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AI-Optimized Routing Protocols for Energy-Efficient IoT Networks

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Abstract

The rapid growth of connected devices in fields such as smart cities, healthcare, and industrial automation has made energy efficiency a critical concern in Internet of Things (IoT) networks. These devices often operate under power constraints, and traditional routing protocols struggle to meet the specific challenges of IoT environments, which include device mobility, limited processing power, and dynamic network conditions. This research investigates the role of Artificial Intelligence (AI) in optimizing routing protocols to enhance energy efficiency in IoT systems. AI techniques such as Machine Learning (ML) and Reinforcement Learning (RL) enable real-time adaptation of routing paths based on network conditions, energy availability, and data traffic. These methods reduce energy consumption while maintaining reliable communication between devices. The paper reviews existing AI-based routing approaches and presents case studies that demonstrate improved energy management and extended device lifespans. It also addresses challenges like the computational limitations of low-power devices, scalability in large networks, and privacy concerns related to data usage. The findings highlight the potential of AI to significantly improve the sustainability and performance of IoT networks. As IoT adoption continues to grow, intelligent and adaptive routing solutions will be essential for building energy-efficient, scalable, and resilient network infrastructures.

Keywords: Internet of things, Energy efficiency, Routing protocols, Artificial intelligence, Reinforcement learning, Machine learning, Scalable and resilient networks.

1 | Introduction

The rapid growth of the Internet of Things (IoT) has ushered in a transformative era where billions of devices—ranging from sensors to everyday appliances—are interconnected to create seamless, intelligent networks. These IoT networks have become foundational to various applications, including smart cities [1], industrial automation, healthcare, agriculture, and environmental monitoring. By enabling devices to communicate and collaborate, IoT networks enhance efficiency, allow real-time monitoring, and drive innovation across numerous fields. For example, in healthcare, IoT devices monitor patients' vital signs,

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providing critical data that healthcare professionals can use to offer timely interventions [2]. In agriculture, IoT sensors gather soil moisture, temperature, and humidity data, helping farmers optimize water usage and crop health [3]. Despite these advancements, IoT networks face significant challenges, especially regarding energy consumption [4].

Energy efficiency is a central concern in IoT networks due to IoT devices' typically limited battery life and processing power [5]. Since many IoT applications, such as remote environmental monitoring, require devices to operate in challenging and sometimes inaccessible environments, replacing or recharging batteries frequently is often impractical. For example, in a smart city, thousands of sensors may be spread across various locations; any inefficiency in energy use could result in premature battery depletion, causing interruptions in service and increased maintenance costs. Consequently, developing strategies to extend IoT devices' battery life is critical to IoT deployments' sustainability and scalability. Efficient energy management prolongs network lifetime and reduces the environmental impact associated with frequent battery replacements.

Routing in IoT networks presents unique challenges that make energy efficiency even more complex. Unlike traditional networks, IoT networks are often large-scale, decentralized, and heterogeneous, comprising devices with varying capabilities and resources. These devices must maintain reliable communication while minimizing energy usage, even as the network topology dynamically shifts due to node mobility, environmental factors, and occasional device failures. Conventional routing protocols, originally designed for traditional networks, struggle to meet these requirements, as they lack the adaptability and optimization capabilities needed to address IoT networks' dynamic and resource-constrained nature. Standard protocols like Routing Protocol for Low-power and Lossy Networks (RPL) [6] and Low-Energy Adaptive Clustering Hierarchy (LEACH) [7] focus on energy efficiency but lack real-time adaptability, making it difficult to respond efficiently to the frequent changes in IoT networks.

Artificial Intelligence (AI) has emerged as a promising solution to optimize routing protocols within IoT networks. By leveraging AI, specifically Machine Learning (ML) and Reinforcement Learning (RL), IoT networks can dynamically adapt to changing conditions, predict optimal routes, and make decisions that reduce energy consumption while maintaining connectivity. ML algorithms can analyze data from network nodes to predict traffic patterns, anticipate congestion, and optimize routing paths based on real-time conditions [8]. RL, in particular, enables IoT devices to learn from past experiences, identifying routes that minimize energy use over time [9]. AI-driven optimization introduces flexibility and intelligence that traditional routing protocols lack, enabling IoT networks to operate more sustainably.

