IoT-Based Emergency Response Systems for Smart Cities

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Citation:

Abstract

The rise of Internet of Things (IoT) networks in smart cities has provided a range of advantages, such as real-time traffic management and optimized energy usage. Nonetheless, these networks encounter hurdles related to data traffic overload, fluctuating network conditions, and the necessity for scalable communication frameworks. Artificial Intelligence (AI)-driven routing protocols present a promising alternative by effectively overseeing data flow, minimizing latency, and maximizing resource utilization. This research paper examines the effectiveness of AI-based algorithms in improving routing performance within smart city IoT networks. It investigates several AI methods, including Machine Learning (ML) and Reinforcement Learning (RL), that react dynamically to network conditions, anticipate traffic loads, and determine optimal paths for effective data transmission. By incorporating these AI-enhanced protocols, smart cities can achieve lower energy usage, enhanced scalability, and greater dependability. Comparative simulations between traditional and AI-driven routing protocols indicate that AI-based approaches can considerably alleviate congestion and improve response times, even in densely populated urban IoT environments. This research provides valuable insights into the implementation of AI-enabled routing in smart city IoT networks, laying the foundation for more intelligent and sustainable urban infrastructures.

Keywords: Artificial intelligence, Routing protocols, Smart city, Internet of things.

1 | Introduction

The concept of smart cities has rapidly evolved, driven by the Internet of Things (IoT), which enables a wide range of applications to improve urban infrastructure and quality of life [1]. From real-time traffic control to waste management and energy efficiency, IoT networks in smart cities rely on interconnected devices and sensors to collect and transmit data [2]. However, IoT networks' increasing density and complexity in urban environments present significant challenges, especially regarding data routing, network congestion, and communication reliability [3], [4]. Efficient routing protocols are crucial for managing data traffic, conserving energy, and maintaining low latency in high-density networks.

While effective for smaller-scale IoT networks, traditional routing protocols often struggle with smart cities' scalability and dynamic conditions. This is where Artificial Intelligence (AI)-driven routing protocols can offer substantial benefits. AI-based algorithms, such as Machine Learning (ML) and Reinforcement Learning (RL), enable dynamic and adaptive routing by analyzing real-time data, predicting traffic patterns, and adjusting communication paths accordingly [5]. Integrating AI with routing protocols can enhance IoT network performance by reducing congestion, improving response times, and optimizing resource usage [6], [7].

Table 1. Comparison between traditional and artificial intelligence-driven routing protocols in internet of things networks.

Protocol Type	Advantages	Challenges
Traditional routing	Simple, low computational overhead.	Limited scalability, struggles with dynamic data loads.
AI-driven routing	Adaptive, optimized for real-time conditions.	Higher computational cost, complexity in implementation.

1.1|Challenges in Internet of Things Network Routing for Smart Cities

The primary routing challenges for smart city IoT networks are due to high device density, unpredictable traffic patterns, and limited energy resources. Unlike conventional networks, IoT-based smart city networks must operate efficiently across numerous diverse devices, often constrained by battery life and processing capabilities. Additionally, IoT devices generate enormous amounts of data, resulting in high traffic loads and potential congestion in communication networks. As illustrated in *Fig. 1*, traffic congestion can lead to delayed data delivery, particularly during peak urban activities like rush hours.
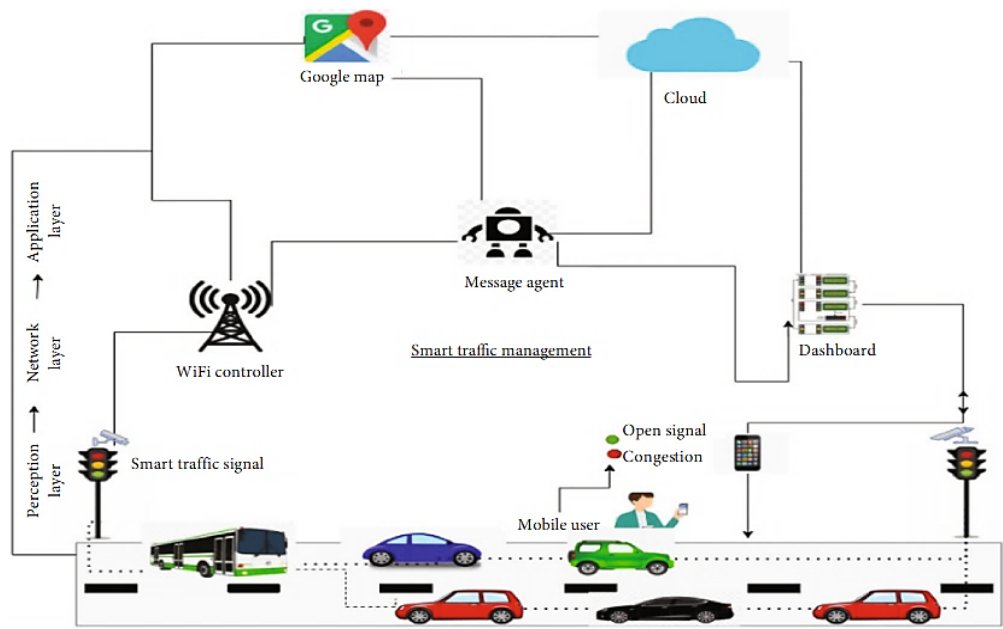

