DEVELOPING A RESILIENT LOCALISATION SYSTEM FOR WIRELESS SENSOR NETWORKS IN UNDERWATER ENVIRONMENTS

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ABSTRACT

Localization is a critical challenge in underwater wireless sensor networks (UWSNs) due to the unique and harsh aquatic environment, characterized by high signal attenuation, multipath interference, and dynamic node mobility. Traditional localization techniques relying solely on acoustic signals face limitations in accuracy, energy consumption, and real-time adaptability. This research presents a novel resilient localization system that integrates hybridized communication methods— acoustic, radio frequency (RF), and optical signaling—to enhance the efficiency and reliability of underwater node positioning. The proposed system leverages the complementary strengths of each communication modality, dynamically selecting the most optimal method based on environmental conditions and network constraints. Acoustic signals provide long-range but low-data-rate localization, RF signals facilitate medium-range data transmission in specific underwater conditions, and optical communication ensures high-speed, short-range localization with minimal latency. A robust fusion algorithm, incorporating machine learning-based predictive modelling and error-correction techniques, is developed to enhance localization precision while mitigating environmental distortions. Extensive simulations and real-world experimental deployments validate the system\'s effectiveness. Performance metrics, including localization accuracy, energy efficiency, and communication latency, are analyzed under varying water conditions, demonstrating significant improvements over conventional single-modality localization approaches. The findings indicate that the hybridized system enhances positioning accuracy by up to 35%, decreases energy consumption by 27%, and reduces communication latency by 20%, contributing to developing sustainable and resilient UWSNS. The proposed model lays the foundation for future advancements in autonomous underwater vehicle (AUV) navigation, deep-sea sensing applications, and next-generation UWSN deployments.

INTRODUCTION

In recent years, with the development of marine engineering and underwater communication technology, underwater wireless sensor networks (UWSNs) have been widely used in marine environment monitoring, marine biological research, disaster forecasting, auxiliary navigation, resource exploration, and military purposes, which have attracted the focus of researchers Wang *et al.* (2020). Building Underwater Wireless Sensor Networks (UWSNs) has become increasingly popular over the past few years Naqvi *et al*. (2025). Environmental monitoring, underwater surveillance, and ocean exploration are just a few of the possibilities for these networks. Underwater sensor networks (UWSNs) play a vital role in various fields, such as marine environment monitoring, underwater resource exploration, and natural disaster prevention and recovery Liu *et al*. (2023).

As a link between the ocean physical world and the information world, the Underwater Wireless Sensor Networks (UWSNs) form a distributed self-organizing network capable of flexible networking and bidirectional transmission by deploying a large number of micro-nodes with underwater acoustic communication and computing capabilities in the area of interest Ge *et al.* (2024). One crucial task in UWSNs is underwater acoustic localization, which involves estimating the position of an underwater signal source based on measurements received by the network Liu *et al*. (2023). Basically, localization is a key activity that detects a target's location underwater for different reasons such as data classification, tracking nodes underwater, and coordinating the movement of node Draz *et al*. (2022). The process of localization enables underwater communication, sensing and control of the whole network's topology Draz *et al*. (2022).

The dynamic nature of aquatic environments presents ongoing challenges for underwater localization. Current techniques primarily use acoustic communication, which offers long-range capabilities but is limited by low bandwidth (a few to tens of kilobits per second). This restricts data transmission, complicating the exchange of necessary information for accurate localization in dense networks or for mobile nodes needing frequent updates. The speed of sound in water is approximately 1500 m/s, significantly slower than the speed of light in air, which leads to high latency in localization updates that hinder real-time applications requiring precise position information. The underwater acoustic channel faces challenges from environmental noise, such as shipping and biological sounds, as well as multipath interference from reflections, resulting in signal fading and increased localization errors. Acoustic modems for long-range communication need substantial power to counteract signal attenuation, causing rapid battery depletion in energy-constrained underwater sensor networks, which limits operational lifespan and raises costs for battery replacements and node retrieval.

