

TRAIL: Trust-Aware Client Scheduling for Semi-Decentralized Federated Learning

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Abstract

Due to the sensitivity of data, Federated Learning (FL) is employed to enable distributed machine learning while safeguarding data privacy and accommodating the requirements of various devices. However, in the context of semi-decentralized FL, clients' communication and training states are dynamic. This variability arises from local training fluctuations, heterogeneous data distributions, and intermittent client participation. Most existing studies primarily focus on stable client states, neglecting the dynamic challenges inherent in real-world scenarios. To tackle this issue, we propose a TRust-Aware Client ScheduLing mechanism called TRAIL, which assesses client states and contributions, enhancing model training efficiency through selective client participation. We focus on a semi-decentralized FL framework where edge servers and clients train a shared global model using unreliable intra-cluster model aggregation and inter-cluster model consensus. First, we propose an adaptive hidden semi-Markov model to estimate clients' communication states and contributions. Next, we address a client-server association optimization problem to minimize global training loss. Using convergence analysis, we propose a greedy client scheduling algorithm. Finally, our experiments conducted on real-world datasets demonstrate that TRAIL outperforms state-of-the-art baselines, achieving an improvement of 8.7% in test accuracy and a reduction of 15.3% in training loss.

Introduction

The integration of advanced communication technologies with industrial manufacturing significantly enhances production efficiency and flexibility, accelerating the transition to smart manufacturing (Chen et al. 2024; Lu et al. 2021; Tan et al. 2023). This integration facilitates seamless connectivity between devices and systems through real-time data collection and analysis, which greatly improves the transparency and controllability of production processes (Yu et al. 2023; Wang et al. 2020). Additionally, the incorporation of Artificial Intelligence (AI) further enhances these capabilities. By enabling systems to process and analyze large vol-

umes of data, AI provides solutions for predictive maintenance, intelligent decision-making, and process optimization (Wu et al. 2024).

In modern AI systems, local data on end devices often contains sensitive or private information, rendering traditional edge AI training architectures impractical (Zhang et al. 2024; Wang et al. 2024a). To address security and privacy concerns while minimizing communication costs, a new distributed machine learning framework called Federated Learning (FL) has emerged (Wu et al. 2023; McMahan et al. 2017; Wang et al. 2024b). In FL, each client uploads only model parameters, safeguarding her local data. Typically, this process involves coordination with a single edge server, which can result in high communication overhead and potential single points of failure, particularly in environments with numerous end devices (Zhang et al. 2023a; Lu et al. 2022).

This paper investigates semi-decentralized FL (SD-FL) as a framework to enhance the reliability of model training. As illustrated in Figure 1, we focus on a multi-edge server and multi-client SD-FL framework (Sun et al. 2021). This framework utilizes a two-tier aggregation approach. The first tier is intra-cluster aggregation, where local models are aggregated by their respective servers. The second tier is inter-cluster consensus, which involves exchanging models from multiple servers and collaboratively aggregating them to train a shared global model. By distributing computational and communication loads, this approach enhances both the robustness and scalability of the FL process. While SD-FL mitigates risks associated with single points of failure, existing research often overlooks the dynamic nature of clients, particularly fluctuations in model contributions and communication quality, which can adversely affect training efficiency (Sun et al. 2023).

Research was conducted to address the issue of unreliable clients. In (Sefati and Navimipour 2021), the authors introduced an effective service composition mechanism based on a hidden Markov model (HMM) and ant colony optimization to tackle IoT service composition challenges related to Quality-of-Service parameters. This approach achieved significant improvements in availability, response time, cost,

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reliability, and energy consumption. In (Ma et al. 2021), the FedClamp algorithm was proposed, which enhanced the performance of the global model in FL environments by utilizing HMM to identify and isolate anomalous nodes. This algorithm was specifically tested on short-term energy forecasting problems. The authors of (Vono et al. 2021) presented the Quantized Langevin Stochastic Dynamics (QLSD) algorithm, which employed Markov Chain Monte Carlo methods to improve dynamic prediction capabilities in FL while addressing challenges related to privacy, communication overhead, and statistical heterogeneity. Additionally, Wang et al. introduced a trust-Age of Information (AoI) aware joint design scheme (TACS) aimed at enhancing control performance and reliability in wireless communication networks within edge-enabled Industrial Internet of Things (IIoT) systems operating in harsh environments. This scheme utilized a learning-based trust model and scheduling strategy. While these studies explored various dynamic aspects, they did not adequately address the interplay between dynamics and client selection strategies.

To bridge this gap, we propose an adaptive hidden semi-Markov model (AHSMM) to predict dynamic changes in training quality and communication quality. AHSMM enhances standard HMM by explicitly modeling state duration distributions, reducing computational complexity, and adapting to dynamic, multi-parameter environments, making it ideal for complex scenarios. To improve SD-FL systems' control and reliability, we propose a joint mechanism combining dynamic prediction with client selection. Extensive experiments and analyses validate the effectiveness and robustness of our approach under varying client dynamics. The main contributions of this paper are as follows:

- We propose a unified optimization mechanism named TRAIL for SD-FL that integrates performance prediction and client scheduling, enhancing model robustness, accelerating convergence speed, and improving overall performance.
- We introduce an AHSMM to predict client performance and channel variations to obtain trust levels. This model effectively accounts for both dynamic and static aspects of clients, enabling efficient state predictions for each one.
- Through convergence analysis, we assess the anticipated effects of client-server relationships on convergence. This analysis allows us to reformulate the initial optimization challenge as an integer nonlinear programming problem, for which we devise a greedy algorithm to optimize client scheduling efficiently.
- Extensive experiments conducted on four real-world datasets (MNIST, EMNIST, CIFAR10, SVHN) demonstrate that our proposed mechanism outperforms state-of-the-art baselines, achieving an 8.7% increase in test accuracy and a 15.3% reduction in training loss.

