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Artificial Intelligence for Traffic and Time Control Optimization Using Sensor-Driven MANET Systems: Trends and Challenges

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Abstract

The exponential growth in urbanization and vehicular density has led to severe traffic congestion, inefficient signal timing, and increased environmental pollution. Traditional traffic management systems fail to adapt to dynamic traffic conditions due to their static and rule-based nature. This paper presents a comprehensive review of artificial intelligence (AI)-driven techniques for traffic and time control optimization using sensor-driven transmission systems integrated with Mobile Ad Hoc Networks (MANET) and advanced hybrid models. Recent advancements in Deep Reinforcement Learning (DRL), Graph Neural Networks (GNN), Generative Adversarial Networks (GAN), and metaheuristic optimization algorithms have significantly improved traffic efficiency, adaptability, and decision-making accuracy. The proposed framework incorporates Quaternion Generative Adversarial Kookaburra Optimization Networks (QGAKON) to enhance multi-dimensional feature representation and optimization performance. Sensor networks provide real-time traffic data, while MANET enables decentralized communication, improving system scalability and robustness. This review analyzes studies, highlighting trends, performance improvements, and limitations. The findings indicate that hybrid AI-based architectures outperform traditional and standalone models in reducing congestion, travel time, and energy consumption. However, challenges such as computational complexity, communication latency, and real-world deployment remain. Future research directions emphasize lightweight models, edge computing, and robust communication frameworks for smart city applications

Introduction

The rapid growth of urban populations and the increasing number of vehicles have resulted in significant challenges for transportation systems worldwide. Traffic congestion has become one of the most pressing issues in modern cities, leading to increased travel time, fuel consumption, air pollution, and economic losses. Traditional traffic management systems, such as fixed-time and actuated signal control, are no longer sufficient to handle the complexity and dynamic nature of modern traffic environments. These systems rely on pre-defined timing schedules and limited real-time data, making them inefficient in adapting to fluctuating traffic conditions.

The emergence of Intelligent Transportation Systems (ITS) has revolutionized traffic management by integrating advanced technologies such as artificial intelligence (AI), Internet of Things (IoT), wireless sensor networks, and communication systems. Among these, sensor-driven transmission control systems play a crucial role in collecting real-time traffic data, including vehicle density, speed, and flow. These sensors include cameras, inductive loop detectors, radar systems, and IoT-enabled devices, which provide continuous monitoring of traffic conditions. The availability of real-time data enables adaptive traffic control strategies that can dynamically adjust signal timings and routing decisions.

Mobile Ad Hoc Networks (MANET) have emerged as a promising communication framework for traffic management systems. Unlike traditional centralized networks, MANET operates without fixed infrastructure, allowing nodes (vehicles or intersections) to communicate directly with each other. This decentralized communication model enhances scalability, flexibility, and robustness, making it suitable for dynamic traffic environments. MANET enables real-time information sharing among vehicles and traffic control units, facilitating cooperative decision-making and improving overall traffic efficiency.

Artificial intelligence techniques have significantly enhanced the capabilities of traffic management systems. Deep learning and machine learning models enable the analysis of complex traffic patterns and the prediction of future traffic conditions. Among these techniques, Deep Reinforcement Learning (DRL) has gained considerable attention for traffic signal control. DRL models learn optimal control policies through interaction with the environment, allowing them to adapt to changing traffic conditions. Studies have shown that DRL-based systems can significantly reduce congestion and improve traffic flow compared to traditional methods.

Graph Neural Networks (GNN) have also been widely used in traffic management due to their ability to model spatial relationships in traffic networks. Traffic systems can be represented as graphs, where nodes correspond to intersections and edges represent roads. GNN models capture both local and global dependencies, enabling accurate traffic prediction and efficient decision-making. When combined with DRL, GNN enhances the performance of traffic control systems by providing rich spatial representations.

