A Survey on Traffic Accident-Induced Congestion Mitigation Using Multi-Objective Collaborative Optimization and Multi-Agent Deep Reinforcement Learning

Abstract

This survey paper explores a sophisticated framework for optimizing traffic flow and mitigating congestion caused by accidents through a multi-objective collaborative approach. By integrating dynamic decision-making processes with Multi-Agent Deep Reinforcement Learning (MADRL) within Intelligent Transportation Systems (ITS), the paper aims to develop and implement effective congestion mitigation strategies. The study highlights the significance of ITS in addressing the challenges posed by traffic accident-induced congestion, emphasizing the role of advanced data analytics and machine learning in enhancing traffic management. Key methodologies include the employment of a multi-modality semantic-aware framework and a centralized platoon-based control system, which optimize signal timing and reduce congestion at intersections. The survey also introduces a multi-objective mathematical model that incorporates stakeholders' preferences in trajectory planning, underscoring the adaptability of traffic management systems. The paper further explores the integration of technologies such as Digital Twin (DT) and Federated Learning (FL) in the Vehicular Internet of Things (V-IoT), addressing security and privacy concerns. Real-world applications and simulation-based evaluations validate the effectiveness of the proposed methodologies, demonstrating significant improvements in traffic flow and congestion reduction. The survey concludes by identifying challenges and future research directions, including the need for enhanced scalability, data efficiency, and model interpretability. By leveraging advanced AI techniques and fostering collaborative frameworks, this study contributes to the development of more efficient, adaptive, and sustainable urban transportation networks.

1 Introduction

1.1 Significance of Traffic Accident-Induced Congestion

Traffic accident-induced congestion significantly challenges urban transportation systems, exacerbating existing inefficiencies in mobility networks strained by increasing vehicle numbers [1]. The sudden reduction in road capacity following accidents leads to severe bottlenecks and prolonged delays, resulting in heightened economic costs and fuel consumption [2]. This issue is further aggravated by the vulnerability of intelligent transportation systems (ITSs) to disruptions that can cascade through interdependent communication and power infrastructures, intensifying congestion and resource wastage [3].

The effective deployment of ITS is essential for mitigating the effects of accident-induced congestion through advanced data collection and predictive analytics [1]. However, challenges such as sparse data availability and unpredictable real-time traffic conditions hinder the efficacy of these systems,

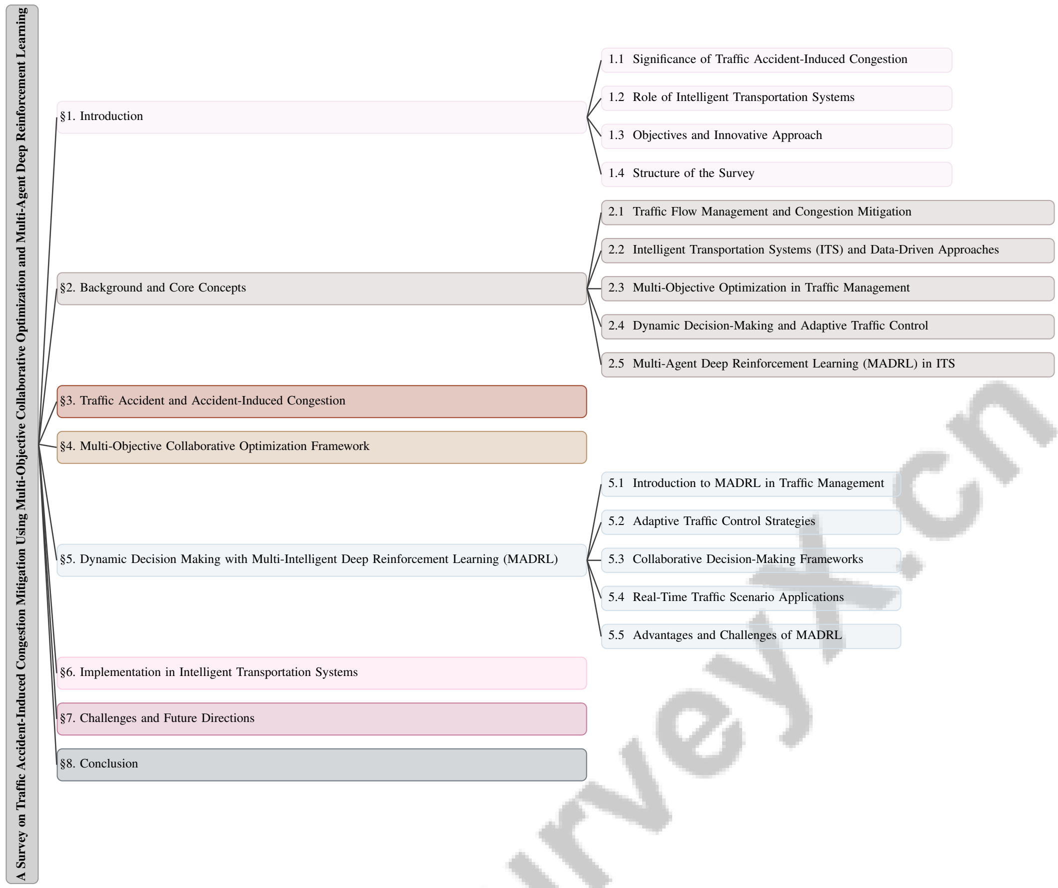

Figure 1: chapter structure

necessitating robust congestion prediction models. The emergence of hybrid vehicular traffic, characterized by varying levels of vehicle autonomy, complicates traffic management and necessitates enhanced communication infrastructures.

Moreover, integrating technologies such as Digital Twin (DT) and Federated Learning (FL) within the Vehicular Internet of Things (V-IoT) highlights the need to address security and privacy concerns for resilient and efficient traffic management. At intersections, intelligent control mechanisms are vital for improving the adaptability and efficiency of traffic light systems, which currently operate suboptimally.

Addressing traffic congestion caused by accidents is crucial for enhancing economic efficiency—evidenced by significant savings in travel time and fuel consumption—and ensuring the long-term sustainability of urban transportation systems. The implementation of ITS facilitates improved decision-making for commuters and enhances traffic management capabilities for local governments [4, 5, 6]. As urban areas expand, developing and implementing advanced congestion mitigation strategies is essential for maintaining efficient and reliable mobility systems.

1.2 Role of Intelligent Transportation Systems

Intelligent Transportation Systems (ITS) play a pivotal role in mitigating traffic congestion by integrating advanced technologies such as machine learning, generative AI, and sophisticated communication networks to enhance traffic management and safety. The orchestration of ITS within the contexts of 5G and emerging 6G technologies amplifies their capabilities, enabling real-time data processing and improved routing decisions that significantly enhance transportation system efficiency [7]. Despite these advancements, effective methods for computing and delivering the safest routes to drivers in real-time remain critically needed [8].

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The integration of real-time data processing within ITS frameworks enhances traffic predictions and routing decisions, thereby improving overall transportation efficiency [9]. However, the massive data generated by ITS poses challenges for traditional data processing systems, necessitating the development of edge-based architectures and data lake solutions for effective data management and analysis [10]. Machine learning-based forecasting models are crucial for accurately predicting traffic patterns, facilitating proactive congestion management strategies [11].

Generative AI techniques applied within ITS offer innovative solutions for congestion mitigation through enhanced data analysis and decision-making processes [12]. Customized models for object detection and novel camera calibration methods enable accurate 3D traffic monitoring, essential for real-time traffic management [13]. Furthermore, integrating federated learning within ITS addresses limitations of centralized training approaches, such as data silos and privacy concerns, ensuring timely and accurate decision-making in dynamic vehicular environments.

Policy-based management significantly enhances security and service delivery within ITS, addressing vulnerabilities from potential stealthy attacks. The rise of ITS and advanced vehicle technology necessitate approaches that accommodate both modern and legacy systems, ensuring seamless integration across diverse vehicular technologies [14].

The adaptability of ITS to various scenarios underscores their importance in modern transportation networks, ensuring resilience and effectiveness in evolving urban mobility demands [15]. By enhancing traffic efficiency, road safety, and environmental sustainability, ITS addresses the increasing demand for urban mobility and associated challenges, playing a crucial role in the future of transportation [16].

1.3 Objectives and Innovative Approach

This survey aims to establish a comprehensive framework for mitigating congestion caused by traffic accidents through multi-agent deep reinforcement learning (MADRL) and multi-objective collaborative optimization, enhancing urban traffic flow via intelligent transportation systems (ITS) that incorporate dynamic decision-making processes. A central focus is leveraging connected and autonomous vehicles (CAVs) to alleviate highway bottlenecks, reducing reliance on human driver compliance [2].

