology has achieved different degrees of success in different aspects of transportation systems. Yet, the system performance of Digital Twins has to be optimized. First, the application of Digital Twins in intelligent transportation systems is analyzed. Then, how the changes in traveler behavior patterns reflect the extent to which the traffic network is affected by uncertain events is analyzed from the traveler's perspective. Finally, an Internet of Vehicles (IoV) system based on Digital Twins and blockchain is established to solve the data redundancy and high computational volume problems of in-vehicle data sharing common in the IoV system. Moreover, the performance of the twin system is optimized by proposing a multi-intelligence body algorithm based on local perception, and a case validation is performed. The results demonstrate that the adaptability of the transportation system to uncertain events and its response and recovery measures taken are reflected to some extent in the traveler behavior model. Besides, data sharing between vehicles and infrastructure in the transportation network can be well solved by Digital Twins Blockchain. The locally-aware multi-intelligent body algorithm saves more than 50% communication overhead and improves operational efficiency by nearly 20% over traditional algorithms by increasing intelligent body infrastructure units. It is adequately suited for large-scale vehicle traffic twins. It can be seen that improving the resilience of Digital Twins is a very obvious change in the adaptability of the traffic system.

1. Introduction

Smart cities have brought about various changes that are revolutionizing people's lives (Chen et al., 2021). The increasing probability of uncertain events in the transportation system has put even higher requirements on the applicability of urban transportation system (Kaffash et al., 2021; Saharan et al., 2020; Yu et al., 2020). Therefore, the urban transportation system should have a strong applicability, thus enhancing the resilience of the urban transportation network (Sodhro et al., 2019). The suitability of transportation systems can also be referred to as resilience or toughness. The International Resilient Cities Alliance defines urban

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resilience as the ability of an urban system to absorb and absorb disturbances. Transportation is one of the key planning elements for connecting urban modular land, and research on resilient urban transportation is emerging accordingly (Wang et al., 2018). Faced with a high car ownership rate and complex and diverse driving scene changes, how to improve the vehicle's self-adaptive ability to ensure the stability of daily driving and the stability of the traffic network has always been the pain point of smart transportation (Jourquin & Beuthe, 2019; Magazzino & Mele, 2021). China already has many new green transportation methods to reduce vehicle traffic and relieve road pressure to alleviate traffic pressure and optimize the imbalance between supply and demand in the transportation network (Mousavi & Ghavidel, 2019). However, in reality, the state of the transportation system is not constant, but there are many uncertainties, which leads to uncertainty in traffic demand and travel perception. Therefore, it is of great significance to accurately evaluate the degree of influence of disturbances in these transportation networks on the system and the resilience of the system.

As the complexity of transportation networks continues to increase and new transportation modes, such as car-sharing, bike-sharing, and motorcycles, develop rapidly, the relationship between various factors in the transportation network becomes close. Thus, the degree of influence caused increases, which makes the transportation network very vulnerable to uncertain events (Pegoraro et al., 2020), resulting in a decrease in the overall degree of applicability. Disturbances caused by uncertain events can easily cause infrastructure and traffic service imbalances in the transportation network, reduce the overall transportation capacity and carrying capacity, and cause a series of decision-making problems for travelers (González-Arribas et al., 2019; Yang et al., 2022). In addition to the common traffic congestion described above, such disturbances also include episodic disorders caused by geological hazards, all of which place higher demands on the transportation system. Digital Twins technology can empower intelligent transportation from multiple aspects, improve the ability of the transportation network to respond to emergencies, and strengthen the flexibility of the transportation system to meet the needs of future travel (Qian et al., 2022; Priyanka et al., 2022; Yan et al., 2021). Digital Twins technology is a cutting-edge trend in smart transportation. Still, there is a certain distance from the Digital Twins traffic system with natural global management, synchronous visualization, and virtual-real interaction (Zhang et al., 2020). The increase in the amount of data will bring tremendous computing pressure (Lv et al., 2021). Therefore, further research needs to optimize the traffic system under Digital Twins to minimize the impact of uncontrollable and uncertain traffic accidents on the traffic system (Hu et al., 2021).

Therefore, this work discussess the current situation of Digital Twins and complex transportation network systems through literature research. Then, the role of Digital Twins in intelligent transportation is discussed. This work innovatively analyzes how the change of the travel mode of travelers reflects the situation of the elastic transportation network under uncertain events and establishes a travel model. The data sharing problem of vehicle to everything is analyzed From the perspective of Digital Twins. Since most of the current Internet of Vehicles (IoV) data sharing has problems such as data redundancy and large amount of computation, an IoV transportation system is established based on Digital Twins and blockchain. The data sharing of virtual vehicles resolves the problem of data contribution in physical space, thereby alleviating traffic congestion and untimely data sharing that are common in the transportation system. This work can provide new research ideas for the development of intelligent transportation.

The overall framework of this work is divided into five parts. Section 1 introduces how traffic systems are handled when they are subject to external disturbances, which is the background of the study. Section 2 investigates and analyzes the current status of traffic transportation and Digital Twins applications, summarizes the current research limitations, and highlights the advantages of this study. Section 3 is the research methodology, which establishes the travel model and the IoV transportation system based on Digital Twins and blockchain and describes the specific research details. Section 4 describes the results derived from the above study using images. Section 5 concludes the whole paper and points out the limitations of the study and future research directions.

2. Literature review

A smart city is an urban area that collects data using various electronic methods and sensors. It relies on information and communication technologies and aims to improve the quality of services by managing public resources and focusing on comfort, maintenance, and sustainability. Digital Twins, together with the Internet of Things (IoT), fifth-generation (5G) wireless systems, Blockchain, collaborative computing, simulation, and Artificial Intelligence (AI) technologies, offer great potential for the transformation of the current urban governance paradigm to smart cities (Wong et al., 2020; Pangbourne et al., 2020). However, there are a large number of problems in modern ITS, such as congestion control, safety and security, and traffic management. The 5G wireless mobile communication techniques enable a new type of communication network to connect every-one and everything. Gohar & Nencioni (2021) discussed the impact of 5G on ITSs from various dimensions and how vital vertical industries in smart cities will be affected, namely energy, healthcare, manufacturing, entertainment, automotive, and public transportation. Sirohi et al. (2020) reviewed different types of Convolutional Neural Network (CNN) models for traffic sign recognition, traffic light detection, vehicle classification, and pedestrian detection in modern intelligent transportation. They also used different performance evaluation indicators and existing schemes and compared various CNN-based models and techniques. Venkatesan et al. (2019) developed health monitoring and prognosis of electric vehicle permanent magnet synchronous motors in transportation systems by creating intelligent Digital Twins in MATLAB/Simulink. Ning & Jiang (2022) believe that a reliable and fail-safe defense-in-depth architecture is crucial to isolate potential attackers. They proposed a multi-layer defense-in-depth approach where the first line of defense, such as access control, may have been compromised for an insider attacker with legitimate access. Given this fact, the authors focused on detection and mitigation and employed both data-driven and model-based techniques that are believed to capture stealth attacks and stop them.

Road traffic is growing exponentially as the number of people and vehicles explodes. Insights-driven real-time traffic management becomes an essential part of building and sustaining smart cities around the world (Young & Farber, 2019; Holguín-Veras et al., 2020; Becker et al., 2020). Xu (2022) designed an IoT-based UAVs based on the information gathering method to study autonomous vehicles with IoT connectivity for field health and safety applications. The author presented the fundamental limitations and drawbacks of current state-of-the-art solutions to achieve the same goal, such as route planning optimization challenges, lightweight machine learning and machine vision algorithms, IoT communication coordination, and IoT network extension. Kumar et al. (2018) proposed some potential and promising technologies and tools, such as reliable and reusable virtual models of vehicles, machine learning models, IoT fog or edge data analytics, data lakes for traffic and vehicle data in public cloud environments, and 5G communications to predict driver intent and mitigate traffic congestion. Kosacka-Olejnik et al. (2021) deeply reviewed the application of Digital Twins in internal traffic systems and prospected the main research trends and future research directions in this research field. They clarified various definitions related to Digital Twins, including misconceptions such as digital shadow, digital model, and digital mirror image. Kliestik et al. (2022) highlighted that Digital Twins cities require data visualization tools, virtual modeling techniques, and IoT-based decision support systems. Kampczyk & Dybeł (2021) proposed an innovative solution for monitoring the state of temperature and other atmospheric conditions. The authors used UbiBot WS1 WIFI wireless temperature recorder and integrated an external DS18B20 temperature sensor into an S49 (49E1) type rail. They also confirmed the elements of the fundamental approach to applying Digital Twins to railway traffic. The approach entails consideration and demonstration of railroad temperature conditions as an integral part of obtaining data on railroad turnout conditions and other constituent atmospheric conditions through an innovative solution. This innovative solution provides effective support for the application of Digital Twins in railroad turnouts and for the ongoing measurement and diagnostic work of other elements of railroad transportation infrastructure. It can be seen that Digital Twins technology has achieved varying degrees of results in different aspects of the transportation system. However, the system performance of Digital Twins still needs to be optimized, so the research reported here can fill this gap.

