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Underwater Communication Network Optimization by Clustering Nodes and Predicting Sensing Data

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Abstract- Underwater communication is challenging environment for the networking and data collection. Many of scholars provide the different solution to increase network life by optimizing hardware and routing. This paper has proposed a model that learn from the network packets and predict the data of packet. Routing of packets plays an important role for the network life optimization hence this work do clustering of network by genetic algorithms. Cluster head learns the packet features to predict the sensing data. It was found that use of genetic and learning model has reduces the energy losses in the underwater network. The experiment was conducted in real-world environmental conditions to assess the proposed model's performance. The results reveal that the model significantly extends the system's lifespan while improving the number of successfully transferred packets. This highlights the model's ability to enhance efficiency and optimize resource utilization in practical scenarios.

Index Terms—Energy Optimization, Genetic Algorithm, UWSN, Communication, Routing.

I. INTRODUCTION

Networks of Underwater Acoustic Sensors (UWSN) have been on the rise in recent years due to their great promise for various roles in water related tasks. These roles comprise of underwater surveying, pollution control, ocean studies, and other sea-based activities. The UWSNs utilize acoustic waves for information transfer, as radio waves are inapplicable when submerged due to high absorption and scattering. It has been suggested that optical waves could perform this function; however they are not effective for long range communications in turbid waters because of excessive loss and dispersion of the signal [1]. As the battery capacity limits of sensor nodes, the most important goal in UWSNs is energy efficiency and network lifetime maximization. The underwater device data transfer, sensing, and handling of data, all actions needs significant energy. So communication network needs protocols and solutions that are energy efficient. The excessive energy consumption involved in these operations stresses the need for energy-efficient substitutes [2].Nonetheless; the unique properties of submerged environments provide significant challenges. Because of the limited battery capacity of sensor nodes, there is a need to maximize network longevity, which leads to the development of energy utilization algorithms, protocols and hardware optimization. The fact that communication, sensing, data transmission, and processing occur underwater consumes a significant amount of energy demonstrates the importance of maximizing energy efficiency in hardware design and networking protocols [3]. As the acoustic waves travel through a medium, the absorption and scattering effects cause a reduction in their amplitude. Moreover, the attenuation of high frequencies occurs rather quickly, which makes acoustic waves reach a short distance and greatly affect the routing and communication protocols. Hence, there is a need to provide fast and high-speed, low latency connections. The reliability of underwater communication depends heavily on noise and interference reduction [4].

Rest of paper was organized in few sections where existing paper work were discuss in the second phase. Further paper has brief proposed model of the paper with block diagram and algorithm.

II. Related Work

In the study [5], a model proposed for underwater acoustic sensor networks life extension. The algorithm leverages the maximum-likelihood ratio criterion to enhance the accuracy of localization. To tackle the computational complexity often associated with ML-based methods, the authors employ the majorization-minimization approach. This method simplifies the resolution process by constructing an auxiliary function that iteratively minimizes the complexity while maintaining accuracy. The proposed localization algorithm, referred to as the T-MM algorithm, integrates the proposed approach with the MM framework, creating a robust solution for underwater localization. Additionally, a gradient-based initialization technique is utilized to determine the starting points of the T-MM scheme, ensuring precise convergence and improved performance under challenging underwater conditions.

The research presented in [6] introduces a model that was designed to enhance the efficiency of underwater wireless sensor networks. This innovative algorithm combines key features from biological algorithms, simulation and ant colony to create a more effective and adaptable solution. To further improve the proposed algorithm, the authors integrate a structure correction function that refines the node deployment strategy. The primary goal is to achieve optimal coverage control by strategically deploying nodes while addressing underwater challenges such as dynamic environments and limited resources. Moreover, the adaptability and independence of autonomous robots are leveraged to facilitate node placement and improve the network’s performance. The study also includes a comparative analysis of the proposed algorithm against other intelligent optimization techniques, demonstrating its superiority in optimizing UWSN node deployment.