Related Work

In FL, model training is distributed across multiple clients to protect data privacy and minimize the need for centralized

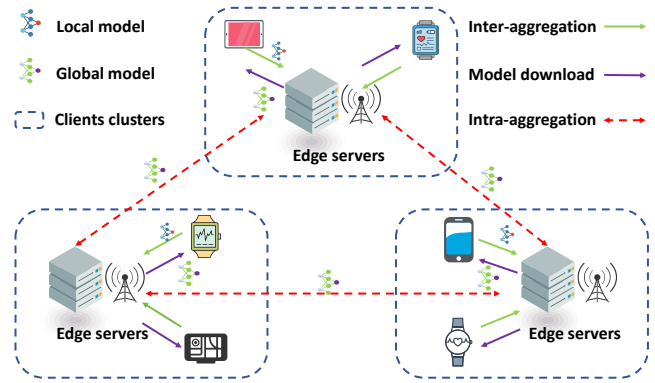


Figure 1: The SD-FL system framework.

data aggregation. Traditional FL assumed reliable and frequent communication between clients and the server. However, this assumption often failed in real-world applications, particularly in environments with heterogeneous devices and unstable communication. To address these challenges, researchers introduced SD-FL. This framework combined the benefits of centralized and distributed architectures by enabling direct communication among some clients, thereby reducing the server's workload and communication costs. SD-FL was better equipped to adapt to dynamic network environments and heterogeneous data distributions, enhancing the system's robustness and efficiency.

Research efforts primarily focused on the following two areas. (i) Client Selection: Mechanisms were developed to select clients for participation in training, ensuring that chosen clients met performance criteria, thereby enhancing the overall effectiveness of the model (Lin et al. 2021; Wang et al. 2024c; Yemini et al. 2022; Sun et al. 2023). (ii) Trust Management: Trust mechanisms were introduced to assess and predict the reliability of clients, ensuring that only reliable clients participated in training. These mechanisms contributed to improved model robustness and performance (Martínez Beltrán et al. 2023; Parasnis et al. 2023; Xu et al. 2024; Valdeira et al. 2023).

While some studies focus separately on client selection and trust management, existing methods often fail to effectively integrate these aspects, which negatively impacts the efficiency and performance of SD-FL systems. Our work proposes an integrated mechanism that addresses client selection and trust management, which is essential for enhancing the robustness and performance of SD-FL, especially in diverse and potentially unreliable environments.

System Model

Here, we explore the SD-FL framework, as illustrated in Figure 1. We first present SD-FL's basic workflow, then establish an adaptive semi-Markov model to estimate each client's model quality and communication quality.

Basics of SD-FL

We examine the SD-FL training process across T rounds, involving S edge servers represented by $\mathcal{S} = \{1, 2, \dots, S\}$,

and U client devices represented by $\mathcal{U} = \{1, 2, \dots, U\}$. Each round consists of the following steps:

- Clients perform T_1 rounds of local training using their datasets. Then, they upload the trained local models to the edge server for intra-cluster aggregation.
- After aggregating the models at the edge server, the merged model is broadcasted to the corresponding clients for model updating.
- After T_2 rounds of intra-cluster aggregation, each edge server sends its latest model to neighboring servers to achieve inter-cluster consensus.
- After aggregating to obtain inter-cluster models, these models are sent back to their respective clients for the next round of training.

AHSMM Model

The Adaptive Hidden Semi-Markov Model (AHSMM) extends the traditional Hidden Semi-Markov Model (HSMM) (McDonald, Gales, and Agarwal 2023) into adaptive training using multi-parameter information (i.e., client training accuracy, packet loss), thereby enhancing both modeling and analytical capabilities. The AHSMM model can be described by the parameters $\Sigma = (\pi, A, B, E)$, where: π represents the initial state probabilities, A denotes the macro state transition probabilities, B corresponds to the observation probabilities after adaptive training, E represents the state dwell time after adaptive training, encompassing both the existing and remaining dwell times. In addition, similar to HSMM, AHSMM addresses three core problems: evaluation, recognition, and training. To this end, AHSMM defines new forward-backward variables and proposes improved algorithms for forward-backward processes, the Viterbi algorithm (Zhang et al. 2023b), and the Baum-Welch algorithm (Zhang et al. 2023c).

The computational complexity of the Hidden Semi-Markov Model (HSMM) is relatively high. To address this complexity, the Adaptive Hidden Semi-Markov Model (AHSMM) introduces a new forward variable, denoted as $\alpha_t(i, e)$. This variable represents the probability of generating the observations z_1, z_2, \dots, z_t , given that the quality state i has a specific dwell time of $e_t(i, e) = e$. In this context, ε_t signifies the current dwell time of the quality state q_t . When (q_t, ε_t) is assigned the value (i, e) , it indicates that the device has remained in its current quality state i up to time t . During this period, the state i has accumulated a dwell time of e and is prepared to transition to a different quality state at time $t+1$. Therefore, for $1 \leq t \leq T-1$ and $e \in [1, E]$, we can define the forward variable as follows:

$$\alpha_t(i, e) = p(z_1^t, (q_{[t-e+1, t]} = i, \varepsilon_t = e) | \Sigma). \quad (1)$$

