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Review

Intelligent Transportation Systems: A Review of Integration of Digital Twin and Machine Learning Control

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Abstract

This paper presents a comprehensive review of the integration of Intelligent Transportation Systems (ITS) and Digital Twin (DT) technologies for intelligent traffic management. It examines the role of key enabling technologies, including the Internet of Things (IoT), machine learning (ML), deep learning (DL), reinforcement learning (RL), Graph Neural Networks (GNNs), vehicle-to-everything (V2X) communication, and edge computing. These technologies support real-time traffic monitoring, traffic prediction, and adaptive control in ITS. The review synthesizes recent research on conventional traffic control methods, optimization-based approaches, learning-based techniques, and DT-enabled traffic management solutions. Particular attention is given to the integration of DTs with intelligent traffic signal control, real-time synchronization, multi-intersection coordination, communication latency, sensing uncertainty, and scalability. The reviewed literature demonstrates the potential of DT-enabled ITS to improve traffic efficiency, reduce congestion, enhance transportation safety, and support sustainable mobility through data-driven decision-making. However, significant challenges remain regarding communication delays, sensor and data uncertainty, computational complexity, scalability, and validation under realistic urban conditions. Based on the reviewed literature, this paper identifies key research gaps and outlines future research directions toward scalable, reliable, adaptive, and real-time DT-enabled ITS architectures for next-generation smart cities.

Keywords: ITS; traffic control; Digital Twin; Graph Neural Networks; reinforcement learning

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1. Introduction

Urbanization is a major challenge as more people move to cities. By 2030, the global urban population is expected to reach about 4.9 billion [1]. This increase brings challenges such as pollution, traffic jams, and resource shortages. With advances in technology, many devices are now connected to networks, collecting and sending data. This data is analyzed using deep learning techniques to make systems smarter and more automated. One of the most important innovations is the Internet of Things (IoT), a network of physical devices, such as smartphones, refrigerators, smartwatches, fire alarms, and door locks, embedded with sensors and software that allow them to communicate and exchange data seamlessly. These advancements have led to the development of “Smart Cities,” which include smart grids, smart transportation, smart buildings, and more. The goal is to make cities more efficient and improve the quality of life. However, as cities grow, transportation systems face

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problems like traffic congestion, noise, and accidents. These challenges make it important to improve transportation systems to handle the increasing demands of urban mobility. As urban areas are facing unprecedented challenges related to congestion, air pollution, and road safety, Intelligent Traffic Systems provide an integrated response. ITS uses technological advancements in areas such as information and communication systems (ICT), Internet of Things (IoT), sensors, automation, and data analytics to enhance every aspect of traffic management. Intelligent Transportation Systems are a promising prospect for improving mobility and traffic flow, reducing congestion, enhancing safety, and fostering sustainability, making cities smarter and transportation more efficient for everyone. ITS's ability to reduce congestion through real-time monitoring of traffic conditions by adjusting traffic signals to manage congestion, rerouting vehicles around bottlenecks, and prioritizing smart bus lanes and public transit routes has attracted significant research in recent years.

This review aims to further explore the potential and applications of ITS for the aforementioned benefits through a recent literature review, identifying existing literature gaps and relevant recent technological advances, while proposing potential solutions. To achieve this objective, the next sections present a detailed review of the literature in the areas of ITS, Digital Twins (DT), and AI/ML integration, along with key enabling technologies. This systematic examination will not only consolidate current knowledge but also motivate promising research directions and practical solutions for overcoming the challenges that limit the full realization of intelligent, resilient, and adaptive transportation ecosystems.

To map research trends in machine learning for Intelligent Transportation Systems integrated with Digital Twins (ITS-DT), a structured literature search was conducted using Google Scholar for the publication years 2022 to 2026, as shown in Figure 1. This captures the last 5-year trend. Advanced Boolean search strings were used to capture the intersection of three key domains: "Intelligent Transportation Systems" OR "ITS", AND "Digital Twin" OR "DT" AND "Machine Learning" OR "Deep Learning" OR "Reinforcement Learning". To ensure accuracy and relevance, the query specifically targeted title, abstract, and keyword metadata. Duplicate entries, non-peer-reviewed patents, and citations without full-text availability were excluded. The resulting annual citation and publication volumes reflect the rapid growth of academic interest, growing from approximately 2000 publications in 2022 to over 9000 in 2025.

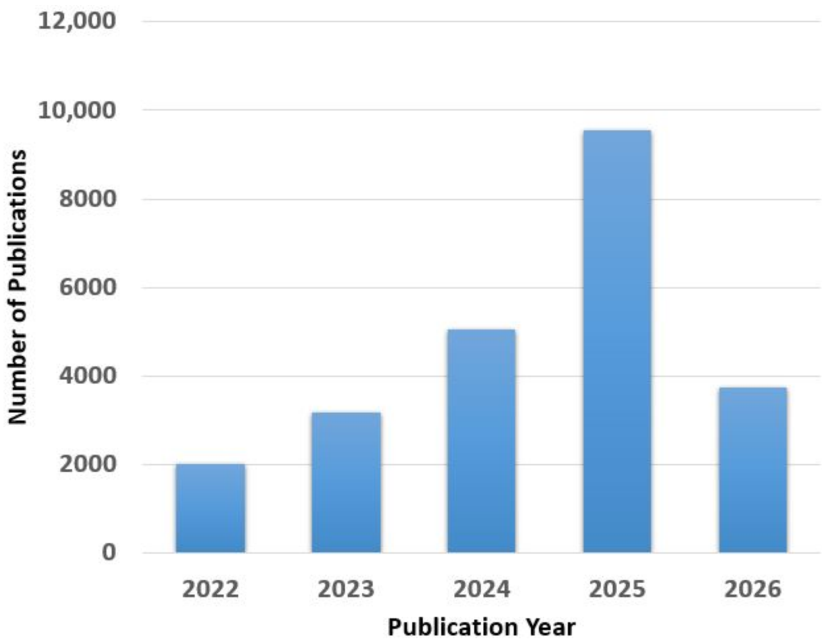

Figure 1. Number of yearly publications on machine learning in ITS-DT (source: Google Scholar).

1.1. Literature Scoping and Article Evaluation

This study uses a structured narrative review approach, involving a predefined search and screening process to select the relevant literature, followed by qualitative synthesis and critical discussion without conducting a formal systematic review. A structured literature search was conducted to identify studies relevant to Intelligent Transportation Systems (ITS), Digital Twin (DT), Cyber-Physical Systems, Intersection Signal Control, and intelligent traffic network management. Searches were performed in IEEE Xplore, Scopus, Web of Science, and ScienceDirect for publications from 2018 to 2026. The search used combinations of the following keywords: Intelligent Transportation System, Digital Twin, Machine Learning, and Intersection Control. Studies were included if they were peer-reviewed, published between 2018 and 2026, and directly relevant to Intelligent Transportation System (ITS), Digital Twin (DT), Cyber-Physical System, Intersection Signal Control, or ML-based traffic signal optimization. Studies were excluded if they were non-peer-reviewed, duplicated across databases, outside the defined publication period, or not directly related to the research objectives. The screening process consisted of three stages: (1) database searching and removal of duplicates, (2) title and abstract screening, and (3) full-text assessment against the inclusion and exclusion criteria. The final set of studies was analyzed to identify key research themes, existing approaches, limitations, and gaps that motivated the proposed Integration of Digital Twin and Machine Learning Control into the Intelligent Transportation System framework. Specifically, the studies that primarily address cybersecurity, privacy, cyberattacks, authentication, and other security-related topics were excluded as they were outside the scope of this review. A total of 200 articles were initially retrieved using the predefined search terms and selection criteria. After removing approximately 30 records identified as duplicates or substantially overlapping studies based on their approaches and methods used, the remaining articles underwent title and abstract screening. The full texts of the potentially relevant studies were subsequently assessed for eligibility, resulting in 65 studies being included in the final literature.

1.2. Research Gap

Although Intelligent Transportation Systems (ITS) have advanced considerably through the integration of the Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), and Reinforcement Learning (RL), several critical research gaps remain that hinder their deployment in real-world urban environments. First, existing learning-based traffic signal control approaches have largely been validated using single intersections or small-scale simulation scenarios. Their scalability to large interconnected urban road networks with dynamic and heterogeneous traffic conditions remains insufficiently investigated. Consequently, the practical applicability of many proposed methods to city-scale traffic management is still uncertain. Second, while Digital Twin (DT) technology has recently emerged as a promising paradigm for real-time traffic monitoring and predictive traffic management, current research has primarily focused on conceptual architectures, isolated case studies, or simulation-based demonstrations. There is a lack of comprehensive studies examining how Digital Twins can be effectively integrated with ML-based traffic signal control to enable continuous synchronization between physical and virtual traffic environments for proactive decision-making. Third, communication latency, delayed V2X feedback, and synchronization delays between physical infrastructure and their digital counterparts remain significant challenges for real-time ITS applications. Most existing studies assume ideal communication conditions and therefore do not adequately evaluate the impact of network latency on traffic control performance, particularly in time-critical urban environments. Fourth, the reliability of traffic state estimation continues to be affected by sensor failures, computer vision inaccuracies, data noise, and occlusion.

Existing ITS frameworks often overlook these uncertainties or assume high-quality sensing, limiting their robustness and resilience under real-world operating conditions. Finally, although Digital Twin technologies, computer vision, V2X communication, and learning-based traffic control have each been extensively studied independently, there is a notable lack of detailed review literature that sufficiently examines their convergence within the context of intelligent traffic signal control. Existing reviews typically focus on individual technologies or provide only high-level discussions of Digital Twins, with limited attention to their integration with ML-driven control, real-time synchronization, scalability, latency, sensing uncertainty, and multi-intersection coordination.

This review addresses these gaps by providing a comprehensive synthesis of the current state of the art in Digital Twin-enabled intelligent traffic signal control. It critically examines the integration of Digital Twins with machine learning, computer vision, IoT sensing, and V2X communication. It also identifies the key technical challenges and limitations, and highlights future research directions for developing scalable, reliable, and real-time ITS architectures capable of supporting next-generation smart cities.

1.3. Contributions of the Review

Major contributions of this literature review are:

1. Comprehensive Taxonomy of ML-ITS-DT Integration. It synthesizes the convergence of Machine Learning (ML), Digital Twins (DT), and Intelligent Transportation Systems (ITS) to demonstrate the potential advantages of data-driven predictive architectures compared to traditional classical and fuzzy-logic control methods.
2. Scalability and Real-World Applicability Gap Analysis, which evaluates the structural limitations of existing traffic control models, specifically highlighting the reliance on small-scale, single-intersection setups and historical data, and identifies the requirements for multi-intersection, network-wide urban deployment.
3. Comparative Synthesis of V2X Communication Protocols. It evaluates the technological evolution and trade-offs between IEEE 802.11-based standards (DSRC/802.11p, 802.11bd) and Cellular V2X technologies (LTE-V2X, 5G-V2X), detailing their physical/MAC layer mechanisms, latency bounds, coverage scalability, and operational constraints in dense vehicular environments.
4. Identifies a critical gap in resilient ITS design and outlines a future research direction: a conceptual Real-Time Digital Twin framework integrating hierarchical graph-based multi-agent reinforcement learning for city-scale traffic optimization, offered as a synthesis-driven opportunity for future empirical investigation.

To address the aforementioned gaps, this structured narrative review centers on a primary question: How can Digital Twins, combined with ML, IoT sensing, and V2X communication, support scalable, reliable, and real-time intelligent traffic control in urban ITS?

The specific review questions are:

1. How are Digital Twin technologies integrated with ML-based traffic signal control to support continuous physical–virtual synchronization, traffic prediction, and proactive decision-making?
2. How do communication latency, V2X delays, and physical–digital synchronization delays affect the performance and real-time applicability of Digital Twin-enabled intelligent traffic signal control?
3. How well have existing ML/RL traffic signal control methods been tested for scalability across multi-intersection and city-scale networks under dynamic, mixed traffic conditions?

4. What are the current research gaps, technical challenges, and future directions for integrating Digital Twins, ML/RL, computer vision, IoT sensing, and V2X communication for next-generation intelligent traffic signal control?