In [7], a Distributed algorithm was proposed that tailored for three-dimensional network architectures. This method focuses on efficient node deployment for underwater applications, with a particular emphasis on tsunami monitoring. The proposed approach minimizes the number of nodes required while ensuring comprehensive coverage and adherence to Quality of Service requirements. Geographic Information Systems data, environmental constraints, and underwater sensor characteristics are incorporated to optimize node placement. The proposed method addresses deployment challenges by guiding node positioning to achieve specific objectives, including reliable environmental monitoring with minimal resource usage.

The research in [8] investigates trajectory optimization in underwater data networks using mobile nodes. Autonomous Underwater Vehicles are tasked with collecting samples from designated mission areas, while Autonomous Surface Vehicles retrieve this data. The optimization framework aims to minimize the travel distances of Autonomous Surface Vehicles while ensuring fair data exchange among the Underwater Vehicles. To achieve this, a nearest-K reinforcement learning method is employed, which selects the most suitable from the nearest-K candidates for data transfer. This technique maximizes operational efficiency by focusing on proximity and optimizing data transmission routes. The framework also considers the dynamics of underwater mobility, ensuring that data mules operate efficiently under diverse environmental conditions.

In [9], authors proposed a model to address the challenges of energy-efficient and reliable underwater communication. The proposed method constructs transmission routes by employing the Q-learning algorithm, which evaluates network parameters such as topology, latency, and residual energy of nodes. By considering these factors, the algorithm enhances the decision-making process for selecting the next-hop node, optimizing both communication reliability and energy efficiency. The cooperative routing policy developed through proposed balances packet forwarding benefits with energy consumption costs, ensuring sustained performance. This method underscores the effectiveness of combining Q-learning with Stackelberg game theory to address the complexities of underwater communication.

The study in [10] introduces a system that aimed to optimizing the energy usage and localization accuracy of floating underwater nodes. The introduced system resolves the coverage problem as a virtual force issue involving underwater relay nodes, obstacles, and sensor nodes. Virtual forces are employed to guide nodes toward optimal positions, mitigating issues like sparse or dense distributions. To address energy depletion in relay nodes, a non-uniform deployment strategy combined with hierarchical routing is proposed, reducing coverage gaps and enhancing network longevity. The system also evaluates localization performance using the Cramer-Rao lower bound, factoring in uncertainties from drifting coordinates and noisy ranging data. This comprehensive approach ensures efficient energy utilization and accurate node positioning, making it a significant contribution to underwater network optimization.

III. **Proposed Methodology**

The block diagram in Figure 1 is used in this section to illustrate the characteristics of the Underwater Network Optimization by Data Prediction and Clustering (UNOPC) model. The task is divided into two parts: the first part involves using the Genetic Algorithm model to build the cluster center, and the second part is about training the neural network to sense and anticipate data during communication. An observation window for identifying the cluster center of the IoT nodes is provided in the first part. Figure 1 depicts the overall model learning flow, as well as node prediction.

Table 1 Proposed model notations.

Symbol	**Significance**
d	Distance between nodes
E	Energy
N	Nodes
V	Volume
L	The packet's bit count
E	Energy required to move L bits
K	Number of Cluster
C	Cluster Center
T	Transmission time
CP	Chromosome population
B	Population Size
Pos	BAT Position

