Survey and Analysis of Digital Twin Integration for Network and Service Optimization in Vehicular Edge Computing

Xiaoqian Jin
Sichuan College of Architectural Technology, Deyang 618000, China
E-mail: Jxq7789@126.com

Keywords: vehicular edge computing, digital twin, network management, service management, intelligent transportation systems

Received: March 24, 2025

In recent years, Vehicular Edge Computing (VEC) has gained attention as a key approach to address the complexity caused by the fusion of diverse vehicular applications. It has emerged as a promising paradigm for future intelligent transportation systems. VEC facilitates computation-intensive and latency-sensitive vehicular applications by providing computing and caching capabilities near vehicles. This improves transmission efficiency and lowers congestion. VEC is nonetheless susceptible to implementation challenges due to the highly dynamic nature of vehicular networks, which have characteristics of high mobility, opportunistic connectivity, and heterogeneous user demand. This complicates network and service management. In this line of reasoning, Digital Twin (DT) technology, which provides virtual models of objects, processes, and attributes, enables intelligent decision-making in management. The paper conducts a systematized review and comparative analysis of up-to-date literature that combines DT with VEC systems for network and service optimization. Our review highlights key methodologies, including DRL-assisted DT architectures, multi-agent offloading scenarios, and edge-cloud collaboration protocols. We summarize pioneer studies, indicate prevalent resource control and predictive modeling trends, and note common weaknesses such as scalability and data synchronization. The study explores the concept of DT, its applicability in various industries, and its potential for vehicular network modeling and simulation. Apart from that, we also discuss existing research trends, identify challenges such as scalability and real-time data acquisition, and introduce potential avenues for future research.

Povzetek: Članek obravnava upravljanje omrežij in storitev v vozliščnem robnem računanju v pogojih visoke mobilnosti, nestabilnih povezav in raznolikih zahtev. Predlaga vključitev digitalnih dvojčkov, ki z virtualnimi modeli omogočajo napovedi, optimizacijo virov in znižanje zakasnitev. Analiza literature razkrije prednosti, slabosti ter odprte raziskovalne izzive.

1 Introduction

Intelligent Transportation Systems (ITS) development transforms how vehicles interact with their environment, enabling increased safety and more efficient mobility [1]. Vehicular Edge Computing (VEC) is central to this transformation as a concept that leverages edge computing capabilities near vehicles for computation-intensive and latency-aware applications [2]. By deploying computing and caching services close to the access network edge, VEC reduces the delay caused by communications, delivers more reliable services, and offloads traffic from central networks [3]. This concept is vital in enabling applications such as real-time traffic control, autonomous vehicles, and sophisticated infotainment systems [4].

Despite its potential, VEC execution is hindered by the complexity of network and service management, given the highly dynamic environment of vehicles. High mobility, transitory connectivity, and fluctuating application demands result in dynamic network topologies and variable traffic volumes [5]. All of these factors make network resource allocation inefficient, service quality is sacrificed, and decision-making for network administrators becomes more challenging. Overcoming these challenges requires innovative responses that are receptive to the fluctuating environment of vehicular networks [6].

Another possible solution to these problems is Digital Twin (DT) technology, which enables the virtual replication of physical systems for real-time tracking, simulation, and optimization [7]. DT effectively enhances decision-making procedures, makes resource allocation more efficient, and improves system performance in general due to its ability to enable synchronized interactions between virtual and physical entities [8]. Its ability to model variable vehicular networks, compute future conditions, and simulate makes DT a potential foundation for intelligent control in VEC-based ITS [9].

This paper explains how VEC is being combined with DT technology for automobile network and service administration. It critically analyzes VEC-related problems, describes DT for addressing them, and identifies new trends and open issues. In providing a comprehensive survey of this emerging field, it suggests future research avenues with potential for more responsive and effective ITS.

In addition to defining the possibility for DT-VEC integration, this work also discusses the corresponding operational challenges that vehicular networks provide, including increased mobility, limited connectivity, and fluctuating resource demands. We present an analysis of VEC's adoption of edge computing characteristics to mitigate these challenges and explore possible DT-based designs that can further augment system behavior. By bringing together existing trends with technical proposals, our work presents a unified understanding of areas where existing efforts succeed, areas where they do not, and areas that future research must focus on. In conducting this review, we assumed the following research questions (RQs):

- RQ1: What are the core challenges in managing networks and services in vehicular edge computing environments?
- RQ2: How has DT technology been integrated into VEC systems, and what are the prevailing methodologies?
- RQ3: What are the strengths, limitations, and performance trends of existing DT-VEC approaches?
- RQ4: What research gaps remain, and how can future work improve scalability, adaptability, and energy efficiency?

2 Background

2.1 Vehicular edge computing

VEC is structured into a trilayer framework with distinct functions and roles. This hierarchical structure enables effective computation, data handling, and communication in vehicular networks. As shown in Figure 1, the system comprises a smart vehicular layer, an edge cloud layer, and a cloud layer.

