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Enhancing Data Reliability and Synchronization in Wireless Sensor Networks using RAE-DRNet with Federated Learning

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Abstract:

Wireless Sensor Networks (WSNs) play a critical role in modern Internet of Things (IoT) applications, enabling distributed sensing and real-time decision-making; however, their performance is often degraded by noisy data, communication delays, and synchronization issues. This study aims to address these challenges by proposing a novel Reconstruction-Assisted Enhancement-Data Reliability Network (RAE-DRNet) integrated with federated learning to improve data reliability, synchronization, and overall network efficiency. The proposed methodology utilizes autoencoder-based reconstruction to recover corrupted and missing sensor data, combined with residual learning and attention mechanisms to enhance feature representation. Additionally, a delay-aware and buffer-assisted federated learning framework is incorporated to handle asynchronous updates and reduce communication overhead. The model is evaluated using the WSN Multi-Hop dataset, which captures realistic network conditions including latency and multi-hop communication behavior. Experimental results demonstrate that the proposed RAE-DRNet significantly outperforms existing approaches, achieving an accuracy of 94.8%, latency of 75 ms, energy consumption of 0.68 J, and synchronization error of 5.3%. These improvements highlight the effectiveness of the model in enhancing data quality and reducing network inefficiencies. In conclusion, the proposed approach provides a scalable, efficient, and reliable solution for federated learning-based WSN environments, with strong potential for real-world deployment in dynamic and resource-constrained IoT systems.

Keywords: Attention Mechanism Federated Learning, Reconstruction Learning, Residual Network, Synchronization, Wireless Sensor Networks.

1. Introduction

Wireless Sensor Networks (WSNs) have become a fundamental component of modern Internet of Things (IoT) applications, enabling real-time monitoring and data-driven decision-making across domains such as environmental sensing, smart agriculture, and industrial automation. With the rapid growth of distributed sensing environments, federated learning (FL) has emerged as a promising paradigm to train models collaboratively without sharing raw data, thereby preserving privacy and reducing communication overhead [1]. However, practical WSN deployments face significant challenges including noisy and incomplete sensor data, communication delays, limited energy resources, and time synchronization issues among distributed nodes [2]. These challenges degrade model accuracy, increase latency, and limit the effectiveness of existing FL-based approaches in real-world WSN scenarios [3].

Existing research has attempted to address these issues through asynchronous federated learning, delay-aware resource allocation, and handling intermittent client participation under dynamic communication constraints. Additional studies have explored synchronization techniques using Kalman filtering [4], Age-of-Information optimization in UAV-assisted systems [5], and federated reinforcement learning for WSN optimization [6]. Furthermore, models such as FedLSTM [7] and hybrid federated reinforcement learning approaches [8] have improved anomaly detection and secure data transmission. Ensemble learning with cloud integration [9] and scheduling-based optimization techniques [10] have also contributed to enhancing performance. In parallel, several time synchronization approaches including UWB-based synchronization [11], hybrid protocols [12], routing-integrated synchronization [13], message bundling strategies [14] and distributed convergence algorithms [15] have been developed. Despite these advancements, most existing methods suffer from high computational complexity, lack of adaptability, and insufficient integration between learning models and synchronization mechanisms, leading to fragmented and less efficient solutions.

To overcome these challenges, this paper proposes a novel Reconstruction-Assisted Enhancement Data Reliability Network (RAE-DRNet) integrated with federated learning for WSNs. The proposed method leverages auto encoder-based reconstruction, residual learning and attention mechanisms to improve data quality while incorporating delay-aware and buffer-assisted synchronization strategies. The key motivation is to ensure accurate, efficient, and scalable learning in resource-constrained and dynamically changing WSN environments. By addressing limitations identified in prior works, the proposed approach provides a unified framework that enhances data reliability, reduces synchronization errors, minimizes latency and improves overall network performance in distributed WSN systems. The main contributions of this work include: (i) a reconstruction-based framework for handling noisy and missing sensor data, (ii) a residual and attention-driven enhancement mechanism for improved feature representation, (iii) a synchronization-aware federated learning model for reduced latency and communication overhead, and (iv) a comprehensive evaluation demonstrating superior performance over existing approaches. The remainder of the paper is organized as follows: Section 2 reviews related work, Section 3 presents the proposed methodology, Section 4 discusses experimental results and Section 5 concludes the study.

