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Review

Next-generation underwater localization: Artificial Intelligence-based and energy-aware approaches☆

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ABSTRACT

Designing accurate, reliable, and energy-efficient localization techniques for underwater acoustic networks is highly challenging due to factors such as large propagation delays, the absence of Global Positioning System (GPS), node mobility, and limited acoustic link capacity. In any underwater sensor network (UWSN) monitoring application, data collected by underwater nodes becomes more meaningful when accompanied by location information. However, traditional localization methods often rely on geometric models and statistical filters that are highly sensitive to sensor noise and communication constraints. Energy consumption is another primary concern in UWSNs, not only because replacing and recharging underwater batteries are challenging, but also due to the energy-hungry nature of underwater acoustic communications. To address these challenges, we provide a comprehensive literature review of research contributions on the integration of Artificial Intelligence (AI) and energy efficiency in underwater localization techniques. First, we introduce the recent advancements in AI-based approaches, including deep learning and machine learning models, which are promising for enhancing accuracy, robustness, and adaptability in complex underwater environments through learning-driven techniques. Subsequently, we review various energy-saving strategies integrated into the localization scheme to address the power constraints of underwater sensor nodes. Finally, we discuss future research directions and conclude with key insights.

Contents

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1. Introduction

Underwater communication and localization are vital for exploring the dynamic nature of the ocean environment. However, the ocean environment introduces severe communications challenges due to limited bandwidth and large propagation delays of underwater communication signals (Hasan et al., 2025c). Since the Global Navigation Satellite System (GNSS) cannot penetrate water, the underwater moving objects often depend on acoustic methods for localization. Autonomous Underwater Vehicles (AUVs) have been widely used for tasks such as seafloor mapping, environmental monitoring, and defense operations (Ludvigsen and Sørensen, 2016), Hasan et al. (2025b). Precise positioning of AUVs is not only essential for search & rescue operations and covert surveillance, but also for reliable underwater communication and long-term ocean monitoring, where it ensures data integrity, mission safety, and sustained network connectivity.

To address these needs, numerous techniques have been introduced for localization, utilizing a variety of sensors, including acoustic modems, vision, Inertial Measurement Unit (IMU), depth sensors, and magnetometers (Samatas and Pachidis, 2022). However, these sensors provide asynchronous measurements and are prone to high short-term noise. Most of them are energy-hungry and rely on simplified acoustic models, often assuming a constant sound speed and uniform Doppler effects, whereas real-world conditions (temperature gradients, salinity variations, and uneven seabeds) can significantly distort signal propagation. To fuse those sensor measurements, many researchers introduced Bayesian filters such as Kalman filter (KF), Extended Kalman filter (EKF), Unscented Kalman filter (UKF), and Particle filter (Chen et al., 2003). For instance, Wang et al. (2024b) proposed a multi-sensor fusion method based on UKF on manifolds to reduce cumulative error in underwater cave datasets, while Jiang et al. (2023) introduced an Unscented Particle Filter (UPF) that improves particle distribution and positioning accuracy. Yet, such methods come with high computational cost and on the assumptions of Gaussian noise and known initial states, which limit their robustness in nonlinear and uncertain underwater environments. Moreover, Doppler-based feature extraction across channels increases the energy burden on sensor nodes, where battery replacement is impractical. When integrated with heavy computational Bayesian filters, this energy cost can severely limit the mission duration. Only a few approaches (Zargelin et al., 2020b), Zargelin et al. (2020a) consider the limitations of sensors and their computational capacity, and these still require further adaptation to be suitable for underwater environments. Thus, next-generation localization approaches must consider the energy-aware innovative techniques with adaptive, data-driven models that capture the true complexity of the underwater channel.

Beyond Bayesian filters, optimization-based methods were proposed to refine positioning accuracy. For instance, Zhang et al. (2022) rectified inertial and acoustic errors during turning maneuvers by leveraging motion states, while Liu et al. (2023) developed a tightly coupled navigation model using two transponders to mitigate multi-path interference. However, as the number of vehicles increases, tightly coupled solutions significantly increase computational complexities. For collaborative missions involving multiple AUVs, Luo et al. (2025) proposed a cooperative positioning framework resilient to underwater noise and delays. Despite these advancements, most existing research still concentrates on robust filtering, coupling strategies, or cooperative schemes. This highlights the need for next-generation approaches that not only ensure accuracy and robustness, but also address energy efficiency and scalability in real underwater environments.

More recently, deep learning has emerged as a promising approach for underwater localization by leveraging data-driven feature extraction and sequence modeling. Convolutional Neural Networks (CNNs) are mostly utilized for visual landmark recognition (Han et al., 2020). It has been adapted to process sonar imagery to mitigate resolution limits by learning robust, high-level descriptors without relying on artificial beacons. Moreover, CNNs are employed to fuse multi-modal oceanographic data and enable real-time regression-based estimation of underwater sound speed profiles (Wu et al., 2024). Meanwhile, Recurrent Neural Networks (RNNs) excel at fusing time-series measurements (acoustic pings, IMU measurements), offering greater fault tolerance and bounded error growth compared to classical Bayesian filters (KF, EKF, PF) (Yu et al., 2019).

Building on these advances, next-generation AI-driven models extend beyond point localization to integrated tasks such as Simultaneous Localization and Mapping (SLAM), which is essential in complex seabed environments. SLAM combined with the EKF (Eitel et al., 2015) is commonly used for estimating robot pose and landmarks. However, EKF-based SLAM (Davison, 2003) often struggles in highly nonlinear conditions due to its reliance on linearization. To overcome these challenges, alternative approaches such as particle SLAM (Liu et al., 2024), graph-based SLAM (Grisetti et al., 2011), and visual SLAM (Hu et al., 2022) have been developed, each addressing nonlinear dynamics, configuration detection, and adaptation to underwater environments, respectively. More recently, the fusion of deep learning with SLAM has achieved notable success, leveraging neural networks to significantly improve mapping and navigation (He et al., 2024a; Chen et al., 2021). These advancements collectively strengthen underwater SLAM algorithms, making deep learning–enhanced systems more accurate and reliable for underwater navigation.

Extending this trajectory, hybrid frameworks have begun to merge SLAM with complementary navigation systems. For instance, the author in Sabra and Fung (2017) introduced a fuzzy-logic fusion scheme where a decision support system was introduced that dynamically blends Ultra-short baseline (USBL), SLAM, and Inertial Navigation System/ Doppler Velocity log (INS/DVL) estimates, demonstrating high availability but imposing heavy onboard compute and memory loads. In contrast, lightweight neural-network architectures can deliver low-latency inference and nonlinear modeling in a single shot, reducing both energy and scheduling overhead for nonlinear systems. To further push next-generation localization, hybrid AI frameworks are now integrating CNN-based feature embedding from horizontal-scan sonars with RNN-driven temporal fusion so that AUVs can navigate complex, time-varying channels with high accuracy and minimal power consumption.

In parallel, several recent studies have targeted energy efficiency in underwater localization by focusing on different elements and algorithm strategies. For example, Misra et al. (2014a) formulated a Stackelberg game to minimize the energy consumption of the anchor node rather than sensor nodes. Similarly, authors in Yuan et al. (2018b) extended this idea by jointly accounting for both sensor and anchor

Table 1
Summary of existing localization surveys.

Reference	Year	Localization Method	Energy-saving strategies	AI Integration	Channel Consideration	Limitations
Toky et al. (2020)	2020	✓	Identified some	NLA used a neural network to refine DV Hop's average hope count.	✓	Time synchronization under mobility.
Luo et al. (2021)	2021	✓	Energy consumption appeared as an evaluation criterion.	X	✓	Mobile drift, energy-accuracy trade-off, beacon path planning.
Christensen et al. (2022)	2022	Navigation only	✓	CNN, RL	Highlighted environmental uncertainties.	Multi-model fusion, absence of energy cost analysis.
Islam et al. (2022)	2022	X	✓	X	Multi-path, Doppler	Briefly discussed.
Osamy et al. (2022)	2022	✓	In the context of optimizing node replacement.	Evaluated methods like fuzzy logic, artificial neural network, and reinforcement learning.	X	Static-anchor assumptions, lack of realistic channel modeling.
Yadav and Khilar (2023a)	2023	Range free	Relied on fewer GPS buoys for cost saving.	Extended Improved PSO (EIPSO)	Considered stratification (sound velocity profile + ray theory)	Environment assumptions; limited real validation.
Yadav and Khilar (2023b)	2023	I-LASP for localization + clustering	Clustering (LEACH-BR) with beacon & reinforced nodes; multi-hop to save energy.	Optimization in I-LASP, clustering thresholds for energy balancing.	Used stratification via I-LASP integration.	Cluster stability issues; no AI/ML adaptation; clustering overhead.
Yadav et al. (2024)	2023	Hybrid: Centroid + Ray theory + IUSSOT (Improved Salp Swarm Optimization)	Focused on reducing computation & convergence, less energy spent.	Metaheuristic (Swarm Intelligence – IUSSOT)	Explicit stratification modeling; both sparse & dense regions.	Still metaheuristic limitations; requires GPS buoys; lacks field validation.
Jwo et al. (2023a)	2023	✓	X	Thorough coverage of Artificial Neural Networks—MLP, RBFNN, GRNN, ARMA NNs, ANFIS, and LSTM/RNN.	GNSS multi-path and shadowing challenges.	No explicit treatment of non-Gaussian or time-varying noise beyond simple statistical assumptions.
Feng et al. (2024)	2024	X	X	ML/DL methods	Attenuation, multi-path and non-Gaussian noise.	Limited datasets, lack of data-driven multi-path fingerprint analysis.
Alexandris et al. (2024)	2024	✓	X	KF/PF only	Sound-speed, multi-path, optical.	DL fusion
Murali and Shankar (2024)	2024	✓	✓	ML method	Multi-path, Doppler, attenuation.	Lack of analysis on RNN multi-path, in-situ harvesting.
Hasan et al. (2024)	2024	X	Battery Swap	X	Accoustic and Optical	Overlooked charging-localization integration.
Merveille et al. (2024)	2024	✓	X	Analyzed deep learning techniques for feature extraction and data fusion.	Noise and multipath in the context of underwater SLAM	Energy constraints.
Aubard et al. (2025)	2025	X	X	CNN, Domain adaptation	Sonar-specific noise	No energy or channel modeling.
Elmezain et al. (2025)	2025	X	X	CNN, transformer	Optical attenuation	Overlooked multi-modal fusion and energy cost analysis.
Heshmat et al. (2025)	2025	✓	X	CNN, RNN, transformer	Optical	Acoustic channel modeling.
Our	2025	✓	✓	Comprehensive review of DL/ML models for localization	✓	–

[✓] - Explicitly addressed; [X] - Explicitly not considered; [–] - Not applicable.

node energy costs, but their proposed method relied on a specific environment, whereas predefined weights were required to set the utility function. In another work, Yu and Choi (2014a) introduced an energy-aware, wake-up/sleep scheduling scheme combined with an interacting multiple-model filter to track maneuvering targets; however, process and measurement noise were assumed to be zero-mean, and the filter required exact initial covariances and mode transition probabilities that are rarely met underwater. The authors in Chen et al. (2017a) proposed a filter that explicitly trades off acoustic transmission cost against localization accuracy; yet they evaluated it only in static network topologies, overlooking the dynamics of real deployments. To reduce the transmission latency, the authors in Basagni et al. (2017) leveraged a model-based reinforcement-learning framework to let nodes learn link-quality metrics, but their performance depends critically on precise link-success estimates, which a noisy channel can easily corrupt. Therefore, it can misguide relay and modem selection, degrade both reliability and energy savings. These works highlight the progress toward next-generation, energy-efficient underwater localization, such as game-theoretic anchor control, topology-aware cost functions, adaptive wake-scheduling, and learning-based link management. However, an ideal framework must go further; it should relax Gaussian and static-network assumptions, adapt in real time to channel variability, co-design sensing, communication, and inference modules to jointly maximize localization accuracy and energy endurance.