The forward recursion is obtained as:

$$\alpha_t(i, e) = \begin{cases} \sum_{j \neq i}^N a_{ji} b_i(z_t) \left(\sum_{\tau=1}^E \alpha_{t-1}(j, \tau) p_j(\tau) \right), & \text{if } e = 1, \\ \alpha_{t-1}(i, e-1) \prod_{s=1}^e b_i(z_{t-s+1}), & \text{if } e > 1, \\ \pi_i b_i(z_1) p_i(e), & \text{if } t = 1, \\ 0, & \text{if } \tau < 1. \end{cases} \quad (2)$$

In the context of AHSMM, let E represent the maximum state dwell time among all quality states. Given the model Σ , the probability of observing the sequence Z is expressed as:

$$p(z_1^T | \Sigma) = \sum_{(i, e)} \alpha_T(i, e). \quad (3)$$

The variable $\alpha_T(i, e)$ is defined as the joint probability of observing the sequence z_1, z_2, \dots, z_T while the system is in quality state i over the dwell time interval from $T-e+1$ to T . Mathematically, it can be expressed as:

$$\alpha_T(i, e) = p(q_{[T-e+1, T]} = i | z_1, z_2, \dots, z_T, \Sigma) \cdot p(z_1, z_2, \dots, z_T | \Sigma). \quad (4)$$

For $1 \leq t \leq T-1$, $e \in [1, E]$, and $i, j \in S$, the backward variable can be defined as:

$$\beta_t(i, e) = p(z_{(t+1):T} | q_{[t-e+1, t]} = i, \Sigma). \quad (5)$$

This formulation improves the efficiency of computing the forward and backward variables in the AHSMM, leading to reduced computational complexity compared to the traditional HSMM. In the backward variable $\beta_t(i, e)$, the quality state i has been active for e time steps. By summing over all quality states and potential dwell times, the backward recursion can be expressed as follows:

$$\beta_t(i, e) = \sum_j (\mathbb{I}(j \neq i) \beta_{t+1}(j, 1) a_{ij} p_i(e) b_j(z_{t+1})) + \beta_{t+1}(j, e+1) \prod_{s=1}^e b_i(z_{t+s}). \quad (6)$$

We estimate the quality state q_t and update the parameters of the model Σ . Using the previously defined forward and backward variables, we derive q_t and adjust the model parameters. Given the model Σ and the observation sequence $Z_{1:T}$, let $\xi_t^e(i, j)$ represent the joint probability of the observation sequence $Z_{1:T}$ and the transition from quality state i to quality state j (where $i \neq j$) at time t . The specific formula is as follows:

$$\xi_t^e(i, j) = p(z_{1:T} | q_{t-1} = i, q_t = j, \Sigma) \cdot p(q_{t-1} = i, q_t = j | \Sigma). \quad (7)$$

To determine quality states from a sequence of observations, it is essential to have both a predefined model and

the sequence of observations. The following equation describes the recursive estimation of quality states based on this model:

$$\gamma_t^e(i) = \sum_{j=1}^E \alpha_t(j, e) \cdot p(q_t = i | \Sigma) \cdot p(z_{1:T} | q_t = i, \Sigma). \quad (8)$$

This recursive formulation allows for the estimation of the quality state at time t based on the observation sequence $Z_{1:T}$ and the given model parameters Σ .

AHSMM Prediction and Client Scheduling

AHSMM Parameter Estimation

Monitoring a device with multiple parameters can significantly improve quality prediction. Given the inherent differences among parameters, effective data fusion is essential for integrating their information. Consequently, estimating the parameters of the AHSMM becomes necessary. This estimation process utilizes Maximum Likelihood Linear Regression (MLLR) transformations to address the variations across parameters. Simultaneously, a canonical model is trained based on a set of MLLR transformations. Linear transformations are then applied to the mean vectors of the state output and dwell time distributions in the standard model, allowing for the derivation of mean vectors for these distributions. The formulas are given by:

$$\begin{cases} b_i(z^{(s)}) = N(Z; \mu_i^{(s)} \Sigma_i), \\ p_i(e) = N(e; \mu_e^{(s)}, \sigma_e^2), \\ \mu_e^{(s)} = \delta^{(s)} m_i + \psi^{(s)}. \end{cases} \quad (9)$$

Here, $b_i(z^{(s)})$ represents the probability density function for the state i based on the observed data $z^{(s)}$ from parameter s , modeled as a multivariate normal distribution with mean $\mu_i^{(s)}$ and covariance Σ_i . The term $p_i(e)$ signifies the probability density function for the dwell time e in state i , also following a normal distribution characterized by mean $\mu_e^{(s)}$ and variance σ_e^2 . The mean dwell time $\mu_e^{(s)}$ is calculated using the formula $\mu_e^{(s)} = \delta^{(s)} m_i + \psi^{(s)}$, where $\delta^{(s)}$ is a scaling factor, m_i represents a parameter related to state i , and $\psi^{(s)}$ is a parameter-specific offset.

Let S denote the number of parameters, and let $\mathbf{Z} = (\mathbf{Z}^{(1)}, \dots, \mathbf{Z}^{(S)})$ represent the monitoring data, where $\mathbf{Z}^{(s)} = (z_{1s}, \dots, z_{Ts})$ represents the monitoring data of parameter s with length T_s . Here, the parameters are estimated by jointly considering the contributions of all parameters and their respective transformations. The term $\gamma_t^e(i)$ represents the probability of being in state i with dwell time d at time t , $\eta^{(s)}$ and $\xi^{(s)}$ are the transformation matrices and vectors for parameter s , and Σ_i is the covariance matrix for state i . This joint estimation process ensures that the model parameters are optimally adjusted for the diverse parameter data. The MAP estimation of state q_t using the AHSMM is calculated in the following way:

$$\hat{q}_t = \arg \max_{\Sigma} \prod_{s=1}^S (p(Z^s | q_t, \Sigma)). \quad (10)$$

In client quality diagnostics and forecasting, parameters like computation, communication, and data quality influence decision-making differently. The AHSMM effectively integrates these diverse parameters by capturing temporal dependencies and assigning appropriate weights. This enables accurate client quality assessment, improving forecasting and scheduling in dynamic environments.

