Federated Learning Over Wireless Channels: Dynamic Resource Allocation and Task Scheduling

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Abstract—With the development of federated learning (FL), mobile devices (MDs) are able to train their local models with private data and sends them to a central server for aggregation, thereby preventing sensitive raw data leakage. In this paper, we aim to improve the training performance of FL systems in the context of wireless channels and stochastic energy arrivals of MDs. To this purpose, we dynamically optimize MDs' transmission power and training task scheduling. We first model this dynamic programming problem as a constrained Markov decision process (CMDP). Due to high dimensions rooted from our CMDP problem, we propose online stochastic learning methods to simplify the CMDP and design online algorithms to obtain an efficient policy for all MDs. Since there are long-term constraints in our CMDP, we utilize Lagrange multipliers approach to tackle this issue. Furthermore, we prove the convergence of the proposed online stochastic learning algorithm. Numerical results indicate that the proposed algorithms can achieve better performance than the benchmark algorithms.

Index Terms—Federated learning, Markov decision processes, stochastic learning, resource allocation, dynamic programming

I. INTRODUCTION

IN the last decade, we have witnessed a series of amazing breakthroughs, such as AlphaGo, machine learning and artificial intelligence (AI), which have become the most cutting-edge technology in both academia and industry communities [1]. Distributed machine learning based on mobile edge computing (MEC) of the wireless networks is also one of the current hot research directions [2]. The sample data for machine learning can be obtained by collecting massive amounts of data from mobile devices (MD) distributed in the wireless network. By training these data, the training performance of machine learning can be greatly improved.

Although offloading the local sample data of distributed MDs for centralized learning significantly improves the performance of machine learning, this mechanism suffers from two flaws. First, transmission delays from distributed MDs to the central cloudy via backbone network are extremely large. Second, the local data often contains the private information of MDs, and uploading the private information to the central

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cloudy will lead to the risk of personal privacy leakage. To cope with these two issues, federated learning (FL) has been introduced to act as an emerging distributed machine learning paradigm, which is indeed a way to combine MEC with traditional machine learning. In this manner, MDs train their local data and send their local model updates to a task publisher iteratively instead of uploading the raw data to a central server [3], [4], which, in general, brings the following two benefits. (I) The communication latency and the energy consumption for computation can be significantly reduced owing to the fact that MDs are not required to upload huge amounts of local data for training to an edge server. (II) MDs upload their local model instead of the raw data to the edge server, which greatly reduces the risk of personal privacy information leakage [5].

Despite the aforementioned advantages of FL, there are still many challenges that have not been solved until now. Some existing studies [6], [7] adopted an idealized assumption that all MDs participating in FL are immune to the wireless and computation resource constraints. [8] only focused on a practical Federated-Averaging algorithm for distributed DNN training and the training performance. Many studies [9]–[12] have been committed to further reducing the communication overhead by developing compression methods. However in practice, MDs usually suffer from energy consumption constraints that may reduce the network lifetime and training efficiency.

In addition, frequent wireless communications is usually required for uploading and downloading the model parameters, which would increase the bandwidth cost and the training latency [13]. Therefore, it is necessary to design a feasible resource scheduling scheme to optimize the resource scheduling problem in the FL process. Without taking into account the energy constraints and battery dynamics of MDs, [14] formulated a FL over a wireless networks as a static optimization problem, and exploited the problem structure to decompose it into three static convex sub-problems. The work [15] proposed a static scheduling scheme to efficiently execute distributed learning tasks in an asynchronous manner while minimizing the gradient staleness on wireless edge nodes with heterogeneous computing and communication capacities. However, many properties of MEC networks are usually time-varying in the FL process and thus the methods in [16] will result in considerable performance loss. The work [16], [17] model the channel and energy dynamically, and exploit the dynamic scheduling algorithm to obtain the asymptotically optimal resluts. Thus, it is of vital importance to develop efficient dynamic resource scheduling schemes to improve the

performance of FL.

