Resource Optimized Federated Learning-Enabled Cognitive Internet of Things for Smart Industries

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ABSTRACT Leveraging the cognitive Internet of things (C-IoT), emerging computing technologies, and machine learning schemes for industries can assist in streamlining manufacturing processes, revolutionizing operational analytics, and maintaining factory efficiency. However, further adoption of centralized machine learning in industries seems to be restricted due to data privacy issues. Federated learning has the potential to bring about predictive features in industrial systems without leaking private information. However, its implementation involves key challenges including resource optimization, robustness, and security. In this article, we propose a novel dispersed federated learning (DFL) framework to provide resource optimization, whereby distributed fashion of learning offers robustness. We formulate an integer linear optimization problem to minimize the overall federated learning cost for the DFL framework. To solve the formulated problem, first, we decompose it into two sub-problems: association and resource allocation problem. Second, we relax the association and resource allocation sub-problems to make them convex optimization problems. Later, we use the rounding technique to obtain binary association and resource allocation variables. Our proposed algorithm works in an iterative manner by fixing one problem variable (for example, association) and compute the other (for example, resource allocation). The iterative algorithm continues until convergence of the formulated cost optimization problem. Furthermore, we compare the proposed DFL with two schemes; namely, random resource allocation and random association. Numerical results show the superiority of the proposed DFL scheme.

INDEX TERMS Smart industry, cognitive Internet of Things, federated learning, convex optimization.

I. INTRODUCTION

The widespread use of collaborative robotics, edge computing, cloud computing, cyber-physical systems, cognitive computing, cognitive Internet of things (C-IoT), and advancements in machine learning has brought groundbreaking innovations in industrial sectors [1]–[3]. C-IoT jointly uses Internet of Things (IoT) and cognitive computing to perform various smart functions with minimum human intervention [4], [5]. Specifically, cognitive computing combines human

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computer interaction, speech processing, natural language processing, reasoning, and machine learning, to improve human decision making [6]. According to statistics, IoT market will reach to 1, 319.08 Billion US Dollar at a growth rate of 25.68% from $2019 - 2026$ [7]. Additionally, cognitive computing market will reach 29.550 Billion US Dollar at a compound annual growth rate (CAGR) of 19.8% from $2021 - 2026$ [8]. Integrating industries and machine learning can lead to optimizing production costs, increasing productivity, reducing errors, enriching automation processes, and bringing better quality control. Therefore, machine learning can be considered an integral part of the smart industry. However,

traditional machine learning poses serious privacy concerns due to the requirement of migrating data from the end devices to a centralized edge/cloud server for training [9]. Most of the industries do not want to share their data with the third party for training of a centralized machine learning model due to the risk of data leakage [10]. Such industries include military, bank, insurance, and health sector. Furthermore, centralized machine learning suffers from high latency for industrial use cases where real-time interaction is necessary [10]. For instance, autonomous cars generate approximately 4,000 gigaoctet of data every day that must be taken into account during machine learning training. Therefore, we can use federated learning in the training of autonomous driving cars machine learning models. Federated learning accounts for newly added data in a resource-efficient way via sending of only learning model updates to the aggregation server.

Smart industries can suffer from several security and privacy attacks. These attacks include denial of service (DoS), false data injection, and physical attacks [11]. On the other hand, enabling smart industries via traditional machine learning might suffer from a variety of privacy concerns. Coping with such issues, *federated learning (FL)* has been proposed to offer learning in a distributed fashion without migrating the data from the end devices to a centralized server. FL is based on the iterative exchange of learning model parameters between the end devices and centralized server till the convergence of the global FL model to a certain accuracy level. However, traditional FL for smart industries has its own challenges as discussed below.

- FL is based on the iterative exchange of learning model parameters between end-devices and the aggregation server. Furthermore, a single, centralized aggregation server might be attacked by a malicious user. Therefore, the failure of the centralized aggregation server due to a physical defect or security attack results in the FL process interruption.
- A collaborative FL model for different industries must take into account the validity of the learning model parameters received from the industry. For traditional FL, the centralized server does not check the validity of the learning model parameters received from different industries, and thus may suffer from false data injection.

The aforementioned limitations can be tackled using blockchain-based collaborative FL for smart industries, which envisions to replace a centralized server with multiple geographically distributed miners. Each miner receives a learning model updates and verifies it before sharing with other miners, and thus offers enhanced reliability through trustful verification. Although blockchain-based collaborative FL offers several advantages, it suffers from a prominent issue of using high communication resources and high-latency due to blockchain consensus algorithm [12], [13]. Another feasible way is to use light-weight authentication scheme for learning models verification. To tackle the issue of high communication resource usage, we can use the

hierarchical fashion for collaborative FL to offer communication resource optimization [14].

The co-location of different industries is expected to gain an immense interest in the future to enable sustainable operation by sharing power supply and other resources [15], [16]. In [15], the co-location of several telecommunication operators for sharing backup power supply is considered, while in [16] the co-location of multiple cloud providers is discussed. Also, in a typical industrial zone, multiple industries exist in a close vicinity. Therefore, a common power supply can be used in such a type of closely located industries. Furthermore, various industries (i.e., military industries, health-care industries, and manufacturing industries) don't want share their data with other industries. Inspired from the immense interest in co-location, close vicinity of the different industries, and data privacy concerns, we can use FL for training of collaborative machine learning models for different industries without data transfer. However, FL for industries has its own challenges such as robustness and security. To cope with these issues, we proposed a novel dispersed federated learning (DFL) framework for smart industries. Enabling DFL for C-IoT enabled smart industries has three main aspects: resource (both communication and computation) optimization, incentive mechanism, and learning algorithm design [17]. In this article, we focus on resource optimization to enable the DFL for C-IoT. To the best of our knowledge, we are the first to consider resource optimization in DFL for C-IoT enabled smart industries.

