Journal of Applied Research and Technology

www.jart.icat.unam.mx

Journal of Applied Research and Technology 23 (2025) 252-265

Original

Enhanced secure path selection model for underwater acoustic sensor networks using advanced machine learning and optimization techniques

S. Palanivel Rajan[a]* • R. Vasanth[b]

[a]*Department of Electronics and Communication Engineering, Velammal College of Engineering and Technology (Autonomous), Madurai - 625009, Tamilnadu, India*
[b]*Department of Computer Science and Engineering, Faculty of Engineering and Technology, Jain Deemed to be University, Jain Global Campus, Kanakapura Road, Ramanagara District-562112, India*

Received 09 05 2024; accepted 10 21 2024
Available 06 30 2025

Abstract: The underwater acoustic sensor network is a large network consisting of many operating sensor nodes that surround a transmitting node. The communication process faces substantial disturbances caused by the ever-changing nature of the underwater acoustic channel, which is characterized by fluctuating properties in both time and location. Therefore, the underwater acoustic communication system has difficulties in reducing interference and improving communication efficiency and quality by using adaptive modulation. This work presents a model that aims to tackle these difficulties by suggesting an optimum route selection and safe data transmission approach in UASN using sophisticated technology. The suggested approach for transferring safe data in UASN via optimum route selection consists of two main stages. Nodes are first chosen based on restrictions such as energy, distance, and connection quality, which are quantified in terms of throughput. Moreover, the process of forecasting energy is made easier by using sophisticated machine learning methods like transformer models. The ideal route is generated using a hybrid optimization technique called enhanced swarm optimization, which combines ideas from particle swarm optimization and genetic algorithms. Afterward, data is safely transported via the most efficient route by using fully homomorphic encryption. Finally, the ESO+ transformer model that was created is tested against established benchmark models, showcasing its strong and reliable performance. The proposed model demonstrates remarkable performance with an accuracy of 95.12%, precision of 94.83%, specificity of 93.65%, sensitivity of 95.28%, false positive rate of 4.72%, F1 score of 94.95%, Matthews correlation coefficient of 94.85%, false negative rate of 4.72%, negative predictive value of 95.15%, and false discovery rate of 5.15% when trained on a learning percentage of 70%.

Keywords: Adaptive modulation, optimal route selection, safe data transmission, enhanced swarm optimization (ESO).

*Corresponding author.
E-mail address: drspalanivelrajan@gmail.com(S. Palanivel Rajan).
Peer Review under the responsibility of Universidad Nacional Autónoma de México.

1. Introduction

Over the last several years, sensor networks have gained significant interest as a potential area of study owing to their wide range of applications in many fields. Routing is a crucial feature in network architecture that plays a vital role in guaranteeing the durability and effectiveness of the network (Khan et al., 2021). As businesses install more sensor nodes, the difficulty of routing increases, especially in situations that include underwater communication. Underwater sensor networks have specific issues that are different from those met by standard terrestrial networks, primarily because of the unique characteristics of the underwater environment (Ramamoorthy & Thangavelu, 2022). In underwater sensor networks, nodes often function on a collective platform, giving priority to optimizing performance rather than ensuring fairness among individual nodes. Furthermore, the connection between the distance of the link, the dependability, and the number of hops becomes crucial, with the preference for multi-hop data transmission generally chosen to enhance energy efficiency (Singh & Gupta, 2022). Notwithstanding these difficulties, underwater audio communication has become an essential tool in several fields, such as weather monitoring, environmental sensing, and marine research (Rajaragavi & Rajan, 2022). Securing the transmission in underwater acoustic sensor networks (UASNs) is a difficult task because of the inherent weaknesses of acoustic channels. The inherent accessibility of the medium makes it vulnerable to interception, while the portability of sensor nodes brings other complications, such as possible security breaches (Anuradha et al., 2022). Therefore, it is essential to create strong systems for the secure transfer of data in UASNs to protect sensitive information and ensure the integrity of the network. While acoustic communication offers benefits, it nevertheless faces problems such as limited bandwidth, time-varying multipath fading, and slower transmission rates compared to electromagnetic radiation (Fazli et al., 2019).

To overcome these difficulties and guarantee dependable communication, it is crucial to include redundancy solutions such as automatic repeat request (ARQ) protocols and forward error correction (FEC) (Palanivel Rajan & Paranthaman, 2019). Nevertheless, these methods meet challenges in establishing efficient data transfer in underwater settings owing to elevated bit error rates (BER) and extended delay (Noorbakhsh & Soltanaghaei, 2022). In underwater environments, traditional ARQ-based protocols like Stop and Wait (S&W) face challenges because of the high bit error rate (BER) and propagation delay that are typical of acoustic channels (Sathya & Sengottuvelan, 2022). This research suggests a new method to address these difficulties by using a transformer model-based energy prediction for selecting the best route and ensuring safe data transmission in UASNs. The suggested approach seeks to improve communication efficiency and overcome the specific problems presented by underwater settings by using sophisticated machine learning methods.

1.1. Problem statement

Table 1 provides a concise overview of the characteristics and difficulties met in previous studies concerning the selection of the best route and the safe transmission of data in UASNs, using various approaches (Chaaf et al., 2021). The TSDBG technique proved superior transmission latency, emphasizing the significance of characterizing players' trust levels via the comparison of other nodes' behavior (Moridi & Barati, 2017). The integration of mobile devices into underwater acoustic sensor networks (UWASNs) using the depth-based routing (DBR) and grey wolf optimization (GWO) algorithm has shown promising results in terms of reducing latency and dead node count (Krishnaswamy & Manvi, 2019). However, more research is needed to fully understand the implications of including mobile devices in UWASNs (Gola & Gupta, 2021). While a separate study proposed a data transmission method that is both energy-efficient and reliable, thereby lowering the amount of communication required and minimizing energy use, accurately forecasting the location of leaks in maritime oil pipelines remains a difficult task (Goutham & Harigovindan, 2021). The DL-HDBT mechanism has successfully created a system with minimal complexity and great efficiency. However, the difficulty of the packet loss ratio persists (Hemavathy & Indumathi, 2021).

Similarly, while there have been advancements in energy efficiency, it is still challenging to create protocols that are both stable and not reliant on certain network configurations (Zhang et al., 2021). An innovative energy-efficient strategy including quality of service-aware routing was used in underwater wireless sensor networks to minimize energy consumption while improving network reliability (Su et al., 2022). However, it remains a challenge to simultaneously address average packet delay and network lifetime. Although CARQ protocols have accomplished relay placement, the issue of managing significant propagation delay persists (Jamshidi, 2019). The use of the fuzzy clustering algorithm resulted in a reduction in the mortality rate of nodes by using a method for selecting cluster heads (Neethu et al., 2022). The edge prediction-based adaptive data transmission algorithm (EP-ADTA) and Mobility prediction optimum data forwarding (MPODF) protocols were designed to achieve a high packet delivery ratio, energy efficiency, and decreased end-to-end latency. Furthermore, a method was proposed to intelligently select modulation schemes in UWA communication systems. This method utilizes a hybrid learning model and energy-balanced reliable clustering for underwater wireless sensor networks (Rajan et al., 2012). The proposed method addresses multiple challenges, but there is still a need for further advancements to reduce redundant data and enhance system efficiency (Wang et al., 2015).

