Optimization of User Selection and Bandwidth Allocation for Federated Learning in VLC/RF Systems

Chuanhong Liu∗, Caili Guo†, Yang Yang∗, Mingzhe Chen‡, H. Vincent Poor‡, and Shuguang Cui§∗†¶

∗Beijing Key Laboratory of Network System Architecture and Convergence, School of Information and Communication Engineering, Beijing University of Posts and Telecommunications, Beijing 100876, China.
Emails: {2016_liuchuanhong, yangyang01}@bupt.edu.cn.
†Beijing Laboratory of Advanced Information Networks, School of Information and Communication Engineering, Beijing University of Posts and Telecommunications, Beijing 100876, China, Email: guccaili@bupt.edu.cn.
‡Department of Electrical Engineering, Princeton University, Princeton, NJ, 08544, USA.
Emails: {mingzhec, poor}@princeton.edu.
§The Future Network of Intelligence Institute, The Chinese University of Hong Kong, Shenzhen, 518172, China.
¶Shenzhen Research Institute of Big Data, The Chinese University of Hong Kong, Shenzhen, 518172, China.
Email: shuguangcui@cuhk.edu.cn.

Abstract—Limited radio frequency (RF) resources restrict the number of users that can participate in federated learning (FL) thus affecting FL convergence speed and performance. In this paper, we first introduce visible light communication (VLC) as a supplement to RF in FL and build a hybrid VLC/RF communication system, in which each indoor user can use both VLC and RF to transmit its FL model parameters. Then, the problem of user selection and bandwidth allocation is studied for FL implemented over a hybrid VLC/RF system aiming to optimize the FL performance. The problem is first separated into two subproblems. The first subproblem is a user selection problem with a given bandwidth allocation, which is solved by a traversal algorithm. The second subproblem is a bandwidth allocation problem with a given user selection, which is solved by a numerical method. The final user selection and bandwidth allocation are obtained by iteratively solving these two subproblems. Simulation results show that the proposed FL algorithm that efficiently uses VLC and RF for FL model transmission can improve the prediction accuracy by up to 10% compared with a conventional FL system using only RF.

I. INTRODUCTION

FEDERATED learning (FL), which allows edge devices to cooperatively train a shared machine learning model without the direct transmission of private data, is an emerging distributed machine learning technique [1], [2]. During the FL training process, the model parameters need to be transmitted iteratively over wireless links. Due to the dynamic wireless channels and imperfect wireless transmission, the performance of FL will be significantly affected by wireless communication and the number of users that can participate in FL is limited. Therefore, it is necessary to optimize wireless network performance for improving FL performance and convergence speed.

A number of prior studies have considered the optimization of FL over wireless networks. These studies include the optimization of energy efficiency and communication cost [3]–[5], framework design and user selection [6]–[11]. Among these studies, user selection is one of the most challenging problems. This is because only a subset of users can participate in FL training due to the limited bandwidth resources, thus significantly affecting the FL performance. The authors in [9] provided a general introduction to FL and demonstrated that user selection is one of the challenges in FL due to the limited wireless bandwidth and users’ computation ability. The work in [5] showed that the number of users that participate in FL will significantly affect the performance of the trained model. A new client selection protocol referred to as federated learning with client selection (FedCS) was presented in [8]. However, the protocol in [8] cannot increase the number of selected users since the wireless radio frequency (RF) bandwidth is limited. The authors in [10] analyzed the effect of three practical scheduling policies on the performance of federated learning. We note that all of the existing works investigated the optimization of FL performance in RF only systems, which limits the number of devices that can participate in FL and thus affecting the FL performance. Visible light communication (VLC) can provide large, license-free bandwidth, hence, it can be a complement to RF in FL. Moreover, there is no interference between the RF and VLC systems, a key benefit of introducing VLC to future heterogeneous networks. Based on this observation, this work introduces VLC to enhance the capability of a conventional RF network to support FL, and investigates the FL performance optimization in the introduced hybrid VLC/RF system.