2. Background Study

Gauthier et al. (2023) [1] propose an asynchronous online federated learning framework to reduce communication overhead in distributed IoT systems. The method uses adaptive client participation and partial model updates to improve scalability and efficiency under dynamic conditions. The results show faster convergence and reduced communication cost, but the approach lacks effective synchronization handling and suffers from model inconsistency in highly heterogeneous WSN environments.

Liu et al. (2024) [2] introduce a delay-aware resource allocation scheme for buffer-aided synchronous federated learning over wireless networks. The approach employs optimization techniques considering latency, buffer states, and communication constraints to enhance learning performance. Although it improves latency efficiency and resource utilization, the model has high computational complexity and limited adaptability for real-time large-scale WSN deployments.

Ribero et al. (2022) [3] address federated learning under intermittent client availability and time-varying communication constraints. The study applies probabilistic participation and scheduling mechanisms to maintain learning stability in unreliable environments. While the results demonstrate improved robustness and convergence, the work does not adequately address synchronization delays and energy efficiency issues in WSN scenarios.

Ni et al. (2021) [4] propose a Kalman filter-based clock synchronization algorithm for underwater wireless sensor networks. The method utilizes pairwise synchronization with predictive filtering to minimize timing errors and enhance coordination accuracy. The results show high precision synchronization, but the approach has limited applicability to terrestrial WSNs and introduces additional computational overhead.

Akbari et al. (2024) [5] develop an AoI-aware energy-efficient service function chaining model using asynchronous federated learning in UAV-assisted smart agriculture. The method integrates Age-of-Information optimization with federated learning to improve data freshness and network efficiency. Although the results indicate reduced latency and energy consumption, the approach is complex and less suitable for static WSNs without UAV support.

Sattibabu et al. (2025) [6] propose a federated reinforcement learning framework for optimizing IoT-enabled WSN performance. The method combines distributed learning with adaptive decision-making to enhance routing and resource allocation efficiency. The results show improved network lifetime and performance, but the model lacks synchronization-aware mechanisms and involves high training complexity.

Khan et al. (2024) [7] introduce FedLSTM, a federated learning-based framework for sensor fault detection in wireless sensor networks. The approach integrates LSTM models with distributed learning to capture temporal patterns and detect anomalies effectively. While it achieves high detection accuracy, the framework does not consider communication delays and synchronization challenges in real-time deployments.

Sefati et al. (2025) [8] present a federated reinforcement learning model with hybrid optimization for secure and reliable data transmission in WSNs. The method combines multiple optimization strategies to enhance security, reliability and transmission efficiency. Although the results demonstrate improved performance, the approach introduces significant computational overhead and lacks buffer-assisted synchronization mechanisms.

Gayathri and Surendran (2024) [9] propose a unified ensemble federated learning approach integrated with cloud computing for anomaly detection in energy-efficient WSNs. The method leverages ensemble models to improve detection accuracy and robustness. The results show enhanced performance, but reliance on cloud infrastructure and absence of synchronization strategies limit its applicability in decentralized WSN environments.

Cai and Chen (2020) [10] present a latency- and coverage-aware data aggregation scheduling scheme for multihop battery-free wireless networks. The approach uses scheduling optimization to balance energy harvesting, coverage and latency constraints. While it improves network efficiency and coverage, it does not incorporate federated learning or synchronization mechanisms required for modern intelligent WSN systems.