Proposed methodologies include developing a multi-modality semantic-aware framework that enhances the reliability and efficiency of information transmission in vehicular networks by integrating text and image data, crucial for improving real-time traffic management and decision-making processes [1]. Additionally, a centralized platoon-based control system employing vehicle-to-infrastructure communication is proposed to manage traffic at intersections efficiently, optimizing signal timing and reducing congestion [3].

The survey introduces a multi-objective mathematical model designed to incorporate stakeholders' preferences and priorities in trajectory planning, highlighting traffic management systems' adaptability and responsiveness. This model aims to balance objectives such as minimizing travel time and enhancing safety [2]. The framework emphasizes data privacy and collaborative learning through Federated Learning (FL) in ITS, enabling insights sharing without centralizing sensitive data.

To address congestion at highly circulated intersections, the survey integrates a 3D simulation model with multi-objective optimization using evolutionary algorithms, allowing detailed analysis of traffic flow and signal timing to provide insights into effective congestion mitigation strategies. Additionally, a system-of-systems model aims to optimize traffic flow through data-driven approaches leveraging real-world sensor data and simulation methods.

These innovative methodologies collectively advance traffic management, offering new insights and solutions for mitigating congestion in urban environments. The integration of collaborative and adaptive strategies within ITS highlights emerging technologies' transformative potential, such as artificial intelligence and generative models, in enhancing urban mobility. As urban populations are projected to increase by nearly 2.5 billion by 2050, these strategies can optimize traffic management, reduce congestion, and promote sustainable practices. By leveraging vast amounts of mobility data and advanced communication technologies, ITS can facilitate more efficient transportation solutions that address current urban mobility challenges and contribute to healthier, more sustainable urban environments [16, 4, 17, 18, 7].

1.4 Structure of the Survey

This survey provides an in-depth analysis of strategies for mitigating congestion caused by traffic accidents, utilizing advanced techniques such as multi-objective collaborative optimization and multi-agent deep reinforcement learning (MADRL) within the framework of intelligent transportation systems (ITS). It explores integrating data-driven approaches, particularly focusing on traffic signal control and the role of connected and autonomous vehicles, highlighting recent advancements and challenges in applying deep reinforcement learning to enhance traffic management and alleviate highway bottlenecks [19, 20]. The paper is organized as follows:

The introductory section establishes the significance of traffic accident-induced congestion and underscores the critical role of ITS in addressing these challenges. It outlines the paper's objectives and innovative methodologies, emphasizing the integration of dynamic decision-making processes and advanced AI technologies.

Section 2 delves into the background and core concepts essential for understanding traffic flow management and congestion mitigation strategies. It explores the role of ITS and data-driven approaches, highlighting the importance of multi-objective optimization and dynamic decision-making processes in traffic management. The section also introduces MADRL and its relevance to ITS.

Section 3 examines the causes and impacts of traffic accidents on congestion, analyzing existing studies and data on accident-induced congestion. It discusses the complexities involved in managing traffic flow following accidents, emphasizing the significant impact of stochastic uncertainties on traffic conditions and providing a foundation for exploring effective mitigation strategies that can enhance overall traffic management and reduce congestion [21, 6, 5, 22].

The multi-objective collaborative optimization framework is detailed in Section 4, discussing the integration of various objectives and collaborative approaches in traffic systems. This section highlights the adaptability and responsiveness of the proposed methodologies in optimizing traffic management.

Section 5 explores implementing Multi-Agent Deep Reinforcement Learning (MADRL) techniques in dynamic decision-making processes for traffic management, emphasizing integrating advanced algorithms to enhance traffic signal control policies. It discusses how MADRL can address challenges such as imperfect observations from degraded communication and stochastic uncertainties in traffic flow, ultimately improving traffic efficiency and reducing congestion. Findings indicate that incorporating these methods can lead to more effective management strategies that adapt to real-time conditions and unforeseen events, such as emergency vehicle passage [23, 6]. This section covers adaptive traffic control strategies, collaborative decision-making frameworks, and real-time traffic scenario applications while discussing the advantages and challenges of implementing MADRL.

In Section 6, the implementation of the proposed framework within Intelligent Transportation Systems (ITS) is thoroughly analyzed, emphasizing integrating advanced communication technologies, such as 5G and emerging 6G networks, alongside machine learning techniques, including Federated Learning, and a modular design approach. This section addresses the orchestration challenges posed by heterogeneous networks and the operational considerations necessary for effective ITS deployment, highlighting potential data-driven research opportunities that could enhance system performance and scalability [7, 24]. Simulation-based evaluations and real-world deployment considerations are discussed to assess the effectiveness of the proposed systems.

Section 7 examines the significant challenges and limitations of existing traffic congestion mitigation strategies, particularly focusing on the effectiveness of Intelligent Transportation Systems (ITS) in urban settings. It highlights empirical findings revealing the variable impact of ITS on congestion reduction, influenced by factors such as road supply and public transit services. Furthermore, the section outlines promising future research directions, including integrating stochastic models in traffic management and applying advanced Artificial Intelligence techniques for traffic prediction, which could enhance the efficiency and resilience of transportation systems [25, 5, 6, 26]. Ethical and regulatory considerations are discussed to address the broader implications of implementing new traffic management systems.

The paper concludes by synthesizing the principal findings and contributions, highlighting the significant role of emerging technologies—particularly artificial intelligence and intelligent transportation systems—in reshaping urban mobility and promoting sustainability. It underscores the urgent need for cities to transition from traditional to smart frameworks to address the challenges posed by rapid urbanization, traffic congestion, and environmental impacts, while emphasizing the importance of data-driven approaches and political support in fostering innovative transportation solutions [4, 27, 16, 7].

The survey categorizes current research into several fields, such as traffic state forecasting, vehicle behavior prediction, traffic safety modeling, and network traffic control, each utilizing advanced data analytics and AI technologies [18]. Additionally, the flexible architecture PAArc is proposed to dynamically enforce security policies in smart M2M environments, enhancing service delivery within ITS [28].The following sections are organized as shown in Figure 1.

2 Background and Core Concepts

2.1 Traffic Flow Management and Congestion Mitigation

Efficient traffic flow management and congestion mitigation are vital for intelligent transportation systems (ITS) in urban settings. Urban traffic dynamics, characterized by nonlinear and spatio-temporal interactions, necessitate advanced predictive models beyond traditional methods [1]. Deep learning architectures, utilizing spatio-temporal data and integrating linear models with tanh activation layers, have proven effective in forecasting traffic flows [1]. Traditional traffic models often inadequately address urban traffic's diverse conditions, focusing on simplistic symmetric two-route systems, thus failing to capture real-world complexities [2]. Innovative methodologies, like the Multi-task Learning Network for Sparse Traffic Forecasting, enhance understanding of spatial dependencies and dynamic features in traffic [29].

Integrating 3D mesoscopic simulation models with evolutionary algorithms optimizes traffic signal plans, reducing congestion and travel times [30]. Non-recurrent congestion (NRC) poses challenges for real-time monitoring, as traditional methods are expensive and lack real-time deployment [31]. Advanced data-driven methodologies, employing decomposition and optimization techniques, capture temporal traffic dynamics while addressing noise and autocorrelation issues [32].

The coexistence of vehicles with varying automation levels introduces additional challenges for traffic flow optimization. Developing policy-based management within M2M architectures is crucial for effective security policy enforcement, enhancing ITS reliability [28]. Centralized models' inadequacies in privacy and latency management necessitate distributed classification methods. Fuzzy representation combined with deep convolutional networks effectively captures traffic flow's spatial and temporal characteristics, essential for effective traffic management and congestion mitigation [32].

Integrating ITS and AI significantly improves urban transportation efficiency and safety, addressing challenges from rapid urbanization and increasing vehicular traffic. ITS enhances traffic management and routing capabilities, while AI-driven predictive models optimize urban planning and traffic flow, reducing congestion, emissions, and energy consumption, contributing to healthier urban environments [5, 4, 16, 33]. Emphasizing predictive models, real-time data analysis, and adaptive control systems highlights emerging technologies' transformative potential in traffic flow management and congestion mitigation.

2.2 Intelligent Transportation Systems (ITS) and Data-Driven Approaches

Intelligent Transportation Systems (ITS) modernize traffic management through data-driven approaches that enhance safety and efficiency. Utilizing real-time data, ITS dynamically adjusts traffic signals and optimizes flow, addressing urban mobility complexities [7]. The orchestration of ITS through enabling technologies like optimization modeling and machine learning ensures inclusivity and efficiency in traffic management [14].

