Energy-Aware Clustered Federated Learning for Underwater Sensor Networks in Naval Surveillance

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Underwater wireless sensor networks (UWSNs) are essential for naval operations, as they are used for object monitoring (surveillance), environmental monitoring, and tactical defense. However, their deployment faces serious challenges due to the limitations of underwater acoustic communication, such as high latency, low bandwidth, high packet loss rates, and severe energy constraints. Under these conditions, conventional centralized data processing approaches are impractical, necessitating a shift toward decentralized intelligence. This paper presents an Energy-Aware Clustered Federated Learning (CFL) framework specifically designed for UWSNs in naval systems. The proposed approach organizes sensor nodes into logical clusters, where local models are trained and aggregated at cluster heads before being transmitted to a central unit. To extend network lifetime, an energy-conscious participation scheme is employed, ensuring that only nodes with sufficient residual energy participate in model training. Moreover, a robust median-based aggregation strategy is introduced at the cluster level to mitigate the effects of noisy and lossy underwater communication. Simulations conducted under realistic underwater conditions demonstrate that the proposed CFL framework achieves a model accuracy of up to 91.2%, which is comparable to centralized learning and outperforms conventional federated learning approaches. Furthermore, CFL improves network lifetime by approximately 40% and reduces communication overhead by nearly 68%, thereby enhancing overall energy efficiency compared to traditional federated learning methods. The results also show improved robustness to packet loss and communication failures, highlighting the suitability of the proposed framework for autonomous underwater operations. Overall, this work illustrates the potential of federated learning to enable intelligent, resilient, and energy-efficient underwater sensor networks, opening new opportunities for future naval and maritime applications in challenging underwater environments.

Povzetek: Članek predstavlja energijsko ozaveščen gručen federativni učni okvir, ki izboljšuje točnost modelov, podaljšuje življenjsko dobo omrežja in zmanjšuje komunikacijske stroške v zahtevnih podvodnih okoljih.

1 Introduction

The underwater sensor networks (UWSNs) have gained significance in a broad spectrum of military applications, such as submarine surveillance, environment, mine detection and strategic maritime domain awareness [1],[2]. Those networks are made up of spatially distributed autonomous sensors in difficult underwater conditions in which radio-frequency communications are not feasible and acoustic communications, though possible, are characterized by high latency, low bandwidth, high energy cost, and high noise. These limitations place vital restraints regarding data aggregation, provision of energy and prompt decision regarding the naval operations [3].

Historically, the sensor systems deployed underwater have been based on centralized architecture, and sensor nodes were transmitting raw or pre-processed data to a central processing unit. Nevertheless, when deployed in under water conditions centralized data collection is energy-intensive, as well as extremely vulnerable to any single points of failure because of the extreme environmental conditions, failure of nodes or communication issues. Furthermore, the transfer of large amounts of raw data across the acoustic channels radically shortens the network life and may result in the loss of important information throughout the process of transmission [4].

In order to overcome these issues, Federated Learning

(FL) has become a promising paradigm. FL allows network nodes to cooperatively learn a common global model without sharing raw data therefore maintaining privacy of data, minimizing communication costs, and localising intelligence at the edge [5]. Although FL has demonstrated tremendous potential in environments that require it to be used in terrestrial scenarios, such as IoT and mobile networks, its direct application to UWSNs presents new challenges, with non-IID data distributions, unstable communications connections, and extremely low-energy limits that characterize the underwater environment [6].

Having identified these issues, this paper comes up with an Energy-Aware Clustered Federated Learning (CFL) framework especially applied to underwater sensor networks in the use of the navy. The key inspirations of this work are:

- Reduction of communication overheads caused by decreasing the rate and volumes of data communications among nodes and the central server.
- Energy efficiency through tuned participation in training rounds with only energy adequate nodes.
- Improving the robustness of the models through the implementation of a robust aggregation mechanism to counter the effect of corrupted or noisy updates due to underwater communication losses.
- Maintaining scalability through the arrangement of sensor nodes into logical groupings, which allows the local model training and aggregation to be effectively performed.

