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A Comprehensive Review of Artificial Intelligence-Driven Underwater Wireless Sensor Networks

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Abstract

UWSNs support oceanographic data acquisition, environmental sensing, offshore infrastructure inspection, and underwater surveillance, but face severe bandwidth, propagation delay, topology, and energy constraints that limit traditional networking. This paper reviews AI-based techniques—machine learning, deep learning, and reinforcement learning—in UWSNs, examining their impact on routing, energy conservation, reliability, localization, and security. A structured comparison identifies performance trends across the literature, and the paper closes with key challenges and future research directions for scalable, intelligent underwater sensing.

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

1. Introduction

Underwater exploration has gained importance amid concerns over climate change, marine ecosystems, resource management, and maritime security. UWSNs enable data collection and transmission from underwater environments to surface stations, supporting applications such as pollution detection, seismic observation, navigation, and defense [1].

UWSNs differ from terrestrial sensor networks: radio signals attenuate severely underwater, making acoustic communication the primary option, though it suffers low bandwidth, high delay, multipath fading, and high error rates. Battery-powered nodes with impractical replacement further make energy efficiency a dominant design concern [2].

Traditional UWSN protocols use static assumptions and mathematical models for routing, energy, and communication. These provide basic functionality but struggle with dynamic conditions—node mobility, channel variability, and fluctuating connectivity—often degrading packet delivery, increasing latency, and unbalancing energy use [3].

AI offers a data-driven, adaptive alternative to rule-based systems. Machine learning predicts link quality and node dynamics, deep learning enables acoustic signal processing, and reinforcement learning supports autonomous decisions through environmental interaction [4], making AI well suited to underwater networking challenges.

This paper reviews AI-based UWSN techniques with three goals: (i) examine UWSN characteristics and challenges, (ii) compare existing AI-based solutions, and (iii) discuss trends and future directions for intelligent underwater sensing, serving as a resource for researchers and practitioners.

2. Overview of Underwater Wireless Sensor Networks

UWSNs consist of sensor nodes below the water surface measuring parameters like temperature, pressure, salinity, seismic activity, and pollutants, collaboratively transmitting data to surface stations. Their ability to operate in harsh, inaccessible areas makes them vital for underwater applications [1].

2.1 Architecture and Components of UWSNs

A conventional UWSN has sensor nodes, communication links, and surface gateways. Nodes include sensing components, processors, acoustic modems, and energy sources, arranged in 2D (seabed-fixed, for seabed/pipeline monitoring) or 3D (buoyancy-suspended, for water-column research) patterns [2].

Acoustic communication dominates UWSNs due to its long range underwater, though it has low bandwidth, high latency, and interference. Optical and RF methods offer short-range alternatives limited by water absorption, motivating hybrid acoustic-optical-RF systems [3].

Surface gateways or buoys relay data between UWSNs and surface networks via radio or satellite. Autonomous underwater vehicles also support data acquisition, maintenance, and reconfiguration in large-scale, mobile UWSNs [4].

2.2 Characteristics and Challenges of Underwater Communication

Underwater communication differs sharply from terrestrial wireless: acoustic propagation is five orders of magnitude slower than radio in air, causing high end-to-end delays and complicating synchronization and medium access control [2].

Limited bandwidth requires effective compression, aggregation, and scheduling. Time-varying channels—from temperature, salinity, and current/wave motion—cause frequent signal fluctuations and packet loss [3].

Energy constraints are significant: batteries are hard to replace after deployment, making efficient routing essential for network lifetime. Uneven energy use can cause early node death, partitioning, and reduced coverage [1].

Localization is challenging without GPS underwater, relying on acoustic methods prone to delay and noise. The broadcast nature of acoustic communication also exposes UWSNs to eavesdropping, spoofing, and denial-of-service attacks [4].

These challenges show the limits of traditional networking concepts underwater and motivate the intelligent, adaptive, data-driven AI-based approaches discussed next.

3. Literature Review and Comparative Analysis

A systematic review helps track UWSN development and AI's growing role in overcoming its challenges. Research has evolved over two decades from model-based networking to intelligent, data-driven solutions; this section critically analyzes that evolution.

