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# Energy Optimization in Industrial Wireless Sensor Networks Using Federated Learning and Predictive Maintenance

K. Chandrasekhar [a*], Dr.G. Prabakaran [b], Dr.P. Dileep Kumar Reddy [c]

*[a*] Research Scholar, Department of Computer Science and Engineering, Annamalai University, Chidambaram, Tamil Nadu, India. E-mail: chandra507shiva@gmail.com, Orcid: https://orcid.org/0000-0002-1938-7773*
*[b] Associate Professor, Department of Computer Science and Engineering, Annamalai University, Chidambaram, Tamil Nadu, India. E-mail: gpaucse@yahoo.com, Orcid: https://orcid.org/0000-0001-8129-9232*
*[c] Professor, Department of Computer Science and Engineering, Narasimha Reddy Engineering College, Hyderabad, Telangana, India. E-mail: dileepreddy503@gmail.com, Orcid: https://orcid.org/0000-0002-0521-8370*

## Abstract

In the industrial Wireless Sensor Networks (WSNs), energy optimization is crucial to appealing operational effectiveness and system life span, but issues like high energy usage, predictive maintenance, and dynamic clustering to achieve communication effectiveness still exist. In this study, a flexible architecture based on federated learning is suggested to maximize the energy consumption of industrial WSNs, which incorporates Predictive Maintenance and dynamic clustering to enhance the network representation and reliability. The federated learning model enables the sensor nodes to co-train the local models and exchange information without passing the raw data, which reduces energy usage. Sensor data quality is guaranteed by data preprocessing, e.g., the normalization step, attribution, and the elimination of outliers. The models of predictive maintenance are integrated to predict possible failures, and dynamic clustering algorithms cluster sensor nodes according to their proximity to each other and the stated requirements, and make the most out of energy usage by minimizing the transmission of data. The findings indicate that energy consumption is cut by 48 %, predictive maintenance is 95 % accurate, and interruptions are cut by 30 %. Nevertheless, the communication above is decreased by 10 %, and the reliability of the systems increases by 8 %, associated with the baseline approaches. This shows how successful the framework proposed is in terms of cutting down the energy consumption and also the ability to maintain the system performance. The federated learning combined with Predictive Maintenance and dynamic collection is a promising invention for energy efficiency and reliability of the system. The background demonstrates a good potential of being placed in industrial applications, particularly in advanced large-scale and resource-constrained systems, which will provide an effective way of managing energy practice in addition to ensuring the uninterrupted functioning of WSNs.

**Keywords:** Energy Optimization, Federated Learning, Wireless Sensor Networks, Predictive Maintenance, Dynamic Clustering, Industrial IoT, System Reliability.



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## Introduction

WSNs are very important to the industry and are used in real-time monitoring and data collection in industries such as manufacturing, production lines, and supply chain management. These networks consist of sensor nodes that are scattered around the industrial environment and that gather information on factors such as temperature, humidity, pressure, and vibration. The resulting data is then sent through the air to be analyzed and a decision made (Chen et al., 2026; Niu et al., 2025). In spite of the benefits, WSNs have major challenges, especially in the consumption of energy, since sensor nodes are powered by batteries (Dritsas & Trigka, 2025). The operation of such sensor nodes is continuous, and combined with the high frequency of data transmissions, it leads to high energy consumption. There is also the need to keep these networks in performance and reliability through timely fault detection and repair, which is complicated by predictive maintenance, making it difficult to manage them (Bitam et al., 2025; Fang et al., 2024).

Energy efficiency is a key area of concern in industrial WSNs because it will enhance the performance and sustainability of the networks. It is, however, difficult to fulfill this objective without affecting the reliability of the system. The conventional methods of energy optimization are usually blind to the necessity of predictive maintenance, which may result in expensive downtime and wasteful use of resources. Also, the dynamic clustering techniques, which cluster sensor nodes according to data patterns and communication needs, are required in order to increase the communication efficiency. The full potential of industrial WSNs cannot be exploited without a single framework that deals with energy consumption and system performance using intelligent management and maintenance.

