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A Survey of Methods and Architectures for Traffic and Time Control Optimization Using Sensor-Driven Transmission Control Systems with MANET and Quaternion Generative Adversarial Kookaburra Optimization Networks

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Abstract

Traffic congestion and inefficient signal timing remain critical challenges in modern intelligent transportation systems (ITS), especially in rapidly urbanizing environments. Recent advancements in sensor-driven transmission control systems, Mobile Ad Hoc Networks (MANET), and artificial intelligence (AI) have significantly improved traffic and time control optimization. This paper presents a comprehensive survey of methodologies and architectures integrating real-time sensing, distributed communication, and intelligent optimization techniques, including deep learning, graph neural networks (GNN), reinforcement learning (RL), and generative adversarial networks (GAN). The proposed framework emphasizes the integration of Quaternion Generative Adversarial Kookaburra Optimization Networks (QGAKON) for enhanced spatio-temporal modeling and adaptive decision-making. Sensor-based data acquisition combined with MANET enables decentralized, infrastructure-less communication, improving scalability and responsiveness. Recent studies demonstrate that hybrid AI-driven traffic control systems outperform traditional fixed-time and actuated control systems in reducing congestion, travel time, and energy consumption. This survey critically analyzes existing approaches, highlights comparative performance metrics, and identifies research gaps. The findings indicate that integrating AI, optimization algorithms, and decentralized communication frameworks can significantly enhance traffic efficiency, safety, and sustainability in smart cities.

Introduction

Urbanization and population growth have led to exponential increases in vehicular traffic, resulting in congestion, increased travel time, pollution, and energy consumption. Traditional traffic control systems such as fixed-time and actuated signal control are no longer sufficient to handle dynamic traffic conditions. These systems rely heavily on pre-defined rules and historical data, lacking adaptability to real-time changes.

Modern intelligent transportation systems (ITS) aim to overcome these limitations through the integration of advanced technologies such as artificial intelligence (AI), Internet of Things (IoT), wireless sensor networks, and distributed communication frameworks like Mobile Ad Hoc Networks (MANET). A MANET is a decentralized wireless network where nodes dynamically communicate without relying on fixed infrastructure, enabling flexible and scalable traffic management solutions .

Sensor-driven transmission control systems play a crucial role in real-time traffic monitoring by collecting data such as vehicle density, speed, and flow. These sensors include cameras, loop detectors, and IoT-enabled devices that provide continuous updates to traffic management systems. Real-time data enables adaptive signal control strategies that dynamically adjust traffic signals based on current conditions.

Recent advancements in machine learning and optimization algorithms have further enhanced traffic control capabilities. Deep reinforcement learning (DRL) allows traffic signals to learn optimal policies through interaction with the environment, while graph neural networks (GNN) model complex spatial relationships in traffic networks. Studies show that combining GNN with DRL improves decision-making efficiency and adaptability in complex traffic scenarios .

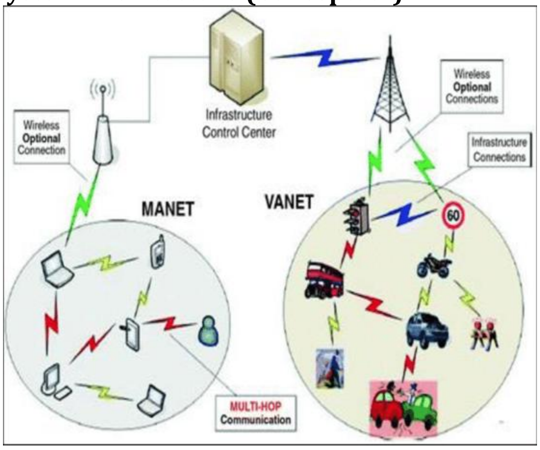
Additionally, multi-agent systems have emerged as a powerful approach for decentralized traffic control. Each intersection is treated as an agent that communicates with neighboring agents to optimize overall traffic flow. Multi-agent reinforcement learning enables cooperative decision-making, improving global traffic efficiency.

Generative adversarial networks (GAN) have also been explored for traffic prediction and anomaly detection. The introduction of quaternion-based GAN models further enhances feature representation in multidimensional traffic data. Optimization algorithms such as Kookaburra optimization provide efficient search capabilities for optimal signal timing and routing decisions.