Table 1. Characteristics and difficulties of existing efforts in UASNs using various approaches.

Methodology	Features	Challenges
TSDBG method	Higher transmission latency	Describing players' trust values by comparing the behavior of other nodes
Depth-Based Routing (DBR) and GWO	Reduced delay and dead node count	Incorporating mobile devices into UWASNs
Energy-efficient scheme	Reduced communication overhead and energy consumption	Predicting leak point of marine oil pipelines
DL-HDBT mechanism	Low complexity system with high efficiency	Addressing packet loss ratio
Quality of service-aware routing	Least energy usage with enhanced network dependability	Addressing average packet latency and network longevity
CARQ protocols	Achieved relay location	Controlling large propagation delay
Fuzzy clustering Algorithm	Decreased death rate of nodes	-
Energy-balanced clustering	Reliable and effective clustering	Designing initial clustering algorithms to lower redundant data

1.2. Motivation

The study effort has addressed many shortcomings such as inadequate packet loss ratio, average packet latency, network durability, delay, security, and redundant data via the implementation of the suggested ESO+ transformer architecture. The suggested ESO+ transformer model determines the most efficient route by considering many factors, including energy consumption, distance, and connection quality. Furthermore, the security of the ESO+ transformer model is bolstered by the implementation of the fully homomorphic encryption method. The study on UASN is motivated by the issues presented by energy prediction for selecting the best way, using hybrid optimization algorithms for path selection, and ensuring secure data transfer. Energy prediction is essential for determining the most efficient method for data transmission in an underwater acoustic sensor network (UASN). This decision-making process must consider several factors, including energy availability, distance, and connection quality. Anticipating the energy use of nodes may aid in identifying the optimal route for data transmission that minimizes energy consumption. This study uses transformer models to forecast the energy levels of nodes in UASN. The suggested model employs a hybrid optimization technique known as enhanced swarm optimization (ESO) to choose the most efficient route. ESO integrates two methods, namely particle swarm optimization (PSO) and genetic methods (GA). The objective of this hybrid technique is to enhance the efficiency and efficacy of route selection in UASN. Secure data transfer: Guaranteeing the security of data transmission is essential in UASN to safeguard sensitive information from unwanted access. The suggested approach integrates fully homomorphic encryption to encrypt the data, hence bolstering the security of the sent data.

2. Contribution of the proposed ESO+ transformer model

The suggested approach enhances the process of selecting the best route and ensuring the safe transmission of data in the underwater acoustic sensor network (UASN). This paper presents a new hybrid optimization technique called ESO+ Transformer. The system effectively identifies the best route in a UASN (underwater acoustic sensor network) by considering several constraints such as energy, distance, and connection quality in terms of throughput. Furthermore, a refined fully homomorphic encryption method is created to guarantee the safe transfer of data. By using transformer models for energy prediction, the model can effectively capture temporal dependencies and trends in energy consumption data, resulting in precise forecasts of future energy levels. Data is secured using the enhanced fully homomorphic encryption method, ensuring safe transmission along the best channel. The performance of the proposed ESO+ transformer model has been validated against conventional benchmarks, yielding impressive results. The model achieved an accuracy of 95.12%, precision of 94.83%, and specificity of 93.65%. To summarize, the literature analysis highlights the urgent need for sophisticated methods to tackle the difficulties faced by underwater acoustic sensor networks (UASNs), namely in areas such as modulation selection, energy prediction, route optimization, and data security. Despite notable advancements, there are still deficiencies in attaining the highest level of performance and dependability under dynamic underwater conditions. The suggested techniques, such as transformer model + ESO, for forecasting energy use and ensuring safe transfer of data, show potential in tackling these difficulties. Incorporating PSO and GA into the ESO framework, combined with the use of transformer models, offers novel approaches to improve route selection and optimize data transmission efficiency in UASNs. The core challenge in underwater acoustic sensor networks (UASNs) lies in establishing reliable, secure, and energy-efficient communication despite the constraints of underwater environments. These constraints include high bit error rates, limited bandwidth, and energy consumption, which can impair the network's performance. This study proposes a comprehensive solution by integrating machine learning, optimization techniques such as particle swarm optimization (PSO) and genetic algorithms (GA), and cryptographic methods to tackle these obstacles. The proposed framework aims to enhance both the network's performance and the security of transmitted data.

3. Methodology

3.1. System model

Within a basic UASNs setting, three categories of nodes are considered: principal nodes (P), medium nodes (M), and superior nodes (S). The nodes are represented as P_i, M_i, and S_i, with i ranging from 1 to n. The superior nodes are intentionally positioned in the network with predetermined coordinates, while primary nodes are haphazardly dispersed across the surroundings. Superior nodes possess a greater initial energy of 1J, whereas main nodes have an initial energy of 0.5J. This distribution of energy guarantees a prolonged lifespan of the network. Intermediary nodes act as a connection between the main and superior nodes, starting with an initial energy level of 0.8J. The placement of sensor nodes is stochastic, enhancing the dependability of communication networks. The network has a sink node that has infinite power and energy consumption capabilities, which enables wireless transmission. The distance between nodes is regulated by the signal transmission intensity.

Energy prediction using transformer Model states that the vitality level of each node is prophesied via transformer model based on exact sorts as well as location of the node lN, distance dist and the node type $N_T\colon N_T \in \{P_i, M_i, S_i\}$. Therefore, the three types of nodes like P_i, M_i, S_i set the energy value as mentioned in Table 2.

Table 2. Energy prediction using the transformer model.

Node Type	Target	Energy (J)
Principal nodes ($\boldsymbol{P_i}$)	0	0.5
Medium nodes ($\boldsymbol{M_i}$)	1	0.8
Superior nodes ($\boldsymbol{S_i}$)	2	1

To predict the energy level of each node within the underwater acoustic sensor network (UASN) using a transformer model, we first encode the input features into numerical representations suitable for input to the model. These features include the node's location (lN), distance (dist), and node type (NT). The node type (NT) is represented as a categorical feature and is encoded using one-hot encoding, where NT_i is mapped to a binary vector depending on the node type. For instance, if NT_i represents a normal node (N_i), it is encoded as [1, 0, 0]. Similarly, an intermediate node (I_i) is encoded as [0, 1, 0], and an advanced node (A_i) is encoded as [0, 0, 1]. Additionally, positional encoding is applied to incorporate the sequential nature of the input data. The positional encoding is calculated using sinusoidal functions, where po's represent the position of the node in the sequence and d is the dimensionality of the positional encoding. The transformer model architecture comprises encoder and decoder layers, each containing multi-head self-attention mechanisms and feed-forward neural networks. The output of the final encoder layer is utilized to predict the energy level for each node. During the model training phase, a dataset containing labeled examples of input feature vectors and their corresponding target energy levels is used to minimize a loss function, such as mean squared error, between the predicted energy levels and the target energy levels. Once the model is trained, it can be employed to predict the energy levels for new input feature vectors by inputting the encoded feature vectors into the trained model. Finally, the performance of the model is evaluated using metrics such as mean absolute error or root mean squared error to assess the accuracy of the energy predictions compared to the target energy values for each node type. This process ensures accurate prediction of energy levels for nodes in the UASN, facilitating network optimization and resource management.