3. Anti-disturbance analysis of the traffic system to uncertain events based on Digital Twins

Smart Transportation in the Context of Digital Twins.

The adaptability of a transportation system encompasses the ability of the transportation network to resist, absorb, adapt, and recover in the face of perturbations. Resilience indicates the ability of a transportation system to maintain normal operations despite a certain level of disruption. Absorption capacity suggests that the traffic system has a certain level of resistance to ongoing disturbances, making the traffic system subject to the least degree of uncertainty(Wan et al.,2018; Zhou et al.,2019). The recovery capability of a traffic system is the ability to recover quickly to the point before a disturbance occurs, either at the time of the disturbance or after the disturbance occurs. The more resilient the transportation system is, the better the ability to withstand the impact of uncertain events on the transportation system, and the more stable the operation of the transportation system can be ensured.

The accelerated development of 5G, in conjunction with the IoT and AI, has given transportation systems the ability to "connect everything". This skill allows Digital Twins to "migrate" the four elements of "people-vehicle–road-environment" transportation from the physical world to the digital world. It will enable the "digitalization, networking, and intelligence" of intelligent transportation to be genuinely implemented. High-speed network performance makes it possible for vehicles to communicate safely and reliably during high-speed movement and ensures the realization of functions, such as vehicle–road collaborative automatic driving, vehicle formation automatic driving, and remote automatic driving.

The visualization technology based on Digital Twins can combine massive 3D models of transportation infrastructure with dynamic data in the operation of transportation facilities. It uses AI, big data, and other technologies to monitor and analyze the operation situation of traffic information, analyzes the operational posture of transportation information, and presents the massive dynamicity

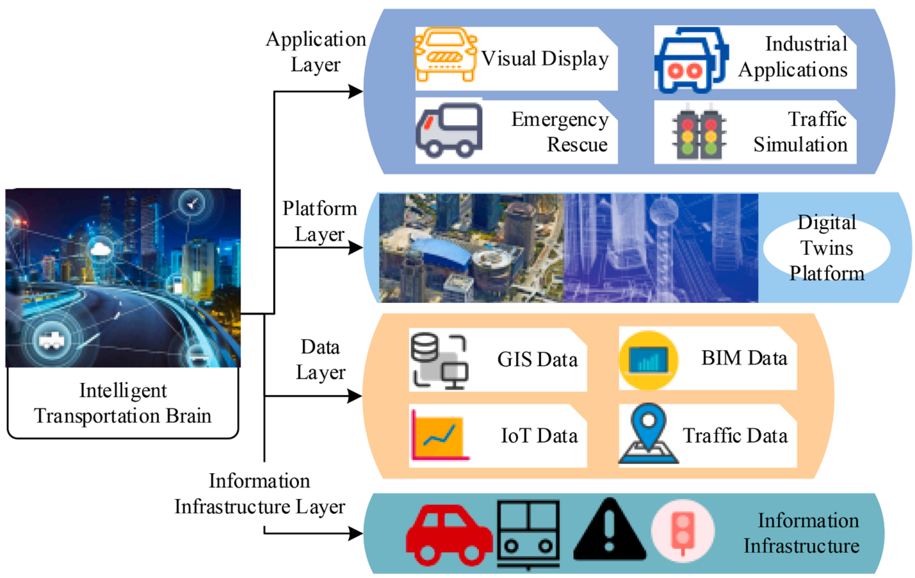

Fig. 1. Architecture of the smart transportation platform based on Digital Twins.

data loaded through twin transportation scenes. Digital Twins can take realistic urban traffic roads as the basic, combined with 3D virtual simulation effects of streets, greenery, vehicles, and other traffic facilities, making the user highly immersed in the traffic of the virtual city. Fig. 1 presents the architecture of the smart transportation platform based on Digital Twins established here.

It can be seen from Fig. 1 that the Digital Twins transportation infrastructure service platform brings together multi-source spatial data and IoT data of transportation infrastructure and uses Digital Twins visualization technology for 3D modeling and simulation to build virtual transportation scenes. The platform realizes multi-view, multi-dimensional, and all-round visualization display and presentation of intelligent transportation digitizes and virtualizes the whole elements of transportation infrastructure in real-time, and helps realize collaborative and intelligent transportation business operation and management. This is particularly beneficial to alleviate traffic network congestion, cope with uncertain and unexpected conditions, solve urban traffic problems, improve the efficiency of urban traffic resource allocation, and improve the adaptability of urban traffic network.

3.1. Travel behavior model based on the impact of uncertain events in the transportation system

In the transportation system, there are uncertainties in transportation supply and demand, such as traffic accidents, bad weather, and traffic control. These factors can cause changes in the supply and demand of the transportation system, resulting in disruptions in the daily activities of travelers. Under certain circumstances, the connectivity reliability of the transportation network is the key to ensuring that emergencies are handled in a timely manner. The length of travel time of a traveler can characterize the performance of the traffic network during the current time period to a certain extent, that is, the adaptability of the traffic system. The adaptability of the traffic system takes into account the ability of the traffic system to maintain a certain performance when it is disturbed and the ability of the traffic system to recover its performance after the disturbance occurs. It covers the whole life cycle of a traffic system disturbed by an uncertain event: the calming period, the preparation period, the response period, and the recovery period. The above life cycle can be summarized as two phases of the network subjected to disturbance. The calm and preparation periods are the phases before the disturbance occurs; the response and recovery periods belong to the phases after the disturbance occurs. Before the disturbance, the traffic network is in the calm and preparation period, the network is maintained in equilibrium, and the performance remains stable. During the calm period, traffic managers work to reduce the probability of a disturbance and weaken the possible consequences of the disturbance. The preparation period allows the network to react faster and effectively after the disturbance by setting up preparatory measures. After a perturbation occurs at a certain point, the network enters a reaction period and performance decreases to a lower level. After the reaction period, the traffic network enters the recovery period, and the performance starts to rebound and returns to the original level or reaches a new equilibrium state at some point. This work adopts a method based on a day-by-day traffic assignment model to quantify the resilience index of the traffic system while considering the ability of the traffic system to resist and recover from disturbances. Equation (1) expresses the specific calculation method.

$$RL = \sum_{i} \frac{t_a\left(v_a^0\right) \cdot v_a^0}{t_a\left(v_a^m\right) \cdot v_a^m} \tag{1}$$

In Equation (1), RL denotes a measure of resilience when the transportation system is disturbed; $t_a\left(v_a^0\right)$ and v_a^0 represent the travel time and flow of the road section a before the disturbance occurs; $t_a\left(v_a^m\right)$ and v_a^m denote the travel time and flow of the road section a at the moment m after the disturbance occurs.

Here, travel time reliability is used to measure the travel time fluctuations caused by uncertain factors to travelers. The value of travel time reliability is then referenced in the travel utility function to model the impact of uncertainty factors in the transportation network on the activity trajectory of travelers and their travel decisions. The travel utility that the traveler expects to achieve is described as Equation (2).

$$E(U) = \nu_1 \cdot \overline{T} + \nu_2 \cdot E(Sde) + \nu_3 \cdot E(Sdl) + \nu_+ \cdot P_L \tag{2}$$

In Equation (2), T stands for the average travel time, Sde and Sdl signify the early and late time, respectively; P_L represents the probability of being late; $\nu_1 - \nu_4$ refers to the model parameters. Travel time variance is an important measure of travel time reliability. The lower the value of the variance, the stronger the predictability of travel time, and the higher the reliability of travel time. Therefore, the travel utility can be measured by the average travel time and the variance of the travel time, as presented in Equation (3).

$$U = \nu_5 \cdot \overline{T} + \nu_6 \cdot \sigma_T + \nu_7 \cdot \mathrm{Cost} \tag{3}$$

In Equation (3), σ_T represents the variance of travel time; Cost indicates the amount of money spent on travel; $\nu_5 - \nu_7$ represents the model parameters. The value of travel time *vot* and the value of reliability *vor* are calculated by means of a bounded rate of substitution of the average travel time T and the travel time variance σ_T with respect to the travel cost *Cost*:

$$vot = \frac{\partial U / \partial \overline{T}}{\partial U / \partial Cost} \tag{4}$$

$$\mathrm{vor} = \frac{\partial U / \partial \sigma_T}{\partial U / \partial Cost} \tag{5}$$

Then, the reliability ratio RR can be written as Equation (6).

$$RR = \frac{\partial U / \partial \sigma_T}{\partial U / \partial \overline{T}} = \frac{\text{vor}}{vot} \tag{6}$$

The reliability value index of the mean–variance model is used to calculate the trip utility, considering the costs arising from fluctuations in travel time. The driving segment impedance $disu^R_{\mathrm{I},i}$ in the traffic network can be expressed as Equation (7).

$$disu^R_{I,i} = disu_{I,i} + vor.\left(t^o_{I,i} cv_i\right) \tag{7}$$

In Equation (7), the standard deviation of travel time for mode i is the product of the average travel time $t^0_{\mathrm{L},i}$ of i and the coefficient of variation cv_i of travel time; $\mathrm{disu}_{\mathrm{I},i}$ denotes the negative utility of travel.

