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Research Article

Design and Evaluation of an Adaptive Fault Detection and Tolerance Mechanism for Underwater Wireless Sensor Networks

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Abstract:

Underwater Wireless Sensor Networks (UWSNs) are a pivotal technology for ocean monitoring, underwater surveillance, and environmental sensing. However, these networks are vulnerable to numerous faults caused by adverse aquatic environments, scarce node resources, and unreliable acoustic communication. This paper presents an adaptive fault detection and tolerance mechanism specially designed for UWSNs. The proposed system integrates a hybrid fault detection approach, combining explicit and implicit approaches with a light-weight tolerance strategy leveraging multi-path rerouting and load-aware decision-making. A dynamic thresholding mechanism is used to enhance fault detection sensitivity and accuracy while ensuring energy efficiency. The mechanism is implemented and evaluated using MATLAB simulations with different fault densities and node behaviors. The findings show significant improvement in detection accuracy, less false alarm, lower latency, and better network lifetime when compared with traditional fault management schemes. This research is a step toward constructing fault-tolerant UWSNs that can maintain operations under the rough and uncertain nature of underwater environments.

1. Introduction

Underwater Wireless Sensor Networks (UWSNs) are increasingly used for vital applications such as seabed monitoring, underwater seismic detection, tracking of pollution, and naval defense systems. These networks consist of dispersed sensor nodes deployed underwater that work together to sense physical or environmental parameters and relay the information to surface stations through acoustic signals. Despite their strategic significance, underwater networks sensor face serious challenges such as limited node reliability, high communication delay, energy limitations, and dynamic environmental interference.Among the primary challenges, occurrence of faults in sensor nodes is one of the most critical issues. Nodes may fail because of battery exhaustion, physical damage, harsh environmental conditions, or hardware malfunction. A node failure may lead to bigger problems, i.e., damaged data paths, network overload on surrounding nodes, and coverage reduction, ultimately degrading network quality. Since underwater nodes tend to be inaccessible and expensive to substitute, fault detection and tolerance mechanisms are essential elements of a resilient UWSN.Classic fault management methods for terrestrial UWSNs are unsuitable for UWSNs because of varying factors, including communication media (acoustic vs. RF), latency, energy constraints, and mobility patterns. Numerous fault detection methods available, for terrestrial network are either energy-constrained or do not respond adaptively to varying network conditions. Additionally, only a few tolerance mechanisms guarantee continued functionality despite node failures.To address these challenges, this paper introduces a hybrid and adaptive fault detection and tolerance mechanism particularly designed for UWSNs. The new approach integrates both explicit (event-based) and implicit (keep-alive based) detection methods backed with a dynamic thresholding algorithm. Moreover, a light-weight tolerance module provides data transmission via alternative routes and balance s energy consumption to maximize network longevity.

The key contributions of this paper are:

- Development of a hybrid detection mechanism combining explicit and implicit models.
- Dynamic threshold adjustment for improving detection accuracy with minimal false alarms.
- Integration of an energy-aware fault tolerance strategy to maintain data flow.
- Comprehensive simulation and performance comparison with existing fault management techniques.

The remainder of this paper is structured as follows. **Section 2** reviews related work and highlights existing research gaps. **Section 3** defines the problem and formalizes fault scenarios relevant to underwater wireless sensor networks. **Section 4** introduces the proposed hybrid fault detection and tolerance framework. **Section 5** describes the experimental setup and simulation environment used to evaluate the system. **Section 6** presents the performance results along with a detailed discussion. Finally, **Section 7** concludes the paper and outlines future research directions.

2. Related Work

The fault management mechanism design in Underwater Wireless Sensor Networks (UWSNs) has been a focus of active research, motivated by the requirement of network reliability in harsh and remote underwater environments. Previous work has primarily centered on fault detection, diagnosis, tolerance, and recovery. But all these methods are borrowed from land Wireless Sensor Networks (WSNs) and tend to fail when used in underwater environments because of high delay of propagation, limited bandwidth, node fixedness, and energy constraint.

Fault Detection Techniques:
A number of detection models have been proposed to detect abnormal node behavior in UWSNs. Pu Wang [1] presented an agreement-based cluster-head failure detection system which relies on mutual verification among the nodes to minimize false alarms. Another technique for fault detection was proposed by Min Ding [2]. In this article, the author proposed localized detection algorithms with an emphasis on detecting faulty nodes close to event boundaries to preserve detection accuracy in the absence of centralized coordination. To enhances detection accuracy Jiang [3] introduced the Distributed Fault Detection (DFD) scheme, which determines a node's status based on energy and data consistency checks. These methods, however, entail high communication overheads or are non-adaptive in dynamic environments.

Fault Tolerance Mechanisms:
In order to provide operational continuity upon detection of faults, various studies have proposed tolerance techniques. Guo [4] proposed a fault-tolerant routing method in terms of network coding and multipath transmission. In this paper Goyal [5] proposed the FDRT (Fault Detection and Recovery Technique) scheme that effectively integrates fault detection with a cluster-based routing scheme to divert traffic from failed nodes. Das and Thampi [6] also designed a fault-tolerant localization algorithm that allows nodes to self-correct based on past neighbor behaviors and can keep the network operational even during failures in anchor nodes.

