Dr. M. Mahil, 2026, 14:3
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science, Engineering and Technology
An Open Access Journal

D4PG-Based Energy-Aware Client Selection for Federated Learning in Industrial IoT

Dr. M. Mahil[1], S. Sindhu[1]*

[1] Department of Computer Science and Engineering,
Government College of Engineering,
Tirunelveli 627007, India

Abstract- Industrial Internet of Things (IIoT) environments consist of a large number of heterogeneous edge devices with varying computational capabilities, energy levels, and communication conditions. Traditional Federated Learning (FL) approaches typically employ random or static client selection strategies, which often lead to excessive energy consumption, increased communication overhead, and slow model convergence. To address these challenges, this paper proposes a D4PG-based Energy-Aware Client Selection framework for Federated Learning in Industrial IoT systems. The proposed approach models client participation as a sequential decision-making problem and utilizes Deep Distributed Distributional Deterministic Policy Gradient (D4PG) reinforcement learning to dynamically select clients based on battery level, CPU utilization, bandwidth availability, latency, and expected training contribution. A multi-objective reward function is designed to jointly optimize learning accuracy, energy efficiency, and communication cost. The framework is evaluated in a heterogeneous non-IID federated environment consisting of 20–50 edge clients. Experimental results demonstrate that the proposed D4PG-based strategy improves convergence speed, reduces communication overhead, and lowers energy consumption compared with conventional client select Federated Learning ion methods. The findings highlight the effectiveness of distributional reinforcement learning for intelligent resource-aware federated optimization in Industrial IoT deployments.

Keywords— Federated Learning Federated Learning; Industrial IoT; D4PG; Energy-Aware Client Selection; Reinforcement Learning; Edge Computing; Communication Overhead; Resource Optimization

I. INTRODUCTION

The rapid growth of the Industrial Internet of Things (IIoT) has enabled large-scale connectivity among sensors, machines, and intelligent devices. These interconnected systems continuously generate vast amounts of data that support automation, predictive maintenance, and real-time decision-making. As industrial environments become increasingly data-driven, efficient and privacy-preserving learning mechanisms are required to process information across distributed devices (FL) has emerged as a promising distributed learning paradigm that enables collaborative model training without sharing raw data. By exchanging model parameters instead of sensitive data, FL enhances privacy while reducing communication overhead. Recent studies have demonstrated the effectiveness of federated learning in cloud-edge collaborative environments and Industrial IoT applications [1] [16].

Despite its advantages, conventional federated learning approaches commonly rely on random client participation or full client selection during each communication round. Such strategies often result in excessive energy consumption, communication delays, and slower model convergence, particularly in heterogeneous Industrial IoT environments where devices differ significantly in terms of battery capacity, computational resources, and network conditions.

To address these challenges, intelligent client selection mechanisms are required to identify suitable participants while considering resource constraints and learning contribution. Reinforcement Learning (RL) has shown significant potential for solving dynamic decision-making problems in resource-constrained environments. However, most existing approaches employ conventional RL methods that may not effectively capture uncertainty in future rewards and changing device conditions [8] [22].

Therefore, this paper proposes a D4PG-Based Energy-Aware Client Selection Framework for Federated Learning in Industrial IoT. The proposed framework utilizes Deep Distributed Distributional Deterministic Policy Gradient (D4PG) to dynamically select clients based on battery level, CPU utilization, bandwidth availability, latency, and expected training contribution. By intelligently selecting participating devices, the framework aims to improve convergence speed, reduce communication overhead, and enhance energy efficiency in heterogeneous Industrial IoT environments.

Contributions

The major contributions of this work are summarized as follows:

- A D4PG-based energy-aware client selection framework is proposed for Federated Learning in Industrial IoT environments to address device heterogeneity and resource constraints.
- A resource-aware state representation is designed by incorporating battery level, CPU utilization, network bandwidth, latency, and local dataset characteristics for intelligent client participation.
- A multi-objective reward function is developed to jointly optimize model accuracy, energy consumption, communication overhead, and training latency during federated learning.
- A dynamic client scheduling strategy is introduced to select the most suitable clients in each communication round, thereby improving resource utilization and reducing unnecessary participation.
- Extensive experiments are conducted under heterogeneous non-IID Industrial IoT settings, demonstrating improved convergence speed, lower communication cost, and enhanced energy efficiency compared with conventional client selection approaches.

