A Survey of Multi-Source Data Fusion and Dynamic Modeling in Urban Traffic Management

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Abstract

In the evolving landscape of urban traffic management, the integration of multi-source data fusion, spatiotemporal and cross-scale dynamic modeling, and intelligent transportation systems (ITS) is pivotal for addressing the complexities of modern transportation networks. This survey paper systematically examines the role of these advanced methodologies and technologies in enhancing traffic management, with a focus on accident congestion precursors and peak hour traffic control. The paper highlights the significance of multi-source data fusion in providing a comprehensive view of traffic dynamics, enabling more accurate predictions and timely interventions. It further explores the benefits of spatiotemporal and cross-scale dynamic modeling in capturing intricate dependencies within traffic systems, thereby improving forecasting accuracy and adaptability. The integration of ITS technologies, including artificial intelligence, machine learning, and connected and automated vehicles, is discussed as a transformative approach to optimizing traffic flow and enhancing safety. Real-time traffic management solutions and predictive modeling techniques are emphasized as crucial strategies for mitigating peak hour congestion. The paper concludes by identifying future research opportunities, such as enhancing the robustness of existing frameworks and exploring novel AI algorithms, to advance urban traffic management and ensure responsive and sustainable mobility solutions for modern cities.

1 Introduction

1.1 Significance of Intelligent Transportation Systems (ITS)

Intelligent Transportation Systems (ITS) are integral to modernizing urban traffic management, effectively addressing challenges posed by urban growth and rising mobility demands [1]. The integration of advanced technologies in ITS enhances data collection and optimizes traffic flow through sophisticated sensing devices [2]. This technological synergy plays a crucial role in alleviating congestion and improving road safety, thus fostering more efficient urban transportation networks.

Advancements in mobile Internet and positioning technologies significantly enhance ITS capabilities, facilitating accurate traffic forecasting and management [3]. These technologies enable real-time data acquisition and analysis, empowering proactive traffic management strategies that adapt to evolving conditions and effectively mitigate congestion.

The implementation of ITS in urban settings, as exemplified by Birmingham, highlights the need for innovative strategies to optimize traffic flow and reduce congestion [1]. By harnessing data-driven insights and predictive modeling, ITS can anticipate traffic patterns and execute timely interventions, thereby improving the overall efficiency of urban transportation systems.

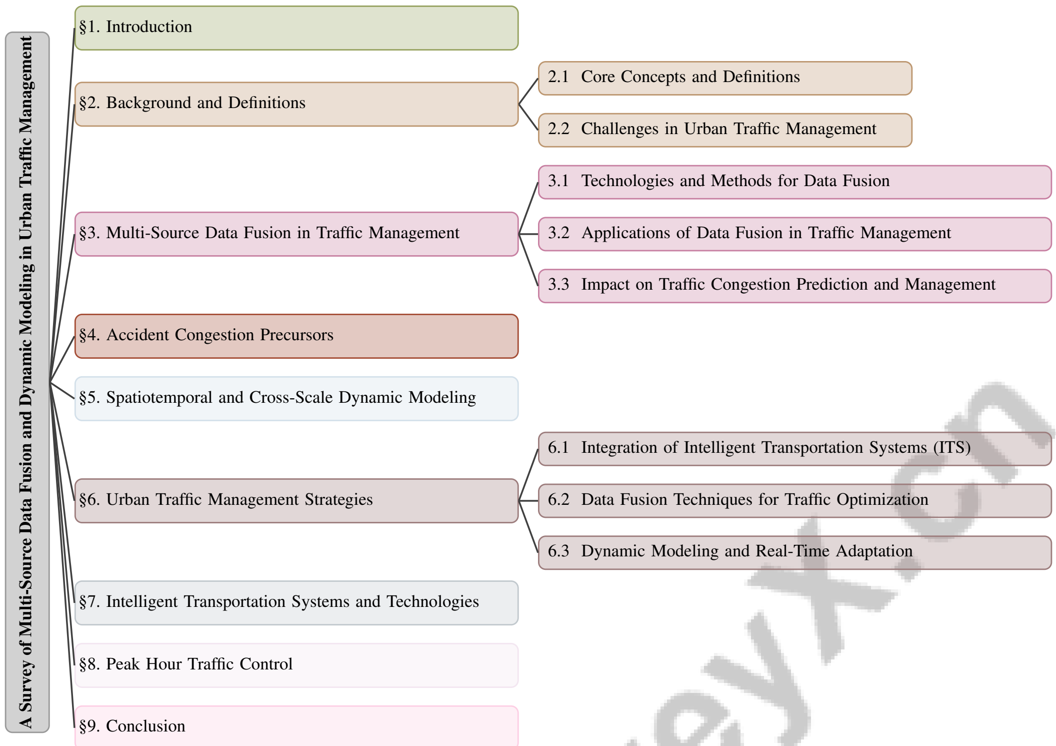

Figure 1: chapter structure

1.2 Structure of the Survey

This survey is systematically organized into sections that collectively provide a comprehensive overview of multi-source data fusion and dynamic modeling's role in urban traffic management. The initial section establishes the significance of ITS, elucidating their essential role in contemporary traffic management and laying the groundwork for an in-depth exploration of the technologies and methodologies that support these systems [1].

Subsequently, the survey clarifies core concepts such as multi-source data fusion, spatiotemporal modeling, and ITS, which are fundamental to understanding traffic management intricacies [2]. The discussion then shifts to the application of multi-source data fusion in traffic management, emphasizing technologies and methods that integrate diverse data sources to enhance management strategies [3].

The survey also addresses the identification of accident congestion precursors, analyzing the challenges and the role of data fusion in detecting early traffic congestion indicators. Following this, it explores spatiotemporal and cross-scale dynamic modeling, presenting various dynamic modeling approaches and their advantages in urban traffic management. This section is further enriched by an analysis of urban traffic management strategies, highlighting the integration of ITS and optimization through data fusion techniques and real-time adaptation.

The penultimate section reviews the technologies that constitute ITS, including applications of artificial intelligence, machine learning, and advanced sensing and communication technologies, alongside the integration of connected and automated vehicles (CAVs). The survey culminates with a discussion on peak hour traffic control, addressing challenges and proposing real-time management solutions and predictive modeling techniques.

The conclusion synthesizes key findings related to urban traffic management challenges, emphasizing the necessity for innovative solutions amid rising urbanization and congestion. It identifies promising research avenues, such as leveraging advanced technologies like artificial intelligence and machine learning for traffic systems, optimizing traffic flow through enhanced data collection and analysis, and developing ITS that utilize real-time data for improved decision-making. These opportunities could significantly advance urban traffic management, fostering more efficient, sustainable, and safer

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urban mobility solutions [2, 4, 5, 6, 7]. This structured approach ensures a thorough examination of the multifaceted aspects of traffic management, offering valuable insights into the integration of innovative technologies and methodologies in urban transportation systems.The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Core Concepts and Definitions

Urban traffic management seeks to optimize transportation networks amidst the challenges of urbanization and rising vehicular activity. Central to this effort are Intelligent Transportation Systems (ITS), which utilize advanced technologies to enhance traffic management efficiency [8]. A key element of ITS is multi-source data fusion, which integrates diverse data sources to improve traffic prediction and management, including parking availability [9].