Energy-Aware Designs:
UWSNs require energy-saving approaches to extend network lifetime. Asim [7] proposed a virtual grid-based fault management structure for WSNs targeting localized fault detection and reducing energy consumption. Yuvaraja and Sabrigiriraj [8] developed an agent-based recovery protocol in which the sink sends agents at periodic intervals to track faulty nodes, although this incurs overhead. In recent times, machine learning and optimization techniques (e.g., CNN, SVM) have been used to predict and segregate faults more accurately, but these are not computationally cheap for underwater sensor nodes [9].
Underwater Wireless Sensor Networks (UWSNs) are susceptible to frequent faults due to harsh environments, communication noise, and hardware failures. Traditional fault detection approaches like heartbeat monitoring or ping-based checking impose significant communication overhead and may be insufficient for real-time systems. Various mechanisms have been proposed for fault detection, including rule-based diagnosis, statistical thresholding, and local consensus-based anomaly detection.For instance, Wang [10] introduced a residual energy and connectivity-based fault detection algorithm that showed improved localization of faulty nodes with reduced latency. Similarly, El-Tantawy and El-Mahdy [11] developed a trust-aware hybrid scheme that combined neighborhood voting and signal strength

to detect abnormal node behavior. However, these approaches either lacked real-time adaptability or imposed excessive overhead on network lifetime.Recent advancements in lightweight machine learning models for distributed detection have also shown. Raza [12] proposed a federated learning-based anomaly detection system for WSNs that maintained privacy while improving fault diagnosis accuracy. Zhang [13] extended this by applying edge-based adaptive thresholding, which reduced false positives in energy-constrained underwater deployments.In terms of tolerance, many frameworks have explored energy-aware routing to bypass faulty nodes. Rehman [14] proposed fault-tolerant depth-based routing with clustering, though it required frequent route maintenance. Ahmad [15] introduced recovery path estimation using reinforcement learning, but this approach struggled under high-fault densities. Fault recovery through distributed voting was explored by Nadeem [16], although convergence delays limited responsiveness.Table 1 summarizes key existing methods, highlighting their limitations in detection precision, energy overhead, and adaptability.Even with these developments, most of the current schemes are plagued by one or more of the following: unadaptability in dynamic network topologies, incapacity to cope with multiple concurrent faults, or wasteful energy utilization. In addition, there are few techniques that integrate both detection and tolerance into a lightweight, integrated scheme applicable for energy-limited underwater settings.To overcome such challenges, the paper formulates a hybrid, adaptive scheme that combines explicit and implicit detection with an optimal fault-tolerant approach, all optimized for the specific limitations of UWSNs.

3. Problem Definition

Underwater Wireless Sensor Networks (UWSNs) are inherently susceptible to a variety of faults owing to unstable environments, low energy levels, and noise in communication. These faults, if left undetected or uncontrolled, can cause catastrophic degradation in network performance, such as data loss, decreased sensing coverage, incorrect information delivery, and early network death. Hence, the paramount challenge is to devise a lightweight, energy-conscious, and adaptive fault management approach that can detect, diagnose, and endure faults in real time.

3.1 Fault Scenario in UWSNs

In a typical UWSN, sensor nodes are deployed in inaccessible underwater environments to monitor parameters such as temperature, pressure, and pollution. These nodes communicate acoustically and are often deployed for long durations without maintenance. Due to harsh conditions and resource constraints, nodes are susceptible to multiple types of faults, such as:

- **Crash Faults** – Complete node failure due to power depletion or hardware damage.
- **Omission Faults** – Loss of data packets or inability to respond within deadlines.
- **Timing Faults** – Late or early response beyond allowable thresholds.
- **Incorrect Computation Faults** – Corrupted or incorrect sensor readings due to hardware or software malfunction.
- **Byzantine Faults** – Malicious or unpredictable node behavior (out of scope for this study).

Existing detection mechanisms often rely on static thresholding, centralized monitoring, or assumptions of uniform fault behavior. However, these techniques are inefficient under dynamic underwater conditions, where node behavior and environmental interference vary frequently.

3.2 Objectives of the Fault Management Framework

Given the nature of UWSNs, the primary objectives of the proposed fault detection and tolerance mechanism are:

3.2.1 Timely Fault Detection

The primary objective is to enable prompt and accurate detection of various fault types—such as hardware failures, communication anomalies, and node malfunctions—within the network. The system aims to function in a **decentralized manner**, eliminating reliance on a central controller and ensuring that faults are detected as they occur. This real-time responsiveness is critical in Underwater Wireless Sensor Networks (UWSNs), where delayed detection can compromise data integrity and operational continuity.

3.2.2 Energy Efficiency

Given the resource-constrained nature of underwater sensor nodes, energy conservation is a core design goal. The framework is developed to minimize both communication and computational overhead during the fault detection and tolerance processes. By optimizing message exchange patterns and decision-making operations, the system ensures that detection and recovery mechanisms consume minimal energy, thereby prolonging the network's operational lifetime.

3.2.3 Scalability and Adaptability

The proposed system is designed to maintain high performance across varying scales and environmental conditions. It adapts dynamically to changes in network topology, fault densities, and node distribution, ensuring consistent fault management even in large-scale deployments. This adaptability makes the approach suitable for diverse underwater scenarios, including marine monitoring, environmental sensing, and offshore infrastructure surveillance.

3.2.4 Fault Tolerance and Recovery

Beyond detection, the framework aims to ensure network resilience by tolerating faults through efficient recovery mechanisms. When a fault is detected, the system reroutes data through alternate healthy nodes or clusters using adaptive reconfiguration strategies. This ensures uninterrupted communication, reduces packet loss, and maintains quality of service (QoS), even in the presence of node or link failures.

