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Acoustic Wireless Sensing Node Network Energy Optimization by Clustering

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Abstract- In underwater acoustic sensor networks (UWASN), ensuring energy-efficient data communication remains a significant challenge due to the harsh and unpredictable underwater environment. Acoustic signal transmission is often affected by high ambient noise, extremely long propagation delays, increased bit error rates, limited available bandwidth, and various forms of interference. As a result, one of the primary objectives of UWASN research is to prolong the operational lifetime of the network by optimizing energy usage. The process of reliably transmitting data from a source node to a destination node in UWASN is inherently complex and continues to be a critical area of investigation. To address this issue, the Acoustic Wireless Node Energy Optimization (AWNEO) model is proposed as an efficient network clustering strategy aimed at minimizing communication-related energy losses. The model leverages a group-based concept inspired by the Teacher Learning Algorithm, which enhances overall operational efficiency by facilitating effective knowledge sharing and optimization among nodes. In the proposed approach, selected nodes act as cluster heads and are responsible for forwarding aggregated data packets to the base station, thereby reducing redundant transmissions and conserving energy. Experimental evaluation demonstrates that the AWNEO model outperforms existing acoustic network optimization algorithms across multiple performance parameters, including energy consumption, network stability, and data transmission efficiency.

Keywords: UWSN, Communication, Routing, Energy Optimization, Genetic Algorithm.

I. INTRODUCTION

Securing Underwater Wireless communication Networks (UWCNs) area unit deep-seated by sensors and Autonomous Underwater Vehicles (AUVs) that move to perform specific applications like underwater observance Coordination and sharing of data between sensors and AUVs create the supply of security difficult[1]. The aquatic surroundings is especially liable to malicious attacks thanks to the high bit error rates, giant and variable propagation delays, and low information measure of acoustic channels. Achieving reliable repose vehicle and sensor-AUV communication is very troublesome thanks to the quality of AUVs and therefore the movement of sensors with water currents. The distinctive characteristics of the underwater acoustic channel, and therefore the variations between underwater detector networks and their ground primarily based counterparts need the event of economical and reliable security mechanisms [2].

Underwater sensor networks nodes are not static like ground-based sensor networks nodes. Instead, they move due to different activities and circumstances of underwater environment, usually 2-3m/sec with water currents. Sensed data is meaningful only when localization is involved. Another major issue that is affecting underwater sensor networks is energy saving [3]. Because of nodes mobility, the majority of offered energy competent protocols become inappropriate for underwater sensor networks. Different protocols regarding land-based sensor networks are, for example, Directed Diffusion, Gradient, Rumor routing, TTDD, and SPIN.

However, because of mobility and rapid change in network topology these existing grounds based routing protocols cannot perform efficiently in underwater environment [4]. Optimal packet size is depending on protocol characteristic like offered load and bit error rate. Poor packet size selection decreases the performance of the network throughput efficiency, latency, and resource utilization and energy consumption in multihop underwater networks can be greatly improved by a using optimum packet size [5, 6]. To improve the better utilization of the available resources in underwater environment considering the energy and life time of network is discussed in detail in this paper. Balancing of energy consumption is carried out in underwater environment using the proposed techniques.

II. RELATED WORK

Recent research in 2024 has highlighted clustering-based energy optimization as one of the most effective techniques for prolonging network lifetime in wireless and underwater sensor networks. These studies emphasize adaptive cluster-head selection and energy-aware cluster formation to reduce redundant data transmission and balance node energy consumption. Intelligent clustering approaches have demonstrated notable improvements in packet delivery ratio and network stability when compared to conventional static clustering mechanisms [7], [8].

Several studies published in 2024 investigate the application of machine learning techniques for dynamic energy optimization. Reinforcement learning and supervised learning models are widely used to optimize routing decisions, transmission power, and sleep scheduling. The surveyed works report that learning-based approaches significantly outperform traditional heuristic methods by adapting to real-time network conditions and reducing unnecessary energy expenditure [9].