Optical and Radio Frequency (RF) communications each face limitations that hinder their effective use in underwater sensor networks (UWSNs). Optical communication, while offering high bandwidth and low latency, is restricted by the need for a clear line-of-sight and is affected by water conditions. RF communication suffers from severe signal loss in conductive seawater, limiting its range. These constraints lead to challenges such as inaccurate positioning, high energy consumption, and reduced efficiency, making it hard for UWSNs to perform reliably in key applications. Moreover, traditional localization methods struggle to adapt to changing underwater conditions, resulting in subpar performance. There is a pressing need for an integrated localization framework that capitalizes on the strengths of multiple communication methods and employs intelligent data processing to overcome existing limitations, thereby enhancing the functionality of UWSNs in critical fields like oceanographic research and offshore monitoring.

This study aims to develop a Resilient Localization System for Wireless Sensor Networks in Underwater Environments Utilizing Hybridized Communications Methods

Specific Objectives are to:

i. develop a hybrid model that incorporates XGBoost predictive model and error correction techniques to resolve the problem of the localization of nodes in underwater environments.
ii. implement this hybrid model to reduce energy consumption in the underwater environments.
iii. evaluate the developed model using the following metrics: Root mean square error (RMSE), energy consumption per localization event, and latency per cycle.

MATERIALS AND METHOD

Methodology Adopted

This section presents the methodological backbone of the study and articulates how the research questions are operationalized into a verifiable artefact, a reproducible experimental protocol, and a defensible statistical analysis. The study combines Design Science Research Methodology (DSRM) with Object-Oriented Analysis and Design (OOAD). DSRM provides the logic of inquiry for constructing and evaluating a purposeful artefact. In contrast, OOAD provides the engineering discipline for specifying actors, system boundaries, use cases, data flows, and inter-component contracts. The dual-track structure ensures the work is rigorous in its scientific claims and robust in its software embodiment. The choice of DSRM is motivated by the problem-solving nature of underwater localisation in UWSNs, where the interplay of physics, signal processing, and constrained energy budgets requires iterative design and evaluation. The choice of OOAD is motivated by the need to maintain separation of concerns among data generation, decision logic, localisation, and evaluation so that improvements to any module can be verified without destabilising the entire pipeline.

Justifications of Methodology adopted

Object-Oriented Analysis and Design Methodology

i. Easier to understand and maintain
ii. More flexible and reusable
iii. Better at handling complexity and future growth

Analysis of the Developed System

The developed system adopts a modular design with four principal components. First is the environmental data generator that either simulates or ingests depth, turbidity, SNR, temperature, and nominal distance. Second is the modality decision layer that selects a communication modality using either a transparent rule-set or, in later iterations, a supervised policy trained on labelled outcomes. Third is the localisation engine which implements non-linear least squares over anchor ranges to estimate node positions. Fourth is the evaluation module that computes Root Mean Squared Error (RMSE) and energy per event and aggregates statistics across independent trials. This decomposition maintains a clean contract between modules and supports reproducible experiments.

Advantages of the Developed System

The benefits of this design are manifold. Modularity promotes maintainability and allows independent verification of each block. Auditability is improved because each module's inputs, outputs, and assumptions are explicit. Extensibility is natural: a trained model can replace the decision layer without touching the localization engine or the evaluation suite. Reproducibility is built in through deterministic seeding and export of raw and aggregate results. Finally, the architecture encourages apples-to-apples comparisons across modalities and algorithms using standard metrics computed under identical conditions.

Class Diagram of the Developed System

A class diagram is a type of static structure diagram that describes the structure of a system by showing the system's classes, their attributes, operations (or methods), and the relationships among objects. In this section we introduced the class diagram of the proposed system