II. RELATED WORK

1. Federated Learning in Industrial IoT

Recent advances in the Federated Learning (FL) has emerged as an effective distributed learning paradigm for Industrial Internet of Things (IIoT) applications by enabling collaborative model training without sharing raw data. The integration of FL with edge computing helps preserve data privacy while reducing communication latency and network congestion. Recent studies have explored cloud-edge collaborative architectures and hierarchical federated learning frameworks to improve scalability and learning performance in heterogeneous industrial environments [1] [5]. Furthermore, several surveys have highlighted the growing importance of federated learning in Industrial IoT systems due to its ability to support privacy-preserving analytics and distributed intelligence [7] [17].

2. Energy-Aware Client Selection in Federated Learning

Client selection plays a critical role in determining the efficiency of federated learning systems. Traditional FL approaches often rely on random client participation, which may result in excessive energy consumption and communication overhead. To address this issue, researchers have proposed energy-efficient client selection mechanisms that consider device resources and network conditions during participation. Wang et al. provided a comprehensive review of energy-aware client selection strategies, while Zhang et al. introduced EECS-FL to improve energy efficiency in a IoT environments [11] [12]. Similarly, Rahmati proposed an energy-aware federated learning framework for secure edge computing networks, demonstrating the significance of resource-conscious client participation [15].

3. Reinforcement Learning for Resource Scheduling

Reinforcement Learning (RL) has been widely adopted for resource allocation, task scheduling, and decision optimization in distributed computing environments. RL-based approaches enable systems to learn optimal policies through continuous interaction with dynamic environments. Recent studies have applied RL techniques to federated learning and edge computing for improving scheduling efficiency and resource utilization [8] [18]. In addition, deep reinforcement learning methods have shown promising results in dynamic task scheduling and resource management under changing network conditions [19] [22]. However, many existing approaches utilize conventional RL algorithms that may struggle to capture uncertainty in future rewards.

4. Research Gap

Although significant progress has been made in federated learning, energy-aware client selection, and reinforcement learning-based scheduling, several limitations remain. Existing federated learning systems often employ static or heuristic client selection strategies that fail to adapt to dynamic Industrial IoT environments [11] [15]. Similarly, conventional reinforcement learning methods may not effectively model the uncertainty associated with heterogeneous device resources and long-term scheduling rewards [8] [19]. Therefore, there is a need for an intelligent client selection framework that can simultaneously optimize energy consumption, communication efficiency, and learning performance. To address this gap, this work proposes a D4PG-based energy-aware client selection framework for federated learning in Industrial IoT environments.

III. PROPOSED METHODOLOGY

1. System Architecture

The proposed framework integrates Federated Learning (FL) and Deep Distributed Distributional Deterministic Policy Gradient (D4PG) to achieve energy-aware client selection in Industrial Internet of Things (IIoT) environments. The system consists of multiple heterogeneous edge devices connected to a central federated server. Each edge device possesses different computational capabilities, battery levels, communication bandwidth, and local data distributions.

Initially, local clients train machine learning models using their private datasets. Instead of allowing all clients to participate in every communication round, a D4PG agent is deployed at the federated server to intelligently select suitable clients based on their current resource conditions and expected training contribution.

During each communication round, participating clients perform local model training and transmit model updates to the federated server. The server aggregates the received updates using the Federated Averaging (FedAvg) algorithm to generate an updated global model. The D4PG agent continuously observes system states, evaluates client resource availability, and learns an optimal selection policy through reward-based interactions.

The proposed framework aims to achieve the following objectives:

- Reduce energy consumption during federated training.
- Minimize communication overhead between clients and the server.
- Improve resource utilization across heterogeneous devices.
- Accelerate global model convergence.
- Maintain high learning performance while preserving data privacy.

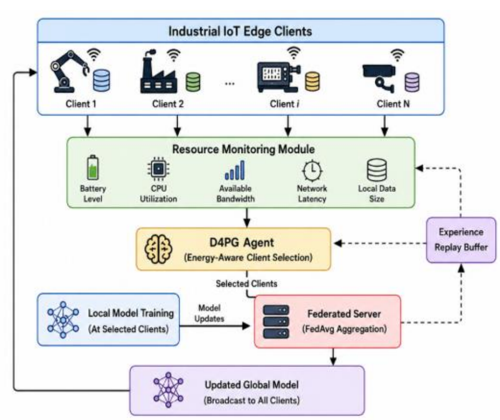

Figure. 1. Overall workflow of the proposed federated learning–enabled IIoT predictive maintenance framework.