Federated learning (FL) within ITS addresses privacy concerns by enabling collaborative model training with decentralized data sources, maintaining model accuracy while mitigating data breach risks and enhancing traffic flow prediction and vehicular edge computing [34]. FL reduces communication overheads and computational demands, suitable for ITS's high-speed and heterogeneous data nature.

Edge-based data lake architectures alleviate communication and computing overheads of centralized cloud systems, supporting real-time data processing and dynamic model adaptation to evolving traffic conditions [7]. Game-theoretic frameworks model interactions between attackers and infrastructure administrators, focusing on strategically allocating backup power sources to mitigate disruptions [35], underscoring ITS infrastructure security's importance for maintaining reliability and efficiency.

Generative AI technologies within ITS address limited communication bandwidth and latency issues, providing innovative solutions for data-driven traffic management through enhanced predictive capabilities [12]. These advancements highlight data-driven approaches' transformative role in promoting smart urban mobility, integrating cutting-edge technologies to enhance routing, prediction, and e-mobility solutions. As ITS evolve, they hold significant potential to improve urban mobility through advanced analytics and AI-driven systems, contributing to more efficient and sustainable transportation networks.

2.3 Multi-Objective Optimization in Traffic Management

Multi-objective optimization is crucial in advancing traffic management systems within ITS, balancing objectives like minimizing travel time, reducing congestion, and enhancing safety [26]. This approach is vital for managing traffic flows' dynamic nature, influenced by infrastructure limitations and traffic condition variability [26]. Technologies like graph convolutional networks with reinforcement learning improve prediction accuracy, supporting informed decision-making [36]. Fuzzy logic in deep learning models enhances handling uncertainties in traffic data, essential for effective optimization [32].

The Receding Horizon Control (RHC) method exemplifies multi-objective optimization in traffic systems by balancing supply-demand ratios and total idle distances for taxis, highlighting adaptive management's practical benefits [37]. Customized multi-objective mathematical models for Air Traffic Flow Management (ATFM) planning incorporate priority mechanisms, ensuring a balanced approach to traffic management [38].

Combining 3D mesoscopic traffic simulation with evolutionary algorithms optimizes traffic signal plans based on real-time data [30], leveraging advanced optimization techniques to adaptively manage traffic flow and minimize congestion. The Analytical Optimized Traffic Flow (AOR) framework employs constrained optimization with quadratic objective functions and l2 norm regularization to estimate link flows from sparse data [22], emphasizing data-driven approaches' significance in supporting multi-objective optimization, enabling accurate and efficient traffic management strategies.

2.4 Dynamic Decision-Making and Adaptive Traffic Control

Dynamic decision-making and adaptive traffic control are crucial in evolving ITS, optimizing traffic flow and enhancing road safety. These systems employ real-time decision-making processes that adapt to fluctuating conditions, leveraging ITS and AI techniques for traffic flow optimization, route planning, and autonomous vehicle support. Extensive mobility data improves urban planning and traffic management, reducing congestion and environmental impacts [6, 39, 40, 5, 4]. Reformulating complex traffic management problems into solvable models executable in real-time is a significant aspect of dynamic decision-making.

Zhao et al.'s [41] method exemplifies this approach, using a coordinated control strategy for trajectory planning through a nonlinear program (NLP) in the spatial domain, optimizing traffic flow and reducing congestion. Uncertainty and variability in human driving behavior challenge adaptive traffic control, as traditional methods struggle to account for these factors, leading to unsafe interactions and suboptimal management [42]. Uncertainty-aware models enhance traffic control systems' robustness, ensuring safe navigation through complex scenarios.

Adaptive traffic control systems leverage advanced sensors and data analytics to continuously monitor and adjust traffic signals, enhancing management strategies' effectiveness. By integrating real-time data from various sources, including predictive analytics and communication technologies, these systems dynamically adjust signal timings to respond to traffic fluctuations. This proactive approach can reduce delays by over 10

Machine learning and predictive analytics integration into dynamic decision-making frameworks significantly enhance traffic condition forecasting, facilitating proactive management. This advance-

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ment addresses global traffic congestion, increasing travel times and fuel consumption. AI-based methodologies, particularly in multivariate traffic time series modeling, effectively utilize vast ITS-generated data. Automated Machine Learning (AutoML) techniques optimize model selection and data preprocessing, simplifying effective traffic forecasting solutions' implementation that adapts to varying transportation circumstances [43, 25]. These technologies support developing adaptive control strategies that predict congestion points and implement preemptive measures to mitigate traffic build-up.

2.5 Multi-Agent Deep Reinforcement Learning (MADRL) in ITS

Multi-Agent Deep Reinforcement Learning (MADRL) is at the forefront of ITS, providing advanced methodologies to address urban traffic management complexities. This approach utilizes deep reinforcement learning to develop adaptive traffic control policies that respond dynamically to real-time traffic conditions, enhancing traffic systems' scalability and flexibility. MADRL is particularly effective in optimizing traffic light control, addressing urban traffic patterns' variability and unpredictability [8].

Incorporating graph-based methodologies within MADRL frameworks, such as the Multi-Agent Graph Convolutional Deep Reinforcement Learning (M-AGCDRL), exemplifies using graph neural networks to model complex vehicle interactions, improving decision-making in multi-agent environments [44]. This cooperative approach is crucial for developing robust traffic management strategies that adapt to urban mobility's dynamic nature. Clustering and graph neural network methods within MADRL enhance understanding of spatial dependencies and dynamic features in traffic data, solidifying its relevance in ITS [29].

MADRL frameworks benefit from advanced neural network architectures, employing a two-stream architecture to process speed and volume data separately, enhancing traffic flow patterns' learning [44]. Integrating decentralized frameworks within MADRL improves communication efficiency and control performance in cooperative adaptive cruise control scenarios, facilitating real-time communication among multiple agents [45].

Federated learning approaches within MADRL frameworks enhance model training efficiency and stability in cooperative ITS applications, addressing privacy concerns and reducing data breach risks while maintaining accuracy. MADRL effectively manages high-speed and diverse ITS data streams, addressing real-time traffic dynamics and varying transportation conditions [43, 27, 46, 47].

MADRL's practical benefits in ITS are underscored by its ability to improve vehicle trajectory predictions and address uncertainties related to vehicle intentions, providing a robust framework for dynamic traffic management [48]. Deploying roadside units (RSUs) for real-time traffic data acquisition and utilizing offline reinforcement learning to optimize maneuvering strategies for connected and autonomous vehicles (CAVs) at intersections further enhance MADRL approaches' adaptability and responsiveness [45].

In recent years, the study of traffic accidents and their subsequent impact on congestion has garnered significant attention within the field of transportation research. Understanding the intricate relationship between these phenomena is crucial for developing effective management strategies. Figure 2 illustrates the hierarchical structure of key concepts related to traffic accidents and congestion. This figure categorizes the causes, impacts, challenges, and existing studies on accident-induced congestion, highlighting the complexity of modern vehicular environments, the exacerbation of congestion due to accidents, and the challenges in traffic flow management. By visualizing these interconnections, we can better appreciate the multifaceted nature of traffic dynamics and the necessity for comprehensive approaches to mitigate congestion in urban settings.

3 Traffic Accident and Accident-Induced Congestion

3.1 Causes of Traffic Accidents and Congestion

Modern vehicular environments, characterized by nonlinear interactions and abrupt traffic changes, significantly contribute to traffic accidents and subsequent congestion, challenging existing management systems [1]. The unpredictability of driver behavior and vehicle interactions complicates traffic flow prediction, exacerbating congestion post-accidents. Traditional intersection management and

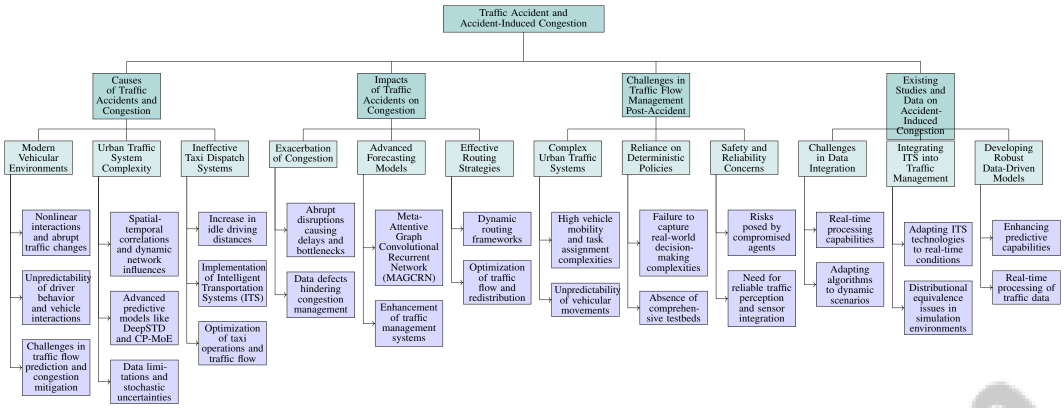

Figure 2: This figure illustrates the hierarchical structure of key concepts related to traffic accidents and congestion. It categorizes the causes, impacts, challenges, and existing studies on accident-induced congestion, highlighting the complexity of modern vehicular environments, the exacerbation of congestion due to accidents, and the challenges in traffic flow management.

signal control methods often fail to address the dynamic nature of traffic flows, especially with the rise of connected and automated vehicles, necessitating advanced strategies for effective congestion mitigation [3].

