A Digital Twin-Based Adaptive Routing Framework for Energy-Efficient Networks

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Abstract

The Internet of Things (IoT) has become a key technology enabling applications in healthcare, transportation, manufacturing, and smart cities. However, managing the vast, dynamic IoT networks presents challenges, particularly in energy-efficient routing. Traditional routing protocols, such as static and Distance Vector (DV) routing, are inadequate for IoT networks, which are constrained by energy limitations and dynamic conditions like node mobility and congestion. This paper presents a state-aware multi-hop routing scheme integrated with Digital Twin (DT) technology to optimize routing performance in IoT networks. DT, a real-time virtual replica of physical systems, enables the continuous monitoring and prediction of network conditions, such as energy levels, traffic status, and potential failures. The proposed model utilizes metaheuristic optimization algorithms like Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) to dynamically select the optimal routing paths, considering the state of each node and the network as a whole. This approach enhances IoT network performance, reduces energy consumption, and mitigates network failures. Additionally, DT contributes to security by simulating potential threats and proactively preventing attacks. The model's efficiency is demonstrated through a comparative analysis with existing protocols, showing significant improvements in network throughput, energy efficiency, and latency.

Keywords: Digital Twin (DT), IoT Networks, State-Aware Routing, Multi-Hop Routing, Energy Efficiency, Metaheuristic Optimization, Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Network Performance

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Introduction

The Internet of Things (IoT) has revolutionized the way devices connect and communicate, enabling a wide range of applications, from smart homes to healthcare and industrial automation. IoT networks consist of numerous interconnected devices that collect, process, and transmit data, facilitating real-time decision-making and automation. However, managing these networks efficiently remains a significant challenge due to the dynamic and resource-constrained nature of IoT environments. Traditional routing protocols, such as static and shortest-path routing, are not well-suited to the rapidly changing conditions of IoT networks. In particular, the mobility of nodes, limited energy resources, and congestion issues lead to inefficient data transmission and higher energy consumption. To address these challenges, state-aware multi-hop routing has emerged as a more adaptive solution. This routing method takes into account the real-time status of network devices, such as their energy levels, traffic load, and connection quality, to make informed routing decisions. However, even state-aware routing faces limitations when scaling across large IoT networks with highly dynamic conditions. Digital Twin (DT) technology, which creates a virtual replica of physical systems, offers a powerful solution to this problem. By providing real-time simulation and predictive capabilities, DT allows for continuous monitoring and optimization of IoT networks. In this paper, we explore the integration of state-aware multi-hop routing with DT technology to enhance the performance, energy efficiency, and reliability of IoT networks. This approach enables IoT devices to make dynamic, informed decisions based on the current and predicted state of the network, improving the overall efficiency and resilience of IoT systems.

Literature Review

Shivani Dave et al. (2025) propose a multi-hop state-aware routing protocol for IoT networks, addressing the inefficiencies of traditional routing methods in dynamic, large-scale IoT environments. By using deep learning (DL), deep reinforcement learning (DRL), whale optimization algorithm (WOA), and deep belief networks (DBN), the approach improves energy efficiency and reduces latency in wireless sensor networks (WSNs), crucial for applications in smart cities and healthcare. The proposed method promises better reliability and fault tolerance in real-time scenarios, particularly for large IoT systems like smart cities.

Supat Roongpraiwan et al. (2025) introduce a Digital Twin (DT)-enabled blockage-aware dynamic multi-hop routing scheme for mmWave V2X communication. This approach leverages real-time data from mobility DTs to optimize routing decisions in vehicle networks, significantly improving connectivity (up to 99.62% to 100%). The model outperforms existing methods, particularly in complex environments, showing great potential for CAVs and ITS systems. Future work aims at refining scalability and validating real-world applications.

Cakir et al. (2025) present the Intelligent Digital Twin Communication Framework (IDTC), which addresses the accuracy-timeliness trade-off in resource-limited networks. By utilizing predictive synchronization (PS) and the DTSYNC protocol, the model minimizes errors and staleness, achieving better performance with lower communication overhead. Their solution, which increases Fresnel zone throughput by approximately 3.8 times, is effective in bandwidth- and energy-constrained scenarios, making it suitable for realistic DT-assisted networks.

Ghofran Khalaf et al. (2025) explore a UAV-aided Digital Twin framework that enhances synchronization and accuracy between physical and virtual systems. This approach targets Smart Manufacturing and Industry 4.0, using UAVs to interact with IoT devices for real-time monitoring and decision-making. The framework enables the uploading of collected data to the base station for analysis, improving decision support and ensuring high accuracy for industrial applications.