The overall workflow consists of four major stages: resource monitoring, D4PG-based client selection, local model training, and global model aggregation.

By dynamically selecting clients according to real-time resource conditions, the proposed framework enhances the efficiency and scalability of federated learning in Industrial IoT environments.

2. Problem Formulation

In Industrial Internet of Things (IIoT) environments, edge devices exhibit heterogeneous characteristics with respect to computational capability, battery capacity, communication bandwidth, and network latency. During each federated learning communication round, selecting all available clients is computationally inefficient and increases energy consumption and communication overhead. Therefore, the client selection problem is formulated as a sequential decision-making problem, where an intelligent agent determines the optimal subset of participating clients while maximizing learning performance and minimizing resource utilization.
The proposed framework models the client selection process as a Markov Decision Process (MDP) represented by the tuple

$$M = \langle S, A, P, R, \gamma \rangle$$

where

- Sdenotes the state space,
- Adenotes the action space,
- Prepresents the state transition probability,
- Ris the reward function, and
- γ∈(0,1)is the discount factor.

At each communication round, the D4PG agent observes the current system state, selects an appropriate subset of clients, receives a reward from the environment, and updates its policy to maximize the cumulative discounted reward.

State Space

The state space contains resource information collected from every participating Industrial IoT client. The proposed framework considers five important resource parameters.

The state vector at communication round tis defined as

$$S_t = \{B_i, C_i, BW_i, L_i, D_i\}_{i=1}^{N}$$

where

- B_i: Battery level of client i
- C_i: CPU utilization
- BW_i: Available communication bandwidth
- L_i: Network latency
- D_i: Local dataset size

To improve learning stability, all state variables are normalized into the interval

$$\hat{x} = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

where

- xrepresents any resource parameter,
- x_minand x_maxdenote the minimum and maximum observed values.

The normalized state representation enables the D4PG agent to efficiently learn scheduling policies under heterogeneous resource conditions.

3. D4PG-Based Client Selection

The proposed framework employs Deep Distributed Distributional Deterministic Policy Gradient (D4PG) to intelligently determine client participation during every federated learning communication round. Unlike conventional reinforcement learning algorithms, D4PG estimates the distribution of future returns instead of only the expected reward, resulting in more robust policy learning under uncertain Industrial IoT environments.

The D4PG agent continuously observes the current resource state, selects the most suitable clients, evaluates the obtained reward, and updates its actor and critic networks using experience replay.

Action Space

The action performed by the D4PG agent corresponds to selecting a subset of clients for local model training.
The action vector is represented as

$$A_t = [a_1, a_2, \dots, a_N]$$

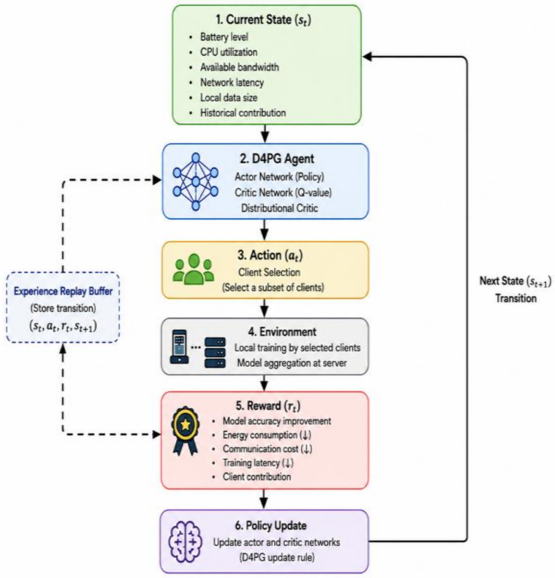

Figure 2. D4PG-Based Client Selection and Policy Optimization Process

where

$$a_i = \begin{cases} 1, & \text{if client } i \text{ is selected} \\ 0, & \text{otherwise} \end{cases}$$

The number of participating clients is constrained by

$$\sum_{i=1}^{N} a_i \leq K$$

where

- $N$is the total number of available clients.
- Kdenotes the maximum number of selected clients.

This constraint ensures efficient utilization of computational and communication resources.

