Dynamic MAC Protocol for Layered Data Aggregation in Underwater Wireless Sensor Networks

Balakiruthiga B
Department of Networking and Communication
SRM Institute of Science and Technology
Chennai, India
balakirb@srmist.edu.in

Angayarkanni. SA
Department of Networking and Communication
SRM Institute of Science and Technology
Chennai, India
angayars@srmist.edu.in

Nikhil Singh Shekhawat
Department of Networking and Communication
SRM Institute of Science and Technology
Chennai, India
nb3299@srmist.edu.in

Nikhil Bathija
Department of Networking and Communication
SRM Institute of Science and Technology
Chennai, India
nr2265@srmist.edu.in

Shubh Shrimali K
Department of Networking and Communication
SRM Institute of Science and Technology
Chennai, India
ss4260@srmist.edu.in

Neeharika Gupta
Department of Networking and Communication
SRM Institute of Science and Technology
Chennai, India
ng0583@srmist.edu.in

Abstract— **The material given describes an energy efficient routing protocol for industrial (WSNs) that makes use of deep learning algorithms like LSTM for movement prediction and a hybrid COOT-HOA optimization technique. Grid construction, base node selection based on distance and residual energy, and ESPRIT-based signal parameter estimation are all part of the protocol. Furthermore, the suggested technique uses a hybrid Adaboost and Random Forest machine learning methodology, incorporates GWO, and combines Hybrid PSO and ACO. Specifically designed for industrial Wireless Sensor Networks (WSNs), this study offers a novel energy efficient routing technique. The protocol uses deep learning methods like LSTM to predict future movements of mobile nodes and a hybrid COOT-HOA optimization algorithm to identify the best base node within each grid. In the experimental zone, grid creation is started, & node distance & residual energy are used to guide selection of base nodes. Finding active zones for data transmission is made easier with the use of ESPIRIT for signal parameter assessment. Notably, the protocol uses a hybrid Adaboost and Random Forest machine learning model, combines GWO characteristics, and offers a unique method by merging Hybrid PSO and ACO.**

Keywords— Underwater acoustic sensor networks, Media Access Protocol, collection of data, Energy efficient routing protocols, Industrial Wireless Sensor Networks, Deep learning algorithms, Movement prediction, Grid construction, Base node selection, Residual energy,

I. INTRODUCTION

The focus of the research publications was on energy efficient routing methods for Internet of Things (IoT) and Wireless Sensor Networks (WSNs). These protocols are intended to alleviate the resource constraints that wireless sensor nodes face, which have proven to be a major obstacle in WSNs. These constraints include memory, processing, and energy-constrained batteries. Clustering techniques such as Power Efficient Gathering in Sensor Information Systems (PEGASIS), Energy Efficient Unequal Clustering, and Low Energy Adaptive Clustering Hierarchy have been introduced to guarantee a uniform distribution of the network load while reducing energy consumption. Efficiency in energy is a major goal in the design and deployment of WSNs[1][2][3].

This research introduces TF-MAC, a novel energy-efficient routing protocol designed to tackle the unique challenges of underwater wireless sensor networks. The protocol's innovative approach combines deep learning for predictive modeling, hybrid optimization for intelligent decision-making, and adaptive resource allocation to enable efficient data collection in the underwater environment.

The report highlights the difficulty of 5G Internet of Things energy efficiency, particularly in data management, as one of the primary drivers. There is a need for energy efficient clustering protocols for IoT systems operating in the context of 5G, even though many of the clustering protocols that have been developed are not appropriate for MIMO-based IoT communication systems [1].

A MIMO-based energy efficient unequal hybrid clustering (MIMO HC) routing protocol for Internet of Things (IoT) communication systems has been suggested to overcome these obstacles. Algorithms for hybrid cluster construction, inter-cluster multi-hop routing, and Cluster Head selection are included in this protocol. To effectively disperse energy usage, The network is split into hierarchically divided, non-equal-sized hybrid clusters via the MIMO HC protocol. An energy efficient Cluster Head selection system (EECHS) protocol has also been suggested to reduce energy depletion inside clusters [1].