Early UWSN research established acoustic communication models, energy-efficient routing, and delay-tolerant networking. These relied on preset assumptions, making them inflexible to changing conditions and mobile nodes [1][2], leading to poor performance at scale.

Later work applied optimization and heuristics using residual energy, hop count, and node depth, improving on static routing but remaining sensitive to environmental change and parameter tuning [4].

As computing power and sensing data grew, researchers applied machine learning to predict link quality, delivery success, and node failure, enabling more informed routing with better efficiency and reliability than conventional methods [6][7]. However, labeled-data availability and generalization to unseen scenarios remained limiting factors.

Deep learning has since been applied to complex signal processing tasks—classification, noise reduction, traffic prediction—learning features directly from raw data to improve robustness against noise and multipath fading [8][9], though at higher computational and energy cost for constrained nodes.

Reinforcement learning has emerged as a paradigm for fully adaptive, autonomous networking, learning policies through environmental interaction rather than labeled data. RL-based routing and MAC show strong gains in adaptability and efficiency under dynamic conditions [10][11], though slow convergenceand stability remain active concerns.

The literature shows a clear shift from static to intelligent, adaptive networking, with AI-based solutions consistently outperforming traditional approaches. Hybrid lightweight ML with adaptive RL is emerging as a promising path to balanced, deployable performance, as summarized in Table 1.

Approach Category	**Key Focus Area**	**Strengths**	**Limitations**
Traditional Methods	Basic routing and saving energy	Low complexity, simple deployment	Poor adaptability, static behavior
Optimization-Based	Energy and delay optimization	Improved efficiency over static methods	Sensitive to parameter tuning
Machine Learning	Prediction and routing decisions	Better adaptability, improved efficiency	Requires training data
Deep Learning	Signal processing, prediction	High accuracy, noise robustness	High computation and energy cost
Reinforcement Learning	Adaptive routing	Autonomous and highly adaptive	Slow convergence, exploration overhead

Table 1: Comparative Literature Review of Approaches in UWSNs

4. Artificial Intelligence Techniques in Underwater Wireless Sensor Networks

AI enables UWSNs to make intelligent decisions across network layers, learning from data and adapting to environmental change rather than relying on fixed rules. This chapter covers the major AI paradigms used in UWSNs—machine learning, deep learning, and reinforcement learning.

4.1 AI-Enabled System Architecture for UWSNs

AI-assisted UWSNs typically use a hierarchical structure: simple computations run at sensor nodes for data collection and filtering, while complex ML runs at surface buoys or AUVs, ensuring efficient use of limited energy and computing resources [6].

AI operates across the network stack: physical-layer ML aids signal detection and noise removal; network-layer AI supports adaptive routing and energy-efficient forwarding; application-layer AI improves data aggregation and anomaly detection [7].

Figure 1 shows the interaction of sensor nodes, the AI decision layer, and surface control infrastructure, highlighting AI's role in routing, energy control, and communication coordination.

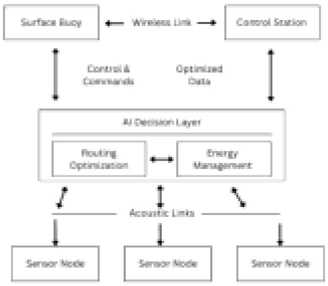

Figure 1: AI-Enabled Underwater Wireless Sensor Network Architecture

4.2 Machine Learning Techniques in UWSNs

Machine learning addresses prediction and classification in UWSNs. Supervised learning predicts link quality, delivery success, and node faults from past traffic, enabling proactive routing that minimizes packet loss and energy use [6][7].

Unsupervised learning—clustering and anomaly detection—suits large-scale UWSNs, organizing nodes by location or energy to cut redundant transmissions and flagging unusual traffic from failures or attacks without labeled data [8].

Energy Consumption Model

To assess the effect of learning-based optimization, the overall energy consumption of the sensor node can be represented as:

$$E_{total} = E_{tx} + E_{rx} + E_{proc}$$

where E_{tx} is the transmission energy, E_{rx} is the reception energy and E_{proc} is the processing energy. The main focus of machine learning-based routing is to reduce E_{tx} and avoid unnecessary retransmissions [7].