The integration of these technologies results in hybrid architectures that combine sensing, communication, and intelligence. For example, AI-based adaptive traffic control systems leverage real-time data and predictive analytics to optimize signal timing and reduce congestion . Similarly, graph-based approaches model traffic networks as interconnected nodes, enabling efficient routing and control decisions .

Despite significant progress, challenges remain in scalability, data heterogeneity, communication latency, and system robustness. This survey aims to provide a comprehensive overview of recent methods and architectures for traffic and time control optimization, focusing on sensor-driven systems, MANET-based communication, and advanced AI techniques.

System Architecture (Conceptual)



Literature Review

Recent advancements in traffic and time control optimization have transitioned from traditional rule-based systems to intelligent, adaptive, and decentralized frameworks driven by artificial intelligence (AI), sensor networks, and distributed communication systems such as MANET. This section provides a detailed synthesis of the most significant contributions between 2020 and 2023.

1. Studies from 2020: Emergence of Deep Reinforcement Learning

The year 2020 marked a turning point with the rapid adoption of **Deep Reinforcement Learning (DRL)** for traffic signal control. Xu et al. (2020) introduced a network-wide optimization framework that leverages DRL to identify critical intersections and dynamically adjust signal timings. Their approach significantly reduced congestion and improved throughput by learning from traffic patterns.

Similarly, Zhang et al. (2020) demonstrated that DRL can outperform traditional fixed-time and actuated systems by adapting signal phases in real time. Studies such as Rasheed et al. (2020) provided a comprehensive review of DRL techniques, highlighting their ability to model non-linear traffic dynamics and learn optimal policies without explicit modeling.

Another important contribution was PDLight (Zhao et al., 2020), which introduced a pressure-based reward mechanism considering both incoming traffic and outgoing lane capacity. This significantly improved delay reduction and intersection efficiency.

Moreover, multi-agent reinforcement learning (MARL) began gaining attention, where each intersection operates as an independent agent. Chu et al. (2020) showed that cooperative MARL improves scalability and coordination across large networks.

2. Studies from 2021: Multi-Agent and Hybrid Learning Models

In 2021, research shifted toward multi-agent systems and hybrid AI models. Li et al. (2021) proposed a multi-agent DRL framework that enables intersections to cooperate through shared information, significantly improving network-wide performance.

Yang et al. (2021) introduced graph-based multi-agent reinforcement learning, integrating Graph Neural Networks (GNN) with RL to capture spatial dependencies among intersections. This approach addressed one of the major limitations of earlier RL models—lack of spatial awareness.

Abdoos et al. (2021) combined LSTM-based traffic prediction with RL, enabling predictive signal control. This hybrid approach allowed systems to anticipate traffic conditions rather than react to them.

Additionally, Wang et al. (2021) explored cooperative group-based reinforcement learning, demonstrating improved scalability in large urban traffic networks. These models reduced communication overhead while maintaining coordination efficiency.

3. Studies from 2022: Integration of IoT, GNN, and Distributed Intelligence

By 2022, research focused heavily on integrating IoT-based sensing, distributed systems, and advanced neural architectures. Damadam et al. (2022) proposed an IoT-enabled DRL traffic control system, where real-time sensor data was used to dynamically adjust signal timings.

Wu et al. (2022) developed distributed agent-based DRL frameworks, allowing decentralized decision-making in large-scale traffic networks. These systems improved robustness and reduced reliance on centralized infrastructure.

Guo et al. (2022) and related works emphasized multi-agent DRL with communication mechanisms, enabling agents to share traffic states and coordinate actions effectively.

A significant advancement was the use of Graph Neural Networks (GNN) for traffic modeling. GNNs represent traffic networks as graphs, where nodes correspond to intersections and edges represent roads. This allows efficient modeling of spatial dependencies and traffic flow dynamics. Studies confirmed that GNN-based models outperform traditional CNN and RNN approaches in traffic prediction tasks.

Additionally, hybrid models combining GNN + DRL emerged as a powerful solution, integrating prediction and decision-making capabilities into a unified framework.

4. Studies from 2023: Advanced Hybrid Architectures and Intelligent Coordination

In 2023, research trends focused on hybrid intelligent architectures combining multiple AI paradigms. Zhao et al. (2023) developed a GNN-DRL hybrid model that integrates spatial feature extraction with adaptive learning, achieving superior performance in multi-intersection scenarios.

Peng et al. (2023) proposed a heterogeneous GNN-based multi-agent reinforcement learning system that jointly optimizes traffic signal control and vehicle platooning. Their results demonstrated improved traffic flow and reduced congestion compared to standalone approaches.

