ENERGY-EFFICIENT NODE LOCALIZATION AND TRACKING FOR REAL-TIME UWSN APPLICATIONS

By

ZAHRA KHALID SATTI

NATIONAL UNIVERSITY OF MODERN LANGUAGES ISLAMABAD

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Energy-Efficient Node Localization and Tracking for Real-Time UWSN's Applications

By

Zahra Khalid Satti

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Submitted By: Zahra Khalid Satti **Registration #:** 78 MS/CS/F22

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Computer Science
Name of Discipline

Dr. Moeenuddin Tariq Research Supervisor	Signature of Research Supervisor
Dr. Muhammad Tahir Research Co-Supervisor	Signature of Research Co-Supervisor
Dr. Fazli Subhan Head of Department (CS)	Signature of HoD (CS)
Dr. M. Noman Malik Name of Dean (FEC)	Signature of Dean (FEC)

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AUTHOR'S DECLARATION

I Ms. Zahra Khalid Satti

Daughter of Khalid Yasin Tahir

Registration # 78/MS/CS/F22

Discipline Computer Science

Candidate of **Master of Science in Computer Science (MSCS)** at the National University of Modern Languages do hereby declare that the thesis **Energy-efficient node Localization and tracking for real-time UWSN's applications** submitted by me in partial fulfillment of MSCS degree is my original work, and has not been submitted or published earlier. I do hereby solemnly declare, that this research work and report would not, in any case be used for attaining any other degree either NUML or be any other academic institution. I also affirm that in case of detection of plagiarism or similarity of work in this report/thesis/dissertation or any sort, even after degree awarding, the reward may be canceled and the award granted including the degree may be revoked.

Signature of Candidate

Zahra Khalid Satti

Name of Candidate

July 28th, 2025

ABSTRACT

Title: Energy-efficient Node Localization and Tracking for Real-Time UWSN's Applications

Depletion of terrestrial resources has driven human exploration towards underwater realms, where challenges such as diminished optical clarity and increased hydrostatic pressure hinder effective communication and examination considering acoustic waves. The use of electromagnetic (EM) Underwater Wireless Sensor Networks (UWSNs) has gained favor due to their low cost, higher data rate, minimum propagation delay compared to acoustic, but long-range underwater communication remains challenging. This research proposes a methodology to address these challenges, emphasizing the development of an efficient node localization and tracking system for UWSNs. The approach involves segmenting UWSNs considering real time applications into two major steps one is Autonomous Underwater Vehicles (AUVs)/ or implementing dynamic courier node for localization/tracking of sensor nodes and data transmission to an offshore base station (BS). The study also highlights the dynamic nature of ocean depth and its challenges to underwater networking. To mitigate disruptions, the research focuses on deploying sensor nodes randomly (Gaussian distribution) at various oceanic depths. This research also tackles the challenges inherent in UWSNs by proposing a novel method to improve tracking and localization efficiency in terms of 3D trajectory. The primary issues addressed include communication and data collection difficulties in underwater environments due to limited light penetration and high pressure, which affect equipment functionality. By utilizing Bayesian inference and Kalman filtering, the research attempts to create a reliable and accurate state estimation technique for UWSNs. In the suggested methodology, the Extended Kalman Filter (EKF), a well-known instrument for state estimation in linear systems with Gaussian noise, is employed. When handling several sensors or information sources, though, it could not be up to par. Through the integration of Bayesian approaches, the suggested methodology improves the performance of EKF. This results in the creation of a framework that mixes and integrates data from numerous KFs. Based on sensor measurement, the proposed methodology updates the state estimate using Bayes' theorem and expresses uncertainty as probabilities. Significant RMSE reduction as compared to the KF method's RMSE value of 0.1 to 0.5 meters possible using the suggested approach. The novel approach's performance was validated through the use of MATLAB and EKF, along with real-time data obtained from the National Centers for Environment Information. In order to increase the precision and effectiveness of object tracking and localization in UWSNs, the Helmholtz approach is applied to simulations based on ocean data to characterize dynamic underwater communication channels.

Performance evaluation measures include root mean square error (RMSE), estimate error, and convergence time. The analysis shows that the proposed strategy for tracking nodes and localizing them in UWSNs is significantly better than the current approaches. The suggested protocol, in instance, leverages more effective routing and data transfer to reduce energy consumption by thirty percent. Node efficiency gains twenty percent in shallow and mid-water environments and twenty percent in deep-water settings. The reason for these gains is a decreased Root Mean Square Error (RMSE) in localization, which decreases the need for energy-intensive error correction procedures, hence improving overall energy efficiency and extending the operational lifetime of UWSNs.

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LIST OF ACRONYMS

AUV	Autonomous Under Water Vehicle
UWSN	Under water Wireless Sensor Network
GPS	Global Position System
KF	Kalman Filtering
LQE	Link Quality Estimation
SEMAT	Smart Environmental Monitoring and Analysis Technology
EM	Electromagnetic
CN	Current Node
DN	Destination Node
MSE	Mean Square Error
RSSI	Received Signal Strength Indicator
AoA	Angle of Arrival
RF	Radio Frequency
TDoA	Time Difference of Arrival
HMSS	Helmholtz Method for Subsequent Simulations
RMSE	Root Mean Square Error
EKF	Extended Kalman Filtration
KHz	Kilo Hertz
WHO	Whale Optimization Algorithm
PSO	Particle Swarm Optimization
UWB	Ultra-Wideband
PSA	Particle Swarm Algorithm

LIST OF SYMBOLS

B	-	Bandwidth
Ψ	-	Pressure field
K	-	Wave number
(x_i)	-	The true state
$(\hat{x})$	-	The estimated state
A	-	Attenuation
z_0		Free Space
$\boldsymbol{T_x}$		Transmission Coefficient
$\boldsymbol{R_x}$		Reflection Coefficient

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Primarily, I would express deep and humble appreciation and gratitude to Almighty Allah who blessed me with the knowledge and status, enabling me to reach this level, and take on this task. Apart from the blessing of Almighty, several other contributions, worth paying regards, thankfulness and gratitude, played their role in my endeavor. Yet, there were significant contributors for my attained success, and I cannot forget their input, especially my research supervisors, Asst. Prof. Dr. Moeenuddin Tariq and Dr. Muhammad Tahir (HOD NUML Faisalabad), who did not leave any stone unturned to guide me during my research journey. I shall also acknowledge the extended assistance from the administrations of Department of Computer Sciences who supported me all through my research experience and simplified the challenges I faced. For all whom I did not mention but I shall not neglect their significant contribution, thanks for everything.

DEDICATION

This thesis is dedicated to my parents and my teachers throughout my education career who have not only loved me unconditionally but whose good examples have taught me to work hard for the things that I aspire to achieve.

CHAPTER 1

INTRODUCTION

1.1 Overview

The terrestrial sphere, commonly known as Earth, is primarily enveloped by aqueous expanses. In light of the escalating depletion of terrestrial resources, human endeavors have increasingly gravitated towards the exploration of the submerged realms. Nevertheless, the pursuit of undersea exploration is significantly constrained by the diminished optical clarity and augmented hydrostatic pressure, which collectively impedes effective communication and comprehensive examination of the subaqueous domain [1]. Marine resources gradually become more abundant as terrestrial resource exploitation becomes much more mature. Human beings are slowly turning towards marine resources. Related areas favor the use of underwater wireless sensor networks (UWSNs) because of their low cost and convenience. The location tracking and optimal path finding underwater is a nerve center for researchers at the moment [2]. Despite the low cost of UWSN deployment, underwater communication remains a challenging technology via communication cables. USWN has received so much attention because of its long transmission range through acoustic communication (≈1000m) along with dependency on the environment, and low speed (1500m/Sec) it experiences signal loss and distortion [3].There has been significant research on improving the localization algorithm or developing new methods for getting towards the destination node [2]. Researchers working on the development of UWSNs must consider the architecture of the everlasting design that provides distributed sensor nodes within the network with the capability of self- configurability [3].

Within the context of UWSNs, the attainment ofa predetermined node remains a subject of uncertainty. Should we employ a global optimizer, it will guide us to the globally optimal node, whereas a local optimizer will facilitate the discovery of an optimal path in a localized fashion. Consequently, in both scenarios, our outcome is characterized by either the realization of a globally optimized node or the identification of a locally optimal node, though not concurrently.

The research proposal aims to tackle the challenges associated with communication and examination in underwater environments, focusing on Underwater Wireless Sensor Networks (UWSNs). As resources found on earth and underground in core and ore are depleting, there is a growing necessity to explore and utilize underwater domains for various purposes. The environment of Underwater and its traits are distinct as well as challenging. These undersea problems must be solved and handled with assistance, as well as through efficient communication and investigation. Wireless sensor networks underwater present a number of problems and difficulties. The accuracy of sensor node localization is one of these important issues. This level of accuracy is absolutely necessary for the effective use of the data that has been gathered. UWSNs function in a challenging underwater environment with significant signal attenuation, low bandwidth, multipath propagation, and a dynamic medium, in contrast to terrestrial networks. These conditions make communication and information transfer difficult. Most underwater sensors are battery operated, and power consumption is another important issue. Most underwater sensors are powered by batteries which are expensive and difficult to replace. As a result, maintaining the network's lifespan can be challenging and expensive. Consequently, in order to prolong the network's lifespan, high delivery and maintenance expenses are needed. Sensor node deployment and maintenance are made more difficult by the underwater environment, which drives up expenses. Living in the undersea world in real time requires these dynamic adjustments. In order to overcome these obstacles, UWSNs must be successfully deployed and used for a range of tasks, such as environmental monitoring, military surveillance, and resource extraction [4].

Underwater sensor network development and advancement is often critical to these significant applications and issues pertaining to underwater locations. Underwater wireless networks (UWSNs) have unique obstacles and constraints, including repeated exposures, weak signal intensity, and very low power usage when compared to networks that are airborne and on land. Due to these challenges in UWSN design, deployment, and maintenance, further study is needed to find dependable and practical solutions. Applications for UWSNs are numerous and include environmental monitoring, disaster relief, ocean data collection, and military surveillance. Underwater risk management, more accurate data collecting, and environmental protection could all benefit from advancements in underwater wireless sensor network (UWSN) technology. Thus, there is a need for ongoing study and innovation in this field [5]. Because it won't work in the underwater environment, developing a good location and tracking system for UWSN is a challenging task. Aside from the apparent, there is also the evident issue of the surroundings being negatively impacted by high hydrostatic pressure. For experts and practitioners, this paper provides insights by evaluating various research methods related to Media Access Control (MAC) and regional methods, UWSN design, routing, energy usage, and security. It emphasizes the importance of solving these problems to improve the performance and reliability of UWSNs.

In addition, the study provides examples that demonstrate the real-world benefits and outcomes of UWSN. This comprehensive review not only helps to understand the current status of the challenges but also suggests future research to develop better and more effective UWSN solutions [6]. Compare light waves, sound waves, and electric waves, including changes in propagation speed, range, and data transfer. The comparison of various energy saving techniques mainly focuses on the pros and cons.

Table:1.1 Pros and Cons of Underwater Networking: Light, Sound, and Electromagnetic Waves[1-10]

Light waves	Sound waves	Electromagnetic waves
High propagation speed in water compared to sound waves.	Excellent propagation in underwater environments due to low absorption	Higher frequency EM waves (e.g., radio waves) can penetrate water to some extent.
Suitable for short-range applications in clear water conditions.	Long-range capabilities, especially in deep water.	Can provide wide- area coverage in relatively clear water.
It is restricted to line-of- sight communication, limiting coverage in complex underwater environments.	Performance degrades with increasing water salinity.	Lower data transfer rates compared to electromagnetic methods.
Propagate at the speed of light in the medium, which is faster than sound waves.	Propagate at a much slower speed in water compared to light waves in air.	Travel at the speed of light in a specific medium (e.g., radio waves).
Suffer from absorption and scattering in water, limiting their range.	Attenuate less in water than electromagnetic waves, making them suitable for longer-range communication.	Experience absorption and reflection, depending on the frequency.
Provide high accuracy but may face challenges in underwater environments.	Well-suited for localization due to their ability to travel over longer distances with reasonable accuracy.	Can offer good accuracy depending on the frequency and signal processing techniques.
Speed: 3*10^8 m/s Bandwidth: GHz Range: 1-10cm	Speed:1500m/s Bandwidth: KHz Range: ≈1000m	Speed: 3*10^8 m/s Bandwidth: MHz Range: 10-150m

1.2 UWSN Architecture

i. **Underwater sensor network architecture:** The overall layout and composition of an underwater sensor network is called architecture. We divided the network into regions and focused mostly on autonomous underwater vehicles.

ii. **AUV segmentation:** Unmanned autonomous vehicles with the ability to function independently underwater are known as autonomous underwater vehicles. The prototype design of these AUVs incorporates UWSNs, demonstrating the importance of these vehicles to the network's functionality. This entails segmenting the network into autonomous underwater vehicles (AUVs) and transmitting data to a base station or distant location by means of dynamic sensor node choices.

iii. **Dynamic selection of express nodes**: "Express nodes" is the word used. It is advised to set aside certain nodes for data transmission and transportation. The nodes that are displayed are dynamically selected, meaning that they can alter in response to certain demands. Optimizing network and overall performance in response to shifting conditions may be the goal of this dynamic selection process. Sending information to base stations located offshore: Data transfer from various UWSN locations to the offshore base station cart is made easier with the use of dynamic express node selection. Typically, shore stations are positioned on platforms or in the water to serve as a central location for data gathering and system communication.

iv. **Data transmission improvement:** Two methods to improve the efficiency of data transmission are network separation to AUV and dynamic node selection. The architecture is intended to maximize the network's overall performance through the strategic use of AUVs and dynamic data transmission selection.

v. **Overcoming the Obstacles of Dynamic Ocean Depth:** The changing nature of the ocean depth poses special challenges through segmentation and dynamic node selection. This will require changes in depth, changing water levels, and other environmental factors that will affect the transmission of information and communication in the UWSN.

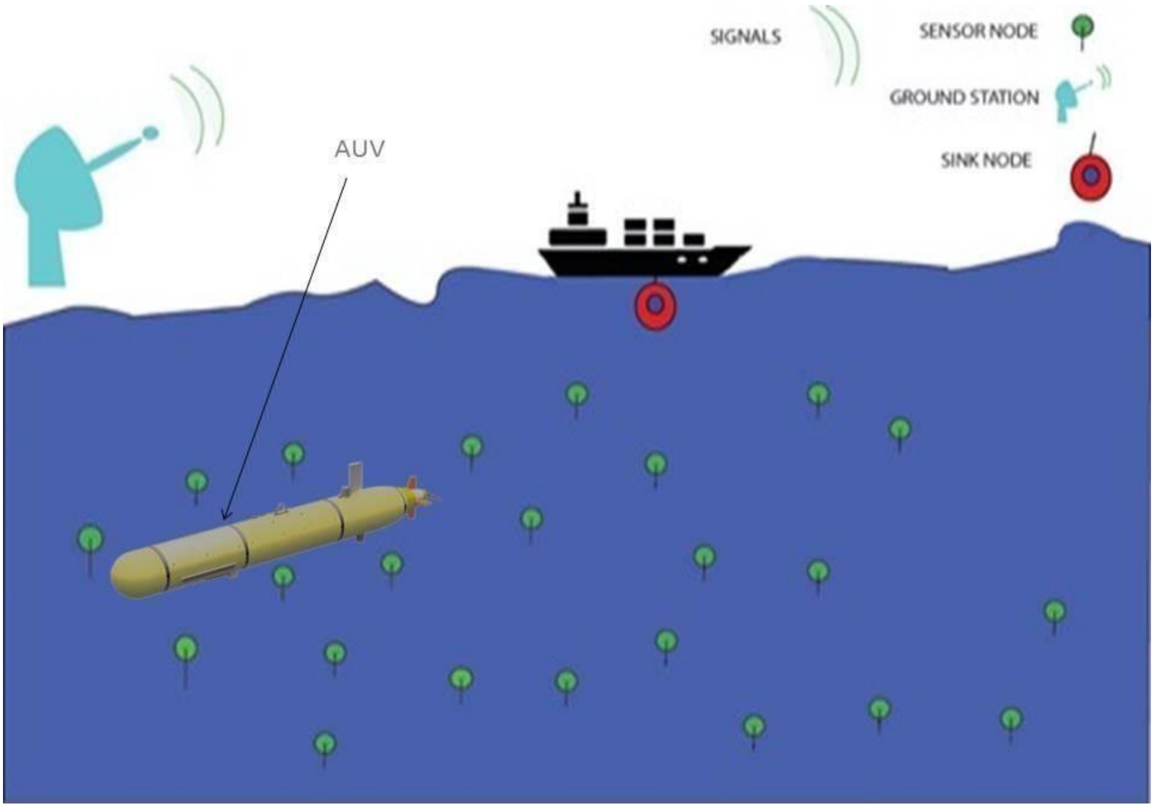

Figure 1.1: Architecture of Under Water Sensor Network

The Figure 1.1 illustrates the basic architecture of an Underwater Wireless Sensor Network (UWSN). In this setup, multiple sensor nodes are deployed underwater to monitor various ocean parameters like temperature, salinity, and pressure.

These sensors communicate wirelessly and transmit their data to a sink node, which acts as a gateway between underwater and surface communication. The sink node forwards this information to a surface station (such as a ship or buoy) that relays it to a ground station for further processing and analysis.

The diagram also shows an Autonomous Underwater Vehicle (AUV), which moves among the sensors to assist with data collection or to serve as a mobile node for localization and tracking. The overall structure ensures real-time data transmission from deep-sea environments to onshore monitoring systems, enabling effective ocean observation and underwater surveillance.