4.3 Deep Learning for Underwater Communication and Sensing

Deep learning manages the complexity of underwater acoustic signals without hand-crafted features. CNNs are widely used for signal classification and modulation recognition, improving robustness to noise and multipath interference [8][9].

RNNs and LSTMs model temporal dependencies in underwater channels, predicting channel and traffic variation so the network can proactively adjust schedules and routing, reducing latency [9].

Signal Classification Function

The signal classification model using deep learning can be expressed as:

$$\hat{y} = f_\theta(x)$$

where x is the input acoustic signal, f_θ is the neural network with parameters θ, and $\hat{y}$ is the predicted signal class. The parameters θ are trained to minimize the classification error in noisy underwater environments [8].

4.4 Reinforcement Learning for Adaptive Network Control

Reinforcement learning suits underwater environments by learning optimal actions without labeled data. Sensor nodes act as agents, choosing actions like next-hop routing or transmission power based on network state [10].

RL maximizes a cumulative reward covering energy consumption, reliability, and delay, letting nodes learn adaptive policies over time for self-optimizing behavior [11].

Reinforcement Learning Reward Function

The generalized reward function for routing can be written as:

$$R = \alpha \cdot PDR - \beta \cdot D - \gamma \cdot E$$

where PDR is the packet delivery ratio, $D$is end-to-end delay, $E$is energy consumption, and α, β, and $\gamma$are the weighting factors [10][11].

4.5 Summary of AI Techniques

To sum up the discussion, the major AI paradigms and their applications in UWSNs are listed below in Table 2.

AI Technique	Application Area	Key Benefit	Limitation
Machine Learning	Routing, prediction	Low complexity, adaptive	Needs training data
Deep Learning	Signal processing	High accuracy	High computation cost
Reinforcement Learning	Adaptive control	Autonomous learning	Slow convergence

Table 2: Summary of AI Techniques Applied in UWSNs

5. Results and Discussion

This section compares performance trends from existing AI-enabled UWSN studies rather than presenting new results, compiling reported trends to show the relative efficacy of AI-based solutions [6]–[11], a common approach in review papers.

5.1 Routing Performance Analysis

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Routing performance is central to UWSN reliability. Conventional methods use fixed parameters like hop count, unreliable in dynamic conditions, while learning-based methods adapt to changing link quality, mobility, and traffic [6][10].

Literature trends show AI-based routing achieves better delivery ratios and stability than traditional methods, with RL-based routing showing especially high adaptability through environmental interaction [10].

Packet Delivery Ratio (PDR) Expression

The formula for the packet delivery ratio is given by:

$$PDR = \frac{N_{received}}{N_{sent}}$$

where $N_{received}$ is the number of packets successfully received and N_{sent} is the total number of packets sent.

AI-based routing maximizes packet delivery ratio through dynamic decisions on link quality, mobility, and congestion, offering more accurate path selection than static routing. Figure 2 compares routing performance and stability across traditional, ML-based, and RL-based techniques.

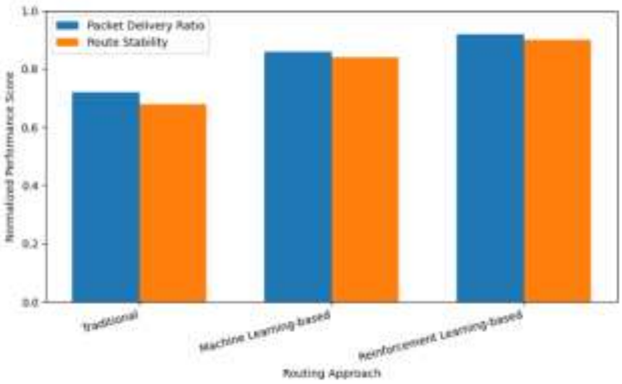

Figure 2: Routing Performance Trend Comparison

5.2 Energy Efficiency Analysis

Energy efficiency directly affects network lifetime. Learning-based solutions cut consumption via fewer retransmissions, optimal transmission power, and load balancing—ML forecasts energy drain while RL dynamically adjusts routing to extend lifetime [7][11].