Provided by CFL framework, it is a hierarchical learning approach in which local models are initially merged at the cluster heads with the help of strong statistical methods, and then relayed to a central server. The engagement in training rounds is dynamic on the basis of the remaining energy in each node, thereby extending the period of operation of a network. In addition, to resist unstable paths of communication and possible loss of packets, the median-based aggregation technique is employed over the more conventional averaging technique, and is more resistant to noisy updates. In contrast to existing federated learning approaches, the proposed CFL framework is not a direct adaptation of terrestrial FL techniques, but is explicitly co-designed to address the unique constraints of underwater sensor networks. In particular, the proposed methodology introduces the following distinguishing design elements:

- Integrated energy-conscious participant selection system and hierarchical federated learning, directly targeted to increase network life in UWSNs.
- A two-level robust aggregation scheme that will be executed at the cluster-head level and also at the global level to overcome the impact of acoustic noise and untrustworthy underwater communication channels.
- A hierarchical learning architecture, that is communication efficient and fits into underwater networking reality e.g. large latencies and low bandwidth, instead of traditional terrestrial FL assumptions.

This paper has made significant contributions as summarized below:

- **Problem Formulation Underwater FL:** We precisely define and describe the shortcomings of conventional FL models to underwater sensor networks with focus on communication, energy, and environmental issues.
- **Clustered FL Architecture Design:** We suggest a hierarchical clustering scheme that will be used to carry out local aggregation and reduce the number of unnecessary long-range communications and improve scalability.
- **Energy-Aware Participation Strategy:** This is a new adaptive method of participation grounded on node energy state, where training will not cause disproportionate consumption of resources in vulnerable nodes.
- **Strong Aggregation with Noisy Communication:** We propose a model Aggregation strategy in cluster heads to deal with the negative impact of packet loss and communication noise.
- **Large-Scale Performance Analysis:** We test the presented CFL framework with complex simulations that simulate real-life conditions in the ocean and prove to be more accurate, energy-saving, have communication savings, and be more robust than the traditional federated learning methods.

The manuscript is presented as follows, section 2 provides a literature review of the work on underwater sensor networks and federated learning. Section 3 presents the proposed methodology, including the architecture and major components of the CFL framework. Section 4 will be about the experimental setup to be used in performance evaluation. Section 5 contains the findings and discussion of the suggested method concerning baseline techniques. Lastly, Section 6 will wrap up the paper and also give directions of possible future research.

2 Related work

The rise of the need of intelligent underwater surveillance in the naval systems has boosted the research in Underwater Wireless Sensor Networks (UWSNs), specifically in regard to the efficiency of communication, energy savings, and resistance to environmental uncertainty. In the meantime, a new strategy, Federated Learning (FL), has proven to be quite a promising solution that allows distributed intelligence without violating data privacy even on edge devices. Nevertheless, further usage of FL in the underwater setting is under-researched, in the first place, because of the extreme conditions and limitations of the resources of such setting.

2.1 Underwater sensor networks and problems

The core differences between UWSNs and terrestrial WSNs are that acoustic communication is utilized and thus it generates high propagation delays, low bandwidth, and is prone to multipath fading and Doppler shifts. Various papers have suggested energy-saving protocols, a self-scheduling topology control and mobility-conscious routing algorithms in order to counter these problems [7,8,9]. As an example, Khedo et al. [7] proposed energy-conscious clustering to UWSNs to increase the node lifetime and the article in [8] optimized MAC protocols in underwater channels. Nevertheless, these solutions normally presuppose the centralized processing architecture, which cannot be employed in long-term autonomous missions of the navy because of high energy prices and possible single point of vulnerability.

Therefore, the requirement to have distributed and energy-conscious intelligence in UWSNs, which work effectively without central management is very clear, especially when it is deployed on a long-term basis.

2.2 Edge intelligence federated learning

FL enables remote devices to train machine learning models jointly without communicating raw data, which minimizes communication overhead and improves privacy of data. It has been effectively used in such areas as mobile computing, IoT, and healthcare [5,6] and client selection, gradient compression, and model training tailored have been offered advanced strategies to use.

Hierarchical federated learning (HFL) has also been proposed recently to be used in terrestrial wireless network where nodes are organized into logical clusters, and aggregation is done at both the local and global levels [10]. The architecture is very cost effective in uplink communication and has a scaling factor. These approaches do, however, presuppose radio-based communication conditions of more stable and higher-bandwidth connections than those in underwater.