Our key contributions are summarized below:
- We devise a novel system model; namely, DFL for C-IoT enabled smart industries. The proposed system model uses distributed and hierarchical FL to offer robustness and communication resources optimization, respectively.
- We formulate an integer linear programming problem to minimize the global FL cost of the proposed DFL. Due to the NP-hard nature of the formulated problem, we decompose the problem into two sub-problems: association problem and resource allocation problem. Then, we relax the association and resource allocation variables into continuous variables for a low-complexity solution using a convex optimization solver. Later, the continuous variables are transformed into binary variables to yield the sub-optimal association and resource allocation.
- Finally, we provide numerical results to validate our proposed DFL scheme for smart industries. We compare the performance of our proposed decomposition-relaxation based scheme with two other schemes such as baseline-1 and baseline-2. Baseline-1 uses the proposed device association algorithm and random resource allocation, whereas baseline-2 uses the proposed resource allocation algorithm and random device association.

The rest of the paper is organized as follows. Section II outlines the recent literature available on C-IoT enabled smart industries, federated learning resource optimization, and

blockchain-based federated learning. The proposed system model and problem formulation are presented in Section III. Section IV presents the proposed decomposition-relaxation based solution for the formulated problem. Finally, results and conclusions are given in Sections V and VI, respectively.

II. RELATED WORKS

Several studies have considered resource optimization in federated learning [14], [17]–[19]. For example, in [17], resource optimization and incentive mechanism for federated learning at the network edge were presented. A Stackelberg game-based incentive mechanism was also proposed. Finally, the authors provided an outlook on future research. Although the authors reviewed resource optimization and incentive mechanism for federated learning, it is preferable to provide a review of the security for federated learning over wireless networks. In [18], Chen *et al.* discussed the performance of federated learning over wireless networks. The effect of packet error rate on the performance of federated learning was studied. The authors derived the closed-form expression for the expected convergence rate of federated learning, which was further used to compute the optimal transmit power for a given resource block allocation and user selection. Subsequently, user selection and resource allocation were optimized for minimizing a federated learning loss function. The work in [18] considered the case of a single base station (BS) and performed resource allocation and user selection. As a future work, one can extend the work for multiple BSs with efficient solutions. On the other hand, hierarchical federated learning has been proposed to offer wireless resource optimization [14]. A heterogeneous cellular network consisting of a macro base station (MBS) and small cell base stations (SBS) was considered. Initially, a sub-global model is trained at every SBS in an iterative manner similar to traditional federated learning. After the computation of the sub-global model by all the SBS, the sub-global models are sent to the MBS for global model aggregation. Finally, the global model updates are sent to the SBS that broadcast the global model parameters to the end devices. The work presented in [14] an attractive solution that can reuse wireless resources. However, their scheme uses centralized MBS for global aggregation which might be out of order due to physical damage. Moreover, a malicious user can attack the centralized global aggregation server and alters the global model updates. Tran *et al.* in [19] analyzed the performance of federated learning over wireless networks and presented two types of trade-offs. The first one deals with federated learning model computation time versus end device energy consumption, and the second one deals with communication and computation latencies for a federated learning model accuracy level.

Machine learning can be considered as a key enabling technology for cognitive industrial Internet of Things (C-IIoT) [20]–[22]. In [22], the authors presented a framework using machine learning for C-IIoT. Several machine learning approaches were discussed to enable C-IIoT. Furthermore,

deep reinforcement learning for scenario-aware dynamic adaptive planning was used that showed impressive results for IIoT. In another paper [21], the C-IoT based framework for the smart city was proposed and discussed different artificial intelligence schemes for enabling it. Mostly, the works presented in [20]–[22] use traditional machine learning that suffers from the issue of privacy leakage. Additionally, the use of traditional machine learning for a massive number of smart industrial devices requires a significant amount of communication resources for transferring data from local devices to the centralized server for training.

In [23], the authors proposed blockchain-based federated learning. First, all the devices compute their local model updates which are then send to their associated miners. The miners cross verification and exchange local model updates without the need for the centralized edge/cloud server. All the miners get the local model updates of different devices after consensus is reached. The miners send back the local model updates of all devices to their corresponding devices where global model aggregation takes place. The proposed approach has the advantage of non-usage of a centralized edge/cloud server but at the cost of extra communication resources usage and high-latency due to blockchain consensus algorithm. Therefore, to enable federated learning using blockchain, one must propose novel consensus algorithms with low latency.

Several techniques such as reinforcement learning, deep neural networks, and fuzzy logic, have been considered for resource allocation and power management in different scenarios [24]–[26]. In [24], the authors proposed a Deep-Q Network-enabled resource allocation and task offloading for edge computing. Mainly, the authors considered the scenario of multiple tasks to be offloaded to the edge server. A cost considering delay, computational cost, and energy was minimized. Reference [25] proposed the use of deep neural network for computational resource allocation in edge computing scenario. The other work in [26] used a fuzzy logic inference based scheme for efficient power management in electric vehicles in a parking lot. On the other hand, the works in [27]–[30] used decomposition and relaxation-based algorithms to solve the resource allocation problem in wireless networks. The work in [27] used the block successive upper bound minimization method to solve the resource allocation problem of joint computing, caching, communication, and control in big data multi-access edge computing (MEC). In [28], the authors leveraged the block coordinate descent and successive convex optimization techniques to solve the joint optimization problem for the unmanned aerial vehicles (UAV's) recharging duration, power allocation as well as trajectory by decomposing it into two sub-problems, which are alternately solved. Moreover, the authors in [29], [30] applied a decomposition-relaxation based approach to solve the resource slicing problem for the enhanced Mobile Broadband (eMBB) and Ultra-Reliable Low Latency Communications (URLLC) coexistence in 5G networks.

