Digital Twin Technology for Intelligent Vehicles and Transportation Systems: A Survey on Applications, Challenges and Future Directions

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***Abstract*—This survey provides a comprehensive analysis of digital twin (DT) technology as a transformative tool for advancing connected and autonomous vehicles (CAVs) and intelligent transportation systems (ITSs), focusing on advancements in vehicle safety, traffic management, and autonomous driving capabilities. The paper begins by discussing the foundational concepts and enabling technologies behind DT systems, setting the stage for their application in transportation networks. We review DT applications in vehicle safety, highlighting their role in real-time monitoring, predictive maintenance, and risk mitigation. Next, we explore the role of DT technology in optimizing traffic flow, enhancing traffic management, and enabling adaptive responses to dynamic conditions. The paper then examines the integration of DTs in intelligent and autonomous vehicles, emphasizing advancements in simulation, testing, and the development of autonomous driving functionalities. Finally, we outline future research opportunities and challenges for DT applications, providing a roadmap for their continued evolution in CAVs and ITS.**

***Index Terms*—Digital twin, connected and autonomous vehicles, intelligent transportation systems, vehicle safety, traffic management, real-time data analytics, predictive maintenance.**

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I. Introduction

The rapid development of connected and autonomous vehicles (CAVs) and intelligent transportation systems (ITSs) is profoundly reshaping global transportation networks, promising substantial improvements in safety, efficiency, and sustainability. Despite these advancements, significant challenges remain in achieving real-time monitoring, predictive analytics, and dynamic decision-making within highly interconnected transportation ecosystems. Digital Twin (DT) technology has emerged as a key enabler, creating dynamic, real-time virtual replicas of physical systems that continuously synchronize with real-world data. DTs provide valuable insights into predictive maintenance, optimized control, and performance enhancement, effectively addressing complex issues faced by CAV and ITS infrastructures. By enabling highly accurate simulations and real-time feedback loops, DTs facilitate the development of smarter, safer, and more efficient transportation systems.

A. Background and Motivation

DT technology has progressed from a conceptual prototype to a foundational pillar of ITS, particularly within the Internet of vehicles (IoVs). First introduced by Dr. Michael Grieves in 2003 for product-lifecycle management, DTs attracted wider attention after NASA's 2012 deployment for aerospace predictive maintenance [1]. During the past decade, adoption has accelerated across manufacturing, energy, healthcare, and, increasingly, transportation [2, 3].

Traditional information systems passively *collect–store–analyze* sensor data. By contrast, a DT constructs a persistent, high-fidelity *virtual replica* of each physical entity, i.e., vehicle, roadway, or infrastructure component, and maintains continuous, bidirectional synchronization between the physical and digital realms. This live coupling enables real-time monitoring, predictive simulation, multi-agent coordination, and closed-loop control, thereby transforming data-driven ITS architectures into *state-driven* systems.

The fundamental differences between DTs and conventional information systems in an IoV context are summarized in Table I.

To underscore the economic impact, Fig. 1 shows the 2023 global DT market by end-use sector [4]. Transportation already accounts for roughly 15% of total revenue, fueled

TABLE I
TRADITIONAL INFORMATION SYSTEMS VS. DIGITAL TWINS IN IOV APPLICATIONS

Aspect	Traditional Information Systems	Digital Twins for IoV
Data Flow	One-way: collection & storage	Two-way: real-time synchronisation & control
Functionality	Passive monitoring and reporting	Predictive simulation, scenario analysis, closed-loop optimisation
Integration	Fragmented, siloed subsystems	Unified cross-domain model with live updates
Decision Making	Reactive, human-centric	Proactive, autonomous, machine-driven
Use Cases	Historical analytics, fault logs	Cooperative perception, predictive maintenance, dynamic optimisation

by connected-vehicle platforms, infrastructure monitoring, and urban-mobility optimization.

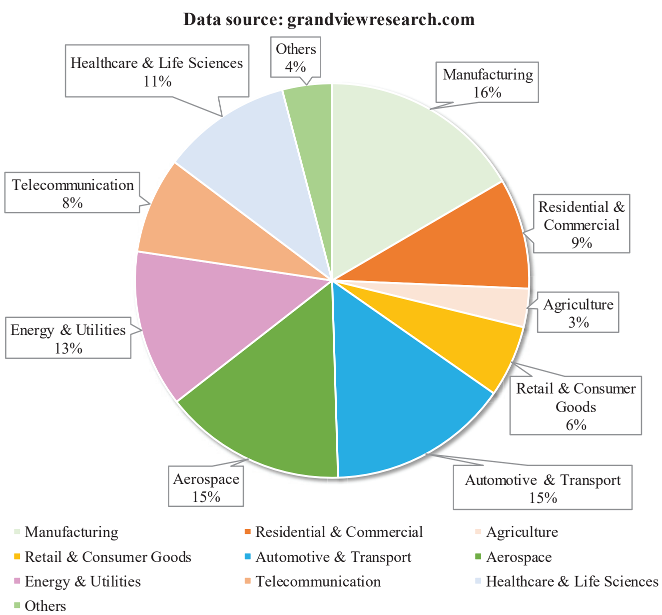

Fig. 1. Global DT market share (2023) by end-use sector.

In network-centric ITS deployments, DTs enable dynamic, real-time coordination among heterogeneous agents, i.e., vehicles, roadside units (RSUs), and traffic-control centers. By exchanging digital-state snapshots over V2X, edge, and cloud links, each agent can not only perceive and react but also *simulate, predict, and collaboratively optimize* system-wide behavior, and such capabilities are beyond traditional data-driven architectures.

Practical exemplars include Singapore's Land Transport Authority and Highways England, where DT-enabled platforms reduced congestion and cut predictive-maintenance costs by up to 30%, boosting asset uptime by 20%. EU projects such as Horizon 2020 AUTOPILOT further highlight DT-facilitated autonomous driving through real-time digital–physical synchronization. Finally, interoperability frameworks (e.g., the IIC Industrial Internet Reference Architecture) provide the standards backbone for scalable DT deployment across IoV ecosystems.

B. *Related Works and Contributions*

Recent surveys have extensively explored theoretical foundations and enabling technologies of DT systems across multiple domains, including manufacturing, smart cities, autonomous driving, and industrial applications. Table II summarizes representative DT surveys relevant to ITS and CAVs.

Errandonea et al. [5] investigate DT's role in maintenance applications, focusing on real-time monitoring, predictive maintenance, and operational efficiency. However, their review lacks empirical case studies, limiting its applicability to real-world systems. Similarly, Niaz et al. [6] propose a DT-based framework for testing autonomous driving systems with vehicle-to-everything (V2X) integration, but challenges such as inconsistent response delays and incomplete traffic databases hinder the framework's reliability.

Mylonas et al. [7] provide a broad review of DT applications in smart manufacturing and smart cities but omit practical implementation details, particularly in complex transportation systems. Bhatti et al. [8] focus on DT applications in smart electric vehicles, highlighting environmental benefits, yet they provide few real-world examples, limiting their conclusions. Martinez et al. [9] discuss DTs in automatic transportation systems within Industry 4.0, but the emerging nature of this technology results in limited practical applications.

Hu et al. [12] explore the potential of DT for driver behavior modeling to enhance safety. However, the field still lacks empirical data, making it difficult to draw reliable conclusions for vehicle safety improvements. De et al. [13] examine the integration of DT with cyber-physical systems (CPS) in commercial vehicles, highlighting significant challenges such as protocol standardization and integration complexity, which require further work for seamless ITS deployment.

Several surveys address DT integration with advanced technologies such as ML, Internet of things (IoT), and edge computing. For example, Hu et al. [14] focus on DTs in traffic safety but suggest a broader scope is needed to fully understand their implications for urban mobility systems. Ibrahim et al. [16] compare model-based and data-driven DT approaches for electric vehicles, but the lack of detailed case studies on real-world applications limits the practical value of their insights. Naseri et al. [17] explore DT in electric vehicle battery systems, but their discussion remains mostly theoretical, with few practical examples. Deng et al. [18] review DT applications in autonomous driving, summarizing

TABLE II
COMPARISON OF RELATED SURVEY PAPERS.

Ref.	Year	Focus Area	Key Contributions	Limitations
[5]	2020	Maintenance	Literature review on DT for maintenance, identifying key trends and research gaps.	Focuses on literature, limited practical insights
[6]	2021	Autonomous Driving	Proposes a DT-based framework for testing autonomous driving, highlights V2X technology integration.	Lacks consensus on response delay in autonomous driving, incomplete traffic database
[7]	2021	Smart Manufacturing and Smart City	Reviews DT applications from manufacturing to smart cities, discussing technological advancements.	Broad overview, may lack detailed case studies
[8]	2021	Smart Electric Vehicles	Reviews DT applications in smart electric vehicles, focusing on environmental benefits.	Primarily theoretical, limited real-world application examples
[9]	2021	Industry 4.0 Transportation	Discusses the role of DT in automatic transportation systems within Industry 4.0.	Emerging technology with limited practical implementation examples
[10]	2022	DT Security	Surveys security threats in DT systems, providing security recommendations.	Limited focus on the real-world implementation of security protocols
[11]	2022	DT of Wireless Systems	Overview of DT applications for wireless systems, with taxonomy and open challenges.	Lack of extensive deployment examples and practical cases
[12]	2022	Driver Digital Twin	Provides an overview of driver DT applications and future directions.	Emerging field, lacks extensive empirical data
[13]	2022	Commercial Vehicles	Discusses integration of DT and CPS in commercial vehicles, addressing challenges and opportunities.	Challenges in real-world implementation, need for standardized protocols
[14]	2022	Traffic Safety and Mobility	Focuses on DT systems for traffic safety and mobility, reviewing current research and future perspectives.	Focuses on safety and mobility, limited coverage of other potential applications
[15]	2023	Industrial IoT	Reviews applications, technologies, and tools of DT for the Industrial Internet of Things.	Limited exploration of implementation challenges in real-world scenarios
[16]	2023	Electric Vehicle Platforms	Provides an overview of different DT platforms for EV applications, comparing model-based and data-driven DTs.	Limited to platform comparisons, lacking detailed case studies
[17]	2023	EV Battery Systems	Review of DT applications in EV battery systems, focusing on use cases and requirements.	Primarily theoretical with limited practical implementation examples
[18]	2023	Autonomous Driving	Systematic review of DT applications in autonomous driving, highlighting current research and trends.	Focuses on current research, lacking future research directions
[19]	2024	Personalized Healthcare	Focuses on networking architecture and supporting technologies for human DT in personalized healthcare.	Faces substantial research challenges and lacks extensive case studies
[20]	2024	Smart Grid, Transportation System, Smart City	Surveys DT applications in smart grid, transportation, and smart cities; discusses challenges and future directions.	Broad scope may lack depth in specific areas, future research needed for practical implementations
[21]	2024	Electric and Autonomous Vehicles	Reviews DT technology applications in electric and autonomous vehicles, discussing technological advancements and future directions.	Limited real-world examples and empirical data
[22]	2024	Cellular Networks	Surveys the use of simulators and DTs in the advancement of emerging cellular networks.	Limited to simulation studies, lacks real-world validation
[23]	2024	Autonomous Driving	Reviews the role of simulation in developing and testing autonomous driving systems, highlighting various simulation techniques.	Limited to simulation studies, lacking real-world validation
This paper		**CAV and ITS**	A comprehensive analysis of DT technology integration into CAVs and ITSs. Highlights technological foundations, practical implementations, and future research directions, identifying research gaps and the roadmap for future studies.	

current trends but failing to provide future research directions for DT integration in autonomous ecosystems.

Recent works also highlight specific challenges such as security and wireless communications in DT deployments. Mihai et al. [24] provide a broad survey on DT enabling technologies and challenges but do not discuss practical applications in ITS or CAVs. Security threats in DT systems are thoroughly reviewed by Alcaraz and Lopez [10], who categorize potential security vulnerabilities and provide security recommendations for the safe implementation of DT technology. However, their focus on general security risks leaves unaddressed the specific security challenges in ITS and CAVs. Khan et al. [11] explore the application of DTs in wireless communication systems, developing a taxonomy of DT applications in 5G and beyond (5G&B) networks. While their work is valuable in the context of telecommunications, the real-world deployment of DT for ITS and CAVs remains underexplored. Similarly, Xu et al. [15] review DT applications in the Industrial Internet of Things (IIoT), discussing the use of AI and blockchain for system security and intelligent decision-making. However, practical implementation challenges for DT in transportation systems are inadequately addressed in their survey.

More recent surveys provide valuable perspectives on the potential applications of DTs in emerging fields. For example, Chen et al. [19] discuss human digital twins (HDT) in personalized healthcare, highlighting the networking architecture and supporting technologies required for real-time data synchronization. Though these insights could inform driver behavior modeling or autonomous driving, the lack of case studies and real-world applications limits their practical relevance to ITS. Jafari et al. [20] provide an overview of DT applications in smart grids, transportation, and smart cities, offering insights into challenges and future directions, though real-world applications remain limited. Ali et al. [21] review DTs in electric and autonomous vehicles, focusing on technological advancements but offering few real-world examples.

Additionally, Manalastas et al. [22] examine DT and simulators in cellular networks, but their work is largely theoretical and focuses on simulation models with no real-world validation. Hu et al. [23] review simulation techniques for autonomous driving systems, but their lack of real-world validation reduces their practical utility.

Despite the foundational insights provided by existing surveys, substantial gaps remain when translating theoretical frameworks and general DT applications into practical deployments within ITS and CAV contexts. Specifically, existing literature demonstrates limited coverage regarding:

- Comprehensive and systematic analyses of DT-enabled safety-critical functions, including cooperative perception, predictive maintenance, and proactive emergency interventions in realistic transportation scenarios.
- In-depth discussions on practical cross-layer integration challenges unique to ITS and CAV environments, including real-time V2X synchronization, edge computing constraints, and simulation-to-reality transitions.
- Experimental validations, field implementations, and detailed case studies explicitly bridging theoretical DT models with practical ITS and CAV applications and operational frameworks.

To address these critical gaps, our survey presents a comprehensive, holistic, and practice-oriented review of DT technologies explicitly tailored to intelligent vehicles and transportation systems. The primary contributions of this survey are summarized as follows:

- A detailed and structured synthesis of DT applications in vehicle safety, traffic management, and autonomous driving, encompassing theoretical insights and tangible real-world implementations.
- Key technical, operational, and security insights drawn from empirical studies and practical deployments, including clearly outlined solutions and best practices.
- An extensive forward-looking discussion on future research opportunities and practical advancements in DT-enabled cooperative perception, scenario-based testing, real-time simulation frameworks, and strategies for developing scalable, resilient, and secure intelligent transportation ecosystems.

C. Structure and Organization

The rest of the paper is organized as follows: Section II provides an overview of the foundational concepts and enabling technologies behind DT systems, setting the stage for their application in ITS. Section III reviews DT applications for vehicle safety, detailing how DTs enhance safety mechanisms, enable predictive maintenance, and support real-time diagnostics in CAVs. Section IV focuses on DT applications in traffic management, exploring their role in optimizing traffic flow, incident response, and infrastructure resilience. Section V examines the integration of DTs in autonomous vehicle systems, emphasizing advancements in simulation, testing, and the development of autonomous driving functionalities. Section VI presents future research directions, outlining critical areas for development to ensure sustainable and scalable DT deployment. Section VII concludes the paper by summarizing the main contributions and reinforcing the importance of DT technology for the future of intelligent transportation systems. Fig. 2 illustrates the organization of this survey.

II. Enabling Technologies for Digital Twins

This section introduces and discusses key enabling technologies crucial for effectively integrating DT systems into intelligent vehicles and transportation networks, as illustrated in Fig. 3. It also explores strategies for accurately identifying, monitoring, and controlling physical components within ITS using DT-based methodologies.

A. Digital-Twin Architecture and Its Network Perspective

DT systems typically adopt a multi-layer architecture that connects physical assets, communication infrastructures, and digital replicas into a tightly coupled control loop. This architecture supports seamless synchronization, low-latency processing, and predictive optimization across ITS and CAVs. It forms the foundational enabler for real-time decision-making and collaborative operations in network-centric ITS environments.

As illustrated in Fig. 4, a representative DT architecture consists of three fundamental layers:

1) Physical Layer: This foundational layer includes vehicles, RSUs, infrastructure sensors, actuators, and other cyber-physical components. It generates real-time operational data through sensing and executes control instructions issued by the digital twin. These physical elements serve as the primary data sources and actuation endpoints that maintain tight coupling with their virtual counterparts [25, 26].

2) Communication Layer: Serving as the communication backbone, this layer enables secure, low-latency, and bi-directional data exchange between physical entities and their digital counterparts. Beyond standard V2X protocols, it supports key functions including: (i) periodic dissemination of twin-state snapshots to nearby vehicles and infrastructure for cooperative perception; (ii) synchronization of digital twins across RSUs, MEC nodes, and cloud servers to ensure consistency and mobility support; and (iii) dynamic allocation of communication resources via network slicing, where ultra-reliable low-latency communication (URLLC) channels handle safety-critical data and enhance mobile broadband (eMBB) channels support high-volume updates. Technologies such as IEEE 802.11p, C-V2X, MQTT, and CoAP-over-5G ensure interoperability across diverse communication stacks [27].

3) Digital Layer: Hosted across distributed edge and cloud infrastructure, this layer maintains high-fidelity geometric, physical, and behavioral models of physical entities. It supports real-time monitoring, simulation, and optimization through hybrid AI pipelines, which fuse live sensor streams with physics-based and data-driven models to derive predictive and prescriptive insights [28, 29].

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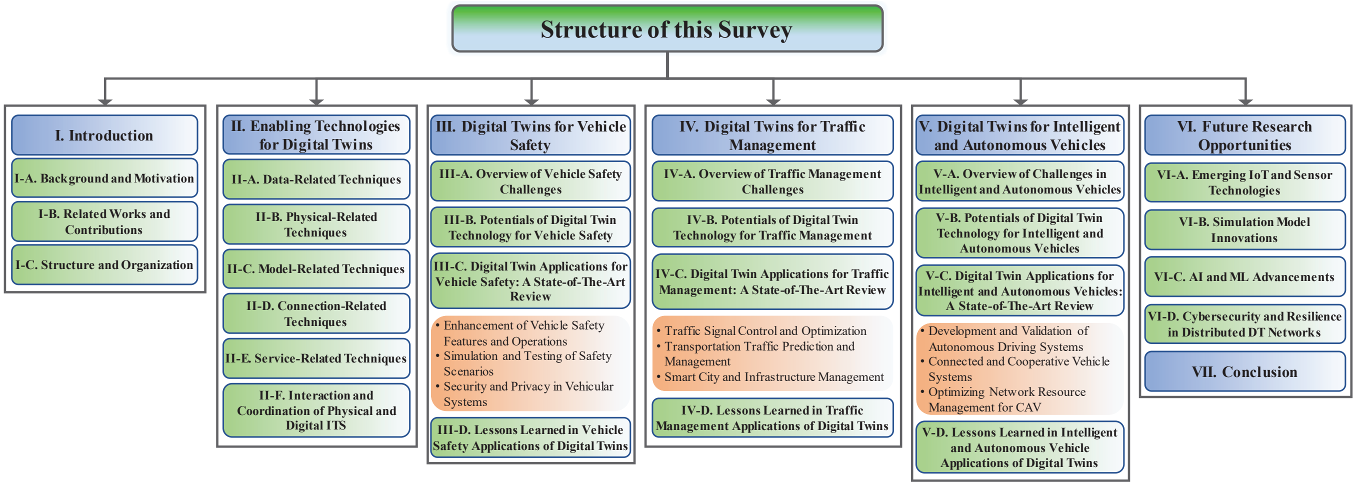

Fig. 2. Organization of this survey.