2.3 Federated learning under harsh conditions

Other researchers have started to modify FL to conditions of intermittent connectivity or severe operational conditions. An example is that methodology explored [11] applications of FL to space-based systems, and the study concentrated on the model robustness to the presence of high-latency and node failures, whereas the research in [12] also ventured into FL on vehicular ad-hoc networks (VANETs) with delay-tolerant aggregation techniques. This fact highlights the fact that conventional FL algorithms cannot be effectively applied in the context of the loss of packets, low power consumption, and dynamic topological dynamics — all of which are worse in underwater systems.

2.4 Federated learning in underwater networks

There is very little literature on the implementation of FL on underwater networks. There were some of the early attempts like the study [9] which applied distributed learning methods in detecting anomalies underwater but did not provide actual federated training. Others looked at model update transmission based on acoustic, but failed to cover energy-conscious participation and resistance to noisy communication channels. In addition, there is no formal proposal of hierarchical FL that uses cluster-level aggregation especially in underwater sensor nodes.

Although the federated learning (FL) has achieved considerable progress and can be utilized in terrestrial networks, the current FL systems cannot be effectively used to address the singular operational conditions of the Underwater Wireless Sensor Networks (UWSNs). The existing solutions are mostly insensitive to critical communication constraints, energy consumption, and packet loss of underwater acoustic communication channels. Furthermore, the strong aggregation techniques that can manage the noisy updates have not been well studied and the energy-adaptive participation schemes that are vital in battery-constricted nodes under water are not common. It has been proposed that hierarchical and clustered FL designs can be applied to terrestrial IoT systems, and these designs have not been adjusted to the unique topology and mobility patterns as well as environmental uncertainties of the underwater deployment.

In order to overcome these shortcomings, this paper suggested a new approach, Energy-Aware Clustered Federated Learning (CFL), that clusters sensor nodes into logical groups to conduct local model training and aggregation. The dynamic participation is achieved by considering residual energy of each node to increase the operation life, and an effective median-based aggregation strategy is proposed to reduce the impacts of the packet corruption and loss. This has been not only scalable and privacy preserving and intelligent underwater naval systems but has also reduced the communication overhead significantly and enhanced the model resiliency in very adverse environments.

2.5 Comparative analysis and research gap

In Table 1, a comparative study of the representative federated learning approaches is provided in relation to the applicability to underwater sensor networks. Current hierarchical and robust FL systems are developed with a terrestrial wireless or IoT setting in mind and do not take into account terrestrial and air configuration changes, as well as the presence of relatively constant and high-bandwidth communication connections and energy supply. Consequently, they fail to clearly discuss the compounded issues of extreme energy limitations, noise from acoustic communication, and long propagation delays that are inherent in UWSNs.

In contrast, the Energy-Aware Clustered Federated Learning (CFL) framework introduced is a joint solution to energy-adaptive participation, clustered hierarchical aggregation, and robust median-based model fusion, which is more applicable to long-term autonomous underwater naval surveillance deployments.

3 Proposed methodology

In this work, we present an energy-aware, clustered federated learning framework tailored for underwater sensor networks (UWSNs) deployed in naval surveillance systems. The methodology is intended to meet the most important challenges of energy limitations, long communication delays, and the presence of a noisy transmission environment, which are specific to underwater operations.

The methodology is organized around three major innovations as illustrated in Figure 1 and they include: (i) Energy-Aware Participant Selection, (ii) Clustered Hierarchical Federated Learning, and (iii) Robust Aggregation under Noisy Conditions.

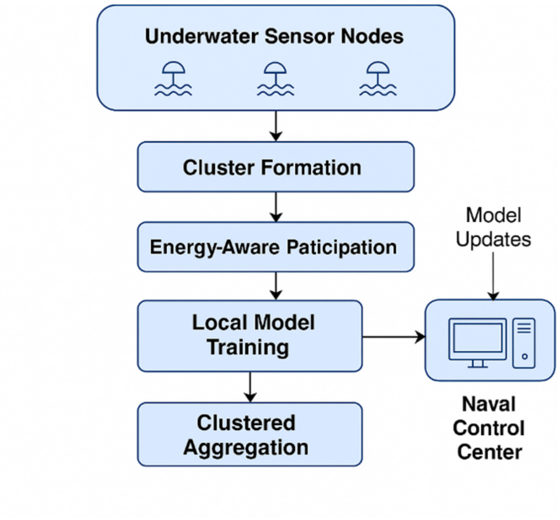

Figure 1: Proposed energy-aware clustered federated learning methodology for underwater sensor networks.

