

Energy-Efficient Clustering and Routing Protocol Using GAN-Based Fuzzy Clustering for AUV-Assisted UWSNs

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Abstract: In recent years, AUV-assisted underwater sensor networks (AUV-UWSNs) have gained significant attention due to their ability to monitor and collect crucial data from the oceanic environment. However, the efficiency of these networks is hindered by several issues, including high energy consumption, limited communication range, and routing/clustering problems. Two of the major challenges affecting other aspects of AUV-UWSNs are the lack of a proper way to choose the right cluster heads and guarantee sound data transmission. This paper proposes a high-efficiency clustered routing technique that tackles these problems by utilizing the Spider Wasp Optimizer (SWO) for optimal cluster head selection and the Deep Fuzzy Gorilla Troops Self-Guided Generative Adversarial Clustering Network (DFGTS-2GACN) for efficient data transmission. The SWO enhances the choice of cluster heads with respect to energy consumption and the DFGTS-2GACN applies deep learning and fuzzy logic control to facilitate data forwarding in the network with enhanced performance. Experimental performance shows 99% improvement compared with the existing methods. In this paper, an effective method to consider for increasing the data transfer rate, reducing energy consumption, and extending the network lifetime of the underwater network facilitated by the AUV in the underwater sensor networks is discussed, thus providing a viable solution to the problems of underwater communication.

Index Terms: AUV-assisted underwater sensor networks, Spider Wasp Optimizer, Self-Guided Deep Clustering Network (SGDCN), Kepler's Optimization (KO), Fuzzy Self-Guided Structure Retention Generative Adversarial Network (FS-GAN).

1. Introduction

A mission-critical tool, using state-of-the-art marine technologies, the Coastal Patrol and Surveillance tool (CPSA) follows, identifies, and keeps an eye on watercraft traffic. In a monitored coastal area, it collects, analyzes, and presents real-time data on activities, such as harbors protected against terrorism or sabotage and asymmetric threats from both known and unknown adversaries [1-2]. Usually, a shore-based control center monitors and inspects assets across a broad area of interest patrolled by AUVs. Nearby AUVs identify and track an asset as it enters the monitored region, obtaining time-stamped data and its trajectory. The CPSA operates more easily thanks to the Delay-Tolerant Network (DTN) protocols. In order to facilitate operations, it is necessary to use the Coastal Patrol and Surveillance Network (CPSN) [3-4]. In explore hybrid CPSNs, where sinks remain stationary while a fleet of AUVs patrols an area of interest

and sends data to the control center. In the UDTN-Prob protocol, the duration of contact is fairly distributed for all nodes sharing data when they are in contact [5-6]. There are two types of protocols that fall into the SAF paradigm: replication-based and forwarding-based protocols. Underwater sensor networks are necessary for practical application and scientific research for collecting underwater data and providing warnings for disasters [7-8]. Underwater environments, however, are energy-limited; hydroacoustic signals are attenuated, signal delays are large, and data reliability is low. Traditional clustering methods such as LEACH do not provide a great solution to these issues. Enhancing underwater sensor networks' energy efficiency has been the subject of recent study [9]. Some protocols have been proposed such as Controlled-LEACH, E-LEACH, EE-MDCHSRP, TCEB, ECHERP, EERBCR, and EECMR. These protocols seek to solve the difficulties of underwater environments, lower energy consumption, and increase network efficiency. This rotates cluster head nodes to optimize selection while ignoring network connectivity difficulties, lowering network overhead and extending network lifetime. Thus, it employs minimum migration factor, node density and residual node energy for selecting cluster head nodes periodically. However, there are still some challenges that must be faced including node mobility constraints which cannot adapt to aquatic environment [10-11]. To advance underwater sensor network technologies more effectively, further study is needed. Underwater example of modes of operation, strategic topics include synergy, decentralization, and sophistication. Subsea work scopes particularly in warfare environment are arduous for the conventional underwater platforms to accomplish. Research of submarine AUV multi-node systems provides new concepts for enhancing underwater operation. Some of these systems include strong anti-interference capacities, fast transfer rate, and high flexibility in nearby communication [12-13]. It increases the efficiency of search, enhances detection equipment and provides comprehensive data. Wireless communication networks are a potential solution since ad hoc networks offer high speed flexibility convenience. Underwater Acoustic Sensor Networks (UASNs) are used to assess ocean environments for military, environmental, and scientific purposes. As with future deployable technologies such as sensor-deployment capability and unmanned vehicles, this is an underwater sensor networking system. UW-ASN is unique for commercial and industrial applications since acoustics technology can be employed for short-range communication notwithstanding communication problems [14-15].

AUV-UWSNs must address the challenges of appropriate cluster head selection, dependable data transmission, and effective energy management. As a result, these networks experience several challenges including restricted communication range, high levels of energy consumption and the possibility of employing dynamic and adaptive routing for data transmission over vast distances in the underwater environment. Furthermore, effective identification of suitable cluster heads is an essential step of minimizing energy consumption while considering the general performance of the network. Such factors prevent the network from operating in the long term and therefore require new methods for optimizing energy and communication to ensure the network functions optimally.

To improve readability and reduce the cognitive load associated with multiple technical acronyms, Table 1 summarizes the major components of the proposed framework and their corresponding functions in relation to standard clustering, routing, and optimization techniques.

Table 1. Mapping of Proposed Framework Components to Standard Clustering, Routing, and Optimization Techniques.

Acronym	Full Name	Standard Technique / Function
SWO	Spider Wasp Optimizer	Metaheuristic cluster-head selection
SGDCN	Self-Guided Deep Clustering Network	Deep clustering
FS-GAN	Fuzzy Self-Guided Structure Retention Generative Adversarial Network	GAN-based routing optimization
KO	Kepler's Optimization	Hyperparameter optimization
DFGTS-2GACN	Deep Fuzzy Gorilla Troops Self-Guided Generative Adversarial Clustering Network	Integrated energy-efficient clustering and routing framework

The proposed DFGTS-2GACN framework combines SWO-based cluster-head selection, deep clustering, GAN-assisted routing optimization, and parameter tuning into a single architecture for reliable and energy-efficient data transport in AUV-supported underwater sensor networks.

1.1. Novelty and contribution

The novelty and contribution of this work is given below:

- **AUV-Assisted Underwater Sensor Network Design:** This work presents a novel design for AUV-assisted underwater sensor networks, incorporating adaptive routing protocols to optimize data transmission and energy consumption.
- **SWO for Cluster Head Selection:** The study proposes a novel technique for optimizing cluster head selection in UWSN through SWO. This metaheuristic strategy helps in optimizing energy with a controlled distribution of load and energy loss.

- **DFGTS-2GACN:** A new clustering network, DFGTS-2GACN, is proposed to improve data transmission efficiency. This method integrates deep fuzzy logic and generative adversarial networks, providing adaptive clustering for dynamic and fluctuating underwater conditions.
- **Energy Efficiency and Reliability:** The suggested solution uses optimization algorithms and machine learning approaches to optimize the network's energy efficiency while maintaining the highest level of communication dependability for long-term underwater operation.
- **Scalability and Adaptability:** The proposed method is scalable and consistently outperforms current methods and thus usable for large-scale AUV-assisted sensor networks of arbitrary size and in different underwater conditions.
- **Enhanced Network Longevity:** The approach ensures longer operational lifetimes for AUV-assisted sensor networks by minimizing energy consumption during data transmission and optimizing the overall energy utilization within the network.
- **Advanced Data Transmission Protocol:** In order to improve overall performance in AUV-UWSNs, a new data transmission protocol is suggested to handle routing problems that could cause transmission delays and packet loss.

The rest of this manuscript is structured as follows: Section 2: Reviews of the literature; Section 3: Suggested methods; Section 4: Results and Discussion; and Section 5: Conclusion and Future Work.

