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# A Review of Intelligent Communication Techniques for Underwater Wireless Sensor Networks

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**Abstract**

Underwater Wireless Sensor Networks (UWSNs) play a significant role in applications such as ocean monitoring, environmental assessment, offshore infrastructure inspection, disaster management, and maritime surveillance. Despite their wide range of applications, the underwater environment presents several communication challenges, including limited bandwidth, long propagation delays, dynamic network topology, high transmission errors, and restricted energy resources. These constraints reduce the effectiveness of conventional networking approaches designed for static environments. Recent developments in intelligent

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data-driven techniques have introduced new opportunities to improve the adaptability and efficiency of underwater communication systems. This review presents a comprehensive analysis of intelligent computational approaches applied to UWSNs, with emphasis on machine learning, deep learning, and reinforcement learning methods. The study examines their contributions to routing optimization, energy management, communication reliability, localization, and network security. A comparative review of existing research is provided to highlight performance trends, advantages, and existing limitations of different techniques. Furthermore, the paper discusses current research challenges and identifies promising future directions for developing scalable, reliable, and energy-efficient underwater sensing systems that support next-generation Internet of Underwater Things (IoUT) applications.

**Keywords:** Underwater Wireless Sensor Networks, Machine Learning, Deep Learning, Reinforcement Learning, Intelligent Routing, Energy Optimization, Internet of Underwater Things.

## 1. Introduction

The increasing need to understand and monitor underwater environments has accelerated research in marine observation technologies. Rising concerns over climate change, marine biodiversity conservation, sustainable resource utilization, and maritime security have created a demand for reliable underwater monitoring systems. Underwater Wireless Sensor Networks (UWSNs) have emerged as an effective solution by enabling continuous sensing, data collection, and communication from submerged environments to surface stations for further analysis. These networks support a wide range of applications, including oceanographic data collection, pollution monitoring, seismic activity detection, offshore infrastructure inspection, underwater navigation, and military surveillance [1].

Unlike terrestrial wireless sensor networks, UWSNs operate under harsh environmental conditions that significantly affect communication performance. Radio frequency signals experience severe attenuation in water, making acoustic communication the most practical medium for long-distance underwater transmission. However, acoustic channels are characterized by limited bandwidth, long propagation delays, multipath fading, high bit error rates, and channel variability. These characteristics reduce communication reliability and increase transmission latency. Furthermore, underwater sensor nodes generally operate on batteries that are difficult or impossible to replace after deployment, making energy conservation a critical design objective [2].

Conventional communication and routing protocols are primarily based on predefined mathematical models and static assumptions. Although these methods provide acceptable performance in stable environments, they often fail to adapt to the dynamic nature of underwater networks. Factors such as water currents, node mobility, fluctuating channel conditions, and intermittent connectivity frequently lead to packet loss, increased delay, and uneven energy consumption, ultimately reducing network lifetime and overall system performance [3].

Recent advances in intelligent computational techniques have provided new opportunities to overcome these limitations. Learning-based methods enable underwater networks to analyse environmental conditions, recognize communication patterns, and make adaptive decisions without relying solely on fixed rules. Machine learning techniques improve routing and link-quality prediction, deep learning enhances underwater acoustic signal processing and feature extraction, while reinforcement learning supports autonomous routing and resource management through continuous interaction with the network environment [4]. These capabilities make learning-based approaches well suited to addressing the uncertainties associated with underwater communication.

This paper presents a comprehensive review of intelligent techniques applied to Underwater Wireless Sensor Networks. The objectives are threefold: (i) to discuss the architecture, characteristics, and communication challenges of UWSNs; (ii) to review and compare recent learning-based approaches proposed for routing, energy optimization, localization, communication reliability, and network security; and (iii) to identify existing research gaps, current challenges, and future directions for developing efficient, scalable, and reliable underwater sensing systems. By consolidating recent research findings, this review provides a useful reference for researchers and practitioners involved in the advancement of next-generation underwater communication networks.

## 2. Overview of Underwater Wireless Sensor Networks

Underwater Wireless Sensor Networks (UWSNs) consist of interconnected sensor nodes deployed beneath the water surface to observe and collect information from aquatic environments. These sensor nodes continuously monitor parameters such as temperature, pressure, salinity, dissolved oxygen, seismic activity, and pollution levels. The collected data are transmitted to surface stations or monitoring centers for storage, analysis, and decision-making. Owing to their ability to operate in remote and inaccessible marine environments, UWSNs have become an essential technology for scientific research, environmental monitoring, offshore exploration, disaster management, and defense applications [1].