3.1 Energy-aware participant selection

Conventional federated learning presumes that the different devices equally contribute to training rounds. Nevertheless, sensor nodes in underwater conditions have a low battery capacity and cannot be recharged during deployments. In order to maximize energy consumption and increase network life time, we propose a network life-time energy conscious participant selection mechanism.

The node has an energy score of the level of residual energy and the communication history of the node. Prior to every round of training, nodes whose energy level meets a dynamic threshold are allowed to participate. This is an adaptive threshold which is determined by the variance and the mean of the residual energy of the network. There is also a participation probability per eligible node that encourages the trade-off between exploiting high-energy nodes and providing low-energy nodes with a participation opportunity every now and then to ensure that the model is diverse.

Formally, the participation probability P_i of node i is given by:

$$P_i = \alpha \times \left(\frac{E_i}{E_{\max}}\right) + (1-\alpha) \times \eta_i \tag{1}$$

where E_i is the residual energy of node i, $E_{\max}$ is the maximum observed energy in the network, η_i is a randomization factor promoting fairness, and $\alpha \in [0,1]$ controls the energy-awareness weight. **Justification:** The parameter α in Eq. (1) balances fairness and energy efficiency. A higher α prioritizes nodes with more residual energy, extending network lifetime, while a lower α allows low-energy nodes to contribute occasionally, enhancing model diversity under non-IID data distributions.

3.2 Clustered hierarchical federated learning

End-to-end communication between all the nodes and a central server is not practical underwater conditions mainly because of bandwidth constraints and high error rates that define acoustic communication channels. As a result, a two-level clustering strategy is taken.

Intra-Cluster Training: Nodes that lie within a geographically/acoustically defined cluster independently train local models and broadcast updates only within a cluster. Each of these local updates is then aggregated by a Cluster Head (CH) which is decided by the amount of residual energy and the reliability of communication.

Inter-Cluster Aggregation: The Cluster Heads then interact with the Naval Base Station which can be any of a surface ship, a buoy, or an underwater gateway. The base station will combine the received cluster models to improve and update the global model.

The hierarchical paradigm significantly reduces overhead in the communication; many local updates are aggregated as one cluster update before communication. Cluster formation is also semi-static: early clusters are formed according to Received Signal Strength Indicator (RSSI) values, and periodically re-evaluated when there is a change of network topology or change in energy availability of nodes. **Justification:** Cluster Heads are elected based on residual energy and link reliability to maximize the lifespan of high-traffic nodes and ensure stable intra-cluster communication. This selection strategy is particularly important in underwater environments where link quality is highly variable.

Table 1: Comparison of federated learning approaches for underwater sensor networks

Approach	**Energy-Aware Participation**	**Hierarchical / Clustered FL**	**Robust Aggregation**	**Suitability for UWSNs**
Conventional FL (FedAvg)	No	No	No	Low
Hierarchical FL (Terrestrial)	No	Yes	No	Low
Energy-Aware FL (IoT-based)	Yes	No	No	Medium
Robust FL (Median / Trimmed Mean)	No	No	Yes	Medium
Proposed CFL (This Work)	**Yes**	**Yes**	**Yes**	**High**

Cluster Head Sustainability: To prevent rapid depletion of high-energy nodes, Cluster Heads (CHs) are dynamically selected at each round based on a combination of residual energy and link reliability. This ensures that no single node is overused across rounds, thereby improving the sustainability of the network. While explicit CH rotation is suggested as a future enhancement, the current dynamic selection already mitigates the risk of early node exhaustion.

3.3 Robust aggregation under noisy conditions

Underwater communication is also prone to error, and so corrupted model updates are obtained. To this we shall suggest a strong aggregation mechanism both on the cluster level and at the base station level. Otherwise, we employ a median-based aggregation technique (rather than conventional weighted averaging such as Fed_Avg). Specifically, for each model parameter, the coordinate-wise median across updates is taken rather than the mean, mitigating the influence of outlier or corrupted updates.

Given updates $\{w_1, w_2, \ldots, w_n\}$ for a particular parameter across n participants, the aggregated parameter w_{agg} is computed as:

$$w_{\text{agg}} = \text{median}(w_1, w_2, \ldots, w_n) \tag{2}$$

This method is computationally very simple and suitable for resource-constrained nodes and empirically more resilient to noisy transmissions compared to traditional averaging. **Justification:** Median-based aggregation is resilient to corrupted or extreme updates, which frequently occur due to acoustic channel noise and partially non-IID local updates. Unlike averaging, it ensures that outliers do not disproportionately affect the global model, improving robustness in real underwater deployments.