2. Literature Survey

The following publications discuss AUV-based underwater routing using deep learning techniques:

In 2023 Azad, S., et al. [16] has introduced a Brynes Rational Behavior Model (RBM) for AUV based Routing in Underwater with Deep learning methods. Automated equipment is used by marine vessel traffic identification, tracking, and monitoring through the Coastal Patrol and Surveillance Application (CPSA). According to the CPSA, a Coastal Patrol and Surveillance Network (CPSN) must deliver adequate data on time. This paper proposes the Underwater Delay Tolerant Protocol with RS (UDTN-RS), a new protocol that combines Reed-Solomon codes in the UDTN-Prob routing protocol. The protocol also enhances binary packet spraying method for node-to-node transmission of encoded packets. The effectiveness of the recommended protocol was then analyzed and a comprehensive simulation was conducted using the DESERT underwater simulator and the WOSS package.

In 2024 Shi, Y., et al. [17] has developed a high-efficiency clustering routing protocol (HECRA) for deep learning-based AUV-based underwater routing. This paper suggests an approach termed HECRA that optimizes cluster head selection, construction, and data transmission in AUV-assisted underwater sensor networks by introducing residual energy and node degree. dynamic relay node, an autonomous underwater vehicle (AUV) is also presented. According to simulation studies, HECRA ensures effective data transmission by greatly enhancing packet transmission, network lifetime, and residual node energy.

In 2024 Feng, X., et al. [18] has introduced a Carrier Sense Multiple Access (CSMA) for AUV-based routing in Underwater with Deep learning methods. Using the Optimized Link State Routing protocol, researchers study AUV multi-node networking on CSMA/CA channels to tackle attenuation, poor reception, and channel blockage. It suggests using a dynamic backoff technique to prevent channel obstruction.

In 2024 Zhu, W., et al. [19] has introduced a packet hierarchy and void processing (PHVP) for AUV based Routing in Underwater with Deep learning methods. Inspired by the marine exploration, underwater wireless sensor networks (UWSNs) have attracted the research interests of researchers. The hybrid acoustic-optical routing technique - PHVP, resolves energy consumption, latency and void problem in UWSN and proved to achieve higher PDR and network life.

In 2023 Zhu, R., et al. [20] has used deep learning techniques to create a Long Short-Term Memory (LSTM) for AUV-based underwater routing. The article suggests T-SAPR, a trust management-based secure routing protocol for Underwater Acoustic Sensor Networks (UASNs) that mitigates security issues caused by underwater sensor node capability limitations and suggests a repair strategy to deal with failure.

In 2023 Sathish, K.,et al. [21] has introduced A time difference of arrival (TDOA) for underwater with deep learning method-based AUV based Routing. The underwater sensor hub helps in the collection of oceanographic data, prevention of disasters, navigation and screening of pollutants. Data is gathered from autonomous underwater vehicles and unmanned submerged vehicles. Wireless information routing is the most advanced maritime surveillance technique, but has limitations. In 2023 Zhang, Y., et al. [22] has introduced a data-driven bi-pattern (DDBP) path planning algorithm for autonomous underwater vehicles (AUVs) for ocean geomorphological survey is proposed. The technique improves AUV-based surveys by focusing on high feature density regions, enhancing efficiency in sand waves and artificial reefs, potentially useful in target search and underwater archaeology. The reviewed approach's summary is displayed in Table 2.

Table 2. An overview of the reviewed methodology.

References	Methods	Advantages	Disadvantages
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Azad, S., et al. 2023 [16]	RBM	Reed-Solomon coding improves delay-tolerant routing. Enhanced dependability by binary packet spraying.	Ignores energy efficiency in favor of concentrating on delay tolerance. - Testing for dynamic underwater settings is limited.
Shi, Y., et al. 2024 [17]	HECRA	Enhances network lifetime by selecting cluster heads optimally. AUV is presented as a dynamic relay node.	Possible overhead in controlling the development of dynamic clusters. - Presupposes optimal AUV communication and navigation conditions.
Feng, X., et al. 2024 [18]	CSMA	Tackles the problems of channel blockage and high attenuation. Dynamic backoff enhances the ability to avoid collisions.	Limited scalability for networks that are dense underwater. Channel management is the main focus; energy optimization techniques are absent.
Zhu, W., et al. 2024 [19]	PHVP	Energy consumption is decreased by hybrid acoustic-optical routing. Reduced transmission delay and efficient void management.	The difficulty of using combination acoustic-optical techniques. Real-world testing challenges are not discussed; the focus is on simulation.
Zhu, R., et al. 2023 [20]	LSTM	Improves security by managing trust. The Attention-LSTM model adjusts to changes in the surroundings.	Computationally demanding for sensor nodes with constrained functionality. Security is the main focus; trade-offs between energy and latency are not explained.
Sathish, K., et al. 2023 [21]	TDOA	It works well for localization in situations that take place underwater. Beneficial for pollutant screening, navigation, and catastrophe prevention.	High data transmission delay and mistake probability; underwater sensor hubs' limited capacity and energy issues.
Zhang, Y., et al. 2023 [22]	DDBP	Improves ocean survey quality and efficiency. Real-time data is used for adaptive path re-planning.	Restricted to geomorphological surveys; it is unclear whether it can be applied to other tasks. Mostly depends on the accuracy of real-time sonar data.

2.1. Problem statement

Appropriate cluster heads selection, reliable data transmission, and efficient energy management are the hurdles that AUV-UWSNs must overcome.

3. Proposed Methodology

This section presents a high-efficiency clustering routing protocol that tackles these problems by using the DFGTS-2GACN for effective data transmission and the SWO for optimal cluster head selection. Figure 1 shows the workflow and system model diagram of DFGTS-2GACN. The SWO enhances the choice of cluster heads with respect to energy consumption and the DFGTS-2GACN applies deep learning and fuzzy logic control to facilitate data forwarding in the network with enhanced performance.

3.1. System model

An automated underwater vehicle (AUV), sink nodes, and sensor nodes are the three primary parts of AUV-UWSNs. They are positioned on the surface of the water and connected via satellite relaying to the station on land. They enable radio connection between the base station and the underwater sensor network to transfer data. Underwater, the sensor nodes are dispersed and in charge of keeping an eye on the surroundings. Every sensor node has the ability to function as a cluster member (CM) or a cluster head (CH).

During every communication cycle, the cluster heads (CHs) compile and combine the information obtained from their corresponding cluster members (CMs). After fusing the data, the CHs transmit the aggregated information to the sink nodes using either one-hop or multi-hop communication. When some CHs are unable to directly communicate with the sink nodes due to long distances, the AUV acts as a dynamic relay node to help CHs forward data to one another, guaranteeing dependable network communication. Figure 1 displays the network model.