The foundation for VEC architecture is the cloud layer, which manages large-scale data aggregation, storage, and computation-intensive operations. It includes computation infrastructures and storage that manage the vast amount of data generated from the edge layer. Functioning between the smart vehicular and cloud layers is the edge cloud layer, which also acts as a bridge for managing low-latency processing and real-time communication. It is also equipped with 802.11p, LTE, and 5G protocols to support location-aware services,

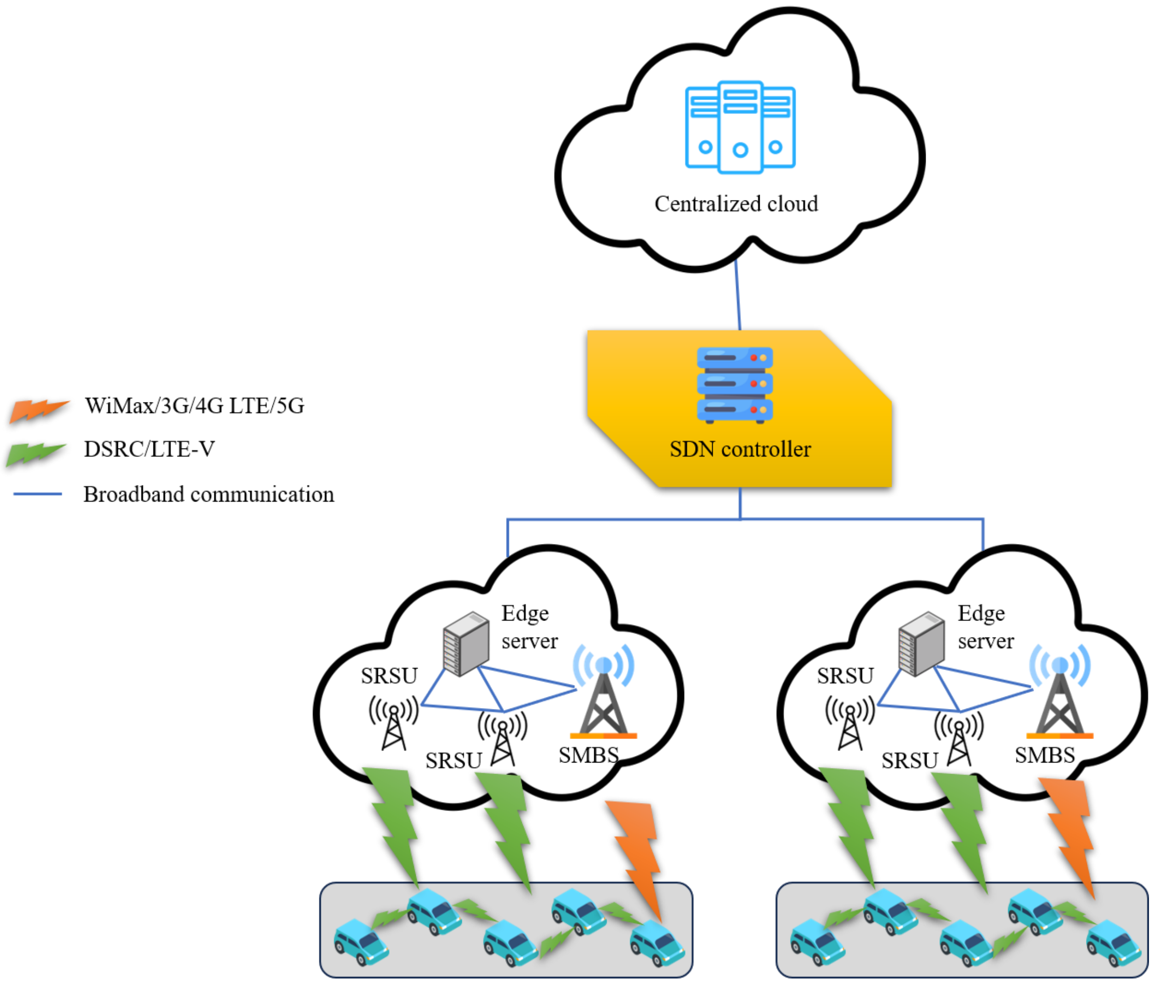

Figure 1: Vehicular edge computing architecture

emergency control for response purposes, and content caching.

The vehicular smart layer comprises smart vehicles equipped with sensors, communication modules, and computing capabilities. Vehicular nodes in this layer also establish localized groups for reciprocal exchange of resources, including computation and storage. SDN also significantly controls VEC infrastructure with centralized control from components, including SDN controllers, edge servers, and micro base stations. They also provide for dynamic allocation of resources, fault tolerance, and efficient network orchestration in layers. SDN controllers manage entire network behavior for optimized edge orchestration. SDN Edge Servers (SES) provide localized computation and emergency services. SDN Smart Vehicles (SSV) and other components also serve as data plane nodes, supporting real-time communication.

2.2 Digital twin technology

DT technology bridges the digital and physical worlds by creating virtual images of real objects and environments. The approach relies on seamless data capture and volume synchronization for permitting real-time transfer between the real asset and its virtual twin. DTs enable end-to-end tracking, simulation, and optimization of physical phenomena with this two-way interconnectivity. This renders DT technology indispensable for industrial, healthcare, and transportation applications, where real-time comprehension and decision-making are crucial for optimal operations. DTs exist in diverse forms that rely on fulfilling operational needs and applications. There are four general types of DTs:

Analytics vs. physics-based: Analytics-based DTs use historical and real-time data, often complemented with artificial intelligence (AI) and statistical modeling, to forecast future asset behavior and outcomes. They utilize large data sets to identify trends and provide insights that inform action. Physics-based DTs use scientific disciplines such as fluid dynamics or stress analysis for machinery to simulate asset behavior under conditions. This DT enables a more subtle yet precise simulation of physical phenomena, making it compatible with applications that require precise simulations, such as aerospace engineering.