To guide this review, four interrelated objectives have been established. First, the review analyzes existing approaches for integrating Digital Twins with ML-based traffic signal control, focusing on mechanisms that enable continuous physical–virtual synchronization and proactive decision-making. Second, it evaluates the reported effects of communication latency, V2X delays, and synchronization constraints on real-time control performance. Third, it critically examines the scalability of ML/RL-based traffic signal control approaches for multi-intersection and large-scale urban networks under dynamic traffic conditions. Finally, it synthesizes the convergence of Digital Twins, ML/RL, IoT, and V2X technologies to identify persistent research gaps and outline future directions for developing scalable, reliable, and real-time ITS architectures for next-generation smart cities.

2. Intelligent Transportation System Integration of Digital Twin

2.1. Transportation System Background

The evolution of transportation has gone through several stages, improving efficiency and meeting human needs. At the most basic level, early civilizations built roads and infrastructure to connect regions. The Romans and Chinese developed road networks to support trade and travel, forming the foundation of transportation systems. As human activities expanded, new travel methods emerged. The Industrial Revolution led to the invention of cars, trains, and ships, making transportation faster and more accessible. The Ford assembly line enabled mass production of vehicles, allowing more people to own and use personal transport. With the increasing use of transportation, coordination and regulation became necessary. Governments introduced traffic laws and international agreements to ensure the smooth operation of roads, railways, air travel, and sea transport. Today, modern transportation focuses on safety, convenience, and environmental sustainability. New technologies like electric vehicles, ride-sharing, and AI-driven traffic control help reduce congestion and pollution. Over time, transportation has evolved from simple roadways to an intelligent system that improves daily life [2].

An Intelligent Transportation System (ITS) integrates traditional transportation modes, such as motor vehicles developed postindustrial revolution, with advanced information and communication technologies. ITS utilizes information and communication technology to enhance sustainability, safety, and efficiency across diverse transport modes, including trains, buses, subways, cars, sea and air transport, bicycles, and pedestrian networks. ITS encompasses various applications, including traffic signal control, smart parking management, electronic toll collection, and route optimization. By utilizing data from sensors, cameras, and GPS devices, ITS enables dynamic management of transportation systems, leading to improved traffic flow and reduced congestion. The implementation of ITS has been shown to reduce traffic incidents, lower emissions, and improve overall transportation efficiency [1,3].

2.2. Intelligent Transportation System (ITS)

An Intelligent Transportation System (ITS) is an advanced application that aims to provide services relating to different modes of transport and traffic management. It enables users to be better informed and make safer, more coordinated, and smarter use of transport networks [4].

Although Intelligent Transport System (ITS) can encompass all modes of transport, Directive 2010/40/EU of the European Union, adopted on 7 July 2010, defines ITS as the application of information and communication technologies to road transport, including infrastructure, vehicles, and users, as well as to traffic and mobility management and interfaces with other transport modes. This framework was further updated by Directive (EU) 2023/2661, which extends the scope to connected, automated, and multimodal mobility, with an emphasis on seamless cross-border services [5]. Overall, ITS technologies are employed to enhance the efficiency, safety, and sustainability of transport systems across a wide range of applications, including road transport, traffic management, and mobility services. Intelligent Transportation Systems are continually evolving by integrating advanced technologies such as machine learning (ML), Reinforcement Learning (RL), the Internet of Things (IoT), Vehicle-to-Everything (V2X) Communication, 5G communication, and GPS to optimize traffic flow during rush hours [1,2,6,7].

In Intelligent Transport Systems (ITS), Transformer architectures improve performance by effectively modeling complex spatiotemporal dynamics and sequential driving data. Their key applications include real-time traffic flow prediction, vehicle trajectory forecasting, vision-based object detection, and the optimization of adaptive traffic signals through reinforcement learning [8]. Furthermore, the potential of Transformers along with their variants CCDSReFormer, HUTFormer, and CASAFormer in closed-loop digital twin (DT) applications has been increasingly recognized, with comprehensive overviews available in recent review papers [9–11]. These technologies can collect real-time traffic information and enhance the safety and efficiency of urban mobility.

2.3. Digital Twin Concept in Intelligent Transportation Systems

A Digital Twin (DT) in Intelligent Transportation Systems (ITS) is a dynamic virtual representation of a physical transportation system that continuously reflects the state and behavior of real-world transportation components, including vehicles, road infrastructure, traffic signals, and road users. Unlike conventional simulation models that operate independently based on predefined inputs and assumptions, a DT maintains a continuous connection with the physical transportation environment through sensing, communication, data processing, and feedback mechanisms. In general, a DT consists of three interconnected components: (1) the physical system, representing real-world transportation entities such as vehicles, road networks, intersections, and traffic infrastructure; (2) the digital system, representing the virtual replica where system states are modelled, simulated, analyzed, and optimized; and (3) the data communication interface, enabling continuous information exchange between the physical and digital domains. In ITS applications, real-time data from sensing technologies such as LiDAR, cameras, radar, connected vehicles, and traffic monitoring systems are integrated into the digital platform to update the virtual representation. The digital environment is used for prediction, performance evaluation, optimization, and decision support. At the same time, control actions generated from the digital system can be transferred back to the physical transportation system.

The fundamental difference between a DT and traditional digital representations lies in the level of connectivity and interaction. Based on the direction and capability of information exchange between the physical and digital systems, digital representations are classified into digital models, digital shadows, and Digital Twins [12]. Unlike conventional offline simulation with fixed parameters, a Digital Twin maintains continuous physical–digital synchronization through real-time IoT data (cameras, LiDAR, radar, connected vehicles). This supports closed-loop feedback where physical observations update the virtual model, which analyzes traffic states and generates control decisions deployed back to signal controllers. Thus, the defining feature is real-time bidirectional interaction for adaptive control, not the offline simulation alone.

2.3.1. Implementation Framework of a Transportation Digital Twin in ITS

A transportation Digital Twin integrates real-world data acquisition, data processing, virtual modeling, and simulation to establish a continuously updated digital representation of the physical transportation system. The implementation process generally consists of two main stages: (1) data collection and processing and (2) digital representation and simulation [13,14].

Data Collection and Processing

The development of a transportation Digital Twin begins with continuous data acquisition from the physical transportation environment. Various sensing and monitoring technologies are employed to capture real-time traffic states, including vehicle movements, road conditions, and infrastructure status. These data sources may include vehicle-based sensors, roadside detection systems, connected vehicles, and remote sensing technologies such as LiDAR and cameras. The collected data may contain traffic states such as speed, acceleration, queue length, and signal status. Continuous data streams from these sources enable the digital representation to reflect the current operating conditions of the physical transportation system. Before integration into the Digital Twin environment, raw data from different sources are processed to improve data quality and compatibility. This process converts heterogeneous traffic observations into structured information for simulation and operational decision-making.

Digital Representation and Simulation

The processed traffic information is integrated into a digital environment that represents the transportation network, including road geometry, traffic demand, and vehicle movements. Traffic modeling and simulation platforms (e.g., microscopic or macroscopic simulation tools) are used to reproduce transportation operations and evaluate system performance. By incorporating real-time traffic information, the digital environment can reflect current operating conditions and support applications such as traffic state analysis, congestion evaluation, and control strategy assessment. In traffic signal control applications, the Digital Twin is used to test and optimize alternative signal timing strategies under different traffic conditions before implementation in the physical system. This capability enables more effective traffic management, operational planning, and decision-making.

2.4. Communication Technologies in ITS

The efficacy of Intelligent Transportation Systems (ITS) hinges on robust, low-latency, and reliable communication links between vehicles (V2V), vehicles and infrastructure (V2I), and vehicles with broader networks (V2N) [15]. The evolution of these enabling technologies is broadly categorized into IEEE 802.11-based standards and Cellular Vehicle-to-Everything (C-V2X) technologies.

Dedicated Short Range Communication (DSRC) is a foundational, mature technology operating in the 5.9 GHz band. It is designed for direct, low-latency, ad-hoc communication primarily for safety applications. Its core advantage lies in its proven reliability in non-line-of-sight conditions and its independence from cellular network coverage, making it ideal for critical safety alerts. The allocation of 75 MHz in the 5.9 GHz band for licensed dedicated short-range communications (DSRC) use may also enable future delivery of rich media content to vehicles at short to medium ranges via vehicle-to-roadside (V2R) links [16]. However, its reliance on a single channel and Carrier Sense Multiple Access (CSMA) can lead to scalability and congestion issues in dense traffic scenarios.

The de facto physical and MAC layer standard for DSRC is IEEE 802.11p, which is an amendment to Wi-Fi tailored for high-mobility environments. It introduces enhancements such as eliminating association procedures and basic service set (BSS) establishment, allowing for rapid network entry and reduced handover latency. Despite these optimizations, the standard is fundamentally limited by its half-duplex communication and its inability to guarantee deterministic Quality of Service (quality of service), a constraint inherited from its Wi-Fi roots.

To overcome these limitations, LTE Vehicle-to-Everything (LTE V2X), standardized in 3GPP Release 14 and 15, introduced a cellular-based approach. It operates in two primary modes: direct communication (PC5 interface/sidelink) for low-latency V2V/V2I safety messages and network-based communication (Uu interface) for infotainment and traffic efficiency services. Leveraging the OFDMA framework, LTE V2X offers significantly enhanced synchronization, resource management, and coverage compared to IEEE 802.11p. 5G augments this ecosystem via MIMO, MEC, and beamforming, drastically elevating the performance of technical services. This technological leap is fostering a new era of intelligent vehicles that are capable of autonomous driving, ubiquitous connectivity, and real-time communication with the smart infrastructure that surrounds them [17]. Crucially, it provides improved reliability and capacity in congested scenarios, though its performance can be sensitive to the Global Navigation Satellite System (GNSS) availability for sidelink synchronization.

The latest advancement is IEEE 802.11bd, often referred to as Next-Generation V2X (NGV). This standard serves as a direct evolution of IEEE 802.11p and is designed to achieve parity with and in some aspects potentially surpass C-V2X capabilities. It is a significant advancement in the context of wireless local area network (WLAN) specifications, primarily designed to cater to the unique and demanding requirements of vehicular networks [18]. It introduces key physical layer enhancements, including dual-carrier modulation, low-density parity-check (LDPC) codes, and the option for 10/20 MHz channel bandwidths. MAC layer improvements include enhanced security, improved synchronization, and better resource allocation. These innovations collectively enhance the communication range, the throughput, and reduce latency compared to IEEE 802.11p, all while maintaining backward compatibility.

The transition from legacy IEEE 802.11p to 5G C-V2X and IEEE 802.11bd directly determines the capabilities of modern traffic control systems. High-throughput 5G and MEC integration supply the low-latency bandwidth needed for real-time Digital Twin synchronization across complex networks. Concurrently, enhanced direct-sidelink protocols minimize control-loop latency, allowing instantaneous decision-making for time-critical maneuvers. By replacing contention-based CSMA with deterministic OFDMA resource allocation and advanced error correction, these technologies maximize communication reliability in dense traffic, ultimately providing the resilient foundation required to ensure operational safety across intelligent transportation ecosystems.

3. ITS Core Technologies and Challenges

Modern Intelligent Transportation Systems (ITS) represent a paradigm shift in urban mobility, relying on a synergistic ecosystem of advanced sensing, communication, computational, and analytical frameworks. To address the complexities of next-generation smart transportation, contemporary research integrates diverse technological pillars ranging from core data intelligence to edge-cloud architectures, computer vision, and traffic simulation models. The following sections provide a comprehensive, structured overview of these core technologies and their associated operational challenges.

3.1. Data Intelligence and Analytics

Artificial Intelligence (AI) and Machine Learning (ML) serve as foundational tools in modern intelligent transportation systems, processing vast quantities of traffic data to predict complex mobility patterns, optimize traffic flow, and enhance overall road safety. As transportation networks expand their data acquisition capabilities through widespread sensor deployment, GPS tracking, and centralized traffic management systems, Big Data analytics supplies the computational frameworks required to store, process, and mine these large-scale data streams effectively [19]. To convert these continuous data flows into actionable spatial insights, Geographic Information Systems (GIS) combine computer science with geography, surveying, and mapping technologies. GIS enables the visual representation of traffic dynamics and manages real-time spatial information, including live road conditions, congestion zones, and vehicle movement [20]. However, deploying advanced AI and deep reinforcement learning (DRL) algorithms across expansive urban networks introduces significant scalability challenges when adapting to dynamic traffic demands across multiple intersections [21].