Spatiotemporal modeling captures dynamic traffic flow patterns across spatial and temporal dimensions, crucial for understanding complex dependencies and improving prediction accuracy in urban traffic systems [10, 11]. Advanced neural network architectures integrated with spatiotemporal models address traditional forecasting methods' limitations, which often overlook intricate dependencies in road network topologies and traffic dynamics [3].

Sophisticated models are necessary for predicting traffic conditions, especially post-incident, to accommodate time-varying confounders and adapt to fluctuating scenarios [12]. The Vehicular Internet of Things (V-IoT) enhances urban traffic systems by enabling real-time data exchange and anomaly detection, improving traffic flow and safety [13].

Innovations like Green Light Optimal Speed Advisory (GLOSA) systems optimize vehicle speed profiles, addressing inefficiencies in traditional traffic light management, especially for urban buses [14]. Additionally, recovering link flow in extensive urban networks using GPS speed data and sparsely observed flow data is critical for improving traffic flow management [2].

These core concepts underpin advanced urban traffic management systems, leveraging technologies such as vehicle ad hoc networks (VANETs), 5G communication, and machine learning algorithms for enhanced traffic prediction and optimization. By integrating real-time traffic information, effective traffic assignment strategies, and dynamic optimization techniques, these systems enhance transportation networks' efficiency and responsiveness, addressing urban environments' evolving demands and mitigating congestion [15, 4, 7].

2.2 Challenges in Urban Traffic Management

Urban traffic management faces numerous challenges due to the complexity and dynamism of modern transportation systems. Inefficiencies in current methodologies, often reliant on two-dimensional clustering, lead to fragmented traffic patterns and reduced predictive accuracy [16]. This is exacerbated by scarce loop counter data and unpredictable real-time traffic conditions, hindering effective forecasting [17].

Current approaches often model time series independently, neglecting interdependencies among related series, resulting in suboptimal predictions [18]. Failing to address spatial and temporal heterogeneity can result in biased predictions and ineffective learning from skewed traffic flow distributions [10]. Additionally, low accuracy in predicting parking availability arises from neglecting spatial-temporal correlation features and flow patterns [9].

The complexity of ITS architectures, alongside diverse attack motivations and the lack of comprehensive risk assessment frameworks, poses significant challenges [19]. The heterogeneous nature of ITS technologies, coupled with scalability issues and stringent performance requirements, complicates their deployment and management [8].

A primary challenge is the heterogeneous traffic flow resulting from the mix of human-driven and connected automated vehicles, increasing the complexity of traffic dynamics [20]. Existing systems struggle with this complexity due to limited communication capabilities and resource competition among technologies [21].

Another critical issue is the limited capacity of current methods to predict sparse events like traffic congestion, as they typically support predictions only within a fixed future time window [22]. Traffic congestion has become a major urban concern, prompting investigations into various route guidance strategies to optimize travel times and alleviate congestion [23]. These multifaceted challenges necessitate innovative solutions and advanced methodologies to enhance urban traffic management systems' effectiveness, ensuring adaptability to urban environments' evolving demands.

3 Multi-Source Data Fusion in Traffic Management

3.1 Technologies and Methods for Data Fusion

Method Name	Data Fusion Techniques	Spatial-Temporal Modeling	Traffic Optimization Strategies
STTM[9]	Multi-source Data	Transformer Architecture	Route Guidance
STHODE[3]	Adaptive Mixhop	Hyperedge Evolving Ode	Route Guidance
AOR[2]	Gps Speed Data	Dynamic Assignment Matrix	Route Guidance
CorrSTN[11]	Dynamic Graph Neural	Spatiotemporal Network Corrstn	Traffic Flow Forecasting
HTSF[24]	Wavelet Transform	Motif-GCRNN	Route Guidance
ST-SSL[10]	Graph Neural Network	Spatial Temporal Heterogeneity	Traffic Flow Prediction

Table 1: Overview of various methods and technologies employed in urban traffic management, highlighting their data fusion techniques, spatial-temporal modeling approaches, and traffic optimization strategies. This table synthesizes the contributions of recent studies to demonstrate the integration of multi-source data for enhancing prediction accuracy and optimizing traffic flow.

Integrating multi-source data fusion technologies is crucial for advancing urban traffic management, especially in prediction and control systems. As illustrated in Figure 2, the hierarchical structure of data fusion technologies and methods for urban traffic management categorizes them into spatial-temporal models, traffic forecasting methods, and route guidance strategies. Each category is supported by specific methods and models that enhance prediction accuracy and optimize traffic flow. Table 1 provides a comprehensive summary of the methods and technologies utilized in urban traffic management, emphasizing the role of data fusion, spatial-temporal modeling, and traffic optimization in improving system efficiency.

The Spatial-Temporal Transformer Model (STTM) uses K-means clustering to effectively fuse multi-source traffic demand data, capturing complex spatial-temporal dependencies to enhance prediction accuracy [9]. Similarly, the Spatial-Temporal Hypergraph Neural Network (STHODE) employs hypergraphs and ordinary differential equations (ODEs) to model high-order spatio-temporal dependencies in traffic data [3].

The Analytical Optimized Recovery (AOR) method integrates dynamic traffic assignment matrices with analytical formulations to estimate link flows, demonstrating the optimization potential of analytical approaches [2]. The Correlation Information-based Spatiotemporal Network (CorrSTN) enhances prediction accuracy by leveraging spatial and temporal correlation information [11].

In traffic speed forecasting, combining discrete wavelet transform (DWT) with a Motif-based Graph Convolutional Recurrent Neural Network (Motif-GCRNN) captures intricate traffic patterns, improving speed predictions [24]. The ST-SSL framework advances traffic flow prediction by modeling spatial and temporal heterogeneity through self-supervised learning, highlighting the value of self-supervised methods in understanding complex traffic dynamics [10].

Route guidance methodologies benefit from data fusion, demonstrated by a benchmark study evaluating eight strategies in an asymmetric two-route traffic network [23]. These technologies and methods collectively underscore the transformative impact of multi-source data fusion in creating responsive and efficient urban traffic management systems capable of adapting to dynamic urban demands.

3.2 Applications of Data Fusion in Traffic Management

Data fusion significantly enhances traffic congestion prediction and management by integrating diverse data sources for a comprehensive view of urban traffic dynamics. This integration improves predictive accuracy, as seen in applications predicting parking availability, where the relationship between origin and destination points is effectively captured, enhancing clustering and predictive

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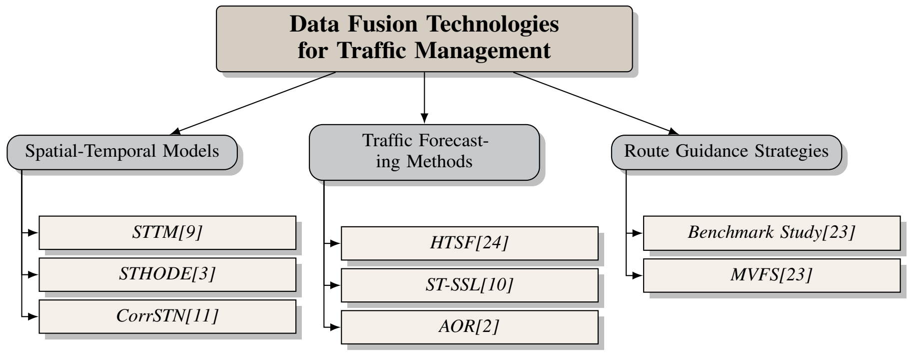

Figure 2: This figure illustrates the hierarchical structure of data fusion technologies and methods for urban traffic management, categorizing them into spatial-temporal models, traffic forecasting methods, and route guidance strategies. Each category is supported by specific methods and models that enhance prediction accuracy and optimize traffic flow.

