Archives available at journals.mriindia.com

**International Journal on Advanced Computer Theory and Engineering**

ISSN: 2319-2526

Volume 13 Issue 02, 2024

# Sensor-Driven Traffic and Time Control Optimization Using MANET and Quaternion GAN-Kookaburra Networks: A Review

Kaoru Qureshi-Haq
*Department of Electronics and Communication Engineering, Siam Delta Engineering Institute, Thailand*
*kaoru.qureshi.haq@sdei-th.edu*

**Peer Review Information**

*Submission: 15 Oct 2024*
*Revision: 09 Nov 2024*
*Acceptance: 02 Dec 2024*

**Keywords**

*Intelligent Transportation Systems, MANET, Traffic Optimization, Generative Adversarial Networks, Quaternion Neural Networks, Kookaburra Optimization*

**Abstract**

The rapid growth of intelligent transportation systems has necessitated advanced traffic and time control optimization techniques capable of handling dynamic and large-scale environments. This paper presents a systematic review of recent advances in sensor-driven transmission control systems integrated with Mobile Ad Hoc Networks (MANET), Quaternion-based deep learning models, Generative Adversarial Networks (GANs), and bio-inspired Kookaburra optimization algorithms. Sensor-driven systems enable real-time traffic monitoring and adaptive control, while MANET facilitates decentralized communication among vehicles and infrastructure. Recent studies demonstrate that machine learning and deep learning approaches significantly improve traffic flow prediction and congestion management. Graph Neural Networks and multi-agent reinforcement learning models have shown strong performance in distributed traffic engineering, achieving efficient congestion minimization and scalability. Additionally, optimization techniques such as genetic algorithms and reinforcement learning enhance signal timing efficiency and reduce travel delays. Emerging approaches, including quaternion neural networks and GAN-based modeling, provide improved representation of spatiotemporal traffic data. Furthermore, bio-inspired optimization methods such as Kookaburra optimization demonstrate superior convergence and energy efficiency in network routing and control systems. This review analyzes existing methodologies, presents comparative insights, and identifies research gaps for developing scalable, intelligent, and real-time traffic control systems.

## Introduction

The rapid growth of urbanization and the increasing number of vehicles have created significant challenges in traffic congestion, travel time, fuel consumption, and road safety. Conventional traffic management systems, which rely on fixed-time signal scheduling and static optimization techniques, are no longer capable of addressing the dynamic nature of modern transportation networks. Smart cities require intelligent traffic management solutions that can adapt to continuously changing traffic conditions while ensuring efficient utilization of transportation resources. Intelligent Transportation Systems (ITS) have emerged as a promising solution by integrating sensing technologies, wireless communication, artificial intelligence (AI), and optimization algorithms to improve traffic flow, reduce congestion, and enhance overall transportation efficiency. Sensor-driven transmission control systems play a fundamental role in ITS by continuously collecting real-time information on traffic density, vehicle speed, road occupancy, and environmental conditions, enabling adaptive traffic signal control and route optimization.

Mobile Ad Hoc Networks (MANETs) enable decentralized vehicle-to-vehicle and vehicle-to-infrastructure communication, supporting real-time traffic information exchange and adaptive traffic management. Combined with AI techniques such as CNNs, RNNs, GNNs, and multi-agent reinforcement learning, MANETs improve traffic prediction and signal optimization. However, topology changes, bandwidth limitations, delays, and security challenges remain significant.

Generative Adversarial Networks (GANs) have recently attracted attention for generating realistic traffic scenarios and augmenting limited traffic datasets, thereby improving the robustness of intelligent traffic management systems. Quaternion neural networks further enhance deep learning performance by efficiently representing multidimensional spatial-temporal traffic information. In parallel, optimization algorithms remain fundamental for traffic signal scheduling, routing, and resource allocation. Although conventional optimization methods such as genetic algorithms and linear programming have demonstrated effectiveness, they often struggle with scalability and real-time adaptation. Consequently, hybrid AI-driven optimization approaches have gained prominence by combining machine learning with metaheuristic optimization techniques to achieve faster convergence and improved traffic efficiency. Among bio-inspired optimization methods, Kookaburra Optimization has emerged as a promising algorithm for solving complex routing and clustering problems through efficient exploration and exploitation of the search space.