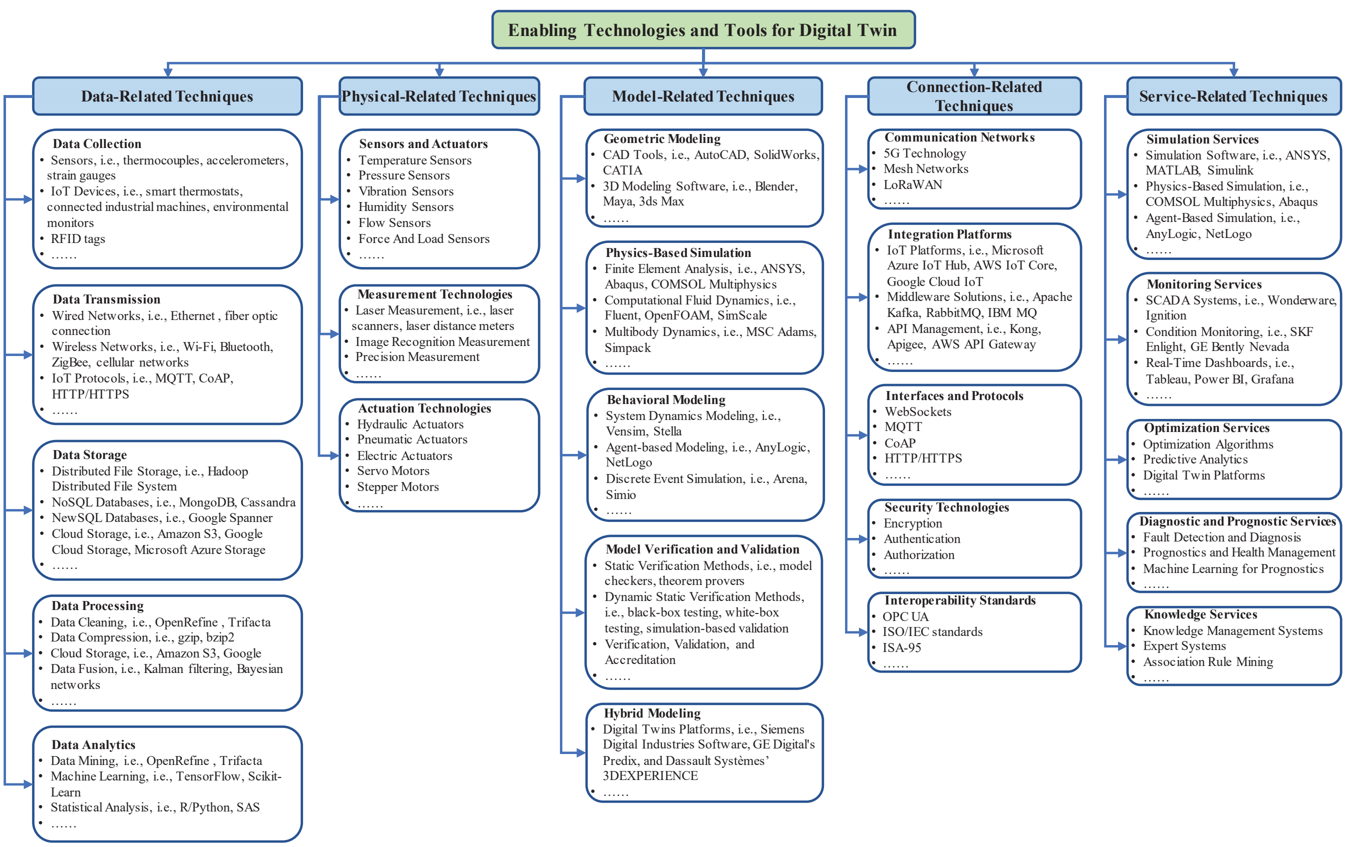

Fig. 3. Categories of enabling technologies and tools for Digital Twins.

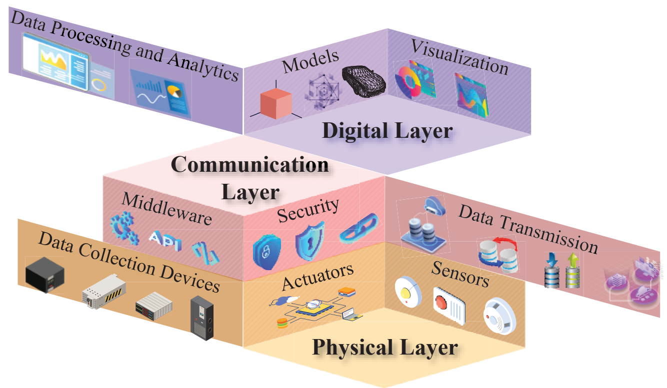

Fig. 4. Three-layer architecture of the Digital Twin model.

In traditional ITS architectures, the communication network primarily serves as a passive channel for transmitting sensor data and control commands. A DT-aware network, however, treats the "twin state" as a core network-visible object. Each node actively publishes its own digital state and subscribes to relevant remote twins. This supports system-wide situational awareness, maintained collaboratively by vehicles, infrastructure, and control centers. At the network edge, local digital twins are cached to enable rapid responses, often within 10 milliseconds. In the cloud, aggregated twin data supports global coordination and city-scale traffic optimization. This twin-centric approach enables several advanced capabilities. First, co-operative perception extends each vehicle's awareness by integrating nearby twin states with its own sensor data, enhancing visibility beyond line-of-sight. Second, predictive closed-loop control leverages real-time simulations within the digital layer to adjust trajectories in advance; these control updates are transmitted over low-latency URLLC links. Third, cross-layer resource optimization is achieved by allocating bandwidth, computing, and storage based on forecasted DT workloads, rather than relying on static configurations. By transforming communication from a reactive transport medium into an active, context-aware control plane, digital twins introduce a fundamental shift in how ITS networks operate. This evolution, from data-driven to twin-driven intelligence, lays the groundwork for the predictive, collaborative, and autonomous features discussed in later sections.

B. Data-Related Technologies

Effective integration and operation of DT technology within intelligent vehicles and ITS demand advanced data management systems that ensure precise modeling, continuous synchronization, and real-time responsiveness. Crucial stages of data lifecycle management, including data collection, transmission, storage, processing, and analysis, are closely interconnected and play indispensable roles in sustaining robust and reliable DT ecosystems.

1) Data Collection and Sensing Technologies: Data collection relies on sensors, IoT devices, and RFID tags that monitor parameters such as temperature, vibration, location, and speed. In intelligent vehicles, sensors like LIDAR, cameras, radar, and GPS provide essential real-time data for DT creation [30]. These sensors, integrated with IoT devices, enable continuous monitoring, ensuring real-time updates of DTs and maintaining accurate system representations.

2) Data Transmission Technologies: Efficient data transmission to DT platforms is achieved through both wired and wireless technologies. Wired solutions like Ethernet and fiber optics ensure high-speed, reliable backhaul communication, while wireless options like Wi-Fi, Bluetooth, ZigBee, and advanced cellular networks (e.g., 5G/B5G) support mobility and flexibility in connected vehicle networks [31]. Protocols such as MQTT, CoAP, and HTTP/HTTPS facilitate low-latency, secure real-time exchanges, which are vital for vehicular environments [32].

3) Data Storage Solutions: The vast amounts of data generated by sensors and IoT devices require scalable and resilient storage solutions. Distributed file systems (DFS) and databases like NoSQL and NewSQL offer high scalability, fault tolerance, and quick data access, critical for real-time data handling in DT ecosystems [31]. Cloud platforms such as AWS and Microsoft Azure provide scalable resources for integrating large datasets across distributed systems in real-time environments.

4) Data Processing and Transformation: Data processing techniques, including cleaning, compression, transformation, and fusion, ensure the accuracy and quality of collected data. Raw sensor data often contains noise and redundancies, which data cleaning addresses, while compression optimizes storage and transmission. Data fusion, such as sensor fusion, combines information from multiple sources, providing a more comprehensive and reliable representation of physical systems [33].

5) Advanced Analytics and Real-Time Decision-Making: AI and ML-driven analytics enable deep insights into system behaviors, using tools like TensorFlow, PyTorch, and Scikit-learn for predictive models, anomaly detection, and optimization [34, 35]. Real-time decision-making is supported by visualization tools like Tableau and Power BI, which help stakeholders make data-driven decisions by presenting complex data in an accessible format [36, 37].

C. Physical-Related Technologies

Physical-related technologies include high-precision sensors, actuators, and advanced measurement systems, enabling real-time data acquisition and operational control for accurate system modeling in ITS.

1) Sensors and Data Acquisition: High-precision sensors monitor parameters like temperature, pressure, and displacement, forming the core of DT data acquisition. Sensors such as thermocouples, piezoelectric accelerometers, and GPS provide essential real-time data for dynamic updates in DT models. Integrated IoT devices allow continuous data streams that reflect changes in vehicle behavior, road conditions, and environmental factors, ensuring synchronization with the physical world [38, 39].

2) Integration with Control Systems: To maintain synchronization, sensors integrate with control systems like SCADA, PLCs, and DCS. These systems ensure continuous data flow and feedback loops, enabling real-time updates in DT models. This integration supports dynamic responses to environmental changes, optimizing performance in autonomous vehicles and ITS by synchronizing physical and virtual actions.

3) Advanced Measurement Technologies: Techniques like laser scanning and coordinate measuring machines (CMMs) capture precise geometric data for infrastructure, vehicles, and environments. Laser scanners use triangulation or time-of-flight methods to generate high-density point clouds, while CMMs offer micron-level precision, essential for creating reliable 3D models. This precision ensures DTs accurately reflect physical characteristics, vital for simulations and system optimizations [40–42].

4) Actuation Technologies and Control: Actuators, such as hydraulic, pneumatic, and electric motors, translate digital commands into physical actions, enabling real-time interaction between virtual and physical systems. These technologies integrate with closed-loop control systems for dynamic adjustments based on sensor and digital twin feedback, supporting precision control in autonomous systems, such as lane changes and speed adjustments [40–43].

D. Model-Related Technologies

Model-related technologies enable the creation, simulation, and optimization of virtual models that replicate the behaviors and conditions of physical systems, ensuring effective monitoring, control, and decision-making in transportation systems.

1) Geometric Modeling: Geometric modeling is fundamental to digital twin creation, providing spatial representations of physical systems. CAD tools (AutoCAD, SolidWorks, CATIA) and advanced 3D modeling applications (Blender, Maya, 3ds Max) are used to design accurate 2D and 3D models for vehicles, infrastructure, and components. These models are critical for simulating geometries and understanding spatial relationships in transportation systems [44, 45].

2) Physics-Based Simulation: Physics-based simulations model real-world system behaviors under physical conditions. Tools like ANSYS Fluent, Abaqus, and OpenFOAM use numerical methods (FEA, CFD) to simulate material properties, stress, and fluid dynamics [46, 47]. Multibody Dynamics (MBD) software like MSC Adams simulates interactions between moving bodies, ensuring accurate digital twins of mechanical behaviors [48, 49].

3) Behavioral Modeling: Behavioral modeling techniques simulate interactions between system entities over time, crucial for modeling complex systems like traffic flow and vehicle interactions. Platforms like Vensim, Stella, AnyLogic, and NetLogo model time-dependent behaviors, enabling prediction of system evolution and testing scenarios without real-world experimentation [50, 51]. Discrete Event Simulation (DES) tools such as Arena and Simio optimize processes and improve system performance [52, 53].

4) Model Verification and Validation: Verification and validation (V&V) ensure the accuracy and reliability of digital twin models. Verification confirms that models meet specifications, while validation ensures that they represent the real-world system accurately. Leading DT platforms like Siemens Digital Industries Software, GE Digital's Predix, and Dassault Systèmes' 3DEXPERIENCE integrate rigorous V&V processes to maintain model fidelity [54, 55].

E. Connection-Related Technologies

Connection technologies ensure the digital twin accurately mirrors the physical system and supports dynamic control and optimization.

1) Communication Networks: Modern communication networks, particularly 5G, are essential for transferring real-time data between physical entities and their digital twins in transportation systems. The low-latency and high-bandwidth capabilities of 5G, including URLLC and mMTC, enable critical applications like autonomous driving, where rapid data transfer is crucial for decision-making and safety [56]. Mesh networks also enhance resilience and reliability, enabling decentralized communication in environments such as vehicle fleets and smart cities. Additionally, LPWAN technologies like LoRaWAN provide long-range, low-power communication, which is ideal for infrastructure monitoring in remote areas, thereby extending the coverage of V2X systems [57].

2) Integration Platforms: Platforms like Microsoft Azure IoT Hub, AWS IoT Core, and Google Cloud IoT are crucial for managing the massive data generated in digital twin ecosystems. They support the seamless collection, processing, and analysis of real-time data, enabling the synchronization of digital twins with physical systems. These platforms provide services like device provisioning, secure communication, and real-time analytics, ensuring effective integration of sensor data and continuous updates of the digital twin's state [57].

3) Middleware Technologies: Middleware solutions such as Apache Kafka, RabbitMQ, and IBM MQ are key for facilitating efficient and secure data exchange across distributed systems. These technologies ensure reliable messaging and enable real-time communication between components in a digital twin ecosystem. API management tools like Kong, Apigee, and AWS API Gateway further ensure secure, scalable interactions, simplifying integration and maintaining operational integrity within ITS [58].

4) Interfaces and Protocols: Standardized communication protocols are essential for ensuring effective communication between devices and systems in digital twin ecosystems. Protocols like MQTT and CoAP are ideal for constrained environments, enabling low-latency, secure data transmission, especially in IoT applications [59]. Industrial protocols like OPC UA ensure seamless data exchange across diverse platforms, facilitating the integration of sensors, actuators, and control systems in complex transportation networks [60].

5) Security Technologies: Security technologies are vital for protecting the integrity of data and communication in digital twin systems. Encryption protocols like SSL/TLS and AES ensure the confidentiality of transmitted data [61]. Authentication mechanisms such as OAuth, JWT, and multi-factor authentication (MFA) protect digital twin systems by restricting access to authorized entities, crucial in V2X systems and autonomous vehicles where data integrity is critical [62, 63].

6) Interoperability Standards: Interoperability standards like OPC UA, MQTT, and ISA-95 ensure seamless communication across platforms, vendors, and devices within digital twin ecosystems. These standards provide a unified framework for data exchange, reducing compatibility issues and enhancing integration between systems. Standardized data formats like XML and JSON, combined with RESTful APIs, further support efficient communication and system integration.

F. Service-Related Technologies

Service-related technologies enable digital twins to adapt dynamically to changes in their physical counterparts, optimizing system performance and predictive capabilities.

1) Simulation Services: Simulation services are key to modeling and predicting the behavior of physical systems. Tools like Ansys, MATLAB, and Simulink are used for finite element analysis (FEA) and multi-domain modeling, simulating interactions such as mechanical stresses and fluid dynamics [64]. These simulations provide insights for optimizing and validating systems in real-world conditions. Platforms like AnyLogic and NetLogo also enable agent-based modeling, allowing dynamic simulations of systems with multiple interacting agents, such as vehicles in traffic management scenarios, improving decision-making [65].

2) Monitoring Services: Monitoring services are essential for ensuring system health and continuous operation. SCADA systems like Wonderware and Ignition enable real-time data acquisition and control in industrial settings, while tools such as SKF Enlight and GE Bently Nevada utilize advanced analytics for anomaly detection and predictive maintenance. Visualization platforms like Tableau and Power BI provide dashboards displaying key performance indicators (KPIs), empowering decision-makers with real-time insights [66].

3) Optimization Services: Optimization services leverage algorithms like genetic algorithms, particle swarm optimization, and simulated annealing to enhance system performance. These methods refine operations, optimizing parameters such as resource allocation, energy consumption, and scheduling. Predictive analytics tools like IBM SPSS and RapidMiner forecast trends, assisting in maintenance and resource management decisions .

4) Diagnostic and Prognostic Services: Diagnostic and prognostic services are essential for fault detection and predictive maintenance. Tools like MATLAB's Fault Diagnosis Toolbox use machine learning to detect faults and predict the remaining useful life (RUL) of components. These services analyze sensor data to identify deviations from expected behavior, providing early warnings and minimizing downtime and maintenance costs [67].

5) Knowledge Services: Knowledge services support the storage, retrieval, and sharing of expertise within digital twin ecosystems. Platforms like Confluence and SharePoint facilitate knowledge management, while data mining tools such as Weka and Orange uncover patterns from large datasets, supporting decision-making and continuous improvement.

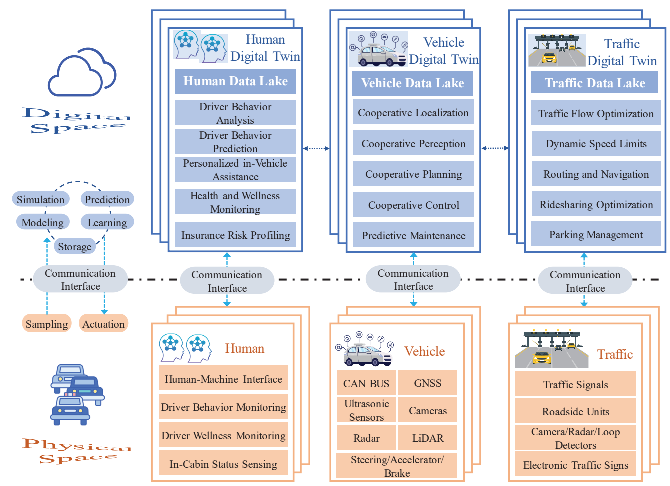

Fig. 5. Illustration of the interaction and coordination of physical/digital ITS.

G. Interaction and Coordination of Physical and Digital ITS

Fig. 5 illustrates a representation of physical and digital ITS, including vehicles, humans and traffic. DT-enabled virtual models of ITS are powered by real-time data from various sensors, enabling continuous interaction and coordination between the physical and digital components of the transportation infrastructure [68]. These virtual models rely on precise, real-time data gathered from a range of sensors such as laser scanners, cameras, and environmental monitors, which capture key parameters like size, shape, and road conditions. This data is constantly fed into the digital models, allowing them to evolve and adapt dynamically in response to changes in the physical world.

The seamless operation of these digital twins is enabled by the interaction between vehicle and infrastructure sensors, including torque, speed, LIDAR, radar, and GPS. These sensors transmit data through advanced communication networks such as 5G, Wi-Fi, and LoRaWAN, ensuring constant synchronization between the physical world and its digital counterpart. Synchronization is critical to maintaining the consistency of data between physical and digital systems, enabling real-time responsiveness and control. Sensor fusion techniques are employed to combine data from multiple sources, improving the accuracy and reliability of the models.

An example synchronization process is depicted in Fig. 6, which illustrates the time synchronization and data exchange between the physical vehicle and its virtual twin. This process ensures that the digital models always reflect the most up-to-date data from the physical system, supporting continuous and dynamic interaction between the physical and virtual components. Through these mechanisms, synchronization is maintained across both local (edge) and global (cloud) layers of the system, ensuring smooth data flow and real-time decision-making.

Advanced analytics, powered by AI and ML, process this data to predict system behavior, detect inefficiencies, and trigger proactive actions. For example, in traffic management, DTs can dynamically adjust traffic signal timing based on real-time traffic flow data, reducing congestion and improving

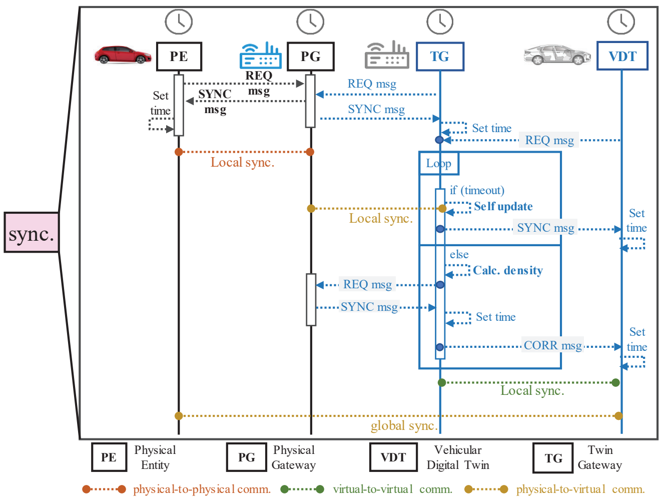

Fig. 6. Synchronization and communication flow between physical and virtual vehicles.

traffic efficiency. This predictive capability allows the system to optimize traffic management strategies on a global scale, adapting to both immediate conditions and long-term patterns.

Additionally, the DT framework interacts with physical control systems, including hydraulic, electrical, and pneumatic actuators, to make real-time adjustments to physical components like traffic signals, barriers, and vehicle routing. This feedback loop ensures that transportation systems are dynamically optimized, responding to changing traffic conditions, accidents, and environmental factors.

The success of DT technology in ITS relies on the interdisciplinary collaboration between fields such as mechanical engineering, data science, and communication technologies. Sensors collect essential data, communication networks transmit it across the system, AI/ML models analyze the information, and control systems execute the necessary adjustments. This continuous interaction enables real-time system optimization, while also laying the foundation for long-term improvements in the overall efficiency and resilience of ITS infrastructures.

