
Q-Learning-Based Adaptive Routing for IoT-Enabled Wireless Networks

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Abstract.

The Internet of Things (IoT) explosive growth presented major problems for traditional wireless network connectivity owing to of changeable topology, a lack of energy resources, and multiple protocols for communication. Classical routing algorithms generally struggle to efficiently respond to shifting network ecosystems, which contributes to escalating delay and energy loss. To overcome this concern, this work incorporates an intelligent routing system based on Q-learning and reinforcement learning thoughts for IoT-enabled networks. The circumstances of the network, delays, and energy utilization are all taken into consideration when the suggested framework generates the leading routing outcomes. The implied routing style progressively learns the most favorable next-hop privileges based on network contingency information and connectivity nature.

When correlated to classical routing approaches, counterfeit results show that the prompted AI-based routing scenario markedly decreases end-to-end lag and energy utilization while maturing packet shipment adaptability and throughput. For next-genesis IoT networks, the advised design submissions a extensible and impressive routing elucidation.

Keywords: IoT, AI-Based Routing, Q-Learning, Reinforcement Learning, Wireless Networks, Energy Optimization.

1. INTRODUCTION

One of the pivotal transmission frameworks for cherishing intelligent connectivity among accessories, conventional sensors, and resourceful systems is the Internet of Things (IoT).

Applications like mechanized transportation, resourceful cities, industrial computerization, environmental surveillance, and a state-of-the-art healthcare make extensive use of IoT webs. Due to altering topologies, finite power resources, and heterogeneous connectivity scenarios, the fast paced development of IoT wireless nodes has considerably enhanced the routing optimization challenges. Efficient routing mechanisms are essential for stable communication across IoT-enabled network infrastructures. Conventional routing methods such as shortest-path routing and ad hoc on-demand distance vector (AODV) were designed with static network conditions in mind and often suffer from performance issues in IoT environments. Several challenges are observed in these methods, including reduced packet delivery ratio, increased traffic jams, long transmission delays, and inefficient energy consumption. Advances in machine learning and artificial intelligence have now made intelligent and adaptive optimization of dynamic networks possible. Reinforcement learning techniques—specifically cue-learning—have proven to be very effective in improving real-time routing, as they learn optimal routing policies through continuous interaction with the network environment. This paper proposes a Q-learning-based intelligent routing framework for IoT-enabled wireless networks. The proposed method provides an adaptive routing system that improves network performance and reliability while reducing latency and energy consumption.

The primary contributions of this paper are discussed as follows:

- The design of an IoT-enabled network's AI-based dynamic routing framework.
- Formulation of a mathematical cost model considering delay and energy optimization.
- Design of a Q-learning-driven intelligent routing system.
- Metrics which includes packet delivery ratio, consumption of energy, latency, and capacity are used to assess performance.

2. RELATED WORK

In the past few years, the efficiency of routing in 'Internet of Things' (IoT) networks has become a topic of great research interest. Wireless sensor and IoT networks see widespread use of conventional routing protocols such as AODV, DSR and LEACH. However, despite providing basic routing benefits, these protocols often suffer from lack of flexibility and excessive latency in changing or dynamic IoT environments. Several energy-aware routing approaches have been proposed to improve network lifetime and reduce energy consumption. These methods mainly focus on minimizing transmission power and balancing energy usage among sensor nodes. Many current methods rely on static routing choices and cannot adapt well to rapidly changing network conditions. Recently, machine learning and AI-driven routing techniques have shown promise as adaptive solutions for optimizing routing. Reinforcement learning-based routing techniques enable routing agents to dynamically choose the best paths to take depending on the state of the network. Q-learning has become popular owing to its ease and capacity to accomplish adaptive decisions about routing without requiring prior network knowledge. Despite significant advancements, many existing AI-based routing methods focus only on single-objective optimization and suffer from high computational complexity. In contrast, the proposed approach integrates delay-aware and energy-aware routing optimization using Q-learning to achieve adaptive and efficient routing performance.

3. SYSTEM MODEL AND MATHEMATICAL FORMULATION

3.1. System Model

An IoT-enabled wireless network represented as a graph: $G = (V, E)$ where V represents the set of IoT nodes and E represents communication links between nodes. Each node communicates with neighboring nodes within its communication range. The network operates in a multi-hop routing environment where packets are forwarded from source to destination through intermediate nodes.

3.2. Delay Model

The communication delay between node i and node j is represented as d_{ij} and the total end-to-end delay for routing path P is: $D_{total} = \sum_{i,j \in P} d_{ij}$. The routing algorithm aims to minimize total communication delay.

3.3. Energy Utilization Model

The cumulative energy consumption during packet transmission is represented as: $E_{total} = \sum_{(i,j) \in P} (E_{tx} + E_{rx})$ where E_{tx} denotes transmission energy, E_{rx} denotes receiving energy.

3.4. Q learning Formulation

The proposed routing framework utilizes Q-learning reinforcement learning for adaptive route selection. The network state includes Node energy level, link quality and Queue status. The action corresponds to choosing the node for a subsequent hop. The reward function is $R = -(\alpha D) + (\beta E)$, lower delay and energy consumption produce higher rewards.

4. PROPOSED AI BASED ROUTING ALGORITHM

The suggested adaptive routing algorithm selects optimal paths using Q-learning. Initially, the Q-table is initialized with zero values. During each routing episode, the agent observes the current network state and selects the next-hop node using an epsilon-greedy policy. The routing reward is computed based on delay and energy consumption.