For underwater applications, there is a clear need for a unified perspective that shows how intelligence and energy efficiency can be jointly designed to achieve higher accuracy and robustness. This review aims to fill that gap by providing a balanced and comprehensive overview that integrates advances in both AI-based and energy-aware localization approaches.

The contributions of this paper are as follows:

- We evaluate the potential of AI-based localization algorithms by analyzing their robustness, accuracy, and efficiency. Specifically, we demonstrate how these algorithms can effectively reduce localization errors in dynamic underwater environments. Furthermore, we provide practical insights into their implementation, highlighting their advantages over traditional approaches in addressing the unique challenges of underwater localization.
- We present a detailed discussion about the existing literature focusing on range-based energy-efficient techniques, and further analyze the trade-offs between accuracy, energy consumption, and deployment complexity in various underwater scenarios.
- Lastly, we identify critical challenges in existing localization methods and highlight potential research directions for overcoming these issues. Our recommendations aim to guide the development of robust, energy-efficient localization techniques that are suited to the specific constraints of underwater networks, such as mobility, resource limitations, and environmental dynamics.

We have organized the remainder of this paper as follows: Section 2 provides existing review articles on underwater localization and outlines the gaps, focusing on AI-integration and energy-saving strategies. Section 3 illustrates an in-depth review of the AI-based underwater localization techniques found in the literature. Section 4 examines various energy-saving methods for underwater localization. We explore future research opportunities and identify challenges for developing robust, reliable, and energy-efficient localization in Section 5. Finally, the article concludes in Section 6.

1.1. Review methodology

To ensure a comprehensive survey, we searched multiple databases, including IEEE Xplore, ScienceDirect, SpringerLink, and MDPI, and other technical reports available in the public domain. The keywords used included “underwater localization”, “UWSN”, “AUV positioning”, “artificial intelligence”, “deep learning”, “energy-efficient localization”, and combinations thereof. The search covered articles published between 2010 and 2025, with a stronger focus on works from 2020 onwards.

We include papers that addressed underwater localization with either AI-driven approaches (end-to-end SLAM, sequential learning, feature-extraction methods, and general machine learning models) or energy-efficient techniques, while excluding purely terrestrial works and studies lacking methodological detail. In particular, AI-driven works demonstrate the growing role of learning-based models in handling acoustic noise, temporal dependencies, and multimodal fusion, whereas energy-efficient strategies are categorized into four distance-based methods (Time of Arrival (ToA), Time Difference of Arrival (TDoA), Received Signal Strength (RSS), and Angle of Arrival (AoA)). For each group, we analyze common limitations such as sensitivity to channel dynamics, scalability issues, and dependency on anchor placement. Reported performance is also compared in terms of RMSE error trends and computational overhead, which reveal that while many methods achieve strong accuracy in controlled simulations, their feasibility under realistic conditions remains uncertain. It is worth noting that the majority of the included studies rely on simulation-based evaluations rather than full-scale ocean experiments, which may bias results toward techniques that excel in idealized settings but degrade in real-world deployments. We highlight this gap throughout the review for more field-validated benchmarks that capture both accuracy and energy trade-offs under operational constraints.

2. Overview of related surveys

Numerous studies have been conducted on underwater localization, primarily focusing on the techniques and algorithms involved; however, only a limited number of articles have addressed AI in underwater sensor networks. Table 1 summarizes the current works and identifies their gaps. The authors in Christensen et al. (2022) reviewed recent developments in AI applications for underwater robotics, specifically covering model learning, control, perception, and navigation. While they covered vision-based SLAM, they overlooked end-to-end neural or hybrid filtering frameworks that fuse acoustic measurements with IMU data, specifically for localization accuracy rather than navigation only. Similarly, Feng et al. (2024) systematically reviewed feature-extraction techniques and classification methods such as shallow ML (Machine Learning), deep neural networks, and transformers, yet their survey only acknowledged propagation effects in passing and omitted data-driven channel models. Aubard et al. (2025) focused on neural-network verification and adversarial attack defense areas by comparing 19 open-source data sets and various simulators. By pinpointing the simulation to real-world mismatch, the authors tried to direct future researchers to extend sonar DL (Deep Learning) from simulation to robust, real-world autonomy. However, the authors overlooked multi-modal fusion strategies, such as integrating sonar DL outputs with IMU and vision data in joint neural or hybrid filter architectures for enhanced state estimation. Elmezain et al. (2025) provided a comprehensive analysis of deep learning architectures for underwater object tracking. Despite reviewing template-based and search-region frameworks, they did not consider an end-to-end deep learning architecture, especially vision-SLAM, that simultaneously tracks objects and estimates their position. In another work (Alexandris et al., 2024), the authors discussed the advancement in INS and acoustic systems, but did not provide any discussion on deep learning based or hybrid model approaches that combine acoustic, inertial, vision, and pressure data together to yield a single pose estimate. Heshmat et al. (2025) reviewed the evolution of the underwater SLAM, highlighting CNNs, transformer models, and multi-modal fusion that improved the feature extraction and mapping under poor visibility, sensor noise, and multi-path. However, the acoustic channel model and deep learning-augmented fusion filters were overlooked.

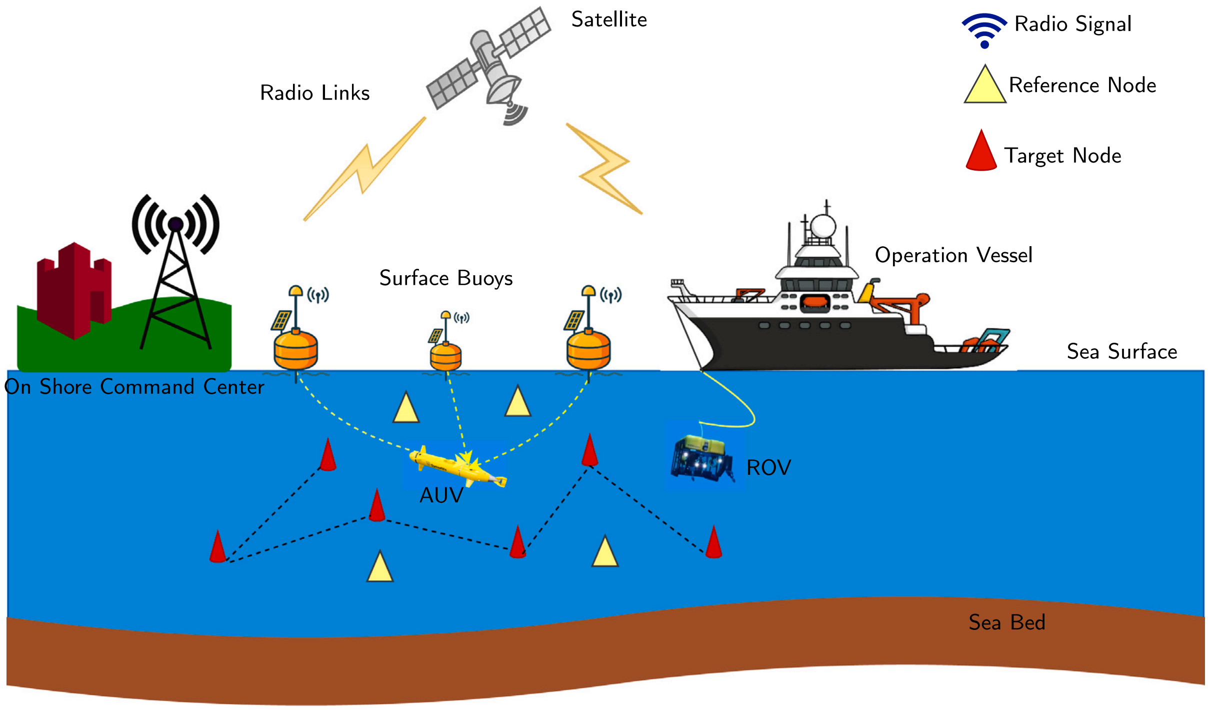

Fig. 1. System architecture of underwater wireless sensor networks (UWSNs).

When it comes to energy-efficient underwater localization, Islam et al. (2022) evaluated four major techniques, such as ToA, TDoA, AoA, and RSS, focusing on synchronization-free methods, reducing the number of anchors, and leveraging energy harvesting. Although they highlighted hyperbolic ranging techniques, they did not explore machine-learning-based multi-path fingerprinting to minimize retransmission. Murali and Shankar (2024) bridged node positioning and power conservation by highlighting supervised or reinforcement-learning models for predicting sleep/wake schedules and adaptive transmission power, but the authors overlooked water stratification effects on ToA/TDoA accuracy, nor did they consider an RNN-based method for learning true multi-path profiles to predict effective time delays. Hasan et al. (2024) provided a comprehensive overview of the charging system for AUV energy autonomy. The review outlined various recharging methods such as battery swapping, solar charging, and submerged docks. However, they did not cover how individual sensor nodes can minimize their energy consumption. Moreover, they overlooked in situ energy harvesting technologies, such as salinity gradient energy harvesters and ocean current turbines.

As illustrated in Table 1, a significant research gap exists in the domain of UWSNs, particularly in addressing comprehensive AI techniques, multi-modal fusion frameworks (combining acoustic, inertial, vision, and environmental data into cohesive deep or hybrid filters). These issues are pivotal for ensuring the reliability and robustness of underwater networks, yet remain underexplored in the existing literature. This study aims to bridge this gap and must not only unify AI-driven, multi-modal fusion frameworks but also embed advanced energy-aware strategies (ML-driven duty cycling, in situ energy harvesting, and multi-path aware channel modeling) to contribute to the ongoing development of reliable, efficient, and intelligent underwater wireless sensor networks.

3. Localization based on AI techniques

A typical UWSN architecture is illustrated in Fig. 1, consisting of multiple target nodes positioned underwater alongside surface buoys placed on the water surface. Typically, these surface buoys are responsible for receiving and transmitting signals, which they then send to the base station located either on the water surface or onshore. Due to the dynamic and complex underwater environment, several core wireless sensor network (WSN) approaches, such as geographic routing (Karp and Kung, 2000), geographic key distribution (Liu and Ning, 2003), blockchain technology (Goyat et al., 2021), and location-based authentication (Sastry et al., 2003), cannot be directly applied to underwater wireless sensor networks (UWSNs). These methods typically assume a stable, known location, frequent position updates, and straightforward physical access, all of which are difficult to achieve underwater. Recent advancements in AI have introduced novel approaches to address the unique challenges of dynamic underwater environments, offering enhanced accuracy and robustness in underwater localization. AI techniques can analyze large amounts of complex data to extract meaningful patterns, improving localization performance (Jwo et al., 2023b). In this section, we explore various AI-driven techniques applied to underwater localization as shown in Fig. 2:

- **Deep learning-based methods:** To extract and integrate features, model temporal dependencies, and perform end-to-end pose estimation or SLAM.
- **Machine learning-based methods:** Multilayer perceptrons, Radial-basis networks, fuzzy systems, and reinforcement-learning agents to fuse inertial, acoustic, or RSSI measurements and optimize beacon scheduling or path planning.