Urban traffic systems' complexity arises from spatial-temporal correlations and dynamic network influences, such as time, weather, and regional functions. Advanced predictive models like DeepSTD and CP-MoE are crucial for enhancing citywide traffic flow predictions and capturing heterogeneous dependencies for more accurate congestion forecasting [49, 50]. However, existing models struggle with these nuanced interactions, leading to inefficiencies. Data limitations and real-time condition unpredictability introduce stochastic uncertainties, undermining traffic management strategies [29, 25, 6, 49].

In metropolitan areas, ineffective taxi dispatch systems increase idle driving distances, worsening congestion. Implementing Intelligent Transportation Systems (ITS) and real-time analytics can optimize taxi operations, significantly reducing idle distances and improving traffic flow [5, 16, 37]. Developing robust algorithms for multi-agent systems in autonomous driving is essential for coordinating vehicles in dynamic environments, mitigating congestion, and enhancing flow.

Addressing these challenges requires a comprehensive understanding of the multifaceted factors contributing to traffic accidents and congestion. As illustrated in Figure 3, the key factors include advanced predictive models, congestion mitigation strategies, and data integration techniques. Enhancing predictive models to account for irregular patterns and external influences, such as weather and road events, is vital. This involves integrating stochastic uncertainty and real-time data processing into decision-making algorithms, leading to more accurate traffic flow predictions and optimized road capacity utilization. Leveraging deep learning techniques and social media data can further refine these models, enabling proactive responses to disruptions and congestion reduction [25, 6, 50, 51].

3.2 Impacts of Traffic Accidents on Congestion

Traffic accidents significantly exacerbate congestion levels due to the abrupt disruptions they cause in traffic systems. The sudden surge in traffic demand post-accident often results in severe delays and bottlenecks, complicating urban traffic network dynamics [9]. Data defects, such as delays and incomplete datasets, further hinder effective post-accident congestion management [36].

Advanced forecasting models like the Meta-Attentive Graph Convolutional Recurrent Network (MAGCRN) are crucial for mitigating congestion caused by traffic accidents by providing timely and accurate forecasts of traffic conditions [52]. These capabilities enhance traffic management systems' ability to anticipate and respond to congestion, reducing accidents' impact on traffic flow.

Effective routing strategies are essential for addressing congestion levels induced by traffic accidents. Implementing dynamic routing frameworks can significantly minimize delays by optimizing traffic

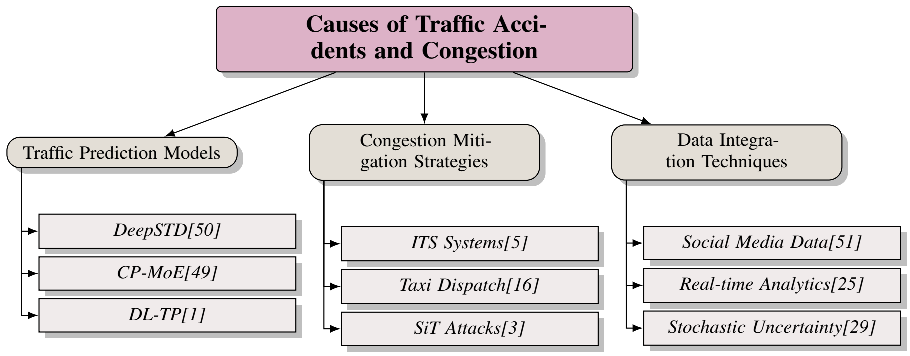

Figure 3: This figure illustrates the key factors contributing to traffic accidents and congestion, highlighting advanced predictive models, congestion mitigation strategies, and data integration techniques.

flow and redistributing traffic loads across the network [9]. These strategies are vital for maintaining efficient traffic movement and mitigating accidents' adverse effects on congestion.

3.3 Challenges in Traffic Flow Management Post-Accident

Managing traffic flow post-accident presents numerous challenges due to the complex and dynamic nature of urban traffic systems. High vehicle mobility and complexities in task assignment processes are crucial for effective traffic management and accident response [53]. The unpredictability of vehicular movements complicates the development of efficient strategies for redirecting traffic and mitigating congestion.

Current methods' reliance on deterministic policies fails to capture real-world decision-making complexities [54], leading to suboptimal management outcomes, especially post-accident, where rapid, adaptive responses are essential. The absence of comprehensive testbeds integrating all aspects of ITS exacerbates these challenges, hindering the development and validation of new management strategies [55].

Existing methods also struggle to manage risks posed by compromised agents, presenting significant safety hazards within transportation systems [56]. Ensuring agents' integrity and reliability in ITS is paramount for maintaining safety and efficiency. Reliable traffic perception and modern sensor integration are essential for secure real-time data distribution in a decentralized manner [40]. The combinatorial nature of the sensor selection problem complicates optimal placements, critical for accurate traffic monitoring and management [57].

Moreover, the lack of optimal display strategies that effectively respond to real-time traffic conditions presents further challenges in managing traffic flow post-accident [58]. The dynamic and unpredictable nature of traffic incidents necessitates adaptive display strategies that provide timely and accurate information to drivers, facilitating smoother traffic flow and reducing congestion.

3.4 Existing Studies and Data on Accident-Induced Congestion

Research on accident-induced congestion highlights challenges in data integration, real-time processing capabilities, and adapting traditional algorithms to dynamic transportation scenarios [33]. The complexity of real-world environments presents significant hurdles for studies, which often struggle with safety, robustness, and generalization across diverse scenarios [59]. Limited comprehensive datasets and constrained real-world experimentation opportunities, especially for autonomous vehicles (AVs), compound these challenges [60].

Integrating ITS into traffic management frameworks is crucial for addressing these challenges. However, adapting ITS technologies to real-time traffic conditions remains a significant obstacle due to urban traffic networks' inherent variability and unpredictability [33]. The lack of distributional equivalence between simulation environments, such as CityFlow and SUMO, complicates applying reinforcement learning (RL) models in transportation, necessitating careful consideration in selecting simulation platforms for training [15].

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Developing robust data-driven models is essential for enhancing traffic management systems' predictive capabilities. These models must account for traffic accidents' multifaceted nature and their subsequent impact on congestion levels. A primary challenge in developing effective ITS is creating algorithms capable of real-time processing and analyzing vast amounts of traffic data. This capability is essential for enabling timely and accurate responses to congestion events, improving traffic management and safety. Recent advancements in big data analytics, particularly through platforms like Apache Spark and artificial intelligence applications, have significantly enhanced traffic prediction methodologies. These advancements allow better modeling and detection of congestion across extensive urban networks by leveraging diverse data sources, including GPS speed data and deep learning techniques [25, 61, 62, 22].

4 Multi-Objective Collaborative Optimization Framework

4.1 Integration of Multi-Objective Approaches

Integrating multi-objective approaches is crucial for reconciling conflicting goals in urban transportation systems, such as minimizing travel time, reducing congestion, enhancing safety, and improving computational efficiency. Figure 4 illustrates the integration of multi-objective approaches in urban transportation systems, emphasizing real-time communication, collaborative strategies, and adaptable traffic solutions. The Personal Virtual Traffic Light System (PVTLS), utilizing Bluetooth Low Energy (BLE) for real-time traffic updates, exemplifies the importance of real-time communication in optimizing traffic flow [14]. Deep learning models further demonstrate the efficacy of this integration by enhancing traffic flow predictions through consideration of factors like construction and weather conditions [1]. These models underscore the need for comprehensive predictive systems to manage urban traffic's dynamic nature effectively.