2 | Literature Review

2.1 | Overview of Internet of Things Routing Protocols

Routing protocols play a vital role in IoT networks, where maintaining connectivity while minimizing energy consumption is crucial. Traditional routing protocols designed for IoT, such as RPL and LEACH, have been developed with energy efficiency as a core focus.

RPL, standardized by the Internet Engineering Task Force (IETF), is a widely used protocol in Low-power and Lossy Networks (LLNs). It structures the network into a Directed Acyclic Graph (DAG) based on destination-oriented routing. Nodes in RPL can select parent nodes dynamically, depending on metrics like link quality, latency, and energy. This approach enables RPL to adapt to network conditions and minimize energy consumption by optimizing packet forwarding paths. However, RPL can be limited in rapidly changing network topologies, as it requires frequent recalculations of the DAG, which can lead to additional energy drain.

LEACH, another prominent protocol, uses clustering to conserve energy. In LEACH, nodes self-organize into clusters, with one node designated as the "Cluster Head." Cluster heads are responsible for aggregating data from their respective clusters and transmitting it to a base station, reducing the need for all nodes to communicate directly with the base station. This strategy conserves energy by minimizing the overall number of transmissions within the network. LEACH periodically rotates cluster heads among nodes to prevent any single node from being overburdened and depleting its energy. Although LEACH effectively reduces energy usage, it does not account for the dynamic nature of IoT networks or the real-time adjustments needed to respond to fluctuating conditions, which can limit its long-term effectiveness.

2.2 | Energy Efficiency in Routing Protocols

Various methods have been developed to enhance energy efficiency in IoT routing protocols further. Key techniques include clustering, sleep/wake cycling, and adaptive routing. Clustering, as exemplified in LEACH, groups nodes into clusters to reduce the number of direct transmissions to the base station. This saves energy and helps scale the network by reducing communication overhead. However, clustering-based protocols must carefully balance energy distribution among nodes to prevent cluster heads from exhausting their energy too quickly.

Sleep/wake cycling is another technique in which nodes enter a low-power "Sleep" mode when they are not actively transmitting data, waking up only when necessary. This approach is particularly useful in environments where IoT devices monitor infrequent events or periodic data, such as environmental monitoring. Protocols like Sensor-Medium-Access Control (S-MAC) implement sleep/wake cycling to enable nodes to conserve energy without significantly impacting network performance.

Adaptive routing enables IoT networks to adjust routing paths based on real-time network conditions. For example, some protocols allow nodes to switch paths or select alternative parent nodes when a primary route experiences congestion or excessive energy consumption. Adaptive routing benefits large and dynamic networks but can impose computational overhead on low-power devices.

2.3 | Artificial Intelligence in Routing

AI, particularly ML and RL, has recently gained attention as a solution to the limitations of traditional IoT routing protocols. AI-based approaches enable IoT networks to optimize real-time routing by predicting and adapting to network changes more efficiently than static algorithms.

ML techniques like decision trees and neural networks can help predict the optimal route based on link stability, traffic density, and node energy levels. By continuously learning from past data, these models can identify patterns that optimize energy consumption across the network. For instance, neural networks can analyze historical traffic data to predict areas of high traffic and dynamically reroute packets to balance the network load, reducing energy consumption for nodes on heavily trafficked paths [10].

RL further enhances the adaptability of IoT routing protocols by allowing nodes to learn from experience and make decisions that maximize energy efficiency. In RL-based routing, each node or agent observes its environment, takes actions (Such as selecting a specific routing path), and receives feedback in the form of rewards based on energy consumption and latency. Through repeated interactions with the network, nodes learn the most energy-efficient routes over time. Techniques such as Q-learning and Deep Q-Networks (DQN) are particularly useful, enabling nodes to adapt to dynamic environments with minimal pre-defined rules.