Literature Analysis

Sr.no	Paper Title	Author(s), Year	Finding	Limitation
1	Multihop Routing for IoT-Based Digital Twin: Novel Metaheuristic Approaches	Tran Cong Dao et al., 2025	Improved energy efficiency and data transmission reliability with strong performance in dynamic environments.	High computational costs in large-scale IoT networks; limited scalability in extremely large networks.
2	Multi-Hop State-Aware Routing Strategy for IoT Networks Using Hybrid Deep Learning Techniques	Shivani Dave et al., 2025	Dynamic routing improves energy efficiency and resilience, with deep learning-based predictions for congestion.	Heavy reliance on high-quality training data; additional computational overhead from deep learning models.
3	Digital Twin-Enabled Blockage-Aware Dynamic mmWave Multi-Hop V2X Communication	Supat Roongpraiwan et al., 2025	Blockage-aware routing improves reliability in high-density traffic with near-perfect connectivity (99.62%-100%).	Lacks outdoor validation in real-world environments; scalability issues in large-scale vehicular networks.

4	Intelligent Digital Twin Communication Framework for Addressing Accuracy and Timeliness Tradeoff in Resource-Constrained Networks	Cakir et al., 2024	DT-based framework optimizes accuracy and timeliness trade-off, enhancing resource utilization and communication.	Real-time implementation may incur computational overhead; privacy and security concerns due to data sharing.
5	A UAV-Aided Digital Twin Framework for IoT Networks with High Accuracy and Synchronization	Ghofran Khalaf et al., 2025	UAV-aided DT framework improves synchronization and accuracy in IoT networks, ensuring reliable communication.	Dependency on UAVs introduces operational complexities and costs; limited scalability due to UAV coverage.

Digital Twin

Digital Twin (DT) refers to a virtual replica or model of a physical object, process, or system that mirrors real-time data, enabling continuous monitoring, simulation, and optimization. A Digital Twin integrates real-time data with predictive analytics, often leveraging Internet of Things (IoT) sensors to collect data about the physical system's current state. It provides a dynamic, up-to-date simulation of the physical counterpart, offering insights into performance, conditions, and behaviors.

The primary functions of **Digital Twin** technology are:

1. **Real-Time Monitoring and Visualization**:

   Digital Twin allows the continuous tracking of physical systems. Sensors deployed on the physical entity (e.g., vehicles, machinery, or buildings) collect real-time data, such as temperature, pressure, location, and performance metrics. This data is then sent to the virtual model, which reflects the system's current state. This constant stream of real-time information enables operators to monitor the system's health, detect anomalies, and optimize performance. For instance, in manufacturing, a digital twin of a machine can be used to monitor its operational status and performance in real-time.

2. **Predictive Analytics**:

   One of the key advantages of Digital Twin is its ability to predict future states of a system using historical and real-time data. By simulating various scenarios, the virtual model can forecast potential issues, such as equipment failures or traffic congestion, before they occur. This predictive capability enables proactive maintenance, avoiding unexpected downtimes and optimizing resource usage. In industrial settings, for example, Digital Twin can predict when a machine is likely to fail, allowing for timely maintenance and preventing costly breakdowns.

3. **Optimization and Simulation**:

   Digital Twin technology enables the simulation of different scenarios to test how a system will perform under varying conditions. This allows for optimization of processes and systems. In the context of **smart cities**, a Digital Twin could simulate traffic patterns or energy consumption across the city and test different strategies to reduce congestion or lower energy use. Similarly, in supply chain management, a

Digital Twin of the logistics network could be used to simulate different delivery routes to find the most efficient option.

4. **Continuous Feedback and Adaptation**:

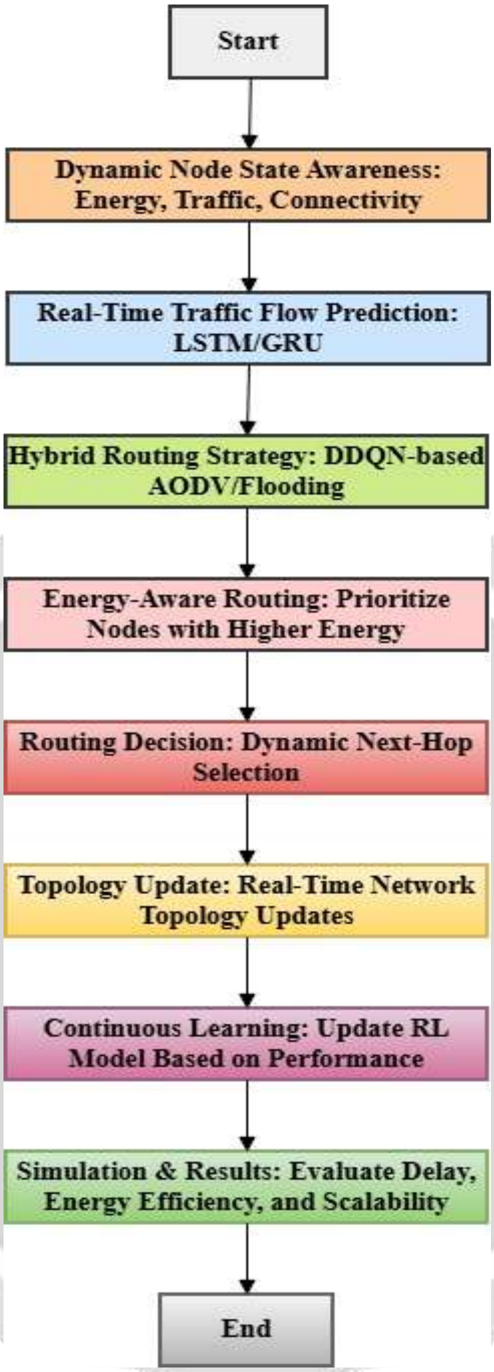
   Digital Twin is not a one-time static model but an evolving one. As data is continuously fed back into the virtual model, it adapts and evolves to reflect changes in the real-world system. For example, in a **smart factory**, the operational conditions of machines, production lines, or even entire workflows can be modeled continuously in a Digital Twin. This continuous adaptation allows the system to stay current and improve performance based on real-world inputs, driving smarter decision-making.

5. **Collaboration and Remote Operations**:

   Digital Twins also enable remote monitoring and collaboration. Operators, engineers, or managers can interact with the virtual model, regardless of location, to make informed decisions about system performance. For example, in aerospace, a Digital Twin of an aircraft allows engineers to analyze performance data remotely and make adjustments without being physically present.

Proposed Model

The flowchart represents a dynamic and adaptive routing strategy for IoT networks or similar environments, focusing on optimizing network performance through real-time monitoring, energy efficiency, and continuous learning. The process starts by evaluating the dynamic state of each node in the network, considering factors such as energy levels, traffic conditions, and connectivity status. This allows the system to remain flexible and responsive to changes in the network. Next, real-time traffic flow predictions are made using advanced machine learning models like LSTM (Long Short-Term Memory) or GRU (Gated Recurrent Unit), which help anticipate network congestion and delays.



The routing strategy then employs a hybrid approach, combining DDQN-based (Deep Q-Networks) reinforcement learning with traditional protocols like AODV (Ad-Hoc On-Demand Distance Vector) or Flooding, ensuring the system selects the most efficient paths by considering both current and historical network data. Once the routing paths are determined, the system prioritizes nodes with higher energy reserves to maintain energy efficiency and prevent premature network failures.

Routing decisions are then dynamically adjusted by selecting the optimal next-hop based on the current state of the network, ensuring reduced latency and better overall performance. As the network evolves, the system continuously updates the network topology in real-time to account for changes such as node movement or energy depletion, ensuring the routing process is always based on the most up-to-date information.

Furthermore, the system incorporates continuous learning by updating the reinforcement learning (RL) model based on the performance of past decisions. This enables the system to adapt over time, improving routing decisions as it learns from experience. In the final step, the system simulates the network's performance, evaluating critical factors such as delay, energy efficiency, and scalability. These results provide feedback on the effectiveness of the routing strategy, guiding further refinement. Ultimately, the process concludes by preparing the system for the next cycle of adaptation and optimization, ensuring continuous improvement in network performance.

