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AI Based Semantic Communication And Digital Twin Integrated Edge Architecture For 6G Vehicular Networks

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Abstract. Internet of Things (IoT) applications in autonomous vehicles (AVs) have significantly driven the need for 6G-enabled vehicular networks with ultra-low latency, reliable and high bandwidth efficiency for the intelligent transportation services. But the conventional Vehicle-to-Everything (V2X) systems transmit a huge amount of raw sensor information, consuming much bandwidth, causing high communication delay, consuming much energy, and not correctly synchronizing digital twins. In order to solve the foregoing issues, a new solution combining Semantic Communication and Digital Twin is proposed for 6G Vehicular Networks, which is called as the Semantic Communication and Digital Twin Integrated Edge Architecture (SC-DTEA) for 6G Vehicular Network. Using semantic information extraction to deliver only data that is relevant to the task, while the use of edge intelligence for computational resource allocation and continuous synchronisation of the vehicular digital twin for real-time decision making. A mathematical optimization model is formulated to simultaneously minimize the latency, energy consumption, and synchronization error and maximize the reliability and spectral efficiency. The simulation results show that this approach can realize 60.9% latency reduction, 53.8% energy saving, 99.9% communication reliability, 1.79 bps/Hz spectral efficiency, 99.85% digital twin synchronization accuracy, and even 80% data reduction compared to conventional V2X approaches, which proves its effectiveness for the future intelligent transportation system of 6G.

Keywords: Semantic Communication, Digital Twin, Edge Intelligence, 6G Vehicular Networks, Vehicle-to-Everything (V2X), Resource Optimization.

1. Introduction

The development of 6G wireless communication technologies is projected to revolutionize Intelligent Transportation Systems (ITS) by ushering in ultra-reliable, low-latency, and high-capacity vehicular communications. Modern Vehicle-to-Everything (V2X) networks transmit vast amounts of data from various sensors and roadside equipment, including cameras, LiDAR sensors, radar systems, onboard diagnostic systems, and connected infrastructure, to support autonomous driving, traffic efficiency, and road safety. While these technologies significantly improve transportation efficiency and situational awareness, the transmission of raw vehicular data imposes substantial demands on communication bandwidth, network infrastructure, and computational resources. Simultaneously, digital twin technology has emerged as a promising paradigm for creating virtual representations of physical vehicles and transportation environments to enable continuous monitoring, predictive analysis, and intelligent decision-making. The integration of semantic communication, digital twins, and edge intelligence offers a promising solution for satisfying the stringent requirements of future 6G vehicular ecosystems.

Despite recent advancements, conventional V2X systems continue to transmit complete data packets irrespective of task relevance, resulting in excessive bandwidth consumption, increased communication latency, higher energy expenditure, and network congestion. Maintaining accurate synchronization between physical vehicles and their digital twins also becomes increasingly challenging as data volume and transmission frequency grow. Furthermore, resource utilization at edge servers remains inefficient under dynamic traffic conditions, heterogeneous workloads, and varying communication demands. These limitations negatively affect the performance of real-time vehicular applications and intelligent transportation services.

Current research has largely investigated semantic communication, digital twin systems, and edge computing as independent domains. Limited attention has been devoted to their unified integration within a 6G vehicular environment while simultaneously optimizing communication efficiency, synchronization accuracy, computational resource utilization, reliability, and energy consumption. To address these challenges, this paper proposes a Semantic Communication and Digital Twin Integrated Edge Architecture for 6G Vehicular Networks. The proposed framework employs semantic-aware data transmission, digital twin synchronization, and edge intelligence-based resource allocation. The major contributions include a semantic-aware communication framework, a digital twin synchronization mechanism, an edge intelligence-based resource allocation strategy, and a joint optimization model that minimizes latency, energy consumption, and synchronization error while maximizing reliability and spectral efficiency.