3.2. Optimal path selection using the proposed ESO

In the realm of underwater acoustic sensor networks (UASNs), there are many nodes positioned between the transmitter (S) and reception (R) nodes. This study classifies these nodes into three unique categories: regular nodes, intermediate nodes, and advanced nodes. Node selection is conducted by taking into account factors such as energy, distance, and connection quality. The suggested hybrid optimization approach, enhanced swarm optimization (ESO), is used to identify optimum pathways from the selected nodes. The ESO algorithm combines the pelican optimization algorithm with the chimp optimization algorithm to accurately identify the most efficient routes. After determining the most efficient route, data packets are sent along these channels. To guarantee the secure transmission of data, the use of fully homomorphic encryption is used to encrypt the data, hence ensuring the secrecy of the sent information.

3.3. Objective function, energy, and distance

The objective function used to determine the best route is described by Equation (1), where E represents energy, D represents distance, Q represents connection quality, and (α, β, γ) are the weight coefficients. It is important to note that the weight coefficients must satisfy the constraint $\sum W_i = 1$.

$$Obj = min_{\alpha}(E * (1 - D) * Q) \tag{1}$$

This work utilizes the energy consumption model (Wang et al., 2015) to facilitate underwater acoustic data transfer. At the transmitting end, the act of sending data requires a greater amount of energy in comparison to the receiving end. Reducing the energy consumption at the sender side might lead to a decrease in the total energy consumption of the network. Equation (2) expresses the least power needed to transmit l bits of data and the energy used at the sender side. In this equation, δ represents the transmitting delay node, θ(x) is the function associated with the underwater acoustic propagation model, and P represents power.

$$E(l,x) = \delta * \theta(x) * P \tag{2}$$

Equation (3) provides the function associated with the underwater sound propagation model. ω is a variable that is connected to frequency, whereas κ is a parameter that is linked to the underwater acoustic propagation model.

$$\theta(x) = \omega^k * x^k \tag{3}$$

Hence, the energy consumption of each node may be forecasted using the method shown in Equation (4), where η is the energy of the node.

$$E(l,x) = Mean(\eta) \tag{4}$$

To incorporate this technique into a transformer model and enhanced swarm optimization (ESO), the goal function (Muthukkumar & Manimegalai, 2021) and energy consumption equations may be merged into the model's structure and optimization procedure, respectively. The transformer model may be trained to forecast energy use by considering input variables such as distance, connection quality, and node type. Meanwhile, ESO can enhance the selection of the best routes by minimizing the objective function. This integration optimizes route selection in UASNs by taking into account energy usage. This research calculates the distance between nodes in the underwater acoustic sensor network using their coordinates (x_1, y_1) and (x_2, y_2). When constructing the network, 100 nodes are chosen based on thorough consideration of criteria such as energy levels and connection quality. The identification of the shortest route for data packet delivery may be achieved by measuring the distance between certain nodes. The computation of distance is stated in Equation (5).

$$Dist = mean(dis) \tag{5}$$

The variable "dis" denotes the distance between nodes, which is determined using the Euclidean distance formula which is denoted in Equation (6).

$$dis = \sqrt{(x_1 - x_2)^2 + (y_2 - y_1)^2} \tag{6}$$

3.4. Link quality in terms of throughput

This study quantifies connection quality in terms of throughput, which represents the quality of received data packets at the receiver side. Throughput quantifies the total number of system data units processed within a certain period. Equation (7) defines throughput as the ratio of packets received at each node (PR) to the total number of packets (P).

$$Thp^* = \frac{\sum PR}{2P} \tag{7}$$

This equation computes the throughput by aggregating the number of packets received at each node and dividing it by twice the total number of packets.

3.5. Proposed enhanced swarm optimization (ESO) algorithm

This research utilizes the enhanced swarm optimization (ESO) algorithm to determine the most efficient route in a network of 100 nodes in an underwater acoustic environment. A random selection process is used to pick certain nodes from a pool of 100 nodes, considering different limitations, to determine the most efficient route between the sender and recipient nodes (i.e., nodes 1 and 100). The ESO method, which integrates the tactics of particle swarm optimization (PSO) and genetic algorithms (GA), is used to discover the most efficient route for delivering data packets. ESO employs a search strategy that is influenced by the behavior of swarm animals, allowing for independent optimization of the search space.

This approach mirrors the collective intelligence exhibited in swarms. In addition, the ESO method incorporates the particle swarm optimization (PSO) approach to include the collective behavior found in swarms, similar to the optimization technique used in PSO algorithms. This collective intelligence assists in identifying the best possible solutions within given limitations, although they may not be completely optimum. This improves the effectiveness of the whole optimization process. The proposed ESO hybrid optimization method combines the capabilities of PSO and GA techniques to reach the global optimum solution. This methodology guarantees optimal route selection for data transmission in underwater acoustic networks, hence improving the overall performance and usage of network resources.

3.6. Mathematical model of the ESO algorithm

The enhanced swarm optimization (ESO) method is based on the behavior of several elements in a chimp colony, including drivers, chasers, attackers, and barricades. Drivers engage in the pursuit of prey but may not successfully apprehend it, while chasers adeptly follow and promptly capture their target. Assailants anticipate the movement of their targets and collaborate with pursuers, while obstacles hinder the advancement of the targets. These entities function in four unique stages: exploitation, usage, exploration, and sexual drive. During the exploitation phase, the algorithm increases its search efforts in regions that show promise. This is followed by the usage phase when the algorithm uses its prior findings to improve its search. Exploration promotes the algorithm's investigation of uncharted territories, while the sexual drive phase cultivates collaboration and communication among entities. The ESO method enables optimization speed enhancement by combining behavioral variables to strike a balance between exploration and exploitation. The mathematical model for the (ESO) method is as follows. Let P represents the population of search agents, and D represent the dimensionality of the search space. Each search agent is defined by its position vector, denoted as $X_i = (x_{i1}, x_{i2}, \dots \dots \dots . x_{iD})$, which represents a possible solution inside the search space. The velocity vector, denoted as $V_i = (v_{i1}, v_{i2}, \dots \dots \dots \dots v_{iD})$ determines the movement of each search agent in the swarm and effects its location update. For every iteration t, the position update of each search agent i is computed in the following Equation (8).

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \tag{8}$$

Where $x_{id}(t+1)$ is the new position of agent ‘i’ in dimension d, and $v_{id}(t+1)$ is the corresponding velocity component. The velocity update equation (9) for each dimension d and agent i is given by the following Equation 9.

$$v_{id}(t+1) = \omega \,.\, v_{id}(t) + c_1 \,.\, rand_1 \,.\, (p_{id} - x_{id}(t)) + c_2 \,.\, rand_2 \,.\, (p_{gd} - x_{id}(t)) \tag{9}$$

Where, ω is the inertia weight. c_1 and c_2 are acceleration coefficients, $rand_1$ and $rand_2$ are random values between 0 and 1. p_{id} is the personal best position of agent ‘i’ in the dimension ‘d’, p_{gd} is the global best position among all agents in dimension ‘d’.