3.1. Deep learning-based methodologies

3.1.1. End-to-end pose/SLAM networks

Recent advancements in deep learning approaches improve underwater localization, each addressing specific challenges inherent to the marine environment. Wang et al. (2025) developed a monocular visual SLAM (EUM-SLAM) tailored for underwater conditions by integrating deep-learning-based optical flow into the DROID-SLAM backbone. The proposed system constructed 3D maps and tracked camera trajectories in real-time, as shown in Eq. (1), outperforming both traditional SLAM and earlier deep SLAM methods. To simulate turbidity and lighting variation, the authors introduced an underwater-specific data augmentation pipeline. In addition, they designed an SE-enhanced

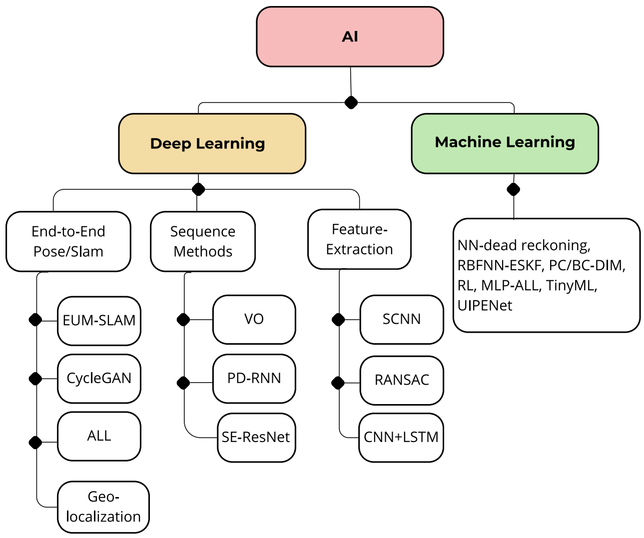

Fig. 2. Overview of AI-based methods for underwater localization.

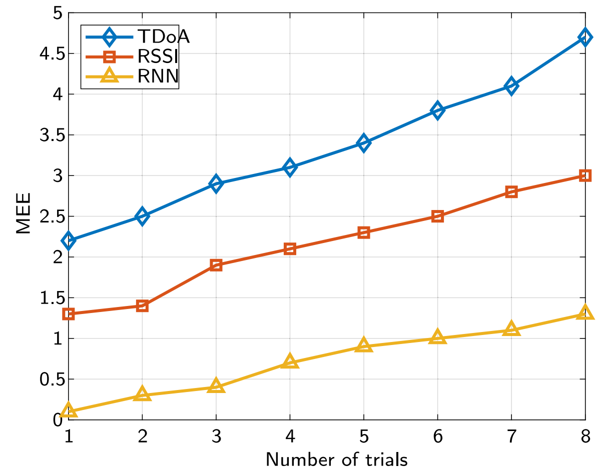

Fig. 3. Comparisons of MEEs (Kumar et al., 2024).

encoder (squeeze and excitation layers) to adaptively recalibrate feature channels under low-contrast conditions. Results showed improved robustness to turbidity, lighting variation, and motion, highlighting the feasibility of dense optical-flow-based SLAM in underwater navigation. Despite these advancements, EUM-SLAM relied solely on visual data, making it vulnerable when visibility was severely degraded. To address the limitations of requiring consistent visual input, authors in Joshi et al. (2020) presented a deep learning-based end-to-end pose estimation framework for underwater relative localization between AUVs. The framework predicted the 6D relative pose from a single camera image by detecting the 2D projection of the 3D model and applying a RANSAC-based Perspective-n-Point (PnP) solver, as presented in Eq. (2). The key innovation lay in its training strategy, where rendered images from Unreal Engine were translated into realistic underwater images using CycleGAN, allowing the system to train without real-world labels. Their approach bypassed traditional SLAM and sequence modeling by processing each frame independently, without constructing maps or trajectories. The method achieved state-of-the-art accuracy in both pool and ocean tests, demonstrating robustness across domains and sensor types. While the proposed framework demonstrated high accuracy across diverse environments, it lacks temporal consistency, and its performance can degrade in poses if the training set is poor or when bounding box detection fails. In contrast to purely vision-based systems, Wolf et al. (2020) explored the use of bio-inspired sensing for 3D underwater localization. By combining CNNs and artificial lateral lines (ALLs), the study estimated the object's position based on the fish's hydrodynamics. In this approach, fluid flow was simulated based on a moving object. A CNN was used to predict the probability of object locations based on an array of sensors. Using the lateral line organ in fish, this method addressed the complex problem of localizing multiple sources simultaneously, representing an advancement over previous approaches. However, the research heavily relied on simulated data in training and evaluation, which may not simulate actual underwater conditions. Additionally, the system's effectiveness in high-noise conditions is uncertain because of its dependence on noise levels.

3.1.2. Sequence & temporal models

Teixeira et al. (2020) conducted a comprehensive benchmark comparing classical and deep-learning-based visual odometry (VO) and visual-SLAM methods on two challenging underwater datasets collected by an AUV. To mitigate trajectory drift in deep VO systems, the study introduced a visual-inertial fusion network, which used a Long Short-Term Memory (LSTM) model trained with IMU data. As shown in Eq. (4), the sensor node locations were obtained by minimizing the translation and rotation errors between the estimated and ground-truth poses. Experiments with the UX-1 underwater robot datasets showed that deep learning VO approaches were more robust to poor textures, turbidity, and lighting variations compared to traditional feature-based methods. While this approach improved trajectory correction, it remained limited to visual-inertial fusion, without addressing optical distortions or integrating other sensing modalities such as acoustics. To enhance robustness in noisy underwater environments, Kumar et al. (2024) proposed a novel Proximity-Driven Recurrent Neural Network (PD-RNN) framework, which addressed the limitations in traditional localization techniques such as TDoA and RSSI. They are prone to errors under environmental noise, multi-path effects, and signal degradation. Their approach integrated proximity information into a recurrent neural network that can model temporal dependencies in the input signals, as presented in Eq. (7). It significantly outperformed traditional RSSI and TDoA techniques under ideal conditions, as shown in Fig. 3, achieving a mean estimation error as low as $0.13-1.24$ m. However, it focused on $2-D$ positioning, while $3-D$ localization is critical for many underwater applications.

In a broader context of ocean sensing, Gou et al. (2020) presented a modular deep learning framework designed to forecast spatio-temporal oceanographic data. It is capable of handling complex multi-dimensional datasets from various sensors using flexible plug-and-play architectures. This system supports multiple architectures such as MLP (Multi-layer Perceptron), CNN, ConvLSTM, and Transformer-based models. The authors validated the system on both simulated and real-world (Argo float) datasets, demonstrating the superiority of ConvLSTM and Transformer-based models in spatio-temporal prediction tasks. It demonstrated a strong ability to predict thermocline distributions, which are critical for robust underwater acoustic communication. Although they require large volumes of training data, which may not always be available in marine contexts. Meanwhile, Bai et al. (2023) explored a novel geolocation approach using polarization-sensitive omnidirectional cameras. It leveraged polarization patterns in water, captured across different global locations under varied conditions (visibility, depth, time of day). The proposed method achieved $\approx$ 55 km longitudinal accuracy during the day and $\approx$ 1000 km at night using deep neural networks (DNNs), outperforming traditional physics-based models. In addition, the authors validated the robustness of polarization images over intensity images for geolocalization under variable water turbidity. However, degraded at depths $<$ 50 m due to low polarization contrast and changes in optical properties. To address unmodeled environmental noise, authors in Chame et al. (2018) proposed a neural network framework known as Behaviors-Prediction-Reliability-Fusion (B-PR-F) that adapts information from redundant black-box estimations. Using this approach, the localization signal was contextually anticipated within an ordered neighborhood of processing. Simulation and real experiments showed that B-PR-F outperformed the Kalman Filter and Augmented Monte Carlo Localization (A-MCL). It delivered more reliable position estimates, reduced error accumulation, and improved robustness in dynamic underwater conditions. Even though the strategy relies on the availability and accuracy of black-box models, which are only sometimes reliable or effective under all circumstances.

3.1.3. Feature-extraction networks (CNNs & autoencoders)

Burguera et al. (2022) introduced a three-stage loop closing front end for underwater visual graph-SLAM. Their approach incorporated a Siamese Convolutional Neural Network (SCNN) to quickly reject non-loop image pairs, followed by random sample consensus (RANSAC)-based pose estimation and a pose-based consistency filter (PLF) to remove remaining outliers. Eq. (8) defines the optimization objective for Pose Graph SLAM, where the sensor node position is obtained by minimizing the global error between odometry and loop-closure constraints. The system significantly reduced the false positive rate to $< 5\%$ while preserving $> 96\%$ true-positive loops. However, the proposed methods trained the SCNN and MLP only once, limiting adaptability to changes in underwater lighting and magnetic conditions. To enhance point cloud processing, Du et al. (2025) designed a density-adaptive filter using kd-tree neighborhood searches to remove outliers while preserving edges. They further developed an unsupervised graph (UIPENet) convolutional network that scored and selected rotation and translation-invariant interest points directly from the denoised cloud. UIPENet achieved higher feature robustness and lower pose estimation error than conventional CNN-based point cloud descriptors. Though the translation invariance was handled via normalization, true translation-robust feature learning was limited. Li et al. (2023) developed a real-time underwater target detection algorithm for AUVs using Side Scan Sonar (SSS) images with improved accuracy and efficiency. The combination of YOLOv7, attention mechanisms, and efficient image screening led to high performance in both simulated and real-world environments. It achieved state-of-the-art performance with a recall of 0.836 and 0.355 s inference time per image. However, challenges remained regarding dataset requirements, target ambiguity, and deployment in diverse underwater conditions.

The authors in Gong et al. (2020) addressed the problem of underwater target detection by designing a proactive acoustic array system where selected nodes emitted linear frequency modulated (LFM) probe signals and others listened for reflections. The Fractional Fourier Transform (FrFT) was applied to each received signal to generate a $2-D$ time-frequency spectrum whose peak encoded target range and radial velocity. A lightweight CNN was trained to detect the characteristics from an undersampled FrFT spectrum, enabling efficient range and velocity estimation. Despite its efficiency, this method assumed a single line-of-sight (LoS) path and constant average sound speed, ignored multi-path, Doppler fluctuations, and stratification effects. Peng et al. (2023) introduced an end-to-end terrain-relative localization framework that combines point cloud feature extraction, keypoint selection, and self-attention-enhanced matching. Their model achieved horizontal RMS ≤ 0.03 m and heading RMS $\leq 0.02°$ outperforming terrain contour matching (TERCOM), iterative closest point (ICP), point pair features (PPF)-FoldNet, and GeoTransformer. However, the computational load (though real-time at ≈ 8.6 ms$/frame$) may be high for AUV-embedded hardware. To address visual degradation in underwater environments, Amarasinghe et al. (2023) proposed $3-D$-Net tailored for underwater visual SLAM. It had three branches, such as interest point detection, descriptor generation, and depth prediction. To enhance localization and mapping, the obtained outputs from these branches were integrated with traditional SLAM systems. To adapt to turbidity, low lighting, and poor feature richness, a generative adversarial network (GAN)-generated synthetic underwater dataset was used for training, which limits the performance to other underwater conditions. Authors in Qiu et al. (2023b) introduced a hybrid neural network-based approach combining a CNN and LSTM to predict underwater glider positions accurately, as presented in Fig. 4. This method effectively addressed the significant influence of ocean currents on underwater gliders by leveraging historical ocean current data. To predict the glider velocity and position, a Current Forecasting Model (CFM) was developed, which was then integrated with the CNN-LSTM network. The hybrid CNN-LSTM model enhanced prediction accuracy by modeling spatial and temporal dependencies in the data. Although the model demonstrated robust performance for the specific type of underwater glider and region tested, its applicability to different types of gliders and various oceanic regions requires further validation. Despite the improvements, the method faced error accumulation over time, potentially affecting long-duration missions. A model-based CNN method was presented in Chen and Schmidt (2021) for estimating the range of underwater acoustic sources. This study evaluated matched-field processing (MFP) as an alternative to conventional MFP. By training the CNN with specific environmental models, the authors examined its performance under slightly varying conditions. Compared to MFP, the CNN approach significantly improved prediction accuracy and lowered Mean Absolute Error (MAE), particularly in environments with slight deviations from the training data. However, it may become highly inaccurate when mismatches between simulated environments and real-world conditions occur. Additionally, the model may not handle complex scenarios involving overlapping sources.