2. Related Work

The emergence of 6G communication technologies has led to a growing research interest in intelligent vehicular networks concerning semantic communication, digital twin systems and edge intelligence [1]–[4], [12]–[14]. Busy traffic, real-time decision making, efficient use of resources and reliable communication are considerations that are already becoming a requirement for next generation transportation systems [2], [6], [7], [12]. These technologies look to satisfy such requirements through advanced communication, computation, and intelligence capabilities. There have been several researchers who have investigated a number of techniques to improve communication efficiency, virtual system representation and edge-assisted computation [3], [7], [11], [13]. However, existing studies largely concentrate on individual technologies instead of their integrated implementation in a cohesive framework for 6G vehicular systems [4], [12], [14].

Semantic communication has emerged as a promising paradigm for reducing communication overhead by transmitting task-relevant information instead of complete raw data. Recent studies have demonstrated the effectiveness of semantic-aware transmission techniques for improving bandwidth utilization, reducing latency, and enhancing communication efficiency in wireless networks [3], [7], [12], [13]. Similarly, digital twin technology has been extensively explored for creating virtual replicas of vehicles, transportation infrastructure, and traffic environments to support monitoring, prediction, and intelligent control [5], [9]. In parallel, edge intelligence has been increasingly adopted in Vehicle-to-Everything (V2X) networks to provide low-latency computing, dynamic resource allocation, and localized decision-making capabilities [7], [11], [13]. Furthermore, large-scale IoT integration, UAV-assisted communications, and federated learning paradigms have been investigated to support future intelligent transportation and 6G ecosystems [6], [8], [10].

However, currently available solutions tend to study semantic communication, digital twins, and edge intelligence separately [5], [7], [9]. Few studies have focused on jointly integrating these technologies within a 6G vehicular environment [1], [4], [12]. In addition, several studies provide partial optimization that primarily addresses communication efficiency, synchronization accuracy, or computational performance independently, without considering a comprehensive optimization framework capable of optimizing multiple objectives simultaneously [3], [7], [13]. The analysis indicates the need for an integrated architecture that combines semantic communication, digital twin synchronization, and edge intelligence while jointly optimizing latency, energy consumption, reliability, and spectral efficiency for future 6G vehicular networks [2], [6], [8], [10], [14].

3. Proposed system architecture

3.1 Semantic Communication and Digital Twin Integrated Edge Architecture

The proposed architecture integrates semantic communication, edge intelligence, digital twins, and 6G-enabled V2X networking to support reliable and low-latency vehicular services. As shown in Figure 1, the

framework contains six layers of interconnection: physical layer of vehicles, semantic communication layer, 6G communication layer, edge intelligence layer, digital twin layer, and control and application layer.
Vehicles and roadside infrastructure both acquire semantic information which is then shared across the 6G network and analyzed by edge intelligence servers to allocate resources, analyze traffic and optimize latency. The resulting information is then utilized to coordinate digital twin models of vehicles, traffic and environmental states. The control layer processes the synchronized digital twin data and the outputs from the edge intelligence to generate route recommendations, safety alerts and decisions on the management of the resources that are fed back to the vehicles. The proposed architecture embeds semantic communication, digital twins, and edge intelligence to enhance the efficiency in communication, synchronization precision, and real-time decision-making in 6G vehicular networks, as illustrated in Figure 1.

