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Prospects of Artificial Intelligence for Cloud-Integrated Intelligent Transportation Systems

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Abstract

Artificial intelligence (AI) is rapidly growing in cloud computing, improving scalability, efficiency, and performance. Therefore, organizations can manage resources more intelligently by adjusting computing power based on demand, anticipating server traffic to reduce downtime, and using advanced data analytics to detect potential security risks. These evolutions play a crucial role in intelligent transportation and promoting sustainability, where AI-enabled cloud systems are poised to improve the performance of transportation networks by significantly reducing the environmental impact. However, the energy consumption associated with processing large volumes of data highlights the need for intelligent and energy-efficient resource management. This study examines how AI can be successfully incorporated into cloud computing to promote environmentally friendly road transportation, reviewing previous studies in the field.

Prospects of Artificial Intelligence for Cloud-Integrated Intelligent Transportation Systems

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***Abstract*—Artificial intelligence (AI) is rapidly growing in cloud computing, improving scalability, efficiency, and performance. Therefore, organizations can manage resources more intelligently by adjusting computing power based on demand, anticipating server traffic to reduce downtime, and using advanced data analytics to detect potential security risks. These evolutions play a crucial role in intelligent transportation and promoting sustainability, where AI-enabled cloud systems are poised to improve the performance of transportation networks by significantly reducing the environmental impact. However, the energy consumption associated with processing large volumes of data highlights the need for intelligent and energy-efficient resource management. This study examines how AI can be successfully incorporated into cloud computing to promote environmentally friendly road transportation, reviewing previous studies in the field.**

***Index Terms*—Artificial Intelligence, Cloud Computing, Energy Efficiency, Intelligent Transportation Systems.**

I. Introduction

Cloud computing is the basis of modern digital infrastructure, offering flexible and scalable virtual resources on demand, including networks, servers, storage, applications, and services [1]. By abstracting infrastructure and enabling ubiquitous access via the Internet, cloud computing minimizes the need for organizations to invest and manage physical hardware and software. This allows them to leverage platforms such as Amazon Web Services (AWS), Microsoft Azure, and Google Cloud to efficiently store and process large-scale data [2]. The three primary cloud service models are infrastructure as a service (IaaS), platform as a service (PaaS), and software as a service (SaaS). These models cater to diverse user needs by offering varying levels of control, resilience, and management [3].

Personalizing cloud services according to security, performance and compliance requirements is made easy through deployment models, including public, private, hybrid, and community clouds [4]. These models impact their deployment in applications of intelligent transportation systems (ITS), including traffic management, vehicle-to-everything (V2X) communications, and smart parking [5]. Notwithstanding the achievements, traditional cloud systems face suboptimal performance, data security, privacy, interoperability, resource utilization, and high energy consumption [6].

The swift growth of artificial intelligence (AI) and cloud computing has significantly transformed many application areas. The key AI techniques, such as machine learning (ML), deep learning, and natural language processing (NLP), have become foundational elements in cloud-based applications [7]. These capabilities enable dynamic decision-making. AI addresses most challenges in cloud computing by optimizing performance through predictive analytics, enhancing security with real-time threat detection, preserving privacy through federated learning, and increasing energy efficiency through resource optimization [8], [9].

This evolution has enabled ITS to provide intelligent automation and improve computational efficiency through real-time data processing and predictive analytics [10]. Predicting vehicular traffic flow and contributing to more efficient traffic management and planning using various AI-based methods [11]. In addition, traffic incident detection by integrating edge and cloud computing with advanced deep learning techniques [12]. The following is an illustrative example.

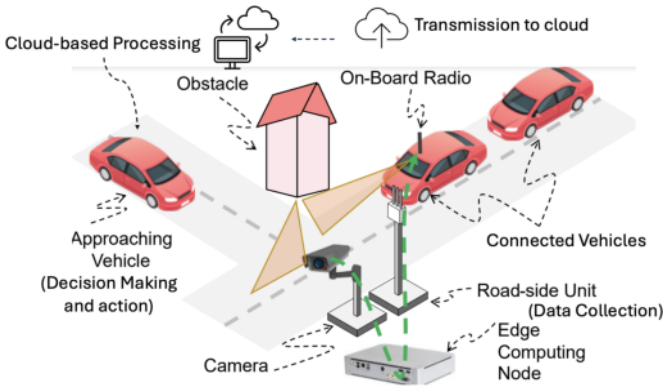

Fig. 1: ITS scenario where connected vehicles offload data to the cloud for real-time processing and decision-making.

