

DEEP LEARNING-BASED ADAPTIVE ROUTING FOR ENERGY-EFFICIENT UNDERWATER ACOUSTIC SENSOR NETWORKS

T Jaya^{1*}, T Aruna Jacintha², Nagajyothi Ch V³, Rajeshwari K N⁴

¹*Department of Electronics and Communication Engineering, Vels Institute of Science Technology & Advanced Studies, Tamil Nadu, India*

²*Department of Electronics & Communication Engineering, R R Institute Of Technology, Karnataka, India.*

³*Department of Electronics & Communication Engineering, R R Institute Of Technology, Karnataka, India.*

⁴*Department of Electronics & Communication Engineering, Sir M V Institute Of Technology, Karnataka, India.*

*Corresponding Author Email: jaya.se@velsuniv.ac.in

Abstract

The growing demand for underwater monitoring and exploration has increased the importance of Underwater Acoustic Sensor Networks (UASNs) in marine environments. These networks accommodate vast range of applications, including pollution monitoring, oceanographic research, disaster prevention, and resource exploration. However, their performance is often limited by factors such as constrained bandwidth, high communication delays, fluctuating channel characteristics, and excessive energy usage. As a result, conventional routing methods struggle to maintain reliable data transmission and efficient network operation over extended periods. This research introduces a Deep Learning-Based Adaptive Routing (DLAR) model to improve routing efficiency in UASNs. The proposed approach employs a deep a trainable neural network capable of automatically learning complex relationships among multiple network attributes, including remaining battery power, signal quality, node position, communication distance, and link stability. Based on these parameters, the model identifies suitable forwarding nodes and dynamically establishes efficient communication paths. The adaptive learning capability of the proposed framework enables it to respond effectively to variations in underwater network conditions. Performance evaluation through simulation demonstrates notable improvements in communication reliability and resource utilization. Compared with traditional routing schemes, the DLAR model achieves lower energy expenditure, higher packet delivery performance, and longer network operational duration. The analysis indicates that deep learning-driven routing mechanisms can substantially improve the effectiveness of underwater acoustic communication systems and support sustainable network deployment in challenging marine environments.

Keywords- Underwater Acoustic Sensor Networks (UASNs), Deep Learning, Adaptive Routing, Energy Efficiency, Neural Networks, Packet Transmission Success Rate, Acoustic Communication, Intelligent Routing, Machine Learning.

1. Introduction

Acoustic Sensor Networks for Underwater Environments have become an important technology for collecting information from aquatic environments where direct human access is difficult. These networks support various activities, including

marine ecosystem observation, underwater infrastructure monitoring, offshore exploration, and disaster warning systems. Communication between underwater devices is primarily achieved through acoustic signals because electromagnetic waves experience severe attenuation in water.

The underwater environment give rise to several challenges that shows impact on network performance. Sensor nodes generally depend on finite battery energy, making energy-efficient operation essential for long-term deployment. Besides Acoustic communication is subject to limited channel capacity, considerable propagation delay, signal fading, and environmental disturbances. These conditions often reduce the effectiveness of transmission of data and maximize network overhead.

Reliable routing represents a key factor in maintaining communication efficiency within UASNs. Many existing routing approaches, such as Depth-Based Routing (DBR) and Vector-Based Forwarding (VBF), utilize predefined forwarding mechanisms. Since these methods do not continuously adapt to variations in network status, their performance may decline under dynamic underwater conditions, resulting in increased energy usage and reduced delivery success.

The rise of deep learning approaches has given rise to new possibilities for intelligent network management. By learning the relationship between network parameters and routing outcomes, deep learning models can enable adaptive decision-making processes. In this work, a Deep Learning-Based Adaptive Routing (DLAR) scheme is introduced for underwater acoustic communication systems. The proposed framework employs a Deep Neural Network (DNN) to determine suitable forwarding paths using information such as residual node energy, transmission distance, signal-to-noise ratio, node depth, and packet loss statistics.

The major objectives and contributions pertaining to the suggested study are:

1. To develop an adaptive routing mechanism the underwater acoustic systems are powered by deep learning sensor networks.
2. To incorporate multiple network performance indicators into the route selection process.
3. To improve packet delivery performance while reducing overall energy consumption.
4. To evaluate the reliability of suggested DLAR model through comparison with DBR and VBF routing approaches.

2. Related Work

Research on Underwater Acoustic Sensor Networks (UASNs) has attracted substantial interest owing to their applications in ocean exploration, environmental monitoring, and military surveillance. However, the unique characteristics of underwater acoustic communication make the design of efficient routing protocols a challenging task.

