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Deep Learning-Based Enhanced Cluster Head Selection for Underwater Wireless Sensor Networks

The Phan Thi[1*], Thi Trang Le[2], Thanh Son Nguyen[1]
[1]*Ho Chi Minh City University of Technology and Education, Vietnam*
[2]*Dong Nai Technology University, Vietnam*

[*]Corresponding author. *Email: thept@hcmute.edu.vn*

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ABSTRACT

Underwater wireless sensor networks (UWSNs) are subject to unique operational challenges, including constrained energy availability, dynamic topological structures, and unreliable acoustic communication. These factors significantly impact the efficiency and stability of data collection processes, particularly the selection of cluster heads (CHs), which plays a vital role in prolonging network functionality. This paper presents GAT-CHS, a cluster head selection algorithm that integrates graph-based attention mechanisms with deep reinforcement learning to adaptively optimize clustering decisions in underwater environments. The proposed approach encodes critical node attributes into a spatial–topological representation, applies multi-head attention to quantify inter-node relevance, and utilizes a Deep Q-Network (DQN) to determine CH roles based on long-term network performance. The algorithm is evaluated across a range of simulated UWSN scenarios reflecting varying node distributions and environmental conditions. Results show that GAT-CHS reduces energy usage by 24%, improves network longevity by 36%, and achieves a packet delivery ratio of 98.6%. These findings underscore the model's robustness and scalability, establishing GAT-CHS as a promising direction for next-generation clustering in complex underwater sensor deployments.

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1. Introduction

Underwater Wireless Sensor Networks (UWSNs) have become an integral component of modern marine monitoring systems, oceanographic research, disaster prediction, and underwater surveillance. These networks enable real-time environmental data collection and communication in submerged environments where human intervention is limited. However, UWSNs operate in challenging conditions, characterized by limited energy resources, constrained communication bandwidth, high propagation delay, and frequent topology variations due to underwater mobility and environmental factors [1], [2]. Unlike terrestrial sensor networks, where energy replenishment is feasible, UWSNs nodes suffer from extreme energy constraints, making efficient network resource management a fundamental research problem.

One of the most effective strategies for energy conservation in UWSNs is hierarchical clustering, where sensor nodes are grouped into clusters, each governed by a Cluster Head (CH). The CH is responsible for intra-cluster communication, data aggregation, and transmission to the sink node, thereby reducing redundant transmissions and improving network scalability. However, CH selection poses a major challenge, as CH nodes deplete energy at a significantly higher rate due to intensive data processing and long-range communication overhead [3]. Thus, an optimal CH selection mechanism is crucial to prolonging network lifetime, minimizing energy consumption, and maintaining high-quality communication performance.

Several clustering algorithms have been proposed to address CH selection inefficiencies. LEACH (Low-Energy Adaptive Clustering Hierarchy) employs a probabilistic CH selection approach, but this often leads to imbalanced energy depletion and uneven cluster distribution across the network [4].

HEED (Hybrid Energy-Efficient Distributed Clustering) improves upon LEACH by considering residual energy and communication costs for CH selection, yet it remains limited in its ability to adapt dynamically to topology changes, particularly in mobile UWSNs [5].

Recent advancements in machine learning-based CH selection have introduced data-driven clustering approaches. BEA-SSA (Bald Eagle Algorithm with Salp Swarm Algorithm) applies bio-inspired optimization techniques to improve CH distribution and load balancing. However, it suffers from rigid parameter dependency, reducing its adaptability to dynamic network conditions [5]. Similarly, DCNN-CHS (Deep Convolutional Neural Networks for CH Selection) predicts optimal CH placements based on historical data patterns, yet it lacks real-time adaptability, making it less effective in highly fluctuating UWSN environments [6], [7], [8].