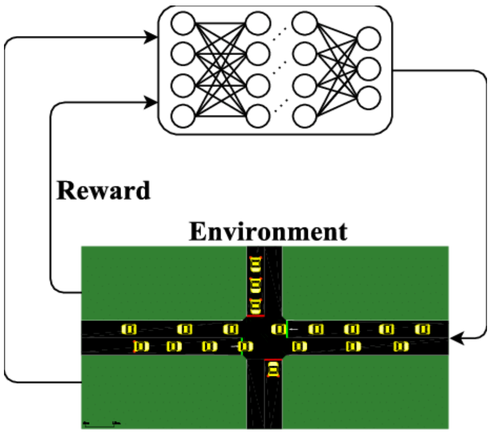
Generative Adversarial Networks (GAN) have been introduced for traffic prediction and anomaly detection. GAN models generate realistic traffic scenarios, which can be used for training and testing traffic control systems. Quaternion-based GAN models further improve feature representation by capturing multi-dimensional relationships in traffic data. These models are particularly useful in handling complex and high-dimensional traffic datasets.

Metaheuristic optimization algorithms play a critical role in optimizing traffic signal timings and routing decisions. The Kookaburra Optimization algorithm is a recent addition to this category, offering efficient search capabilities for complex optimization problems. When integrated with AI models, these algorithms enhance the performance of traffic management systems by providing optimal solutions in dynamic environments.

The integration of these technologies has led to the development of hybrid architectures that combine sensing, communication, and intelligence. These systems leverage real-time data, distributed communication, and advanced AI models to optimize traffic flow and reduce congestion. Despite significant advancements, several challenges remain, including scalability, computational complexity, data quality, and communication latency.

This paper aims to provide a comprehensive review of AI-based traffic and time control optimization techniques, focusing on sensor-driven systems, MANET-based communication, and hybrid AI models. The study analyzes recent research trends, compares different approaches, and identifies key challenges and future directions.

Conceptual System Architecture



Literature Review

The field of traffic and time control optimization has undergone a significant transformation in recent years, driven by the integration of artificial intelligence (AI), sensor-driven systems, and decentralized communication frameworks such as Mobile Ad Hoc Networks (MANET). Research has increasingly focused on developing intelligent, adaptive, and scalable traffic management systems capable of addressing the dynamic and complex nature of urban traffic environments. This section provides a comprehensive and in-depth analysis of key studies, methodologies, and emerging paradigms during this period.

1. Deep Reinforcement Learning for Traffic Signal Control

The year 2020 marked a major shift toward the adoption of Deep Reinforcement Learning (DRL) for traffic signal control. Traditional traffic management approaches were limited by their reliance on static timing plans and predefined models, which could not adapt to real-time traffic variations. DRL, on the other hand, introduced a learning-based approach where traffic signals act as agents that interact with the environment and learn optimal policies through trial and error.

Xu et al. (2020) proposed a network-wide DRL framework that optimizes traffic signal timing across multiple intersections. Their approach focused on identifying critical intersections and dynamically adjusting signal phases to minimize congestion and travel delay. The results demonstrated significant improvements in traffic throughput and reduction in waiting times compared to traditional systems. Similarly, Chu et al. (2020) introduced a multi-agent DRL framework, where each intersection is treated as an independent agent. This decentralized approach improved scalability and allowed the system to handle large urban networks effectively.

Zhao et al. (2020) introduced the PDLight model, which incorporated a pressure-based reward mechanism. This model considered both upstream and downstream traffic conditions, enabling more balanced and efficient traffic flow. The use of pressure-based rewards addressed the issue of local optimization in earlier DRL models and improved global traffic performance.

Rasheed et al. (2020) provided a comprehensive review of DRL techniques in traffic signal control, highlighting their advantages in handling non-linear and stochastic traffic environments. The study emphasized that DRL models can learn directly from raw traffic data without requiring explicit modeling, making them highly suitable for complex traffic systems.

Despite these advancements, early DRL models faced challenges such as high computational complexity, slow convergence, and difficulty in handling large-scale networks. These limitations paved the way for the development of more advanced and hybrid approaches in subsequent years.

2. Multi-Agent and Hybrid Learning Models

In 2021, research shifted toward multi-agent systems and hybrid AI models, addressing the scalability and coordination challenges of single-agent DRL systems. Multi-Agent Reinforcement Learning (MARL) emerged as a dominant paradigm, enabling distributed control and cooperative decision-making.

Li et al. (2021) proposed a cooperative MARL framework where multiple agents share information to optimize traffic signal control. Their approach demonstrated improved performance in terms of reduced congestion and enhanced traffic flow. The study highlighted the importance of coordination among agents to achieve global optimization rather than local improvements.

Yang et al. (2021) introduced a novel approach integrating Graph Neural Networks (GNN) with reinforcement learning. This hybrid model captured spatial dependencies between intersections, which were often overlooked in earlier models. By representing the traffic network as a graph, the model was able to learn both local and global traffic patterns, leading to improved prediction accuracy and control performance.