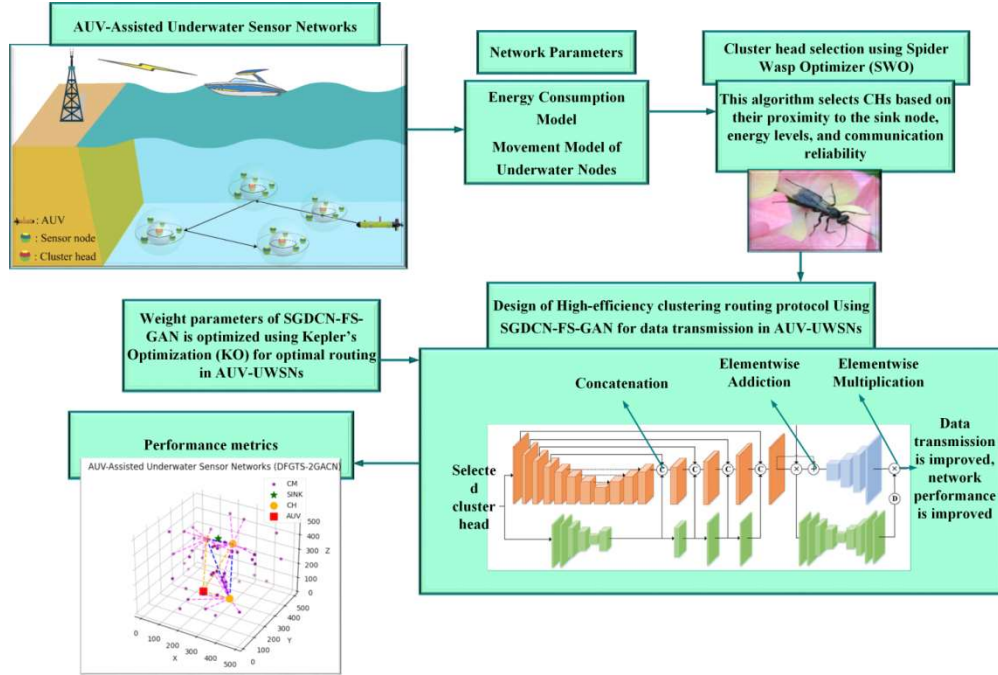


Fig. 1. Workflow diagram of DFGTS-2GACN.

3.1.1. Energy Consumption Model

Optimizing the system's performance depends on how much energy each sensor node in the network uses. The hydroacoustic communication energy consumption model is predicated on the idea that a sensor node transmits lc data points at a rate of transmission S_q over a distance dis . Equation (1) provides the energy used during transmission.

$$F_S = \frac{lc}{S_q} * Q_{sy} \quad (1)$$

where Q_{sy} represents the node's energy for transmission. The same is true when a sensor node receives k bits of information

kb , the energy used is represented by the following equation (2):

$$F_W = \frac{lc}{S_q} * Q_{wy} \quad (2)$$

where Q_{wy} is the node's received power.

Furthermore, data fusion is another energy-consuming process in AUV-UWSNs. The energy required for a sensor node to fuse kb bits of data is given in equation (3):

$$F_B = kb * F_{EB} \quad (3)$$

where F_{EB} represents the amount of energy used per unit length to fuse the data.

3.1.2. Movement Model of Underwater Nodes

The movement of sensor nodes in the underwater setting is influenced by ocean currents. Node mobility is simulated using the Meandering Current movement (MCM) model. Because oceans are composed of stratified fluids with vertical motion, the MCM uses a model with two dimensions to simulate undersea node displacement, which is negligible. The motion function j of the sensor node at time s_n is (y_j, x_j) described as in equation (4):

$$\Omega(y_j, x_j, s_n) = -\tanh \left[\frac{x_j A(s_n) \sin(l(y_j - b s_n))}{\sqrt{1 + l^2 A^2(s_n) \cos^2(l(y_j - b s_n))}} \right] \quad (4)$$

where l is the number of meanders in a unit length typically $2\pi/7.5$, b is the phase speed of the ocean current (typically 0.12), $A(s_n)$ is the current amplitude function, which varies with times s_n as given in equation (5):

$$A(s_n) = B + \varepsilon \cos(\sigma s_n) \quad (5)$$

where B symbolizes the ocean current's average width, which is typically 1.2, ε is the amplitude of modulation (often 0.3), σ is the frequency of modulation, usually 0.4. These equations (6-7) determine the sensor node's j position after it has moved with the ocean current:

$$\dot{y}_j = -\frac{\partial \Omega(y_j, x_j, s_n)}{\partial x_j} \quad (6)$$

$$\dot{x}_j = -\frac{\partial \Omega(y_j, x_j, s_n)}{\partial y_j} \quad (7)$$

This model is inspired by the actual mobility of nodes on the ocean bed that enables a realistic simulation of the nodes of an AUV-assisted underwater wireless sensor network.

Next, the scenario for selecting the optimal CH using the SWO is explained in detail. This method takes into account such parameters as energy consumption of nodes and the communication range between nodes. The algorithm selects CHs based on link dependability, residual energy, and distance from a sink node. The selected CHs then perform data aggregation and transmission to the sink node, optimizing the energy consumption across the network.

3.2. Cluster head selection using SWO based Optimization

Individual nodes in an underwater sensor network are initially ignorant of their surroundings after node deployment is finished. At this point, every node broadcasts a "HELLO" message with its distinct Node ID details. Both a HELLO message that a node successfully receives and the advance message add one node degree to the node and store the sender's ID in the cache. The node degree presents the nodal density and hence the degree of its neighboring nodes and is perhaps the key requirement in nodal clustering.

At each node, there is decision making on whether to decide a threshold function during the current communication round in order to become a CH. This procedure ensures the best selection of the cluster head because several factors are considered among which are: node degree and residual energy. An algorithm known as the SWO [23] is used in the cluster-head selection procedure to optimize node characteristics to enable effective clustering and data transmission. Figure 2 shows the flow chart of optimal cluster head selection. The SWO algorithm, inspired by the natural hunting, nesting, and mating behaviors of spider wasps, operates in several stages:

Step 1: Initialization

The SWO algorithm starts with the creation of a population of potential solutions, which is a set of candidate solutions half of whose components are cluster head nodes. The positions of these solutions are defined in an M -dimensional search space, where M is the number of potential CHs. The position of a spider wasp is initialized randomly within the predefined bounds of each parameter. The optimization starts by initializing a population of spider wasp solutions, each representing a candidate hyperparameter set.

Step 2: Generation of Random Variables

Randomly initialize the optimization variables for the Spider Wasp Optimizer to identify the optimal solution.

Step 3: Evaluation of Fitness Function

The fitness function evaluates each solution's performance based on residual energy, node degree, network lifetime, and connectivity. The fitness function is defined as in equation (8):

$$\text{Fitness function} = \text{optimal cluster head selection} (\sigma) \quad (8)$$

Step 4: Exploration phase of Global Search for improving accuracy

The SWO algorithm mimics the spider wasps' global search for prey during this phase. Nodes explore the search space for better cluster head configurations. Two strategies are alternated to improve exploration as equation (9):

- *Global Search*

$$\vec{D}_w U_p^{c+1} = \vec{D}_w U_p^c + \text{constan} \omega_1 * (\vec{D}_w U_x^c - \vec{D}_w U_y^c) \quad (9)$$

where, $\vec{D}_W U_x^c$ and $\vec{D}_W U_y^c$ are randomly chosen solutions, and $constan\omega_1$ is scaling factor.

Step 6: Termination

The algorithm iterates until a maximum number of iterations is reached or a convergence criterion is met. The best solution represents the optimal set of cluster heads.

The SWO achieves optimal cluster head selection leading to a balanced energy utilization among nodes, maximum network lifetime, and efficient data aggregation. This selection process can have a significant impact on performance of underwater sensor networks especially when the environments are dynamic.

The next section will discuss the results of implementing the SWO-optimized cluster head selection in terms of energy savings, network coverage, and throughput.