Figure 1 shows an intersection in the city. Consider the Singapore Smart Mobility 2030 initiative [15], in which the intersection is congested during rush hour, that is, at 8:00 AM on a working day, and equipped with advanced ITS technologies. The road infrastructure for ITS includes traffic cameras, V2X systems, loop detectors, and roadside units (RSUs), all sharing data using real-time communication. This case aims to show that all these elements cooperate to control traffic, minimize delay, improve safety, and mitigate environmental challenges, as discussed below.

A. Data Collection

Roadside sensors, such as loop detectors and cameras, measure the presence of vehicles at various locations on the roads, their speed and density, and collect detailed data on traffic movement. The RSUs are located at crossroads along the highways and are used as

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localized communication providers [20]. As specified above, traffic data collected in real-time from various sources can be used to identify possible events such as accidents or vehicle failures. For this purpose, the Junction Electronic Eyes (J-Eyes) system can utilize these cameras for incident detection [13]. Connected vehicles, i.e., vehicles with V2X communication capabilities, transmit their speed, location, and crossing-related data to other vehicles and processing units via RSUs and other micro/macro cells. This V2X capability provides low-latency real-time data exchange essential for dynamic and efficient traffic management. In Fig. 1, V2X communications are emphasized as facilitating vehicle-to-vehicle, infrastructure-to-vehicle, and cloud-to-vehicle communication. The collected traffic data is transmitted to a central cloud platform for processing.

B. Cloud analytics

The collected data from multiple sensors is combined and routed to a cloud computing infrastructure, such as AWS or Microsoft Azure platforms, as referenced in the study [1], [2]. In this regard, the cloud infrastructure provides elastic computing, dynamically providing resources, and real-time processing capabilities suitable for varying data volumes, especially during peak traffic hours (Section III-B). The cloud infrastructure also houses different AI models that scan incoming data using advanced techniques, as described in Section III-A; to predict traffic patterns, such as light, moderate, or congested; to identify traffic incidents such as accidents; and to optimize traffic signals accordingly [11], [19]. This cloud analytics component also aggregates data from additional sources, such as IoT sensors (e.g., weather sensors) and GPS sensors (e.g., from taxis or public transport), to provide a holistic view of the traffic network, as discussed in Section III-C. Thus, it makes data-driven decision-making efficient.

C. Decision making

The AI algorithms can optimize traffic light control (TLC) signals in real time. For example, when cloud analytics predict heavy traffic on one route (light traffic on other routes), the TLC system must prolong the green light for the route on which heavy traffic was predicted, thus shortening queue lengths. Under the incident detection and response mechanism of ITS, when an incident occurs, for example, an accident or vehicle breakdown, or even serving emergency vehicles (e.g., ambulance) in a priority situation, computer vision and image processing techniques can be used to detect that incident accurately [10], [12], [13]. Therefore, the response system notifies the concerned officials with precise location information, enabling a rapid response. Another ITS service is electronic message sign improvements, such as the Expressway Monitoring and Advisory System (EMAS), which alerts drivers to take alternative routes in real time due to traffic events [15].

D. Feedback and Improvement

RSUs and connected vehicles continuously transmit traffic data in real time to the cloud, enabling ongoing updates to predictive and optimization algorithms [11], [14]. This ensures that the system remains adaptive and responsive to evolving traffic conditions. This feedback loop is essential for dynamic resource allocation in cloud-based traffic management systems. In addition, reinforcement learning techniques are key to adapting system behavior based on accumulated experience [19]. For example, in recurring traffic disruptions caused by local construction, the system can autonomously adjust signal timings to minimize delays, thereby improving overall traffic flow over time [10].