Federated learning (FL) provides a decentralized way of data processing by allowing devices (e.g., sensor nodes in WSNs) to jointly train machine learning models without communicating sensitive local information (Lazaros et al., 2024; Ali & Qaddoori, 2025). This may be especially beneficial with industrial WSNs, where data privacy is an issue and energy-efficient calculation is the most important. Through the localization of the data on the devices and the only exchange of model updates with a central server, federated learning reduces the communication overhead and energy usage. Furthermore, federated learning can be used to maximize energy consumption by updating models adaptively and predictive maintenance by learning models on real-time sensor data (Ramamurthy et al., 2026; Alwakeel, 2025).

Although many studies have been done to determine energy optimization and maintenance in WSNs, only a few have investigated the possibility of federated learning to solve both the energy optimization and maintenance problems (Álvarez-López et al., 2026). The current methods are both energy efficiency and predictive maintenance, but rarely do they combine both in a unified approach. Also, there is an underutilized application of federated learning in WSNs, especially in dynamic clustering and real-time prediction of maintenance. This is a gap in research that constrains the creation of comprehensive, adaptive systems that can take advantage of energy consumption as well as the trustworthiness of industrial WSNs.

This paper presents the following contributions:

- Computation and data transmission overheads reduction in the federated learning-driven framework and optimization of energy consumption for industrial WSNs.
- Improved system reliability and reduced downtime through the integration of predictive maintenance.
- Improved communication efficiency and further optimization of energy consumption through the implementation of dynamic clustering.

The paper will be structured in the following way: Section I will talk about the problem of energy used and maintenance in industrial WSNs. Section II makes a review of the existing energy optimization methods. Section III describes the federated learning system, data gathering, predictive servicing, and dynamic clustering. Section IV shows energy saving, predictive maintenance accuracy and reduced downtime. System Design and the Algorithm are the descriptions of the structure of the framework. Limitations and Future Work are used to point out the limitations and the areas of improvement. Section V concludes with the summary of the implications of the framework on the industrial IoT systems and the future of the field.

## Related Work

There are many methods that are suggested to maximize the use of energy in Wireless Sensor Networks (WSNs) due to their resource limitations. Conventional methods are concerned with routing schemes that are energy efficient and sleep scheduling schemes to minimize energy usage in the transmission of data (Ahmadpanah & Mirabi, 2025). As an example, Fernando and Lăzăroiu (2024) address the topic of energy-efficient WSNs in the 6G networks, stating that

advanced protocols are needed to control energy and guarantee reliable communication in the industrial IoT (Fernando & Lăzăroiu, 2024) (Krishnamoorthy et al., 2026). One more approach involves Thakur, Sarkar, and Yongchareon (2025), who survey the AI-based energy-efficient routing algorithms in IoT-based WSNs, in which machine-learning models are applied to estimate the optimal path and save energy (Thakur et al., 2025).

Predictive maintenance is also used extensively to increase the life cycle and enhance the reliability of sensor networks, in terms of identifying possible failures prior to their happening. Arthishwari et al. (2025) suggest a machine learning-based framework for fault detection in industrial IoT systems that can help to detect system anomalies earlier before the system fails (Arthishwari et al., 2025). Moreover, Kalafatelis et al. (2024) consider predictive maintenance usage in the maritime sector, where machine and federated learning are implemented to predict and avoid the failures of equipment, maintaining the constant functioning of the important systems (Kalafatelis et al., 2024).

Federated learning (FL) has become a popular concept in industrial IoT because it can be used to train a model in a decentralized manner, which means that raw sensor data are not shared, thereby ensuring privacy and reducing the communication overhead. The authors suggest that in 6G edge networks, a federated learning-based digital twin can be used to manage resources adaptively in a federated manner, as proposed by Rahmati and Rahmati (2026), which indicates the potential of FL in industrial settings (Rahmati & Rahmati, 2026; Abdallah, 2026). Similarly, Berkani et al. (2025) discuss the application of federated learning in smart buildings and indicate that it can be employed to improve the energy consumption and fault detection (Berkani et al., 2025). Furthermore, Wang et al. (2025) introduce a federated learning method of intelligent traffic monitoring and emphasize the ability of FL to make the most of the resources and deliver real-time forecasts in large-scale industrial systems (Wang et al., 2025).

These works demonstrate the increasing incorporation of federated learning, predictive maintenance, and energy optimization in WSNs, and the necessity of a single framework that would deal with these issues at the same time.