All in all, these research publications highlight how crucial energy efficient routing protocols are to overcoming resource constraints and improving the general durability and performance of WSNs and IoT systems.

II. RELATED WORK

In the field of terrestrial sensor networks, a great deal of work has gone into developing fair and traffic-aware MAC protocols. Effective methods for controlling congestion and guaranteeing equitable bandwidth distribution among various data streams are protocols such as rate-based Fair-Aware Congestion Control (FACC) and rate-aware congestion control (RACC) [4]. The deployment of UWA sensor networks (UASNs) has distinct obstacles due to their high energy consumption and significant propagation delays, which limit the use of established approaches in the underwater communication medium.

Many MAC protocols designed specifically for UASNs have been put out over the years; they may be generally divided into contention-based and contention-free methods. Random-access systems such as Aloha and its variations and channel-reservation protocols based on handshakes are examples of contention-based protocols. Although these protocols show encouraging delay performance, problems such concealed terminals make collision probability worsen as network traffic increases [5]. Contention-free MAC protocols have drawn attention as a solution to these problems, allocating network resources to certain users using techniques like Time Division Multiple Access (TDMA) or multi-channel methods.

By assigning unique time slots or frequency channels to nodes, TDMA-based protocols such as the graph coloring MAC (GC-MAC) and efficient depth-based MAC (ED-MAC) provide collision-free communication [6]. But in highly congested networks, these methods could come with trade-offs like decreased throughput or longer access delays. Multi-channel MAC protocols, such as cooperative undersea multichannel MAC (CUMAC) and multiple-rendezvous multichannel MAC (MM-MAC), are examples of how to distribute competing nodes across many channels in order to reduce transmission conflicts [7]. However, issues still exist, such as more sophisticated technology and less-than-ideal performance in situations with sudden spikes in traffic.

Hybrid systems have arisen as MAC protocol research advances, fusing the flexibility of random-access schemes with the scheduling-based techniques' advantages for conflict resolution. For two-tier UASNs, data-collection-oriented (DCO-MAC) protocols have been developed, which incorporate both contention-based and reservation-based MAC methods to accommodate different network loads [8]. These protocols are noteworthy. Even with these developments, there is still a significant lack of experience designing MAC protocols for data-centric UASNs, where effective data collection from dispersed sensor nodes to a centralized sink node is crucial. In order to close this gap, sophisticated strategies that strike a compromise between application-specific needs and operational efficiency are needed, opening up new possibilities for the design of MAC protocols for underwater settings.

The TF-MAC protocol distinguishes itself from existing approaches by combining predictive modeling of mobile node movement with adaptive channel allocation and packet length optimization. This holistic approach aims to enhance energy efficiency, throughput, and reliability in data-centric UWSNs, addressing a critical gap in current research.

III. SYSTEM ARCHITECTURE

A. Network Model

Figure 1 shows the suggested TF MAC's network model. A tree-topped, layered, data collection-focused UASN is taken into consideration. N levels of submerged nodes make up the N-hop network, and no two layers are designed to be the same depth. There are less nodes in the top layer of the network, that is, layers nearer the water's surface than in the bottom layer.The reasons for selecting the TF-MAC protocol includes its ability to deal with imbalances in the traffic load, its adaptability to underwater environment scenarios, and its effectiveness in data collection scenarios.

There are four types of nodes in the network. A surface-based sink node is outfitted with a radio modem to facilitate connection with the onshore monitoring center and a half-duplex acoustic modem for underwater communication. Between the sink and anchor nodes are different depths where the relay nodes are situated. Relay nodes transmit both their own produced data and the data they got from the last hop deeper nodes. Data is gathered via mobile nodes, including autonomous underwater vehicles (AUVs), up to a specific waterline height. There is no more than one mobile node installed in each tier due to the large mobility range of mobile nodes. Every undersea node makes use of audio.