Energy Consumption Model

The overall energy used by a node in a particular time period can be written as:

$$E_{node} = \sum_{i=1}^{n} (E_{tx}^{(i)} + E_{rx}^{(i)})$$

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where E_{tx} and E_{rx} represent the energy used for transmission and reception per packet.

AI-enabled routing and energy control substantially lower total consumption by avoiding unnecessary transmissions. Figure 3 shows AI-based methods achieving better energy efficiency than traditional approaches.

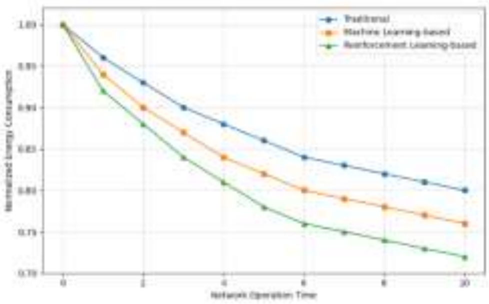

Figure 3: Energy Consumption Reduction Trend

5.3 End-to-End Delay Analysis

End-to-end delay is a key drawback of underwater acoustic communication given the low speed of sound in water. AI-based routing reduces this by analyzing congestion, while deep learning further cuts delay through predictive scheduling [8][9].

End-to-End Delay Equation

$$D_{e2e} = D_{tx} + D_{prop} + D_{queue} + D_{proc}$$

where D_{tx}, D_{prop}, D_{queue}, and D_{proc} represent transmission, propagation, queuing, and processing delays respectively.

AI-based dynamic routing and scheduling substantially reduce end-to-end delay versus traditional solutions, as Figure 4 shows for underwater communication.

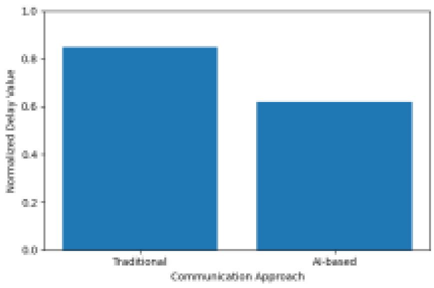

Figure 4: Delay Reduction Trend

5.4 Localization Accuracy Analysis

High localization accuracy is essential for target tracking and data analysis. Traditional methods have high error rates from synchronization and delay issues, while AI-based methods improve accuracy by identifying spatial-temporal patterns in acoustic signals [12].

Localization Error Metric

$$E_{loc} = \sqrt{(x-\hat{x})^2 + (y-\hat{y})^2}$$

where $(x|y)$ is the actual node position and $(\hat{x}|\hat{y})$ is the estimated position.

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AI-powered localization consistently shows lower estimation error than traditional methods, as Figure 5 illustrates via normalized accuracy trends.

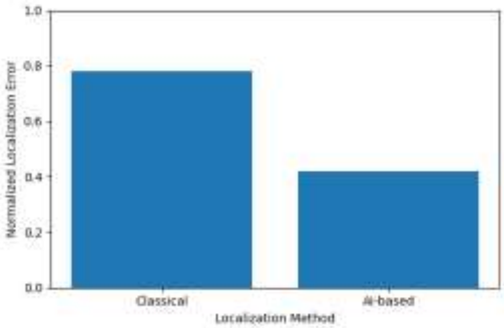

Figure 5: Localization Accuracy Trend

5.5 Comparative Result Summary

Table 3 summarizes literature performance trends, highlighting the merits and limitations of each approach category and reaffirming AI's benefits in dynamic underwater environments.

Performance Metric	Traditional Methods	ML-Based Methods	RL-Based Methods
Packet Delivery Ratio	Low–Moderate	Moderate–High	High
Energy Efficiency	Low	Moderate	High
End-to-End Delay	High	Moderate	Low
Localization Accuracy	Low	Moderate	High
Adaptability	Static	Semi-adaptive	Fully adaptive

Table 3: Summary of Result Trends in AI-Enabled UWSNs

5.6 Discussion

The comparative study confirms AI-based solutions consistently improve UWSN performance. Machine learning offers a favorable trade-off between gains and overhead for moderately dynamic environments. Deep learning delivers the highest accuracy in signal processing but requires managing energy and computation limits. Reinforcement learning shows the greatest adaptability and long-term gains in dynamic environments, though convergence and stability remain challenges [10][11]—overall, AI-based solutions are needed to overcome traditional networking's limitations.