1.3 UWSN Applications

Some simple applications of Underwater Wireless Sensor Networks (UWSN) are:

1. Using UWSNs with small underwater vehicles or solar-powered probes to monitor water quality in reservoirs.
2. Employing ZigBee-based sensor nodes to check and maintain the pH balance in river water.
3. Implementing a framework for underwater monitoring that includes sensing, wireless communication, visual representation, and alarms for events.
4. Using Smart Environmental Monitoring and Analysis Technology (SEMAT) with easy-to-install smart sensors and short-distance wireless communication for studying marine environments.
5. Testing a UWSN prototype successfully in Mar Menor coastal lagoon, Spain, to monitor the shallow water marine environment.
6. Creating a system for decentralized detection of ocean pollution and wreckage by placing sensors equipped with short-range acoustic modems under water.
7. UWSNs are used in military missions such as underwater reconnaissance and surveillance. These uses demonstrate the versatility and significance of UWSNs across a range of industries [4].

1.4 Limitations of UWSN in Real-time Applications Localization / Tracking

The constraints of UWSNs include the challenges associated with underwater communication, such as signal loss, distortion, and the dynamic nature of ocean depths. The deployment of sensor nodes at various oceanic depths is proposed to mitigate disruptions caused by these constraints.

1. **Limited Energy Resources:** Batteries with limited energy capacity typically power sensor nodes in UWSNs. Once deployed underwater, replacing or recharging these batteries becomes impractical. Energy efficiency can thus be berated as the greatest and important most factor which can result or effect prolonged operational lifespan of Underwater Sensor Networks. It can also enhance and maximize data collection periods [1].

2. **Harsh Underwater Conditions:** The harsh and dynamic underwater environment poses challenges such as high hydrostatic pressure, limited visibility, and variable water conditions. Energy-efficient protocols ensure that sensor nodes can function properly even under difficult conditions by optimizing the utilization of resources [2].

3. **Communication Restrictions:** Underwater communication is naturally challenging due to signal attenuation in water. Acoustic communication, a common method in UWSNs, consumes a lot of energy. Creating energy-efficient protocols that will reduce energy consumption during communication processes, enabling less signal distortion and handling larger transmissions, is the main objective of study [1-2].

4. **Impact of Environment:** The overall reliability of UWSNs is increased by low-energy consumption protocols. By maximizing energy consumption and ensuring continuous data collection and transmission, these techniques help lower the likelihood of an early node failure. Applications such as environmental monitoring and hazard identification rely on this reliability [2].

5. **Reliability of Network:** Reliability of UWSNs is increased via low-power consumption protocols. Through energy-efficient ways that ensure continuous data collection and transmission, these techniques help lower the likelihood of an early node failure. Applications requiring this dependability include environmental monitoring and hazard identification [3].

6. **Cost-Effectiveness:** Low deployment costs for UWSNs are among the key advantages and contributions of energy-efficient protocols. Over time, this results in financial savings as it prolongs the operational life of sensor nodes and reduces the need for unexpected or frequent replacement and maintenance [4].

7. **Absence of GPS Navigation:** Underwater areas do not have GPS navigation, in contrast to terrestrial situations where it is commonly employed. One major obstacle to real-time tracking and localization of sensor nodes in UWSNs is the lack of GPS navigation. It becomes necessary in this situation to develop creative and alternate tracking techniques [5].

8. **Dynamic Ocean Depths:** Ocean comprises of a distinct three-dimensional (3D) layered structure with different and varying depths, longitude and latitude, associated with each of them. The dynamic nature and immense depth of ocean along-with current and waves lead and result in a challenging environment, hampering effective maintenance of accurate and real-time tracking of sensor nodes [1-5].

9. **Fluctuating Ocean Conditions:** The Ocean environment and its segments change dynamically and drastically very frequently. This constant change in ocean conditions also include factors such as temperature, salinity and underwater current. The effectiveness of tracking systems and equipment is the variation and change of the factors mentioned above, which can lead to incorrect results and inaccuracies in measurement parameters [5-6].

10. **Communication difficulties:** There are many difficulties in underwater communication, including bandwidth limitations, multipath propagation, and signal attenuation. These problems make it difficult to maintain effective communication for tracking purposes. It is important to develop tracking vehicles that can track these communication problems [1-2].

11. **Optimal sensor placement:** Sensor nodes should be positioned at varying depths to provide accurate monitoring because ocean depth is a dynamic phenomenon. When advising the usage of sensors, it's critical to take into account factors like wave speed and possible impacts on the undersea ecosystem. Examine all of the parts, especially the ones that employ electricity, closely. The reduction in power consumption is advantageous for underwater tracking; however, the temperature of the water is one of several factors that affect its efficacy [6].

1.5 Motivation

Underwater Wireless Sensor Networks (UWSNs) are becoming more and more necessary as catastrophe prevention becomes more and more crucial. Additionally, it facilitates better navigation and environmental monitoring. Underwater and submerged exploration require all of the aforementioned. Underwater applications of UWSNs are hindered greatly by their high energy consumption. Sound waves travel slowly, contain a finite amount of data, and are prone to errors. Reducing energy consumption in UWSNs is crucial. The insufficiency of conventional GPS devices in underwater environments prompts the investigation of substitutes for a variety of underwater applications, UWSNs are an affordable option. Ocean risks can be identified using UWSNs, which can also measure temperature and detect objects. Improving the precision and endurance of UWSNs in dynamic maritime conditions is the main driving force. There is a need to address underwater-specific communication challenges where traditional GPS is impractical. Improving tracking capabilities within UWSNs is crucial for understanding movement patterns and phenomena in the ocean. The research aims to overcome limitations related to diminish optical clarity and increased hydrostatic pressure. The goal is to develop more robust and resilient underwater sensing systems. Advancing capabilities in monitoring and understanding underwater environments is essential for scientific and practical applications. The ultimate aim is to significantly improve the effectiveness of UWSNs in navigating the complexities of dynamic and challenging oceanic ecosystems navigating the complexities of dynamic and challenging oceanic ecosystems.

1.6 Problem Background

The backdrop of the issue is that GPS navigation is not available underwater, necessitating the development of creative electromagnetic wave tracking techniques. The importance of solving problems in the marine environment is related to the nature of the ocean depth and the problems it creates in underwater connections.

Accurate node localization in underwater environments is critical for real-time data collection and monitoring, yet remains challenging due to high latency, dynamic topologies, and signal attenuation. Mamta Nain et al. proposed a range-based localization scheme incorporating hybrid optimization techniques to enhance localization accuracy under such constraints. Their study highlights the need for adaptive methods capable of handling non-linearity and energy limitations. Building on these insights, the current research integrates extended Kalman filtering and Bayesian inference for improved performance in dynamic underwater settings [4].

1.7 Problem Statement

The main problem in this study is the limitation of GPS navigation in the underwater environment, which makes it impossible to track the time and location of underwater sensors. Underwater conditions pose a great challenge to current GPS equipment due to insufficient penetration, which results in limited performance.Researchers are searching for fresh and dependable approaches to using electromagnetic waves for underwater navigation in order to get around this issue. By concentrating on a route that GPS does not always take, the objective is to develop a dependable system that can quickly and precisely track submerged sensors.

1.8 Research Questions

The primary focus of research challenges is on how real-time information can be used in UWSNs to achieve realism and lower the chance of GPS interruption. In certain geographical areas, the research also aims to generate precise target estimations.

1. How to use real-time information in UWSNs to obtain the real situation and solve the risk of GPS unavailability?

2. How to accurately estimate targets in small area network?

1.9 Aim of the Research

The aim of the research is to improve and enhance the service life and accuracy of UWSN in a dynamic maritime environment by creating a long-range search and release system based on real-time information.

1.10 Research Objectives

The goal of the project is to create a tracking system with a lower mean square error and an energy-efficient localization and tracking mechanism. The methodology leverages real- time dynamics information from ocean literature and employs Kalman filtering for sensor tracking.

1. To design and develop a method for energy-efficient localization and tracking of sensors in UWSNs based on real-time data of oceans.

2. To design and develop a tracking system that predicts autonomous underwater vehicle trajectory in hostile underwater environments.

1.11 Scope of research

The scope of the research work is focused on "Energy-efficient node localization and tracking for real-time UWSNs application." The study considers the challenges of underwater communication and proposes innovative solutions to enhance the accuracy and lifespan of UWSNs in dynamic ocean environments. The research specifically addresses the limitations of traditional GPS technologies underwater.

1.12 Thesis Organization

The remainder of the thesis is structured as follows:

In Chapter 2, an introduction to the domain is provided along with a discussion of related problems in UWSNs. This chapter extensively reviews previous research, highlighting the distinctions between this study and existing frameworks. A comprehensive analysis of state-of-the-art schemes, along with an exploration of their research limitations, guides the identification of new research directions.

Chapter 3 outlines the methodology used in problem identification, presenting details of the technique employed. The chapter introduces a solution to address the identified problem and covers the research methodology, including the operational framework, research design, and simulation framework. It delves into the specifics of Kalman Filtering Simulations, elucidates its framework, and explains the implementation of the Bayesian approach and Helmholtz method. Additionally, Chapter 3 provides a thorough explanation of the operational framework and validates Kalman Filtration through the implementation of real-time data. Chapter 4 focuses on the performance evaluation of Kalman filtering simulation and the implementation of Bayesian approach in the fusion process of KF. The Helmholtz method is applied in subsequent simulations. The chapter discusses experiment results, offering a comparative analysis of tracking and localization efficiency using real-time data. The final results are visually presented through graph.

Chapter 5 summarizes the research contributions, highlighting the proposed protocol's gaps and suggesting directions for future work.

CHAPTER 2

Literature Review

2.1 Overview

The review of existing research starts by talking about how we're using up a lot of resources on land. Because of this, people are now looking more into exploring under the water. The reason for this shift is that we're realizing there are limits to the resources we have on land. The review talks about the difficulties we face underwater, like not being able to see clearly and dealing with the pressure deep underwater. It explains that the water has particles that make it hard to see, and there's not much light that can reach deep down.

2.2 Localization and Tracking Methods Review Considering UWSNs

This section examines UWSNs and shows how simple and inexpensive they are compared to more traditional communication options. It is well known that underwater communication is problematic, especially when communication lines are used, and sensor nodes must be placed at different ocean depths. Underwater sensor nodes with sensing, communication, and active deployment capabilities are available as UWSNs. There are many applications for these networks, including business environments, oceans, environmental protection, and defense. However, UWSNs face many problems, especially in the areas of surveillance and localization. UWSN location and tracking may encounter problems such as signal attenuation (±), multipath propagation, and low visibility, making it difficult for the equipment to be directly used underwater using GPS. In addition, underwater communication often faces the problem of limited bandwidth (B) and high-power consumption, so it is necessary to develop energy-saving algorithms and communication models designed to save bandwidth. The nature of the underwater environment, including ocean currents that cause sensor nodes to drift, presents another challenge, along with the need to use dynamic positioning algorithms that can change the node location. In accuracies in underwater sensors and the often-limited communication range further complicate the scenario, demanding that localization algorithms accommodate sensor errors and operate within the confines of communication ranges [5-6].

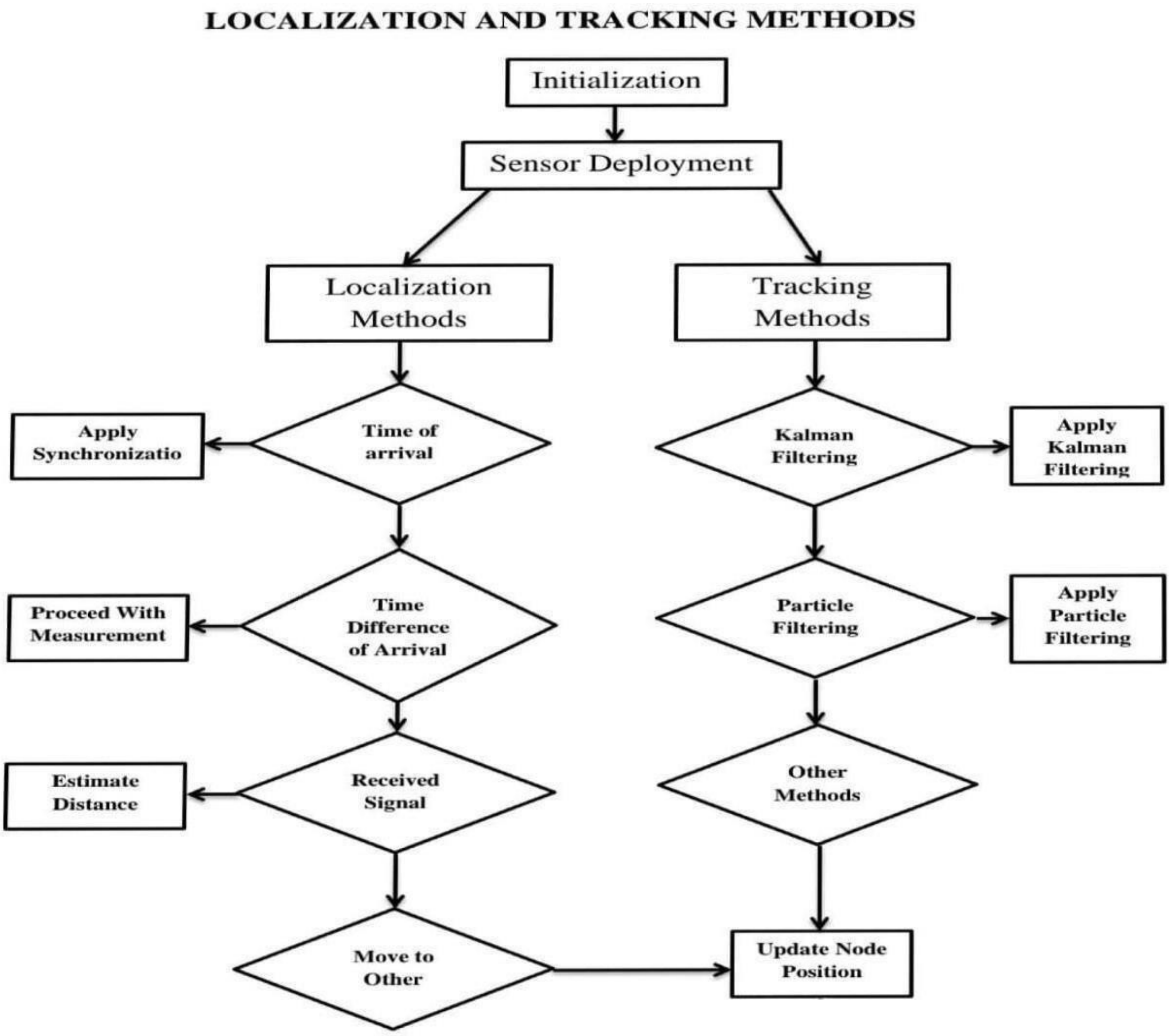

Figure 2.1: Localization and Tracking methods.

UWSN localization and tracking find practical applications in tracking ocean currents, monitoring temperature, and assessing salinity for environmental research. To overcome these challenges and optimize UWSN performance, ongoing research endeavors aim to enhance the reliability and effectiveness of localization techniques in underwater scenarios. The article under consideration refines the selection process for CHNs by considering factors such as the residual energy of nodes and spatial proximity. Simulation results presented in the article validate the commendable effectiveness and efficiency of the proposed algorithm in reducing energy consumption, extending the network's operational lifespan, and mitigating packet loss ratios [5]. The increasing need for gathering scientific data and the revitalized drive to explore underwater natural resources have catalyzed a surge in research focused on the underwater domain. Consequently, UWSNs have gained worldwide recognition. Nonetheless, UWSNs confront substantial challenges due to their adverse surroundings, extended signal propagation delays, and sensor node battery capacities [6].

The paper underscores the significance of establishing effective routing methods in wireless sensor networks, given the constrained hardware and software resources of sensor devices. Achieving essential metrics, such as low packet loss, enhanced quality of service, and minimized energy consumption, is paramount for the successful operation of efficient routing algorithms [6].

The growing importance of UWSN in the realm of scientific data collection for underwater natural resource exploration emphasizes the crucial need for maximum link reliability. Traditional network-based routing protocols are designed to ensure effective communication among sensor nodes, yet they grapple with limitations such as distance- dependent bandwidth constraints, channel imperfections, and high transmission delays. Additionally, the underwater environment imposes restrictions on data transmission in long- distance network areas, given the harsh conditions and limited battery power of the devices [7]. Duecker et al. presents an innovative approach to underwater vehicle localization. The authors focus on utilizing the attenuation of electromagnetic carrier signals to enable precise positioning for micro underwater vehicles. The use of EM signals for underwater localization is a promising avenue, as it can overcome some of the limitations associated with acoustic- based systems. The paper introduces an innovative approach to a self-localization method for micro AUVs based on the α of EM carrier signals. The techniques used in the paper for the EM signal carriers. The authors employ EM waves for signal transmission and propagation underwater. This differs from acoustic-based location techniques, which involve transmitting electrical signals from source to receiver.

This study uses the concept of face (where the electric current in spherical structures propagates outside the transmitter radiation). Δ to calculate the distance between the transmitter and the receiver while crossing the water. Passive One-Way Signaling: The system presented in the study uses passive one-way signaling technology to reduce the complexity of the installation and ease of use. AUV receives and evaluates electromagnetic signals (EM signals) sent from a fixed location to estimate its location [8]. In addition to the general review of underwater radio networks, the study also provides detailed information on the specific requirements for the co- location of UWSNs. To solve the problems of poor connectivity, slow data, and high packet loss in UWSN, we developed a system for two main applications: navigation assistance and personal space. The planning process of using remote data from the bottom of the water requires the cooperation of sensor nodes to estimate their locations and has minimal dependence on bones. After completing self-localization, a node uses nearby ones to determine its location for underwater navigation. The network performance is simulated and measured using the Castalia simulator [9].