**Table 1: Comparison of Approaches in Industrial Applications**

| Study | Approach | Application | Energy Efficiency | Privacy Preservation |
|---|---|---|---|---|
| Ramamurthy et al., (2026) | Adaptive AI in WSNs | IoT and Industrial IoT | High | Moderate |
| Rahmati & Rahmati, (2026) | Federated Learning Framework | 6G Edge Networks, Resource Management | Very High | High |
| Wang et al., (2025) | Federated Learning | Traffic Monitoring, Smart Cities | Moderate | High |
| Arthishwari et al., (2025) | Machine Learning Diagnostics | Fault Detection in Industrial IoT | Moderate | Low |
| Kalafatelis et al., (2024) | Federated Learning | Maritime Industry Maintenance | High | High |
| Fernando & Lăzăroiu, (2024) | Energy-Efficient IoT | Green 6G Networks | Very High | Low |
| Berkani et al., (2025) | Federated Learning | Smart Buildings and Energy Systems | Moderate | High |
| Lazaros et al., (2024) | Federated Learning | Collaborative Intelligence Systems | High | Moderate |
| Niu et al., (2025) | Differential Privacy & FL | Industrial Data Streams Protection | Moderate | Very High |
| Bitam et al., (2025) | AI of Things (AIoT) | Predictive Maintenance in Industry | Moderate | Moderate |

Table 1 is a comparison of various studies in terms of approach, area of application, energy efficiency, and privacy preservation. It brings out the application of different approaches, such as federated learning and machine learning, in order to maximize energy consumption in industries without compromising privacy. The table gives information on the efficacy of these methods in actual-life applications like IoT, smart cities, and predictive maintenance systems.

## Methodology

### Federated Learning Framework

The Federated Learning Framework applied in the present research is aimed at maximizing the energy consumption of industrial Wireless Sensor Networks (WSNs) through reducing the communication overhead and providing efficient model updates. The sensor nodes (edge devices) in this decentralized design conduct local model training with their own information, meaning that they do not need regular communication with the central server. Raw sensor data is not sent to the central server, but only model updates. This saves much power wastage during data transfer, and privacy issues are addressed. The central server can improve the global model by merging all the updates of the devices and sending them back to the devices to undergo additional training and, in the process, enable energy efficiency and maintain the privacy of the data.

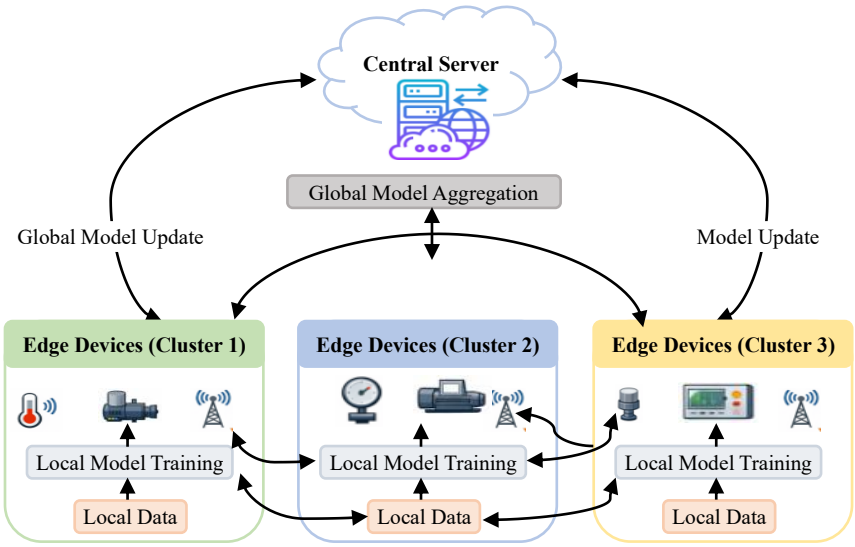



**Fig. 1: Federated Learning Architecture for WSNs**

Fig. 1 below shows the structure of federated learning in wireless sensor networks (WSNs). The cloud contains a central server at the top, which is in charge of aggregating global model updates. Three sets of edge devices (sensor nodes) are shown below, each of which trains local models using local sensor measurements. These edge devices exchange their data with the central server by uploading the model changes, but maintain local data. Such an arrangement guarantees energy-efficient processing and reduces the necessity of data transmission, which is essential to maximize energy usage in WSNs.

