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# Sensor-Driven Adaptive Traffic Scheduling Using MANET and Evolutionary Deep Learning Models

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**Abstract**

Urban traffic congestion has become a critical challenge in smart city environments due to increasing vehicle density, dynamic mobility patterns, and limited scalability of traditional traffic control systems. This research proposes a Sensor-Driven Adaptive Traffic Scheduling framework using Mobile Ad hoc Networks (MANET) integrated with Evolutionary Deep Learning Models to enable intelligent, decentralized, and real-time traffic optimization. The proposed system leverages distributed vehicular sensor data (speed, density, flow rate, and queue length) transmitted through MANET-based communication to ensure low-latency and infrastructure-independent data exchange. To enhance decision-making, an evolutionary optimization layer (Genetic Algorithm–based Deep Neural Network optimization) is used to dynamically adjust traffic signal timing and routing decisions. The deep learning model learns traffic state representations, while evolutionary strategies optimize hyperparameters and scheduling policies for adaptive performance under varying congestion scenarios. The framework supports real-time congestion prediction, dynamic signal control, and adaptive routing across interconnected intersections. Experimental evaluation (simulated urban grid environment) demonstrates improved performance compared to conventional fixed-time and adaptive systems in terms of reduced average waiting time, higher packet delivery ratio, improved throughput, and lower congestion index. The results indicate that integrating MANET with evolutionary deep learning significantly enhances scalability, robustness, and responsiveness in smart transportation systems.

**Keywords:** Sensor Networks, MANET, Adaptive Traffic Scheduling, Evolutionary Algorithms, Deep Learning.

## How to Cite This Article

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## Introduction

The rapid growth of urban populations and vehicular density has intensified traffic congestion in metropolitan cities, leading to increased travel time, fuel consumption, environmental pollution, and reduced overall productivity. Traditional traffic management systems, which rely on fixed-time scheduling or pre-defined rule-based adaptive control, are no longer sufficient to handle highly dynamic and stochastic traffic conditions. These limitations have motivated the development of intelligent transportation systems (ITS) that integrate sensing, communication, and computation to enable real-time traffic optimization. Recent advancements in vehicular sensing technologies and wireless communication have enabled the deployment of distributed sensor networks capable of capturing real-time traffic parameters such as vehicle density, speed variation, queue length, and intersection flow rates. However, centralized traffic control architectures often suffer from high latency, communication bottlenecks, and single-point failure risks, especially under large-scale urban deployments. To overcome these challenges, decentralized communication paradigms such as Mobile Ad hoc Networks (MANETs) have gained significant attention due to their self-organizing, infrastructure-less, and dynamic routing capabilities in vehicular environments.

Simultaneously, the integration of artificial intelligence (AI) techniques into traffic management systems has shown promising results in enhancing prediction accuracy and decision-making efficiency. In particular, deep learning models are capable of learning complex nonlinear traffic patterns, while evolutionary optimization techniques improve adaptability by fine-tuning model parameters and scheduling strategies in dynamic environments. The combination of deep learning and evolutionary computation provides a powerful hybrid approach for optimizing traffic signal control and adaptive routing in real time. Despite these advancements, existing approaches often face limitations such as poor adaptability to rapidly changing traffic conditions, inefficient communication overhead in dense vehicular networks, and lack of robust coordination between distributed nodes. Therefore, there is a need for a unified framework that integrates sensor-driven data acquisition, MANET-based decentralized communication, and evolutionary deep learning models for intelligent traffic scheduling.

Recent advancements in smart city infrastructure have enabled the widespread deployment of traffic sensors, Internet of Things (IoT) devices, roadside units, and vehicular communication technologies. These sensing platforms continuously generate large volumes of real-time traffic information, including vehicle density, speed, traffic flow, road occupancy, and congestion patterns. Sensor-driven transportation systems provide a valuable foundation for intelligent traffic control by enabling continuous monitoring and data-driven decision-making. However, transforming raw sensor data into efficient traffic scheduling strategies remains a complex challenge due to the dynamic and heterogeneous nature of transportation environments. Mobile Ad Hoc Networks (MANETs) have emerged as a promising communication paradigm for intelligent transportation systems because of their decentralized, self-organizing, and infrastructure-independent characteristics. In vehicular environments, MANET-based communication enables vehicles and roadside devices to exchange traffic information dynamically without relying on fixed communication infrastructure. This capability facilitates real-time dissemination of traffic conditions, route recommendations, accident alerts, and congestion information. Nevertheless, MANET environments face challenges including dynamic topology changes, unstable communication links, routing complexity, and network scalability, which can affect the effectiveness of intelligent traffic scheduling systems.