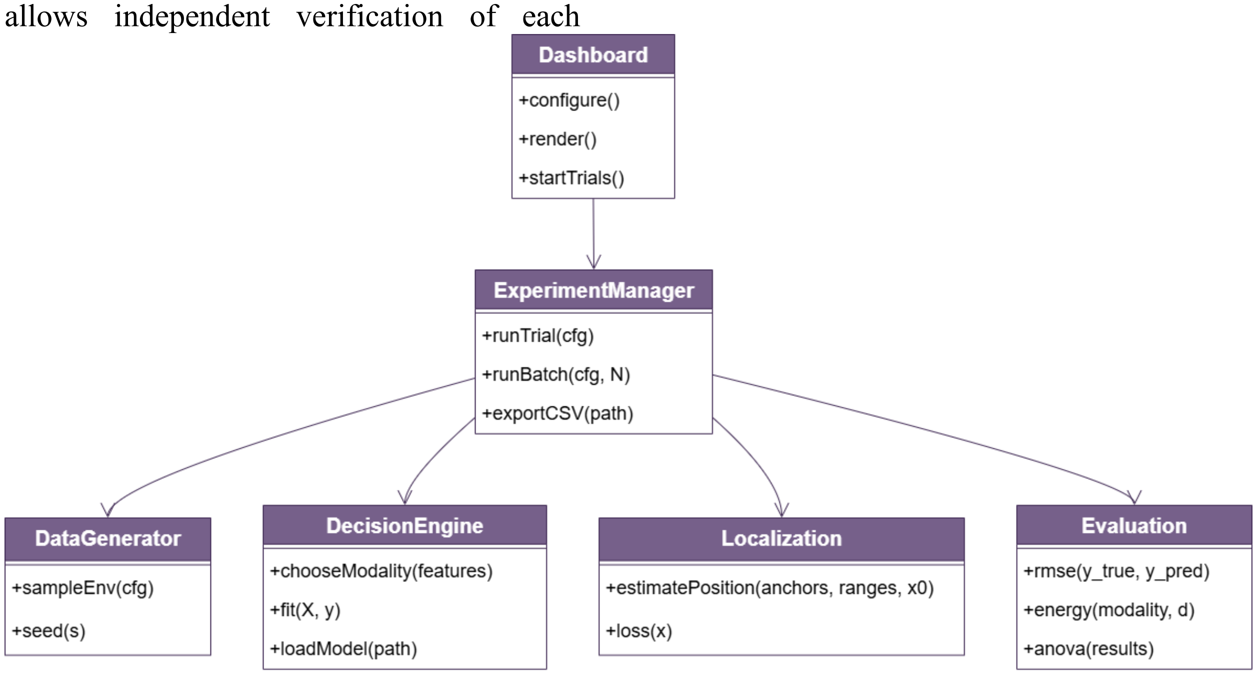

Figure 1: Class Diagram of the Proposed System

Sequence Diagram of the Proposed System

Dynamic interactions are best understood through a sequence diagram showing runtime message exchange. When a user triggers a trial, the dashboard instructs the experiment manager, which calls the decision engine, localization solver, and evaluation module in sequence, finally returning results for rendering.