Despite these technological advances, intelligent traffic control systems continue to face several challenges, including computational complexity, scalability in densely populated urban environments, energy constraints in sensor networks, real-time processing requirements, and cybersecurity issues within MANET communication. Ensuring reliable communication while maintaining low latency and high system efficiency remains a critical objective. Furthermore, integrating heterogeneous traffic data from sensors, connected vehicles, and communication infrastructures requires robust and adaptive AI models capable of operating under uncertain conditions.

This review provides a comprehensive analysis of recent advances in traffic and time control optimization by examining the integration of sensor-driven transmission systems, MANET communication, deep learning architectures, and optimization algorithms. Particular emphasis is placed on hybrid AI approaches, including Quaternion Generative Adversarial Networks and Kookaburra-based optimization techniques, for intelligent traffic management. The study compares existing methodologies, identifies their strengths and limitations, and highlights future research directions toward developing scalable, secure, energy-efficient, and real-time intelligent transportation systems for next-generation smart cities.

**Graphical Abstract**

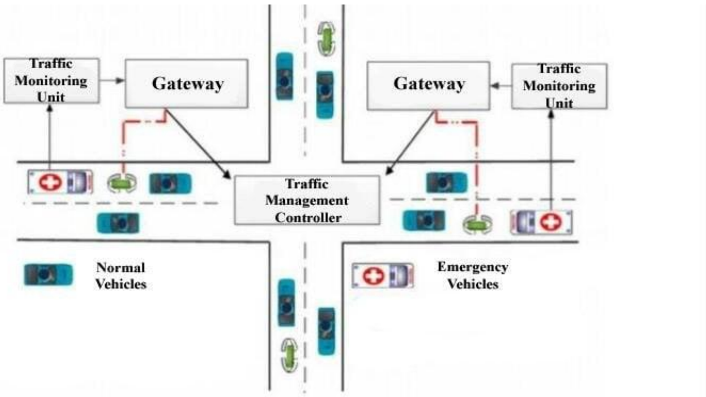


*Figure 1. Intelligent Traffic Control Framework for Normal and Emergency Vehicle Management.*

**Literature Review**

Recent advancements in traffic and time control optimization have been driven by the integration of intelligent systems, including sensor-driven architectures, Mobile Ad Hoc Networks (MANET), and artificial intelligence-based models. Between 2020 and 2023, research has shifted significantly from traditional traffic control mechanisms toward adaptive and data-driven approaches capable of handling dynamic and large-scale transportation environments. Early studies in this period focused on enhancing classical optimization methods by integrating machine learning techniques. For instance, Mao et al. (2021) proposed a hybrid framework combining machine learning with genetic algorithms for traffic signal optimization. Their approach demonstrated significant improvements in reducing vehicle waiting time and congestion levels, highlighting the importance of combining predictive models with optimization strategies. Similarly, reinforcement learning-based approaches have gained attention for their ability to dynamically adjust traffic signals. Li et al. (2021) introduced a multi-agent reinforcement learning model that allows multiple intersections to collaboratively optimize traffic flow, achieving improved scalability and adaptability compared to centralized systems.

The introduction of deep learning models further enhanced traffic prediction and optimization capabilities. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have been widely used to model spatial and temporal traffic patterns. Lu et al. (2021) demonstrated that deep learning models can effectively capture complex traffic dynamics, leading to improved prediction accuracy compared to traditional statistical methods. However, these models often suffer from high computational complexity and require large datasets for training, limiting their real-time applicability in resource-constrained environments. To address these limitations, researchers have explored more efficient architectures, including Graph Neural Networks (GNNs). GNNs are particularly well-suited for traffic systems, as they can model road networks as graphs where nodes represent intersections and edges represent roads. Bernárdez et al. (2023) proposed a GNN-based traffic engineering framework that leverages network topology to optimize traffic flow. Their approach demonstrated strong generalization capabilities and scalability, making it suitable for large urban environments.