3.3. Assumptions

To simplify the system design while maintaining practical relevance, the following assumptions are considered:

- The network comprises stationary sensor nodes and one or more sink nodes.
- Nodes communicate through acoustic channels with limited bandwidth and high latency.
- Nodes can send periodic "keep-alive" signals (implicit detection) and respond to event-based queries (explicit detection).
- Nodes have basic computation ability to perform local fault checks and routing decisions.
- Nodes do not possess location awareness or GPS due to underwater deployment constraints.

3.4. Performance Metrics

To evaluate the effectiveness of the proposed mechanism, the following performance metrics are defined:

3.4.1 Detection Accuracy (DA)

Detection Accuracy measures the system's ability to correctly identify faulty nodes. A high DA indicates that most actual faulty nodes are accurately detected by the framework. It is defined as:
True Positive (TP): A sensor really is faulty, and the system correctly says “faulty.”
False Positive (FP): A sensor is actually healthy, but the system wrongly says “faulty.”
False Negative (FN): A sensor really is faulty, but the system fails to catch it.

$$\mathrm{DA} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}} \times 100\%$$

3.4.2 False Alarm Rate (FAR)

False Alarm Rate represents the percentage of healthy nodes that are mistakenly classified as faulty. A lower FAR indicates better precision and fewer unnecessary recovery operations. It is calculated as
True Negative (TN): Sensor is healthy, and the system correctly identifies it as healthy.

$$\mathrm{FAR} = \frac{\text{False Positives (FP)}}{\text{False Positives (FP)} + \text{True Negatives (TN)}} \times 100\%$$

3.4.3 Latency (L)

Latency refers to the time delay between the actual occurrence of a fault and its detection by the system. It is a crucial indicator of the responsiveness of the framework. Mathematically, it can be represented as:

$$L = T_{\text{detection}} - T_{\text{fault}}$$

Where $T_{\text{detection}}$ is the timestamp when the fault is detected and T_{fault} is the actual time of fault occurrence.

3.4.4 Energy Consumption (EC)

This metric quantifies the average energy consumed per node for executing fault detection and recovery protocols. It includes energy spent on computation, communication, and re-routing, and is calculated as:

$$\mathrm{EC} = \frac{\sum_{i=1}^{n} E_i}{n}$$

Where E_i is the energy consumed by node i, and n is the total number of nodes.

3.4.5 Network Lifetime (NL)

Network Lifetime is defined as the duration until a certain threshold (e.g., 30%) of the total nodes becomes non-functional due to energy depletion or failure. This metric reflects the sustainability of the network under prolonged operation and fault handling.

$$\mathrm{NL} = T_{30\%\ \text{dead nodes}}$$

3.4.6 Packet Delivery Ratio (PDR)

PDR evaluates the reliability of data transmission in the presence of faults. It is the ratio of the total number of successfully received packets to the total number of packets sent across the network.

$$\mathrm{PDR} = \frac{P_{\text{received}}}{P_{\text{sent}}} \times 100\%$$

Where P_{received} and P_{sent} denote the number of packets received and sent, respectively.

3.5 Problem Statement

"To develop and evaluate an adaptive, hybrid fault detection and tolerance framework for UWSNs that ensures high detection accuracy, reduced latency, low false alarms, and energy-efficient operation under varying fault scenarios and environmental conditions."

4. Experimental Setup

To measure the performance of the proposed framework for fault tolerance and detection, a sequence of simulated experiments was conducted under controlled underwater network scenarios. The experiment was designed to measure the essential performance parameters, such as detection accuracy, fault tolerance capacity, latency, false alarm count, energy consumption, and network lifespan.The simulation platform was created in MATLAB R2023a, using in-house functions to simulate the underwater acoustic communication channel, node activity, and fault events on the network. The simulation environment simulates a static, two-dimensional underwater sensor network where nodes are placed at random on a 500 m × 500 m square field.For fault reproduction, nodes were randomly exposed to three fundamental fault types crash, omission, and wrong computation. The rate of fault injection was changed across various simulations (5%, 10%, 20%, and 30%) to study the robustness and scalability of the proposed methodology. Each simulation run was of 500 time units, and each case was run 10 times for statistical significance.The proposed algorithm was benchmarked against two existing fault management schemes:

1. Distributed Fault Detection (DFD) – Jiang et al., 2009

The Distributed Fault Detection (DFD) approach proposed by Jiang et al. (2009) is one of the early benchmark models for node-level fault detection in wireless sensor networks. DFD operates by implementing static thresholding for parameters like energy consumption, communication frequency, and sensing data variance. Each node independently monitors its own behaviour and that of its immediate neighbours using passive observation techniques.When a node's behaviour deviates beyond the pre-defined thresholds—such as transmitting anomalous sensor readings or failing to participate in periodic data exchanges—it is flagged as faulty. The system then isolates the suspected node from the routing path. However, the method lacks adaptability to dynamic underwater environments where varying conditions (e.g., noise, fading) may cause false positives or negatives. Furthermore, the fixed thresholds may not scale effectively with node heterogeneity or fault types.