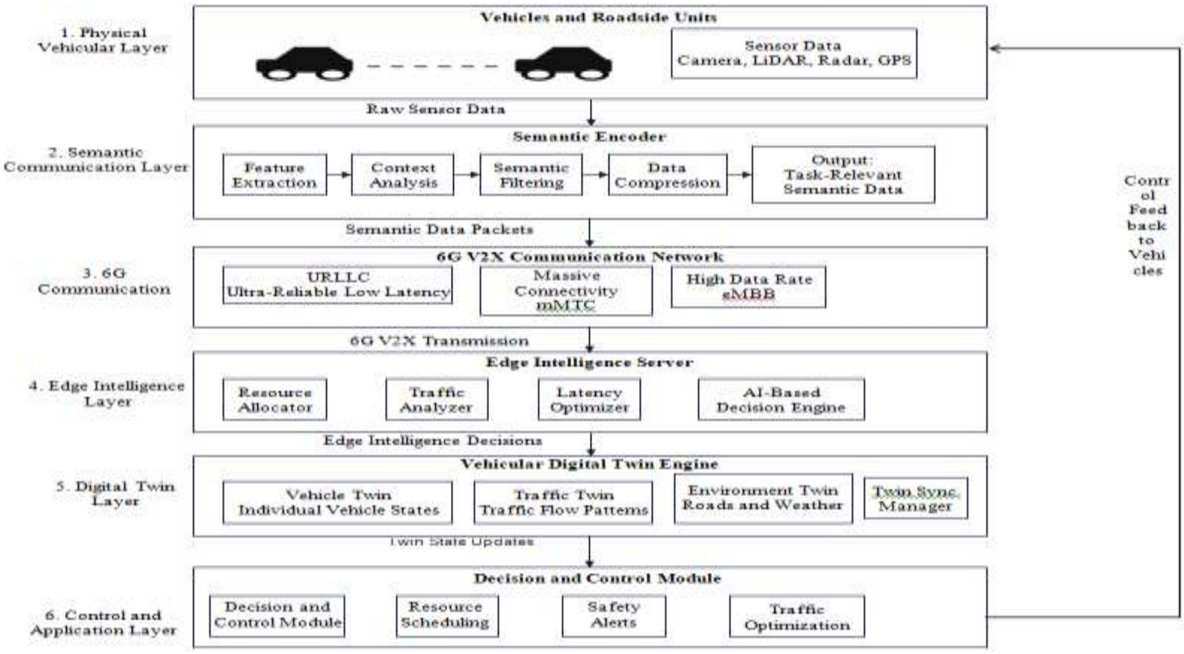

Fig 1. Semantic-Digital Twin Edge Architecture

3.2 Operational Workflow

The operational workflow of the proposed framework is illustrated in Figure 2. The workflow starts with the collection of vehicular and environmental information for which task relevant information are identified and compressed by using the process of semantic communications before the information is transmitted.
The semantic data packets are transmitted through the 6G V2X communication network and delivered to the edge intelligence layer for real-time processing. Edge servers perform resource allocation, traffic analysis, and latency-aware optimization to generate an efficient representation of the current vehicular environment. The processed information is subsequently utilized to update and synchronize the digital twin models, ensuring consistency between physical and virtual transportation entities.
Following synchronization, intelligent decision-making mechanisms analyze the updated digital twin states to generate control actions, route recommendations, and safety-related responses. These decisions are transmitted back to vehicles through a feedback loop, enabling continuous adaptation to dynamic traffic and network conditions.