3.2. Machine learning-based methodologies

Hou et al. (2019) proposed an online 2-D SLAM system that integrated low-frequency magnetic beacon ranging with a single fixed acoustic beacon via a Multi-layer perceptrons- Extended Kalman Filter (MLP-EKF) pipeline. By replacing heavy sonar/vision feature extraction with lightweight neural inference and leveraging low-power magnetic fields, acoustic and magnetic beacon (AMB)-SLAM aimed to deliver real-time localization and mapping with minimal energy overhead. This approach removed the feature-extraction burden by relying on MLP inference and avoiding seabed deployment. Simulation results showed that AMB-SLAM achieved RMSE < 6 m, compared to > 15 m for magnetic-only SLAM. Although promising, its performance was validated only in calm and small-scale environments, assuming a stable geomagnetic environment. Authors in Song et al. (2020) described a navigation method for AUVs using neural networks in rapidly changing environments. The proposed method (NN-DR) integrated a KF, a neural network, and velocity compensation to mitigate accumulated errors from inertial sensors. Pitch angles can be predicted by reducing gyroscope measurement errors, especially in dynamic environments. In an extensive simulation study (at 300 s), NN-DR significantly improved navigation accuracy (160x more accurate) compared to traditional dead-reckoning methods. Furthermore, it is highly suitable for fast-changing underwater environments since it can withstand dynamic environmental changes like waves. However, adapting to changes in highly dynamic environments in real time may be challenging. A similar approach to Chame et al. (2018) was proposed in Ali et al. (2021), which utilized a predictive coding-biased competition/divisive input modulation (PC/BC-DIM) neural network for underwater robot self-localization. This method aimed to address the challenges inherent in underwater environments, such as non-Gaussian noise and high computational costs, by offering a more accurate and efficient localization solution than traditional techniques. Utilizing this approach, computational costs were significantly reduced, enhancing real-time applications. The method produced a low mean localization error ≈ 1.27 m and a low computation cost ≈ 2.2 ms, outperforming the Kalman filter and Monte Carlo localization in non-Gaussian noise conditions. Furthermore, it effectively managed underwater non-Gaussian noise, resulting in a more reliable localization estimate. However, the method

Table 2
Comparison of existing AI-based localization schemes based on learning architecture and sensor fusion.

Reference	Neural Network Type	Sensor Modalities	Fusion/Filter	Real-Time
Wang et al. (2025)	CNN, SE layers, Attention ConvGRU	Monocular Visual	SLAM (Monocular + Optical Flow)	Yes
Joshi et al. (2020)	CNN, CycleGAN	Visual (RGB images)	PnP (no temporal fusion)	Yes
Wolf et al. (2020)	CNN	Artificial Lateral Line (Pressure)	–	–
Teixeira et al. (2020)	CNN, LSTM	Visual + IMU	Visual-Inertial Fusion	X
Kumar et al. (2024)	RNN	Acoustic (RSSI, TDoA)	Proximity-driven RNN	–
Bai et al. (2023)	DNN	Polarization-Sensitive Camera	X	–
Chame et al. (2018)	Neural Net (black-box fusion)	Contextual signals (unspecified)	Black-box info fusion	–
Gong et al. (2020)	Lightweight CNN	Acoustic (FrFT spectra)	Peak Detection via CNN	Yes
Hou et al. (2019)	MLP	Magnetic + Acoustic Beacon	MLP + EKF	Yes
Song et al. (2020)	Neural Network + KF	IMU (Dead Reckoning)	Kalman Filter + Velocity Compensation	–
Ali et al. (2021)	PC/BC-DIM Neural Network	Unspecified (Positional Input)	Predictive Coding + Biased Competition	–
Pu et al. (2022)	MLP	Pressure (Artificial Lateral Line)	MLP Estimation	–
Saha et al. (2024)	TinyML	Piezo-Acoustic + Energy Harvesting	CNN + On-device TinyML	Yes
Shaukat et al. (2021)	RBF Neural Network	IMU + External Sensors	RBF + Error-State Kalman Filter (ESKF)	–

[X] - Explicitly not considered; [–] - Not applicable.

Table 3
Comparison of AI-based localization schemes based on application and performance metrics.

Reference	Application	Output	Dimen-sionality	Performance	Limitation
Wang et al. (2025)	Underwater Visual SLAM	Trajectory and Loop Closure	3D	Robust visual SLAM, handled turbidity	Relied on visual-only input; struggled in poor visibility
Joshi et al. (2020)	Relative Pose Estimation	6-DOF Pose	3D	State-of-the-art accuracy across domains	Failed with poor detection or unseen poses
Wolf et al. (2020)	Hydrodynamic Object Localization	Object Location	3D	Multi-object capability; biologically inspired	Simulation-based
Teixeira et al. (2020)	VO Drift Correction	Trajectory	3D	Improved drift via IMU	Ignored optical distortions
Kumar et al. (2024)	Target Localization	Position	3D	0.13–1.24 m MEE	Only 2D
Burguera et al. (2022)	Loop Closure Detection	Relative Pose	3D	FP $< 5\%$, TP $>96\%$	Static training; may not adapt to scene change
Du et al. (2025)	Point Cloud Registration	Pose (Rotation and Translation)	3D	Edge preservation and descriptor invariance	Translation-robustness was limited
Peng et al. (2023)	Terrain-based Localization	RMS Position and Heading	3D	$\leq 0.03m$, $\leq 0.02^{\circ}$ RMS	Required high computational load
Hou et al. (2019)	2D SLAM with Low Power	Trajectory	2D	Accurate real-time mapping without seabed deployment	Tested only in calm, small-scale, geomagnetically stable settings
Song et al. (2020)	Dead-Reckoning Navigation in Dynamic Waters	Pose Estimation	3D	Improved accuracy in fast-changing underwater environments	Challenging to adapt to rapid real-time changes
Ali et al. (2021)	Self-localization of Underwater Robots	Pose	3D	Reduced computational cost, handles non-Gaussian noise	Performance depended on quality of extracted features
Pu et al. (2022)	Pressure-Based Localization	Coordinates of Vibrating Source	2D	Enhanced accuracy; supports multiple sources	Interference at same frequency increased localization errors
Saha et al. (2024)	Low-Power Underwater Tracking with Sensing	Location and Communication	2D	High accuracy; energy-efficient with tinyML	Scalability challenges and mutual interference in dense setup
Shaukat et al. (2021)	Navigation and Localization with Nonlinear Modeling	State Estimation (Trajectory)	3D	Improved over ESKF; handled nonlinearity and disturbances	Scalability issues in large networks

is based on provided features for the neural network, which can impact accuracy if the correct features are not identified.

An artificial lateral line system for underwater localization was proposed in Pu et al. (2022), based on the fish mechanosensory lateral line system. An MLP neural network was used in this system to detect and process pressure variations caused by vibrating sources and predict their coordinates in two dimensions. As a result of the integration of MLP neural networks, localization accuracy was significantly enhanced, and the simultaneous localization of multiple vibration sources was effectively managed. Furthermore, data augmentation techniques enhanced the robustness and accuracy of models. Despite this, the method also relied on manually provided features for the neural network, which may affect the accuracy of the model. Moreover, mutual interference between sources, particularly those operating at the same frequency, can increase localization errors. The work in Saha et al. (2024) introduced a novel, artificial intelligence-driven sensor tag, LocoMote, which allowed undersea localization and sensing to be fine-grained. A tiny machine learning (tinyML) technique was integrated into this system to provide precise underwater tracking and real-time communication. For accurate localization, it utilized CNNs, employed piezo-acoustic ultrasonics, and was powered by an energy-harvesting system. LocoMote aimed to provide a comprehensive solution for long-term, fine-grained monitoring of marine environments with minimal footprint and power consumption. However, maintaining communication efficiency may become more challenging as the number of nodes increases. Additionally, mutual interference between multiple tags is possible, especially in densely populated areas. The work in Shaukat et al. (2021) proposed an innovative technique for improving underwater vehicle localization and navigation accuracy through the integration of a radial basis function neural network (RBF) with an Error-State Kalman Filter (ESKF). This hybrid algorithm aimed to improve state estimation in highly nonlinear underwater environments by utilizing the RBF neural network's ability to approximate nonlinear functions. As a result of the RBF neural network, the limitations of the ESKF were compensated, as well as the effects of high nonlinearity, modeling uncertainty, and external disturbances. The RBF-augmented ESKF showed significantly improved navigation and localization accuracy compared to the conventional ESKF based on Monte Carlo simulations. However, as the number of underwater nodes increases, scalability may become an issue, causing latency and performance problems.

Table 4
Comparison of recent underwater localization studies: techniques, data, outcomes, and limitations.

Reference	Year	Localization technique	Sensors	Dataset	Outcomes	Advantages/Limitations
Qiu et al. (2023a)	2023	CNN + LSTM hybrid NN + Ocean current forecast	Glider IMU + Current model	Underwater Glider field trials + Simulation	More accurate speed + position prediction vs. classic DR; reduced drift error	Overcome current-induced drift; Worked without GPS/acoustic aid. Model-dependent; Performance was limited if the current forecast was inaccurate.
Li et al. (2023)	2023	MA-YOLOv7 + Attention + Multi-scale fusion	Side Scan Sonar (SSS)	Field AUV trials + Simulation	Recall = 0.836; 0.355s per image; accurate real-time detection/localization of targets	Real-time; Effective for small targets. Required labeled sonar datasets; computational load for embedded AUV.
He et al. (2024b)	2024	Pure inertial deep model with dual-mode switching (Transformer + CNN)	Low-cost IMU (SINS), time-interval cues	Long sea trial, 261.5 km, 28 h	Improved inertial prediction accuracy over mainstream baselines; suppressed error divergence over long runs	No external beacons; long-run stability. Quantitative error breakdown vs. each baseline was not uniformly reported.
Pu et al. (2024)	2024	CNN + Mobility Prediction (HLCM)	Acoustic ToA, anchor speeds, pressure sensors	UWSN Simulation	Achieved high localization accuracy and fault tolerance with CNN-based error correction and drift compensation	Handled heterogeneous errors and mobility drift; High coverage. Computational overhead; Dependent on CNN training
Wang et al. (2024a)	2024	YOLO + IOU matching + DeepSort tracking	Imaging Sonar + Acoustic image sequences	AUV Dynamic Docking	Real-time robust feature tracking in noisy sonar images; effective against distortion	Robust against noise and reverberation; Real-time tracking. Required large datasets; sensitive in cluttered sonar.
Kumar et al. (2024)	2024	Proximity-driven RNN (CogniLoc)	Hydrophone arrays, acoustic emissions	Simulation + Real experiments	Significant reduction in mean estimation error (MEE); robust under noise	Exploited temporal + proximity patterns; Effective in dynamic conditions. Needed sequential data; training complexity.
Du et al. (2025)	2025	Graph Convolutional Network (GCN) for SLAM front-end	3D Point Cloud	Simulation + Underwater SLAM test	Improved feature extraction, denoising, robust inter-frame matching (RANSAC+ICP)	Handled noise in point clouds; Real-time feasible. High compute; training unsupervised but needed tuning.
Wang et al. (2025)	2025	Monocular visual SLAM with DL optical-flow	Monocular camera (underwater)	Aqualoc, TUM-RGBD	18.7% RMSE reduction vs. DROID on Aqualoc; mean ATE 3.4 cm on TUM-RGBD	Better robustness in turbidity/illumination. Vision-only: degraded in severe visibility loss.
Shamshad et al. (2025)	2025	KNN-based ML localization with cost optimization	RSS + Neighbor orientation features	Testbed (tank) + NS-3 simulations	99.98% accuracy; reduced error from 4.59 m to 3.88×10^{-8} m; energy 0.0045J; delay 0.067 s	Extremely accurate; Very low energy/time cost. Sensitive to dataset quality; NLoS harshness may degrade

In summary, we have explored localization schemes for UWSNs that leverage AI techniques such as machine learning and deep learning. We provide a detailed comparison of the existing works, highlighting aspects such as neural architectures, sensor modalities, fusion techniques, application domains, and key performance metrics. These areas present opportunities for further research and development, as outlined in Table 2, 3, and Table 4. While the existing approaches demonstrated high accuracy and robustness, their methodological quality and potential biases must also be considered. A key limitation across many studies is the reliance on simulation-only validation. Only a few works conducted field trials, and even those were typically small-scale or constrained to tank experiments. Another concern is incomplete