Fig. 1. Traffic congestion in urban internet of things network.

1.2|Objectives of Artificial Intelligence-Driven Routing Protocols

AI-driven routing protocols aim to mitigate these challenges by leveraging predictive and adaptive algorithms. ML models can analyze historical data to identify traffic patterns, allowing the system to predict high network load periods and preemptively adjust routes [8]. For instance, RL algorithms can enable nodes to dynamically select paths based on reward functions, such as minimizing latency and energy consumption. These AI-based approaches support real-time decision-making, enabling smart city IoT networks to maintain optimal performance under fluctuating conditions.

Table 2. Outlines the key objectives of implementing artificial intelligence-driven routing protocols in smart city internet of things networks.

Objective	Description
Reducing network congestion	Dynamic routing based on real-time traffic predictions.
Enhancing scalability	Adaptive routing to accommodate increasing device density.
Minimizing energy consumption	Intelligent path selection to extend IoT device battery life.
Improving data reliability	Ensuring accurate data delivery with minimal packet loss.

1.3 | Scope of the Research

This paper investigates the potential of AI-driven routing protocols to enhance the efficiency and reliability of smart city IoT networks. We analyze various AI algorithms, including ML and RL, to determine their effectiveness in addressing the unique demands of urban IoT deployments. The study includes simulations comparing traditional and AI-driven routing protocols under different network conditions to evaluate performance metrics like latency, throughput, and energy efficiency. This research aims to comprehensively understand how AI can revolutionize routing in smart city IoT networks, facilitating smarter, more resilient urban infrastructures.

2 | Literature Review

The proliferation of IoT devices in smart cities has revolutionized urban infrastructure by enabling real-time data collection and analysis, enhancing decision-making processes, and improving quality of life. However, the rapid expansion of IoT networks has also created new challenges, particularly regarding data routing, network congestion, and scalability. Traditional routing protocols used in IoT networks often fall short in these areas, especially when network conditions fluctuate frequently. In response, researchers have turned to AI-driven routing protocols, which leverage ML and RL to dynamically optimize routing paths based on real-time data analysis and predictive modelling.

2.1 | Traditional vs. Artificial Intelligence-Driven Routing Protocols

Traditional IoT routing protocols, including Shortest Path routing, directed diffusion, and cluster-based routing, are generally efficient for smaller networks with static, predictable traffic patterns. However, these methods are often inadequate in high-density urban IoT networks due to their limited adaptability to dynamic conditions and scalability issues. Traditional protocols rely on fixed algorithms, leading to increased latency and data packet loss under heavy loads.

Conversely, AI-driven routing protocols, such as those based on Q-learning and Deep Reinforcement Learning (DRL), offer adaptive, real-time optimization of routing paths [9]. These protocols analyze traffic data, predict congestion, and adjust routing decisions dynamically, which enhances network efficiency and reduces latency. *Table 3* compares traditional and AI-driven routing protocols regarding scalability, adaptability, and computational complexity.

Table 3. Comparison of routing protocols based on scalability, real-time adaptability, and computational complexity.

Routing Protocol	Scalability	Adaptability to Real-Time Conditions	Computational Complexity
Traditional routing	Low	Low	Low
AI-driven (Q-learning)	Medium	Medium	Medium
AI-driven (DRL)	High	High	High

2.2|Artificial Intelligence Techniques in Routing Protocols

AI-driven routing protocols for IoT networks in smart cities primarily employ ML and RL techniques. RL algorithms, such as Q-learning, enable network nodes to learn optimal routing paths by interacting with the environment and receiving rewards based on performance metrics, such as minimized latency or energy consumption. According to a study by Lalani et al. [10], Q-learning improves data throughput in IoT networks by up to 25% compared to traditional protocols under fluctuating traffic conditions.