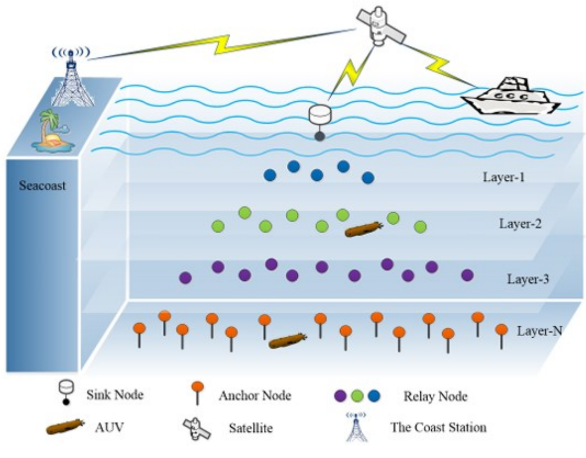

Figure 1: Network model of TF-MAC

Layers differ because various hops are required for data transmission from sensor nodes to the sink node. Layer-N includes sensor nodes that have to make N hops in order to provide data to the sink node. Furthermore, as a relay, a layer-N node may reach at least one layer-N-1 node within its transmission range, but none of the layer-N-2 nodes are inside it.

We take it for granted that all of the network's clocks are synced, which may be done using any synchronization technique [9]. Every node is identified by a unique ID. Every node is aware of the three-dimensional coordinates that are using Anode Hierarchical placement mechanisms for large-scale multi-hop that UASNs can do this [10]. We take it for granted that every node is stationary or very minimally drifts with the ocean's current in the vicinity of its fixed point.

B. UWA Channel Model

In an UWA channel, operating frequency and distance between receiver & transmitter determine the channel gain. Equation (1) is used as an UWA channel attenuation model [11] in this work.

$$h(d, f) = 1/A_0 d^k \alpha(f)^d \quad (1)$$

where k is the route loss exponent represents propagation geometry of the acoustic signal and A^0 is unit normalization constant. Practically speaking, we use k = 1.5 for spreading. The 3-D coordinates of sender & recipient may be used to compute the distance d.
Equation (2), which uses Thorp's formula, may be used to obtain the absorption coefficient (f)[12].

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

C. Interference Model

If the communication is effective in reaching the intended recipient, it may be described by the interference model. Two prevalent models in UASN scheduling difficulties are the physical interference model and the protocol model [13].

The protocol interference model establishes two ranges and takes into account the interference domain issue [14]. The greatest distance at which the transmitter and receiver can be apart while the recipient is able to accurately decipher the data it has received is known as transmission range. Greatest distance at which a transmitter & receiver can suffer interference from another node during a transmission is known as the interference range (Ri). For instance, data transmission from Node A to Node B is anticipated. The channel that Nodes A and B utilize is also used by Node C. B can only receive the data supplied by A accurately if both of the subsequent two inequalities[15] in Equation (3) are met.

$$\begin{cases} d_{AB} \leqslant R_d \\ d_{BC} \geqslant R_i \end{cases} . \quad (3)$$

The signal to interference plus noise ratio of the receiving node is a prerequisite for physical interference model [16]. We are able to establish a signal to interference plus noise ratio threshold $SINR^{th}$ based on the network's physical layer. The signal may be effectively demodulated if the receiver's SINR is higher than the threshold [17]. Equation (4) expresses the physical interference model, assuming that the noise in the undersea environment is Ns.

$$SINR = \frac{p_i \cdot h_i}{N_s + \sum_{j=1}^{n-1} p_j h_j} \geqslant SINR_{th} \quad . \quad (4)$$

where hi/hj is channel pi/pj gain between the receiving & sending node, and is power of transmission of the sending node. Number of interference node's that prevent receivers from successfully decoding is n1. There can be no assurance of interference in the network when employing the physical interference model.In this model ,
efficiency is worked on by making use of Optimized base node selection, Dynamic channel allocation and Adaptive packet length adjustment.