In 2025, bio-inspired and metaheuristic optimization algorithms have gained increased attention for energy-efficient communication in sensor networks. Algorithms such as genetic algorithms, particle swarm optimization, whale optimization, and teacher–learner-based optimization have been successfully applied to address multi-objective energy optimization problems. Surveyed studies indicate that hybrid metaheuristic models achieve superior energy savings, faster convergence, and improved scalability in comparison with single-optimization techniques [10], [11].

Cross-layer optimization frameworks proposed in 2025 integrate physical, MAC, and network-layer parameters to achieve holistic energy efficiency. By jointly optimizing transmission power, channel access strategies, and routing protocols, these frameworks significantly reduce packet retransmissions and communication overhead. The literature confirms that cross-layer energy optimization enhances network lifetime and reliability, especially in resource-constrained and delay-sensitive environments [12].

Recent surveys focusing on harsh environments such as underwater, underground, and disaster-prone regions highlight the importance of lightweight and adaptive energy optimization techniques. Due to limited battery replacement options, researchers prioritize low-complexity clustering and scheduling mechanisms. Findings show that adaptive clustering combined with intelligent energy-aware routing ensures reliable communication while minimizing energy consumption in extreme environments [13], [14].

III. PROPOSED METHODOLOGY

Acoustic Wireless Network need communication system that reduces the energy uses. For this clustering of nodes plays an important role. But as water waves shift nodes position hence dynamic approach is required that not need any guidance. This paper has developed a AWNEO (Acoustic wireless Node Energy Optimization) model to cluster Acoustic network nodes. Fig. 1 shows various steps of clustering.

Develop ACOUSTIC Environment

Develop an V volume under water, place N number of nodes present in the region. Relegate their starting energy level before transmitting and getting any bundles. Energy utilization per unit node is required to be evaluate [13].
The transmission energy (ETx) and accepting energy (ERx) can be processed for a packet of length L bit, d the space among source and next/base/cluster node,.

The model to estimate the minimum transmission power in underwater acoustic communication is adopted based on the model in [14, 8]. Denote P0 as the minimum received power to successful receive a packet. Let U (d) be the attenuation of transmitting underwater acoustic signals between two nodes with the distance of d . Then, the minimum transmission power.

P = P0 · U (d)

where

$$U(d) = (1000xd)^m[\gamma(f)]^d$$

Here, m is the environmental coefficient (where we take m D 1:5 for shallow water acoustic channels) and γ (f) is the absorption coefficient under carrier frequency f .We often use
the Thorp's formula to formulate (f), i.e.,

$$10log_{10}\gamma(f) = \frac{0.11f^2}{1+f^2} + \frac{44f^2}{4100+f^2} + 2.75 \times 10^{-4}f^2 + 0.003$$

The optimal choice of f is based on the empirical formula
below [30]:

$$f_{opt} = \left(\frac{200}{d}\right)^{2/3}$$

If cooperative nodes participate in the DCC transmissions,
the total energy consumption of a transmission is the sum of
the energy consumption of node i, node i + 1, and the corre-
sponding cooperative node. The formula for calculating the
total energy consumption for transmitting a packet, denoted
as E, is

$$E = P_o \frac{U(d_{i,i+1}) + \delta \times U(d_{c,i+1})}{1+\delta} \times T$$

where $U(d_{i,i+1})$ and $U(d_{c,i+1})$ are the underwater sound attenuation between node i and node i + 1 and between the cooperative node and node i + 1, respectively, T is the transmission time of node i, and δ is a binary indicator to imply if DCC is needed, i.e.,

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

where r_max is the maximum distance between two nodes to determine if a cooperation node is needed for achieving the DCC transmission [14].