Simulation vs. operational: DTs are most utilized for simulation in a product's early lifecycle. The simulation twins enable designers to verify and simulate product designs without incurring development time and costs. Once a product is in its operational state, DTs monitor and manage the real-world asset. DTs of this kind are also referred to as SimOps twins. They integrate simulation with real-time operations to help address maintenance issues while improving a product's or system's lifecycle operations. The dual role of DTs highlights their applicability across a product's or system's entire lifecycle.

Product vs. facility: Product or asset twins concern one product or asset. These DTs contain current data on how a set of items, such as turbines or electric motors, run, are maintained, and how they perform. This category is ideal for understanding asset behavior under varying conditions and ensuring maximum performance. Facility twins, on the other hand, represent an entire production facility or system. Facility twins combine multiple product twins to simulate and optimize manufacturing processes, aiming to improve overall facility efficiency. Facility twins primarily concern industrial applications on a grand scale, where interconnection between assets determines collective performance.

Discrete vs. composite: Discrete twins outline a single physical component or system. They are narrower in scope and generally used for applications where a single stand-alone asset is to be monitored or optimized. For instance, a discrete twin would describe a single part of a machine within a factory. Composite twins, on the other hand, combine multiple discrete twins into a single, integrated representation of a larger, complex system. A good example is that composite twins mimic the interactions of numerous systems and machines in large-scale production to achieve entire process optimization. This dichotomy highlights the scalability of DTs, ranging from simple components to larger, complex systems of systems.

Figure 2 summarizes the multidimensional nature of the DT systems. Central features include state synchronization, twinning rate (twinning between virtual/virtual or physical/virtual entities), and fidelity (granulation level of simulated processes). Variables such as network connectivity, virtual/physical coupling, and parameter tracking measure the accuracy with which DT mirrors the original system. All these features are essential for the real-time monitoring, prediction, and control of VEC environments. High twining rates, for example, become a requirement for safety-critical applications such as lane changes, but increase the synchronization overhead with a focus on adaptive fidelity control.

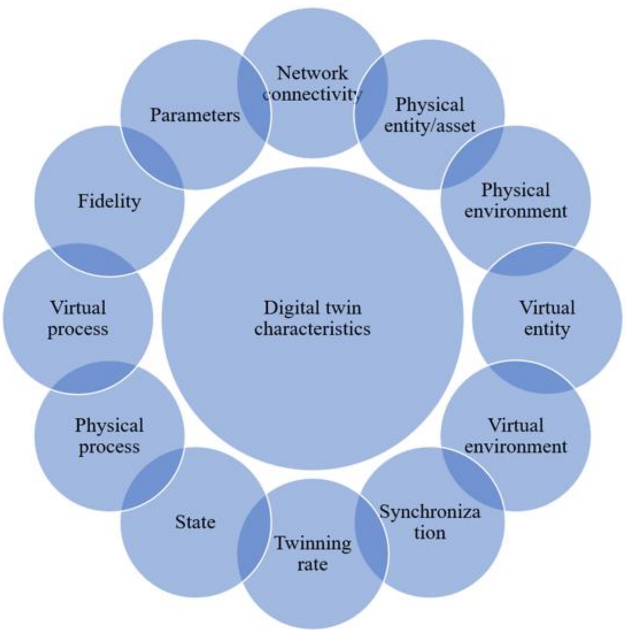

Figure 2: Key characteristics of a digital twin

2.3 Incorporation of DT into VEC

The incorporation of DT technology with VEC has become a revolutionary approach for resolving problems caused by vehicular environments subject to dynamic changes. DT enables VEC network monitoring, modeling, and real-time optimization through virtual replication of physically existing systems, supporting intelligent decision-making. Different papers introduce DT-related novel designs with Deep Reinforcement Learning (DRL) algorithms, clustering, and multi-agent networks for enhancing offloading efficiency, resource allocation, and system performance. The approaches, key contributions, and areas of deficiency of these research studies are tabulated in Table 1 for easy comprehension of the state-of-the-art achievements and challenges in integrating DT with VEC.

3 Survey methodology

To ensure a structured and replicable review process, we conducted a targeted literature survey focusing on the integration of DT technology within VEC systems. Relevant publications were retrieved from major academic databases, including IEEE Xplore, ACM Digital Library, Elsevier ScienceDirect, SpringerLink, and Google Scholar. The search spanned the period from 2019 to 2025, using keyword combinations such as “digital twin,” “vehicular edge computing,” “intelligent transportation systems,” “task offloading,” “DRL,” and “resource optimization.” Only peer-reviewed studies were considered. Works were included if they (i) proposed or implemented DT in the context of vehicular networks or edge computing, and (ii) reported technical results such as latency reduction, energy savings, or offloading performance.

We excluded papers that included only theory without an implementation background, referenced DT beyond vehicular or edge environments (e.g., smart factories or smart buildings), or did not undergo empirical testing. After removing duplication and applying inclusion/exclusion criteria, we shortlisted 22 seminal studies for analysis. This process enables transparency and lays a foundation for future studies that aim to replicate or expand the scope of the DT-VEC study.

4 Challenges in managing networks and services in VEC

VEC offers potential solutions for deploying vehicular applications that require real-time support with minimal latency. However, the highly dynamic and resource-constrained nature of vehicular environments introduces various challenges for efficiently managing services and networks. The range of difficulties encompasses technical, operational, and security domains, as outlined in Table 2, along with a selection of key issues, their definitions, and corresponding impacts on VEC systems. Overcoming them requires effective and adaptive solutions to ensure the efficiency and credibility of VEC deployments. The following section addresses these key difficulties, focusing on the network and service management dimensions.