III. Digital Twins for Vehicle Safety

This section provides a comprehensive overview of the role of DT technology in enhancing vehicle safety. It begins by identifying the key challenges in vehicle safety, followed by the potential applications of DTs in vehicle safety and a state-of-the-art review of existing implementations. Then, the section discusses the critical aspects of security and privacy in vehicular systems. Lessons learned from vehicle safety applications of DTs are presented, highlighting both successes and challenges to guide future developments in this field.

A. Overview of Vehicle Safety Challenges

Vehicle safety in CAVs and ITS depends on reliable, secure, and timely data communication across vehicles, infrastructure, and users. It must address challenges in data transmission, network reliability, real-time processing, and sensor integration to ensure effective safety mechanisms.

1) Technological Challenges in Data Communications: CAV safety relies heavily on sensor systems, secure V2X communications, and real-time data processing algorithms. Sensors such as LiDAR, radar, and cameras transmit data with high fidelity, but their performance can degrade in adverse conditions. For example, LiDAR's accuracy drops by up to 60% in dense fog, impacting the data shared across networks [69]. Additionally, V2X communications are vulnerable to cyber-attacks (e.g., denial-of-service or malware), which threaten vehicle operations and inter-vehicle communication [70]. Given the reliance on continuous data for safe operation, such threats are critical. Furthermore, real-time processing demands stable networks with minimal latency to handle tasks like adaptive control algorithms [71].

2) Network-Dependent Interaction with Infrastructure: Effective CAV safety requires a reliable V2X infrastructure, especially in diverse geographical areas. Variations between urban and rural infrastructures impact V2I communication, limiting coordination efforts [72]. Accurate, real-time mapping and network-supported localization are crucial for navigation and incident prevention. Failures in mapping systems, as shown by the 2018 Uber incident, underline the importance of precise geolocation data [73]. Additionally, interoperability issues with protocols such as DSRC and C-V2X hinder seamless connectivity, which is critical for real-time safety interventions [74].

3) Human Factors and Network-Based Situational Awareness: In semi-autonomous CAVs, human factors like driver engagement and situational awareness are vital for safety. Network feedback and data-driven alerts can mitigate risks from driver disengagement, but over-reliance on automation can delay human response times, as seen in the "mode confusion" of the 2018 Uber crash [75]. Reliable data communication ensures smooth transitions between manual and automated control [76]. Trust in CAV systems is shaped by the perceived reliability of communication-based safety features [77].

DT technology enables real-time, network-centric data communications for predictive maintenance, diagnostics, and resilient operations. By integrating V2X data streams with diagnostic models, DTs facilitate early detection of system failures. While intelligent processing may introduce some delay, DTs ultimately reduce response times by enabling proactive actions and enhancing vehicle reliability through continuous monitoring.

B. Potentials of Digital Twin Technology for Vehicle Safety

DT technology transforms vehicle-safety management from a data-driven paradigm, where the network merely transports sensor streams, into a state-driven, twin-centric paradigm in which each physical entity is mirrored by a continuously-synchronized virtual replica. This architectural shift enables network-visible "twin states" to flow bidirectionally across V2X links, edge nodes, and the cloud, supporting predictive maintenance, real-time diagnostics, and resilient, cooperative vehicle operations that conventional information systems cannot achieve.

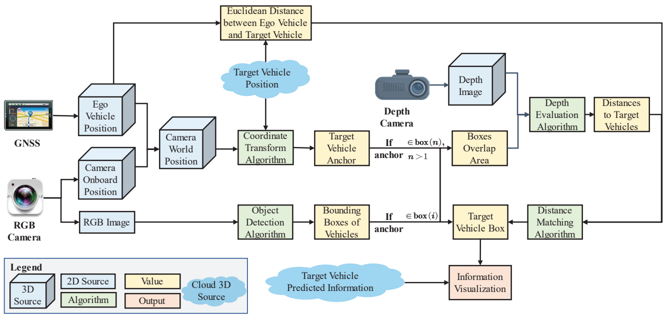

Fig. 7. DT-enhanced sensor fusion: live camera data are fused with cloud twin information to extend perception and prediction.

1) Enhancing Safety Features through Digital-Twin Integration: From reactive fusion to predictive fusion. Traditional sensor-fusion pipelines depend solely on instantaneous onboard measurements, limiting foresight to the sensor horizon. As shown in Fig. 7, a DT-enabled pipeline combines live sensor data with historical patterns and predictive analytics maintained in cloud/edge twin servers. This twin-assisted context enriches object classification, trajectory forecasting, and hazard anticipation. The outcome is earlier activation of safety-critical functions, e.g., automatic emergency braking (AEB) and evasive steering, than is possible with sensor-only or cloud-AI systems.

Emergency braking: network-aware, twin-driven. Traditional AEB systems react only when local sensors detect an imminent threat, often constrained by sensor range and environmental factors. In contrast, a DT-aware AEB continuously maintains a synchronized virtual replica of the vehicle and its surroundings, updated in real time through V2X telemetry and infrastructure-integrated digital twins. This enables the system to compute time-to-collision (TTC) estimates across multiple hypothetical scenarios and dynamically adjust braking profiles in advance. By exchanging twin-state information with neighboring vehicles and roadside units, coordinated braking strategies can be applied to handle cut-ins, sudden stops, or multi-vehicle hazard patterns. Although this approach introduces additional computation, edge-hosted DT instances and prioritized communication channels ensure that decision latency remains within acceptable safety bounds.

2) Optimizing Traffic Flow and Network-Aware Safety Interventions: DTs raise traffic management from reactive to proactive. Continuous twin updates allow the system to forecast queue build-up, then broadcast lane-changing, speed-harmonization, or rerouting instructions before congestion materialists. Unlike post-hoc measures in conventional ITS, twin-centric prediction lowers secondary-collision rates and dampens stop-and-go waves in dense traffic [78].

3) Digital-Twin-Enabled Virtual Prototyping and System Resilience: The framework in Fig. 8 shows how DTs support design-time virtual prototyping. Simulated V2X stresses and fault injections reveal weaknesses early, allowing refinement of safety algorithms and network protocols before on-road deployment [79]. Although additional simulation time is required, downstream risk and recall costs are markedly reduced.

4) High-Fidelity Scenario-Based Testing for Autonomous Vehicles: As depicted in Fig. 9, DTs synthesize rare, safety-critical scenarios (e.g., road-work occlusions, extreme weather) that would be risky or costly to reproduce physically. Real-time V2V/V2I emulation allows AV algorithms to adjust policies on the fly, yielding more robust deployment readiness.

5) Predictive Maintenance and Fault Detection in Real Time: DTs blend physics-based models and streaming analytics (Fig. 10) to catch anomalies, e.g., incipient bearing wear—before failure. Continuous twin-state evaluation reduces unplanned downtime and accident risk [79]. Edge-level execution ensures detection latency stays within operational constraints.

6) Adaptive Network Management in Vehicular Edge Computing: The dual-loop DT framework in Fig. 11 feeds inner-loop performance metrics (e.g., channel quality, queue length) to an outer-loop optimizer, which reallocates spectrum, compute, and storage resources based on predicted twin workloads. This network-aware orchestration guarantees low-latency delivery of safety-critical messages even under heavy load, a capability unattainable by static slice configurations.

C. Digital Twin Applications for Vehicle Safety: A State-of-The-Art Review

This subsection reviews the applications of DT technology in enhancing vehicle safety, focusing on its role in real-time monitoring, predictive maintenance, and risk mitigation for CAVs. It covers advancements in sensor fusion, collision avoidance, and virtual safety testing, demonstrating how DTs, in conjunction with professional technologies, are transforming vehicle safety practices.

1) Enhancement of Vehicle Safety Features and Operations: Advances in sensor technology, advanced driver assistance systems (ADAS), and predictive algorithms have enabled the integration of DT technology into ITS, significantly enhancing vehicle safety. DTs provide real-time simulation, continuous monitoring, and proactive safety mechanisms, contributing to operational efficiency and improved decision-making processes in CAVs. By merging physical vehicle systems with digital counterparts, DTs offer dynamic feedback to ensure the timely and accurate response to potential risks, ultimately improving safety outcomes.

Several studies have demonstrated how DTs can enhance vehicle safety in CAVs by leveraging various approaches. Liu et al. [80] emphasize the role of sensor fusion in improving decision-making, combining real-time sensor data with cloud-based DTs for enhanced situational awareness and object detection. Similarly, Wang et al. [81] highlight the use of DTs in conjunction with 5G technology to predict traffic flow, effectively reducing network inefficiencies and improving overall traffic management. Kumar et al. [82] further decentralize traffic management by integrating DTs with edge analytics, facilitating real-time modeling of driver behavior and minimizing latency.

For addressing distracted driving, Ma et al. [83] develop a DT framework that integrates cognitive indicators for detecting distracted driving behaviors, as shown in Fig. 12.

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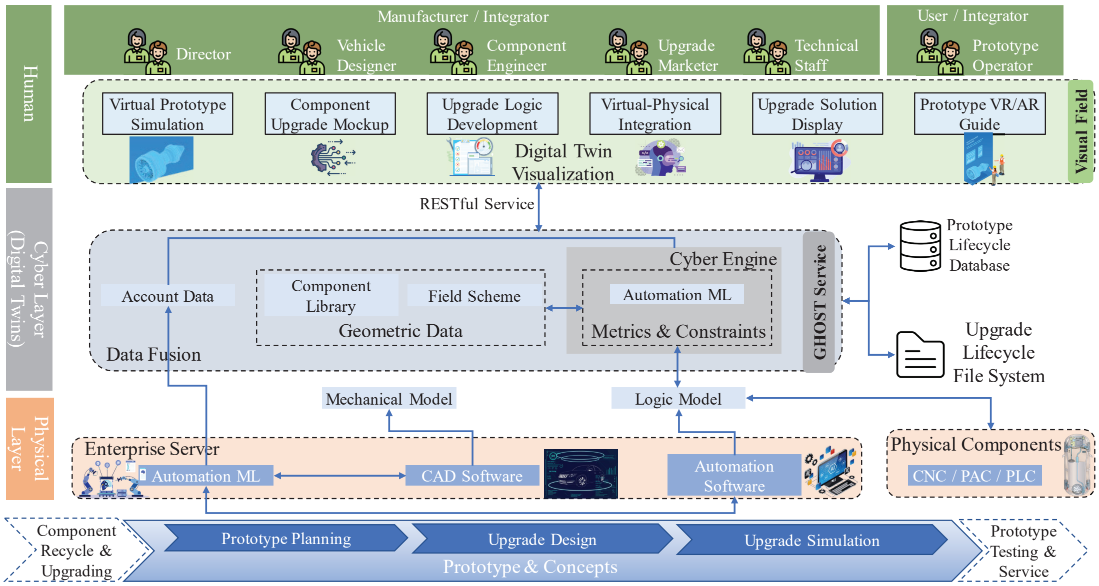

Fig. 8. DT framework for virtual prototyping and component upgrades.

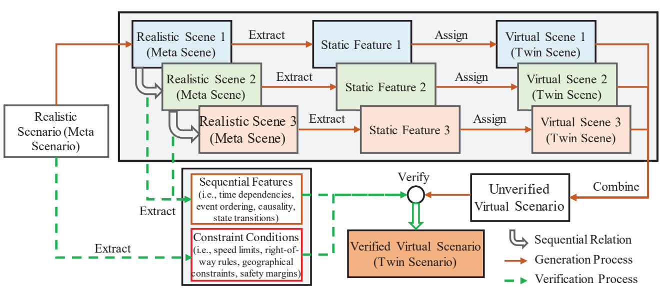

Fig. 9. Twin-scenario generation for autonomous-vehicle testing.

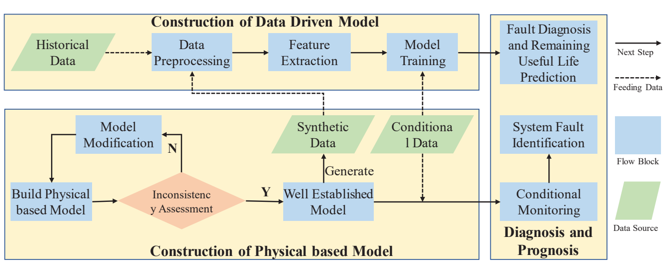

Fig. 10. Predictive-maintenance workflow in a DT environment.

Their approach uses a transformer-based model, incorporating temporal dynamics and the driver's cognitive state, with a pseudo-labeled multi-task learning technique for improved detection accuracy. This method allows real-time identification of driver distractions, a key factor in preventing accidents caused by inattentiveness.

In enhancing lane-change safety, Liao et al. [84] personalize DTs to predict lane-change behavior and improve situational awareness in CAVs. They used an inverse reinforcement learning (IRL) framework to personalize predictions for individual drivers, which enables more accurate trajectory planning and decision-making. Additionally, the authors in [85] introduce a DT-as-a-Service (DTaaS) architecture with blockchain integration, ensuring secure and efficient transactions across ITS, an essential component for ensuring privacy and data security in autonomous vehicle systems.

Shadrin et al. [86] further demonstrate the utility of DTs for real-time monitoring and diagnostics, where they apply continuous data analysis to ensure the reliability and safety of highly automated vehicles. By integrating predictive maintenance features, they enable early fault detection and system recalibration before failures occur. Lv et al. [87] utilize DTs in a VR-based simulation platform for traffic accident prediction, enabling comprehensive risk assessments and improved safety protocols.

Duan et al. [88] showcase the effectiveness of DTs in scenario-based testing by simulating critical conditions such as emergency braking, where vehicle performance is evaluated in various hazardous contexts. Their use of DTs with LTE-V2X allows for the simulation of real-time data synchronization between vehicles, improving safety in high-risk scenarios. Fig. 13 illustrates the personalized lane-change behavior modeling process, which includes an offline learning phase for developing a neural network model and an online prediction phase for real-time application.

To prevent collisions and enhance safety, Tang et al. [89] combine DTs with federated learning techniques to optimize collision warning systems, reducing false alarms and improving the system's decision-making capability. Similarly, Du et al. [90] focus on platooning, utilizing DTs to predict vehicle trajectories and improve group driving dynamics, enhancing safety and fuel efficiency in platoon-based vehicle systems. Wang et al. [91] implement internet of vehicles (IoV)-integrated DTs to analyze driver behavior patterns and predict dangerous zones for collision risk. Their approach helps identify high-risk areas and provides preemptive warnings to nearby vehicles and pedestrians, reducing the chances of

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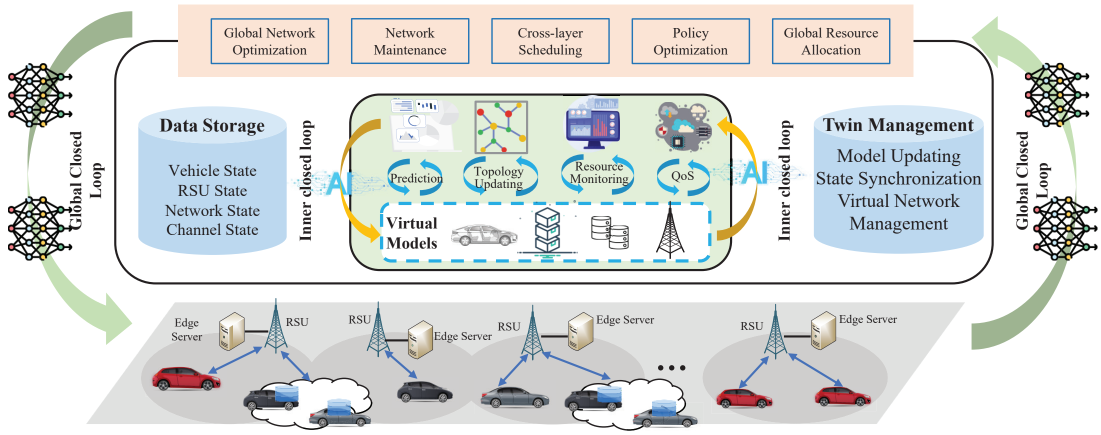

Fig. 11. Adaptive DT-enabled vehicular edge-computing network.

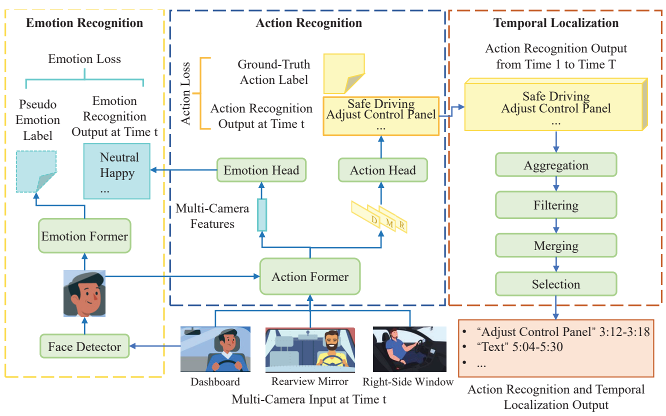

Fig. 12. Driver Digital Twin framework for online recognition of distracted driving behaviors.

accidents in busy environments.

Table III consolidates the reviewed studies that showcase the diverse applications of DT technology in enhancing vehicle safety. Each solution in the table employs DTs in different ways, focusing on functions such as data fusion, driver behavior monitoring, and trajectory prediction. These DT-driven functions contribute to critical safety features, including collision prevention, traffic flow optimization, and enhanced situational awareness. To help identify the most suitable solutions based on specific needs, the table examines the optimization techniques employed in these studies, including machine learning, deep learning, and federated learning. Additionally, the validation methods used, including simulations and real-world testing, provide valuable insights into the robustness of each solution in practical environments.

2) Simulation and Testing of Safety Scenarios: Simulating and testing safety scenarios in virtual environments is a cornerstone for ensuring the safety and reliability of autonomous and connected vehicles. The integration of DT technology significantly enhances the precision and comprehensiveness of safety testing by creating high-fidelity virtual models that mirror real-world conditions. These virtual models allow for the simulation of complex, dynamic environments and enable testing of safety-critical scenarios that would be challenging, costly, or hazardous to replicate in the physical world.

In their work, Hou et al. [92] leverage DT-generated meta-scenarios to improve the safety of the intended functionality (SOTIF) assessments for autonomous trucks. This method uses high-fidelity twin scenarios that simulate real-world conditions, enhancing hazard detection capabilities. Similarly, Hong et al. [93] integrate fuzz testing with DTs to dynamically test the safety of electronic components in real-time, uncovering potential failures under varied operational scenarios. Formal methods also play a critical role in safety validation, as demonstrated by Fremont et al. [94], who combine scenario specifications with simulation-based verification to rigorously test AV behaviors.

For dynamic testing of AV behaviors, Li et al. [95] introduce a genetic algorithm-based framework that explores and exposes safety violations, while Chen et al. [96] enhance collision prevention systems by sharing behavioral models among connected vehicles. In highway safety, Liu et al. [97] integrate DTs with unmanned aerial vehicle (UAV) data to monitor traffic flow and assess risks at critical highway sections. Qu et al. [98] further advance crash detection by merging macro and micro traffic data in real-time to improve safety management on expressways.