The personal best position p_{id} and global best position p_{gd} are updated as agents to explore the search space and improve their solutions. The ESO algorithm's ability to explore and exploit is affected by the inertia weight, denoted as ω, which determines the balance between the impact of the preceding velocity and the discrepancy between personal and global best locations. The ESO method successfully explores the search space and improves optimization performance by repeatedly updating the locations and velocities of search agents using these equations, which allow for both exploration and exploitation of interesting areas. The executed pseudocode presents a systematic representation of the procedures included in the Enhanced swarm optimization (ESO) method. This approach integrates the particle swarm optimization (PSO) technique to facilitate exploration and the use of genetic algorithms (GA) to enhance exploitation. The process involves initializing the particles, updating their locations and velocities using particle swarm optimization (PSO), assessing their fitness, and executing genetic algorithm (GA) operations such as selection, crossover, and mutation.

4. Proposed secured data transmission via fully homomorphic encryption

The data packets are transferred between nodes indiscriminately, regardless of their kind. Ensuring the confidentiality and integrity of the data during transmission is of utmost importance. Thus, this study suggests using fully homomorphic encryption (FHE) to encrypt the initial data. Fully homomorphic encryption (FHE) is a strong cryptographic solution that enables computations to be conducted on encrypted data without requiring decryption. This ensures that the secrecy and integrity of the transmitted data are maintained during the whole communication process.

4.1. Fully homomorphic encryption (FHE)

Fully homomorphic encryption (FHE) is an innovative cryptographic method that radically alters the way data may be safely managed. Unlike conventional encryption techniques, which need data to be decrypted before doing calculations, fully homomorphic encryption (FHE) enables computations to be conducted directly on encrypted data without the necessity of decryption. This implies that secret information may stay encrypted during thewhole calculation process, hence maintaining its secrecy and integrity. The encryption process starts by transforming plaintext data using a designated encryption key, which produces ciphertext that seems random and incomprehensible to anyone without the associated decryption key. However, what distinguishes FHE is its capacity to do mathematical operations on the ciphertext directly, without the need to decode it first. By performing calculations on encrypted data, sensitive information is protected and never revealed in its unencrypted state. The consequences of fully homomorphic encryption (FHE) are extensive, with applications across several sectors. Within the realm of secure cloud computing, fully homomorphic encryption (FHE) allows for the safe processing of data on distant servers, while ensuring that the plaintext remains concealed from the server at all times. Similarly, in the field of privacy-preserving data analysis, fully homomorphic encryption (FHE) enables researchers to conduct computations on encrypted data while ensuring the confidentiality of individuals' sensitive information. In the context of private communication systems, fully homomorphic encryption (FHE) may be used to encrypt messages and conduct computations on them without jeopardizing the secrecy of the conversation. FHE is a notable breakthrough in cryptography, providing a robust solution for the secure manipulation and examination of data, all the while preserving the secrecy and confidentiality of sensitive information. Fully homomorphic encryption (FHE) offers a potential solution to meet the specific demands and difficulties faced in the realm of underwater acoustic sensor network (UASN) communication. Ensuring data security and secrecy is of utmost importance in UASN, since nodes function in a demanding underwater setting. This is owing to the possible existence of adversaries and the susceptibility of wireless transmissions to interception. The use of FHE has many benefits that specifically tackle these demands and obstacles. Fully homomorphic encryption (FHE) ensures that data remains encrypted at all stages of the computing process, including storage, transport, and processing. This guarantees the confidentiality and security of critical information, even in the face of hostile individuals or unlawful efforts to get access. Data integrity is maintained by the use of fully homomorphic encryption (FHE), which enables calculations to be carried out on encrypted data. This prevents any unauthorized alterations or tampering of the data. Data integrity is of utmost importance in UASN, as it plays a critical role in guaranteeing the precision and dependability of environmental monitoring and surveillance applications. Fully homomorphic encryption (FHE) allows for safe calculations to be executed on encrypted data without requiring decryption, thereby reducing the possibility of data disclosure or leakage during processing. This is particularly advantageous in UASN, where computational activities such as optimizing routing, aggregating data, and detecting anomalies may be conducted safely without exposing sensitive information. Resource-constrained systems, like UASNs, may have limited processing power, memory, and energy resources. FHE algorithms may be improved to effectively function in such contexts, showcasing adaptability to resource constraints. Fully homomorphic encryption (FHE) offers data security without excessively straining the network infrastructure by reducing the computational cost of encryption and decryption processes. UASN communication is vulnerable to variations in the underwater acoustic channel, which may impact the way signals travel, and data is sent and received. The capacity of fully homomorphic encryption (FHE) to carry out computations on encrypted data regardless of the characteristics of the communication channel makes it resistant to such variations, guaranteeing constant protection and secrecy of data even when the environmental conditions change. In summary, FHE provides a strong and adaptable solution for dealing with the unique demands and obstacles related to UASN communication. It establishes a basis for safe and confidential data interchange and processing in underwater situations.

5. Results and discussion

5.1. Simulation procedure

The suggested approach, which prioritizes safe data transfer by selecting the most efficient route, was executed using MATLAB. The accuracy of energy prediction is assessed by comparing the transformer model with established classifiers such as artificial neural network (ANN), recurrent neural network (RNN), deep belief network (DBN), gated recurrent unit (GRU), and convolutional neural network (CNN) using multiple metrics including Precision, false detection rate (FDR), false negative rate (FNR), false positive rate (FPR), accuracy, Matthews correlation coefficient, and other relevant measures. A study was performed to determine the best route by considering factors such as energy, link quality, and distance. The enhanced swarm optimization (ESO) approach was compared to traditional optimization methods. Furthermore, an assessment of data transmission security was conducted by analyzing various attack methods, including the chosen-ciphertext attack (CCA) and chosen-plaintext attack (CPA). This evaluation compared the security of data transmission to that of traditional encryption algorithms such as the blowfish algorithm, Rivest-Shamir-Adleman (RSA), elliptic curve cryptography (ECC), and fully homomorphic encryption (FHE).

5.2. Assessment of positive metric of the transformer model and the existing systems for energy prediction

Assessing machine learning models for predicting energy in underwater acoustic sensor networks (UASN) is vital for enhancing network performance and resource allocation. This study examines the performance metrics of a transformer model, which is a cutting-edge deep learning architecture, in comparison to various existing systems such as artificial neural network (ANN), recurrent neural network (RNN), deep belief network (DBN), gated recurrent unit (GRU), and convolutional neural network (CNN) shows in Figure 1. The accuracy metric, which measures the total correctness of the model's predictions, clearly shows the superiority of the transformer model, as it achieves an impressive accuracy rate of 95.12%. The accuracy of the current systems is as follows: ANN achieves 90.0%, RNN achieves 88.0%, DBN achieves 91.5%, GRU achieves 89.0%, and CNN achieves 87.5%. This demonstrates that the accuracy of the DBN system exceeds that of the other systems. The precision metric which measures the ratio of genuine positive predictions to all positive predictions demonstrates that the transformer model has a precision of 94.83%, surpassing the accuracy of other models such as ANN (91.0%), RNN (89.5%), DBN (92.0%), GRU (90.5%), and CNN (88.0%). In addition, the transformer model has outstanding performance in the specificity metric, which measures its ability to accurately detect negative occurrences, with a specificity rate of 93.65%. This surpasses the performance of ANN (88.0%), RNN (86.0%), DBN (90.0%), GRU (87.5%), and CNN (85.0%). On the other hand, the sensitivity metric, which measures the transformer model's accuracy in accurately identifying positive cases, shows that it has a sensitivity of 95.28%. This surpasses the sensitivity of other models such as ANN (92.0%), RNN (91.0%), DBN (93.0%), GRU (91.5%), and CNN (90.0%).