Method Name	Data Integration	Predictive Techniques	Traffic Management Systems
SRN[25]	Real-time Data	Bayesian Network Model	Safernet
MTL-STF[17]	Clustering	Graph Neural Networks	Safernet And Glosa
BGA-ML[26]	-	Machine Learning Techniques	Real-time Traffic
B-GLOSA[14]	Statistical Data Integration	Statistical Analysis	Glosa Implementation
PVTL[27]	Ble Technology	Centralized Controller	Virtual Traffic Signals

Table 2: Comparison of Various Traffic Management Methods Utilizing Data Integration and Predictive Techniques. This table presents an overview of different traffic management methodologies, highlighting their approaches to data integration, predictive techniques employed, and the specific traffic management systems implemented. The methods include SRN, MTL-STF, BGA-ML, B-GLOSA, and PVTL, each leveraging distinct technologies to enhance urban traffic management.

performance. The SafeRNet system exemplifies this by integrating Mobile Crowd Sensing and Internet of Vehicles data with cloud computing to compute and deliver safe routes dynamically [25].

Advanced machine learning techniques, such as multi-task learning networks, enable simultaneous predictions of congestion classes and speeds, utilizing clustering and graph neural network approaches to enhance traffic flow predictions [17]. The application of BGA-ML for optimizing traffic signal plans under incident conditions further illustrates data fusion's utility by dynamically adjusting signals to improve flow [26].

Moreover, the GLOSA system, particularly the B-GLOSA variant, synchronizes bus operations with traffic signals, improving traffic flow and reducing delays [14]. The orchestration of Intelligent Transportation Systems (ITS) through coordinated resource allocation and the integration of various enabling technologies highlights data fusion's role in managing complex urban traffic environments [8].

Additionally, personal virtual traffic lights allow users to access traffic information on their devices without dedicated infrastructure, enhancing management through seamless data integration [27]. These applications collectively illustrate data fusion's transformative potential in fostering responsive and efficient urban traffic management systems. Table 2 provides a comprehensive comparison of various methodologies applied in traffic management, emphasizing the role of data integration and predictive techniques in enhancing urban traffic systems.

3.3 Impact on Traffic Congestion Prediction and Management

Multi-source data fusion technologies have fundamentally transformed traffic congestion prediction and management by providing nuanced insights into urban traffic dynamics. The Spatial-Temporal Hypergraph Neural Network (STHODE) exemplifies this impact, demonstrating superior forecasting capabilities by effectively capturing high-order spatio-temporal dependencies, validated through extensive experiments across multiple datasets [3]. This capability is crucial for accurate traffic pattern predictions and congestion management in complex urban settings.

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The Correlation Information-based Spatiotemporal Network (CorrSTN) further illustrates data fusion's benefits, significantly enhancing prediction accuracy over traditional methods by capturing intricate interactions within traffic data [11]. The STTM excels in predicting parking availability, outperforming traditional and machine learning models through its adept handling of diverse traffic patterns [9].

Incorporating causal inference into deep learning models, as demonstrated by the MSCT model, highlights the necessity for adapting to varying traffic conditions. This model excels in predicting counterfactual traffic speeds, especially over extended prediction horizons, underscoring the importance of accurate forecasts for effective traffic management [12].

The integration of Digital Twin (DT) technology with Hierarchical Federated Learning (HFL) has bolstered anomaly detection capabilities, enhancing the robustness of urban traffic management systems [13]. The Multi-Agent System (MAS) leverages real-time data and machine learning algorithms for timely forecasts and fault detection, improving urban traffic management [1].

In terms of real-time adaptability, the Spatial-Temporal Multi-Factor (STMF) framework effectively mitigates congestion and enhances mobility by adapting to real-time traffic conditions [20]. The AOR framework further demonstrates robustness in accurately modeling traffic flow dynamics, showcasing data fusion's potential in optimizing traffic flow [2].

Advancements in multi-source data fusion, particularly through spatial-temporal deep learning models and various transportation data streams, significantly enhance the predictive accuracy and operational efficiency of urban traffic systems. This enables more effective adaptation to the evolving demands of modern transportation networks, addressing critical challenges such as parking availability and traffic congestion. Technologies like the Transformer model and advanced object detection algorithms empower urban planners and traffic managers to achieve precise predictions and informed decision-making, ultimately fostering sustainable urban mobility and improving overall traffic management [28, 29, 7, 30, 9].

4 Accident Congestion Precursors

4.1 Challenges in Identifying Accident Congestion Precursors

Identifying accident congestion precursors in urban traffic management is challenging due to the complexity and variability of traffic conditions. Existing methods often struggle to model the spatial-temporal dependencies in traffic data, particularly the directed propagation of traffic flow, leading to frequent misrepresentations [24]. The dynamic, non-stationary nature of traffic signals exacerbates prediction difficulties, with models prone to overfitting, thus limiting their practical applicability.

The reliance on costly sensor data and extensive user-contributed information further complicates matters, especially in mixed traffic environments where human-driven and automated vehicles coexist, affecting flow dynamics and causing potential delays [20, 23]. Traditional sensors often provide incomplete data, necessitating advanced modeling techniques tailored to these challenges.

Non-recurrent incidents add complexity by disrupting normal traffic patterns, challenging existing management strategies. Current benchmarks for route guidance often focus on symmetric conditions, overlooking asymmetric scenarios' complexities [23]. This highlights the need for adaptable frameworks to the dynamic urban traffic systems.

Despite advancements in Intelligent Transportation Systems (ITS), scalability and integration of modern and legacy communication technologies remain issues. While ITS implementations can enhance management efficiency with real-time traffic information, they struggle with orchestration due to diverse supporting technologies. The increasing complexity of traffic environments necessitates improved situational awareness, particularly in high-density scenarios where communication overload can compromise safety. Future research should focus on developing reliable traffic perception mechanisms, plug-and-play capabilities, and secure real-time data distribution methods to enhance ITS deployment [31, 32, 8]. Addressing these challenges is crucial for improving the detection and prediction of accident congestion precursors, ensuring urban traffic management systems remain responsive and efficient.

4.2 Role of Data Fusion in Identifying Precursors

Data fusion is pivotal in identifying accident congestion precursors by integrating diverse datasets to provide a comprehensive understanding of traffic dynamics. The Multi-Agent System (MAS) framework exemplifies this integration, offering real-time traffic forecasts and fault detection, thus enhancing decision-making and resource allocation in urban settings [1]. This capability is essential for proactively identifying potential congestion scenarios and facilitating timely interventions.