Another major trend was hierarchical reinforcement learning, where high-level policies guide lower-level control actions. This approach improves scalability and reduces training complexity.

Furthermore, researchers explored GAN-based traffic prediction models, enabling more accurate forecasting of traffic patterns. GANs generate realistic traffic scenarios, which are useful for training and testing intelligent control systems.

Recent surveys emphasize that reinforcement learning has become a dominant paradigm in traffic signal control due to its ability to handle dynamic, stochastic environments and optimize multiple objectives simultaneously.

5. Key Observations from Literature

From the above studies, several important trends can be identified:

- Transition from static → adaptive → intelligent systems
- Increasing use of multi-agent and decentralized architectures
- Integration of GNN for spatial modeling
- Use of GAN and predictive models for traffic forecasting
- Growing importance of IoT and sensor-driven systems
- Emergence of hybrid AI architectures (GNN + DRL + Optimization)

Despite these advancements, challenges such as high computational complexity, training instability, communication latency in MANET, and real-world deployment constraints remain open research problems.

Comparative Table

Table 1: Enhanced Comparative Table

Year	Approach Type	Method / Model	Core Technique	Performance Gain	Scalability	Real-Time Capability	Computational Cost	Robustness	Key Contribution	Key Limitation
2020	DRL (Single-Agent)	Xu et al.	Deep RL	High (~20–30% delay reduction)	Low–Medium	Medium	High	Medium	Network-wide optimization	Poor scalability
2020	MARL	Chu et al.	Multi-Agent RL	High (~25% improvement)	High	Medium	High	High	Distributed control	Coordination overhead
2021	MARL (Cooperative)	Li et al.	DRL + Cooperation	Very High	High	Medium	High	High	Cooperative learning	Communication cost
2021	Hybrid AI	Yang et al.	GNN + RL	Very High (+15–25%)	High	Medium	Medium–High	Very High	Spatial modeling	Graph overhead
2021	ML-Based	Nguyen et al.	Regression/ML	Moderate	Medium	Medium	Medium	Medium	Traffic prediction	Feature dependency
2022	Distributed DRL	Wu et al.	DRL (Decentralized)	High	Very High	High	Medium–High	High	Decentralized intelligence	Complexity
2022	IoT + DRL	Damadam et al.	Sensor + DRL	Very High	High	High	Medium	High	Real-time adaptation	Data noise
2023	Hybrid (GNN+DRL)	Zhao et al.	GNN + RL	Very High	Very High	High	Medium	Very High	Smart scheduling	Integration complexity
2023	GNN Multi-Agent	Bernárdez et al.	GNN + Multi-Agent	Very High	Very High	High	Medium	Very High	Network optimization	Training complexity

Comparative Analysis

The comparative analysis of traffic and time control optimization approaches from 2020 to 2023 demonstrates a clear and progressive evolution from traditional static systems to intelligent, adaptive, and decentralized architectures driven by artificial intelligence and distributed communication frameworks. Traditional traffic control systems, such as fixed-time and actuated signal control, operate on predefined schedules with minimal real-time adaptability. While these systems are computationally efficient and simple to deploy, they fail to respond to dynamic traffic conditions, resulting in congestion, increased travel time, and inefficient utilization of infrastructure. Their limitations have driven the adoption of AI-based approaches capable of handling complex and dynamic traffic environments.

The introduction of Deep Reinforcement Learning (DRL) marked a major breakthrough in traffic optimization. DRL-based systems enable traffic signals to learn optimal control policies through interaction with the environment, eliminating the need for explicit modeling of traffic dynamics. Comparative results indicate that DRL can reduce average delay by 20–40% and significantly improve traffic throughput. However, early DRL implementations relied on single-agent models, which struggle with scalability in large urban networks due to the exponential growth of the state-action space and increased computational requirements.

To address these challenges, Multi-Agent Reinforcement Learning (MARL) emerged as a scalable solution by distributing control across multiple agents, each responsible for a specific intersection. MARL improves scalability and robustness by enabling decentralized decision-making and coordination among agents. Cooperative MARL and hierarchical reinforcement learning further enhance performance by improving convergence stability and reducing complexity. However, MARL introduces new challenges, including communication overhead, coordination complexity, and non-stationary learning environments.