The works in [14], [17]–[19] considered federated learning based on communication between the end devices
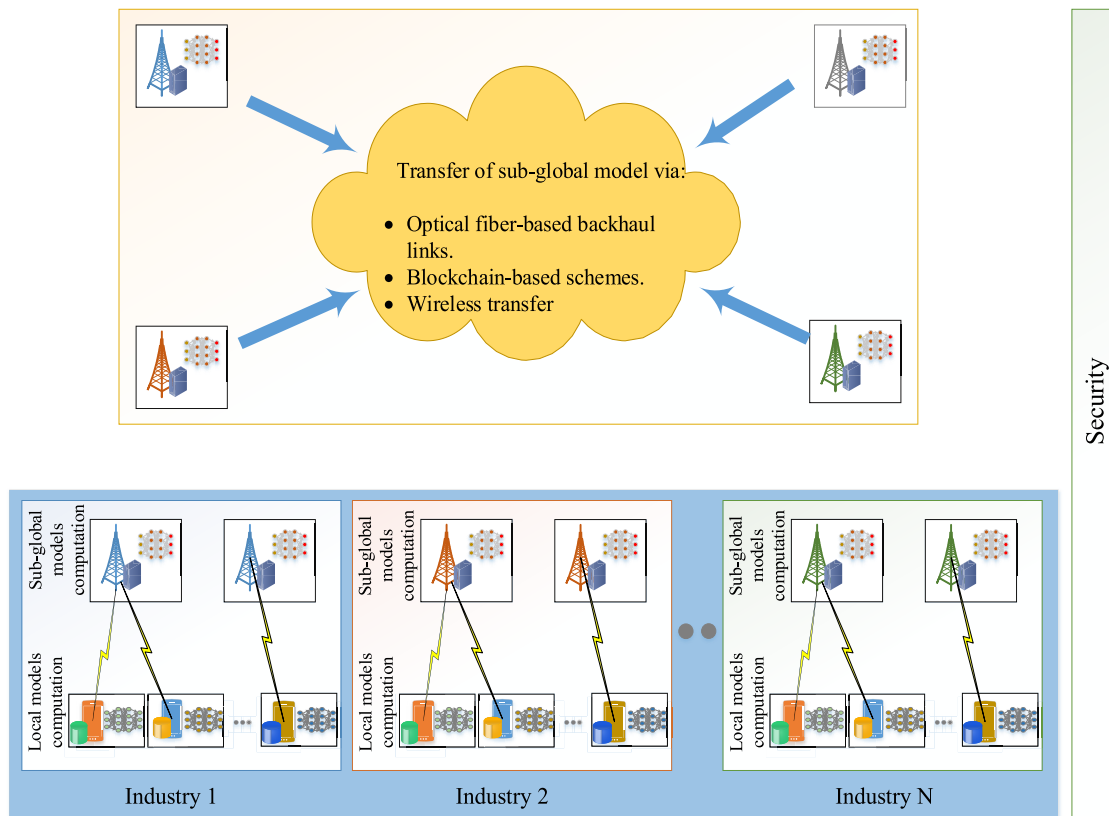
FIGURE 1. Proposed federated learning framework for smart industries.

and edge/cloud server. Such fashion of federated learning might suffer from robustness issue which occurs when the edge/cloud server gets malfunctioned. Another disadvantage is the possibility of a malicious user that can easily access the edge/cloud server and alters the global model aggregation, and thus introduces error. On the other hand, the blockchain-based approach presented in [23] suffers from the extra communication overhead to reach consensus among the miners used for transferring learning model parameters. Additionally, the blockchain consensus algorithm generates high latency which is not desirable for federated learning. Therefore, it is necessary to propose distributed and hierarchical fashion based federated learning for offering enhanced security, robustness, and communication resources optimization.

III. PROPOSED FRAMEWORK AND PROBLEM FORMULATION

In this section, we present a DFL framework for smart industries as shown in Fig. 1. We consider a system that consists of a set $\mathcal{I}$ of I industries. Each industry has set $\mathcal{U}_i, \forall i \in \mathcal{I}$ of $U_i, \forall i \in \mathcal{I}$ users with local datasets. To serve these devices, the set $\mathcal{B}_i, \forall i \in \mathcal{I}$ of $B_i, \forall i \in \mathcal{I}$ of edge computing-based SBS are installed at the industries. A set $\mathcal{R}$ of R orthogonal resource blocks already in use by the macro cell users are reused by SBS users to enable resource-efficient operation. The set of IoT devices from different industries want to train a global FL model. To enable resource efficient and robust FL

for different industries, we propose the use of DFL scheme, whose steps (shown in Fig. 2) are given below.

- Each device computes its local learning model in an iterative manner using its local dataset.
- All the local devices are associated with the SBS for transferring the local model updates. Then, the devices sent their local learning model to their corresponding edge computing enabled SBS.
- The edge computing enabled SBS first verifies the local devices before starting computing sub-global models. After verification, the learning model updates received from the devices are aggregated to compute the sub-global model. The computed sub-global model is then transmitted to the devices. Such type of sub-global model aggregation takes place in an iterative manner between devices and SBS.
- All the edge computing enabled SBS use a light-weight authentication scheme for the trustful transferring of sub-global model updates with other edge computing enabled SBS.
- After a transfer of sub-global model updates is completed, every edge computing enabled SBS computes the global model via aggregation of sub-global models. Finally, the global model updates are sent to the end devices.

Our proposed framework (shown in Fig. 1) can offer robustness due to the use of multiple distributed aggregation servers. In contrast to centralized aggregation server-based
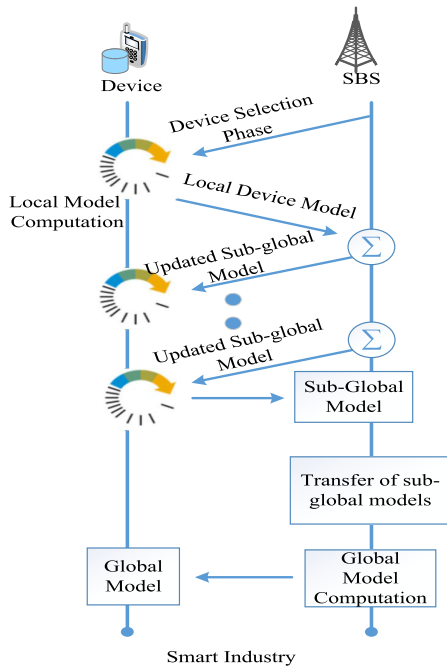
FIGURE 2. Proposed federated learning framework sequence diagram.

FL which results in learning process interruption in case of a malicious user attack, DFL can still continue the learning process without complete interruption. On the other hand, transferring the learning model parameters between end-devices and aggregation servers might suffer from a malicious third party attack. To cope with this issue, we can use encryption schemes.

