Low-Latency Cooperative Spectrum Sensing via Truncated Vertical Federated Learning

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Abstract—In recent years, the exponential increase in the demand of wireless data transmission rises the urgency for accurate spectrum sensing approaches to improve spectrum efficiency. The unreliability of conventional spectrum sensing methods by using measurements from a single secondary user (SU) has motivated research on cooperative spectrum sensing (CSS). In this work, we propose a vertical federated learning (VFL) framework to exploit the distributed features across multiple SUs without compromising the data privacy. However, the repetitive training process in VFL faces the issue of high communication latency. To accelerate the training process, we propose a truncated vertical federated learning (T-VFL) algorithm, where the training latency is highly reduced by integrating the standard VFL algorithm with a channel-aware user scheduling policy. The convergence performance of T-VFL is provided via mathematical analysis and justified by simulation results. Moreover, to guarantee the convergence performance of the T-VFL algorithm, we conclude three design rules on the neural architectures used under the VFL framework, whose effectiveness is proved through simulations.

I. INTRODUCTION

Since the emergence of wireless communication technology, the reuse of radio spectrum resources has remained as an inherent issue. The usage of the spectrum resources is regulated by the Federal Communications Commission (FCC), according to whom cognitive radio is defined as an intelligent device that can sense the environment and autonomously adjust its radio operating parameters. A key functionality provided by cognitive radio is opportunistic spectrum access (OSA), where non-licensed secondary users (SUs) are allowed to utilize the idle licensed spectrum resources to maximize its performance objectives. To this end, accurate and informative spectrum sensing results are crucial. However, conventional spectrum sensing by cognitive radio devices faces the issue of reliability of measurements made by a single user. The signals emitted from the primary users (PUs) are coupled with multi-path fading and shadowing, making the SUs unable to detect the PUs’ states from its measurements in a certain moment or location [1].

To provide more reliable detection on the PUs’ states, cooperative spectrum sensing (CSS) has been proposed in the existing literature, divided into two categories according to the decision modes, i.e., hard decision and soft decision. In the hard decision mode, each SU makes binary decision based on threshold levels and then sends it to the server for final decision. On the other hand, intermediate features are extracted and uploaded to the server for the soft decision mode, where every local measurement contributes to the final decision. The informative intermediate features make the soft decision mode more accurate and robust compared to the hard decision mode. A straightforward approach under the soft decision mode is to upload the exact received signal strength (RSS). An optimal linear fusion algorithm was also proposed in [2]. However, uploading the raw measurements encounters privacy issues, e.g., the server can infer the SUs’ locations based on the local RSS information if uploaded. Addressing this issue has motivated researchers to apply federated learning that preserves data privacy to CSS. As originally proposed for the federated learning, the federated learning framework offloads partial data processing procedures to the SUs [3], [4] for privacy protection, which also helps exploit the distributed computation resources. In this work, we adopt the vertical federated learning (VFL) framework [5] in view of the fact that at each time slot, the RSSs measured at each SU can be considered as partial features of the PUs’ states. In the existing literature, early attempts to apply VFL to the CSS task have been made in [6], [7]. The authors in [6] adopt the hard decision mode with scalar local output. In [7], a VFL design with the soft decision mode is considered and a RNN-based model is used to exploit the time consistency of data samples. However, in the above works [5]–[7], the authors consider the case that all SUs participate in each round, where all local models and the central model are trained with the aid of data exchange between the server and the SUs. In this case, high communication latency takes place once if some wireless links experience deep channel fadings. The repetitive communication during the training process makes
communication latency the bottleneck [3]. Therefore, the main challenge of deploying the VFL framework in a wireless network is how to achieve fast convergence under limited communication and computation resources.

In view of the drawbacks of the existing works, in this paper we propose a VFL framework to detect the PUs’ states, including their transmit power levels and locations. To minimize the total training latency, which consists of the communication and computation latency through the whole training process, we propose a truncated VFL (T-VFL) algorithm by integrating the standard VFL algorithm with a channel-aware user scheduling policy. The convergence performance of the T-VFL algorithm is provided through both analysis and simulations. Moreover, to cope with the scheduling policy, we also provide some design rules on the neural architectures used under the VFL framework to ensure fast convergence. The key contributions of this work is concluded as follows.