Advanced anomaly detection models in V-IoT systems further aid in recognizing early indicators of traffic congestion by leveraging real-time data to identify anomalies signaling impending disruptions [13]. The Correlation Information-based Spatiotemporal Network (CorrSTN) refines traffic flow forecasting by utilizing correlation information, improving the detection of accident congestion precursors [11].

The Spatial-Temporal Hypergraph Neural Network (STHODE) addresses complex interactions within traffic systems often overlooked by traditional models. By capturing high-order spatio-temporal dependencies, it enables early identification of congestion precursors, enhancing traffic management accuracy [3]. The Analytical Optimized Recovery (AOR) framework further aids precursor identification by recovering high-resolution link flow data in large-scale urban networks using GPS-acquired speed data alongside sparsely observed flow data [2].

Methods predicting parking availability also serve as indirect indicators of traffic demand fluctuations, signaling potential congestion precursors. Accurate parking availability forecasts provide insights into traffic demand shifts, facilitating proactive urban traffic management [9].

The integration of advanced methodologies, including computer vision, deep learning, and social media analytics, underscores data fusion's transformative potential in detecting and managing accident congestion precursors. Utilizing algorithms like YOLOv5 for vehicle detection and DeepSORT for tracking, along with real-time incident detection through Twitter analysis, enhances urban traffic management systems. This multifaceted approach improves the accuracy of traffic incident identification and supports proactive management, leading to more responsive and efficient urban transportation networks [7, 29, 33].

In recent years, the need for effective traffic management has become increasingly critical, prompting the exploration of various modeling approaches. These approaches can be categorized into hierarchical structures that reflect their spatiotemporal and cross-scale dynamics. As illustrated in Figure 3, this figure provides a comprehensive overview of these hierarchical structures, categorizing different dynamic modeling techniques alongside cross-scale modeling frameworks. Notably, it emphasizes the benefits of implementing these models, which include their scalability, adaptability, and overall impact on traffic management. This visual representation not only enhances our understanding of the complexities involved in traffic modeling but also serves as a valuable reference for further discussions on the efficacy of these approaches.

5 Spatiotemporal and Cross-Scale Dynamic Modeling

5.1 Dynamic Modeling Approaches

Dynamic modeling in traffic management employs advanced techniques to capture complex interactions within transportation networks, enhancing predictive accuracy and adaptability. The Correlation Information-based Spatiotemporal Network (CorrSTN) integrates dynamic graph neural networks with multi-head attention mechanisms to model intricate spatiotemporal dependencies [11]. Similarly, the Spatial-Temporal Hypergraph Neural Network (STHODE) addresses spatial and temporal dynamics, improving traffic forecasting precision [3].

The integration of smart vehicle data and traffic management systems enhances these capabilities, as demonstrated by frameworks like Digital Twin (DT) and Hierarchical Federated Learning (HFL), which enable real-time data processing for responsive solutions [13]. The Multi-Agent System (MAS) framework further innovates by combining forecasting and fault detection via machine learning, surpassing traditional methods in accuracy and responsiveness [1].

Dynamic approaches such as the B-GLOSA method optimize flow by integrating traffic signal data with vehicle dynamics, while the personal virtual traffic light system highlights the role of smart

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devices in timely information dissemination [14, 27]. The sequence-to-sequence architecture, integrating LSTM and Transformer components, effectively captures temporal dependencies, addressing time-varying factors in traffic data [12]. Additionally, hybrid traffic speed forecasting combines signal processing with neural networks for enhanced predictions [24].

These methodologies illustrate the diverse strategies to improve urban traffic management, including network capacity expansion and real-time vehicle tracking using computer vision and deep learning. Innovations such as mobile crowdsensing and integrating large language models with specialized traffic models are advancing intelligent, data-driven urban traffic management solutions [34, 4, 35, 7].

5.2 Cross-Scale Modeling Approaches

Cross-scale modeling is crucial for analyzing and predicting traffic dynamics across various spatial and temporal scales. Hierarchical frameworks integrate data from different scales to enhance understanding of traffic patterns [13]. The combination of Hierarchical Federated Learning (HFL) with Digital Twin (DT) technology exemplifies this, aggregating data from multiple sources to improve accuracy and responsiveness [13].

Multi-resolution spatial-temporal networks capture traffic dynamics at varying granularities, using both fine-grained and coarse-grained data to model complex dependencies [11]. Graph-based approaches like STHODE capture high-order dependencies across scales, providing insights into the relationships influencing traffic flow and congestion [3].

Hybrid frameworks combining traditional statistical methods with machine learning enhance cross-scale modeling by improving accuracy and reliability in predictions while accommodating the complexities of urban traffic systems [24]. These approaches highlight the importance of multi-scale data integration for comprehensive traffic management. Advanced predictive frameworks leverage technologies such as computer vision, deep learning, and graph wavelet networks to optimize management strategies, addressing challenges like congestion and resource allocation in urban environments [36, 4, 37, 34, 7].

5.3 Benefits of Implementing Dynamic Models

Dynamic models offer scalable, efficient, and adaptive solutions to contemporary transportation challenges, incorporating localized correlations and cross-domain knowledge for enhanced prediction accuracy. These models align traffic management strategies with real-time conditions, minimizing congestion and optimizing flow, thus improving urban mobility. Advanced systems utilizing computer vision and machine learning provide accurate data for traffic prediction and optimization, contributing to smarter urban transport solutions [4, 5, 35, 38, 7].

The adaptability of dynamic models to real-time changes is critical. Frameworks like the AOR minimize estimation errors while maintaining efficiency, suitable for large-scale urban traffic flow recovery [2]. This adaptability extends to generalizing across junctions and handling missing data, enhancing robustness.

Moreover, dynamic models improve the integration of crowdsourced data, enhancing monitoring and response capabilities. This enables timely interventions crucial for efficient traffic flow, with data-driven approaches like reinforcement learning and federated learning enhancing ITS orchestration [8].

Implementing dynamic models leads to improved traffic flow, reduced delays, and lower fuel consumption. These models adapt to drivers' cognitive states and dynamic environments, providing accurate predictions over different time horizons. Enhanced adaptability in management strategies significantly improves effectiveness, enabling networks to meet urban demands. By leveraging advanced systems incorporating traffic information, assignment, optimization, and prediction, urban planners can optimize infrastructure and manage congestion efficiently, minimizing trip times and maximizing flow while integrating innovative technologies for real-time decision-making [4, 35, 39].

6 Urban Traffic Management Strategies

The integration of advanced technologies and methodologies is pivotal in addressing the complexities of contemporary urban traffic management, enhancing operational efficiency while promoting safety and sustainability. A key component is the application of Intelligent Transportation Systems (ITS), which leverage real-time data and collaborative learning to optimize traffic management strategies. The following subsection explores the mechanisms of ITS integration, emphasizing the role of data fusion techniques in traffic optimization.