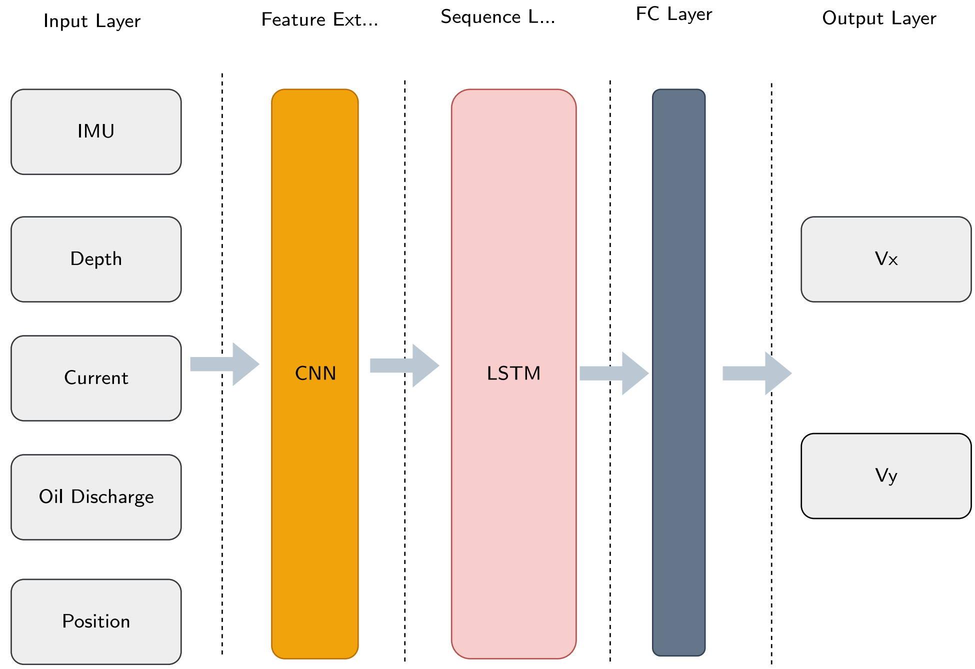

Fig. 4. CNN-LSTM hybrid neural network structure (Qiu et al., 2023b).

performance reporting. Many studies emphasized accuracy improvements (RMSE reduction or higher detection rates), but overlooked other crucial factors such as energy consumption, computational overhead, scalability, or robustness under harsh noise conditions. Future studies should adopt more standardized evaluation frameworks, disclose full performance trade-offs, and validate methods in diverse real-world settings to strengthen the reliability of claims.

4. Energy-efficient localization

Reducing energy costs is a goal in many application fields (Ali et al., 2019; Ning et al., 2019). Since battery replacement or recharging opportunities are restricted, designing energy-aware schemes is particularly vital in underwater communication. This section first highlights the energy-saving scheme in underwater localization in detail and provides a comparative summary in Table 5.

Underwater localization techniques can be categorized into range-based and range-free approaches. Range-based methods exploit node position by combining distance measurements, often obtained through specialized hardware or via existing radio communication resources, between known beacon nodes and regular sensor nodes. Depending on which signal attributes are measured at the receiver, common range-based indicators include TDoA, ToA, AoA, and RSSI. These methods offer high theoretical accuracy but are often constrained by the need for synchronization, susceptibility to multipath and stratification effects, and high energy cost due to frequent beacon transmissions. By contrast, range-free methods (centroid localization, DV-hop) do not rely on precise timing or distance measurements but instead use coarse neighborhood or hop-count information, making them less accurate but more energy efficient and simpler to deploy. Despite these advances, both range-based and range-free methods face scalability and sustainability issues in practical deployments. While numerous studies addressed challenges such as node mobility, node deployment, and routing strategies, the majority are limited to focusing on the network layer (Kumar et al., 2022b). Achieving significant energy savings often requires embedding a degree of autonomy and intelligence, enabling nodes to learn and adapt their behavior (Sutton and Craven, 1998). When a localization model exhibits intelligence, it can learn from its own and other models' experiences and use that information to enhance its performance when navigating uncertainty in underwater settings. In localization, autonomy refers to the ability of the sensor nodes to locate enough anchor nodes to determine their location. This is because most localization systems need many anchor nodes to assist a single sensor node in deciding its location (Rezazadeh et al., 2018; Yuan et al., 2018a). To enable sensor nodes to localize even with limited reference nodes, Misra et al. (2014b) introduced a framework, Opportunistic Localization by Topology Control (OLTC), focusing on establishing interaction between unlocalized nodes and localized nodes as a Single-Leader-Multi-Follower Stackelberg game. The leader requested a beacon and aimed to minimize the localization delay, whereas the followers adjusted transmission power to maximize the profit, which balanced energy consumption and localization utility. However, game-theoretic computations may increase overhead in large networks. Similarly, Yuan et al. (2018c) made use of a Stackelberg game to allow sensor nodes to connect with enough anchor nodes to determine their positions while consuming the least energy. Unlike the method in Misra et al. (2014b), this approach reduced the energy consumption per node by accounting for the energy cost of both anchor and sensor nodes. Nevertheless, the effectiveness of this technique was limited to a single environment, and the utility functions must be specified using predetermined weights. This technique requires time and energy-consuming recalculation of the utility weights if the environment changes, such as the number of nodes or network size. In another work, Karmakar et al. (2018) introduced a protocol to deliver the data efficiently for AUV-equipped underwater networks. The proposed protocol improved the packet delivery ratio and reduced energy consumption. However, the authors focused only on AUV-only networks, limiting applicability to hybrid networks involving fixed nodes. While these techniques yield encouraging outcomes, they cannot manage the network dynamic fluctuations or submerged surroundings. Therefore, future prospective researchers must consider the unpredictable environment while designing localization in UWSNs.

4.1. Received signal strength indicator (RSSI)

Unlike techniques such as ToA and TDoA, which rely on precise time synchronization and involve significant communication overhead, RSSI operates without the need for strict time synchronization, making

Table 5
Comparison of existing energy-efficient localization scheme.

Reference	Year	Measurement modality	Energy-saving strategies	AI/ML component	Channel modeling	Real-time	Limitations
Mei et al. (2020a)	2020	RSSI	Min–max absorption-mitigation optimization.	–	Depth dependent absorption and path loss.	✓	Required known absorption bounds.
Poursheikhali and Zamiri-Jafarian (2019a)	2019	RSSI	No synchronization required.	–	Curved-ray propagation, absorption loss, flat fading.	✓	Neglected multi-path beyond flat fading.
Islam and Lee (2019a)	2019	TDoA (multi-antenna)	Clustering and retransmission control.	–	Assumed ideal TDoA with three non-collinear hydrophones.	✓	Required time synchronization and surface resurfacing.
Sahana and Singh (2020a)	2020	ToA/TDoA (acoustic ranging via cluster head)	Clustering and backup Heads (only higher energy cluster heads perform ranging).	–	Basic underwater acoustic path-loss assumed.	✓	Assumed stable cluster partitions.
Liao et al. (2021)	2021	ToA (one-way beacon listening)	Selected an optimal time window via RL.	RL	Modeled LOS/NLOS delay errors.	✓	Assumed accurate IMU and clock.
You et al. (2020)	2020	ToA	RL agent learned which anchors to query to minimize redundant way ranging.	RL	Accounted for LOS vs NLOS via reward shaping; did not explicitly model multi-path or Doppler.	✓	Required extensive offline training.
Chen et al. (2018a)	2018	ToA/TDoA (acoustic ranging)	Sensor locations were refined on-the-fly during tracking, avoiding standalone re-localization phases.	–	Assumed known, static sound-speed profile.	✓	Required periodic contact with GPS-enabled super-nodes (buoys) for ground-truth.
Mirza and Schurgers (2008a)	2008	Inter-drifter range via broadcast TOA.	Broadcast-only ranging with post-facto processing.	–	Accounted for clock skew (0.02 ppm), node mobility during flight, and MAC back-off.	Post-mission	Assumed highly accurate clocks (skew $\leq$ 0.02 ppm), known sound-speed, stable topology over sync period.
Murgod and Sundaram (2020a)	2020	ToA	Clustering with sleep/active modes.	–	Assumed ideal acoustic ToA with constant sound speed.	✓	Required GPS-equipped anchors, time sync, and backup-head selection overhead.
Mirza and Schurgers (2007)	2007	Pairwise acoustic ToA ranging.	Link-selection policy.	–	Assumed simple ToA propagation with fixed speed of sound.	Post-mission	Required post-mission collection of all ToA logs and assumed accurate initial clock sync.
Zhou et al. (2010a)	2010	Acoustic ranging (implicit ToA/TDoA)	Mobility prediction	–	Accounted for acoustic constraints but used an idealized range-error model.	✓	Required accurate initial GPS at surface buoys, time synchronization, and assumed known mobility patterns.
Moradi et al. (2012a)	2012	ToA (one way)	Event-driven one-way beacons.	–	Assumed direct-path ToA.	✓	Required synchronized clocks initially.
Yi et al. (2015a)	2015	ToA (one-way beacon receptions).	Eliminated two-way handshakes.	–	Modeled clock offset drift.	✓	Required accurate crystal clock ($\approx$ 0.02 ppm) and IMU.

[✓] - Explicitly addressed; [–] - Not applicable.

it a more energy-efficient option (Zhang et al., 2023). A localization technique for energy-harvesting wireless underwater optical sensor networks based on RSSI was proposed by Saeed et al. (2019). It allowed low-energy nodes to gather ambient energy and reactivate after enough harvested energy, as depicted in Fig. 5. Subject to the limitations of the optical underwater channel, distances were computed for position estimation by the active nodes using RSS. The block kernel matrices for the RSS distance estimations were then calculated. A matrix completion approach reduced the error in the shortest path estimate in the block kernel matrices. When block kernel matrices were finished,

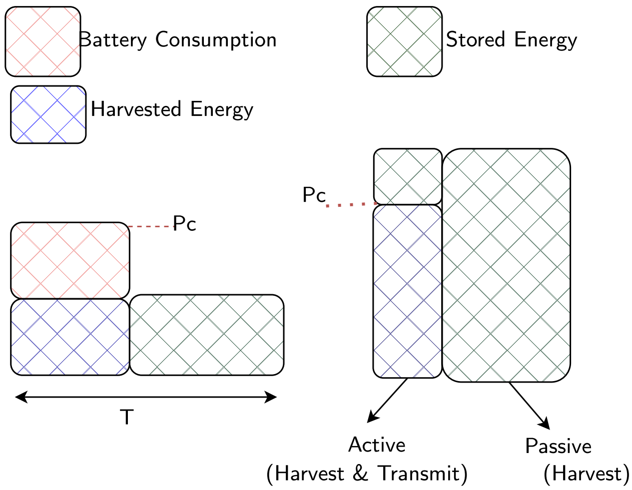

Fig. 5. Time-slotted operation of sensor nodes (Saeed et al., 2019).

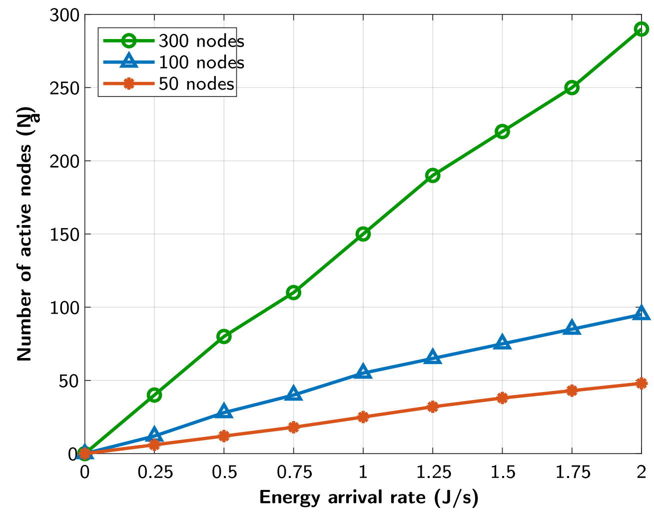

Fig. 6. RMSPE Vs. Energy arrival rate (Saeed et al., 2019).

nodes were localized using a closed-form location estimate process. The suggested plan used energy collection to increase robustness and lengthen the network lifespan. Fig. 6 demonstrates that energy harvesting directly controls the number of active nodes, and higher energy availability significantly improves network connectivity and localization capability. However, it must consider how node mobility affects node localizability, which might lead to highly inaccurate predictions.