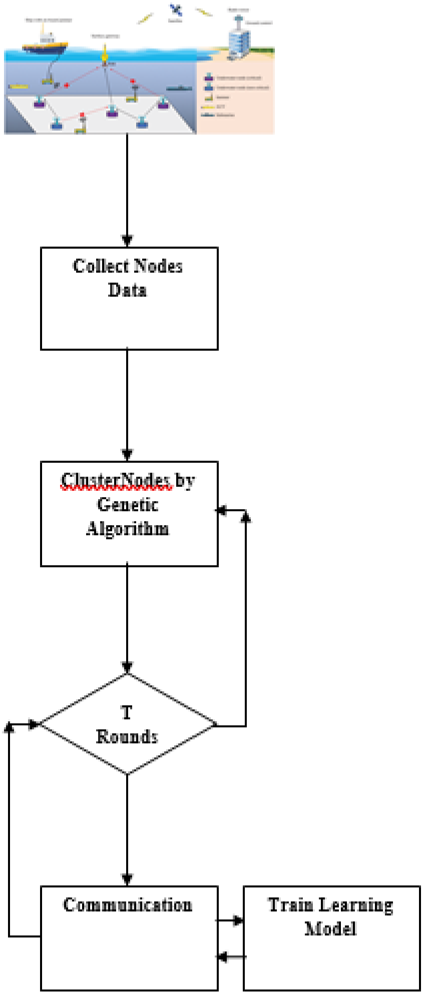

Fig. 1 Gathering of sensor node data and model training.

Observation Window: Data gathered from various IoT nodes throughout the network is centrally stored in the observation window [11, 12]. This repository plays a crucial role in ensuring the continuity of operations, especially in scenarios where data transmission fails. The data stored in the observation window is leveraged to analyze and predict the sensing information of the nodes, enabling the system to fill in missing data seamlessly. The length of the observation window is directly linked to the initial rounds of communication, encompassing the period during which the system collects and processes the necessary data to build predictive models and ensure reliable functionality.

Node Communication Energy Consumption-To provide effective data transmission throughout the network, IoT nodes work collaboratively to establish and maintain communication routes between them. This cooperative behavior ensures that data is successfully transmitted across multiple nodes, creating a functional and interconnected system. However, this process incurs energy costs, as each node involved in the communication expends energy to transmit, receive, or relay data. The total energy loss during communication is the combined energy consumed by all devices participating in the data transfer process [13]. The energy required to transmit a file, referred to as ETX, is a critical parameter in evaluating the energy efficiency of the network. This formula can be used to calculate it:

$$E_{TX} = P_o \frac{U(d_{i,i+1}) + \delta \times U(d_{c,i+1})}{1+\delta} \times T \text{------Eq. 5}$$

Lets $U\ (d\ (i,\ i+1))$ U(d (i,i+1)) and $U\ (d\ (c,\ i+1))$ U(d (c,i+1)), which are sequential routing devices. Binary indicator T required completing routing for devices 'i' and 'δ'. The definition of the indicator 'δ' is as follows:

$$\delta = \begin{cases} 0, & d_{i,i+1} < r_{max} \text{ for non DCC cooperation} \\ 1, & d_{i,i+1} > r_{max} \text{ for DCC cooperation} \end{cases}$$ ------Eq. 6

denotes the maximum allowable distance between two nodes in an underwater network, which is crucial in determining whether direct communication is possible or if a cooperative device is needed. If the distance between nodes exceeds r max r max , the communication signal can degrade due to the limitations of underwater acoustic channels. In such cases, cooperative communication is employed, where an additional device is introduced to help bridge the communication gap between distant nodes. This cooperative device assists in relaying data, ensuring that nodes can still exchange information despite the distance constraints, thus maintaining the reliability and efficiency of the underwater transmission system [14].