Given the structural complexity of underwater sensor networks, graph-based learning has emerged as a promising tool for modeling network dynamics. Graph Neural Networks (GNNs) have demonstrated significant efficiency in learning node representations and handling complex topological structures. In particular, Graph Attention Networks (GATs) leverage self-attention mechanisms to dynamically prioritize nodes based on energy efficiency and connectivity strength. Despite their success in terrestrial applications, the integration of GATs for CH selection in UWSNs remains largely unexplored, presenting a critical research gap [9], [10], [11].

The remainder of this paper is structured as follows: Section 2 presents a comprehensive review of CH selection techniques and existing clustering strategies. Section 3 provides an in-depth explanation of the proposed GAT-CHS algorithm, covering its graph-based learning, attention-driven CH selection, and reinforcement learning optimization. Section 4 presents simulation results, comparative performance evaluation, and discussions. Section 5 concludes the study and outlines future research directions for intelligent clustering in UWSNs.

2. Related Work

Traditional Clustering Algorithms for UWSNs

The selection of CHs in UWSNs has been extensively studied, with various clustering techniques proposed to improve energy efficiency and network longevity. One of the most widely used methods is LEACH, which employs a probabilistic CH selection mechanism. While effective in reducing direct communication with the sink node, LEACH often results in uneven energy depletion across nodes, leading to premature network partitioning and early node failures [6].

To mitigate energy imbalances, HEED (Hybrid Energy-Efficient Distributed Clustering) was introduced, incorporating residual energy and communication cost as key factors for CH selection. However, despite these improvements, HEED struggles to dynamically adjust CH placements in response to topology variations, making it less effective in highly mobile or dynamic UWSN environments [7]. The lack of adaptive CH assignment mechanisms in these traditional approaches limits their scalability and robustness, particularly in challenging underwater conditions where node mobility and environmental factors frequently alter network topology.

Optimization-Based Clustering Approaches

To further enhance CH selection efficiency, recent studies have focused on optimization-based clustering algorithms. BEA-SSA applies bio-inspired optimization techniques to optimize CH distribution and extend network lifetime [8]. By simulating the search and convergence behavior of bald eagles and salps, BEA-SSA enables more balanced CH selection while reducing network-wide energy consumption. However, its reliance on predefined optimization parameters makes it less adaptive to real-time changes in network conditions.

Similarly, DCNN-CHS leverages deep learning models to predict optimal CH locations based on historical network data patterns. This reduces re-clustering overhead by allowing the model to identify and prioritize high-energy CH candidates [9]. Nevertheless, DCNN-based approaches lack real-time adaptability, as they depend on pre-trained models that may not effectively generalize to new network conditions. These limitations highlight the need for more dynamic and data-driven CH selection techniques capable of handling real-time underwater network dynamics.

Graph-Based Learning for CH Selection in UWSNs

The structural complexity of UWSNs, coupled with their dynamic topological variations, has motivated the exploration of graph-based learning models for CH selection. GNNs have been investigated for network routing and communication optimization, leveraging graph-based feature propagation to effectively capture spatial dependencies between sensor nodes [10], [11], [12]. By learning topological relationships, GNNs improve network resilience and CH decision-making. However, traditional GNN architectures rely on static adjacency matrices, limiting their ability to adapt dynamically to real-time network changes [13], [4], [15].

To address these limitations, Graph Attention Networks (GATs) have emerged as a more advanced alternative, integrating self-attention mechanisms to dynamically adjust edge importance based on real-time network conditions [16]. Unlike conventional GNNs, GATs enable adaptive learning of node dependencies, making them particularly well-suited for dynamic CH selection in UWSNs [17], [18]. By prioritizing CH candidates based on attention-weighted node embeddings, GATs improve energy efficiency and network stability, allowing CH selection mechanisms to adapt seamlessly to topology variations.