E. Benefits and Outcomes

The benefits and results of the AI-enabled cloud-driven ITS system can be described in terms of efficiency, safety, environmental impact, and economic savings. As mentioned in Singapore's ITS initiative [15], by integrating AI and cloud, an **efficiency** of 20% peak-hour travel delay can be achieved. Additionally, using J-Eyes, an increase in 20% **safety** can be observed for increased incident detection rates and associated response.

Concerning **environmental impact**, Eco-routing techniques employed in Caceres and Madrid, Spain, select alternative routes to minimize fuel consumption. The reduced engine idling time leads to minimized CO_2 emissions [30]. As studied in [23], shorter engine idling times at traffic stations lead to lower fuel consumption and associated emissions, eventually reducing the economic burden towards **economic savings**.

II. Real-life ITS Case Studies

This section briefly presents some real-life case studies that confirm the efficiency of ITS solutions in traffic management, public transportation optimization, security, safety, and environmental monitoring.

We review the prototype Coordinated Highways Action Response Team (CHART) [24] for the **traffic management** case study. The CHART predicts traffic clearance times based on historical crash data of ATMS (advanced traffic management system). For prediction, the researchers used traditional regression and classification analysis on traffic, lanes, and location. The reliability and confidence levels of the CHART reached greater than 80%.

In **public transportation optimization**, we consider Chalo[1], an Android-based e-ticketing system in India, to help more than 15000 public vehicles. This facility allows passengers to buy digital tickets, book seats, and make cashless payments through RFID cards, with real-time synchronization through WiFi devices locked in KIOSK mode to prevent misuse. The overall operational impact of Chalo was reduced 40% data management, minimized 60% security incidents, simplified access control, and reduced task times by 50%. Chalo used AWS infrastructure for scalability, reliability, and remote access.

ITS improves **safety** by preventing accidents, regulating traffic flow, and delivering real-time alerts. After detecting traffic events using computer vision and AI techniques [13], adaptive traffic control systems, such as the one implemented in Hefei, China, aim to alleviate traffic congestion. Meanwhile, the TAPCO Wrong-Way Driving Detection System deployed in Arkansas alerts authorities about wrong-way drivers [26]. These alerts drive drivers to correct their driving behaviors, preventing potential collisions and improving safety.

From a **security** perspective, Chalo's E-Ticketing leverages contactless payment through RFID cards, with system evaluations

[1] https://cloud.google.com/customers/chalo

showing a reduction in ticket forgery and unauthorized entries by up to 60%. In contrast, [29] examined the Security Credential Management System (SCMS) used in the Tampa Hillsborough Expressway Authority Connected Vehicle Pilot (THEA). SCMS validates the identity of vehicles and infrastructure through electronic certificates, encrypts V2X communications to protect against threats, and preserves user privacy with short-term pseudonym certificates. It also features a misbehavior detection and certificate revocation mechanism to remove compromised devices from the network.

Coloma et al. [30] analyzed eco-routes in the small city of Spain, Cáceres, comparing fuel consumption and emissions on various routes under **environmental monitoring**. Their trade-off analysis shows that the city routes reduced about 54% CO_2 emissions against bypasses, despite the latter offering shorter travel times. To mitigate traffic congestion and associated emissions, this study recommends restricting the access of heavy vehicles to the city center, establishing pedestrian and cycling zones, and imposing speed limits in sensitive areas.

Real-world examples of ITS highlight key challenges. Singapore's ITS improves safety and efficiency, but is costly, raises data privacy concerns, and requires frequent upgrades to manage growing traffic. The Chalo e-ticketing system in India reduces security issues but is dependent on digital access, potentially excluding those without smartphones or RFID cards, and is vulnerable to cyberattacks. Hefei's adaptive TLC is expensive to implement and maintain, making it less feasible for smaller cities. Additionally, the deployment of SCMS is limited to operational complexity, connectivity requirements, limited misbehavior detection, and vendor cooperation. These issues hinder integration with existing transport systems and limit broader adoption.

III. AI-driven Cloud Computing for ITS

To address the challenges highlighted in the previous section, integrating AI with cloud computing presents a promising approach for real-time and sustainable traffic management [12]. These technologies enable scalable, data-driven solutions that can adapt to the dynamic traffic demands of urban areas. This section provides a brief overview of these core technologies.