In this paper, we utilize constrained Markov decision processes (CMDP) as a mathematical tool to obtain an optimal algorithm for dynamic resource scheduling for FL, where each MD send local model updates trained on their local raw data iteratively to a common edge server, and the edge server aggregates the parameters from MDs participating in local training and broadcasts the aggregated parameters to all the MDs. In particular, each MD possesses computing units with computing capability, which can be used for local machine learning with local raw data. In order to improve the training performance of FL[1], we propose an efficient stochastic optimization algorithm for scheduling resources of MDs in the FL processes by obtaining an efficient setting of the size of raw data for local training, and the transmission power of MDs to upload the local model.

Our main contributions are listed as follows.

1) Due to the dynamic nature of wireless network and battery status of MDs, we consider resource scheduling of FL in dynamic scenarios. Thus, we model the resource scheduling problem of the FL process as a CMDP problem, and improve the performance of FL by optimizing the size of the local training data at the MD side.

2) Since the state-action space dimension in the constrained MDP problem is large and there are a few constraints in the dynamic problem, we simplify the stochastic optimization problem by proving an equivalent Bellman equation and using the Lagrange multiplier method.

3) We use approximate MDP and stochastic learning methods to analyze the constrained MDP problem, and design centralized online algorithms to obtain resource scheduling policy for all MDs.

4) We also provide effective analysis for the convergence of the online stochastic learning algorithms.

Although the idea of applying CMDP to design dynamic resource scheduling is not new, we are motivated to address the resource scheduling issues of resource constraints and dynamics of FL. To achieve high-quality learning performance, a reasonable constrained dynamic scene is essential to the resource scheduling issues [19], [20]. Previous work has utilized CMDP as a mathematical model to design effective algorithms for resource scheduling in wireless networks [13], [21], [22], which is considered as an effective tool for solving dynamic problems and time-related state problems. Inspired by this, we apply CMDP as the mathematical scene to address the resource scheduling problem in the FL process. Nevertheless, previous work still has some shortcomings in solving CMDP problems. The literature [13] adopted a deep learning algorithm that allows the edge server to learn and find optimal decisions without any a priori knowledge of network dynamics in the CMDP. However, reinforcement learning is poorly scalable and requires a lot of computing power and duration for training. The literature [21] obtained the optimal

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[1]In general FL, existing work [18] used the accuracy of the test set to measure the performance of machine learning after training. Since the quantitative analysis of the accuracy in the test set is relatively difficult, we use the size of local dataset accumulated from MDs over iterations to evaluate the accuracy of the machine learning model [13].

TABLE I
SUMMARY OF MAIN NOTATIONS

Notation	Description
N	The number of all MDs
n	The index of the MD
t	The number of iterations of FL
$b_n(\cdot)$	The number of bits of training data for the n-th MD
$P_n(\cdot)$	The transmission power of the n-th MD
$E_n^{\max}$	The battery capacity of the n-th MD
$E_n^{\text{sta}}(\cdot)$	The n-th MD's energy state
$E_n^{\text{cop}}(\cdot)$	The n-th MD's computation energy for local model training
$E_n^{\text{com}}(\cdot)$	The n-th communication energy for parameter transmission
$E_n^{\text{arr}}(\cdot)$	The harvesting energy for the n-th MD
C_n	The CPU cycles to train a unit sampled data on the n-th MD
f_n	The CPU frequency of the n-th MD
$\tau_n^{\text{cop}}(\cdot)$	The processing time of local training on the n-th MD
$\epsilon_n(\cdot)$	The upload decision of the n-th MD
$h_n(\cdot)$	The channel gain between the n-th MD and the edge server
$R_n(\cdot)$	The uplink transmission rate for the n-th MD

solution for the formulated CMDP offloading problem by linear programming and Q-learning method. Neither method is suitable for large-scale networks, which will lead to the curse of dimension. The work [22] developed a threshold-based algorithm to obtain the optimal delay-power tradeoff efficiently, in which the authors used the special structure of the mathematical model to solve the CMDP problem, and this method does not possess the universality of solving the problem.

The rest of this paper is organized as follows. Section II describes the system model and dynamic analysis. CMDP-based dynamic resource scheduling problem is formulated in Section III. Section IV proposes approximate Markov decision process and stochastic learning methods to simplify the CMDP problem, and designs online algorithms to obtain an efficient policy. Section V presents the simulation results. Finally, Section VI concludes this paper.

