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# Multi-Hop State-Aware Routing Strategy for IoT Networks Using Hybrid Deep Learning Techniques

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## 1. Introduction

The rapid expansion of IoT networks has resulted in a discernible increase in the number of connected devices. This expansion requires the formulation of effective routing strategies to facilitate uninterrupted communication and tackle the significant issue of efficient routing in IoT networks, where conventional methods frequently falter under challenges of network scalability, dynamic topology, and energy limitations [1][2]. Devices within these networks typically transmit data across multiple hops, often under dynamic conditions characterized by node failures, fluctuating network statuses, and varying energy levels. Consequently, it is crucial to optimize network performance by enhancing data transmission efficiency, minimizing delays, and prolonging the network's lifespan through energy conservation, thereby ensuring that IoT networks function more reliably in diverse and dynamic environments [3]. WSNs (Wireless Sensor Networks) have been widely adopted in such fields, including environmental monitoring, healthcare, industrial automation, and smart cities. The primary challenge in WSNs is energy efficiency, as the sensor nodes are often deployed in remote or hard-to-reach areas with limited battery life. In such kind of networks Effective routing is essential for maximizing data transfer, improving energy efficiency, and ensuring network resilience [4]. A General scenario of a cluster based WSN IoT network is shown in Figure 1 [5]. As IoT networks expand, traditional routing techniques frequently inadequately manage the intricate and dynamic characteristics of multi-hop communication [6]. This has highlighted the necessity for novel strategies that can adjust to fluctuating network conditions while maintaining dependability and performance [7].

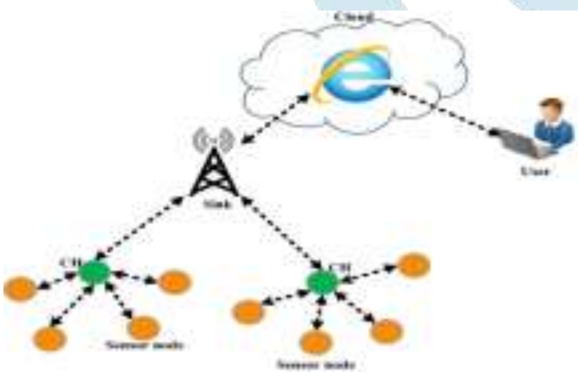

**Figure 1:** A General scenario of a cluster-based WSN IoT network [5].

A hybrid deep learning-based solution was selected for state-aware routing in IoT networks, due to its capacity to tackle the difficulties posed by dynamic and multi-hop environments [8]. Deep Learning (DL) models are very appropriate for situations where network states vary often because of their shown ability to learn and adapt to intricate patterns in network behaviour [9]. The hybrid approach integrates various DL approaches to optimize routing predictions and decisions by utilizing the strengths of diverse models [10]. This proposed technique creates more dependable and efficient routing paths by making the routing approach more adaptable to real-time changes in network traffic, energy usage, and node availability [11].

One of the main features of a state-aware approach to multi-hop routing is the ability to continuously monitor and adjust to the network's current state [12]. Conventional routing algorithms frequently depend on established measurements, which may prove inadequate for managing the dynamic characteristics of IoT networks [13]. Conversely, a state-aware model perpetually acquires knowledge from network conditions, allowing it to make judicious decisions regarding route prioritization based on real-time data [14]. Preventing problems like bottlenecks and node failures makes the network more resilient and able to adjust to changing circumstances, which eventually improves performance [15].

This hybrid DL routing method markedly improves the performance and stability of multi-hop IoT networks through the integration of state awareness and dynamic adaptation [16]. It provides a strong response to the difficulties presented by expansive, dynamic IoT environments, guaranteeing more effective and long-lasting network operations [17].

## 2. Literature Review

An overview of the literature that analyzes related works by various authors.

**Musaddiq et al., (2023) [18]** addressed routing as well as resource management issues in IoT settings with Reinforcement Learning (RL) techniques. Comparing the outcomes to conventional techniques, a significant boost in network throughput and a 25% improvement in resource usage efficiency were observed.

**Sattari et al., (2022) [19]** provided a hybrid Deep Learning (DL) strategy to handle the problem of bottleneck identification in IoT systems. The methodology integrated Long Short-Term Memory (LSTM) networks with Convolutional Neural Networks (CNN) to improve real-time identification accuracy. The proposed method produced a 98.23% detection accuracy when tested on data from IoT networks and achieved a 20% enhancement in detection efficiency.