A. Artificial Intelligence

AI simulates human cognitive functions such as learning, reasoning, and decision-making and has become increasingly valuable in ITS. We list the five key AI technologies shown in Fig. 2, including predictive analytics, computer vision, optimization, reinforcement learning, and NLP. In predictive analytics, ML models analyze historical and real-time traffic data to forecast traffic patterns, including congestion, enabling proactive traffic control strategies [11]. In computer vision, AI systems process live traffic camera feeds to detect vehicles, pedestrians, and traffic events, including accidents in real-time; thus improving traffic awareness and road safety [12]. Optimization algorithms dynamically adjust TLC phases and their timings and optimize routing decisions based on evolving traffic conditions [21].

RL is another AI technology that supports dynamic and adaptive decision-making in complex traffic environments [21]. It is used for TLC signal control, autonomous driving, route planning, and emergency vehicle prioritization. RL agents learn optimal strategies through interaction with real-time data, and when integrated with IoT, V2X communication, and edge computing, they can respond more effectively to changing traffic conditions. NLP is also an AI technology that analyzes traffic-related information and incident reports from social media in real-time to inform traffic management decisions. For example, NLP can extract incident details from X posts to alert authorities, supplementing sensor data [22]. These AI-driven techniques contribute to more efficient, responsive, and sustainable traffic management systems.

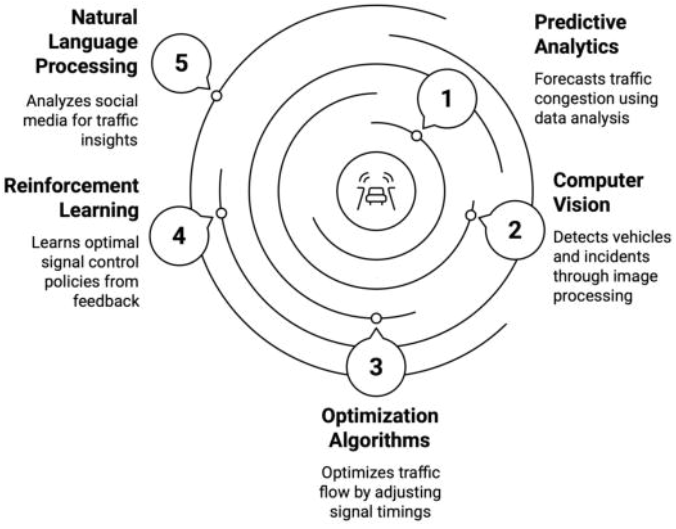

Fig. 2: AI technologies for intelligent transportation systems.

B. Cloud Computing

As discussed earlier, cloud computing uses third-party servers and data centers to provide scalable on-demand computing services through the Internet [1], [3]. From the detailed survey presented in [5], [10], [12], we listed various ITS applications as shown in Fig. 3 that use cloud computing services. Cloud computing collects and analyzes traffic data integrated from various roadside sensors, RSUs, Global Positioning System (GPS), and vehicles for traffic management. On top of this, integrated real-time traffic data and ML techniques can be applied to optimize the driving behavior and routes of autonomous vehicles (AVs). In addition, mobile cloud computing (MCC) architectures extend cloud computing services to AVs to offload computation, storage, and other intensive tasks to powerful cloud servers [31]. It also sends alerts to adjust vehicle speed, consequently reducing stopping time and improving fuel efficiency based on traffic routes, congestion, and vehicle conditions.

In addition to live data processing, ML algorithms, including regression and time series prediction, analyze historical data to predict traffic patterns and anticipate congestion. When the system detects vehicle surge, it can anticipate a probable bottleneck in 10 minutes and facilitate pre-emptive adjustment [11]. This facilitates dynamic TLCs, cooperation and coordination between neighboring intersections, and congestion management.