Prediction Process Based on AHSMM

Assuming $F(0) = 0$ and the failure probability density function $f(t) = F'(t)$, the HR function is defined as:

$$\Sigma(t) = \frac{f(t)}{1 - F(t)} = \frac{dk(t)}{N - k(t)dt}. \quad (11)$$

A device transitions through multiple quality states before ultimately reaching a failure state. Let $E(i)$ represent the residence time in quality state i . We can express $E(i)$ as follows:

$$E(i) = m(i) + \rho \sigma^2(i),$$

where $m(i)$ denotes the mean dwell time in state i and $\sigma^2(i)$ is the variance of the dwell time in that state, and the term ρ serves as a proportionality constant, which adjusts the influence of the variance on the overall residence time.

This formulation captures the idea that the total time spent in a quality state is influenced not only by the average time spent there but also by the variability of that time. A higher variance indicates greater uncertainty in the duration spent in state i , which can lead to longer overall residence times. By incorporating both mean and variance, we obtain a more comprehensive view of the dynamics in quality states. The proportionality constant ρ is defined as:

$$\rho = \frac{T - \sum_{i=1}^N m(i)}{\sum_{i=1}^N \sigma^2(i)}, \quad (12)$$

where T is the total lifespan, $m(i)$ is the mean dwell time in state i , and $\sigma^2(i)$ is the variance.

The reliability function $R(t + e\Delta t)$ represents the probability that the client remains in the current quality state i at time $t + e\Delta t$. Thus, we can get

$$\gamma_t^e(i) = R(t + e\Delta t). \quad (13)$$

and

$$\frac{\bar{\Sigma}(t + e\Delta t)}{\gamma_t^e(i)} = \frac{\xi_t^e(i, j)}{\Delta t}. \quad (14)$$

Based on the above equations, $\bar{E}(i, e)$ can be expressed as:

$$\bar{E}(i, e) = E(i) - \frac{E(i) \xi_t^e(i, j)}{\gamma_t^e(i)}. \quad (15)$$

According to equations (13,14,15), once the client reaches state i and has a dwell time, the trust level (TL) is determined as:

$$TL_{(i,e)} = \bar{E}(i, e) + \left(\sum_{j=1}^N E(j) - \sum_{j=1}^i E(j) \right). \quad (16)$$

Client Selection

Considering the configuration in SD-FL, the model aggregation within the cluster at server s can be described as follows:

$$\mathbf{w}_{s,t} = \sum_{i \in U_s} \frac{n_i}{\sum_{i \in U_s} n_i} \mathbf{w}_{i,t}, \quad (17)$$

where U_s represents the set of clients assigned to server s , n_i is the size of the local dataset for client i , and $\mathbf{w}_{i,t}$ denotes the local model of client i at training round t . This weighted aggregation ensures that clients with larger datasets contribute proportionally more to the cluster model, improving the robustness of the overall learning process.

Furthermore, the model consensus between clusters at server s during training round t is characterized as follows:

$$\mathbf{g}_{s,t} = \sum_{s=1}^S \frac{N_s}{\sum_{s=1}^S N_s} \mathbf{w}_{s,t}, \quad (18)$$

where N_s corresponds to the total size of the datasets managed by server s , and S is the number of servers. This global aggregation step aligns the models from different clusters, ensuring consistency and convergence across the distributed system.

In the subsequent training round, each client utilizes the updated global model $\mathbf{g}_{s,t}$ as the initialization for their local model updates. Clients then train their local models using their respective datasets through the gradient descent mechanism, defined as follows:

$$\mathbf{w}_{i,t+1} = \mathbf{w}_{i,t} - \eta \nabla F_i(\mathbf{w}_{i,t}), \quad (19)$$

where η is the learning rate, and $\nabla F_i(\mathbf{w}_{i,t})$ represents the gradient of the local loss function F_i with respect to the current model $\mathbf{w}_{i,t}$.

This decentralized training mechanism enables clients to collaboratively train a global model while keeping their data local, thereby addressing privacy concerns and minimizing the communication overhead associated with transmitting raw data. The combination of local training, cluster-level aggregation, and global consensus helps achieve a balance between computational efficiency, communication cost, and model accuracy in distributed learning systems.

Problem Formulation

Client scheduling determines the optimal client-server association matrix \mathbf{d} to minimize the global model loss. Each element d_{ij} is binary (1 if client i is assigned to server j , 0 otherwise). The configuration of \mathbf{d} directly impacts the global loss by influencing data locality, communication overhead, and computational load balancing. Adaptive scheduling dynamically adjusts \mathbf{d} to further enhance system performance and ensure efficient training. The global loss function is defined as:

$$F(\mathbf{g}) = \frac{1}{N} \sum_{s=1}^S \sum_{i \in U_s} F_i(\mathbf{g}_s). \quad (20)$$

Therefore, the optimization of the client-server association matrix can be achieved by solving the problem of minimizing the global training loss:

$$\begin{aligned} \min_{\mathbf{d}} \quad & F(\mathbf{g}) = \frac{1}{N} \sum_{s=1}^S \sum_{i \in U_s} F_i(\mathbf{g}_s) \\ \text{subject to} \quad & \sum_{\forall s \in S} d_{i,s} \leq 1, \\ & d_{i,s} \in \{0, 1\}, \\ & TL_{i,s} \geq \Theta. \end{aligned} \quad (21)$$

Convergence Analysis

We rely on current trust levels of client i to tackle these challenges, reduce data loss, and guarantee consistent model updates. Θ denotes the threshold for the trust level of clients involved in training. Reformulating the optimization problem to incorporate parameters that reflect communication link stability will enhance the modeling of the SD-FL system's conditions.