3.2. Infrastructure and Computational Architectures

Supporting these data-driven applications requires robust computational architectures split between centralized and decentralized paradigms. Cloud computing offers high-capacity, centralized storage and computational processing for macro-level transportation data, providing the core infrastructure required for long-term traffic analysis and comprehensive ITS applications. Complementing this, edge computing processes data closer to the source at the network perimeter, drastically reducing processing latency and enabling real-time operational responses critical for autonomous vehicles, smart signalized intersections, and emergency vehicle prioritization systems. To safeguard data exchange across this distributed infrastructure, Blockchain technology provides a decentralized storage framework that enhances security, data sharing, and end-to-end traceability. By mitigating privacy risks, preventing data tampering, and eliminating single-point-of-failure vulnerabilities, blockchain significantly reduces operational overhead across smart transportation networks [22].

3.3. Wireless Connectivity and Communication Frameworks

Seamless data exchange across modern transit networks relies on high-speed wireless connectivity frameworks. The Fifth Generation of wireless communication technology (5G) provides the ultra-low latency necessary for real-time interaction between vehicles and surrounding infrastructure, substantially improving safety and operational efficiency across intelligent transport systems [3]. Building upon this wireless backbone, Vehicle-to-Everything (V2X) communication establishes an advanced interconnected ecosystem where vehicles continuously communicate with infrastructure, pedestrians, and broader network services. V2X systems deploy a combination of onboard units (OBUs), roadside units (RSUs), and integrated sensors to collect, transmit, and process mobility data for optimized traffic management [23]. Serving as the underlying automation infrastructure, the Internet of Things (IoT) links physical devices, sensor suites, and vehicle control networks to enable continuous data exchange and automated decision-making [24]. Nevertheless, real-time connected environments remain vulnerable to communication latency and delayed feedback loops, which can degrade overall control performance in time-sensitive traffic applications [25].

3.4. Perception and Object Identification Technologies

Accurate physical perception and automated identification form the frontline of intelligent transportation data collection. LiDAR technology operates by emitting rapid laser pulses and measuring their return reflection times, creating highly detailed 3D spatial representations of the surrounding environment. It is extensively utilized in autonomous platforms for precise 3D object detection, real-time navigation, and collision avoidance in tandem with vision systems [26]. For localized tracking and automated access control, Radio Frequency Identification (RFID) uses electromagnetic fields to identify and track tagged vehicles, serving as a primary technology for electronic toll collection and automated parking management. Complementing RFID, Automatic Number Plate Recognition (ANPR) applies Optical Character Recognition (OCR) to camera feeds to automatically read vehicle license plates, aiding law enforcement in detecting stolen or unregistered vehicles while supporting smart parking platforms [27]. Despite these perception capabilities, hardware-level sensor failures, noisy data feeds, and environmental interference can degrade traffic state estimation accuracy and reduce system reliability [28].

3.5. Advanced Mobility Platforms and Aerial Systems

Advanced mobility platforms expand intelligent transportation both horizontally and vertically. Drone-assisted transportation utilizes networked, remotely programmable aerial devices to conduct traffic flow monitoring and congestion analysis, offering flexible surveillance capabilities that support physical traffic engineering [29,30]. On the ground, Autonomous Vehicles (AVs) represent fully automated self-driving systems that operate without human intervention by integrating advanced onboard sensors, machine learning algorithms, and real-time data processing engines. Successful large-scale integration of AVs requires modernized physical and digital infrastructure, clear regulatory frameworks, and adaptive traffic control systems to ensure safe and efficient coexistence alongside conventional human-driven vehicles [31].

3.6. Computer Vision Algorithms and Libraries

Processing visual data from camera networks and vehicle sensors relies on specialized computer vision models and development libraries. YOLO (You Only Look Once) is a deep-learning-based object detection algorithm renowned for its high accuracy and real-time processing speeds, making it widely applicable in autonomous driving, traffic surveillance, and Advanced Driver Assistance Systems (ADAS). However, YOLO still faces performance challenges when detecting small objects or processing low-resolution and occluded real-world images [32]. To construct these vision capabilities, OpenCV serves as a comprehensive, cross-platform open-source library supporting languages such as C++, Python, Java, and MATLAB across operating systems like Linux, Windows, Android, and macOS. OpenCV supplies a wide array of foundational algorithms essential for image processing, lane detection, vehicle tracking, and License Plate Recognition (LPR) [33,34].

3.7. Traffic Simulation Environments

Before physical deployment, intelligent transportation algorithms and control strategies are rigorously tested within microscopic and macroscopic traffic simulation software. VISSIM is a commercial, microscopic, time-step-based traffic simulation tool that models detailed urban traffic dynamics, accounting for varying road layouts, signal timings, public transit stops, and individual vehicle interactions. Complementing VISSIM, SUMO (Simulation of Urban Mobility) provides an open-source, highly portable road traffic simulation framework tailored for large-scale network modeling, offering a user-friendly

Graphical User Interface (GUI) and flexible execution environment for evaluating complex transportation systems [35].

Despite the rapid development of Intelligent Transportation Systems (ITS) and its core technologies, many challenges still affect the efficiency and reliability of smart transportation systems. Recent ITS research has focused on integrating Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), and Reinforcement Learning (RL) methods for adaptive traffic signal control, traffic prediction, and real-time decision making [3]. In particular, deep reinforcement learning and multi-agent learning approaches have been widely used to handle complex urban traffic control problems. However, scalability remains a major issue when deploying these methods in large-scale urban networks with multiple intersections and dynamic traffic demand [21]. In addition, real-time ITS applications face significant challenges due to communication latency and delayed feedback in connected environments, which can reduce control performance in time-sensitive traffic systems [25]. Furthermore, sensor failures, noisy data, and unreliable detection from IoT and vision-based systems can degrade the accuracy of traffic state estimation and affect decision-making reliability [28]. Therefore, there is a growing need for intelligent, scalable, low-latency, and fault-tolerant ITS control frameworks capable of supporting next-generation smart transportation systems. Overall, the general conceptual architecture of traffic control in ITS can be illustrated as in Figure 2.

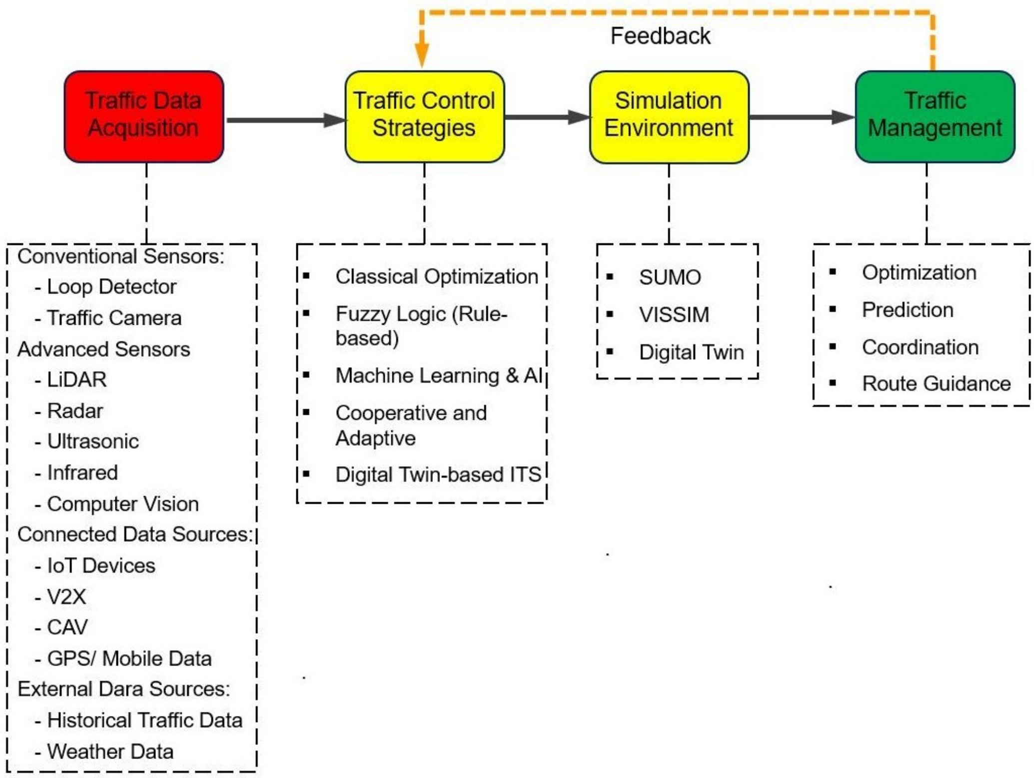

Figure 2. Conceptual architecture of traffic control in intelligent transportation systems (ITS).

4. Related Works

The following section examines recent advancements in traffic management and control approaches in transportation systems. This review analyzes recent studies related to Intelligent Transportation System (ITS) traffic control methods and Digital Twin integration published between 2018 and 2026. The literature review table includes selected journal and conference papers focusing on intelligent traffic signal control, machine learning, reinforcement learning, multi-agent systems, IoT integration, V2X communication, and Digital

Twin-based traffic optimization. Most of the reviewed studies were published in IEEE and MDPI journals, reflecting the growing research interest in intelligent and adaptive traffic control systems. Table 1 summarizes the reviewed studies' control method, key technique, simulation platforms, benchmark datasets, key performance evaluation metrics, and primary operational limitations.

Many studies have developed intelligent transportation system improvements to minimize traffic congestion and to improve safety. Generally, the current traffic management research literature can be classified into five groups based on control methodology. These are the classical optimization-based methods, fuzzy and rule-based methods, machine learning and reinforcement learning-based methods, cooperative and adaptive signal control, and Digital Twin-based traffic control methods, as shown in Figure 3.

Classical optimization approaches address traffic management problems using mathematical modeling and algorithmic control techniques, aiming to improve traffic flow based on redefined objectives such as delay reduction, queue minimization, or throughput maximization. Widely adopted methods include Proportional–Integral–Derivative (PID) control, Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Bee Colony Optimization (BCO). These approaches are generally well understood, computationally tractable, and capable of improving traffic performance under stable conditions. However, their effectiveness often degrades in highly dynamic and heterogeneous traffic environments.

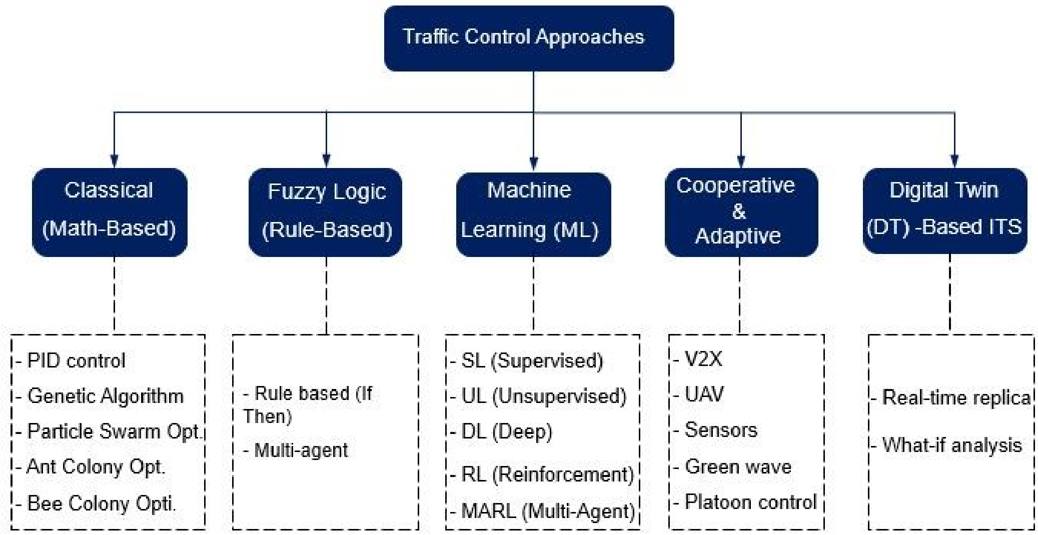

Figure 3. Classification of traffic signal control approaches.