Table IV presents an overview of the reviewed studies that utilize DT-enabled simulation and testing in autonomous vehicles. The table details key DT functions such as scenario generation, real-time monitoring, formal verification, and model sharing, each playing a crucial role in enhancing safety assessments, hazard detection, and collision prediction. By leveraging DTs, these studies enable comprehensive testing across a wide range of simulated environments, identifying potential safety risks and vulnerabilities that may not be evident in real-world conditions. For example, scenario generation allows testing under extreme or rare conditions, while real-time monitoring ensures continuous system evaluation. Formal verification techniques ensure compliance with safety standards, and model sharing fosters collaboration and coordination between connected vehicles. These studies also utilize simulators like UPPAAL, Apollo, and SUMO to validate DT-driven safety functions. These simulators enable dynamic test-

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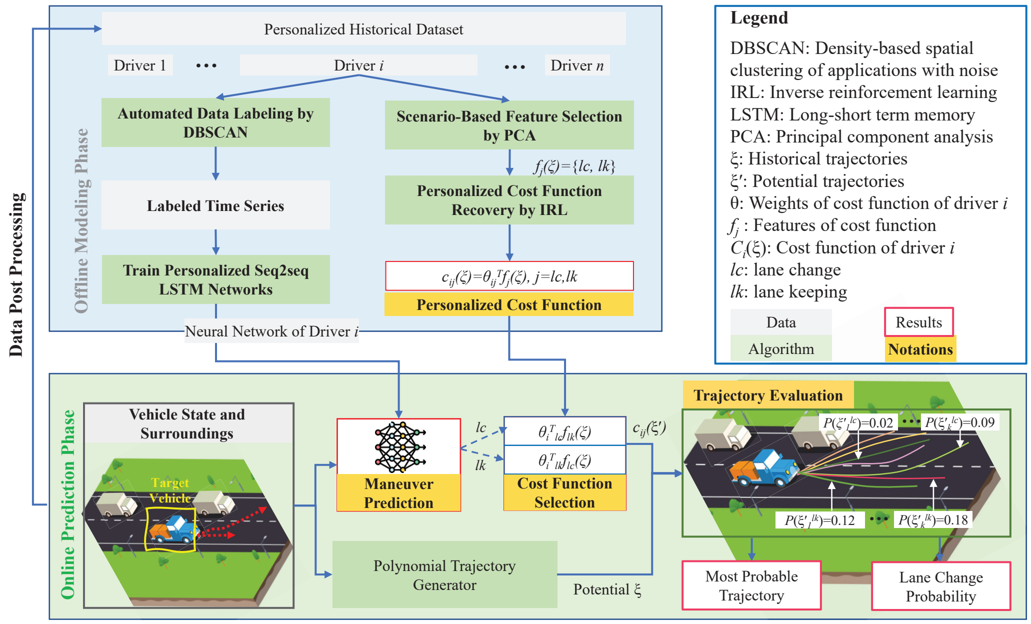

Fig. 13. Personalized lane-change behavior modeling: offline learning and online prediction.

TABLE III
REVIEW OF VEHICLE SAFETY FEATURES AND OPERATIONS ENHANCED BY DIGITAL TWINS.

Ref.	DT Functions and Effects	Safety Feature Enhanced	Optimization Techniques	Validation Methods	Simulators
[80]	Fusion of camera and cloud data for object detection and situational awareness in real-time	Object detection and situational awareness	YOLOv3 for localization and classification	Human-in-the-loop simulation, real-world testing	Unity
[81]	DTs simulate near-collision scenarios for low-speed collision prevention	Collision detection and prevention	CNN with spatial attention for fine-grained detection	Real-world testing, deep learning training	N/A
[82]	DTs simulate traffic flow and driver intentions for congestion reduction	Traffic management and congestion avoidance	Coalition game algorithm, ML/DL for traffic prediction	Real-world and simulation-based testing	SUMO
[83]	DTs model driver mental state to detect distractions and enable timely intervention	Driver behavior monitoring for distraction prevention	Multitask learning, CNN, ViT for context detection	Data aggregation and localization tasks on SynDD2 dataset	N/A
[84]	DTs predict lane-change behavior to improve safety	Lane-change safety and prediction	Inverse reinforcement learning, Seq2seq LSTM	Field experiments, edge-cloud validation	Unity, SUMO
[85]	Blockchain-based DTs for secure communication and data integrity in ITS	Security and data privacy in ITS	Double-auction model, DT-DPoS consensus	Simulation-based validation	N/A
[86]	DTs monitor automated vehicles for diagnostics and safety evaluation	Vehicle reliability and operational safety	ML for diagnostics, statistical analysis	Field tests, virtual testing	Siemens Prescan, MATLAB/Simulink
[87]	DTs use VR simulations for accident prediction and safety evaluation	Accident prevention and safety assessment	LSTM, BI-LSTM for traffic prediction	VR-based simulations for safety prediction	CityEngine, Civil3D, GIS
[88]	DTs simulate hazardous scenarios for vehicle dynamics and collision avoidance	Vehicle performance and collision avoidance	Kalman filtering, fault tree analysis	Field tests, virtual safety validation	PanoSim, NVIDIA DRIVE PX
[89]	DTs optimize collision warnings and response in dynamic environments	Collision warning accuracy and response time	A3C-based federated learning, GRU-SVM for warning models	Real-time data synchronization using NGSIM dataset	Pytorch
[90]	DTs predict vehicle trajectories for platooning and collision avoidance	Safe platooning and collision avoidance	deep Q-networks (DQN), LSTM for trajectory prediction	Simulations with KITTI datasets	Python
[91]	DTs predict driver behavior and hazards for IoV applications	Collision and hazard warnings for IoV	K-means for classification, Random Forest for prediction	Simulation, real-world testing	MATLAB, SUMO

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TABLE IV
REVIEW OF DIGITAL TWIN-EMPOWERED AUTONOMOUS VEHICLE SIMULATION AND TESTING.

Ref.	DT Functions and Effects	Safety Feature Enhanced	Optimization Techniques	Field/ Simulation Setup	Simulators
[92]	Model real-world traffic and environmental scenarios for hazard detection and SOTIF assessment	Enhanced hazard detection and safety assessment	Formal verification using UPPAAL	Autonomous trucks in diverse traffic scenarios	UPPAAL
[93]	Simulate failure conditions via fuzz testing, detecting vulnerabilities in unpredictable environments	Improved resilience to edge cases	Fuzzing for failure scenario generation	AVs under network failure conditions	Webots
[94]	Specify realistic scenarios with formal methods for AV safety verification	Improved verification and real-world transition	SCENIC for rigorous simulation-based verification	GoMentum Station for AV testing in traffic	Apollo, SCENIC, VERIFAI
[95]	Simulate critical driving scenarios to uncover safety issues before deployment	Better identification of critical safety risks	Genetic algorithm for failure mode optimization	Testing on Baidu Apollo platform in real-world conditions	Apollo, LGSVL
[96]	Enable model sharing among vehicles for collaborative safety testing	Improved collision risk prediction and coordination	MDP for prediction	Highway driving with connected AVs	MATLAB, MQTT, Unity
[97]	Use UAV data to model highway sections for real-time risk monitoring	Traffic risk assessment and proactive safety management	Data fusion and machine vision for risk detection	Highway scenarios with drone data	Prescan, Vissim
[98]	Fuse macro and micro data for crash detection and traffic updates	Improved crash detection and road response	ThunderGBM for crash prediction, SHAP for explainability	Real-time simulation of Nanjing Ring Expressway	SUMO, PC-Crash

ing of AV behavior, traffic flow, and communication systems under varied traffic conditions, ensuring AVs can handle real-world complexities and risks.

3) Security and Privacy in Vehicular Systems: As vehicular networks grow in connectivity and intelligence, security and privacy challenges become increasingly significant. The integration of DT technology into vehicular systems enhances security by enabling real-time monitoring and decision-making. However, it also introduces new challenges related to data protection, operational integrity, and privacy preservation.

He et al. [99] explore the vulnerabilities of vehicular DTs (VDTs), focusing on secure authentication and blockchain to prevent data manipulation and unauthorized access. In dynamic vehicular environments, Li et al. [100] propose a proxy ring signature technique within 6G V2X networks, ensuring secure handovers and communication during vehicle mobility. Yigit et al. [101] combine DTs and AI for real-time threat detection in vehicular ad-hoc networks (VANETs), addressing distributed DOS (DDoS) attacks and optimizing network resource allocation.

Federated learning has also emerged as a solution to address privacy concerns in DT-based vehicular networks. Khan et al. [102] leverage FL to ensure secure data processing in vehicular applications, while Liu et al. [103] integrate blockchain within DTs to enhance secure, collaborative resource sharing across connected vehicles. Gautam et al. [104] further highlight blockchain's role in securing V2X communications from common cyber threats, promoting data integrity and preventing unauthorized access.

Emerging vehicular metaverse environments introduce unique privacy concerns, particularly regarding user identity and location tracking. Luo et al. [105] propose pseudonym schemes that significantly improve privacy by anonymizing user identity and location within DT-powered vehicular metaverses, increasing privacy protection by 33.8%. For secure data dissemination in the IoV, Kumar et al. [106] combine DTs with blockchain, integrating trust management and intrusion detection systems to further ensure data integrity and privacy.

Table V presents the reviewed studies in the area of enhancing security and privacy in vehicular systems. These studies include secure resource sharing, real-time attack detection, and privacy-preserving techniques, critical for maintaining the integrity and confidentiality of vehicular data. Advanced tools such as blockchain for secure communication, federated learning for privacy-preserving data processing, and RL for dynamic attack mitigation are leveraged to strengthen the resilience of vehicular networks against cyber threats. Validation through simulations and real-world test cases ensures these DT-powered solutions are robust, scalable, and effective in addressing evolving security challenges in connected vehicles. This table helps identify the most suitable DT-based approach depending on specific security needs, such as enhancing data privacy, preventing cyberattacks, or ensuring secure communication in V2X environments.

D. Lessons Learned in Vehicle Safety Applications of Digital Twins

- *Twin-state visibility enhances network-wide safety orchestration.* Practical deployments suggest that the full safety potential of DTs is better realized when each vehicle's twin state (its continuously updated virtual representation) is made accessible to the V2X network. Systems where twin data remains confined within the vehicle often miss opportunities for cooperative perception and coordinated control. Broadcasting lightweight twin-state summaries over low-latency channels and caching them at nearby RSUs or MEC nodes has shown potential for improving multi-vehicle safety responsiveness.
- *Reliable prediction benefits from edge-assisted sensor fusion and calibration.* Field studies highlight that minor misalignment among onboard sensors, such as cameras and LiDAR, can adversely impact prediction accuracy. Integrating self-calibration mechanisms—preferably supported by machine learning techniques—at the network

TABLE V
REVIEW OF VEHICULAR SECURITY AND PRIVACY EMPOWERED BY DIGITAL TWINS

Ref.	DT Functions and Effects	Safety Feature Enhanced	Mathematical Tools	Validation Methods	Simulators
[103]	Enhance secure resource sharing and decision-making across decentralized networks	Secure resource sharing in vehicular networks	Blockchain consensus for integrity	Simulation of network behaviors and trust models	Pytorch
[104]	Apply blockchain for secure vehicle-infrastructure communication, ensuring data integrity	Data integrity and access control between vehicles and infrastructure	Oracle model for data validation	Security assessment under various threat models	N/A
[105]	Use pseudonym schemes to mask real user data, enhancing privacy in vehicular networks	Identity and location privacy for users	Dual pseudonym scheme with privacy-preserving algorithms	Testing pseudonym schemes in different environments	N/A
[107]	Optimize secure communication channels in satellite-terrestrial networks to prevent unauthorized access	Secure communication in satellite-terrestrial networks	SDR and SDP for secure channel establishment	Validation of secure transmission across satellite-terrestrial links	N/A
[108]	Apply federated learning for privacy-preserving training, maintaining data confidentiality	Privacy preservation in collaborative training	Federated learning with differential privacy	Experimentation with Minst and Fmnist datasets under privacy constraints	Python, PyTorch
[109]	Enhance V2G cybersecurity by detecting and mitigating threats via AI-based analysis	Attack detection and mitigation in V2G systems	LSTM-based deep reinforcement learning (RL) for threat detection	Case studies and simulations for attack validation	MATLAB, Python
[110]	Improve optical wireless communication security using adaptive decision feedback to prevent eavesdropping	Communication security in vehicular systems	CNN with adaptive feedback for signal integrity	Real-time hardware testing for communication evaluation	VPI transmission Maker
[111]	Simulate safety scenarios to analyze attack/failure modes and assess system risks	Safety assessment in critical vehicular systems	Safety scenario simulation for vulnerability assessment	Use case testing with failure scenarios for resilience	ViSE platform
[106]	Ensure secure data transmission by integrating blockchain with intrusion detection systems (IDS)	Data security and integrity in vehicular networks	Blockchain and deep learning-based IDS	Simulation to validate trust management under attack scenarios	TensorFlow, Ethereum Rinkeby
[112]	Evaluate and enhance trustworthiness in communication between vehicles and infrastructure	Trust and security in vehicular communication	Reputation Trust Framework (RTF) for evaluation	Simulation of vehicular communication using real-world data	SUMO, NS2
[113]	Apply blockchain and smart contracts for secure smart parking, preserving vehicle data privacy	Privacy and data security in smart parking systems	Blockchain and smart contracts for secure interactions	Proof of concept for secure parking management	Hyperledger Fabric
[114]	Enable shared steering control and dynamic risk assessment to improve vehicle safety	Risk assessment for driver and vehicle safety	Multi-objective MPC for safety optimization	Simulation of driving scenarios to validate control adjustments	SILAB, Matlab/Simulink

edge, where raw sensor data is still available and latency is minimal, has proven effective. Additionally, combining local sensor inputs with distributed twin-state data can improve detection robustness in environments with poor visibility or sparse infrastructure.

- *Twin synchronization latency affects control reliability.* Case studies involving emergency braking and evasive maneuvers indicate that delays in updating digital twins can lead to suboptimal or even unsafe actuation. Maintaining tight synchronization between the physical and digital layers—through techniques such as hardware time-stamping, predictive updates, and communication-efficient encoding—helps reduce this mismatch and supports more reliable real-time control.
- *Coordinated safety performance requires system-level optimization.* Treating functions like collision avoidance, lane-keeping, and adaptive cruise control as separate modules can result in conflicting behaviors, especially in dense or dynamic traffic. Embedding these features within a unified DT framework and applying model-based predictive control techniques has been observed to yield more balanced, coordinated safety responses, avoiding unnecessary mode switching or instability.
- *Edge–cloud task distribution should reflect real-time constraints.* Experiences from prototype fleets suggest that offloading all DT tasks to the cloud can strain communication infrastructure and introduce critical delays. A more effective approach involves allocating time-sensitive tasks—such as collision risk estimation or sensor fusion—to edge nodes, while offloading longer-term analytics and what-if simulations to cloud services. This layered distribution balances responsiveness and computational scalability.

IV. DIGITAL TWINS FOR TRAFFIC MANAGEMENT

This section examines the application of DT technology in the context of traffic management. It begins by outlining the major challenges faced in current traffic management systems, followed by an exploration of the potential of DT technology to address these issues. A comprehensive review of the state-of-the-art applications of DTs in traffic management is provided, showcasing the advancements and use cases that have been implemented to date. The section concludes with a discussion on the lessons learned from traffic management applications of DTs, emphasizing the successes and limitations in this field.

A. Overview Traffic Management Challenges

Urban traffic control has evolved from static, manual operations to AI-driven real-time optimization, shifting the focus from fixed-time control to dynamic flow management. Integrating traffic signals with vehicle communication systems has improved interactions between conventional and autonomous vehicles, as shown in Fig. 14. Effective traffic management in CAV and ITS environments requires highly reliable data communications for safe, coordinated vehicle interactions. However, latency, network congestion, and data integrity remain significant obstacles in high-density urban environments.

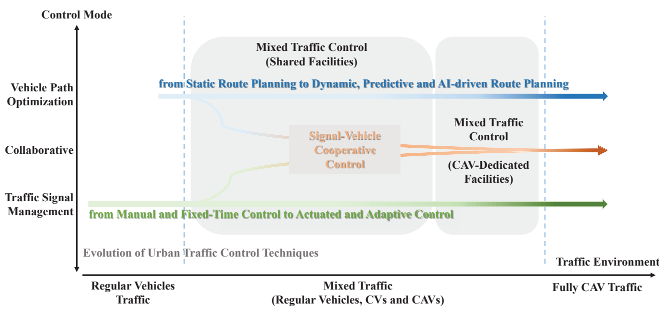

Fig. 14. Evolution of urban traffic control techniques.

1) Latency Constraints in Real-Time Data Exchange: A major challenge in traffic management for CAVs and ITS is ensuring ultra-low latency for real-time data exchange. These systems depend on continuous data streams for immediate decisions, particularly in high-density urban environments. Even minimal delays caused by network congestion or signal propagation issues can disrupt synchronization and delay critical interventions like emergency braking or adaptive routing.

2) Network Congestion in High-Density Traffic Scenarios: As CAVs become more prevalent, especially in urban areas, the data exchanged through V2X networks increases rapidly. This surge can overwhelm network bandwidth, leading to congestion, packet loss, higher latency, and reduced data fidelity. Such congestion undermines the accuracy and timeliness of traffic management, impeding effective real-time coordination and optimization.

3) Reliability and Resilience in Networked Traffic Systems: The effectiveness of CAV and ITS traffic management relies on the resilience of network communications, particularly during disruptions or network failures. Traffic management systems must handle data surges, environmental interference, and network failures common in urban settings. Current V2X networks often lack sufficient resilience, resulting in lapses in data availability and quality, thereby hindering real-time response to shifting traffic conditions.

4) Data Integrity and Quality Control in Real-Time Networks: Maintaining high data integrity is crucial for accurate decision-making in traffic management systems. However, network-induced errors such as packet loss, jitter, and interference degrade data quality, affecting the reliability of exchanged information. These errors can lead to inaccurate predictions and unsafe responses, particularly in critical applications like collision avoidance and congestion forecasting. Ensuring data consistency across fluctuating network conditions remains a key challenge.

5) Coordination Complexity with High Data Volume and Velocity: Traffic management in CAV and ITS environments involves processing large volumes of data at high speeds to monitor patterns, predict congestion, and control signals dynamically. Coordinating and synchronizing these data streams in real-time introduces significant complexity, particularly when integrating multiple data sources across decentralized networks. This can strain network bandwidth and processing power, delaying responses and affecting the accuracy of time-sensitive applications.

B. Potentials of Digital Twin Technology for Traffic Management

DTs bring three fundamental strengths to traffic management that conventional sensor–cloud architectures struggle to deliver: (i) holistic, real-time perception of the entire road network; (ii) predictive control that anticipates, rather than reacts to, congestion and incidents; and (iii) closed-loop orchestration that continuously aligns physical infrastructure and communication resources with evolving demand. The following subsections clarify how these strengths translate into tangible operational gains.

1) Unified, High-Fidelity Network Perception: DTs aggregate live V2X telemetry, i.e., vehicles, RSUs, signal cabinets, CCTV, and enrich it with static topology and historical patterns. The resulting "city twin" maintains a time-synchronized view of speed, density, and queue length on every road segment. Edge-hosted sub-twins enable intersection controllers to detect detector failure or sudden demand spikes almost instantly, while the cloud instance blends local snapshots into a coherent metropolitan picture. Compared with siloed loop-detector feeds, this unified perception exposes hidden bottlenecks (e.g., spill-back from downstream intersections) and supports more informed control decisions.

2) Predictive, Simulation-Driven Traffic Control: Continuous what-if simulation on the digital model allows operators to forecast queue formation, crash risk, or bus bunching several minutes in advance. The controller can then enact preventative measures (phase re-splits, offset shifts, dynamic lane reassignment) before queues materialise. Field pilots report lower average delay and fewer secondary crashes than fixed-time or actuated plans that respond only after congestion is observed.

3) Network-Aware Resource Orchestration: Because DT workloads are network-visible, an SDN/NFV orchestrator can tailor slices to task urgency: URLLC channels carry safety-critical signal updates; eMBB links transport low-priority CCTV archives. Such cross-layer alignment of compute, storage, and bandwidth reduces packet loss, maintains deterministic latency for control loops, and avoids over-provisioning.

4) Virtual Testbed for Policy Experimentation: Cloud-hosted DT instances form a non-intrusive sandbox for event traffic, road-closure plans, or evacuation strategies. Engineers can iterate on control scripts, validate outcomes, and only then deploy the proven schedules to edge controllers, minimising disruption and political risk.