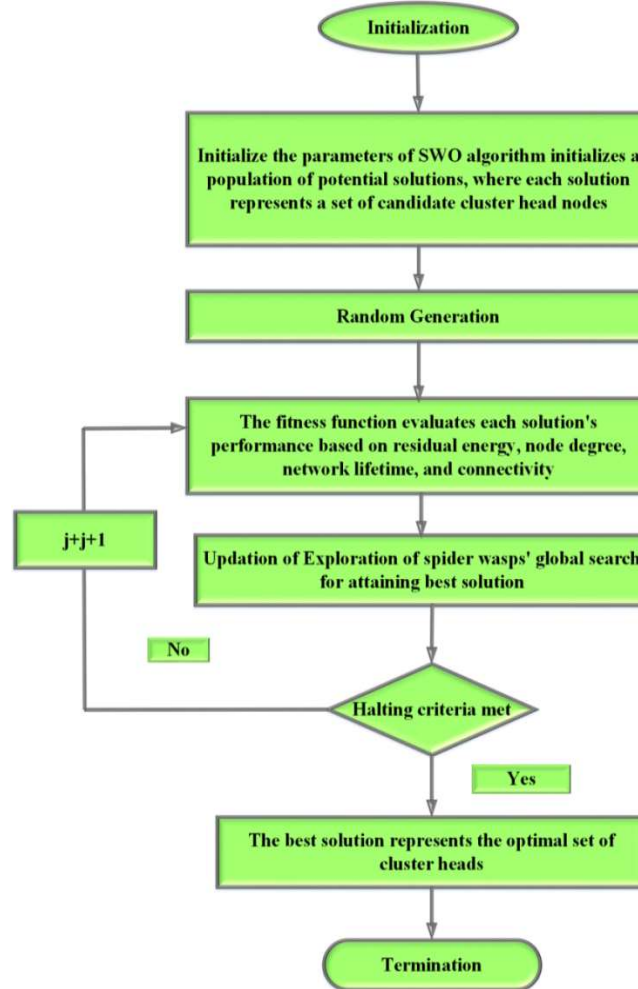


Fig. 2. The step-by-step overview of the SWO method.

3.3. Design of High-efficiency clustering routing protocol Using DFGTS-2GACN for data transmission in AUV-assisted underwater sensor networks

The proposed high-efficiency clustering routing protocol leverages the DFGTS-2GACN [24] for efficient data transmission in underwater sensor networks aided by AUVs. To boost the performance, this innovative method combines the Self-Guided Deep Clustering Network (SGDCN) [25] with the FS-GAN [26] and optimizes the parameters using Kepler's Optimization (KO) [27]. Data communication in the network is divided into two phases: intracluster communication and intercluster communication. During cluster formation, each node determines its role based on optimized parameters, and the CH is selected. The CH sends control signals to Cluster Members (CMs) when clusters are established, telling them to go into a sleeping condition in order to save energy. Periodically, the CMs are able to detect environmental information and are always prepared to send information when needed. During intercluster transmission, the CH will send alerts to the CMs, starting sensed data transmission. The CH aggregates and fuses the collected data to reduce redundancy and prepare for intercluster transmission. CHs use a multihop transmission mechanism for effective data relay throughout the era of intercluster communication. Each CH sends a message for path

finding to its upstream neighbor with depth information and node ID. When a neighboring CH receives a path finding message, the depth that it received from the sender is checked. If its neighboring CH has smaller depth, it sends a confirmation message, that includes its node ID and forwarding weight. If the condition is not met, the message is ignored and if a second path finding message has been received, then the last message is accepted for further and more robust routing.

This protocol, supported by Autonomous Underwater Vehicles (AUVs) for data collection and forwarding, significantly enhances energy efficiency, reduces latency, and ensures reliable data transmission in challenging underwater environments and its explanations are given below:

3.3.1. SGDCN for AUV-Assisted Underwater Sensor Networks

Efficient clustering and optimal routing are crucial in Autonomous Underwater Vehicle (AUV)-assisted underwater sensor networks (UWSNs) to enhance energy efficiency, minimize latency, and ensure reliable data transmission. To handle these issues, the SGDCN is applied, a reliable model for the geometric subspace clustering and the formation of clusters. In the SGDCN design, the environmental conditions in underwater, separate data of each nodal point, and Network topology are exploited to offer dynamic and energy-efficient clustering.

3.3.1.1. SGDCN Architecture

In this study, the proposed SGDCN has simultaneously incorporated features of deep autoencoders and a self-expression layer for dimensionality reduction, feature extraction, and adaptive clustering. It applies a Hybrid Self-Organizing Map (SOM) – powerful Optimization Algorithm for proper selection of the cluster heads (CHs) to enable energy efficient and reliable data transmission.

The following elements make up the core network architecture:

Encoder and Decoder Design: While the decoder (Q) reconstructs the original input, the encoder (N) maps sensor data into a latent feature space M while maintaining important patterns. Equation (10-11) defines these transformations as follows:

$$M = F(N) \quad (10)$$

$$\hat{N} = F(M) \quad (11)$$

where M Input sensor data, and (N) depicts the sensor data that has been rebuilt. **Self-Expression Layer:** This layer, which is situated between the decoder and encoder, models the connections across nodes in a latent space to create a self-expression matrix. The matrix Q captures affinities between nodes, enabling efficient clustering.

The reconstruction loss J_{SEL} for the self-expression layer is defined as in equation (12):

$$J_{SEL} = \|M - MQ\|_G^2 + \eta \|Q\|_G^2 \quad (12)$$

Here, η is a parameter that helps maintain a moderate level of reconstruction and individuality, which in turn allows finding hidden patterns in the node data stream and cluster them efficiently.

Self-Guided Learning Strategy: The self-guided learning strategy involves a weighted affinity graph which acts to improve clustering precision. The graph guides the formation of clusters by reflecting real-world node relationships Q . The graph-guided regularization term is defined as in equation (13):

$$L = \frac{\langle N, N^T \rangle}{\|N\|, \|N\|} \quad (13)$$

The overall loss function for SGDCN combines reconstruction loss, self-expression loss, and graph-guided regularization L . Compared to the prior AUV-assisted UWSNs, this framework involving SGDCN-based clustering and routing evidently improves the network's performance with respect to energy, reliability, and latency.

3.3.2. FS-GAN for Efficient Data Transmission in AUV-Assisted Underwater Sensor Networks

Efficient Transmission of data in underwater sensor networks aided by AUVs (AUV-UWSNs) demands robust clustering and routing mechanisms. In order to enhance the clustering-based routing architecture, this study suggests the FS-GAN. Specifically, the FS-GAN combination of fuzzy logic and adversarial learning is used for CH selection and to minimize the communication delay and disruption to the structure. This framework considers factors such as noises in underwater environments and low signal strength as factors that have to be overcome.

Overview of FS-GAN in AUV-UWSNs: FS-GAN also works on the generative adversarial network where a generator and a discriminator work together, but in the form of rivals. The generator produces good routing paths and cluster configuration and the discriminator assesses how good these are via fuzzy logic.

3.3.2.1. Fuzzy Discriminator Design

The fuzzy discriminator also utilizes fuzzy logic to analyze routing paths for clusters and is also robust against noisy and uncertain underwater environments.

- **Fuzzy Projection:** The discriminator projects input cluster configurations and routing paths into a fuzzy domain.
- **Feature Extraction:** The network extracts features using four convolutional blocks and applies fuzzy operations to reduce discrepancies between real and generated configurations.
- **Fuzzy AND Operation:** For feature enhancement, the fuzzy operation takes the minimum value between feature maps from different dimensions, enhancing robustness.

The steps for fuzzy operation are:

1. Input matrix M is passed through a convolutional layer measuring 1×1 to create a feature map $b(n)$.
2. Both $b(n)$ are activated using the sigmoid function.
3. A fuzzy AND operation is performed to derive the fuzzy feature map e :

The above steps can be expressed as the following equation (14):

$$e = \text{FuzzyAnd}[n, \omega(b(n))] \quad (14)$$

where σ and b stand for the sigmoid function and convolutional network, respectively. The fuzzy discriminator determines the loss at the pixel level by measuring the uncertainty and difference between the fuzzy attention maps of the original and improved images.