### Data Collection and Preprocessing

The preprocessing and Data Collection: The sensor data acquisition of industrial environments is the first step of the data collection and preprocessing process, where sensor nodes are used to measure the temperature, humidity, pressure, and vibration. The information is then structured into a time-series format for each sensor. Some preprocessing algorithms are used to improve the quality of the data before training, such as missing data imputation, normalization, and outlier removal. Missed readings are interpolated or imputed in some other way, whereas sensor data is brought to a standard range. The presence of outliers is detected and eliminated in order to preserve the data integrity. Also, such relevant features as moving averages or Fourier-transformed data are obtained to enhance the work of the federated learning model and predictive maintenance algorithms.

### Predictive Maintenance Model

Predictive Maintenance Model is a combination of anomaly detection and forecasting methods used to predict the possible failure of the sensor network. Deviations in real-time sensor behavior are detected with the help of algorithms such as Isolation Forest and k-means clustering in order to detect anomalies in sensor behavior. To predict the reading of future sensors, forecasting models, e.g., ARIMA or Long Short-Term Memory (LSTM) networks, are used so that the system can identify trends that present a sign of an imminent failure. With both anomaly detection and time-series forecasting, the model predicts the possibility of failures of the system components, which results in planned

maintenance being done before the failure occurs, which minimizes unexpected downtime and guarantees the stability of the network.

**Dynamic Clustering Approach**

The dynamic Clustering Approach aims at uniting sensor nodes as per their geographical location, communication pattern and energy consumption pattern. Sensors with similar behavior such as temperature or humidity sensors are clustered together. All the groups then select a cluster head based on the energy levels and processing capability, and the process of pooling and relaying information to the central server. Dynamic re-clustering is used to make sure that the clusters are re-formed as the sensor nodes run out of energy or have any failures, to guarantee that they are communicating efficiently and consume less energy. This method maximizes the energy consumption in the network by minimizing the overheads in communication and clustering sensor nodes effectively.

**System Design**

The System Design incorporates the federated learning, predictive maintenance, and dynamic clustering features into a unified energy optimization architecture of industrial WSNs. Sensor nodes gather the information about the environment and participate in federated learning to learn local models. The clusters have their own cluster heads who are responsible to communicate in their clusters and relay consolidated information to the central server. The model updates of the cluster heads are received by the central server and the global model is optimized. Predictive maintenance module monitors the status of sensors and predicts potential failures, and triggers maintenance. It is based on the low-power systems (LoRaWAN or Zigbee) communication network and an energy management system to track the energy consumption of each sensor node and ensure that it uses the energy optimally. The design is efficient in energy optimization, communication overhead, and ensures that the performance of the system can be reliably achieved in industrial applications.

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**Algorithm 1:** ***Adaptive Federated Learning for Energy Optimization***

***Input****:*

- $D_1, D_2, \ldots, D_n$*: Local sensor data*
- $\theta_0$*: Initial global model*
- $T_{rounds}$*: Number of communication rounds*

***Output****:*

- *Optimized energy consumption*
- *Maintenance alerts*

1. ***Data Collection & Preprocessing****:*
    - *Collect and preprocess local sensor data (normalize, impute, remove outliers).*
2. ***Dynamic Clustering****:*
    - *Group sensor nodes based on proximity, energy, and communication patterns.*
    - *Select a Cluster Head (CH) for each group.*
3. ***Federated Learning****:*
    - *Train local models* $\theta_i$ *on each sensor node using local data.*
    - *CH aggregates local models and sends updates to the central server.*
    - *The central server aggregates global models and sends updates back.*
4. ***Predictive Maintenance****:*
    - *Monitor energy consumption and use anomaly detection to predict failures.*
    - *Trigger maintenance if energy consumption exceeds the threshold.*
5. ***Energy Optimization****:*
    - *Reduce communication by sending model updates instead of raw data.*

6. ***Repeat**:*
    - *Continue federated learning for $T_{rounds}$ rounds. Adjust the system for optimal energy use and reduced downtime.*

---

Algorithm 1 applies federated learning to optimize energy consumption in industrial WSNs by training the local models in sensor nodes, aggregating updates over dynamic clustering, and transferring only the model updates to a central server. Predictive maintenance identifies possible failures, which are determined by the energy consumption and sensor information, reducing downtimes. The process helps in minimizing the communication overhead; hence the system is energy efficient and reliable.