**Arya et al., (2022) [20]** assessed 5G Wireless Sensor Networks (WSN) data transmission using deep learning-based routing methods. DL has been employed to optimize routing, data transmission efficiency, and latency utilizing IEEE Access 10. Data transmission accuracy increased by 15% and network latency decreased by 20%, demonstrating the protocol's value in 5G WSN communication.

**Emeç and Özcanhan (2022) [21]** designed to evaluate deep learning-based routing strategies' effectiveness in 5G WSN for effective data transfer. Employed a DL model using the IEEE Access 10 dataset to improve data transmission efficiency, lower latency, and optimize routing patterns. Findings showed a noteworthy enhancement, with a 15% rise in data transmission accuracy and a 20% decrease in network latency, underscoring the protocol's usefulness in 5G WSN communication.

**Janani and Ramamurthy (2022) [22]** intended to tackle security issues in IoT networks, with particular emphasis on routing attacks. Utilized a threat analysis model based on deep learning, to find and fix these vulnerabilities. A neural network was trained using an anomalous IoT traffic dataset as part of the process. With a detection accuracy of 94.7%, the model considerably lessened the impact of attacks on the network.

**Quy et al., (2022) [23]** examined the issue of maximizing routing efficiency in extremely dynamic environments by doing a thorough survey of routing algorithms for Mobile Ad hoc Network (MANET)-IoT networks. The research sought to evaluate the adaptability and scalability of different algorithms inside these networks. The findings indicated that proactive protocols enhanced packet delivery by as much as 15%, whilst hybrid approaches provided superior scalability during network development.

**Natarajan et al., (2022) [24]** improved the efficiency of routing protocols for IoT frameworks' reconfigurable engineering applications. Utilized an ML (Machine Learning) methodology, using IoT devices to dynamically optimize routing selections. Employed an IoT-MQTT (Message Queuing Telemetry Transport) framework incorporating an adaptive clustering technique. The suggested model could reduce energy consumption by 24.8% when compared to the current protocols.

**Malik et al., (2022) [25]** explored the problem of effective routing in Internet of Things networks with cognitive radio technology. Employed an RL methodology to enhance route selection and augment communication efficiency. The findings indicated a 35 % enhancement in network performance and a 20% decrease in latency relative to conventional routing methods.

**Ergun et al., (2022) [26]** addressed the problem of fault tolerance and energy efficiency to solve the issue of routing dependability in IoT networks. RL was utilized, to create a reliability-aware routing protocol. The findings indicated a 30% enhancement in network stability and a 25% reduction in energy consumption, successfully optimizing both factors for improved IoT network performance.

**Arya et al., (2022) [27]** addressed the problem of 5G Wireless Sensor Networks' poor data transmission. Improved network performance and energy efficiency with deep learning-based routing. DL techniques were used for smart routing, which improved data transmission efficiency, latency, and network lifetime in 5G wireless sensor networks.

**Dhiman et al., (2021) [28]** provided a multi-layered routing system to handle latency and energy efficiency problems in IoT networks. With the help of the Spotted Hyena Optimizer, presented a reconfigurable CRN (Cognitive Radio Network)-based cross-layer routing protocol, an edge routing protocol enhanced by ML. The results indicated a 25% decrease in network latency and an 18% enhancement in energy efficiency, highlighting the protocol's efficacy in boosting IoT performance.

## 3. Research Objective

The proposed study uses hybrid deep learning to improve IoT network routing. The primary objectives encompass:

• To design a state-aware routing mechanism that adapts to real-time network conditions, ensuring optimal data transmission across multi-hop IoT networks.

• To improve data packet delivery rates by reducing latency and avoiding congestion in high traffic network scenarios.

• To evaluate the performance and scalability of the proposed routing strategy in diverse IoT network environments, ensuring its applicability in various real-world scenarios.

## 4. Research Questions

The potential research questions for this proposed approach could be:

**RQ1:** How can a hybrid deep learning-based multi-hop routing strategy, incorporating a real-time network improve energy efficiency?

**RQ2:** How much data transmission reliability by this proposed integrated approach could be the result?

**RQ3:** How can this proposed integrated approach improve overall performance in IoT networks?

## 5. Proposed Hypothesis

Hypotheses to be considered for this proposed study are as follows:

• **H1:** The use of hybrid deep learning techniques would significantly improve routing efficiency compared to traditional routing methods in IoT networks.

• **H2:** Multi-hop state-aware routing strategies would result in lower energy consumption, thus extending the lifespan of IoT networks.