Federated Learning (FL) offers a decentralized solution, enhancing data privacy while supporting collaborative learning, which is crucial for incorporating multiple objectives in traffic optimization without compromising sensitive information [3]. The Multi-Agent Graph Convolutional Deep Reinforcement Learning (M-AGCDRL) method exemplifies collaborative strategies by using local observations and low-resolution global maps to optimize Internet of Vehicles (IoVs) services. This method enhances user Quality of Experience (QoE) and facilitates joint policy learning through graph attention networks [12, 44, 63, 24]. Such frameworks highlight the necessity of collaborative efforts and advanced machine learning techniques in navigating modern traffic systems' complexities.

Route guidance strategies in asymmetric two-route networks have proven effective in achieving user optimality, informing the development of efficient traffic management strategies tailored to specific network conditions [2]. These strategies emphasize the need for adaptable traffic solutions that ensure effective management approaches.

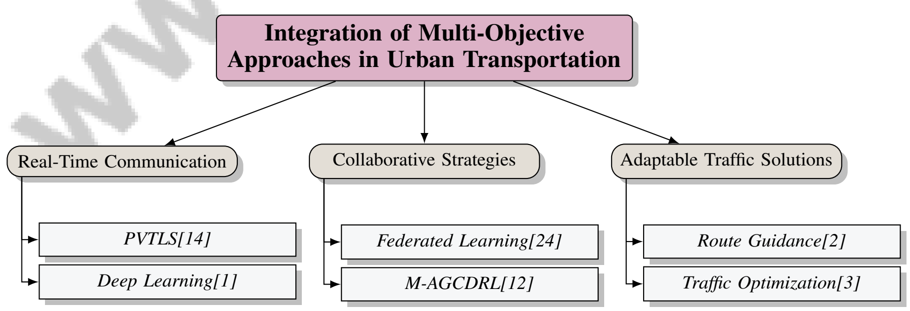


Figure 4: This figure illustrates the integration of multi-objective approaches in urban transportation systems, emphasizing real-time communication, collaborative strategies, and adaptable traffic solutions.

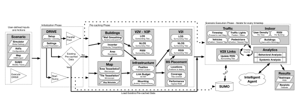
4.2 Collaborative Frameworks in Traffic Systems

Collaborative frameworks are vital for optimizing vehicle flow and enhancing transportation network efficiency by leveraging the interconnected nature of modern ITS. These frameworks enable real-time communication and coordination among diverse traffic entities, with multi-agent systems facilitating distributed decision-making and improving traffic management strategies' adaptability [53].

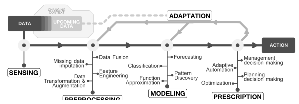
Multi-agent reinforcement learning (MARL) techniques exemplify the implementation of collaborative frameworks, allowing dynamic task and resource allocation among vehicles and infrastructure. This enhances traffic systems' responsiveness to changing conditions, optimizing real-time traffic flow [59]. By fostering cooperation among autonomous agents, MARL frameworks contribute to scalable and robust traffic management solutions.

Decentralized communication architectures within these frameworks address traditional centralized systems' limitations, such as high latency and data bottlenecks. They enable efficient data exchange and processing, supporting real-time adaptation of traffic control strategies to fluctuating conditions [45]. This approach is particularly advantageous in urban settings, where rapid and reliable communication is essential due to high vehicle and infrastructure density.

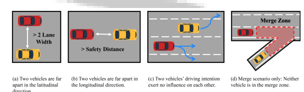
Incorporating edge computing technologies further enhances collaborative frameworks by improving traffic systems' processing capabilities, allowing real-time analysis of extensive traffic data. This reduces reliance on centralized cloud resources, minimizing latency and enhancing traffic management solutions' responsiveness [7]. Such advancements support the development of adaptive and scalable traffic systems capable of effectively managing complex urban mobility challenges.



(a) The image depicts a flowchart illustrating the process of a scenario execution phase in a simulation environment.[64]



(b) The image depicts a flowchart illustrating the process of data-driven decision-making in a business context.[65]



(c) Driving Scenarios in a Road Environment[66]

Figure 5: Examples of Collaborative Frameworks in Traffic Systems

As shown in Figure 5, the Multi-Objective Collaborative Optimization Framework is essential for enhancing efficiency and decision-making in modern transportation networks. The figure illustrates various collaborative frameworks that address traffic system complexities through simulation environments, data-driven decision-making, and real-world driving scenarios. The first subfigure outlines the scenario execution phase in a simulation environment, detailing the processes of Initialization, Pre-caching, and Scenario Execution to optimize outcomes. The second subfigure transitions to a business context, showcasing a flowchart of the data-driven decision-making process, emphasizing the Sensing, Preprocessing, and Prescription stages that inform strategic choices. The third subfigure visualizes different driving scenarios, highlighting the analysis of spatial relationships between vehicles to improve traffic flow and safety. Collectively, these examples underscore the transformative potential of collaborative frameworks in traffic systems through integrated, multifaceted approaches that accommodate various objectives and stakeholders [64, 65, 66].

5 Dynamic Decision Making with Multi-Intelligent Deep Reinforcement Learning (MADRL)

The exploration of Multi-Agent Deep Reinforcement Learning (MADRL) in traffic management represents a significant shift in optimizing urban transportation systems. This section delves into MADRL's foundational aspects, highlighting its innovative methodologies that enhance decision-making processes. The subsequent subsection, "Introduction to MADRL in Traffic Management," provides an overview of MADRL's integration with intelligent transportation systems (ITS) to improve traffic flow, resource allocation, and system efficiency.

5.1 Introduction to MADRL in Traffic Management

MADRL significantly advances traffic management by enhancing coordination and efficiency through distributed and adaptive learning. Leveraging deep reinforcement learning, MADRL collaboratively develops optimal control policies among multiple agents in complex environments, effectively addressing urban traffic's non-stationary and unpredictable nature [1]. Integrating MADRL into ITS enables dynamic resource allocation and real-time traffic flow optimization, with techniques like DL-TP modeling nonlinear dynamics in traffic data to enhance adaptability [1]. Real-world sensor data and simulation techniques further drive optimization in hybrid traffic scenarios, promoting responsive traffic management [48]. Advanced methodologies, such as fuzzy deep learning approaches like the FDCN model, merge fuzzy logic with deep learning to enhance traffic flow prediction for effective control strategies [32]. Additionally, RSU-assisted cooperative maneuvering systems demonstrate offline reinforcement learning's role in improving CAV strategies by adapting to unique intersection characteristics [45]. Distributed classification methods for urban congestion extract traffic features from vehicle data, applying machine learning models to improve predictions and decision-making in multi-agent environments [31]. Benchmark tests of various route guidance strategies, such as the Mean Velocity Feedback Strategy (MVFS) and Travel Time Feedback Strategy (TTFS), underscore the importance of adaptive strategies in diverse traffic conditions [2].

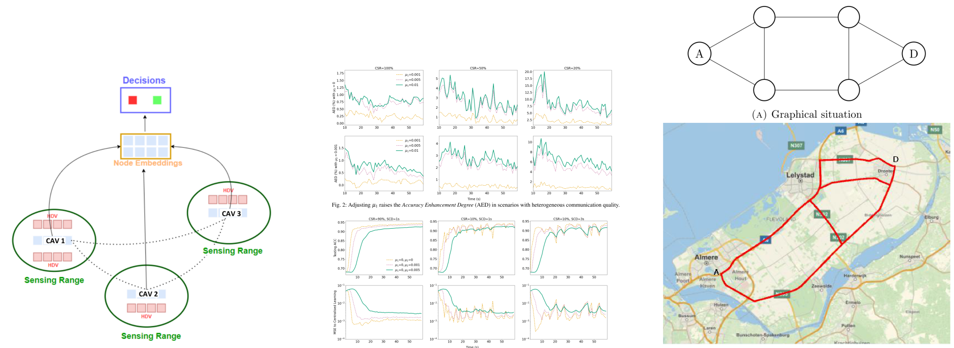
5.2 Adaptive Traffic Control Strategies

Adaptive traffic control strategies are vital for modernizing ITS, utilizing MADRL to address urban traffic's dynamic and complex nature. These strategies focus on real-time adjustments of traffic signals and control mechanisms to optimize flow and reduce congestion, enhancing system efficiency [1]. Integrating MADRL into adaptive control frameworks fosters decentralized systems where traffic lights and vehicles collaboratively learn optimal policies through continuous environmental interaction, enhancing scalability and flexibility [3]. Advanced neural network architectures in MADRL effectively model complex agent interactions, facilitating adaptive strategies that improve flow and reduce travel times [44]. Real-time data analytics are crucial for informing decision-making in adaptive traffic control, enabling continuous monitoring and analysis for dynamic adjustments of signals and routing decisions [45]. This adaptability is essential for managing urban traffic variability, ensuring control strategies remain effective amid changing patterns. Furthermore, MADRL's application in adaptive control promotes cooperative systems where agents optimize traffic flow collaboratively. Graph-based methodologies and clustering techniques enhance understanding of spatial dependencies and dynamic features in traffic data [29]. This cooperation fosters more efficient and coordinated traffic management solutions, contributing to the resilience and sustainability of urban transportation networks.