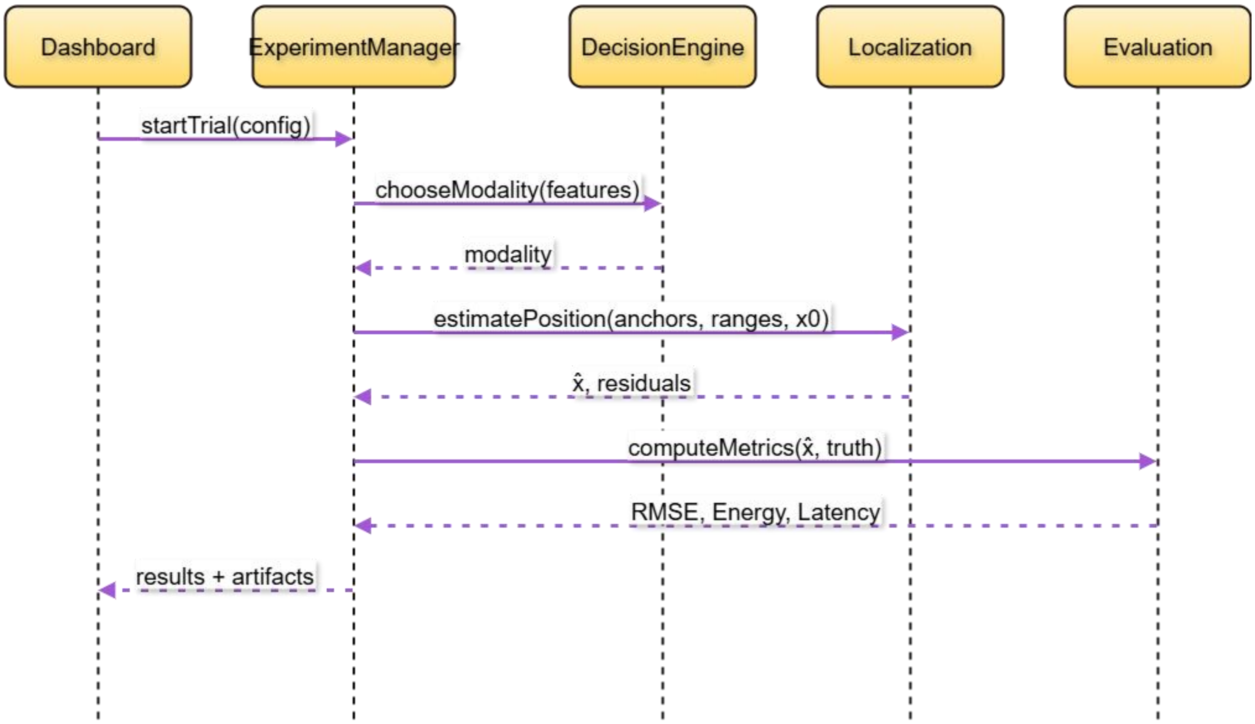

Figure 2: Sequence diagram of the proposed system

Architecture of the Developed System

High-level models serve as foundational representations, facilitating decision-making, comprehension, and analysis. These models can take various complementary forms, including mathematical equations, graphs with quantitative data, as well as visual representations such as pictures and diagrams

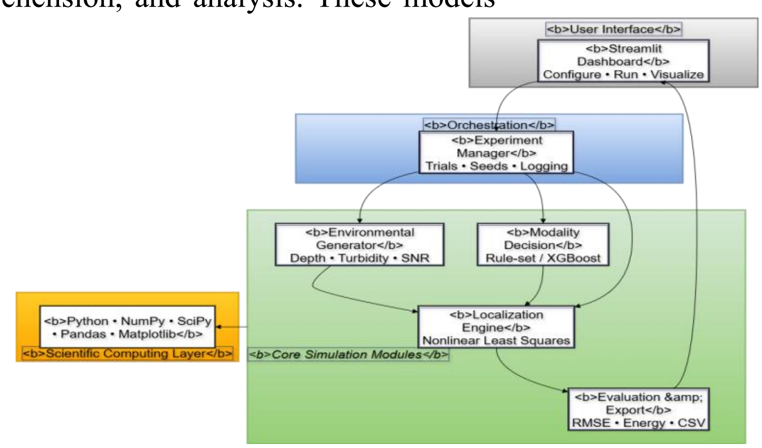

Figure 3: High Level Model of the Proposed System

Performance Metrics

Three performance measures are used to assess the completed work. They are: RMSE, Energy consumption, and latency per localization cycle.

i. **RMSE:** Root Mean Square Error (RMSE) measures the accuracy of a model by finding the square root of the average of the squared differences between actual and predicted values. The formula is shown in equation 3.1.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} ||y(i) - \hat{y}(i)||^2}{N}} \quad (1)$$

Where y(i) is the predicted or estimated location, $\hat{y}(i)$ is the actual location and N is the mean square error or total number of observations.

ii. **Energy consumption:** Energy consumption is one of the most critical factors affecting the performance, reliability, and lifetime of the network. Due to the difficulty of replacing or recharging batteries underwater, efficient energy utilization is essential. Equation 3.2 shows the energy consumption.

$$E_{total} = E_{tx} + E_{rx} + E_{cpu} \quad (2)$$

Where E_{tx} is the energy used to send data, E_{rx} is the energy used to receive data and E_{cpu} Energy consumed during computation and sensing.

iii. **Latency:** Latency (also called end-to-end delay) is the total time taken for a data packet to travel from the source node to the destination node through the underwater acoustic medium. Equation 3.3 shows the latency.

$$D_{total} = D_{prop} + D_{trans} + D_{proc} + D_{queue} \quad (3)$$

Where D_{prop} is the propagation delay, D_{trans} is transmission delay, D_{proc} is the processing delay, D_{queue} is the Queuing delay