A. FEDERATED LEARNING MODEL

In this subsection, we first find the expression in terms of the packet error rate for traditional FL to reflect the effect of wireless channel uncertainties on the global FL model accuracy. Then, the expression for the proposed model is derived. All the devices involved in FL has their own datasets $\mathcal{D}_u^i = [d_{u1}^i, d_{u2}^i, \ldots, d_{uk_u^i}^i]$, where k_u^i denotes the total number of data samples for a device u of industry i. Different FL task has different input sizes and a number of outputs depending on the application nature. For simplicity, we assume a single output Θ_{uk}^i which is determined by w_u^i for a given input d_{uk}^i. The goal of the FL is to minimize the loss function f.

$$\underset{w_1^i, w_2^i, \ldots, w_{U_u}^i}{\text{minimize}} \frac{1}{K} \sum_{i=1}^{I} \sum_{u=1}^{U_i} \sum_{k=1}^{k_u^i} f(w_u^i, d_{uk}^i, \Theta_{uk}^i), \quad (1a)$$

$$s.t. \; w_u^1 = w_u^2 = \ldots = w_u^i = z, \quad \forall u \in \mathcal{U}_i, \; \forall i \in \mathcal{I}, \quad (1b)$$

where K and z denote the total number of data points of all devices and global FL model, respectively. Function f is the loss function that is application dependent. The same learning model for all devices is ensured by the constraint (1b). The global model update is given by:

$$z = \frac{\sum_{i=1}^{I} \sum_{u=1}^{U_i} k_u^i w_u^i}{K}. \quad (2)$$

As FL is based on an iterative exchange of learning model parameters between the end devices and SBS, the random channel variations have significant degradation effect on the global FL model accuracy. To capture the effect of random channel variations on the performance of FL model, we consider a packet error rate which is given by:

$$e_{u,i}(X, Y) = x_i^{u \to b_i} y_i^{u \to b_i} \Xi, \quad (3)$$

where

$$\Xi = \left(1 - \exp \left(\frac{-\vartheta \left(\sum_{c \in \mathcal{C}_r} h_c^r P_c^r + \sigma^2 \right)}{p_i^u h_i^{u \to b_i}} \right) \right), \quad (4)$$

where p_i^u, $h_i^{u \to b_i}$, and σ^2 denote the transmitted power by device u of industry i, channel gain between device u and SBS b_i of industry i, and noise, respectively. ϑ represents the waterfall threshold [31]. The binary variable $x_i^{u \to b_i}$ is the association variable and is given by:

$$x_i^{u \to b_i}$$
$$= \begin{cases} 1, & \text{If device } u \text{ of industry } i \text{ is connected to SBS } b_i, \\ 0, & \text{otherwise.} \end{cases}$$
$$(5)$$

Every SBS in an industry can serve a limited number of devices due to hardware limitations. The maximum number of devices served by a SBS is restricted by the following constraint:

$$\sum_{u \in \mathcal{U}_i} x_i^{u \to b_i} \leq \Delta_{b_i}, \quad \forall b_i \in \mathcal{B}_i, \; \forall i \in \mathcal{I}. \quad (6)$$

On the other hand, every device must not be associated to more than one SBS of every industry:

$$\sum_{b_i \in \mathcal{B}_i} x_i^{u \to b_i} \leq 1, \quad \forall u \in \mathcal{U}_i, \; \forall i \in \mathcal{I}. \quad (7)$$

The binary resource block allocation variable $y_i^{u \to b_i}(r)$ is given by:

$$y_i^{u \to b_i}(r) = \begin{cases} 1, & \text{If device } u \text{ of industry } i \text{ is assigned } r, \\ 0, & \text{otherwise.} \end{cases}$$
$$(8)$$

The packet error rate strictly determines the FL model accuracy. For higher values of the packet error rate, it is desirable not to consider the corresponding local learning model in computation of the global model. To consider this effect, we define a binary variable Q_u^i for device u of industry i, whose value is taken $Q_u^i = 1$ if the packet error rate is less than a certain threshold, and $Q_u^i = 0$ otherwise. We can re-write (2) as:

$$z = \frac{\sum_{i=1}^{I} \sum_{u=1}^{U_i} k_i^u w_u^i Q_u^i}{\sum_{i=1}^{I} \sum_{u=1}^{U_i} k_u^i Q_u^i}. \quad (9)$$

A standard gradient decent method is considered in this article to update the local learning model and assume that

$F(z) = \frac{1}{K} \sum_{i=1}^{I} \sum_{u=1}^{U_i} \sum_{k=1}^{k_i^u} f(z, d_{uk}^i, \Theta_{uk}^i)$. Furthermore, we made several assumptions as follows [18], [19]:

- *Assumption 1:* The gradient $\bigtriangledown(F(z))$ with respect to z have uniform Lipschitz continuous nature [32].

$$\| \bigtriangledown(F(z_{t+1})) - \bigtriangledown(F(z_t)) \| \leq L \| z_{t+1} - z_t \|, \quad (10)$$

where $\| * \|$ and L denote the norm of $*$ and positive constant, respectively.

- *Assumption 2:* The function $F(z)$ is assumed to be strongly convex for a positive constant μ:

$$F(z_{t+1}) \geq F(z_t) + (z_{t+1} - z_t)^T \bigtriangledown F(z_t)$$
$$+ \frac{\mu}{2} \| z_{t+1} - z_t \|^2 . \quad (11)$$

- *Assumption 3:* Function $F(z)$ is assumed to have strongly differentiable nature. Using (10) and (11), we can write:

$$\mu \boldsymbol{I} \preceq \overset{2}{\bigtriangledown} F(z) \preceq L \boldsymbol{I}. \quad (12)$$

- *Assumption 4:* It is assumed that $\| \bigtriangledown f(z_t, d_{uk}^i, \Theta_{uk}^i) \|^2 \leq \zeta_1 + \zeta_2 \bigtriangledown \| F(z_t) \|^2$ for positive constants $\zeta_1 \geq 0$ and $\zeta_2 \geq 1$.