6.1 Integration of Intelligent Transportation Systems (ITS)

Integrating Intelligent Transportation Systems (ITS) is crucial for improving the efficiency, safety, and sustainability of transportation networks. This integration utilizes advanced technologies to address the challenges of modern urban environments. Federated learning enhances data privacy and facilitates collaborative learning across systems, safeguarding sensitive information while refining traffic management strategies [40]. Real-time data integration from diverse sources exemplifies ITS's capabilities, as evidenced by the SafeRNet system, which computes safe routes based on current traffic conditions [25]. B-GLOSA further enhances public transportation by synchronizing vehicle operations with traffic signals, minimizing delays [14]. Personal virtual traffic lights offer a cost-effective solution by providing real-time traffic information without physical infrastructure [27]. The integration of AI sensors and cloud computing within ITS frameworks optimizes traffic flow and mitigates congestion, showcasing the transformative potential of these technologies [20]. The Multi-Agent System (MAS) framework enhances decision-making and resource allocation through real-time traffic forecasts and fault detection [1]. Insights from benchmarking route guidance strategies in asymmetric traffic systems contribute to developing effective traffic management solutions [23].

6.2 Data Fusion Techniques for Traffic Optimization

Data fusion techniques are essential for optimizing traffic management by integrating diverse datasets to enhance prediction accuracy and operational efficiency. The Hierarchical Federated Learning with Anomaly Detection Models (HFL-ADM) facilitates real-time data processing and anomaly detection, underscoring the importance of secure and efficient data handling in modern traffic systems [13]. The Correlation Information-based Spatiotemporal Network (CorrSTN) optimizes traffic management through effective modeling of spatial and temporal dependencies [11]. Similarly, the Spatial-Temporal Hypergraph Neural Network (STHODE) improves predictive accuracy by modeling complex interactions in traffic data [3]. The hybrid traffic speed forecasting method enhances prediction accuracy by combining signal processing techniques with neural networks [24]. The MSCT model optimizes management strategies by addressing complex causal relationships in traffic data [12]. Advanced data fusion techniques, including computer vision, deep learning, and multi-source data analysis, revolutionize traffic management by improving vehicle detection, tracking, and parking availability predictions [7, 28, 9]. By employing advanced modeling approaches and integrating diverse data sources, these techniques enhance the ability to predict, manage, and optimize traffic flows.

6.3 Dynamic Modeling and Real-Time Adaptation

Dynamic modeling is crucial for real-time adaptation of traffic management strategies, providing flexibility to swiftly respond to changing traffic conditions. The AdaEnsemble approach captures nonlinear and periodic patterns in metro passenger flow, significantly improving forecasting accuracy [41]. ITS integration enhances real-time adaptability by facilitating efficient data exchange among agents, crucial for timely responses to evolving traffic scenarios [42]. The coordinated control method for connected and automated vehicles (CAVs) ensures collision-free and smooth trajectories, demonstrating the effectiveness of real-time data and control mechanisms [43]. Simulations based on varying vehicle compositions and traffic light timings illustrate how management strategies can adapt in real-time to optimize flow [44]. Predictive models like STATVTPred leverage spatial-temporal attention to anticipate traffic dynamics, informing proactive management strategies [45]. Future research should extend these frameworks to more complex networks and incorporate additional strategies, such as traffic signal control, to bolster proactive management capabilities [46]. Generative AI techniques offer promising avenues for enhancing adaptability through improved data generation and modeling uncertainty [47]. The Spatiotemporal Dual Graph Neural Network model demonstrates significant improvements in predictive accuracy, showcasing the potential of advanced modeling techniques in real-time traffic management [48]. These advancements illustrate the transformative impact of dynamic modeling on the adaptability of traffic management strategies, ensuring urban transportation systems remain efficient and responsive to evolving demands.

7 Intelligent Transportation Systems and Technologies

7.1 Artificial Intelligence and Machine Learning Applications

Artificial Intelligence (AI) and Machine Learning (ML) are pivotal in modernizing traffic management systems, offering advanced solutions to urban transportation complexities. Adaptive cruise control systems illustrate this advancement by employing sensor technologies and control algorithms to optimize vehicle operations and traffic flow [49]. Machine learning methods, such as reinforcement learning and neural networks, enhance traffic pattern prediction and signal timing optimization. Through computer vision and real-time data analysis, these algorithms alleviate congestion and improve mobility, overcoming outdated infrastructure challenges and aiding urban planning [2, 4, 35, 7, 30]. Deep learning in traffic forecasting has notably improved predictive accuracy, allowing timely interventions in traffic management.

AI significantly bolsters Connected and Automated Vehicles (CAVs), utilizing advanced ML algorithms for navigation in complex urban settings. CAVs leverage onboard sensors and connectivity for data sharing, enhancing traffic flow and reducing congestion. Research indicates that CAVs can achieve speeds up to 300

AI applications extend to anomaly detection and fault diagnosis, where ML models analyze traffic data to identify irregularities. The anticipated urbanization, set to add nearly 2.5 billion people by 2050 and over 1.2 billion vehicles, highlights the necessity for advanced traffic management systems utilizing AI and ML. These systems optimize traffic flow, predict congestion, and enhance route safety, contributing to sustainable urban mobility and addressing environmental concerns related to congestion and pollution [25, 4, 5, 7].

7.2 Advanced Sensing and Communication Technologies

Advanced sensing and communication technologies are essential for developing Intelligent Transportation Systems (ITS), enhancing urban traffic management. These technologies enable real-time data collection, transmission, and analysis, using mobile crowdsensing and Big Data analytics to improve responsiveness and efficiency during peak congestion [50, 31, 35].

The Internet of Things (IoT) facilitates seamless data exchange between vehicles, infrastructure, and traffic management centers. IoT devices equipped with sensors collect data on traffic flow, vehicle speed, and environmental conditions, providing crucial insights for real-time monitoring and management [50, 7, 51, 35]. Algorithms like YOLOv5 and DeepSORT enhance vehicle detection and tracking, supporting informed decision-making within ITS.

Vehicle-to-Everything (V2X) communication technologies improve ITS connectivity by enabling information exchange between vehicles and infrastructure, supporting applications like adaptive traffic signal control and collision avoidance, crucial for urban traffic environments [7, 35, 4]. Advanced computer vision and deep learning techniques enable real-time vehicle tracking and classification, significantly enhancing traffic management strategies.

Sensor technologies, including LiDAR and radar, improve traffic data collection accuracy and reliability, vital for autonomous vehicle systems and advanced driver assistance systems (ADAS). Integrating data from various sources allows effective monitoring of dynamic traffic conditions, contributing to smarter transportation systems [51, 52, 53, 54, 32].

Cloud and edge computing technologies further enhance ITS data processing and analysis capabilities, enabling efficient management and real-time analytics. This synergy improves scalability and performance, addressing data privacy and operational efficiency challenges [13, 55, 56, 8]. Cloud computing provides computational power, while edge computing enhances real-time data processing, reducing latency in traffic management systems.

7.3 Integration of Connected and Automated Vehicles (CAVs)

Integrating Connected and Automated Vehicles (CAVs) into Intelligent Transportation Systems (ITS) marks a significant advancement in urban traffic management, enhancing safety, efficiency, and sustainability. CAVs use V2X communication for data exchange with infrastructure, improving traffic flow and reducing congestion. Studies show that CAVs can decrease congestion by up to 75

CAVs enhance safety by using advanced sensors and communication systems to detect and respond to hazards in real time, reducing accident likelihood. Cooperative Intelligent Transportation Systems (C-ITS) ensure reliable and timely information sharing among vehicles and infrastructure, crucial for safety in complex traffic environments [57, 32, 49].