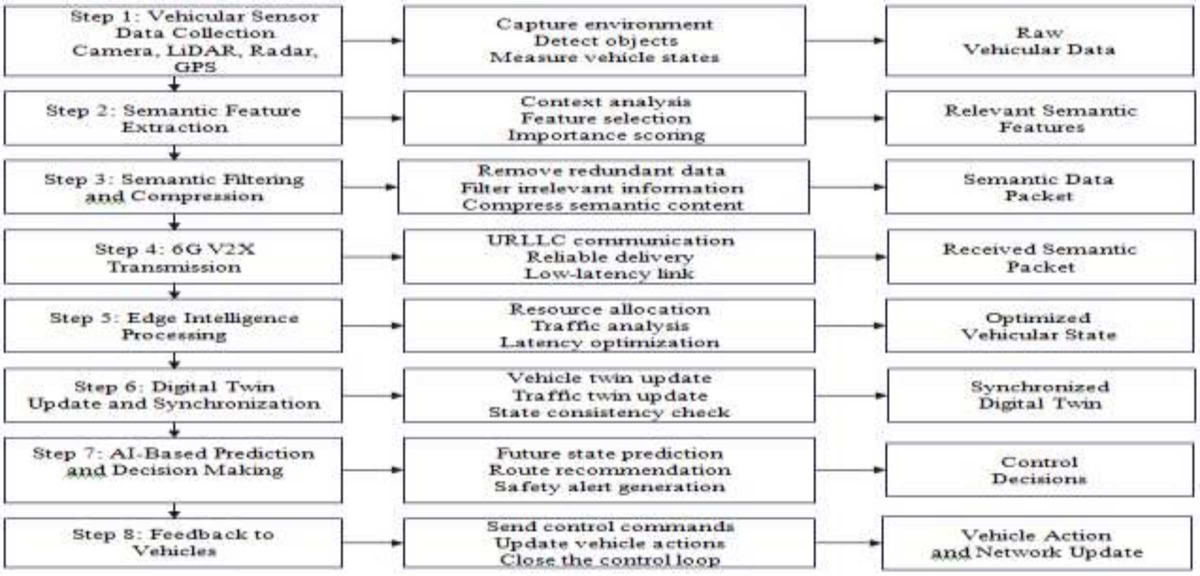

Fig. 2. Semantic-Twin Processing Workflow

3.3 Problem Formulation

The proposed Semantic Communication and Digital Twin Integrated Edge Architecture aims to improve the efficiency and reliability of 6G vehicular networks by jointly optimizing communication, computation, and synchronization processes. The framework uses semantic communication for conveying relevant information for a specific task, edge intelligence for fast allocation of resources and digital twins for the precise virtual representation of the real-world environment of a vehicle. The goal of the optimization is to reduce the latency, energy consumption, synchronization error, and increase the reliability of communication, spectral efficiency and accuracy of the digital twin. These goals cover the utilization of resources, information delivery, virtual representation, and real-time decision making in dynamic vehicular environment.

4. System Modeling and Optimization Framework

In this section, the mathematic models for semantic communication, digital twin synchronization, latency analysis, energy consumption, and joint optimization in the proposed framework are presented.

4.1 Semantic Communication Model

The proposed framework uses the semantic communication to send only the information required to perform a task but not the raw sensor signals. Before the transmission of the collected vehicular information, the importance of the collected information is evaluated by a measure called semantic relevance score, which is expressed as

$$S_r = \alpha I + \beta C + \gamma T, \quad (1)$$

where I, C, and T denote information importance, contextual significance, and task relevance, respectively, while α, β, and γ are weighting coefficients.

The semantic compression ratio is defined as:

$$CR = \frac{D_s}{D_0}, \quad (2)$$

where D_s represents the semantic data size and D_0 denotes the original raw data size. Higher compression ratios permit greater semantics filtering and smaller communications overhead.

4.2 Communication and Digital Twin Synchronization Model

Based on the formulation of Shannon capacity, the possible speed of communication of semantic data communications is determined.

$$R = B\log_2(1 + SIN\,R), \quad (3)$$

where R denotes the transmission rate, B represents the communication bandwidth, and SIN R is the signal-to-interference-plus-noise ratio of the wireless channel. The virtual representation of the physical vehicle could not be made consistent with its physical identity, so digital twin synchronization error is modeled as:

$$E_{sync} = \|X - X_{DT}\|, \quad (4)$$

where X represents the physical vehicle state and X_{DT} denotes the corresponding digital twin state. A smaller alignment error is better suited for better alignment between the actual transportation environment and the virtual transportation environment.

4.3 Latency and Energy Model

The end-to-end latency of the proposed framework consists of communication delay, edge processing delay, and queuing delay. It is expressed as

$$L_{total} = L_{tx} + L_{proc} + L_q, \quad (5)$$

where L_{tx} is the communication transmission delay, L_{proc} is the edge processing delay, and L_q denotes the queuing delay at the edge server.

The total system energy consumption is modeled as

$$E_{total} = P_{comm} + P_{edge}, \quad (6)$$

where P_{comm} represents communication power consumption and P_{edge} denotes edge-processing power consumption.