While adjusting to the dynamic changes in the environment, Yuan et al. (2021) introduced the Adaptive Energy-Efficient Localization Algorithm (Adaptive EELA). By allowing sensor nodes to be localized with the least amount of energy consumption possible, the suggested method seeks to achieve energy-efficient localization. The proposed method balanced energy consumption and localization accuracy by optimizing the transmission power of both sensor and anchor nodes. Large amounts of processing power and offline data were needed for the training set. Initially, distributing fuzzy variables might require a significant amount of energy. Sathish et al. (2023) followed a similar RSSI-based advanced efficiency-driven localization method to achieve precise localization with minimal energy consumption, but focused on optimizing for varying network scales. The proposed method achieved high accuracy in underwater environments and handles varying network sizes. However, careful anchor node placement and fine-tuning RSSI parameters were required. In addition, the accuracy depends on calibrating the path loss model for specific underwater conditions.

Clustering techniques have also proved effective in minimizing energy consumption. In Sahana and Singh (2020b), the authors developed a clustering protocol that formed clusters and a cluster head within a random time. To extend the network lifetime, the authors introduced a backup node responsible for gathering information on other cluster nodes and transferring it to the floating nodes. The proposed work decreased energy consumption by deploying nodes with different energy sources. Islam and Lee (2019b) extended the clustering idea further by assigning the primary localization responsibilities to cluster heads, rather than involving all nodes equally. This strategy substantially reduced the energy consumption per node. Additionally, they introduced a retransmission control mechanism to minimize redundant communications, further enhancing energy efficiency.

Some studies address the physics of acoustic propagation to improve both energy efficiency and localization accuracy. The authors in Poursheikhali and Zamiri-Jafarian (2019b) developed a model that accounted for curved acoustic wave paths in inhomogeneous media, such as linear sounds and non-linear sound speed profiles. The authors formulated a novel RSSI measurement technique that can overcome dependency on signal attenuation and synchronization. Moreover, they investigated the fading effect caused by underwater obstacles or non-line-of-sight (NLOS) paths. Nevertheless, the model relies on specific sound speed profiles, which may not reflect realistic ocean environments.

Mei et al. (2020b) transformed localization as a min–max operations problem, seeking to minimize energy consumption while ensuring robust distance estimation under varying noise levels, absorption coefficients, and transmit-power settings. However, it assumed prior knowledge of the worst-case absorption coefficient and maximum communication range. Verma et al. (2001) took a holistic approach by combining energy-efficient localization with secure routing. Their proposed energy-efficient localization-based secure routing (OEEL-SR) protocol employed an enhanced version of the gravitational search optimization (IGSO) method to determine node locations, while the chaotic wolf optimization (CWO) method was used to identify the secure path throughout the routing process. This approach used the trust notation of nodes to transport packets to sink nodes while improving the transmission ratio and data energy consumption. Compared to the current approach, OEEL-SR increased accuracy by 55% and decreased energy usage by 20%. However, the protocol was predicated on ideal circumstances that could not exist in the real world.

4.2. Time of arrival (ToA)

Two-way communication consumes energy. To avoid the two-way handshaking and mitigate the effect of beacon transmission loss, the authors in Yi et al. (2015b) proposed Time of Arrival Tracked Synchronization (ToA-TS) techniques. Instead of exchanging round-trip messages, each node used an accurate crystal clock and its onboard IMU to timestamp incoming beacons, maintaining synchronization with minimal communications. This eliminated the need for reply messages, directly reducing per-node transmission energy.

To design an even-triggered operation, Moradi et al. (2012b) developed an event-driven localization framework. Rather than periodic broadcasting localization packets, nodes only transmitted when a predefined event occurred (detection of a target or a significant topology change). Moreover, the model shifted localization computation to a centralized sink to minimize the computational burden on sensor nodes. Although the divide response time increased with water depth, it remains manageable due to reduced propagation delays. However, anchors must be carefully deployed to ensure adequate coverage and minimize packet loss. To further cut down on ToA-based beacon exchanges, Zhou et al. (2010b) proposed a mobility prediction-based localization scheme where node mobility was predicted using historical data and current velocity vectors. The model conserved energy by

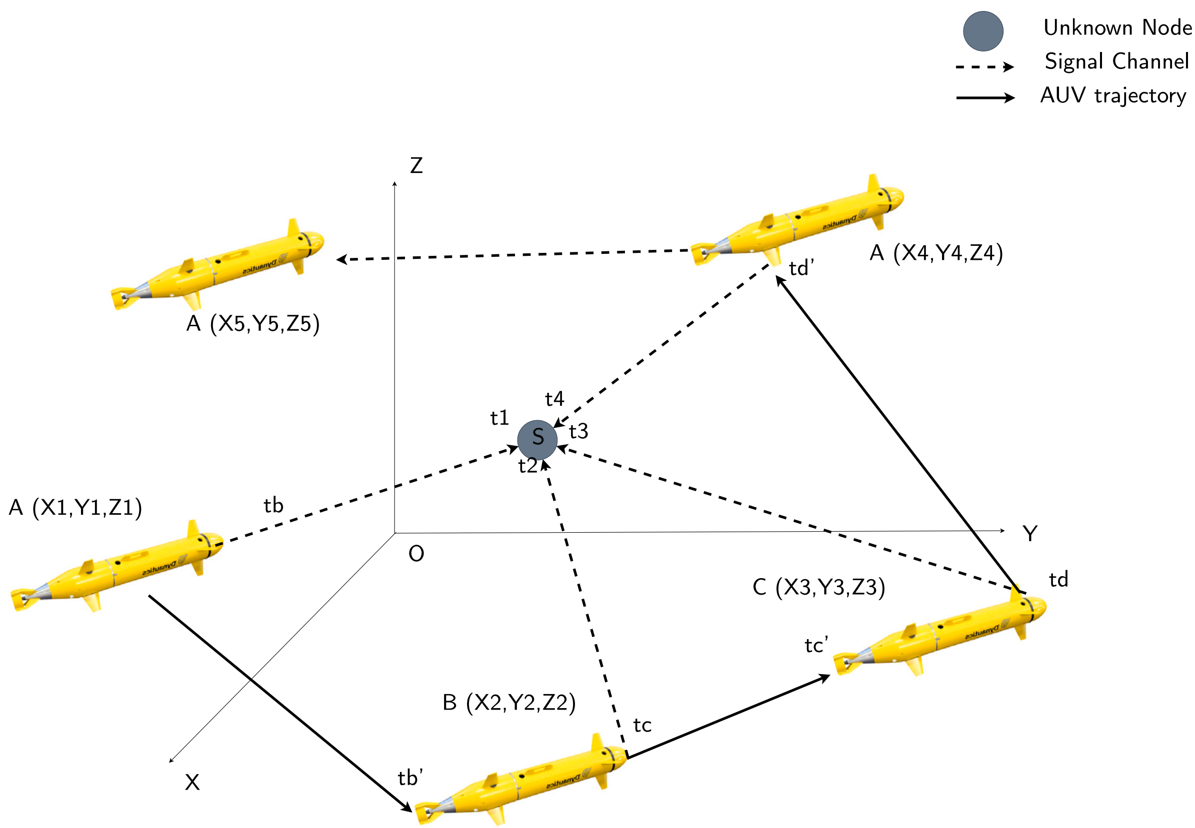

Fig. 7. Mathematical model for AUV-aided TDoA-based localization.

reducing the frequency of anchor-node communication. Nonetheless, the accuracy of mobility prediction can degrade in highly unpredictable environments. In a network of drifting sensors, where nodes move unpredictably with currents, a post-mission ToA localization framework tailored in Mirza and Schurgers (2007), focusing on reducing the energy cost of localization in dynamic underwater networks and adapting the accuracy to meet application-specific needs. The model demonstrated robust performance for large-scale networks with varying densities of drifters and beacons. However, it is unsuitable for real-time applications.

Clustering can also reduce ToA costs.
Murgod and Sundaram (2020b) divided the network into clusters, elected a cluster head, and only the head performed ToA ranging on behalf of its members. All the nodes slept until called, significantly reducing their energy. The energy-efficient cluster-based localization algorithm (EECBLA) also applied a ToA-based distance estimate to refine the cluster head position. Compared to previous approaches, it reduced localization error to around 4 to 6 m. The constant activity of the anchor node may cause rapid energy loss. Mirza and Schurgers (2008b) presented Sufficient Distance Map Estimation (SDME), a revolutionary energy-aware distributed approach for drifters using inter-drifter range measurement as the foundation. It used synchronization and broadcast-based range to ensure precise position estimates while consuming the least energy. Significant energy savings were attained by lowering the number of transmissions—on average, 0.4 to 0.7 transmissions were required for each localization step. Their suggested investigation indicated that real-time localization was not feasible. Clock drift and synchronization mistakes can build up and affect the localization accuracy without regular resynchronization.

Chen et al. (2018b) developed a simultaneous localization and target tracking (SLAT) method with high-accuracy localization with mobility prediction (HLMP) to get reasonably accurate sensor position estimations. These techniques minimized the requirement for frequent localization updates, which decreased energy usage. Real-time localization is unsuitable for the suggested approach as it concentrates on post-mission localization. Reinforcement Learning (RL) can also optimize ToA-based beacon selection. The authors in You et al. (2020) suggested an energy-efficient underwater localization technique based on RL without depending on predefined channel models. The scheme was dependent on the two-way travel time of underwater acoustic signals. The energy needed for localization dropped from 8.1 Joules to 6.3 Joules. There was a 72.2% improvement in the balance between energy use and localization accuracy. However, it necessitated a training period that may take more energy. In their subsequent work (Liao et al., 2021), the authors lowered the localization concealed mobile node error and energy consumption. The goal was to reduce the amount of energy used by a hidden mobile node (HMN) that did not communicate with anchor nodes via acoustic signals to remain hidden and conserve energy. Furthermore, the concealed mobile node can only locate itself by receiving signals from anchor nodes. Compared to previous methods, the suggested approach used 85.6% less energy, and the balance improved by 49.6% and 76.9%, respectively.

4.3. Time difference of arrival (TDoA)

In Ullah et al. (2019), distance-based and angle-based localization algorithms with comparatively lower energy consumption and mean estimate errors (MEEs) were introduced for the underwater environment. The location of the sensor node can be estimated by solving the nonlinear range equations given in Eq. (10), where $r_n(k)$ denotes the estimated distance between the unknown node and the nth anchor. It concentrated on the localization of underwater nodes with a particular emphasis on MEEs. With variances between 2.7494 and 3.4789 m and between 91.0353 and 104.9206 m for the angle-based system, the distance-based strategy produced lower MEEs. Although it helped to save energy, its effectiveness was diminished by increasing MEEs, which made localization accuracy less specific.

Table 6
AI-enabled underwater localization roadmap: now, near-term, and long-term.

Axis	Current State	Next-Generation Approaches	Future Directions
Algorithms	Classical PF/KF/EKF, early DL front-ends	RL for adaptive updates, hybrid AI+filters, self-/weakly-supervised models	Multimodal end-to-end (acoustic+IMU+vision), graph/transformer models.
Energy	Energy as evaluation metric	TinyML at edge, RL-driven duty cycling, event-triggered updates	Cross-layer co-design, in-situ harvesting-aware AI.
Channel	Simple SSP assumptions, limited multipath/Doppler handling	Learned denoising for ToA/TDoA, domain adaptation across sites	Data-driven channel twins; robust, uncertainty-aware inference.
Systems	Sim/small pilots, centralized training	Federated learning across nodes; on-AUV inference	Digital twins for design-time optimization; trustworthy AI.
Validation	Mostly simulation	Public benchmarks; multi-site field trials	Standardized testbeds; certification-style evaluation.

