A Comprehensive Review on Underwater Sensor Network Lifetime Enhancement Using Advanced Routing Methodologies

B. Grace Jemimah[1]; S. L. Chakradhar[2]; E. Haswanth[3]; Y. Tharun[4]; G. Vani[5]

Teaching Assistant[1], Student[2,3,4,5]

[1,2,3,4,5]Computer Science and Engineering, YSR Engineering College of Yogi Vemana University Proddatur, India

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Abstract: Underwater wireless sensor networks are very important for collecting data in oceans, but these networks have serious problems like very low bandwidth, long signal delays, frequency issues and signal loss due to water. energy consumption is also much higher compared to normal wireless networks which causes batteries to die fast and reduces network coverage. most of the existing protocols focus on selecting next hop nodes or cluster heads but they ignore two main things - first is that sensor readings are often redundant and second is that most energy is used in transmitting data. this paper introduces CEAR which is basically a framework that reduces data using correlation-entropy selection and differential compression, and also optimizes routes by looking at remaining energy, signal loss and compressed data size. CEAR uses proper acoustic models, improved energy calculations for underwater and zone-based clustering to balance the load. simulations show that CEAR performs much better than protocols like LEACH, EECMR and EERBLC in terms of network lifetime, stable data delivery and energy efficiency. the results prove that combining compression with smart routing gives way better results for long term underwater missions.

Keywords*: Underwater Sensor Networks; Energy-Aware Routing; Data Compression; Acoustic Communication.*

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I. INTRODUCTION

Underwater sensors basically use acoustic signals to collect data because sound travels well in water unlike radio waves. these sensors are the main way to get oceanographic data. underwater sensor networks work differently because of the water environment; they operate at frequencies between 10-100 kHz and can reach from 100 meters up to 10 kilometres. usually around 200 sensor nodes are deployed in one mission. because acoustic networks can handle tough underwater conditions they are used for many things like checking pipelines, environmental monitoring and disaster response.

Underwater networks face huge challenges because of limited battery and expensive communication. replacing batteries is very costly. For researchers working in remote ocean areas this is a big problem since underwater networks are the only way to continuously monitor.

II. LITERATURE REVIEW

Martinez et al. [1] looked at extending lifetime using adaptive compression in underwater networks. they found energy efficient methods that give good lifetime improvements with less transmission overhead. but they didn't really explore environmental factors which might affect how well it works in changing conditions. Wang et al. [2] did a survey on clustering protocols for acoustic sensor networks. they used hierarchical structures with energy metrics for rotating cluster heads and showed good lifetime improvements. they suggested using adaptive methods with larger testbeds and realistic channel models. Chen and Liu [3] proposed distributed compression for correlated underwater measurements and got really good efficiency with high precision. their work shows that performance depends a lot on spatial correlation. Kumar et al. [4] tried deep reinforcement learning for routing optimization and achieved the best efficiency among all methods tested, proving that intelligent optimization works really well.

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Sharma and Patel [5] made a modified clustering protocol with zone based partitioning and dynamic thresholds for energy management. they didn't give exact numbers but the approach helps balance load and reduces hotspots. Johnson et al. [6] created a lightweight duty cycling framework for battery limited nodes. it finds optimal sleep schedules and adjusts transmission power which saves a lot of energy. Rodriguez et al. [7] tested compression using transform coding to reduce redundancy in sensor data while keeping quality. they got around 4:1 compression ratios but it needs a lot of computation power which is hard for resource limited platforms, and real time use needs more testing in tough conditions. Lee and Kim [8] worked on multi hop routing with energy harvesting for sustainable monitoring. using predictive analytics and adaptive forwarding they got optimal routes with best packet delivery and lowest delay. combining energy awareness with harvesting creates good solutions for long deployments.