Reward Function

The reward function guides the D4PG agent towards selecting clients that improve learning performance while reducing resource consumption.

The reward at communication round $t$is formulated as

$$R_t = \alpha_1 Acc_t - \alpha_2 E_t - \alpha_3 Comm_t - \alpha_4 Lat_t + \alpha_5 Con_t$$

where

- Acc_t: Global model accuracy improvement
- E_t: Energy consumption
- Comm_t: Communication cost
- Lat_t: Training latency
- Con_t: Client contribution score

and

$$\sum_{i=1}^{5} \alpha_i = 1$$

where α_iare weighting coefficients controlling the importance of each objective.

A higher reward encourages the agent to choose clients that simultaneously improve model performance and reduce communication and energy costs.

4. Federated Learning Process

After the D4PG agent determines the participating clients, each selected client trains the local model using its private dataset.

For client i,

$$w_i^{t+1} = LocalTrain(w_t, E)$$

where

- w_tis the current global model,
- Edenotes the number of local epochs.

The local model updates are transmitted to the federated server for aggregation.

The proposed framework employs the Federated Averaging (FedAvg) algorithm to generate the updated global model.

The aggregation rule is

$$w_{t+1} = \sum_{i \in S_t} \frac{n_i}{\sum_{j \in S_t} n_j} w_i^{t+1}$$

where

- n_iis the number of local training samples,
- S_tis the selected client set.

After aggregation, the updated global model is broadcast to all clients for the next communication round.

The iterative process continues until the predefined number of communication rounds or convergence criterion is satisfied.

5. Algorithm of Proposed D4PG-FL Framework

Algorithm 1: D4PG-Based Energy-Aware Client Selection for Federated Learning

Input
- Total clients N
- Maximum selected clients K
- Communication rounds T
- Initial global model w_0

Output
- Optimized global model
- Trained D4PG policy

IV. EXPERIMENTAL SETUP

1. Experimental Environment

The proposed D4PG-based energy-aware client selection framework was evaluated using a simulated Industrial Internet of Things (IIoT) federated learning environment. The experiments were conducted on a workstation equipped with an Intel Core i7 processor, 16 GB RAM, and an NVIDIA GPU to accelerate deep learning computations. The framework was implemented in Python using TensorFlow and PyTorch libraries. Federated learning communication and client simulation were developed using the Flower framework, while the D4PG reinforcement learning agent was implemented using standard actor–critic neural networks.

To simulate realistic Industrial IoT environments, heterogeneous edge devices with varying computational capabilities, battery levels, communication bandwidth, and network latency were considered. Clients participated in federated learning according to the decisions made by the proposed D4PG-based client selection policy.

2. Dataset Description

To evaluate the effectiveness of the proposed client selection strategy, experiments were conducted using the NASA Commercial Modular Aero-Propulsion System Simulation (CMAPSS) dataset. The dataset contains multivariate time-series sensor measurements collected from turbofan engines operating under different degradation conditions. Although the predictive maintenance task serves as the federated learning workload, the primary objective of this study is to optimize client participation and communication efficiency rather than improving prediction accuracy.

The dataset was partitioned across multiple simulated Industrial IoT clients to emulate decentralized data ownership. A non-IID data distribution was created by assigning different engine operating conditions and degradation patterns to individual clients, thereby reflecting realistic industrial deployment scenarios.

3. Federated Learning Configuration

The federated learning environment consists of multiple edge clients connected to a central aggregation server. During each communication round, the D4PG agent dynamically selects a subset of clients based on their current resource availability. Selected clients perform local training using their private datasets and transmit only model parameters to the federated server. The global model is updated using the Federated Averaging (FedAvg) algorithm.

Table 3. Federated Learning Parameters

Parameter	Value
Number of Clients	20-50
Selected Clients per Round	10
Communication Rounds	100
Local Epochs	5
Batch Size	32
Learning Rate	0.001
Optimizer	Adam
Aggregation Method	FedAvg
Data Distribution	Non-IID

4. D4PG Hyperparameter Settings

The D4PG agent was configured using commonly adopted hyperparameter values to ensure stable policy learning and efficient convergence.