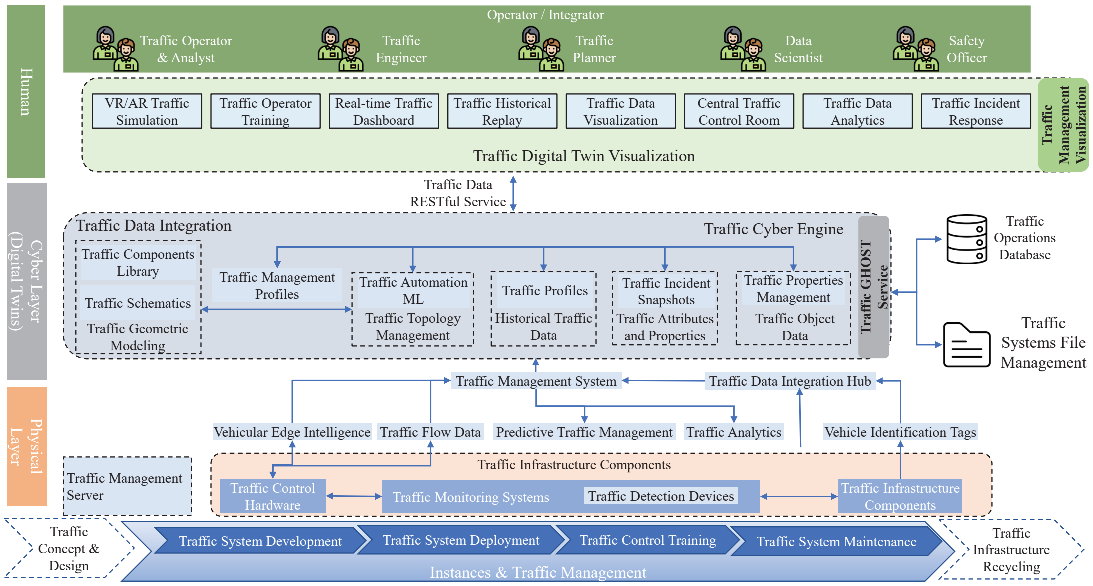

Fig. 15. Integrated Digital-Twin framework for network-centric traffic management and operations

5) Continuous Anomaly Detection And Rapid Incident Recovery: Embedded ML models compare live conditions against the twin's predicted baseline. Significant deviations—sudden speed drops, atypical queue growth—trigger automatic incident responses: rerouting advisories, dynamic speed limits, emergency-vehicle pre-emption, and recalibrated signal timings. This swift loop shortens incident duration and mitigates network-wide shockwaves.

C. Digital Twin Applications for Traffic Management: A State-of-The-Art Review

This subsection provides a state-of-the-art review of the applications of DT technology in traffic management, focusing on its role in optimizing traffic flow, improving signal control, and enhancing the management of transportation infrastructure. The review highlights recent advancements and real-world applications of DTs across different traffic management strategies, illustrating their potential to revolutionize urban transportation systems.

1) Traffic Signal Control and Optimization: DT technology provides a sophisticated framework for real-time traffic signal control and optimization by synchronizing sensor and camera data with a virtual traffic model. Unlike traditional static signal systems, DT-based frameworks enable dynamic adjustments to signal timings based on real-time traffic conditions, thereby improving traffic flow and reducing delays, especially during peak traffic hours. This adaptability offers a substantial improvement over fixed-time control strategies, which are less responsive to fluctuations in traffic demand.

Recent studies have highlighted the effectiveness of DT-based traffic signal control. For instance, Dasgupta et al. [115] propose an adaptive signal control framework utilizing real-time vehicle trajectory data to enhance the performance of urban intersections. Similarly, Shams et al. [116] introduce a DT-powered signal controller that optimizes signal phase lengths by analyzing real-time vehicle trajectories, improving intersection performance. Furthermore, Wang et al. [117] employ genetic algorithms within a DT framework to optimize signal timing in urban road networks, achieving improved traffic flow and reduced vehicle emissions.

DT frameworks also enable the deployment of decentralized and multi-agent systems for traffic management. Kumarasamy et al. [118] advocate for a decentralized, multi-agent reinforcement learning (MARL) model that learns dynamic traffic patterns and adapts in real-time. This approach leads to significant reductions in fuel consumption and congestion. Kamal et al. [119] integrate DTs with deep reinforcement learning (DRL) to optimize traffic signal control, demonstrating potential environmental benefits, such as reduced fuel consumption and emissions. These contributions underscore the dual benefit of DTs in improving both traffic flow and environmental sustainability.

The integration of DTs in traffic signal control not only improves operational efficiency but also supports environmentally conscious traffic management. By optimizing traffic flow, DT systems reduce fuel consumption and emissions, contributing to greener transportation systems. Fig. 16 illustrates the DT-based adaptive traffic signal control framework [115], which integrates real-time vehicle data, algorithmic assessments, and simulation environments to predict and control traffic flow. This model allows for dynamic adjustments in response to varying traffic conditions, enhancing the overall performance of urban intersections.

Table VI summarizes the reviewed studies on DT-based traffic signal control, highlighting deployment scenarios such as urban intersections, corridors, and multi-intersection networks. The table provides insights into how DT technology is applied across diverse traffic management settings, assessing key performance metrics such as delay reduction, traffic flow, travel time, and emission reductions. These studies employ various validation methods, including simulations conducted with tools like SUMO, VISSIM, and CTwin, providing quanti-

TABLE VI
REVIEW OF DIGITAL TWIN-AIDED TRAFFIC SIGNAL CONTROL AND OPTIMIZATION

Ref.	Deployment Scenarios	DT Applications	DT Data Sources	Performance Metrics	Validation Methods	Simulators
[115]	Urban intersections	Adaptive control, real-time signal adjustments	Vehicle trajectory, V2X data	Delay reduction, throughput	Simulation	SUMO
[116]	Intersections	Trajectory-based signal control, phase optimization	RADAR, LiDAR, vehicle trajectories, sensors	Phase optimization, reduced delay	Field trial	VISSIM, GBSC
[117]	Urban road networks	Signal timing optimization based on environmental data	Environmental data, weather, traffic history	Improved signal timing, lower emissions	Simulation	SUMO
[120]	Urban traffic system	Real-time control, dynamic signal adjustments	IoT sensors, vehicle positioning, V2I data	Reduced congestion, improved fuel efficiency	Field trial	CTwin platform
[119]	Multi-intersection road networks	DRL-based signal control powered by DTs	Traffic data, V2X communication	Reduced travel time, fuel consumption	Simulation	SUMO
[118]	Smart corridor	MARL-based signal optimization with DTs	Archived data, traffic sensors, GPS	Enhanced Eco PI, reduced stop delays	Simulation	PTV-Vissim

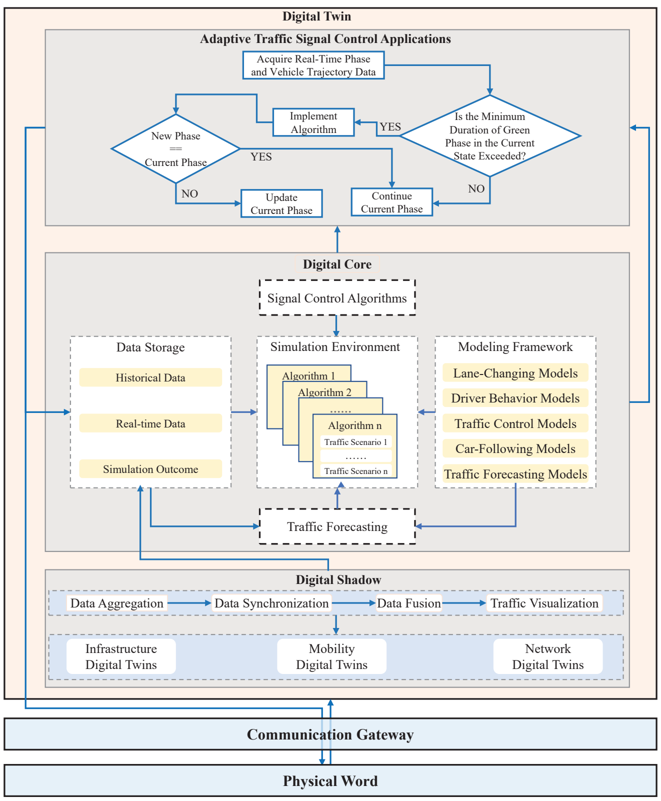

Fig. 16. Illustration of traffic Digital Twin based adaptive traffic signal control.

tative evidence of the impact of DTs on traffic optimization. By comparing these studies, we can identify the most effective DT configurations for specific use cases, whether optimizing signal timings, improving fuel efficiency, or reducing congestion in high-density environments. The table also highlights the integration of real-time data and machine learning models, demonstrating how DTs adapt to changing traffic conditions and enhance system performance.

2) Transportation Traffic Prediction and Management: DT technology has significantly transformed the field of transportation traffic prediction and management by creating dynamic virtual models of traffic networks that are continuously updated with real-time data from sensors, cameras, and GPS systems. This integration enables DTs to enhance traffic predictions and facilitate proactive management strategies in real time.

In traffic prediction, DTs leverage advanced ML algorithms to analyze both historical and real-time data, allowing for the identification of recurring traffic patterns and more accurate flow forecasts. Saroj et al. [121] demonstrate the potential of combining DTs with reinforcement learning to optimize traffic signal timings, leading to substantial improvements in fuel efficiency and reductions in travel time within the Chattanooga MLK Smart Corridor. In another example, Kuvsic et al. [122] utilize DTs for real-time mirroring of the Geneva motorway, enabling immediate responses to disruptions such as accidents or road blockages.

Furthermore, DTs offer a platform for testing and evaluating traffic management strategies within virtual environments. For instance, Ji et al. [123] employ Conv-LSTM networks within a DT framework to predict urban congestion following accidents, demonstrating the ability to test different mitigation strategies without physically implementing them on the road. Collaborative DT platforms also facilitate multi-stakeholder coordination in traffic management. Argota et al. [124] exemplify this by using agent-based simulation and mobile data to manage traffic flow in Barcelona, enabling multiple entities to coordinate efforts for optimal traffic flow and safety.

The iterative nature of DTs allows for continuous refinement of traffic management algorithms. Thonhofer et al. [125] showcase the adaptability of DTs in cooperative automated mobility systems, where real-time feedback optimizes system safety and performance. Additionally, specialized traffic scenarios, such as tunnel management, are effectively addressed with DTs, as Zhao et al. [126] illustrate through the integration of dynamic lighting systems to enhance safety in tunnels.

3) Smart City and Infrastructure Management: DTs are essential in the development of smart cities, as they enable the integration of data across various urban infrastructure domains, including transportation, energy grids, and public safety systems, into a unified virtual representation. This integration facilitates predictive maintenance, extends asset lifespans, and reduces maintenance costs while enhancing public safety through real-time situational awareness, particularly in emergency and disaster scenarios.

Liu et al. [127] highlight the use of a lightweight DT framework for optimizing urban mobility and traffic safety, integrating sensors and algorithms for real-time decision-making. Consilvio et al. [128] propose a DT-based system for road maintenance that utilizes AI clustering techniques

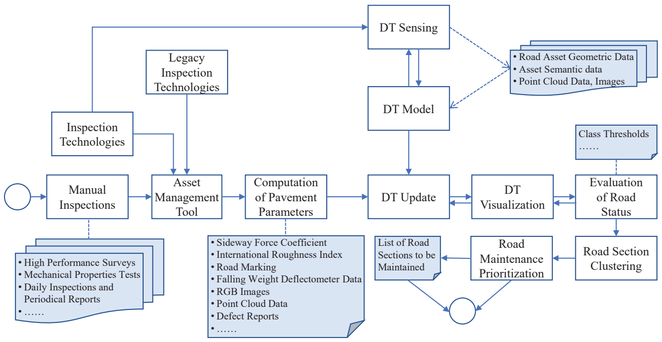

Fig. 17. Workflow for Digital Twin-supported road pavement maintenance.

to efficiently manage resources and monitor road conditions, as illustrated in Fig. 17. In a similar vein, Hidayat et al. [129] present a DT framework integrated with IoT and big data analytics for infrastructure management in Indonesia, improving maintenance planning and resource allocation.

DTs are also applied to specific infrastructure components, such as bridge monitoring and road safety. Sofia et al. [130] utilize mobile mapping and LiDAR data for infrastructure monitoring, while Dan et al. [131] enhance bridge monitoring systems in Shanghai through the integration of sensor data for traffic load assessment. Xu et al. [132] leverage DTs to simulate real-world road conditions, enhancing the accuracy of road safety models, while Wang et al. [133] incorporate radar and camera technologies for adaptive traffic control and emission reduction.

In the realm of sustainable urban planning, Jiang et al. [134] integrate DTs with multi-criteria decision making (MCDM) and geographic information systems (GIS) to balance economic, environmental, and social factors in urban road development. Similarly, Demiyanushko et al. [135] explore DT applications in road safety and infrastructure testing, while Yu et al. [136] investigate the use of DTs for object detection, demonstrating their utility in both safety evaluation and autonomous vehicle systems.

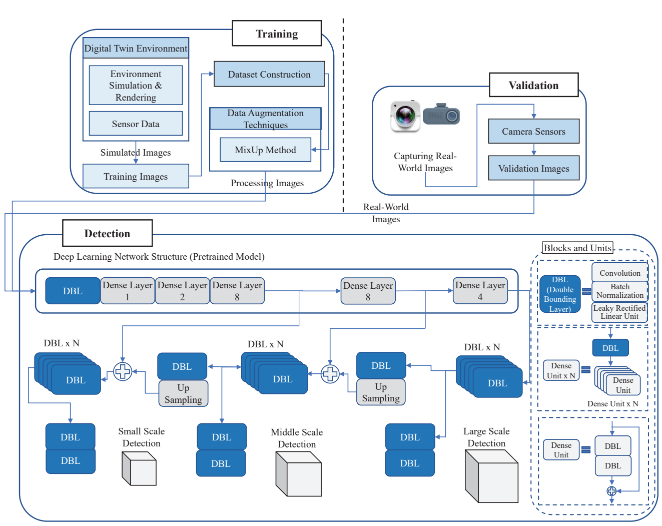

Fig. 18. Process of situation awareness.

Figure 18 illustrates a situation awareness framework for real-time obstacle detection using DTs [137]. The framework integrates various stages, including environment simulation, data augmentation, model training, and real-world validation, to facilitate efficient and accurate detection of obstacles in dynamic environments. This methodology utilizes simulated data for training, with additional augmentation techniques such as MixUp, ensuring the model generalizes effectively across diverse scenarios. The system is further validated with real-world images captured via camera sensors, confirming its practical applicability. The deep learning model, built upon a pretrained network structure, employs double bounding layers (DBL) and multiple detection scales, addressing the challenges of recognizing objects at varying sizes and complexities.

Table VII provides an overview of the reviewed DT applications in smart cities, categorizing their use in asset monitoring, urban planning, and safety management. The table emphasizes how DTs integrate diverse data sources, such as IoT sensors, traffic data, and environmental information, to enhance the functionality and efficiency of urban infrastructures. By examining various studies, the table helps identify the most suitable DT applications based on specific urban needs, whether optimizing traffic flow, improving public safety, or managing infrastructure assets. The table also highlights the mathematical tools used in each study, such as AI algorithms or machine learning models, and specifies the evaluation setups for measuring the effectiveness of DT implementations, thereby guiding the selection of appropriate solutions for urban challenges.

D. Lessons Learned in Traffic-Management Applications of Digital Twins

- *Distributed, twin-aware edge processing is indispensable for city-scale deployments.* Early pilots that concentrated all traffic-twin analytics in a central cloud suffered from back-haul saturation and multi-second control latency at peak demand. Subsequent roll-outs demonstrated that hosting sub-twins at RSUs or intersection controllers, while synchronizing only lightweight state deltas to the cloud—keeps end-to-end response below 100 ms and sustains system throughput during rush-hour bursts.
- *Layered fusion and quality assurance of heterogeneous data streams are mandatory for reliable prediction.* Experience shows that raw feeds from CCTV, loop detectors, GNSS probes, and V2X packets differ in sampling rate, latency, and error profile. A two-stage pipeline: (i) local pre-processing for time-alignment, noise filtering, and format normalization, followed by (ii) edge/cloud fusion assisted by ML-based outlier and missing-data imputation—substantially improves congestion-forecast accuracy and incident-detection recall.
- *Interoperability and open protocols unlock network-wide coordination.* Field trials revealed that proprietary signal-controller APIs and non-standard V2X stacks impede the exchange of twin state across administrative boundaries. Adopting open standards (e.g., IEEE 1609.x, ISO 21217) and deploying middleware that translates legacy messages

TABLE VII
OVERVIEW OF DIGITAL TWIN-AIDED SMART CITY AND INFRASTRUCTURE MANAGEMENT

Ref.	DT Data Sources	Mathematical Tools	Evaluation Setup	DT Applications
[128]	IoT sensors, traffic, UAV, GPS	AI, ML	A24 highway, road pavement evaluation	Resource optimization, proactive maintenance
[129]	Structural, site, environmental sensors	AI, ML, computer vision	Road/bridge construction monitoring	Structural health monitoring, predictive maintenance
[130]	Mapping, structural, IoT data	ML, 3D GIS, BIM	Mohammed VI Bridge	Infrastructure monitoring, failure prediction
[131]	Weigh-in-motion, data fusion	Traffic load monitoring	Shanghai bridge network	Real-time traffic load evaluation, bridge usage optimization
[132]	Sensor, DT data	Not specified	Road simulation examples	Road simulation, predictive analysis for management
[133]	Traffic, sensor data	ML, multi-camera tracking	Tonglu County roads	Adaptive traffic management, safety, emissions reduction
[134]	Land use, traffic, air quality, noise data	MCDM, GIS, AHP	Urban planning, southwest London	Sustainable road planning, balancing factors
[135]	FEA, dynamic simulations	Virtual testing, vehicle-road interaction	Sensor data, simulations	Vehicle-road interaction, road safety improvement
[136]	LiDAR, point cloud, camera, traffic data	ML, 3D modeling, AI	City Engine, Unreal Engine 4	Object detection, traffic safety for AVs
[138]	Security logs, network data	Cryptographic algorithms, risk assessment	Critical infrastructure, cyber-attacks simulation	Dynamic security assessments, threat mitigation
[139]	V2X, sensor, vehicle dynamics data	Game theory, multi-agent systems	CAVs in mixed traffic simulation	CAV optimization for safer traffic
[140]	IoT sensor, photometry data	Photometry, VR modeling	VR-based street lighting scenarios	Real-time street lighting control and optimization
[141]	Traffic sensor, TTC calculations	Transformer models, TTC method	Pedestrian safety at intersections simulation	Pedestrian safety optimization through real-time traffic analysis
[142]	Urban data, DT models	Data integration, 3D modeling	Smart city applications	Enhanced decision-making and sustainability in planning
[143]	Citizen feedback, IoT data	Data analytics, ML	Smart city feedback systems	Urban governance through real-time citizen feedback
[144]	IoT, network, waste management data	NETCONF, CoAP, ML	NS-3 simulation for wireless protocols	Optimized waste management in smart cities
[145]	Sensor, historical, real-time data	RMT, DL, high-dimensional stats	Energy IoT systems simulation	Optimized energy distribution, waste reduction
[146]	Warehouse, sensor, RFID data	Reinforcement learning, Monte Carlo sampling	3D warehouse model	Efficiency and cost reduction in logistics management
[147]	Sensor, metro, simulation data	Simulation models	Smart metro simulations	Improved metro safety, efficiency, failure management

into twin-state JSON objects have proven effective in enabling cross-vendor, cross-jurisdiction cooperation.

- *Twin-driven Quality-of-Service (QoS) orchestration is required for predictable latency.* Studies showed that treating all traffic data equally leads to packet contention and delayed actuation during incidents. Prioritizing twin-state updates over URLLC slices, while relegating non-critical CCTV video to eMBB channels, preserves deterministic delay for safety-critical control loops.
- *Scenario-based digital experimentation accelerates policy roll-out.* Municipal agencies that validated signal plans, lane-reversal schemes, and event-traffic strategies in the digital twin before field deployment reported up to 30% reduction in on-street trial time and a marked decline in citizen complaints. Continuous A/B testing in the virtual environment therefore emerges as a best practice for risk-free optimization.

V. DIGITAL TWINS FOR INTELLIGENT AND AUTONOMOUS VEHICLES

This section explores the application of DT technology in intelligent and autonomous vehicles. It begins by discussing the key challenges faced in the development and operation of these vehicles. The potential of DT technology to address these challenges is then examined, highlighting its role in enhancing vehicle performance, safety, and decision-making. A state-of-the-art review of existing DT applications in intelligent and autonomous vehicles is provided, showcasing the most recent advancements and implementations. The section concludes with a discussion on the lessons learned from DTs applications in intelligent and autonomous vehicles, emphasizing both the achievements and challenges that inform future research directions.

A. Overview of Challenges in Intelligent and Autonomous Vehicles

1) High Data Volume and Transfer Rates: Intelligent vehicles generate substantial data from various sensors. Transmitting these high data volumes over networks presents challenges, requiring both high throughput and stable connections. Current networks are often insufficient to handle this load, leading to transmission bottlenecks, particularly in peak traffic conditions.

2) Latency Sensitivity: Autonomous driving systems require real-time data exchange with minimal latency. Even millisecond delays can impact decision-making processes. Maintaining ultra-low latency is particularly challenging in high-density urban areas, where network congestion is frequent, and high latency can impair vehicle safety and performance.