4.1. Classical Control and Mathematical Optimization

Classical approaches utilize rule-governed mathematical models and heuristic algorithms to optimize traffic flow. Early implementations relied on Proportional–Integral–Derivative (PID) control to minimize state errors in real time. However, they struggle with nonlinear dynamics unless integrated with optimization techniques like Webster control and Genetic Algorithms (GA) [36]. GAs are widely deployed to explore large solution spaces in constrained environments, optimizing signal timing for work zones [37], pre-signals with waiting lanes [38], and Vehicle-to-Infrastructure (V2I) communication at isolated intersections [39]. Particle Swarm Optimization (PSO) expands this to multi-intersection coordination, demonstrating effectiveness in autonomous intersection management for Connected Autonomous Vehicles (CAVs) [40]. Swarm-based intelligence such as Ant Colony Optimization (ACO) [41] and Bee Colony Optimization (BCO) [42] leverages artificial pheromone trails and cooperative foraging to minimize network delay, particularly when aligned with Vehicle-to-Vehicle (V2V) communications. Purely mathematical and analytical formulations include cooperative supply–demand control [43], delay-based optimization [44], linear quadratic Model Predictive Control (MPC) [45], stochastic optimization [46], and entrance-based saturation control (SEFP) [47]. While these foundational methods potentially outperform fixed-time systems, their reliance on predefined dynamics limits adaptability in non-recurrent, highly dynamic, and mixed-traffic scenarios involving pedestrians and cyclists.

4.2. Fuzzy Logic (Rule-Based) Control

Fuzzy logic emulates human reasoning to handle traffic imprecision and variability without strict mathematical modeling. Single-intersection controllers with reduced rule bases improve traffic fluidity in simulated environments [48]. To address scalability, decentralized multi-agent fuzzy systems assign autonomous agents to evaluate queue lengths, waiting times, and vehicle types at individual junctions [49]. Hybrids combining fuzzy logic with mathematical flow models (via TraCI/SUMO interfaces) [50] or historical signal timing datasets [51] offer practical, low-cost options for resource-constrained environments. Despite their robustness against uncertain inputs, rule-based systems lack adaptive self-learning mechanisms and suffer from inter-agent coordination overhead and performance degradation in large-scale, complex topographies.

4.3. Machine Learning (ML)-Based Control

Data-driven methods leverage real-time and historical sensor data to adapt to dynamic conditions. Spatiotemporal feature extractors such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks are combined with Proximal Policy Optimization (PPO) for autonomous signal control [52]. Supervised learning hybrids, such as KNN combined with bidirectional LSTMs, enhance short-term expressway forecasting [53], while computer vision (UAV aerial data) [54] and ensemble techniques (Gradient Boosting, Random Forests) [55] improve traffic density estimation, albeit with sensitivity to non-recurrent events. Model-free RL, particularly Q-learning, optimizes signal timing through environmental interactions [56]. To scale beyond isolated junctions, Multi-Agent Reinforcement Learning (MARL) and Deep Q-Networks (DQN) facilitate cooperative green-wave control, reducing delay and oversaturated queue lengths [57–59]. Advanced paradigms integrate Deep RL (DRL) with speed guidance for CAVs [60], Software-Defined IoT (SD-IoT) architectures [61,62], imitation learning [63], and neuroevolutionary methods [64]. Despite promising adaptability over classical rules, ML/RL methods present challenges regarding heavy computational demands, high data dependencies, non-stationarity, and sensor/communication latency.

4.4. Cooperative and Adaptive Control

Cooperative control leverages Vehicle-to-Everything (V2X), computer vision, and edge sensing to enable proactive network-wide decisions. Early frameworks prioritized situational awareness by fusing vision and V2X to broadcast Basic Safety Messages (BSMs) and Signal Phase and Timing (SPaT) data [65], or combining LiDAR with V2X for obstructed intersections [66]. Platoon-based cooperative strategies reduce stops and fuel consumption across signalized [67] and non-signalized [68] intersections. Dynamic adaptive extensions incorporate pedestrian safety via PIR sensors/IoT [69], queue estimation via connected vehicle penetration [70], and priority routing for emergency vehicles [71]. At the network level, virtual-grid architectures [72], joint signal-speed optimization [73,74], Green Wave coordination [75], edge-computing with PSO optimization [76], and live API integrations (e.g., Google Maps Distance Matrix API) [77] optimize flow across mixed-traffic and unsignalized corridors [78,79]. However, deployment remains constrained by roadside unit (RSU) infrastructure costs, V2X market penetration, packet latency, and cybersecurity risks.

4.5. Digital Twin (DT)-Based Control

Digital Twin (DT)-based traffic control has emerged as a promising paradigm in Intelligent Transportation Systems (ITS), enabling the creation of a virtual replica of real-time traffic environments through integration with roadside sensors, connected vehicles, and communication networks. By synchronizing physical and digital traffic systems, DTs support congestion prediction, scenario testing, and traffic optimization without disrupting real-world operations. Despite challenges such as high infrastructure costs, communication latency, cybersecurity threats, data reliability, and the lack of standardized protocols across heterogeneous junction types, DT-based approaches are increasingly demonstrating their potential in smart transportation management.

Recent studies have explored DT-enabled traffic monitoring, simulation calibration, and adaptive control. Afshari et al. [13] proposed a DT platform for coordinated intersections that integrates LiDAR data with VISSIM simulation, using closed-loop calibration and genetic algorithms to improve trajectory-level accuracy. While effective, the framework requires validation with more diverse sensing modalities. Zhu et al. [80] addressed DT–physical twin (PT) mismatch under non-ideal synchronization by introducing a DT-based adaptive signal control model using a modified Cell Transmission Model (CTM) and connected vehicle data, combined with genetic and Bayesian optimization for signal timing. Dasgupta et al. [14] developed a DT-based adaptive traffic signal control framework using SUMO, demonstrating performance gains over conventional systems. However, the authors did not consider factors such as weather-induced sensor uncertainty.

Beyond intersection control, DTs have been applied to driver behavior modeling and cooperative traffic operations. Liao et al. [81] introduced a Driver Digital Twin (DDT) to predict personalized lane-changing behavior in mixed traffic with connected and automated vehicles (CAVs), improving prediction accuracy and computational efficiency. Related work using vehicle-to-cloud (V2C) communication [82] demonstrated safety and emission benefits, though latency and fail-safe mechanisms remain critical concerns. At the network level, Kušić et al. [83] developed a microscopic DT for motorway traffic using real-time roadside and vehicle data, while Llagostera-Brugarola et al. [84] employed a macroscopic DT to manage congestion and pollution on an interurban highway, highlighting the importance of sensing accuracy and low-latency data transmission.

DT integration with advanced communication and learning techniques has further expanded its scope. Hu et al. [85] proposed a DT-based real-time traffic prediction framework for Internet of Vehicles (IoV) environments using 5G networks, achieving improved short-term flow prediction at the cost of increased privacy and latency challenges. Kamal et al. [86] applied multi-agent deep reinforcement learning to DT-based adaptive signal control, reporting reductions in fuel consumption and carbon dioxide emissions under heavy traffic. However, real-time communication delays remain a bottleneck. Similarly, Basheer et al. [87] introduced a DT-driven traffic optimization framework combining computer vision and edge computing, with performance sensitive to adverse weather conditions.

DT-based cooperative and multimodal traffic management has also gained attention. Wang et al. [88] proposed DT-assisted cooperative driving for non-signalized intersections, demonstrating improved efficiency over traditional signal control, though heterogeneous traffic and emergency scenarios require further study. Wang et al. [89] extended DT co-simulation to include pedestrians, addressing a key research gap, but emphasized the need for real-time deployment. Other works have explored DT-enabled deep reinforcement learning for CAV trajectory planning [90], vision-based DT signal control using YOLO and SUMO [91], and DT-integrated mobile edge computing for lane-changing decisions [92], all reporting performance improvements while consistently identifying communication reliability and latency as critical limitations.

Digital Twin (DT)-based frameworks improve real-time traffic control and intersection performance, especially when combined with learning-based and data-driven methods. In recent years, reinforcement learning approaches such as graph-based methods and hierarchical structures have been integrated with Multi-Agent Reinforcement Learning for traffic control [21,93,94]. These approaches are increasingly used in intelligent traffic systems as they support both local decision-making at intersections and coordinated control across larger traffic networks.

Graph-based reinforcement learning models traffic networks as graphs, where intersections are treated as points (nodes) and roads as the connections (edges) between them. This representation helps learning algorithms better understand how traffic moves across a network and how congestion in one area can influence other connected regions. In particular, Graph Neural Networks (GNNs) allow each intersection to combine information from its neighboring intersections through message passing. This enables the system to learn spatial relationships in traffic patterns more naturally. As a result, it improves coordination between connected intersections and better reflects real-world road structures. These methods are also scalable and suitable for large traffic networks. However, most existing models mainly focus on nearby intersections and use relatively simple architectures, which limits their ability to capture long-distance dependencies and overall city-wide traffic behavior. In addition, computational cost can increase significantly as the network grows.

Multi-Agent Reinforcement Learning (MARL) extends traditional reinforcement learning by allowing multiple agents to learn and act at the same time. In traffic signal control, each intersection is typically treated as an independent agent that observes its local traffic conditions and learns a policy to optimize signal timing. MARL frameworks can be divided into independent learning, where each agent learns separately without coordination, and cooperative learning, where agents share information or jointly optimize a shared objective. This decentralized structure improves scalability and allows the system to adapt to real-time traffic changes more effectively. However, MARL also introduces challenges such as non-stationarity, where the environment keeps changing because all agents are learning simultaneously, partial observability, where each agent only sees limited information, and communication overhead when coordination is required. As a result, although MARL is effective for distributed traffic control, achieving stable learning and strong global coordination remain difficult.

Hierarchical Multi-Agent Reinforcement Learning (HMARL) extends MARL by introducing a multi-level structure to improve coordination in large-scale traffic systems. Instead of treating all intersections equally, HMARL organizes agents into hierarchical levels. A high-level controller is responsible for broader decision-making, such as coordinating traffic flow across different regions or defining overall control strategies. At the same time, low-level agents manage individual intersections by adjusting signal timings based on local observations and guidance from the higher level. This structure allows the system to combine global and local decision-making in a more organized way. Compared to MARL systems, HMARL improves coordination across large networks by reducing the burden on individual agents and introducing structured guidance from higher levels. It is particularly useful for city-scale traffic systems where purely decentralized methods struggle to maintain consistent global behavior. However, HMARL increases design complexity because defining interactions between multiple agents and hierarchical levels is challenging, and it can also make training more difficult due to the added structure.

The integration of graph-based learning, MARL, and HMARL provides a powerful framework for traffic control. Graph-based methods improve communication among agents by modeling spatial relationships, while HMARL introduces structured multi-level coordination to overcome the limitations of purely local decision-making. In such integrated systems, GNNs can be applied at different levels, both for local neighborhood interaction and for broader region-level aggregation. This allows the model to capture both short-range and long-range traffic dependencies. Despite these advantages, challenges remain in designing efficient communication strategies, ensuring scalability to large urban networks, and maintaining stable learning in complex multi-agent environments.

Building on these foundations, Kumarasamy et al. [21] proposed a decentralized graph-based multi-agent reinforcement learning (MARL) approach for traffic signal control. Each intersection is treated as an independent agent using a VISSIM-based Digital Twin to provide real-time traffic state information. The agents coordinate using local and neighboring traffic data to optimize signal timing. The method reduces delay, queue length, and emissions compared to conventional actuated signal control. Compared to other studies, this approach is more suitable for large-scale traffic networks because it supports multi-intersection coordination.

Zhao et al. [93] and Cao et al. [94] proposed hierarchical multi-agent reinforcement learning (HMARL) frameworks for urban traffic signal control. In these approaches, traffic intersections are modeled as multiple agents, while a higher-level controller is introduced to coordinate traffic behavior across different regions of the network. The low-level agents control individual intersections based on local traffic conditions, while the high-level policies coordinate groups of intersections to ensure more globally consistent traffic flow. Both studies focus on improving scalability and coordination in large urban traffic systems, with objectives such as reducing congestion, travel time, and emissions, particularly in sustainability-oriented scenarios. Compared to standard multi-agent reinforcement learning methods, these HMARL-based approaches provide better-structured coordination and improved adaptability in complex, dynamic traffic environments, making them more suitable for city-scale traffic signal control.

Ceapă et al. [95] developed an IoT-supported Digital Twin framework that focuses on real-time integration between the physical traffic system and the virtual model. Traffic data collected from IoT sensors are continuously used to update the DT, and reinforcement learning is applied for signal optimization. The framework shows better performance than fixed-time and vehicle-actuated control in terms of congestion reduction, travel time, and queue length. Compared to Kumarasamy et al. [21], this method focuses more on real-time data synchronization through IoT than on multi-agent coordination across intersections. However, it assumes ideal sensing conditions and does not fully consider communication delay, sensor noise, or occlusion effects.