CAVs optimize traffic flow through dynamic management strategies, enabling real-time data exchange for adaptive signal timings, route selection, and speed adjustments. This adaptability enhances urban traffic networks' performance by reducing congestion and minimizing travel times [4, 35, 58, 59, 39].

Moreover, CAVs contribute to sustainable transportation by minimizing stop-and-go conditions, reducing emissions, and improving fuel efficiency. CAVs can significantly reduce congestion and enhance energy efficiency, emphasizing their role in advancing ITS and integrating AI for energy conservation and emission reduction [60, 59]. Operating in platoons further optimizes fuel savings and environmental impact.

Deploying CAVs within ITS frameworks facilitates extensive traffic data collection and analysis, informing infrastructure planning and improving traffic predictions. This data-driven approach leverages ITS and AI to enhance decision-making, leading to innovative urban mobility solutions that address urbanization, congestion, and sustainability challenges [61, 28, 5, 62, 7].

8 Peak Hour Traffic Control

8.1 Challenges of Peak Hour Traffic Management

Peak hour traffic management is fraught with challenges due to high vehicle volumes and the dynamic nature of urban transport networks. A significant issue is the rigidity of current traffic management systems, which often struggle to adapt to rapid changes in traffic demand, leading to congestion and delays [41]. The diversity among traffic participants, including both human-driven and connected automated vehicles, adds complexity by introducing variability in traffic flow patterns, complicating the implementation of uniform management strategies [43]. Additionally, limited communication capabilities and resource competition among technologies hinder effective data integration, crucial for management [42]. Predictive models often fall short in accurately forecasting peak hour conditions due to their inability to account for urban environments' spatial and temporal heterogeneity, resulting in suboptimal predictions [48]. The lack of real-time data further restricts traffic systems' proactive response capabilities [44]. Moreover, many infrastructures are not designed to handle peak period traffic volumes, leading to bottlenecks and increased travel times. The absence of adaptive systems capable of dynamically adjusting to changing conditions exacerbates these challenges [46].

8.2 Real-Time Traffic Management Solutions

Real-time traffic management solutions are vital for alleviating peak hour congestion, utilizing dynamic approaches to optimize flow and minimize delays. Adaptive traffic signal control systems that adjust timings based on real-time data enhance coordination and reduce stop-and-go traffic [43]. The integration of connected and automated vehicles (CAVs) into management systems significantly boosts real-time capabilities, as CAVs communicate with infrastructure and each other to optimize routing and speed, improving efficiency during peak periods [42]. Vehicle-to-Everything (V2X) technologies facilitate timely traffic information exchange, enabling informed decision-making [43]. Predictive models, like those in the STATVTPred framework, use spatial-temporal attention mechanisms to anticipate traffic dynamics, allowing for proactive congestion mitigation [45]. Generative AI techniques enhance data generation and uncertainty modeling, providing robust real-time solutions [47]. Multi-agent systems (MAS) improve adaptability by facilitating efficient data exchange and coordination among traffic agents, optimizing flow during peak times [1]. Simulations of varying vehicle compositions and traffic light timings offer insights into effective strategies, supporting tailored solutions for specific scenarios [44].

8.3 Predictive Modeling and Forecasting Techniques

Predictive modeling and forecasting techniques are crucial for managing peak hour traffic, enabling managers to anticipate patterns and implement proactive strategies. The use of spatial-temporal attention mechanisms, as in the STATVTPred framework, enhances predictive accuracy by capturing complex dependencies in traffic data [45]. Advanced machine learning algorithms forecast traffic dynamics, facilitating timely interventions to alleviate congestion. Generative AI techniques advance predictive modeling by improving data generation and uncertainty modeling, essential for robust forecasts [47]. These techniques develop models that adapt to urban traffic's dynamic characteristics, ensuring accurate predictions that inform effective strategies. The integration of multi-agent systems (MAS) strengthens predictive capabilities by enabling efficient data exchange and coordination among agents, vital for real-time management [1]. Simulations exploring vehicle compositions and traffic light timings provide insights into predictive strategies' effectiveness, aiding tailored solutions for specific scenarios [44]. These simulations highlight the importance of adaptive modeling in addressing urban traffic complexities, ensuring smoother mobility for all road users.

9 Conclusion

9.1 Future Directions and Research Opportunities

Urban traffic management stands at the cusp of significant evolution, driven by technological progress and novel research trajectories. Enhancing the resilience of current systems like Multi-Agent Systems (MAS) through the integration of varied data sources and the refinement of machine learning algorithms is crucial for improving their precision and flexibility in dynamic traffic environments. Similarly, advancements in the Spatial-Temporal Hypergraph Neural Network (STHODE) via improved hypergraph structures and expanded data integration promise to enhance model efficacy.

Expanding the application of correlation information calculations to diverse forecasting tasks, as demonstrated by the Correlation Information-based Spatiotemporal Network (CorrSTN), is imperative. Exploring different mother wavelets in wavelet transformation processes and applying these to other spatiotemporal forecasting challenges also present valuable research opportunities.

Practically, it is essential to advance data collection techniques and validate link locations to ensure precise traffic flow predictions, as highlighted by the Analytical Optimized Recovery (AOR) framework. Furthermore, refining benchmark strategies to encompass a wider array of traffic scenarios and developing adaptive strategies that respond to evolving conditions are vital for the progression of route guidance methodologies.

The integration of sophisticated AI algorithms to enhance traffic management frameworks across diverse urban contexts remains a pivotal focus. Future research should evaluate the effectiveness of various AI methodologies, including reinforcement learning and federated learning, to improve the efficiency and adaptability of Intelligent Transportation Systems (ITS).

These research pathways underscore the potential for significant advancements in urban traffic management, paving the way for the creation of more intelligent and sustainable urban mobility solutions that meet the changing needs of contemporary cities.

References

[1] Maria Viorela Muntean. Multi-agent system for intelligent urban traffic management using wireless sensor networks data. *Sensors*, 22(1):208, 2021.

[2] Sicheng Fu, Haotian Shi, Shixiao Liang, Xin Wang, and Bin Ran. Analytical optimized traffic flow recovery for large-scale urban transportation network, 2024.

[3] Chengzhi Yao, Zhi Li, and Junbo Wang. Spatial-temporal hypergraph neural network for traffic forecasting, 2023.

[4] M Shahgholian and Davood Gharavian. Advanced traffic management systems: an overview and a development strategy. *arXiv preprint arXiv:1810.02530*, 2018.

[5] Zineb Mahrez, Essaid Sabir, Elarbi Badidi, Walid Saad, and Mohamed Sadik. Smart urban mobility: When mobility systems meet smart data, 2020.

[6] Hany Kamal, Marco Picone, and Michele Amoretti. A survey and taxonomy of urban traffic management: Towards vehicular networks, 2014.

[7] Enhancing urban traffic manageme.

[8] Abdallah Moubayed, Abdallah Shami, and Abbas Ibrahim. Intelligent transportation systems' orchestration: Lessons learned potential opportunities, 2022.