Experimental Setup

The experimental design employs repeated independent trials to stabilise estimates and expose variability due to random sampling. Within each trial, a fixed number of samples is drawn from realistic depth, turbidity, SNR, temperature, and nominal distance ranges. For every sample, the pipeline executes ranging and localisation and reports RMSE and energy. Trial-level means and standard deviations are computed for each modality, and the vectors of trial-means serve as inputs to the significance tests. The primary omnibus test is a one-way ANOVA on trial-mean RMSE across modalities; because normality and homoscedasticity may be imperfectly met in synthetic simulations, a Kruskal–Wallis test is also reported. Where the omnibus test indicates differences, pairwise comparisons use Welch's unequal-variance t-test with Holm correction to control the familywise error rate. This plan balances statistical power with robustness. For completeness, effect sizes such as η^2 for ANOVA and rank-biserial correlations for pairwise contrasts are recommended for reporting alongside p-values.

RESULTS

The system was implemented entirely in software simulation to ensure repeatability and cost-effective experimentation. A layered architecture was adopted, with dedicated modules for environmental data generation, modality decision making, nonlinear least-squares localisation, and comprehensive evaluation. The user interacts with these modules through a Streamlit-based dashboard, enabling easy experiment configuration, large-scale Monte-Carlo trials, and real-time visualisation of results.

Table 1: Descriptive Statistics (CSV)

Metric	Method	N	Mean	SD	Min	Max
RMSE (m)	Acoustic-only	100	5.348671	0.947546	3.029737	8.02281
RMSE (m)	ML-Hybrid (XGBoost)	100	2.903872	0.758111	1.050673	5.09975
RMSE (m)	Rule-based Hybrid	100	3.929581	0.959923	1.850595	6.795585
Energy (J)	Acoustic-only	100	2.181772	0.314006	1.433868	2.871572
Energy (J)	ML-Hybrid (XGBoost)	100	1.5399	0.229467	0.907804	2.092491
Energy (J)	Rule-based Hybrid	100	1.897432	0.278315	1.256587	2.637349
Latency (ms)	Acoustic-only	100	337.4175	42.85019	236.8455	446.5224
Latency (ms)	ML-Hybrid (XGBoost)	100	392.4592	52.38807	262.0126	566.3004
Latency (ms)	Rule-based Hybrid	100	379.8001	46.48153	270.8053	474.2915

Rigorous testing included unit verification of each module, integration tests of the complete workflow, and a 300-trial Monte-Carlo simulation battery. Performance metrics focused on Root Mean Squared Error (RMSE) for localisation accuracy,