IV. ALGORITHMS

A. Fuzzy C Means Algorithm with Centralized Mechanism and CHSRA

The Fuzzy C-Means algorithm with centralized mechanism and incorporation of the Cluster Head Selection and Rotation Model (CHSRA) presents a sophisticated approach to clustering in Wireless Sensor Networks (WSNs) [18]. This algorithm leverages fuzzy logic to assign cluster memberships based on data characteristics, allowing for a more flexible and nuanced clustering process [19]. By integrating a centralized mechanism, the algorithm enhances coordination and decision-making at a higher level, optimizing cluster formation and management. The Cluster Head Selection and Rotation Model (CHSRA) model introduces a dynamic approach to selecting and rotating cluster heads, ensuring efficient utilization of resources and prolonging network lifetime through strategic leadership transitions within clusters.

B. Hybrid Grey Wolf Optimizer (HGWO)

The Hybrid Grey Wolf Optimizer (GWO) algorithm combines the strengths of the Grey Wolf Optimization technique with other optimization methods to enhance clustering efficiency in WSNs [18]. By integrating the GWO algorithm with other optimization strategies, such as genetic algorithms or particle swarm optimization, the Hybrid GWO offers a robust and adaptive approach to cluster formation.

This hybridization enables the algorithm to leverage the unique strengths of each optimization technique, resulting in improved convergence speed, solution quality, and overall performance in clustering applications.

C. K Means Clustering Algorithm

The K Means clustering algorithm is a fundamental method for dividing data into distinct clusters based on similarity metrics [19]. In the context of WSNs, the K-Means algorithm plays a crucial role in organizing sensor nodes into clusters for efficient data aggregation and management. By iteratively assigning nodes to clusters and recalculating cluster centroids, K-Means optimizes cluster formation based on data proximity, facilitating effective data processing and communication within the network.

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D. Improved Energy Efficient Clustering Protocol (IEECP)

The Improved Energy Efficient Clustering Protocol (IEECP) represents an advanced protocol designed to enhance energy efficiency and prolong the lifetime of WSNs [20]. By incorporating optimized cluster formation strategies, energy-aware routing mechanisms, and intelligent cluster head selection algorithms, IEECP aims to minimize energy consumption while maintaining network performance. This protocol leverages innovative approaches to cluster formation, data aggregation, and communication, ensuring sustainable operation and prolonged network longevity in IoT-based WSN environments.

E. Radio Energy Consumption Model

The Radio Energy Consumption Model provides a mathematical framework for estimating energy consumption in wireless communication systems, particularly in the context of WSNs [21]. By considering factors such as transmission power, data rate, and communication distance, this model offers insights into the energy requirements of radio communication processes. Through the formulation of energy consumption equations and parameters, the model enables network designers to optimize radio usage, increase energy economy and extend wireless sensor networks' operational life.

V. RESULT

This study is an extensive analysis of the TF-MAC system's performance in UWA sensor networks. The spatial distribution of all nodes, demonstrated through the deployment of 50 nodes, is depicted in Figure 2, elucidating the network's topology and node arrangement. This graphical depiction serves to offer insights into the distribution pattern, laying the groundwork for assessing network coverage and density, which are pivotal for evaluating communication efficiency and network connectivity.

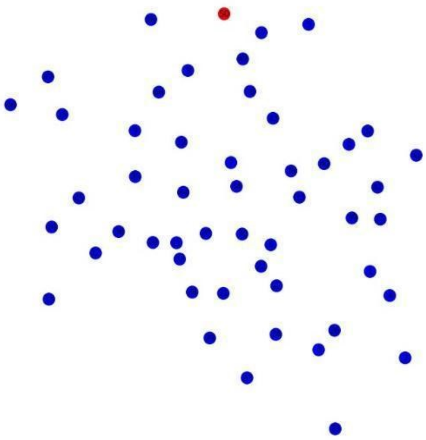

Figure 2: Representation of 50 nodes

Subsequently, a graphical illustration featuring two nodes, with distinct highlighting of sender and receiver nodes in red, portrayed in Figure 3 depicts a specific data transmission scenario within the network. This graph provides a detailed visualization of signal propagation paths and communication links between key nodes, emphasizing the direct communication dynamics between sender and receiver nodes. By visually depicting this interaction, the graph enhances comprehension of data exchange processes and transmission pathways in UWA channels.