The main contribution of this paper is a joint user selection and bandwidth allocation algorithm that minimizes the training loss of FL implemented over the proposed hybrid VLC/RF system. To our best knowledge, this is the first work that introduces the use of VLC technique for FL performance optimization. The contributions are summarized as follows:

• We introduce VLC into conventional RF systems to improve FL performance. In the hybrid VLC/RF system, the bandwidth of RF and VLC must be appropriately allocated, which enables more users to participate in FL training. A joint user selection and bandwidth allocation problem is formulated, whose goal is to minimize the FL...
training loss.
- To solve this problem, we first separate it into two sub-problems. The first subproblem is a user selection problem with a given bandwidth allocation, which is solved by a traversal algorithm. Based on the obtained subset of selected users, the second subproblem is to find the optimal bandwidth allocation, which is solved by a numerical method. The two subproblems are then updated iteratively until a convergent solution is obtained.

Simulation results verify that the proposed algorithm in a hybrid system can obtain 20% and 10% gains in terms of the number of selected users and the model accuracy, respectively, when compared with a conventional FL system using only RF.

The remainder of this paper is organized as follows. In Section II, we introduce the hybrid VLC/RF system. Section III introduces the system model used in this work. The joint user selection and bandwidth allocation algorithm is described in Section IV. Simulation and numerical results are presented and discussed in Section V. Finally, Section VI draws some important conclusions.

II. DESIGN OF HYBRID VLC/RF SYSTEMS

In this section, we first review a traditional FL model based on an RF system and then summarize some challenges for training FL. To overcome these challenges, we then design a hybrid VLC/RF system for FL.

A. FL based on RF system

In this model, each user $n$ stores a local dataset $D_n$ with $D_n$ being the number of training data samples. Hence, the total number of training data samples of all users is $D = \sum_{n=1}^{N} D_n$. We assume that training data of user $n$ can be expressed by $\{x_n, y_n\}$ with $x_n = [x_{n1}, ..., x_{nD_n}]$ and $y_n = [y_{n1}, ..., y_{nD_n}]$, where each element $x_{ni}$ is an input vector of the FL algorithm and $y_{ni}$ is the output of $x_{ni}$.

For user $n$, the FL training purpose is to find the model parameter $\omega$ that minimizes the loss function:

$$J_n(\omega) := \frac{1}{D_n} \sum_{i \in D_n} f_{ni}(\omega),$$

where $f_{ni}(\omega)$ is a loss function that captures the performance of the FL algorithm. For example, for a linear regression FL, the loss function is $f_{ni}(\omega) = \frac{1}{2}(x_{ni}^T \omega - y_{ni})^2$.

Then, the goal is to minimize the following global loss function:

$$\min J(\omega) := \sum_{n=1}^{N} \frac{D_n}{D} J_n(\omega).$$

To solve (2), the BS will transmit the global FL model parameters to its users and users will use the received global FL model parameters to train their local FL models. Then, the users will transmit their trained local FL model parameters to the BS to update the global FL model. For strongly convex objective $J(\omega)$, the general upper bound on global iterations is $K(\epsilon, \theta)$.

$$K(\epsilon, \theta) = \frac{o(\log(\frac{1}{\epsilon}))}{1 - \theta},$$

where $\epsilon$ is the accuracy of global model and $\theta$ is the accuracy of local model. On the other hand, each global iteration consists of both computational and communication time. We consider a fixed global accuracy $\epsilon$. Besides, $o(\log(\frac{1}{\epsilon}))$ is normalized to 1 so that $K(\theta) = \frac{1}{1 - \theta}$ for ease of presentation.

Due to the limited wireless bandwidth, only a subset of users can be selected for FL training, which can seriously degrade the training accuracy. To enable more users to join the FL training process, we design a hybrid VLC/RF system.

B. FL based on hybrid VLC/RF system

Consider a cellular network that consists of one BS, home gateways, and users cooperatively performing an FL algorithm for data analysis and inference. Denote the total users by a set $N$ of $N$ users. Denote the indoor users by a set $N_1$ of $N_1$ users and the outdoor users by a set $N_2$ of $N_2$ users. In this work, we do not consider the mobility of users for simplicity. The system architecture is shown in Fig. 1. In this model, the BS will send the global FL model parameters to outdoor users by RF. Meanwhile, the BS transmits the global model parameters to the home gateways which are connected to the indoor VLC access points (APs). Then, the VLC APs transmit the global FL model parameters to indoor users through the visible light signal. Assuming that the BS and home gateways are connected by fiber on which the bit error can be negligible.