Zhang et al. [96] proposed a DT-based traffic prediction model using a Temporal Convolutional Network (TCN) with an attention mechanism. This study focuses on improving traffic state prediction rather than direct signal control. The model captures temporal patterns in traffic flow and selects the most relevant historical data to improve prediction accuracy. The predicted results are then used within the DT for traffic signal adjustment. Compared to control-based approaches such as [21,93,95], this method improves decision support through better prediction, but its performance depends strongly on data quality and forecasting accuracy. Adarbah et al. [97] introduced a DT-based traffic signal control system using the BIRCH clustering algorithm with a SUMO–CARLA simulation environment. Unlike reinforcement learning-based methods, this approach does not rely on learning-based control. Instead, it groups traffic patterns using clustering and adjusts signal timings based on traffic behavior. The method performs well under different traffic demand levels but is less adaptive compared to learning-based approaches when traffic conditions change rapidly.

Lis et al. [98] focused on DT-based traffic planning and infrastructure evaluation rather than real-time signal control. Their study uses a VISSIM-based DT to test different intersection designs, including roundabout, turbo-roundabout, and flyover, combined with an Adaptive Inflow Metering (AIM) strategy. The DT is used for scenario testing and comparison before real-world implementation. Compared to other studies, this work is more suitable for long-term planning and infrastructure optimization than for real-time traffic signal control.

Overall, MARL-based approaches such as Kumarasamy et al. show better performance in dynamic multi-intersection environments compared to single-agent RL methods such as Ceapă et al. [95], which mainly focus on real-time IoT integration. Prediction-based methods [96] improve control performance indirectly through better traffic forecasting but depend strongly on data quality. Clustering-based methods [97] are simpler and more stable but less adaptive compared to learning-based control approaches. DT-based planning methods [98] are useful for infrastructure evaluation but are not directly designed for real-time signal optimization. Reinforcement learning is more suitable for real-time control than traditional machine learning because it learns optimal sequential decisions through interaction with the environment, rather than only making static predictions.

Recent traffic signal control methods work well at individual intersections and small groups of intersections. However, most of them mainly focus on local or decentralized control, and do not fully consider coordination at the city level. Approaches based on Multi-Agent Reinforcement Learning can handle multiple intersections at the same time, but their coordination is usually limited to nearby intersections. In addition, Graph-based MARL has been used to model spatial relationships by allowing intersections to share information with their neighbors. Still, these methods are generally implemented in a flat structure without higher-level control. As a result, large-scale traffic patterns and long-distance interactions across the network are still not well captured.

Based on the above, a hierarchical graph-based multi-agent reinforcement learning framework can improve traffic control at the city scale. A higher-level component can guide overall traffic behavior, while GNN captures spatial relationships between intersections. At the same time, decentralized agents control individual traffic signals using both local and neighboring information. This structure allows decisions to be made at different levels, improving both local performance and overall traffic flow across the city. The existing literature demonstrates the growing maturity of DT-based traffic control across intersections, motorways, and cooperative driving scenarios. However, persistent research gaps remain in scalable real-time synchronization, robust sensing under adverse conditions, latency-aware communication, cybersecurity, and standardized DT architectures, which remain challenges to enable large-scale, real-world ITS deployment. Based on these recent studies, DT-integrated traffic control frameworks can support near-future decision-making, where different signal timing strategies can be tested in advance within the Digital Twin environment, compared, and the most suitable option selected for real-world traffic signal deployment. However, several challenges remain. Data latency and communication delays can affect real-time synchronization between the physical system and the Digital Twin. At the same time, sensor errors and uncertainty can reduce the accuracy of traffic state estimation. In addition, sufficient computational power is required to ensure real-time processing and scalable deployment in complex urban traffic networks.

A comparative summary of these control methods is shown in Table 1 including datasets, simulation platforms, evaluation metrics, and main limitations.

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Table 1. Summary of traffic control methods and their evaluation characteristics.

Method, Reference	Key Technique	Simulation Platforms	Benchmark Datasets	Evaluation Metrics	Limitations
Classical [36]	PID, GA, K-means, Webster	SUMO	Geomagnetic and radar sensor data	Road occupancy	Sensor infrastructure dependency
Classical [37]	GA	MATLAB	Custom real-world traffic data	Vehicle speed & number	Scalability limit
Classical [38]	GA	MATLAB	Custom real-world traffic data	Intersection delay time	Scalability limit
Classical [39]	V2I, GA	VISSIM & MATLAB	Not specified	Average delay, stops & queue length	Computational cost
Classical [40]	PSO	Not specified	Not specified	Vehicle speed & flow	High communication dependency
Classical [41]	ACO	Python-based simulation	Custom real-world traffic data	Density, speed, accident rate	Single-area validation
Classical [42]	BCO	C++-based simulation	Not specified	Passing, stop, delay, mean calculation time, entrance speed	High communication dependency
Classical [43]	Traditional Mathematical Model	C language-based simulation	Custom real-world traffic data	Number of stops and throughput	Single-area validation
Classical [44]	Delay-Based Traffic Signal Control	Numerical simulation	Not specified	Queue length & fairness of delay	Isolated Intersection validation
Classical [45]	Linear Quadratic Model	MATLAB	Not specified	Queue length	computation time
Classical [46]	Traditional Mathematical Model	Monte Carlo simulation experiments	Not specified	Throughput	Scalability limit
Classical [47]	Traditional Mathematical Model	VISSIM	Not specified	Queue length, vehicle delay & traffic volume	Limited evaluation on complex networks
Rule-based [48]	Fuzzy Rule Base Reduction	SUMO	Not specified	Vehicle waiting time, Fuel consumption & carbon emission	Scalability limit
Rule-based [49]	Agent-Based Fuzzy Control	SUMO	Not specified	Waiting time, Fuel usage & carbon emission	Simulation-only validation
Rule-based [50]	Fuzzy-Based Traffic Signal Control	SUMO	Not specified	Waiting time, number of signal changes & speed	Simulation-only validation
Rule-based [51]	Adaptive Fuzzy Logic	SUMO	Custom real-world traffic data	Traffic volume, travel speed & mean flow rate	Isolated Intersection validation
ML/RL [52]	DRL, CNN-LSTN & PPO	SUMO	Not specified	Waiting time	Limited evaluation on complex networks
ML/RL [53]	KNN & Bi-directional LSTM	MATLAB	Custom real-world traffic data	MAE error, RMSE error & MAPE error	Limited by the exclusion of weather & road blockage factors
ML/RL [54]	Deep Neural Network	Not specified	UAV video dataset	Traffic density estimation accuracy	High-quality UAV image dependency
ML/RL [54]	GBRT, Random Forest (RF) & XGBoost	Not specified	VicTraffic & Victorian Government Data Directory	MSE error & MAE error	Limited data quality
ML/RL [56]	Modified Q-learning	Taiwan Highway Capacity Software	Taipei City Government Department of Transportation Traffic Dataset	Vehicle delay	Coordination among neighboring intersections
ML/RL [57]	MARL	Python-based simulation	Not specified (Poisson distribution)	Averaged intersection delay	Isolated Intersection validation
ML/RL [58]	MADRL	SUMO	Bangkok Metropolitan Administration (BMA) traffic Dataset	Throughput, traffic backlog, mean vehicle speed & total jam length	Scalability limit
ML/RL [59]	MADRL	SUMO	Not specified	Traffic pressure, queue length & speed	Scalability limit
ML/RL [60]	RL	PTV VISSIM	Not specified	Queue length &stop delay	Scalability limit & communication dependency
ML/RL [61]	DRL Cooperative & Adaptive, [65]	SUMO	Shiraz transportation organization & municipality	Queue length & delay	Reliable sensor and communication dependency

Table 1. *Cont.*

Method, Reference	Key Technique	Simulation Platforms	Benchmark Datasets	Evaluation Metrics	Limitations
ML/RL [62]	Software-Defined IoT & MADRL	Not specified	Not specified	Average reward	Simulation-only validation
ML/RL [63]	Deep Learning	SUMO	Not specified	Queue length	Communication dependency
ML/RL [64]	Neural Network & Evolutionary Algorithm	Fuzzy Cellular Automata traffic simulator	Not specified	Delay, velocity & travel time	Reliable sensor & communication dependency
Cooperative & Adaptive [65]	V2X	Not specified	Custom real-world traffic data	Object detection & classification accuracy	Limited infrastructure
Cooperative & Adaptive [66]	V2X, LiDAR	Real-world implementation & testing	Custom real-world traffic data	Object detection & latency	Communication dependency
Cooperative & Adaptive [67]	Platoon control	VENTOS	Not specified	Travel time, fuel consumption & speed	Infrastructure & communication dependency
Cooperative & Adaptive [68]	Platoon control	SUMO	Not specified	Fuel consumption, speed, acceleration & waiting time	Infrastructure & communication dependency
Cooperative & Adaptive [69]	PIR, IoT & CV	Real-world implementation & testing	Custom real-world traffic data	Object detection	Sensor accuracy & weather influence
Cooperative & Adaptive [70]	CAV	VISSIM & MATLAB	Not specified	Queue length	Communication dependency
Cooperative & Adaptive [71]	IoT & GPS	PTV VISSIM	Not specified	Lane opening time, delay & control messages sent	Sensor accuracy & communication dependency
Cooperative & Adaptive [72]	Virtual Grid-Based Cooperative control	SUMO & prototype testing	Not specified	Throughput & delay	Dynamic traffic condition
Cooperative & Adaptive [73]	V2I	VISSIM & MATLAB	Not specified	Fuel consumption, travel time, traffic volume & stop rate	CAV-only scenario
Cooperative & Adaptive [74]	V2I	Not specified	Not specified	Delay, utility (social welfare) & run-time	Communication dependency
Cooperative & Adaptive [75]	V2X	SUMO & MATLAB	Not specified	Stop time & lane occupation	Communication error & scalability limit
Cooperative & Adaptive [76]	Edge Computing, V2I & PSO	MATLAB	Not specified	Waiting time & speed	CAV-only scenario
Cooperative & Adaptive [76]	Google Maps APIs	Prototype testing	Google API	Estimated arrival time	Google Maps API availability & data accuracy
Cooperative & Adaptive [78]	V2V	Numerical simulation	Not specified	Travel time	High traffic volume & Communication dependency
Cooperative & Adaptive [79]	V2I	MATLAB	Not specified	Input traffic density, speed, stop delay, passing time, fuel & CO_2 emission	Vehicle trajectory prediction accuracy, Sensor accuracy & communication dependency
DT [13]	LiDAR	VISSIM	BlueCity API	Intersection information	Sensor accuracy & communication dependency
DT [14]	ATSC	SUMO	Not specified	Delay & stop frequency	Sensor error & communication dependency
DT [80]	GA & BO	SUMO, C++ & Python	Not specified	Waiting time, traffic demand & delay	CV-only scenario
DT [81]	Driver digital twin	SUMO	Custom real-world traffic data	Speed, lane merging urgency, lateral deviation & fuel usage	Computational time & communication dependency
DT [82]	V2C	Real-world implementation	Real-world field test data	Fuel usage, pollution, traffic delay & communication delay	Limited field test scale & communication dependency