Due to FL loss function satisfying the assumptions $1-4$ and exactly one resource block per device, the cost function E_p that counts for the effect of packet loss rate on the FL model accuracy is given by [18]:

$$E_p(\boldsymbol{X}, \boldsymbol{Y}) = \sum_{i=1}^{I} \sum_{u=1}^{U_i} k_u^i e_{u,i}(\boldsymbol{X}, \boldsymbol{Y}). \quad (13)$$

Considering assumptions $1-4$, we get the intuition of cost function that captures the effect of packet error rate on our FL model accuracy for our proposed model. The term k_u^i in (13) is constant, and therefore it is assumed to be equal to 1 and cost function for our model can be written as follows:

$$E(\boldsymbol{X}, \boldsymbol{Y}) = \sum_{i=1}^{I} \sum_{u=1}^{U_i} e_{u,i}(\boldsymbol{X}, \boldsymbol{Y}). \quad (14)$$

B. COMMUNICATION MODEL

All SBSs are assigned different orthogonal resource blocks, and thus there is no interference between them. However, SBSs will receive interference from cellular users because of reusing the cellular users' resource blocks for communication by devices involved in FL. In our model, a single resource block can be assigned to a maximum of one device:

$$\sum_{i \in \mathcal{I}} \sum_{u \in \mathcal{U}_i} y_i^{u \to b_i}(r) \leq 1, \quad \forall r \in \mathcal{R}. \quad (15)$$

On the other hand, every device must not be assigned more than one resource block:

$$\sum_{r \in \mathcal{R}} y_i^{u \to b_i}(r) \leq 1, \quad \forall i \in \mathcal{I}, \ u \in \mathcal{U}_i. \quad (16)$$

Other than a maximum number of resource blocks per user, the total number of resource blocks assigned to devices must not exceed the total number of available resource blocks:

$$\sum_{r \in \mathcal{R}} \sum_{i \in \mathcal{I}} \sum_{u \in \mathcal{U}_i} y_i^{u \to b_i}(r) \leq R. \quad (17)$$

The signal-to-interference-plus-noise ratio (SINR) for a device u of industry i connected to SBS b_i using resource block r is given by:

$$\Gamma_r^{u \to b_i} = \frac{p_{i,u}^r h_{i,r}^{u \to b_i}}{\sum_{c \in \mathcal{C}_r} h_c^r P_c^r + \sigma^2}, \quad (18)$$

where $p_{i,u}^r$ and $h_{i,r}^{u \to b_i}$ denote the transmission power of device u of industry i and channel gain between device u of industry i and base station b_i, respectively. σ^2 and $\mathcal{C}_r$ represent the noise and set of cellular users using the resource resource block r, respectively. In our model, we assume that all devices involved in FL transmit signals with equal power. The term $\sum_{y \in \mathcal{C}_r} h_c^r P_c^r$ denotes the interference due to cellular users. The data rate of the device u of industry i using resource block r with bandwidth $A_{u,i}^r$ is given by:

$$R_r^{u \to b_i} = A_{u,i}^r \log_2(1 + \Gamma_r^{u \to b_i}). \quad (19)$$

We consider only the transmission delay in our system model for sub-global model computation. The up-link delay is considered only and downlink delay is assumed negligible. Let the local learning model of device u_i of industry i consist of g_u^i bits. The total time taken by computation of the sub-global model of size g_u^i and I_{sg} sub-global iterations is given by:

$$T_{sg}^{b_i}(\boldsymbol{X}, \boldsymbol{Y}) = I_{sg} \left(\sum_{u \in \mathcal{U}_i} \frac{y_i^{u \to b_i}(r) x_i^{u \to b_i} g_u^i}{R_r^{u \to b_i}} \right), \quad \forall b_i \in \mathcal{B}_i. \quad (20)$$

C. PROBLEM FORMULATION

In this subsection, we formulate a problem to minimize the cost C_{DFL} of the proposed FL model computation. First, we compute the total time taken during FL model computation that is given by:

$$T(\boldsymbol{X}, \boldsymbol{Y}) = \sum_{i \in \mathcal{I}} \sum_{b \in \mathcal{B}_i} T_{sg}^{b_i}(\boldsymbol{X}, \boldsymbol{Y}). \quad (21)$$

Now, we can write the cost function C_{DFL} as follows:

$$C_{DFL}(\boldsymbol{X}, \boldsymbol{Y}) = \alpha T(\boldsymbol{X}, \boldsymbol{Y}) + (1 - \alpha) E(\boldsymbol{X}, \boldsymbol{Y}). \quad (22)$$

where $\alpha \in (0, 1)$ is a constant that enables us to strike the balance between the FL model computation delay T and global model accuracy loss due to packet error rate E. Now, we formulate problem **P** that minimizes the cost C_{DFL} as follows:

$$\underset{\boldsymbol{X}, \boldsymbol{Y}}{\text{minimize}} \ C_{DFL}(\boldsymbol{X}, \boldsymbol{Y}) \quad (23)$$

$$\text{subject to: } \sum_{i \in \mathcal{I}} \sum_{u \in \mathcal{U}_i} y_i^{u \to b_i}(r) \leq 1, \quad \forall r \in \mathcal{R}, \quad (23a)$$

$$\sum_{r \in \mathcal{R}} y_i^{u \to b_i}(r) \leq 1, \quad \forall i \in \mathcal{I}, \ u \in \mathcal{U}_i, \quad (23b)$$

$$\sum_{r \in \mathcal{R}} \sum_{i \in \mathcal{I}} \sum_{u \in \mathcal{U}_i} y_i^{u \to b_i}(r) \leq R, \quad (23c)$$

$$\sum_{u \in \mathcal{U}_i} x_i^{u \to b_i} \leq \Delta_{b_i}, \quad \forall b_i \in \mathcal{B}_i, \quad \forall i \in \mathcal{I}, \quad (23d)$$

$$\sum_{b_i \in \mathcal{B}_i} x_i^{u \to b_i} \leq 1, \forall u \in \mathcal{U}_i, \quad \forall i \in \mathcal{I}, \quad (23e)$$

$$x_i^{u \to b_i} \in \{0, 1\} \quad \forall i \in \mathcal{I}, \ u \in \mathcal{U}_i, \quad (23f)$$

$$y_i^{u \to b_i}(r) \in \{0, 1\} \quad \forall i \in \mathcal{I}, \ u \in \mathcal{U}_i. \quad (23g)$$

Problem **P** is an integer linear programming problem and has combinatorial nature due to the presence of two binary variables $x_i^{u \to b_i}$ and $y_i^{u \to b_i}(r)$. Constraints (23a) and (23b) restricts the assignment of the orthogonal resource block to a maximum of one device and maximum of one resource block per device, respectively. Constraint (23c) ensures that the total number of resource blocks assigned to devices must not exceed the maximum limit of the available resource blocks. The maximum number of devices that can be associated with the SBS of an industry is restricted by the maximum limit indicated by constraint (23d). Constraint (23e) limits the association of a device to a maximum of one SBS. Finally, constraints (23f) and (23g) restrict the variables $x_i^{u \to b_i}$ and $y_i^{u \to b_i}(r)$ to be assigned only binary values.