- **Low-Latency VFL via User Scheduling**: The standard VFL algorithm requires updating the whole deep neural network (DNN) in each round, which brings in high communication latency when some SUs experience deep channel fading. To tackle this problem, we propose the T-VFL algorithm. By scheduling SUs with channel gains above a given threshold, the per-round communication latency can be highly reduced. The effect of the proposed user scheduling policy on the convergence speed is also described mathematically in virtual of learning theory.

- **Neural Architecture Designs**: Based on the convergence analysis, we draw an upper bound on the total training latency of the T-VFL algorithm. The bound clearly shows the effect of different wireless parameters, according to which we give some design rules on neural architectures to enhance its convergence performance. We show by simulations that the T-VFL algorithm outperforms the standard VFL algorithm with an arbitrary activation ratio when using the proposed neural architectures.

II. **COLLABORATIVE SPECTRUM SENSING MODEL**

In this section, we present the model of a distributed wireless communication system, design the CSS algorithm, and describe its implementation in the system.

A. **Distributed Wireless Communication System**

We consider a cellular network with an arbitrary number of PUs and K SUs. In each time slot, the licensed spectrum is partially or fully occupied by the PUs for communication. To fully exploit the spectrum resources without interfering the communication quality of the PUs, the SUs can reuse the spectrum once it is idle or the active PUs are far away. To this end, the SUs need to first detect the states of the PUs, i.e., their locations and transmit power levels.

Following the idea of cognitive radio, the states of the PUs can be inferred by exploiting the RSSs at the SUs [1], [2], which are interpreted as implicit features. For the RSSs at each SU, the signal propagation paths are determined by the environment between the PUs and the SU. Hence the RSSs follow distinct distributions at different SUs, indicating that the features observed at different SUs are not fully overlapped with each other. Intuitively, by intelligently combining the features across all SUs, the PUs’ states can be detected with higher accuracy than using features from a single SU. In practice, the correlation among features at different SUs is usually unknown, which calls for a general solution to the CSS problem by taking all the features equally as direct input information for decision. By exploiting the advantage of supervised learning techniques which train neural networks using labeled data without any constraint or assumption on the input features, we present a VFL framework and its deployment in the wireless system in the sequel.

B. **Collaborative Spectrum Sensing Algorithm**

1) **Machine Learning Model**: Suppose the data collection process lasts for M time slots where each SU records the RSSs and its own location at the current time slot as the local features. In this case, the local dataset at each SU k is denoted as \( \{ x^k_i \in \mathbb{R}^{d_k \times 1} \}_{i=1}^{M} \), consisting of M feature vectors of dimension \( d_k \). The PUs’ states are identical to all SUs at a given time slot, while the propagation paths depend on the environment around each SU, making the local features distinct across the SUs. To improve the accuracy of estimating the state of the PUs, we propose the following VFL framework, where the features from all SUs are concatenated as a complete data sample for inference.

Denote the complete feature vector sampled at time slot \( i \) as \( x_i = [x^1_i^T, \ldots, x^K_i^T]^T \), and suppose the associated label \( y_i \) is available at the server. Hence the complete data sample \( i \) is given as \( D_i = \{ x_i, y_i \} \), and the global dataset is denoted as \( D = \{ D_i \}_{i=1}^{M} \). The idea of VFL is to train a DNN which is divided into \( K+1 \) parts and distributed across the SUs and the server. Each SU owns a local model with parameters denoted as \( \theta_k \) and the server owns a central model with parameters denoted as \( \theta_0 \). All the \( K+1 \) models constitute the whole DNN, given as \( \Theta = \{ \theta_0, \ldots, \theta_K \} \). The cooperative training problem can be formulated as

\[
(P1) \quad \min_{\Theta} \mathcal{L}(\Theta; D) = \frac{1}{2M} \sum_{i=1}^{M} \ell(\theta_0, \ldots, \theta_K; D_i) + \lambda \sum_{k=0}^{K} \gamma(\theta_k),
\]

where \( \gamma(\cdot) \) denotes the regularizer and \( \lambda \) is the hyperparameter.

Training the whole DNN requires multiple rounds of communication between the server and SUs, where each round is divided into a forward and backward transmission phases. We give an example to illustrate the training process in each round. Without loss of generality, we use mean squared error (MSE) as the loss function and the round index \( t \) is omitted.