### 2.1 Architecture and Components of UWSNs

A typical UWSN is composed of three primary elements: underwater sensor nodes, communication links, and surface gateways. Sensor nodes are equipped with sensing devices, processing units, memory, acoustic communication modules, and battery-powered energy sources. Depending on the application, these nodes may be deployed in either two-dimensional or three-dimensional configurations. In two-dimensional deployments, sensors are generally anchored to the seabed to monitor pipelines, underwater structures, or geological activities and it is represented in Fig 1. Three-dimensional deployments position sensor nodes at different water depths using buoyancy mechanisms, enabling comprehensive monitoring of the water column and marine ecosystems [2].

Communication in underwater environments primarily relies on acoustic signals because radio frequency waves experience severe attenuation in water. Acoustic communication supports long-distance transmission but is affected by limited bandwidth, high propagation delay, ambient noise, and multipath interference, all of which reduce communication efficiency. Optical and electromagnetic communication technologies have also been investigated for short-range, high-speed data transmission. However, their performance is limited by absorption and scattering effects in water. Consequently, recent research has focused on hybrid communication architectures that combine acoustic, optical, and electromagnetic techniques to improve network performance under varying underwater conditions [3].

Surface gateways, often deployed as floating buoys, act as communication bridges between underwater sensor networks and terrestrial monitoring systems. These gateways receive data from submerged nodes and forward the information to onshore control centers through radio or satellite communication links. In large-scale monitoring systems, Autonomous Underwater Vehicles (AUVs) are frequently incorporated to assist with data collection, network maintenance, node replacement, and adaptive network reconfiguration, thereby improving coverage and operational flexibility [4].

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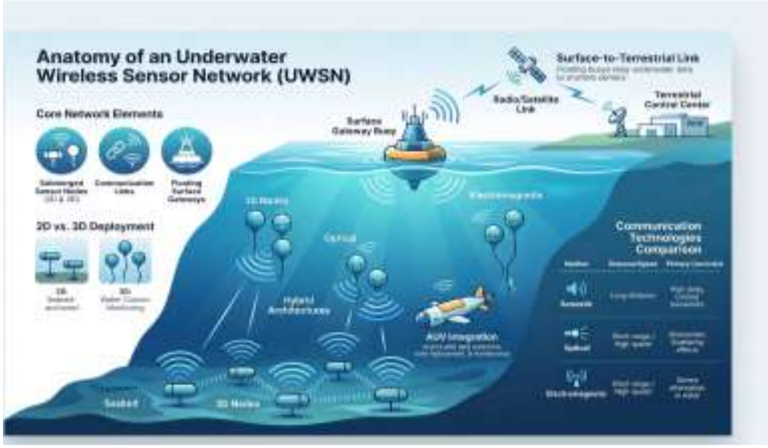


**Fig 1: Architecture of Under Water wireless sensor network**

### 2.2 Characteristics and Challenges of Underwater Communication

The underwater communication environment differs significantly from terrestrial wireless networks and introduces several technical challenges. One of the major limitations is the slow propagation speed of acoustic signals, which is considerably lower than that of radio waves in air. This results in long transmission delays that complicate synchronization, channel access, and real-time communication [2].

Limited channel bandwidth further restricts the achievable data transmission rate, making efficient bandwidth utilization an important design objective. In addition, underwater channels are highly dynamic because of variations in temperature, salinity, water pressure, and ocean currents. These environmental factors continuously alter signal propagation characteristics, leading to frequent fluctuations in channel quality and increased packet loss [3].

Energy efficiency is another critical concern in UWSNs. Since underwater sensor nodes typically operate on batteries that cannot be easily replaced or recharged after deployment, communication protocols must minimize energy consumption while maintaining reliable data delivery. Excessive energy usage by a subset of nodes may lead to premature battery depletion, resulting in network partitioning and reduced sensing coverage [1].

Accurate localization and time synchronization also remain challenging because Global Positioning System (GPS) signals cannot penetrate underwater environments. Alternative localization techniques rely mainly on acoustic ranging, which is susceptible to propagation delays and environmental noise. Furthermore, underwater communication systems face

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security threats such as eavesdropping, spoofing, packet modification, and denial-of-service attacks due to the broadcast nature of acoustic communication channels [4].