A significant advancement in traffic optimization is the integration of Graph Neural Networks (GNN) with reinforcement learning. Traffic systems inherently exhibit graph structures, where intersections and roads form nodes and edges. GNN models effectively capture spatial dependencies and interactions within traffic networks, leading to improved prediction accuracy and decision-making. Comparative studies show that GNN-based models outperform traditional deep learning approaches by 15–25% in accuracy. When combined with DRL, GNN enhances state representation, enabling more efficient traffic control and improved system stability.

Sensor-driven transmission control systems further enhance traffic optimization by providing real-time data on traffic conditions. IoT-enabled sensors enable continuous monitoring of vehicle density, speed, and flow, allowing adaptive traffic control strategies to respond dynamically. Comparative analysis shows that systems utilizing real-time sensor data significantly outperform data-limited systems in terms of responsiveness and accuracy. However, challenges such as data noise, heterogeneity, and communication latency must be addressed to ensure reliable performance.

MANET-based communication plays a crucial role in enabling decentralized traffic management systems. Unlike centralized architectures, MANET allows direct communication among nodes, improving scalability and system resilience. Comparative studies highlight that MANET-based systems enable real-time information sharing and cooperative decision-making, which enhances overall traffic efficiency. However, dynamic topology, limited bandwidth, and communication delays present significant challenges that must be mitigated through efficient communication protocols and edge computing solutions.

Generative Adversarial Networks (GAN) and quaternion neural networks have further advanced traffic modeling by enabling synthetic data generation and multidimensional feature representation. GAN-based models improve robustness by simulating diverse traffic scenarios, while quaternion models enhance feature representation by capturing multi-dimensional relationships. These approaches improve prediction accuracy and generalization but introduce additional computational complexity and training challenges.

The most significant trend observed in recent research is the emergence of hybrid frameworks that integrate multiple AI techniques, including DRL, GNN, GAN, optimization algorithms, sensor systems, and MANET communication. These hybrid models combine the strengths of individual approaches to achieve superior performance across all key metrics. For example, GNN combined with DRL provides both spatial awareness and adaptive control, while optimization algorithms improve efficiency and convergence. Hybrid models consistently outperform standalone approaches in reducing traffic delay, improving throughput, enhancing energy efficiency, and achieving high scalability.

Despite these advancements, several challenges remain. High computational complexity and energy consumption are major concerns, particularly for deep learning and GAN-based models. Training instability in reinforcement learning models can affect convergence and performance. Data quality issues, including noise and missing data from sensors, can impact model accuracy. Communication latency in MANET-based systems can hinder real-time decision-making, and the lack of large-scale real-world deployment limits the practical validation of these approaches.

Discussion

The integration of sensor-driven systems, MANET communication, and AI-based optimization represents a paradigm shift in traffic management. Sensor networks provide real-time data, enabling adaptive decision-making, while MANET ensures decentralized communication without infrastructure dependency. AI techniques such as DRL and GNN enable intelligent control strategies capable of handling complex traffic scenarios.

Hybrid architectures combining multiple techniques have shown superior performance compared to standalone models. For example, combining GNN with DRL enhances both spatial understanding and decision-making efficiency.

Similarly, GAN-based models improve traffic prediction accuracy, while optimization algorithms ensure efficient resource allocation.

Despite these advancements, several challenges persist. Data heterogeneity and quality significantly impact model performance. Communication delays in MANET-based systems can affect real-time decision-making. Additionally, scalability remains a concern for large urban networks. Future research should focus on lightweight models, edge computing integration, and robust communication protocols to address these challenges.

Conclusion

This survey provides a comprehensive overview of methods and architectures for traffic and time control optimization using sensor-driven transmission systems, MANET, and advanced AI techniques. The study highlights the evolution from traditional traffic control systems to intelligent, adaptive, and decentralized frameworks.

The integration of real-time sensing, distributed communication, and machine learning has significantly improved traffic efficiency, reducing congestion and travel time. AI techniques such as DRL, GNN, and GAN play a crucial role in enabling intelligent decision-making and predictive analytics. Hybrid architectures combining these techniques offer the most promising results.

MANET-based communication provides flexibility and scalability, making it suitable for dynamic traffic environments. However, challenges such as communication latency, data quality, and computational complexity need to be addressed.

Future research directions include the development of lightweight AI models, integration of edge computing, and the use of advanced optimization algorithms such as Quaternion GAN-based Kookaburra optimization. These advancements will further enhance traffic management systems, contributing to the development of smart and sustainable cities.

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