Ian F. Akyildiz et al. [1] presented a comprehensive overview of underwater acoustic sensor networks and discussed the critical issues related to underwater communication, including Low bandwidth capacity and increased transmission latency, node mobility, and energy constraints. Their work highlighted the necessity of developing specialized routing techniques suitable for underwater environments.

Li et al. [2] reviewed several underwater routing protocols and classified them based on their operational characteristics. The authors observed that many existing protocols employ predefined routing mechanisms that may not perform efficiently under dynamic network conditions. They emphasized the need for more adaptive routing strategies capable of responding to environmental variations.

Islam and Lee [3] investigated current advancements in underwater routing methodologies and identified Power efficiency and communication robustness as critical performance requirements. Their analysis revealed that maintaining reliable packet transmission remains a significant challenge due to the dynamic nature of acoustic channels.

Han et al. [4] focused on energy-aware routing techniques and examined different forwarding approaches designed to reduce energy expenditure in underwater sensor nodes. Their study demonstrated that routing decisions significantly influence network lifetime and overall system performance.

Coutinho et al. [5] explored topology control and routing issues in underwater networks. The authors reported that node mobility, changing link quality,

and environmental disturbances have a substantial impact on communication effectiveness. Their findings suggested that adaptive routing mechanisms can enhance overall performance than conventional fixed-routing approaches.

2.1 Research Gap

On the basis of the reviewed literature, the below mentioned research gaps have been identified:

1. Most existing routing protocols depend on predefined forwarding rules and provide limited adaptability to changing underwater conditions.
2. Route selection is often performed using a restricted set of network metrics that may not effectively characterize the overall network state.
3. Communication reliability continues to be affected by node mobility, channel fluctuations, and varying link quality.
4. Conventional routing mechanisms lack cognitive capabilities that enable continuous improvement in routing decisions.
5. Relatively few studies have explored deep learning-based routing frameworks for the joint optimization of Energy utilization, Data delivery efficiency, and Network lifetime.

To address these limitations, this research introduces a Deep Learning-Based Adaptive Routing (DLAR) framework. The proposed method employs a Deep Neural Network (DNN) to evaluate multiple network attributes, including residual energy, signal-to-noise ratio, node depth, packet loss rate, and inter-node distance. By utilizing these parameters, the framework dynamically selects efficient routing paths, thereby enhancing communication reliability, reducing energy consumption, and extending network lifetime in underwater acoustic sensor networks.

3. Materials and Methods

The proposed Deep Learning-Based Adaptive Routing (DLAR) framework is developed to enhance communication efficiency and prolong network lifetime in Underwater Acoustic Sensor Networks (UASNs). The framework incorporates deep learning

techniques to perform intelligent route selection by analyzing real-time network conditions. Unlike conventional routing schemes that rely on fixed routing rules, the proposed approach dynamically identifies efficient communication paths using a Deep Neural Network (DNN).

3.1 Network Architecture

The organization of the proposed DLAR framework is composed of four functional entities: underwater sensor nodes, relay nodes, a surface sink node, and a Deep Learning Routing Engine. These components collectively facilitate data sensing, route discovery, packet forwarding, and network management.

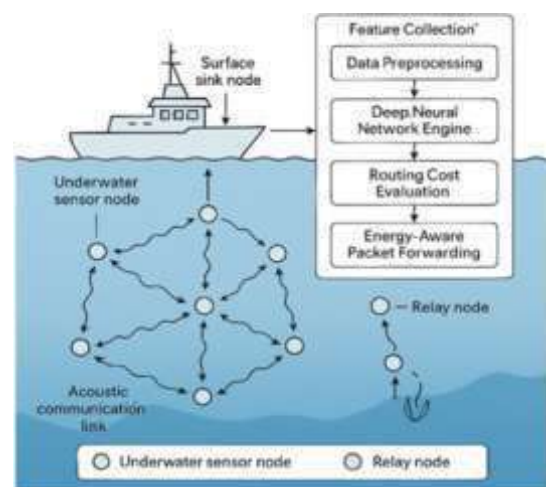


Figure 1. Proposed Network schematic of the Deep Learning-Based Adaptive Routing (DLAR) Framework for Underwater Acoustic Sensor Networks

Underwater sensor nodes are arbitrarily distributed within the sensing region to monitor environmental parameters and generate data packets. Because of constrained transmission range of acoustic communication, direct node-to-sink communication is often impractical. Therefore, packet transmission is done through intermediate nodes using a multi-hop communication mechanism.

Relay nodes act as supporting communication entities that assist in routing packets from source nodes toward the destination. Their presence helps reduce transmission distance, improve connectivity, and minimize packet loss caused by channel impairments.

A surface sink node is deployed in the water surface to collect information transmitted by underwater nodes. The received data is subsequently forwarded

to external monitoring centers for storage, visualization, and analysis.