3) Network Reliability and Stability: Continuous, reliable connectivity is crucial for V2X communications. However, ensuring consistent network reliability across varied geographic regions and under different environmental conditions remains a significant challenge. Network interruptions or unstable connections can disrupt critical data flows, leading to delays in communication between vehicles and infrastructure.

4) Spectrum Scarcity and Interference: With the increasing number of connected vehicles, spectrum congestion has become a pressing issue. The limited availability of communication frequencies, coupled with interference from surrounding vehicles and infrastructure, exacerbates the challenge of maintaining high-quality communication links, particularly in urban environments where spectrum resources are shared.

5) Human-Machine Interaction (HMI) Complexity: Effective HMI in intelligent vehicles requires seamless and immediate data exchange between the vehicle's systems and human occupants. This includes real-time feedback on critical vehicle states, navigation guidance, and safety alerts. Ensuring responsive, reliable communication for HMI systems is challenging due to the need for ultra-low latency. Interruptions or delays in the network can lead to incomplete or delayed information, which can confuse or endanger users relying on immediate feedback from the vehicle's systems.

B. Potentials of Digital Twin Technology for Intelligent and Autonomous Vehicles

DT technology transforms intelligent and autonomous vehicles (IAVs) from locally optimized agents into network-aware, system-integrated entities. By maintaining a continuously updated virtual replica of each vehicle and broadcasting this state across the vehicular network, DTs enable predictive QoS control, adaptive V2X communication, and large-scale coordination mechanisms that surpass the capabilities of traditional sensor-based or isolated edge/cloud systems.

1) Predictive QoS Control and Dynamic Resource Allocation: DTs provide foresight into network resource demands by simulating future mobility patterns, environmental interactions, and data traffic loads. These insights inform the proactive allocation of communication resources, allowing the system to dynamically assign low-latency and high-reliability channels to critical data streams (e.g., cooperative perception or motion coordination), while deferring non-urgent content to best-effort services. This anticipatory strategy supports smoother data delivery even under high-density vehicular conditions.

2) Twin-Guided Channel Adaptation and Interference Awareness: Conventional communication strategies often rely on static assumptions about link conditions. In contrast, DTs maintain contextualized channel models that account for real-time environmental factors, including mobility-induced Doppler effects, signal occlusions, and multipath interference from surrounding vehicles and infrastructure. By feeding these dynamic models into the communication stack, IAVs can make fine-grained adjustments to modulation, coding, and transmission strategies, enhancing communication reliability and spectral efficiency under diverse conditions.

3) Edge–Cloud Partitioning for Hierarchical Autonomy: To balance responsiveness with computational demand, DT-enabled systems distribute tasks across edge and cloud domains. Edge-hosted sub-twins at RSUs or MEC servers handle latency-sensitive functions such as sensor fusion, short-term planning, and collision avoidance, ensuring swift reaction to environmental changes. Meanwhile, the cloud twin conducts more computationally intensive tasks, including long-horizon path planning and policy evaluation across uncertain traffic scenarios. This layered partitioning framework supports both real-time actuation and strategic decision-making at scale.

4) Fleet-Level Coordination and Efficient Spectrum Usage: By aggregating digital twins from multiple vehicles, fleet-level controllers gain a holistic view of network demand and mobility patterns. This enables dynamic load balancing across communication cells, coordinated clustering for sidelink operations, and adaptive spectrum sharing strategies. Such coordination prevents network congestion in localized hotspots, particularly in scenarios where autonomous fleets converge in high-demand areas such as transit hubs or event venues.

5) Scenario-Based Policy Validation and Safe Over-the-Air (OTA) Deployment: Before new perception or control algorithms are deployed to vehicles, they are first evaluated in the cloud twin using a wide range of synthetic yet realistic traffic scenarios. This pre-deployment testing ensures that only policies meeting predefined safety thresholds are pushed to the field. Furthermore, the DT architecture supports continuous monitoring of post-deployment performance, with mechanisms for automatic rollback in case of behavioral discrepancies. This closed validation loop enhances the robustness of OTA updates and supports adaptive learning without compromising safety.

C. Digital Twin Applications for Intelligent and Autonomous Vehicles: A State-of-The-Art Review

This subsection reviews the cutting-edge applications of DT technology in the development and optimization of intelligent and autonomous vehicles. The review highlights the latest research on DT applications, showcasing their impact on safety, performance, and efficiency in intelligent and autonomous vehicle systems.

1) Development and Validation of Autonomous Driving Systems: DT technology plays a pivotal role in the development and validation of autonomous driving systems by providing high-fidelity virtual environments for testing and simulation across diverse and dynamic conditions. By utilizing the principles of structural, physical, and logical twins, DTs enable the rapid iteration of autonomous systems and minimize the reliance on costly physical prototypes. The integration of these virtual models allows for the simulation of complex real-world driving scenarios, ensuring a thorough and efficient validation process.

Yu et al. [148] present a DT system that integrates high-definition mapping and sensor simulation, significantly improving the testing process and reducing the need for extensive physical trials. Similarly, Xiong et al. [149] investigate car-following scenarios, demonstrating that DT-assisted simulations provide greater accuracy in collision avoidance testing, which is critical for refining autonomous vehicle behavior in traffic. Ge et al. [150] introduce a three-layered architecture that combines virtual and physical tests, enabling synchronized validation and ensuring that autonomous systems perform reliably across both simulated and real-world conditions.

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In the realm of RL, Wu et al. [151] propose a DT-enabled RL framework that enhances the efficiency of training autonomous systems by predicting state transitions in simulated environments. This approach results in faster policy training in platforms like the CARLA simulator, outperforming traditional RL methods that rely solely on real-world data collection.

Further expanding on this, Liu et al. [80] utilize DTs to enhance ADAS, specifically improving lane change prediction through cloud-based data fusion and vehicle-to-cloud (V2C) communication. This method, verified through human-in-the-loop simulations, allows for more precise real-time decision-making in dynamic driving environments. In high-speed autonomous racing applications, Culley et al. [152] leverage DTs for real-time simulation, refining control algorithms that govern vehicle behavior under extreme conditions, thereby demonstrating the utility of DTs in high-performance autonomous systems.

Simulation and testing remain critical to ensuring the safety, reliability, and overall performance of autonomous driving systems. The use of DTs facilitates the synchronization of virtual models with physical systems, enabling continuous feedback and iterative improvements. Wang et al. [153] propose an end-to-end DT framework that ensures real-time data synchronization and optimal route planning, thus improving both the safety and efficiency of autonomous driving. Similarly, Wang et al. [154] employ LiDAR data to replicate specific traffic scenarios in simulations, bridging the gap between virtual models and real-world conditions, which is essential for training and validating autonomous vehicles in a variety of environments.

In industrial settings, Alexandru et al. [155] apply DTs for optimizing task allocation and path planning in automated guided vehicles (AGVs), enhancing operational efficiency in manufacturing environments. Campolo et al. [156] use DTs integrated with multi-access edge computing (MEC) to track mobility in mobility-as-a-service (MaaS) applications, improving public transportation service planning and management.

For navigation accuracy, Hu et al. [157] demonstrate how integrating DTs with control algorithms improves trajectory tracking and stability in autonomous systems. Shoukat et al. [139] integrate DTs with V2X communication for Hardware-in-the-Loop (HiL) simulations, enhancing collision avoidance and optimizing traffic flow in mixed-traffic environments, where autonomous vehicles must interact with human-driven vehicles.

The exploration of human-vehicle interaction through DTs has also gained attention, with studies such as Serrano et al. [158] indicating that external HMIs in autonomous vehicles can significantly enhance pedestrian safety and boost public confidence in AV technology. Furthermore, in high-speed environments like motorsports, Ju et al. [159] apply DT-driven reinforcement learning to simulate and optimize race car driver behavior, demonstrating the utility of DTs in achieving human-like performance in competitive settings.

ADAS enhancement remains a major area of focus, particularly in improving traffic safety and reducing environmental impact. As shown in Fig. 19, Liao et al. [160] propose a DT framework that uses V2C communication for real-time advisory speed recommendations during ramp merging, showing how DTs can reduce speed variance and improve fuel efficiency. Wang et al. [161] employ fuzzy logic models for safe, comfortable autonomous lane changes, with validation through vehicle-in-the-loop tests. Similarly, Ye et al. [162] combine DT-assisted lane-changing with variable speed control, leveraging cloud-based vision data to improve decision-making in complex driving scenarios.

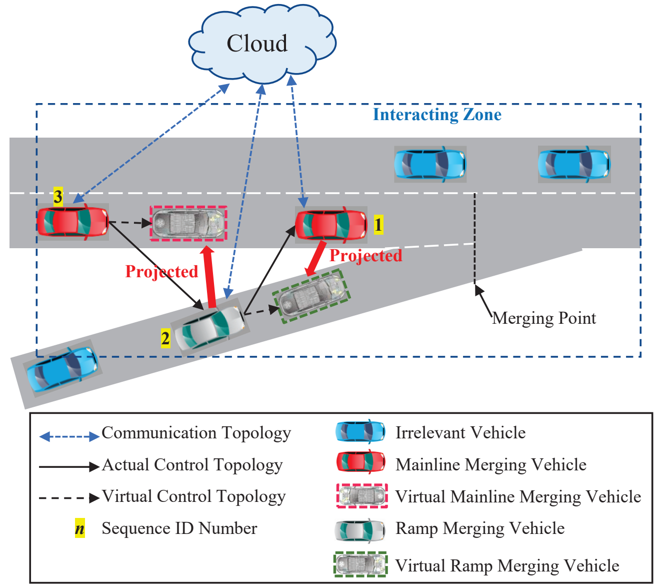
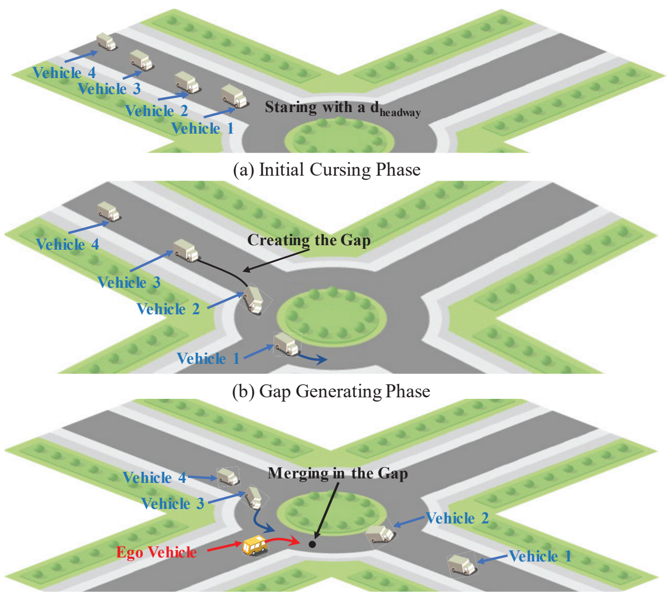


Fig. 19. Cloud-based cooperative merging scenario at on-ramp.

Machine learning innovations such as the generative adversarial network (GAN)-enhanced decision framework by Shuvo et al. [163] enable predictive responses in dynamic driving conditions, while Bariah et al. [164] demonstrate how cyber twins, driven by GANs, generate synthetic data that can be used to enhance the training of autonomous systems in diverse network conditions. Wang et al. [165] expand the use of DTs in non-signalized intersections, where they optimize traffic flow and reduce energy consumption, and Liu et al. [97] integrate drone-based DT risk management to improve safety at highway entries and exits, using aerial video data to identify and mitigate risks in real time.

2) Connected and Cooperative Vehicle Systems: The role of DT technology in connected vehicle systems is advancing rapidly, particularly in enhancing real-time simulation, situational awareness, and operational efficiency. In urban environments, where traffic density poses significant challenges, DTs provide a platform for optimized navigation and traffic management. Wang et al. [166] demonstrate a DT-enabled system that utilizes cloud-edge integration to improve the real-time navigation of CAVs, significantly increasing both traffic efficiency and safety. Liu et al. [167] further illustrate how DTs facilitate optimized lane changing and variable speed control, addressing the critical issue of collision avoidance in complex traffic scenarios.

In the context of cooperative driving, Olayemi et al. [168] integrate DT perception with DRL, enhancing the adaptability of ground vehicles in dynamically changing environments. Li



(a) Initial Cursing Phase

(b) Gap Generating Phase

(c) Merging Phase

Fig. 20. The process of cooperative driving at the roundabout.

et al. [169] focus on sustainability by demonstrating a DT-based cooperative driving system at roundabouts, which not only improves traffic flow but also reduces emissions and speed variance through consensus motion control. Fig. 20 illustrates the cooperative driving process at a roundabout, outlining the stages from initial cruising to the final merging phase, where vehicles adjust to create necessary gaps and merge smoothly into the traffic flow.

Lu et al. [170] and Fan et al. [171] explore DT-based traffic control strategies that employ variable speed limits and lane management to optimize traffic flow and minimize collision risks. These strategies highlight the importance of DTs in handling the complexities of urban traffic environments and ensuring safe, efficient movement of vehicles.

DTs also support personalized systems within CAVs. Wang et al. [68] use DTs in adaptive cruise control (ACC) systems, employing cloud-based services (AWS) to make real-time adjustments that enhance driving comfort and safety. Additionally, Kremer et al. [172] advance teleoperated driving by reducing the need for high-bandwidth data transmission while maintaining situational awareness, thus improving teleoperation safety, especially in urban contexts.

Vehicular edge computing (VEC) networks support the demanding operational requirements of connected vehicles, particularly in terms of low latency, dynamic adaptability, and handling large data volumes. DTs strengthen VEC by creating virtual models that optimize resource allocation and decision-making processes. Zhao et al. [173] introduce the IGNITE framework, which combines DTs with reinforcement learning (RL) to optimize task offloading, effectively minimizing delays and reducing computational costs in distributed vehicular networks. Zhang et al. [174] employ DTs with multi-agent RL to improve coordination and resource utilization in dynamic environments, enhancing the overall efficiency of vehicular systems.

Further, Zhang et al. [175] apply DTs in social-aware caching, where real-time cache management between RSUs and vehicles boosts content delivery speed. Qu et al. [176] propose a hierarchical DT framework to adapt VEC networks to the evolving conditions of 6G, moving from isolated optimization to a more comprehensive and automated system.

DT frameworks are also indispensable for resource management in VEC. Li et al. [177] implement a two-tier DT framework for real-time resource allocation across edge servers, ensuring seamless service continuity. Similarly, Xie et al. [178] leverage multi-agent approaches to collaborative scheduling, enabling simultaneous resource allocation and maintenance, which is critical for maintaining high-performance standards in connected vehicle networks.

The adaptability of task offloading is further enhanced by integrating DTs with RL, as shown by Zheng et al. [179], who use DTs to improve task scheduling and resource management in distributed edge networks. Additionally, Paul et al. [180] explore the incorporation of quantum computing to elevate decision-making in vehicular networks, particularly for URLLC, which are essential for real-time vehicle coordination.

Collaboration between VEC nodes for optimal network performance is demonstrated by Jeremiah et al. [181], who use DTs and RL to optimize node collaboration. Extending beyond terrestrial networks, Hazarika et al. [182, 183] integrate UAVs with hybrid machine learning models to enhance task offloading in the IoV, ensuring connectivity even in remote areas. Yang et al. [184] emphasize the utility of DTs in load balancing across MEC servers, which improves traffic safety and network management.

Table VIII provides a detailed overview of the reviewed researches on DT-empowered VEC networks, presenting key data sources, optimization techniques, and performance metrics across various studies. The table highlights a variety of methodologies employed, ranging from DRL and multi-agent systems to meta-learning and quantum-enhanced decision-making. Each study emphasizes a unique aspect of DT integration, such as offloading optimization, resource allocation, caching efficiency, and task scheduling within dynamic vehicular environments. By examining these contributions, one can identify specific DT applications that align with particular needs, such as optimizing task offloading, reducing latency, or enhancing system scalability. The diverse approaches and performance outcomes offer reference solutions based on system requirements, including real-time data synchronization, energy efficiency, or resource utilization.

3) Optimizing Network Resource Management for CAV: The evolution of intelligent vehicular networks is largely driven by the necessity for low-latency, high-reliability communications and the efficient management of network resources, especially in complex environments where CAVs operate. DT technology, when combined with cloud-native and edge computing, facilitates real-time interactions between physical and cyberspaces, thereby enhancing both decision-making and resource allocation processes in these networks.

Tan et al. [185] introduce a DT-cloud vehicular network (DT-CVN) that leverages microservices to improve communi-

TABLE VIII
REVIEW OF DIGITAL TWIN-EMPOWERED VEHICULAR EDGE COMPUTING NETWORKS.

Ref.	DT Data Source	Optimization Technique	Performance Metrics	Methodology	Effect of DTs
[173]	Real-time VEC data	DRL, clustering	Computational cost, delay, offloading rate	DDPG for task offloading, DT-based prediction	DTs optimize offloading by predicting resource availability, reducing costs and delays
[174]	Traffic datasets	MADRL	Offloading cost, cooperation gains	MADDPG for service matching	DTs enhance offloading by modeling network conditions, improving coordination and reducing costs
[175]	Social and network data	DRL	Caching efficiency, service utility	DDPG for cache management	DTs improve caching by dynamically allocating resources based on real-time interactions
[176]	Vehicular network data	Meta learning	Adaptation speed, efficiency	Two-tier DT-based meta-learning	DTs accelerate learning adaptation, improving efficiency in dynamic networks
[177]	VEC servers, DT models	DRL	Offloading latency, resource utilization	Two-tier DT with AI for allocation	DTs optimize real-time resource allocation, reducing latency and improving efficiency
[178]	VEC, DT maintenance data	MADRL	Resource utility, task delay	MADRL-CSTC for scheduling	DTs enhance maintenance planning, reducing delays and optimizing resource use
[179]	IoV network conditions	RL	Scheduling efficiency, resource use	A3C-based task offloading	DTs synchronize network conditions, improving scheduling and resource allocation
[180]	Vehicular DT models	Quantum-DRL	Latency, reward maximization	Quantum computing + DRL	DTs integrate quantum computing, improving decision-making and reducing latency
[181]	Edge collaboration data	A2C	Computation rate, task delay	A2C for resource allocation	DTs synchronize real-time data, boosting computation rates and reducing delays
[182]	UAV, vehicular data	Multi-network DRL	Energy efficiency, delay reduction	Multi-network DRL for allocation	DTs optimize UAV-VEC connectivity, improving energy efficiency and reducing delays
[183]	UAV, IoV data	AFL, MADRL	Task rate, energy efficiency	AFL and multi-agent DRL	DTs enhance hybrid network allocation, reducing energy use and improving task completion
[184]	Vehicular network data	Genetic Algorithm, PSO	System cost, load balance	Adaptive PSO with GA scheduling	DTs balance load in MEC networks, optimizing traffic flow and reducing costs

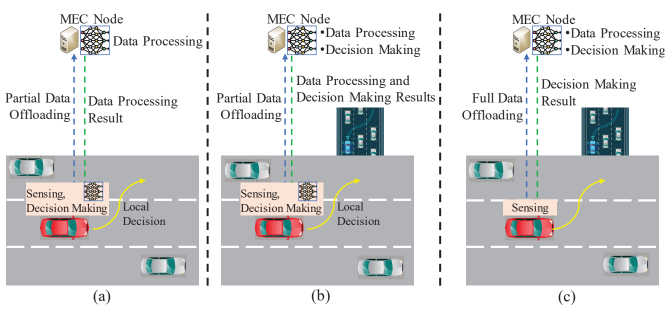


Fig. 21. The three paradigms of lane-changing decisions in the MEC domain: (a) distributed, (b) Semi-distributed.

cation efficiency, ultimately reducing both time and energy consumption. This integration streamlines task scheduling and resource management, ensuring that the system adapts efficiently to dynamic conditions. Similarly, Fan et al. [186] propose a DT and MEC-based framework for lane-changing in CAVs, optimizing decision-making across distributed, semi-distributed, and centralized paradigms. These optimization strategies lead to significant improvements in traffic speed and flow. Fig. 21 illustrates the three paradigms, distributed, semi-distributed, and centralized, each enhancing traffic management in different ways depending on the system's computational architecture.

Safety remains a critical concern in CAV systems, and DT technology plays an essential role in addressing this. Parrish et al. [187] implement a DT-based V2V system that adjusts transmission ranges based on human reaction time, successfully reducing accident risks by 36%. This approach highlights the capacity of DTs to simulate and respond to human behavior in real-time, improving safety across the network. Hu et al. [188] introduce a time-aware locality-sensitive hashing (LSH) method to enhance traffic predictions by addressing data sparsity, significantly improving prediction accuracy in real-world traffic environments.