These architectural characteristics and communication challenges demonstrate that conventional networking approaches are often inadequate for underwater environments. Consequently, adaptive and intelligent networking strategies have become increasingly important for improving communication reliability, energy efficiency, and overall network performance in Underwater Wireless Sensor Networks.

**Problem Statement**

Underwater Wireless Sensor Networks (UWSNs) face significant challenges due to limited bandwidth, long propagation delays, dynamic channel conditions, and energy constraints, which reduce communication reliability and network lifetime. Conventional routing and communication techniques are unable to adapt effectively to these changing underwater environments. Although intelligent computational approaches have shown promising improvements in routing, energy efficiency, and network performance, existing studies are dispersed and lack comprehensive comparison. Therefore, a systematic review is needed to evaluate current approaches, identify research gaps, and highlight future directions for developing reliable and energy-efficient UWSNs.

## Motivation

Underwater Wireless Sensor Networks (UWSNs) are increasingly used in marine environmental monitoring, ocean exploration, disaster management, and offshore surveillance. However, underwater communication continues to face challenges such as high propagation delay, limited bandwidth, dynamic channel conditions, low packet delivery, and high energy consumption. Conventional networking approaches are often unable to adapt effectively to these constraints. Recent advances in Machine Learning, Deep Learning, and Reinforcement Learning have demonstrated significant potential for improving routing, communication reliability, throughput, and energy efficiency in UWSNs. Nevertheless, existing research is scattered across different studies, making it difficult to obtain a comprehensive understanding of current developments. This motivated the present review to systematically analyze AI-based techniques, compare their performance using key network metrics, identify existing research gaps, and highlight future research directions for developing intelligent and energy-efficient underwater communication systems.

**Objectives**

The main objectives are:

- To examine the architecture, characteristics, and communication challenges of Underwater Wireless Sensor Networks (UWSNs).
- To review and compare intelligent computational techniques, including machine learning, deep learning, and reinforcement learning, used in UWSNs.
- To evaluate the effectiveness of these techniques in improving routing, energy efficiency, communication reliability, localization, and network security.
- To identify existing research challenges, limitations, and future research directions for developing scalable and energy-efficient underwater sensor networks.

## 3. Literature Review

Extensive research has been conducted to address the communication and networking challenges associated with Underwater Wireless Sensor Networks (UWSNs). Early investigations mainly concentrated on acoustic communication models, routing protocols, and energy-efficient mechanisms suitable for underwater environments.

Akyildiz et al. [1] presented one of the earliest comprehensive studies on underwater acoustic sensor networks and identified major challenges such as limited bandwidth, long propagation delays, high error rates, and energy constraints. Heidemann et al. [2] examined the applications and technological progress of UWSNs while emphasizing the influence of underwater acoustic communication on network performance. Domingo [3] reviewed underwater channel models and explained how channel variability affects communication reliability.

Ayaz et al. [4] surveyed routing strategies developed specifically for underwater environments and classified them according to forwarding methods, energy conservation, and localization techniques. Khan et al. [5] provided an extensive review of routing protocols and highlighted issues related to scalability, packet delivery, and network lifetime.

Luo et al. [6] demonstrated that machine learning techniques can enhance communication efficiency by predicting link quality and supporting adaptive routing decisions. Javaid et al. [7]

proposed machine learning-based routing mechanisms that reduced energy consumption while improving packet delivery performance.

Li et al. [8] developed deep learning models for underwater signal detection and reported improved robustness against channel noise and multipath interference. Zhang et al. [9] applied convolutional neural networks for underwater acoustic signal classification and achieved higher classification accuracy than conventional feature-based methods.

Li et al. [10] introduced reinforcement learning-based routing strategies that dynamically optimize packet forwarding under changing network conditions. Huang et al. [11] developed a Q-learning-based MAC protocol that improved energy efficiency while maintaining communication reliability.

The reviewed literature indicates a gradual transition from conventional rule-based communication protocols to adaptive learning-based approaches. Traditional methods offer low computational complexity but have limited adaptability in dynamic underwater environments. Machine learning improves routing decisions and resource utilization, deep learning enhances signal processing accuracy, and reinforcement learning enables autonomous decision-making under varying network conditions. Nevertheless, challenges related to computational overhead, limited underwater datasets, model interpretability, and real-world deployment remain important research concerns.