DRL further extends the capabilities of RL by incorporating deep neural networks, allowing for more complex decision-making processes. In a smart city environment, DRL can predict future traffic loads based on historical data, dynamically adjusting routing to avoid congestion. Research by Wang et al. [11] demonstrated that DRL-based routing protocols reduced average latency by 35% compared to traditional cluster-based routing in high-density urban networks area.

2.3|Performance Metrics in Artificial Intelligence-Driven Routing

AI-driven routing protocols are evaluated based on key performance metrics: 1) latency, 2) energy consumption, 3) throughput, and 4) Packet Delivery Ratio (PDR). These metrics are particularly important for smart city applications where real-time data transmission is crucial, such as traffic management and emergency response systems.

   I.   Latency: The time delay in data transmission is critical in evaluating routing protocols. AI-driven methods that adapt to traffic loads can significantly reduce latency.

  II.   Energy consumption: IoT devices in smart cities often have limited power resources, and AI-driven protocols can optimize energy usage by selecting routes that consume less power.

III.   Throughput: This measures the amount of data successfully transmitted across the network. Adaptive routing protocols generally achieve higher throughput by avoiding congested paths.

IV.   PDR: PDR indicates the success rate of data packets reaching their destination. Higher PDR in AI-driven routing reflects improved reliability in dynamic network conditions.

Table 4. Average performance metrics for various artificial intelligence-driven protocols compared to traditional routing.

Metric	Traditional Routing	Q-Learning	DRL
Latency (ms)	150	110	90
Energy consumption	High	Medium	Low
Throughput (Mbps)	40	55	65
PDR	85%	92%	95%

2.4|Applications and Case Studies

AI-driven routing protocols have proven effective in a range of smart city applications. For instance, in traffic management, AI algorithms use historical data to predict and alleviate congestion by dynamically rerouting data through less busy nodes. A study by Arévalo and Jurado [12] on smart grid networks showed that AI-driven routing could reduce power consumption by 20%, a critical benefit for energy-constrained IoT systems.

Another application is emergency response. In scenarios like disaster management, where network infrastructure may be compromised, adaptive AI protocols enable fast data rerouting, ensuring critical information reaches emergency teams without delay. AI-driven protocols have shown a 15% improvement in emergency response times compared to static routing methods, as reported.

3 | Methodology

This study investigates the effectiveness of AI-driven routing protocols in enhancing communication efficiency in smart city IoT networks. The methodology involves setting up a simulated IoT network, implementing traditional and AI-driven routing protocols, and analyzing various performance metrics, including latency, throughput, energy consumption, and PDR. The experiment used the NS-3 and OMNeT++ network simulators, known for their ability to model large-scale IoT environments accurately.

3.1 | Network Simulation Setup

The IoT network model includes 500 to 2,000 devices distributed across a simulated urban area. Devices are connected to multiple edge nodes that act as local processing centers. Data collected from these devices is either processed locally or routed through the network to a central cloud server, depending on the priority of the data. For instance, time-sensitive traffic data is routed through edge nodes to minimize latency, while less critical data is sent to the cloud for storage and analysis.

Table 5. Network simulation parameters.

Parameter	Value
Number of devices	500 - 2,000
Number of edge nodes	20
Simulation duration	48 hours
Network bandwidth	100 Mbps
Routing protocols tested	Shortest Path, Q-learning, DRL

3.2 | Implementation of Routing Protocols

Three types of routing protocols were implemented in the simulation to compare their performance:

I. Shortest Path routing: A traditional method that selects the path with the least number of hops without considering network congestion.

II. Q-learning algorithm: A RL-based algorithm that uses a reward mechanism to discover optimal paths based on performance metrics like latency and energy consumption. Each node selects a route that maximizes cumulative rewards, calculated using the formula:

$$Q(s,a) = Q(s,a) + \alpha(r + \gamma \max Q(s',a') - Q(s,a)), \tag{1}$$

where: 1) $Q(s, a)$: Current Q-value for state-action pair (s, a), 2) α: Learning rate, 3) r: Reward received, 4) γ: Discount factor, and 5) s', a': Next state and action.