In the realm of collaborative driving, Hui et al. [189] use a DT-based model that incorporates a Nash-stable auction mechanism to optimize group driving strategies, ultimately reducing the costs of autonomous driving. Similarly, Wagner et al. [190] enhance traffic flow by using DTs for real-time traffic light-vehicle interaction data, improving both flow efficiency and reducing emissions.

DTs also play a crucial role in URLLC, which are essential for real-time decision-making in CAVs. Hao et al. [191] propose a DT-based task offloading scheme that ensures low latency in dynamic mobile edge networks, a key component for the upcoming 6G applications. In heterogeneous vehicular networks (HetVNets), Hui et al. [192] utilize DTs to optimize content caching through a double auction model, addressing resource constraints while improving collaborative recommendations and data delivery efficiency.

For V2X communication, Cazzella et al. [193] use multi-modal sensor data and DTs, applying ray-tracing models to overcome line-of-sight blockages in high-frequency communication, thus enhancing the reliability and efficiency of V2X networks. Sun et al. [194] propose a DT-based C-V2X architecture that integrates reinforcement learning and mean-field game theory (MFG) to improve task offloading, optimizing the allocation of computational resources in real-time.

Table IX provides an in-depth summary of how DTs optimize resource management and enable real-time decision-making in intelligent vehicular networks. It categorizes each study based on its use of DTs to address key challenges, such as scalability, heterogeneity, and real-time operational demands in CAV systems. The table outlines the roles of DTs, such as enabling virtual replicas for dynamic task scheduling, traffic flow prediction, and resource allocation. It also

TABLE IX
OVERVIEW OF DIGITAL TWIN-AIDED INTELLIGENT VEHICULAR NETWORKS

Ref.	DT Functions	Optimization Techniques	Performance Metrics	Methodology	Challenges Addressed
[185]	Manage resources and task scheduling	DQN-based task scheduling	Task efficiency, energy consumption, resource utilization	Virtual replicas of vehicles and infrastructure for real-time decision-making	DTs improve task scheduling and resource management, reducing delays in large-scale networks
[186]	Real-time lane-changing decisions	Virtualization, offline learning with MEC	Safety, efficiency, real-time decisions	Simulate vehicle and environment interactions to optimize lane changes in real-time	DTs enable rapid response to dynamic traffic, but computational complexity remains a challenge
[187]	Adapt transmission range using reaction time data	DT-based transmission range modulation	Transmission delay, safety, accident reduction	Model human reaction times to adjust transmission ranges in V2V systems	DTs improve V2V communication by adjusting range based on predicted driver behavior
[188]	Predict real-time traffic flow and speed	Time-aware LSH	Prediction accuracy, computational efficiency	Model traffic flow and speed under 5G conditions for real-time predictions	DTs enhance traffic prediction accuracy while reducing data processing time
[189]	Support collaborative autonomous driving	Auction and coalition game theory	Cost, collaboration stability	Use game theory to enable cooperative decision-making among AVs	DTs enhance collaboration among AVs, improving stability and reducing system costs
[191]	Optimize task offloading in URLLC	Robust combinatorial optimization	Latency, energy, task efficiency	Use DTs to optimize task offloading in URLLC systems	DTs ensure low-latency offloading, critical for real-time mobile edge networks
[192]	Manage dynamic content delivery	Double auction game	Utility, hit ratio, delay	Simulate network conditions and user demands for adaptive content delivery	DTs optimize content distribution by adjusting for dynamic network conditions and user behavior
[193]	Model urban dynamics for V2X	High-frequency band modeling	Channel estimation, link restoration	Simulate urban traffic dynamics for V2X communication optimization	DTs improve channel estimation and link restoration, reducing errors in urban V2X networks
[195]	Control heterogeneous vehicle interactions	DRL for CAV control	Traffic efficiency, safety, control effectiveness	Optimize fleet control and interaction strategies using DTs and edge AI	DTs enable smooth interactions across diverse vehicle types, ensuring system efficiency
[196]	Develop and tests vehicle platoons	Co-simulation techniques	System resilience, performance under cyber-attacks	Combine DTs with edge computing to optimize platoon control	DTs enhance platoon stability by simulating environmental and attack scenarios
[194]	Support collaborative context offloading	DT with DRL and MFG	Offloading latency, QoS, efficiency	Use DTs and DRL for context offloading and optimal resource allocation in distributed networks	DTs enable efficient offloading decisions, improving QoS in dynamic environments

discusses optimization techniques like reinforcement learning, game theory, and combinatorial optimization, showcasing their application in improving performance metrics such as latency, energy efficiency, and safety. By linking these approaches to measurable outcomes, the table provides insights into how DTs enhance the adaptability and robustness of CAV networks, while highlighting practical challenges such as computational complexity and system coordination.

In the realm of network resource optimization and management, a variety of approaches leverage DT technology to address challenges inherent to dynamic, high-mobility environments. These challenges arise from the need to maintain high levels of connectivity and optimize resource allocation in scenarios characterized by frequent changes in network topology and varying vehicle behaviors. Zhao et al. [197] propose the ELITE routing scheme within a DT-based framework to improve packet delivery and reduce overhead under fluctuating network conditions. This scheme employs a four-phase process that includes policy training, generation, deployment, and relay selection, effectively optimizing inter-vehicle communication in highly dynamic settings. For high-mobility environments, Alam et al. [198] utilize DT-enabled coordination graphs and multi-agent deep reinforcement learning (DCG-MADDPG) to optimize routing, improving reliability and reducing latency in vehicular networks.

In urban vehicular networks, Ding et al. [199] integrate DTs with deep learning to enhance channel estimation. They employ city models for improved accuracy, leveraging a combined CMA DNN and BEM (boundary element method) approach to optimize communication in urban environments. Gong et al. [200] introduce a DT-driven virtualization framework with network slicing to enable more efficient offloading, incorporating sensing and communication integration to minimize response times in IoV systems. Zheng et al. [201] implement a DT-based learning method for better data synchronization, ensuring efficient communication and reducing synchronization costs in highly dynamic networks. In parallel, Tan et al. [202] propose a cloud-native DT microservice-based framework for scalable task scheduling. They design a DQN-based adaptive task scheduling algorithm to improve system scalability and task scheduling efficiency, particularly for real-time vehicular applications, as depicted in Fig. 22.

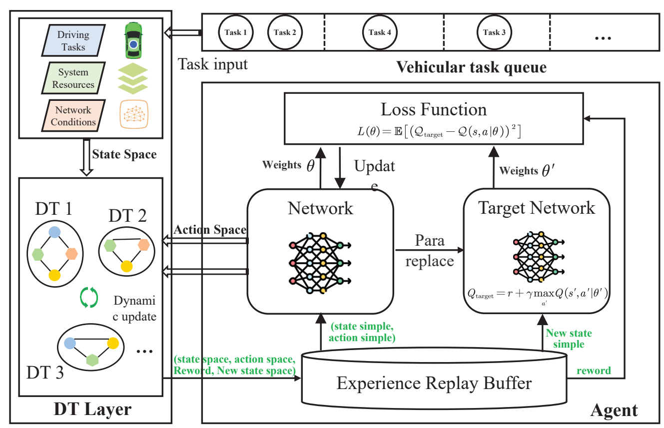


Fig. 22. The architecture of DQN-based adaptive task scheduling algorithm.

Further advancements come from Yuan et al. [203], who integrate DTs with intelligent reflecting surfaces (IRS) in 6G vehicular networks. They employ DRL to optimize task offloading and minimize delays. Cao et al. [204] present a multi-objective DT model that applies evolutionary optimization strategies to enhance task offloading, improving both system efficiency and user satisfaction. Additionally, Cai et al. [205] propose a DT-empowered V2X architecture to optimize traffic safety and communication via behavior analysis. Zheng et al. [206] apply game theory to achieve efficient VUE-DT data synchronization, further enhancing network performance in HetVNets. Zhao et al. [207] combine GANs with genetic-

TABLE X
OVERVIEW OF DIGITAL TWIN-AIDED RESOURCE OPTIMIZATION AND MANAGEMENT FOR VEHICULAR NETWORKS

Ref.	DT Functions	Optimization Techniques	Performance Metrics	Objectives	Simulators	Effects of DTs
[197]	Virtual network space for routing	Four-phase process: policy training, relay selection	Packet delivery, delay, overhead	Improve communication stability	SUMO	DTs simulate real-time conditions, improving routing and reducing delays
[198]	Virtual representation of mobility	DCG-MADDPG for multi-agent learning	Latency, reliability, queue stability	Optimize routing in high-mobility networks	TensorFlow	DTs improve routing under high-mobility, enhancing reliability and queue stability
[199]	3D city model for channel estimation	CMA DNN with BEM	Bit error rate, complexity	Enhance channel estimation in urban networks	TensorFlow	DTs provide accurate 3D models, reducing errors and improving communication
[200]	Environment-aware offloading	DDPG with Shapley Q-values	Response time, latency	Optimize resource allocation in IoV	Python	DTs enable offloading decisions based on environment, reducing latency and improving allocation
[201]	Knowledge transfer for network selection	Actor-critic with MDP	Convergence speed, cost efficiency	Optimize network selection	TensorFlow, Keras	DTs enhance synchronization efficiency, reducing costs
[202]	DT-enabled cloud-native architecture	DQN-based adaptive task scheduling	Execution time, energy use	Improve task scheduling	N/A	DTs adapt scheduling, reducing task time and energy consumption
[203]	MEC and IRS for task offloading	DDQN and DDPG optimization	System delays, energy use	Optimize resource use	Python, SUMO, Pytorch	DTs optimize offloading, improving resource use and reducing delays
[204]	DT for VEC optimization	Multi-objective optimization	Delay, energy, satisfaction	Balance VEC performance	PanoSim	DTs balance delay, energy, and satisfaction for better VEC performance
[205]	DT for V2X communications	Deep reinforcement learning	Task efficiency, resource use	Improve task efficiency in V2X	N/A	DTs optimize task efficiency, reducing resource consumption in V2X
[206]	DT for data synchronization	Game theory-based selection	Sync latency, service quality	Optimize data synchronization	Python	DTs improve synchronization and service quality in vehicular UEs
[207]	DT for trajectory prediction	ML, PSO, genetic algorithm	Delay, energy use	Improve offloading and reduce system costs	SUMO, Python	DTs predict trajectories, optimizing energy use and reducing delays in VEC

based particle swarm optimization to adaptively manage offloading in highly dynamic environments, thereby maximizing overall network efficiency.

Table X offers a comprehensive summary of various DT-aided resource optimization techniques, highlighting the distinct functions of DT technology, the optimization methods employed, and the corresponding performance metrics used to evaluate their effectiveness. By comparing the studies presented, the table illustrates how DTs contribute to improving network resource management in vehicular systems. It clarifies how different DT applications address specific challenges, such as reducing latency, enhancing energy efficiency, and optimizing task scheduling. Each entry demonstrates how DTs facilitate real-time decision-making, improve system scalability, and enable more efficient resource utilization. This comparison serves as a valuable resource for selecting the most appropriate DT-driven optimization techniques, depending on the performance objectives of a given vehicular network, whether focused on minimizing delays, improving communication quality, or balancing multi-objective requirements.

D. Lessons Learned in Intelligent- and Autonomous-Vehicle Applications of Digital Twins

- *Probabilistic twin models are essential for robust decision-making under uncertainty.* Field trials reveal that a deterministic twin—even if high-fidelity—cannot capture the stochastic behavior of pedestrians, human-driven vehicles, or abrupt weather changes. Embedding Bayesian filtering, Monte-Carlo tree search, or Gaussian-process priors inside the vehicle twin allows the planner to reason over a distribution of future states and to select actions that remain safe across a spectrum of likely outcomes.
- *Edge–cloud partitioning is mandatory to meet the dual challenge of high data volume and sub-100 ms latency.* Early prototypes that streamed raw LiDAR/vision data to a cloud twin experienced multi-second round-trip delays. A hybrid architecture—in which the edge twin performs time-critical perception fusion and collision-risk prediction while the cloud twin undertakes long-horizon route optimization and model retraining—proved capable of sustaining 10 Gbit/s sensor throughput with control-loop latency below 30 ms.
- *Twin-state exchange over URLLC sidelinks enables co-operative manoeuvres at scale.* Simulations show that broadcasting compact twin snapshots 1kB every 20 ms allows vehicles to merge, platoon, and negotiate intersections with 25% shorter headway than V2X message sets that carry only raw kinematics. Prioritizing these snapshots in the 5G/NR resource scheduler is therefore a best practice for safety-critical cooperation.
- *Transparent and explainable twin reasoning builds human–machine trust.* Driver-in-the-loop studies indicate that occupants are more willing to cede control when the augmented-reality (AR) HUD visualizes the twin's predicted trajectories—and when a natural-language interface can justify sudden braking or detours. Exposing the twin's intent, rather than merely its raw sensor view, reduces takeover-reaction time by up to 40%.
- *Continuous twin validation guards against model drift and sensor degradation.* Long-duration fleet deployments uncovered slow drifts in camera calibration and LiDAR reflectivity that silently eroded perception accuracy. A background process that compares live telemetry against twin predictions and triggers re-calibration or online re-training has proven critical to maintaining safety margins over months of operation.

VI. FUTURE RESEARCH OPPORTUNITIES

This section outlines key research opportunities for advancing DT technology in intelligent vehicles and transportation systems. As the integration of DTs evolves, several promising areas of research will enable more accurate, scalable, and resilient solutions in both vehicle safety and broader transportation management. This section focuses on advancements in IoT and sensor technologies, simulation modeling, AI, ML, and cybersecurity to enhance DT applications.

A. Emerging IoT and Sensor Technologies

1) 5G and Beyond for Low-Latency, High-Bandwidth Connectivity: A significant area of research in IoT and sensor technologies lies in the advancement of 5G and beyond networks. 5G technologies offer ultra-low latency and high bandwidth, which are crucial for ensuring the seamless operation of DT systems in intelligent transportation. Real-time data transmission, such as V2X communication, is essential for applications like autonomous driving, traffic management, and emergency vehicle prioritization. The URLLC capabilities of 5G, with latency as low as 1 millisecond, are particularly valuable for safety-critical applications where immediate decision-making is required.

Moreover, millimeter-wave (mmWave) technologies in 5G offer high data transfer rates that are necessary for transmitting large volumes of sensor data, including high-resolution camera feeds, LiDAR data, and real-time traffic information. Looking ahead, 6G technologies are expected to push the boundaries even further, providing terahertz frequencies that will enable advanced communication capabilities such as holographic communication and real-time immersive experiences. Research into AI-driven network optimization for 5G and 6G could ensure dynamic, self-healing communication systems capable of adapting to the needs of various transportation scenarios.

2) Multi-Sensor Fusion and Advanced Sensors: The integration of various sensor modalities is fundamental to creating accurate and reliable DT models. As vehicles and transportation systems rely on increasingly sophisticated sensing technologies, multi-sensor fusion becomes critical. Advanced algorithms are necessary to integrate data from different sensor types, which each have their strengths and weaknesses depending on environmental conditions. For example, LiDAR offers high-resolution 3D point clouds, while radar is better suited for long-range detection in poor weather conditions.

The future of DT systems will rely on fusion algorithms such as Kalman filters and Particle filters, which help combine information from different sensors to produce a more comprehensive understanding of the environment. Research into deep learning-based fusion models will improve system performance, allowing for real-time data processing and more accurate environmental modeling, particularly in dynamic, urban settings.

In addition to traditional sensors, advanced sensing technologies such as terahertz (THz) imaging will enable better visibility under extreme conditions like fog or heavy rain, which current technologies struggle to handle. As these sensors become more widely integrated into transportation systems, they will provide more comprehensive environmental data, helping autonomous vehicles to better perceive their surroundings and make safer, more accurate decisions.

3) Distributed Sensing with Edge Intelligence: As the need for real-time decision-making grows, distributed sensing and edge intelligence are becoming increasingly vital for transportation systems. Traditional centralized computing systems often face challenges due to latency and bandwidth constraints. To overcome this, edge computing enables data processing closer to the source of the data, such as within vehicles or at intersections, rather than relying solely on centralized cloud servers. By distributing the processing tasks across various nodes, the system can respond much more quickly to real-time events, which is essential for safety-critical applications like autonomous driving.

This approach reduces the amount of data transmitted over networks, optimizing bandwidth usage and decreasing response times. Additionally, collaborative sensing is a key research area, where vehicles, infrastructure, and other devices in the transportation ecosystem share sensor data to improve situational awareness. Distributed sensor networks, combined with edge intelligence, will enable more scalable, resilient, and efficient digital twin systems for traffic management and autonomous vehicles.

Furthermore, research into decentralized control systems will ensure that distributed sensing can be performed in a collaborative and synchronized manner across various devices and vehicles. By adopting these technologies, DT systems can better integrate dynamic, real-time data into their operational models, enhancing performance and scalability in complex transportation environments.

4) Energy-Efficient IoT: As the number of IoT devices used in transportation systems continues to grow, energy efficiency becomes a critical factor for their long-term viability and sustainability. Many IoT devices, particularly those used in urban infrastructure and autonomous vehicles, require continuous operation and must be able to function for extended periods without frequent maintenance or battery replacement.

One area of focus for future research is Low Power Wide Area Networks (LPWANs), such as LoRaWAN and NB-IoT, which provide long-range communication capabilities while consuming very little power. These networks are particularly well-suited for applications like environmental monitoring, smart parking, and asset tracking, where devices need to operate in the background without frequent data transmission.

Additionally, energy harvesting technologies are becoming more relevant for IoT devices in transportation systems. Devices that can collect energy from their environment, such as solar-powered sensors or those utilizing piezoelectric and thermoelectric generators, can drastically reduce dependency on batteries. Research into improving the efficiency and cost-effectiveness of these energy harvesting techniques will ensure that sensors in transportation networks can operate autonomously for longer periods, making them more sustainable.

Moreover, developing dynamic power management algorithms that adjust the power consumption of devices based on real-time needs is critical. By using techniques such as adaptive sleep modes and on-demand activation, IoT devices can conserve energy during low-activity periods, ensuring that they are only fully operational when needed. These advancements will enable long-term deployments of IoT systems in large-scale, smart transportation environments.

B. Simulation Model Innovations

1) High-Fidelity Modeling for Complex Scenarios: The increasing complexity of transportation systems necessitates the use of high-fidelity models that can accurately simulate real-world scenarios involving multiple agents (e.g., vehicles, pedestrians, cyclists) and environmental variables (e.g., road conditions, weather, traffic). Future research should focus on advancing the precision and realism of vehicle dynamics models, environmental simulations, and traffic flow modeling within DT systems.

For example, the integration of non-linear vehicle dynamics, such as those that account for tire-road interaction and suspension behavior, is crucial for ensuring that simulated vehicles react realistically in different road conditions. High-fidelity models also need to simulate more than just vehicle behavior; they must account for pedestrian movement, cyclist actions, and how these agents interact within the traffic ecosystem. Models that incorporate dynamic weather conditions and nighttime driving are also necessary to simulate various driving environments and improve the accuracy of safety-critical systems.

Research into multi-agent simulation techniques can enhance the realism of such models. These techniques allow for simultaneous simulations of multiple interacting agents, making it possible to evaluate complex scenarios like congestion, accidents, or cooperative driving behavior. Combining these high-fidelity simulations with real-time traffic data can lead to the creation of adaptive models that evolve based on actual traffic conditions.

2) Cloud-based and Distributed Simulation Systems: As transportation systems grow in complexity, the demand for scalable, high-performance simulation tools increases. Cloud-based and distributed simulation systems are key to enabling large-scale simulations that model entire cities or regions in real-time. These systems allow for parallel processing of simulation tasks, which is particularly beneficial when dealing with the computationally intensive nature of autonomous driving simulations or large-scale transportation network modeling.

Future research should focus on developing cloud-based platforms capable of supporting real-time multi-user simulations where multiple stakeholders (e.g., transportation authorities, vehicle manufacturers, urban planners) can access and interact with simulations simultaneously. Additionally, distributed computing frameworks that leverage edge computing will be vital for handling large volumes of data generated by DT systems, reducing the dependency on centralized cloud resources and ensuring low-latency processing for mission-critical applications.

For example, edge computing nodes can process data locally from sensors on vehicles or infrastructure, feeding real-time information into a central simulation engine for further analysis. This approach will significantly enhance the responsiveness of DT systems in real-world applications, such as dynamic traffic signal control, incident detection, and autonomous vehicle behavior modeling.