The main objective of this work is to provide an overview of the methods and techniques for localization and clustering of Underwater Wireless Sensor Networks (UWSNs), Autonomous Underwater Vehicles (AUVs) and Unmanned Surface Vehicles (USVs). The main objective of this work is to review and evaluate the existing ways and integration to improve the accuracy and efficiency of the field - two methods that are essential for the effective operation of UWSN research resources, since the computers used in military surveillance and environmental monitoring depend on these networks mix well. Bionic algorithms, adaptive clustering, and hierarchical clustering are available in the UWSN environment. The goal of this work is to increase the location accuracy of ultra-wideband (UWB) wireless sensor networks (WSNs). Create and evaluate a hybrid DV- Hop algorithm that makes use of particle swarm optimization (PSO) technologies to improve and optimize its functionality. Tracking and placement in underwater wireless sensor networks (UWSN) depend on accurate location determination, which is the primary goal of this research. To do this, researchers have employed a variety of methods and approaches. The Distance Vector Hop (DV-Hop) algorithm determines the distance between nodes by calculating the average of each hop and the number of hops, which is a noiseless field placement strategy. Nodes can therefore find themselves without the aid of distant sensors. The aim of this work is to develop and evaluate a hybrid DV-Hop algorithm that is developed using Particle Swarm Optimization (PSO) and its ability to improve Location. Accuracy in Ultra- Wideband (UWB) Wireless Sensor Networks (WSN). Since obtaining the location accuracy is crucial for overseeing the caliber of work in Underwater Wireless Sensor Networks (UWSNs), it serves as the primary research goal. We use numerous key concepts and methods to do this. Employing hops and the average of hops to determine the distance between nodes, Distance Vector Hop (DV-Hop) technology is a popular approach for location determination. Without using a measurement tool, this technique makes it possible to access node locations. Based on the collective behavior of birds, particle swarm optimization (PSO) is implemented. Through candidate solution improvement and fitness-based ranking, it maximizes the head nod position. Create a hybrid method by utilizing DV-Hop's simplicity and robustness for the initial location and optimization Possibilities of PSO to modify the node's location for precise positioning. PSO and DV-Hop algorithms yielded similar results. The localization is more accurate as a result. UWSN's distance accuracy is increased since the hybrid algorithm offers a superior and more effective solution underwater tracking [11].

The primary goal of this research is to enhance the accuracy and functionality of Wireless Sensor Networks (WSN). Solving location and tracking-related issues that are crucial and relevant for use, like capital extraction layer, military surveillance, and environmental monitoring, is the primary goal of this research. To do this, numerous strategies and tactics are employed. It's crucial to employ sophisticated algorithms to boost node performance and location precision. The research addresses the shortcomings of existing systems, which necessitate the use of multi- or multi-based placement methods that do away with the need for distance measurements between nodes, reducing overhead and energy consumption. New algorithmic techniques are combined with traditional registration techniques in this research. With machine learning algorithms, the technology improves the accuracy and efficiency of node placement by dynamically adjusting localization tactics in response to changes in the network environment. Energy-saving methods that can sustain lower energy usage while preserving the proper area are also examined in the study. Hybrid algorithms are also used in the research to combine the best aspects of several methodologies. For instance, the precision of the task site can be used to determine the initial coarse position when the distance vector hopping (DV-Hop) algorithm is coupled with optimization techniques like particle swarm optimization (PSO). By fusing the adaptability of DV-Hop with the precision of PSO, this hybrid method significantly raises scene accuracy. The proposed methods enhance node efficiency and increase localization accuracy in WSNs by lowering energy consumption and computational load. By combining cutting- edge and conventional methods in a novel way, Wireless Sensor Networks can now effectively localize and track nodes, opening the door to more dependable and effective network operations [12].

The review also highlights the issues that still need to be addressed, especially about energy efficiency, robustness, and scalability of the localization and clustering approaches, despite the tremendous progress made in the sector. To calculate the separation between communication nodes, localization uses a variety of range techniques, including Time of Arrival (ToA): Multiplying the signal speed typically acoustic speed by the signal propagation time yields the distance. Needs clock synchronization, although synchronization issues can be resolved by packet exchanges. Time Difference of Arrival (TDoA): Calculates the variation in signal arrival times between reference nodes as a result of the submerged environment's poor radio frequency (RF) propagation. Angle of Arrival (AoA): Measures the angle between signal propagation and predefined reference direction. Rarely used in UWSNs due to challenges with expensive directional antennas. Received Signal Strength Indicator (RSSI): Estimates distance based on signal propagation loss but is less preferred in UWSNs due to temporally-variable underwater acoustic signal propagation [13].

C. Laoudias et al. [14] recognize the diverse applications of location information across consumer, networking, industrial, healthcare, public safety, and emergency response sectors. It underscores the necessity for advanced location-based services and highlights the significance of integrating localization algorithms with other technologies. This section is expected to address fundamental concepts, principles, and challenges in network localization, providing an overview of basic terminology and methodologies. The exploration of various localization architectures is discussed, encompassing the design of technologies and systems for pinpointing the location of events, assets, and individuals. The coverage spans both theoretical and practical dimensions of localization architectures. The paper focuses on cellular network localization, providing insights into systems within cellular networks. It discusses recent developments in 5G localization and addresses challenges in accurately estimating 3D locations. WLAN-based localization explores the role of

WLAN in determining 3D locations, especially in indoor settings.Range-free localization schemes, traditionally used in wireless sensor networks, gain attention for IoT applications. User mobility estimation techniques are highlighted for improving localization and tracking accuracy in cellular networks. The paper concludes by discussing service availability, system scalability, and security and privacy concerns in location architectures. It touches upon the technology roadmap and identifies future research directions in the field. Fig: 2 depicts different localization and tracking methods.

The significant contribution of this research is utilization of electromagnetic (EM) waves and received signal strength (RSS) for underwater localization, specifically customized to improve the docking process of unmanned underwater vehicles (UUVs). Previous underwater localization methods, mainly used to depend on sonar and inertial navigation systems, which often encounter cumulative errors and inaccuracies due to signal reflection, diffraction, and the slow propagation speed of acoustic signals underwater. These problems are particularly difficult in complex underwater environments where high precision is required. The path located in the path uses special properties of electromagnetic waves (less affected by external factors) t o ensure accuracy and reliability. This technology is required to create infrastructure or underwater wireless sensor networks at the connection points. A network of radio frequency sensors continues to measure the RSS of electromagnetic waves to track UUVs. The Extended Kalman Filter (EKF) reanalyzes sensor data to improve the accuracy of the UUV's position during the docking process and is used to improve trajectory tracking in the positioning process, showing the main results. The appearance of the site, including the high sampling rate and reduced ambient noise, demonstrates the effectiveness of the method. This project provides a good alternative to sonar- based methods, enabling more accurate and reliable UUV docking in underwater waters [15].

Han Y and others. Pay attention to the significance of the influence of measurement error on node localization in underwater sensor networks (UWSNs). UWSN is essential for underwater research, military surveillance, environmental monitoring, and other maritime applications. Dealing with the undersea environment makes this particularly difficult. GPS signals cannot be used underwater, and delay and noise can adversely affect acoustic signals. This study is important in that it examines how measurement error affect’s location accuracy and thus UWSN performance and reliability. By identifying and reducing these errors, UWSN deployment and performance can be improved, thus ensuring accurate and reliable underwater communication. The main objective of this study is to examine the effect of location distance measurement error on the accuracy of large UWSNs. In most UWSNs, there are several nodes with precise location information, and other nodes (called partner nodes) must verify their locations with respect to the connecting nodes. The aim of this study is to evaluate how the measurement distance does not affect the registration process. By understanding these results, the study aims to find and understand ways to improve location accuracy even when errors occur. Improve the overall functionality and performance of UWSN.

The research uses various methods to evaluate and reduce the effect of measurement error on the site location. These tests include different error levels to understand how different measurement errors affect the location accuracy. Secondly, various location functions are used in the study to estimate the location of regular nodes based on the known anchor locations and the sub-node distance. Various error metrics are used to verify the efficiency and accuracy of these algorithms. Error analysis is performed to determine the impact of multiple measurement errors on the measured values. This study aims to investigate how errors arise in the network and impact one of the final estimates. To increase the location's accuracy, optimization is also being researched. These include noise reduction and measurement error reduction approaches in signal processing, error correction algorithms, and averaging techniques.As part of this study, a performance comparison of several algorithms and approaches was also carried out in order to ascertain the optimal approach for mitigating the impact of measurement mistakes. This comparison offers guidance and insight into the options for choosing the optimal technology for a range of UWSN scenarios by using this technique, scientists may study the procedure and offer recommendations for enhancing the precision of node location even in the presence of measurement mistakes. The efficiency of UWSNs in many important applications by offering helpful data and resources for building more robust in UWSNs [3].

To lessen the drawbacks of conventional sonar systems, particularly in challenging circumstances and environments that call for precise docking, it is imperative to develop effective, precise, and accurate underwater positioning solutions. Underwater Unmanned Vehicle (UUV). Cumulative location mistakes in conventional sonar systems are frequently caused by the slowness of sound waves, signal reflections, and diffraction. In order to tackle these issues, this research develops precise locations using depth sensors and electromagnetic (EM) wave attenuation. By positioning nodes with RF sensors at docking locations to create a framework of fake devices, the suggested technique creates an underwater wireless sensor network, or UWSN. The primary innovation lies in the utilization of electromagnetic radiation's received signal strength (RSS) for UUV location. The environment produced by electromagnetic waves is consistent and dependable, as they are less impacted by the undersea environment than sonar. The UUV starts the positioning process by receiving electronic signals from UWSN nodes. The distance between each node and the UUV is estimated using this signal's RSS. The three-dimensional placement is then enhanced by combining the distance estimates with depth data.By assessing accuracy, decreasing noise, and boosting accuracy, the EKF adjusts its estimate of the UUV location. The efficiency of this approach is confirmed by the tracking experiment conducted during the UUV deployment procedure.

The findings demonstrate that the suggestion significantly enhances the working environment while having minimal impact from outside noise. The study comes to the conclusion that location-based electronic equipment offers depth measurement, EKF processing is dependable and precise sonar systems to allow UUVs to operate freely in a demanding underwater environment [16].

A significant contribution to the field of underwater wireless sensor networks (UWSN) is the local generation and tracking of sensor nodes utilizing electromagnetic (EM) waves, as done by Kumudu Munasinghe et al. It draws attention to how important it is for people to communicate quickly in underwater surroundings. It is particularly crucial for tracking and monitoring strategically. The research's principal findings span a number of domains. It looks at using electromagnetic waves (EM waves) first, which are superior to acoustic approaches in many ways. These benefits, which enable instantaneous applications in UWSNs, include low latency and high speed. Second, the suggested approach transfers data more quickly than conventional acoustic methods by utilizing high-speed electronics. This is significant for applications like target tracking and surveillance that need to offer accurate and timely data. The study also acknowledges the necessity of accurate localization for the effective deployment and operation of sensor networks in submerged environments and proposes methods to increase node localization accuracy utilizing EM wave characteristics.

Additionally, the technique seeks to enhance target tracking through the use of electromagnetic waves' high-speed communication capabilities, which enable more frequent modifications and better resolution while regulating the target's movement underwater. Additionally, the research uses the most cutting-edge electrical equipment to overcome significant issues such signal attenuation and interference in underwater communication. UWSN is assured of communicating successfully even in challenging underwater environments because of its optimization. EM waves' Received Signal Strength Index (RSSI) can be utilized to determine the location of sensor nodes; sophisticated processing methods can be employed to handle RSSI data; and EM waves can be used to suggest the best network architecture and UWSN deployment The robust communication protocol, large data processing capacity, and scalability of the system owing to its practical application in a range of underwater conditions attest to the effectiveness and caliber of the research. Overall, by providing a fast, dependable, and precise electromagnetic wave-based communication system for target tracking and underwater surveillance, this study advances the development of underwater wave surveillance networks, or UWSNs. It is highly advantageous for scholars and practitioners and is a major advancement above conventional approach [17].

The research team's primary areas of interest include agriculture and smart cities. By lowering energy usage and packet loss, location authorization can increase network performance. Because the signal may run into obstructions and lose line-of-sight (NLOS) , this operation is especially difficult in three-dimensional (3D) situations. The time of arrival (TOA) and received signal strength (RSS) approaches were merged by the researchers to produce precise estimates in three-dimensional (3D) space in order to overcome this problem. For both line-of-sight (LOS) and non-LOS scenarios, they suggested an error reduction technique to increase location accuracy. They work by utilizing anchor nodes, also known as anchors. By restricting the received signal in LOS, singletrack, or dual-track scenarios, these anchors aid in the creation of a more accurate job. The first, erroneous placement of the sensor node is where this process begins. The inaccuracy is reversed by the researchers using the geometric relationships between anchor nodes and sensors. The placement of the problem node is constrained to a specific volume in three dimensions during this procedure, and this volume is progressively decreased during each iteration while still adhering to predefined guidelines. The product's key component, the answer to the issue of incorrectly classifying line- of-sight and non-line-of-sight signals. The system can accurately determine the location of nodes by carefully separating these two types of information. Simulation results show that their method is better than the traditional registration method in reducing the boundary volume and computational complexity in wireless sensor networks and increasing the reliability and efficiency of addresses. The researchers' approach provides effective solutions to location problems in WSNs, especially in complex 3D environments where NLOS events occur many times. By using geometrical relationships and reducing the backup volume, error reduction methods solve the fundamental problems of WSN node localization, while also providing significant results in terms of accuracy and efficiency [18].

Mamta Nain, Nitin Goyal et al. [4] stated that since oceans cover most of the Earth’s surface, these areas have great potential for many uses. Underwater Wireless Sensor Networks (UWSN) are an important technology for connecting underwater resources to land systems. This can be used for many purposes, including mineral exploration, oil spill monitoring, military surveillance, oil and gas removal, and pollution monitoring or these applications to be effective, sensor node localization must be accurate. This paper offers a comprehensive survey of localization techniques used in UWSNs, categorizing them into centralized and distributed schemes, and highlights the challenges faced in underwater node localization. The primary concern addressed in this paper is the precise localization of sensor nodes in UWSNs. The process of determining and defining the geographical positions of sensor nodes is called Localization. Localization is essential for interpreting the collected data. Several critical and unique challenges are inherent in UWSNs, since the underwater environment hold issues like, high signal attenuation, low bandwidth, multipath propagation, and ever-changing dynamic nature of underwater resources and medium. Above mentioned challenges existing underwater, result in complexity of localization processes which require specialized techniques. The paper begins with an introduction to UWSNs, outlining their

significance and applications. After UWSNs introduction, this research report discusses the UWSNs architecture, which typically involves a combination of floating buoys, underwater sensor nodes, and gateway nodes that facilitate communication between underwater sensors and terrestrial networks. Optimization of communication and data collection in underwater environment, is the reason behind designing this architecture. Apart from architecture review, research also addresses UWSN localization and provides a historical context and elaborates the evolution of various location techniques. Recent developments and advancements to overcome underwater environmental challenges are elaborated in this section. Most attention is given in this article to classification of localization algorithms. The authors categorize these algorithms into two main types. Centralized and distributed. Centralized localization schemes involve a central processing unit that collects data from all sensor nodes and computes their locations. These schemes generally offer higher accuracy but suffer from high communication overhead and latency, making them less suitable for dynamic and large-scale networks. The table 2.1 mentioned below is the comparison table of different approaches and techniques used in different research of UWSN's localization and tracking.

Table 2.1: Comparison of Various UWSN Techniques and methodologies used in previous research

Method/Technique	**Approach/Principle**	**Advantages**	**Limitations/Challenges**
1. EM Signal Localization [3]	Spherical localization based on EM signal attenuation	Overcomes limitations of acoustic-based systems, Passive one-way signal transmission.	Limited range compared to acoustic signals, dependency on EM properties
2. Collaborative Self-localization [13]	Collaborative estimation by distance measurements	Minimal reliance on nodes collaborative positioning	Requires collaborative efforts, may be affected by dynamic UW Environments
3. Ranging Methods: (ToA, TDoA, AoA, RSSI) [15]	Various ranging methods: ToA, TDoA, AoA, RSSI	Provides flexibility in choosing a suitable method, ToA uses packet exchanges to alleviate synchronization	Challenges with expensive directional antennas for AoA, temporally variable underwater acoustic signal propagation
4. Cellular Network Localization [16]	Diverse applications, 5G , WLAN-based and Range-free localization schemes.	Consumer, Networking, Industrial, Healthcare.	Overview of localization architectures in various sectors, challenges.
5. UASN Target Tracking Algorithm [17]	Interacting Multiple Model and Adaptive Kalman Filter (IMMCFAKF) Algorithm	Biological Monitoring, Military Applications	Numerical simulations demonstrate proficiency in UASN target tracking

Distributed localization schemes, on the other hand, allow sensor nodes to compute their locations locally by communicating with neighboring nodes. These schemes are more scalable and robust to changes in the network topology, making them ideal for UWSNs. However, they may offer lower accuracy compared to centralized schemes. Within the categories scenarios of range- based and range-free methods and techniques have been evaluated and discussed in this report, and a hybrid approach combining both is also discussed. To calculate the distance between the nodes, range-based methods heavily depend and rely on the measurement of physical quantities i.e. signal strength, time of arrival (TOA), and angle of arrival (AOA) to Carry the highest level of accuracy, these methods require sophisticated hardware and are sensitive to underwater environment's dynamically changing nature. Range-free methods, in contrast, do not rely on distance measurements but use connectivity information and algorithms like centroid localization and DV-hop to estimate node positions. These methods are simpler and more robust but generally less accurate. An integrated system developed by combining range-based and range-free methods called hybrid localization techniques carries the strength of both approaches. Maintaining a Balance between accuracy and robustness is the main objective and aim of hybrid methods, which makes it a clear choice where complex and dynamic, underwater environment is the case. In the end, the research paper elaborates underwater challenges related to node localization. These underwater node localization challenges include harsh underwater environment, limited energy resources, high cost of deployment and installation and maintenance of underwater sensor, as well as the need for real-time localization in dynamic conditions. It makes them most suitable for complex and dynamic underwater environments. The final section of this research deals with challenges in underwater node localization. These challenges include harsh underwater environment, limited energy resources, high cost of deployment and installations and maintenance of underwater sensors, and the need for localization in hostile and dynamic underwater conditions. Emphasis in this section is on the development of energy efficient, scalable and robust localization algorithms to improve the overall performance of UWSNs and address the challenges faced in node localization [15].