As presented in Fig. 7, an enhanced AUV-aided TDoA localization algorithm (EATLA) was proposed in Hao et al. (2020b), where the AUV dived into the predefined depth and transmitted the data packet periodically. After that, the unknown node received the data packet and calculated its position. A time delay system was proposed to save energy consumption. The position of the unknown sensor node was determined by solving the trilateration system, as shown in Eq. (12). Due to the use of mobile AUV underwater, the localization coverage was improved, resulting in fewer localization errors and a relatively shortened localization time. Similarly, Ojha et al. (2020) utilized a high-speed AUV as a location provider to create a virtual anchor plane. This approach achieved high localization coverage despite the absence of synchronization between the sensor nodes and the AUV.

To compensate for residual errors in TDoA approaches, Kaveripakam et al. (2023) combined TDoA and AoA to leverage their respective strengths, overcoming the limitations of individual techniques. The authors implemented adaptive beamforming and array processing techniques to mitigate multi-path propagation and improve signal quality. In addition, a machine learning model was introduced to predict localization errors and refine estimates dynamically. Although this hybrid scheme demanded precise anchor placement and careful synchronization among anchors, it significantly reduced the number of required TDoA exchanges and thus the total energy expended without repeated retransmissions.

4.4. Angle of arrival (AoA)

A hybrid localization algorithm for a 3-D network model based on Doppler Shift and AoA (DAHL) was proposed in Hao et al. (2020a). Rather than relying solely on TDoA pings, DAHL combined Doppler-shift and AoA measurements in a two-stage algebraic solver. The mobile node position and velocity estimation errors were optimized by introducing auxiliary parameters. The two-stage algebraic approach was employed to simplify the complex, high-dimensional nonlinear relationship between Doppler shift measurements and the mobile node's position. Even under increased measurement noise, the method demonstrated strong performance in accurately estimating both the position and velocity of the node. Once these parameters were determined, real-time tracking of the mobile node became feasible. To enhance the effectiveness of the DAHL method, the study strategically balanced energy consumption between anchor nodes and regular nodes.

Building on the same idea of minimizing TDoA exchanges, Kumar et al. (2022a) selected a Primary Anchor (PA) that provided AoA measurements, using a small, directional array to determine the bearing of the node's acoustic ping and a Secondary Anchor (SA) that supplied an RSS-based distance estimate. By fusing AoA from the PA with RSS from the SA, they can derive a rough position without initiating a full TDoA handshake. The model evaluated utility functions such as residual energy, transmission distance, and measurement error to optimize the SA selection. The proposed technique maintained a higher packet delivery ratio by avoiding packet collisions and optimizing directional transmission. The node position was determined using a PA equipped with GPS and capable of reliable data processing. As a result, if the PA fails, localization accuracy is compromised, since the SA will begin transmitting data randomly to another anchor node, which then communicates directly with the sink, potentially disrupting the coordination and precision of the system.

In summary, we have illustrated an energy-efficient localization scheme for UWSNs. We classified the existing literature into four categories: RSSI, ToA, TDoA, and AoA. The methods described are energy efficient and achieved comparatively low localization error, network lifetime, and packet delivery ratio. Besides, we analyzed their simulation result and identified the drawbacks of each research work. We also present a detailed comparison of existing works, highlighting their limitations and scope for further research in Table 5.

5. Future research direction

While numerous energy-efficient and reliable schemes have been developed in terrestrial wireless sensor networks, these approaches are unsuitable for underwater environments because of the distinct properties of communication channels. Moreover, existing localization schemes often struggle to meet the constraints of underwater networks. In these future underwater sensor networks, localization services will face new possibilities and challenges in terms of robustness and adaptability. The recent ground-breaking proposed algorithms are promising for optimizing both localization accuracy and energy consumption, and will likely impact UWSNs localization. Before discussing these approaches in detail, it is useful to first outline how underwater localization is progressing along four key dimensions: algorithms, energy strategies, channel modeling, and system validation. Table 6 presents an AI-enabled roadmap, illustrating the current state of the field, anticipated short-term developments, and long-term research directions.

5.1. AI-driven localization

Many approaches (Wang et al., 2025; Peng et al., 2023; Bai et al., 2023) highlighted the need for better generalization across different underwater domains, suggesting the development of adaptive or domain-transfer learning strategies. Many approaches still depend heavily on simulated data and require improvements, as shown in Table 7. Domain adaptation and transfer learning remain underexplored despite the clear domain shift between simulation and ocean deployment. Therefore, future efforts should focus on real-world validation under diverse and dynamic marine conditions (Teixeira et al., 2020; Wolf et al., 2020; Burguera et al., 2022). In addition, while several approaches employ supervised learning, only a few leverage self-supervised or unsupervised techniques, which are more scalable and data-efficient for underwater applications. Additionally, as underwater sensor networks scale up, addressing computational efficiency, energy consumption, and real-time adaptability becomes increasingly important. Lightweight

Table 7
Comparison based on dataset, validation environment, and training approach.

Reference	Dataset	Validation Environment	Training Approach
Wang et al. (2025)	Augmented underwater images (custom)	Simulated (turbid lighting) and real images	Self-supervised optical flow and SE encoder
Joshi et al. (2020)	Synthetic (Unreal Engine), CycleGAN	Pool and ocean trials	Unsupervised image translation and pose regression
Chen et al. (2023)	RGB images (PoseNet dataset)	Indoor/outdoor visual scenes	Supervised single image pose estimation
Wolf et al. (2020)	Simulated hydrodynamics	Simulation only	Supervised CNN on ALL sensor data
Teixeira et al. (2020)	Underwater AUV dataset	Real AUV trials	LSTM trained on VO trajectory and IMU correction
Kumar et al. (2024)	Synthetic signal simulation	Ideal and multi-path noise	Supervised RNN with proximity info
Burguera et al. (2022)	Underwater visual images	Field AUV deployment	SCNN and RANSAC
Du et al. (2025)	3D underwater cloud data	Simulated and real cloud edges	Unsupervised graph scoring (UIPENet)
Peng et al. (2023)	Terrain maps and simulated point clouds	Simulated and real terrain	Self-attention and keypoint learning
Hou et al. (2019)	Small-scale magnetic and acoustic	Not specified (presumed controlled)	MLP trained offline for EKF fusion
Song et al. (2020)	Simulated dynamic underwater environment	Extensive simulation	NN prediction and velocity compensation
Ali et al. (2021)	Feature-based simulation data	Synthetic	PC/BC-DIM training with encoded features
Pu et al. (2022)	Pressure sensor simulation	Vibration sources	Supervised MLP with feature engineering
Saha et al. (2024)	Real marine tag trials	Field and simulated	TinyML with CNN for classification
Shaukat et al. (2021)	Monte Carlo simulation	Nonlinear trajectory test	RBFNN and ESKF integration

models such as TinyML and decentralized training methods like federated learning can help mitigate these concerns. Incorporating temporal modeling into pose estimation frameworks currently operating frame by frame (Joshi et al., 2020) and can improve consistency and accuracy in long-duration missions. 2D approaches to 3D are still a critical need to support real-time, low-power interference on embedded systems like AUVs and underwater sensor tags (Hou et al., 2019), Saha et al. (2024). Another critical direction lies in the automatic extraction of features and multimodal sensor fusion, enabling systems to adapt to complex and dynamic environments. AI techniques also offer new avenues for addressing security threats in underwater localization, such as Sybil and wormhole attacks. By learning patterns of legitimate behavior over time, machine learning models can be trained to detect anomalies in distance measurements, signal timing, or node identity. For instance, neural networks can classify abnormal transmission patterns indicative of spoofed nodes (Sybil) or shortcut routing paths (wormholes). Integrating trust models with AI, or using reinforcement learning to dynamically adjust trust scores based on behavior, may further enhance secure and resilient localization. Future studies should investigate how to combine these detection mechanisms with localization algorithms to provide both accurate and secure positioning in hostile underwater environments.

A promising direction is the integration of federated learning, reinforcement learning, and hybrid AI models to jointly optimize localization accuracy and energy efficiency. Federated learning enables collaborative model training across distributed underwater nodes without requiring raw data exchange, reducing communication overhead and energy cost while preserving privacy. Reinforcement learning can dynamically adjust beacon transmission rates, duty cycling, or anchor selection based on real-time error growth. Hybrid AI models that combine data-driven deep learning with physics-based constraints or Bayesian filtering can further reduce drift while keeping computational load manageable for energy-limited nodes. Together, these approaches point toward next-generation frameworks where localization, communication, and energy management are co-designed, extending mission duration while maintaining reliable positioning in harsh underwater environments.

5.2. Reinforcement learning

Energy-efficient underwater localization schemes still face several critical challenges that limit their scalability and real-world applicability, as presented in Table 8. Future energy-efficient underwater localization research is increasingly focusing on intelligent, adaptive frameworks that dynamically respond to environmental uncertainty, mobility, and communication constraints. One promising approach lies in the use of RL because of its ability to autonomously make decisions regarding mobility, energy optimization, and adaptation to dynamic environments (Frikha et al., 2021), Yu et al. (2025). One proposed scheme in You et al. (2020) enabled the target to optimize the beacon selection policy without knowing the channel model between the target and the beacon, thereby reducing the error and energy consumption. Moreover, NLOS transmission of underwater acoustic signals leads to increased localization errors when algorithms assume line-of-sight (LOS) conditions. Therefore, localization algorithms must detect and avoid using nodes affected by NLOS transmission. To address this challenge, a reinforcement learning (RL)-based mobile hidden passive localization algorithm has been proposed (Liao et al., 2021). This approach aimed to reduce both the energy consumption of HMNs and localization errors. By allowing HMNs-restricted to receive signals from anchor nodes only to intelligently determine their positions and select the most suitable time window for localization, the algorithm remained effective even under uncertain underwater environmental conditions.

5.3. Mobility and delay prediction

Propagation delay is a critical factor that disrupts node synchronization and affects localization accuracy (Hasan et al., 2025a). It is essential to adjust lengthy propagation delays to achieve precise localization. A mobility prediction algorithm for anchor nodes has been proposed (Zhou et al., 2010b), wherein each anchor node calculates and records its speed during each localization interval. This approach enables predicting and compensating propagation delays, thereby improving localization accuracy. Ordinary nodes utilize the predicted speed from anchor nodes to perform the localization process.

Many UWSN localization schemes require enough anchor nodes to assist sensor nodes in determining their positions. These localization processes depend on various factors, including the locations of reference nodes, the number of sensor and anchor nodes, the localization method employed, and the distribution of anchor nodes. An energy-aware solution is necessary to enhance efficiency, enabling each sensor node to identify the required anchor nodes while considering localization through effective topology management.

5.4. Quantum-inspired positioning techniques

Quantum sensing and quantum-inspired techniques offer a promising frontier for underwater localization with the potential to improve traditional limitations in accuracy, drift, robustness, and synchronization. The authors in Mei et al. (2024) proposed quantum-inspired optimization algorithms to increase population diversity instead of relying on closed-form solutions, which require assumptions. Integrating quantum-enhanced sensors with AI-driven models can redefine localization accuracy and reliability in GPS-denied underwater environments. Warrier et al. (2024) focused on image classification rather than position estimation, but quantum advantages can extend to underwater localization. Hybrid quantum models can reduce the computational time and handle sensor drift, enabling richer multi-sensor fusion.

Table 8
Limitations and future scope of energy-efficient localization schemes.