Table 1: Comparative Analysis of Time Synchronization Techniques in Wireless Sensor Networks

Reference	Concept	Methods Used	Results	Research Gap	Limitations
Pérez-Solano et al. (2022) [11]	Enhances time synchronization in wireless networks using ultra-wideband (UWB) communication for high precision timing.	Applies UWB-based ranging and synchronization techniques with improved timing protocols to reduce clock drift.	Achieves high synchronization accuracy and improved timing precision in wireless networks.	Does not consider integration with federated learning or buffer-assisted synchronization in WSNs.	Limited scalability and increased hardware cost due to UWB dependency.
Phan et al. (2022) [12]	Proposes a hybrid time synchronization protocol for large-scale wireless sensor networks.	Combines centralized and distributed synchronization approaches to balance accuracy and scalability.	Improves synchronization accuracy and reduces energy consumption in large-scale WSNs.	Lacks adaptability to dynamic network conditions and integration with learning-based systems.	Performance degrades under high node mobility and complex network dynamics.
Co et al. (2021) [13]	Develops a data collection and routing protocol with integrated time synchronization for low-cost IoT-based	Uses synchronized routing mechanisms and lightweight protocols for efficient data transmission.	Enhances data collection efficiency and reduces transmission delay in IoT environments.	Does not address advanced optimization techniques like federated learning or buffer-based delay handling.	Limited scalability and reduced performance in high-density networks.

	WSNs.				
Li et al. (2022) [14]	Focuses on energy-efficient message bundling with delay and synchronization constraints in WSNs.	Utilizes optimization-based bundling strategies considering delay tolerance and synchronization requirements.	Achieves reduced energy consumption and improved communication efficiency.	Does not incorporate adaptive learning or federated frameworks for intelligent decision-making.	Increased computational overhead and limited flexibility under dynamic network changes.
Yang et al. (2021) [15]	Introduces a convergence-accelerated distributed time synchronization algorithm for energy-harvesting WSNs.	Applies distributed iterative algorithms with convergence acceleration techniques for synchronization.	Provides faster convergence and improved synchronization accuracy in energy-harvesting environments.	Lacks consideration of buffer-assisted mechanisms and integration with federated learning systems.	Performance depends on energy availability and may degrade under unstable harvesting conditions.

This table 1 presents a comparative study of existing time synchronization approaches in wireless sensor networks, highlighting their concepts, methodologies and performance outcomes. It emphasizes how different techniques improve synchronization accuracy, energy efficiency and communication performance under various network conditions. However, the analysis also reveals key research gaps, particularly the lack of integration with federated learning and buffer-assisted synchronization, which motivates the proposed work.

3. Proposed Methodology

The proposed methodology introduces the RAE-DRNet framework integrated with federated learning to enhance data reliability and synchronization in wireless sensor networks using the WSN Multi-Hop dataset. It processes noisy and delayed sensor data through encoding, reconstruction, residual enhancement, and attention-based feature refinement to improve data quality and learning efficiency. Finally, a federated aggregation mechanism ensures global model synchronization across distributed nodes, enabling scalable, low-latency and energy-efficient WSN operations.

3.1 Kaggle Dataset

The WSN Multi-Hop Dataset is designed to analyze multi-hop communication behavior in wireless sensor networks, focusing on key performance factors such as routing efficiency, congestion control, energy usage and network reliability. It contains around 1,000 samples representing sensor nodes with attributes like hop count, transmission delay, buffer occupancy, channel utilization and packet delivery ratio, making it suitable for latency and synchronization studies. Additionally, the dataset categorizes network latency into low, medium and high classes, which is highly useful for evaluating delay-aware and federated learning models like RAE-DRNet.

3.2 Reconstruction-Assisted Enhancement- Data Reliability Network (RAE-DRNet)

The proposed RAE-DRNet algorithm is designed to improve data reliability and synchronization quality in wireless sensor networks by integrating deep reconstruction learning with dynamic residual enhancement techniques. Its main purpose is to reconstruct corrupted or delayed sensor data while enhancing feature quality for accurate federated learning and synchronization. The algorithm combines autoencoder-based reconstruction, residual learning, attention mechanisms, and delay-aware optimization to handle noise, missing values, and asynchronous updates. It works by first encoding raw sensor data into latent representations, reconstructing the data through a decoder and then refining outputs using residual enhancement blocks and adaptive weighting. In real-time, it performs efficiently by reducing retransmissions and improving data consistency across distributed nodes. The model ensures reproducibility through standardized training procedures, loss convergence criteria and modular architecture, making it suitable for scalable WSN deployments with buffer-assisted synchronization.