We also plan to enhance SD-FL system robustness through redundancy strategies, like multiple communication paths or backup servers, to mitigate risks from unreliable links. Dynamically adjusting client-server associations based on real-time assessments will help maintain optimal performance despite trust fluctuations. This approach maximizes resource utilization and minimizes training time, leading to more robust convergence and broader adoption in real-world applications.

Theorem 1 *By setting the learning rate $\lambda = \frac{1}{L}$, the upper bound of the expected difference $\mathbb{E}(F(\mathbf{g}_{t+1}) - F(\mathbf{g}^*))$ can be established as follows:*

$$\begin{aligned} \mathbb{E}(F(\mathbf{g}_{t+1}) - F(\mathbf{g}^*)) &\leq D^t \mathbb{E}(F(\mathbf{g}_0) - F(\mathbf{g}^*)) \\ &\quad + \frac{2\omega_1 B}{L} \frac{1 - D^t}{1 - D}, \end{aligned} \quad (22)$$

where $D = 1 - \frac{\mu}{L} + \frac{4\omega_2 \mu B}{L}$, $B = \sum_{m \in S} \frac{1}{N_m^{(S)}} \Psi$, and $\Psi = (\sum_{i \in U} n_i d_{i,m} (D_m - 1 + \mathbb{I}(TL_{i,s} < \Theta)))$.

In the definition of B , the following equations hold:

$$N_m^{(S)} = \sum_{i \in U} n_i d_{i,m}, \quad (23)$$

and

$$D_m = \frac{1}{1 + |S|}. \quad (24)$$

From Theorem 1, the global training loss minimization initially outlined in the problem can be reinterpreted to focus primarily on minimizing the parameter B . This revised formulation, therefore, positions B as the central target for reduction, aiming to directly influence and improve the overall system performance by addressing the underlying factors contributing to B 's value, i.e.,

$$\min_{\mathbf{d}} \sum_{m \in S} \frac{1}{N_m^{(S)}} \left(\sum_{i \in U} n_i d_{i,m} (D_m - 1 + \mathbb{I}(TL_i < \Theta)) \right). \quad (25)$$

Algorithm 1: Greedy Algorithm for Solving the Optimization Problem

Input: Set of clients \mathcal{U} , set of servers \mathcal{S} , maximum clients per server U_{\max} , the allocation status x_i ;

Output: Assignment matrix \mathbf{d} ;

- 1 Initialize $\mathbf{d}_{i,s} = 0, \forall i \in \mathcal{U}, \forall s \in \mathcal{S}$;
- 2 Initialize client count $u_s = 0, \forall s \in \mathcal{S}$;
- 3 Sort $(i, s) \in (\mathcal{U}, \mathcal{S})$ in increasing order based on $TL_{i,s}$ for each server s ;
- 4 **for** (i, s) **in** $(\mathcal{U}, \mathcal{S})$ **do**
- 5 **if** $u_s < U_{\max}$ **and** $x_i = 0$ **and** $TL_{i,s} \geq \Theta$ **then**
- 6 Assign client i to server s : $\mathbf{d}_{i,s} = 1$;
- 7 Increment client count for server s :
 $u_s = u_s + 1$;
- 8 $x_i = 1$;
- 9 **end**
- 10 **end**

To address this nonlinear integer programming problem, we propose a greedy algorithm outlined in Algorithm 1, with a time complexity of $O(nm \log nm)$.

Experiments Evaluation

This section evaluates our proposed mechanism using real-world datasets to demonstrate its effectiveness and practicality. We begin by introducing the experiment setting. Then, we present our experimental comparisons' results, highlighting our mechanism's performance relative to the baselines.

Experiments Setting

We provide a detailed explanation of the fundamental experimental setup, including the basic setup, datasets, training configurations, baselines, and evaluation metrics.

Basic Setup: We design a SD-FL system comprising five edge servers and fifty clients, with each client assigned 1,000 local training samples. To emulate real-world challenges, 10%, 30%, and 50% of the clients gradually experience degradation in both training quality (e.g., training accuracy) and communication quality (e.g., packet loss) as training progresses.

Datasets: Real-world Datasets. Four standard real-world datasets, e.g. MNIST (Rana, Kabir, and Sobur 2023), EMNIST (Majeed et al. 2024), SVHN (Pradhan et al. 2024), and CIFAR-10 (Aslam and Nassif 2023) are utilized to make performance evaluation.

Training Configurations: Training Parameters. We adopt a CNN architecture for its effectiveness in image processing tasks. The batch size is 32, balancing computational efficiency and model performance. Each client performs 100 local training rounds ($T_1 = 100$) before aggregation, with 100 inter-cluster aggregations ($T_2 = 100$) to synchronize updates across edge servers. The learning rate (η) is set to 0.01, ensuring stable and efficient optimization, and SGD with a momentum of 0.05. The model uses ReLU as the activation function for non-linearity and cross-entropy loss for

classification tasks.

Baselines: In order to validate the effectiveness of our proposed mechanism, we compared our mechanism with the following three mechanisms.