Table 1. *Cont.*

Method, Reference	Key Technique	Simulation Platforms	Benchmark Datasets	Evaluation Metrics	Limitations
DT [83]	Traffic counter, sensors & V2X	SUMO	Real-world traffic-counter data	Traffic volume	Traffic counter accuracy & communication dependency
DT [84]	V2X	Aimsun Next	Custom real-world traffic data	Occupancy, flow, speed, speed deviation, travel time, pollution & fuel usage	Communication dependency
DT [85]	IoV	Python	Custom real-world traffic data	MAPE error, MAE error & RMSE error	Data quality & communication dependency
DT [86]	RL	SUMO	Custom real-world traffic data	Fuel usage & CO_2 emission	Scalability limit & communication dependency
DT [87]	CV & edge computing	Not specified	The Indian Driving Dataset (IDD)	Object detection	Data quality
DT [88]	V2X	Unity game engine	Not specified	Speed, vehicle position error & update frequency	Limited field test scale
DT [88]	V2P	CARLA-SUMO & Unity	Custom real-world traffic data	V2P warning performance	Limited field test scale & communication dependency
DT [90]	DRL	MATLAB/Simulink & Highwayenv	Not specified	Speed, delay & computational time	Communication dependency
DT [91]	YOLO	SUMO	Bellevue Traffic Video Dataset	Traffic throughput	Communication dependency
DT [92]	Edge computing	Cellular automata & LTE-V-based MEC	Custom real-world traffic data	CAV Lane-changing performance	Unauthorized CAV control & computational time
ML/RL [93]	Hierarchical MARL	SUMO	Custom real-world traffic data	Reward, queue length, speed & waiting time	Computational complexity upon network size
ML/RL [94]	Hierarchical MARL	SUMO	Custom real-world traffic data	Travel time, delay, throughput & emission	Data quality & privacy
DT [95]	IoT & Q-learning	SUMO	UDOT dataset	Waiting time, queue length & throughput	Single-area validation, sensor noise & pedestrian Interaction
DT [96]	TCN attention	Python, PyTorch & Cuda	Custom real-world &traffic data	MAPE error, delay, stop & queue	Single-area validation & pedestrian Interaction
DT [97]	BIRCH clustering	SUMO & CARLA	Not specified	Stop rate & fuel consumption	Scalability limit
DT [98]	Adaptive Inflow Metering	PTV VISSIM	Municipal Transport Authority in Rzeszów (ZTM)	Stop delay, queue length, speed & level of service	Single-roundabout evaluation & sensor error

Of the 19 studies classified as Digital Twins (DTs) in Table 1, only four ([13,81–83]) demonstrate online or connected interaction with the physical traffic system, while the remaining 15 are evaluated offline. Of these, seven ([84–86,91,95,96,98]) use real-world traffic or video datasets, whereas the others rely primarily on software-generated traffic. This indicates that online DT implementations remain limited, motivating the proposed online DT framework for continuous physical–digital interaction.

The methodological categories used in Table 1 are intended to provide a structured means of organizing the reviewed literature rather than strictly exclusive classifications. Because several studies combine multiple techniques, for example, Digital Twins with ML/RL, IoT, or cooperative V2X control, a study may conceptually span multiple categories. For consistency, each study is assigned to the category that best represents its primary methodological contribution.

5. Open Research Challenges

Despite recent progress in Intelligent Transportation Systems (ITS) traffic control, several challenges remain for large-scale real-world deployment. One major issue is communication delay in real-time data exchange between sensors, vehicles, and control centers, which can significantly reduce the effectiveness of traffic signal optimization and

Digital Twin synchronization. Similarly, sensor failures and inaccurate detections from IoT devices and vision-based systems can lead to incorrect traffic state estimation, affecting the reliability of decision-making in intelligent control systems. These issues become more critical in highly dynamic urban environments where traffic conditions change rapidly.

In addition, scalability remains a key limitation in deploying ITS solutions across large metropolitan areas. Many existing control methods perform well at isolated intersections, but they struggle to maintain efficiency when extended to large-scale networks with multiple interconnected junctions. The high computational requirements of advanced learning-based methods, particularly deep reinforcement learning and multi-agent systems, further increase the complexity of real-time deployment. Moreover, the cost of implementing large-scale ITS infrastructure, including sensors, communication networks, roadside units, and cloud or edge computing platforms, remains a significant barrier for practical implementation.

Furthermore, cybersecurity and data privacy concerns present additional challenges in connected transportation systems. ITS environments rely heavily on continuous data exchange between vehicles, infrastructure, and cloud systems, making them vulnerable to cyberattacks such as data manipulation, spoofing, and unauthorized access. Such attacks can severely affect system performance, compromise traffic safety, and reduce public trust in intelligent mobility systems. Therefore, ensuring secure, reliable, and resilient ITS operations is essential for real-world implementation.

6. Future Directions

Current DT frameworks rely heavily on microscopic traffic simulators (e.g., SUMO, VISSIM, CARLA) to validate signal control algorithms, driver behavior models, and cooperative intersection strategies. However, simulation environments assume idealized vehicle dynamics, static roadway friction, and deterministic driver responses, creating a significant domain gap when transferring policies to physical deployment. Future research must prioritize physical-world testbeds and empirical validation protocols. This includes evaluating DT platforms against unexpected real-world edge cases, e.g., illegal lane changes, vehicle breakdowns, non-compliant pedestrians, and adverse weather, to demonstrate closed-loop operational fidelity before real-world actuation. Future research should focus on developing scalable, reliable, and intelligent ITS traffic control frameworks capable of operating efficiently in large urban environments. Key directions include integrating Connected and Autonomous Vehicles (CAVs), Vehicle-to-Everything (V2X) communication, and edge computing for decentralized decision-making, as well as designing failsafe mechanisms to handle communication failures. One promising direction is integrating hierarchical and graph-based multi-agent reinforcement learning with Digital Twin technology, which can enable both local intersection-level optimization and global network-level traffic coordination. This combination can improve adaptability and enhance system-wide traffic efficiency under dynamic and uncertain conditions.

The integration of Digital Twin (DT) technology with advanced techniques has significantly advanced intelligent transportation systems (ITS). In particular, hierarchical graph-based multi-agent reinforcement learning (HG-MARL) has emerged as an effective framework for large-scale traffic signal control by combining graph-structured modeling, decentralized decision-making, and hierarchical coordination. DT-integrated HG-MARL frameworks enable predictive and adaptive traffic control by allowing multiple signal strategies to be evaluated in a virtual environment before deployment. Despite their advantages, challenges remain in real-time synchronization, communication latency, sensing uncertainty, cybersecurity, and computational scalability, which limit reliable large-scale ITS deployment.

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In addition, future ITS frameworks should emphasize fault-tolerant and safety-aware control mechanisms to handle real-world uncertainties such as sensor failures, communication delays, and sudden traffic disturbances. Integrating predictive models with real-time Digital Twin synchronization can further enhance system robustness and enable proactive traffic management strategies rather than purely reactive control. Moreover, the adoption of edge computing and distributed cloud architectures can help reduce latency and improve real-time decision-making performance by processing data closer to the source. Next-generation communication technologies such as 5G and 6G will also enhance data transmission speed and reliability in connected transportation systems. Finally, stronger cybersecurity methods are needed to protect data and prevent unauthorized access in connected transportation systems, improving overall safety and reliability in ITS applications. Modern traffic management relies on fragmented subsystems: IoT environmental sensors, connected and autonomous vehicles (CAVs), unmanned aerial vehicles (UAVs), computer vision feeds, and cloud routing APIs (e.g., Google Maps). The existing literature largely evaluates these technologies in isolation. The ultimate challenge lies in establishing unified, interoperable ITS standards. Future architectures must seamlessly synthesize multimodal data streams, along with sparse CAV trajectory data, continuous camera feeds, IoT queue metrics, and macro-level routing data, into a standardized data bus. Building open, interoperable control standards will enable cooperative decision-making across public infrastructure, private autonomous fleets, emergency priority networks, and vulnerable road users (VRUs).

7. Conclusions

This review has presented recent developments in intelligent transportation system (ITS) traffic control, focusing on classical optimization methods, learning-based approaches, graph-based models, cooperative control, and Digital Twin-based frameworks. The discussion shows that while traditional methods perform well in limited scenarios, modern data-driven and multi-agent approaches offer greater adaptability for complex, dynamic traffic environments. In particular, graph-based multi-agent reinforcement learning and Digital Twin integration have shown strong potential for improving both local intersection control and overall city-scale traffic coordination.

However, several limitations remain, including scalability issues, communication delays, sensor reliability problems, computational requirements, and safety concerns in real-time deployment. These challenges highlight the need for more robust, efficient, and fault-tolerant traffic control systems that can operate reliably in large urban networks. In conclusion, ITS traffic control is shifting towards more intelligent and connected solutions. Future work should focus on improving scalability and enhancing system reliability. The integration of hierarchical learning, graph-based methods, and Digital Twin technology is expected to play an important role in next-generation traffic management systems.

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Abbreviations

The following abbreviations are used in this manuscript:

ADAS	Advanced Driver Assistance Systems
AIM	Adaptive Inflow Metering
ANPR	Automatic Number Plate Recognition
ATSC	Adaptive Traffic Signal Control
BIRCH	Balanced Iterative Reducing and Clustering using Hierarchies
BO	Bayesian Optimization
BSMs	Basic Safety Messages
BSS	Basic Service Set
DDT	Driver Digital Twin
GBRT	Gradient Boosting Regression Trees
GNN	Graph Neural Network
HG-MARL	Hierarchical Graph Multi-Agent Reinforcement Learning
HMARL	Hierarchical Multi-Agent Reinforcement Learning
LDPC	Low-Density Parity-Check
MEC	Multi-access Edge Computing
MPC	Model Predictive Control
PC5	PC5 Sidelink Interface
PPO	Proximal Policy Optimization
PSO	Particle Swarm Optimization
RF	Random Forest
RL	Reinforcement Learning
RSUs	Roadside Units
SDIoT	Software-Defined Internet of Things
SEFP	Same Entrance Full-Pass
SPaT	Signal Phase and Timing
SUMO	Simulation of Urban MObility
TCN	Temporal Convolutional Network
XGBoost	Extreme Gradient Boosting
YOLO	You Only Look Once

References

1. Oladimeji, D.; Gupta, K.; Kose, N.A.; Gundogan, K.; Ge, L.; Liang, F. Smart Transportation: An Overview of Technologies and Applications. *Sensors* **2023**, *23*, 3880. [CrossRef]
2. Wang, F.Y.; Lin, Y.; Ioannou, P.A.; Vlacic, L.; Liu, X.; Eskandarian, A.; Lv, Y.; Na, X.; Cebon, D.; Ma, J.; et al. Transportation 5.0: The DAO to Safe, Secure, and Sustainable Intelligent Transportation Systems. *IEEE Trans. Intell. Transp. Syst.* **2023**, *24*, 10262–10278. [CrossRef]
3. Avcı, İ.; Koca, M. Intelligent transportation system technologies, challenges and security. *Appl. Sci.* **2024**, *14*, 4646. [CrossRef]
4. Mahmood, A.; Siddiqui, S.A.; Sheng, Q.Z.; Zhang, W.E.; Suzuki, H.; Ni, W. Trust on wheels: Towards secure and resource efficient IoV networks. *Computing* **2022**, *104*, 1337–1358. [CrossRef]
5. Mueck, M.; Gaie, C. Introduction to the European Intelligent Transport Systems Regulation. In *European Digital Regulations*; Mueck, M., Gaie, C., Eds.; Springer Nature: Cham, Switzerland, 2025; pp. 139–159. [CrossRef]
6. Alabdouli, H.; Hassan, M.S.; Abdelfatah, A. Enhancing Route Guidance with Integrated V2X Communication and Transportation Systems: A Review. *Smart Cities* **2025**, *8*, 24. [CrossRef]