In indoor scenarios, each VLC AP consists of an LED lamp. Each user is served by the AP that provides the strongest signal. In addition, we assume that all indoor users can be covered by visible lights. It is assumed that there is a central unit (CU) which controls both VLC and RF systems. Note that there is no interference between the RF and VLC systems, which is a key benefit of introducing VLC to the future heterogeneous networks.

III. SYSTEM MODEL AND PROBLEM FORMULATION

In this section, we elaborate the time and energy consumption for training FL. In particular, the computational model is first given. Then the communication models of both RF and VLC are detailed. Finally, based on the established model, we formulate a user selection and bandwidth allocation problem in the proposed hybrid VLC/RF system.

A. Computational model

Let $c_n$ be the number of CPU cycles for user $n$ to process one sample of data. Since the data size of each training data sample is equal, the number of CPU cycles required for user $n$ to execute one local iteration is $c_n D_n$. Denote the CPU-cycle frequency of user $n$ by $f_n$. Then the CPU computational...
energy consumption of user $n$ in one global iteration can be expressed as follows:

$$E_{n}^{\text{comp}} = \sum_{i=1}^{c_{n}D_{n}} \frac{c_{n}D_{n}}{2} f_{n}^{2} = \nu c_{n}D_{n} \frac{f_{n}^{2}}{2} \log(1/\theta),$$  \hspace{1cm} (4)

where $n = 1, 2, \ldots, N$, and $\alpha_{n}$ is the effective capacitance coefficient of the computing chipset of user $n$, and $\nu$ is a positive constant that depends on the data size of training data sample and the number of conditions in the local problem [7].

Furthermore, the computation time per local iteration of user $n$ can be denoted as $\frac{d_{n}}{f_{n}}$, $n = 1, 2, \ldots, N$. The computation time, however, depends on the number of local iterations, which is upper bounded by $o(\log(1/\theta))$. Therefore, the required computation time of user $n$ for data processing is

$$t_{n}^{\text{comp}} = \frac{\nu c_{n}D_{n} \log(1/\theta)}{f_{n}}.$$  \hspace{1cm} (5)

B. RF Transmission Model

We use the orthogonal frequency division multiple access (OFDMA) technique for both uplink and downlink RF transmissions. The uplink rate of user $n$ is given by

$$r_{n}^{U} = \sum_{i=1}^{R_{n}^{U}} \sum_{j \in U_{n}^{i}} B_{n,j}^{U} \log_{2}(1 + \sum_{l \in U_{n}^{i}} P_{l} h_{l,n} + B_{n,j}^{U} N_{0}^{RF}),$$  \hspace{1cm} (6)

where $r_{n}^{U} = [r_{n,1}^{U}, \ldots, r_{n,R_{n}^{U}}]$ is a resource block (RB) allocation vector and $R_{n}^{U}$ is the total number of RBs allocated to RF uplink; $r_{n,i}^{U} = 0$; $U_{n}^{i}$ represents the set of users that are located at the other service areas and transmit data over RB $i$; $B_{n,j}^{U}$ is the bandwidth of each RB and $P_{l}$ is the transmit power of user $n$; $h_{l,n}$ is the channel gain between user $n$ and the BS; $N_{0}^{RF}$ is the noise power spectral density; $\sum_{l \in U_{n}^{i}} P_{l} h_{l,n} + B_{n,j}^{U} N_{0}^{RF}$ is the interference caused by the users that are located in other service areas and use the same RB.

On the other hand, the downlink data rate achieved by the BS to each user $n$ is given by

$$r_{n}^{D} = \sum_{i=1}^{R_{n}^{D}} r_{n,i}^{D} B_{n,i}^{D} \log_{2}(1 + \sum_{j \in B_{n,i}^{D}} P_{j} h_{j,n} + B_{n,i}^{D} N_{0}^{RF}),$$  \hspace{1cm} (7)