- **Forward Phase**: For each data sample \( i \), each SU feeds its local feature vector \( x^k_i \) into the local model \( \theta_k \), which outputs an intermediate result \( p^k_i = c_k(\theta_k; x^k_i) \). Then the intermediate results at all SUs are uploaded to the server as the input to the central model \( \theta_0 \). The output of
the central model is denoted as \( \hat{y}_t = C_2(\theta_0; p_1, \ldots, p^K) \), based on which the function loss is expressed as

\[
L(\Theta; D) = -\frac{1}{M} \sum_{i=1}^{M} || y_i - \hat{y}_i ||^2 + \lambda \sum_{k=0}^{K} \gamma (\theta_k).
\]  

(1)

**Backward Phase:** With the loss value calculated according to (1), the gradient of the central model can be obtained at the server as \( g(\theta_0) = \frac{\partial L(\Theta; D)}{\partial \theta_0} \). To calculate the local gradient for the model at SU \( k \), whose expression is given as \( g(\theta_k) = \frac{\partial L(\Theta; D)}{\partial \theta_k} \). The server sends the information of \( \frac{\partial L(\Theta; D)}{\partial \theta_k} \) to SU \( k \) and \( \frac{\partial \theta_k}{\partial \theta_k} \) can be computed locally. Then all the SUs and the server update their model using gradient descent as

\[
\theta_k \leftarrow \theta_k - \eta g(\theta_k), \quad k = 0, \ldots, K,
\]

with step-size \( \eta \).

**C. Transmission Model**

As described in the previous subsection, the whole DNN is updated in each round, which requires frequent information exchange via wireless links. Specifically, all devices upload the intermediate results calculated using the latest local models to the server in the uplink, and the server sends the gradient of the input link layer in the central model to SUs in the downlink to facilitate the local gradient calculation and model update. We consider the downlink transmission the high SNR case with negligible error and only focus on the uplink phase.

Consider the uplink phase of an arbitrary round. Assume that the local outputs of each SU are of the same dimension \( d \), and each output symbol is represented by \( q \) bits after quantization. By using BPSK modulation, \( D = q Md \) symbols need to be transmitted at each SU when \( M \) data samples are used for training. The channel coefficient from server to SU \( k \) in round \( t \) is denoted as \( H_{k,t} = \sqrt{p_{k,t}h_{k,t}} \), where \( p_{k,t} = \phi_{k,t}d_{k,t}^\kappa \) is the large-scale fading coefficient with shadowing factor \( \phi_{k,t} \) and pathloss exponent \( \kappa \), and \( h_{k,t} \sim CN(0,1) \) represents the small-scale fading coefficient. Then the \( i \)-th symbol received at the server in round \( t \), denoted as \( y_{k,t}^{(i)} \in C^{D \times 1} \), is given as

\[
y_{k,t}^{(i)} = H_{k,t}p_{k,t}s_{k,t} + z_{k,t}, \quad 1 \leq k \leq K, \quad t \geq 1,
\]

(3)

where \( s_{k,t} \in \mathbb{C}^{D \times 1} \) is the symbols transmitted by device \( k \), in which each element has unit variance. The complex Gaussian vector \( z_{k,t} \in \mathbb{C}^{D \times 1} \) is the noise vector, with each element of zero mean and variance \( \sigma^2 \). Let \( B \) be the bandwidth allocated to each SU for transmission, the achievable data transmission rate of the link from SU to server is given by

\[
r_{k,t} = B\log_2 \left( 1 + \frac{p_{k,t}^2 H_{k,t}^2}{\sigma^2} \right),
\]

(4)

where \( p_{k,t} \) is the power coefficient. The transmission of each SU is subject to an average power constraint:

\[
\mathbb{E}_t[p_{k,t}^2] \leq P,
\]

(5)

for a given constant \( P \), which can be further simplified as \( \mathbb{E}_t[p_{k,t}^2] = P \).