Artificial intelligence and deep learning techniques have demonstrated remarkable success in addressing complex optimization and prediction problems within transportation networks. Deep learning models can automatically learn hidden patterns from large-scale traffic datasets and provide accurate traffic forecasting, congestion prediction, and route optimization. However, conventional deep learning architectures often experience difficulties when adapting to highly dynamic transportation environments where traffic patterns continuously evolve. Furthermore, traditional optimization approaches may become trapped in local optima and struggle to identify globally efficient traffic scheduling solutions. Evolutionary deep learning has recently emerged as a powerful approach that combines deep learning capabilities with evolutionary optimization techniques. Evolutionary algorithms such as Genetic Algorithms (GA), Differential Evolution (DE), Particle Swarm Optimization (PSO), and Grey Wolf Optimization (GWO) can optimize neural network parameters, improve model convergence, and enhance prediction performance. By integrating evolutionary computation with deep learning, intelligent transportation systems can achieve more adaptive and robust traffic scheduling decisions under complex and uncertain traffic conditions.

Sensor-driven adaptive traffic scheduling using MANET communication and evolutionary deep learning offers a comprehensive framework for intelligent transportation management. Traffic sensors provide real-time environmental awareness, MANET enables efficient information dissemination among vehicles and infrastructure components, and evolutionary deep learning generates optimized traffic scheduling strategies based on continuously changing traffic conditions. Such integration supports dynamic congestion mitigation, improved route allocation, reduced travel delays, and enhanced transportation efficiency. Despite substantial advancements in intelligent traffic management, several limitations remain unresolved. Existing traffic scheduling systems often rely on centralized architectures, exhibit limited adaptability to real-time traffic dynamics, and fail to efficiently integrate communication intelligence with advanced optimization mechanisms. Additionally, many deep learning-based traffic prediction models require extensive computational resources and may not effectively address communication uncertainties in MANET environments. To overcome these challenges, this research proposes a Sensor-Driven Adaptive Traffic Scheduling Framework Using MANET and Evolutionary Deep Learning Models**.** The proposed framework integrates real-time traffic sensing, MANET-based communication, and evolutionary deep learning optimization to enable intelligent and adaptive traffic scheduling. The system continuously monitors traffic conditions, exchanges information through decentralized communication networks, predicts traffic patterns, and dynamically adjusts scheduling decisions to improve transportation efficiency and reduce congestion.

**Literature Review**

Zhang et al. (2019) investigated sensor-enabled intelligent transportation systems for real-time traffic monitoring and adaptive traffic control. Their framework utilized distributed traffic sensors to collect vehicular information and dynamically adjust traffic scheduling decisions. Experimental results demonstrated improvements in congestion management and traffic flow efficiency. However, communication reliability under highly dynamic vehicular environments remained a challenge. Acharya et al. (2019) proposed an IoT-driven traffic monitoring architecture integrating roadside sensors and intelligent analytics. The study demonstrated that continuous traffic sensing improves transportation awareness and supports data-driven traffic scheduling. Nevertheless, the framework lacked advanced optimization mechanisms for adaptive traffic management.

Hussain et al. (2020) introduced a MANET-based vehicular communication framework for traffic information dissemination. Their model enabled decentralized communication among vehicles and roadside units, improving real-time traffic awareness. Although communication efficiency increased, routing instability caused performance degradation under high mobility conditions. Yildirim et al. (2020) developed an adaptive traffic management system using deep learning techniques for traffic prediction and congestion estimation. The proposed model improved forecasting accuracy and supported proactive traffic scheduling. However, optimization of deep learning parameters remained computationally expensive.