3.4 Communication scheduling and compression

To make communication even more efficient, update compression methods are added, in which model updates are quantized prior to transmission. Also, asynchronous communication timing is used where nodes and clusters are free to send updates at any time depending on the conditions at the local level and not at global rounds. This can be adapted to the very inconsistent communication delays of underwater conditions.

Justification: Asynchronous updates accommodate the highly variable communication delays typical in underwater networks, allowing nodes to transmit updates when available rather than waiting for synchronous rounds. This reduces idle time and mitigates the impact of network heterogeneity on model convergence.

On the whole, the suggested energy-conscious, clustered federated learning strategy is specific to the specifics of underwater naval sensor networks. The system can also generate efficient and resilient hierarchical collaborative intelligence by intelligently choosing participants, hierarchically updating and using robust aggregation techniques without compromising operational life and mission objectives of underwater surveillance networks. The overall procedure of the proposed energy-aware clustered federated learning framework is summarized in Algorithm 1.

4 Experimental setup

In order to test the efficiency of the proposed energy-aware clustered federated learning (CFL) structure to the underwater sensor networks in the naval systems, we create a simulation environment, which is realistic and mimics the specifics of the underwater environment, energy restrictions, communication delays, and noisy transmissions.

4.1 Simulation environment

We conduct a high-fidelity simulation of a 3 km × 3 km underwater operational area with the most recent edition of the Python (3.12.3) programming language, and with scientific computing packages such as NumPy, SciPy and PyTorch and a CUDA-enabled graphics card to operate with great efficiency in parallel. There are 200 randomly distributed underwater sensor nodes on the spatial grid and they are

Algorithm 1: Energy-Aware Clustered Federated Learning for UWSNs

```
Input: Set of underwater sensor nodes $\mathcal{N} = \{1, 2, \ldots, N\}$; Initial global model $w^{(0)}$; Residual energy $E_i^{(t)}$ for
    node $i$ at round $t$; Clustering function $\mathcal{C}(\cdot)$; Maximum training rounds $T$
Output: Optimized global model $w^{(T)}$
for $t = 1$ to $T$ do
    Energy-Aware Participant Selection:
    Compute dynamic energy threshold $\theta^{(t)}$ using mean and variance of $\{E_i^{(t)}\}$;
    Determine eligible nodes:
        $\mathcal{S}^{(t)} = \left\{ i \in \mathcal{N} \mid E_i^{(t)} \geq \theta^{(t)} \right\}$
    Select participating nodes based on probability:
        $P_i^{(t)} = \alpha \frac{E_i^{(t)}}{E_{\max}} + (1 - \alpha)\eta_i$
    Cluster Formation:
    Partition $\mathcal{S}^{(t)}$ into clusters:
        $\mathcal{S}^{(t)} \xrightarrow{\mathcal{C}} \{\mathcal{C}_1, \mathcal{C}_2, \ldots, \mathcal{C}_K\}$
    Elect Cluster Head (CH) for each cluster based on energy and link reliability;
    Intra-Cluster Local Training:
    for each cluster $\mathcal{C}_k$ do
        Each node $i \in \mathcal{C}_k$ performs local update:
            $w_i^{(t)} = w^{(t-1)} - \mu \nabla \ell_i(w^{(t-1)})$
        Cluster-level aggregation using coordinate-wise median:
            $w_k^{(t)} = \text{median}\left(\{w_i^{(t)} \mid i \in \mathcal{C}_k\}\right)$
    Inter-Cluster Aggregation:
    Base station aggregates cluster models:
        $w^{(t)} = \text{median}\left(\{w_k^{(t)} \mid k = 1, \ldots, K\}\right)$
    Energy Update:
    Update residual energy $E_i^{(t+1)}$ based on computation and communication costs;
return $w^{(T)}$
```

programmed to observe multi-dimensional environmental and security such as; the presence of hydroacoustic signals, object detection and thermal gradients.

The nodes are modelled with realistic underwater acoustic modem characteristics including:

- **Bandwidth:** Limited to 10–20 kbps.
- **Latency:** 0.5–2 seconds per message as a function of distance.
- **Packet Loss:** 5%–10% randomly modelled to model noise to communication and environmental interruptions.