The intelligence of the proposed framework is provided by the Deep Learning Routing Engine. This module gathers important routing-related information from neighboring nodes, including residual energy (Eres), signal-to-noise ratio (SNR), node depth (D), packet loss rate (PLR), and inter-node distance (d). These parameters are supplied to a Deep Learning-Based Neural Architecture, which learns the relationship between network conditions and routing performance. Depending on the network state, the DNN recommends suitable forwarding candidates. The selected candidate nodes are subjected to evaluation using routing cost criteria, and the node offering the most efficient communication path is chosen for packet forwarding. This adaptive mechanism enables reliable data transmission while conserving network energy resources.

3.2 DLAR Algorithm Workflow

The operation of the proposed DLAR framework follows a sequence of interconnected stages that support intelligent routing and efficient packet delivery.

Initially, underwater sensor nodes, relay nodes, and the surface sink node are deployed throughout the monitoring region. After deployment, each node periodically measures and exchanges network information required for routing decisions. The collected parameters include residual energy, communication distance, signal-to-noise ratio, node depth, and packet loss statistics.

Before being processed by the learning model, the collected information undergoes preprocessing operations such as normalization and feature preparation. The processed data is represented as a feature vector:

$$X = [Eres, d, SNR, D, PLR]$$

The feature vector is provided as input to the Deep Neural Network. Using knowledge acquired during training, the DNN analyzes the current network state and identifies a collection of possible relay nodes that can efficiently deliver packets toward the sink node.

To further improve routing accuracy, the candidate nodes are assessed using a routing cost evaluation mechanism. The cost calculation considers multiple communication factors, including energy availability, link quality, transmission distance, and packet delivery reliability. The relay node associated with the lowest routing cost is taken for the next hop.

After the next-hop node is determined, the data packet is transmitted toward the sink node through the selected route. This procedure is repeated at every forwarding stage until the packet successfully reaches the destination. Since routing decisions are continuously updated according to current network conditions, the proposed DLAR framework can effectively balance energy consumption, improve packet delivery ratio, and extend overall network lifetime.

4. Results and Discussion

4.1 Simulation Environment

The proposed Deep Learning-Based Adaptive Routing (DLAR) framework was implemented using Python in the Jupyter Notebook environment. A three-dimensional underwater acoustic sensor network consisting of 50 sensor nodes, 10 relay nodes, and one surface sink node was considered for simulation. The network was deployed within a monitoring area of 1000 m × 1000 m × 1000 m. Each node was initialized with a finite energy source and communicated through acoustic links. The effectiveness of the suggested DLAR framework was compared with two widely used underwater routing protocols, namely Vector-Based Forwarding (VBF) and Depth-Based Routing (DBR).

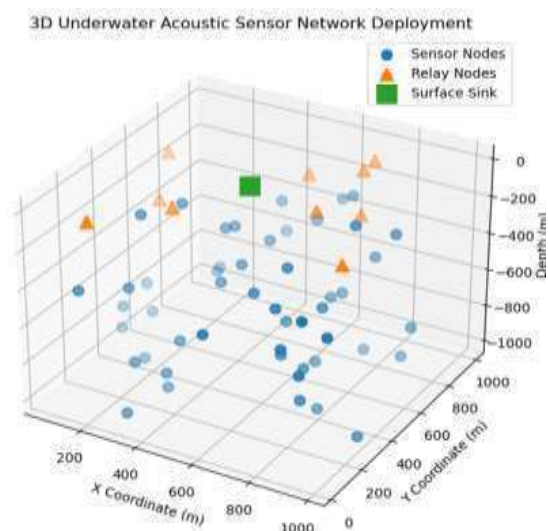


Figure 3. Three-Dimensional Deployment of Underwater Sensor Nodes, Relay Nodes, and Surface Sink Node

Figure 3 illustrates the three-dimensional deployment of underwater sensor nodes, relay nodes, and the surface sink node used in the simulation. Sensor nodes were randomly distributed throughout the underwater region, while relay nodes were positioned at intermediate depths to support multi-hop communication toward the sink node.

4.2 Route Selection Analysis

Figure 5 presents the optimal routing path selected by the proposed DLAR framework. The Deep Neural Network evaluates neighboring nodes based on residual energy, communication distance, signal-to-noise ratio, node depth, and packet loss rate. Based on these metrics, the routing engine identifies the most suitable relay node and establishes an efficient communication path toward the surface sink.