There is uncertainty in the traveler's perception of the activity-travel utility. Thus. a random value U^{n-1}_r is used here to represent the perceived utility of the activity-travel mode r on the $n-1$ day:

$$U^{n-1}_r = u^{n-1}_r + \xi^{n-1}_r \tag{8}$$

$$r \in R \tag{9}$$

where R stands for the set of all activity-travel modes; u^{n-1}_r represents the actual utility of the activity-travel mode r on the $n-$ day; ξ^{n-1}_r represents the error of perceived utility. Assume that the error of perceived utility obeys the Gumbel distribution. Then, the initial probability p^n_r of the traveler who reconsiders the activity-travel decision on the n th day to choose the activity-travel mode r is expressed as Equation (10).

$$p^n_r = \frac{e^{-\theta u^{n-1}_r}}{\sum_{r \in R} e^{-\theta u^{n-1}_r}}, \forall r \in R \tag{10}$$

In Equation (10), θ refers to the parameter of perceptual accuracy.

Equation (11) indicates the initial selection probability $\breve{p}^n_r$ of the activity-travel mode r on the n th day based on p^n_r.

$$\breve{p}^n_r = p_{adj} \cdot p^n_r + \frac{(1 - p_{adj}) f^{n-1}_r}{q} \tag{11}$$

$$\forall r \in R \tag{12}$$

In Equation (11), p_{adj} represents the proportion of travelers who reconsider the activity-travel decision; q refers to the total traffic demand in the network; f^{n-1}_r signifies the actual number of people who choose the activity-travel mode r on the $n-1$ day. Traditional transportation research cannot accurately simulate traveler activity patterns and cannot directly reflect the impact of uncertain events on the temporal and spatial distribution of traffic flow. As a fast and economical way to travel between public transportation and cabs, customized bus service combined with travelers with similar needs can help reduce traffic congestion and improve the resilience of urban transportation networks. The reservation probability of customized bus is affected by the traveler's reservation willingness.

The booking probability $\tilde{p}^n_r$ of the activity-travel mode r of the customized bus service on the nth day is calculated according to:

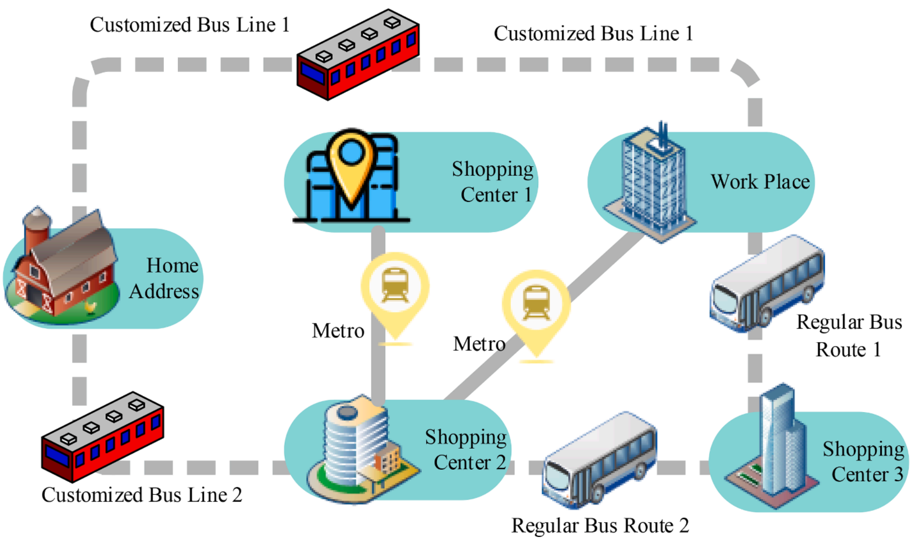

Fig. 2. Multimodal bus network with customized bus services.

$$p_r^n = p_b^{r,n} \cdot \breve{p}_r^n \tag{13}$$

$$\forall r \in R_{CB} \tag{14}$$

where R_{CB} represents the activity-travel mode set, including customized public transportation; $p_b^{r,n}$ denotes the probability of the customized public transportation service included in the scheduled travel mode r on the nth day. The booking probability of customized buses will be affected by capacity constraints. When the number of people booking a customized bus exceeds the capacity of the bus system, travelers cannot successfully book a customized bus. Thus, the probability $\overline{p}_r^n$ of successfully booking a customized bus under the travel mode r on the nth day is calculated according to Equation (15).

$$p_r^n = p_c^{r,n} \cdot p_b^{r,n} \cdot \breve{p}_r^n, \forall r \in R_{CB} \tag{15}$$

In Equation (15), $p_c^{r,n}$ represents the success of the scheduled travel mode r on the n th day, including the probability of customized bus services. The multimodal traffic network architecture in Fig. 2 is adopted to verify the impact of traffic network changes on travel modes.

In Fig. 2, the network nodes represent the different places that travelers go to; “Home” refers to the home address; “Work” represents the workplace; “Sale1” represents the shopping center 1; “Sale2” represents the shopping center 2; “Sale3” indicates the shopping center 3. The segments in this transportation network represent the transportation services that connect the various network nodes, such as subways, taxis, buses, and customized buses. Choose 6 a.m. to 10p.m. daily for the forecast.

Traffic Vehicle Data Sharing Mechanism Optimized by Digital Twins.

The above predicts the change of traffic system adaptability due to uncertain events in the traffic system by predicting the travel patterns of travelers effectively. However, with the rapid increase in the motor vehicles, it becomes increasingly challenging to guarantee traffic driving safety and traffic system adaptation. The emergence of the IoV has allowed data sharing to increase technical support for the improvement of traffic operation efficiency. It enables the vehicles in the traffic network to better grasp the information related to the surrounding traffic conditions by sharing the videos, images, and signals collected by themselves between vehicles. Data security is the basis for ensuring data sharing between vehicles. For example, Blockchain technology can implement data sharing by adopting a Blockchain architecture and consensus mechanism that match the shared traffic scenario. However, vehicles need to be authenticated during network entry and migration, which will increase the scalability and communication overhead of the IoV system to a certain extent.

Digital Twins technology helps physical entities establish virtual nodes in edge servers via edge computing to simulate the state of real nodes and complete the mapping between virtual space and physical space. IoV supported by Digital Twins can convert the physical communication between vehicles into a virtual space. There is high efficiency and quality of communication between virtual space nodes that are not affected by the physical location of the car. This makes it possible to share transactions between vehicles, block packing, etc., more lightweight. Therefore, this work establishes a vehicle networking system model based on the Digital Twins and Blockchain, as shown in Fig. 3.