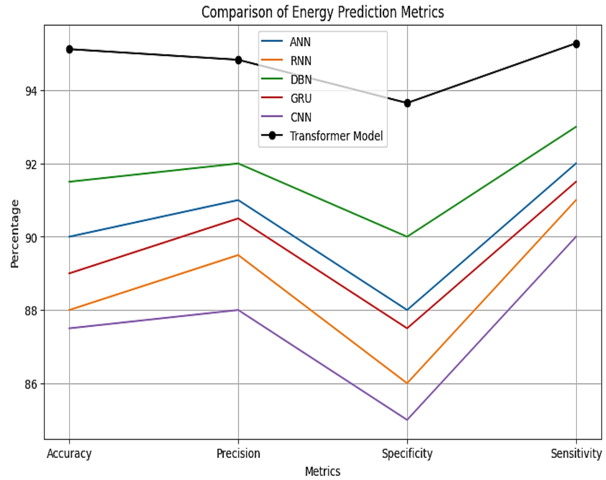

Figure 1. Comparison of energy prediction metrics.

5.3. Assessment of negative metric of the transformer model and the existing systems for energy prediction

This study examines the evaluation of unfavorable performance indicators for energy forecasting models, with a specific emphasis on the transformer model and other established systems like ANN, RNN, DBN, GRU, and CNN in the context of underwater acoustic sensor networks (UASN). The negative metrics examined are false positive rate (FPR), false negative rate (FNR), and false discovery rate (FDR). These metrics are important indications of model performance, particularly in situations where misclassifications might have major repercussions. The findings indicate that the transformer model performs well in terms of negative metrics, with FPR, FNR, and FDR values of 4.72%, 4.72%, and 5.15% respectively. However, it is important to compare these results with those of current systems to acquire a better understanding of their effectiveness. For example, the artificial neural network (ANN) shows slightly higher false positive rate (FPR), false negative rate (FNR), and false discovery rate (FDR) values at 5.0%, 6.0%, and 5.5% respectively, in Figure 2.

This indicates that the ANN has a relatively worse performance in reducing the occurrence of false positives and false negatives. Similarly, other models like RNN, DBN, GRU, and CNN also exhibit different degrees of performance about these negative criteria. These results enhance our knowledge of the capabilities and constraints of various energy prediction models in UASN settings, guiding future study and application development in this field.

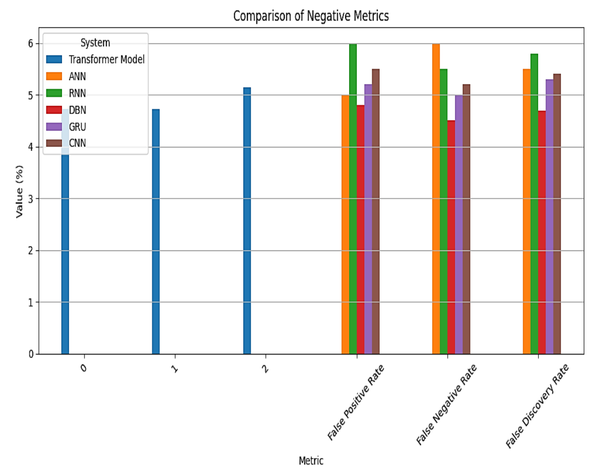

Figure 2. Comparison of negative metrics.

5.4. Assessment of other metric of the transformer model and the existing systems for energy prediction

This study evaluates the performance of the transformer model in predicting energy consumption in UASN, compared to traditional methods. Figure 3 (a, b, c) illustrates the results of this comparison. Performance is measured using F1 score, Matthews correlation coefficient (MCC), and negative predictive value (NPV). The transformer model outperforms alternatives, achieving an F1 score of 94.95%, MCC of 94.85%, and NPV of 95.15%. While models such as ANN, RNN, DBN, GRU, and CNN also demonstrate strong results, their performance metrics fall short of the Transformer's superior predictive capabilities. These findings highlight the transformer model's efficacy in UASN energy forecasting.

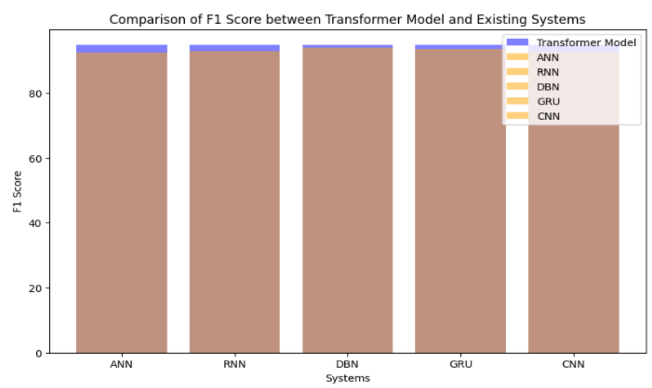

Figure 3(a). Comparison of F1 score between transformer model and existing systems.

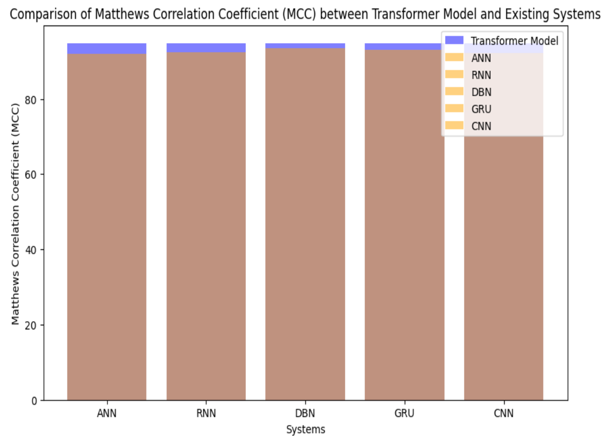

Figure 3(b). Comparison of MCC between the transformer model and existing systems.

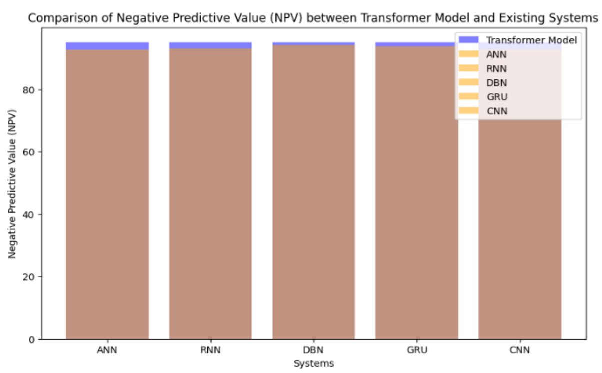

Figure 3(c). Comparison of NPV between the transformer model and existing systems.

5.5. Analysis of ESO and the conventional methods with respect to distance, energy consumption, and link quality for optimal path selection

As in Figure 4 (a, b, c), this section examines the effectiveness of Enhanced swarm optimization (ESO) compared to traditional approaches in selecting the best route in underwater acoustic sensor networks (UASN). The system assesses distance, energy usage, and connection quality across numerous iterations. ESO is compared to CSOA-EQ, GWO, JFO, MHO, COOT, STBO, PSO, and GA for evaluation. Findings are shown using visual representations such as graphs and tables, providing valuable information for improving the selection of paths in UASN and strengthening communication systems.