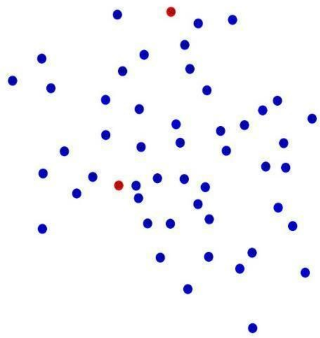

Figure 3: Representation with sender and seed node marked in red

Following this, a visual representation of clustering within the network demonstrated by Figure 4, showcases the effectiveness of the clustering algorithm in organizing nodes based on proximity and communication requirements. The graph displaying clustering not only accentuates cluster formation but also underscores the system's capacity to optimize data transmission efficiency through structured communication groups. This visual representation offers valuable insights into cluster formation dynamics and their influence on network organization and data routing strategies.

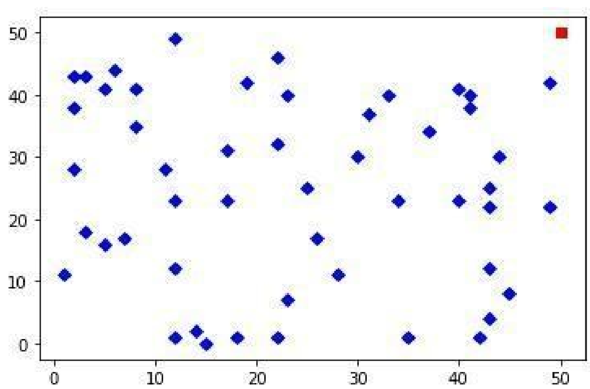

Figure 4: Clustering graph

In this research project, a comprehensive table encapsulating the various variables involved in the study serves as a pivotal visual aid for understanding the project's intricacies. This table depicted in Figure 5, meticulously outlines and categorizes the key variables, parameters, and factors central to the project's investigation in a structured format. By presenting this information in a tabular layout, the table offers a concise and organized overview of the variables under consideration, facilitating clarity and ease of reference for researchers and readers alike. The inclusion of such a detailed table enhances the project's documentation and provides a valuable reference point for comprehending the interrelationships and dependencies among the diverse variables shaping the study's outcomes and analyses.

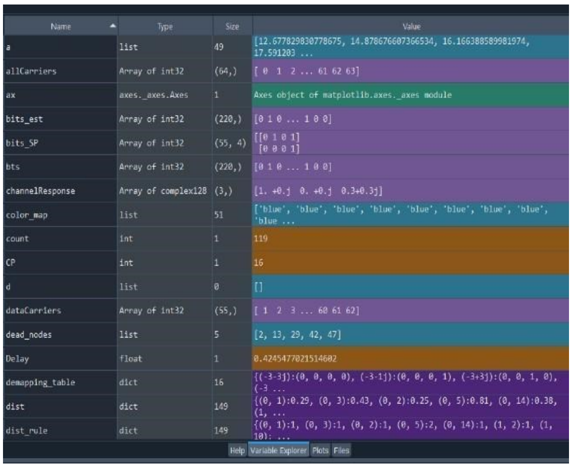

Figure 5: Data Types and Structures with Values

The graph illustrated in Figure 6 demonstrates the number of communication rounds necessary for data dissemination provides insights into message propagation latency and network responsiveness. By analyzing trends in communication rounds over time, this graph offers a comprehensive view of data dissemination dynamics, highlighting variations in message delivery times and network efficiency. Understanding communication round patterns is crucial for evaluating network performance under diverse operational conditions and traffic scenarios.