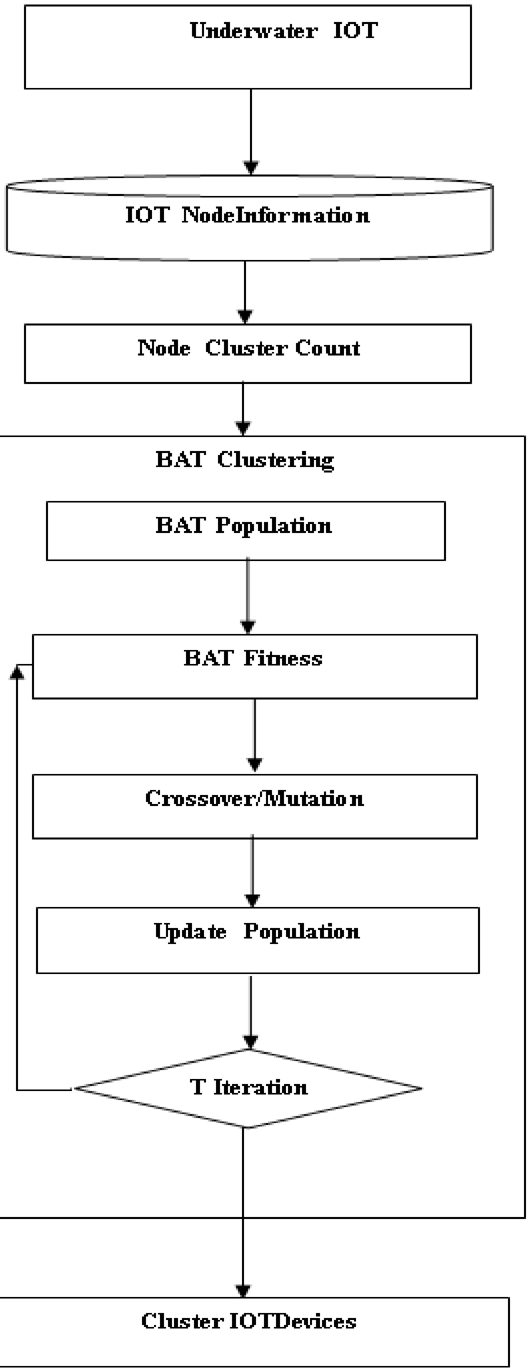

Fig. 2 Cluster of Underwater nodes

Node Cluster Count

To perform clustering of IoT nodes, the genetic algorithm requires count of clusters. The cluster count K is determined using Equation 7:

$K = \frac{3V^3}{4\pi r^3}$---------------Eq. 7

BAT Population

A collection of possible cluster head devices, each acting as the hub for undersea nodes, is represented by a chromosome. It is organized as a vector with n elements, which match the Cluster Device's (CD) columns. Each chromosome is made up of a cooperative collection of devices that work in tandem. If the number of cluster center devices is denoted by b:

B🡐Generate_Population(p, K)------Eq. 2

BAT Fitness

This approach evaluates and assigns a fitness score to each subsea node, which is represented as a chromosome, according to its positional efficiency. The efficacy of the node in terms of communication distance is gauged by this fitness score. The cluster center devices determine the fitness value by summing the total energy consumed to transmit data, while a group of chromosome-based devices operate underwater.

Crossover

The success of the genetic algorithm relies heavily on modifying the chromosomes to enhance performance. During the crossover process, changes are applied by adjusting the parameter X, which involves altering the values of random positions within several chromosome nodes. For the remaining chromosome, In the current algorithm iteration, some of their components are swapped out for matching values from the randomly selected top-performing chromosomal nodes.

Population Update

Every chromosome's fitness value is reassessed by contrasting it with that of its parent chromosome. If the offspring chromosome exhibits a higher fitness value, it replaces the parent chromosome in the population. If not, the parent chromosome remains unchanged. This iterative process continues until the algorithm reaches the predefined maximum number of steps. The procedure moves on to the filter feature block when this limit is reached. If not, the optimization process continues and the fitness values are recalculated.

Cluster IOT Devices The clustering process in an underwater IoT network selects the best chromosome from the updated population to identify cluster center devices. This selection is based on evaluating the fitness of each chromosome for efficient clustering. Once the cluster centers are established, sensor data transmission begins and continues over multiple iterations. During these iterations, cluster centers are dynamically updated to reflect changes in device positions and energy levels, ensuring optimal network performance. This flexible strategy reduces energy usage, improves the effectiveness of data transfer, and keeps the network operational even under difficult underwater circumstances. The goal is to strike a balance between energy conservation and efficient communication in order to guarantee the network's dependability and lifespan.

Sensor Node Train for Data Prediction

The study focuses on reducing energy waste in communication networks caused by resending lost packets. It uses a neural network to predict and fill in the missing data, avoiding the need to resend packets. This saves energy, lowers costs, and helps the network last longer. The method makes the network more efficient, reliable, and sustainable, especially for underwater communication.

