Routing Problem of Mesh Remote Sensor IoT Networks

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***Abstract*—** Wireless Sensor Networks (WSNs) consist of autonomous sensors that monitor environmental factors such as temperature, humidity, sound, and pressure. These networks are important for applications such as environmental monitoring, smart cities, industrial automation, and information gathering. As IoT devices continue to proliferate, addressing the challenges of energy efficiency, scalability, and reliability has become increasingly important. This paper proposes an innovative reinforcement learning (RL)-based routing algorithm designed to enhance the energy efficiency of remote sensor IoT networks. The study outlines the mechanism for implementing this algorithm and the anticipated results.

Keywords—*WSNs, IoT, reinforcement learning (RL), Machine learning*

I.INTRODUCTION

The widespread deployment of IoT devices has significantly transformed industries such as manufacturing, agriculture, and various other sectors, particularly those involving extensive remote areas. Wireless Sensor Networks (WSNs) equipped with environmental monitoring capabilities have been developed and utilized across diverse applications by integrating various sensor types. In traditional star network configurations, such as Ethernet, routing is commonly managed using Shortest Path First (SPF) algorithms [1]. However, these algorithms are not suitable for Wireless Mesh Networks (WMNs) due to their decentralized topology. In WMNs, the absence of a hierarchical structure complicates the calculation of the shortest path without centralized topology storage. Instead, proactive link-state routing protocols like the Optimized Link State Routing Protocol (OLSR) are better suited for decentralized mesh networks due to their ability to manage dynamic and distributed environments effectively.[2]. Addressing the routing challenges in Wireless Multimedia Sensor Networks (WMSNs) requires algorithms with enhanced intelligence capabilities, particularly considering the diverse energy consumption patterns of monitoring nodes [3]. Machine learning (ML) offers three primary approaches: supervised learning (SL), unsupervised learning (USL), and reinforcement learning (RL). SL algorithms generate a function from training datasets to map inputs to outputs, enabling predictions for unseen inputs. In contrast, RL leverages past experiences and current options to make optimal decisions for specific problems. In the context of energy-aware IoT networks, the exponential growth of datasets with the number of devices poses a challenge for deep learning, making RL a more practical solution. RL is particularly advantageous for updating and managing routing tables in a distributed manner [4]. By continuously learning from the network's operational dynamics, RL ensures adaptive decision-making while maintaining a balance between exploration and exploitation. Wireless Mesh Networks (WMNs) are increasingly being recognized as a viable solution for remote monitoring applications due to their decentralized and adaptive nature. However, challenges such as scalability, interference, and energy constraints limit their effectiveness, especially in applications like soil and air quality monitoring [5]. To overcome these limitations, this study proposes a reinforcement learning-based routing algorithm designed to optimize energy consumption and adapt to dynamic network conditions. This approach aims to enhance the efficiency and applicability of WMNs in IoT-based monitoring systems. the rest of this paper is organized as follows: the next section shows related research, section 3 explains the research problem and objectives of the proposal, section 4 includes research methodology, section 5 contains a routing mechanism for the proposed algorithm, finally, this paper is concluded with section 6.

II.BACKGROUND AND RELATED RESEARCH

The Internet of Things (IoT) has revolutionized various aspects of our lives, and remote sensor networks are a crucial component of this revolution. These networks, often deployed in challenging environments like remote areas or disaster zones, rely on efficient routing protocols to transmit data from sensors to gateways or central hubs. However, traditional routing protocols designed for wired networks often fall short in these resource-constrained settings. Below is a presentation of the latest scientific papers related to the research topic:

Recent research has highlighted various aspects of Wireless Mesh Sensor Networks (WMSNs) and their potential applications in IoT environments. Zhanserik Nurlan from Astana IT University explored the integration of wireless sensor and mesh networks in his work, "Wireless Sensor Network as a Mesh: Vision and Challenges." This study identified key challenges and opportunities, such as power management, scalability, connectivity, reliability, and privacy. Although it provided a vision for intelligent environments like smart cities and video analytics, the research lacked a practical routing mechanism for addressing energy efficiency and scalability issues. Building on this, our thesis aims to develop a machine learning-based routing algorithm that optimizes energy consumption and enhances network scalability.[6]