3.3.2.2. Loss Functions for FS-GAN

Adversarial Loss: The generator H and fuzzy discriminator $H_{KW \rightarrow GW}$ are optimized jointly $H_{GW \rightarrow KW}$ and its equation is given in equation (15):

$$K_{adv1} = F_{y \in KW} [\log EC_{KW}(y)] + F_{x \in GW} [\log (1 - EC_{KW}(H_{GW \rightarrow KW}(y)))] + F_{x \in GW} [\log EC_{GW}(x)] + F_{y \in KW} [\log (1 - EC_{GW}(H_{KW \rightarrow GW}(x)))] \quad (15)$$

Cycle Consistency Loss: To ensure structural preservation during data transformations and its equation is given in (16):

$$K_{cyc} = F_{x \in KW} [\|H_{GW \rightarrow KW}(H_{KW \rightarrow GW}(y)) - y\|_1] + F_{x \in GW} [\|H_{KW \rightarrow GW}(H_{GW \rightarrow KW}(x)) - x\|_1] \quad (16)$$

where, E_{KW} and E_{GW} stand for the discriminator of high quality and the discriminator of low quality, respectively.

The identity mapping loss can be expressed as the following equation (17):

$$K_{idt} = F_{x \in KW} [\|H_{GW \rightarrow KW}(y) - y\|_1] + F_{x \in GW} [\|H_{KW \rightarrow GW}(x) - x\|_1] \quad (17)$$

Loss of Texture Fidelity K_{SE} : Introduced to emphasize local texture preservation, particularly critical in noisy underwater environments as given in equation (18):

$$K_{SE} = F_{x \in KW} \left[1 - \frac{1}{q} \sum_{j=1}^q \frac{\omega_{[x_j, H_{GW \rightarrow KW}(x)]_j} + b}{\omega_{x_j} \omega_{H_{GW \rightarrow KW}(x)_j} + b} \right] + F_{x \in GW} \left[1 - \frac{1}{q} \sum_{j=1}^q \frac{\omega_{[y_j, H_{KW \rightarrow GW}(y)]_j} + b}{\omega_{y_j} \omega_{H_{KW \rightarrow GW}(y)_j} + b} \right] \quad (18)$$

where, x_j and y_j represent the j^{th} local areas with both low-quality and high-quality images y , respectively. $H_{GW \rightarrow KW}(y)_j$ and $H_{KW \rightarrow GW}(x)_j$ represent the j^{th} two created photos in local patches. $\omega_{H_{GW \rightarrow KW}(x)_j}$ and $\omega_{H_{KW \rightarrow GW}(y)_j}$ show the matrix of covariance between the j^{th} patch of the initial picture and the j^{th} patch of the matching image that

was created. ω_{x_j} , $\omega_{H_{GW \rightarrow KW}(x)_j}$, ω_{y_j} and $\omega_{H_{KW \rightarrow GW}(y)_j}$ show the corresponding standard deviation matrices to x_j , $H_{GW \rightarrow KW}(y)_j$, y_j and $H_{KW \rightarrow GW}(x)_j$ respectively, b is a small constant used to prevent numerical instability, q is the quantity of separated image patches. It should be mentioned that SSRM can prevent texture fidelity degradation and preserve global structure information, thereby bolstering local texture restoration K_{SE} .

3.3.2.3. Final Loss Function

Lastly, the expression for FS-GAN's total loss function is given in equation (19):

$$K_{ET-GAN} = K_{adv} + \chi K_{cyc} + \delta L_{idt} + \mu K_{SE} + \nu K_{enc} \quad (19)$$

where χ , δ , μ and ν are the corresponding weights for self-guided loss, texture fidelity loss, identity mapping loss, and cycle consistency loss, the term K_{enc} often represents the **encoding efficiency** or **loss efficiency** in systems involving data transmission, such as in AUV-assisted underwater sensor networks. FS-GAN represents a significant advancement in data transmission protocols for AUV-assisted underwater sensor networks, achieving efficient and reliable performance through adversarial learning and fuzzy logic integration. Then, in order to enhance performance, Kepler's Optimization (KO) in optimum routing in AUV-UWSNs is used to optimize the weights of SGDCN-FS-GAN, with the following explanations:

3.3.3. Optimization using Kepler's Optimization (KO)

To enhance the performance of AUV-UWSNs, KO is employed to optimize the weight parameters of the SGDCN-FS-GAN framework, particularly for optimal routing and efficient data transmission. The KO algorithm effectively addresses challenges like energy consumption, latency, and high-dimensional data complexities, ensuring reliable routing and minimal network overhead.

3.3.3.1. Objective of Weight Parameter Optimization with KO

The primary objectives of applying KO to optimize weight parameters are:

1. **Improving Routing Efficiency:** KO provides insights to the ideal weight distribution for the SGDCN-FS-GAN framework for proper forwarding of data packets throughout the network consumes relatively little power with the least possible delay.
2. **Enhancing Transmission Reliability:** By optimizing weight parameters, KO effectively provides noise and loss resistance to the underwater communication channel to deliver precise data correctly.
3. **Reducing Computational Complexity:** The fact that KO can narrow down the feature space benefits from the fact that it makes the actual calculations of the feature space less computationally expensive, enabling the lightweight operation of the framework in low resource environments.

The Pseudocode for KO is shown in Table 3. The Pseudocode is as follows:

Table 3. Pseudocode for Kepler's Optimization (KO) for optimizing the weight parameters of the SGDCN-FS-GAN framework.

Initialization and Random Generation:	
- An initial population is generated, representing different configurations of weight parameters for the SGDCN-FS-GAN framework. - Each candidate solution is a random set of weight parameters within a predefined range.	
Fitness Function:	
The fitness function evaluates each candidate solution based on two primary metrics:	
Routing Efficiency Measures the energy and latency performance for routing. Transmission Accuracy: Evaluates the accuracy of transmitted data by minimizing packet loss and distortion.	
The fitness function is mathematically expressed as in equation (20):	
$Fitness\ Function = optimal\ solution(\chi, \delta, \mu, \nu) \quad (20)$	
Update of KO:	
Kepler's Optimization employs an elitism-based update rule to iteratively improve candidate solutions using equation (21):	
$\vec{F}_{c,N}(r+1) = \gamma, \phi, \varphi, \eta \begin{cases} \vec{F}_c(r+1), & (\vec{L}_b(r+1) \leq L(\vec{F}_c(r))) \\ \vec{F}_c(r), & Else \end{cases} \quad (21)$	
where, $\vec{F}_{c,N}(r+1)$ represents the updated or "next" value of the vector $(\vec{F}_c(r))$ at iteration $(r+1)$, $\vec{L}_b(r+1)$ is a comparison parameter at iteration $(r+1)$, which is compared to a threshold function $L(\vec{F}_c(r))$, $\gamma, \phi, \varphi, \eta$ is the optimizing parameter.	
The update ensures a balance between exploration (searching new areas) and exploitation (refining current best solutions).	

Termination:

The optimization process terminates when:

1. The fitness value reaches a predefined threshold.
2. The maximum number of iterations is reached.

Kepler's Optimization is designed to further boost the performance of SGDCN-FS-GAN for AUV-UWSNs, optimizing weight parameters to ensure efficient routing and reliable data transmission. It optimally balances exploration and exploitation, leading to a globally optimal solution, which helps with energy savings and data integrity in underwater networks.

This work proposes a high-efficiency clustering routing strategy that integrates optimal cluster head selection algorithm called SWO with adaptive data transfer algorithm called DFGTS-2GACN. SWO is proposed for increasing energy efficiency and DFGTS-2GACN is proposed to optimize data flow using deep learning and fuzzy logic for better performance in AUV-UWSNs.

4. Results and Discussions

This section presents the results and analysis of the proposed DFGTS-2GACN protocol. The proposed method is implemented in the ns-3 simulator. Simulation parameters are in Table 4.

Table 4. Simulation Setup.