where $R_{n}^{D}$ is the bandwidth of each RB that the BS used to transmit the global FL model to each user $n$; $r_{n,i}^{D} = [r_{n,1}, \ldots, r_{n,R_{n}^{D}}]$ is a RB allocation vector with $R_{n}^{D}$ being the total number of RBs allocated to RF downlink; $r_{n,i}^{D} = 0$; $R_{n}^{D}$ is the bandwidth of each RB; $\sum_{j \in B_{n,i}^{D}} P_{j} h_{j,n} + B_{n,i}^{D} N_{0}^{RF}$ is the interference caused by the BS that performs the FL algorithm; $h_{j,n}$ is the channel gain between user $n$ and BS $j$. Let $B_{R}$ be the total RB bandwidth, and we have $B_{n}^{U} \times B_{n}^{D} + R_{n}^{D} \times B_{n}^{D} \leq B_{R}$. For simplicity, we assume $B_{n}^{U} = B_{n}^{D}$ which means the bandwidth of uplink resource block is equal to that of downlink RB.

Denote the data size of the FL model that each user needs to upload by $s$. To upload the local FL model within transmission time $t_{n}^{U}$, we have $r_{n}^{U} \geq t_{n}^{U}$. Similarly, to download the global FL model within transmission time $t_{n}^{D}$, we have $t_{n}^{D} \geq s$.

C. VLC Transmission Model

According to [13] and [14], the optical channel gain of a line-of-sight (LoS) channel can be expressed as

$$u = \left\{ \begin{array}{ll} \frac{\nu_{m}^{0} A_{0}}{d_{n}^{2}} T_{0}(\theta) \cos^{m}(\varphi) \cos(\theta), & 0 < \theta \leq \Theta_{F}, \\ 0, & \theta > \Theta_{F}, \end{array} \right.$$  \hspace{1cm} (8)

where $m = \log_{2}(\cos(\theta/2))$; $A_{0}$ is a function of the half-intensity radiation angle $\theta_{1/2}$; $A_{0}$ is the receiver’s physical area of the photo-diode; $d$ is the distance from the VLC AP to the optical receiver; $\varphi$ is the angle of irradiation and $\theta$ is the angle of incidence; $\Theta_{F}$ is the half angle of the receiver’s file of view (FoV); $T_{0}(\theta)$ is the gain of the optical filter; and the concentrator gain $g(\theta)$ can be written as

$$g(\theta) = \left\{ \begin{array}{ll} \frac{n_{0}^{2}}{\sin(\theta)}, & 0 < \theta \leq \Theta_{F}, \\ 0, & \theta > \Theta_{F}. \end{array} \right.$$  \hspace{1cm} (9)

where $n_{0}$ is the refractive index. For a given user $n$ connected to a VLC AP $k$, the signal-to-interference-plus-noise ratio (SINR) can be written as

$$s_{nk} = \frac{(\gamma u_{nk} P_{k})^{2}}{N_{0}^{VLC} B + \sum_{l \neq k} (\gamma u_{nl} P_{l})^{2}},$$  \hspace{1cm} (10)

where $\gamma$ is the optical to electric conversion efficiency; $P_{k}$ is the transmitted optical power of a VLC AP; $N_{0}^{VLC}$ is the noise power spectral density; $u_{nk}$ is the channel gain between user $n$ and the VLC AP $k$; $u_{nl}$ is the channel gain between user $n$ and the interfering VLC AP $l$; $B$ is the bandwidth of each VLC RB. Each user is served by a single VLC AP which has the largest SINR for the user. In the VLC system, optical OFDMA is employed. It is known that the input signal of the LEDs is amplitude constrained. Therefore, the classical Shannon capacity formula for complex and average power constrained signal is not applicable in VLC. Therefore, the lower bound of achievable data rate is used, which can be expressed as [15]

$$r_{n} = \sum_{i=1}^{R_{n}^{V}} V_{n,i}^{V} B_{n,i}^{V} \frac{2}{\log_{2}(1 + \frac{2}{\pi c_{s}})},$$  \hspace{1cm} (11)

where $s_{n}$ is the largest SINR which is evaluated as $s_{n} = \max\{s_{n,1}, \ldots, s_{n,K}\}$, where $K$ is the total number of VLC APs; $r_{n}^{V} = [r_{n,1}^{V}, \ldots, r_{n,R_{n}^{V}}]$ is an RB allocation vector with $R_{n}^{V}$ being the total number of VLC RBs, $r_{n,i}^{V} = 0$; $R_{n}^{V}$ is the bandwidth of each VLC. We assume that the data size of global FL model parameters which are transmitted to users can also be denoted by $s$. Therefore, the downlink communication time of indoor user $n$ in each global iteration will be $t_{dn} = \frac{d_{n}}{r_{n}}$. 