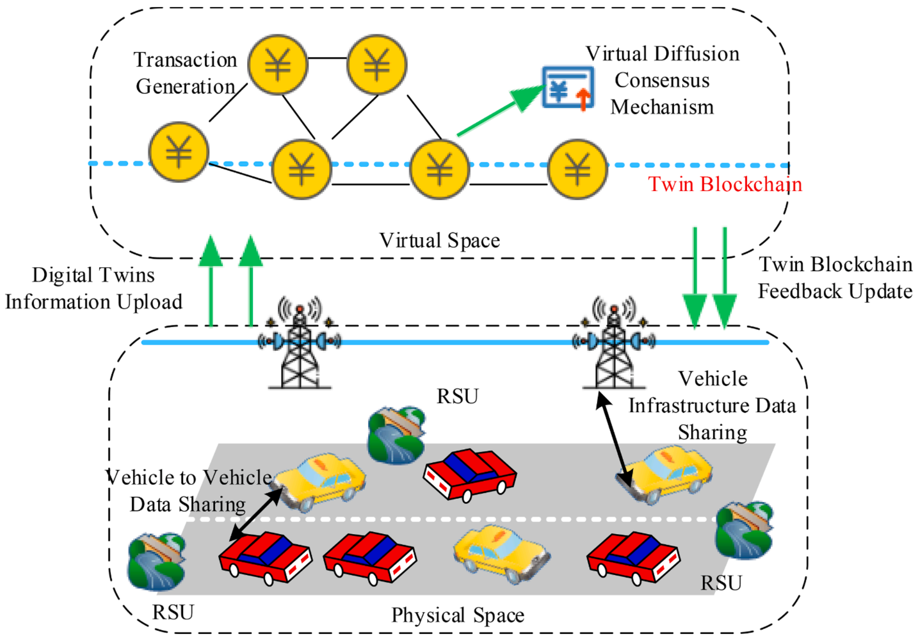

Fig. 3. Car networking system model based on Digital Twins and Blockchain.

The system in Fig. 3 consists of two parts: physical space and virtual space. The physical space includes vehicles and roadside units (RSUs). Data sharing between vehicles and infrastructure is logically equal. Vehicles and infrastructure are able to share data with each other and have a logically equal relationship. The virtual space contains virtual mappings of the multiple ground chain (GC), meaning there are multiple virtual spaces. Vehicles in the virtual space can build their Digital Twins on the RSU, and one RSU can build Digital Twins for multiple vehicles. The system data-sharing process can be simulated by the Digital Twins node of the vehicle in the virtual space. With the computing power of RSU, the Digital Twins can complete the virtual communication between vehicles and then return the final result to the vehicle in the physical space, thus establishing twin Blockchain. The specific process is as follows.

First, the Digital Twins state model is uploaded. Assume that the vehicle V_i generates a Digital Twins state model, representing the state and actions taken by the vehicle during the data-sharing process. Then, the car uploads the state model θ_i to its own twin V_t^i. Equation (16) describes θ_i.

$$\theta_i = \{\tau(m), A, s_i\} \tag{16}$$

In Equation (16), $\tau(m)$ represents data characteristics, such as data type and storage location, as well as the attributes of the vehicle itself; A stands for the operation data of the vehicle in data sharing, such as delivery and request; s_i signifies the digital signature of the vehicle. After receiving the state model, the vehicle twin encapsulates the state model as a virtual transaction for other operations. The virtual transaction χ_i is expressed as Equation (17).

$$\chi_i = \{\theta_i, d_i, t_0\} \tag{17}$$

In Equation (17), d_i represents the address of the twin V_t^i; t_0 refers to the timestamp generated by the virtual transaction, which is used to identify the uniqueness of the existence of the transaction.

Then, virtual consensus and transaction verification are performed. After the virtual transaction is generated, the vehicle twin broadcasts the transaction to other vehicles in the current twin Blockchain system for fast verification and transaction recording.

Finally, when the virtual feedback consensus is completed, the data overview $\tau(m)$ is recorded by the ledger in the current twin Blockchain system. At this time, V_t^i passes the consensus result o_i back to the vehicle physical entity in the form of feedback updates. Equation (18) describes this process.

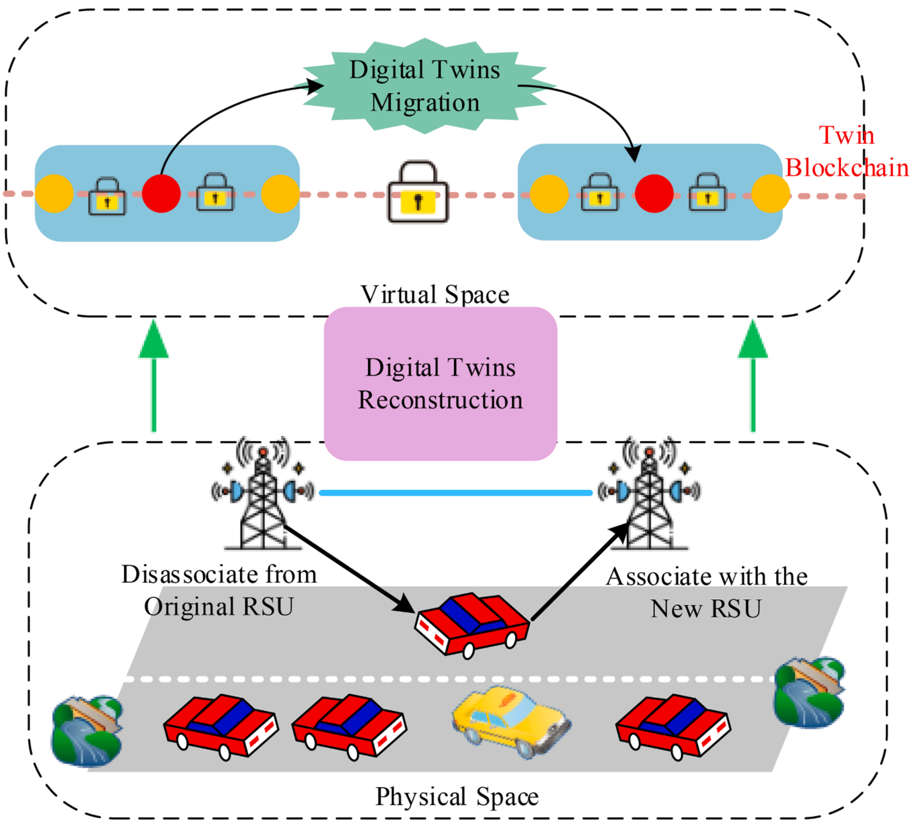

Fig. 4. Migration and reconstruction of Digital Twins vehicles.

$$\theta_t^i = \{\tau(m), o_i, t_0\} \tag{18}$$

In a large-scale dynamic IoV scenario, the communication quality of the link will be inconsistent with the moving speed of the vehicle, which will also overload the calculation of the RSU. Therefore, the Digital Twins need to be reconstructed along with the moving trajectory of the vehicle and the state of the RSU, as shown in Fig. 4.

It can be seen from Fig. 4 that the distance between the vehicle and the physical vehicle needs to be as short as possible after the reconstruction of the Digital Twins to ensure the quality of link communication. However, in addition to the distance factor, it is also necessary to consider the problem that the excessive number of vehicles in the peak period will cause the RSU to be overloaded. Therefore, the dynamic Digital Twins construction and migration method is proposed here by comprehensively considering the location strategy and computing power allocation in the process of Digital Twins migration.

Assume that the number of RSUs in a single GC is N, and the number of vehicles is V. Then, there are:

$$\mathbb{N} = \{n_i, i \in (0, N]\} \tag{19}$$

$$\mathbb{V} = \{v_j, j \in (0, V]\} \tag{20}$$

Then, $\mathbb{N}_i^c$ is defined as the collection of Digital Twins built for vehicles by RSUn_i. If n_i constructs the Digital Twins V_j^t for the vehicle v_j, the relationship presented in Equation (22) holds.

$$V_j^t \in \mathbb{N}_i^c \tag{21}$$

Here, $|*|$ represents the cardinality of the set. Then, the relationship in Equation (22) exists.

$$\sum_{i\in\mathbb{N}} |\mathbb{N}_i^c| = |\mathbb{V}| \tag{22}$$

This work defines the time span from the generation of a transaction by a vehicle to the final adoption of consensus in the sharing process as the transaction time delay. The transaction delay is divided into state model upload delay, virtual diffusion local consensus delay, and large-scale diffusion delay. Let m_0 represent the data size of the state model θ_j. Equation (23) indicates the upload delay.

$$t_{i,j}^{(0)} = \frac{m_0 B^{-1}}{\log\left\{1 + p_j\left[\tau + 10\beta\log\left(d_{i,j}\right) + X_\gamma\right]/\sigma^2\right\}} \tag{23}$$

In Equation (23), B stands for the bandwidth between vehicles and RSU; p_j represents the transmission power of the vehicle; σ^2 indicates the interference signal gain; τ and β refer to the parameters of the float-intercept model; X_γ denotes a Gaussian distribution with variance γ. The overall transaction delay is expressed as Equation (24).

$$y_i = t_{i,j}^{(0)} + t_{i,j}^{(1)} + t_i^{(2)} \tag{24}$$

In Equation (24), $t_{i,j}^{(1)}$ and $t_i^{(2)}$ represent virtual diffusion local consensus delay and large-scale diffusion delay.