6. Challenges, Open Issues, and Future Research Directions

Despite AI's potential to improve UWSN performance and adaptability, unresolved challenges remain from both harsh underwater conditions and current AI limitations, and addressing them is essential for reliable, scalable intelligent networks.

6.1 Key Challenges in AI-Enabled UWSNs

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Data availability and quality are major concerns since AI depends on training data, and collecting large-scale labeled underwater data is difficult due to cost, inaccessibility, and unpredictability. Most work relies on simulated data that may not capture real dynamics, limiting real-world generalization [6][8].

Computational and energy constraints matter too: advanced models need substantial power and memory, but nodes are resource-constrained and battery-powered, so on-node execution can shorten lifetime. Offloading to surface stations or AUVs helps but adds overhead and latency [10][11].

The dynamic, non-stationary underwater environment—varying channels, mobility, and noise—complicates AI deployment, potentially destabilizing learning and decisions. RL models especially can suffer slow convergence and degraded performance [10].

Security and robustness matter: AI-based intrusion detection improves accuracy but remains vulnerable to adversarial attacks, data poisoning, and exploitation, making secure, robust underwater learning an open issue [13][14].

6.2 Open Research Issues

A key open problem is the lack of standardized evaluation frameworks—varied simulation environments, metrics, and assumptions make fair comparison difficult; standardization would strengthen research credibility [7].

Another issue is limited interpretability: most AI models are black boxes, hindering trust in critical applications like disaster response and defense. Explainable AI that reveals decision-making is important for trust and human oversight [9].

Real-time, online learning under uncertainty is also underexplored, as most solutions assume stable conditions unlike real underwater settings. Algorithms that respond quickly to sudden change while maintaining stability remain a key challenge [11].

6.3 Future Research Directions

Future work will likely focus on energy-efficient learning models, with model compression, transfer learning, and adaptive strategies offering promising paths to efficient computation.

Federated and other distributed learning models are promising, letting nodes learn collaboratively without exchanging raw data—reducing overhead, improving privacy, and increasing scalability [15].

Edge intelligence and autonomous underwater vehicles will likely grow in importance as mobile learning agents for data collection, model updates, and maintenance, improving robustness and coverage [15].

Future UWSNs are expected to evolve into intelligent Internet of Underwater Things (IoUT) networks integrating AI-assisted sensing, communication, and decision-making for applications like ocean observation and sustainable resource management [15].

Aspect	**Current Challenge**	**Future Research Direction**
Data Availability	Limited real-world datasets	Federated and transfer learning

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Energy Constraints	High computation cost	Lightweight AI models
Environmental Dynamics	Non-stationary conditions	Adaptive and online learning
Security	Model poisoning, spoofing	Robust and explainable AI
Scalability	Limited coordination	IoUT-based intelligent systems

Table 4: Challenges and Future Research Directions in AI-Enabled UWSNs

7. Conclusion

UWSNs are a key technology for environmental monitoring, offshore exploration, disaster prevention, and surveillance. However, bandwidth, delay, topology, and energy constraints challenge traditional solutions, requiring intelligent, adaptive, autonomous approaches.

This review has analyzed AI's role in addressing core UWSN challenges. Through structured analysis of architecture, communication, and literature, it highlights the shift from static, rule-based methods to data-driven, learning-based approaches—ML improving prediction and energy-efficient decisions, deep learning improving signal processing and reliability, and RL enabling autonomous, adaptive control in dynamic environments.

Comparative trends confirm AI-based solutions consistently outperform traditional approaches across packet delivery, energy efficiency, delay, localization, and adaptability. RL shows the greatest potential for long-term optimization, while ML and deep learning offer effective performance-complexity trade-offs.

Despite these gains, challenges remain: limited data, computational and energy constraints, environmental non-stationarity, and security concerns. Future research should focus on lightweight and distributed learning, explainable AI, and integration with autonomous platforms and IoUT.

In conclusion, this review highlights AI's transformative impact on the future of UWSNs, offering a comprehensive reference for developing intelligent, scalable, sustainable underwater sensing systems.

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