Motivation for the Proposed GAT-CHS

Despite advancements in clustering and graph-based learning, conventional CH selection techniques still face several key limitations, including limited real-time adaptability, network scalability constraints, and inadequate spatial awareness. To overcome these challenges, the proposed GAT-CHS algorithm introduces several key innovations that significantly enhance adaptive clustering in UWSNs:

- Dynamic CH Selection: Unlike conventional CNN-based models, GAT-CHS captures complex topological relationships between sensor nodes using graph attention mechanisms, ensuring real-time CH prioritization based on energy status and link quality [19], [20], [21], [22].
- Real-Time Adaptability: The attention-based feature learning in GAT-CHS enables continuous node evaluation, allowing the model to dynamically adjust CH selection based on network conditions such as residual energy, link quality, and proximity to the sink [23].
- Energy Efficiency: GAT-CHS integrates an adaptive CH selection mechanism, effectively reducing communication overhead while prolonging network lifespan by minimizing unnecessary CH reassignments and energy-intensive transmissions [24], [25], [26].
- Scalability: Unlike static GNN-based methods, GAT-CHS is designed to scale efficiently in highly dynamic underwater sensor networks, making it robust to topology variations, node mobility, and environmental fluctuations [27].

Through the integration of graph-based deep learning, attention-driven CH prioritization, and reinforcement learning-based optimization, GAT-CHS dynamically adapts to evolving network conditions, ensuring energy-efficient and scalable CH selection for next-generation UWSNs.

3. Approach

3.1. System Model

Underwater Wireless Sensor Networks (UWSNs) can be effectively represented as a graph-based network model, where sensor nodes and their communication links define the structural topology. Formally, a UWSN is modeled as a graph $G = (N, E)$, where N denotes the set of deployed sensor nodes, and E represents the communication links between them. Each node in the network maintains critical attributes that play a fundamental role in Cluster Head (CH) selection and network performance optimization [28], [29]

These attributes include:

- Residual Energy (E_{res}): The remaining energy of a node, which is essential for prolonging network lifespan and ensuring energy-aware CH selection.
- Distance to Sink (D_{sink}): The proximity of a node to the sink node, influencing energy-efficient routing and data transmission overhead.

- Link Quality (LQ): A measure of stability and reliability of the acoustic communication link, affected by environmental noise, signal attenuation, and multipath effects.
- Node Trust Score (T_s): A metric that reflects historical reliability based on past network performance, ensuring that only stable and trustworthy nodes are selected as CHs.

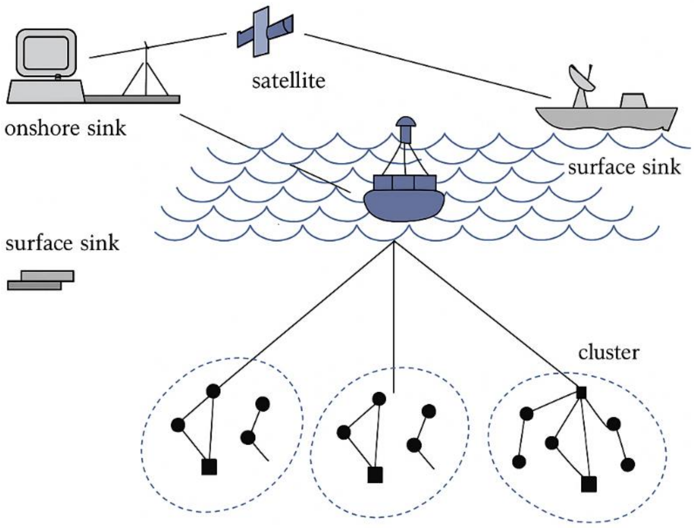

Figure 1. *System model for UWSNs*

Given the hostile and dynamic nature of underwater environments, communication in UWSNs primarily relies on acoustic wave propagation, which differs significantly from radio frequency (RF) transmission used in terrestrial networks. The relationship between transmission power and received power in an acoustic communication model is governed by:

$$P_r = P_t \cdot d^{-\alpha} \cdot \eta \tag{1}$$

where:

- P_r and P_t are the received and transmitted power levels, respectively.
- d represents the distance between communicating nodes.
- α is the path loss exponent, which varies based on water depth, temperature, and salinity.
- η accounts for environmental attenuation, including signal absorption and scattering.