The highly dynamic vehicle position and speed changes will increase the difficulty of solving the state space. The Digital Twins Blockchain system established here is distributed. Therefore, the Multi-Agent Deep Deterministic Policy Gradient (MADDPG) algorithm is utilized to solve the distributed problem of the twin Blockchain system. As the name suggests, MADDPG is a multi-agent version of the Deep Deterministic Policy Gradient (DDPG) algorithm. The difference between it and DDPG is that its unique core idea is to use global information to learn Critic and use local information to learn Actor. The MADDPG algorithm extends the DDPG algorithm to a multi-agent environment. The MADDPG algorithm assumes that each agent has its own independent Critic network and

Table 1
Dynamic Digital Twins vehicle migration algorithm based on LPMADDPG.

Initialization: Set the number of agents to N, RSU local awareness set to $\mathbb{N}_i^{lp}$, and local vehicle awareness set to V^{ad}.

for episode $= 0 \rightarrow \varepsilon - 1$ **do**
  Initialize the scene of the Digital Twins migration transportation system. Initial state:
    $o^0 = \{o_1, o_2, \cdots, o_N\}$
  for Step k $= 0 \rightarrow \xi - 1$ **do**
    Execute the action decision of the agent to obtain the differential cumulative income.
    Storage transfer probability matrix.
    If memory is full, **then**
      for Agent i $= 1 \rightarrow$N **do**
        Randomly sample K transfer matrices from memory
        Update critical network model
        Update actor network model
      end
    end
    Update network model parameters of all agents.
  end
end

Actor network, and each agent has its own independent reward function. Then, the MADDPG algorithm can simultaneously solve Multi-agent problems in collaborative, competitive, and hybrid environments. The local perception multi-agent enhancement algorithm is selected here to reduce the communication overhead, that is, the Local Perception Multi-Agent Deep Deterministic Policy Gradient (LPMADDPG). The reason for choosing local perception is that in the IoV scenario, the traffic environment data that is far away from the target infrastructure has little to do with the final establishment of the control strategy. Therefore, LPMADDPG fully considers the vehicle and state information closest to the infrastructure set. Table 1 displays the specific algorithm process.

According to Table 1, the LPMADDPG algorithm utilizes two perceptual sets, that is, the RSU local perceptual sets, as presented in Equation (25).

$$\mathbb{N}_i^{lp} = \{n_1, n_2, \cdots, n_i\} \tag{25}$$

In Equation (25), $\mathbb{N}_i^{lp}$ represents the set of RSUs where n_i is within the sensing range; the vehicle sensing set includes all vehicles within the sensing range of n_i, represented by Equation (26).

$$W_i^{ad} = \{w_1, w_2, \cdots, w_j\} \tag{26}$$

The differentiated cumulative return function is expressed as Equation (27).

$$r_i = \sum_{k\in \mathrm{T}} \sum_{i\in \mathbb{N}_i^{lp}} \sum_{j\in \mathbb{V}_i^{ad}} \gamma^{k-1} U_{i,j}^k \tag{27}$$

Finally, the gradient of the differentiated cumulative receiver function of each agent can be obtained.

Based on the above method, the case analysis of the twin blockchain transportation system is carried out to verify the communication overhead and consensus success rate of the virtual diffusion mechanism. Then, a real traffic dataset from the physical world is used to make a validation of the migration mechanism of the Digital Twins in the twin Blockchain. Finally, the practicality of the data-sharing strategy is verified. The Digital Twins of the case analysis process use the serial bus and RSU to communicate and employ the Central Processing Unit frequency to verify the computing overhead of the Digital Twins for virtual transactions, signatures, consensus, etc., in the process of maintaining the Blockchain. Other parameters are set as follows. The number of RSUs is set to 9; the number of vehicles is set to 30; the size of the state model is 50 kb; the size of the virtual transaction is 100 kb; the maximum episode ε of the local perception algorithm is 400.

3.2. Experimental data

The actual traffic data on some regional roads of Xi'an Railway Station from May 1, 2021 to April 30, 2022 are selected to further verify the role of Digital Twins in traffic system adaptation as mentioned above. Monitoring points are set up on key roads in the test area. A total of 10 monitoring points are designed to collect 104,236 traffic flow samples. Among them, 88,254 samples are collected from May 1, 2021 to February 28, 2022, and 15,982 samples are collected from March 1, 2022 to April 30, 2022. Table 2 lists some traffic data.

The historical data of actual traffic monitoring points can be obtained through the traffic-travel model above and the intelligent transportation system based on Digital Twins. Digital Twins can achieve rapid modeling of the traffic system, including real-time prediction of vehicle number data, vehicle congestion time, congested road sections, and traffic accident time and location.

4. Results and discussion

4.1. Prediction results of the travel model under uncertain factors

Fig. 5 provides the statistical impact of adopting multimodal transportation modes on the travel situation according to the travel mode chosen by the traveler.

It can be seen from Fig. 5(a) that before the customized bus operation, the traveler's activity time in Sale 1 was relatively long. With the adoption of customized bus service, travelers spend more time working and shopping, less time moving around at home and on the

Table 2
Part of the traffic data of Xi'an Railway Station.

Time of Collection	Traffic Flow	Occupancy Volume	Large Vehicle Flow	…	Delay
2021/5/2 8:00:00	659	23.6	6	…	0.3
2021/5/2 8:05:00	643	25.9	1	…	1.0
2021/5/2 8:10:00	639	24.9	6	…	2.4
2021/5/2 8:15:00	641	25.1	12	…	1.3
…	…	…	…	…	…
2022/4/29 18:30:00	469	22.5	24	…	0.8
2022/4/29 18:35:00	458	23.2	26	…	1.6
2022/4/29 18:40:00	472	18.6	31	…	0.9
2022/4/29 18:45:00	481	19.8	36	…	1.8

road, and more time shopping. As shown in Fig. 5(b), there is a significant increase in the average trip utility in the transportation network after the custom bus operation. This indicates that the custom bus routes increase traffic smoothness and the willingness and length of trips reflect the excellent performance of the transportation network from the side.

Fig. 6 illustrates the impact of customized bus service on travel traffic flow.

Fig. 6 suggests that the evolution process of travelers' daily trips is divided into three stages: the initial stage, the adjustment stage, and the stable stage. In the initial phase, travelers are familiar with the changes in the transportation network, such as citing customized bus services. A large number of travelers choose customized bus services to improve travel efficiency, and the bus share rate and passenger flow increase rapidly. The level of all aspects has declined after the failure rate grows. In the stable stage, as travelers continue to adjust their strategies, the passenger flow of the transportation network is also constantly changing, showing a certain periodicity. It can be seen that predicting the travel rules of travelers can reflect the current situation of the traffic network and have an impact on the results and measures of adjusting the traffic system.

4.2. Results of case study of Digital Twins Blockchain transportation system

Fig. 7 reveals the communication overhead and storage overhead of the virtual consensus mechanism in the transportation system based on Digital Twins and Blockchain with the increase of vehicle size in IoV.

It can be seen from Fig. 7 (a) that the virtual diffusion consensus can maintain a relatively low communication overhead when the number of RSUs in the transportation network is 2 and 9. Compared with the traditional Blockchain, the overall communication overhead is reduced by at least 30 % with the addition of the virtual diffusion mechanism. This is due to the fact that the consensus mechanism divides the original communication link into smaller consensus sub-regions. Digital Twins in each region will perform a local consensus and broadcast the result to other RSUs for a second consensus. This operation saves the large-scale communication overhead caused by the multiplication of communication between each Digital Twin. In Fig. 7(b), ζ represents the minimum number of Digital Twins in each sub-region. It can be found that as the number of ζ decreases, the ledger storage overhead decreases. The twin Blockchain system's storage overhead is reduced by at least half Compared with the traditional public chain. Fig. 8 shows the security performance.

In Fig. 8, V represents the number of vehicles, and C represents the computing power of the RSU. When the computing power of the RSU is the same, as the number of vehicles increases, the probability of consensus success increases. For instance, when $V = 21$, $C = 3000$; when $V = 27$, $C = 3000$. This is because the Digital Twins Blockchain transportation system reported here is a distributed system, so the interaction between the twins is carried out according to the public chain. An appropriate increase in the network scale can improve the system safety performance. However, there are certain limitations. If the network scale increases to a certain extent, the computing power of the RSU will be overloaded and malfunction.