5.3 Collaborative Decision-Making Frameworks

Collaborative decision-making frameworks are integral to optimizing traffic systems, facilitating coordination among diverse agents within ITS. These frameworks leverage MADRL to enable distributed and adaptive processes, enhancing the scalability and efficiency of traffic management solutions [59]. By integrating advanced machine learning techniques, collaborative frameworks support robust traffic management strategies adaptable to dynamic urban environments. A key aspect of these frameworks is decentralized communication architectures, enabling real-time data exchange and coordination among agents. This mitigates traditional centralized system limitations, such as high latency and data bottlenecks, allowing for more responsive traffic management [45]. Edge computing technologies further enhance processing capabilities, enabling real-time analysis of large traffic data volumes and supporting adaptive decision-making processes [7]. Incorporating game-theoretic frameworks within collaborative systems addresses strategic interactions among traffic entities, facilitating optimal resource allocation and conflict mitigation [35]. This enhances the robustness and reliability of traffic management solutions, effectively managing urban traffic network complexities. The application of collaborative decision-making frameworks is exemplified by multi-agent reinforcement learning (MARL) techniques, enabling dynamic task and resource allocation among vehicles and infrastructure components. By fostering cooperation among autonomous agents, MARL enhances scalability and robustness, contributing to more efficient and resilient transportation networks [53].

As shown in Figure 6, dynamic decision-making in complex environments often requires sophisticated frameworks that integrate multiple intelligent agents to enhance collaborative efforts. The concept of MADRL serves as a pivotal approach in developing such frameworks, illustrated through various visual representations that capture the intricate dynamics of networked systems. For instance, node embeddings in a network demonstrate interactions among different nodes, such as HDVs and CAVs,



(a) Node Embeddings in a Network[19]

(b) Adjusting 1 raises the Accuracy Enhancement Degree (AED) in scenarios with heterogeneous communication quality.[67]

(c) A Graphical Situation[9]

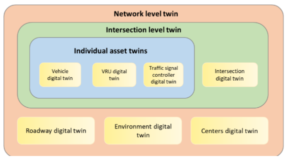
Figure 6: Examples of Collaborative Decision-Making Frameworks

highlighting the importance of connectivity and communication. Adjusting parameters like 1 to enhance the Accuracy Enhancement Degree (AED) in heterogeneous communication scenarios underscores the adaptability required in dynamic environments. Lastly, a graphical representation of a network map illustrates the spatial complexities involved in coordinating intelligent agents across diverse settings. Together, these examples underscore MADRL's critical role in fostering robust and efficient decision-making processes in multi-agent systems [19, 67, 9].

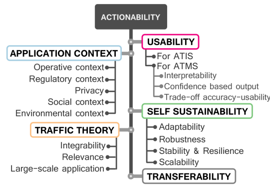
5.4 Real-Time Traffic Scenario Applications

Real-time traffic scenario applications are crucial for effectively implementing MADRL within ITS, facilitating dynamic adaptation of management strategies to real-time conditions, thereby enhancing flow and reducing congestion. A notable example is the field trials in Pittsburgh, PA, utilizing a prototype DSRC-ATL system that communicates with DSRC-equipped vehicles to reduce waiting times at intersections, demonstrating the potential of real-time adaptive systems to improve efficiency [68]. Evaluation of real-world data from Riverside, California, provides insights into real-time MADRL applications' effectiveness, focusing on a rear-end accident on May 16, 2017, highlighting real-time data's role in understanding and mitigating traffic incident impacts on congestion [21]. Moreover, novel probabilistic V2X data fusion methods enhance situational awareness and decision-making in various traffic scenarios. Performance assessments of these methods, based on the accuracy and reliability of fused perception data, underscore their effectiveness in improving real-time traffic management [69]. These real-time applications illustrate MADRL's transformative potential in traffic management, leveraging advanced AI techniques, including Large Language Models (LLMs), to optimize urban mobility by enhancing decision-making processes, improving data interpretation, and providing innovative solutions to modern transportation challenges [70, 47]. By utilizing real-time data and advanced machine learning methods, MADRL enhances the adaptability and efficiency of traffic management strategies, contributing to more sustainable transportation networks.

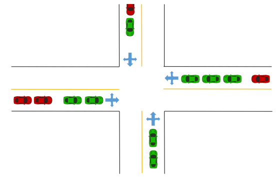
As shown in Figure 7, the integration of MADRL presents a transformative approach in real-time traffic scenarios, illustrated through images that delve into digital twins and traffic management intricacies. The first image highlights the layered structure of digital twins within a networked environment, emphasizing the roles of intersection level and individual asset twins in creating a synchronized traffic ecosystem. The second image explores actionability within traffic theory, categorizing key elements like application context and transferability, underscoring practical applications of theoretical insights. Lastly, the depiction of traffic at a four-lane intersection visualizes typical flow and management challenges, emphasizing the need for sophisticated solutions like MADRL to optimize efficiency and safety. Together, these images encapsulate MADRL's potential to revolutionize real-time traffic management through intelligent, adaptive decision-making in complex environments [71, 65, 72].



(a) The image depicts a layered structure of digital twins in a networked environment, focusing on the intersection level and individual asset twins.[71]



(b) Traffic Theory and Actionability[65]



(c) Traffic at a Four-Lane Intersection[72]

Figure 7: Examples of Real-Time Traffic Scenario Applications

5.5 Advantages and Challenges of MADRL

Implementing MADRL within ITS offers notable advantages in enhancing adaptability, scalability, and efficiency of traffic management strategies. A primary advantage is its ability to dynamically adapt routes based on real-time conditions, significantly reducing travel times and improving overall flow [9]. The framework's capacity to handle high-dimensional data and improve sample efficiency further underscores its potential in managing complex urban environments [73]. MADRL frameworks, such as those using the edsger algorithm, demonstrate the ability to adjust routing decisions dynamically in response to real-time data, optimizing flow and minimizing congestion [9]. This adaptability is crucial for managing urban traffic's dynamic nature, where conditions can change rapidly. However, several challenges accompany MADRL implementation. One significant limitation is the potential for overfitting, which can arise from training models on extensive datasets without adequate validation [73]. The need for extensive training data presents another challenge, as acquiring and processing such data can be resource-intensive and time-consuming. Additionally, performance may be constrained by the technological limitations of supporting systems, such as reliance on BLE technology, which may not perform optimally in high-traffic scenarios [14]. Moreover, inaccuracies in model responses, especially with complex queries, highlight the necessity for continuous improvement and validation of MADRL outputs [74]. Ensuring the reliability and accuracy of MADRL frameworks is essential for their effective deployment in real-world traffic management applications.

6 Implementation in Intelligent Transportation Systems

The deployment of Intelligent Transportation Systems (ITS) involves integrating diverse technologies to enhance urban mobility. The evolution of ITS is significantly supported by advanced communication technologies, notably 5G and the anticipated 6G, which provide a robust framework for real-time data exchange and dynamic decision-making. This integration facilitates seamless interaction across multiple transportation modes, thereby improving overall system efficiency. Addressing challenges such as data integration, interoperability, and user experience is crucial for effective orchestration and deployment [40, 7, 17]. Furthermore, these systems support the development of adaptive frameworks capable of responding to dynamic urban conditions.

The following subsection will delve into the role of communication technologies, emphasizing their importance in the operational framework of ITS. These technologies enable seamless interaction among vehicles, infrastructure, and traffic management systems, laying the groundwork for more efficient transportation networks.

6.1 Integration of Communication Technologies

Communication technologies are essential in implementing Intelligent Transportation Systems (ITS), enabling real-time data exchange and dynamic decision-making crucial for efficient traffic management in rapidly changing urban environments [75]. Federated Learning (FL) emerges as a significant advancement, offering enhanced privacy, reduced communication costs, and scalability for real-time decision-making [76]. By decentralizing the training process, FL allows collaborative model development across multiple devices without centralized data storage, thus preserving data privacy and minimizing breach risks. This approach is particularly beneficial in ITS, where vast amounts of data generated by connected vehicles and infrastructure can be efficiently processed to improve traffic flow and safety.