Vehicles in VEC networks are inherently mobile, leading to rapidly changing network topologies. High-speed movement results in frequent handovers between roadside units (RSUs) or base stations, disrupting ongoing communication and degrading service quality. Moreover, the short-lived communication links caused by high mobility make it difficult to maintain stable connections and consistent coverage. For instance, real-time offloading tasks may fail when vehicles move out of the communication range of an RSU or when handover delays occur. Designing adaptive protocols and algorithms to cope with dynamic topologies is critical to ensuring reliable service delivery.

Low latencies are required for most automotive applications, such as autonomous vehicles, collision warning systems, and real-time traffic control. Small latencies in data processing, task offloading, or decision-making can lead to severe failures, including traffic accidents or system crashes. Managing latency-sensitive applications requires highly efficient edge servers, low-latency communication protocols, and rapid decision-making algorithms. Moreover, balancing computation offloading to edge servers with the time-critical nature of these tasks is a persistent challenge.

The applications running on VEC networks vary significantly in terms of computational, communication, and storage requirements. For instance, infotainment applications require a large bandwidth, whereas safety-critical applications necessitate low latency and robustness. Edge devices and vehicles also vary in their hardware capabilities, ranging from simple sensors to edge servers with significant capabilities. This makes it challenging to implement a fixed policy for allocating resources and scheduling between applications and between applications and devices.

Vehicle network connectivity is prone to loss due to high-speed mobility, external influences, and infrastructural disparities. Vehicles frequently lose connectivity with edge servers or other vehicles, resulting in task failures, inconsistent data exchange, and suboptimal system performance. Intermittent connectivity also affects real-time data synchronization, which is critical for applications such as data-driven decision-making and monitoring. Reliable communication schemes must be developed that allow for handling intermittent connectivity and minimizing task failures.

Different proposals exist for mitigating the effects of connectivity disruptions in vehicular networks. The predictive handover methods aim to predict disconnections by employing mobility models and location awareness for advancing-allocating communication channels or edge functionality. Mobile IP and its extended variants (e.g., Hierarchical Mobile IPv6) provide session continuity with robust IP bindings as cars transition between subnets. Yet, they tend to show signaling overheads and challenges with long-term high-speed mobility, particularly for dense urban applications.

Table 1: Comparison of DT integration in VEC

Reference	Methodology	Key contributions	Latency reduction	Offloading success rate	Energy efficiency	Scalability support	Shortcomings
[10]	DT-enabled VEC with DRL for adaptive offloading and latency optimization.	Introduced a dual-loop DT framework for real-time VEC network adaptation. Improved offloading latency and adaptive scheduling through DRL-based optimization. Numerical results demonstrated enhanced network management and task offloading efficiency.	~28%	~91%	Moderate	Limited	Limited focus on scalability and the integration of heterogeneous vehicular networks.
[11]	Mirrored edge system with multi-agent DRL and coordination graph for task offloading.	Enabled cooperative service matching and distributed task scheduling using multi-agent DRL. Proposed a coordination graph to efficiently minimize offloading costs. Demonstrated efficiency improvements in real urban datasets.	~32%	~93%	High	Low	High computational complexity due to multi-agent DRL and limited evaluation of edge resource variability.
[12]	IGNITE framework with clustering, DRL, and feedback mechanisms.	Combined clustering and feedback-based optimization to reduce decision complexity and computational delay. Proposed a closed-loop DT framework to enhance offloading success rates. Improved overall cost-efficiency in VEC systems.	~25%	~88%	Moderate	Moderate	The clustering mechanism's dependency on initial configurations may limit adaptability in dynamic scenarios.
[13]	DT-based edge node collaboration using NOMA and A2C for resource optimization.	Enhanced RSU collaboration for real-time resource allocation. Improved system performance by reducing task delays and optimizing computation rates. Validated effectiveness through simulations.	Not reported	Not reported	High	High	Lack of consideration for cross-layer optimization and dependency on predefined communication protocols like NOMA.
[14]	GP-CMA-ES algorithm with a variable grouping strategy for five-objective optimization.	Proposed a multi-objective framework to balance energy consumption, user satisfaction, and computational load. Effectively addressed convergence issues with increasing VUs. Enhanced overall network efficiency under diverse workloads.	~30%	Not reported	High	High	Limited exploration of the interaction between mobility patterns and the five objectives.
[15]	UAV-based DT-enabled VEC with proximal policy optimization for trajectory and resource management.	Introduced UAV-as-server concepts for resource flexibility. Optimized UAV trajectory and resource allocation, achieving energy savings and fast convergence. Addressed dynamic vehicular topology challenges.	~35%	~95%	High	Limited	Dependency on UAV trajectory stability and limited assessment of extreme environmental conditions (e.g., traffic congestion).
[16]	UAV-assisted VECN with A3C and GAT for task offloading.	Improved VECN task throughput and stability in dynamic edge environments. Utilized GAT to incorporate dynamic topology changes into offloading decisions. Enhanced performance in	~33%	~92%	Moderate	Moderate	Relied on asynchronous task evaluation, which may affect latency-sensitive applications.