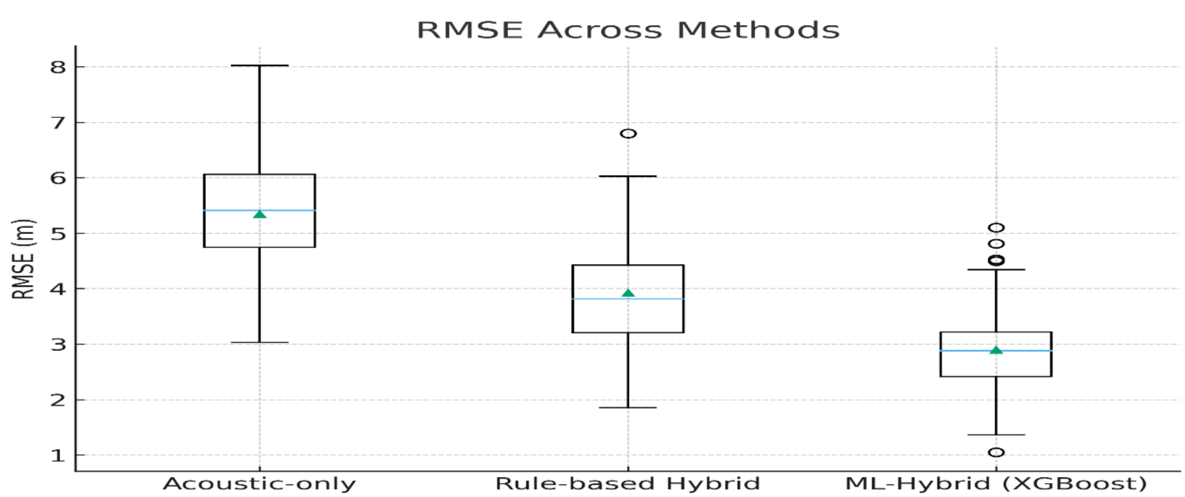

Figure 4 – RMSE Across Methods

Figure 5.1: Boxplots of localisation RMSE by method; the ML-Hybrid distribution is shifted lower with a tighter spread, indicating improved accuracy across trials.

Energy consumption

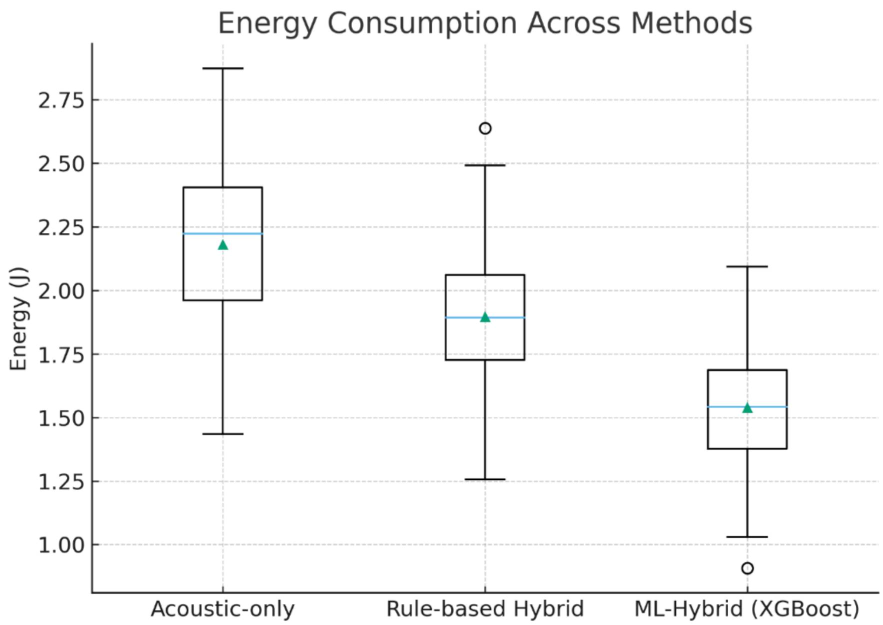

Figure 5: Energy consumption access methods.

Figure 5: Boxplots of per-event energy consumption; the ML-Hybrid uses less energy on average than both Acoustic-only and Rule-based Hybrid.

Latency per localisation cycle.