Computer vision is another vital technology that enables real-time monitoring and decision-making through visual data analysis. Applications include vehicle detection and classification, traffic flow

monitoring, accident detection, lane departure warning, pedestrian recognition, and automatic license plate recognition (ALPR). These tasks are powered by advanced algorithms that process video feeds from roadside cameras using deep learning models such as convolutional neural networks (CNNs) and object detection frameworks like YOLO and Faster R-CNN. The algorithms first detect and classify objects (e.g., vehicles, pedestrians, traffic signs), then track their movements across frames to analyze behavior and traffic patterns. For example, Lu et al. studied real-time processing of traffic incident data in the cloud, enabling emergency response vehicles to be supported [12].

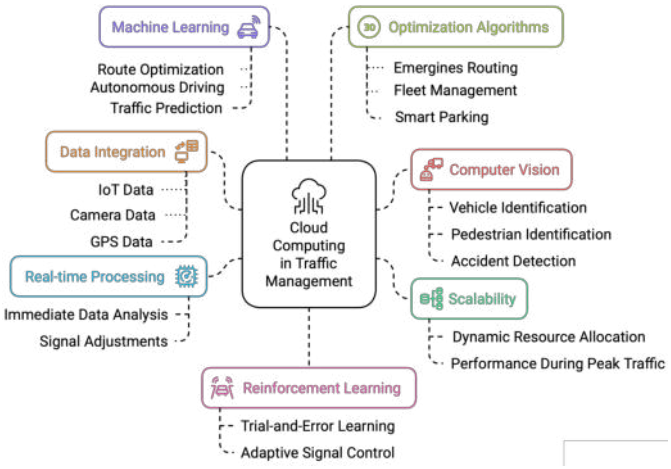

Fig. 3: Cloud-enabled services for ITS.

Optimization algorithms are metaheuristic and heuristic methods, such as linear programming, ant colony optimization (ACO), particle swarm optimization (PSO), and genetic algorithms (GA), that dynamically adapt traffic signal phases and their timing based on the incoming traffic flow information. One such is Green Link Determining (GLIDE) [15], as explained in the paper (Section IV.A), which uses optimization algorithms to compute "green wave" signal times to minimize delays by signal coordination at intersections.

RL techniques encompass algorithms that acquire optimal policies in a trial-and-error fashion by adapting traffic signal control according to traffic feedback. By leveraging cloud platforms vast computational resources and scalability, RL models can be trained on large-scale, real-time traffic data collected from sensors, connected vehicles, and UAVs [32]. Gradually, the system adapts to becoming more effective by consolidating data from emerging patterns, including unexpected road closures or one-time events [21]. These models learn optimal strategies for ITS applications such as traffic signal control, dynamic route planning, fleet management, and emergency vehicle coordination.

C. Integration of AI and Cloud Computing

Integrating AI with cloud computing develops a strong framework within ITS for data-driven mobility [5], [7], [12], [18]. AI techniques such as ML, RL, and NLP are employed to model complex traffic patterns, predict congestion, optimize routing, and enable autonomous decision-making in dynamic transportation environments. Cloud computing provides a flexible and high-performance infrastructure for large-scale data ingestion, storage, model training, and real-time analytics, supporting the computational demands of advanced AI algorithms. Therefore, large volumes of traffic data can be processed in real-time with the processing capabilities of the cloud. These are a few examples of how this combination is applied in ITS.

- **Adaptive traffic signal control:** AI models predict the traffic inflow at intersections in real-time. Thus, multiple intersections coordinate and cooperate by adjusting their signals.
- **Traffic event detection and response:** AI models on cloud platforms analyze traffic videos or images captured through cameras and UAVs. When any traffic event, like an accident, occurs, an alert will be sent to the concerned emergency services, providing a green route.
- **Optimizing public transportation:** AI models predict and forecast passenger demand using historical and real-time data in the cloud, especially during events like games, festivals, and carnivals.

D. Connected and Autonomous Vehicles

AI and cloud technologies unlock their true potential for ITS only when integrated with connected and automated vehicles (CAVs) [33]. Without CAVs, AI-driven insights and cloud-based processing remain isolated from real-world ITS applications. CAVs serve as dynamic data generators feeding real-time information to AI systems hosted in the cloud. At the same time, CAV technologies rely on cloud intelligence for route optimization and predictive maintenance decision-making. This synergy enables safer, smarter, and more efficient transportation ecosystems.