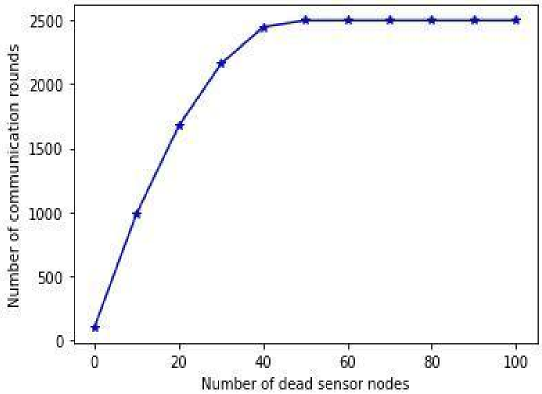

Figure 6: Graph showing no. Of communication rounds per node

Additionally, three graphs, Figure 7, Figure 8 and Figure 9, focus on key performance metrics - delay, energy consumption, and throughput - further enhance the analysis.These graphs visually represent data transmission delays, energy utilization patterns, and throughput variations, enabling a comprehensive assessment of system efficiency, reliability, and resource utilization in UWA sensor networks. By strategically placing these graphical illustrations within the results section, the study effectively combines visual representations with analytical insights to offer a holistic understanding of the TF-MAC system's performance characteristics in underwater communication scenarios.Compared to previous works ,performance is enhanced by implementing LSTM for movement prediction, Hybrid COOT-HOA optimization for base node selection, Multi-channel TDMA for efficient channel utilization and Adaptive packet length adjustment , dealing with previous gaps and issues.

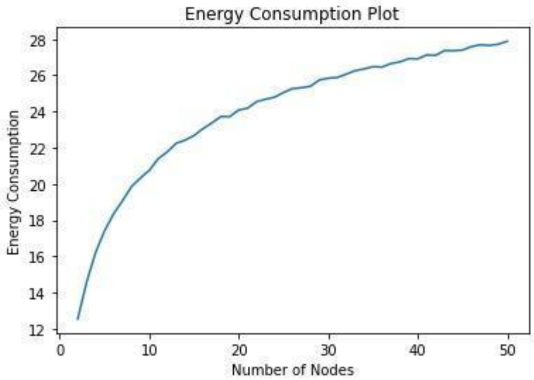

Figure 7: Energy Consumption Plot

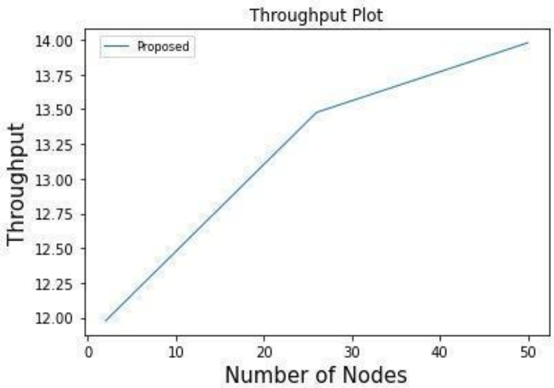

Figure 8: Throughput Plot

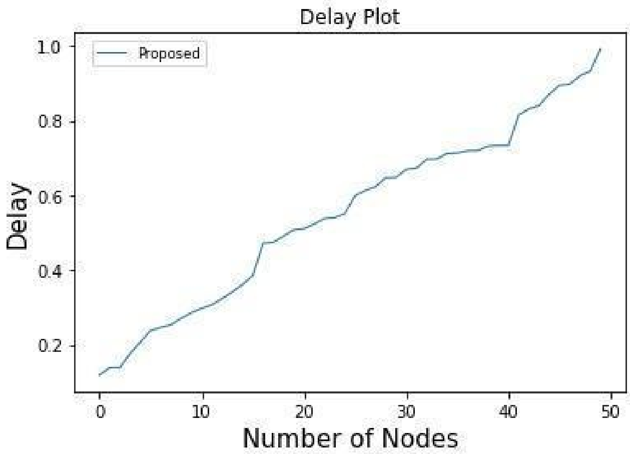

Figure 9: Delay Plot

VI. Conclusion

In order to overcome traffic load imbalances in underwater data collecting inside stacked UASNs, the research reported in this paper focuses on the development and implementation of the TF-MAC protocol. In data-collection-oriented UASNs, TF-MAC shows potential performance by combining TDMA mechanisms, multi-channel techniques, and adaptive algorithms for packet length and time slot allocation. The validation via marine tests verifies that TF-MAC can adapt to underwater spatial-temporal ambiguity. Future research will concentrate on assessing TF-MAC's viability and efficiency in dynamic network situations.

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