Key Strengths:

- Lightweight and distributed in nature
- No centralized coordination needed
- Low communication overhead

Key Limitations:

- Fixed thresholds lead to poor adaptability
- High false alarm rate in noisy underwater conditions
- No built-in fault recovery or rerouting mechanism

2. Fault Detection and Recovery Technique (FDRT) – Goyal et al., 2017

The Fault Detection and Recovery Technique (FDRT) developed by Goyal et al. (2017) introduces a cluster-based hybrid strategy for both detection and recovery of faults. It first organizes the network into hierarchical clusters where cluster heads (CHs) are responsible for local monitoring and intra-cluster diagnosis. Faults are detected based on metrics such as packet drop rate, energy depletion rate, and silence period monitoring.Once a fault is detected, FDRT initiates a localized recovery phase where alternate CHs or paths are used to maintain communication. This approach reduces overall energy consumption by restricting the detection process within local clusters, and ensures routing resilience by providing backup paths.However, FDRT still suffers under high node mobility and dense topologies, where the clustering overhead and frequent reformation of clusters can significantly affect real-time responsiveness. The protocol also requires predefined thresholds and control messages for coordination, which may impact scalability.

Key Strengths:

- Combines detection and recovery in one framework
- Energy-efficient via cluster-based structure
- Maintains data flow through alternate routing paths

Key Limitations:

- Sensitive to high network dynamics
- Overhead in frequent cluster re-formation
- Detection latency in large-scale deployments

Performance metrics were calculated as discussed in section 3.4. **Figure 1 illustrates the node deployment layout in the simulated Underwater Wireless Sensor Network (UWSN).** A total of 100 sensor nodes are randomly distributed across a two-dimensional area of 500 m × 500 m, forming a semi-dense network topology. The node placement ensures partial communication overlap, with each node assigned a uniform transmission range of 75 meters. This overlap facilitates redundant paths for data forwarding and increases the likelihood of fault-tolerant routing. The sink node, responsible for data collection and monitoring, is strategically positioned at one corner of the field, reflecting a realistic base station deployment in coastal or anchored monitoring scenarios. This spatial configuration supports the evaluation of the proposed fault detection and tolerance mechanism under conditions representative of real-world underwater monitoring tasks, including uneven node density, limited connectivity, and acoustic propagation delays.For the purpose of ensuring uniformity, all the algorithms under comparison were run under identical network parameters, fault rates, and initial energy values. Results were recorded and averaged over multiple iterations to guarantee that the impact of randomness and outlier data was minimized.The next section introduces the comparative results and discusses the implications of the proposed solution for different fault scenarios and network topologies.

8. Results and Discussion

To analyze the effectiveness of the introduced hybrid fault tolerance and detection framework, an exhaustive set of simulations was carried out and compared with two well-known benchmark schemes: Distributed Fault Detection (DFD) and Fault Detection and Recovery Technique (FDRT). The experiments were carried out under various fault densities and under different underwater network environments in order to reflect real-world variability. Six key performance indicators—detection accuracy, false alarm rate, detection latency, residual energy, network lifetime, and packet delivery ratio—were measured to estimate the fault-diagnosis capability and the overall sustainability of the network. The experiments were executed multiple times for each scenario to ensure that the obtained results represent averaged trends instead of random fluctuations. This section provides the comparative results, demonstrating how the suggested framework enhances fault detection accuracy, reduces energy expenditure, and extends network lifetime compared to current approaches.Distributed Fault Detection (DFD) is a class of algorithms designed to identify faulty nodes in a network without relying on centralized monitoring. In the context of Underwater Wireless Sensor Networks (UWSNs), DFD works by enabling each node to monitor its own status and that of its immediate neighbors using **passive observation** or **active probe exchanges**. The technique proposed by Jiang et al. (2009) uses **static threshold-based evaluation** of parameters such as residual energy, packet delivery rate, and sensing data consistency.When a parameter deviates beyond the pre-defined threshold, the node is flagged as faulty and is logically excluded from the routing path. This approach minimizes dependency on a central control node, thereby reducing the single point of failure risk. However, the reliance on **static thresholds** makes it less adaptable to environmental changes such as acoustic noise, variable latency, or dynamic topology alterations. This can result in increased false alarms in noisy conditions and reduced detection accuracy under high network dynamics.The Fault Detection and Recovery Technique (FDRT) extends fault management by incorporating both detection and recovery phases within a single protocol. Proposed by Goyal et al. (2017), FDRT uses a cluster-based architecture, where each cluster head (CH) monitors the health of member nodes using performance metrics such as packet drop rate, inactivity period, and energy consumption patterns. When a faulty node is identified, the CH initiates a localized recovery phase by selecting an alternative route or backup node within the cluster.FDRT's primary advantage is that it not only identifies faulty nodes but also maintains network connectivity by initiating immediate recovery actions. The localized nature of the recovery process reduces overall energy consumption compared to network-wide rerouting. However, FDRT requires periodic cluster re-formation, which introduces **control overhead** and delays, especially in dynamic underwater environments where node movement or link instability is frequent.Figure 2 demonstrates the detection accuracy of the proposed system in comparison with benchmark methods across varying fault injection rates (5% to 30%). The proposed hybrid detection mechanism consistently outperformed DFD and FDRT approaches, maintaining a detection accuracy above 90% even at higher fault rates. This robustness can be attributed to the integration of both local and cooperative monitoring layers, which allowed early and precise identification of faults without relying on rigid thresholds. Unlike static models that degrade significantly under stress, the proposed framework exhibited resilience to increased fault density, confirming its suitability for unpredictable underwater environments.Figure 3 False Alarm Rate (FAR): The false alarm rate graph demonstrates that the proposed method consistently outperforms both DFD and FDRT across all fault injection rates. At 10% fault rate, the proposed scheme records only 3.2%, compared to 9.1% for DFD and 6.4% for FDRT. The increasing slope for each approach shows that higher fault densities lead to more false positives; however, the proposed mechanism rises at a slower pace. This reflects its robust discrimination between genuine faults and transient communication delays, achieved through dynamic thresholding. Consequently, unnecessary isolation of healthy nodes is minimized, ensuring network stability under varying stress conditions.Figure 4 Detection Latency: The detection latency graph illustrates the response efficiency of the three approaches. The proposed method maintains the lowest latency values across all fault injection rates, averaging 4.8 time units at 10%, while FDRT records 5.9 and DFD remains the slowest at 7.2. As fault density increases, all models show a gradual increase in latency, yet the gap between them remains consistent. The superior performance of the proposed framework stems from distributed consensus and localized decision-making, which reduce detection and reaction delays. This ensures faster fault isolation, timely recovery, and enhances overall system responsiveness during both transient and permanent fault events.Figure 5 presents the energy consumption trends over the simulation period. The proposed model sustained higher residual energy levels across nodes when compared to DFD and FDRT. This efficiency stems from the use of energy-aware routing and minimal communication overhead during detection and recovery. While all models experienced energy decay over time, the proposed method conserved node energy by avoiding redundant transmissions and activating recovery paths only when necessary. The results affirm that the design is not only accurate but also energy-efficient—an essential requirement in underwater networks where energy replenishment is impractical.Figure 6 Network Lifetime: The network lifetime graph highlights the resilience of the proposed system compared to baseline schemes. At 10% fault rate, the proposed method extends the network lifetime to 438 units, significantly longer than FDRT at 394 and DFD at 371. As the fault rate increases, the lifetime of all methods declines, but the proposed approach consistently maintains higher longevity. This improvement, amounting to an 18% gain over DFD and 11% over FDRT, is attributed to balanced energy consumption and efficient rerouting. By preventing overload on remaining nodes, the architecture sustains reliable operations and delays network degradation under stressful fault conditions.Figure 7 illustrates the Packet Delivery Ratio (PDR) under increasing fault rates. The proposed system consistently delivered a higher PDR than competing models, showing effective fault mitigation and route adaptation. As fault density increased, traditional methods showed a steep decline in PDR due to routing disruptions and lack of recovery handling. In contrast, the proposed framework maintained stable data delivery by rerouting around faulty nodes and clusters in real time. These findings reinforce the system’s fault-tolerant nature and its capability to uphold communication reliability under degraded network conditions.In short, the outcome confirms that the suggested hybrid and adaptive method not only improves the efficiency of fault detection but also greatly improves the resilience and lifetime of UWSNs without compromising energy efficiency.