Amira Zrelli from the National Engineering School of Tunis provided a comprehensive survey of IoT hardware, software, and routing protocols in her study, "Hardware, Software Platforms, Operating Systems, and Routing Protocols for IoT

Applications". She compared protocols like AODV and RPL, concluding that RPL is more energy-efficient but less effective in dynamic and large-scale networks. This limitation underscores the need for a more adaptable solution, which we aim to achieve through a reinforcement learning-based approach. [7]

Maisam Ali from Bahria University, Pakistan, addressed routing challenges in IoT networks supported by UAVs in her research, "Decision-Based Routing for Unmanned Aerial Vehicles and IoT Networks." While her proposed protocol improved data delivery and reduced delay, it did not address energy consumption or scalability issues, particularly for WMSNs. Our thesis intends to incorporate machine learning to overcome these shortcomings. [8]

Hailiang from Shenzhen ORVIBO Technology Co. proposed the O-Mesh algorithm in "Narrow-Band and Low Latency Routing Algorithms in Wireless Mesh Networks for IoT Applications." Although this work enhanced network throughput and reduced latency, it did not address energy consumption or leverage artificial intelligence. Our research will fill this gap by integrating reinforcement learning to optimize routing efficiency. [9]

Odongo Steven from Kyungpook National University, South Korea, developed a deep learning-based routing approach in his paper, "A Deep Learning-Based Routing Approach for Wireless Mesh Backbone Networks." His use of LSTM models improved packet delivery and throughput but did not consider energy consumption or network congestion. Our thesis will focus on reinforcement learning to tackle energy efficiency, scalability, and routing under congestion, providing a more comprehensive solution. [10]

Dubey and Sharma [14] proposed an energy-aware routing algorithm using reinforcement learning for IoT-enabled WSNs. Their approach demonstrated improved packet delivery and energy efficiency. However, it did not address deployment challenges in extremely remote or infrastructure-less areas like the Libyan desert. Our research complements their findings by targeting reinforcement learning adaptations specifically tailored for harsh environmental conditions.

The integration of advanced algorithms such as temporal difference learning and the Boltzmann algorithm has proven essential in enhancing the performance of IoT wireless multimedia sensor networks (WMSNs). These algorithms address critical challenges related to scalability, security, and routing efficiency, making IoT WMSNs more reliable and effective in dynamic environments.

There is also a pipeline network for the Man-Made River, spanning 2,820 kilometers, designed to transport water from aquifers in southern Libya to coastal regions [12]. This extensive network requires regular monitoring to ensure proper operation. Given that many of these pipelines are located in remote areas with challenging terrain and no electricity or network coverage, monitoring becomes a complex task. To address this, we propose the implementation of a Wireless Mesh Sensor Network (WMSN) that collects data from these rugged areas without the need for traditional infrastructure. To solve the issue of powering the sensor nodes in such a network, we suggest designing an energy-efficient algorithm based on reinforcement learning to reduce energy consumption and ensure the network's sustainability.

III.RESEARCH PROBLEM

Libya is a vast country with a total area of approximately 1,759,540 square kilometers, of which over 90% is classified as desert [11]. The remote areas, particularly in regions such as Fezzan in the southwest and the Sahara Desert in the south, encompass a significant portion of the country. These regions are sparsely populated due to their harsh desert conditions and limited infrastructure, the total length of oil and gas pipelines spans approximately 6,000 kilometers, his network plays a crucial role in transporting oil and gas from production fields, primarily in the south and east of the country, to export terminals on the coast.

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IV.OBJECTIVES OF THE RESEARCH PROPOSAL

Some possible objectives for a PhD proposal on the routing problem of mesh-based remote sensor IoT networks are

A. To design and implement a distributed and energy-efficient reinforcement learning-based routing algorithm for wireless mesh IoT networks.
B. To evaluate and compare the performance of the proposed algorithm with existing routing algorithms in terms of failure rate, energy consumption, and carrier band usage rate.
C. To analyze and demonstrate the effectiveness and adaptability of the proposed algorithm under different network scenarios and conditions.