- **GUROBI:** In (Muley 2021), the authors utilize the GUROBI optimizer for the client's optimal allocation problem. The prediction part of the front end does not utilize the prediction mechanism of AHSMM.
- **TRUST.** In (Wang et al. 2024c), the authors introduce a trust-age of information (AoI)-aware co-design scheme (TACS), employing a learning-based trust model and trust-AoI-aware scheduling to optimize data selection for plant control dynamically.
- **RANDOM.** Here, we continue to use the AHSMM for the prediction component, while employing random allocation for client assignments.

Evaluation Metrics: We use two metrics to evaluate our mechanisms: test accuracy and training loss. The results are obtained from the average of multiple experiments.

- **Test accuracy.** Test accuracy measures a model's performance on unseen data, reflecting its generalization ability and effectiveness in SD-FL, critical for real-world usability and reliability.
- **Training loss.** Training loss quantifies the discrepancy between the predicted outputs of a model and the actual data, guiding the optimization process to improve model accuracy and performance.

Experiments Results

In Figure 2, we analyze the variations in test accuracy and training loss over multiple training rounds for four distinct mechanisms, specifically under conditions where only 10% of clients are classified as low quality. Our proposed mechanism stands out by achieving the highest performance across four real datasets. This result is due to the effective integration of our AHSMM model with a greedy algorithm, which works together to predict fluctuations in client learning and communication quality reasonably. By optimizing the participation of low-quality clients, our mechanism significantly enhances overall training outcomes. In contrast, the TRUST mechanism, despite employing a predictive approach, lacks an effective client distribution strategy. This deficiency leads to suboptimal performance, as it fails to adaptively manage client participation based on their quality. Similarly, the RANDOM mechanism incorporates the AHSMM to forecast client behavior, but it does not allocate clients efficiently, leading to less effective training sessions. Although the GUROBI mechanism can determine the optimal client allocation scheme, it does not incorporate client quality predictions, which hampers its ability to promptly exclude low-quality clients from participating in training, ultimately affecting training efficiency. Overall, our mechanism demonstrates a superior ability to navigate the complexities of client quality by leveraging predictive modeling and strategic allocation, ensuring robust training performance in SD-FL environments.

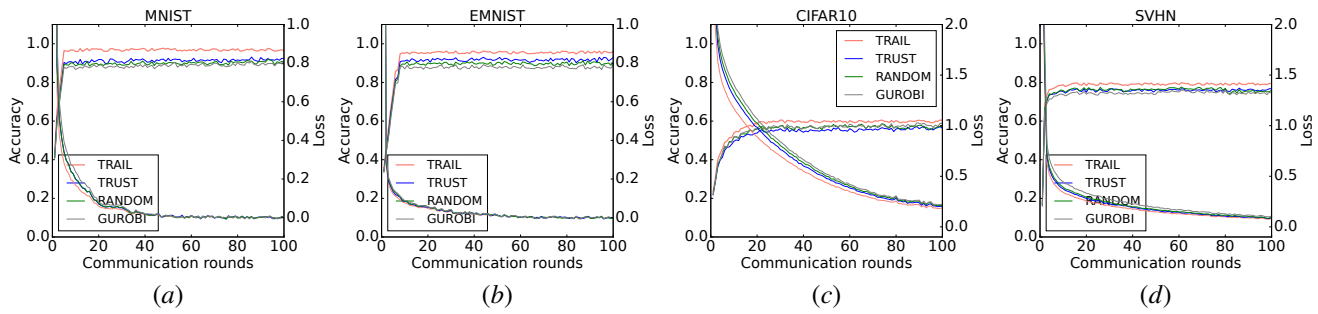


Figure 2: The test accuracy and training loss in scenarios with 10% low-quality clients: (a) MNIST, (b) EMNIST, (c) CIFAR10, and (d) SVHN.

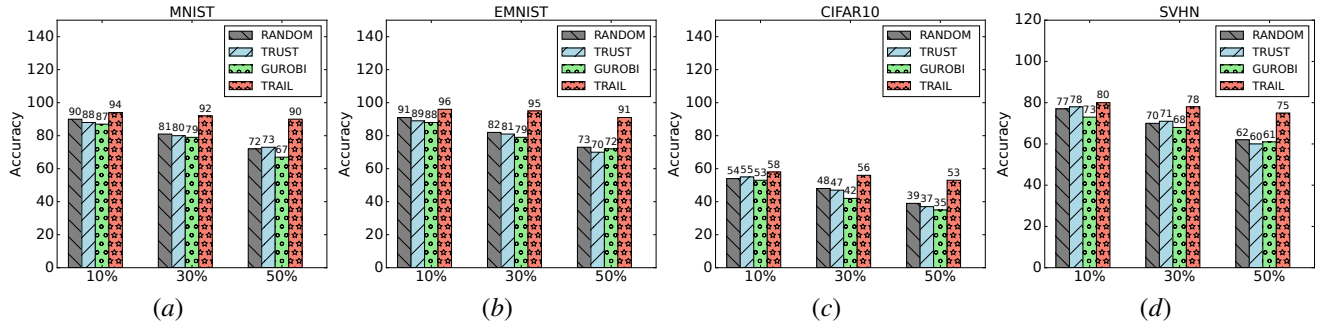


Figure 3: The test accuracy in scenarios with 10%,30%,50% low-quality clients: (a) MNIST, (b) EMNIST, (c) CIFAR10, and (d) SVHN.