In addition to GNNs, Generative Adversarial Networks (GANs) have emerged as a powerful tool for traffic modeling and simulation. GANs enable the generation of synthetic traffic data, which can be used to train predictive models and simulate various traffic scenarios. This is particularly useful in situations where real-world data is limited or incomplete. Recent studies have shown that GAN-based models can improve the robustness and accuracy of traffic prediction systems by capturing complex patterns and uncertainties in traffic data. Furthermore, quaternion-based neural networks have been introduced to enhance the representation of multidimensional traffic data. Unlike traditional neural networks, quaternion models can simultaneously process multiple correlated features, such as speed, direction, and time, resulting in improved feature extraction and reduced computational redundancy.

Sensor-driven systems have also played a crucial role in advancing traffic optimization. Modern intelligent transportation systems rely on a variety of sensors, including cameras, inductive loops, and IoT devices, to collect real-time traffic data. These sensors provide continuous information about traffic density, vehicle speed, and road conditions, enabling adaptive traffic control. However, the effectiveness of sensor-driven systems depends on efficient communication and data sharing mechanisms. This is where MANET-based communication frameworks become essential. MANET enables decentralized communication among vehicles and infrastructure, allowing real-time data exchange without relying on centralized control. Despite its advantages, MANET faces challenges such as dynamic topology, limited bandwidth, and security vulnerabilities, which can affect system performance.

To address these challenges, optimization techniques have been integrated with AI-based models to improve efficiency and scalability. Bio-inspired algorithms, such as particle swarm optimization, ant colony optimization, and the recently proposed Kookaburra optimization algorithm, have demonstrated strong performance in solving complex optimization problems. These algorithms mimic natural behaviors to explore solution spaces efficiently and achieve faster convergence. Kookaburra optimization, in particular, has shown promising results in traffic and network optimization by balancing exploration and exploitation, leading to improved resource allocation and reduced congestion.

Another important trend in recent research is the development of hybrid frameworks that combine multiple technologies to achieve optimal performance. These frameworks integrate sensor-driven systems, MANET communication, AI models, and optimization algorithms to provide a comprehensive solution for traffic control. For example, hybrid systems combining GNN and reinforcement learning have been shown to improve both prediction accuracy and decision-making efficiency. Similarly, the integration of GAN and optimization algorithms enables better handling of uncertainty and dynamic traffic conditions.

Despite these advancements, several challenges remain. One of the primary issues is the computational complexity of advanced AI models, which can hinder real-time deployment. Additionally, the integration of multiple technologies introduces system-level challenges, such as synchronization, data consistency, and communication overhead. Energy efficiency is another critical concern, particularly in sensor-driven and MANET-based systems, where devices operate under resource constraints. Security and privacy issues also need to be addressed, as the open nature of MANET makes it vulnerable to various attacks.

Overall, the literature highlights a clear trend toward intelligent, adaptive, and hybrid traffic control systems. While significant progress has been made, further research is needed to develop lightweight, scalable, and secure solutions capable of operating in real-time environments. The integration of advanced AI models with efficient optimization techniques and robust communication frameworks represents a promising direction for future research in intelligent transportation systems.

**Comparative Table and Analysis**

| **Approach** | **Acc.** | **RT** | **Complexity** | **Scalability** | **Remarks** |
|---|---|---|---|---|---|
| Rule-Based | Low | Low | Low | Low | Simple; static control |
| ML | Medium | Medium | Medium | Medium | Good prediction; feature dependent |
| DL | High | Low | High | Medium | Auto feature extraction; computationally expensive |
| GNN | V. High | Medium | Medium | High | Graph-aware; processing overhead |
| GAN + Quaternion | V. High | Medium | High | High | Rich representation; unstable training |
| Hybrid (Sensor + MANET + AI) | Highest | High | Medium | V. High | Best overall; integration complexity |