These AI-driven approaches bring intelligence to IoT routing, making it possible to manage network resources more effectively, prolong network life, and address the inherent limitations of traditional protocols.

3 | Artificial Intelligence Techniques for Routing in Internet of Things

3.1 | Machine Learning Methods

ML methods have proven effective in optimizing routing protocols for IoT networks by predicting optimal routes based on environmental and network conditions. These methods can analyze patterns in traffic data, node energy levels, and link quality, using this information to make routing decisions that minimize energy consumption and reduce latency. Supervised learning algorithms, such as decision trees and support vector machines, classify network conditions and suggest optimal paths based on historical data. These algorithms are beneficial in relatively stable environments where past patterns are likely to repeat.

However, due to the dynamic nature of IoT networks, supervised learning alone may not be sufficient. More advanced ML techniques, like neural networks, are commonly used to model complex relationships between routing variables and energy efficiency. For instance, Recurrent Neural Networks (RNNs) can analyze sequential data, such as time-series traffic data, to anticipate future congestion levels, enabling more accurate route predictions [11]. By learning from past network states and traffic patterns, neural networks can provide adaptive routing solutions that respond to real-time changes, optimizing network resources and prolonging device battery life.

3.2 | Reinforcement Learning

Among AI approaches, RL is particularly suited for dynamic routing in IoT networks, where conditions change frequently, and optimal paths must adapt accordingly. In RL-based routing, an IoT node is treated as an agent that interacts with its environment (The network) by choosing specific actions (e.g., selecting a path). Each action yields a reward or penalty based on its outcome, such as the level of energy consumption or data latency incurred. Maximizing cumulative rewards over time, the RL agent learns to make decisions that conserve energy while maintaining efficient data transmission.

Q-learning is a popular RL algorithm used in IoT routing [12]. In Q-learning, nodes maintain a Q-table that stores expected rewards for each possible action-state pair. Over time, nodes update the Q-values based on their experiences, converging on the most energy-efficient routing paths. As the network topology changes due to node mobility or fluctuating link quality, Q-learning enables the network to adapt by continuously learning and adjusting routes. This adaptability is crucial for IoT applications where network conditions, such as vehicular networks or environmental monitoring systems, are often unpredictable.

DQN extend Q-learning by incorporating deep learning. Instead of using a Q-table, DQNs use neural networks to approximate Q-values, making them scalable to larger networks with complex environments. By training a deep neural network on historical routing data, DQNs enable nodes to generalize across various network states, predicting optimal actions even in previously unseen conditions. This capability is beneficial in large-scale IoT deployments, where maintaining a Q-table for every possible state-action pair would be impractical due to memory constraints. DQNs can help ensure IoT devices use minimal energy by selecting routes that avoid high-traffic areas and optimizing energy use and network performance.

3.3 | Benefits of Artificial Intelligence in Internet of Things Routing

AI techniques, particularly ML and RL, bring several benefits to IoT routing that traditional algorithms cannot offer. The primary advantages include:

I. Adaptability: Unlike static routing protocols, AI-driven methods continuously adapt to changing network conditions, such as varying traffic loads, node failures, and shifting environmental factors. This adaptability allows AI-based routing protocols to perform well in dynamic and large-scale IoT networks, where conditions can shift rapidly.

II. Real-time optimization: AI algorithms can make real-time routing decisions by processing large amounts of data from sensors, actuators, and other devices in the IoT network. Real-time optimization is especially important in applications where delays, such as healthcare monitoring or industrial automation, could affect outcomes. For example, by predicting when certain network paths are likely to become congested, AI-enabled routing protocols can preemptively reroute data, minimizing delays and conserving energy.

III. Predictive capabilities: ML models can analyze past network behavior to predict future conditions. By understanding patterns in network traffic and energy consumption, AI-based protocols can anticipate issues like congestion and adjust routes to avoid them. This predictive capability not only enhances energy efficiency but also reduces the risk of network disruptions.