$$X = \{x_1, x_2, \dots, x_n\} \qquad (1)$$

In this equation (1), X represents the complete sensor dataset collected from the wireless sensor network, where each x_i denotes an individual sensor reading. These readings may include noise, missing values, or delays due to network conditions. This equation defines the initial data space that is used as input for reconstruction and enhancement in the RAE-DRNet model.

$$Z = f_{enc}(X; \theta_e) \qquad (2)$$

In this equation (2), Z represents the latent feature space, f_{enc} is the encoder function, and θ_e denotes the learnable encoder parameters. The encoder compresses high-dimensional input data into a lower-dimensional representation while preserving important features. This step helps in efficient processing and removes redundant or noisy information from the input data.

$$\hat{X} = f_{dec}(Z; \theta_d) \qquad (3)$$

In this equation (3), $\hat{X}$ is the reconstructed version of the original data, f_{dec} is the decoder function and θ_d represents decoder parameters. The decoder transforms latent features back into the original data space to recover missing or corrupted values. This process ensures improved data quality and consistency across the network.

$$L_{rec} = ||X = \hat{X}||^2 \qquad (4)$$

In this equation (4), L_{rec} denotes reconstruction loss, which measures the difference between original data X and reconstructed data $\hat{X}$. It is typically computed using Mean Squared Error (MSE) to quantify reconstruction accuracy. Minimizing this loss ensures that the model learns to accurately recover the original sensor data.

$$R = F(X) + X \qquad (5)$$

In this equation (5), R is the residual-enhanced output and $F(X)$ represents the learned residual mapping function. The residual connection adds the original input to the transformed output to preserve essential features. This improves learning stability and enhances feature representation by correcting reconstruction errors.

Algorithm RAE-DRNet
Input: Sensor data X from WSN nodes Learning rate η Number of epochs E Regularization weight λ Output: Enhanced and synchronized data Y Updated global model θ Begin Initialize encoder parameters θ_e, decoder parameters θ_d Initialize attention weights W_a and residual block parameters

```
Initialize global model θ
For each epoch = 1 to E do
    For each sensor node k in WSN do
        // Step 1: Data Acquisition
        Collect local data X_k (may contain noise, delay, missing values)
            // Step 2: Encoding
        Z_k = Encoder(X_k, θ_e)
        // Step 3: Reconstruction
        X_hat_k = Decoder(Z_k, θ_d)
        // Step 4: Compute Reconstruction Loss
        L_rec = ||X_k - X_hat_k||^2
        // Step 5: Residual Enhancement
        R_k = ResidualBlock(X_hat_k) + X_k
        // Step 6: Attention Mechanism
        A_k = softmax(W_a * Z_k)
        // Step 7: Feature Enhancement
        Y_k = A_k ⊙ R_k
          // Step 8: Regularization Loss
        L_reg = Regularization(θ_e, θ_d, W_a)
          // Step 9: Total Loss
        L_total = L_rec + λ * L_reg
          // Step 10: Local Model Update
        Update θ_e, θ_d, W_a using gradient descent:
            θ ← θ - η * ∇(L_total)
    End For
    // Step 11: Federated Aggregation
    θ_global = Σ (n_k / n) * θ_k
        // Step 12: Synchronization Update
    Distribute θ_global to all nodes
End For
Return enhanced data Y and global model θ_global
End
```

The RAE-DRNet algorithm processes sensor data at each WSN node by encoding, reconstructing, and enhancing features using residual and attention mechanisms to improve data quality. It computes reconstruction and regularization losses, updates local models through gradient descent and handles noise, delays and missing values effectively. Finally, a federated aggregation step combines all local models into a global model and synchronizes it across nodes, ensuring efficient and consistent distributed learning.