In Figure 3, we analyze the comparative performance of four mechanisms across scenarios characterized by varying proportions of low-quality clients. As the percentage of low-quality clients increases, all mechanisms demonstrate a decline in both training and testing accuracy, albeit to different extents. Notably, our proposed mechanism consistently delivers the best results across four real datasets, showcasing its robustness in challenging environments. The superior performance of our mechanism can be attributed to the integration of the AHSM and a greedy-based client allocation algorithm. This combination effectively predicts fluctuations in client learning and communication quality, enabling efficient client allocation that significantly enhances model training quality, even under adverse conditions. By optimizing the participation of higher-quality clients, we mitigate the negative impact of low-quality clients on overall performance. In contrast, while the TRUST mechanism is capable of identifying unreliable clients, it lacks an efficient client distribution strategy. This limitation results in poorer training outcomes compared to our mechanism, as it fails to adaptively manage client participation based on their quality. Similarly, the RANDOM mechanism employs the AHSM to accurately predict changes in client training quality but relies on a random allocation strategy during the client distribution phase. Consequently, this randomness undermines the final training effectiveness, leading to suboptimal results. The GUROBI mechanism, despite its potential for determining optimal client distributions, performs the worst in our experiments. Its inability to accurately predict changes in

client learning quality restricts its effectiveness, as it cannot exclude low-quality clients in a timely manner. Experiments reveal a notable 8.7% increase in test accuracy and a 15.3% reduction in training loss compared to existing baselines, demonstrating the superiority of our mechanism in SD-FL settings. These results underscore the importance of both predictive modeling and strategic client allocation in achieving high-quality training outcomes.

Conclusion

This paper proposes TRAIL, a novel mechanism specifically designed to address the dynamic challenges in SD-FL. TRAIL integrates an AHSM to accurately predict client states, including communication quality and contributions, and employs a greedy algorithm to optimize client-server associations, effectively minimizing global training loss. Through rigorous convergence analysis, the impact of client-server relationships on model convergence is theoretically assessed and quantified. Extensive experiments conducted on four real-world datasets demonstrate that TRAIL significantly improves test accuracy and training loss, achieving an 8.7% increase in accuracy and a 15.3% reduction in loss, outperforming state-of-the-art baselines. This work highlights the potential of combining advanced predictive modeling and strategic client allocation to enhance efficiency, robustness, and performance in distributed learning systems, particularly in dynamic and heterogeneous environments.

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References

- Aslam, S.; and Nassif, A. B. 2023. Deep learning based CIFAR-10 classification. In *2023 Advances in Science and Engineering Technology International Conferences (ASET)*, 01–04.
- Chen, H.; Zhang, Y.; Krompass, D.; Gu, J.; and Tresp, V. 2024. Feddat: An approach for foundation model finetuning in multi-modal heterogeneous federated learning. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 38, 11285–11293.
- Lin, F. P.-C.; Hosseinalipour, S.; Azam, S. S.; Brinton, C. G.; and Michelusi, N. 2021. Semi-decentralized federated learning with cooperative D2D local model aggregations. *IEEE Journal on Selected Areas in Communications*, 39(12): 3851–3869.
- Lu, J.; Liu, H.; Jia, R.; Wang, J.; Sun, L.; and Wan, S. 2022. Toward personalized federated learning via group collaboration in IIoT. *IEEE Transactions on Industrial Informatics*, 19(8): 8923–8932.
- Lu, J.; Liu, H.; Zhang, Z.; Wang, J.; Goudos, S. K.; and Wan, S. 2021. Toward fairness-aware time-sensitive asynchronous federated learning for critical energy infrastructure. *IEEE Transactions on Industrial Informatics*, 18(5): 3462–3472.
- Ma, Q.; Xu, Y.; Xu, H.; Jiang, Z.; Huang, L.; and Huang, H. 2021. FedSA: A Semi-Asynchronous Federated Learning Mechanism in Heterogeneous Edge Computing. *IEEE Journal on Selected Areas in Communications*, 39(12): 3654–3672.
- Majeed, H. D.; Nariman, G. S.; Azeez, R. S.; and Abdulqadir, B. B. 2024. Kurdish standard EMNIST-like character dataset. *Data in Brief*, 52: 110038.
- Martínez Beltrán, E. T.; Pérez, M. Q.; Sánchez, P. M. S.; Bernal, S. L.; Bovet, G.; Pérez, M. G.; Pérez, G. M.; and Celdrán, A. H. 2023. Decentralized Federated Learning: Fundamentals, State of the Art, Frameworks, Trends, and Challenges. *IEEE Communications Surveys & Tutorials*, 25(4): 2983–3013.
- McDonald, A.; Gales, M. J. F.; and Agarwal, A. 2023. A recurrent neural network and parallel hidden Markov model algorithm to segment and detect heart murmurs in phonocardiograms. *PLOS Digital Health*, 3.
- McMahan, B.; Moore, E.; Ramage, D.; Hampson, S.; and y Arcas, B. A. 2017. Communication-efficient learning of deep networks from decentralized data. In *Artificial intelligence and statistics*, 1273–1282. PMLR.
- Muley, V. Y. 2021. Mathematical programming for modeling expression of a gene using gurobi optimizer to identify its transcriptional regulators. *Modeling transcriptional regulation: Methods and protocols*, 99–113.
- Parasnis, R.; Hosseinalipour, S.; Chu, Y.-W.; Chiang, M.; and Brinton, C. G. 2023. Connectivity-aware semi-decentralized federated learning over time-varying D2D networks. In *Proceedings of the Twenty-fourth International Symposium on Theory, Algorithmic Foundations, and Protocol Design for Mobile Networks and Mobile Computing*, 31–40.
- Pradhan, O.; Tang, G.; Makris, C.; and Gudipati, R. 2024. Reading and Understanding House Numbers for Delivery Robots Using the “SVHN Dataset”. In *2024 IEEE International Conference on Industrial Technology (ICIT)*, 1–7. IEEE.
- Rana, M. S.; Kabir, M. H.; and Sobur, A. 2023. Comparison of the Error Rates of MNIST Datasets Using Different Type of Machine Learning Model. *North American Academic Research*, 6(5): 173–181.
- Sefati, S.; and Navimipour, N. J. 2021. A QoS-Aware Service Composition Mechanism in the Internet of Things Using a Hidden-Markov-Model-Based Optimization Algorithm. *IEEE Internet of Things Journal*, 8: 15620–15627.
- Sun, Y.; Shao, J.; Mao, Y.; Wang, J. H.; and Zhang, J. 2023. Semi-decentralized federated edge learning with data and device heterogeneity. *IEEE Transactions on Network and Service Management*, 20(2): 1487–1501.
- Sun, Y.; Shao, J.; Mao, Y.; and Zhang, J. 2021. Semi-Decentralized Federated Edge Learning for Fast Convergence on Non-IID Data. *2022 IEEE Wireless Communications and Networking Conference (WCNC)*, 1898–1903.
- Tan, Y.; Liu, Y.; Long, G.; Jiang, J.; Lu, Q.; and Zhang, C. 2023. Federated learning on non-iid graphs via structural knowledge sharing. In *Proceedings of the AAAI conference on artificial intelligence*, volume 37, 9953–9961.
- Valdeira, P.; Chi, Y.; Soares, C.; and Xavier, J. 2023. A Multi-Token Coordinate Descent Method for Semi-Decentralized Vertical Federated Learning. *arXiv preprint arXiv:2309.09977*.
- Vono, M.; Plassier, V.; Durmus, A.; Dieuleveut, A.; and Moulines, É. 2021. QLSD: Quantised Langevin stochastic dynamics for Bayesian federated learning. *ArXiv*, abs/2106.00797.
- Wang, H.; Jia, Y.; Zhang, M.; Hu, Q.; Ren, H.; Sun, P.; Wen, Y.; and Zhang, T. 2024a. FedDSE: Distribution-aware Sub-model Extraction for Federated Learning over Resource-constrained Devices. In *Proceedings of the ACM on Web Conference 2024*, 2902–2913.
- Wang, H.; Kaplan, Z.; Niu, D.; and Li, B. 2020. Optimizing federated learning on non-iid data with reinforcement learning. In *IEEE INFOCOM 2020-IEEE conference on computer communications*, 1698–1707. IEEE.
- Wang, H.; Zheng, P.; Han, X.; Xu, W.; Li, R.; and Zhang, T. 2024b. FedNLR: Federated Learning with Neuron-wise Learning Rates. In *Proceedings of the 30th ACM SIGKDD*