4.4 Joint Optimization Framework

The proposed Semantic Communication and Digital Twin Integrated Edge Architecture will aim to enhance communication efficiency and digital twin performance at the same time. Thus, a multi-objective optimization function is designed to optimize the accuracy of the digital twin, reliability of the communication, spectral efficiency and reduce latency and energy consumption.

$$\max(\omega_1 A_{DT} + \omega_2 R + \omega_3 SE - \omega_4 L - \omega_5 E), \quad (7)$$

where A_{DT} denotes digital twin accuracy, R represents communication reliability, SE denotes spectral efficiency, L represents end-to-end latency, E denotes total energy consumption, and $\omega_1 - \omega_5$ are weighting coefficients that control the relative importance of each performance metric. The optimization framework enhances the value of communication in 6G vehicular networks, while sustaining the reliability of synchronization and resource utilization.

5. Proposed edge intelligence algorithm

The proposed edge intelligence algorithm is to design the semantic-aware resource allocation and digital twin synchronization algorithm in 6G vehicular network. The algorithm is fed into the following inputs: the vehicle state information, the semantic scores, the channel information and the resources on the edge. It receives these inputs and prioritizes relevant vehicular information, shares the edge computing resources, updates the digital twin state, and creates a priority transmission schedule. The whole procedure is described below in Algorithm 1.

Algorithm 1. Semantic-Aware Digital Twin Edge Optimization

Input: Vehicle state X_v, semantic score S_r, channel state H, available edge resources R_e

Output: Optimized resource allocation A_r, updated digital twin state X_t, priority transmission schedule T_s

1. Collect vehicular and channel state information.
2. Compute semantic relevance scores for all vehicles.
3. Generate semantic data packets and estimate transmission rate.
4. Prioritize vehicles according to semantic importance.
5. Allocate edge computing resources based on semantic priority.
6. Calculate communication latency and energy consumption.
7. Update digital twin states and compute synchronization error.
8. Optimize resource allocation and transmission scheduling subject to latency and reliability constraints.
9. Transmit control decisions and repeat for the next time slot.

6. Performance evaluation

6.1 Simulation Environment and Baseline Methods

The proposed architecture is verified through a 6G vehicular simulation environment in MATLAB takes into account semantic communication, digital twin synchronization, and edge intelligence. The parameters used for the simulations are listed in Table 1.

Table 1. Simulation Parameters

Parameter	Value
Number of Vehicles	50
Vehicle Speed	20–35 m/s
Bandwidth	100 MHz
Transmit Power	0.5 W

Edge CPU Capacity	100 GHz
Raw Data Size	10 MB
Semantic Data Size	2 MB
Simulation Time	100 s
Time Slot Duration	0.1 s
Road Length	1000 m

The simulation assumes 50 vehicles in a 1000m stretch of road, each with a 100MHz bandwidth, and each with an edge computing capability of 100GHz. The proposed framework is compared with Traditional V2X, Edge-V2X, and Digital Twin Assisted V2X approaches. The mathematical models described in Equations (1)–(7) are realised by taking a 0.1 s time slot and averaging over many simulation runs.

6.2 Communication Performance Analysis

The performance of communication is measured based on latency, energy consumption, reliability and spectral efficiency. As illustrated in Figure 3, the proposed framework provides the lowest latency result (21.4ms), which is 60.9% less than that of Traditional V2X, and lowest energy consumption (0.024J) result, which is 53.8% less than that of Traditional V2X. These results confirm the latency model in Equation (5) and the energy consumption model in Equation (6).