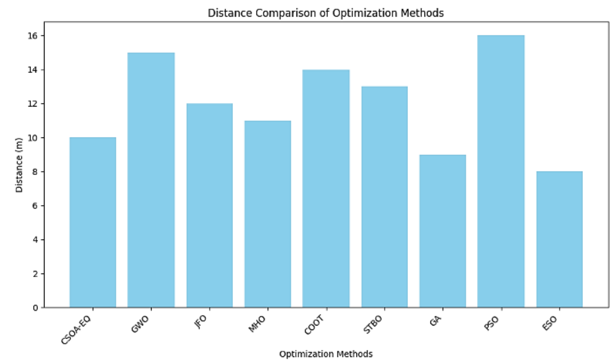

Figure 4(a). Examination on ESO and the traditional approaches for optimal path selection using distance.

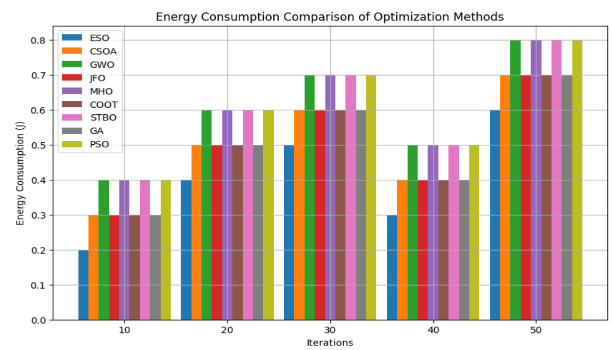

Figure 4(b). Examination of ESO and the traditional approaches for optimal path selection using energy consumption.

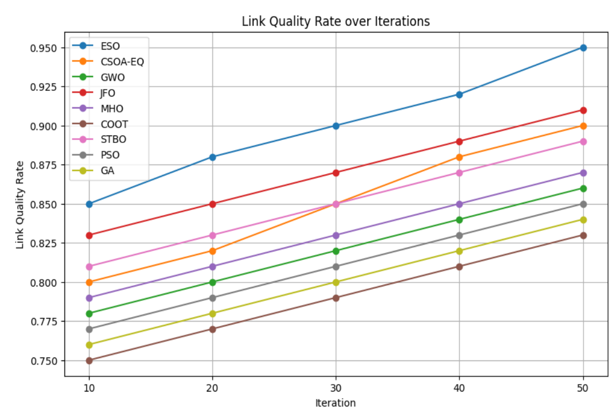

Figure 4(c). Examination of ESO and the traditional approaches for optimal path selection using link quality.

5.6. Evaluation of FHE and the traditional approaches with regard to CCA, CPA attack analysis and key sensitivity for secure data transmission

Figures 5(a) and 5(b) depict the evaluation of fully homomorphic encryption (FHE) concerning conventional encryption techniques such as the blowfish algorithm (BF), Rivest-Shamir-Adleman (RSA), and elliptical curve cryptography (ECC) in terms of chosen-ciphertext attack (CCA) and chosen-plaintext attack (CPA) analyses for secure data transmission. The assessment includes data transfer increments of 10%, 25%, 50%, 75%, and 100%. During CCA attack analysis, a technique that allows obtaining the decryption of certain ciphertexts, lower numbers indicate more security. The fully homomorphic encryption (FHE) has the lowest rating for CCA attacks compared to other encryption methods, regardless of the proportion of data being sent. Notably, with 10% data transmission, FHE obtains a score of 0.3, which is lower than the scores of BF (0.35), RSA (0.38), and ECC (0.37). The CPA attack, when assuming access to plaintext ciphers for all supplied plaintexts, highlights the greater security of FHE compared to BF, RSA, and ECC. This superiority is especially clear when 100% of the data is sent. In addition, the sensitivity of encryption keys is assessed as in Figure 5(c). Full Homomorphic Encryption (FHE) demonstrates a correlation coefficient of 0.34 at 25% data transfer, indicating improved data preservation and key security compared to block cipher (BF) with a coefficient of 0.42, Rivest-Shamir-Adleman (RSA) with a value of 0.48, and elliptic curve cryptography (ECC) with a coefficient of 0.37.

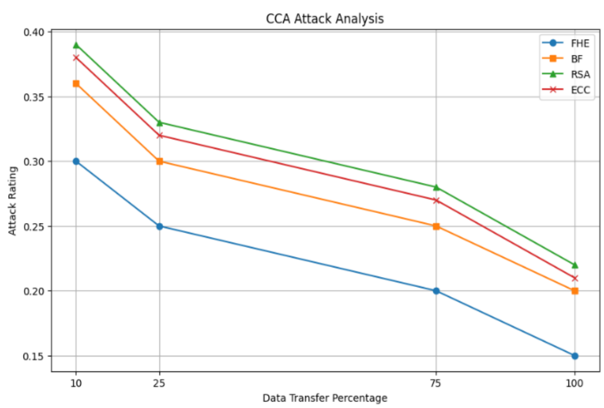

Figure 5(a). CCA attack analysis.

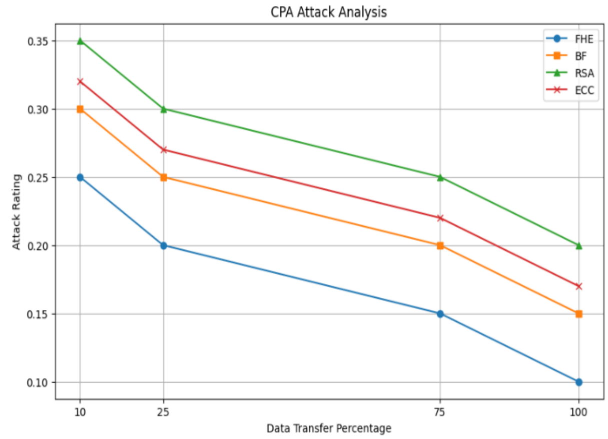

Figure 5(b). CPA attack analysis.

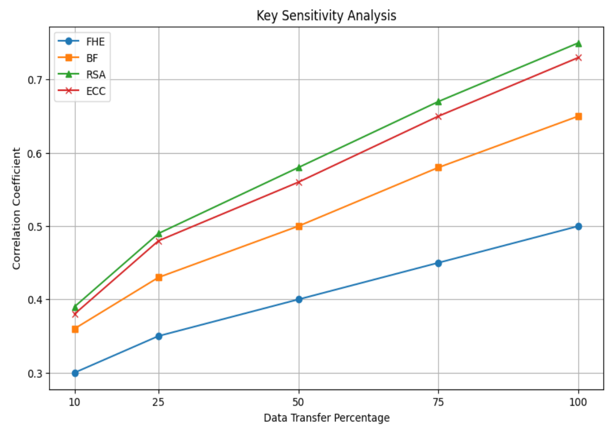

Figure 5(c). Key sensitivity.