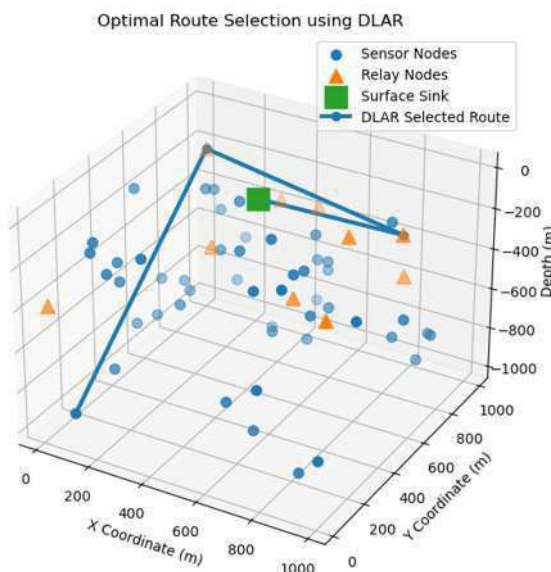


Figure 4. Optimal Routing Path Selection Using the Proposed DLAR Framework

Unlike conventional routing protocols that rely on predefined forwarding rules, the proposed approach dynamically adapts to changing network conditions. This adaptive behavior reduces unnecessary retransmissions and improves communication reliability.

4.3 Packet Delivery Ratio Analysis

The Packet Delivery Ratio (PDR) attained by VBF, DBR, and the suggested DLAR framework during various simulation intervals is contrasted in Figure 5. The percentage of correctly delivered packets in relation to all packets transmitted is known as the packet delivery ratio.

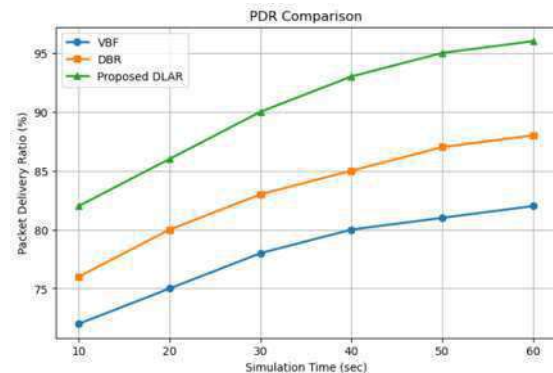


Figure 5. Packet Delivery Ratio (PDR) Comparison of VBF, DBR, and Proposed DLAR

The analysis indicate that the proposed DLAR framework consistently outperforms both VBF and DBR throughout the simulation period. In the final stage of the simulation, DLAR achieved a PDR of approximately 96%, while DBR and VBF achieved 88% and 82%, respectively.

The improvement in packet delivery performance can be attributed to the intelligent route prediction capability of the Deep Neural Network. By selecting forwarding nodes with favorable energy levels and communication quality, the proposed method minimizes packet losses and enhances communication reliability.

4.4 Energy Consumption Analysis

Energy efficiency is the most important critical requirements in underwater acoustic sensor networks because sensor nodes operate using limited battery resources. Figure 8 presents the graphical representation of utilization and consumption of Energy of the evaluated routing protocols.

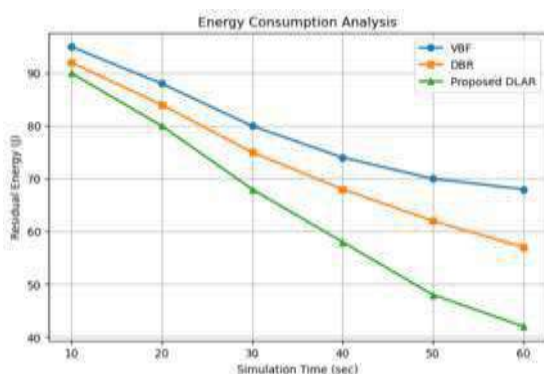


Figure 6. Energy Consumption Comparison of VBF, DBR, and Proposed DLAR

The proposed DLAR framework illustrated less consumption of Energy compared to VBF and DBR. The routing decisions generated by the DNN avoid unnecessary transmissions and reduce communication overhead. Consequently, energy resources utilization is more effective across the network.

The observations reveal that DLAR preserves a larger amount of residual energy throughout the simulation period, thereby extending the operational lifetime of the network.

5. Conclusion

This paper presented a Deep Learning-Based Adaptive Routing (DLAR) architecture for Underwater Acoustic Sensor Networks (UASNs). By utilizing a Deep Neural Network (DNN) and network parameters such as residual energy, distance, signal-to-noise ratio, node depth, and packet loss rate, the proposed framework enables intelligent route selection. Simulation results demonstrated that DLAR achieves enhanced data delivery efficiency and decreased energy expenditure relative to existing routing protocols such as VBF and DBR, making it a promising solution for reliable and energy-efficient underwater communication. Future work will focus on enhancing the model and evaluating its performance in larger network environments.

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