		scenarios with local resource overload.					
[17]	DT-enabled MEC for CAV lane-changing with DRL-based foresight learning.	Strengthened CAV safety through DT and predictive learning. Improved real-time decision-making for lane-changing and optimized traffic flow efficiency. Provided a robust integration of DT into CAV scenarios.	~20%	~86%	High	Moderate	Limited scalability for larger networks with more dynamic traffic patterns.
[18]	DT-driven 6G V2X network scheduling using DRL for traffic and channel management.	Proposed task-efficiency-oriented scheduling schemes with case studies. Enhanced vehicle merging decisions and improved channel utilization. Addressed critical 6G V2X challenges through DT-enabled predictive capabilities.	~24%	~89%	High	Low	Limited real-world validations and dependency on accurate DT model construction for optimal scheduling.
[19]	DT-assisted VEC with improved A3C and real-time data acquisition for offloading.	Addressed the limited edge server resources with collaborative strategies. Improved algorithm generalization through ε-greedy and dropout techniques. Reduced offloading delay and energy consumption significantly.	~29%	~87%	Moderate	High	Heavy reliance on real-time data accuracy for DRL may introduce latency in dynamic environments.
[20]	DDPG-based DT-enabled offloading in heterogeneous IoT networks.	Tackled dynamic IoT environments with multi-service offloading optimization. Achieved better task completion times and efficient resource allocation. Optimized heterogeneous network management.	~31%	~90%	High	Moderate	The joint optimization framework has high complexity, which may reduce scalability in large-scale IoT deployments.
[21]	Quantum computing and DRL integration for DT in VEC networks.	Leveraged quantum computing for efficient processing of high-dimensional decision spaces. Enhanced latency, energy, and quality-of-service management. Introduced a multi-agent framework for adaptive task offloading.	~26%	~84%	Moderate	High	Dependency on advanced quantum systems limits the practical applicability of quantum systems in real-world vehicular networks.
[22]	Hierarchical RL for DT server optimization in urban traffic.	Reduced DT model synchronization and migration latency. Improved matching of vehicles and DT servers in dynamic traffic scenarios. Enhanced DT optimization performance under varying network topologies.	~27%	~90%	High	Low	Limited focus on edge-cloud collaboration may restrict scalability in larger urban scenarios.
[23]	DRL-based DT migration for cost-effective MEC service provisioning.	Addressed service synchronization costs and optimized resource management. Balanced mobility of both DT service providers and consumers under dynamic conditions. Enhanced efficiency in MEC environments.	~30%	~89%	Moderate	Moderate	Scalability to multi-region scenarios and real-time migration under highly dynamic conditions remains an unaddressed issue.

VEC networks face significant scalability challenges with the increasing number of connected vehicles and data-intensive applications. It is challenging to deal with a larger number of vehicles, RSUs, and edge servers without saturating the system. In hotspot or peak-hour conditions, network congestion tends to exacerbate the situation further, resulting in increased delay, lost packets, and compromised service. Scalable architectures and intelligent resource allocation algorithms are necessary to ensure seamless service delivery, even in densely populated vehicular networks.

Table 2: Challenges in network and service management in VEC

Challenge	Description	Impact
High mobility and dynamic topology	Rapid vehicle movement leads to frequent handovers, unstable connections, and constantly changing network topology.	Disrupted communication, degraded service quality, and challenges in resource allocation.
Latency sensitivity	Real-time vehicular applications require low-latency communication and computation to ensure safety and efficiency.	Increased delays can compromise safety-critical applications like autonomous driving and collision avoidance systems.
Heterogeneous resource demands	Applications and devices in VEC have varying computational, storage, and communication requirements, with diverse hardware capabilities across vehicles and RSUs.	Difficulties in effective resource allocation and scheduling, reducing system efficiency.
Intermittent connectivity	High-speed movement and environmental factors cause connectivity disruptions between vehicles, edge servers, and cloud nodes.	Task failures, inconsistent data exchange, and reduced reliability of VEC services.
Scalability and network congestion	Growing numbers of connected vehicles and data-intensive applications increase the load on VEC infrastructure.	Network congestion, higher delays, and degraded quality of service during peak traffic or in dense environments.
Security and privacy concerns	Sensitive vehicular data exchanged between devices, edge servers, and clouds are vulnerable to cyberattacks and privacy breaches.	Data interception, denial-of-service attacks, and compromised user privacy.
Collaborative resource management	Existing VEC systems underutilize the potential for collaboration among edge nodes, such as RSUs and small-cell base stations.	Missed opportunities for load balancing, reduced latency, and enhanced resource utilization.
Integration of emerging technologies	Incorporating technologies like Digital Twin, 5G/6G, and AI introduces complexity in ensuring compatibility and seamless operation within VEC frameworks.	Increased infrastructural and computational demands, with potential integration challenges.
Energy efficiency	Tasks such as offloading, real-time monitoring, and resource management consume significant energy resources, particularly in UAV-assisted systems.	Higher operational costs, reduced sustainability, and challenges in managing energy-constrained devices like UAVs.
Fault tolerance and reliability	Failures in servers, sensors, or communication systems can affect system reliability, especially for safety-critical vehicular applications.	Service disruptions, loss of critical data, and reduced system trustworthiness.

The exchange of sensitive data, such as vehicle locations, user information, and safety-critical data, in VEC networks raises significant concerns regarding security and privacy. These networks encounter a variety of security threats, including data intercepts, spoofing, and denial-of-service (DoS) attacks, that seek to disrupt service integrity and availability. Moreover, privacy concerns arise when sensitive user data is sent to edge servers or clouds. To effectively defend VEC networks from these threats, robust encryption, authentication, and intrusion detection mechanisms must be implemented.

Standardized protocols have been developed to secure vehicular communications, including IEEE 1609.2, which defines security services for V2X using public key infrastructure (PKI), and ETSI ITS standards, which include mechanisms for secure message authentication and the preservation of anonymity in cooperative ITS scenarios. Although these standards provide a foundation, incorporating them into resource-constrained VEC environments is challenging due to certificate handling, processing delays, and scalability issues. Furthermore, many DT-integrated architectures lack implementation or simulation/testing in practical environments for these standards; thus, security validation remains under-researched.