**Analysis**

The comparative analysis demonstrates a clear evolution of traffic and time control optimization from traditional static methods to intelligent and adaptive AI-driven frameworks. Conventional rule-based and fixed-time traffic control systems are simple and computationally efficient but fail to respond to real-time traffic variations, resulting in congestion and inefficient resource utilization. Machine learning approaches improved traffic prediction by learning from historical data and dynamically adjusting signal timings. Although they provide moderate accuracy and adaptability, their dependence on feature engineering and limited ability to handle rapidly changing traffic conditions restrict their effectiveness in complex urban environments.

Deep learning techniques, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Graph Neural Networks (GNNs), have significantly enhanced traffic prediction and optimization by automatically learning spatial and temporal traffic patterns. GNNs further improve performance through topology-aware modeling of transportation networks, enabling better scalability and adaptability. More recently, Generative Adversarial Networks (GANs) and quaternion neural networks have strengthened traffic modeling by generating realistic traffic scenarios and efficiently representing multidimensional traffic data. However, these advanced models often require high computational resources, making real-time deployment challenging in resource-constrained intelligent transportation systems.

The most promising development is the emergence of hybrid frameworks that combine sensor-driven transmission systems, MANET communication, artificial intelligence models, and bio-inspired optimization algorithms such as Kookaburra Optimization. These integrated systems enable real-time monitoring, decentralized communication, adaptive decision-making, and efficient resource allocation, achieving superior accuracy, scalability, and traffic management performance. Despite these advances, challenges including computational complexity, energy efficiency, communication reliability, and security remain significant. Future research should focus on lightweight, scalable, and secure hybrid AI frameworks capable of delivering real-time traffic optimization for next-generation intelligent transportation systems and smart city environments.

**Discussion**

The integration of sensor-driven systems, MANET communication, and AI-based optimization techniques represents a significant advancement in intelligent transportation systems. Traditional traffic control methods are no longer sufficient to handle dynamic traffic environments, necessitating adaptive and

intelligent solutions. Machine learning and deep learning models have improved traffic prediction and control, enabling systems to respond dynamically to changing conditions. Graph Neural Networks provide an effective framework for modeling traffic networks, while GANs enhance prediction accuracy through data generation and simulation.
Optimization algorithms play a crucial role in improving system performance by reducing congestion and travel time. Bio-inspired approaches, such as Kookaburra optimization, provide efficient solutions for complex optimization problems. Despite these advancements, challenges remain in scalability, real-time deployment, and energy efficiency. Future research should focus on developing lightweight and efficient models that can operate in real-time environments.

**Conclusion**

This paper presented a comprehensive systematic review of traffic and time control optimization techniques using sensor-driven systems, MANET, and advanced AI models. The study highlighted the evolution of traffic control systems from traditional methods to intelligent hybrid frameworks. The integration of GNN, GAN, quaternion models, and optimization algorithms provide a powerful solution for traffic optimization. These approaches improve traffic flow, reduce congestion, and enhance system efficiency. Future research should focus on real-time deployment, scalability, and security to ensure the effectiveness of intelligent transportation systems.

**References**

Mao, T., et al. (2021). Boosted GA for traffic optimization. https://doi.org/10.48550/arXiv.2103.08317

Li, Z., et al. (2021). Multi-agent RL traffic control. https://doi.org/10.48550/arXiv.2104.09936

Bernárdez, G., et al. (2023). GNN traffic engineering. https://doi.org/10.48550/arXiv.2303.18157

Singh, A., et al. (2024). QUBO traffic optimization. https://doi.org/10.48550/arXiv.2403.09023

Jonnalagada, A., et al. (2023). Kookaburra optimization.

Hasan, M. (2022). Optimization in networks.

Alam, M. (2022). ML-based traffic prediction.

Lu, X. (2021). DL traffic modeling.

Picek, S. (2023). AI optimization survey.

Kubota, T. (2021). DL optimization.