7. Sikarwar, S.S.; Chawla, N.; Agarwal, P.; Afzal, M.; Rathore, S.P.S.; Valecha, N. Improving Lane Management: Leveraging OpenCV and IoT to Empower Smart Environments. In Proceedings of the 2023 International Conference on Smart Devices (ICSD), Dehradun, India, 2–3 May 2024; pp. 1–5. [CrossRef]
8. Duan, C.; Rao, D.D.; Subbalakshmi, C.; Mishra, S.; Soliman, N.F.; Hassan, M.M. Real-time Traffic Forecasting for Smart Cities using a Hybrid Transformer Architecture with Adaptive Optimization. *Int. J. Intell. Transp. Syst. Res.* **2026**, *24*, 957–976. [CrossRef]
9. Shao, Z.; Bell, M.G.; Wang, Z.; Geers, D.G.; Yao, X.; Gao, J. CCDSReFormer: Traffic flow prediction with a criss-crossed dual-stream enhanced rectified transformer model. *Commun. Transp. Res.* **2025**, *5*, 100189. [CrossRef]
10. Shao, Z.; Wang, F.; Sun, T.; Yu, C.; Fang, Y.; Jin, G.; An, Z.; Liu, Y.; Qu, X.; Xu, Y. HUTFormer: Hierarchical U-Net transformer for long-term traffic forecasting. *Commun. Transp. Res.* **2025**, *5*, 100218. [CrossRef]
11. Zhang, Y.; Zhou, Q.; Wang, J.; Kouvelas, A.; Makridis, M.A. CASAformer: Congestion-aware sparse attention transformer for traffic speed prediction. *Commun. Transp. Res.* **2025**, *5*, 100174. [CrossRef]
12. Qian, C.; Liu, X.; Ripley, C.; Qian, M.; Liang, F.; Yu, W. Digital Twin—Cyber Replica of Physical Things: Architecture, Applications and Future Research Directions. *Future Internet* **2022**, *14*, 64. [CrossRef]
13. Afshari, A.; Lee, J.; Besenski, D. A Digital Twin Platform for Real-Time Intersection Traffic Monitoring, Performance Evaluation, and Calibration. *Infrastructures* **2025**, *10*, 204. [CrossRef]
14. Dasgupta, S.; Rahman, M.; Jon, S. Harnessing Digital Twin Technology for Adaptive Traffic Signal Control: Improving Signalized Intersection Performance and User Satisfaction. *IEEE Internet Things J.* **2024**, *11*, 36596–36618. [CrossRef]
15. Letaief, K.B.; Chen, W.; Shi, Y.; Zhang, J.; Zhang, Y.J.A. The Roadmap to 6G: AI Empowered Wireless Networks. *IEEE Commun. Mag.* **2019**, *57*, 84–90. [CrossRef]
16. Zhu, J.; Roy, S. MAC for dedicated short range communications in intelligent transport system. *IEEE Commun. Mag.* **2003**, *41*, 60–67. [CrossRef]
17. Pawar, V.; Zade, N.; Vora, D.; Khairnar, V.; Oliveira, A.; Kotecha, K.; Kulkarni, A. Intelligent Transportation System with 5G Vehicle-to-Everything (V2X): Architectures, Vehicular Use Cases, Emergency Vehicles, Current Challenges, and Future Directions. *IEEE Access* **2024**, *12*, 183937–183960. [CrossRef]
18. Iliopoulos, C.; Iossifides, A.; Foh, C.H.; Chatzimisios, P. IEEE 802.11BD for Next-Generation V2X Communications: From Protocol to Services. *IEEE Commun. Stand. Mag.* **2025**, *9*, 88–98. [CrossRef]
19. Sbai, I.; Krichen, S. Big Data Analytics architecture for intelligent transportation systems: A tunisian case study. In Proceedings of the 2023 International Conference on Innovations in Intelligent Systems and Applications (INISTA), Hammamet, Tunisia, 20–23 September 2023; pp. 1–6. [CrossRef]
20. Ding, C.; Chen, Y.; Chen, Y. Construction of Urban Intelligent Traffic Sharing Information Platform Based on GIS. In Proceedings of the 2020 5th International Conference on Electromechanical Control Technology and Transportation (ICECTT), Nanchang, China, 15–17 May 2020; pp. 579–584. [CrossRef]
21. Kumarasamy, V.K.; Saroj, A.J.; Liang, Y.; Wu, D.; Hunter, M.P.; Guin, A.; Sartipi, M. Integration of Decentralized Graph-Based Multi-Agent Reinforcement Learning with Digital Twin for Traffic Signal Optimization. *Symmetry* **2024**, *16*, 448. [CrossRef]
22. Guo, X.; Guo, X. A Research on Blockchain Technology: Urban Intelligent Transportation Systems in Developing Countries. *IEEE Access* **2023**, *11*, 40724–40740. [CrossRef]
23. Naeem, M.A.; Chaudhary, S.; Meng, Y. Road to Efficiency: V2V Enabled Intelligent Transportation System. *Electronics* **2024**, *13*, 2673. [CrossRef]
24. Sumit; Chhillar, R.S. IoT Enabled Security Management Approach for Intelligent Transportation System in Smart Cities. In Proceedings of the 2022 IEEE 6th Conference on Information and Communication Technology (CICT), Gwalior, India, 18–20 November 2022; pp. 1–5. [CrossRef]
25. Kamtam, S.B.; Lu, Q.; Bouali, F.; Haas, O.C.L.; Birrell, S. Network Latency in Teleoperation of Connected and Autonomous Vehicles: A Review of Trends, Challenges, and Mitigation Strategies. *Sensors* **2024**, *24*, 3957. [CrossRef]
26. Royo, S.; Ballesta-Garcia, M. An Overview of Lidar Imaging Systems for Autonomous Vehicles. *Appl. Sci.* **2019**, *9*, 4093. [CrossRef]
27. Lubna; Mufti, N.; Shah, S.A.A. Automatic Number Plate Recognition:A Detailed Survey of Relevant Algorithms. *Sensors* **2021**, *21*, 3028. [CrossRef]
28. Bakibillah, A.; Tan, Y.H.; Loo, J.Y.; Tan, C.P.; Kamal, M.; Pu, Z. Robust estimation of traffic density with missing data using an adaptive-R extended Kalman filter. *Appl. Math. Comput.* **2022**, *421*, 126915. [CrossRef]
29. Saputro, N.; Akkaya, K.; Algin, R.; Uluagac, S. Drone-Assisted Multi-Purpose Roadside Units for Intelligent Transportation Systems. In Proceedings of the 2018 IEEE 88th Vehicular Technology Conference (VTC-Fall), Chicago, IL, USA, 27–30 August 2018; pp. 1–5. [CrossRef]
30. Cvitanić, D. Drone applications in transportation. In Proceedings of the 2020 5th International Conference on Smart and Sustainable Technologies (SpliTech), Split, Croatia, 23–26 September 2020; pp. 1–4. [CrossRef]
31. Łach, Ł.; Svyetlichnyy, D. Comprehensive Review of Traffic Modeling: Towards Autonomous Vehicles. *Appl. Sci.* **2024**, *14*, 8456. [CrossRef]

32. Flores-Calero, M.; Astudillo, C.A.; Guevara, D.; Maza, J.; Lita, B.S.; Defaz, B.; Ante, J.S.; Zabala-Blanco, D.; Armingol Moreno, J.M. Traffic Sign Detection and Recognition Using YOLO Object Detection Algorithm: A Systematic Review. *Mathematics* **2024**, *12*, 297. [CrossRef]
33. Nigam, N.; Singh, D.P.; Choudhary, J. A Review of Different Components of the Intelligent Traffic Management System (ITMS). *Symmetry* **2023**, *15*, 583. [CrossRef]
34. Lu, X. Design and Implementation of Intelligent Parking Management System Based on OpenCV and B/S Architecture. In Proceedings of the 2023 IEEE International Conference on Image Processing and Computer Applications (ICIPCA), Changchun, China, 11–13 August 2023; pp. 1746–1750. [CrossRef]
35. Ejercito, P.M.; Nebrija, K.G.E.; Feria, R.P.; Lara-Figueroa, L.L. Traffic simulation software review. In Proceedings of the 2017 8th International Conference on Information, Intelligence, Systems & Applications (IISA), Larnaca, Cyprus, 27–30 August 2017; pp. 1–4. [CrossRef]
36. Wang, X.; Shao, W. Networked Sensor-Based Adaptive Traffic Signal Control for Dynamic Flow Optimization. *Sensors* **2025**, *25*, 3501. [CrossRef]
37. Yang, D.; Zhou, X.; Su, G.; Liu, S. Model and Simulation of the Heterogeneous Traffic Flow of the Urban Signalized Intersection with an Island Work Zone. *IEEE Trans. Intell. Transp. Syst.* **2019**, *20*, 1719–1727. [CrossRef]
38. Zhao, C.; Chang, Y.; Zhang, P. Coordinated Control Model of Main-Signal and Pre-Signal for Intersections with Dynamic Waiting Lanes. *Sustainability* **2018**, *10*, 2849. [CrossRef]
39. Qiao, Y.; Meng, T.; Qin, H.; Hu, Z.; Zhong, Z. Vehicle-to-Infrastructure-Based Traffic Signal Optimization for Isolated Intersection. *Sustainability* **2023**, *15*, 6631. [CrossRef]
40. Abbas-Turki, A.; Mualla, Y.; Gaud, N.; Calvaresi, D.; Du, W.; Lombard, A.; Dridi, M.; Koukam, A. Autonomous Intersection Management: Optimal Trajectories and Efficient Scheduling. *Sensors* **2023**, *23*, 1509. [CrossRef]
41. Li, Z.; Huang, J. How to Mitigate Traffic Congestion Based on Improved Ant Colony Algorithm: A Case Study of a Congested Old Area of a Metropolis. *Sustainability* **2019**, *11*, 1140. [CrossRef]
42. Li, J.; He, C. A Novel Dynamic Cooperative Traffic Control Algorithm for the Reduction of Traffic Delay. *Machines* **2022**, *10*, 831. [CrossRef]
43. Zhihui, L.; Qian, C.; Yonghua, Z.; Rui, Z. Signal Cooperative Control with Traffic Supply and Demand on a Single Intersection. *IEEE Access* **2018**, *6*, 54407–54416. [CrossRef]
44. Wu, J.; Ghosal, D.; Zhang, M.; Chuah, C.N. Delay-Based Traffic Signal Control for Throughput Optimality and Fairness at an Isolated Intersection. *IEEE Trans. Veh. Technol.* **2018**, *67*, 896–909. [CrossRef]
45. Han, Y.; Hegyi, A.; Yuan, Y.; Roncoli, C.; Hoogendoorn, S. An Extended Linear Quadratic Model Predictive Control Approach for Multi-Destination Urban Traffic Networks. *IEEE Trans. Intell. Transp. Syst.* **2019**, *20*, 3647–3660. [CrossRef]
46. Wang, S.; Ahmed, N.U.; Yeap, T.H. Optimum Management of Urban Traffic Flow Based on a Stochastic Dynamic Model. *IEEE Trans. Intell. Transp. Syst.* **2019**, *20*, 4377–4389. [CrossRef]
47. Shen, H.; Liu, D.; Liu, Z. The Same Entrance Full-Pass (SEFP) Control Method for the Prevention of Over-Saturation at the Critical Intersection. *IEEE Access* **2020**, *8*, 143975–143984. [CrossRef]
48. Chala, T.D.; Kóczy, L.T. Intelligent Fuzzy Traffic Signal Control System for Complex Intersections Using Fuzzy Rule Base Reduction. *Symmetry* **2024**, *16*, 1177. [CrossRef]
49. Chala, T.D.; Kóczy, L.T. Agent-Based Intelligent Fuzzy Traffic Signal Control System for Multiple Road Intersection Systems. *Mathematics* **2025**, *13*, 124. [CrossRef]
50. Zahwa, F.; Cheng, C.T.; Simic, M. Novel Intelligent Traffic Light Controller Design. *Machines* **2024**, *12*, 469. [CrossRef]
51. Madrigal Arteaga, V.M.; Pérez Cruz, J.R.; Hurtado-Beltrán, A.; Trumpold, J. Efficient Intersection Management Based on an Adaptive Fuzzy-Logic Traffic Signal. *Appl. Sci.* **2022**, *12*, 6024. [CrossRef]
52. Faqir, N.; Ennaji, Y.; Chakir, L.; Boumhidi, J. Hybrid CNN-LSTM and Proximal Policy Optimization Model for Traffic Light Control in a Multi-Agent Environment. *IEEE Access* **2025**, *13*, 29577–29588. [CrossRef]
53. Zhuang, W.; Cao, Y. Short-Term Traffic Flow Prediction Based on a K-Nearest Neighbor and Bidirectional Long Short-Term Memory Model. *Appl. Sci.* **2023**, *13*, 2681. [CrossRef]
54. Zhu, J.; Sun, K.; Jia, S.; Li, Q.; Hou, X.; Lin, W.; Liu, B.; Qiu, G. Urban Traffic Density Estimation Based on Ultrahigh-Resolution UAV Video and Deep Neural Network. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2018**, *11*, 4968–4981. [CrossRef]
55. Alajali, W.; Zhou, W.; Wen, S.; Wang, Y. Intersection Traffic Prediction Using Decision Tree Models. *Symmetry* **2018**, *10*, 386. [CrossRef]
56. Chu, H.C.; Liao, Y.X.; Chang, L.H.; Lee, Y.H. Traffic Light Cycle Configuration of Single Intersection Based on Modified Q-Learning. *Appl. Sci.* **2019**, *9*, 558. [CrossRef]
57. Wu, Y.; Chen, H.; Zhu, F. DCL-AIM: Decentralized coordination learning of autonomous intersection management for connected and automated vehicles. *Transp. Res. Part C Emerg. Technol.* **2019**, *103*, 246–260. [CrossRef]