**D. User Scheduling Policy**

Note that the server needs to collect the intermediate results from all SUs before subsequent computing using the central model. Therefore, the communication latency is determined by the SU with the lowest transmission rate. Hence it is power-efficient to align the transmission rate of all SUs since scheduling other SUs with high transmission rates does not accelerates process. To this end, we propose the following user scheduling policy evolved from the so-called truncated channel inversion scheme [8] to align the transmission rates and avoid high communication latency due to severe channel fadings. Specifically, the power coefficient in (4) is given as

\[
p_{k,t} = \begin{cases} \sqrt{P_{k,t}^\star}, & |h_{k,t}|^2 \geq G_{k,t}, \\ \sqrt{P_{k,t}}, & |h_{k,t}|^2 < G_{k,t}, \\ 0, & \end{cases}
\]

(6)

where \( G_{k,t} \) is the truncation threshold. To fulfill the average power constraint in (5), it can be obtained that \( P_{k,t}^\star = \frac{P_k}{E_i(G_{k,t})} \), where \( E_i(X) = \int_X \frac{1}{2} \exp(-x^2) dx \), and \( \hat{E}_i(G_{k,t}) \) represents the activation ratio of SU \( k \). Note that \( P_{k,t}^\star \) determines the received SNR and the transmission rate, we require

\[
\frac{P_{k,t}}{E_i(G_{k,t})} = \frac{\hat{p}_{k,t}}{E(G_{k,t})},
\]

(7)

Without loss of generality, we suppose SU 1 suffers the deepest channel fading. Moreover, the large-scale fading coefficients \( \{p_{k,t}, \forall k, t\} \), which keep unchanged over multiple time slots, are usually easy to be obtained at the server a prior. Then we control the activation ratio of the SUs by tuning the truncation threshold \( G_{1,t} \) of SU 1. The truncation thresholds of other SUs can be adjusted according to (7) by numerical search given that \( E_i() \) is a monotonic function.

The SUs with channel gain lower than their truncation thresholds are silenced in the current round. The server uses the latest intermediate results received from the silenced SUs. The proposed user scheduling policy prevents high communication latency in each round. However, by cutting down the number of active SUs, it also has an effect of slowing down the convergence of the training process, which is mathematically depicted in Theorem 1 in the sequel.

## III. CONVERGENCE ANALYSIS

To give a tractable analysis on the VFL framework, we first adopt the following two assumptions.

**Assumption 1** (Lipschitz Smoothness).

\[
\nabla L(\Theta_{t+1}) - \nabla L(\Theta_t) \leq L(\Theta_{t+1} - \Theta_t), \quad \forall \Theta_t, \Theta_{t+1}.
\]

(8)

**Assumption 2** (Convexity).

\[
\nabla L(\Theta_{t+1}) - \nabla L(\Theta_t) \geq \mu(\Theta_{t+1} - \Theta_t), \quad \forall \Theta_t, \Theta_{t+1}.
\]

(9)

**Assumption 3** (Limited Range).

\[
|L(\Theta_{t+1}) - L(\Theta_t)| \leq C, \quad \forall \Theta_t, \Theta_{t+1}.
\]

(10)
Assumption 4 (Limited Variance). By using constant batch size, the gradient variance is bounded by
\[ \text{Var}[\nabla L(\Theta_t)] \leq c, \quad \forall \Theta_t. \] (11)

By exploiting the above assumptions, we have the following theorem on the convergence rate of the VFL algorithm.

Theorem 1 (Convergence Rate). By scheduling an active set of users \( K_A(t) \) to participate in the learning process in each round, the convergence rate of the VFL algorithm is given as
\[ \mathbb{E}[L(\Theta_{t+1})] - L(\Theta^*) \leq \left[ 1 - \frac{\mu v + \mu L}{\mu v + \mu L} \right] \mathbb{E}[L(\Theta_t)] - L(\Theta^*) + \frac{c}{2\mu v}, \] (12)
with step-size \( \eta \leq \frac{1}{4} \). The factor \( v \) is a lower bound given as
\[ v \leq t_0 + \sum_{k \in K_A} v_{k,t}, \quad \forall t, \] (13)
where \( v_{k,t} = \frac{1}{\sum_{k \in K} \|\nabla_k L(\Theta_{k,t})\|^2} \).

Proof. Please refer to Appendix A.

Theorem 1 shows the convergence properties of the training process. The coefficient \( 1 - \frac{\mu v + \mu L}{\mu v + \mu L} \) describes the speed of the reduction on \( \mathbb{E}[L(\Theta_t)] - L(\Theta^*) \). The bound \( v \) depicts the effect of user scheduling on the convergence rate, and thereby called as the effective activation level.