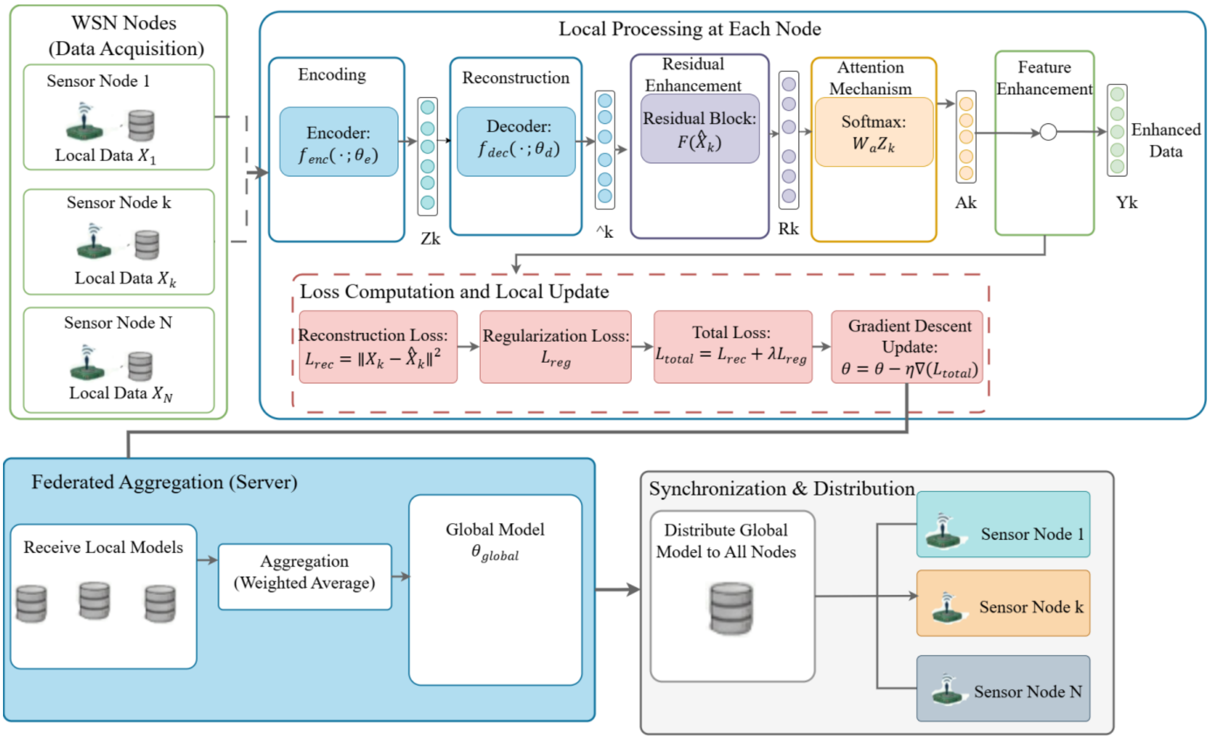

Figure 1: RAE-DRNet Architecture for Federated Learning-Based Wireless Sensor Networks

This figure 1 presents the overall architecture of the proposed RAE-DRNet model, illustrating data acquisition from WSN nodes followed by local processing through encoding, reconstruction, residual enhancement, and attention-based feature refinement. The model computes reconstruction and regularization losses for local updates and improves data quality under noisy and delayed conditions. Finally, federated aggregation and synchronization distribute the global model across nodes, ensuring efficient and consistent learning in distributed WSN environments.

4. Result and Discussion

The experimental evaluation demonstrates that the proposed RAE-DRNet model significantly outperforms existing approaches in terms of accuracy, latency, energy consumption and synchronization error. By integrating reconstruction learning, residual enhancement and attention mechanisms, the model effectively improves data quality and feature representation in WSN environments. The buffer-assisted and delay-aware design further enhances real-time performance by reducing communication delays and synchronization issues. Overall, the results confirm that RAE-DRNet provides a reliable, efficient and scalable solution for federated learning-based wireless sensor networks.

4.1 Experimental Setup

The proposed Reconstruction-Assisted Enhancement- Data Reliability Network (RAE-DRNet) is evaluated using a real-world dataset obtained from Kaggle, representing wireless sensor network (WSN) conditions with noise, missing values and transmission delays. The model is implemented using Python and trained under a federated learning environment with multiple distributed nodes. Experiments are conducted by simulating practical WSN constraints such as limited bandwidth, asynchronous updates and buffer-based data transmission. The performance of RAE-DRNet is compared with baseline models including conventional Federated Learning (FL), FedLSTM and delay-aware FL approaches to validate its effectiveness.