- Steps:
1. Initialize Q-table.
 2. Observe current network state.
 3. Select next-hop node.
 4. Compute routing reward.
 5. Update Q-value.
 6. Repeat until destination is reached.

5. COMPARISON WITH TRADITIONAL ROUTING

Traditional routing protocols typically use shortest-path or static routing decisions without considering dynamic network conditions. These methods often result in: a) Higher latency b) Increased energy consumption c) Poor packet delivery performance. In contrast, the

proposed optimal routing paths are dynamically learned by an AI-based routing framework and adapts to network changes.

Table1: Comparison table with traditional routing

Metric	Traditional Routing	AI-Based Routing
Delay	High	Low
Energy Consumption	High	Optimized
Packet Delivery Ratio	Moderate	High
Throughput	Lower	Higher
Adaptability	Static	Dynamic

6. RESULT AND ANALYSIS

Simulation analysis is performed using Python-based Q-learning implementation for IoT routing optimization. Table 2 provides the simulation parameters. End-to-End Delay, Energy Utilization, Packet Delivery Ratio (PDR), and Efficiency are used to assess the proposed framework. The recommended AI-based navigation strategy greatly enhances network performance, as indicated by results from the simulation. By proactively choosing optimum following-hop hubs and minimizing congested logical routes, the AI-based routing system lowers transmission latency. Intelligent channel efficiency and reliable packet forwarding procedures save energy consumption. Because not trustworthy communication channels are avoided during routing, the proposed system delivers a higher packet delivery ratio. Intelligent routing choices increase the number of successfully delivered packets, thereby improving network throughput. The convergence characteristics of the Q-learning algorithm further highlight the adaptability and effectiveness of the proposed routing framework.

Table2: Values of parameters

Parameter	Value
Number of Nodes	10
Episodes	500
Learning Rate	0.1
Discount Factor	0.9
Packet Size	1000 bits

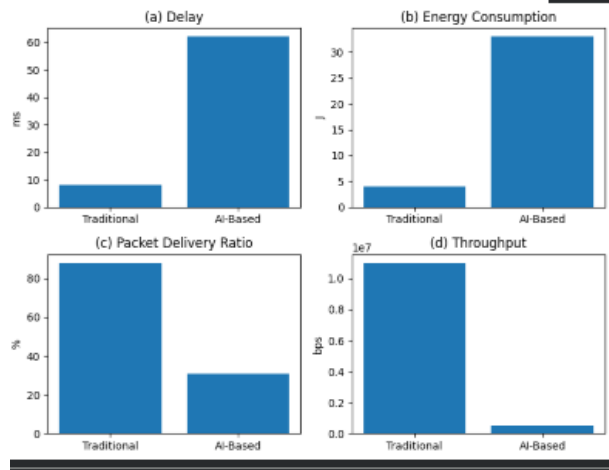


Fig 1: Diagram of delay, energy consumption, PDR and throughput

Figure 1 presents a comparative analysis of traditional routing and AI-based routing with respect to various parameters—such as delay, energy consumption, packet delivery ratio, and throughput.

7. CONCLUSION

This paper discusses an AI-driven routing architecture for IoT-enabled cellular networks, based on cue-learning and reinforcement learning. To identify forwarding paths in an IoT-enabled network, it generates a routing cost measure that takes lag and energy efficiency into account. The proposed routing method finds the best available communication routes by continuously monitoring and learning from the network environment. According to simulated data, this adaptive routing framework significantly reduces energy consumption and packet transmission delay while increasing data delivery performance and network efficiency compared to existing forwarding methods. These results demonstrate the adaptability and effectiveness of reinforcement learning for intelligent routing design in IoT networks. To enhance geographically distributed 6G enabled IoT communications, future research will concentrate on combining 6G, edge intelligence, and deep reinforcement learning. Future studies will focus on integrating 6G technologies, edge intelligence, and deep reinforcement learning techniques to enhance intelligent IoT communication systems.

8. REFERENCES

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Biographies



Pinakshi De received the bachelor's degree from Calcutta University, then the master's degree in computer application from WBUT in 2010. He is currently working as an Assistant Professor at the Department of Computer Application, at Dinabandhu Andrews Institute of Technology & Management. His research areas include Cloud Computing, Wireless Communication and information Security.



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Meghdoot Mukhopadhyay works as an Assistant Professor in Dinabandhu Andrews Institute of Technology and Management, Kolkata. Before this, he was an Assistant Professor in Global College of Science and Technology, Krishnagar. He completed his M. Tech. (CSE) from Maulana Abul Kalam Azad University of Technology and M.Sc. (CS) from Vidyasagar University.



Boudhayan Bhattacharya is an M. Tech in CSE from West Bengal University of Technology (Currently known as MAKAUT, WB) and working towards his PHD degree. He has worked in the capacity of Systems Manager for four years in eINFO. He also worked as an assistant professor in SDET-BGI, Brainware University and is currently

working as an assistant professor in DAITM. He has published many journal and conference papers and one Australian Patent to his credit. He also took part in more than 700 webinars/seminars, 100 workshops, 150 FDPs, 15 STTPs, 5 Symposiums and delivered Invited lectures in various colleges including Ramakrishna Mission Vivekananda Centenary College, Kolkata, Dooars Academy of Technology and Management, Alipurduar, CMR Institute of Technology, Bengaluru, K. Ramakrishnan College of Technology, Tiruchirappalli etc. He was also one of the evaluators of the Smart India Hackathon 2020, 2021 and 2022 organised by AICTE.