IV. NEURAL ARCHITECTURE DESIGNS FOR FAST CONVERGENCE

In this section, we first derive the per-round latency and the number of rounds required to achieve a given accuracy, based on which the expression of the total training time is also obtained. Then we propose neural architecture designs, which are able to accelerate the VFL algorithm when combined with the truncated channel inversion scheme. The effectiveness of the designs are verified through simulations in the next section.

Per-round Latency: By adopting the truncated channel inversion scheme in Sec. II-C, the per-round communication latency during the VFL training process is
\[ T_{\text{comm}} = \frac{qM}{B \log_2(1 + \frac{\rho_i}{\sigma^2 \mathbb{E}[\Theta_i])}}, \] (14)
which is the communication latency of transmission from SU 1 to the server. The computation time at the SUs, denoted by \( T_{\text{comp}} \), is proportional to the size of local model and thereby considered to be constant in each round. The total latency of each communication round is then given as \( T_{\text{total}} = T_{\text{comm}} + T_{\text{comp}} \).

Number of Rounds: According to Theorem 1, we have the following lemma on the number of rounds required to achieve a given accuracy.

Lemma 1. To achieve \( \varepsilon \)-accuracy, defined as \( \mathbb{E}[L(\Theta_t)] - L(\Theta^*) \leq \varepsilon \), the expected number of rounds required for the training process is upper-bounded by
\[ N_{\text{expect}} \leq \ln \left( \frac{c}{c - \frac{\mu v + \mu L}{\mu v + \mu L}} \right) / \ln (1 - \frac{\mu v + \mu L}{\mu v + \mu L}). \] (15)

Proof. The result can be directly derived from (12).

According to the above derivation, the total training time can be upper bounded by
\[ T_{\text{expect}} \leq N_{\text{expect}} T_{\text{round}} \]
\[ \leq \frac{qM}{B \log_2(1 + \frac{\rho_i}{\sigma^2 \mathbb{E}[\Theta_i])}} + T_{\text{comp}} \times \ln \left( \frac{c}{c - \frac{\mu v + \mu L}{\mu v + \mu L}} \right) / \ln (1 - \frac{\mu v + \mu L}{\mu v + \mu L}). \] (16)
This upper bound clearly describes the effects of wireless parameters, e.g., the truncation threshold \( G_t \), the effective activation level \( v \) and the accuracy \( \varepsilon \), on the total training time of the VFL algorithm. Moreover, it provides a feasible approach to reduce the training time by minimizing the upper bound in (16). However, direct optimization on the theoretical bound is not an appropriate solution due to the following several reasons. Firstly, the effects of some parameters on the total training time are complicated. For example, it can be observed that the truncation threshold \( G_t \) plays a key role. It not only scales the SNR with a factor \( 1/\mathbb{E}[\Theta_i] \), but also has an effect on the effective activation level \( v \) which is difficult to characterize, making the optimization problem intractable. Secondly, the theoretical bound is valid only when the assumptions in Sec. III strictly hold, which may not be exactly the case in practice. Moreover, it is difficult to obtain the knowledge of hyperparameters \( \mu \) and \( L \) a priori. In view of the above facts, we propose a neural architecture design to accelerate the training process for general cases as follows.

Design Rule 1: The dimension of the local output features \( d \) determines the communication overhead in each round, which thereby should be chosen as small as possible. To be specific, \( d \) can be set slightly larger than the number of features necessary for subsequent decision at the server, which can be estimated empirically according to the type of the task and data samples.

Design Rule 2: The weight of \( v_{0,t} \) in the effective activation level \( v \) should be set as the largest value in its feasible range. Since \( v_{0,t} = \sum_{k \in K} \frac{\|\nabla_k L(\Theta_{k,t})\|^2}{\|\nabla_k L(\Theta_{k,t})\|^2} \) depends on the gradient power of the central model at the server, which cannot be controlled during the training process, we increase the weight of \( v_{0,t} \) in an intuitive way by using neural networks with larger size at the server. The feasible range of the central model size is further discussed in Remark 1.

Design Rule 3: Given that \( v_{0,t} \) is dominant in \( v \), an increase on the truncation threshold \( G_t \), or a reduction on the activation ratio, has a positive effect on shortening the total training latency if it comes to the extreme case where the probability that all SUs are truncated tends to 1.