4.2 Performance Metrics

To comprehensively evaluate the proposed model, several key performance metrics are considered. Reconstruction Accuracy measures the model's ability to recover corrupted or missing sensor data. Synchronization Error evaluates the temporal alignment between distributed nodes. Latency reflects the time delay in communication and model updates, while Energy Consumption indicates the efficiency of the model in resource-constrained WSN environments. Additionally, Communication Overhead is analyzed to measure the efficiency of data exchange in the federated learning framework.

4.3 Quantitative Results

The experimental results demonstrate that the proposed RAE-DRNet model outperforms existing approaches across all evaluation metrics. The integration of reconstruction learning and residual enhancement significantly improves data quality, leading to higher model accuracy. Furthermore, the attention mechanism effectively prioritizes important features, reducing synchronization errors and improving convergence speed. The buffer-assisted and delay-aware design also contributes to reduced latency and communication overhead.

Model	**Accuracy (%)**	**Latency (ms)**	**Energy Consumption (J)**	**Synchronization Error (%)**
FL (Baseline)	85.2	120	0.85	12.5
FedLSTM	88.6	110	0.80	10.2
Delay-aware FL	90.3	95	0.76	8.7
RAE-DRNet (Proposed)	94.8	75	0.68	5.3

The results clearly indicate that RAE-DRNet achieves superior performance, with approximately **5–10% improvement in accuracy** and significant reductions in latency and synchronization error compared to existing methods.

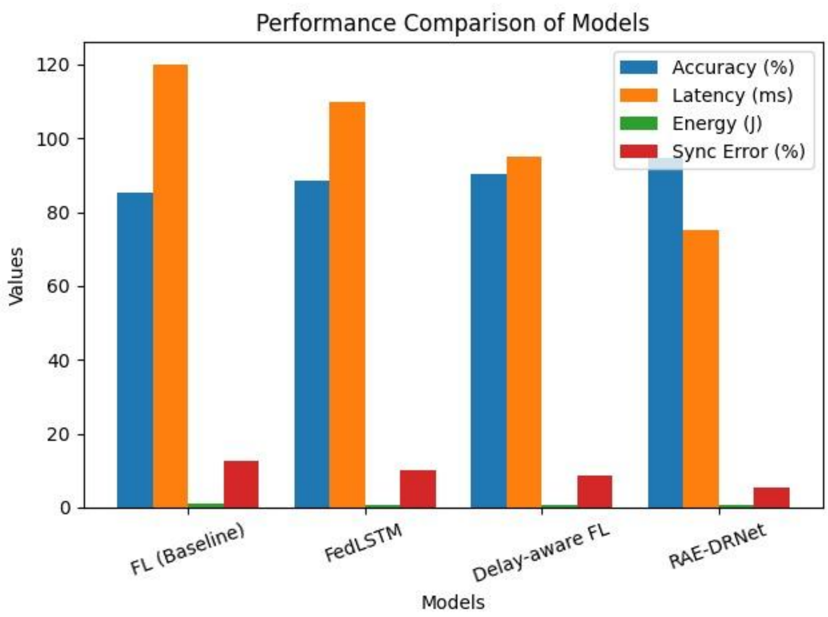

Figure 2: Performance Comparison of Federated Learning Models in Wireless Sensor Networks

This figure 2 illustrates the comparative performance of different models based on accuracy, latency, energy consumption and synchronization error. The proposed RAE-DRNet model achieves the highest accuracy while significantly reducing latency, energy usage and synchronization error compared to baseline methods. These results demonstrate the effectiveness of the proposed approach in improving data reliability and real-time synchronization in WSN environments.