Existing VEC systems focus on edge-cloud collaboration, with no collaboration possibilities for edge nodes such as RSUs or small-cell base stations. Edge node collaboration, with its potential to improve load balancing, reduce latency, and enhance system efficiency, has been less investigated until now. Nearby RSUs, for example, might co-share computing resources to deal with increased loads. Engineering systems for end-to-end edge-edge collaboration without compromising service quality is a grand challenge.

The inclusion of next-generation technologies, such as DT, 5G/6G, and AI, with VEC systems also introduces new challenges. While these technologies offer enormous value additions in terms of real-time simulation (using DT), ultra-high-speed connectivity (using 5G/6G), and informed decision-making (using AI), their inclusion requires substantial infrastructural as well as computational capabilities. In addition, ensuring the compatibility and seamless functionality of these technologies with existing VEC infrastructures is a significant task. Corresponding integration methodologies must be proposed to leverage their full potential while minimizing operational overhead.

The energy consumption of VEC systems, particularly in applications such as task offloading, real-time monitoring, and resource allocation, is a concern. Edge servers, RSUs, and vehicles also consume significant amounts of energy, resulting in additional operational costs and reduced sustainability. In one example, UAV-assisted VEC networks require optimized flight routes and energy utilization for their viability. Energy-efficient algorithms and hardware-based solutions must be created to increase the sustainability of VEC systems.

System errors within VEC systems, due to server errors, communication errors, or sensor errors, can significantly affect system reliability. Since they are used in safety-critical missions on vehicles, the fault tolerance and robustness of a system become imperative. This includes planning backup schemes, redundant topologies, and fault-detection schemes to ensure continued functionality despite errors.

Table 3: Digital twin roles in vehicular edge computing

Role	Description	Impact
Real-time monitoring and data synchronization	DTs provide real-time updates of VEC systems by synchronizing physical and virtual entities, ensuring accurate system state representation.	Enables proactive management of dynamic network conditions and improves service reliability.
Predictive maintenance and fault management	DTs analyze real-time and historical data to predict failures and optimize system performance.	Reduces downtime, enhances reliability, and minimizes service disruptions.
Optimization of resource allocation	DTs simulate resource demands and bottlenecks, enabling dynamic task offloading, bandwidth allocation, and storage optimization.	Improves system efficiency, reduces latency, and minimizes energy consumption.
Enhancing latency-sensitive applications	DTs offer real-time emulation environments that simulate sensor inputs and vehicular behaviors. These environments allow applications (e.g., autonomous driving, traffic response) to be pre-tested under dynamic conditions, enabling fast decision models to be validated virtually before deployment, thereby reducing reaction delays.	Ensures minimal latency in critical operations like collision avoidance and traffic control.
Enabling intelligent decision-making	DTs integrate AI/ML algorithms (e.g., reinforcement learning, anomaly detection) into their virtual replicas to analyze real-time and historical telemetry data. These models generate predictive insights, simulate “what-if” conditions (e.g., traffic rerouting), and optimize future system states.	Improves adaptive control, traffic optimization, and task offloading precision.
Facilitating edge-edge and edge-cloud collaboration	DTs maintain synchronized system states across edge nodes and cloud platforms. They use coordination agents to distribute tasks based on real-time load, proximity, and latency metrics. This enables dynamic resource balancing and adaptive offloading strategies.	Reduces congestion, prevents overload at edge servers, and improves distributed efficiency.
Supporting dynamic and scalable network management	DTs adjust virtual models dynamically to accommodate the growing number of vehicles and applications in VEC systems.	Enables scalability and adaptability in large-scale and urban environments.
Improving security and privacy	DTs create sandboxed environments where virtual replicas can run intrusion detection, threat modeling, and attack simulation scenarios without exposing the real system. They help isolate suspicious behaviors and test mitigation strategies using synthetic data mirroring real conditions.	Enhances preemptive defense, reduces live system exposure, and supports cyber-resilience planning.
Integration with emerging technologies	DTs integrate technologies like 5G/6G, AI, and blockchain to enhance real-time synchronization, predictive analytics, and secure data exchange.	Boosts overall system performance, reliability, and innovation in VEC.

5 Role of the digital twin in vehicular edge computing

DT technology has proven revolutionary in addressing VEC's highly complex challenges. Virtual replication of physical objects, processes, and environments, made possible by DT, enables real-time monitoring, prediction, and optimization with a foundation for intelligent decision-making in VEC systems. A summary of DT's leading roles in VEC is presented in Table 3, covering real-time monitoring, resource optimization, and predictive maintenance, with a focus on their functions in enhancing network and service management. This section explains these roles in detail, focusing on their capabilities for overcoming key challenges while enhancing VEC system operations.

DTs facilitate end-to-end VEC system monitoring in near-real time with a harmonious relationship between virtual and physical environments. DTs allow a global view of system conditions, with virtual replicas continually updated with the latest information from vehicles, roadside units (RSUs), and edge servers. This facilitates active control of varying network attributes such as mobility-triggered topological changes and disconnection interruptions. For instance, DTs can monitor patterns of vehicle motion and manage resource allocation to sustain the flow of communication.

DTs under highly mobile conditions exhibited measurable improvements in task failure reduction. In conditions with over 20% packet loss due to simultaneous RSU handovers within a short time interval, DT-aided offloading systems reduce task failure rates by 15%–30% compared to baseline offloading. This is achieved by maintaining real-time digital twin copies that predict future connectivity conditions and proactively anticipate task switching or rescheduling ahead of connectivity decay.