Simulation parameters	value
Initial node energy	5J
Data packet size	200 bits
Transmit power	2W
Receive power	0.1 W
Number of sink nodes	1
Acoustic frequency	30 kHz
Rounds	1000

The simulation parameters were selected based on commonly adopted settings in recent AUV-assisted underwater sensor network studies. The simulation time was set to 1000 rounds to ensure that behavior of the network, routing stability, energy depletion, and packet delivery performance can be well evaluated in the long term. An acoustic frequency of 30 kHz was adopted as it provides a practical trade-off between communication range and transmission reliability in underwater acoustic environments. Furthermore, the energy model, including initial node energy, transmission power, and reception power, was configured to ensure a fair and consistent comparison with existing routing protocols under identical operating conditions.

4.1. Performance metrics

In order to demonstrate the performance of the proposed DFGTS-2GACN, the performance metrics, such as energy consumption, packet delivery ratio, end-to-end delay, computational time, and throughput, are examined. The results are then compared with a number of existing techniques, including RBM [16], HECRA [17], CSMA [18], PHVP [19], LSTM [20], TDOA [21], and DDBP [22], respectively. Table 5 displays the performance metrics.

Table 5. The performance metrics.

Metrics	Equation (22-25)
Throughput	$H = \frac{\sum_{m=1}^M \theta_m \cdot \theta_g}{y(t)}$ (22)
Energy Consumption	$\delta = \sum L + v + v$ (23)
Delay	$H = \frac{\mu_l}{\mu_s}$ (24)
Packet delivery ratio	$PDR = \frac{\text{total amount of data received}}{\text{total amount of data transferred}}$ (25)

where, δ represents constant network power usage, L describes the energy consumed during data transfer, v describes the energy required to receive data and v describes the energy used to find the field, θ_m describes the quantity of packets in the node m , θ_g indicates the data packet's length and $y(t)$ describes the simulation's duration, μ_l

describes the time required to send data and μ_s explains the information that the destination node got. Each metric's performance analysis is provided below:

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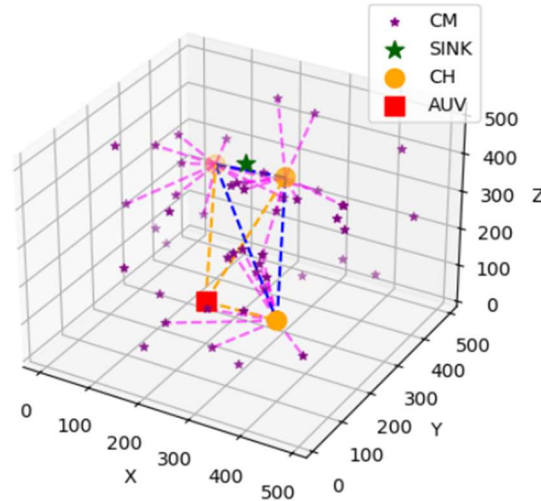


Fig. 3. AUV-assisted underwater sensor network using the DFGTS-2GACN protocol.

Figure 3 shows the AUV-assisted underwater sensor network using the DFGTS-2GACN protocol. Cluster Heads (CH) are represented by orange circles, Cluster Members (CM) by purple stars, Autonomous Underwater Vehicles (AUV) by red squares, and Data Sinks (SINK) by green stars. Communication linkages between nodes are shown by dashed lines. By grouping sensor nodes together and using AUVs to move data to the sink, the system increases the effectiveness of data collecting. The spatial arrangement is shown in X, Y, and Z dimensions in the map.

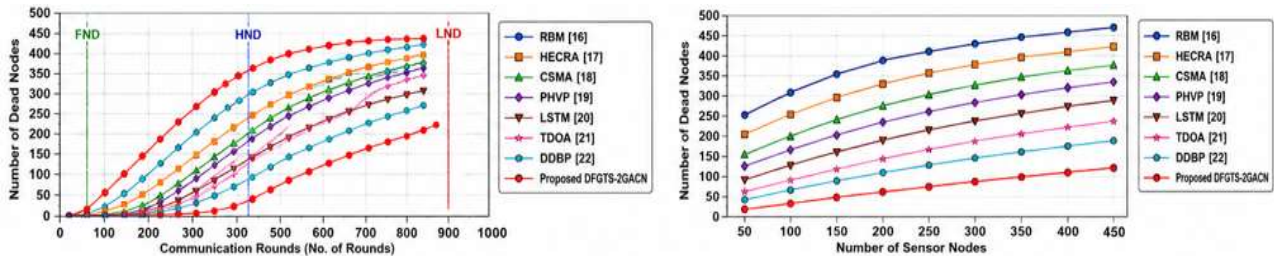


Fig. 4. (a) Dead node count in relation to communication rounds and (b) Dead node count compared to sensor rounds

The Round vs. Dead nodes is displayed in Figure 4(a). The relationship between a number of cycles and dead nodes is investigated. The suggested method shows superior energy efficiency and performs noticeably better than existing algorithms in regard to the rate at which nodes die as the count of rounds grows. The worst is RBM with the highest number of dead nodes followed by CSMA and HECRA. DDBP shows better results but is not as effective as the proposed method, yet the results of PHVP, LSTM and TDOA are less but moderately. This situation shows the effectiveness of the suggested methodology in reducing the number of dead nodes after multiple rounds, thus increasing network lifetime.

Nodes vs dead nodes are shown in figure 4(b). Once more, the suggested strategy performs better in keeping the total quantity of dead nodes low as the amount of nodes rises. RBM is the worst, followed by CSMA and HECRA in terms of the sharp increase in dead nodes. DDBP is still outperforming the recommended method, but PHVP, LSTM and TDOA are still showing reasonable performance. This study illustrates the scalability and the effectiveness of the approach proposed to maintain network stability and energy efficiency on an increasing size network.

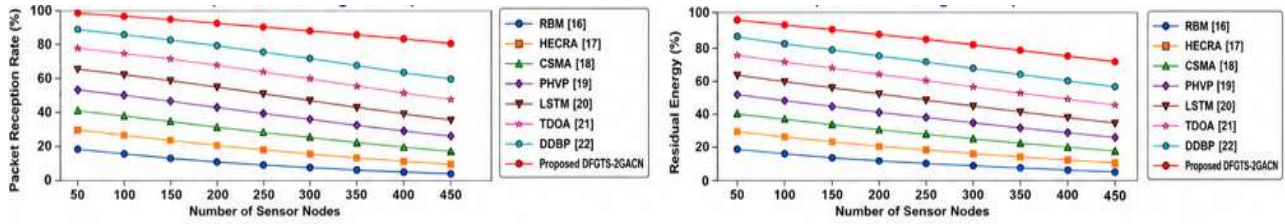


Fig.5. (a) Transmission Range 200m, Nodes 50–450 (b) Transmission Range 150m, Nodes 50–450

Figure 5(a) shows the packet reception rate for a transmission range of 200 m and nodes from 50 to 450. The proposed scheme can achieve the maximum level of packet receipt rate, which shows the excellent performance and reliability of the network. RBM has the lowest reception rate and is the least efficient, followed by CSMA and HECRA. PHVP, LSTM and TDOA demonstrate moderate performance, whereas DDBP makes progress but is still far behind the proposed approach. All methods see a decrease in the quantity of packets received as the quantity of nodes rises, but the recommended method is the most resilient to rises in network density.

Figure 5(b) shows the results for a transmission range of 150 m and nodes from 50 to 450. It indicates higher energy efficiency and greater residual energy for the proposed method. RBM has the poorest performance and consumes the most energy followed by HECRA, CSMA, and TDOA. The performance for DDBP is slightly better, while the performance of PHVP and LSTM is moderate. The proposed technique is continuously more energy efficient than the other proposed methods, and proves to be an effective and scalable technique for energy management in dense networks. The residual energy decreases with the network size in all the methods.