The principles behind the design rules 2 and 3 are further elaborated as follows. Firstly, a higher truncation threshold \( G_t \) leads to lower communication latency and a smaller effective activation level \( v \) which requires more training rounds to achieve the \( \varepsilon \)-accuracy. This makes the choice on \( G_t \) very crucial. However, as we can observe from (13), the presence of \( v_{0,t} \) is independent of user scheduling, which corresponds
to the property of the VFL framework that the central model is updated in each round. Therefore, a larger \( \nu_{0,t} \) alleviates the effect of user scheduling on the effective activation level. In this sense, it is favorable to keep \( \nu_{0,t} \) dominant so that we can tune the truncation threshold \( G_{1,t} \) within a large range without affecting the number of rounds much.

**Remark 1 (Feasible Range of the Central Model Size).** When increasing the size of central model at the server according to the Design Point 2, it usually requires smaller local models to prevent over-fitting. However, a too small local model can lose too much information of the input feature and distort the final decision at the server. Therefore, we only manipulate the size of the central model within an empirical feasible range.

V. Simulations

We consider a typical wireless network with 400m \( \times \) 400m area, where 4 SUs keep detecting the states of 2 PUs, as illustrated in Fig. 1. Each PU has 3 optional transmit power levels \{1, 2, 3\}. The pathloss exponent is 4 and a 3dB shadowing effect is considered. The SUs collect the RSSs and their own locations as local feature vectors across multiple time slots, where the channel states and the locations of all SUs and PUs keep to be constant within 1 time slot. Each time slot is further divided into 200 mini-slots, where the RSS in each mini-slot is recorded as a feature at each SU. For each SU, a local feature vector is of 203 dimensions which consists of the SU’s own 3D location and 200 RSSs within 1 time slot. The label of each data sample has 8 dimensions, consisting of the transmit power levels and the 3D locations of the 2 PUs. The distribution of the users in the \( X \) – \( Y \) plane are illustrated in Fig. 1, where each user keeps moving within a rectangular region. The height of each location is a function of its coordinate in the \( X \) – \( Y \) plane as \( z = 10 \cdot [\sin(\frac{\pi x}{100}) + \cos(\frac{\pi y}{100})] \). We generate 60000 data samples, divided into a training set with 50000 samples and a testing set with 10000 samples. Fully-connected networks (FCNs) are used for models at each SU and the server, and the models at all SUs are identical. All tasks run on an Nvidia 1070Ti GPU, and we assume the computation capability of each SU is \( \frac{1}{4} \) of the server’s computation capability. We using VFL algorithm with a large activation ratio \( \epsilon_{1,t} = 0.9 \) as an approximation of the centralized learning algorithm, which is also used as the baseline for comparison.

Firstly, we show the convergence performance of the VFL algorithm in Fig. 2. We first use a neural architecture Network I, where a 3-layer FCN of size \( (203, 32, 8) \) is used at each SU and a 3-layer FCN of size \( (32, 24, 8) \) is deployed at the server. The step-size is \( \eta = 10^{-4} \). The activation ratio of SU \( 1 \) is set as \( \epsilon_{1,t} = \alpha \) with \( \alpha = \{0.9, 0.8, 0.6, 0.4, 0.2, 0.1\} \). It can be observed from Fig. 2(a) that when the activation ratio reduces, it requires more number of rounds to achieve the target accuracy, which coincides with the result in Theorem 1. The centralized learning algorithm, which is marked in blue, gives the fastest descent speed. On the other hand, in Fig. 2(b), we show the test accuracy versus the training latency. As the activation ratio reduces from 1 to 0, the training latency first reduces due to the reduction on communication latency, then it turns to increase when \( \epsilon_{1,t} \) is close to 0 because truncating most SUs highly increases the number of round required to converge. Note that an extreme activation ratio, e.g., \( \epsilon_{1,t} = 0.1 \), gives slower convergence compared with the baseline, which indicates that reducing the activation ratio is not always favorable under the neural architecture Network I.

Following the design rules in Sec. IV, we further propose another neural architecture Network II, where a 3-layer FCN of size \( (203, 32, 8) \) is used at each SU and a 3-layer FCN of size \( (32, 512, 8) \) is deployed at the server. The convergence performance of Network II is shown in Fig. 3. Compared with Network I, Network II features a larger central model, which shifts more computation load to the server. The architecture of Network II follows the Design Rule 2 in Sec. IV, where a large central model makes \( \nu_{0,t} \) dominant in \( v \). According to (16), by using the proposed architecture Network II, choosing the activation ratio within a large range, say \((0.1, 0.8)\), always gives a better performance compared to the baseline, which is not the case for Network I. Moreover, in Fig. 3, different...
unscheduled devices in round
the finite training dataset or mini-batch. When an active set of

A. Proof of Theorem 1

Figure 4: Detection accuracy on the transmit power level of PU 1.