IV. PROPOSED DECOMPOSITION-RELAXATION BASED ALGORITHM

The formulated problem **P** is NP-hard for a large number of smart factory devices. We first decompose (23) into two sub-problems: **P-1:** *Association Problem* and **P-2:** *Resource Blocks Allocation Problem*. Then, we relax x and y to continuous variables. Later, we perform a binary conversion techniques to meet the constraints of the original problem (23). Finally, we iteratively solve **P-1** and **P-2** till convergence as shown in Algorithm 1.

A. ASSOCIATION PROBLEM

In this subsection, we formulate the devices association problem for a fixed resource block assignment. For any fixed feasible RBs allocation y, problem **P** can be represented as follows:

$$P - 1: \ \underset{X}{\text{minimize}} \ C_{DFL}(X) \quad (24a)$$

$$\text{subject to} \sum_{u \in \mathcal{U}_i} x_i^{u \to b_i} \leq \Delta_{b_i}, \quad \forall b_i \in \mathcal{B}_i, \quad \forall i \in \mathcal{I},$$

$$\quad (24b)$$

$$\sum_{b_i \in \mathcal{B}_i} x_i^{u \to b_i} \leq 1, \quad \forall u \in \mathcal{U}_i, \quad \forall i \in \mathcal{I},$$

$$\quad (24c)$$

$$x_i^{u \to b_i} \in \{0, 1\} \quad \forall i \in \mathcal{I}, \ u \in \mathcal{U}_i. \quad (24d)$$

Algorithm 1 Proposed Decomposition-Relaxation Based Algorithm

1: **Inputs**
2: Industries set $\mathcal{I}$, Devices set $\mathcal{U}_i, \forall i \in \mathcal{I}$.
3: Resource blocks set $\mathcal{R}$, SBS set $\mathcal{B}_i, \forall i \in \mathcal{I}$.
4: **Outputs**
5: Device-SBS association matrix X.
6: Resource block matrix Y.
7: **Initialization**
8: Set $k = 0, \epsilon_1, \epsilon_2 > 0$.
9: Find initial feasible solutions $(x^{(0)}, y^{(0)})$.
10: **repeat**
11:    **Association Phase**
12:    Compute $x^{(k+1)}$ from (**P-1**) at given y^k.
13:    **Resource Allocation Phase**
14:    Compute $y^{(k+1)}$ from (**P-2**) at given $x^{(k+1)}$.
15: **until** Convergence.

The optimization problem **P-1** is an integer linear programming problem, which can be relaxed to a problem whose solution is within a constant approximation from the optimal. The fractional solution is then rounded to get a solution to the original integer problem. Accordingly, the optimization problem in (24) can be approximated as follows:

$$\underset{X}{\text{minimize}} \ C_{DFL}(X) \quad (25a)$$

$$\text{subject to} \sum_{u \in \mathcal{U}_i} x_i^{u \to b_i} \leq \Delta_{b_i}, \quad \forall b_i \in \mathcal{B}_i, \quad \forall i \in \mathcal{I},$$

$$\quad (25b)$$

$$\sum_{b_i \in \mathcal{B}_i} x_i^{u \to b_i} \leq 1, \quad \forall u \in \mathcal{U}_i, \ \forall i \in \mathcal{I}, \quad (25c)$$

$$0 \leq x_i^{u \to b_i} \leq 1 \quad \forall i \in \mathcal{I}, u \in \mathcal{U}_i. \quad (25d)$$

To solve the optimization problem in (25), we first analyze its convexity in the following lemma.

Lemma 1: For a given y, (25) is a convex optimization problem.

Proof: We first prove the convexity of the objective function $C_{DFL}(X)$ with respect to X. Then, we prove the convexity of the feasible region. We can notice that both $T(X)$ and $E(X)$ are linear functions in x which are convex functions for $0 \leq x \leq 1$. Therefore, C_{DFL} is a convex function as it is a summation of two convex functions. Moreover, the constraints (25b) and (25c) are linear constraints. Therefore, (25) is a convex optimization problem. ∎

According to lemma 1, we can obtain an optimal solution for (25) using the standard convex optimization toolkits, e.g. CVXPY. Next, we use the threshold rounding technique to convert the relaxed x to be a binary form. Let $\eta_x \in [0, 1]$ be a rounding threshold, we set x_i^{u*} as

$$x_i^{*u \to b} = \begin{cases} 1, & \text{if } x_i^{*u \to b} \geq \eta_x, \\ 0, & \text{otherwise.} \end{cases} \quad (26)$$

B. RESOURCE BLOCKS ALLOCATION PROBLEM

In this sub-section, we formulate the resource block alloca-tion sub-problem for fixed devices association. For any given devices association matrix X, (23) can be written as follows:

$$P-2: \quad \underset{Y}{\text{minimize}} \, C_{DFL}(Y) \tag{27a}$$

$$\text{subject to} \sum_{i \in \mathcal{I}} \sum_{u \in \mathcal{U}_i} y_i^{u \to b_i}(r) \leq 1, \quad \forall r \in \mathcal{R}, \tag{27b}$$

$$\sum_{r \in \mathcal{R}} y_i^{u \to b_i}(r) \leq 1, \quad \forall i \in \mathcal{I}, \, u \in \mathcal{U}_i, \tag{27c}$$

$$\sum_{r \in \mathcal{R}} y_i^{u \to b_i}(r) \leq 1, \quad \forall i \in \mathcal{I}, \, u \in \mathcal{U}_i, \tag{27d}$$

$$\sum_{r \in \mathcal{R}} \sum_{i \in \mathcal{I}} \sum_{u \in \mathcal{U}_i} y_i^{u \to b_i}(r) \leq R, \tag{27e}$$

$$y_i^{u \to b_i}(r) \in \{0, 1\} \quad \forall i \in \mathcal{I}, \, u \in \mathcal{U}_i. \tag{27f}$$