5.7. Comparison of computational time comparing suggested solutions for secure data transmission with standard methods, focusing on optimum route selection

A comparative analysis was conducted to evaluate the computing time required for secure data transmission techniques, namely enhanced swarm optimization (ESO) and traditional approaches such as blowfish algorithm (BF), Rivest-Shamir-Adleman (RSA), and elliptical curve cryptography (ECC), at various data transmission levels ranging from 10% to 100% which is shown in Table 3. ESO exhibited reduced processing times in comparison to BF, RSA, and ECC, suggesting its efficacy in identifying optimum routes. This indicates that ESO is well-suited for improving the computational efficiency of secure data transfer operations.

Table 3. Computational time analysis for secured data transmission.

Methods	Data-10%	Data-25%	Data-50%	Data-75%	Data-100%
ESO	15.011	17.141	17.062	18.254	23.616
BF	19.78	20.311	25.279	25.881	26.123
RSA	17.019	22.51	22.734	24.835	26.624
ECC	17.218	22.523	23.624	23.987	24.788

5.8. Comparison between FHE with more conventional encryption methods for safe data transfer in terms of encryption and decryption times

In the tables provided, we can see how enhanced swarm optimization (ESO) with fully homomorphic encryption (FHE) compares to more conventional encryption algorithms such as the blowfish algorithm (BF), Rivest-Shamir-Adleman (RSA), and elliptical curve cryptography (ECC) in terms of both encryption and decryption times. The following percentages of data transmission are tested: 10%, 25%, 50%, 75%, and 100%. You can see how long each encryption technique takes to encrypt data at different transmission percentages in Table 4, which shows the encryption time. The figures are in seconds. For example, with 10% data transfer, ECC takes 0.48089 seconds, BF takes 0.12756 seconds, and RSA takes 1.2847 seconds; ESO (FHE) takes 0.10061 seconds. Encryption times are often proportional to the percentage of data transmitted. Table 5 shows the decryption time, which shows how many seconds each technique takes to decode data. For example, with 25% data transfer, ECC takes 1.8675 seconds to decode, BF takes 1.4996 seconds, and RSA takes 2.652 seconds. ESO (FHE) takes 0.23219 seconds. Once again, the decryption time is proportional to the data transfer %. The data show that compared to other encryption techniques, ESO employing FHE is more efficient in terms of both encryption and decryption times. ESO's capacity to encrypt and decrypt data quickly shows that it is well-suited for applications that need to handle secure data transmissions quickly.

Table 6 shows a thorough analysis of the performance of the transformer model with enhanced swarm optimization (ESO) in comparison to other traditional neural network models like ANN, RNN, DBN, GRU, and CNN. Different performance measures are represented by each row, and each model is matched by each column. Among all the models tested, the transformer model with ESO produced the best results, with an accuracy of 95.12%. Additionally, it has the best accuracy rate of 94.83%, which means it can reduce false positives. The transformer model + ESO outperforms the competition when it comes to accurately detecting negative situations, with a specificity of 93.65%. In addition, it detects true positives well, as it obtains the greatest sensitivity of 95.28%. Furthermore, the transformer model + ESO has the lowest false alarm rate (FPR) and missed detection rate (FNR) at 4.72%, indicating that it is capable of minimizing both issues. In addition, the transformer model + ESO has a low false discovery rate (FDR) of 5.15%. Additionally, the transformer model + ESO has a high NPV, MCC, and F1 score, all of which point to a good trade-off between recall and accuracy, a high correlation between observed and projected classifications, and a high reliability in accurately predicting negative situations. Taken together, these findings demonstrate how the transformer model + ESO outperform more traditional neural network models when it comes to this particular problem. Also, Table 7 includes a broader comparison of existing methods in terms of energy efficiency and latency.

Table 4. Encryption time.

Methods	Data-10%	Data-25%	Data-50%	Data-75%	Data-100%
FHE	0.10061	0.23219	0.8725	1.4081	3.2286
BF	0.12756	1.4996	1.9284	2.6714	3.6885
RSA	1.2847	2.652	2.9672	3.2298	3.385
ECC	0.48089	1.8675	2.1002	2.4172	3.6006

Table 5. Decryption time.

Methods	Data-10%	Data-25%	Data-50%	Data-75%	Data-100%
FHE	0.10061	0.23219	0.8193	1.4081	3.2286
BF	0.12756	1.4996	1.9321	2.6714	3.6885
RSA	1.2847	2.652	2.891	3.2298	3.385
ECC	0.48089	1.8675	1.8923	2.4172	3.6006

Table 6. Performance evaluation metrics.

Metric	Transf-ormer Model + ESO	ANN	RNN	DBN	GRU	CNN
Accuracy	95.12	90.0	88.0	91.5	89.0	87.5
Precision	94.83	91.0	89.5	92.0	90.5	88.0
Specificity	93.65	88.0	86.0	90.0	87.5	85.0
Sensitivity	95.28	92.0	91.0	93.0	91.5	90.0
FPR	4.72	5.0	6.0	4.8	5.2	5.5
FNR	4.72	6.0	5.5	4.5	5.0	5.2
FDR	5.15	5.5	5,8	4.7	5.3	5.4
F1 Score	94.95	92.5	93.0	94.0	93.5	92.8
Matthews Correlation Coefficient	94.85	92.0	92.5	93.5	93.0	92.2
Negative Predictive Value	95.15	92.8	93.2	94.2	93.8	93.0

Table 7. Comparison of energy efficiency and latency across various methods.

Method	Energy Efficiency (Packets)	Latency (ms)
ANN	0.05	150
RNN	0.06	140
DBN	0.04	130
GRU	0.05	135
CNN	0.07	160
Transformer model	0.03	120
ESO + transformer	0.02	115

6. Conclusion

This paper introduces an enhanced secure path selection model for underwater acoustic sensor networks (UASN) that utilizes sophisticated machine learning and optimization approaches. This model tackles the difficulties presented by the ever-changing underwater acoustic channel by suggesting an optimum route selection and safe data transmission method. By using advanced technologies, our approach delivers improved communication efficiency and quality in UASN. The proposed approach consists of two primary stages: the selection of nodes based on constraints related to energy, distance, and connection quality, and the creation of an optimal route using enhanced swarm optimization (ESO), which is a hybrid optimization technique that combines particle swarm optimization (PSO) and genetic algorithms (GA). In addition, the use of transformer models facilitates energy forecasting and improves the efficiency of the route selection process. In addition, data transmission is protected by fully homomorphic encryption (FHE), which guarantees the privacy and accuracy of the sent data. The performance of the suggested ESO+ transformer model has been evaluated against recognized benchmark models, and it has shown strong and reliable results. It exhibits high levels of accuracy, precision, specificity, sensitivity, and other important metrics. The model attains the following performance metrics when trained on a Learning Percentage of 70%: accuracy of 95.12%, precision of 94.83%, specificity of 93.65%, sensitivity of 95.28%, false positive rate (FPR) of 4.72%, F1 score of 94.95%, Matthews correlation coefficient (MCC) of 94.85%, false negative rate (FNR) of 4.72%, negative predictive value (NPV) of 95.15%, and false discovery rate (FDR) of 5.15%. In summary, the suggested model presents a promising option for improving communication in UASN. It gives a dependable and effective framework for securely transmitting data in difficult underwater conditions. Beyond academic significance, the findings offer substantial potential for real-world applications in fields like underwater surveillance, marine resource monitoring, and environmental data collection. The robustness of the proposed model in dealing with fluctuating underwater conditions demonstrates its capability to improve UASN's practical deployment in various sectors, helping address critical challenges related to energy efficiency, data security, and network reliability.