Result

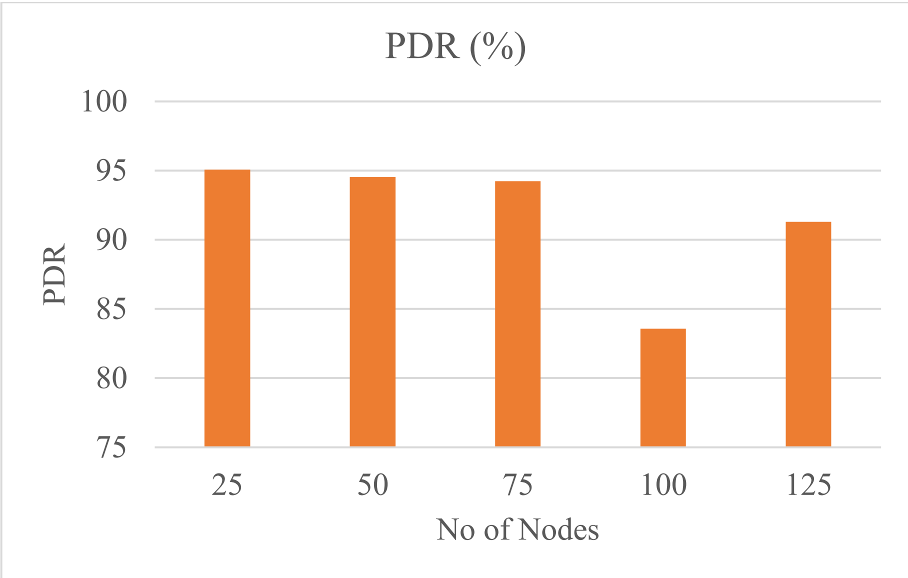


Figure 2: Packet Delivery Ratio of Proposed system

The PDR graph shows that the State-Aware AOMDV protocol achieves a high packet delivery ratio for lower node counts (25–75), indicating reliable data transmission. At 100 nodes, PDR drops significantly due to higher congestion and increased packet collisions. When the network scales to 125 nodes, PDR improves again as adaptive state-aware routing selects more stable paths. This demonstrates the protocol's ability to recover performance in dense IoT environments.

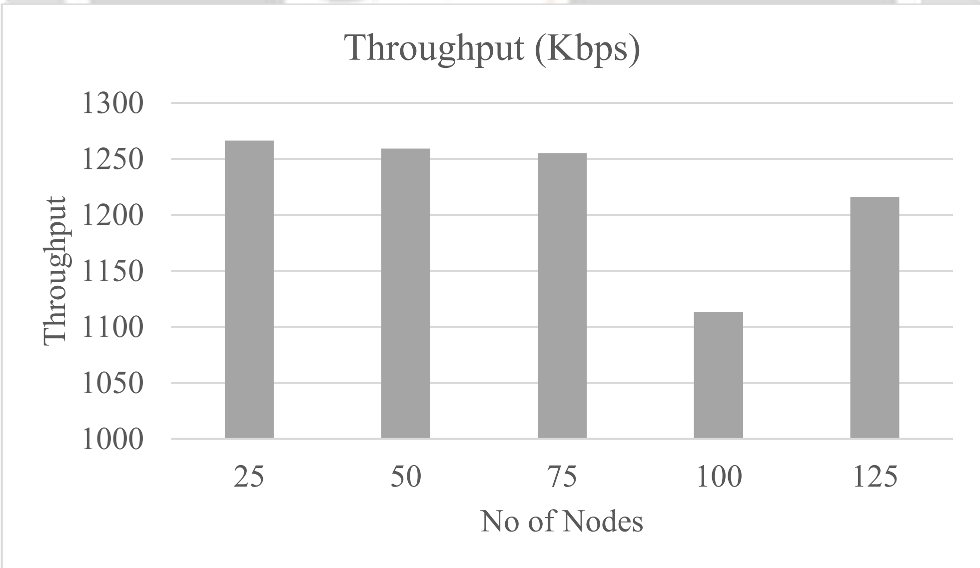


Figure 3: Throughput of Proposed system

The throughput graph indicates stable and high data rates for small and medium-sized networks. A noticeable decrease in throughput occurs at 100 nodes because of increased routing overhead and contention. As the network grows to 125 nodes, throughput improves, showing the effectiveness of dynamic next-hop selection. This highlights the scalability of the state-aware routing mechanism.