Similar to **P-1**, **P-2** is an integer linear programming problem which becomes NP-had for large number of devices and SBSs. Therefore, for a simple solution, we use a relaxation-based technique to compute the resource block allocation matrix Y. First, we relax the problem (27b) as follows:

$$\underset{Y}{\text{minimize}} \, C_{DFL}(Y) \tag{28a}$$

$$\text{subject to} \sum_{i \in \mathcal{I}} \sum_{u \in \mathcal{U}_i} y_i^{u \to b_i}(r) \leq 1, \quad \forall r \in \mathcal{R}, \tag{28b}$$

$$\sum_{r \in \mathcal{R}} y_i^{u \to b_i}(r) \leq 1, \quad \forall i \in \mathcal{I}, \, u \in \mathcal{U}_i, \tag{28c}$$

$$\sum_{r \in \mathcal{R}} y_i^{u \to b_i}(r) \leq 1, \quad \forall i \in \mathcal{I}, \, u \in \mathcal{U}_i, \tag{28d}$$

$$\sum_{r \in \mathcal{R}} \sum_{i \in \mathcal{I}} \sum_{u \in \mathcal{U}_i} y_i^{u \to b_i}(r) \leq R, \tag{28e}$$

$$0 \leq y_i^{u \to b_i}(r) \leq 1 \quad \forall i \in \mathcal{I}, \, u \in \mathcal{U}_i. \tag{28f}$$

We prove the convexity of the optimization problem in (28) in the following lemma.

Lemma 2: For a given x, (28) is a convex optimization problem.

Proof: We can notice that the objective function of (28) is a summation of two linear functions in Y. Hence, $C_{DFL}(Y)$ is a convex function for $0 \leq Y \leq 1$. Moreover, the constraints (28b), (28c), (28d), (28e), and (28b) are linear inequality constraints. Thus, the problem in (28) is a convex optimization problem. ∎

An optimal solution can be obtained for (28) using the stan-dard convex toolkits as it is a convex optimization problem. Finally, a rounding technique is used to obtain a binary form of the realxed variable y. We set y_{iu}^* as

$$y_i^{*u \to b} = \begin{cases} 1, & \text{if } y_i^{*u \to b} \geq \eta_y, \\ 0, & \text{otherwise,} \end{cases} \tag{29}$$

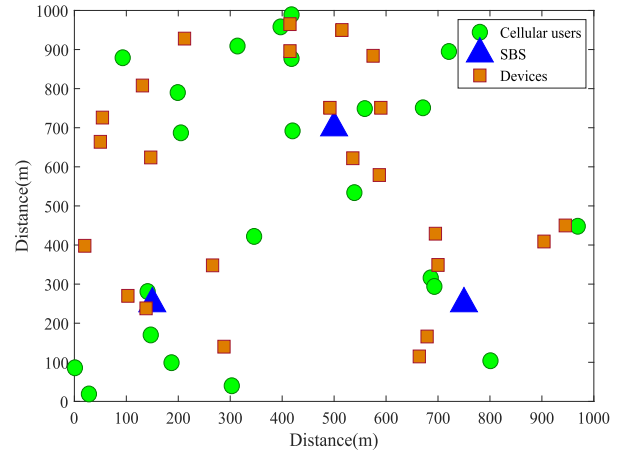where $\eta_y \in [0, 1]$ is a rounding threshold.

FIGURE 3. Sample simulation scenario.

V. PERFORMANCE EVALUATION

In this section, we present numerical results for the validation of our proposed DFL. For comparison, we use two baseline algorithms. Baseline-1 uses the proposed device association scheme and random resource allocation, whereas baseline-2 uses proposed resource allocation and random device asso-ciation. We consider the LTE-based network that consists of three SBS for one industry deployed at fixed locations in an area of $1000 \times 1000 \, m^2$. The sample simulation scenario for 3 SBS, 30 industrial devices, and cellular users each, are shown in Fig. 3. A single MBS is deployed with cellular users equal in the number to industrial devices. The devices used for training of FL models are deployed randomly according to uniform distribution and all the values are computed using an average of 30 different runs for different positioning of indus-trial devices and cellular users. Other simulation parameters are given in Table. 1.

TABLE 1. Simulation parameters [33].

Simulation Parameter	Value
Industrial network area	$1000 \times 1000 m^2$
Industrial devices	30
Cellular users	30
Frame Structure	Type 1 (FDD)
Carrier frequency (f)	2 GHz
Devices transmit power	23 dBm
Sub carriers per resource block	12
Resource block bandwidth (W)	180 kHz
Thermal noise for 1 Hz at 20. C	-174 dBm

Fig. 4a shows C_{DFL} vs. iterations using 42 devices and 3 SBSs for proposed, baseline-1, and baseline-2 schemes. It is clear from Fig. 4a that all the three algorithms converge rapidly with an increase in numbers of iterations. The reason for the lowest cost C_{DFL} of the proposed scheme compared to baseline-1 and baseline-2 is because of the fact that it consid-ers both resource allocation and device-SBS association. The reason for the lower cost of baseline-1 than baseline-2 is due to the dependency of C_{DFL} more on device-SBS association
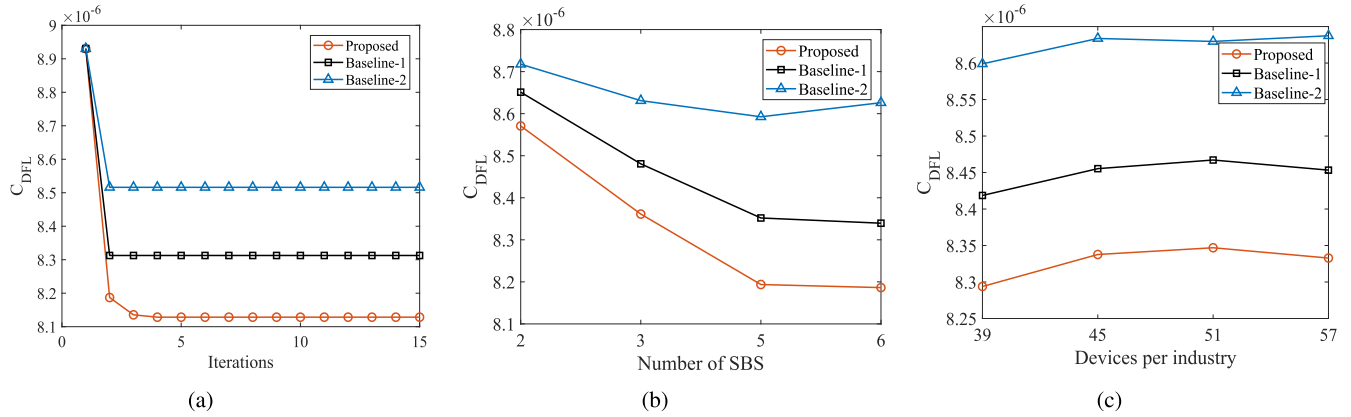
FIGURE 4. (a) C_{DFL} vs. iterations for $\alpha = 0.5$, (b) C_{DFL} vs. SBS for $\alpha = 0.5$ and 30 devices, (c) C_{DFL} vs. devices for $\alpha = 0.5$ and 3 SBS.