To identify and address the challenges and limitations of the proposed algorithm and suggest possible improvements and extensions .

V.RESEARCH METHODOLOGY

The routing problem in mesh-based remote sensor IoT networks presents a complex challenge, requiring a structured and tailored research methodology to address the issues effectively. Below are the key components of the research methodology:

A. Area of Focus: The research will focus on specific aspects of the routing problem, particularly energy efficiency and scalability in wireless mesh IoT networks. These factors are critical to ensuring long-term network sustainability and reliable data transmission.
B. Evaluation Criteria: To assess the performance of the proposed solutions, several metrics will be used, including:
    a. Packet delivery ratio: Measures the success rate of data transmission.

b. Delay: Assesses the time taken for packets to travel across the network.
c. Resource utilization: Evaluates the efficient use of network resources, particularly energy and bandwidth

C. Simulation and Evaluation: The research will involve modeling the remote sensing network and simulating real-world conditions. The network model will include the following critical elements:
   a. Radio channel: Simulating wireless communication between nodes.
   b. Sensor nodes: Representing the devices operating within the network.
   c. Links between sensor nodes: Modeling the connectivity and data paths between nodes.
   d. Packet routes and transmissions: Tracking the paths that data packets take across the network and the associated transmissions.

D. Reinforcement Learning Application: Once the network model is established, the proposed RL algorithm will be applied to test its effectiveness in optimizing routing decisions. The simulation environment (e.g., MATLAB, OMNeT++) will be used to implement the RL-based algorithm.

E. Comparison with Existing Protocols: The performance of the proposed RL algorithm will be compared against existing routing protocols, such as:
   a. AODV (Ad-hoc On-Demand Distance Vector)
   b. CSPF (Constrained Shortest Path First)
   c. OLSR (Optimized Link State Routing Protocol)

Material Requirements for Implementation
To bring the proposed reinforcement learning-based routing algorithm to life in real-world scenarios, the following materials are necessary:

Hardware Components
IoT Sensor Nodes: These devices must be equipped with energy-efficient communication modules like LoRa transceivers or equivalent technology to ensure stable and reliable data transmission across the network.
Gateways: The gateways should support mesh sensor network protocols and have internet connectivity.
Energy Sources: Solar panels or other renewable power solutions are required to provide a continuous energy supply, particularly for nodes deployed in remote or hard-to-reach areas.

Software Tools
Implementing the algorithm will require software tools designed for network simulation and design. Programs like MATLAB or OMNeT++ will play a key role in creating a model of the network, simulating the interactions between sensor nodes, and analyzing performance metrics. These tools help ensure the design is both effective and ready for real-world deployment.

Expected Outcomes
- Energy Efficiency: The algorithm is anticipated to significantly reduce energy consumption across wireless IoT networks compared to traditional routing methods.
- Prolonged Network Lifetime: By optimizing energy usage and resource management, the network's overall operational lifespan, particularly in remote environments, will be extended.
- Scalability and Adaptability: The system will support easy scalability, allowing the addition of new nodes without negatively affecting the performance of the existing network.
- Routing Reliability: The algorithm aims to minimize routing failures and enhance the successful delivery rate of data packets, improving overall network reliability.
- Support for Practical Applications: The developed solution will be suitable for real-world applications, including smart agriculture systems and environmental monitoring setups, ensuring its practicality and relevance.