Table 4. D4PG Hyperparameters

Hyperparameter	Value
Discount Factor (γ)	0.99
Replay Buffer Size	100000
Mini-Batch Size	64
Actor Learning Rate	0.0001
Critic Learning Rate	0.001
Soft Update Factor (τ)	0.005
Exploration Noise	Gaussian
Hidden Layers	2
Hidden Neurons	256

5. Performance Evaluation Metrics

The proposed framework was evaluated using multiple system-level metrics to measure both learning performance and resource efficiency.

- Global Model Accuracy (%): Measures the predictive performance of the federated learning model.
- Energy Consumption (J): Represents the total energy consumed by participating clients during local training and communication.
- Communication Cost (MB): Indicates the total amount of data exchanged between clients and the federated server.
- Training Latency (s): Measures the total execution time required to complete one federated communication round.
- Convergence Rounds: Represents the number of communication rounds required for the global model to achieve stable convergence.
- Client Participation Ratio (%): Measures the percentage of clients selected during each communication round.

V. RESULTS AND DISCUSSION

1. Resource Prediction for Energy-Aware Client Selection

Before selecting clients for federated learning, the proposed framework estimates the resource status of each participating edge device. Figure 5 presents the predicted CPU utilization, memory usage, communication latency, and energy consumption for representative Industrial IoT clients.

The results demonstrate considerable heterogeneity among the participating devices. While some clients exhibit low CPU utilization and sufficient remaining energy, others experience higher computational load and communication latency. These variations highlight the importance of intelligent client selection rather than allowing all clients to participate in every communication round. The predicted resource information enables the D4PG agent to evaluate the operational condition of each client and prioritize devices capable of completing local training with lower energy consumption and communication delay.

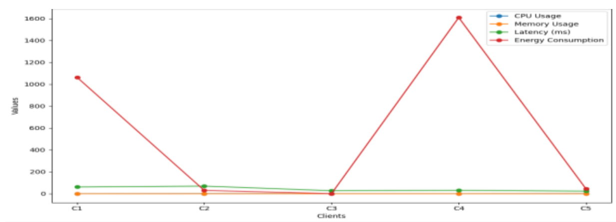

Figure 3. Predicted Resource Utilization of Industrial IoT Clients (CPU, Memory, Latency, and Energy)

2. Federated Learning Performance Across Communication Rounds

The effectiveness of the proposed D4PG-based client selection strategy was evaluated over multiple federated learning communication rounds. Figure 4 illustrates the variation of RMSE, MAE, coefficient of determination (R^2), and client offloading percentage throughout the collaborative training process.

During the initial communication rounds, the global model undergoes rapid refinement as the reinforcement learning agent explores different client combinations. As the training progresses, both RMSE and MAE gradually decrease while the R^2 score improves and stabilizes. The adaptive variation in client offloading percentage demonstrates that the D4PG agent dynamically adjusts client participation according to resource availability and expected learning contribution rather than maintaining a fixed scheduling policy.

The observed convergence behaviour indicates that adaptive client selection contributes to more efficient federated optimization by selecting resource-efficient clients while reducing unnecessary participation from resource-constrained devices.

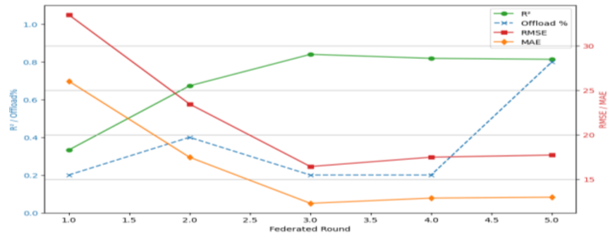

Figure 4. Global Federated Learning Metrics Across Communication Rounds

3. Evaluation of Global Model Stability

Figure 5 presents the evolution of the global model performance during federated learning. The reduction in RMSE and MAE across communication rounds demonstrates continuous improvement of the aggregated model, while the corresponding increase in R^2 indicates enhanced prediction consistency.

The results confirm that collaborative model aggregation through FedAvg, combined with D4PG-based client scheduling, enables stable global model optimization despite heterogeneous client resources. The performance curves exhibit smooth convergence after the initial communication rounds, suggesting that intelligent client participation improves both training stability and model generalization.