Error Back Propagation Neural Network Training: This step involved training packet predictions using the Error Back Propagation neural network. The time period, values, current temperature, and pressure are all considered input. It is assumed that a layer neural network consists of three layers. J found hidden layer neurons, while I found input layer neurons. The letter k stands for the output layer neuron. The weights between layers of neurons are represented by Wij. $X_j = \sum x_i . w_{ij}$ ------------Eq. 2

With 1£ i £ n, n is the number of inputs to node j, and bj is node j's biasing. As a result, the network will learn how to distribute weight between levels. This inaccuracy should be corrected by altering the weight values of each layer. As a result, the error was estimated using equation 3 [13]. $e_k(n) = d_k(n) - y_k(n)$---------Eq. 3

This error should be fixed by changing each layer's weight values. So, the neural network's forward movement is complete, and error back propagation begins.

$$\frac{\partial E_i}{\partial O_i} = (-1 * ((y_i * \log(O_i) + (1 - y_i) * \log(1 - O_i) - -Eq.4$$

$$\frac{\partial O_i}{\partial H_i} = ((1/(1 + e^{-x}) \times (1 - (1/(1 + e^{-x}))) - - - -Eq.5$$

Let us use eq. 5 to determine the derivative of each input to a neuron in relation to each weight. Now, let's look at the final derivative using equation 6.

$$\sum_{i=1:n} \frac{\partial H_i}{\partial W_{i\,(j,k)}} = \frac{\partial (h_{i\,(ouput)} * W_{i\,(j,k)})}{\partial W_{i\,(j,k)}} - - - -Eq.6$$

The final derivatives for Equation 7 were derived using the chain rule. The multiplication of each derivative was done in the following way:

$$\frac{\partial E_i}{\partial W_i} = \frac{\partial E_i}{\partial O_i} * \frac{\partial O_i}{\partial H_i} * \frac{\partial H_i}{\partial W_i} - - - -Eq.7$$

The total ∂W_i can be derived by obtaining the weight value from the previous equation. Here, the values in equation 8 alter all of the weights that require updating.

$$\partial W_i = \begin{bmatrix} \frac{\partial E_1}{\partial W_{1,1}} & \frac{\partial E_2}{\partial W_{1,2}} & \frac{\partial E_3}{\partial W_{1,3}} \\ \frac{\partial E_1}{\partial W_{2,1}} & \frac{\partial E_2}{\partial W_{2,2}} & \frac{\partial E_3}{\partial W_{2,3}} \\ \frac{\partial E_1}{\partial W_{3,1}} & \frac{\partial E_2}{\partial W_{3,2}} & \frac{\partial E_3}{\partial W_{3,3}} \end{bmatrix} - - - -Eq.8$$

Proposed Work Algorithm

```
Input: N, V
Output: CIOTD // Cluster IOT devices
1. UN ←Underwater_IOT_Network(N, V) // UN: Underwater IOT Network
2. [d K e]←Collect_Data(UN, N)
3. B←Generate_Population(b, K)
4. Loop 1:T
```

```
F←Fitness(B,N)
B'←Crossover(b, B)
B←Update_Population(B,B')
End Loop
F← Fitness(B,N)
b←Best(F)
CIOTN←Cluster_Devices(b, N)
```

IV. Experiment and Result

The proposed model for optimizing Internet of Things networks was developed and executed on the MATLAB platform. To assess its effectiveness, the performance of different genetic algorithms was compared against existing IoT energy optimization models: the ECRKQ model [16]. This comparative analysis aimed to highlight the advancements and efficiency improvements achieved by over current methods. The experimental setup utilized a hardware configuration consisting of an Intel i3 processor and 4GB of RAM. This setup was chosen to ensure efficient execution of the experiments and to provide consistent and reproducible results, enabling a reliable evaluation of the proposed model's performance. This work has compared BAT (ANOBDPM) [17] with prediction, BAT (AIOTOPC) [18], without prediction model and BGO model (UIOTNBO) [19] with prediction of packet.