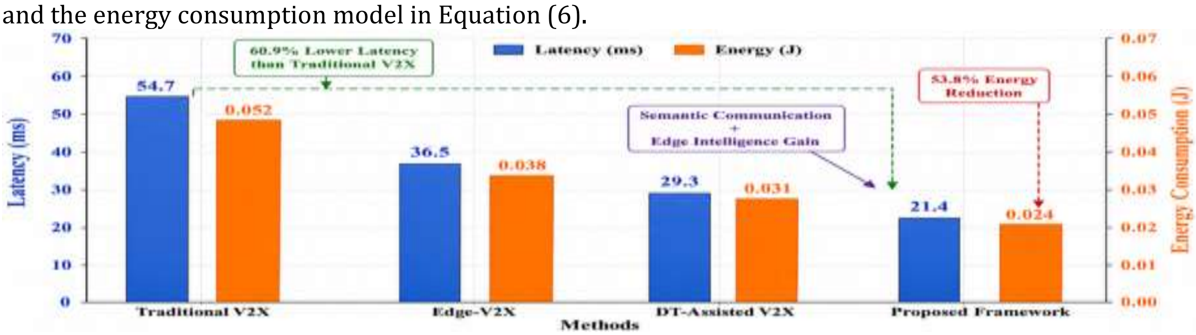

Fig. 3. Latency and Energy Comparison

The proposed framework can be observed as having the highest communication reliability (99.9%) and spectral efficiency (1.79 bps/Hz) compared with Traditional V2X, Edge-V2X and Digital Twin Assisted V2X approaches as illustrated in Figure 4. These results confirm the communication rate model in Equation (3) and the proposed joint optimization scheme in Equation(7).

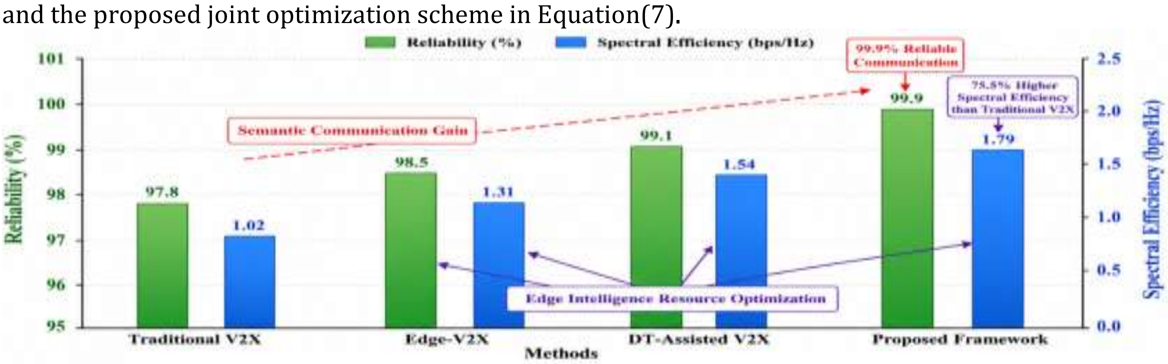

Fig. 4. Reliability and Spectral Efficiency Comparison

Overall, the outcomes reported in Figures 3 and 4 validate the proposed framework to enhance the communication performance for 6G vehicular networks.

6.3 Digital Twin Performance Analysis

Synchronization error and digital twin accuracy are used to assess the efficacy of the proposed digital twin synchronisation mechanism.

Figure 5 reveals that the synchronization error is reduced from 8.2 at time slot 20 to 1.5 at time slot 100 and digital twin accuracy is improved from 95.1% to 99.85%. The results show an ongoing development and progression towards improved synchronisation between the physical vehicles and their digital twins.

The results shown in Figure 5 confirm the synchronization error model in Equation (4).The synchronization results from dynamic vehicle conditions are successfully achieved through the observed convergence behavior, proving the capability of the proposed framework to keep the digital twin synchronized with the actual vehicle.