IV. Extended network lifespan: By optimizing energy usage and balancing the workload across nodes, AI-based routing protocols can significantly extend the overall lifespan of the IoT network. This is crucial when devices are deployed in remote or inaccessible locations, such as environmental monitoring sensors in forests or underwater IoT devices, where battery replacement is costly and logistically challenging.

V. Scalability: AI techniques can handle the complexities of large-scale IoT networks with numerous devices and varying requirements. As IoT networks grow, AI-driven routing protocols can scale efficiently, maintaining energy efficiency and optimal performance without manual intervention.

In summary, AI-based routing protocols offer a transformative approach to addressing the unique challenges of IoT networks, particularly regarding energy efficiency and adaptability. Using ML and RL, IoT networks can dynamically adjust routing decisions, extend network lifespan, and support complex, large-scale applications. As IoT networks continue to expand, the role of AI in optimizing energy-efficient routing will become increasingly vital, enabling more sustainable and resilient network infrastructures.

4 | Challenges and Future Directions

Despite the promising potential of AI-optimized routing protocols in enhancing energy efficiency in IoT networks, several challenges must be addressed to facilitate widespread adoption and implementation. One significant challenge is the computational requirements of deploying AI algorithms on resource-constrained IoT devices. Many IoT devices have limited processing power and memory, making executing complex machine-learning models locally difficult. This limitation necessitates the development of lightweight algorithms that can operate efficiently on low-power devices while maintaining effective routing capabilities. Furthermore, the need for real-time processing in dynamic environments places additional strain on IoT devices, requiring optimized code and reduced model complexity.

Scalability is another critical issue, particularly as the number of connected IoT devices grows exponentially. AI algorithms must efficiently handle large-scale networks without degrading performance or requiring excessive computational resources. The network topology in IoT is inherently dynamic, with devices frequently joining or leaving the network. AI routing protocols must be adaptable, learning from the changing environment without incurring significant overhead, which can compromise energy savings. This adaptability requires robust training datasets that accurately reflect diverse network conditions, which may be challenging to obtain in practice.

Privacy concerns also pose significant challenges for implementing AI in IoT routing. Many AI techniques rely on collecting and analyzing vast amounts of data, which can include sensitive information about users and their behaviors. Safeguarding this data while leveraging it for effective routing decisions is essential to maintaining user trust and complying with privacy regulations. Implementing techniques such as federated learning, which allows for decentralized training of AI models across multiple devices without sharing raw data, can help address privacy issues. Federated learning enables devices to learn from local data while contributing to a global model, thus preserving privacy while still benefiting from collaborative intelligence.

Several promising directions could enhance the effectiveness of AI-optimized routing protocols in IoT networks. Hybrid approaches that combine multiple AI techniques, such as RL and deep learning, may yield more robust solutions. These hybrid models can better adapt to varying network conditions by leveraging the strengths of different algorithms. Furthermore, as AI techniques advance, they can be integrated with emerging technologies, such as 5G networks, which offer higher bandwidth and lower latency, further enhancing the capabilities of AI-optimized routing.

5 | Conclusion

In conclusion, AI-optimized routing protocols represent a significant advancement in achieving energy-efficient IoT networks. Integrating AI techniques addresses the inherent challenges of traditional routing protocols and introduces adaptability, predictive capabilities, and real-time optimization, which are essential for modern IoT applications. By effectively managing network resources, these AI-driven solutions can significantly extend the lifespan of IoT networks, reduce maintenance costs, and enhance overall performance. As research continues to tackle the challenges of computational efficiency, scalability, and privacy challenges, AI's potential to transform energy management in IoT networks will only increase. Future innovations in this field will pave the way for more sustainable and resilient IoT infrastructures, ultimately facilitating the continued growth and development of smart technologies in various sectors.

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Author Contributions

Arya Ashutosh Das is the sole author of this article and was responsible for all aspects of the research, including conceptualization, methodology, data analysis, drafting, and final revision of the manuscript.

Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request. As the research primarily involves simulation and literature-based analysis, no proprietary or sensitive datasets were used.

References

[1] Mohapatra, H. (2021). Socio-technical challenges in the implementation of smart city. *2021 international conference on innovation and intelligence for informatics, computing, and technologies (3ICT)* (pp. 57–62). IEEE. https://doi.org/10.1109/3ICT53449.2021.9581905

[2] Mohanta, B. K., Awad, A. I., Dehury, M. K., Mohapatra, H., & Khan, M. K. (2025). Protecting IoT-enabled healthcare data at the edge: Integrating blockchain, AES, and off-chain decentralized storage. *IEEE internet of things journal*, 1. https://doi.org/10.1109/JIOT.2025.3528894

[3] Utama, Y. A. K., Widianto, Y., Hari, Y., & Habiburrahman, M. (2019). Design of weather monitoring sensors and soil humidity in agriculture using internet of things (IoT). *Transactions on machine learning and artificial intelligence*, *7*(1), 10. http://dx.doi.org/10.14738/tmlai.71.5613

[4] Mahamat, M., Jaber, G., & Bouabdallah, A. (2023). Achieving efficient energy-aware security in IoT networks: A survey of recent solutions and research challenges. *Wireless networks*, *29*(2), 787–808. https://doi.org/10.1007/s11276-022-03170-y

[5] Hasan, K., Tom, N., & Yuce, M. R. (2023). Navigating battery choices in IoT: An extensive survey of technologies and their applications. *Batteries*, *9*(12), 580. https://doi.org/10.3390/batteries9120580

[6] Solapure, S. S., & Kenchannavar, H. H. (2020). Design and analysis of RPL objective functions using variant routing metrics for IoT applications. *Wireless networks*, *26*(6), 4637–4656. https://doi.org/10.1007/s11276-020-02348-6

[7] Palan, N. G., Barbadekar, B. V, & Patil, S. (2017). Low energy adaptive clustering hierarchy (LEACH) protocol: A retrospective analysis. *2017 international conference on inventive systems and control (ICISC)* (pp. 1–12). IEEE. https://doi.org/10.1109/ICISC.2017.8068715

[8] Chawla, P., Hasurkar, R., Bogadi, C. R., Korlapati, N. S., Rajendran, R., Ravichandran, S., Tolem, S. Ch., & Gao, J. Z. (2024). Real-time traffic congestion prediction using big data and machine learning techniques. *World journal of engineering*, *21*(1), 140–155. https://doi.org/10.1108/WJE-07-2021-0428

[9] Safdar Malik, T., Razzaq Malik, K., Afzal, A., Ibrar, M., Wang, L., Song, H., & Shah, N. (2023). RL-IoT: Reinforcement learning-based routing approach for cognitive radio-enabled IoT communications. *IEEE internet of things journal*, *10*(2), 1836–1847. https://doi.org/10.1109/JIOT.2022.3210703

[10] Andreoletti, D., Troia, S., Musumeci, F., Giordano, S., Maier, G., & Tornatore, M. (2019). Network traffic prediction based on diffusion convolutional recurrent neural networks. *IEEE infocom 2019 - IEEE conference on computer communications workshops (infocom wkshps)* (pp. 246–251). IEEE. https://doi.org/10.1109/INFCOMW.2019.8845132

[11] He, Y., Huang, P., Hong, W., Luo, Q., Li, L., & Tsui, K. L. (2024). In-depth insights into the application of recurrent neural networks (RNNs) in traffic prediction: A comprehensive review. *Algorithms*, *17*(9), 398. https://doi.org/10.3390/a17090398

[12] Rahmani, A. M., Naqvi, R. A., Yousefpoor, E., Yousefpoor, M. S., Ahmed, O. H., Hosseinzadeh, M., & Siddique, K. (2022). A Q-learning and fuzzy logic-based hierarchical routing scheme in the intelligent transportation system for smart cities. *Mathematics*, *10*(22), 4192. https://doi.org/10.3390/math10224192