D. Problem Formulation

Our goal is to fully exploit the complementary function of VLC systems and appropriately allocate the precious bandwidth of both RF and VLC for enhancing FL performance. To this end, we formulate an optimization problem whose goal is to minimize the global loss function under time, energy, and bandwidth allocation constraints. The minimization problem is given by

\[
\min_{B, B^U, B^V, S} J(\omega) \tag{12}
\]

s. t. \[
R^U \times B^U + R^D \times B^D \leq B_R, \tag{12a}
\]

\[
R^V \times B \leq B_V, \tag{12b}
\]

\[
t_n + t_n^U + t_n^\text{comp} + t_d \leq T_{\text{round}}, \forall n \in S_1, \tag{12c}
\]

\[
t_n^D + t_n^U + t_n^\text{comp} \leq T_{\text{round}}, \forall n \in S_2, \tag{12d}
\]

\[
S_1 \cup S_2 = S, \tag{12e}
\]

\[
E_n^{\text{com}} + E_n^{\text{comp}} \leq \gamma_n E, \forall n \in N, \tag{12f}
\]

\[
R^U = |S|, R^D = |S_2|, R^V = |S_1|, \tag{12g}
\]

where \( S \) denotes the set of selected users participating in FL, \( S_1 \) denotes the set of selected indoor users, \( S_2 \) denotes the set of selected outdoor users, and \(|\cdot|\) denotes the cardinality of a set. In addition, \( T_{\text{round}} \) is the time threshold for each round and \( t_d \) denotes the delay between the BS and the home gateway. In addition, \( \gamma_n E \) is the energy constraint of user \( n \). Constraint (12c) is the delay constraint of each round for all selected indoor users while (12d) is the delay constraint of each round. In addition, (12f) is the energy consumption requirement of performing an FL algorithm.

IV. THE PROPOSED ALGORITHM

Next, we first analyze the optimization problem (12) so as to figure out how the user selection and bandwidth allocation affect the FL performance. Then, a joint user selection and bandwidth allocation (USBA) algorithm is proposed to solve the optimization problem.

Lemma 1. The optimization problem (12) can be transformed into an optimization problem with the objective function of maximizing the total sample size of the selected users when the users’ transmit power are fixed, which can be denoted as

\[
\max_{B, B^U, B^V, S} \sum_{n=1}^{N_1} \sum_{i=1}^{R_n^U} D_n r_{n,i}^U + \sum_{n=N_1+1}^{N} \sum_{i=1}^{R_n^D} D_n r_{n,i}^D \tag{13}
\]

s. t. \hspace{1cm} (12a) \hspace{1cm} (12g)

Proof. Minimizing the global loss function is equivalent to minimize the gap between the global loss function \( J(\omega) \) at time \( t \) and the optimal global loss function \( J(\omega^\ast) \). According to Theorem 1 in [6], the gap is caused by the packet error rate (PER) and number of selected users. Here, we do not consider the packet errors and hence, we have \( q_t = 0 \). Using the same simplification method in [6], the optimization problem can be transformed to problem (13). This ends the proof.

Algorithm 1 GetS\((B^U, B^D, B)\)

1. Input: \( N_1, N_2 \)
2. for \( n \in N_1 \) do
3. \hspace{1cm} if \( t_n + t_n^U + t_n^\text{comp} + t_d \leq T_{\text{round}}, \forall n \in S_1 \) then
4. \hspace{2cm} \( S_1 \leftarrow n \)
5. \hspace{1cm} end if
6. \hspace{1cm} end for
7. for \( n \in N_2 \) do
8. \hspace{1cm} if \( t_n^D + t_n^U + t_n^\text{comp} \leq T_{\text{round}}, \forall n \in S_2 \) then
9. \hspace{2cm} \( S_2 \leftarrow n \)
10. \hspace{1cm} end if
11. \hspace{1cm} end for
12. return \( S_1, S_2 \)

We can observe from (15) that if the bandwidth of each RB is fixed, the subset of selected users is determined by the user’s computing power and channel condition. We denote the algorithm that select users under fixed bandwidth allocation by GetS\((B^U, B^D, B)\), which is summarized in Algorithm 1.