Comparative Analysis of Existing Approaches

| **Approach** | **Primary Objective** | **Advantages** | **Limitations** |
|---|---|---|---|
| Traditional Routing | Reliable communication and energy conservation | Simple implementation and low computational cost | Limited adaptability to dynamic |
| Machine Learning | Link prediction and routing optimization | Improved packet delivery and energy efficiency | Requires training datasets |
| Deep Learning | Acoustic signal processing and traffic prediction | High prediction accuracy and noise resilience | High computational and memory requirements |
| Reinforcement Learning | Adaptive routing and resource management | Autonomous decision-making and dynamic adaptation | Slow convergence and training complexity |

**Table 1: Comparative Analysis of Existing Approaches**

The comparative analysis shows that learning-based approaches generally outperform conventional methods in dynamic underwater environments by improving communication reliability, energy efficiency, and network adaptability. However, the development of lightweight, scalable, and resource-efficient learning models remains an important direction for future research.

## 4. Artificial Intelligence Techniques in Underwater Wireless Sensor Networks

Artificial Intelligence (AI) techniques have become an effective solution for addressing the limitations of conventional communication methods in Underwater Wireless Sensor Networks (UWSNs). Unlike traditional rule-based approaches, AI enables sensor nodes to learn from network conditions, adapt to environmental changes, and make intelligent decisions with minimal human intervention. These capabilities improve routing efficiency, communication reliability, energy conservation, localization accuracy, and network security. The major AI techniques applied in UWSNs include Machine Learning (ML), Deep Learning (DL), and Reinforcement Learning (RL).

### 4.1 Machine Learning Techniques in UWSNs

Machine Learning enables underwater sensor nodes to identify communication patterns and make predictions using previously collected data. Supervised learning algorithms are commonly employed to estimate link quality, predict node failures, and improve routing decisions, resulting in higher packet delivery rates and lower energy consumption. Unsupervised learning techniques, such as clustering and anomaly detection, help organize sensor nodes based on location or residual energy while identifying abnormal network behavior without requiring labelled data. These techniques improve network efficiency and reduce redundant transmissions [6], [7].

### 4.2 Deep Learning for Underwater Communication

Deep Learning techniques have demonstrated significant improvements in underwater acoustic communication by automatically extracting meaningful features from complex acoustic signals. Convolutional Neural Networks (CNNs) are widely used for signal classification and noise reduction, whereas Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks effectively model temporal variations in underwater communication channels. These models improve signal detection, traffic prediction, channel estimation, and communication reliability under dynamic underwater conditions [8], [9].

### 4.3 Reinforcement Learning for Adaptive Routing

Reinforcement Learning enables underwater sensor nodes to learn optimal routing strategies through continuous interaction with the network environment. Each sensor node functions as an intelligent agent that selects forwarding paths based on current network conditions and receives rewards according to communication performance. The learning process continuously updates routing decisions to maximize packet delivery, reduce transmission delay, and minimize energy consumption. Compared with conventional routing methods, reinforcement learning provides greater adaptability in highly dynamic underwater environments [10], [11].

### 4.4 AI-Based Applications in UWSNs

AI techniques have been successfully applied across multiple functional areas of UWSNs. Learning-based routing protocols improve packet forwarding decisions by selecting reliable communication paths. Intelligent energy management techniques reduce battery consumption and extend network lifetime. AI-assisted localization methods enhance node position estimation despite the absence of GPS signals underwater. In addition, learning algorithms improve underwater acoustic signal processing, intrusion detection, fault prediction, congestion control, and resource allocation, thereby enhancing the overall performance and reliability of underwater communication systems [6]–[12].

Overall, AI-based techniques significantly enhance the performance of Underwater Wireless Sensor Networks by improving communication efficiency, network adaptability, and resource utilization. Machine Learning provides reliable predictive capabilities, Deep Learning offers superior performance in underwater signal processing, and Reinforcement Learning enables autonomous network optimization under dynamic operating conditions. Despite these advantages, challenges related to computational complexity, energy limitations, availability of training data, and practical deployment remain important areas for future investigation.

### 5. Results and Discussion

The performance of intelligent techniques in Underwater Wireless Sensor Networks (UWSNs) is commonly evaluated using four key metrics: **end-to-end delay, throughput, packet delivery ratio (PDR), and energy consumption**. A comparative analysis of the reviewed studies indicates that Machine Learning (ML), Deep Learning (DL), and Reinforcement Learning (RL) significantly improve these performance indicators compared with conventional routing protocols.