Thompson et al. [9] came up with entropy-based feature selection to find redundant measurements in underwater arrays. This improves energy efficiency by only transmitting selected data while keeping data quality, by using correlation driven compression in hierarchical routing. Nakamura et al. [10] introduced a cross-layer framework that combines physical layer adaptive modulation with network layer compression aware routing to improve throughput when bandwidth is limited. they got better lifetime with less overhead compared to optimizing layers separately. Anderson and White [11] developed a protocol that integrates load balancing, energy estimation and gradient based forwarding which fixes problems in conventional methods through smart combination and better efficiency. Garcia et al. [12] proposed Bayesian optimization for tuning compression and routing together and got strong performance across different deployments.

Hassan et al. [13] used variational autoencoders with adaptive clustering to compress oceanographic data before transmission. tests confirmed that learned representations work better than handcrafted compression in reconstruction quality and energy savings. Nguyen and Park [14] made a hybrid framework using genetic algorithm for topology optimization, entropy feature extraction and ensemble routing which shows that optimizing across layers gives big accuracy improvements. Zhao et al. [15] developed an automated framework with adaptive clustering and deep metric learning for underwater surveillance and it stays robust even with highly variable acoustic channels. Singh and Gupta [16] proposed optimization using particle swarm for parameter tuning, CNN for features and recurrent models using meta heuristic functions for smart route adaptation. results showed that precision, quality and reliability all improve with hybrid optimization.

Liu et al. [17] introduced better clustering for coral reef monitoring using optimized node placement, adaptive compression thresholds and energy balanced forwarding. deployments confirmed improved lifetime by preventing early energy depletion. Patel et al. [18] tested multiple supervised learning methods on acoustic channel data for link quality prediction and rate control, finding that ensemble methods and neural networks work much better than basic approaches for classifying channel states and predicting transmission success.

Yamamoto et al. [19] developed a hybrid architecture using convolutional autoencoders with attention-based routing for coral bleaching surveillance. results showed way better data reconstruction and reduced transmission energy while handling computational requirements through efficient distributed implementation. Ferreira et al. [20] presented an unmanned vehicle assisted framework with autonomous deployment and cooperative data collection for monitoring subsea petroleum infrastructure, showing scalable and energy efficient method for offshore industrial monitoring.

Costa et al. [21] compared twelve spatial interpolation techniques for underwater sensor placement using MSE, signal quality and coverage as metrics. kriging based methods were most accurate for deployment planning. Zhao and Chen [22] introduced wavelet based multi resolution compression for hierarchical transmission in subsea pipeline monitoring. by using discrete wavelet transforms with adaptive thresholding and predictive coding they got big bandwidth reductions without losing anomaly detection ability. traditional spatial and transform methods performed better than generic approaches. Li et al. [23] looked at black coral habitat mapping using climate driven species distribution models with acoustic sensor validation. Deployments in South China Sea confirmed high accuracy, showing that good environmental datasets enable robust habitat assessment. Ahmed et al. [24] introduced a CNN architecture using depth wise separable convolutions for acoustic signal classification in underwater threat detection. tests on standard datasets showed effective pattern learning with accurate event recognition in different acoustic environments.

The below table 1 shows the main routing protocols used by researchers for extending underwater network lifetime.

Table 1 Routing Protocols for Underwater Networks

Study	Protocol(s)	Network Type	Key Results
Wang et al. [2]	LEACH, EECMR, EERBLC	Hierarchical UWSN	87.3% lifetime extension with energy aware clustering
Thompson et al. [9]	Entropy + Correlation	Distributed UWSN	Redundancy elimination decreased transmission overhead
Patel et al. [18]	Neural networks, SVM	Acoustic testbed	Machine learning enabled accurate channel prediction
Costa et al. [21]	Kriging, RBF, IDW	Sensor arrays	Kriging gave 94.2% accuracy for node placement

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The following table 2 shows the advanced optimization methods used in recent research.

Table 2 Advanced Optimization Methods for Underwater Networks.