Conference on Knowledge Discovery and Data Mining, 3069–3080.

Wang, X.; Zhang, J.; Chen, C.; He, J.; Ma, Y.; and Guan, X. 2024c. Trust-AoI-Aware Codesign of Scheduling and Control for Edge-Enabled IIoT Systems. *IEEE Transactions on Industrial Informatics*, 20: 2833–2842.

Wu, S.; Chen, N.; Wen, G.; Xu, L.; Zhang, P.; and Zhu, H. 2024. Virtual Network Embedding for Task Offloading in IIoT: A DRL-Assisted Federated Learning Scheme. *IEEE Transactions on Industrial Informatics*, 20(4): 6814–6824.

Wu, X.; Huang, F.; Hu, Z.; and Huang, H. 2023. Faster adaptive federated learning. In *Proceedings of the AAAI conference on artificial intelligence*, volume 37, 10379–10387.

Xu, B.; Zhao, H.; Cao, H.; Garg, S.; Kaddoum, G.; and Hassan, M. M. 2024. Edge aggregation placement for semi-decentralized federated learning in Industrial Internet of Things. *Future Generation Computer Systems*, 150: 160–170.

Yemini, M.; Saha, R.; Ozfatura, E.; Gündüz, D.; and Goldsmith, A. J. 2022. Semi-decentralized federated learning with collaborative relaying. In *2022 IEEE International Symposium on Information Theory (ISIT)*, 1471–1476. IEEE.

Yu, X.; Liu, Z.; Sun, Y.; and Wang, W. 2023. Clustered federated learning for heterogeneous data (student abstract). In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 37, 16378–16379.

Zhang, J.; Li, B.; Chen, C.; Lyu, L.; Wu, S.; Ding, S.; and Wu, C. 2023a. Delving into the adversarial robustness of federated learning. In *Proceedings of the AAAI conference on artificial intelligence*, volume 37, 11245–11253.

Zhang, K.; Lin, N.; Yang, J.; Zhang, D.; Cui, Y.; and Jin, Z. 2023b. An intelligent approach for gas reservoir identification and structural evaluation by ANN and Viterbi algorithm—A case study from the Xujiahe Formation, Western Sichuan Depression, China. *IEEE Transactions on Geoscience and Remote Sensing*, 61: 1–12.

Zhang, R.; Li, H.; Tian, L.; Hao, M.; and Zhang, Y. 2024. Vertical Federated Learning Across Heterogeneous Regions for Industry 4.0. *IEEE Transactions on Industrial Informatics*, 20(8): 10145–10155.

Zhang, S.; Yang, L. T.; Zhang, Y.; Lu, Z.; Yu, J.; and Cui, Z. 2023c. Tensor-Based Baum–Welch Algorithms in Coupled Hidden Markov Model for Responsible Activity Prediction. *IEEE Transactions on Computational Social Systems*, 10(6): 2924–2937.