**Delay**

End-to-end delay represents the time required for a data packet to travel from the source node to the destination. Conventional routing protocols often experience higher delays because of long acoustic propagation times, frequent route rediscovery, and dynamic underwater channel conditions. Learning-based approaches reduce transmission delay by selecting stable communication paths, predicting link quality, and adapting routing decisions according to changing network conditions. Among the reviewed techniques, Reinforcement Learning demonstrates the lowest delay due to its ability to dynamically optimize routing paths.

**Throughput**

Throughput refers to the amount of successfully transmitted data within a given period. Traditional routing protocols suffer from packet collisions, retransmissions, and unstable communication links, resulting in lower throughput. Machine Learning and Deep Learning techniques improve throughput by predicting channel conditions, minimizing packet loss, and selecting reliable forwarding paths. Reinforcement Learning further enhances throughput by continuously adapting routing decisions to varying underwater environments.

**Packet Delivery Ratio (PDR)**

Packet Delivery Ratio measures the percentage of data packets successfully received at the destination. Higher PDR indicates improved communication reliability. The reviewed studies consistently report that intelligent routing techniques achieve higher packet delivery ratios than conventional methods by reducing packet loss caused by link failures, channel interference, and node mobility. Reinforcement Learning and Deep Learning approaches generally achieve the highest PDR because of their adaptive routing and accurate prediction capabilities.

**Energy Consumption**

Energy consumption is one of the most critical performance metrics in UWSNs because underwater sensor nodes are battery-powered and battery replacement is often impractical. Conventional protocols frequently consume excessive energy due to repeated retransmissions

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and inefficient routing decisions. Machine Learning-based routing balances network traffic and minimizes redundant transmissions, while Reinforcement Learning identifies energy-efficient forwarding paths through continuous learning. Consequently, intelligent techniques significantly reduce overall energy consumption and extend network lifetime.

### Comparative Discussion

Table 1: summarizes the comparative performance of intelligent techniques based on the selected evaluation metrics.

| Performance Metric | Conventional Routing | Machine Learning | Deep Learning | Reinforcement Learning |
|---|---|---|---|---|
| End-to-End Delay | High | Moderate | Low | Very Low |
| Throughput | Low | High | High | Very High |
| Packet Delivery Ratio | Moderate | High | Very High | Very High |
| Energy Consumption | High | Low | Moderate | Low |

**Table 1: Analysis of Performance Metrics**

The comparative analysis indicates that intelligent computational techniques consistently outperform conventional routing methods. Reinforcement Learning provides superior adaptability and routing performance, Deep Learning offers accurate prediction and signal processing capabilities, while Machine Learning achieves a balanced trade-off between computational complexity and communication efficiency. These improvements contribute to more reliable, energy-efficient, and scalable Underwater Wireless Sensor Networks suitable for future Internet of Underwater Things (IoUT) applications.

## 6. Conclusion

Underwater Wireless Sensor Networks have become an essential technology for marine environmental monitoring, ocean exploration, offshore infrastructure inspection, disaster management, and defense applications. However, the unique characteristics of underwater acoustic communication, including limited bandwidth, long propagation delays, dynamic channel conditions, and energy constraints, continue to present significant challenges for reliable communication and network management.

This review has presented a comprehensive analysis of intelligent computational techniques applied to Underwater Wireless Sensor Networks. The study examined recent developments in Machine Learning, Deep Learning, and Reinforcement Learning and compared their contributions toward routing optimization, energy efficiency, communication reliability, localization, and network security. The comparative review indicates that learning-based approaches consistently achieve better performance than conventional communication techniques by improving network adaptability and resource utilization.

Among the reviewed approaches, Machine Learning offers efficient predictive capabilities with moderate computational requirements, Deep Learning provides high accuracy for underwater signal processing and channel prediction, while Reinforcement Learning enables autonomous and adaptive network optimization in dynamic environments. Although these approaches have demonstrated considerable improvements, challenges related to computational complexity, limited training datasets, energy consumption, and real-world deployment remain active research issues.

Future research should focus on developing lightweight and energy-efficient learning algorithms, integrating edge intelligence and autonomous underwater vehicles, and adopting distributed learning frameworks such as federated learning. These advancements will contribute to the development of scalable, reliable, and intelligent Underwater Wireless Sensor Networks capable of supporting next-generation Internet of Underwater Things (IoUT) applications.

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