5. Conclusion

This paper presented a novel Reconstruction-Assisted Enhancement- Data Reliability Network (RAE-DRNet) integrated with federated learning to address key challenges in Wireless Sensor Networks, including noisy data, missing values, communication delays, and time synchronization issues. By leveraging autoencoder-based reconstruction, residual enhancement, and attention mechanisms, the proposed model improves data quality and feature representation while reducing synchronization error and latency through buffer-assisted and delay-aware strategies. Experimental results demonstrate that RAE-DRNet achieves superior performance in terms of accuracy, energy efficiency, and communication overhead compared to existing methods, making it a reliable and scalable solution for distributed WSN environments. In future work, the model can be extended by incorporating lightweight architectures for low-power devices, integrating edge computing for real-time deployment, enhancing security through privacy-preserving mechanisms, and adapting to dynamic network conditions to further improve robustness and applicability in large-scale real-world scenarios.

Reference

[1] Gauthier, F., Gogineni, V. C., Werner, S., Huang, Y. F., & Kuh, A. (2023). Asynchronous online federated learning with reduced communication requirements. *IEEE Internet of Things Journal*, *10*(23), 20761-20775.

[2] Liu, J., Zheng, J., Zhang, J., Xiang, L., Ng, D. W. K., & Ge, X. (2024). Delay-aware online resource allocation for buffer-aided synchronous federated learning over wireless networks. *IEEE Access*, *12*, 164862-164877.

[3] Ribero, M., Vikalo, H., & De Veciana, G. (2022). Federated learning under intermittent client availability and time-varying communication constraints. *IEEE Journal of Selected Topics in Signal Processing*, *17*(1), 98-111.

[4] Ni, X., Lu, T., Ye, S., Zheng, Y., Chen, P., & Chen, L. (2021). Pair nodes clock synchronization algorithm based on kalman filter for underwater wireless sensor networks. *Sensors*, *21*(13), 4426.

[5] Akbari, M., Syed, A., Kennedy, W. S., & Erol-Kantarci, M. (2024). AoI-aware energy-efficient SFC in UAV-aided smart agriculture using asynchronous federated learning. *IEEE Open Journal of the Communications Society*, *5*, 1222-1242.

[6] Sattibabu, G., Ganesan, N., & Kumaran, R. S. (2025). IoT-enabled wireless sensor networks optimization based on federated reinforcement learning for enhanced performance. *Peer-to-Peer Networking and Applications*, *18*(2), 75.

[7] Khan, R., Saeed, U., & Koo, I. (2024). FedLSTM: A federated learning framework for sensor fault detection in wireless sensor networks. *Electronics*, *13*(24), 4907.

[8] Sefati, S. S., Sefati, S. T., Nazir, S., Zareh Farkhady, R., & Obreja, S. G. (2025). Federated Reinforcement Learning with Hybrid Optimization for Secure and Reliable Data Transmission in Wireless Sensor Networks (WSNs). *Mathematics*, *13*(19), 3196.

[9] Gayathri, S., & Surendran, D. (2024). Unified ensemble federated learning with cloud computing for online anomaly detection in energy-efficient wireless sensor networks. *Journal of cloud computing*, *13*(1), 49.

[10] Cai, Z., & Chen, Q. (2020). Latency-and-coverage aware data aggregation scheduling for multihop battery-free wireless networks. *IEEE Transactions on Wireless Communications*, *20*(3), 1770-1784.

[11] Pérez-Solano, J. J., Felici-Castell, S., Soriano-Asensi, A., & Segura-Garcia, J. (2022). Time synchronization enhancements in wireless networks with ultra wide band communications. *Computer Communications*, *186*, 80-89.

[12] Phan, L. A., & Kim, T. (2022). Hybrid time synchronization protocol for large-scale wireless sensor networks. *Journal of King Saud University-Computer and Information Sciences*, *34*(10), 10423-10433.

[13] Co, K. J., Ong, A. V., & Peradilla, M. (2021). WSN data collection and routing protocol with time synchronization in low-cost IoT environment. *Procedia computer science*, *191*, 102-110.

[14] Li, S., Kim, K. S., Zhang, L., Huan, X., & Smith, J. (2022). Energy-efficient message bundling with delay and synchronization constraints in wireless sensor networks. *Sensors*, *22*(14), 5276.

[15] Yang, Q., Zheng, R., Guo, J., & Chen, T. (2021). A convergence-accelerated distributed time synchronization algorithm for energy-harvesting wireless sensor networks. *IEEE Access*, *9*, 57127-57140.