Estimate K Cluster

Find number of cluster in the volume. Where r is range of devices to transmit [11].

$$K = \frac{3M^3}{4\pi r^3}$$

Generate Teacher Learning

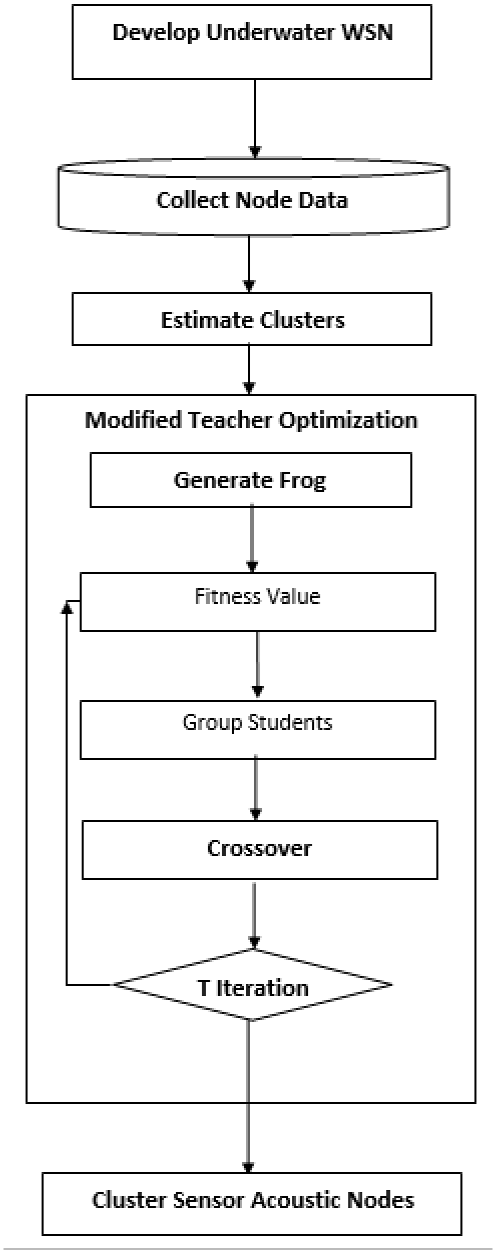

Fig. 2 Block diagram of proposed AWNEO model.

The cluster center devices set is made up of chromosomes, and each chromosome is a possible Teacher Learning [15]. So a Teacher Learning is a vector with n items, where n is the number of columns in the CD. The heart of each Teacher Learning is a group of nodes that work together. So, if b is the number of

F·Teacher Learning_Population(p, K)----------Eq. 2

Teacher Learning Fitness Function

Each Teacher Learning was ranked by how far it was. So the health number is used to judge the distance run. A group of Teacher Learning-based gadgets were found underwater. Teacher Learnings cluster center devices figure out the fitness value by adding up how much energy it takes to send one message from each sensor device to the base station.

Group Students: Estimate the fitness value of each Teacher where accuracy of intrusion detection were sort in descending order. After sorting some set of Teacher Learnings were cluster which is term as group. Hence whole population Pf is divide into g cluster where each group have t number of Teacher Learning. So M = g x t.

Crossover

In this step of genetic algorithm crossover of the algorithm was done by selecting one best parent in group. So as per fitness value crossover with other set of Teacher Learnings were perform. So selection of this common parent depends on fitness value. Here best fitness values Teacher Learning act as common parent in all crossover operation in a group. So other set of chromosome undergoes crossover by randomly replacing a feature presence or absence status as per common parent Teacher Learning set. So if best set of Teacher Learning is $\{f_1^0, f_2^0, f_3^1, f_4^1 \ldots\ldots\ldots\ldots f_n^0\}$ and random feature position is three than status of third feature in other Teacher Learning is set as presence. Seletion of position and umber of position s are random.

Update Teacher Learning Population

The fitness value of these Teacher Learning was further assessed by testing with their parent Teacher Learning. If the kid Teacher Learning exhibits superior values, the parent will be eliminated; otherwise, the parent will persist. If the maximum iteration steps are reached, go to the filter feature block; otherwise, assess the fitness value of each Teacher Learning.