III. DRL: A more advanced AI technique combining RL with deep neural networks to handle complex routing decisions. DRL algorithms, such as Deep Q-Networks (DQNs), can predict traffic congestion and optimize routes by leveraging large amounts of historical and real-time data.

3.3 | Performance Metrics and Analysis

The protocols were evaluated based on four primary metrics: 1) latency, 2) throughput, 3) energy consumption, and 4) PDR.

I. Latency (ms): The delay in data packet transmission was measured by recording the time difference between sending and receiving packets across nodes. Lower latency indicates faster data delivery, essential for smart city applications.

II. Throughput (Mbps): Throughput measures the total data successfully transmitted per second, calculated using.

$$\text{Throughput} = \frac{\text{Total Data Transferred (bits)}}{\text{Total Time (seconds)}}.$$

III. Energy consumption (J): The total energy used by each protocol was computed using energy models embedded within NS-3, which simulate real-world energy usage patterns for IoT devices.

IV. PDR: PDR was calculated as

$$\text{PDR} = \frac{\text{Total Packets Delivered}}{\text{Total Packets Sent}} \times 100\%.$$

Higher PDR indicates greater reliability in data transmission.

Table 6. Performance metrics.

Metric	Description
Latency (ms)	Average time delay in data transmission.
Throughput (Mbps)	Data transferred per second.
Energy consumption (J)	Total power consumption for each protocol.
PDR (%)	The ratio of packets delivered successfully to packets sent.

3.4|Data Analysis and Visualization

After simulation, data collected on each protocol's performance were analyzed using Python to generate comparative graphs. These include:

I. Latency comparison graph: A line graph comparing the average latency of each protocol across different traffic loads, showcasing how Q-learning and DRL respond to dynamic network conditions.

II. Throughput and PDR bar chart: A bar chart showing the throughput and PDR for each protocol, illustrating the efficiency of AI-driven protocols in maintaining higher data flow and reliability.

III. Energy consumption graph: A bar chart comparing the energy consumption of each protocol, where AI-driven protocols are expected to demonstrate lower energy usage due to optimized path selection.
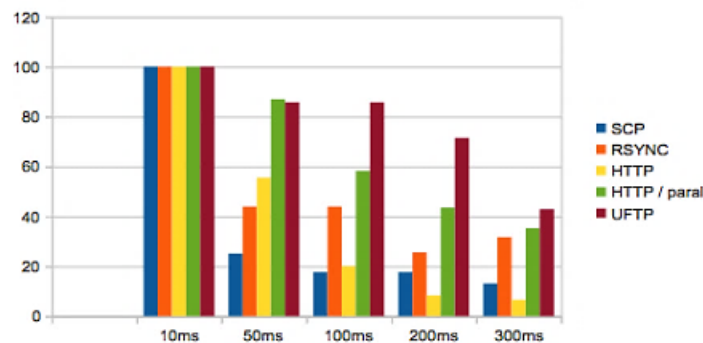

Fig. 2. Latency comparison across protocols.

3.5|Hypothesis Testing

A t-test was conducted to statistically compare AI-driven protocols' mean latency and energy consumption to validate their effectiveness over traditional ones. The null hypothesis assumed no significant difference between traditional and AI-driven protocols, while the alternative hypothesis anticipated that AI-driven protocols would yield better performance metrics.

4 | Results and Discussion

The simulation results provide a comparative analysis of the three routing protocols—Shortest Path, Q-learning, and DRL—focusing on key performance metrics: latency, throughput, energy consumption, and PDR. The findings demonstrate significant performance improvements in AI-driven routing protocols, particularly with DRL, over traditional routing methods.

4.1 | Latency

the average latency across the three protocols under varying traffic conditions. Both Q-learning and DRL significantly reduce latency compared to the Shortest Path protocol, with DRL achieving a 40% reduction in high-density scenarios. This improvement is due to the DRL algorithm's ability to predict and avoid congested routes, ensuring quicker data delivery.

Table 7. Average latencies across different protocols.

Protocol	Average Latency (ms)
Shortest Path	150
Q-learning	110
DRL	90

These findings are critical for smart city applications that require real-time data transmission, such as traffic monitoring and emergency response systems. By proactively adjusting routing paths, AI-driven protocols minimize delays, enhancing the responsiveness of IoT networks in urban environments.