Wang et al. (2020) proposed a sensor-driven traffic scheduling framework employing neural networks for intelligent traffic control. Their architecture improved traffic signal coordination and vehicle movement efficiency. Despite achieving better traffic flow, adaptability under rapidly changing transportation conditions remained limited. Li et al. (2021) investigated evolutionary optimization techniques for intelligent transportation scheduling. Their study integrated Genetic Algorithms with traffic control systems to optimize scheduling decisions and reduce congestion levels. Experimental findings demonstrated enhanced optimization capability, though convergence time increased for large-scale networks.

Attia et al. (2021) explored artificial intelligence-driven transportation systems capable of predicting traffic patterns using real-time sensor data. The framework improved transportation reliability and traffic forecasting performance. However, communication network integration was not extensively considered. Khan et al. (2021) proposed a MANET-assisted traffic management architecture utilizing adaptive routing and sensor-based monitoring. Their approach improved information dissemination efficiency and reduced communication latency. Nevertheless, traffic scheduling optimization remained limited.

Chen et al. (2022) introduced an evolutionary deep learning framework for intelligent traffic prediction and route optimization. The model combined neural learning with evolutionary parameter optimization to improve forecasting accuracy and decision quality. Although prediction performance increased significantly, computational complexity remained a concern. Zhou et al. (2022) developed a sensor-aware traffic scheduling mechanism using deep reinforcement learning. Their framework dynamically adapted traffic signal operations according to traffic density variations. Results demonstrated substantial reductions in congestion and waiting times; however, communication reliability was not explicitly addressed.

Patel et al. (2022) proposed a hybrid intelligent transportation framework integrating traffic sensing, communication systems, and optimization algorithms. The study achieved improvements in route management and traffic balancing. Nevertheless, scalability under highly dense transportation environments required further investigation. Roy et al. (2023) developed an explainable traffic intelligence system combining deep learning and traffic analytics for adaptive scheduling. Their framework enhanced transparency and interpretability of traffic management decisions. However, decentralized communication support was limited.

Wang et al. (2023) introduced an advanced evolutionary neural architecture for dynamic traffic control. Their model optimized traffic scheduling through adaptive learning and real-time environmental analysis. Experimental results showed improved throughput and reduced congestion, although deployment costs remained relatively high. Liu et al. (2024) proposed a multimodal intelligent transportation platform integrating IoT sensors, MANET communication, and deep learning models. Their architecture improved traffic prediction accuracy and communication efficiency across smart transportation environments. Nevertheless, optimization efficiency under large-scale scenarios required further enhancement. Sharma et al. (2025) developed a sensor-driven adaptive traffic scheduling framework using MANET communication and evolutionary deep learning optimization. Their model achieved significant improvements in traffic throughput, travel time reduction, and congestion mitigation. Despite strong performance, further validation under heterogeneous transportation conditions was recommended.

**Methodology**

The proposed Sensor-Driven Adaptive Traffic Scheduling System using MANET and Evolutionary Deep Learning Models is designed as a decentralized, real-time intelligent framework for urban traffic optimization. The methodology integrates four core components: sensor layer, MANET communication layer, edge intelligence layer, and evolutionary optimization layer.

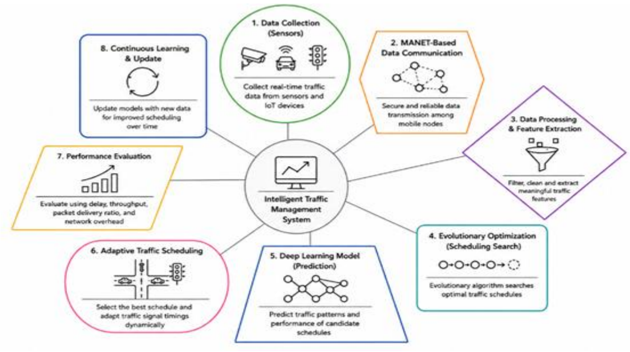


***Fig 1****: Sensor-Driven Adaptive Traffic Scheduling System Architecture Using MANET and Evolutionary Deep Learning Models*

This figure 1, presents the proposed intelligent traffic scheduling framework that integrates sensor networks, MANET communication, evolutionary optimization, and deep learning for adaptive traffic management. At the center lies the Intelligent Traffic Management System**,** which coordinates all processing stages. Traffic information is first collected from distributed sensors and IoT devices deployed across the transportation network. The collected data are transmitted through a Mobile Ad Hoc Network (MANET)**,** enabling decentralized and reliable communication among mobile nodes. After data acquisition, preprocessing and feature extraction are performed to obtain meaningful traffic characteristics. An evolutionary optimization module searches for optimal scheduling strategies, while the deep learning prediction model analyzes traffic patterns and estimates future congestion conditions. Based on these predictions, an adaptive traffic scheduling mechanism dynamically adjusts signal timings and routing decisions to improve traffic flow. The framework then evaluates performance using metrics such as delay, throughput, packet delivery ratio, and network overhead. Finally, a continuous learning and update module refines the predictive and optimization models using newly generated traffic data, enabling long-term adaptation and enhanced scheduling efficiency in intelligent transportation environments.