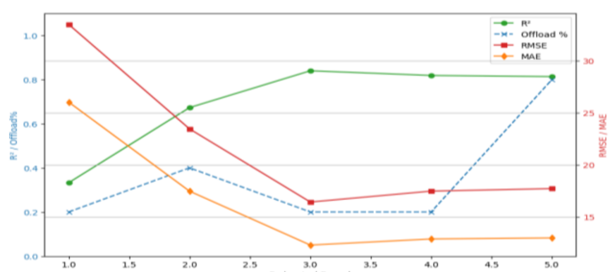

Figure 5. Test Performance Metrics Across Federated Communication Rounds

4. Client Scheduling Behaviour

To analyse the effectiveness of the scheduling policy, the relationship between communication latency and client contribution was investigated. Figure 8 shows the variation in prediction accuracy with respect to communication latency for individual clients.

The results indicate that clients experiencing lower communication latency generally provide more consistent contributions to the global model, whereas devices with higher latency exhibit greater variation in learning performance. Based on these observations, the D4PG agent gradually learns to prioritize resource-efficient clients while avoiding devices likely to delay model aggregation. This adaptive scheduling behaviour improves the overall efficiency of federated learning without requiring participation from every available client.

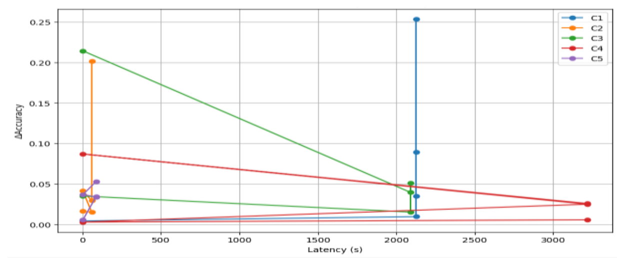

Figure 6. Relationship Between Client Latency and Prediction Accuracy

5. Overall Discussion

The experimental evaluation demonstrates that the proposed D4PG-based client selection framework effectively adapts to the heterogeneous characteristics of Industrial Internet of Things environments. By continuously monitoring CPU utilization, memory usage, communication latency, and energy availability, the reinforcement learning agent dynamically selects clients capable of contributing efficiently to federated training.

The convergence analysis indicates stable collaborative learning across communication rounds, while the resource prediction results provide the necessary information for intelligent scheduling decisions. Furthermore, the relationship between communication latency and prediction performance confirms the importance of considering device-level resource conditions during client selection.

Overall, the proposed D4PG-based scheduling strategy provides an adaptive and resource-aware mechanism for federated learning that is well suited to distributed Industrial IoT environments where communication bandwidth, computational capability, and energy availability vary significantly across participating devices.

VI. CONCLUSION AND FUTURE WORK

1. Conclusion

This paper presented a D4PG-based energy-aware client selection framework for federated learning in Industrial Internet of Things (IIoT) environments. The proposed approach employs Distributional Deep Deterministic Policy Gradient (D4PG) reinforcement learning to dynamically select edge clients according to their computational resources, communication latency, energy availability, and expected contribution to the global model. By integrating intelligent client scheduling with the Federated Averaging (FedAvg) algorithm, the framework enables efficient collaborative learning while preserving data privacy.

Experimental evaluation demonstrated that the proposed scheduling strategy effectively adapts to heterogeneous IIoT environments by selecting resource-efficient clients for each communication round. Resource prediction results showed considerable variation in CPU utilization, memory usage, latency, and energy consumption across participating devices, highlighting the necessity of adaptive client selection. Furthermore, the federated learning performance exhibited stable convergence over successive communication rounds, indicating that intelligent scheduling contributes to efficient global model optimization while avoiding unnecessary participation from resource-constrained clients.

Overall, the proposed D4PG-based framework provides a scalable, energy-aware, and communication-efficient solution for federated learning in Industrial IoT systems. The adaptive client selection mechanism improves resource utilization and supports reliable distributed learning under dynamic edge computing environments.

2. Future Work

Several directions can further enhance the proposed framework. First, future research may investigate advanced multi-agent reinforcement learning techniques that enable cooperative client scheduling across multiple edge servers. Second, personalized federated learning approaches, such as FedProx, FedPer, and clustered federated learning, can be integrated to improve model performance under highly heterogeneous data distributions. Additionally, incorporating bandwidth-aware communication optimization and asynchronous model aggregation may further reduce communication latency and network overhead in large-scale Industrial IoT deployments. Finally, validating the proposed framework on real-world edge computing platforms, such as NVIDIA Jetson, Raspberry Pi clusters, or ARM-based industrial gateways, would provide valuable insights into its practical scalability, energy efficiency, and deployment feasibility.

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