## 6. Methodology

This approach combines Deep Reinforcement Learning (DRL) for optimal cluster formation and the Whale Optimization Algorithm (WOA) for selecting Cluster Heads (CH) in WSN-assisted IoT networks. A Deep Belief Network (DBN) then optimizes routing paths, ensuring energy efficiency, scalability, and adaptive performance in resource-constrained, dynamic IoT environments.

### 6.1 Technique Used

Techniques utilized in this proposed methodology are network model, cluster formation, cluster head selection and determining the optimal multi-hop routing path are mentioned below:

**(i) Wireless Sensor Network (WSN)**

In the proposed methodology, WSNs play a crucial role as the underlying infrastructure for multi hop communication in IoT networks. WSNs consist of distributed sensor nodes that gather and transmit data across the network, often in resource-constrained environments [29]. In the multi hop state-aware routing strategy, WSNs enable efficient data transmission between nodes over multiple hops, ensuring communication reliability [30]. The hybrid deep learning techniques enhance WSN performance by optimizing routing decisions based on network state, energy levels, and dynamic conditions, improving overall IoT connectivity.

**(ii) Deep Reinforcement Learning (DRL)**

DRL is utilized for optimizing cluster formation and multi-hop routing by dynamically adapting to the network's state [31]. DRL agents learn optimal routing policies by interacting with the environment, considering factors such as node energy, link quality, and traffic load. Through continuous learning, DRL ensures energy-efficient cluster formation and robust routing, improving network lifetime, adaptability, and communication efficiency in dynamic IoT networks.

**(iii) Whale Optimization Algorithm (WOA)**

The WOA is employed for Cluster Head (CH) selection. WOA efficiently optimizes CH selection by balancing factors like node energy, distance to base stations, and communication load, ensuring energy-efficient clustering. By mimicking whale hunting behaviour, WOA identifies optimal CHs, enhancing network lifetime and reducing communication overhead [32]. This integration with deep learning further refines CH selection in dynamic IoT environments, improving scalability and overall performance.

**(iv) Deep Belief Network (DBN)**

DBN is used for optimizing routing paths by learning hierarchical representations of network states, such as node energy levels, link quality, and traffic conditions. By extracting these complex patterns, the DBN helps predict the most efficient multi-hop routes, reducing energy consumption and latency [33]. Combined with other deep learning techniques, DBNs enable more intelligent, adaptive routing decisions, ensuring optimal data transmission in dynamic IoT environments.

### 6.2 Proposed Methodology

In this proposed approach, the goal is to optimize routing in WSNs within an IoT environment using DRL for cluster formation and the WOA for selecting Cluster Heads (CHs). The process starts with data collection from sensor nodes, where energy, traffic, and distance parameters are recorded. DRL is employed to group the sensor nodes into clusters based on these parameters, rewarding clustering configurations that maximize energy efficiency and reduce network congestion.

Once clusters are formed, the WOA is used to select the optimal CH from each cluster. WOA optimizes the selection based on multiple factors, such as residual energy, traffic load, and the distance to the sink node, ensuring that the CH is energy-efficient and well-positioned for communication. After CH selection, the DBN is used to determine the optimal multi-hop routing path from the CHs to the sink node. The DBN evaluates the residual energy, network traffic, and node connectivity to select the most efficient path.

The process involves iterative decision-making, ensuring that clusters and CHs are optimally selected, and data transmission occurs through the best routes. The overall approach improves energy efficiency, reduces latency, and extends the network's lifespan, making it well-suited for large-scale IoT deployments.

## 7. Limitations

Regardless of the strengths of the proposed approach, the Multi-Hop State-Aware Routing Strategy for IoT Networks Using Hybrid DL Techniques has some limitations. One major challenge is the computational complexity involved in employing deep learning models, particularly in resource constrained IoT environments. The real-time processing required for continuous state monitoring and decision-making can lead to higher energy consumption and latency. Additionally, the need for large training datasets to optimize the deep learning models may pose difficulties in dynamic environments where data availability is limited. These factors could hinder the scalability and efficiency of the proposed solution.

## 8. Conclusion and Future Scope

The proposed approach demonstrates a significant improvement in IoT network performance by leveraging DL to enhance energy efficiency, data transmission reliability, and scalability. The conclusion highlights that integrating DRL, WOA, and DBN allows real-time adaptability to dynamic network conditions, optimizing multi-hop routing. The future scope involves extending this hybrid approach to more complex IoT environments, exploring its applicability in large-scale smart city implementations, and improving fault tolerance and security mechanisms to address vulnerabilities in real-time communication systems.

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