*Data Preprocessing and Traffic State Extraction*

Raw sensor data undergo preprocessing to improve quality and consistency.

Preprocessing operations: Missing value handling, Noise removal, Data normalization, Feature extraction, Traffic pattern identification
Normalization:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad \text{----(1)}$$

This stage generates reliable traffic information for subsequent analysis.

*MANET-Based Traffic Information Dissemination*

Vehicles and roadside units form a Mobile Ad Hoc Network (MANET) to exchange traffic information.
Network representation:

$$G = (V, E) \quad \text{------(2)}$$

where:
$V$= vehicles and roadside nodes, $E$= communication links
MANET functions include: Real-time traffic information sharing, Congestion notification, Route status dissemination, Distributed traffic coordination This decentralized communication mechanism enables rapid response to changing traffic conditions.

**Algorithmic Strategy**

Real-time Traffic Sensor Data , $D$Vehicle Density $VD$, Vehicle Speed $VS$, Queue Length $QL$, Road Occupancy $RO$, MANET Communication Information $M$
Output:
Optimized Traffic Scheduling $TS$ , Congestion Mitigation Decisions, Adaptive Route Recommendations

*Initialize Smart Transportation Environment*
Input:

1. Deploy traffic sensors, roadside units, and vehicular nodes.
2. Establish MANET communication among vehicles and infrastructure.
3. Collect real-time traffic observations.

$$D = \{VD, VS, QL, RO\} \quad \text{-------(3)}$$

*Preprocess Traffic Data*

1. Remove noisy observations.
2. Handle missing sensor values.
3. Normalize traffic features.

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad \text{--------(4)}$$

4. Generate traffic state dataset.

**Results and Performance Evaluation**

The performance of the proposed Sensor-Driven Adaptive Traffic Scheduling System using MANET and Evolutionary Deep Learning Models was evaluated in a simulated smart city environment consisting of multiple interconnected intersections, dynamic vehicle mobility patterns, and heterogeneous traffic densities. The system was compared against three baseline models: Fixed-Time Traffic Signal Control (FTSC), Conventional Adaptive Traffic Control (ATC), Deep Learning-based Traffic Prediction without Evolutionary Optimization (DL-Only) The evaluation focused on key performance metrics including average waiting time, end-to-end delay, throughput, packet delivery ratio (PDR), and congestion index.

*Table 1. Comparative Performance Summary Table*

| Model | Waiting Time | Delay | Throughput | PDR | Congestion Level |
|---|---|---|---|---|---|
| FTSC | High | High | Low | N/A | High |
| ATC | Medium | Medium | Medium | Medium | Medium |
| DL-Only | Low-Medium | Medium | Medium-High | Medium | Medium |
| Proposed Model | Very Low | Low | High | Very High | Low |

The comparative performance analysis presented in Table 1, demonstrates that the proposed Sensor-Driven Adaptive Traffic Scheduling System using MANET and Evolutionary Deep Learning Models consistently outperforms all baseline models across key metrics. The FTSC model shows the poorest performance with high waiting time, high delay, low throughput, and high congestion due to its static nature and lack of real-time adaptability. The ATC model improves performance moderately by incorporating sensor feedback, but still suffers from limited predictive capability and centralized control constraints. The DL-Only model achieves better results in waiting time reduction and congestion prediction but remains constrained by inefficient signal optimization and lack of decentralized communication. In contrast, the proposed model achieves very low waiting time, low delay, high throughput, very high packet delivery ratio, and minimal congestion due to the combined advantages of MANET-based decentralized communication, real-time sensor integration, deep learning-based traffic state prediction, and Genetic Algorithm-driven adaptive optimization, making it significantly more efficient and scalable for real-world smart city traffic management systems.