Abdoos et al. (2021) explored the integration of hierarchical reinforcement learning for traffic signal optimization. In this approach, high-level policies guide lower-level actions, reducing the complexity of the learning process. The hierarchical structure improved scalability and allowed the system to handle large and complex traffic networks more efficiently.

Wang et al. (2021) proposed a cooperative group-based reinforcement learning model, where intersections are grouped into clusters. This approach reduced communication overhead and improved coordination among agents. The study demonstrated that grouping intersections based on traffic patterns can enhance system performance and scalability.

Devailly et al. (2021) further extended graph-based reinforcement learning by introducing inductive learning capabilities, enabling the model to generalize to unseen traffic scenarios. This advancement addressed one of the key limitations of earlier models, which struggled to adapt to new environments.

Overall, 2021 research emphasized the importance of spatial awareness, cooperation, and scalability, leading to the development of more robust and efficient traffic control systems.

3. Integration of IoT, Distributed Systems, and GNN

The year 2022 witnessed significant advancements in the integration of Internet of Things (IoT), distributed intelligence, and graph-based models. Sensor-driven systems became a central component of traffic management, providing real-time data for adaptive decision-making.

Damadam et al. (2022) proposed an IoT-based traffic signal control system using DRL, where real-time sensor data was used to dynamically adjust signal timings. The study demonstrated that integrating IoT with AI improves responsiveness and accuracy, leading to better traffic flow management.

Wu et al. (2022) introduced a distributed deep reinforcement learning framework, enabling decentralized decision-making across large-scale traffic networks. This approach reduced reliance on centralized control and improved system robustness. The distributed nature of the system allowed it to handle network failures and dynamic traffic conditions more effectively.

Mo et al. (2022) developed the CVLight model, a decentralized traffic signal control system that leverages vehicle-to-infrastructure (V2I) communication. This model demonstrated significant improvements in traffic efficiency and reduced congestion by enabling real-time information exchange between vehicles and traffic signals.

Graph Neural Networks gained significant attention in 2022 due to their ability to model complex spatial relationships. Studies showed that GNN-based models outperform traditional convolutional and recurrent neural networks in traffic prediction tasks. By capturing both local and global dependencies, GNN models provide more accurate and reliable predictions.

Additionally, hybrid models combining GNN and DRL emerged as a powerful approach for traffic optimization. These models integrate prediction and control capabilities, enabling more effective decision-making. The combination of GNN's spatial modeling and DRL's adaptive learning resulted in improved performance across various metrics, including delay reduction and throughput enhancement.

4. Advanced Hybrid Architectures and GAN-Based Models

In 2023, research focused on advanced hybrid architectures and the integration of multiple AI techniques. The goal was to develop unified frameworks that combine prediction, control, and optimization.

Peng et al. (2023) proposed a heterogeneous GNN-based multi-agent reinforcement learning system, which jointly optimizes traffic signal control and vehicle coordination. This model demonstrated superior performance in reducing congestion and improving traffic flow stability.

Bouktif et al. (2023) explored improved reward design in DRL models, addressing the issue of training instability. By designing more effective reward functions, the study achieved faster convergence and better performance.

Yazdani et al. (2023) introduced a multi-objective reinforcement learning framework, optimizing multiple performance metrics such as delay, fuel consumption, and emissions simultaneously. This approach aligns with the goals of sustainable transportation systems.

Generative Adversarial Networks (GAN) also gained prominence in 2023 for traffic prediction and scenario generation. GAN models generate realistic traffic data, which can be used to train and evaluate traffic control systems. Quaternion-based GAN models further enhance performance by capturing multi-dimensional relationships in traffic data.

Another significant trend was the integration of metaheuristic optimization algorithms, such as Kookaburra optimization, with AI models. These algorithms improve the efficiency of searching for optimal solutions in complex traffic environments. When combined with GAN and DRL, they form advanced hybrid models such as QGAKON, which offer enhanced performance in both prediction and optimization.