4.3. Performance change of the twin systems through the LPMADDPG algorithm

Fig. 9 compares the transaction delay between the traditional MADDPG algorithm and the LPMADDPG reported here.

In Fig. 9, the delay of a single transaction, the local perception range, and the RSU in the whole range all show that the LPMADDPG algorithm and the traditional MADDPG algorithm are almost similar in the convergence speed and inflection point of convergence. This is because in a large-scale IoV scenario, the RSU and vehicle construction conditions that are far away from the vehicle have little influence on the algorithm itself. Fig. 9(d) compares the transaction delays of different migration and reconstruction strategies. The

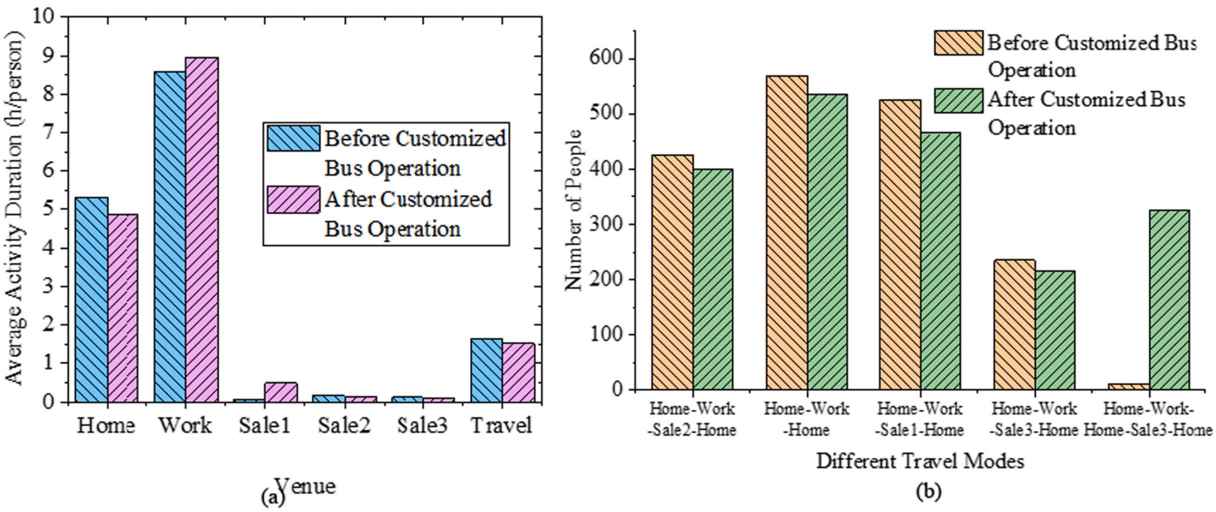

Fig. 5. The impact of customized bus service on travelers' travel (a: the impact of activity duration; b: the influence of activity-travel decision-making utility).

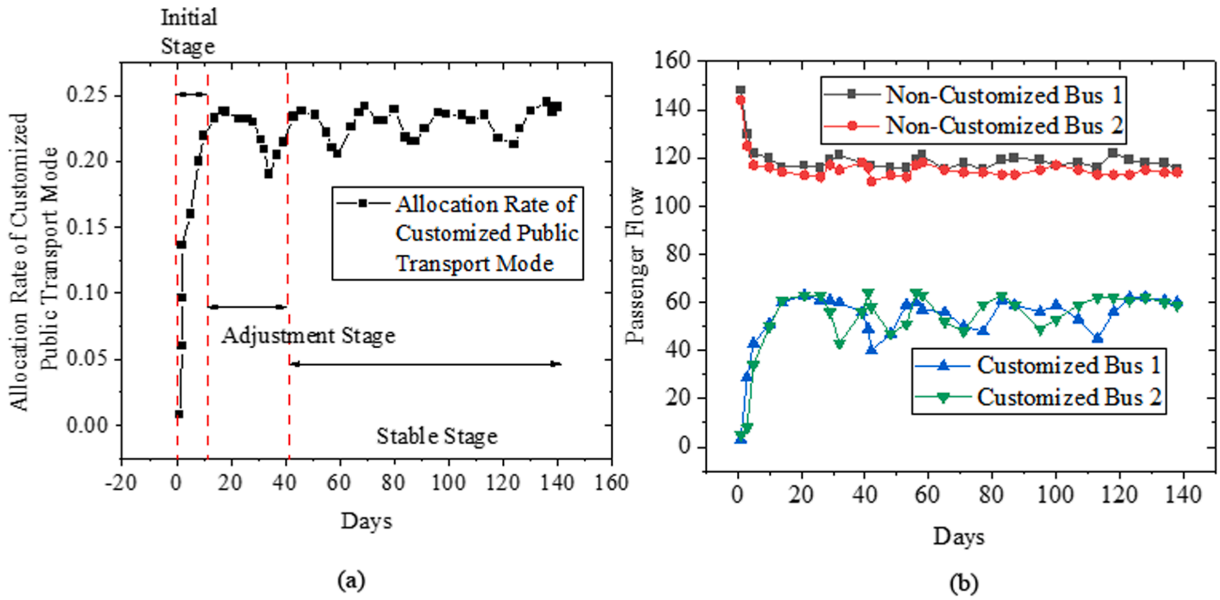

Fig. 6. Impact of customized bus service on travel traffic flow (a: daily evolution of customized bus sharing rate; b: daily activity-travel mode flow evolution).

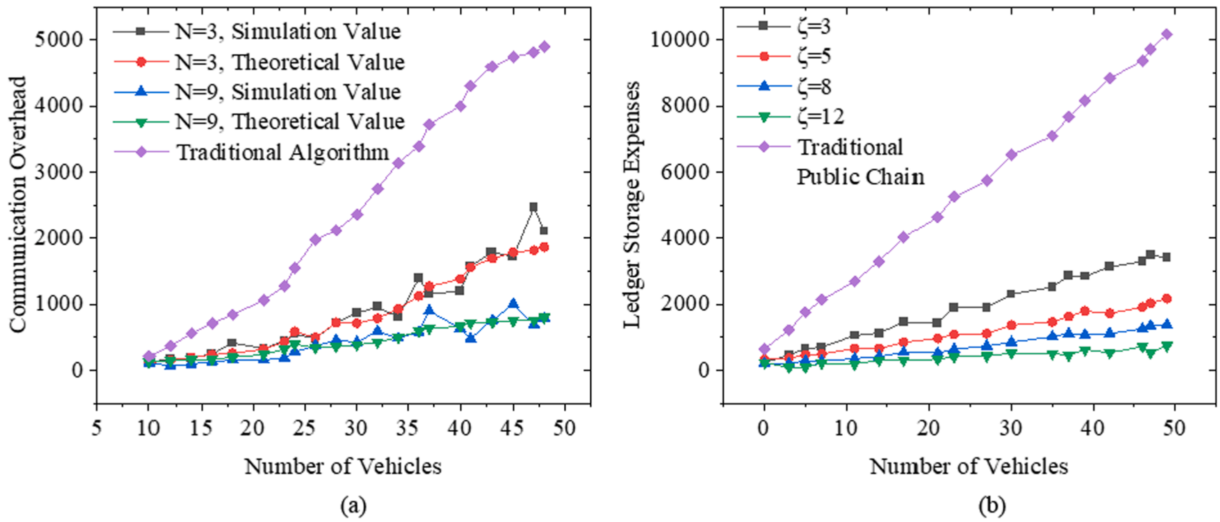

Fig. 7. The overhead of the Digital Twins Blockchain transportation system (a: consensus communication overhead; b: ledger storage overhead).

dynamic migration strategy presents a low transaction delay, which can ensure that the vehicle maintains a high communication condition in the principle of proximity. Fig. 10 further compares the communication overhead and training efficiency of these two algorithms. The iterations in Fig. 10(b) depict a portion of the data with the number of iterations between 4,800 and 16,000. Besides, some of the values of the number of iterations are selected for display due to the large amount of data.

It can be seen from Fig. 10 that the LPMADDPG algorithm increases with the growth of the number of agent RSUs, and the communication overhead increases accordingly. However, compared with the traditional MADDPG algorithm, the LPMADDPG algorithm saves more than half of the communication overhead. It is more suitable for the traffic twin system of large-scale vehicles. In terms of algorithm training efficiency, both algorithms take longer to train as the number of vehicle plants within the network increases. Still, the LPMADDPG algorithm outperforms the traditional algorithm and improves the training efficiency by nearly 30 %. Fig. 11 shows the physical world data supply of different types of vehicles under the adaptive sharing strategy.