To provide the global aggregation, a symbolic Naval Base Station (NBS) is placed at a fixed position (which is usually in the form of a ship or a buoy in real scenarios).

The entire Python implementation of the simulation is based on a simulation framework written in Python and the framework combines both underwater network modelling and federated learning orchestration components. NumPy, SimPy, and custom communication layer scripts are used to simulate the underlying underwater communication dynamics (delay in the propagation of acoustic signals, packets loss, bandwidth limitations), which do not need external network simulators such as NS-3.

To implement federated learning, TensorFlow Federated (TFF) is employed to determine and control the decentralized training rounds over virtual sensor nodes. PyTorch and CUDA acceleration are used to improve the environment by simulating computations on the edges and nodes (energy modeling).

4.2 Node characteristics

Each node is modelled with:

- **Initial Energy (I.E.):** Randomized between 1000–1200 joules to reflect battery variations.
- **Computation Power (C.P.):** Equivalent to a low-power microcontroller (such as ARM Cortex-M series). The local model (∼5,000 parameters) is lightweight and fits comfortably within the RAM constraints of typical low-power ARM Cortex-M microcontrollers (e.g., M4 or M7 series), assuming 32-bit floats and minimal memory overhead.

Sensing and Local Model:

- **Task:** Local anomaly detection (binary classification) based on time-series acoustic features.
- **Model:** Lightweight two-layer neural network (∼5,000 parameters).

Nodes consume:

- **Computation Energy:** 0.5 joules per local epoch.
- **Transmission Energy:** 2 joules per kilobyte transmitted.

Energy consumption values are based on empirical studies of underwater acoustic modems and microcontrollers.

4.3 Federated learning settings

Baseline Methods:

- **Centralized Learning (CL):** Serves as an upper-bound reference, representing the ideal scenario where all data is collected centrally at the Naval Base Station (NBS). It allows assessment of the maximum achievable accuracy without communication constraints.
- **Conventional Federated Learning (FedAvg):** Standard FL method with synchronous updates from all participating nodes. This baseline allows a direct evaluation of the benefits introduced by energy-aware participant selection, hierarchical clustering, and robust aggregation in our proposed CFL framework.

Justification for Baseline Selection: While other hierarchical or robust FL variants exist in terrestrial or IoT networks, their direct implementation in underwater sensor networks is not feasible due to severe constraints of underwater acoustic communication, including low bandwidth, high latency, high packet loss, and strict energy limitations. Therefore, the selected baselines provide a meaningful and fair evaluation of the proposed CFL approach, highlighting improvements in energy efficiency, communication overhead reduction, and robustness under realistic underwater conditions.

Proposed CFL Method:

- **Cluster size:** Average 10–12 nodes per cluster.
- **Energy threshold:** Dynamic, initially set at 60% of maximum energy.
- **Aggregation:** Median-based at both cluster heads and NBS.
- **Training Rounds:** 200 communication rounds.
- **Local Epochs per Round:** 2.
- **Update Compression:** 8-bit quantization applied before communication.

4.4 Evaluation metrics

Performance is assessed using the following metrics:

- **Global Model Accuracy:** Final detection accuracy on a held-out test set.
- **Energy Consumption:** Average energy spent per node until convergence.
- **Network Lifetime:** Number of rounds until 50% of the nodes deplete their energy.
- **Communication Overhead:** Average bytes transmitted per round.
- **Resilience to Noise:** Degradation in model accuracy under varying packet loss rates (0%, 5%, 10%).

4.5 Experiment variants

To validate robustness, we further simulate two additional environments:

- **High-noise environment:** Packet loss up to 15%.
- **Dynamic cluster reformation:** Triggered every 50 rounds based on node energy depletion.

5 Results and evaluation

5.1 Global model accuracy

The progression of model-accuracy within 200 communication rounds is shown in Table 2. The developed constrained federated learning (CFL) paradigm achieves a final detection accuracy of 91.2%, which is quite close to the centralized training accuracy (92.5%) and out of range of the regular federated learning techniques (88.3%). The small difference compared with centralized training is expected considering the non-identical (non-IID) data allocation between nodes and random packet loss. However, a strong median-based aggregation strategy coupled with a hierarchical aggregation mechanism instrumental in mitigating the effects of noisy updates makes the model accuracy very high. CFL achieves even higher accuracy than Fed_Avg in noised conditions (up to 15 per cent packet loss) which highlights its increased resilience to untrustworthy communications.