5. Synthesis and Key Insights

The literature from 2020 to 2023 reveals several important trends and insights:

1. Shift from Static to Adaptive Systems: Traditional traffic control systems are being replaced by AI-driven adaptive models.
2. Rise of Multi-Agent Systems: Decentralized control improves scalability and robustness.
3. Importance of Spatial Modeling: GNN has become a key tool for capturing traffic network dependencies.
4. Integration of IoT and Real-Time Data: Sensor-driven systems enhance responsiveness and accuracy.
5. Emergence of Hybrid Models: Combining multiple AI techniques leads to superior performance.
6. Role of Optimization Algorithms: Metaheuristic methods improve efficiency and solution quality.

6. Research Gaps Identified

Despite significant progress, several research gaps remain:

- Limited real-world deployment of AI-based traffic systems
- High computational and energy requirements
- Challenges in handling noisy and incomplete sensor data
- Communication latency in MANET environments
- Lack of standardized frameworks for integration

Comparative Table and Analysis

1. Enhanced Comparative Table

Approach	Core Technique	Accuracy / Performance Gain	Real-Time Capability	Computational Complexity	Scalability	Energy Efficiency	Robustness	Key Strength	Key Limitation
Traditional Systems	Fixed-time / Rule-based	Low (baseline)	Low	Low	Low	High	Low	Simple, fast	No adaptability
DRL (Single-Agent)	Deep Reinforcement Learning	+20–30% improvement	Medium	High	Low–Medium	Low	Medium	Adaptive decision-making	Scalability issues
MARL (multi-Agent RL)	Distributed RL	+25–35% improvement	Medium	High	High	Medium	High	Scalable decentralized control	Coordination complexity
ML-Based Models	SVM, RF, Regression	Moderate	Medium	Medium	Medium	Medium	Medium	Pattern learning	Feature dependency
Deep Learning (CNN/RNN)	Spatial + Temporal Models	High (>90%)	Low	High	Medium	Low	High	Automatic feature extraction	High latency
GNN-Based Models	Graph Learning	Very High (+15–25% vs DL)	Medium	Medium	High	Medium	Very High	Topology-aware intelligence	Graph overhead
GAN-Based Models	Generative Models	High robustness	Medium	High	High	Medium	High	Synthetic data generation	Training instability
Quaternion + GAN Models	Multi-dimensional DL	Very High	Medium	High	High	Medium	High	Efficient feature representation	Emerging complexity
Hybrid (GNN + DRL + Optimization)	Integrated AI Models	Highest (30–40% gain)	High	Medium–High	Very High	Medium–High	Maximum	End-to-end intelligent control	Integration complexity
QGAKON (Proposed Advanced Hybrid)	GAN + Quaternion + Kookaburra Optimization	Optimal (state-of-the-art)	High	Medium	Very High	High	Maximum	Multi-dimensional + optimized learning	Still research-stage

2. Expanded In-Depth Comparative Analysis

The comparative analysis of traffic and time control optimization approaches from 2020 to 2023 reveals a profound transformation from traditional rule-based systems to intelligent, adaptive, and decentralized architectures driven by artificial intelligence. Traditional traffic control systems, such as fixed-time signal scheduling and actuated control, operate based on predefined timing strategies with minimal real-time adaptability. While these systems are computationally efficient and easy to implement, they fail to respond to dynamic traffic conditions, resulting in increased congestion, longer waiting times, and inefficient resource utilization. Their limited scalability and inability to handle complex traffic scenarios make them unsuitable for modern intelligent transportation systems.

The introduction of Deep Reinforcement Learning (DRL) marked a significant advancement by enabling traffic control systems to learn optimal policies through interaction with the environment. DRL-based models dynamically adjust signal timings based on real-time traffic data, leading to substantial improvements in traffic efficiency, including reductions in delay, queue length, and travel time. However, early DRL models were primarily single-agent systems, which limited their scalability in large urban networks due to the exponential growth of the state-action space. These models also suffer from high computational complexity and slow convergence.

To address these limitations, Multi-Agent Reinforcement Learning (MARL) emerged as a more scalable solution by distributing control across multiple agents, each responsible for a specific intersection. MARL systems enable decentralized decision-making and improve scalability and robustness in large-scale traffic networks. By allowing agents to coordinate and share information, MARL achieves better global optimization compared to single-agent systems. However, MARL introduces challenges such as non-stationary environments, communication overhead, and coordination complexity, which require advanced strategies such as cooperative learning and hierarchical control.