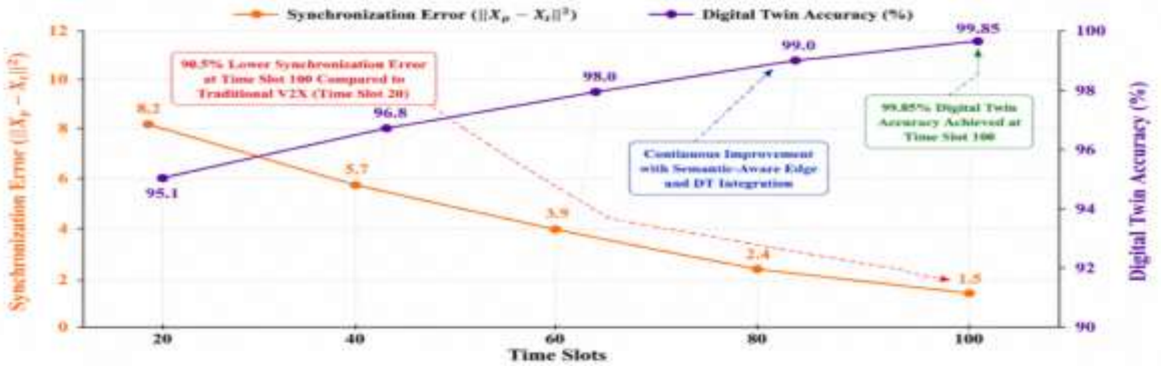

Fig. 5. Digital Twin Synchronization Accuracy Comparison

The proposed framework can represent the states of the vehicles with very high level of accuracy over the virtual world, and can monitor and make real time decisions about the vehicle safely.

6.4 Comparative and Optimization Analysis

Table 2 makes comparisons with Traditional V2X and Edge-V2X and Digital Twin Assisted V2X based on the following metrics: latency, energy consumption, reliability, spectral efficiency and digital twin accuracy.

Table 2. Performance Comparison with Existing Methods

Method	Latency (ms)	Energy (J)	Reliability (%)	Spectral Efficiency (bps/Hz)	DT Accuracy (%)
Traditional V2X	54.7	0.052	97.8	1.02	—
Edge-V2X	36.5	0.038	98.5	1.31	—
DT-Assisted V2X	29.3	0.031	99.1	1.54	96.2
Proposed Framework	21.4	0.024	99.9	1.79	99.85

Table 3 shows system performance evaluation of semantic compression ratio. The results show that semantic compression improves both communication overhead and reduces latency, energy consumption and digital twin accuracy.

Table 3 Impact of Semantic Compression Ratio

Compression Ratio	Data Reduction (%)	Latency (ms)	Energy (J)	DT Accuracy (%)
0.80	20	41.8	0.043	97.1
0.60	40	34.5	0.036	98.0
0.40	60	28.7	0.030	99.0
0.20	80	21.4	0.024	99.85

The findings broadly confirm the benefits of combining semantic communication, digital twin and edge intelligence into a single optimization process for 6G vehicular networks.

7. Conclusion and Future Work

The paper presented a Semantic Communication and Digital Twin Integrated Edge Architecture for 6G Vehicular Network to overcome the drawbacks of huge data transmission, delays in communication, energy consumption, and inaccurate synchronization in traditional V2X systems. Proposed framework combines semantic-enabled communication, digital-twin synchronization and edge intelligence-based resource allocation in a single optimization framework. This is because the major contributions consist of a semantic-aware data transmission framework, a real-time digital twin synchronization mechanism, an edge intelligence-based resource allocation strategy, and a co-optimization model to minimize the latency, energy, and synchronization error while maximizing the reliability and spectral efficiency. From the simulation results, the novel method has reduced the latency by 60.9%, energy by 53.8%, communication loss rate to 99.9%, achieved spectral efficiency of 1.79 bps/Hz, and the accuracy of digital twin as 99.85%, while data reduction as 80% as compared with the conventional methods.

The results received in this study are encouraging, but in the present study, the study of the simulated environment can be limited to a simulation like evaluation and a single vehicular environment where edge assistance is used. Further exploration of emerging challenges in real world, large mobility scenarios and heterogeneous vehicular ecosystem, are required.
With the future introduction of next generation 6G vehicular networks (VNs), a higher level of scalability, adaptability and intelligence can be realized through the use of federated digital twins, semantic-aware network slicing, AI-based twin synchronization, and autonomous cooperative vehicular intelligence.

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