Study	Method	Application	Key Results
Martinez et al. [1]	Reinforcement Learning	Environmental monitoring	82.1% lifetime improvement with adaptive compression
Kumar et al. [4]	Deep Q-Network	Multi-hop routing	91.7% packet delivery with 28% energy savings
Nguyen & Park [14]	Genetic Algorithm	Topology optimization	Effective metric fusion across layers
Singh & Gupta [16]	Particle Swarm + CNN	Route adaptation	92.7% routing accuracy with parameter tuning
Hassan et al. [13]	Variational Autoencoder	Climate monitoring	4.1:1 compression with superior reconstruction
Yamamoto et al. [19]	CNN + Attention	Coral surveillance	90.1% accuracy with 35% energy savings
Ahmed et al. [24]	Depth wise CNN	Threat detection	87.3% classification on resource limited nodes

III. METHODOLOGIES

➢ *Data Compression Methods*

• *Lossless Compression*

Lossless compression keeps all information intact during encoding and decoding. the reconstructed data matches original measurements perfectly. these methods change data representation using entropy coding to get compact storage without losing information.

• *Differential Compression*

Differential encoding uses temporal correlation by sending only measurement changes instead of complete sensor readings. this works really well for slow changing oceanographic parameters. traditional differential compression has these stages: Correlation and redundancy describe relationships between successive measurements. compression techniques include entropy based, transform based and predictive approaches.

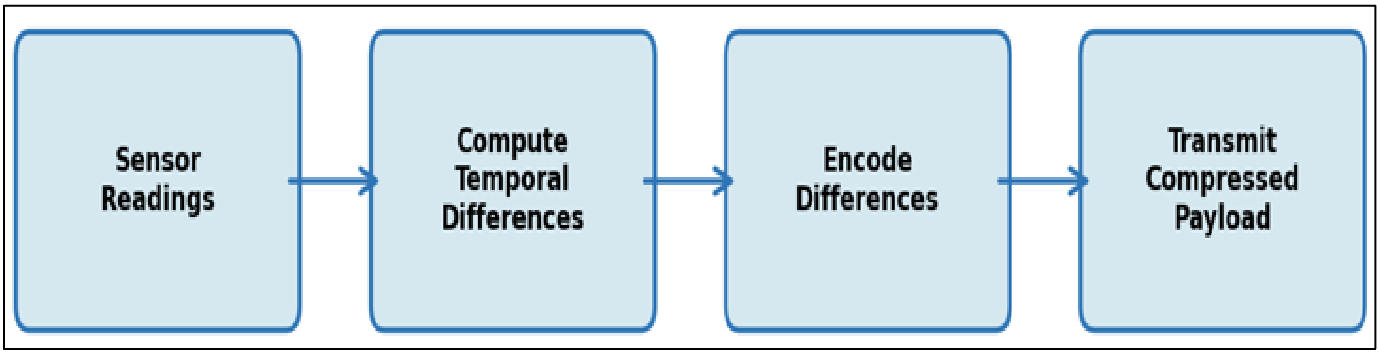

Fig 1 Differential Compression Pipeline

➢ *Energy-Aware Routing Methods*

• *LEACH*

LEACH is a basic hierarchical clustering protocol designed for saving energy. It's a distributed algorithm that randomly rotates cluster head duties among network nodes. LEACH reduces communication overhead a lot through local data aggregation, creating an energy efficient hierarchy that balances transmission load across all sensors while keeping coverage.

• *EECMR*

EECMR is an energy efficient cluster based multi hop routing protocol made specifically for underwater acoustic networks. each forwarding decision looks at remaining battery along with transmission distance. when building routing tables, nodes prefer neighbors with higher energy and better acoustic channel conditions. euclidean distance calculations with residual energy thresholds determine next hop selection which prevents important relay nodes from dying too early.