[9] Yin Huang, Yongqi Dong, Youhua Tang, and Li Li. Leverage multi-source traffic demand data fusion with transformer model for urban parking prediction, 2024.

[10] Jiahao Ji, Jingyuan Wang, Chao Huang, Junjie Wu, Boren Xu, Zhenhe Wu, Junbo Zhang, and Yu Zheng. Spatio-temporal self-supervised learning for traffic flow prediction, 2024.

[11] Weiguo Zhu, Yongqi Sun, Xintong Yi, and Yan Wang. A correlation information-based spatiotemporal network for traffic flow forecasting, 2022.

[12] Shuang Li, Ziyuan Pu, Nan Zhang, Duxin Chen, Lu Dong, Daniel J. Graham, and Yinhai Wang. Msct: Addressing time-varying confounding with marginal structural causal transformer for counterfactual post-crash traffic prediction, 2024.

[13] Deepti Gupta, Shafika Showkat Moni, and Ali Saman Tosun. Integration of digital twin and federated learning for securing vehicular internet of things, 2023.

[14] Daniele Vignarca, Stefano Arrigoni, Edoardo Sabbioni, and Federico Cheli. Speed profile definition for glosa implementation on buses based on statistical analysis of experimental data, 2024.

[15] Jianqi Liu, Jiafu Wan, Dongyao Jia, Bi Zeng, Di Li, Ching-Hsien Hsu, and Haibo Chen. High-efficiency urban traffic management in context-aware computing and 5g communication. *IEEE Communications Magazine*, 55(1):34–40, 2017.

[16] Pouria Golshanrad, Hamid Mahini, and Behnam Bahrak. Proposing a model for predicting passenger origin-destination in online taxi-hailing systems, 2023.

[17] Jiezhang Li, Junjun Li, and Yue-Jiao Gong. Multi-task learning for sparse traffic forecasting, 2022.

[18] Boris Chidlovskii. Multi-task learning of time series and its application to the travel demand, 2017.

[19] Feilong Wang, Xin Wang, and Xuegang Ban. Data poisoning attacks in intelligent transportation systems: A survey, 2024.

[20] Auwal Alhassan Musa, Salim Idris Malami, Fayez Alanazi, Wassef Ounaies, Mohammed Alshammari, and Sadi Ibrahim Haruna. Sustainable traffic management for smart cities using internet-of-things-oriented intelligent transportation systems (its): challenges and recommendations. *Sustainability*, 15(13):9859, 2023.

[21] Benjamin Sliwa, Thomas Liebig, Tim Vranken, Michael Schreckenberg, and Christian Wietfeld. System-of-systems modeling, analysis and optimization of hybrid vehicular traffic, 2019.

[22] Guangyin Jin, Lingbo Liu, Fuxian Li, and Jincai Huang. Spatio-temporal graph neural point process for traffic congestion event prediction, 2023.

[23] Zhengbing He, Ning Jia, and Wei Guan. Route guidance strategies revisited: Comparison and evaluation in an asymmetric two-route traffic system, 2013.

[24] Na Zhang, Xuefeng Guan, Jun Cao, Xinglei Wang, and Huayi Wu. A hybrid traffic speed forecasting approach integrating wavelet transform and motif-based graph convolutional recurrent neural network, 2019.

[25] Qun Liu, Suman Kumar, and Vijay Mago. Safernet: Safe transportation routing in the era of internet of vehicles and mobile crowd sensing, 2018.

[26] Tuo Mao, Adriana-Simona Mihăiţă, Fang Chen, and Hai L Vu. Boosted genetic algorithm using machine learning for traffic control optimization. *IEEE Transactions on Intelligent Transportation Systems*, 23(7):7112–7141, 2021.

[27] Vanessa Martins, João Rufino, Bruno Fernandes, Luís Silva, João Almeida, Joaquim Ferreira, and José Fonseca. Personal virtual traffic light systems, 2018.

[28] Chenxing Wang. Towards effective fusion and forecasting of multimodal spatio-temporal data for smart mobility, 2024.

[29] Xintao Yan, Yan Zhao, and Henry X. Liu. A probabilistic model for missing traffic volume reconstruction based on data fusion, 2021.

[30] Maryam Shaygan, Collin Meese, Wanxin Li, Xiaolong Zhao, and Mark Nejad. Traffic prediction using artificial intelligence: Review of recent advances and emerging opportunities, 2023.

[31] Christian Creß, Zhenshan Bing, and Alois C. Knoll. Intelligent transportation systems using external infrastructure: A literature survey, 2022.

[32] Adnan Mahmood, Bernard Butler, and Brendan Jennings. Potential of augmented reality for intelligent transportation systems, 2018.

[33] Angelica Salas, Panagiotis Georgakis, and Yannis Petalas. Incident detection using data from social media. In *2017 IEEE 20th International conference on intelligent transportation systems (ITSC)*, pages 751–755. IEEE, 2017.

[34] Siyao Zhang, Daocheng Fu, Zhao Zhang, Bin Yu, and Pinlong Cai. Trafficgpt: Viewing, processing and interacting with traffic foundation models, 2023.

[35] Article.

[36] Zhanyu Liu, Guanjie Zheng, and Yanwei Yu. Multi-scale traffic pattern bank for cross-city few-shot traffic forecasting, 2024.

[37] Zilin Bian, Jingqin Gao, Kaan Ozbay, and Zhenning Li. Traffic prediction considering multiple levels of spatial-temporal information: A multi-scale graph wavelet-based approach, 2024.

[38] Matt Grote, Ben Waterson, and Felix Rudolph. The impact of strategic transport policies on future urban traffic management systems. *Transport policy*, 110:402–414, 2021.

[39] Matteo Vasirani and Sascha Ossowski. A market-inspired approach for intersection management in urban road traffic networks, 2014.

[40] Rongqing Zhang, Hanqiu Wang, Bing Li, Xiang Cheng, and Liuqing Yang. A survey on federated learning in intelligent transportation systems, 2024.

[41] Shaolong Sun, Dongchuan Yang, Ju e Guo, and Shouyang Wang. Adaensemble learning approach for metro passenger flow forecasting, 2020.

[42] Nizar Hamadeh, Ali Karouni, Zeinab Farhat, Hussein El Ghor, Mohamad El Ghor, and Israa Katea. Intelligent transportation systems to mitigate road traffic congestion, 2021.

[43] Tong Zhao, Nikolce Murgovski, and Wei ShangGuan. A spatial-domain coordinated control method for connected and automated vehicles at unsignalized intersections considering motion uncertainty, 2024.

[44] Raihanah Adawiyah Shaharuddin and Md Yushalify Misro. Controlling traffic congestion in urbanised city: A framework using agent-based modelling and simulation approach. *ISPRS International Journal of Geo-Information*, 12(6):226, 2023.

[45] Ouhan Huang, Huanle Rao, Xiaowen Cai, Tianyun Wang, Aolong Sun, Sizhe Xing, Yifan Sun, and Gangyong Jia. Spatial temporal attention based target vehicle trajectory prediction for internet of vehicles, 2025.

[46] Takao Dantsuji, Dong Ngoduy, Ziyuan Pu, Seunghyeon Lee, and Hai L. Vu. A hybrid neural network for real-time od demand calibration under disruptions, 2024.