Cluster WSN Devices

After each cycle is completed, the best Teacher Learning is determined from the most recently updated population. In order to obtain the cluster center devices within a Wireless Sensor Network (WSN). Once devices are clustered, the process of transmitting sensor data transmission commences. The transmission of data persists for a limited number of iterations, during which the cluster center is updated based on the new positions and energy values of the devices.

III. EXPERIMENT AND RESULT

The suggested model for the acoustic WSN was implemented using the MATLAB platform. The experimental results were compared with the current model of WSN energy optimization, namely the Previous Model model [16]. The hardware arrangement utilized for the experimental work consists of a configuration including 4GB of RAM and an Intel I3 CPU.

Results

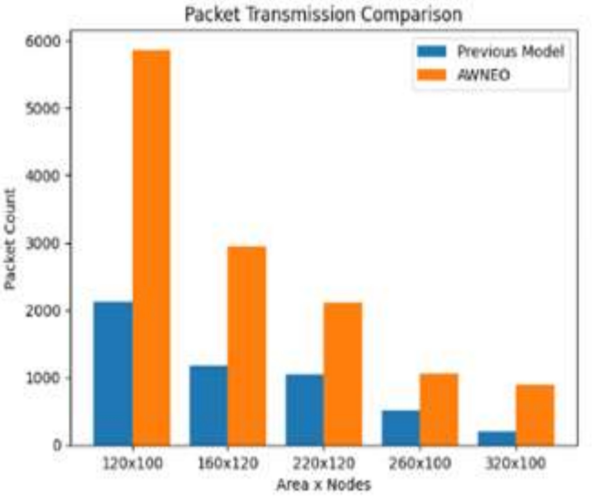

Fig. 2 Comparison on number of packet cunts.

Table 1 Comparison of acoustic WSN packets counts.

Area × Nodes	Existing Model	AWNEO
120 m × 100	2,120	5,860
160 m × 120	1,180	2,940
220 m × 120	1,050	2,110
260 m × 100	510	1,060
320 m × 100	190	890

Table 1 presents a comparative analysis of packet transmission counts for the existing model and the proposed AWNEO approach under different network sizes. It is clearly observed that the AWNEO model consistently achieves a significantly higher number of successfully transmitted packets across all deployment scenarios. Fig. 2 shows the improvement is primarily attributed to the application of the Teacher Learning Leaping Algorithm (TLLA)–based clustering strategy, which enhances node coordination and reduces unnecessary retransmissions. As a result, energy utilization is optimized, enabling nodes to sustain communication for longer durations and deliver more data packets efficiently.

Table 2 Comparison of acoustic WSN Rounds counts.

Area × Nodes	Previous Model	AWNEO
120 m × 100	260	810
160 m × 100	85	190
220 m × 100	230	780
260 m × 120	35	160
320 m × 120	42	115

Table 2 compares the total number of communication rounds sustained by the network before energy depletion. The proposed AWNEO framework demonstrates a substantial improvement in network lifetime. On average, the number of operational rounds increases by approximately 72% compared to the existing approach. Fig. 3 shows the enhancement confirms that clustering-based energy optimization significantly prolongs node activity and balances energy consumption across the network.

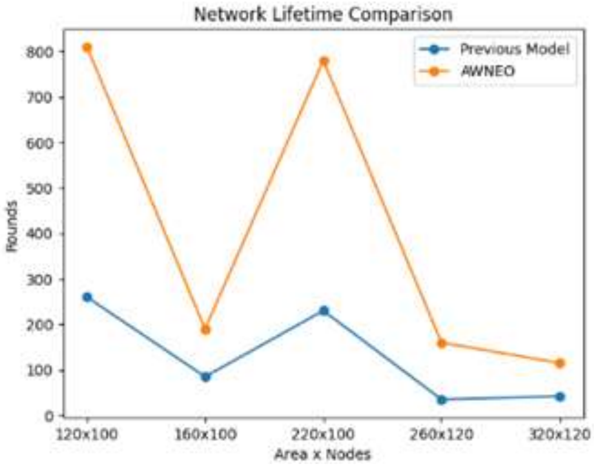

Fig. 3 Lifetime comparison of comparing models.