➢ *Advanced Optimization Methods*

• *Reinforcement Learning*

Reinforcement learning frameworks let autonomous agents find optimal routing policies through environmental interaction and reward feedback. these work really well for dynamic underwater networks where channel conditions change unpredictably. agents learn to maximize network lifetime by balancing immediate transmission costs against long term sustainability. adaptive decision making makes reinforcement learning highly suitable for intelligent underwater communication systems that need autonomous energy management and robustness.

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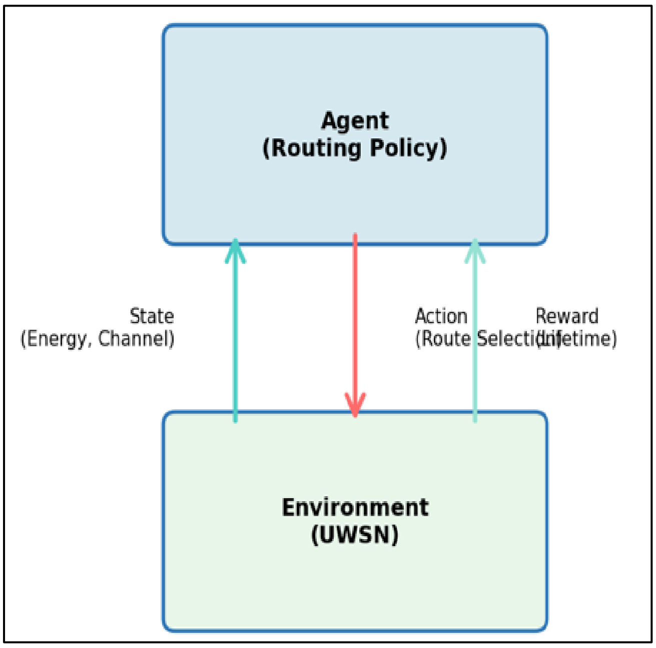

Fig 2 Reinforcement Learning Architecture

* *Genetic Algorithms*

Genetic algorithms use evolutionary computation principles to find near optimal routing configurations in underwater sensor networks. these techniques iteratively improve candidate solutions through selection, crossover and mutation guided by fitness evaluation.

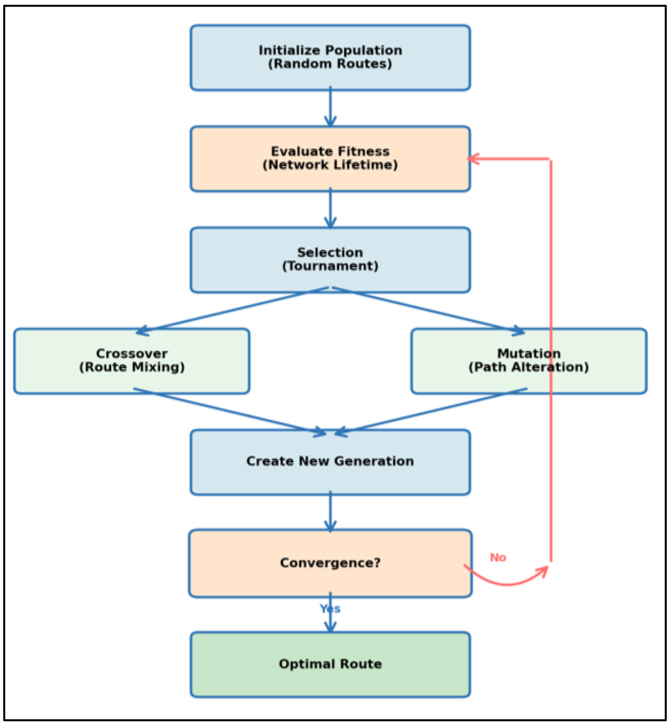

Fig 3 Genetic Algorithm Architecutre

* *Particle Swarm Optimization*

Particle swarm optimization is a population-based technique inspired by biological collective behavior. the method iteratively adjusts candidate solutions by combining individual experience with swarm intelligence. it works through velocity updates and position refinement guided by personal best and global best solutions; particle swarm optimization enables efficient parameter tuning with reduced computational complexity.