[47] Huan Yan and Yong Li. A survey of generative ai for intelligent transportation systems: Road transportation perspective, 2024.

[48] Guangyin Jin, Huan Yan, Fuxian Li, Jincai Huang, and Yong Li. Spatio-temporal dual graph neural networks for travel time estimation, 2021.

[49] Emre Kural, Tahsin Hacibekir, and Bilin Aksun-Guvenc. State of the art of adaptive cruise control and stop and go systems, 2022.

[50] Sasan Amini, Ilias Gerostathopoulos, and Christian Prehofer. Big data analytics architecture for real-time traffic control. In *2017 5th IEEE international conference on models and technologies for intelligent transportation systems (MT-ITS)*, pages 710–715. IEEE, 2017.

[51] Zijian Hu, William H. K. Lam, S. C. Wong, Andy H. F. Chow, and Wei Ma. Turning traffic monitoring cameras into intelligent sensors for traffic density estimation, 2021.

[52] Nawfal Guefrachi, Hakim Ghazzai, and Ahmad Alsharoa. Empowering urban traffic management: Elevated 3d lidar for data collection and advanced object detection analysis, 2024.

[53] Kafeng Wang, Haoyi Xiong, Jie Zhang, Hongyang Chen, Dejing Dou, and Cheng-Zhong Xu. Sensemag: Enabling low-cost traffic monitoring using non-invasive magnetic sensing, 2021.

[54] Juan Guerrero-Ibáñez, Sherali Zeadally, and Juan Contreras-Castillo. Sensor technologies for intelligent transportation systems. *Sensors*, 18(4):1212, 2018.

[55] Dimitrios Michael Manias and Abdallah Shami. Making a case for federated learning in the internet of vehicles and intelligent transportation systems, 2021.

[56] Danilo Fernandes, Douglas L. L. Moura, Gean Santos, Geymerson S. Ramos, Fabiane Queiroz, and Andre L. L. Aquino. Towards edge-based data lake architecture for intelligent transportation system, 2024.

[57] Sehyun Tak and Seongjin Choi. Development of safety monitoring system of connected and automated vehicles considering the trade-off between communication efficiency and data reliability, 2021.

[58] ANDRÁS Szele and Lajos Kisgyörgy. Traffic operation on a road network with recurrent congestion. *WIT Transactions on the Built Environment*, 179:233–243, 2018.

[59] Omar Rinchi, Ahmad Alsharoa, Ibrahem Shatnawi, and Anvita Arora. The role of intelligent transportation systems and artificial intelligence in energy efficiency and emission reduction, 2024.

[60] Ioannis Mavromatis, Andrea Tassi, Robert J. Piechocki, and Mahesh Sooriyabandara. On urban traffic flow benefits of connected and automated vehicles, 2020.

[61] Guilong Li, Yixian Chen, Jun Xie, Qinghai Lin, and Zhaocheng He. Urban vehicle mobility characteristic mining and trip generation based on knowledge graph, 2022.

[62] Ana L. C. Bazzan. Improving urban mobility: using artificial intelligence and new technologies to connect supply and demand, 2022.

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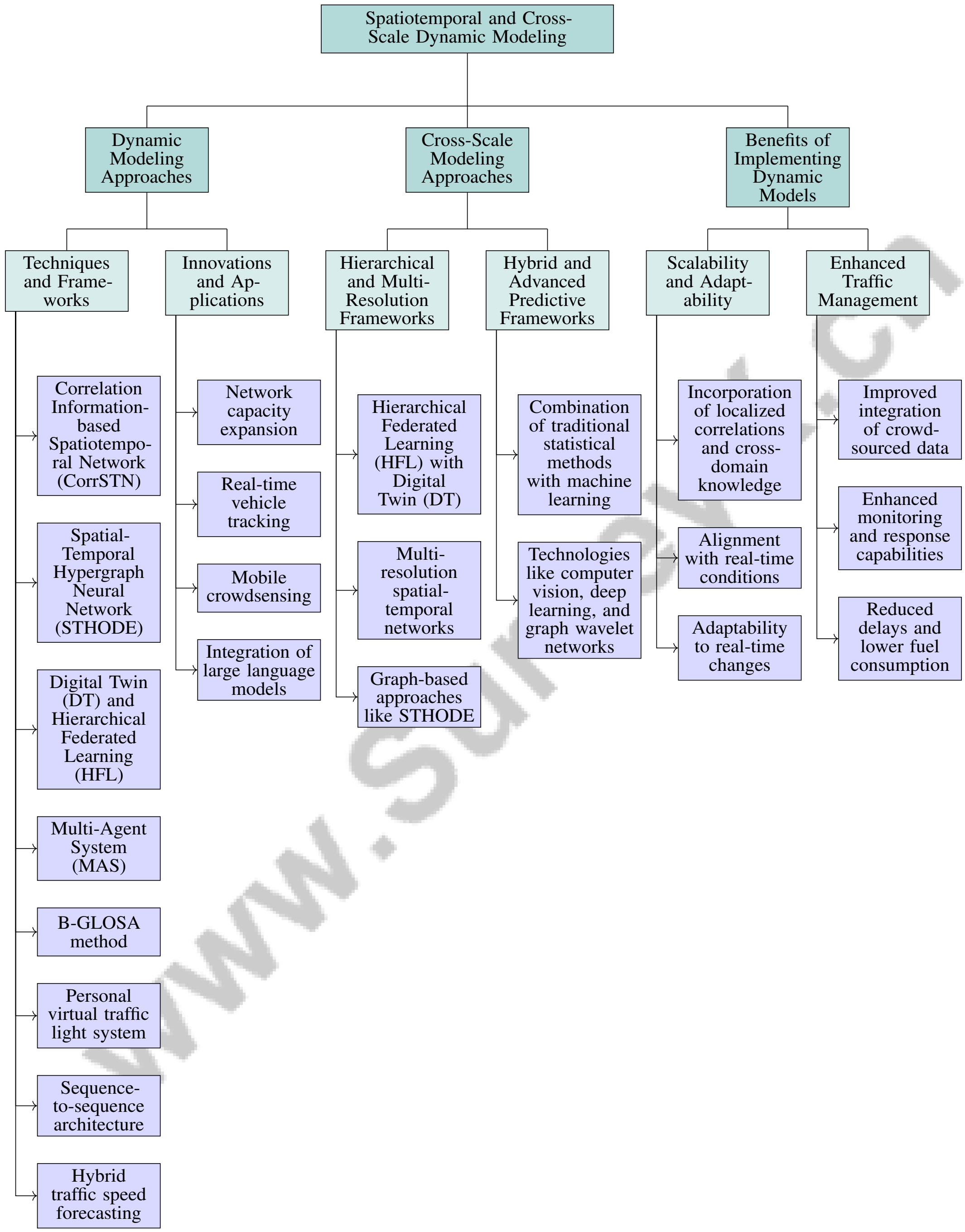

Figure 3: This figure illustrates the hierarchical structure of spatiotemporal and cross-scale dynamic modeling approaches in traffic management. It categorizes various dynamic modeling techniques, cross-scale modeling frameworks, and the benefits of implementing these models, highlighting their scalability, adaptability, and impact on traffic management.

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