According to Fig. 11, compared to the amount of data provisioning uploaded in the physical world, an analysis of the current data provisioning of IoVs based on Digital Twins shows that each vehicle reduces the amount of data provisioning to varying degrees. This is caused by the fact that the overall demand is smaller than the supply. Therefore, Digital Twins need to sufficiently consider the balance

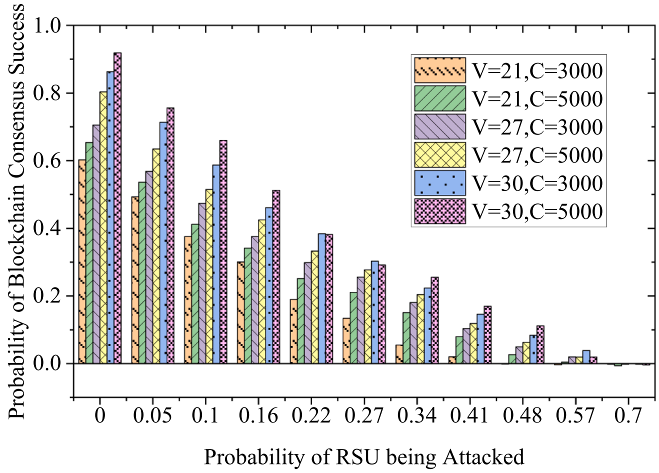

Fig. 8. The security performance of the Digital Twins Blockchain transportation system under attack.

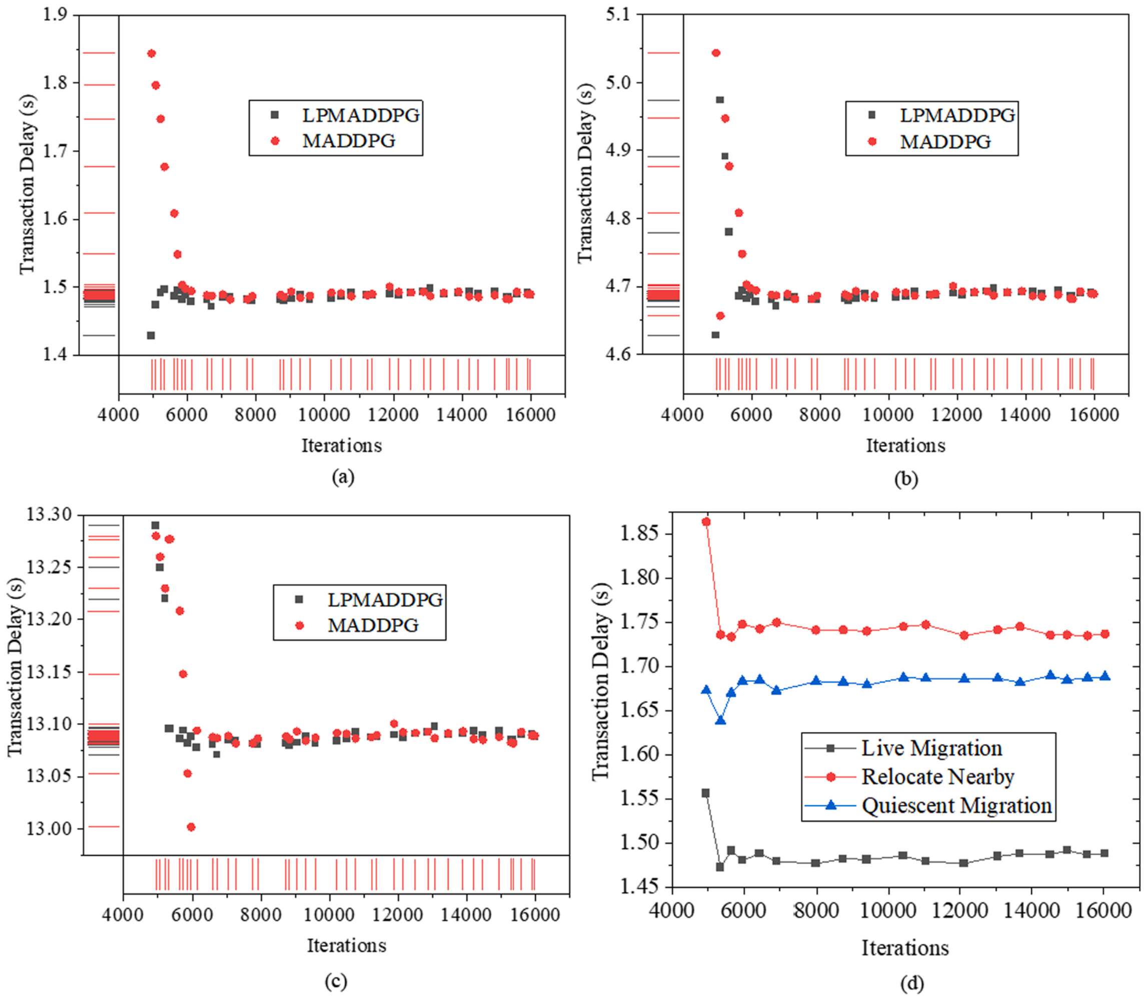

Fig. 9. The vehicle transaction delay of the migration reconstruction strategy (a: single transaction; b: local perception; c: full range perception; d: comparison of different strategies).

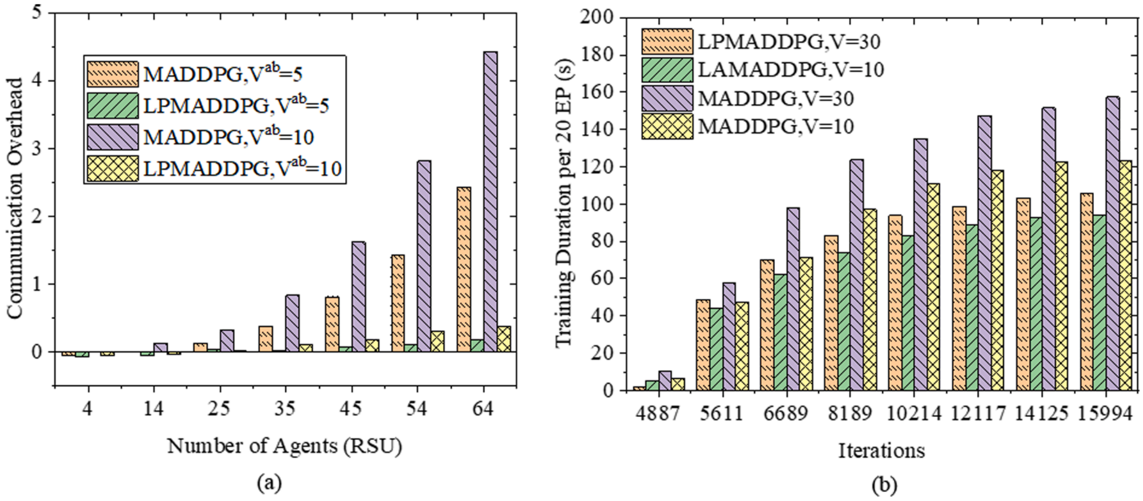

Fig. 10. Algorithm performance comparison (a: communication overhead; b: training efficiency).

of supply and demand in the transportation network to reduce the resource redundancy phenomenon. The different data-sharing strategies demonstrate that the adaptive data-sharing strategy based on Digital Twins presents much higher system utility than the other two schemes, which will lead to a further increase in vehicle revenue.

4.4. Prediction results of practical cases of the Digital Twins traffic system

The Digital Twins traffic system is used to predict the traffic condition of Xi'an Railway Station in a day. The predicted result is compared with the actual traffic state. The red marker refers to the actual occurring traffic state, and the blue marker represents the predicted traffic state. The traffic operation situation is divided into three different levels of traffic state congestion degree: smooth, crowded, and congested. Fig. 12 provides the prediction results.

As can be seen from Fig. 12, the traffic status 24 h a day is predicted. Traffic is congested from 7:45 to 9:00, crowded from 12:45 to 13:15, and congested from 17:35 to 18:55, which is consistent with the actual situation. There are many vehicles traveling in the morning peak and evening peaks so the traffic state is congested. It is meal time during the noon time period, and the traffic situation has eased slightly. The flow of people and vehicles a railway station is relatively large, and it is normal to be crowded because it's a railway station.