Results

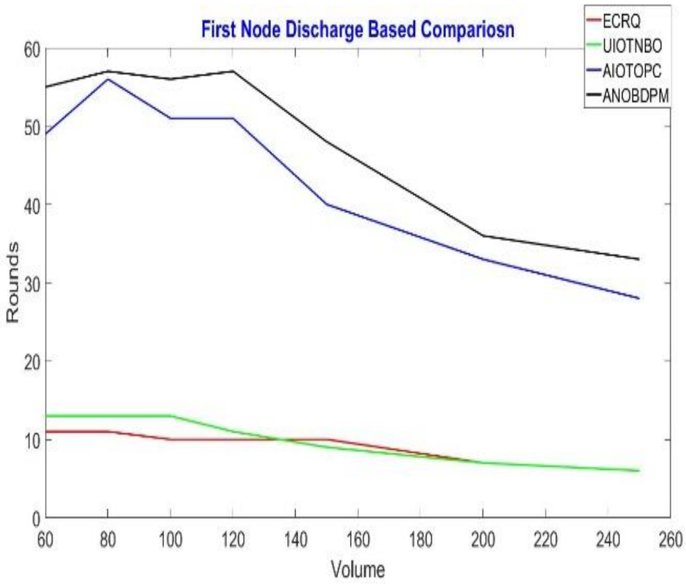

Fig. 3 First node discharge based comparison.

Fig. 3 demonstrates that the proposed model enhances network efficiency by significantly reducing energy losses. The use of the genetic algorithm improves the accuracy of cluster head selection, leading to more effective network management. Additionally, it was found that as network volume increases, the first node discharge count decreases across all models, indicating a longer energy lifespan for the nodes. This result highlights the model's ability to optimize energy consumption and extend the network's operational performance.

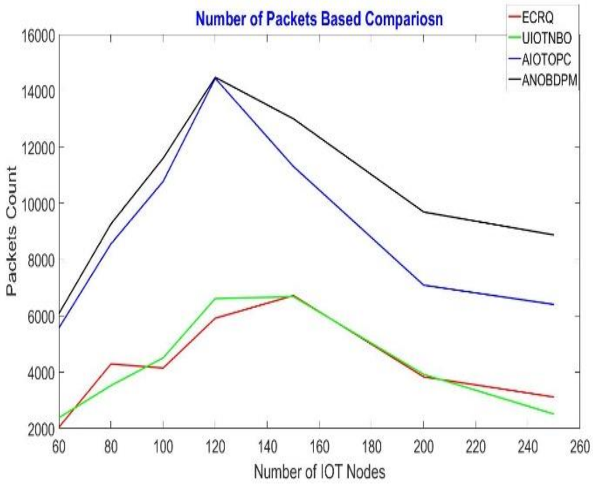

Fig. 4 Number of packets based comparison.

As the volume size increases up to 150x150x150m³, the number of packets transferred also increases. This trend indicates that larger network volumes contribute to an increased volume of data transmission. Furthermore, it was observed that employing a learning model to predict packet losses within the network leads to a noticeable reduction in packet losses. This prediction mechanism allows the network to adapt and mitigate loss, ensuring more reliable communication. Additionally, it was discovered that the use of the Bat Algorithm (BAT) outperforms the Biogeographic Optimization (BGO) algorithm in terms of overall performance, demonstrating its superior efficiency in optimizing the network's routing and energy consumption.

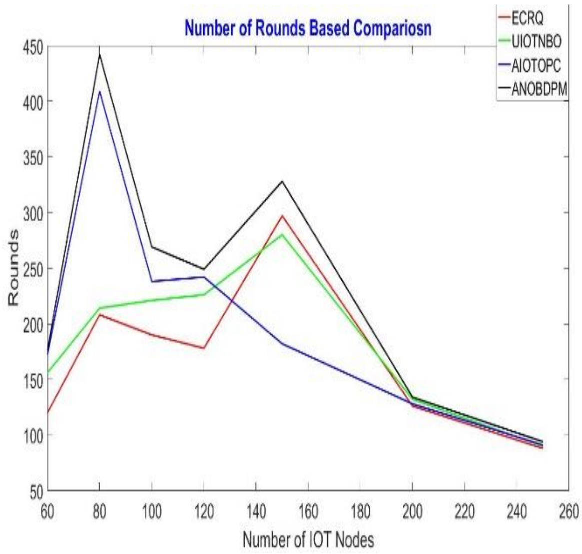

Fig. 5 Number of rounds based comparison.