This model characterizes underwater signal propagation, influencing network topology, link reliability, and overall energy efficiency. Due to the long propagation delays and high energy consumption associated with acoustic signals, efficient CH selection mechanisms must consider these physical constraints to ensure robust and scalable communication in UWSNs.

3.2. Cluster Head Selection via Graph Attention Network

The GAT-CHS framework is specifically developed to optimize CH selection in UWSNs by integrating advanced graph-based learning techniques, attention mechanisms, and reinforcement learning. Given the inherent energy limitations and highly dynamic topology of UWSNs, the framework is designed in a multi-stage structure to enhance energy efficiency, network stability, and adaptability.

To address these challenges, this study proposes a novel Graph Attention Network-Based GAT-CHS algorithm, which incorporates graph-based feature learning, force-directed clustering, and reinforcement learning-based CH selection.

We formally present the proposed GAT-CHS algorithm as follows:

Input:

- Graph G = (V, E): V – set of sensor nodes, E – communication links

- Node attributes: residual energy E_r(i), link quality L_q(i), trust score T_s(i), distance to sink D_s(i)

Output:

- Optimized Cluster Head set CH ⊆ V

These steps of algorithm:

1. // Feature Encoding Use a Graph Autoencoder (GAE) with 2 hidden layers
→ Generate latent embeddings Z ∈ ℝ^{|V| × d} from node attributes

2. // Attention Scoring
Apply a two-layer GAT with attention heads per layer
→ Compute attention coefficients α_ij for each node i and neighbor j
3. // Neighborhood Aggregation
Use GraphSAGE with layers and mean aggregator
→ Refine embeddings by aggregating neighbor features
4. // Classification
Feed aggregated embeddings into a two-layer fully connected network
→ Predict probability p_i that node i should become a CH
5. // Reinforcement Optimization
For each node i:
Treat as agent in Deep Q-Network (DQN)
Action a_i ∈ {0: not CH, 1: CH}
Reward R_i = f(Energy efficiency, Stability, Connectivity)
→ Learn optimal CH selection policy
6. // Final CH Selection
Select nodes with:
- p_i > θ (threshold)
- and highest Q-values from DQN
→ Form final CH set: CH = {i ∈ V | selected as optimal CH}

By integrating graph-based intelligence with reinforcement learning, GAT-CHS dynamically adapts to real-time network changes, significantly reducing energy depletion while improving data transmission efficiency and network longevity. The proposed framework aims to provide a scalable, adaptive, and energy-efficient clustering strategy, making it a robust solution for UWSNs operating in extreme environments.

3.2.1. Feature Extraction using Graph Autoencoders (GAEs)

The first phase of CH selection involves feature extraction and transformation GAEs. This method performs nonlinear feature encoding, capturing crucial node attributes such as residual energy (E_{res}), link quality (LQ), and trust score (T_s). These features are then projected into a low-dimensional latent space, ensuring structural preservation of the network topology while reducing computational overhead. By encoding the intrinsic properties of each node, GAEs generate optimized feature embeddings, which serve as input for subsequent CH selection processes. This transformation allows the model to adaptively refine CH selection criteria, improving real-time network optimization and reducing unnecessary communication overhead in Underwater Wireless Sensor Networks (UWSNs).