VI. ROUTING MECHANISM FOR THE PROPOSED ALGORITHM

The use of temporal difference learning and the Boltzmann algorithm plays a pivotal role in enhancing the performance of IoT wireless mesh sensor networks (WMSNs). These advanced algorithms effectively address challenges such as scalability, security, and routing efficiency, thereby improving network reliability and adaptability in dynamic environments, as demonstrated in previous studies [13].
Building on this foundation, the proposed routing algorithm leverages these capabilities to enable the deployment of fully interconnected sensor networks in highly remote and challenging areas. With an AI-driven system that dynamically adjusts routing in response to environmental changes, these networks can operate more independently of traditional service providers. This approach not only extends network coverage to previously inaccessible regions but also ensures enhanced reliability and energy efficiency, enabling longer operational durability and broader reach without relying on network operators. The proposed mechanism for integrating the two techniques can be summarized as follows:

A. TD learning is an appropriate method to support the routing requirements in the remote monitoring networks, as the best routing decisions need to be predicted from the feedback of the previous transmissions while the decision will impact the energy level of each node along the route.
B. Temporal Difference (TD): A learning method used to update the values of an agent based on the difference between predictions and actual outcomes.
C. TD updates the value estimates using the Bellman equation and bootstrapping. The update rule in TD (0) is:

$V(s) = V(s) + \alpha \cdot [R + \gamma \cdot V(s') - V(s)]$
where:
$V(s)$: current value estimate of the state.
- α: learning rate.
- R: received reward.
- γ: discount factor.
- s': next state.

D. Reinforcement learning uses TD to populate and update the routing table to find the best path for data transfer in the network.
E. Each node must have a memory to store the information gained from the feedback of each transmission.
F. The TD technique requires minimal storage space because it stores only the most recent predictive value.
G. All routing operations are done within a single node, each node learns independently, and in the event of a node failure, the rest of the nodes continue learning because they have their own information stored in their memory.
H. TD does not need a training dataset.
I. TD learns faster and adapts to network changes.
J. Boltzmann Exploration is a technique in reinforcement learning for action selection based on Q-values.
K. The goal is to balance exploration (trying new actions) and exploitation (choosing known best actions).
L. The Boltzmann distribution (softmax function) calculates the probabilities of selecting actions based on their Q-values.
M. It adjusts the balance between exploring new actions and exploiting the best-known actions.
N. $P(a/s) = \frac{e^{Q(s,a)/t}}{\sum_b e^{Q(s,b)/t}}$
O. P(a|s) is the probability of selecting action a in state s.
P. Q(s,a) is the Q-value of action a in state s.
Q. τ is the temperature parameter, which controls the balance between exploration and exploitation.

The TD technique requires minimal storage space because it stores only the most recent predictive value. And TD does not need a training dataset.

VII. LIMITATIONS AND FUTURE SCOPE

Despite the promising results of the proposed reinforcement learning-based routing algorithm, there are certain limitations that warrant consideration. First, the proposed solution assumes the availability of consistent environmental data, which may not always be feasible in dynamic outdoor conditions. Second, the algorithm's efficiency largely depends on the computational capability and energy resources of the sensor nodes, which may be limited in real-world deployments.

Furthermore, the current research focuses primarily on simulation-based validation, which may not fully capture the uncertainties of actual remote environments such as harsh climates or unexpected hardware failures. Security aspects related to routing decisions were also outside the scope of this study.

For future work, the following directions are proposed:

A. Real-world deployment and validation in large-scale testbeds across various terrains to evaluate adaptability and robustness.
B. Integration with edge and fog computing to enhance local decision-making and reduce latency.
C. Incorporation of security mechanisms such as blockchain or anomaly detection to ensure data integrity and trust.
D. Comparison with emerging AI models, including federated learning or hybrid learning approaches for decentralized environments. [14]

VIII. CONCLUSION

Wireless sensor networks are a vital technology for monitoring environmental conditions and enhancing various applications across multiple domains. Understanding their components, applications, and challenges is crucial for leveraging their full potential and addressing the issues they face. As technology advances, WSNs will continue to evolve, offering even more innovative solutions for real-world problems. This paper presents a doctoral research proposal addressing the routing challenges in wireless sensor networks (WSNs) deployed in remote areas lacking network coverage and reliable energy sources. The proposed solution introduces a routing algorithm designed using reinforcement learning, specifically leveraging Temporal Difference (TD) Learning and Boltzmann Exploration. This approach aims to optimize battery consumption for sensor nodes while enhancing the scalability of the network.

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