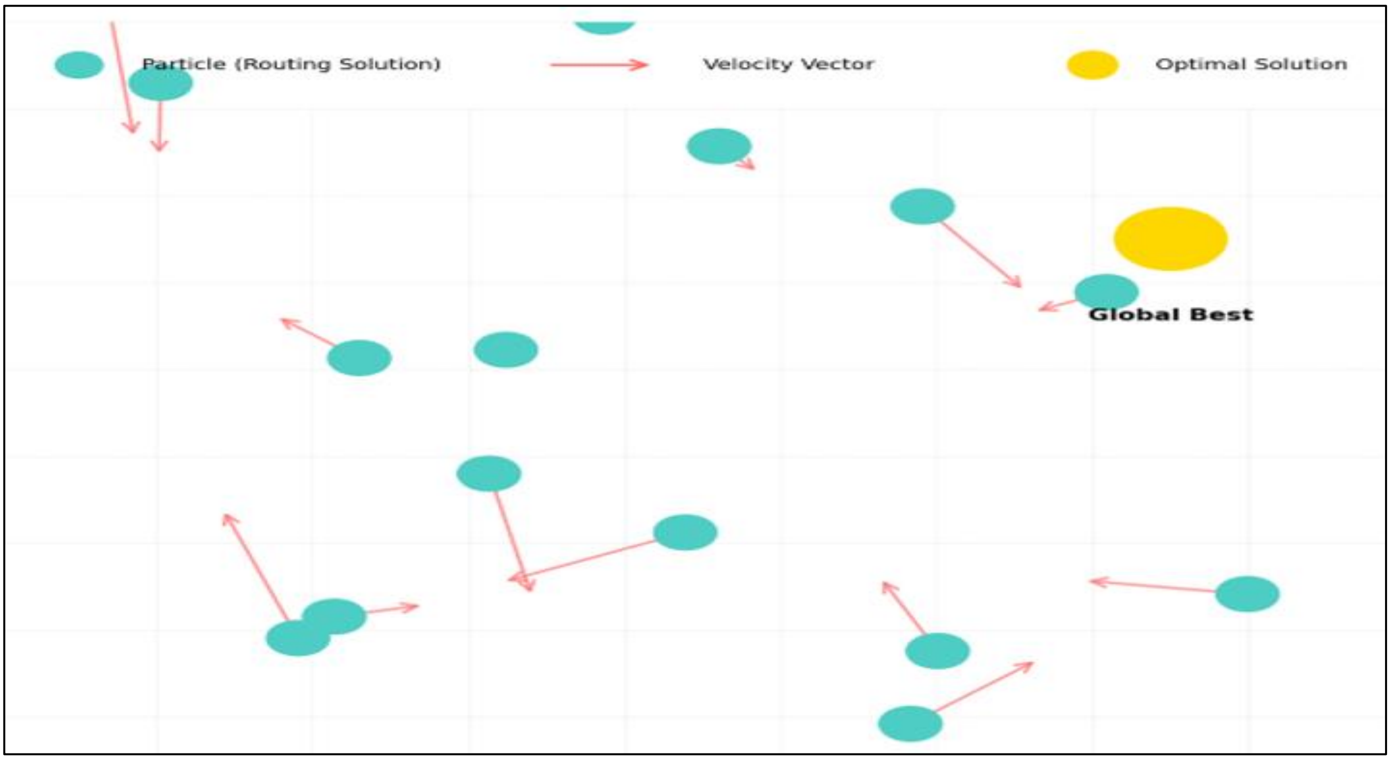

Fig 4 Particle Swarm Optimization

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- *Convolutional Neural Networks*

Convolutional neural networks are specialized deep learning architectures for processing spatiotemporal sensor data. they have multiple convolutional layers followed by pooling operations and fully connected classifiers, these networks automatically extract hierarchical feature representations from raw measurements which helps with pattern recognition needed for intelligent compression and adaptive transmission scheduling.