The number of rounds required for data transmission increases when the learning model is utilized at the cluster head level. In this configuration, the network load is significantly reduced due to the accurate prediction of packet losses. By improving the ability to predict and manage losses, the learning model helps optimize the overall efficiency of the network. As a result, the nodes are able to transfer more packets by selecting more efficient routes for packet transmission. This not only increases the data throughput but also enhances the overall performance of the network by minimizing unnecessary energy expenditure and reducing delays in communication.

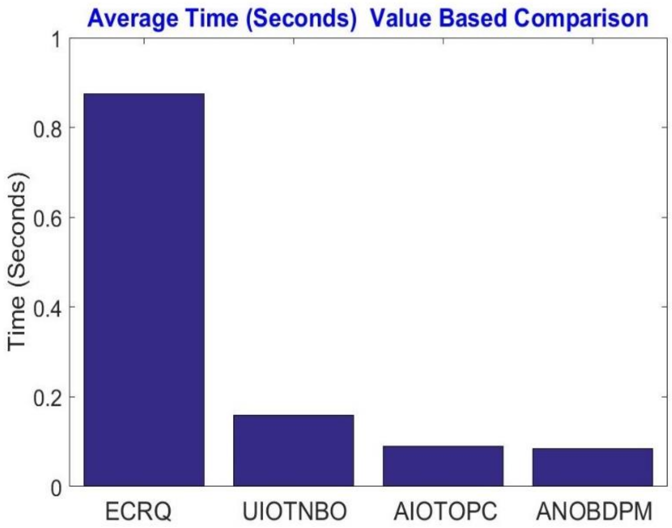

Fig. 6 Average time based comparison.

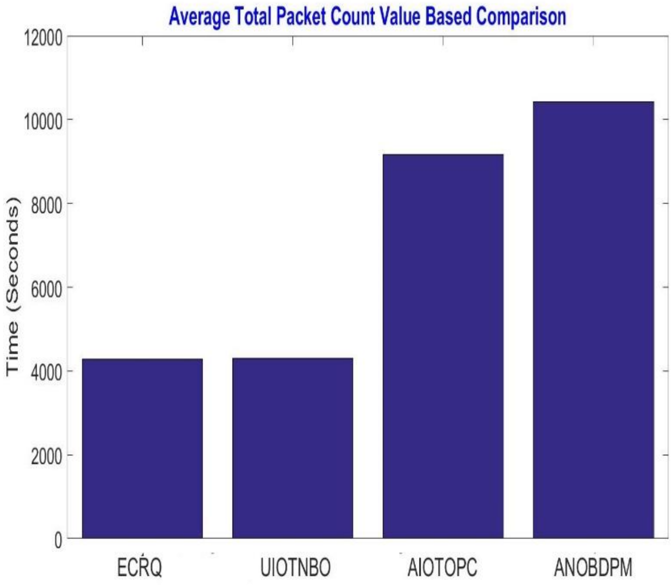

Fig. 7 Average total packets count based comparison.

Figures 6 and 7 illustrate that employing a genetic algorithm to identify cluster heads effectively reduces the execution time of clustering operations. This approach enhances the efficiency of the clustering process, leading to a more streamlined network performance. Additionally, the study indicates that increasing the number of packet transfers contributes to a reduction in energy losses, thereby improving the overall energy efficiency of the system.

V. Conclusion

This research demonstrates that implementing node clustering for packet routing significantly enhances the performance of underwater networks. The integration of a learning model to generate missing data further extends the network's operational lifespan. The findings reveal that combining genetic algorithms with neural network learning techniques effectively minimizes energy losses. Experiments conducted with various node configurations and data volumes provide a comprehensive analysis of the proposed methodology. The results consistently show that the suggested model increases both the network's operational lifespan and the number of successful packet transfers across all experimental setups.

Furthermore, among the algorithms compared, the genetic algorithm outperforms others, including the Bat Algorithm, in terms of efficiency and effectiveness.

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