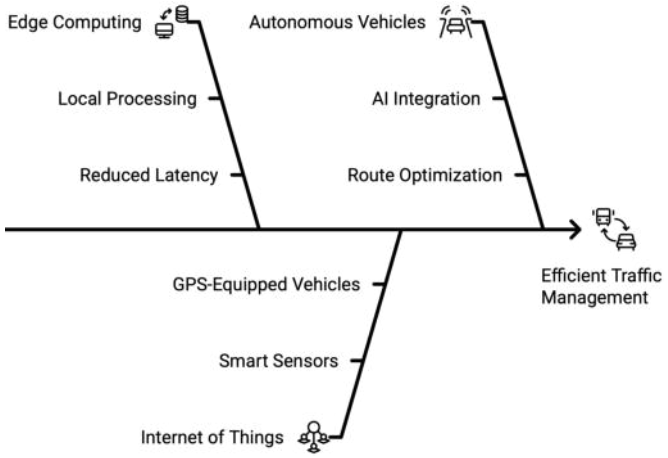

Fig. 4: Enhancing traffic management with AI and Cloud.

Figure 4 illustrates a high-level architecture involving the components of AI and cloud for ITS. At its foundation, the road infrastructure includes RSUs, which facilitate V2X communication by collecting data such as vehicle speed, location, count, and braking activity from passing vehicles. In addition to RSUs, edge devices and sensors, such as cameras, LiDARs, radars, and environmental sensors, are deployed to gather detailed information about road and weather conditions. These edge devices also perform initial data preprocessing tasks, including accident detection and license plate recognition, before forwarding selected information to higher system levels.

Vehicles, particularly CAVs, are equipped with advanced sensors and communication modules and generate massive volumes of real-time data, including telemetry, driving behavior, and surrounding conditions, and communicate via V2X. The communication layer connects vehicles, RSUs, and cloud systems, enabling real-time operations through ultra-fast, low-latency networks like 5G and 6G. Specialized protocols such as Dedicated Short-Range Communications (DSRC) further ensure swift and reliable data exchange, critical for safety and efficiency in vehicular environments.

Edge computing forms a critical layer by positioning servers and gateways near RSUs to handle early data processing, such as traffic incident detection and vehicle classification. By preprocessing information locally, edge systems can reduce data volume and send it to the cloud. This will improve responsiveness and minimize bandwidth use. The cloud layer manages large-scale data storage and advanced analytics. Here, big data tools analyze extensive datasets to reveal traffic patterns, predict congestion, and identify accident hotspots. AI and ML models are trained in the cloud to perform complex tasks like traffic forecasting, accident detection, and route optimization, driving smarter urban mobility solutions.

ITS applications include dynamic traffic management systems that adjust traffic signals based on real-time congestion, incident detection systems that automatically alert emergency services, and driver behavior analysis platforms that monitor and report unsafe driving. Therefore, the system benefits drivers by allowing them to receive real-time updates on traffic conditions, rerouting suggestions, and hazard warnings, and improving safety and travel efficiency. On the other hand, city authorities gain access to long-term analytics for better planning and policy making toward sustainable and intelligent urban mobility.

E. Challenges

Despite the great potential of AI and cloud in ITS, several challenges must be addressed. Real-time or near-real-time decision-making is needed in traffic events and dynamic traffic control applications. While cloud computing provides immense computational resources, it introduces network latency that can critically delay responses. Although edge computing reduces latency, processing complex AI models locally remains challenging. Edge devices deployed in ITS environments, including RSUs, TLCs, and vehicle units, often have limited computational, memory, and power resources. Running sophisticated AI models on these devices is difficult, which adds complexity and cost to the system design.

ITS systems generate massive and diverse data streams; thus, it is challenging to ensure efficient, lossless, and timely data transfer between edge devices and cloud servers. In addition, maintaining data consistency and synchronization across distributed nodes without introducing bottlenecks or errors is critical to reliable AI-driven decision-making. Integrating AI, cloud, and edge in ITS uncovers sensitive data about drivers, vehicles, and road users to potential cyber threats. Additionally, AI models can be targeted through adversarial attacks, making robust cybersecurity measures and privacy-preserving techniques essential.