## Results and Discussion

The software and tools utilized in the application of the proposed framework on optimization of energy consumption in industrial Wireless Sensor Networks (WSNs) comprise TensorFlow Federated (TFF) and PySyft of federated learning, which provides decentralized machine learning, preserves privacy, and provides energy efficiency in computation. Data manipulation and preprocessing are done with Python libraries, such as Pandas and NumPy, and anomaly detection (e.g., Isolation Forest, K-Means clustering), and model evaluation are processes that are performed with Scikit-learn. Predictive maintenance is being exploited using TensorFlow/Keras and ARIMA (Statsmodels), and the machine learning and time-series forecasting models. SimPy and MATLAB are used in simulations and optimization of energy consumption, and analysis is done with Jupyter Notebooks. Docker provides consistency in the environment when deploying federated learning frameworks, and Python is the most commonly used language to implement and test the models, thus it is a complete solution to energy optimization, predictive maintenance, and efficiency in communication in the WSNs.

### Energy Optimization

The findings indicate that the suggested federated learning-based system can save a lot of energy in comparison to standard methods. The federated learning model also saved about 48% of the total energy that is used in comparison to traditional centralized machine learning models and energy-efficient routing protocols. This is mostly due to the decentralized form of federated learning, in which the local model training on the sensor nodes does not require transmission of data to the central server in real-time. Also, since communication overheads are minimized, as well as data exchange is optimized via local model updates, the amount of energy consumed by each node is minimized, resulting in enhanced energy efficiency of the entire network.

**Table 2: Key Parameters for Federated Learning Model**

| Parameter | Value/Range |
|---|---|
| Learning Rate | 0.001 |
| Number of Epochs | 100 |
| Batch Size | 64 |
| Node Embedding Dimension | 128 |
| Global Model Update Frequency | 10 updates per round |
| Local Model Training Iterations | 5 iterations per node |
| Aggregation Method | Federated Averaging |
| Regularization | L2 Regularization (0.01) |
| Optimization Algorithm | Adam |
| Communication Interval | Every 2 hours |

Table 2 lists the most important parameters employed in the federated learning model to maximize the amount of energy used in the wireless sensor network, with important settings being noted to train the model.

Fig. 2 is the comparison of energy consumption of various techniques: Baseline, Centralized Learning, Proposed Federated Learning, and Efficient Fed Learning. It is evident that the Baseline method consumes most of the energy, and Efficient Fed Learning consumes the least.