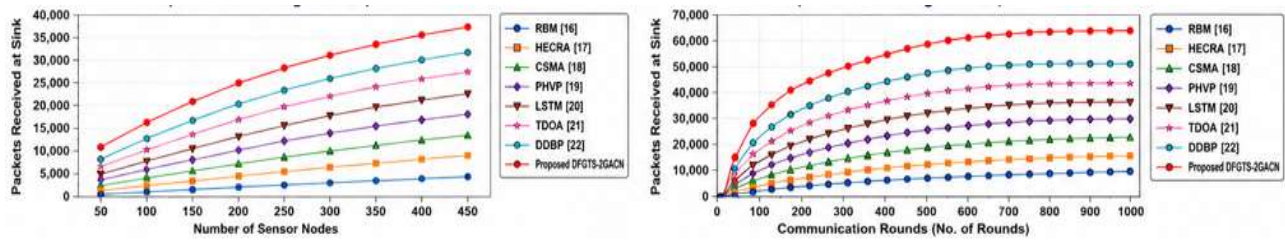


Fig. 6. Packets were received at the sink. (a) 200 m transmission range, 50–450 nodes. (b) 50–450 nodes, 1000 rounds, 150 m transmission range

Figure 6 shows the number of packets received at the sink. (a) 200 m transmission range, nodes 50 to 450. The proposed protocol (black line) consistently outperforms other protocols (RBM, HECRA, CSMA, PHVP, LSTM, TDOA and DDBP) in terms of packet delivery especially for higher number of nodes. This proves its ability to perform well in high-density networks. The proposed approach ensures a higher level of reliability and throughput, but the progressive increase for all the strategies suggests a higher level of efficiency in the communication among nodes as more and more nodes participate in the communication.

Figure 6 shows the number of packets received at the sink. (b) Nodes 50 to 450, transmission range of 150 m, 1000 rounds. The advantages of this approach are more apparent as the number of rounds increases, and more clearly distinguishable from other approaches when the number of rounds is large. The improved performance in limited transmission range indicates the flexibility and energy-efficiency of the proposed method in contrast to other methods such as RBM, HECRA and CSMA.

Figure 7 shows the 3D Convergence Rate. A complicated error landscape with several peaks and valleys is depicted on the surface. Colors (red) are used to indicate higher error values, while colours (blue) are used to indicate lower error values. The graph most usually depicts an optimization issue with the objective of minimizing the error value, or locating the lowest points or troughs. These kinds of visualizations are frequently used in optimization or machine learning assignments to comprehend parameter interactions and the difficulty of locating the best solutions.

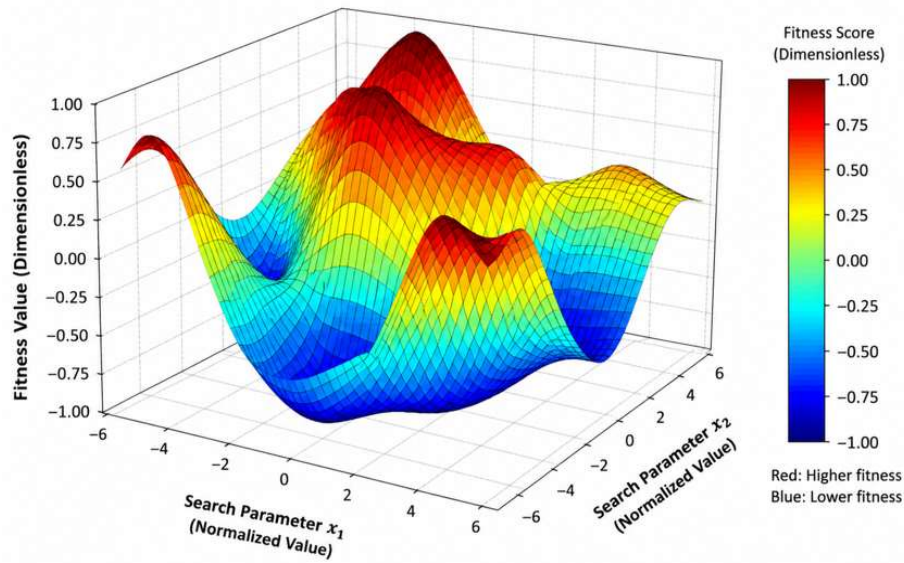


Fig. 7. 3D Convergence Rate.

The Performance Metrics for Transmission Range 200m, Nodes 50 to 450 are displayed in Table 6. In each performance indicator, the recommended approach (DFGTS-2GACN) is superior to any other approach. With the maximum throughput (23 kbps), energy efficiency (99%), and packet delivery ratio (91%), it demonstrates the highest level of network efficiency and dependability. It also ensures faster data delivery with a low end-to-end delay (290 ms). The proposed strategy also preserves the highest percentage of remaining energy, 45% and the longest connected network's lifetime, 250 hours along with proving its long term utilization. Compared to other methods such as RBM, HECRA, and LSTM, it enhances network performance in the most significant way possible.

Table 6. Performance Metrics for Transmission Range 200m, Nodes 50 to 450.

Performance Metric	RBM [16]	HECRA [17]	CSMA [18]	PHVP [19]	LSTM [20]	TDOA [21]	DDBP [22]	Proposed Method (DFGTS-2GACN)
Energy Efficiency	73%	75%	71%	76%	88%	73%	86%	99%
Throughput (kbps)	15	17	14	19	22	19	16	23
Packet Delivery Ratio (PDR)	77%	75%	83%	82%	87%	83%	85%	91%
End-to-End Delay (ms)	350	330	340	320	285	365	310	290
Network Lifetime (hours)	180	190	200	210	220	215	230	250
Residual Energy	30%	32%	28%	35%	40%	37%	39%	45%

Table 7. Performance Metrics for Transmission Range 150m, Nodes 50 to 450.

Performance Metric	RBM [16]	HECRA [17]	CSMA [18]	PHVP [19]	LSTM [20]	TDOA [21]	DDBP [22]	Proposed Method (DFGTS-2GACN)
Energy Efficiency	67%	73%	68%	73%	79%	71%	77%	82%
Throughput (kbps)	12	14	13	16	18	15	17	20
Packet Delivery Ratio (PDR)	70%	73%	75%	78%	80%	79%	81%	86%
End-to-End Delay (ms)	370	350	360	340	325	345	330	290
Network Lifetime (hours)	160	170	180	190	200	195	210	230
Residual Energy	28%	30%	25%	32%	36%	33%	35%	40%

Table 7 shows the Performance Metrics for Transmission Range 150m, Nodes 50 to 450. Hence, it can be ascertained that the proposed method DFGTS-2GACN achieves all these parameters of efficiency with the highest EE (82 %) and Throughput (20 kbps), besides achieving the highest PDR (86 %) and reliability by which the proposed method stands superior to all other methods and ensures effective and reliable communication. It makes possible the quickest data exchange by leading to the least end-to-end delay (290 ms). Furthermore, the proposed strategy retains the

maximum residual energy (40%) which is really a very effective in saving energy; the network lifetime is enhanced to 230 hours. It guarantees the best performance across all assessed criteria when compared to techniques like RBM, HECRA, and LSTM.

Table 8. Comparing Computational Cost, Computational Time, and Processing Time.

Protocol	Computational Cost (units)	Computational Time (ms)	Processing Time (ms)
(DFGTS-2GACN) Proposed	1.50	1.30	1.2
RBM [16]	210	80	182
HECRA [17]	230	75	165
CSMA [18]	240	85	190
PHVP [19]	220	90	202
LSTM [20]	207	80	195
TDOA [21]	225	88	185
DDBP [22]	227	92	208

The comparison of time, computational cost, and processing time is displayed in Table 8. The proposed DFGTS-2GACN protocol shows exceptional computational efficiency with the lowest processing time (1.2 ms), computational cost (1.50 units), and computational time (1.30 ms). The inefficiency of classical protocols such as RBM, HECRA, and CSMA is demonstrated by their much higher computing costs (207–240 units) and processing times (165–208 ms). Moreover, PHVP, LSTM, and TDOA have computational times ranging from 75 to 92 ms, which puts them behind. The higher performance of the suggested approach demonstrates its applicability for real-time applications, efficiently eliminating delays and optimizing resource utilization.