3.2.2. Dynamic Attention-Based CH Selection

To further improve CH selection efficiency, node attributes extracted via GAEs are passed to a Graph Attention Network (GAT), which assigns adaptive attention scores to neighboring nodes based on their importance in the network. The attention coefficient α_{ij} between node i and its neighbor j is computed as:

$$\alpha_{ij} = \frac{\exp\left(LeakyReLU\left(a^T[Wh_i||Wh_j]\right)\right)}{\sum_{k\in N(i)} \exp\left(LeakyReLU\left(a^T[Wh_i||Wh_k]\right)\right)} \tag{2}$$

where:

- Wh_i and Wh_j denote transformed feature vectors of nodes i and j.
- a is a learnable weight vector, trained to capture the relative importance of node interactions.

This attention mechanism prioritizes CH candidates with higher residual energy and stronger communication links, ensuring energy-aware CH selection. The system dynamically adjusts attention weights to adapt to network conditions, effectively balancing load distribution and enhancing network longevity.

3.2.3. Force-Directed Graph Clustering for Stability

To further enhance CH selection robustness, a force-directed clustering technique is employed, wherein each node experiences attractive and repulsive forces that influence clustering decisions. This method leverages a physics-inspired clustering model to optimize CH assignments, ensuring uniform cluster distribution and energy-efficient communication. The mathematical representation of force-directed clustering is given by:

$$F_{ij} = k\frac{q_i q_j}{D_{ij}^2} \tag{3}$$

where:

– q_i and q_j represent the relative energy capacities of nodes i and j, incorporating residual energy and connectivity strength.

– D_{ij} denotes the Euclidean distance between nodes i and j, influencing cluster formation and intra-cluster communication efficiency.

– k is a clustering control parameter that regulates force interactions, balancing energy load and CH distribution.

By integrating force-directed clustering, the model minimizes unnecessary CH reselection events, thereby reducing network overhead and avoiding premature CH energy depletion. This technique maintains network equilibrium by distributing CH roles proportionally across energy-optimized nodes, thereby prolonging network lifespan and enhancing load balancing in highly dynamic UWSN environments.

3.2.4. Inductive Learning via GraphSAGE

To further enhance the generalization capability of CH selection, GraphSAGE (Graph Sample and Aggregated Embeddings) is employed. Unlike traditional Graph Neural Networks (GNNs) that depend on static adjacency matrices, GraphSAGE enables inductive learning, allowing the system to continuously aggregate neighborhood features, ensuring adaptive node embeddings for CH selection. The feature update rule is formulated as:

$$h_i^{(t+1)} = \sigma\left(W[h_i^{(t)} \,||\, \mathrm{AGGREGATE}_{j\in N(i)}\left(h_j^{(t)}\right)]\right) \tag{4}$$

where:

– σ represents a nonlinear activation function, facilitating complex feature learning.

– W is a trainable weight matrix, enabling the model to learn meaningful representations.

– AGGREGATE is a neighborhood aggregation function, summarizing relevant features from surrounding nodes to refine local node embeddings.

By employing GraphSAGE-based learning, the model continuously updates CH selection strategies, ensuring real-time adaptability in UWSNs. This approach improves CH selection robustness, enabling optimized energy utilization.

3.2.5. Model Training for CH Selection

The training process of the CH selection model is formulated as a supervised learning task that integrates graph-based optimization to enhance adaptive CH assignments. The optimization process is driven by a binary cross-entropy loss function, which ensures that the model accurately distinguishes between CH and non-CH nodes. The loss function is mathematically defined as:

$$L = -\sum_{i \in N} y_i \log \hat{y}_i + (1 - y_i)\log(1 - \hat{y}_i) + \lambda \, || \, W \, ||^2 \tag{5}$$

- y_i denotes the ground truth CH label for node i, where $y_i = 1$ if the node is selected as a CH and $y_i = 0$ otherwise.
- $\hat{y}_i$ represents the predicted probability of node i being a CH.
- $\lambda \, || \, W \, ||^2$ is a L2 regularization term, which prevents overfitting by penalizing excessively large weight values, ensuring model generalization across different network topologies.