Technologies such as Dedicated Short-Range Communications (DSRC) and Vehicle-to-Everything (V2X) communication significantly enhance ITS capabilities by enabling real-time traffic management. DSRC actuates traffic signals based on vehicle communication, leading to substantial reductions in travel times, particularly during peak hours, even with low penetration rates of DSRC-equipped vehicles. V2X communication facilitates a distributed traffic control system where connected vehicles and infrastructure interact dynamically, optimizing traffic flow and minimizing wait times, fuel consumption, and emissions. As 5G and future 6G networks are deployed, these technologies will be crucial in addressing the unique challenges of ITS orchestration, ultimately improving traffic efficiency through data-driven approaches and enhanced coordination among connected vehicles [77, 68, 7, 78]. This integration is essential for developing adaptive traffic control systems that dynamically adjust to changing traffic patterns.

6.2 Machine Learning and Modular Design

Integrating machine learning and modular design within Intelligent Transportation Systems (ITS) enhances adaptability and efficiency in traffic management solutions. Machine learning algorithms are crucial for processing extensive traffic data, enabling predictive models that accurately forecast traffic patterns, optimizing decision-making processes, and mitigating congestion [43, 25]. Recent advancements, such as Automated Machine Learning (AutoML), simplify model selection and data preprocessing, facilitating effective traffic forecasting across various scenarios. These models leverage historical and real-time data to optimize traffic flow, reduce congestion, and enhance safety.

Modular design principles complement machine learning by allowing flexible deployment and scalability of ITS components. This approach enables independent deployment of system modules, such as traffic signal control and vehicle routing, minimizing computational costs and enhancing scalability [79]. A modular architecture allows ITS to efficiently integrate new technologies and adapt to evolving urban mobility demands, ensuring effective and resilient traffic management solutions.

The synergy between machine learning and modular design is evident in adaptive traffic control systems that dynamically adjust to real-time conditions. These systems utilize machine learning algorithms to process data from various sources, enabling real-time optimization of traffic signals and routing decisions. The modular architecture facilitates the incorporation of advanced functionalities, such as predictive analytics and incident detection, significantly improving effectiveness in managing complex urban traffic scenarios. This capability is further enhanced by decentralized machine learning techniques, like Network Lasso, which optimize data processing while ensuring local governance, leveraging large volumes of mobility data generated by users to improve urban planning and traffic flow analysis. Moreover, emerging technologies, including 5G and anticipated 6G networks, support the orchestration of these systems, addressing challenges posed by heterogeneous infrastructures and enabling real-time data-driven decision-making [40, 80, 4, 70, 7].

6.3 Simulation-Based Evaluations

Benchmark	Size	Domain	Task Format	Metric
MVFS[2]	10,000	Traffic Optimization	Route Guidance Evaluation	Mean Velocity Feedback Strategy, Travel Time Feedback Strategy
DQN-ITS[75]	1,000,000	Traffic Management	Traffic Light Control	Congestion Cost, Q-value
ITS-511[5]	2,079	Transportation Economics	Traffic Congestion Analysis	COST, TIME
ChatGPT-ITS[81]	70	Traffic Control	Mdp Formulation	Success Rate, Policy Performance
RL-Traffic[15]	2,484	Traffic Simulation	Traffic Signal Control	RMSE, KL Divergence

Table 1: This table presents a comprehensive overview of representative benchmarks used in simulation-based evaluations of intelligent transportation systems (ITS). It includes details on benchmark size, domain, task format, and the metrics employed for evaluation, highlighting the diversity and scope of methodologies applied in traffic optimization and management.

Simulation-based evaluations are critical for assessing the effectiveness of intelligent transportation systems (ITS) and their methodologies. These evaluations utilize advanced simulation tools to replicate real-world vehicular scenarios, providing insights into the practical implications and performance of traffic management solutions. Traffic simulation software, such as VISSIM, allows for comparing proposed methods against traditional traffic light policies, highlighting improvements in traffic flow and congestion reduction [72]. Table 1 provides a detailed overview of representative benchmarks utilized in simulation-based evaluations, illustrating the varied approaches and metrics used in assessing intelligent transportation systems.

The effectiveness of Multi-Agent Graph Convolutional Deep Reinforcement Learning (M-AGCDRL) algorithms has been demonstrated through simulation-based evaluations in the SUMO environment, assessing Quality of Experience (QoE) and offloading rates [44]. The Simulation of Urban MObility (SUMO) platform has also been employed to validate methodologies in large urban networks, such as Shenzhen's Futian District, confirming the viability of these approaches in optimizing traffic flow [22].

Additionally, integrating game-theoretic frameworks within ITS has been evaluated using simulation models that incorporate various configurations of power sources and backup power sources. These simulations analyze flow deviations under different attack scenarios, underscoring the importance of secure and resilient traffic management solutions [35].

The effectiveness of systems utilizing roadside units (RSUs) for real-time data acquisition has been assessed through hardware-in-loop simulations. These simulations use real-time point cloud data to evaluate proposed system performance, demonstrating significant improvements in traffic management [45].

Moreover, simulation datasets capturing the performance of different route guidance strategies under varying traffic conditions provide valuable insights into optimizing traffic systems [2]. These evaluations highlight the potential of advanced methodologies to enhance traffic flow and reduce congestion.

6.4 Real-World Deployment Considerations

The real-world deployment of intelligent transportation systems (ITS) utilizing advanced methodologies such as Multi-Agent Deep Reinforcement Learning (MADRL) and collaborative optimization frameworks necessitates careful consideration of several key factors to ensure effectiveness and sustainability. A primary consideration is addressing communication challenges inherent in centralized approaches, which can hinder the scalability and responsiveness of traffic management systems. The MACACC framework exemplifies a solution by enabling decentralized communication among agents, enhancing the efficiency and reliability of ITS in real-world applications [82].

The integration of bi-directional communication devices across all vehicles is also crucial for successful ITS implementation, as demonstrated by a proposed approach for real-time collision handling in railway systems. This integration ensures seamless data exchange and coordination among vehicles, facilitating the dynamic adaptation of traffic management strategies to real-time conditions [83].

Deploying ITS in urban environments necessitates consideration of infrastructure compatibility and the scalability of proposed systems. Ensuring that new technologies can integrate into existing transportation networks without significant disruptions is essential for minimizing implementation costs and maximizing the benefits of advanced traffic management solutions. The effectiveness and widespread adoption of ITS in enhancing urban mobility depend on their ability to adapt to various traffic conditions and urban layouts, particularly as cities experience significant population growth and increased vehicular traffic. By leveraging real-time data and advanced artificial intelligence models, ITS can optimize traffic management, improve vehicle routing, and address congestion challenges, fostering a more efficient and sustainable urban transport ecosystem. This adaptability is crucial for meeting the rising demand for mobility and ensuring that ITS can effectively integrate with existing infrastructure and respond to the dynamic needs of urban environments [84, 4, 16].

7 Challenges and Future Directions

7.1 Limitations in Current Traffic Congestion Mitigation Approaches

Current strategies for mitigating traffic congestion face significant limitations, particularly in urban environments. Centralized control mechanisms often lead to impractical communication overheads and reduced scalability, creating bottlenecks in high-traffic areas where real-time responsiveness is crucial [34]. Integrating legacy systems with modern vehicular communication technologies presents additional challenges, limiting the effectiveness of existing traffic management solutions [14].

Data sparsity and the complexity of deep learning models pose further challenges. Techniques like the FDCN method require substantial computational resources and fine-tuning, complicating large-scale implementation [32]. The low interpretability of some deep learning models hinders understanding of traffic dynamics [1], exacerbated by insufficient roadside units (RSUs) in urban areas [45].

Security vulnerabilities are another concern, with machine learning approaches in connected and autonomous vehicles (CAVs) susceptible to adversarial threats [34]. Complex defense mechanisms required to counter these threats can increase resource consumption [35]. Additionally, managing hierarchical structures and ensuring seamless communication among traffic management entities adds complexity [85].

The assumption of full market penetration of connected and automated vehicles is unrealistic, limiting the applicability of some methods [72]. Scalability concerns arise in congested conditions where excessive priorities may lead to impractical solutions [38]. Federated Learning (FL) integration in diverse environments also presents challenges, including complexity and the need for robust security measures [34].

Existing benchmarks may not fully capture real-world complexities, such as unexpected traffic events or driver behavior variations, affecting congestion mitigation strategies [2]. Addressing these limitations requires developing adaptable, decentralized, and data-efficient strategies. Future research should focus on enhancing model robustness, improving communication infrastructures, and incorporating comprehensive operational strategies to bolster traffic management system resilience and effectiveness. Exploring under-researched areas like Advanced Public Transportation Systems and Fully Integrated ITS is also crucial for advancing the field.