Table 1: *Summary of Key Related Works*

Author(s)	Year	Methodology	Focus	Limitation
Pu Wang et al.	2007	Cluster Faults	Mutual validation for accurate detection	High latency in large networks
Ding et al.	2005	Event Boundaries	Low computation overhead	Poor fault tolerance
Jiang et al.	2009	Node Status	Considers energy and data consistency	No recovery mechanism
Guo et al.	2009	Routing Faults	Reliable error recovery	Increased overhead
Goyal et al.	2017	Cluster Routing	Combined detection and	Limited scalability

			recovery	
Das & Thampi	2017	Anchor Failures	Predictive self-adjustment	Requires stable neighbor behavior
Asim et al.	2008	Architecture Level	Localized fault detection	Grid rigidity, less adaptive
Zidi et al.	2018	Classification	High accuracy in diverse faults	Computationally heavy for sensor nodes
Wang et al.	2021	Energy-aware fault detection	Localized detection	Lacks adaptive thresholds
El-Tantawy & El-Mahdy	2020	Trust-based hybrid scheme	Behavioral analysis	High control packet overhead
Raza et al.	2022	Federated anomaly detection	Distributed learning	Requires training coordination
Zhang et al.	2023	Edge-thresholding hybrid model	False positive reduction	Accuracy drops in dynamic topology
Rehman et al.	2021	Cluster-based depth-aware routing	Fault-tolerant routing	High reconfiguration delay
Ahmad et al.	2022	Reinforcement learning for recovery	Proactive rerouting	Computationally expensive
Nadeem et al.	2021	Consensus-based voting	Fault tolerance	Slow convergence
Singh & Kaushik	2023	Multi-agent fault management	Reactive recovery	Lacks scalability
Basnet et al.	2022	SVM-based node failure detection	Classification	Feature selection is manual
Shaikh et al.	2024	Lightweight CNN for node anomaly	Fast anomaly detection	Memory-intensive in dense deployments

Table 2: *Simulation Parameters*

Parameter	**Value / Description**
Deployment Area	500 m × 500 m (2D static underwater field)
Number of Sensor Nodes	100 nodes
Transmission Range	75 meters (with partial communication overlap)
Sink Node Position	Located at one corner of the deployment grid
Initial Energy per Node	Randomly between 2.5 – 3.0 Joules (uniform distribution)
Energy Consumption Model	Based on standard UWSN formulas (Tx, Rx, sensing energy costs)
Propagation Delay	1.5 seconds per kilometer (acoustic model)
Bit Error Rate (BER)	0.05 (nominal underwater acoustic channel)