Reference	Categories	Limitation	Scope
Misra et al. (2014b)	Range based	Assuming time synchronization for nodes may not be feasible in the natural underwater environment.	(i) Investigate the proposed scheme in the presence of shadow zones, jamming, and natural interference. (ii) Adopt a mixed strategy to select the appropriate transmission power level for the nodes.
Yuan et al. (2018c)	Range based	Energy consumption for the anchor node was higher than the existing one due to building their two-hop neighboring list.	Adopt incorporating learning strategies to enhance the robustness of the proposed method.
Ullah et al. (2019)	Dynamic, range-based, angle-based	(i) Less feasible for many sensor nodes and network fields than for a small area. (ii) Angle-based measurement could have been more accurate than distance-based measurement due to the water current and other obstacles.	(i) Implement RSSI for underwater localization. (ii) Reduce the MEEs further.
Li et al. (2016)	Dynamic, range-based	(i) Measurement and time measurement noise affected the localization accuracy. (ii) Tested in a shallow water environment (depth <500 m).	(i) Investigate the algorithm in the actual underwater environment to verify the feasibility of the proposed sound speed solution. (ii) Improving the immunity of the proposed algorithm against time measurement noise.
Liu et al. (2015)	Dynamic, range-based	The error can accumulate in the presence of unpredictable mobility patterns.	(i) Investigate the effect of time-variable transmission rate and clock skew in the proposed strategies. (ii) Evaluate the proposed work in the natural underwater environment.
Zhang et al. (2020)	Dynamic, range-based	Simulator could not capture the actual complexity of the natural environment.	Consider power management of nodes during the silent period.
Xu et al. (2019)	Dynamic, range-based	Environmental factors like noise and seawater current can affect positioning accuracy. Only salinity and wind speed were considered.	(i) Conduct the test underwater to improve the proposed algorithm. (ii) Consider the other environmental factors to validate the algorithm.
Yu and Choi (2014b)	Range based	Assuming the position of the all-sensor node may not be feasible in the natural complex underwater environment.	Reducing the computational complexity.
Chen et al. (2017b)	Range based	Managing the complexity of artificial measurements and the adaptive filter might be challenging.	Consider more complex underwater environmental factors to validate the proposed work.

5.5. Lesson learned

Based on the review of the existing literature on underwater localization, as summarized in Table 1, 2, 3, 4, 5, 6, 7, and 8, several promising methods for underwater positioning have been identified and discussed in terms of AI-driven techniques and energy efficiency. According to the literature, the dynamic nature of underwater communication is impacted by factors such as node mobility, multipath, and refractive properties of the sound signal, which pose significant challenges for accurate and robust localization. Since underwater nodes are constantly drifting with water currents, the localization algorithm must be designed to operate with sufficient efficiency and adapt to these node drifts in real-time. One of the main challenges behind developing an intelligent and energy-efficient localization scheme is ensuring that AI models remain lightweight. The narrow band of underwater channels and the energy limitation of underwater nodes make this more complicated. Although the recent advancement in developing lightweight learning models and hybrid AI-based frameworks that balance performance with resource constraints is promising, but still in the initial phase. These approaches leverage onboard processing, adaptive learning, and minimal communication overhead to preserve node energy while maintaining localization accuracy.

Adapting to dynamic environment changes is challenging when designing energy-efficient localization schemes due to the short sensor lifetime. One potential solution involves enabling nodes to operate in two distinct modes, active and sleep mode, to optimize energy consumption. Another approach is post-facto processing, which delays data analysis until data collection is complete, thereby significantly reducing energy costs associated with periodic real-time localization.

However, the performance will degrade quickly. Based on this idea, authors in Mirza and Schurgers (2008b) developed SDME, which used minimal communication while ensuring sufficient information for accurate localization was stored in the network. Most of the energy was consumed in predicting the location of a dead mobile sensor node (MSN). By avoiding beacon transmissions from the source to the MSN, communication overhead and energy consumption can be reduced. Researchers have proposed a passive localization algorithm to reduce energy consumption and localization errors for hidden mobile nodes.

Moreover, absorption and path loss can degrade the accuracy of localization. A practical energy-efficient localization approach involves minimizing the required range measurements. This can be achieved through link selection, which is only necessary during significant topology changes that occur less frequently than re-localization processes. Consequently, the total number of links utilized for ranging can be significantly reduced.

6. Conclusion

Underwater localization presents a wide range of challenges due to the harsh, complex, and constantly changing underwater environment. Among these, two of the most critical issues are high energy consumption and the need for intelligent, adaptive localization strategies. In recent years, significant research efforts have focused on overcoming these obstacles, with a growing emphasis on leveraging AI to enhance both the accuracy and efficiency of underwater localization systems. However, there has been no comprehensive review of these research works to guide future research on designing reliable, accurate, and efficient underwater localization schemes. In this work, we have reviewed and classified some key research studies on localization. First, we present a detailed discussion of AI-based localization techniques in underwater sensor networks, followed by a review of energy-efficient localization techniques.

Additionally, we have outlined promising future research directions in AI-driven UWSN localization, emphasizing the need to design lightweight, energy-efficient schemes and real-world testbeds to evaluate the performance of these techniques. This review paper aims to serve as a valuable resource for researchers focused on developing innovative strategies and frameworks to address key challenges in underwater localization, particularly those related to reliability, accuracy, and energy efficiency.

CRediT authorship contribution statement

Mainul Islam Chowdhury: Writing – review & editing, Writing – original draft, Funding acquisition, Formal analysis. **Quoc Viet Phung:** Writing – review & editing, Supervision, Funding acquisition. **Iftekhar Ahmed:** Supervision, Funding acquisition. **Walid K. Hasan:** Writing – review & editing. **Daryoush Habibi:** Supervision.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Mainul Islam Chowdhury reports fnancial support was provided by Western Australia Department of Jobs Tourism Science and Innovaton. If there are other authors, they declare that they have no known competng fnancial interests or personal relatonships that could have appeared to influence the work reported in this paper.

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Appendix

The following equation defines the dense bundle adjustment optimization used in EUM-SLAM (Wang et al., 2025) to recover the location of the sensor node. The method minimized the reprojection error between the observed 2D image points and the projected 3D map points. By optimizing over all camera poses R, t and 3D landmarks X, the system estimated the most accurate trajectory of the underwater sensor node.

$$E(R,t,X) = \sum_{i=1}^{N}\sum_{j=1}^{M} \rho\left(\left\| u_{ij} - \pi(R_i, t_i, X_j)\right\|^2\right) \tag{1}$$

where R_i and t_i denote the rotation matrix and translation vector (pose) of the ith camera, X_j represents the 3-D coordinates of the jth point, $\pi(R_i, t_i, X_j)$ is the projection of X_j onto the ith camera image plane, u_{ij} is the observed 2-D feature point, and $\rho(\cdot)$ is a robust loss function that reduces the influence of outliers.

In DeepURL (Joshi et al., 2020), the final localization equation came from solving the PnP problem: the 6D pose (R, t) of the underwater robot was estimated by aligning the predicted 2D keypoints with the known 3D model points using the camera projection model. This optimization was solved robustly with RANSAC-based PnP, yielding the sensor node's relative position and orientation.

$$\{\hat{R}_{ot}, \hat{t}\} = \text{PnP-RANSAC}\left(\{(X_i, x_i)\}_{i=1}^{N}\right) \tag{2}$$

This equation computes the 6D pose (rotation $\hat{R}_{ot}$ and translation $\hat{t}$) of the AUV by solving the Perspective-n-Point (PnP) problem with RANSAC, using N pairs of 3D model points X_i and their detected 2D projections x_i.

$$\phi(R_{ot}, \hat{R}_{ot}) = \arccos\left(\frac{\text{tr}(R_{ot}^T \hat{R}_{ot}) - 1}{2}\right) \tag{3}$$

This equation defines the orientation error between the ground truth rotation R_{ot} and the estimated rotation $\hat{R}_{ot}$, where $\text{tr}(\cdot)$ is the matrix trace.

The authors in Teixeira et al. (2020) defined the optimization used to estimate the sensor node (robot) location. The method regressed a 6-DoF pose (3D translation + rotation) from image sequences via deep networks (SfMLearner, GeoNet). The translation part of the pose corresponds to the sensor node's location in space. The fusion network refined these estimates by minimizing the combined translation error and quaternion rotation error with respect to ground truth.

$$\text{loss} = \sqrt{\sum (E_x^2 + E_y^2 + E_z^2) \; + \; \sum \|q_e - q\|} \tag{4}$$

The position of nodes in Kumar et al. (2024) was estimated by feeding sequential RSSI measurements from anchor nodes into an RNN. The RNN captured temporal dependencies through hidden states and outputs the predicted node location.

Input Layer:

$$X_t = \begin{bmatrix} x_{1,t} \\ x_{2,t} \\ \vdots \\ x_{N,t} \end{bmatrix} \tag{5}$$

Recurrent Layer:

$$h_t = \tanh\left(W_{hx} h_t + W_{hh} h_{t-1} + b_h\right) \tag{6}$$

Output Layer (location prediction):

$$\hat{y}_t = \text{softmax}\left(h_t W_{hy} + b_y\right) \tag{7}$$

The localization was formulated in Burguera et al. (2022) through Pose Graph optimization. The error function minimized is:

$$e(G_t) = \sum_{\forall X_{di}^{si} \in E_t} \left\| X_{di}^{si} - \left(\ominus(X_{si}^{W}) \oplus X_{di}^{W}\right)\right\|^2 \tag{8}$$

where (x^{si}_{di}) are the measured relative pose constraints (from odometry or loop closure) between nodes s_i and d_i, E_t is the set of edges (constraints) in the pose graph, $e(G_t)$ is the total error to be minimized in graph optimization.

The work in Peng et al. (2023) proposed a deep learning–based underwater terrain matching localization. The final localization was expressed as offsets $(\Delta x, \Delta y, \Delta u)$ (x-position, y-position, heading) that minimized the difference between predicted and actual poses.

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \sin \Delta\varphi_k & -\cos \Delta\varphi_k \\ \cos \Delta\varphi_k & \sin \Delta\varphi_k \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} \Delta x_i \\ \Delta y_i \end{bmatrix} \tag{9}$$

where x, y are the predicted position coordinates from inertial measurements, x', y' are the corrected position coordinates after terrain matching, $\Delta x, \Delta y$ are the translation offsets, $\Delta\varphi_k$ is the heading (yaw) offset.

The authors in Ullah et al. (2019) proposed two final equations for estimating the location of a sensor node, depending on whether distance-based or angle-based measurements were used.

$$r_n(k) = \sqrt{\left(x(k) - x_n\right)^2 + \left(y(k) - y_n\right)^2 + \left(z(k) - z_n\right)^2} \tag{10}$$

where $r_n(k)$ is the estimated distance between the unknown sensor node $(x(k), y(k), z(k))$ and the anchor node (x_n, y_n, z_n).

$$\theta = \cos^{-1}\left(\frac{X_1 X_2 + Y_1 Y_2}{\sqrt{X_1^2 + Y_1^2}\sqrt{X_2^2 + Y_2^2}} \right) \tag{11}$$

where θ is the angle between nodes $A(X_1, Y_1)$ and $B(X_2, Y_2)$.

The final equation in Hao et al. (2020b) showed how the unknown sensor node's coordinates were obtained using trilateration based on distances measured via TDoA between the sensor and multiple AUV positions. By substituting measured delays into these equations, the node's position (x, y, z) is uniquely determined.

$$\begin{cases} (x - x_1)^2 + (y - y_1)^2 + (z - z_1)^2 = d_{s1}^2 \\ (x - x_2)^2 + (y - y_2)^2 + (z - z_2)^2 = (d_{s1} + \varphi_1)^2 \\ (x - x_3)^2 + (y - y_3)^2 + (z - z_3)^2 = (d_{s1} + \varphi_2)^2 \\ (x - x_4)^2 + (y - y_4)^2 + (z - z_4)^2 = (d_{s1} + \varphi_3)^2 \end{cases} \tag{12}$$

where, $d_{s1} = \frac{-B \pm \sqrt{B^2 - 4AC}}{2A}$, $x = A_x d_{s1} + B_x$, $y = A_y d_{s1} + B_y$, $z = A_z d_{s1} + B_z$

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