7.2 Future Research Directions in Traffic Management

Future research in traffic management seeks to address critical challenges and explore innovative methodologies to enhance urban transportation systems' efficiency and resilience. A key focus is improving traffic flow models' robustness to handle sparse data conditions, ensuring accurate estimates even with limited information [22]. This requires validating observed link locations and integrating advanced data analytics to bolster model accuracy.

Implementing and testing proposed systems in real-world scenarios is crucial for addressing communication, scalability, and robustness challenges [45]. Strategies to optimize roadside unit (RSU) deployment and enhance communication infrastructure are essential for real-time data exchange and decision-making.

Enhancing feature selection for improved policy performance and developing defense mechanisms against stealthy attacks, such as SiT attacks, are vital for maintaining traffic management system security and reliability [3]. Future research should investigate randomization techniques to obscure admission ratios and bolster ITS resilience against potential threats.

Improving deep learning models' interpretability and integrating additional data sources, like weather forecasts, can enhance prediction accuracy and provide comprehensive traffic dynamics insights [1]. Developing more transparent models capable of effectively communicating their decision-making processes is necessary to foster stakeholder understanding and trust.

The exploration of federated learning (FL) within ITS holds considerable potential, enhancing communication efficiency and developing privacy-preserving techniques. By decentralizing the training process, FL enhances scalability and significantly reduces communication costs, addressing challenges in managing vast data generated by connected vehicles and infrastructure components. This approach mitigates data silos and privacy concerns inherent in traditional centralized methods, improving real-time ITS performance. With FL integration, applications like traffic flow prediction and vehicular edge computing can leverage distributed intelligence, leading to more efficient and responsive urban traffic management solutions [34, 24, 80].

7.3 Advancements in Intelligent Transportation Systems

Advancements in Intelligent Transportation Systems (ITS) aim to revolutionize urban mobility by integrating advanced communication technologies and artificial intelligence to enhance traffic management, safety, and operational efficiency. With urban populations projected to grow by nearly 2.5 billion by 2050 and road traffic expected to rise significantly, implementing ITS is imperative. These systems utilize vast mobility data to optimize urban planning, manage traffic flow, and facilitate autonomous vehicles, addressing congestion, accidents, and pollution challenges in rapidly expanding cities. Emerging 5G and future 6G technologies promise to support more reliable and effective transportation solutions [40, 4, 16, 7]. Future ITS developments are expected to harness advanced machine learning, communication technologies, and data analytics convergence to create more adaptive and resilient transportation networks.

A significant advancement area is integrating machine learning algorithms with ITS to enhance traffic prediction and decision-making processes. These algorithms enable predictive models that anticipate traffic patterns and optimize traffic flow, reducing congestion and improving safety [1]. Deep learning techniques, like the Multi-task Learning Network, facilitate sparse traffic data analysis, providing insights into spatial dependencies and dynamic features crucial for effective traffic management [29].

The incorporation of federated learning (FL) within ITS represents a pivotal advancement, offering enhanced privacy protection and scalability for real-time decision-making. FL enables decentralized model training across multiple devices, reducing communication costs and preserving data privacy [34]. This approach is particularly advantageous in managing vast data generated by connected vehicles and infrastructure components, facilitating more efficient and secure traffic management solutions.

Furthermore, integrating communication technologies, such as Vehicle-to-Everything (V2X) and Dedicated Short-Range Communications (DSRC), is expected to enhance ITS capability to manage traffic in real-time. These technologies facilitate seamless communication between vehicles and infrastructure, enabling coordinated responses to congestion and accidents while improving overall traffic efficiency [76].

Advancements in ITS also encompass developing decentralized communication architectures that enhance traffic management systems' scalability and responsiveness. By enabling real-time data exchange and coordination among multiple agents, these architectures support the dynamic adaptation of traffic control strategies to fluctuating traffic conditions [45]. This decentralized approach mitigates traditional centralized systems' limitations, such as high latency and data bottlenecks, allowing for more responsive and efficient traffic management.

7.4 Ethical and Regulatory Considerations

The deployment of intelligent transportation systems (ITS) and advanced traffic management solutions necessitates careful consideration of ethical and regulatory frameworks to ensure responsible implementation. As these systems increasingly rely on machine learning and data-driven technologies, addressing ethical implications associated with data privacy, security, and potential biases in algorithmic decision-making is crucial. The ethical use of machine learning, as emphasized in healthcare applications, applies equally to ITS, where regulatory frameworks must guide technology development and deployment to protect user privacy and prevent discrimination [86].

Regulatory considerations are vital for ensuring ITS implementations adhere to established legal standards while effectively addressing complexities introduced by integrating autonomous vehicles and connected infrastructure, particularly amid rapid urbanization and the pressing need for sustainable mobility solutions. As cities expand and traffic volumes rise, regulatory frameworks become more pronounced in guiding ITS technologies' development and deployment that leverage artificial intelligence and advanced communication networks to optimize traffic management, enhance energy efficiency, and reduce vehicular emissions [40, 7, 4, 33]. These systems must comply with data protection regulations, such as the General Data Protection Regulation (GDPR), to safeguard personal information collected from vehicles and infrastructure components. Additionally, regulatory frameworks should establish clear guidelines for data sharing and collaboration among stakeholders, fostering a cooperative environment that facilitates ITS advancement while maintaining public trust.

The ethical challenges associated with ITS encompass the need to address algorithmic biases that may emerge from deploying machine learning models, particularly as these models can lead to misinterpretations and unjust outcomes in critical applications such as connected and autonomous vehicles (CAVs). These biases can stem from deep learning algorithms' inherent limitations, which often lack interpretability and robustness, potentially compromising road safety and efficiency. As research progresses in developing interpretable and causally-enabled machine learning methods, ensuring these technologies are effective, equitable, and transparent in their decision-making processes is crucial [27, 87]. Such biases can result in unfair treatment of certain groups or individuals, necessitating the development of transparent and accountable AI systems that ensure equitable outcomes. Regulatory bodies must enforce standards for algorithmic transparency and fairness, requiring developers to regularly audit and validate their models to mitigate biases and ensure ethical decision-making processes.

Furthermore, integrating ITS into urban environments raises concerns about the displacement of traditional transportation jobs and potential socioeconomic impacts. Ethical considerations in the transition to a technology-driven transportation landscape must encompass comprehensive workforce adaptation strategies, including targeted training programs designed to equip individuals with the necessary skills to navigate the evolving demands of intelligent transportation systems (ITS) and artificial intelligence (AI) applications, essential for enhancing energy efficiency and reducing emissions in urban mobility. As cities expand rapidly and face increasing traffic challenges, fostering a skilled workforce will be critical to ensuring communities can effectively leverage new technologies and contribute to sustainable urban development [4, 33].

8 Conclusion

The deployment of multi-objective collaborative optimization and Multi-Agent Deep Reinforcement Learning (MADRL) within intelligent transportation systems (ITS) marks a significant advancement in addressing traffic congestion resulting from accidents. These methodologies have proven effective in enhancing traffic flow management, as evidenced by various studies. The MAGCRN model demonstrates exceptional accuracy in both short- and long-term traffic forecasts, surpassing existing models. Similarly, the UMLLMF framework achieves remarkable accuracy across multiple datasets, underscoring its viability for real-world ITS applications.

The RHC framework's ability to reduce average total idle distance and improve supply-demand ratio accuracy exemplifies its impact on taxi dispatch efficiency. Additionally, the MS-FTGCN model's superior performance in traffic flow prediction highlights its practical applicability. Furthermore, the xTP-LLM framework provides competitive accuracy alongside interpretable predictions, enhancing decision-making processes.

Incorporating stakeholder preferences through simulated annealing algorithms, as seen in air traffic flow management, effectively addresses complex transportation challenges. The P90 traffic signal plan optimizes vehicle flow and reduces average travel times during peak periods, offering substantial potential for urban traffic improvement. Moreover, integrating smart devices into traffic management, as demonstrated by virtual traffic light systems, enhances urban mobility.

The synergy of MADRL and multi-objective optimization within ITS offers a promising pathway for mitigating traffic congestion. By leveraging advanced AI techniques and fostering collaborative frameworks, these approaches facilitate the development of more efficient, adaptive, and sustainable urban transportation networks. Future research should focus on improving scalability, data efficiency, security, and model interpretability to further advance traffic management systems.

AI-generated, for reference only.

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