According to Fig. 13, with the adjustment of the number of lanes on the congested road section, that is, the distribution of traffic flow on the congested road section, the change trend of the congestion diffusion speed is roughly the same as that of the upstream traffic flow. It shows that the speed of traffic congestion spread is positively correlated with the change of traffic flow. In the case of two-lane traffic flow, the fluctuation range of the congestion diffusion speed is relatively large. In the late stage of traffic congestion, the congestion diffusion speed decreases greatly. However, in the case of a single lane or a closed double lane, the fluctuation range of the congestion diffusion is roughly similar, and the fluctuation range is gentle. Therefore, the road should be reasonably occupied in advance using the vehicle safety queuing factor under the consideration of potential future congested road sections to effectively reduce the speed of congestion spread.

4.5. Discussion

The above findings suggest that Digital Twins technology plays an imperative role in intelligent transportation systems. In particular, the LPMADDPG algorithm and the IoV traffic system based on Digital Twins and blockchain effectively alleviate data sharing. The dynamic migration strategy even presents a low transaction delay, which can ensure the vehicles to maintain a high communication status under the proximity principle. It can be seen that the resilience of Digital Twins has a great impact on the intelligent transportation system. These findings are similar to those of Rudskoy et al. (2021). They analyzed the case of intelligent transportation system, developed a reference model for such system services, and introduced the main problems that can be solved in transportation networks. Liu et al. (2022) proposed a secure communication architecture for IoV systems based on immutable and traceable blockchain data for the current IoV communication security issues. In addition, a distance-based generative adversarial network model is constructed to predict the risk of IoV nodes to improve the accuracy and response efficiency of access control. Their research is valuable for improving the security of IoV information sharing. Bhatti et al.(2021) screened the contribution of the Digital Twins domain to intelligent vehicle systems and explored the potential of its implementation and the challenges it faces at the same time. Chen et al.(2022) introduced blockchain technology and deep learning algorithms combined with BiLSTM to build a blockchain-based Digital Twins model for COVID-2019 outbreak. It can be seen that Digital Twins technology will revolutionize the barriers to the development of mainstream vehicle technology and intelligent transportation systems.

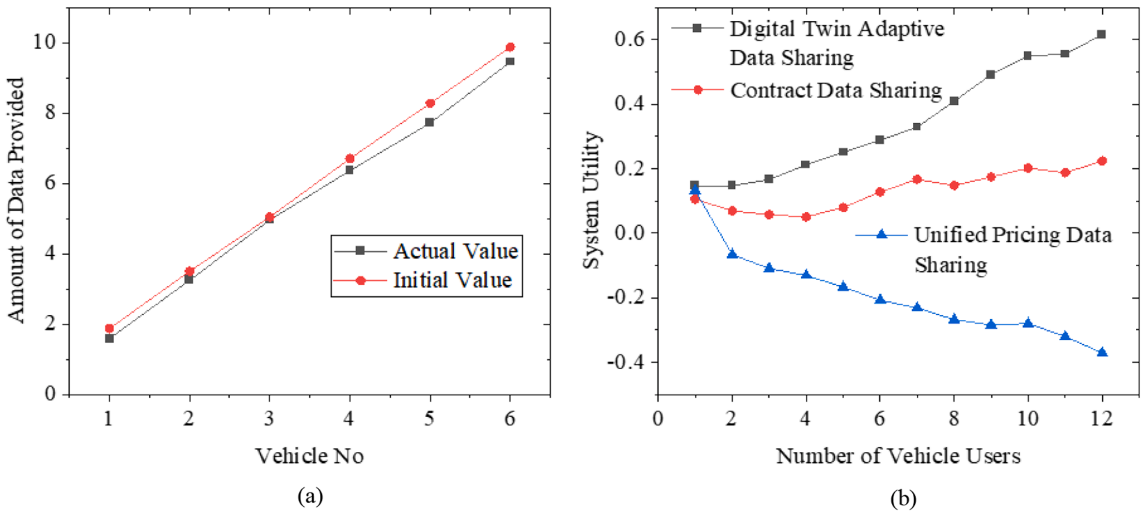

Fig. 11. Data sharing strategy situation (a: data supply situation of different vehicles for adaptive data sharing; b: system utility of different sharing strategies).

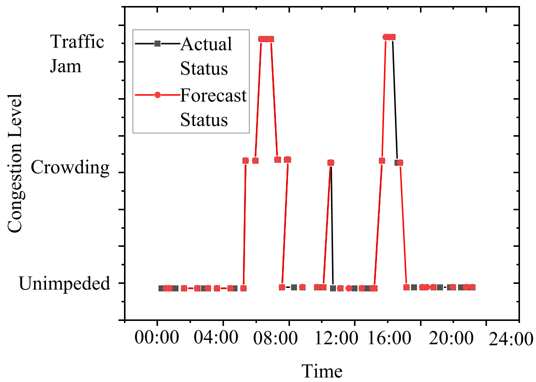

Fig. 12. Prediction results of road traffic data.

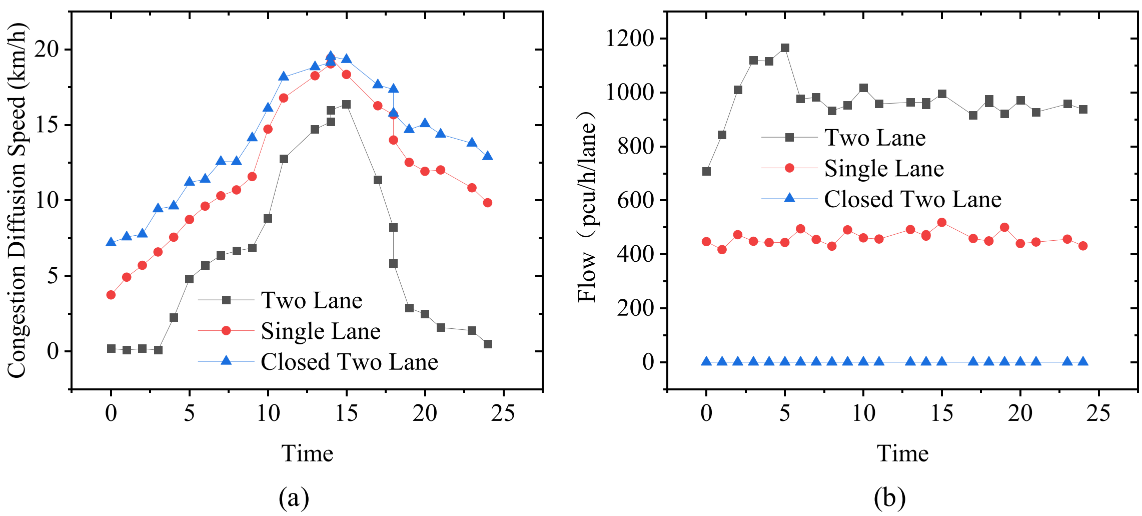

Fig. 13. Changes in traffic flow of different lanes (a: upstream congestion control area; b: Downstream congestion control area).

5. Conclusion

Digital Twins technology is a crucial direction and application scenario for the development of informatization in the road transportation industry. Therefore, improving the resilience of Digital Twins in transportation system applications can strengthen the ability of the entire transportation network to cope with perturbations from uncertain events and the adaptability of the transportation system. This work studies the current research status of traffic systems and Digital Twins, and then studies the application of Digital Twins in ITSs and establishes an innovative transportation platform based on Digital Twins. Then, the impact of the adaptability of the transportation network on travel behavior is studied from the perspective of the impact of uncertain events in the transportation network on travel conditions of travelers. Besides, a travel behavior model is built based on the impact of uncertain events to improve the impact of traffic conditions on travel through a multi-modal transportation form such as customized public transportation. Finally, the problem of data sharing in the IoV traffic system is analyzed from the perspective of Digital Twins. Meanwhile, an LPMADDPG algorithm is proposed to optimize the drawbacks of data sharing in Blockchain in IoV, and a Digital Twins Blockchain traffic system is established and experimentally verified. The results demonstrate that the IoV system based on Digital Twins reported here significantly optimizes data sharing and improves the ability of the transportation network to withstand and repair the impact of external uncertainty on the transportation system. Besides, it saves more than 50 % of the communication overhead and improves operational efficiency by nearly 20 % over traditional algorithms. However, there are still some deficiencies in the research. Customized public transport is only one of the various ways to improve the traffic network from the perspective of travel behavior patterns. Future research will consider the role of Digital Twins and multimodal transportation modes in improving the resilience of the transportation system from multiple perspectives.

CRediT authorship contribution statement

Hailin Feng: Methodology, Software, Investigation, Writing – original draft, Writing – review & editing. **Haibin Lv:** Conceptualization, Software, Writing – original draft. **Zhihan Lv:** Writing – original draft, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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