II. SYSTEM MODEL

Consider a wireless FL system consisting of an edge server and N MDs as shown in Fig. 1. Each MD is equipped with computing and energy harvesting modules. Having access to a vast range of local data, each MD is able to train the machine learning model locally using the harvested energy from the environment. To improve the model training efficiency and protect data privacy, the FL technique is adopted as an iterative model updating process between the edge server and MDs.

We first briefly introduce the main procedures as follows. In each learning iteration t, the n-th MD first selects $b_n(t)$ bits of training data from the local data set, where the size of selected data is determined by the edge server according to the energy status of the MD, i.e., the battery energy at the beginning of this iteration. Here, we assume that the edge server knows the energy status of all MDs in advance at the beginning of the learning iteration. Then, each MD performs local training and obtains the local model parameters. Afterwards, the edge server decides whether or not to upload the local parameters for MDs for aggregation according to MDs' remaining energy and channel state. If the n-th MD participates, it transmits the parameters to the edge server in the uplink using the
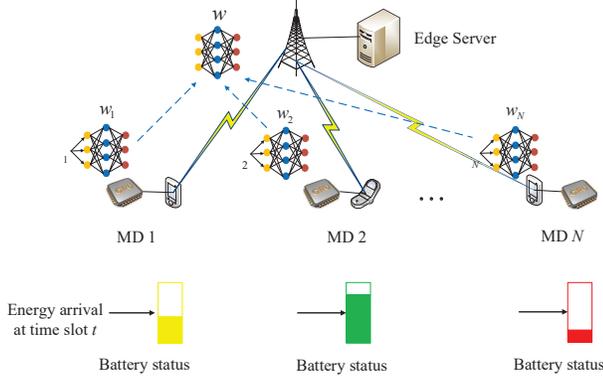
Fig. 1. The federated learning aided MEC network

power of $P_n(t)$. Finally, the edge server aggregates the local training parameters from all the participating MDs and then it broadcasts the updated global training parameters (e.g., weighted average over the local parameters) back to all the MDs. At the end of this iteration, each MD opportunistically harvests energy from the environment and stores the energy in the rechargeable battery. The above process is repeated until the learning model reaches the desired accuracy level.

In the following subsections, we will explain the above process in more details. We mainly discuss each learning iteration in three stages: dynamic energy harvesting, local model training, model parameter transmission and aggregation.

A. Dynamic Energy Harvesting

We assume that the n-th MD is equipped with a rechargeable battery with a limited capacity of $E_n^{\max}$.[2] At the beginning of each iteration t, we denote the n-th MD's energy state as $E_n^{\text{sta}}(t)$ which is the remaining energy carried from the previous iteration. According its energy state, the edge server decides whether or not to proceed to local model training and uplink parameter transmission for each MD. We let $E_n^{\text{cop}}(t)$ denote the n-th MD's computation energy for local model training and $E_n^{\text{com}}(t)$ denote the communication energy for uplink parameter transmission, respectively, which will be discussed in more details in the next two subsections. Note that each MD's energy consumption cannot exceed the energy state in this iteration. At the end of the iteration t, we consider that each MD is able to harvest energy from the environment and store the energy in the rechargeable battery. We denote the energy harvesting process for the n-th MD by $\{\boldsymbol{E}_n^{\text{arr}}(\cdot) : n \in \mathcal{N}\}$, which follows an independent stationary Poisson distribution with average arrival rate $\mathbb{E}[E_n^{\text{arr}}] = \lambda_n$ [24].

Similar to [25], the energy state of the n-th MD at the beginning of iteration $t + 1$ can be updated by the following

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[2]For the ease of analysis, we quantize the battery capacity in to $E_n^{\max} + 1$ uniform levels $\{0, 1, \cdots, E_n^{\max}\}$ [23].

recursion,

$$E_n^{\text{sta}}(t+1) = \min \left\{ [E_n^{\text{sta}}(t) - \lceil E_n^{\text{com}}(t) + E_n^{\text{cop}}(t) \rceil]^+ \\ + E_n^{\text{arr}}(t), E_n^{\max} \right\}, \quad t \geq 1, \tag{1}$$

where $\lceil \cdot \rceil$ denotes the ceiling operator, and $x^+ \triangleq \max\{x, 0\}$.