than resource allocation. For both baseline-1 and baseline-2, C_{DFL} converges in the first iteration because of the fact that output vector (e.g., X) of the CVX optimizer does not change with further increase number of iterations for a fixed value of another vector (e.g., Y).

Fig. 4b shows variations in C_{DFL} with an increase in number of SBSs for 30 devices. The proposed scheme outperformed both baseline-1 and baseline-2. The reason for the decrease in cost C_{DFL} with an increase in the number of SBSs is the overall throughput enhancement. For a higher number of SBSs, the devices will have more chances to connect to nearby SBSs, and thus there will be less path loss. Such type of low path loss results in overall high throughput which causes a reduction in cost C_{DFL}. One thing must be noted here that for a fixed area and a fixed number of devices, increasing the number of SBSs beyond a certain number does not cause a significant decrease in cost C_{DFL}. The reason is the existing number of SBSs is sufficient to serve the fixed number of devices with high throughput. For instance, consider two different cases of 5 SBS and 6 SBS serving a fixed number of devices in a fixed area. For 6 SBS case, the probability for devices to achieve high throughput by getting connectivity to the nearby SBS almost remain similar to 5 SBS case. Furthermore, increasing the number of SBSs causes an increase in deployment cost. Therefore, we must make a trade off between the number of SBSs and devices vs. performance. On the other hand, Fig. 4c shows the variations in C_{DFL} with an increase in number of devices for constant $\alpha = 0.5$ and 3 SBSs. There is an increasing trend in cost for all three schemes with an increase in the number of devices for a fixed number of SBSs. Similar to Fig. 4b, the proposed algorithm outperformed baseline-1 and baseline-2 for different numbers of devices and fixed numbers of SBSs.

Finally, we analyze the convergence of the proposed algorithm using training loss vs. communication rounds and accuracy vs. communication rounds for 50 industrial devices and 5 SBS in Figs. 5 and 6. We use MNIST dataset which contains images of handwritten digits and perform image classification task [34], [35]. It is clear that the proposed scheme converges fast for different number of sub-global iterations.
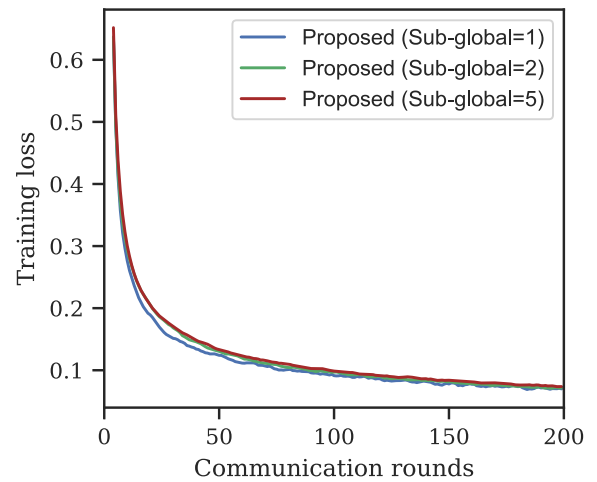

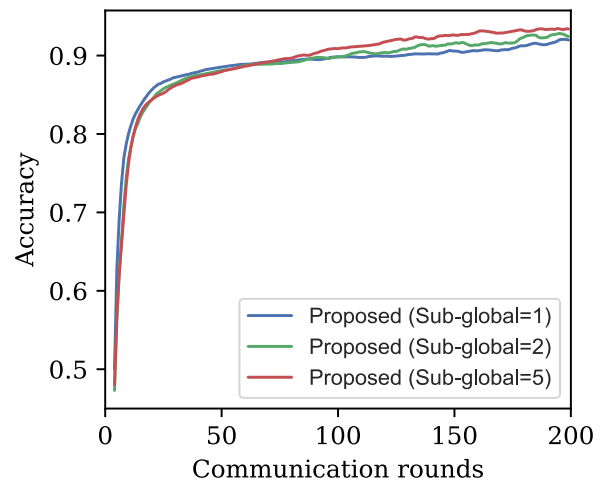**FIGURE 5.** Training loss vs. communication rounds.

FIGURE 6. Accuracy vs. communication rounds.

Generally, increasing the number of sub-global model iterations causes performance improvement. However, increasing the number of sub-global model iterations is at the cost of communication and local computation resources. In DFL,

we reuse already occupied communication resources by cellular users to enable communication resources efficient operation. The proposed FL scheme offers a trade-off between the sub-global model iterations and global communication rounds. For a fixed accuracy, increasing the number of subglobal iterations causes a decrease in global communication rounds, and vice versa.

VI. CONCLUSION

In this article, we have proposed a novel collaborative federated learning framework for smart industries. We have formulated an integer linear programming problem. To solve the formulated problem, we have used a decomposition and relaxation-based algorithm. Additionally, we have proved the convexity of the sub-problems and solve them using a convex optimization solver. Numerical results have shown fast convergence of the proposed decomposition and relaxation-based algorithm. Furthermore, we have tested the training loss and accuracy of the proposed FL scheme. Therefore, we can conclude that the proposed DFL scheme can be effectively used in future smart industries for enabling various smart functions while preserving the users' privacy. We have shown that the joint optimization of device association and resource block allocation can significantly improve the performance of FL for smart industries.

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