AI models deployed in ITS must adapt to evolving traffic patterns, environmental changes, and new behaviors. Managing model training, periodic updates, and deployment across thousands of edge devices is complex. Challenges include preventing model drift, ensuring compatibility, and securely distributing updates without disrupting critical ITS operations. ITS systems operate at scales ranging from small urban areas to metropolitan cities. Achieving consistent performance and reliability across such large deployments is difficult. Scalability challenges arise due to heterogeneous devices, varied network providers (interoperability), and the need to balance computational load between cloud and edge resources efficiently.

Energy consumption becomes critical when AI is deployed at the edge in ITS, particularly for battery-operated or remote devices. Running high-performance models locally can drain energy resources quickly, affecting system reliability. Designing AI algorithms and hardware that are both powerful and energy-efficient remains a key challenge.

IV. Future Directions

In this section, we discuss some of the possible future scopes in line with AI-enabled cloud-driven ITS:

1) Hybrid edge and cloud model: Hosting AI will be one of the critical challenges for future ITS solutions. Time-sensitive tasks like collision avoidance and dynamic TLC must be handled on edge servers to achieve the necessary quality of service (QoS) measures. On the other hand, complex analytics and long-term model training can be managed in the cloud. Existing platforms fail to consider the high real-time latency demand of enabling these complex QoS-demanding applications. State-of-the-art platforms like NVIDIA's Metropolis [34] try to enable smart city applications through cloud-edge deployments; however, the possibilities of enabling large-scale deployments remain questionable.

2) Federated learning: Novel ML techniques like federated learning can protect sensitive traffic data by allowing distributed devices to train shared models without transferring raw data. For instance, Google uses federated learning for Android devices, and it can be extended to ITS applications where CAVs and RSUs can collaboratively improve traffic prediction models without sharing private data. However, the data involved in these methodologies are non-independent and identically distributed (non-IID), degrading model convergence and generalization possibilities. Concepts like biasing in the model and changes in data distribution over time have to be analyzed to devise an efficient federated model to support ITS applications.

3) Cloud-backed Action Coordination: Cloud-backed ITS will promote V2X ecosystems by coordinating CAV actions in real time. Existing Connected Vehicle Pilot Programs [29] of the US Department of Transportation in cities such as New York and Tampa deploy V2X communication technologies to reduce accidents and improve traffic flow. Technical challenges like real-time requirements towards ultra-low-latency communication and rapid cloud-edge data processing must be addressed. Infrastructure challenges like a lack of interoperability must be addressed to enable seamless data exchange for coordination across regions and CAVs.

4) Energy Optimization: AI models can be optimized for low-power operations, addressing *energy concerns* associated with large-scale ITS deployments. State-of-the-art Tesla Dojo supercomputers are designed for energy-efficient AI modelling training [35], maintaining high performance. Whenever optimization of a QoS

is involved, trade-offs must always be considered. Reducing power consumption comes at the cost of lowering model accuracy or slower inference, which can be catastrophic considering the criticality of ITS applications. Solutions such as dynamically managing computation between infrastructures like cloud, edge, and vehicle nodes to minimize energy consumption must be developed.

V. Conclusion

Enabling ITS systems through traditional methods can be challenging due to the lack of real-time responsiveness and poor scalability. Due to their lack of predictive analytics, it is challenging to integrate emerging technologies that require dynamic adaptation, such as autonomous vehicle coordination or proactive traffic management. Through the advent of AI and cloud technologies to enable ITS, new and safer opportunities are devised to enable sustainable urban mobility. From this survey, we understand that future ITS solutions will rely on hybrid models combining edge computing for real-time responsiveness with cloud platforms for data analysis and optimization. Some emerging approaches, such as federated learning, hybrid cloud models, predictive traffic management, and energy-efficient AI models, will eventually address the critical challenges, such as energy consumption and high operational costs. As ITS continues to evolve, there will be a balanced focus on technological advancement and sustainability, thus building the intelligent transportation networks of the future.

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