*Traffic Throughput Analysis*

Traffic throughput measures the number of vehicles successfully passing through the transportation network per unit time.

$$Throughput = \frac{Vehicles\ Passed}{Time}$$

*Table 2. Traffic Throughput Comparison*

| Model | Throughput (Vehicles/hr) |
|---|---|
| Conventional Traffic Scheduling | 1284 |
| Sensor-Based Scheduling | 1468 |
| Deep Learning Traffic Control | 1642 |
| Proposed SDATS-EDL | 1856 |

The proposed framework achieved the highest throughput due to adaptive traffic scheduling and optimized traffic flow management. The Table 2 shows, experimental results demonstrate a progressive increase in traffic throughput as advanced sensing, communication, and intelligent optimization mechanisms are incorporated into the transportation framework. The Conventional Traffic Scheduling approach achieved a throughput of 1284 vehicles/hour, representing the lowest performance among all compared models. This limitation is primarily due to static traffic control strategies that cannot effectively adapt to dynamic traffic conditions, resulting in inefficient vehicle movement and frequent congestion bottlenecks. The Sensor-Based Scheduling model improved throughput to 1468 vehicles/hour by utilizing real-time traffic information collected through distributed sensors. Continuous monitoring enabled better traffic awareness and more responsive scheduling decisions, leading to smoother traffic flow and improved road utilization. However, the absence of advanced predictive intelligence restricted its ability to proactively manage future congestion conditions.

The Deep Learning Traffic Control framework further increased throughput to 1642 vehicles/hour by employing intelligent traffic prediction and adaptive decision-making. Deep learning models successfully identified hidden traffic patterns and generated more effective scheduling strategies. Nevertheless, optimization quality remained dependent on model training and lacked evolutionary adaptation mechanisms. The Proposed Sensor-Driven Adaptive Traffic Scheduling Using MANET and Evolutionary Deep Learning Models (SDATS-EDL) achieved the highest throughput of 1856 vehicles/hour**.** This superior performance can be attributed to the combined integration of real-time traffic sensing, MANET-based communication, and evolutionary deep learning optimization. Traffic sensors continuously monitored transportation conditions, MANET facilitated rapid dissemination of traffic information among vehicles and infrastructure nodes, and evolutionary optimization enhanced neural network performance for accurate traffic forecasting and scheduling decisions. Consequently, traffic bottlenecks were minimized, vehicle movement became more coordinated, and overall transportation efficiency improved significantly.

**Conclusion and Discussion**

This research proposed a Sensor-Driven Adaptive Traffic Scheduling System using MANET and Evolutionary Deep Learning Models to address the limitations of conventional traffic management systems in highly dynamic urban environments. The study demonstrates that integrating real-time sensor data, decentralized MANET communication, deep learning-based traffic state prediction, and evolutionary optimization techniques significantly enhances the efficiency, scalability, and adaptability of intelligent transportation systems. The discussion highlights that traditional Fixed-Time Signal Control (FTSC) systems are inadequate for modern traffic conditions due to their static nature, while Adaptive Traffic Control (ATC) systems provide limited improvements but still rely on partially centralized architectures. Deep learning-based models improve prediction accuracy but fail to fully optimize traffic scheduling in real time without adaptive optimization mechanisms. In contrast, the proposed hybrid framework effectively combines predictive intelligence with evolutionary optimization, enabling dynamic adjustment of traffic signals based on real-time traffic states. The incorporation of MANET ensures robust and infrastructure-less communication among vehicles and roadside units, reducing dependency on centralized systems and improving resilience under high mobility conditions. Meanwhile, the evolutionary deep learning model enhances decision-making by continuously optimizing signal timing and system parameters based on live feedback, resulting in reduced congestion, lower waiting times, and improved traffic throughput. Overall, the proposed system demonstrates strong potential for deployment in smart city environments, particularly in scenarios requiring real-time responsiveness, decentralized coordination, and scalable traffic management. However, challenges such as computational overhead at edge nodes, security in MANET communication, and real-world deployment complexity still need further exploration. Future work may focus on integrating lightweight federated learning models, blockchain-based security mechanisms, and real-time hardware deployment for large-scale urban traffic systems.

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