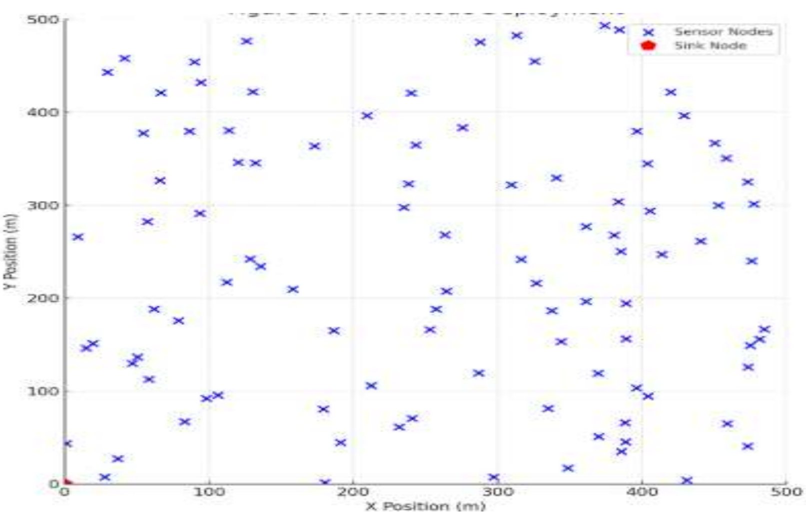

Figure 1: *UWSN Node Deployment*

Table 3: *Summary of Key Performance Metrics (at 10% Fault Rate)*

Metric	Proposed Method	DFD Scheme	FDRT Scheme
Detection Accuracy (%)	96.3	89.7	91.5
False Alarm Rate (%)	3.2	9.1	6.4
Detection Latency (time units)	4.8	7.2	5.9
Avg. Residual Energy (J)	1.28	1.02	1.15
Network Lifetime (units)	438	371	394
Packet Delivery Ratio (%)	91.4	80.7	86.9