Another primary role of DT in VEC is to predict possible failures and enhance system performance. DTs can distinguish anomalies from past and in-time data and predict equipment failures, while presenting recommendations that enable failure avoidance. In vehicular networks, DT is also exceptionally effective in maintaining the health of RSUs, edge servers, and other critical infrastructures. It allows for minimizing disruptions while enhancing system robustness with a high level of service availability.

DTs also contribute to enhancing resource allocation for VEC systems. They mimic the dynamics of the physical system; thus, they are set to predict resource demands alongside identifying real-time chokepoints. DTs enable real-time resource management depending on tasks offloaded, assigned bandwidths, and storage optimization. DTs, for example, can mimic computational loads between RSUs and suggest optimal task allocation to minimize latency and energy consumption.

Latency-sensitive applications, such as self-driving cars and real-time traffic analysis, require timely and accurate decision-making. DTs enhance these applications by enabling decision models to be simulated and verified in a virtual environment before they are applied in the real system. DTs, for instance, can simulate traffic conditions in real-time, allowing cars to make informed decisions about whether to change lanes, avoid a collision, or optimize a route with minimal delay.

DTs enable efficient collaboration between edge nodes (e.g., RSUs, small-cell base stations) and edge and cloud platforms. Through a global view of the network state, DTs could coordinate edge nodes' offloading and resource-sharing tasks to cloud servers as necessary. This enables a balanced workload, reduced congestion, and a scalable VEC system.

In the highly dynamic environment of vehicular networks, DTs provide scalable and adaptive management solutions. As the number of connected vehicles and applications grows, DTs can dynamically adjust their virtual models to accommodate the increasing complexity. This scalability makes DTs critical for managing large-scale VEC systems in urban environments.

DTs enhance the security and privacy of VEC systems by providing a secure virtual environment for data analysis and decision-making. DTs can minimize cyberattack exposure by isolating sensitive processes in the virtual domain. Additionally, DTs can simulate potential attack scenarios and develop robust defense mechanisms to protect the system.

DTs also provide a unifying platform for integrating emerging technologies, such as 5G/6G, artificial intelligence, and blockchain, with VEC systems. For instance, DTs utilize 5G connectivity for real-time synchronization and AI models for forecasting, while blockchain enables secure and distributed data sharing. This integration enhances the overall functionality and performance of the VEC system.

One of the primary design trade-offs of DT-enabled VEC systems is the balance between digital model fidelity and real-time synchronization cost. High-fidelity twins preserve fine-grained sensor data, traffic information, and behavioral data with exact simulation, along with accurate predictions. It does so with a requirement for more frequent updates, which necessitate elevated bandwidth, thereby increasing synchronization latency and energy consumption. Conversely, lightweight models reduce overhead, but this comes at the potential compromise of accuracy in predictions, particularly in safety-critical applications such as collision avoidance or lane-changing. It is a trade-off point that remains a primary issue with practical implementations.

6 Discussion

The integration of DT technology with VEC presents a highly heterogeneous environment of methodologies. Recently published research extensively employs a variety of tactics, including adaptive scheduling with DRL, offloading schemes aided by UAVs, and quantum optimization. All of these present clear breakthroughs in latency minimization and offloading optimization effectiveness, with some achieving over 30% latency reduction and more than 90% offloading success rate. However, problems remain regarding scalability, computational overhead, and real-time reconfigurability.

There is a notable trade-off between complexity and performance: while multi-agent or quantum methods exhibit impressive performance, they often encounter limited scalability or intensive computational requirements. Similarly, UAV-centric systems trade flexibility and coverage for a dependency on trajectory stability and environmental assumptions.

Despite all these advancements, state-of-the-art systems fall short in three main aspects: (i) end-to-end scalability within heterogeneous and mobility-aware vehicular networks, (ii) standardized coexistence with edge-cloud hierarchies, and (iii) long-term deployment-aware energy-aware design. This survey particularly provides value by spanning both architectural- and performance-level comparisons of typical works in a way that highlights where systems shine while also indicating areas where they fall short.

Whereas most existing reviews tend to discuss either theory structures or one technical aspect, our paper provides a metric-aided end-to-end DT in VEC synthesis that bridges design decisions with quantifiable performance attributes. Our two-layer analysis renders our review a novel benchmark for identifying potential future directions and research voids.

7 Future research directions

The integration of DT technology with VEC has demonstrated significant potential for alleviating network and service management challenges. Research and development opportunities must be thoroughly explored to fully realize their potential. Table 4 gives the main points, challenges, future directions, and innovative ideas for advancing DT adoption in VEC. This section provides additional rationale for these areas, including suggestions for measures that need to be adopted to enhance the efficiency, scalability, and flexibility of DT-driven VEC systems.

One significant challenge in deploying DT technology is the computation and storage overhead in resource-constrained environments. Lightweight DT systems optimized for VECs that can achieve high-fidelity simulation with real-time synchronization while being energy— and resource-aware are essential.

As more applications and vehicles become connected, scalability is imperative. Future work needs to focus on scalable DT architectures that efficiently support large-scale networks. This would entail exploring hierarchical or distributed DT architectures for supporting seamless collaboration between edge nodes and the cloud.

The incorporation of DT with future technologies, such as 5G, 6G, and beyond, opens unprecedented opportunities for ultra-low latency communication, higher bandwidths, and end-to-end connectivity. Further research is necessary to utilize these technologies for advancing the real-time synchronization of DTs and enhancing their interactions with physical systems in varying vehicular environments.