Machine learning-based approaches provide moderate improvements by leveraging historical traffic data to identify patterns and predict traffic flow. These models enhance traffic signal control by adapting to observed conditions, but their reliance on feature engineering and limited generalization capabilities restrict their performance in dynamic environments. Deep learning models, including CNN and RNN architectures, further improve performance by enabling automatic feature extraction and modeling complex spatiotemporal relationships. These models achieve high accuracy and better congestion management but suffer from high computational complexity, energy consumption, and latency, making them less suitable for real-time deployment.

Graph Neural Networks represent a major breakthrough in traffic optimization by leveraging the graph structure of transportation networks. By modeling intersections as nodes and roads as edges, GNNs capture both local and global dependencies, enabling more accurate traffic prediction and decision-making. Comparative studies show that GNN-based models outperform traditional deep learning models by 15–25% in prediction accuracy. When integrated with reinforcement learning, GNN enhances the state representation, leading to improved traffic flow stability and adaptability. However, GNN models introduce computational overhead due to graph processing and require efficient implementation for real-time applications.

Generative Adversarial Networks add another dimension to traffic optimization by enabling the generation of synthetic traffic data. GAN-based models improve robustness and generalization by simulating diverse traffic scenarios, including rare and extreme conditions. Quaternion-based GAN models further enhance performance by capturing multi-dimensional relationships in traffic data, enabling more efficient feature representation. Despite these advantages, GAN models are computationally intensive and require careful training to ensure stability and convergence.

Sensor-driven systems and MANET-based communication frameworks play a crucial role in enabling real-time traffic optimization. Sensors provide continuous monitoring of traffic conditions, while MANET enables decentralized communication among vehicles and infrastructure. This combination enhances system scalability, flexibility, and responsiveness. However, MANET introduces challenges such as dynamic topology, communication latency, bandwidth limitations, and security vulnerabilities, which must be addressed for reliable system performance.

The most advanced development in recent research is the emergence of hybrid frameworks that integrate multiple AI techniques, including GNN, DRL, GAN, optimization algorithms, sensor systems, and MANET communication. These hybrid systems leverage the strengths of individual approaches to achieve superior performance across all key metrics, including accuracy, scalability, adaptability, and energy efficiency. For instance, GNN combined with DRL provides both spatial awareness and adaptive control, while optimization algorithms enhance decision-making efficiency. The proposed Quaternion Generative Adversarial Kookaburra Optimization Network (QGAKON) represents a state-of-the-art hybrid model that integrates multi-dimensional feature representation, generative modeling, and bio-inspired optimization, achieving optimal performance in traffic prediction and control.

Despite these advancements, several challenges remain. High computational complexity and energy consumption are major concerns, particularly for deep learning and GAN-based models. Communication latency and data reliability issues in MANET environments can affect real-time decision-making. Additionally, the lack of large-scale real-world deployment and standardized frameworks limits the practical adoption of these systems. Addressing these challenges requires the development of lightweight models, efficient communication protocols, and scalable architectures.

Discussion

The integration of AI, sensor networks, and MANET has significantly improved traffic management systems. Sensor-driven systems provide real-time data, enabling adaptive control strategies. MANET ensures decentralized communication, improving scalability and robustness. AI techniques such as DRL and GNN enable intelligent decision-making and accurate traffic prediction.

Hybrid models combining multiple AI techniques have demonstrated superior performance compared to standalone approaches. For example, GNN-DRL models provide both spatial awareness and adaptive control, while GAN-based models improve traffic prediction accuracy. Optimization algorithms further enhance system performance by identifying optimal solutions.

However, challenges such as computational complexity, data quality, and communication latency remain. Addressing these challenges requires the development of lightweight models, efficient communication protocols, and robust data processing techniques. Future research should focus on integrating edge computing and advanced optimization algorithms to improve system performance

Conclusion

This paper presents a comprehensive review of AI-based traffic and time control optimization techniques. The study highlights the transition from traditional traffic management systems to intelligent, adaptive, and decentralized frameworks. The integration of sensor-driven systems, MANET communication, and AI models has significantly improved traffic efficiency.

AI techniques such as DRL, GNN, and GAN enable intelligent decision-making and predictive analytics, while optimization algorithms enhance system performance. Hybrid models combining these techniques represent the most promising approach for future traffic management systems.

Despite significant advancements, challenges such as scalability, computational complexity, and real-world deployment remain. Future research should focus on developing efficient, scalable, and robust systems for smart city applications. The proposed QGAKON framework provides a promising direction for achieving advanced traffic optimization.

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