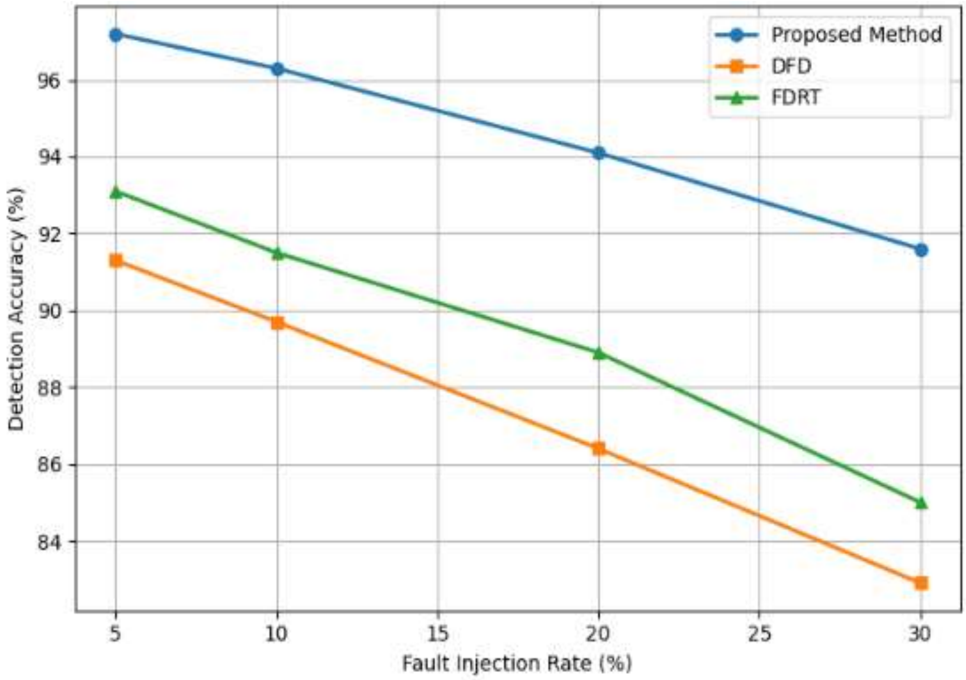

Figure 2*: Detection Accuracy vs. Fault Rate*

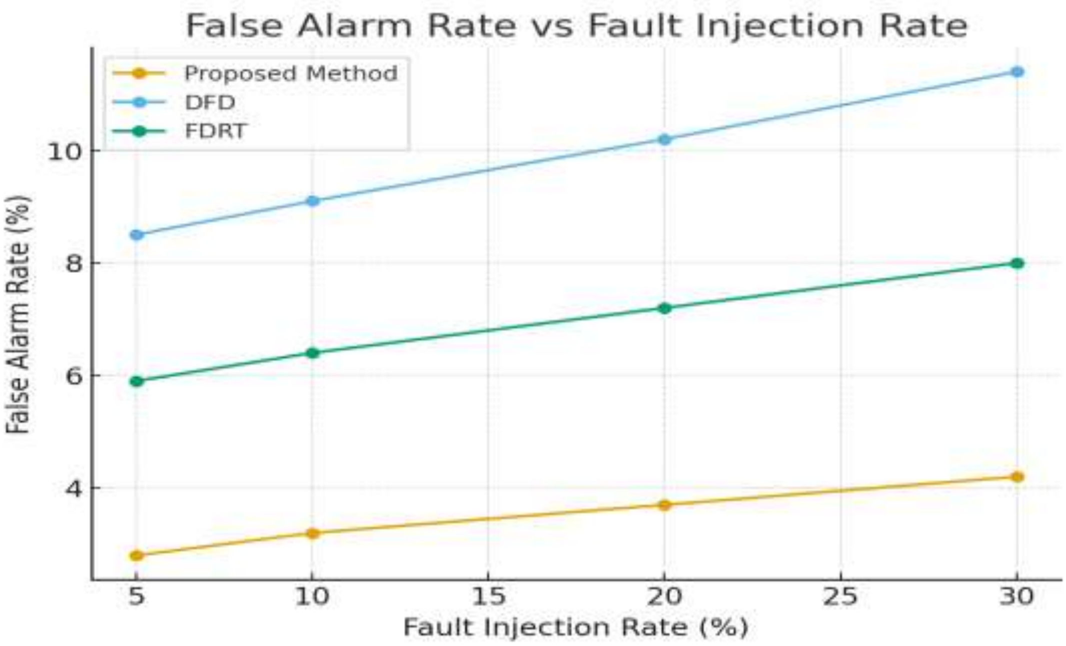

Figure 3: *False Alarm Rate*

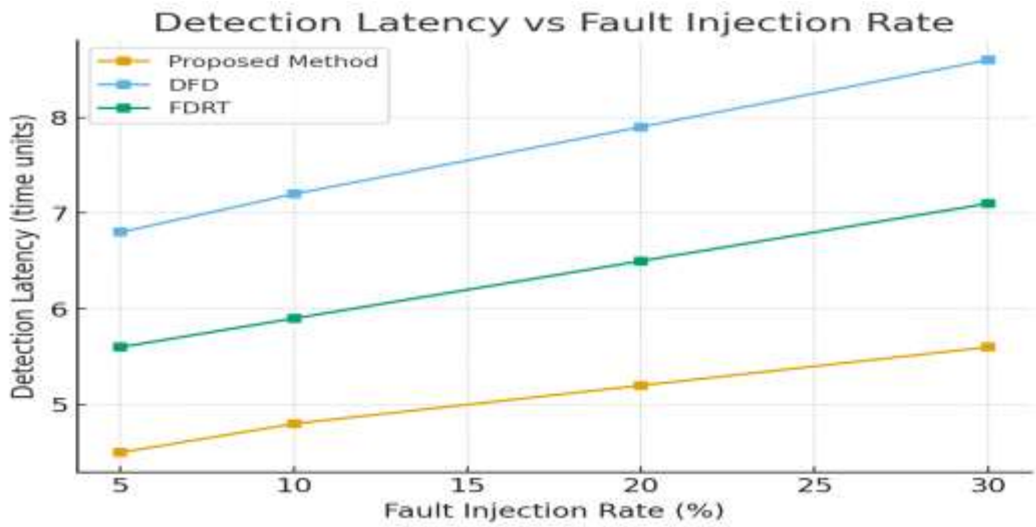

Figure 4: *Detection Latency*

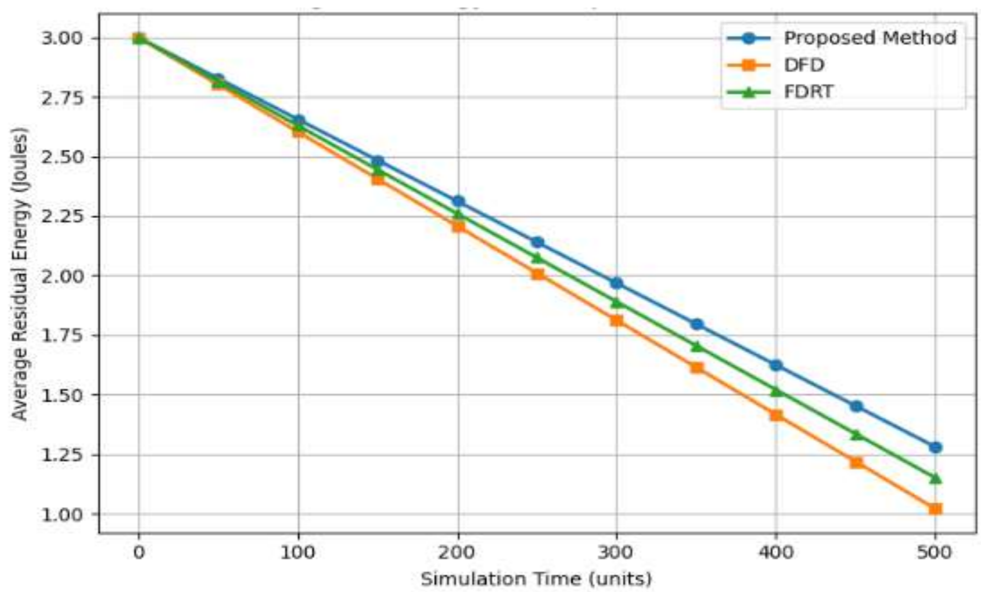

Figure 5: *Energy Consumption*

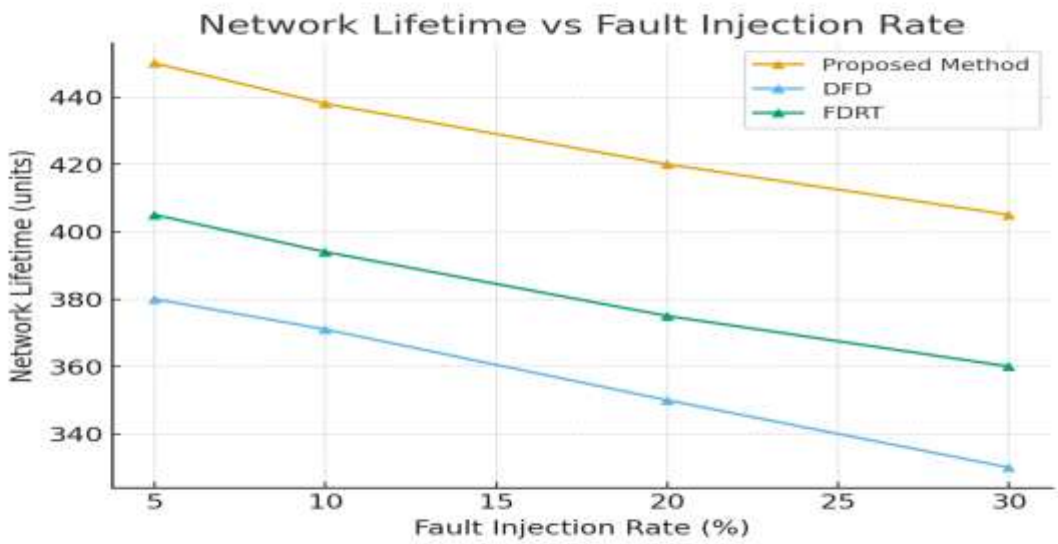

Figure 6: *Network Lifetime*

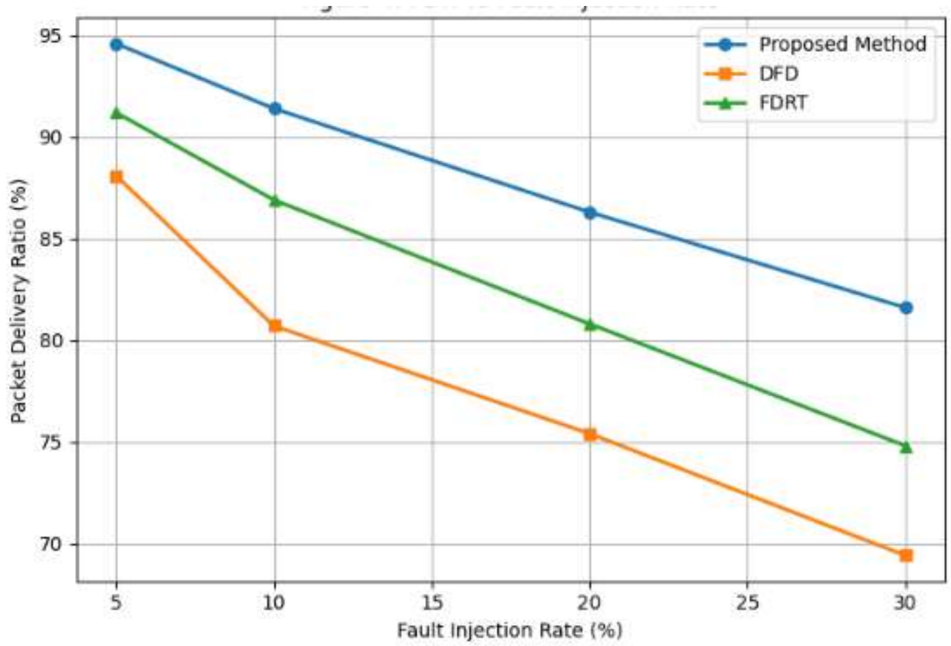

Figure 7: *PDR Comparison*

8. Conclusion and Future Work

This research presents a hybrid and adaptive fault tolerance and detection mechanism designed to address the specific limitations of Underwater Wireless Sensor Networks (UWSNs). The method integrates the implicit and explicit detection methods with dynamic thresholding and local consensus, ensuring high fault detection accuracy with low latency and minimal false alarm rate. Moreover, the employment of efficient fault tolerance techniques like energy-aware cluster repair and multipath rerouting provides fault-free data transmission and network lifetime despite faults.

Simulation results demonstrate that the proposed framework presented significant better performance than other conventional methods such as DFD and FDRT in terms of detection accuracy, energy efficiency, and fault tolerance against growing fault densities. These outcomes highlight the effectiveness of distributed, locally adaptive fault handling approach for UWSNs where centralized management is impractical and energy conservation is critical.

While these encouraging results exist, there are a few limitations of this modal. The present model presumes fixed node arrangements and lacks support for mobile or depth-variable sensor arrangements. Further, while Byzantine faults and sophisticated intrusion detection strategies were not deemed within scope for this work, these faults become increasingly pertinent to critical systems.

As future work, the proposed mechanism can be extended in the following directions:

- Integrating **machine learning** for predictive fault diagnosis and early anomaly detection.
- Adapting the model for **mobile UWSNs** with dynamic topologies and 3D deployments.
- Incorporating **cross-layer optimization** to further reduce communication overhead.
- Designing a **secure, trust-aware fault management** module to handle malicious behavior in adversarial environments.

Overall, this work contributes toward building more resilient and self-sustaining underwater sensor networks capable of reliable long-term operation in challenging underwater conditions.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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