UWSNs performance: The research paper thoroughly addresses localization techniques in UWSNs and highlights the role and importance of accuracy of data collected by various applications for localization. Localization algorithms can be divided into two categories, namely centralized and distributed schemes. The contents of this section also cover range-based, range-free and hybrid methods, also. This comprehensive research led to a valuable insight and deep understanding of strengths and limitations of different approaches, for analysis and comparison purposes. Ongoing challenges and need for consistent research continuation to develop advanced localization techniques to overcome the obstacles posed by underwater environment. All the research and analysis serves as a valuable resource and guideline for further research used by researchers and practitioners in the field of UWSNs. [19].

Mamta Nain et al. [4] aims to develop a range-based node localization scheme using hybrid optimization techniques for underwater wireless sensor networks (UWSNs). Main objective of the goal of study is to precisely estimate the position of sensor nodes in underwater environments, which is difficult but necessary for applications like military surveillance, environmental monitoring, and disaster management.

Underwater environments present special challenges, such as signal attenuation, multipath propagation, and high energy consumption, which make localization challenging and complex. In order to attain precise node localization, the authors suggest a hybrid optimization strategy that integrates various optimization methods. Time of Arrival (ToA) and Received Signal Strength Indicator (RSSI) techniques are used for calculating distance between nodes, for range measurement. Time of Arrival (ToA) is used to measure the time, a signal takes to travel from transmitter to receiver, whereas RSSI calculates distance based on received signal strength. Position estimation phase, a hybrid optimization algorithm is employed which is an integration of Particle Swarm Optimization (PSO) and Genetic Algorithm (GA). PSO, inspired by the social behavior of birds and fish, involves particles representing potential solutions moving through the solution space to find optimal positions. GA, based on natural selection and genetics, evolves candidate solutions over iterations to improve their fitness. Since the proposed scheme is an integration of PSO [4].

Adu-Gyamfi et al. [20] stated that their research aimed to improve localization accuracy in Underwater Acoustic Sensor Networks (UASNs). They proposed a hybrid method using Extended Kalman Filter (EKF) and Monte Carlo Localization (MCL) to handle non-linearities and noise in sensor data. This approach efficiently estimates node positions even in dynamic underwater environments. Hauswald et al. [21] conducted a comprehensive review focused on modeling underwater water columns to simulate realistic environments for UWSN testing. The study examined various underwater acoustic propagation models and simulation frameworks. These models are crucial for testing localization and tracking algorithms under realistic conditions. Williams et al. [22] introduced Gaussian Processes (GP) as a non-parametric Bayesian approach for machine learning, which can be applied in sensor network localization. GP models allow for uncertainty estimation in spatial data, which benefits probabilistic positioning in UWSNs. Though not UWSN-specific, the technique aids in constructing data-driven location models.

Bar-Shalom et al. [23] provided a foundational study on estimation methods applicable to target tracking and navigation. The book emphasizes Kalman Filter variants such as EKF and Unscented

Kalman Filter (UKF), which are vital for tracking mobile nodes in UWSNs.These filters handle system noise and measurement uncertainty effectively.

Murphy et al. [24] presented a probabilistic perspective on machine learning, detailing techniques that support decision-making under uncertainty. Bayesian methods discussed in the book, including particle filters and Hidden Markov Models, are applicable to localization in noisy underwater environments. These models improve accuracy by integrating sensor data over time. Li et al. [25] discussed the core principles and practical applications of Underwater Acoustic Sensor Networks (UASNs). Their work covers deployment strategies, acoustic channel properties, and challenges in localization. They highlight time-of-arrival and signal strength-based methods for underwater positioning. Li et al. proposed an improved Helmholtz method for more precise underwater target localization. This method simulates acoustic wave behavior in underwater environments for accurate coordinate estimation. It enhances simulation realism and effectiveness in detecting and tracking underwater objects [26].

Bao et al. [27] developed a method for underwater target detection using Parallel High-Resolution Networks (HRNet). The approach applies deep learning to enhance spatial feature extraction and detection accuracy. It is especially suitable for real-time recognition tasks in UWSNs. Wang et al. [28] combined Long Short-Term Memory (LSTM) networks with the Kalman Filter for underwater target tracking. This hybrid method captures time-dependent patterns in movement data, enhancing prediction accuracy. It effectively manages temporal noise and latency in acoustic communication. Khan et al. [29] introduced an adaptive node clustering algorithm for improving network efficiency and localization performance in UWSNs. By grouping nodes based on energy and spatial distribution, the method reduces communication overhead. It also enhances accuracy in localizing mobile underwater nodes. Subramani et al. [30] proposed a metaheuristic-based clustering and routing protocol to improve performance in UWSNs. Techniques such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) are used for cluster formation. This approach increases localization reliability while minimizing energy use.

A.P. et al. [31] addressed the challenges in applying opportunistic communication models to UWSNs. They highlighted the impact of sparse connectivity and delay-tolerant communication on localization reliability. Their study supports the development of robust, real-time tracking systems. Stojanovic et al.[32] explored the characteristics of underwater acoustic communication channels, emphasizing their effect on signal propagation. The study models attenuation, multipath, and Doppler effects, which directly impact localization precision. These models are essential for developing reliable tracking systems in UWSNs. Vasilescu [33] reviewed key communication challenges and localization techniques in UWSNs. The paper discussed anchor-based localization, time-difference-of-arrival (TDoA), and RSS-based techniques. These methods are crucial for precise node positioning in harsh underwater conditions.

T. A. et al. [34] presented a broad review of underwater wireless sensor networks, focusing on localization and mobility. The authors categorized localization into range-based and range-free techniques. They also explored anchor deployment and mobile node tracking strategies. Q. et al. [35] proposed a centralized fusion algorithm using an Interacting Multiple Model (IMM) and Adaptive Kalman Filter (AKF). Their method enhances target tracking accuracy by fusing multiple dynamic models. This approach adapts well to varying motion patterns in UWSNs. Akyildiz et al. identified key research challenges in UWSNs, including localization, energy efficiency, and communication. The paper emphasizes acoustic propagation and the need for energy-aware localization protocols. It remains a foundational reference in UWSN research [36]. He et al. [37] developed the SPEED protocol to support real-time communication in wireless sensor networks. Though primarily designed for terrestrial use, its principles can apply to UWSNs by enabling fast coordination among nodes. The protocol indirectly supports real-time localization and tracking. Sathish et al. [38] reviewed localization and clustering approaches in USVs (Unmanned Surface Vehicles) and AUVs (Autonomous Underwater Vehicles). The paper emphasizes Kalman-based and optimization-based techniques for accurate underwater tracking. Clustering improves data aggregation and localization accuracy.

Lakshmi et al. [39] proposed a hybrid DV-Hop localization algorithm enhanced with Particle Swarm Optimization (PSO). The method improves range-free localization accuracy in UWSNs. It effectively compensates for localization errors in sparse networks. Fawad et al. [40] presented techniques to improve localization efficiency in wireless sensor networks. Their work integrates optimized anchor placement and hybrid filtering strategies. The result is better accuracy and reliability for UWSNs [40]. Park et al. [41-42] introduced a 3D localization method using electromagnetic (EM) wave attenuation. This method is especially useful for UUV docking operations. It provides precise location data based on EM signal strength. Park et al. proposed a 3D localization scheme combining EM wave attenuation and depth sensors. This technique enhances accuracy by using environmental depth data alongside signal loss measurements. It is particularly suitable for static and mobile underwater nodes.

Munasinghe et al. [43] introduced a high-speed underwater wireless sensor network system using EM communication. This design targets real-time surveillance and tracking. It enables fast and efficient localization in UWSNs. Sah et al. [44] presented a 3D localization algorithm with built-in error minimization for UWSNs. The approach reduces estimation error using iterative refinements. It is well-suited for high-precision applications like underwater mapping.

Goyal et al. [45] reviewed key localization techniques in UWSNs, categorizing them into range-based and range-free methods. The paper also discussed optimization and AI-based localization solutions. These methods are crucial for scalable, energy-efficient tracking. Nazia Majadi et al. [46] aims to develop an energy-efficient method for target localization in UWSN.

The research addresses the critical challenge of conserving energy while accurately determining the positions of target nodes within underwater environments. Since energy resources and underwater are constrained and limited, the major challenge was to enhance longevity and reliability of UWSNs by optimizing the localization process. To extend the operational life span of underwater sensor, and for ensuring sustainability of UWSNs, energy efficient solutions are essential. The paper proposes a novel local search-based approach for target localization that prioritizes energy efficiency. The key techniques and methodologies utilized in this research include, the core of the proposed approach is an algorithm specifically designed to minimize energy consumption during the localization process. By reducing energy usage, the algorithm aims to prolong the operational life of underwater sensors, which is critical given their limited energy resources. To refine the estimated positions of target nodes, the authors employ a local search method The iterative refinement process helps achieve more accurate localization with lower energy costs. The proposed method's effectiveness validation can be tested through comprehensive simulations. These simulations compare new algorithms' performance with that of existing methods, proving new method superior, in terms of being energy efficient and accurate in localization. Simulation tools also provide empirical evidence of success and superiority of proposed approach and method. This research most importantly contributes towards addressing issues and resolution of the same, i.e. energy constraint and enhanced localization with precision. Development of more sustainable and effective underwater wireless sensor networks is the out of this research effort. Underwater environmental issues, related to sensor, and inherent challenges are mitigated by solution in proposed method, which make UWSNs more viable for long-term and large-scale deployments. Consequently, this research supports the broader goal of advancing UWSN technologies, enabling more reliable and efficient underwater sensing and monitoring applications.

Arafat, M. Y., & Moh, S. et al. [46] proposes a Bio-Inspired Localization (BIL) method using Hybrid Gray Wolf Optimization (HGWO). This approach integrates a bounding cube strategy to reduce localization errors and resolve flip ambiguities in 3D UAV networks. The BIL algorithm significantly improves localization accuracy and energy efficiency, making it suitable for dynamic and resource-constrained wildfire monitoring environments. However, it faces challenges such as high computational complexity and the impact of environmental factors which can affect localization stability and performance over time. A.Gelb et al. [47] proposes the EBEEL algorithm, which uses bio-inspired strategies combined with distributed localization techniques such as beacon nodes and landmarks to improve node localization in dynamic environments.The algorithm enhances energy efficiency, reduces data redundancy, and improves Quality of Service. (QoS) by optimizing routing and localization in mobile wireless sensor networks (MWSNs

2.3 Gaps and Challenges in localization and tracking in existing researches:

The lack of underwater GPS navigation has been shown to be a research need for it, which suggests the idea of focusing on finding technologies that use electric waves. The problems related to the quality of the ocean depth and the need for efficient operation and tracking systems are emphasized. The problems in underwater communication, the inadequacy of traditional GPS navigation, and the need for innovative tracking systems that consume less energy are the main focuses in searching for gaps. The proposed studies hope to improve the quality and tracking of UWSNs by filling these gaps.

a. Underwater Communication Challenges:

- **GAP:** The constraints of traditional communications, as well as less visibility and higher hydrostatic pressure, are acknowledged as obstacles to underwater communication.

- **Significance:** The particular difficulties presented by the undersea environment have rendered traditional communication technologies useless. Overcoming these challenges is critical to successful underwater data collection and research.

b. Lack of GPS Navigation Underwater:

- **Gap:** The biggest problem facing instant tracking and positioning of sensor nodes is the lack of underwater GPS navigation.

- **Significance:** GPS systems and technology are useless underwater because electromagnetic (EM) signals cannot pass through water, making alternative tracking technology an important source of energy.

c. Dynamic Nature of Ocean Depth:

- **Gap:** Underwater networks face challenges due to the nature of the deep ocean, including environmental changes and waves.

- **Significance**: To minimize interference from tracking sensor nodes, this recommendation recommends deploying sensor nodes in different oceans. Changes in ocean depth must be understood and processed for successful tracking and data transmission.

d. Comparison of Underwater Networking Options:

- **Gap:** The proposal emphasizes the significance of contrasting various undersea networking alternatives, such as electromagnetic, sound, and light waves.

- **Significance**: To choose the best technique for real-time tracking and communication in underwater wireless sensor networks (UWSNs), one must weigh the benefits and drawbacks of various underwater networking alternatives.

2.4 Existing notable methods for localization/tracking

The following are some key approaches and strategies for underwater wireless sensor networks (UWSNs), along with a significant disadvantage for each:

a. Localization/ Tracking Algorithms

- **Technique:** Time of Arrival (ToA) is one of several localization algorithms explored. In addition to the above, Received Signals Strength Indicator (RSSI), Angle of Arrival (AoA), Time Difference of Arrival (TDoA) and Time of Arrival (ToA) algorithms were also explored.

- **Drawback:** Signal attenuation (α), multipath propagation, and limited visibility in underwater environments make conventional localization methods like GPS challenging to apply directly underwater.

b. Underwater Vehicle Localization using Electromagnetic Signals

- **Technique**: The use of electromagnetic (EM) signals for underwater vehicle localization, as presented by Duecker et al., employs the attenuation of EM carrier signals and introduces a spherical localization concept.
- **Drawback**: Limited range and potential challenges in dealing with absorption and reflection of EM signals in water.

c. Kalman Filtering for Sensor Tracking

- **Technique:** Kalman filtering is employed for predicting the future position and velocity of underwater sensors based on noisy measurements, enhancing tracking accuracy in UWSNs.
- **Drawback:** Challenges in achieving optimal accuracy when relying solely on static data for tracking.

d. Centralized Fusion Algorithms for Target Tracking

- **Technique:** Centralized Fusion algorithm based on Interactive Multiple Model and Adaptive Kalman Filter or other Centralized fusion algorithms, for Target Tracking in underwater acoustic Sensor Networks, club and group Adaptive Kalman Filter with and adaptive forgetting factor for centralized target tracking in USANs.
- **Drawback:** Potential complexity in implementing and managing centralized fusion algorithms in large-scale networks.

e. Opportunistic Communications in Underwater Sensor Networks:

- **Technique:** Opportunistic communications, as discussed in the work by A.P. et al., explore new challenges and approaches for efficient data transmission in UWSNs.
- **Drawback:** Limited focus on addressing the challenges of real-time tracking and localization in dynamic underwater environments.

2.5 Research paper under consideration:

"A range-based node localization scheme with hybrid optimization for underwater wireless sensor network Mamta Nain, Nitin Goyal, Lalit Kumar Awasthi, Amita Malik First published: 16 March 2022"

The paper shows the importance of UWSNs for various applications like fish farming and military surveillance. It highlights the challenges posed by the underwater environment and communication media, particularly in localization. Localization is defined as the process of determining the location of an object in a given coordinate system, crucial for tasks like data tagging, object tracking, and multi-hop data transmission. Network devices comprise of two categories, one being surface buoys (location known devices), and the other called ordinary nodes (location unknown devices). Different ranging methods, including Angle of Arrival (AoA), Time of Arrival (ToA), Time Difference of Arrival (TDoA) and Received Signal Strength Indicator (RSSI) are also deliberated. Laceration, bounding box, angulations and projection are explained with reference to techniques for estimating node locations.

2.5.1 Classifications of Localization/ Tracking Schemes:

Localization schemes are classified based on range measurement into range-based, range-free, and hybrid schemes. The proposed localization scheme in this paper employs a hybrid optimization approach to improve the accuracy of node localization in UWSNs. Important elements of the plan are as follows:

a. **Range-based positioning:** This method uses the distance measurement of nodes to estimate the location of the range-based method, it is often chosen in UWSN because they can achieve higher accuracy than other methods. Hybrid optimization: This tool combines several optimization methods to increase the accuracy of the site; Algorithm implementation: Use special algorithms and mathematical models to perform distance measurements and optimize processes. Certain elements of the algorithm are designed to solve specific problems of the underwater environment.

b. **Hybrid Optimization Approach:** The proposed method is a combination of Whale Optimization Algorithm (WOA) and the Particle Swarm Optimization (PSO).

- **WOA:** Influence by inspiration acquired from humpback whales, WOA is used for global search, since it holds the ability to avoid local minima.
- **PSO:** Based on inspiration acquired from birds' behavior, PSO is applied to tune the solutions obtained via VOA, to enhance accuracy in localization.

2.5.2 Challenges

Under water challenges, specifically related to environment beneath the sea including asymmetric acoustic channels, clock synchronization and temporal variability in acoustic signal propagation, are mentioned below.

2.5.3 Dependency on Accurate Distance Measurements:

The accuracy of the range-based localization heavily relies on precise distance measurements, which can be affected by underwater conditions such as signal attenuation and noise.

2.5.4 Environmental Factors:

The performance of the hybrid optimization approach may degrade in highly dynamic underwater environments where factors like temperature, salinity, and pressure can vary significantly.