5.2 Energy consumption

Resource average node energy consumption is significantly lower in the CFL paradigm compared to the conventional federated learning. Specifically, the standard FL algorithm needs an average of 640 joules per node, but the CFL plan has been able to cut it down to 470 joules per node.

This reduction could be explained by a number of design considerations: firstly, selective participation is preconditioned by the current energy level of each node; secondly, local aggregation leads to a reduction in the number of long-range communications; and fourthly, the transmission of updates is compressed, which reduces the spending on energy further. Besides, nodes with relatively low energy reserves have a prolonged survival period because of the adaptive probability of participation, thus improving the overall network lifetime.

5.3 Network lifetime

Network lifetime, defined as the number of rounds until 50% node depletion, is critical for naval surveillance missions. CFL prolongs the network lifetime by approximately 40% compared to conventional FL.

This improvement ensures that mission-critical coverage is maintained for longer periods without human intervention.

5.4 Communication overhead

One of the major impediments in underwater systems is communication overhead.

- **Traditional FL:** 20 KB/node/round.
- **Proposed CFL:** 6.5 KB/node/round.

Hierarchical aggregation and compression schemes foster an element of 68% reduction in communication cost and thus significantly increase the feasibility of these systems under the limit of low-bandwidth underwater acoustic channels. At the same time, the asynchronous communication system minimizes the periods of idle time as well as the heterogeneous latency situations.

5.5 Impact of packet loss

Experiments were performed regarding three cases of packet loss, namely 0%, 5%, and 10%. CFL had less degradation in accuracy than Conventional FL, and this was evident in Table 4.

The median aggregation technique played a crucial role in filtering out corrupted updates, preserving model performance even under adverse channel conditions.

6 Discussion

The results of the experiments confirm the idea that the suggested CFL framework:

- Has a high model accuracy similar to the centralized methods without breaking data privacy.
- Prolongs the network life significantly by enhancing the energy-usage.
- Reduces the overheads of communication, making real-world use across acoustic channels practicable.
- Improves resiliency to underwater noise of communication and lost packets.

The implications of these benefits in the case of operational naval operations are that underwater sensor networks may be used to conduct extended autonomous patrol operations with little risk of communication failure or node depletion. More so, the architecture itself is scalable by nature — more clusters can be added to monitor larger areas but this does not overwhelm the network.

Still, there are some limitations, though. The selection of cluster head has not been fully refined yet to achieve a load balance on a per-need basis and the extreme cases of network partitions (e.g., disconnection of the whole cluster) have not been properly managed yet and are left as areas of future research. Additionally, it should be noted that the experimental validation is currently limited to simulations. Although the simulation environment has been carefully designed to reflect realistic underwater conditions, generalization to real-world underwater deployments or more complex learning tasks may present additional challenges. Future work will focus on testbed-based evaluation and extend the approach to more complex applications to further validate the effectiveness of the proposed CFL framework.

7 Conclusion and future work

This article presents a proposal for an Energy-Conscious Clustered Federated Learning (CFL) protocol used in underwater sensor networks applied in underwater naval surveillance. The given CFL method has a number of advantages because it focuses on the specifics of underwater conditions such as low energy, low-bandwidth acoustic communications, and high packet loss.

First, it employs hierarchical clustering, which enables local aggregation of the model in clusters and thereafter, sends to the central naval base. Second, an adaptive energy-conscience participation strategy will guarantee that only nodes with adequate energy are used in training, which will conserve the longevity of the node. Third, the framework

Table 2: Model accuracy progression

Method	Final Accuracy (%)
Centralized Learning (CL)	92.5
Conventional FL (Fed_Avg)	88.3
Proposed CFL	91.2

Table 3: Network lifetime analysis

Method	Rounds before 50% Node Depletion
Conventional FL	120
Proposed CFL	170

Table 4: Packet loss vs. accuracy

Packet Loss (%)	Accuracy (Conventional FL)	Accuracy (Proposed CFL)
0	88.3	91.2
5	85.1	89.5
10	81.8	86.9

uses a median-based aggregation method to reduce the effect of noisy transmissions.

According to the simulation findings, the CFL has a high model accuracy (91.2 percent), which is equal to centralized learning and higher than the traditional federated approaches. It also means that it has about 40-percent long network life and 68-percent communication overhead, which are that it would be possible to apply in extended duration application in underwater environment with low bandwidth.