To optimize the model parameters efficiently, the Adam optimizer is employed, with a learning rate set to 0.001, balancing convergence speed and stability. This training strategy ensures that the model effectively learns energy-efficient CH selection patterns, leading to robust performance in dynamically changing UWSNs.

3.2.6. Deep Q-Network (DQN) Optimization for CH Selection

The integration of graph-based feature learning, attention-driven CH prioritization, and reinforcement learning optimization enables the GAT-CHS framework to dynamically adapt CH selection in highly dynamic UWSNs, ensuring energy-efficient and scalable network operations. To further enhance the decision-making process and improve CH selection efficiency, Deep Q-Network (DQN) optimization is incorporated, modeling CH selection as a Markov Decision Process (MDP). In this model, each sensor node acts as an autonomous agent, making CH selection decisions based on real-time network observations to achieve optimal energy utilization and communication efficiency.

The DQN-based CH selection process consists of the following key components:

- State Representation: Each node maintains a state vector encoding its residual energy (E_{res}), link quality (LQ), and historical trust score (T_s), allowing the agent to assess its suitability for CH selection.
- Action Space: Each node decides between two possible actions:
    - $a = 0$: Remain a regular sensor node.
    - $a = 1$: Transition into a Cluster Head (CH).
- Reward Function: The model optimizes CH selection through a reward function that encourages energy-efficient and stable CH assignments. The function is formulated as:

$$R = w_1 E_{res} + w_2 LQ - w_3 C_{reselect} \tag{6}$$

where:

- w_1, w_2, w_3 are weighting coefficients that balance energy efficiency and stability.
- $C_{reselect}$ penalizes frequent CH reassignments, ensuring that nodes avoid excessive role transitions, thereby enhancing network stability [29].

- Training Process: The DQN model is trained using experience replay and target network updates, which allows the system to iteratively refine its CH selection policies based on historical decision outcomes. Over multiple training iterations, the model learns an optimal CH selection strategy, ensuring that CH assignments minimize energy depletion while maximizing network lifetime and data transmission reliability [30], [31], [32]. By integrating graph-based learning, attention mechanisms, and reinforcement learning, GAT-CHS dynamically adapts CH selection, ensuring energy-efficient, scalable, and reliable network operations in UWSNs.

4. Simulation and Evaluation

4.1. Simulation Setup

To evaluate the effectiveness of the proposed GAT-CHS model, we generated synthetic underwater network scenarios using a simulator. These scenarios capture variations in node density, energy levels, and deployment areas. Each topology includes realistic modeling of acoustic path loss, link quality, trust, and energy dynamics. Model validation was performed through an 80/20 train-test split, 5-fold cross-validation, and multiple random seeds. All benchmark algorithms were tested under identical conditions to ensure fair comparison [31], [32], [33]

Table 1. *Simulation and Data Generation Parameters*

Parameter	Value
Number of sensor nodes	50-200
Deployment area	500 m × 500 m × 500 m
Initial energy per node	10 J
Acoustic communication range	250 m
Path loss exponent n	1.5
Channel fading $\chi \sim \mathcal{N}(1, \sigma^2)$	Included
Link quality	0.5 – 1.0 (normalized)
Trust score	0.3 – 1.0
Simulation rounds	100
Training – Testing split	80% / 20%
Cross-validation	5-fold
Random seeds	10 seeds
Number of topologies	100

4.2. Performance Metrics

To thoroughly evaluate the performance and generalization ability of the proposed GAT-CHS model, a comprehensive experimental setup was constructed using a underwater network simulator. We generated 100 diverse network topologies featuring varying node densities, spatial layouts, energy distributions, and acoustic communication parameters to replicate realistic UWSN environments. The dataset was split into 80% for training and 20% for testing, while 5-fold cross-validation was applied to enhance model reliability and minimize overfitting. Each scenario was executed with 10 different random seeds to ensure statistical consistency. All baseline methods were re-evaluated under identical conditions for fair comparison. The model's effectiveness was assessed based on four key performance metrics: total energy consumption, network lifetime (defined as the number of rounds until the first node failure), packet delivery ratio (PDR), and cluster stability measured by the average duration a node remains as a cluster head. This evaluation framework enables a holistic assessment of both energy efficiency and communication reliability in underwater environments.