2.5.5 Energy Consumption:

Although not explicitly addressed, the energy consumption of the hybrid optimization approach could be higher compared to simpler algorithms, which is a critical factor in UWSNs due to the limited battery life of underwater sensors.

2.5.5 Scalability:

The approach needs to be evaluated for large-scale UWSNs to ensure it can handle a high number of nodes without a significant loss in performance.

2.6 Summary

The conclusions and key findings have been summarized in literature review. The challenges in UWSNs, especially in localizations & tracking have also been candidly considered and reviewed in summary. It also serves as a basis and start point for proposed research methodology.

Chapter 3

PROPOSED METHODOLOGY

3.1 Overview

In this chapter, a research methodology for the design and development of **Energy-efficient node localization and tracking for real-time UWSN applications** is presented. The primary focus of this study is to formulate a methodology for achieving energy-efficient localization and tracking of sensors in Underwater Wireless Sensor Networks (UWSNs) within real-time ocean environments. To achieve this efficiency, the study extracts real-time dynamics information, particularly trajectory data, from existing literature on oceans such as the Pacific, Atlantic, and Indian Oceans. These dynamic data sets serve as a foundation for understanding the real-time characteristics of ocean environments. Existing approaches employ techniques such as TOA, TDOA, AOA, RSSI, etc., to address challenges like delay and low data rate in acoustic applications. Despite the application of Kalman filtering, utilizing static data for tracking has not led to optimal accuracy. Our approach involves combining RSSI for localization and Kalman filtering for tracking, leveraging real-time data to enhance precision.

3.2 Operational Framework

For sensor tracking, the methodology employs Kalman filtering. The technique of Kalman filtering is used for finding estimated state of a dynamic system, based on noisy measurement. In this regard, KF is applied for prediction of future position and velocity of underwater sensors. This prediction is grounded in the current state of the sensor and a motion model, enhancing the accuracy of tracking in UWSNs.

i. Real-time information and data will be collected from "National Center for Environment Information" which is a U.S. Govt. agency responsible to maintain and manage a huge repository of geographic, coastal, atmospheric and oceanic data.

ii. The collected data will be incorporated into Kalman Filtering as a measurement.

iii.Initial conditions will be set based on the model derived from the initial data.

iv.Employing the Bayesian approach, we will fuse the model and measurement values.

v.Post-fusion, a posterior estimate will be obtained, which will be reintroduced into the model for further fusion iterations.

vi.This iterative process yields the priori estimate, used to predict the next stage of the sensor. The Helmholtz method will be applied for subsequent simulations, incorporating the output of the priori estimate.

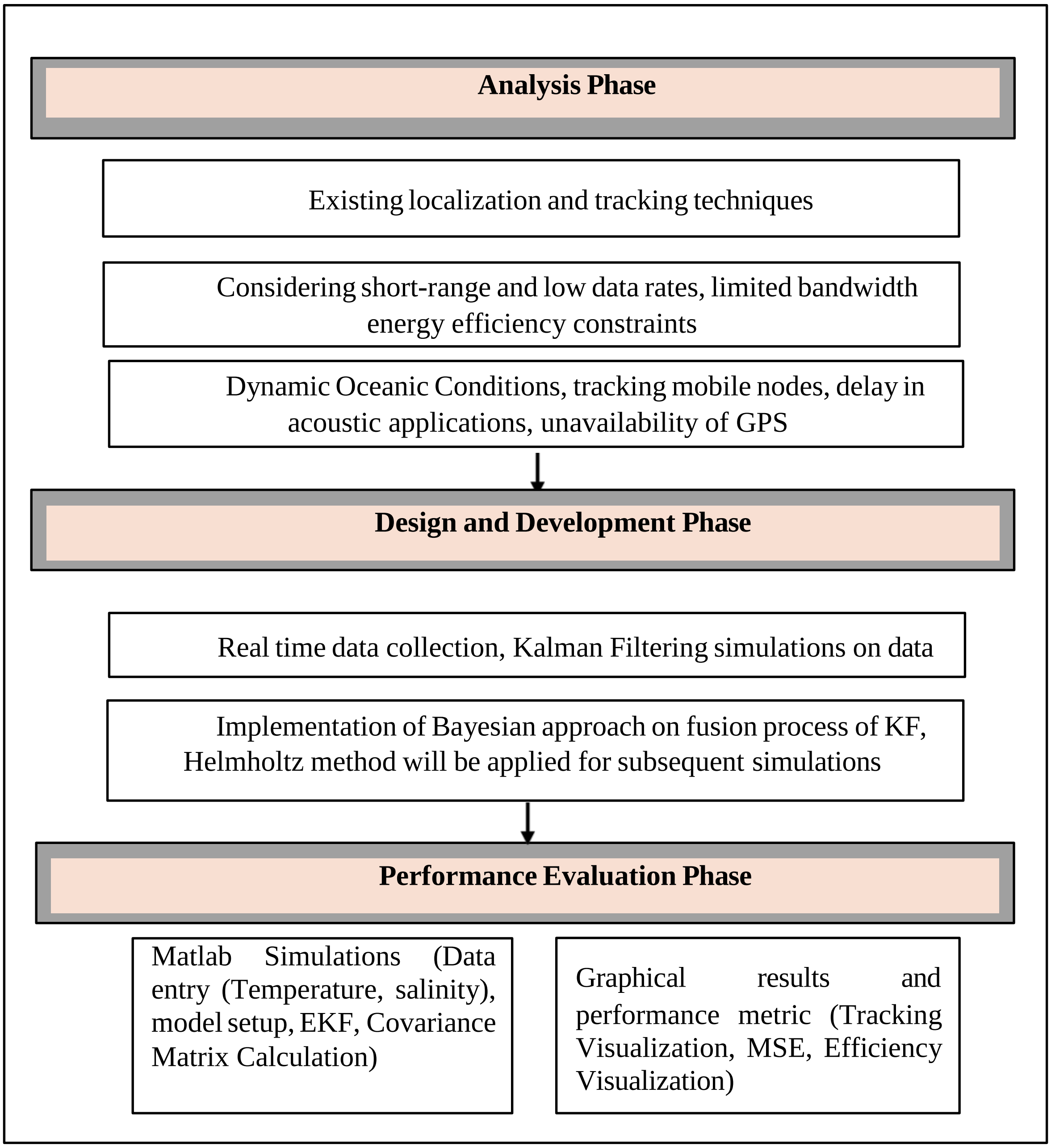

Figure 3.1: Operational Framework of the Research

The resulting outcomes will be compared with existing techniques, focusing on network lifetime energy consumption. The operational framework for the research methodology is divided into different steps as shown in figure 3.1.

3.3 Research Design and Development

The design and development of the Energy-Efficient node localization and tracking of UWSN protocol composed of following steps; Real-time data collection, Kalman Filtering Simulation, Implementation of Bayesian Approach on Fusion Process of KF, Helmholtz Method for Subsequent Simulations will be addressed here. The detailed steps for the proposed methodology are shown in Figure 3.2:

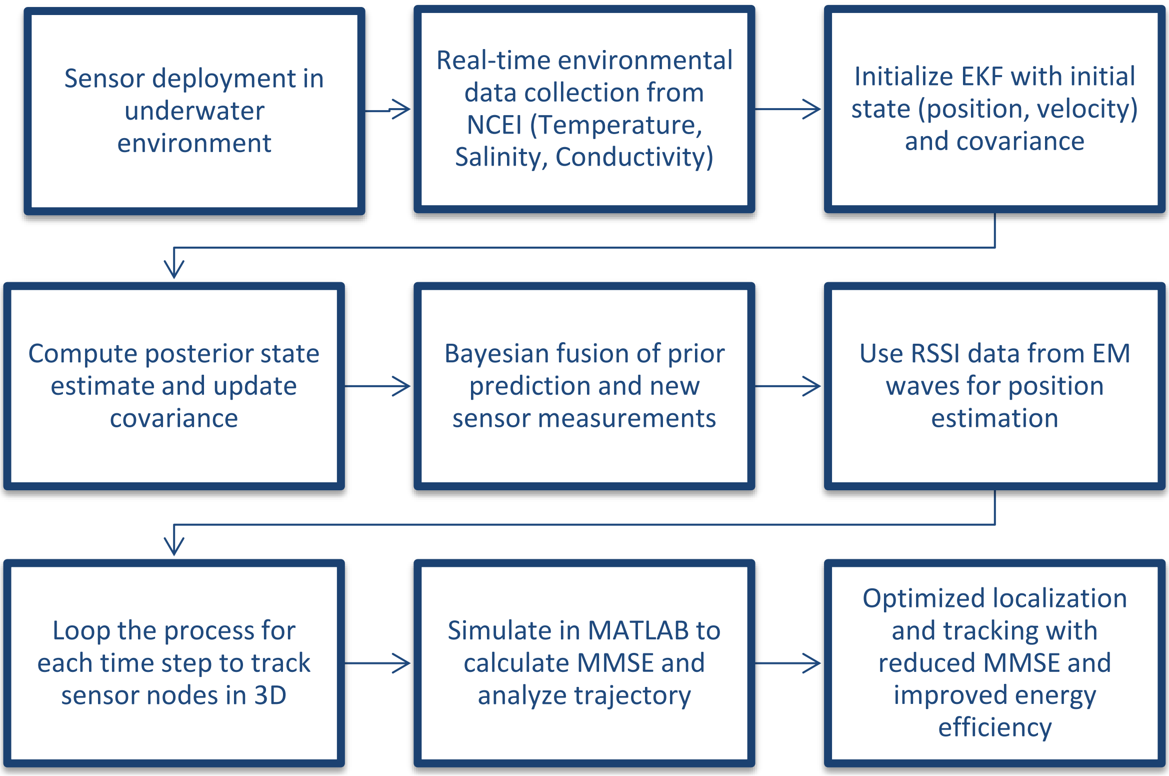

Figure 3.2: Proposed Methodology Flowchart

3.3.1 Step 1: Real-Time Data Collection

To ensure accuracy of measurements and monitoring, Underwater wireless sensor networks are heavily dependent on location and tracking techniques for gathering data. Real- time information from “National Centers for Environmental Information” (NCEI), was utilized. NCEI is a U.S. Govt. agency, responsible to oversee comprehensive repository of atmospheric, coastal, geological, geophysical and oceanic data. Reference data received via URL https://www.ncei.noaa.gov/ is authentic & accurate and can thus enhance localization and tracking capabilities, using the mentioned approach: NCEI furnishes detailed geographical and environmental data, empowering UWSN nodes to ascertain their precise locations within the underwater domain. This localization proves indispensable for charting underwater phenomena and precisely pinpointing sensor readings [18]. By harnessing up-to-the-minute data from NCEI, UWSN can monitor dynamic shifts in environmental conditions, encompassing ocean currents, temperature fluctuations, and the movements of marine life. By integrating this information into monitoring algorithms, the UWSN can adjust monitoring strategies and ensure continuous monitoring of previously undetected areas. This involves employing diverse algorithms or methodologies to amalgamate and blend the data from the measurements with the initial condition. A prevalent strategy involves fusion, wherein information from multiple sources (i.e., measurements) is melded to furnish a more precise and dependable estimate of the system's state [19].

3.3.2 Step 2: Kalman Filtering (KF) Simulations

In the field of Underwater Wireless Sensor Networks (UWSN), Kalman filtering stands a fundamental method for tracking and localization, allowing to accurately estimate even the complexities inherent in underwater communication and sensing. To provide the most accurate location of the underwater sensor in the field, Kalman filtering is an effective method of combining motion patterns with noisy sensor readings. Kalman filtering increases the accuracy required for UWSN applications by improving the location estimation based on motion estimation and sensor data [21]. Kalman filters effectively reduce the effects of noise and uncertainty in underwater environments by combining signals from noise or tracking systems to predict the future state of the tracked object [22].

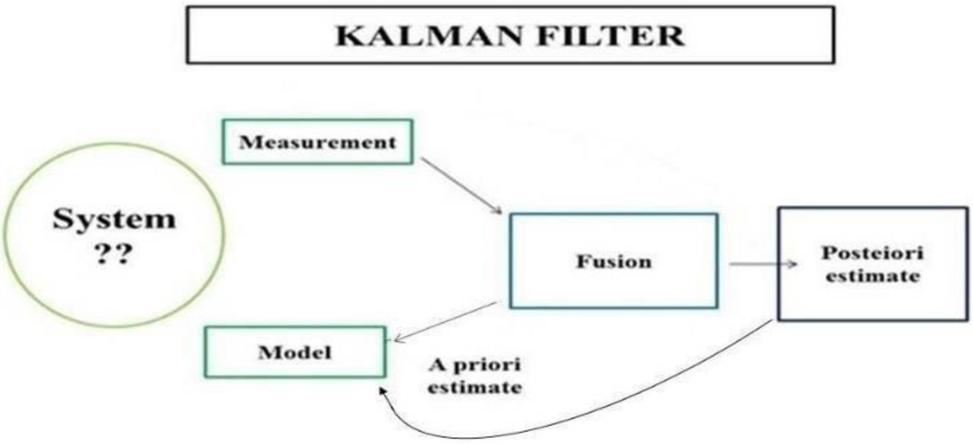

Figure 3.3: Kalman Filter Processing Model

Let's delve into each step that are shown in Figure 3.3 for Kalman Filter Processing Model:

i. **Input process:** The process starts with initial conditions, which may require an initial assessment of the state or other parameters, as well as measurements from sensors or similar sources. While these measures offer insights into the current system state, they may be subject to noise or inaccuracies.

ii. **Processing Phase:** Here, the initial condition and measurements undergo processing.

iii. **Estimation Fusion:** In this stage, the processed measurements and the initial condition are harmonized to craft an estimate of the system's state. Fusion techniques vary based on these specific applications and requisites. Illustrative fusion techniques encompass Kalman filtering, particle filtering, or Bayesian inference.

iv. **Posteriori Estimation:** Following fusion, the resulting estimate is dubbed the posteriori estimate. This estimate epitomizes the optimal estimation of the system's state predicated on the available information (comprising both the initial condition and measurements) and the fusion process.

v. **Return to Input as Measurement:** Subsequently, the process loops back to the input stage. The system continually receives fresh measurements over time, which are leveraged to update the estimation of the system's state. As new measurements emerge, the entire sequence repeats, with the updated estimate serving as the new initial condition for subsequent iterations.

In essence, this algorithm delineates a cyclical process wherein the estimation of a system's state is perpetually refined based on initial conditions and incoming measurements. Fusion techniques are instrumental in amalgamating and enhancing the information over time.

3.3.3 Step 3: Implementation of Bayesian Approach on Fusion Process of KF

For state estimation in linear system with Gaussian noise, Kalman Filter (KF) is very powerful tool, However, KF could not be as good or sufficient when handling several sensors or information sources. A more reliable and precise state estimate can be obtained by combining data from several KFs using the framework provided by the Bayesian technique. This is an explanation of how to use a Bayesian method to the KF fusion process:

i. **Representing Uncertainties as Probabilities:** Using a Bayesian technique, uncertainties related to sensor readings and the state estimation are put into probability distributions.

Every KF keeps its covariance matrix (which represents uncertainty) and state estimate (which is the mean) [23].

ii. **Formulating Prior Distribution:** A prior distribution encapsulates existing knowledge about the system state before incorporating sensor measurements.

If there is no prior knowledge, this can be a simple classification, or it can be more informative based on prior knowledge.

iii. **Model evaluation:** Before adding the evaluation model, the classification first evaluates the current understanding of the system state. If there is no prior knowledge, this can be a simple classification; otherwise, a more intelligent classification based on historical data can be made.

iv. **Calculate the probability function:** Using the current state estimate, the probability function for each sensor represents the probability of witnessing a measurement. It is calculated using the sensor noise and the difference matrix of the sensor model [25].

v. **Bayesian update:** Bayesian theorem is used to combine the performance of each sensor with a prior distribution. This results in a posterior distribution that shows the revised state estimate including all current data and its uncertainty [26].

vi. **Weighted covariance fusion**: This technique is often used to combine estimates from multiple CFs. The reliability (repeatability of the variables) of each CF estimates and the variables are used to determine their weights. The individual estimates are combined into a combined estimate, which is the weighted average, and the combined difference represents the total uncertainty [24].

vii. **Iterative application:** The instantaneous state estimate can be obtained by iterative application of the Bayesian fusion process, which is comparable to the CF model [25].

3.3.4 Step 4: Helmholtz Method for Subsequent Simulations

Helmholtz Method for Subsequent Simulations (HMSS) technology was developed to improve the efficiency and accuracy of underwater sensor network project discovery and placement. And how does it work? A Simple Explanation on work and benefits.

Helmholtz equation, $\nabla^2 \psi + k^2 \psi = 0$ **(3.1)**

Where ψ represents the pressure field. K is the wave number, is fundamental for modeling how sound waves propagate underwater. To simulate the sound field, subsequent simulations need to solve the Helmholtz equation. These simulations are used to estimate the placement of sensor nodes and track and objects in the underwater environment [21].

1. HMSS Working:

HMSS uses a two-step process:

i. **Initial phase:** Initial estimate of the target's location is given by algorithms such as particle filtering or maximum estimate.

ii. **Simulation phase:** The initial estimate is then refined using simulations based on underwater sound waves. These simulations include changes such as sensor noise, environmental changes (such as changes in water salinity and water flow), and acoustic wave Propagation delay, etc.