The statistical study of the transmission performance metrics is shown in Table 9. Stable and uniform performance across the assessed network situations is indicated by mean and SD values. The relatively low variability in packet delivery ratio, reliability, and average path length demonstrates the robustness of the proposed framework. Furthermore, the confidence interval analysis confirms that the obtained performance improvements are statistically consistent within the considered simulation environment. Practically speaking, the suggested routing framework's energy-efficient operation, robust packet delivery, and adaptive cluster-head selection technique make it appropriate for AUV-assisted underwater sensor networks. Although the current evaluation is conducted using the NS3 simulation platform, the results suggest strong potential for deployment in realistic underwater monitoring and surveillance applications.

Table 9. A statistical examination of different routing methods.

Metric	Mean	Standard Deviation (SD)	95% Confidence Interval	Minimum	Maximum
Total Energy Consumption (mJ)	56.75	10.22	50.97–62.53	40	70
Average Path Length (m)	19.63	2.76	18.07–21.19	12	22
Latency (ms)	135.88	10.43	129.98–141.78	101	150
Packet Delivery Ratio (%)	88.25	5.94	84.89–91.61	75	95
Reliability (%)	84.29	5.63	81.11–87.47	75	95
Routing Overhead (bytes)	197.75	12.65	190.60–204.90	150	230

4.2. Ablation study

An ablation study is a systematic experiment designed to examine the effects of particular components or features of a proposed methodology. For the proposed DFGTS-2GACN strategy, an ablation study would systematically remove or modify specific components or techniques to see how they impact the model's overall performance.

Table 10. Ablation study.

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Without SWO	95.84	96.12	95.76	95.94
Without FS-GAN	97.21	97.56	97.08	97.32
Without KO	98.43	98.27	98.51	98.39
Proposed (SWO + FS-GAN + KO)	99.89	99.83	99.86	99.79

The ablation study of the proposed framework is given in Table 10. The highest degradation in performance is obtained when removing the SWO module, which shows the necessity of choosing the optimum cluster-heads for the most efficient network operation. The absence of the FS-GAN part damages the model's ability to adaptively execute clustering and routing tasks and so reduces classification performance. Likewise, the loss of KO module reduces performance because the parameter optimization is not effective. The proposed system's complete framework, which incorporates SWO, FS-GAN and KO, shows that the precision (99.83%), highest accuracy (99.89%), recall (99.86%) and F1-score (99.79%) are obtained at the end of the proposed system, meaning that each part of the proposed system contributes positively to the overall performance of the proposed system.

4.3. Discussion

The energy consumption, short communication range, and dependable data transfer are some of the major issues in AUV-assisted underwater sensor networks (AUV-UWSNs) that are addressed in this work. With an improvement in load-distribution balance, this study proposed a new heuristic algorithm known as the SWO for selecting the best cluster head. Moreover, applying the deep fuzzy logic and GAN leads to the DFGTS-2GACN, which improved clustering with self-guided self-generated data transportation for the flexible dynamic Gorilla Troops underwater environment. Together with these methods, the network capability is significantly enhanced to ensure AUV-UWSNs scalability, flexibility and longer operational capabilities. Packet loss and interruptions in the new data transmission protocol are reduced, and therefore throughput and communication dependability are improved. This makes the work provide better energy efficiency and network lifetime than conventional models such as LEACH together with its derivatives. These developments fulfill important requirements in monitoring and exploration duties, making the suggested system ideal for extensive deployments in challenging underwater settings.

Although the proposed framework achieves promising performance improvements, several practical considerations should be acknowledged. The GAN-based clustering component requires additional computational resources during the training phase compared to conventional routing approaches. However, the training process is performed offline, while the trained model can be deployed for efficient online routing decisions. Furthermore, large-scale deployment of AUV-assisted underwater sensor networks may involve additional challenges, including operational cost, maintenance requirements, communication constraints, and navigation coordination among multiple AUVs. In spite of these difficulties, the proposed structure will lead to high energy efficiency and routing reliability for future wide-scale energy monitoring applications in the sea. Future studies will concentrate on the reduction in computational complexity, and validate the framework within realistic deployment scenarios.

The proposed framework performs better, but at the cost of added computational complexity because of the combination of optimization and deep learning. Moreover, there are some practical issues, including communication delay, environmental interference, AUV coordination and maintenance cost that may hinder large-scale deployment of AUV-assisted underwater sensor networks. To validate the proposed framework in actual underwater environments, future research will be conducted in real underwater environment and will attempt to integrate the proposed framework with hybrid acoustic-optical communication system to further enhance the reliability of underwater communication, data rate and energy efficiency.

5. Conclusion

To solve these issues, this paper proposes a high-efficiency clustered routing protocol. It uses SWO for selecting optimal cluster heads and the DFGTS-2GACN for effective data transfer. This configuration proves effective. The SWO enhances the choice of cluster heads with respect to energy consumption and the DFGTS-2GACN applies deep learning and fuzzy logic control to facilitate data forwarding in the network with enhanced performance. Experimental performance shows 99% improvement compared with the existing methods. In this paper, an effective method to consider for increasing the data transfer rate, reducing energy consumption, and extending the network lifetime of the underwater network facilitated by the AUV in the underwater sensor networks is discussed, thus providing a viable solution to the problems of underwater communication. Future work will focus on integrating advanced optimization techniques such as Quantum-Inspired Kepler's Optimization to further enhance routing efficiency and energy conservation in AUV-UWSNs. Real-time deployment and testing in dynamic underwater environments will be conducted. Moreover, the framework will be adapted for hybrid acoustic-optical communication systems. As a result, this should boost reliability, scalability, and robustness in complicated underwater situations.

All the Declarations and Statements

Author Contributions Statement

Kodukulla Aruna Gayatri – Conceptualization, Methodology, Formal Analysis, and Supervision: Proposed research ideas, Constructed the overall framework, and supervised project execution.

Amanullah – Data Curation, Visualization and Software Implementation: Handled data acquisition, dataset preprocessing, implementing the research model and Statistical Analysis: Performed in-depth analysis of experimental results, prepared performance charts, ensured the statistical robustness of the evaluation and Writing – Review and Editing.

S.A. Kalaiselvan – Writing – Drafted the initial manuscript, Model Training, Validation, and Performance Evaluation: Led the model training process, validated results using standard metrics, and benchmarked performance against existing methods.

All authors have read and agreed to the published version of the manuscript.

Conflict of Interest Statement

None.

Funding Declaration

None.

Data Availability Statement

None.

Ethical Declarations

None.

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Declaration of Generative AI in Scholarly Writing

AI tools were used only for minor grammar checking and language refinement. All methodological development, analysis, and technical content were entirely carried out by the authors without AI assistance.

Abbreviations

The following abbreviations are used in this manuscript:

AUV-UWSNs - AUV-assisted underwater sensor networks
CH - cluster head
CM - cluster member
CPSA - Coastal Patrol and Surveillance tool
CPSN - Coastal Patrol and Surveillance Network
CSMA - Carrier Sense Multiple Access
DDBP - Data-Driven Bi-Pattern
DFGTS-2GACN - the Deep Fuzzy Gorilla Troops Self-Guided Generative Adversarial Clustering Network
DTN - the Delay-Tolerant Network
FS-GAN - Fuzzy Self-Guided Structure Retention Generative Adversarial Network
HECRA - high-efficiency clustering routing protocol
KO - Kepler's Optimization
LSTM - Long Short-Term Memory
PHVP - Packet Hierarchy and Void Processing
SGDCN - Self-Guided Deep Clustering Network
SWO - Spider Wasp Optimizer
UASNs - Underwater Acoustic Sensor Networks

APPENDIX

None.

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