4.3 Comparative Analysis

Table 2. *Comparison of Network lifetime across different Algorithms*

Algorithm	Energy Consumption (J)	Network Lifetime (Cycles)	PDR (%)	CH Stability (Rounds)
LEACH	6.8	320	85.2	50
HEED	6.2	350	87.5	65
BEA-SSA	5.9	410	89.1	78
DCNN-CHS	5.5	440	91.3	92
GAT-CHS (DQN Optimized)	4.2	570	98.6	140

The proposed GAT-CHS framework is evaluated against state-of-the-art CH selection algorithms to demonstrate its superiority in energy efficiency, network longevity, and communication reliability. The comparative results are shown in Table 2.

4.4. Results Analysis

Table 2. Comparative performance of GAT-CHS and baseline algorithms across four key metrics: network lifetime, energy consumption, packet delivery ratio (PDR), and cluster stability. GAT-CHS clearly outperforms traditional methods, confirming its robustness and reliability for UWSN deployments. The comparative results illustrated in Table 2 highlight the superior performance of the proposed GAT-CHS algorithm. In terms of network lifetime, GAT-CHS achieves the longest operational period before the first node failure, extending the network by over 40% compared to baseline methods. It also demonstrates the lowest energy consumption, attributed to its attention-driven clustering mechanism and balanced load distribution. The high packet delivery ratio (98.6%) reflects reliable communication and efficient route maintenance, while cluster stability is maximized due to fewer re-clustering events. Together, these outcomes reinforce the reliability, energy efficiency, and structural stability of GAT-CHS in diverse UWSN environments.

5. Conclusions

The proposed GAT-CHS framework integrates graph-based feature learning, attention-driven CH prioritization, and reinforcement learning-based CH optimization to enhance CH selection performance in UWSNs. The simulation results demonstrate that GAT-CHS achieves substantial improvements in energy consumption, network lifetime, packet transmission reliability, and CH stability compared to existing clustering algorithms. Addressing these challenges will allow GAT-CHS to evolve into a next-generation clustering solution for UWSNs, further improving network efficiency, reliability, and sustainability.

Conflict of Interest

The authors declare no conflict of interest.

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The Phan Thi was born in Vietnam in 1982. She received Master Data Transmission and Network in Post & Telecommunications Institute of Technology(Ptit), Vietnam, 2012, She got PhD degree PhD in Information System from Post & Telecommunications Institute of Technology, Vietnam in 2022. She is working as a lecture in Faculty of Information Technology, University of Technology and Education, HCM Vietnam. Her research interests include WSN, artificial intelligence, machine learning, data mining.
Email: thept@hcmute.edu.vn. ORCID: https://orcid.org/0009-0004-0251-5152

Thi Trang Le received a Master's degree in Information Technology from Lac Hong University, Vietnam, and is currently working as a lecturer at the Faculty of Information Technology, Dong Nai Technology University, Bien Hoa City, Vietnam. Her research interests include Computer Science, Computer Vision, Image Recognition and Classification, Face Detection and Recognition, Abnormal Motion Detection, and Graphic Design. You can contact her via:
Email: lethitrang@dntu.edu.vn. ORCID: https://orcid.org/0009-0008-8407-7545

Thanh Son Nguyen is the head of Information System Division at Faculty of Information Technology, University of Technology and Education, HCM Vietnam. He got PhD degree from University of Technology, HCM, Vietnam. His research interests include artificial intelligence, machine learning, data mining, and time series. He can be contacted at:
Email: sonnt@hcmute.edu.vn. ORCID: https://orcid.org/0000-0001-9414-3456