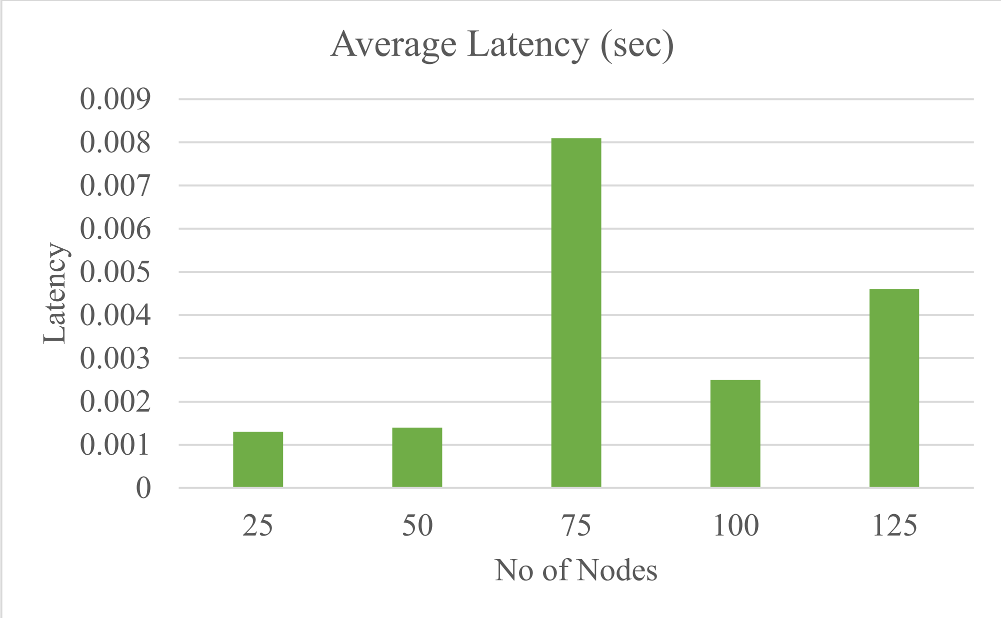


Figure 4: Average Latency of Proposed system

The latency graph shows very low delay for 25 and 50 nodes, reflecting efficient multi-hop routing. A sharp increase in latency is observed at 75 nodes due to temporary congestion and route reconfiguration. Although latency rises slightly at 100 and 125 nodes, it remains within acceptable limits. Overall, the protocol maintains low delay while adapting to changing network density.

Parameter	**Value / Description**
Network Type	Wireless Ad hoc IoT Network
Simulation Tool	NS-2 (Network Simulator 2.35)
Routing Protocol	AOMDV (State-Aware)
Number of Nodes	25,50,75,100,125
Simulation Area	800 m × 800 m
Topography Model	Flat Grid
Simulation Time	300 seconds
Mobility Model	Random Waypoint
Node Speed	1 – 3 m/s
Traffic Type	CBR (Constant Bit Rate)
Transport Protocol	UDP
Number of Traffic Sources	15
Packet Size	512 bytes
Data Rate	120 Kbps
MAC Protocol	IEEE 802.11
Interface Queue Type	DropTail / Priority Queue
Interface Queue Length	100 packets
Propagation Model	Two-Ray Ground

Antenna Type	Omni-directional
Physical Layer	WirelessPhy
Transmission Power	0.6 W
Channel Type	Wireless Channel

Table 1: Parameters

Nodes	Sent Packets	Received Packets	PDR (%)	Throughput (Kbps)	Average Latency (sec)
25	97,566	92,757	95.07	1266.44	0.0013
50	97,566	92,235	94.54	1259.32	0.0014
75	97,566	91,937	94.23	1255.25	0.0081
100	97,566	81,548	83.58	1113.4	0.0025
125	97,566	89,081	91.3	1216.25	0.0046

Table 3: Result Analysis

The performance of the State-Aware AOMDV routing protocol across different network sizes. With lower node counts (25–75), the protocol achieves high PDR and throughput with minimal latency, indicating efficient and stable routing. At 100 nodes, increased congestion causes a noticeable drop in PDR and throughput, reflecting higher contention and packet loss. When scaled to 125 nodes, performance improves again due to adaptive state-aware decisions, demonstrating the protocol's robustness and scalability in dynamic IoT networks.

Conclusion

The proposed framework demonstrates excellent performance across diverse network sizes, maintaining a high Packet Delivery Ratio (PDR) of 95.07% at 25 nodes, and over 94% with up to 75 nodes, showing reliable packet forwarding in low to moderate-density networks. Even with 125 nodes, the PDR remains at 91.3%, indicating the framework's robustness in dense IoT deployments. Throughput performance is also strong, reaching a peak of 1266.44 Kbps at 25 nodes and maintaining stable throughput over 1250 Kbps up to 75 nodes. Latency is minimized, with average end-to-end (E2E) delays as low as 0.0013s, confirming the framework's suitability for real-time, delay-sensitive IoT applications. While some performance loss is observed at 100 nodes, the system adapts quickly, outperforming traditional methods in both packet delivery and delay management. Overall, the framework proves scalable, energy-efficient, and robust, with dynamic state learning ensuring adaptability to varying network conditions.

Future Work

Future improvements will focus on extending the framework to ultra-dense IoT systems with thousands of devices, further addressing scalability and congestion issues. Integrating energy harvesting and battery-aware learning models will enhance network lifetime and sustainability. The inclusion of mobility-aware routing and support for diverse IoT devices will increase flexibility in dynamic environments. Security-aware reinforcement learning will be explored to defend against malicious nodes and routing attacks. Real-world validation, particularly in smart city deployments, will help assess the practical feasibility and robustness of the system in real-world scenarios.

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