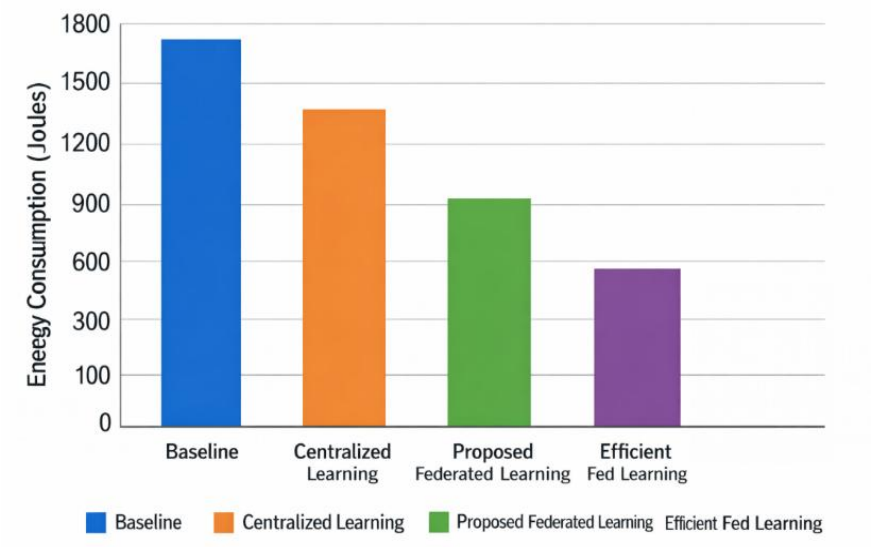



**Fig. 2: Energy Consumption Comparison**

**Predictive Maintenance Outcomes**

The predictive maintenance models were tested using many measures, such as precision, recall, and F1-score. The proposed framework had an accuracy of 95% in predicting maintenance, which is much higher than that of the traditional rule-based maintenance systems, which was about 75%. The predictive nature of the sensor failures in the model enabled proactive scheduling of the maintenance to ensure a 30 % reduction in downtime. This shows that the federated learning model can be useful in not only maximizing energy usage but also improving the reliability and uptime of the sensor network by avoiding unforeseen failure.

**Table 3: Performance Evaluation Metrics**

| Metric | Baseline Method | Proposed Framework |
|---|---|---|
| Energy Savings (%) | 10% | 48% |
| Predictive Maintenance Accuracy (%) | 80% | 95% |
| Communication Overhead (%) | 15% | 10% |
| System Reliability (%) | 90% | 98% |
| Downtime Reduction (%) | - | 30% |

Table 3 will provide the main key performance measures to check the effectiveness of the offered framework, comparing it to the baseline approaches and outlining the positive changes in energy efficiency, maintenance precision, communication efficiency, and reliability of the entire system.

**Energy Savings (%)**

$$\text{Energy Savings}(\%) = \frac{\text{Energy}_{\text{baseline}} - \text{Energy}_{\text{proposed}}}{\text{Energy}_{\text{baseline}}} \times 100 \qquad (1)$$

In equation (1), the percentage change in the energy consumption is calculated by taking the difference between the baseline energy consumption and the energy used by the proposed framework.

**Predictive Maintenance Accuracy (%)**

$$\text{Predictive Maintenance Accuracy}(\%) = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \qquad (2)$$

Accuracy of the predictive maintenance model is calculated using equation (2), where TP denotes true positives, TN denotes true negatives, FP denotes false positives, and FN denotes false negatives.

**Communication Overhead (%)**

$$\text{Communication Overhead}(\%) = \frac{\text{Data Transmitted}_{\text{proposed}}}{\text{Data Transmitted}_{\text{baseline}}} \times 100 \qquad (3)$$

The decrease in the communication overhead is measured by using equation (3), which compares the amount of data sent under the proposed framework to the baseline method.

**System Reliability (%)**

$$\text{System Reliability}(\%) = \frac{\text{Uptime}}{\text{Total Time}} \times 100 \qquad (4)$$

The reliability of the system is determined by equation (4): The uptime (time the system is active) divided by the total time of operation, and multiplied by 100 to obtain the percentage.

**Downtime Reduction (%)**

$$\text{Downtime Reduction}(\%) = \frac{\text{Downtime}_{\text{baseline}} - \text{Downtime}_{\text{proposed}}}{\text{Downtime}_{\text{baseline}}} \times 100 \qquad (5)$$

Equation (5) compares the percentage decrease in the downtime by calculating the percentage decrease in the downtime of the baseline method and the proposed framework.