58. Ei Mon, E.; Ochiai, H.; Aswakul, C. Application of Traffic Light Control in Oversaturated Urban Network Using Multi-Agent Deep Reinforcement Learning. *IEEE Access* **2024**, *12*, 82384–82395. [CrossRef]
59. Angela Jennifa Sujana, J.; Namasivaayam, L. Pressure, Queue, and Average Speed - Based Multi-Agent DQN for Optimizing Traffic Signal Control. In Proceedings of the 2024 International Conference on Advances in Data Engineering and Intelligent Computing Systems (ADICS), Chennai, India, 18–19 April 2024; pp. 1–6. [CrossRef]
60. Maadi, S.; Stein, S.; Hong, J.; Murray-Smith, R. Real-Time Adaptive Traffic Signal Control in a Connected and Automated Vehicle Environment: Optimisation of Signal Planning with Reinforcement Learning under Vehicle Speed Guidance. *Sensors* **2022**, *22*, 7501. [CrossRef]
61. Damadam, S.; Zourbakhsh, M.; Javidan, R.; Faroughi, A. An Intelligent IoT Based Traffic Light Management System: Deep Reinforcement Learning. *Smart Cities* **2022**, *5*, 1293–1311. [CrossRef]
62. Yang, J.; Zhang, J.; Wang, H. Urban Traffic Control in Software Defined Internet of Things via a Multi-Agent Deep Reinforcement Learning Approach. *IEEE Trans. Intell. Transp. Syst.* **2021**, *22*, 3742–3754. [CrossRef]
63. Huo, Y.; Tao, Q.; Hu, J. Cooperative Control for Multi-Intersection Traffic Signal Based on Deep Reinforcement Learning and Imitation Learning. *IEEE Access* **2020**, *8*, 199573–199585. [CrossRef]
64. Bernas, M.; Płaczek, B.; Smyła, J. A Neuroevolutionary Approach to Controlling Traffic Signals Based on Data from Sensor Network. *Sensors* **2019**, *19*, 1776. [CrossRef]
65. Moradi-Pari, E.; Tian, D.; Mahjoub, H.N.; Bai, S. The Smart Intersection: A Solution to Early-Stage Vehicle-to-Everything Deployment. *IEEE Intell. Transp. Syst. Mag.* **2022**, *14*, 88–102. [CrossRef]
66. Mo, Y.; Vijay, R.; Rufus, R.; Boer, N.d.; Kim, J.; Yu, M. Enhanced Perception for Autonomous Vehicles at Obstructed Intersections: An Implementation of Vehicle to Infrastructure (V2I) Collaboration. *Sensors* **2024**, *24*, 936. [CrossRef]
67. Pu, Y.; Wu, L.; Zhang, Z.; Deng, X.; Liu, B.; Wang, E.; Liu, S. APC: Adaptive Platoon Control Scheme for Urban Traffic Signal Intersections. *IEEE Trans. Veh. Technol.* **2025**, *74*, 12951–12965. [CrossRef]
68. Chen, X.; Xu, B.; Qin, X.; Bian, Y.; Hu, M.; Sun, N. Non-Signalized Intersection Network Management with Connected and Automated Vehicles. *IEEE Access* **2020**, *8*, 122065–122077. [CrossRef]
69. M.E, M.; Adiline Macriga, G. Smart Automated Zebra Crossing System Using PIR Sensors, IoT Integration, and IP Camera-Based Headcount for Enhanced Road Safety. In Proceedings of the 2025 International Conference on Computing and Communication Technologies (ICCCT), Chennai, India, 16–17 April 2025; pp. 1–6. [CrossRef]
70. Gao, K.; Han, F.; Dong, P.; Xiong, N.; Du, R. Connected Vehicle as a Mobile Sensor for Real Time Queue Length at Signalized Intersections. *Sensors* **2019**, *19*, 2059. [CrossRef]
71. Khan, A.; Ullah, F.; Kaleem, Z.; Ur Rahman, S.; Anwar, H.; Cho, Y.Z. EVP-STC: Emergency Vehicle Priority and Self-Organising Traffic Control at Intersections Using Internet-of-Things Platform. *IEEE Access* **2018**, *6*, 68242–68254. [CrossRef]
72. Hou, Y.; Wang, G.; Zhou, Y. Virtual-Grid Based Traffic Control Strategy with Multiple Intersections Collaboration. *IEEE Access* **2018**, *6*, 40105–40119. [CrossRef]
73. Xu, B.; Ban, X.J.; Bian, Y.; Li, W.; Wang, J.; Li, S.E.; Li, K. Cooperative Method of Traffic Signal Optimization and Speed Control of Connected Vehicles at Isolated Intersections. *IEEE Trans. Intell. Transp. Syst.* **2019**, *20*, 1390–1403. [CrossRef]
74. Sayin, M.O.; Lin, C.W.; Shiraishi, S.; Shen, J.; Başar, T. Information-Driven Autonomous Intersection Control via Incentive Compatible Mechanisms. *IEEE Trans. Intell. Transp. Syst.* **2019**, *20*, 912–924. [CrossRef]
75. Shi, Y.; Li, J.; Han, Q.; Lv, L. A Coordination Algorithm for Signalized Multi-Intersection to Maximize Green Wave Band in V2X Network. *IEEE Access* **2020**, *8*, 213706–213717. [CrossRef]
76. Zhang, Y.; Liu, L.; Lu, Z.; Wang, L.; Wen, X. Robust Autonomous Intersection Control Approach for Connected Autonomous Vehicles. *IEEE Access* **2020**, *8*, 124486–124502. [CrossRef]
77. Mishra, S.; Bhattacharya, D.; Gupta, A. Congestion Adaptive Traffic Light Control and Notification Architecture Using Google Maps APIs. *Data* **2018**, *3*, 67. [CrossRef]
78. Bian, Y.; Li, S.E.; Ren, W.; Wang, J.; Li, K.; Liu, H.X. Cooperation of Multiple Connected Vehicles at Unsignalized Intersections: Distributed Observation, Optimization, and Control. *IEEE Trans. Ind. Electron.* **2020**, *67*, 10744–10754. [CrossRef]
79. Kamal, M.A.S.; Hayakawa, T.; Imura, J.i. Development and Evaluation of an Adaptive Traffic Signal Control Scheme Under a Mixed-Automated Traffic Scenario. *IEEE Trans. Intell. Transp. Syst.* **2020**, *21*, 590–602. [CrossRef]
80. Zhu, H.; Sun, F.; Tang, K.; Wu, H.; Feng, J.; Tang, Z. Digital Twin-Enhanced Adaptive Traffic Signal Framework under Limited Synchronization Conditions. *Sustainability* **2024**, *16*, 5502. [CrossRef]
81. Liao, X.; Zhao, X.; Wang, Z.; Zhao, Z.; Han, K.; Gupta, R.; Barth, M.J.; Wu, G. Driver Digital Twin for Online Prediction of Personalized Lane-Change Behavior. *IEEE Internet Things J.* **2023**, *10*, 13235–13246. [CrossRef]
82. Liao, X.; Wang, Z.; Zhao, X.; Han, K.; Tiwari, P.; Barth, M.J.; Wu, G. Cooperative Ramp Merging Design and Field Implementation: A Digital Twin Approach Based on Vehicle-to-Cloud Communication. *IEEE Trans. Intell. Transp. Syst.* **2022**, *23*, 4490–4500. [CrossRef]

83. Kušić, K.; Schumann, R.; Ivanjko, E. A digital twin in transportation: Real-time synergy of traffic data streams and simulation for virtualizing motorway dynamics. *Adv. Eng. Inform.* **2023**, *55*, 101858. [CrossRef]
84. Llagostera-Brugarola, E.; Corpas-Marco, E.; Victorio-Vergel, C.; Lopez-Aguilera, E.; Vázquez-Gallego, F.; Alonso-Zarate, J. A Digital Twin for Intelligent Transportation Systems in Interurban Scenarios. *Appl. Sci.* **2025**, *15*, 7454. [CrossRef]
85. Hu, C.; Fan, W.; Zeng, E.; Hang, Z.; Wang, F.; Qi, L.; Bhuiyan, M.Z.A. Digital Twin-Assisted Real-Time Traffic Data Prediction Method for 5G-Enabled Internet of Vehicles. *IEEE Trans. Ind. Inform.* **2022**, *18*, 2811–2819. [CrossRef]
86. Kamal, H.; Yánez, W.; Hassan, S.; Sobhy, D. Digital-Twin-Based Deep Reinforcement Learning Approach for Adaptive Traffic Signal Control. *IEEE Internet Things J.* **2024**, *11*, 21946–21953. [CrossRef]
87. Basheer, Z.; Karthick, S.; Pichhika, H.C.; Vara Prasad Yerra, R.; Venkataraman, H.; Shah, P.; Nalli, G.; Trestian, R.; Comşa, I.S. Leveraging Digital Twin Technology for Traffic Optimization: A Pathway to Sustainable Urban Transportation. In Proceedings of the 2025 IEEE International Symposium on Broadband Multimedia Systems and Broadcasting (BMSB), Dublin, Ireland, 11–13 June 2025; pp. 1–6. [CrossRef]
88. Wang, Z.; Han, K.; Tiwari, P. Digital Twin-Assisted Cooperative Driving at Non-Signalized Intersections. *IEEE Trans. Intell. Veh.* **2022**, *7*, 198–209. [CrossRef]
89. Wang, Z.; Zheng, O.; Li, L.; Abdel-Aty, M.; Cruz-Neira, C.; Islam, Z. Towards Next Generation of Pedestrian and Connected Vehicle In-the-Loop Research: A Digital Twin Co-Simulation Framework. *IEEE Trans. Intell. Veh.* **2023**, *8*, 2674–2683. [CrossRef]
90. Mohd Aslam, A.; Chaudhary, R.; Bhardwaj, A. An AIoT-Enabled Digital Twin CAVs with a DRL-Based Framework for Trajectory Planning. *IEEE Trans. Intell. Transp. Syst.* **2025**, *26*, 18101–18115. [CrossRef]
91. Pradhananga, R.; Williams, S.; Aygun, S.; Chen, L.; Tu, Y.; Crow, W.; Aakur, S.; Tzeng, N.F. Digital Twin-Aided Municipal Traffic Control. In *Proceedings of the SUMO Conference Proceedings, Berlin-Adlershof, Germany, 12–14 May 2025*; TIB Open Publishing: Hanover, Germany, 2025; Volume 6, pp. 149–161.
92. Fan, B.; Wu, Y.; He, Z.; Chen, Y.; Quek, T.Q.; Xu, C.Z. Digital Twin Empowered Mobile Edge Computing for Intelligent Vehicular Lane-Changing. *IEEE Netw.* **2021**, *35*, 194–201. [CrossRef]
93. Zhao, P.; Yuan, Y.; Guo, T. Extensible Hierarchical Multi-Agent Reinforcement-Learning Algorithm in Traffic Signal Control. *Appl. Sci.* **2022**, *12*, 12783. [CrossRef]
94. Cao, Q.; Li, J.; Trucco, P. Sustainability-Oriented Urban Traffic System Optimization Through a Hierarchical Multi-Agent Deep Reinforcement Learning Framework. *Sustainability* **2026**, *18*, 1606. [CrossRef]
95. Ceapă, V.C.D.; Apostol, V.A.; Sacală, I.S.; Căruntu, C.F.; Ross, R.; Holt, D.; Segărceanu, M.; Burlacu, L.E. IoT-Simulated Digital Twin with AI Traffic Signal Control for Real-Time Traffic Optimization in SUMO. *Sensors* **2026**, *26*, 1880. [CrossRef]
96. Zhang, Y.; Shang, K.; Cui, Z.; Zhang, Z.; Zhang, F. Research on Traffic Flow Prediction at Intersections Based on DT-TCN-Attention. *Sensors* **2023**, *23*, 6683. [CrossRef]
97. Adarbah, H.Y.; Sookhak, M.; Atiquzzaman, M. A digital twin-based traffic light management system using BIRCH algorithm. *Ad Hoc Netw.* **2024**, *164*, 103613. [CrossRef]
98. Lis, M.; Mądziel, M. Green Transportation Planning for Smart Cities: Digital Twins and Real-Time Traffic Optimization in Urban Mobility Networks. *Appl. Sci.* **2026**, *16*, 678. [CrossRef]