Figure 5: 3D location detection error of the 2 PUs.

activation ratios give similar convergence rates, indicating that
an arbitrary activation ratio gives a near-optimal solution.
Therefore, the proposed neural architecture Network II is more
robust than Network I under practical situations.

In the next, we show the detection accuracy of the
proposed VFL algorithm on both PUs’ transmit power levels
and their locations. We compare the estimated PUs’ state and
and the labels.

VI. APPENDIX

A. Proof of Theorem 1

Given the L-smoothness in (8), the loss function follows

\[ L(\Theta_{t+1}) \leq L(\Theta_t) + \langle \Theta_{t+1} - \Theta_t, \nabla L(\Theta_t) \rangle + \frac{L}{2} \| \Theta_{t+1} - \Theta_t \|^2, \]  

(17)

In the same way, the µ-convexity also gives a result as

\[ L(\Theta_{t+1}) \geq L(\Theta_t) + \langle \Theta_{t+1} - \Theta_t, \nabla L(\Theta_t) \rangle + \frac{\mu}{2} \| \Theta_{t+1} - \Theta_t \|^2. \]  

(18)

By using gradient descent to update the model, we have

\[ L(\Theta_{t+1}) \leq L(\Theta_t) - \eta \| \nabla L(\Theta_t) \| - e - o \| \nabla L(\Theta_t) \| + \frac{L\eta^2}{2} \| \nabla L(\Theta_t) \| - e - o \| \nabla L(\Theta_t) \|^2, \]  

(19)

where \( e \) is the error in gradient due to the absence of
unscheduled devices in round \( t \) and \( o \) is the error introduced by
the finite training dataset or mini-batch. When an active set of
users \( K_A(t) \) is scheduled in round \( t \), the expected optimization function \( E[\mathcal{L}(\Theta_{t+1})] \) is bounded by

\[ E[\mathcal{L}(\Theta_{t+1})] \leq E\left[ L(\Theta_t) - \eta \sum_{k \in K_A(t) \cup \{0\}} \| \nabla k L(\Theta_t) \|^2 + \frac{L\eta^2}{2} \| \Theta_t - \Theta^* \|^2 \right] + \frac{L\eta^2}{2} \| o \|^2. \]  

(20)

where \( \nabla k L(\Theta_t) = \frac{\partial L(\Theta_t)}{\partial \Theta} \) is the gradient of parameters in
device \( k \)’s local model, and \( \| \nabla L(\Theta_t) \| = \sum_{k \in K_C(t) \cup \{0\}} \| \nabla k L(\Theta_t) \|^2 \). Moreover, by minimizing both sides of (18) in terms of \( \Theta \), we have the following inequality

\[ \min_{\Theta_{t+1}} L(\Theta_{t+1}) \geq \min_{\Theta_{t+1}} L(\Theta_t) + \langle \Theta_{t+1} - \Theta_t, \nabla L(\Theta_t) \rangle + \frac{\mu}{2} \| \Theta_{t+1} - \Theta_t \|^2. \]  

(21)

Minimizing both sides of the expression further gives

\[ E[\| \nabla L(\Theta_t) \|^2] \geq 2\mu E[\| L(\Theta_t) - L(\Theta^*) \|^2]. \]  

(22)

By plugging (22) into (20), we have

\[ E[\mathcal{L}(\Theta_{t+1})] \leq \left[ 1 - 2\mu \eta v (1 - \frac{L\eta^2}{2}) \right] E[\mathcal{L}(\Theta_t)] + \frac{L\mu}{2\eta} \]  

(23)

where \( v = \min\{\eta t, \forall t\} \). By choosing appropriately small
step-size \( \eta \leq \frac{1}{L} \), the convergence process can be further
described as

\[ E[\mathcal{L}(\Theta_{t+1}) - L(\Theta^*)] \leq \left[ 1 - \frac{\mu}{L} \right]^{t+1} E[\mathcal{L}(\Theta_t)] - L(\Theta^*)] + \frac{c}{2\mu \eta}. \]  

(24)

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