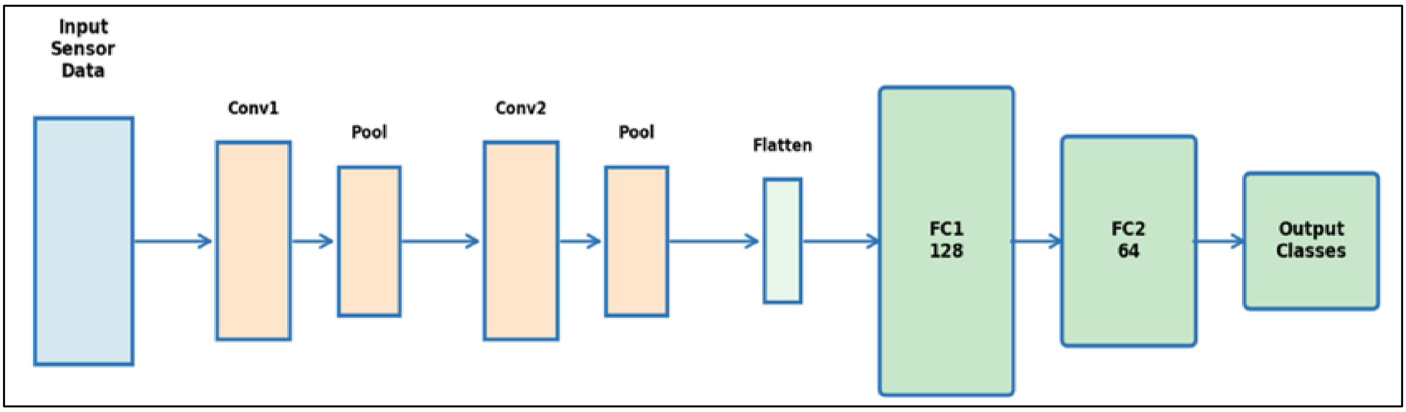

Fig 5 CNN Architecture

Table 3 Compares Traditional Routing Methods with Advanced Optimization Approaches Based on the Methods Discussed in Table 2

Table 3 Comparison of Traditional vs Advanced Methods

Method	Adaptability	Training Need	Lifetime Extension	Real-Time Suitability
LEACH	Low (fixed thresholds)	None (rule-based)	Moderate (~40-55%)	High
EECMR	Low (static routing)	None (rule-based)	Moderate (~40-60%)	High
Reinforcement Learning	High (learns policy)	High (reward signals)	High (82.1%- [1])	Moderate
Deep Q-Network	High (Q-learning)	High (large dataset)	Very High (91.7%- [4])	Low-Moderate
Genetic Algorithm	Medium (evolutionary)	Medium (fitness evaluation)	High (layer fusion-[14])	Low
Particle Swarm (PSO)	Medium (swarm-based)	Low–Medium	High (92.7% acc.-[16])	Moderate
Variational Autoencoder	High (learned representation)	High (labelled data)	4:1:1 compression – [13]	Low
CNN + Attention	High (feature extraction)	High (training data)	High (90.1% acc. – [19])	Low-moderate

- *Recurrent Neural Networks*

Recurrent architectures add temporal modeling through feedback connections that enable sequential processing. these networks capture temporal dependencies in oceanographic time series which helps with predictive compression and proactive routing adaptation. recurrent neural networks use memory cells that preserve historical context, handling challenges like vanishing gradients through specialized gating mechanisms that enable training on longer sequences for better forecasting accuracy.