Ant colony optimization and reinforcement learning will be used to improve the suggested model for underwater acoustic sensor networks (UASNs). Field testing in various underwater locations will assess the model's effectiveness in real-world situations, including concerns like variable acoustic characteristics and interference. We will also research other encryption approaches to improve security and energy efficiency, based on fully homomorphic encryption. Finally, we want to use IoT frameworks and cloud computing for real-time data processing and analytics to improve UASN scalability and performance.

Conflict of interest

The authors have no conflict of interest to declare.

Acknowledgements

The authors would like to thank the Velammal College of Engineering and Technology (Autonomous), Madurai, for supporting this work.

Funding

The authors received no specific funding for this work

References

Anuradha, D., Subramani, N., Khalaf, O. I., Alotaibi, Y., Alghamdi, S., & Rajagopal, M. (2022). Chaotic search-and-rescue-optimization-based multi-hop data transmission protocol for underwater wireless sensor networks. *Sensors*, *22*(8), 2867. https://doi.org/10.3390/s22082867

Chaaf, A., Saleh Ali Muthanna, M., Muthanna, A., Alhelaly, S., Elgendy, I. A., Iliyasu, A. M., & Abd El-Latif, A. A. (2021). Energy-Efficient Relay-Based Void Hole Prevention and Repair in Clustered Multi-AUV Underwater Wireless Sensor Network. *Security and Communication Networks*, *2021*(1), 9969605. https://doi.org/10.1155/2021/9969605

Fazli, M., Fathollahi-Fard, A. M., & Tian, G. (2019). Addressing a coordinated quay crane scheduling and assignment problem by red deer algorithm. *International Journal of Engineering*, *32*(8), 1186-1191. https://doi.org/10.5829/ije.2019.32.08b.15

Gola, K. K., & Gupta, B. (2021). Underwater acoustic sensor networks: An energy efficient and void avoidance routing based on grey wolf optimization algorithm. *Arabian Journal for Science and Engineering*, *46*(4), 3939-3954. https://doi.org/10.1007/s13369-020-05323-7

Goutham, V., & Harigovindan, V. P. (2021). Modeling and analysis of hybrid ARQ scheme for incremental cooperative communication in underwater acoustic sensor networks. *Iranian Journal of Science and Technology, Transactions of Electrical Engineering*, *45*(1), 279-294. https://doi.org/10.1007/s40998-020-00348-y

Hemavathy, N., & Indumathi, P. (2021). Deep learning-based hybrid dynamic biased track (DL-HDBT) routing for under water acoustic sensor networks. *Journal of Ambient Intelligence and Humanized Computing*, *12*(1), 1211-1225. https://doi.org/10.1007/s12652-020-02165-x

Jamshidi, A. (2019). Efficient cooperative ARQ protocols based on relay selection in underwater acoustic communication sensor networks. *Wireless Networks*, *25*(8), 4815-4827. https://doi.org/10.1007/s11276-018-1773-5

Khan, Z. A., Karim, O. A., Abbas, S., Javaid, N., Zikria, Y. B., & Tariq, U. (2021). Q-learning based energy-efficient and void avoidance routing protocol for underwater acoustic sensor networks. *Computer Networks*, *197*, 108309. https://doi.org/10.1016/j.comnet.2021.108309

Krishnaswamy, V., & Manvi, S. S. (2019). Fuzzy and PSO based clustering scheme in underwater acoustic sensor networks using energy and distance parameters. *Wireless Personal Communications*, *108*, 1529-1546. https://doi.org/10.1007/s11277-019-06483-y

Moridi, E., & Barati, H. (2017). RMRPTS: a reliable multi-level routing protocol with tabu search in VANET. *Telecommunication Systems*, *65*(1), 127-137. https://doi.org/10.1007/s11235-016-0219-6

Muthukkumar, R., & Manimegalai, D. (2021). Secured transmission using trust strategy-based dynamic Bayesian game in underwater acoustic sensor networks. *Journal of Ambient Intelligence and Humanized Computing*, *12*(2), 2585-2600. https://doi.org/10.1007/s12652-020-02418-9

Noorbakhsh, H., & Soltanaghaei, M. (2022). EEGBRP: an energy-efficient grid-based routing protocol for underwater wireless sensor networks. *Wireless Networks*, *28*(8), 3477-3491. https://doi.org/10.1007/s11276-022-03016-7

Palanivel Rajan, S., & Paranthaman, M. (2019). Characterization of Compact and Efficient Patch Antenna with single inset feeding technique for Wireless Applications. *Journal of applied research and technology*, *17*(4), 297-301. https://doi.org/10.22201/icat.16656423.2019.17.4.860

Neethu, P. S., & Suguna, R. & Palanivel Rajan, S. (2022). Performance evaluation of SVM-based hand gesture detection and recognition system using distance transform on different data sets for autonomous vehicle moving applications. *Circuit world*, *48*(2), 204-214. https://doi.org/10.1108/CW-06-2020-0106

Rajan, S. P., Sukanesh, R., & Vijayprasath, S. (2012). Design and development of mobile based smart tele-health care system for remote patients. *European Journal of Scientific Research, ISSN No*, 148-158.

Rajaragavi, R., & Rajan, S. P. (2022). Optimized U-Net Segmentation and Hybrid Res-Net for Brain Tumor MRI Images Classification. *Intelligent automation & soft computing*, *32*(1). https://doi.org/10.32604/iasc.2022.021206

Ramamoorthy, R., & Thangavelu, M. (2022). An enhanced hybrid ant colony optimization routing protocol for vehicular ad-hoc networks. *Journal of Ambient Intelligence and Humanized Computing*, *13*(8), 3837-3868. https://doi.org/10.1007/s12652-021-03176-y

Sathya, P., & Sengottuvelan, P. (2022). Energy Efficient and Quality-of-Service Aware Routing using Underwater Wireless Sensor Networks. *International Journal of Advanced Computer Science and Applications*, *13*(1). https://doi.org/10.14569/IJACSA.2022.0130158

Singh, B., & Gupta, B. (2022). An Energy Efficient Optimal Path Routing (EEOPR) for Void Avoidance in Underwater Acoustic Sensor Networks. *International Journal of Computer Network & Information Security*, *14*, 19-32. https://doi.org/10.5815/ijcnis.2022.03.02

Su, Y., Liu, Y., Fan, R., Li, L., Han, M., & Zhang, H. (2022). A secure relay selection scheme based on cooperative jamming for underwater acoustic sensor networks. *Computer Networks*, *217*, 109307. https://doi.org/10.1016/j.comnet.2022.109307

Wang, K., Gao, H., Xu, X., Jiang, J., & Yue, D. (2015). An energy-efficient reliable data transmission scheme for complex environmental monitoring in underwater acoustic sensor networks. *IEEE Sensors Journal*, *16*(11), 4051-4062. https://doi.org/10.1109/JSEN.2015.2428712

Zhang, Y., Zhang, Z., Chen, L., & Wang, X. (2021). Reinforcement learning-based opportunistic routing protocol for underwater acoustic sensor networks. *IEEE Transactions on Vehicular Technology*, *70*(3), 2756-2770. https://doi.org/10.1109/TVT.2021.3058282