In addition, CFL can support small footprint underwater nodes through lightweight construction of the local models and the compression of updates, offering an efficient and privacy-preserving decentralized intelligence platform to be used in the navy.

Future challenges will involve various extensions such as cluster head rotation to make the energy consumption balanced, solve node mobility and cluster reformation in the drifting underwater scenarios, enable wider sense by using multi-task federated learning, and use reinforcement learning to optimize real-time communication scheduling. Further, there will be an attempt to test the results of the simulated research by real-life underwater deployment experiments.

On the whole, this work preconditions the development of the effective and sustainable underwater surveillance systems, but it also clearly mentions that all the conclusions are made on the basis of the simulation experiments and the real implementation is another direction of research in the future.

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References

[1] Domingo MC, Prior R (2007) A distributed clustering scheme for underwater wireless sensor networks, *Proceedings of the IEEE 18th International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)*, IEEE, pp. 1–5. https://doi.org/10.1109/PIMRC.2007.4394038

[2] Ayaz M, Baig I, Abdullah A, Faye I (2011) A survey on routing techniques in underwater wireless sensor networks, *Journal of Network and Computer Applications*, Elsevier, 34(6), pp. 1908–1927. https://doi.org/10.1016/j.jnca.2011.06.009

[3] Fei W, Hexiang B, Deyu L, Jianjun W (2020) Energy-efficient clustering algorithm in underwater sensor networks based on fuzzy C means and moth-flame optimization method, *IEEE Access*, IEEE, 8, pp. 97474–97484. https://doi.org/10.1109/ACCESS.2020.2997066

[4] Lin H, Wei W, Zhao P, Ma X, Zhang R, Liu W, Deng T, Peng K (2016) Energy-efficient compressed data aggregation in underwater acoustic sensor networks, *Wireless Networks*, Springer, 22, pp. 1985–1997. https://doi.org/10.1007/s11276-015-1076-z

[5] McMahan B, Moore E, Ramage D, Hampson S, y Arcas BA (2017) Communication-efficient learning of deep networks from decentralized data, *Proceedings of Artificial Intelligence and Statistics*, PMLR, pp. 1273–1282/. https://doi.org/10.48550/arXiv.1602.05629

[6] Kang J, Xiong Z, Niyato D, Yu H, Liang YC, Kim DI (2019) Incentive design for efficient federated learning in mobile networks: A contract theory approach, *Proceedings of the IEEE VTS Asia Pacific*

Wireless Communications Symposium, IEEE, pp. 1–5. https://doi.org/10.48550/arXiv.1905.07479

[7] Khedo KK, Perseedoss R, Mungur A (2010) A wireless sensor network air pollution monitoring system, *arXiv preprint arXiv:1005.1737*. https://doi.org/10.48550/arXiv.1005.1737

[8] Pantazis NA, Nikolidakis SA, Vergados DD (2012) Energy-efficient routing protocols in wireless sensor networks: A survey, *IEEE Communications Surveys & Tutorials*, IEEE, 15(2), pp. 551–591. https://doi.org/10.1109/SURV.2012.062612.00084

[9] Das AP, Thampi SM (2019) Unsupervised anomaly detection in underwater acoustic sensor networks, *Journal of Intelligent & Fuzzy Systems*, IOS Press, 36(3), pp. 2367–2372. https://doi.org/10.3233/JIFS-169947

[10] Yu Z, Hu J, Min G, Wang Z, Miao W, Li S (2022) Privacy-preserving federated deep learning for cooperative hierarchical caching in fog computing, *IEEE Internet of Things Journal*, IEEE, 9(22), pp. 22246–22255. https://doi.org/10.1109/JIOT.2021.3081480

[11] Uddin R, Kumar SA (2023) SDN-based federated learning approach for satellite-IoT framework to enhance data security and privacy in space communication, *IEEE Journal of Radio Frequency Identification*, IEEE, 7, pp. 424–440. https://doi.org/10.1109/JRFID.2023.3279329

[12] Samarakoon S, Bennis M, Saad W, Debbah M (2019) Distributed federated learning for ultra-reliable low-latency vehicular communications, *IEEE Transactions on Communications*, IEEE, 68(2), pp. 1146–1159. https://doi.org/10.1109/TCOMM.2019.2956472