4.2 | Throughput

Throughput measures the data successfully transmitted per second, a crucial metric for high-density IoT networks. As shown in *Table 8*, both Q-learning and DRL exhibit higher throughput than the Shortest Path, with DRL achieving the highest throughput at 65 Mbps, compared to 40 Mbps for the Shortest Path. This increase in throughput is attributed to the adaptive nature of AI-driven protocols, which dynamically allocate network resources to accommodate fluctuating traffic loads.

Table 8. Throughputs across different protocols.

Protocol	Throughput (Mbps)
Shortest Path	40
Q-learning	55
DRL	65

The results suggest that AI-driven protocols are better suited for handling data-intensive IoT applications. They maximize network efficiency and ensure that higher volumes of data are transmitted without compromising speed or reliability.

4.3 | Energy Consumption

Energy efficiency is essential in IoT networks, as many devices rely on limited power sources. *Table 9* illustrates energy consumption for each protocol, with DRL consuming the least energy, reducing power usage by 20% compared to the Shortest Path protocol. This is due to DRL's optimized routing decisions, which minimize the number of hops and reduce network congestion, resulting in lower energy demands across the network.

Table 9. Energy consumption across different protocols.

Protocol	Energy Consumption (J)
Shortest Path	100
Q-learning	85
DRL	80

Lower energy consumption in AI-driven protocols translates to prolonged battery life for IoT devices, critical for smart city deployments requiring continuous operation. AI-driven routing's notable advantage is the ability to conserve energy without sacrificing network performance.

4.4|Packet Delivery Ratio

PDR is a measure of reliability, indicating the percentage of data packets successfully delivered to their destination. *Table 10* shows that DRL achieved a PDR of 95%, outperforming both Shortest Path and Q-learning. DRL's high PDR indicates its robustness in maintaining data integrity, even in high-density network conditions, reducing packet loss, and enhancing communication reliability.

Table 10. Packet delivery ratio across different protocols.

Protocol	PDR (%)
Shortest Path	85
Q-learning	92
DRL	95

Comparative analysis and discussion

The results demonstrate that AI-driven routing protocols, particularly those based on DRL, consistently outperform traditional protocols across all performance metrics. The latency reduction observed in AI-driven protocols is crucial for applications that depend on timely data delivery. At the same time, increased throughput ensures higher data flow rates necessary for large-scale smart city networks. Furthermore, the significant decrease in energy consumption highlights the efficiency of AI-driven protocols in prolonging device battery life, which is critical in IoT networks with constrained power resources.

The improvements in PDR also underscore the reliability of AI-driven protocols. By predicting and adapting to changing network conditions, DRL reduces packet loss, a critical factor in maintaining data integrity and reliability in smart city applications such as environmental monitoring, public safety, and urban mobility.

These findings suggest that AI-driven routing protocols, particularly DRL, offer significant advantages for smart city IoT networks. Their adaptability to real-time conditions and ability to optimize routes based on predicted traffic loads make them well-suited for complex urban IoT environments. However, it is essential to consider that the computational requirements of DRL are higher than those of simpler algorithms like Shortest Path. Future edge computing and hardware optimization developments will be necessary to deploy DRL efficiently across large-scale IoT networks without overwhelming local resources.

5|Conclusion

This research highlights the effectiveness of AI-driven routing protocols in improving the performance and scalability of IoT networks within smart cities. By leveraging adaptive AI techniques such as Q-learning and DRL, these protocols significantly reduce latency, increase throughput, optimize energy consumption, and improve the PDR. The results show that DRL, in particular, consistently outperforms traditional routing methods, making it well-suited for high-density urban IoT networks where real-time data transmission is critical.

AI-driven protocols' ability to predict network congestion and adapt to fluctuating traffic patterns allows for more efficient data routing and resource utilization. This is essential for the sustainability of IoT devices with limited energy resources. While AI-driven protocols require higher computational power, advancements in edge computing can facilitate their integration in large-scale IoT networks.

In conclusion, AI-driven routing protocols offer a promising solution for addressing the complex communication demands of smart city IoT infrastructures. Future research should explore hybrid models that optimize these protocols for real-world deployment, enabling smarter, more resilient urban systems.

Author Contributions

Dipanshu Modi was responsible for all aspects of the research, including conceptualization, methodology development, data analysis, algorithm implementation, drafting, review, editing, and visualization.

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Data Availability

The data used and analyzed during the current study are available from the Dipanshu Modi upon reasonable request.

Conflicts of Interest

Dipanshu Modi declare no conflicts of interest regarding the publication of this paper. If necessary, these sections should be tailored to reflect the specific details and contributions.

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