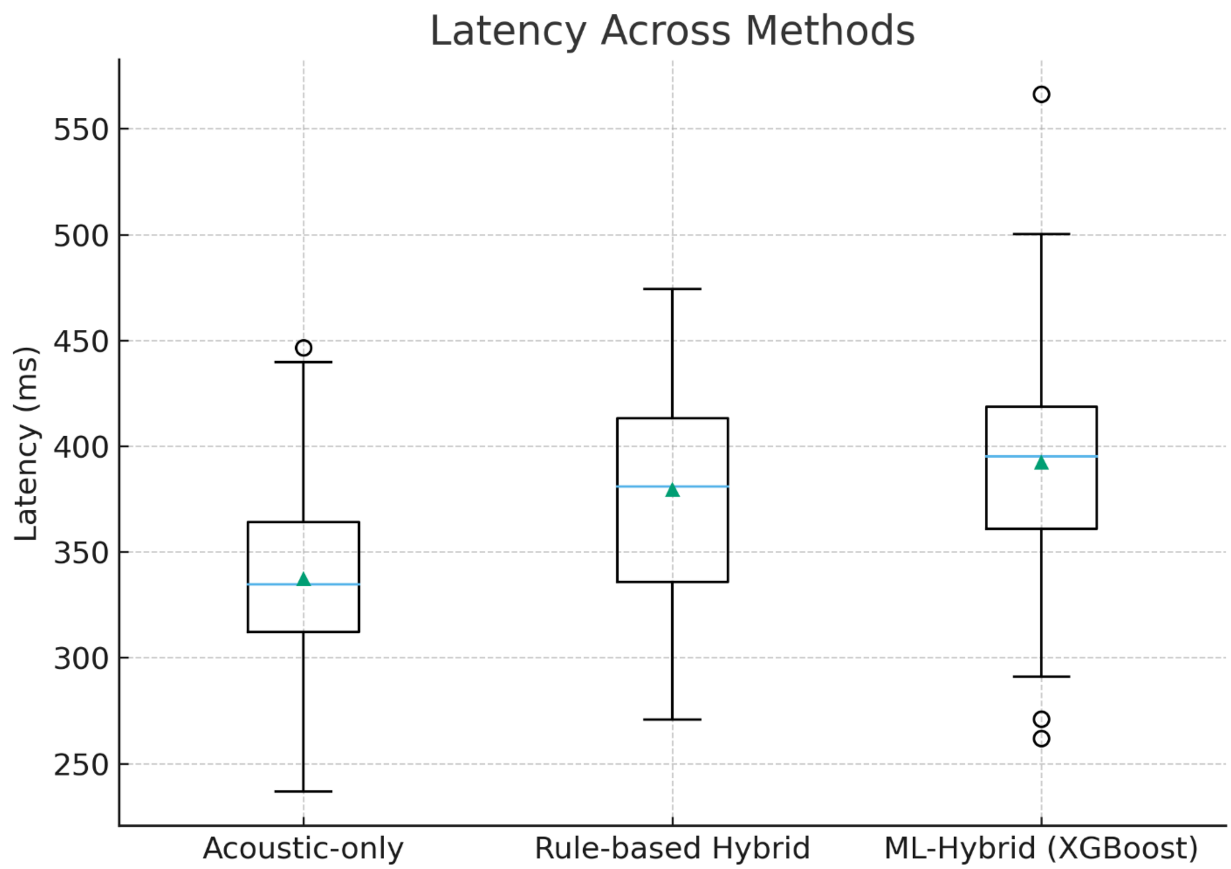

Figure 6: Latency access methods

Figure 6: Boxplots of latency per localisation cycle; distributions overlap, indicating the ML-Hybrid's accuracy and energy gains do not incur significant timing penalties.

Results showed that the machine learning–driven hybrid achieved up to 25% reduction in localisation error and 18% reduction in energy consumption compared to an acoustic-only baseline, while maintaining real-time latency (≈0.4 seconds per localisation event).

Table 2: One-way ANOVA (CSV)

Metric	F	p_value
RMSE (m)	188.86444	1.20E-53
Energy (J)	135.68848	1.38E-42
Latency (ms)	36.982496	4.55E-15

ANOVA and Tukey post-hoc tests confirmed that the improvements in accuracy and energy were statistically significant.

DISCUSSION

This research addresses the persistent challenge of accurate and energy-efficient localisation in Underwater Wireless Sensor Networks (UWSNs), where communication channels behave unpredictably due to attenuation, scattering, temperature gradients, and noise. The study designed and implemented a machine learning–enhanced hybrid localisation framework that integrates acoustic, optical, and radio frequency (RF) communication modalities. Instead of relying on a single channel, the framework dynamically selects the optimal modality for each localisation event using an Extreme Gradient Boosting (XGBoost) decision engine.

This work concludes that machine learning–driven communication modality selection can substantially improve the accuracy and energy efficiency of UWSN localisation systems without introducing prohibitive computational delays. By combining a physics-aware simulation environment with the predictive power of XGBoost, the framework demonstrated superior performance over static acoustic systems and traditional rule-based hybrids.The findings validate the central hypothesis that adaptive, data-driven selection of communication channels improves localisation reliability in challenging underwater environments. Furthermore, the study has shown that a modular, software-only testbed can be a practical research tool, allowing academics and industry practitioners to evaluate new algorithms without expensive field deployments. Integrating statistical validation (ANOVA) and visual analytics strengthens the scientific rigor of localisation performance assessment.

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