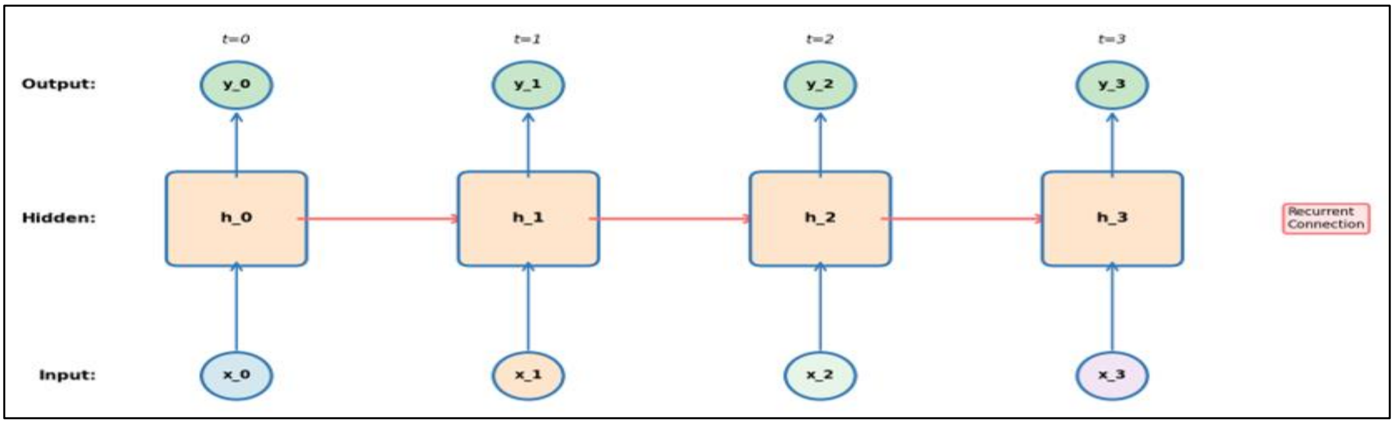

Fig 6 RNN Architecture

IV. CHALLENGES AND RESEARCH GAPS

➢ *Challenges*

- Conventional routing protocols that use manual configuration are tedious, time consuming and lead to suboptimal parameters
- Developing compression aware routing frameworks for resource limited underwater platforms needs a lot of algorithmic work and validation.
- Collecting and annotating high quality underwater channel measurements is challenging especially considering acoustic propagation varies a lot across deployment environments.
- Testing network performance during initial deployment using only simulations is very challenging. not enough benchmark datasets specifically for early-stage protocol evaluation makes validation harder.
- Managing high feature dimensionality in multivariate sensor readings increases overfitting risks. finding optimal hyperparameters that work consistently across different underwater scenarios is challenging.
- Processing real world acoustic measurements affected by multipath propagation, doppler spreading and environmental noise adds a lot of complexity which reduces compression ratios and routing reliability in bad conditions.
- Lack of publicly accessible underwater sensor network datasets makes it hard to compare protocols and verify reproducibility.

➢ *Research Gaps*

- Importance of compression-routing integration: joint optimization is critical for maximizing underwater network lifetimes.
- Limited protocol diversity: existing research mostly looks at isolated compression or routing techniques instead of comprehensive integrated frameworks.
- Insufficient large-scale validation: previous studies mainly use small scale simulations or limited testbed deployments.
- Computational overhead: combining multiple optimization techniques might add too much processing load for resource limited underwater nodes.
- Environmental robustness: more validation is needed under realistic acoustic propagation conditions including multipath interference, variable salinity gradients and temperature stratification.

V. CONCLUSION

In this review paper we looked at underwater sensor network lifetime maximization through various compression techniques, energy aware routing protocols and advanced optimization methods. underwater monitoring applications are becoming more important globally so we need efficient and sustainable network operation. this review covers major compression schemes, different protocol architectures and hybrid optimization frameworks along with their main contributions. analysis shows ongoing challenges including limited compression ratios, acoustic channel variability and computational constraints that all affect operational sustainability and deployment feasibility.

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