B. Optimal RB Bandwidth

With an obtained subset of users, we then need to find the optimal \( B, B^U \), and \( B^D \) that can further optimize the capability of the hybrid VLC/RF system. Note that the larger the bandwidth of each RB is, the smaller the delay can be, implying more users can be potentially selected. Based on this observation, the optimal RB bandwidth allocation is

\[
\max B \tag{16}
\]

s. t. \hspace{1cm} (15a) \hspace{1cm} (15b) \hspace{1cm} (15c)

\[
R^U \times B^U + R^D \times B^D \leq B_R, \tag{15a}
\]

\[
B^U = B^D, \tag{15b}
\]

\[
R^U = |S|, R^D = |S_2|, \tag{15c}
\]

and

\[
\max B \tag{16}
\]

s. t. \hspace{1cm} (16a) \hspace{1cm} (16b)

\[
R^V \times B \leq B_V, \tag{16a}
\]

\[
R^V = |S_1|, \tag{16b}
\]

Lemma 2. The maximum bandwidth of each RB can be obtained when \( R^U \times B^U + R^D \times B^D = B_R \) and \( R^V \times B = B_V \).
Algorithm 2 USBA Algorithm.

1: Input: \$ \emptyset \leftarrow \{B_0, B_D^0, B_0^D\}.
2: function GetB(\$)
3: \$B_D' = B_D = \frac{|B_0|}{|S| + |S_2|},
4: B = \frac{B_V}{B_0},
5: end function
6: function main()
7: \$n = 1
8: \$S^0 \leftarrow GetS(B_0^D, B_D^0, B_0)
9: while \$l \neq 0 do
10: \$[B_{n-1}^U, B_{n-1}^D, B_n] \leftarrow GetS(S^{n-1})
11: \$S^n \leftarrow GetS([B_{n-1}^U, B_{n-1}^D, B_n])
12: if \$S^n = S^{n-1} \text{ and } [B_n^U, B_n^D, B_n] = [B_{n-1}^U, B_{n-1}^D, B_{n-1}] \text{ then}
13: \text{break}
14: end if
15: n = n + 1
16: end while
17: end function

Proof. We use the contradiction method to prove Lemma 2. First, we assume that maximum \$B_0^U, B_0^D, \text{ and } B_0 \text{ exist when (16a) and (17a) are not equal. Hence, we have}
\[ B_0^U = B_0^D < \frac{B_R}{|S| + |S_2|}. \] (17)

and
\[ B_0 < \frac{B_V}{|S_1|}. \] (18)

However, when (16a) and (17a) are equal, \$B_1^U, B_1^D, \text{ and } B_1 \text{ satisfy the following equations:}
\[ B_1^U = B_1^D = \frac{B_R}{|S| + |S_2|}. \] (19)

and
\[ B_1 = \frac{B_V}{|S_1|}. \] (20)

Obviously, \$B_1^U = B_1^D > B_1^U = B_1^D \text{ and } B_1 > B_0, \text{ which contradicts the assumption. This ends the proof.}

Therefore, we have
\[ B^U = B^D = \frac{B_R}{R^U + R^D} = \frac{B_R}{|S| + |S_2|}, \] (21)

and
\[ B = \frac{B_V}{R^V} = \frac{B_V}{|S_1|}. \] (22)

C. Iterative Solution

Once we obtain the bandwidth of each RB, we can obtain the optimal subset of selected users. Accordingly, we can obtain the optimal bandwidth allocation based on the obtained selected users, which is denoted by \$\text{GetB}()$. Then, the selected users can be updated again based on the bandwidth allocation. The iteration ends when both the user selection and bandwidth allocation remain fixed. Obviously, the algorithm can always reach convergence after a certain number of iterations. We summarize the proposed USBA algorithm in Algorithm 2.