Table 3 Comparison of acoustic WSN first node discharge Rounds counts.

Area × Nodes	Existing Model	AWNEO
120 m × 100	5	18
160 m × 100	3	13
220 m × 100	3	10
260 m × 120	2	9
320 m × 120	2	7

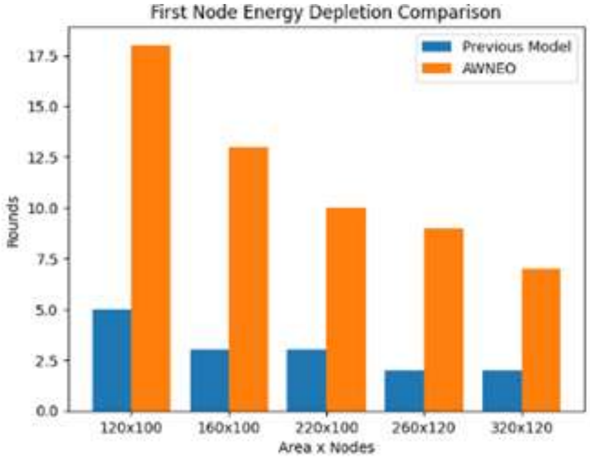

Fig. 4 First node discharge round counts.

Table 3 illustrates the number of rounds completed before the first node exhausts its energy. The proposed AWNEO model significantly delays the first node failure, indicating better energy distribution among nodes. Fig. 4 shows the incorporation of intelligent cluster head selection using the Teacher Learning Leaping Algorithm ensures that energyintensive tasks are not concentrated on a single node, thereby enhancing overall network stability.

Table 4 Comparison of acoustic WSN clustering algorithm time (seconds).

Area × Nodes	Existing Model	AWNEO
120 m × 100	0.182	0.024
160 m × 100	0.297	0.056
220 m × 100	0.193	0.019
260 m × 120	0.468	0.062

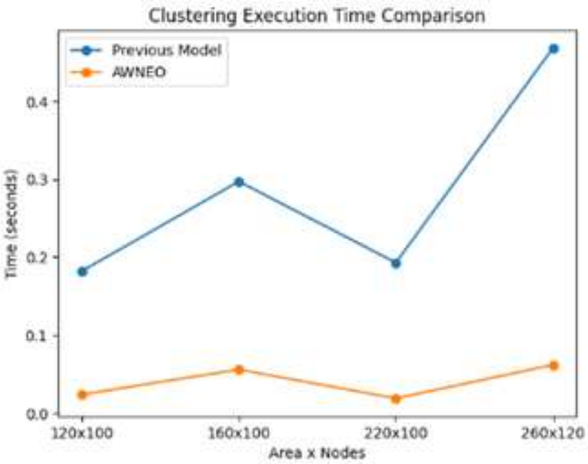

Fig. 5 execution time based comparison of models.

Table 4 compares the computational time required for clustering operations. The proposed AWNEO model exhibits a significant reduction in execution time, highlighting the efficiency of the adopted clustering mechanism. Fig. 5 shows the computation time directly contributes to lower processing overhead and energy savings, making the approach suitable for real-time underwater acoustic applications.

IV. CONCLUSION

Wireless sensor networks play a crucial role in enabling communication in harsh and inaccessible environments, particularly in underwater scenarios where traditional communication techniques are ineffective. This study presents an energy-efficient clustering-based optimization model, AWNEO, for underwater acoustic sensor networks. By integrating the Teacher Learning Leaping Algorithm, the proposed approach minimizes communication overhead, balances energy consumption, and extends network lifetime. Experimental evaluations conducted under varying network conditions demonstrate that the AWNEO model significantly outperforms existing methods in terms of packet delivery, network longevity, stability, and execution efficiency. Future research may extend this work by applying the proposed optimization framework to other challenging environments, such as underground coal mines or disaster-prone areas.

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