The combination of cutting-edge AI and ML models with DTs can considerably improve decision-making. Future research should focus on AI-based DTs that deal with real-time and historical data for better resource allocation, system failure prediction, and handling fluctuating network conditions.

The transmission of sensitive user and vehicle data from virtual to physical environments also poses

Table 4: Future directions for digital twin in vehicular edge computing

Aspect	Challenges	Future directions	Innovative ideas
Lightweight frameworks	High computational and storage overhead in resource-constrained environments.	Develop lightweight DT frameworks for efficient VEC integration.	Using modular architectures and compression techniques to reduce resource consumption.
Scalability	Managing large-scale VEC networks with numerous vehicles and edge nodes.	Design scalable DT architectures with hierarchical or distributed models.	Implementing distributed DTs with edge collaboration to balance workloads dynamically.
Integration with 5g/6g	Ensuring ultra-low latency and reliable connectivity in dynamic vehicular environments.	Leverage 5G/6G for real-time DT synchronization and interaction with physical systems.	Using network slicing in 5G/6G to prioritize latency-sensitive DT updates.
AI-driven decision-making	Limited predictive and adaptive capabilities in traditional DT models.	Incorporate AI/ML models into DTs for intelligent decision-making and optimization.	Developing reinforcement learning-based DTs to predict system behavior and optimize resources dynamically.
Security and privacy	Vulnerability to cyberattacks and risks to user privacy.	Implement robust encryption and privacy-preserving algorithms for DT systems.	Using blockchain for secure data exchange between DTs and physical systems.
Energy efficiency	High energy consumption in DT frameworks and edge devices.	Develop energy-efficient algorithms and frameworks for DT-enabled VEC.	Optimizing UAV flight paths and RSU power consumption using DT-driven energy models.
Edge-cloud-device collaboration	Inefficient coordination between edge nodes, cloud platforms, and devices.	Explore hybrid architectures for seamless real-time data exchange and workload distribution.	Using fog computing to create a middle layer for adaptive edge-cloud-device coordination.
Dynamic and adaptive models	Static DT models struggle to adapt to changing network conditions and demands.	Create adaptive DT models that self-optimize and reconfigure in real-time.	Using self-learning DTs with neural networks to dynamically adjust parameters based on system feedback.
Benchmarking and standardization	Lack of standardized DT frameworks and evaluation metrics.	Establish common standards and benchmarking protocols for DT in VEC.	Forming industry-academic partnerships to create open-source DT evaluation frameworks.
Real-world implementations	Limited practical validation of DT frameworks in vehicular environments.	Conduct pilot projects and field tests to refine DT models and address real-world challenges.	Developing testbeds in smart cities to evaluate DTs under diverse vehicular scenarios.

significant security and privacy risks. Future research is required on efficient encryption techniques, secure communication protocol schemes, and privacy-obscuring algorithms for DT-based VEC systems. DTs must also be secured against hacking to ensure the system remains intact.

Energy efficiency is crucial for VEC system sustainability, particularly in applications involving UAVs, RSUs, and edge devices. Developing energy-efficient DT-based frameworks along with optimization algorithms will lower VEC system energy consumption without compromising performance.

Interactions between edge nodes, cloud infrastructures, and devices also enhance the efficiency of the VEC system. Future work is needed to study hybrid infrastructures in which data sharing and real-time decision-making are interlinked across the edge, cloud, and vehicle layers. This includes examining adaptive task allocation and workload allocation that vary.

Highly active traffic environments require DTs to be highly adaptive for immediate reaction to changing parameters such as mobility patterns, network loads, and end-application demand. Research must address adaptive DT modeling that enables real-time reconfiguration and self-optimization, ensuring sustained high-grade levels of performance and reliability.

Current research lacks unified benchmarks for evaluating DT-based VEC systems. For instance, task offloading delay (average and worst-case), packet delivery ratio, energy consumption per task, and latency jitter are inconsistently reported across studies. While some works use synthetic traces, publicly available datasets such as the Beijing T-Drive and Cologne SUMO mobility sets are rarely standardized in comparative evaluations. Establishing a benchmark suite with these datasets, coupled with common metrics like task completion time under 50 ms, energy per offloaded task (in Joules/task), and scalability thresholds (tasks/sec/ edge server), is essential for reproducibility.

On the standards front, while protocols such as IEEE 1609.2 and ETSI ITS-G5 address V2X security, there is no standardized interface for DT synchronization, update frequency, or data abstraction levels. A critical missing element is a middleware-level specification for DT orchestration across heterogeneous VEC layers (vehicle, RSU, edge cloud), including service handovers and version control.

8 Conclusion

This paper provides a thorough survey of DT technology integration within VEC, presenting its transformative potential for handling network and service management complexities in changing vehicular environments. DT enables the real-time virtualization of physical infrastructures, making it possible for intelligent decision-making, proactive repair, resource optimization, and seamless collaboration among edge, device, and cloud layers. All these capabilities enable DT to be a foundation for advancing intelligent transportation systems. This paper provides a thorough survey of DT technology integration within VEC, focusing on its transformative potential for addressing challenges such as elevated mobility, sensitivity to latency, and resource constraints. Although our mandate was more than a mere summary of recent trends, we also identified critical shortcomings due to a lack of scalability, synchronization, and standardization. Our consideration of a future path forward includes a requirement for lightweight DT infrastructures, ground-realistic testbeds, benchmarking with standardization, and DT architectures with secure flexibility. Focusing on these directions further will be necessary for DT-based intelligent transportation systems to realize their full potential.

Conflict of interest

The authors declare that they have no conflicts of interest.

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