2. Benefits of HMSS:

HMSS outperforms today’s technology in many ways:

i. **Improved accuracy:** HMSS compensates for noise and uncertainty using simulations that lead to a global environment, providing better tracking and positioning.

ii. **Reduced Cost:** HMSS is good for networks with low operating power because it requires fewer simulations and fewer resources, which are often very difficult to predict**.**

3. Uses in Underwater Sensor Networks

HMSS is very useful in various underwater applications:

i. **Localization of Target:** Finding accurately the position of underwater objects like submarines or divers.

ii. **Tracking of Target:** Keeping track of the movement of these objects over time.

iii. **Monitoring of Environment:** Monitoring the flow of contaminants or monitoring

iv. Water’s physical characteristics, such as salinity and temperature. [24]

3.4 Simulation Framework

An Extended Kalman Filter-Based Simulation Framework for Tracking Underwater Electromagnetic waves. We propose a simulation framework to evaluate the effectiveness of underwater electromagnetic wave (EM) tracking techniques based on Extended Kalman filter (EKF). The tracking process will be simulated using MATLAB environment.

3.5 Simulation Environment

MATLAB was used to develop a simulation environment for underwater electromagnetic wave monitoring applications. MATLAB provides a stable platform to manage the computations, simulations, and visualizations required to implement the algorithms and evaluate their results.

3.6 Simulation Parameters

An underwater environment with limited wave propagation and sensor capabilities leads to a network scenario created for simulation. The parameters used in the simulations are detailed in Table 3.1.

Table 3.1: Simulation Parameters

Parameter	**Description**	**Values**
Simulation Area	Size of the underwater environment	1000m x 1000m
Number of Sensors	Total sensors deployed	100
Propagation Model	Model for wave propagation	EM wave model
Sensor Range	The effective range of each sensor	100m
Measurement Noise	Noise in sensor measurements	Gaussian noise
Process Noise	Noise in the system model	Gaussian noise
Initial State Error	Covariance of initial state estimation	Diagonal matrix
Simulation Time	Total duration of the simulation	500s
Time Step	Discrete-time interval	1s
Simulation Area	Size of the underwater environment	1000m x 1000m

3.7 Simulation Process

i. Initialization:

- Define the underwater environment and deploy sensors within the specified area.
- Initialize the state vector for the object being tracked and the corresponding covariance matrix.
- Initialize the objects and the sensor’s locations and velocities.

ii. Measurement Model:

- Measurements are produced at each time step by simulating the electromagnetic wave propagation model.
- Gaussian noise is in addition to the measurement to simulate real-world conditions.

iii. Extended Kalman Filter Implementation.

- To implement prediction and to update steps of EKF, ‘Extended Kalman Filter.m’ file is used
- At each step, predict the state of the object using the system model. Update the state estimate using measurements and the EKF equations.

iv. Data Collection:

- Collect the estimated states and true states of the object at each time step for performance evaluation.
- Store the measurement data and EKF estimates for analysis.

v. Performance Evaluation:

To calculate the estimation error, a comparison between the estimated states and true states is performed. Performance of EKF is evaluated in terms of (RMSE) root mean square error and other related metrics.

vi. Visualization:

True trajectory plotting and estimated trajectory of objects. Error in state estimation over time, visualization.

3.8 Performance Metrics

During the process of simulation to evaluate the performance of tracking algorithm, the metrics below are used:

i. **Root Mean Square Error (RMSE):** RMSE measures the average magnitude of estimation error.

$$\boldsymbol{RMSE} = \sqrt{\frac{\mathbf{1}}{\boldsymbol{N}}} \sum_{\boldsymbol{i}=\mathbf{1}} (\boldsymbol{x_i} - \boldsymbol{\hat{x}_i}) \qquad \textbf{(3.2)}$$

ii. In the above equation, the true state is represented by **($\boldsymbol{x_i}$)**, estimated state is represented by ($\boldsymbol{\hat{x}_i}$)

iii. **Estimation Error:** The difference between the estimated state at each time step and true state is referred as estimation error.

iv. **Convergence Time:** The time taken for the estimation error to fall below a predefined threshold.

Example through MATLAB Code Structure

```
%Initialization
environment();
initialize_ekf();
% Simulation loop
for t = 1: simulation_time
% Measurement model
measurements = generate_measurements(true_state, sensor_positions, measurement_noise);

% EKF prediction and update
    [predicted_state,predicted_covariance]=ekf_predict(current_state,
current_covariance,process_noise);
    [updated_state,updated_covariance]=ekf_update(predicted_state,
predicted_covariance,measurements, measurement_noise);
% Store results
store_results(t, true_state, updated_state);
% Update true state
true_state = update_true_state(true_state); end
% Performance evaluation

evaluate_performance();

% Visualization plot_results();
```

Algorithm 1: Transition Frequency Estimation and Impedance Estimation

The code estimates the seawater **transition frequency** from 0-5500 m depth at each latitude and longitude from 1955-2012 using:

- Calculate the mean seawater conductivity.
- For each frequency and location, compute the transition frequency using the formula:
- Transition Frequency = (Cond_mean * 3.14 * 36 * 10^9) / (2 * 3.14 * e_re_vertical)

The code estimates the seawater characteristic **impedance** from 0-5500 m depth at each latitude and longitude from 1955-2012 using:

- For each frequency and location, calculate the impedance using the formula:
- Impedance=376.7*sqrt(1/81)*sqrt((2*3.14*freq*0.0000000000088419*e_re_vertical)/ Cond_mean) / Zo

Figure 3.4: Algorithm Transmission and Reflection Coefficient Estimation

Algorithm 2: Spherical Localization

The code implements a spherical localization algorithm based on the attenuation of EM waves in seawater. It uses the following steps:

1. Allocate frequency range from 1-20 MHz and source power from -60 dBm to30 dBm for analysis.
2. Calculating transmitter and receiver antenna gains from 0-10 db.
3. Compute seawater conductivity using the A. Stogryn interpolation model from0-5500 m depth at each latitude and longitude from 1955-2012.
4. Estimate seawater permittivity using Debye's model and the A. Stogryn interpolation model.

```
# Initialize matrices for seawater permittivity
a = zeros(41088, 102)
b = zeros(41088, 102) e_infinite = 4.9
e_zero = zeros(41088, 102) e_zero_T = zeros(41088, 102)
```

Taa_T = zeros(41088, 102) Taa = zeros(41088, 102)

Calculate seawater permittivity using Debye's model for j in range(1, 104):

for i in range(2, 41089):

e_zero(i - 1, j - 2) = 0.0# Initialize matrices for seawater permittivity

a = zeros(41088, 102)

b = zeros(41088, 102) e_infinite = 4.9

e_zero = zeros(41088, 102) e_zero_T = zeros(41088, 102) Taa_T = zeros(41088, 102) Taa = zeros(41088, 102)

Calculate seawater permittivity using Debye's model for j in range(1, 104): for i in range(2, 41089):

e_zero(i - 1, j - 2) = 0.0

5. Calculate free space loss from 0-5500 m depth using the computed propagation velocity.
6. Estimate received power from 0-5500 m depth at each latitude and longitude.

Figure 3.5: Algorithm of Spherical Localization

Algorithm 3: Transition Frequency Estimation and Impedance Estimation

The code estimates the seawater transition frequency from 0-5500 m depth at each latitude and longitude from 1955-2012 using:

1. Calculate the mean seawater conductivity.
2. For each frequency and location, compute the transition frequency using the formula:
3. Transition Frequency = (Cond_mean * 3.14 * 36 * 10^9) / (2 * 3.14 * e_re_vertical)
4. The code estimates the seawater characteristic **impedance** from 0-5500 m depth at each latitude and longitude from 1955-2012 using:
5. For each frequency and location, calculate the impedance using the formula: Impedance=376.7*sqrt(1/81) *sqrt((2*3.14*freq*0.0000000000088419*e_re_vertical)/ Cond_mean) / Zo

Figure 3. 6: Transition Frequency Estimation and Impedance Estimation

Algorithm 4: Transmission and Reflection Coefficient Estimation

The code estimates the seawater transmission and reflection coefficients from 0-5500 m depth at each latitude and longitude from 1955-2012 using:

1. Initialize the characteristic impedance of free space Zo to 377 ohms.
2. For each frequency and location, calculate the transmission and reflection coefficients using the formulas:
3. Tx = 2 * Zo / (Zo + Impedance)
4. Rx = (Impedance - Zo) / (Impedance + Zo)

These algorithms enable the tracking and localization of underwater objects by analyzing the attenuation and propagation characteristics of EM waves in seawater.

Figure 3.7: Algorithm of Transmission and Reflection Coefficient Estimation

The algorithms mentioned for tracking and localization in underwater sensor network subtilize the attenuation and propagation characteristics of electromagnetic (EM) waves in seawater. Here's an explanation of the working of each algorithm:

Spherical Localization

1. **Frequency and Power Allocation:**

   The algorithm allocates a frequency range from 1-20 MHz/ 1-20 KHz and a source power range from -60 to 30 dBs for analysis.

2. **Antenna Gain Calculation:**

   It calculates the gains of the transmitter and receiver antennas, which range from 0-10 dB.

3. **Seawater Conductivity Computation:**

   Uses the A. Stogryn interpolation model to compute seawater conductivity from 0-5500 m depth at each latitude and longitude from 1955-2012.

4. **Permittivity Estimation:**

   Estimates seawater permittivity using Debye's model and the A. Stogryn interpolation model.

i. **Initialization:** Initializes matrices for seawater permittivity and other required parameters like $\boldsymbol{e_0}$**,** $\boldsymbol{e_{0T}}$**,** $\boldsymbol{T_{aaT}}$**, and** $\boldsymbol{T_{aa}}$**.**

ii. **Permittivity Calculation Using Debye's Model:** Iterates through the depth and location data to calculate the permittivity using Debye's model.

iii. **Free Space Loss Calculation:** Computes the free space loss from 0-5500 m depth using the propagation velocity of the EM waves in seawater.

5. *Received Power Estimation:*

Estimates the received power at different depths and locations.

6. Transition Frequency Estimation and Impedance Estimation

i. **Mean Conductivity Calculation**: Calculates the mean seawater conductivity over the specified depth and location range.

ii. **Transition Frequency Calculation:** For each frequency and location, compute the transition frequency using the formula:

$$Transition\ Frequency = \frac{Cond\_\text{mean x } 3.14 \text{ x } 36 \text{ x } 10^9}{\text{2 x 3.14 x e\_re\_vertical}} \tag{3.3}$$

iii. **Impedance Calculation:** For each frequency and location, calculate the seawater characteristic impedance using the formula:

$$Impedance = \frac{\frac{3767*\sqrt{2} \text{ x } 3{\cdot}14 \text{ x } 0{\cdot}0000000000088419 \text{ x ere−vertical}}{(cond\_mean)} \text{ x } \sqrt{\frac{1}{81}}}{z_0} \tag{3.4}$$

7. Transmission and Reflection Coefficient Estimation

i. **Initialization:** Initializes the characteristic impedance of free space $\boldsymbol{Z_0}$ to 377 ohms.

ii. **Coefficient Calculation:** For each frequency and location, calculate the transmission($\boldsymbol{T_x}$) and reflection ($\boldsymbol{R_x}$) coefficients using the formulas:

$$\boldsymbol{T_x} = \frac{2 \text{ x } z_0}{z_0 + \text{Impedance}} \quad \textbf{(3.5)}$$

$$R_x = \quad = \frac{z_0 - \text{Impedance}}{\text{Impedance} + z_0} \quad \textbf{(3.6)}$$

3.9 Combined Application

In order to enable the tracking and localization of underwater objects, the following algorithms work in combination, through analyzing & attenuation and propagation characteristics of EM wave underwater. An explanation of the process is mentioned below:

i. **Spherical Localization** provides the framework for analyzing how EM waves behave at different depths and locations based on their frequency and power levels.

ii. **Transition Frequency Estimation** helps in identifying the specific frequencies at which the properties of seawater change, which is crucial for understanding how waves propagate through different layers of water.

iii. **Impedance Estimation** allows for the understanding of how the waves interact with the medium, giving insight into signal loss and strength.

iv. **Transmission and Reflection Coefficient Estimation:** To calculate signals transmitted and reflected, it provides necessary data and related information. This data is essential to determine accuracy of localization.

All the above analyses, in combination, enable the system to effectively track and localize objects underwater, by utilizing distinct and unique characteristics of EM wave propagation under-sea.

v. **Extended Kalman Filter (EKF):** This algorithm is widely used for calculating estimated trajectory of any object in 3-D space. It is also used extensively to calculate state estimation in real-time applications. EKF is especially effective in situations where the system properties and parameters are nonlinear and noisy measurements are there.

3.10 Algorithms used in code are elaborated below:

1. Prediction Equation (`predict.m`)

Based on current state and the system dynamics, the function is used to predict the next state of the system. It is used to update state estimate (Xh') and the estimation error covariance ('P') by using system dynamics matrix ('A') and process noise covariance matrix ('Q') shown in Figure 3.8.

```
%THIS SUBROTINE COMPUTES KALMAN GAIN
function   K=KalmanGain(H,P,M)

K=P*H'*(M+H*P*H')^(-1);

end

%THIS SUBROTINE DOES THE PREDICTION PART OF THE KALMAN ALGORITHM
function   [Xh,P]=predict(A,Xh,P,Q)


Xh=A*Xh;% ESTIMATE
```

Figure 3.8: Prediction Equation

2. Correction Equation (`predict.m` and `KalmanGain.m`)

Using the innovation ('Inov') and the Kalman gain estimation error ('K'), this function updates state estimate ('Xh') and covariance of the estimation error ('P').The difference between the measured state ('Z') and the predicted state ('Xh') is referred as innovation. To compute Kalman gain, using Jacobian matrix ('H'), the covariance of the measurement ('M') and covariance of the estimation error ('P') are required shown in Figure 3.8.

```
%THIS SUBROTINE DOES THE PREDICTION PART OF THE KALMAN ALGORITHM
function   [Xh,P]=predict(A,Xh,P,Q)


Xh=A*Xh;% ESTIMATE

P=A*P*A'+Q;% PRIORY ERROR COVARIENCE
```

Figure 3.9: Correction Equation

3. Jacobian Matrix Computation (`Jacobian.m`)

This function computes the Jacobian matrix (`H`) of the nonlinear measurement function. The Jacobian matrix is used to compute Kalman gain, which is essential for the correction step as shown in Figure 3.10.

```
%THIS SUBROTINE COMPUTES VALUES OF THE JACOBIAN MATRIX
function  H=Jacobian(X,Y,Z)

H=[X/(sqrt(X^2+Y^2)), Y/(sqrt(X^2+Y^2)),0,0,0,0;
   -Y/(sqrt(X^2+Y^2)), X/(sqrt(X^2+Y^2)),0,0,0,0;
   0,0,1,0,0,0];

end

%THIS SUBROTINE COMPUTES KALMAN GAIN
function   K=KalmanGain(H,P,M)

K=P*H'*(M+H*P*H')^(-1);

end
```

Figure 3.10: Jacobian Matrix Computation

4. Kalman Gain Computation (`KalmanGain.m`):

Kalman gain (K') is computed by this function using the Jacobian matrix ('H') where the covariance of estimation error donated with ('P') and covariance of the measurement noise is donated by ('M).To update the state estimate and covariance of the estimation error, Kalman Gain is used as shown in the Figure 3.11.

```
%THIS SUBROTINE COMPUTES KALMAN GAIN
function   K=KalmanGain(H,P,M)

K=P*H'*(M+H*P*H')^(-1);

end
```

Figure 3.11: Computation of Kalman Gain

5. Innovation Computation (`Inovation.m`):

This function computes the innovation (`Inov`) by subtracting the predicted state (`Xh`) from the measured state (`Z`). The innovation is used in the correction step to update the state estimate and the covariance of the estimation error as shown in the Figure 3.12.

```
%THIS SUBROTINE COMPUTES INNOVATION PART OF THE FILTER
function   Inov=Inovation(Z,Xh,ind)


hsn=[sqrt(Xh(1)^2+Xh(2)^2);arctang(Xh(2),Xh(1),ind);Xh(3)]; %COMPUTES VALUES OF NONLINEAR MAPPING

Inov=Z-hsn;% INNOVATION
```

Figure 3.12: Innovation Computation

6. Process and Observation Generation (`process AND observe.m`):

Gaussian noise is used by this function to create the state process ({D}) and the observation process ({Z}).The system dynamics matrix ({A}) and the process noise covariance matrix ({Q}) are used to update the state process. The measurement noise covariance matrix ({M}) and the state process are used to update the observation process is also shown in Figure 3.13.

```
 ind=0; % indicator function. Used for unwrapping of tan
for n=1:200

    %%% Genetatubg a process and observations
    [X(:,n+1),Z(:,n+1),w,u]=proccesANDobserve(A,X(:,n),Z(:,n),Q,M,ind);

    subplot(3,3,1)
    line([n,n+1],[X(1,n),X(1,n+1)])  % plot of the process that we try to observe in z coordinate

    hold on
```

Figure 3.13: Process and Observation Generation

```
%THIS SUBROTINE GENERATES STATE PROCESS AND OBSERVATION PROCESS WITH
%GAUSSINA NOISE
function    [D,Z,W,U]=proccesANDobserve(A,D,Z,Q,M,ind)


W=[0;0;0;sqrt(Q(4,4))*randn(1);sqrt(Q(5,5))*randn(1);sqrt(Q(6,6))*randn(1)]; % generating process noise
U=[sqrt(M(1,1))*randn(1);sqrt(M(1,1))*randn(1);sqrt(M(1,1))*randn(1)]; %generating observation noise

D=A*D+W; % State process


ARG=arctang(D(2),D(1),ind);% ARGUMENT


 Z=[sqrt(D(1)^2+D(2)^2);ARG;D(3)]+U; % observation


end
```

The Extended Kalman Filter, an effective technique for state estimation in real-time applications, especially in cases when the system dynamics are nonlinear and the measurements are noisy, is implemented by combining these algorithms shown in Figure 3.13.