V. SIMULATION RESULTS AND ANALYSIS

Consider a circular network area having a radius \$r = 50 \text{ m}$ with one BS at its center. There are \$N = 50$ uniformly distributed users, and 80% of the users are in indoors and 20% of them are in outdoors. The system specifications are summarized in Table I. The dataset used to train the FL algorithm is Boston housing dataset\[^1\] that is randomly allocated to users. The number of samples of each user is equal. The goal of the FL algorithm is to train a simple Back Propagation (BP) neural network with only one hidden layer composed of 10 neurons. For comparison, we also execute the FL in RF-only systems.

As show in Fig. 2, the FL algorithm is used for predicting the housing price. In this figure, the green line is the true values of data samples. Before training, we randomly select 17 samples to form a test set for testing. Here, we use the coefficient of determination \$(R^2)\$ to measure the quality of the model. The higher value of \$R^2\$ is, the higher prediction accuracy is. From Fig. 2 we can observe that the proposed USBA algorithm can achieve better performance than baseline. The \$R^2\$ has increased by 10% when compared with RF-only system. This is because the proposed USBA algorithm introduces visible light communication, which can get higher communication rate and quality, thereby increasing the number of selected users and further improving the FL performance.

To evaluate the performance of the proposed USBA algorithm with different users, Fig. 3 shows how the number of selected users changes as the total number of users varies. Fig. 3 shows that, compared to RF-only system, more users can participate FL in the hybrid VLC/RF system. This trend is more obvious with the increase of the number of users. In particular, when the number of users is 50, the number of users selected by the proposed USBA algorithm is 20% higher than that of the benchmark. When the number of users is 100, the number of users selected by the proposed USBA algorithm is 25% higher than that of the benchmark. Fig. 4 also compares the user selection under different VLC and RF bandwidths.

\[^1\]http://lib.stat.cmu.edu/datasets/boston

| Parameter | Value |
|-----------|-------|
| Transmitted optical power per VLC AP, \(P_o\) | 9 W |
| Modulation bandwidth for LED lamp, \(B\) | 40 MHz |
| The physical area of a PD, \(A_p\) | 1 cm² |
| Half-intensity radiation angle, \(\theta_{1/2}\) | 60 deg. |
| Gain of optical filter, \(T_o(\theta)\) | 1.0 |
| Receiver FOV semitangle, \(\Theta_P\) | 90 deg. |
| Refractive index, \(n\) | 1.5 |
| Optical to electric conversion efficiency, \(\gamma\) | 0.53 A/W |
| Noise power spectral density, \(N_0^{\text{VLC}}\), \(N_0^{\text{RF}}\) | \(10^{-21}\) A²/Hz |
| RF total bandwidth, \(B_R\) | 20 MHz |
| Transmit power of BS, \(P_B\) | 1 W |
| The number of users, \(N\) | 50 |
| Delay requirement, \(T_{\text{round}}\) | 2.5 s |
| Energy consumption requirement, \(\gamma_{c}E\) | 2 J |
| Energy consumption coefficient, \(\alpha\) | \(2 \times 10^{-28}\) |
| Data size of FL model, \(s\) | 1 Mb |
can be observed that the proposed USBA algorithm is better than the benchmark under different bandwidth settings.

Figure 3 compares the values of $R^2$ of the hybrid VLC/RF system with the RF only system under different configurations. It can be observed that the hybrid VLC/RF system can achieve higher $R^2$ values, which means that the proposed USBA algorithm can make FL performance better. We can also observe that the proposed USBA algorithm can always achieve better performance regardless the variations of VLC/RF bandwidth. Furthermore, the performance gain of the proposed USBA algorithm increases with the increase of the number of total users.

VI. CONCLUSION

This paper has proposed the introduction of VLC into conventional RF systems for better FL performance. In particular, we have formulated a joint user selection and bandwidth allocation problem for FL over hybrid VLC/RF system under time, energy and bandwidth constraints to minimize the FL training loss. We have first separated the problem into two subproblems. The first subproblem is a user selection problem with a given bandwidth allocation, which is solved by a traversal algorithm. Based on the obtained user subset, the second subproblem finds the optimal bandwidth allocation, which is solved by a numerical method. The two subproblems are then updated iteratively until a convergent solution is obtained. Simulation results show that the proposed joint algorithm can improve the number of selected users and $R^2$ by up to 20% and 10%, respectively, compared with RF-only system, which indicates that the proposed algorithm is promising for FL training in future hybrid VLC/RF networks.

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