3) Sim-to-Real Transfer and Virtual Prototyping: A major challenge in developing autonomous vehicle systems is ensuring that simulated models translate effectively to real-world performance. Table XI provides a summary of various simulators employed in autonomous driving research, highlighting their capabilities in sensor modeling, path planning, and traffic scene support. The ability to transfer insights from simulations to real-world applications, known as Sim-to-Real Transfer, is essential for testing and validating autonomous driving systems in complex, real-world environments. As illustrated in Fig. 23 [23], enhancing autonomous driving performance through simulation techniques: Sim2Real, DTs, and parallel intelligence.

Key innovations in this area include the use of domain adaptation and domain randomization methods to improve the generalization of simulations. Domain randomization involves intentionally varying the simulated environment (e.g., different lighting conditions, weather patterns, or sensor noise) to make the model more robust to changes in the real world. Transfer learning can also be applied, where knowledge gained from one environment or simulation is adapted to another, ensuring that digital twins accurately reflect the complexities of real-world conditions.

Research into virtual prototyping will further advance the ability to create digital replicas of vehicles, sensors, and entire transportation systems. These prototypes can be tested in a variety of scenarios before deployment, significantly reducing the time and cost required for physical testing. Platforms such as CARLA, SUMO, and Webots, which support high-fidelity simulations of driving environments and vehicle dynamics, can be used to develop these prototypes and verify the safety and performance of autonomous vehicles in various traffic conditions.

4) Real-Time Simulation and Optimization: The ability to simulate and optimize transportation systems in real-time is essential for the efficient management of smart cities and autonomous vehicle fleets. Real-time simulation involves dynamically updating models as new data is received, enabling instant feedback and adjustments to traffic flow, vehicle behavior, or network management.

Research into real-time traffic simulation platforms can help improve traffic signal control, incident detection, and route optimization for autonomous vehicles. By continuously updating traffic conditions and modeling the flow of vehicles in real-time, DT systems can optimize traffic management strategies, reducing congestion and improving safety. Techniques such as MPC can be used to predict future traffic conditions and optimize vehicle routes, minimizing delays and fuel consumption.

Moreover, integrating AI-based optimization algorithms, such as RL and genetic algorithms, can enable DT systems to continuously learn from real-time data and adjust their operations accordingly. This would allow for the continuous improvement of traffic management strategies, resource allocation, and autonomous vehicle decision-making in an ever-changing environment.

TABLE XI
SIMULATORS FOR AUTONOMOUS DRIVING

Simulators	AirSim	Gazebo	CARLA	LGSVL	Torcs	Metadrive	SUMO	SUMMIT	Autoware
Brief description	Robotics simulator with photorealistic graphics	Robotics simulator for indoor and outdoor scenarios	Unreal engine open source autopilot simulator	Simulator designed for ADAS development and testing	Vehicle driving games and racing simulator	Simulator with an emphasis on urban driving	Simulator for traffic flow and transportation studies	Traffic flow simulator based on CARLA extension	Autonomous driving platform for research and prototyping
Sensor model	RGB camera, Depth camera, LiDAR	Custom sensor plugins, LiDAR	Camera, LiDAR, mmWave radar	LiDAR, Camera, Ultrasonic radar	N/A	Camera, LiDAR	N/A	LiDAR, Camera	LiDAR, Camera, mmWave radar
Path Planning	✓	✓	✓	✓	✓	✓	✓	✓	✓
Weather Conditions	×	✓	✓	✓	✓	✓	×	✓	✓
Traffic Facilities	✓	✓	✓	✓	✓	✓	✓	✓	✓
2D/3D Ground View	3D	3D	3D	3D	2D	3D	2D	3D	2D/3D
Traffic Scene Support	✓	✓	✓	✓	×	✓	✓	✓	✓
3D Virtual Environment	✓	✓	✓	✓	✓	✓	✓	✓	✓
Camera Calibration	✓	✓	✓	✓	✓	✓	×	✓	✓
Vehicle Control	✓	✓	✓	✓	✓	✓	×	✓	✓
Open Source	✓	✓	✓	✓	×	✓	✓	✓	✓
Advantages	High realism, multi-platform support	High versatility, multi-robot simulation	Multi-vehicle, multi-sensor support	ADAS simulation focus	Customizable for vehicle control and dynamics	Urban driving scene support	Open source traffic flow simulator	Combination of traffic flow and advanced driving functions	Integrated platform for AD functions

Simulators	Apollo	UPPAAL	Webots	SCENIC	MATLAB	Prescan [208]	PanoSim [209]	Hyperledger Fabric [210]	Python	Unity [211]
Brief description	Autonomous driving software platform for both urban and highway scenarios	Formal verification tool for real-time systems	Robot simulator for real-time monitoring and testing	Scenario specification and simulation language	Simulation environment for a variety of engineering applications	Advanced driving simulation environment for ADAS and AV testing	Simulation platform for vehicle dynamics and collision scenarios	Blockchain platform for decentralized applications	General-purpose programming language, used for simulations	Real-time 3D development platform
Sensor model	LiDAR, Camera	N/A	Cameras, LiDAR	N/A	N/A	Cameras, LiDAR	N/A	N/A	N/A	Cameras, LiDAR, GPS, Ultrasonic, IMU
Path Planning	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Weather Conditions	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Traffic Facilities	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
2D/3D Ground View	3D	N/A	3D	N/A	2D/3D	3D	N/A	N/A	3D	3D
Traffic Scene Support	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
3D Virtual Environment	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Camera Calibration	✓	N/A	✓	N/A	✓	✓	N/A	N/A	✓	✓
Vehicle Control	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Open Source	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Advantages	Scene reproduction and playback	Formal verification, real-time systems	Real-time monitoring, robotics integration	Scenario specification, safety verification	Versatile simulation environment	High fidelity ADAS and AV testing	High-fidelity vehicle dynamics and collision testing	Blockchain integration, decentralized systems	General-purpose simulation scripting	High-fidelity 3D simulations

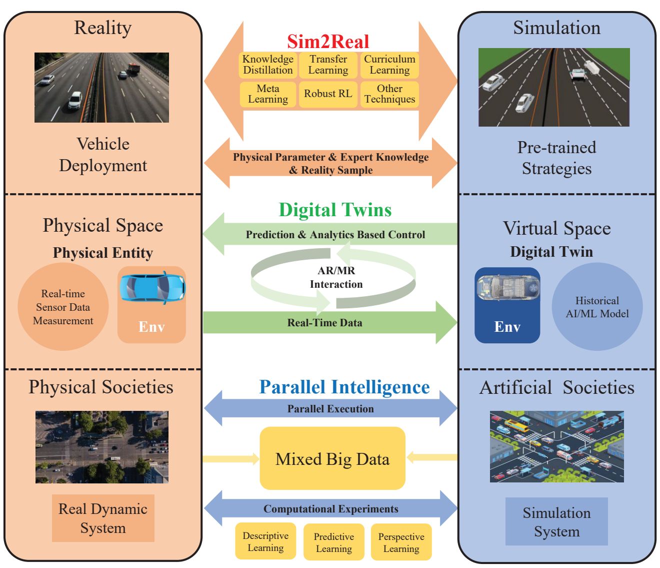


Fig. 23. Enhancing autonomous driving performance through simulation techniques: Sim2Real, DTs, and parallel intelligence.

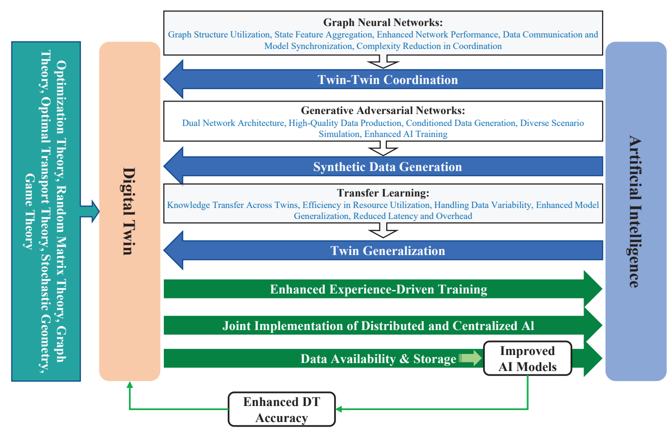


Fig. 24. The interplay of AI and Digital Twin: Bridging the gap between data-driven and model-driven approaches.

C. AI and ML Advancements

As shown in Fig. 24, AI-driven methodologies, including GNNs, GANs, RL, and FL, enhance the precision, adaptability, and scalability of DT applications. Future research in AI and ML will focus on optimizing decision-making, improving system interoperability, and ensuring transparency in autonomous systems.

1) RL for Autonomous Vehicle Decision-Making: RL is emerging as a pivotal technique in enabling autonomous vehicle decision-making within DT environments. RL allows autonomous systems to learn optimal actions through interactions with their environment, using rewards and penalties to adjust behavior. This is particularly relevant for dynamic, real-time environments where an autonomous vehicle must make split-second decisions based on changing traffic conditions, pedestrian movements, and environmental factors.

One of the primary advantages of RL in autonomous vehicles is its ability to optimize long-term decision-making. For instance, RL can enhance a vehicle's ability to balance short-term safety with long-term objectives like fuel efficiency or traffic flow optimization. Advanced DQN and proximal policy optimization (PPO) algorithms can be integrated into DT systems to allow vehicles to simulate diverse driving scenarios, learn from simulated environments, and improve their decision-making processes before real-world deployment.

Moreover, multi-agent reinforcement learning can facilitate cooperative decision-making in scenarios involving multiple autonomous vehicles or agents, such as platooning or coordinated vehicle behavior in traffic flow. Research into safe RL methods that minimize the risk of failures during learning processes will be crucial for ensuring the safety and reliability of RL-based autonomous vehicle systems.

2) FL for for Distributed DT Systems: FL is a decentralized machine learning paradigm that allows multiple devices, such as vehicles or roadside units, to collaboratively train a model without sharing raw data. This is particularly relevant in the context of Distributed DT systems, where numerous IoT devices and sensors generate vast amounts of data that need to be processed and analyzed to maintain accurate digital replicas of vehicles, infrastructure, and environments.

FL enables privacy-preserving learning, as only model updates (not raw data) are shared among the devices in the network. This makes FL ideal for applications in autonomous vehicles, where data privacy is critical, and in smart cities, where personal information could be sensitive. In DT systems, FL can be used to train models for traffic prediction, vehicle behavior simulation, or road condition monitoring, while ensuring that private data remains local to the source device.

The research focus on FL for DT systems will involve improving model accuracy and training efficiency, as well as developing methods to ensure consistency and reliability across multiple, geographically distributed devices. Edge computing and local data processing will be essential components of FL systems in transportation networks, as they reduce the need for centralized data storage and minimize latency.

Moreover, heterogeneous learning techniques will be needed to account for differences in the devices' computing power, network capabilities, and sensor data types, allowing FL to be applied across a wide range of devices within transportation systems. This will allow for better scalability and adaptability in DT-based traffic management systems and autonomous vehicle networks.

3) Explainable AI (XAI) for Autonomous Systems: As AI and ML methods become more integral to the operation of autonomous vehicles and smart transportation systems, the transparency of these systems becomes increasingly important, particularly for safety-critical applications. XAI focuses on providing human-understandable explanations for decisions made by AI models, which is critical for autonomous systems such as self-driving cars, where decision-making transparency is crucial for trust and accountability.

XAI techniques can help autonomous systems justify their actions in understandable terms. For example, a self-driving car's decision to brake suddenly or avoid an obstacle can be accompanied by explanations that detail the reasoning behind the decision, such as "avoiding collision with a pedestrian" or "slowing down due to slippery road conditions." In the context of DT systems, incorporating XAI into vehicle and traffic simulations would allow operators and regulators to audit decisions and ensure compliance with safety protocols and ethical standards.

Research into interpretable models, such as decision trees, rule-based systems, and attention-based neural networks, will be crucial in making AI-based decision-making systems in autonomous vehicles and traffic management systems more understandable and predictable. These models will allow human operators to assess the system's behavior, intervene when necessary, and ultimately increase the public's trust in autonomous systems.

4) Vehicular AI models Improved by Digital Twin: The integration of DT technology into vehicular AI models opens several avenues for research, particularly in the areas of autonomous driving, traffic management, and ITS. One key research opportunity lies in enhancing real-time learning and adaptation for vehicular AI models. As autonomous vehicles interact with their environments, they continuously generate valuable data, which can be fed back into their digital twins. This real-time feedback loop, combined with advanced machine learning techniques can enable AI models to continuously improve their decision-making capabilities. Future research should focus on improving the scalability of these systems by allowing AI models to process vast amounts of data generated by DTs, optimizing performance across fleets of vehicles and transportation networks.

Another promising research direction involves synthetic data generation and scenario modeling for rare and edge-case driving conditions. Currently, AI models often face challenges in generalizing to unusual scenarios, such as extreme weather conditions, complex urban environments, or accident-prone situations. By leveraging the power of GANs within DT frameworks, researchers can generate high-quality synthetic data to augment AI training. This data can simulate extreme or rare driving scenarios, allowing AI models to become more robust in real-world applications. Additionally, multi-agent systems within DTs could be explored to improve V2V and V2I communication, enabling AI models to collaborate across connected systems to optimize traffic flow, enhance safety, and reduce congestion.

Transfer learning also holds significant potential for improving AI models within the context of digital twins. By transferring knowledge from one environment (e.g., urban driving) to another (e.g., rural or highway conditions), AI models can quickly adapt to new driving conditions without the need for extensive retraining. This would allow for faster deployment and adaptability of autonomous vehicles across different regions with varying driving conditions. Future research should focus on optimizing transfer learning techniques, particularly in distributed systems, to ensure that digital twins representing different vehicles, infrastructure, and environmental conditions can share and adapt knowledge efficiently.

D. Cybersecurity and Resilience in Distributed DT Networks

The increasing complexity and scale of DT systems in intelligent vehicles and transportation networks make cybersecurity and system resilience critical aspects of their development. Future research should focus on securing these systems from potential cyber-attacks while maintaining their resilience in dynamic and distributed environments.

1) Secure Communication Protocols for V2X Systems: One of the most pressing challenges in the deployment of V2X systems is ensuring the security of communication channels between vehicles, infrastructure, and external devices. As digital twins increasingly enable real-time data exchange for traffic management and autonomous vehicle operations, the need for secure communication protocols becomes paramount. Future research should focus on developing robust cryptographic protocols for V2X communication that ensure data integrity, confidentiality, and authenticity across the network. Specifically, blockchain-based solutions could be explored to provide a secure and decentralized method of verifying transactions and messages between connected vehicles and infrastructure. Moreover, quantum-safe cryptography will be essential as the potential for quantum computing poses a future threat to traditional encryption methods. Research could also focus on optimizing protocols for low-latency communication in real-time vehicular applications while maintaining security across multiple communication channels, such as 5G and Wi-Fi 6.

2) Anomaly Detection and Intrusion Prevention: As the volume of data and the complexity of distributed DT networks grow, anomaly detection and intrusion prevention mechanisms become critical to identifying and mitigating potential security threats. ML and AI are becoming increasingly useful in detecting deviations from normal operational patterns, identifying potential attacks, and responding in real time. Future research could explore advanced techniques in AI-driven anomaly detection, where algorithms are trained on large datasets of normal system behaviors and then used to identify potential intrusions or performance anomalies. Techniques such as unsupervised learning, deep learning, and neural networks can help enhance detection accuracy in large-scale DT systems. Additionally, distributed intrusion prevention systems (DIPS) could be developed, where threat detection and mitigation capabilities are spread across multiple nodes in the network, reducing the risk of a single point of failure. This would improve the resilience of DT systems against cyber-attacks by allowing rapid local responses to detected threats, ensuring the continuous operation of critical transportation infrastructure.

3) Resilient System Architectures: The resilience of distributed DT networks is critical for maintaining continuous operations in the face of cyber-attacks, hardware failures, or network disruptions. A resilient system architecture should be capable of maintaining system performance even when parts of the network are compromised. Research into self-healing architectures could enable DT systems to automatically detect failures, isolate damaged components, and recover lost functionalities without requiring manual intervention. Redundancy and failover mechanisms will be vital to ensuring the availability and reliability of the system, particularly in safety-critical applications like autonomous vehicles and traffic management. Additionally, edge computing can be leveraged to distribute processing power across the network, reducing the reliance on a centralized cloud and ensuring that vehicle and infrastructure systems can continue to function even if some parts of the network are temporarily unavailable. Future research could also focus on autonomous recovery systems that use real-time data from DTs to identify optimal recovery strategies, enabling the system to quickly resume normal operations after an attack or failure.

4) Privacy-Preserving Techniques: As DT systems for intelligent vehicles and transportation networks generate vast amounts of data, ensuring data privacy is a key concern, especially in environments that involve personal or sensitive information, such as location tracking and driver behavior. Privacy-preserving techniques are essential for ensuring that data collected by connected vehicles and infrastructure is protected against unauthorized access while still enabling the system to function effectively. One key area of research is the development of differential privacy mechanisms, which ensure that data sharing and analysis do not compromise individual privacy. In DTs, this could involve adding noise to sensitive data in such a way that it still provides useful insights without revealing specific details about individuals. Homomorphic encryption is another promising technique, allowing data to be encrypted and processed without needing to be decrypted, ensuring that sensitive information remains secure throughout its lifecycle. Additionally, secure multi-party computation (SMPC) could be explored as a way for multiple parties (e.g., vehicles, traffic management systems) to collaboratively process data without sharing sensitive information, further enhancing privacy while enabling useful data analysis.

VII. Conclusion

This survey has provided a comprehensive overview of DT technology and its transformative impact on CAVs and ITS. By enabling real-time monitoring, predictive maintenance, and dynamic optimization, DTs significantly enhance vehicle safety, traffic management, and the efficiency of autonomous driving systems. However, challenges such as data synchronization, scalability, and security remain critical barriers to widespread adoption. As DT technology evolves, future research will focus on improving integration across heterogeneous systems, addressing security concerns, and advancing sensor fusion to enable more reliable and resilient transportation networks. Continued innovation in AI, 5G, and edge computing will be pivotal in unlocking the full potential of DTs, contributing to the creation of smarter, safer, and more sustainable transportation systems.

Appendix

List of Key Acronyms

AI	Artificial Intelligence
AR	Augmented Reality
AES	Advanced Encryption Standard
BIM	Building Information Modeling
CAV	Connected and Autonomous Vehicle
CAD	Computer-Aided Design
CNN	Convolutional Neural Network
CPS	Cyber-Physical System
C-V2X	Cellular Vehicle-to-Everything
CoAP	Constrained Application Protocol
CFD	Computational Fluid Dynamics
DDoS	Distributed Denial of Service
DQN	Deep-Q Networks
DRL	Deep Reinforcement Learning
DT	Digital Twin

DTaaS	Digital Twin as a Service
FL	Federated Learning
GAN	Generative Adversarial Networks
GNN	Graph Neural Networks
HMI	Human-Machine Interface
HetVNet	Heterogeneous Vehicular Networks
IRS	Intelligent Reflective Surface
IoT	Internet of Things
ISO	International Organization for Standardization
ITS	Intelligent Transportation Systems
LSTM	Long Short-Term Memory
LoRaWAN	Long Range Wide-Area Network
LPWAN	Low-Power Wide-Area Network
MADDPG	Multi-Agent Deep Deterministic Policy Gradient
ML	Machine Learning
MaaS	Mobility as a Service
MDP	Markov Decision Process
MEMS	Micro-Electro-Mechanical Systems
MEC	Multi-access/mobile Edge Computing
MQTT	Message Queuing Telemetry Transport
mMTC	Massive Machine-Type Communications
NB-IoT	Narrowband Internet of Things
ACC	Personalized Adaptive Cruise Control
RFID	Radio Frequency Identification
RL	Reinforcement Learning
RSU	Roadside Unit
SCADA	Supervisory Control and Data Acquisition
SSL	Secure Sockets Layer
URLLC	Ultra-Reliable Low-Latency Communications
VANET	Vehicular Ad-hoc Networks
V2V	Vehicle-to-Vehicle
V2I	Vehicle-to-Infrastructure
V2X	Vehicle-to-Everything
VEC	Vehicular Edge Computing
VDT	Vehicular Digital Twin
VLC	Visible Light Communication
VR	Virtual Reality
XAI	Explainable AI

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