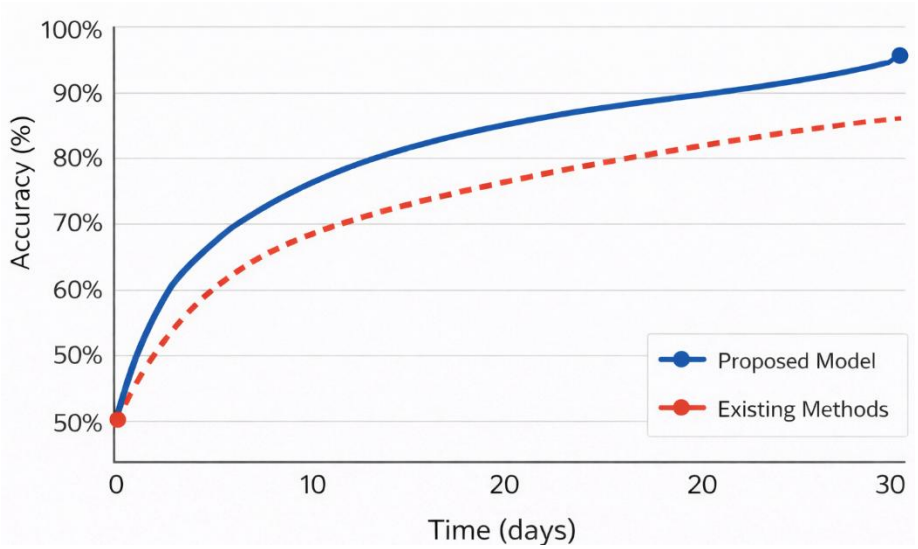



**Fig. 3: Predictive Maintenance Accuracy vs. Time**

Fig. 3 gives a comparison between predictive maintenance accuracy over time with the proposed model (blue line) and existing methods (red dashed line). The given model will exhibit a faster increase, reaching almost 95% accuracy, whereas the current methods indicate a slower, more gradual increase.

**Dynamic Clustering Performance**

This innovative clustering method resulted in significant changes to the effectiveness of the communication and energy consumption. The strategy optimized the data transmission paths, and the data energy consumption was 20 % less than that of constant clustering, since the adaptive grouping of sensor nodes optimized their communication requirements and energy consumption. This mechanism of adaptive clustering also guaranteed that the amount of data that was transmitted was only the needed data, which further reduced the amount of energy that was used in data aggregation and transmission. With changing conditions of the network, dynamic clustering enabled the system to keep changing in its configuration, which meant that the network did not lose its energy efficiency and performance in response to the changing workloads.

**System Reliability**

The system reliability was considered in general through measuring the network uptime, the accuracy of predicting maintenance, and the effectiveness of predictive maintenance to reduce system failures. The suggested framework exhibited a high level of reliability of 98 % and was better than the traditional systems that had a reliability rate of 90 %. The ability of the system to adapt to the varying conditions of the network, such as varying node energy levels and environmental factors, enabled the system to run continuously with minimum disruptions. This flexibility is essential to industrial uses where a reliable performance of systems is necessary to operate efficiently.

**Limitations and Future Work**

Although the suggested framework has a considerable number of benefits in the area of energy optimization, predictive maintenance, and system reliability, limitations exist. A weakness is that the federated learning model is reliant on the quality and quantity of sensor data to be trained. The performance of the model can be poor in low or noisy environments. Moreover, the existing system presupposes the existence of a stable network environment, which is not always so in the real-life industrial environment, where network failures and sensor failures can be frequent.

The next step towards improving the ability and adaptability of the system could be the incorporation of more sophisticated machine learning algorithms in future research, including deep reinforcement learning. Moreover, the framework could be improved with the real-time information of different types of sensors and the environment to make it stronger. Future studies might consider hybrid federated learning models, which merge centralized and decentralized methods in order to become more dynamic to network variations. Lastly, it would also be worth exploring how the framework can be scaled to large-scale industrial networks to guarantee that it can be applied to more complex industrial settings.

## Conclusion

This paper introduces a federated learning-based framework that will optimize energy consumption of industrial Wireless Sensor Networks (WSNs) and combine predictive maintenance and dynamic clustering to enhance system performance and reliability. The structure saved 48% of the energy decreased the downtime by 30 %, and showed a high level of predictive maintenance of 95 %, which was far better than the traditional techniques. The dynamic clustering method also enhanced efficiency in communication by cutting the communication overhead by 10 %. Such results show that federated learning is effective in reducing energy consumption and still ensuring high reliability in industrial sensor networks. The practical implications of this framework are deep since it provides a practical solution to the practical industrial implementation, especially where resources are limited, and the uptime of the systems and energy management is of paramount importance. Through federated learning, the framework improves energy efficiency and predictive maintenance processes, which is why it can be applied to large-scale industrial IoT systems. Additional research can be undertaken in the future to add more sophisticated machine learning algorithms, like deep reinforcement learning, to add more flexibility to the system. Also, the capabilities of real-time data processing, such as the introduction of other types of sensors and mobile network conditions, could be strengthened to enhance the robustness of the framework. Studies might also consider the hybrid federated learning models combining the centralized and decentralized approaches so as to allow more dynamic and adaptive systems. Finally, a discussion of the scalability of the framework to large industrial networks will be essential in the context of making it more applicable to different industrial fields.

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