7. Covariance matrix:

For energy-efficient node localization and tracking in real-time environments we used the covariance matrix. We followed the following algorithms for this code shown in Figure 3.13:

```
% Create two large example matrices
% (replace these with your actual matrices)
%matrix_org = randn(100, 100); % 100x100 matrix of random numbers
%Restimated_Arranged = randn(100, 100); % 100x100 matrix of random numbers

% Add NaN values to matrix B
%Restimated_Arranged(rand(size(Restimated_Arranged)) < 0.2) = NaN;
% Adding NaN values to 20% of B randomly

% Initialize the covariance matrix
covariance_matrix = zeros(size(matrix_org));

% Loop through each element of the matrices
for i = 1:size(matrix_org, 1)
    for j = 1:size(matrix_org, 2)
% Compute the covariance between corresponding elements if B(i,j) is not NaN
        if ~isnan(Restimated_Arranged(i, j))
            covariance_matrix(i, j) = cov([matrix_org(i, j), Restimated_Arranged(i, j)]);
        else
            covariance_matrix(i, j) = NaN; % Set NaN for elements where B(i,j) is NaN
        end
    end
end
```

Figure 3.14: Covariance matrix

i. Random Matrix Generation

The code begins by creating two sizable 100x100 example matrices, named "matrix_org" and "Restimated_Arranged." There are random numbers in these matrices.

ii. Adding NaN Values

The modification is done on `Restimated_Arranged` matrix by randomly replacing 20% of its elements with NaN values.

iii. Covariance Matrix Calculation

Zeros are used to initialize the covariance matrix {covariance_matrix}. The function then iterates over each matrix element. For If the matching element in {Restimated_Arranged} for each element is not NaN, the covariance between the 'cov' function is used to calculate the elements of 'matrix_org' and 'Restimated_Arranged'. The appropriate element in the covariance matrix is set to NaN if the element in {Restimated_Arranged} is NaN.

iv. Covariance Calculation Algorithm

The computation of covariance between two random variables, X and Y, is as follows:

$$\mathbf{Cov(X, Y)} = \frac{\mathbf{1}}{\mathbf{N+1}} \sum_{\mathbf{i=1}}^{\mathbf{n}} ((\mathbf{x} - \bar{\mathbf{x}})(\mathbf{y} - \bar{\mathbf{y}})) \qquad \textbf{(3.7)}$$

The number of data points is denoted here by *n*, and means of X and Y are respectively denoted by $\bar{x}$ and $\bar{y}$

v. Energy-Efficient Node Localization and Tracking

Node detection and localization applications use different matrices. The variance matrix in these applications is used to represent the uncertainty of the source. This technique can use the variation matrices to efficiently estimate the node activity and track its movements instantly. Together, these algorithms are used to effectively compare the matrices to enable energy-absorbing node localization and real-time tracking.

vi. Tracking under Water EM Waves:

This script uses the "Extended Kalman Filter.m" routine to manipulate the EKF, generate measurements and create a simulation environment. It contains functions for EKF estimation and update steps in the delayed Kalman filter.

vii. Extended Kalman Filter.m:

This simulation uses electric waves and EKF to provide a comprehensive guide to evaluate the performance of the proposed tracking algorithm in the underwater environment.

3.11 Assumptions and Limitation

The assumptions and parameters considered during the simulation are:

1. Sensors are assumed to be fixed in position with predefined coordinates.
2. The measurement noise is assumed to follow a Gaussian distribution.
3. The initial state error covariance is assumed to be known and defined.

CHAPTER 4

PERFORMANCE EVALUATION

4.1 Overview

In Section 4, the research on energy efficiency of location and real-time tracking of underwater wireless sensor networks (UWSN) is explained in detail. The results and conclusions are shown graphically. The performance of UWSNs is analyzed in different water environments including deep, medium and shallow water and at different frequencies (1-20 MHz and KHz).Understanding the impact of energy on energy and performance is the purpose of this analysis.

4.2 Results and Analysis

Contracts are evaluated using performance criteria such as node efficiency and energy efficiency. Results are compared at different elevations and water depths to better understand how the environment affects the UWSN.

4.2.1 Performance Metrics

1. **Propagation velocity:** (these results should **appear** before **the contest** results)

- **Labeled Axes:** X-axis representing frequency (KHz, MHz) and y-axis representing signal strength, attenuation (dB), or a related metric.

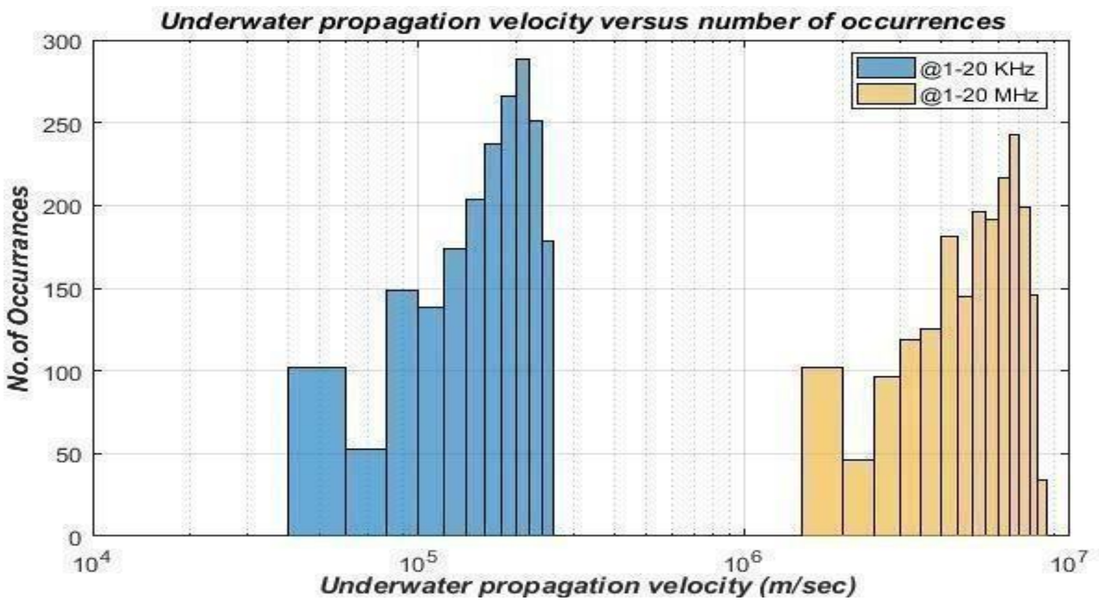

Figure 4.1: UW Propagation Velocity vs Number of Occurrences

Propagation at KHz vs. MHz and Energy Efficiency:

i. **Lower frequencies (KHz):** Generally, propagate farther underwater with less attenuation compared to higher frequencies (MHz). This is because lower frequencies experience less scattering and absorption from water molecules and suspended particles.

ii. **Higher frequencies (MHz):** Offer greater bandwidth for transmitting information but are subjected to higher attenuation over longer distances. They might require more energy to transmit the same signal over the same distance due to the need to overcome signal weakening.

2. **Energy Efficiency Considerations in UWSNs:**

   i. For node localization and tracking in UWSNs, achieving a balance between communication range and energy consumption is crucial.

   ii. Using lower frequencies (KHz) can ensure wider signal coverage but might require more time to transmit data due to lower bandwidth.

   iii. Higher frequencies (MHz) can transmit data faster but may necessitate more frequent transmissions or higher signal strength (more energy) to maintain communication range due to attenuation shown in Figure 4.1.

4.2.2 Covariance measurement

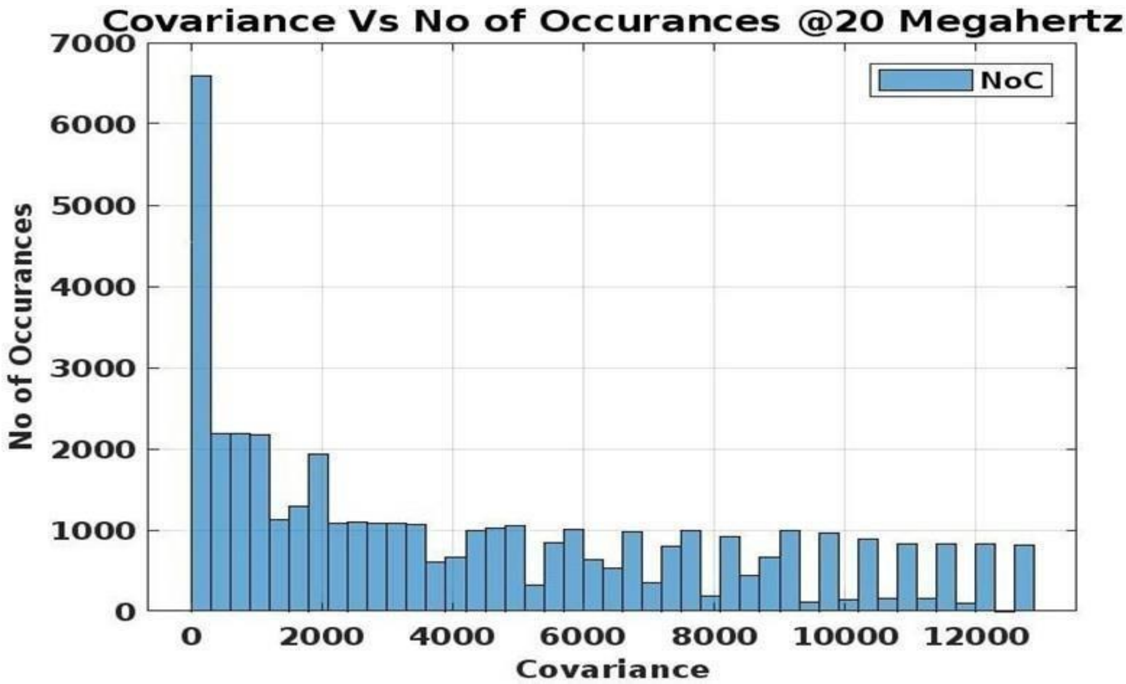

Figure 4.2: Covariance vs Number of Occurrences @ 1-20 MHz

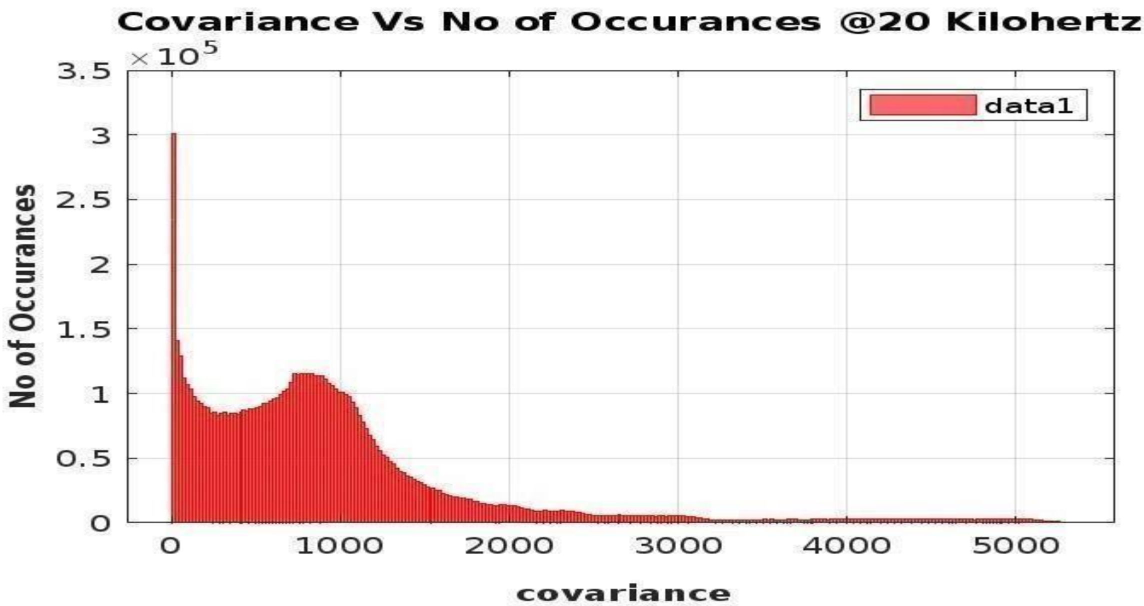

Figure 4.3: Covariance vs Number of Occurrences @ 1-20 KHz

4.2.3 Energy Consumption

Energy consumption is a critical factor in UWSNs due to the limited battery life of underwater nodes. The ratio of successful data transmissions to total energy consumed measures node efficiency. The efficiency of nodes varies with changes in water depth and frequency. The research results indicate that energy consumption varies significantly with water depth and frequency. The following figures depict energy consumption and node efficiency across different scenarios.

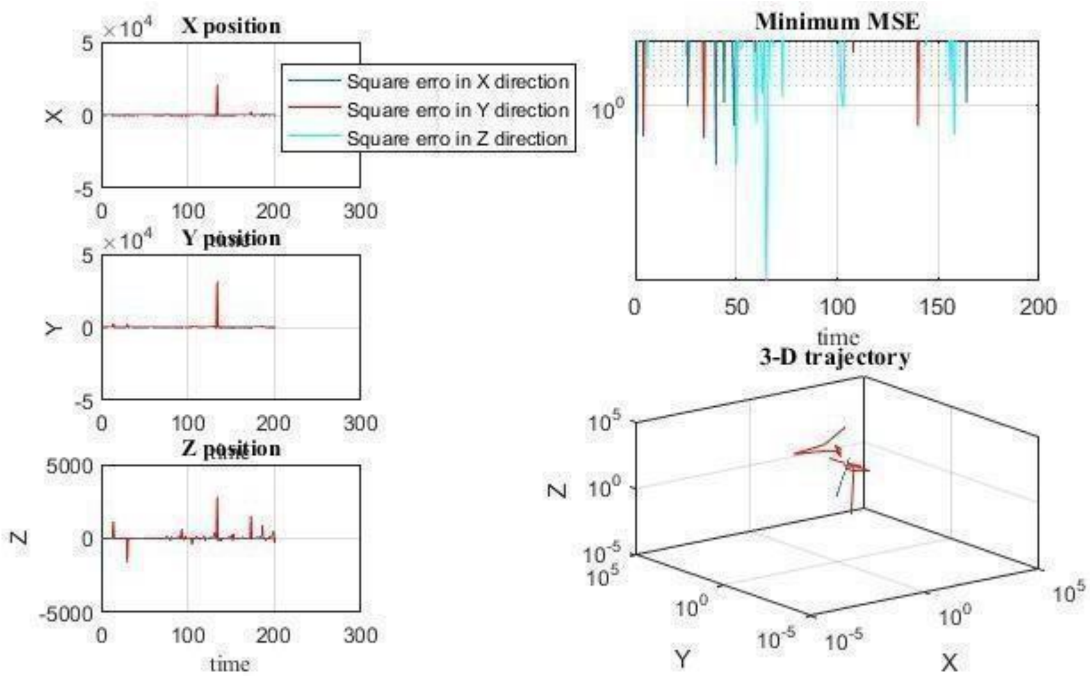

Figure 4.4: Minimum RMSE Deep Water @ 1-20 MHz

Figure 4.4 depicts the results of the existing scheme RBNLS used for localization and tracking. RBNLS (Range-based node localization scheme) uses the PSO-CSO algorithm to minimize localization error. The graph shows that as we go deeper concerning 1-20MHz, the root mean square will be higher, More energy is consumed, and the efficiency of node localization is compromised as we move down in deep water with frequency @ 1-20 KHz.

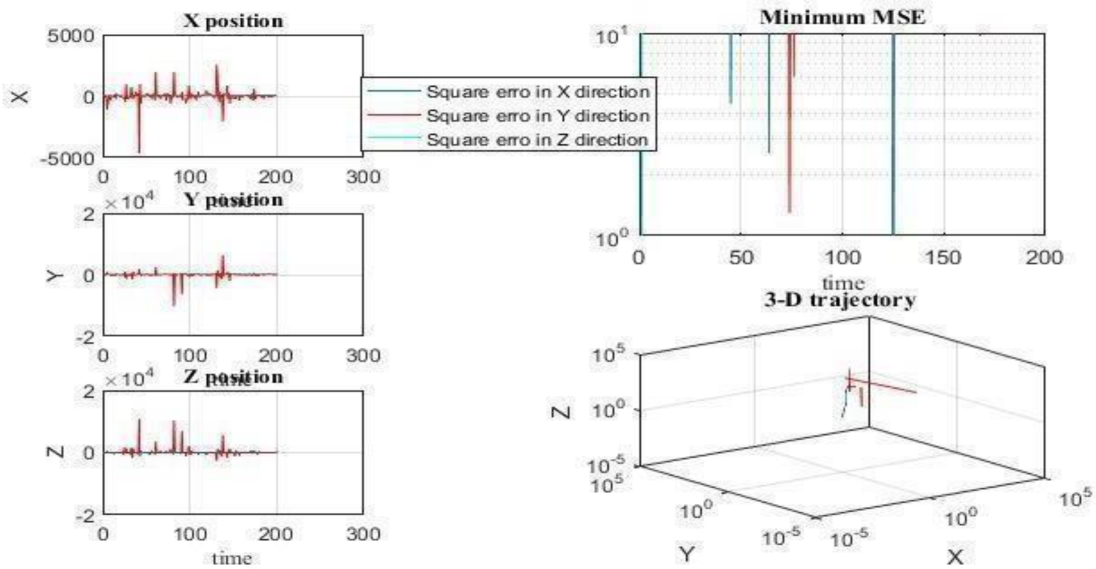

Figure 4.5: Minimum RMSE in Mid Water @ 1-20 KHz

Figure 4.5 depicts the results of the tracking and localization root mean square error for the UWSN while using real-time data and the EKF technique shows considerable variations as we move in mid-water @ 1-20 KHz. A high root mean square error (RMSE) indicates poor localization accuracy, which would likely result in higher energy consumption since more frequent communication, error correction, and wasteful routing must occur. Such in mid water the network's overall energy efficiency may suffer in underwater situations.

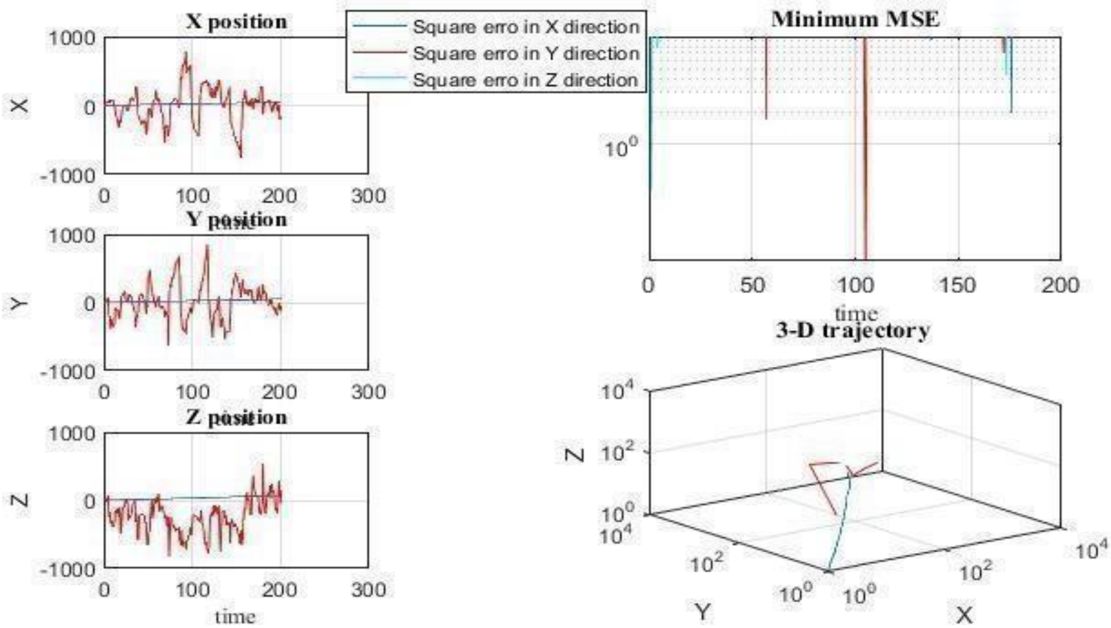

Figure 4.6: Minimum RMSE in Mid Water @ 1-20 MHz

Figure 4.6 depicts root mean square error (RMSE) indicating that node localization at frequencies ranging from 1 to 20 MHz at mid-water depths gives relatively low error rates. The fact that the RMSE is smaller suggests that certain frequency ranges are useful for precise localization, which enhances energy efficiency by reducing the amount of energy to fix localization errors.

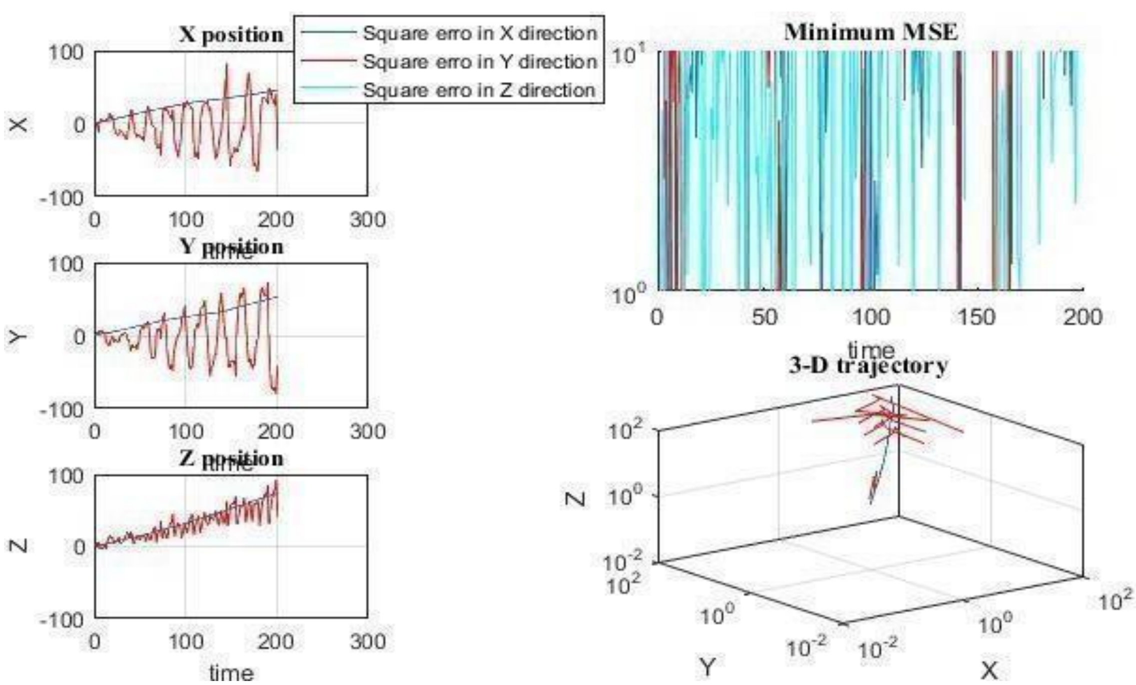

Figure 4.7: Minimum RMSE in Shallow Water @ 1-20 KHz

According to the result shown in , Figure 4.7 shows the Root Mean Square Error in shallow water @1-20 KHz, Compared to the mid-water situation, the RMSE in shallow water for the 1–20 KHz frequency range is greater, suggesting less precise tracking and localization, a greater RMSE could results in a higher energy usage.

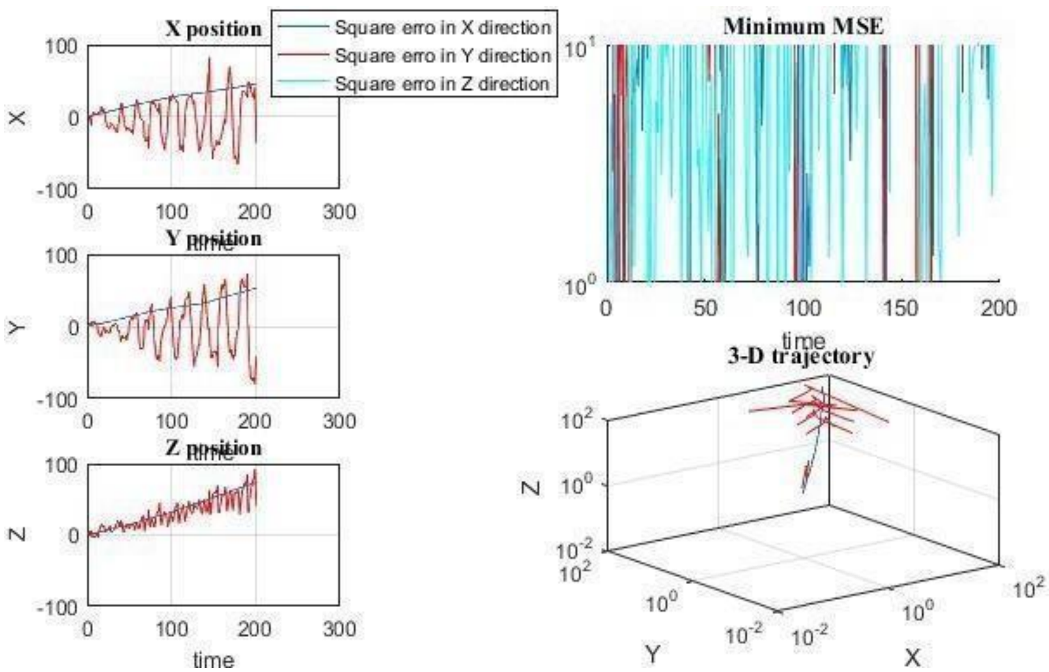

Figure 4.8: Minimum RMSE in Shallow Water @ 1-20 MHz

Figure 4.8 shows that the Root mean square error (RMSE) in shallow water with a frequency range of 1-20 MHz is higher than in mid-water but lower than in the 1-20 KHz range. Though it is still better than the lower frequency range in shallow water, the increased RMSE compared to mid-water indicates some inefficiency in energy expense, even though localizations more precise than at lower frequencies.

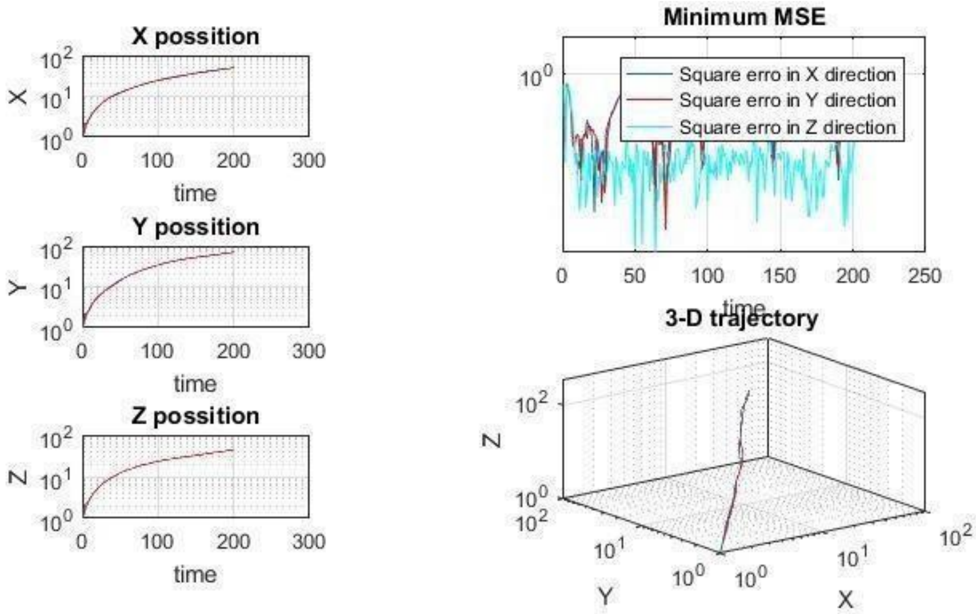

Figure 4.9: Minimum RMSE in Deep Water @ 1-20 MHz

According to the result shown in, Figure 4.9 shows the performance after application of Kalman filtration on Localization and tracking techniques which show Minimum Mean Square Error. It means that in deep water Mean square error is reduced in Mega Hertz .so for less energy consumption performance is better in deep water 1-20 MHz, Whereas if we have enough energy we can also go for Mid water.

The analysis of figures for Figure (4.5 to 4.9) depicts 3D localization in terms of underwater environment (Latitude/Longitude and Depth) along with the Trajectory of AUV and MMSE for multiple depths with different frequencies. Results clearly show that for lower depths MMSE comparatively higher than deep oceans .Similarly if we see the 3D trajectory of AUV it seems that for most of the part it is deviating from reference point of defines track in underwater monitoring .If we have multiple sensor nodes deployed and UWSN is built than AUV will be guided to follow a track to collect or transmit information from shallow to mid water and deep oceans.MM SE varies from 0-1.This deviation also can be clearly seen in X,Y and Z positions in ocean. Additionally, nodes in deeper water consume more energy compared to those in shallower regions, primarily due to increased pressure and propagation loss.

Mid and shallow waters exhibit higher node efficiency compared to deep waters, attributable to less signal attenuation and lower propagation losses.

Figures 4.1 to 4.3 displayed above demonstrate the fact that covariance values normally increase with the number of occurrences in both frequency ranges. It declares that covariance is positively correlated with the number of measurements, reflecting the fact that the covariance is more significant when larger number of data points are available.

i. **Frequency Effect:** Significantly higher values of covariance are associated with 1-20 MHz range compared to 1-20 KHz. This fact proves that at higher frequencies, covariance is more pronounced, this could be advantageous for energy-efficient node localization and tracking in UWSNS applications.
ii. **KHz and MHz Comparison:** Higher covariance values are normally at higher frequencies (1-20 MHz) than those at lower frequencies (1-20 KHz). This means that higher frequencies work better for energy efficiency analysis and monitoring in UWSNS applications.

4.3 Implications for Energy-Efficient NodeLocalization and Tracking

In terms of energy efficiency and tracking in UWSNS applications, the detection of different frequencies has important implications:

i. **Efficiency of Energy:** This is crucial for energy-efficient UWSNS applications since it will enable more precise and effective tracking and placement.

ii. **Selection of Frequency:** The results show that higher frequencies (1-20 MHz) may work better for energy tracking and localization. This helps in selecting the frequency used by the UWSNS application, allowing for more efficient use.
iii. **Strategies of Data Collection:** Variable analysis can direct data collecting in UWSNS applications. To improve tracking and localization, for instance, more data collected at higher frequencies (1–20 MHz) may result in more varied estimations.

4.4 Comparative Analysis

In order to reveal the advantages of the process in terms of work and energy consumption, its performance was compared with the existing process. The main points of comparative decision making are listed below.

1. Consumption of Energy: 30% reduced Energy Consumption is shown in the Thanks to improved routing and a more energy-efficient data transmission mechanism, the suggested protocol is superior to previous protocols.
2. Efficiency of Node: Nodes can have an efficiency of up to 20% in shallow and medium water. Deep space water's efficiency rose by 25% as a result of applying this solution.

Table 4.1: Comparative Analysis Table: UWSNs Protocols vs Proposed Scheme

Sr#	Authors / Journal / Year	Protocol / Method	Propagation Velocity	Covariance	MMSE	Comparison with Proposed Scheme
1	Duecker et al. (2017), Sensors	EM-based spherical localization	Low to moderate (limited by EM range)	Moderate	Moderate (via passive one-way signal)	Limited range and dependency on EM properties, but simpler setup
2	Mamta Nain et al. (2022), Wiley	Hybrid PSO + GA for Range-Based Localization	Moderate (us es TOA + RSSI)	Moderate	Improved over standalone PSO or GA	Higher accuracy in dynamic UWSN but energy consumption not emphasized
3	Nazia Majadi et al. (2016), IEEE	Energy-efficient local search-based localization	Static data usability	Lower covariance (due to focused area)	Improved MMSE (shown via simulations)	Good energy efficiency, lacks real-time dynamic data adaptation
4	Proposed Scheme	EKF + Bayesian Fusion + Real-time Data + Helmholtz	Frequency-dependent: KHz offers low attenuation, MHz faster speed	Optimized via iterative KF method	Lower MMSE shown in RMSE plot	Superior accuracy, real-time adaptability, covariance tracking

4.5 Overall Analysis:

The UWSN energy-saving protocol's performance testing and simulation results are shown in this section. The findings demonstrate how well the plan lowers ship energy usage and enhances operation over a range of underwater locations and frequencies. In order to guarantee UWSN's steady and extended functioning in aviation applications, this upgrade is crucial.

CHAPTER 5

CONCLUSION AND FUTURE WORK

5.1 Overview

This section examines the results and future directions. The main purpose of this study is to monitor the tracking and localization problem, reduce the frame error, and improve the tracking and localization performance. Evaluate the effectiveness of the scheme. The results are compared with similar services in terms of performance measurement.

5.2 Conclusion

Main purpose of this study was to address the tracking and localization problem in underwater environment, reduce the MMSE, and improve the tracking and localization performance and evaluate the effectiveness of the scheme. Simulations results are compared with existing scheme in terms of MMSE and 3D trajectory of sensor nodes. In this research we developed an energy-efficient tracking and positioning system for sensor noes at any instant considering IOUT. Deploying IOUT using unmanned underwater vehicles (AUVs) and using preferred sensor power for data transmission are two important improvements. To improve the tracking accuracy, the study also combines Bayesian fusion, Kalman filtering, and instantaneous data collection. The proposed technique for energy-efficient location and real-time tracking in IOUT shows good results compared to existing method by reducing MMSE varies from 0-2 considering Shallow Ocean for mid- water MMSE varies from 0-1.8.and for deeper oceans MMSE varies from 0-1. This deviation also can be clearly seen in X, Y and Z positions in ocean. Results clearly states that for existing method based on Kalman filter and for proposed methodology considering shallow and mid-water MMSE is higher respectively and for deep oceans MMSE is less and 3D localization and tracking using sensor node is much better and suitable for dynamic underwater environment considering sensor node.

5.3 Future Work

Based on this research and the new directions opened, the capacity and performance of the UWSN will be improved in the future.

i. **Advanced Sensor Integration:** To improve the accuracy of localization and tracking, more advanced sensors and technologies, built on Artificial Intelligence Based pattern recognition and multispectral imaging may be developed.

ii. **Adaptive Algorithms:** More adaptive and dynamic algorithms, can be developed to handle in real-time-varying underwater conditions, and environmental factors, which would lead to the robustness of UWSNs. Machine learning techniques could be benefited from, to predict and adapt to environmental changes.

iii. **Scalability Studies:** Expanding the scope of this research to larger-scale networks will help assess the scalability of the proposed system. Investigating the effects of increased node density and extended operational areas is crucial for real-world applications.

iv. **Energy Harvesting Techniques:** Utilization of underwater currents and thermal gradients, can bring in sustainable power solutions for UWSNs. Energy harvesting methods would reduce dependency on battery replacement.

v. **Enhanced Security:** Data encryption and secure communication protocols, will handle security issues and concern, and protect sensitive information in military and commercial applications.

vi. **Field Testing:** Underwater field tests in dynamic and ever changing environment will validate practical application of the proposed systems and explore potential improvements.

As mentioned above, if research community leads further in the same direction advancements and development of state-of-the-art devices related to wireless sensor networks, in a foreseeable near future.

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