B. Local Model Training

At the beginning of each learning iteration t, each MD first selects $b_n(t)$ bits of data samples from the local dataset to perform a machine learning algorithm, and then it obtains the local model parameters. Intuitively, the choice of b_n depends on the available energy in the battery. The MD can train a larger size of the training data if it has more sufficient battery energy in this iteration. Otherwise, it trains less data or takes no training for this iteration. We assume it consumes C_n CPU cycles to train a unit sampled data on the n-th MD. The CPU frequency, denoted by f_n (in CPU cycle/s), is considered as a measurement of computation capacity of the n-th MD. In iteration t, the processing time of local training on the n-th MD is given by

$$\tau_n^{\text{cop}}(t) = \frac{b_n(t)C_n}{f_n}, \tag{2}$$

According to [14], the computation energy $E_n^{\text{cop}}(t)$ consumed by local training of the n-th MD in the iteration t is given by

$$E_n^{\text{cop}}(t) = \alpha b_n(t)C_n f_n^2, \tag{3}$$

where α is the effective capacitance of the computing chipset for each MD.

C. Model Parameter Transmission and Aggregation

After performing the local training, the MDs then upload their updated local model parameters back to the edge server. Let $\epsilon_n(t)$ denote the upload decision of the n-th MD at the iteration t, where $\epsilon_n(t) = 1$ means the n-th MD is assigned to a subchannel and is willing to upload parameters to the edge server through the assigned channel, and $\epsilon_n(t) = 0$ indicates that it is not assigned to a subchannel or keeps silent. Intuitively, an MD is more likely to upload if it has sufficient remaining energy while in a good channel state. For the uplink transmission, we adopt OFDMA technique, where the channels are orthogonal cross the different links. We assume that there are L orthogonal subchannels in the FL system and each MD can only occupy at most one subchannel. Let $h_n(t)$ denote the uplink channel gain between the n-th MD and the edge server in the iteration t, where the channel gains of all sub-channels between the server and a single MD are same.

We model the channel gain $h_n(t)$ as a discrete-state block fading, where the channel gain between the n-th MD and edge server stay is discrete random variable with a general distribution $\Pr[\bar{h}_n]$ [26]–[30]. We further assume that $h_n(t)$ stays invariant within each iteration and are independently and identically distributed (i.i.d.) across different iterations and MDs.

If the n-th MD is allowed to upload ($\epsilon_n(t) = 1$), it will transmit the local model parameter to the edge server with power $P_n(t)$ ($P_n(t) > 0$) in the uplink. Otherwise, the n-th MD keeps silent ($P_n(t) = 0$). We assume that the size of the local training parameters of all MDs is the same, which is denoted by M.[3] The uplink transmission rate for the n-th MD is given by

$$R_n(t) = \epsilon_n(t)W\log_2\left(1 + \frac{P_n(t)h_n(t)}{\sigma^2}\right), \qquad (4)$$

where W is the bandwidth of subchannel between each MD and the server, and σ^2 is the power of the additive white Gaussian noise. Moreover, the corresponding uplink transmission time is expressed as

$$\tau_n^{\text{com}}(t) = \frac{\epsilon_n(t)M}{R_n(t)}. \qquad (5)$$

The energy consumption of parameter uploading for the n-th MD can be expressed as

$$E_n^{\text{com}}(t) = P_n(t)\tau_n^{\text{com}}(t) = \frac{\epsilon_n(t)P_n(t)M}{R_n(t)}. \qquad (6)$$

Upon receiving the updated local parameters from the MDs, the edge server aggregates them into a global parameter and then broadcasts it to all MDs through a downlink broadcast channel. Assume that the bandwidth of the broadcast channel is sufficiently wide and the transmit power of the edge server is much higher than that of the MDs. Therefore, we ignore the downlink transmission time without much loss of generality.

III. CONSTRAINED MARKOV DECISION PROCESS

In this section, we design and analyze the joint scheduling problem of computing and communication resources in the FL network. In the FL system, sequential decisions on local training and parameter transmission needs to be made for each iteration. From (1), we know that the remaining energy at the MD sides are correlated among adjacent iterations. We therefore formulate the joint computing and communication resource scheduling problem as a CMDP to maximize the long term system reward under energy and delay constraints.

A. The composition of CMDP

At the beginning of each iteration, each MD uploads its current local channel state and battery energy state to the edge server. Therefore, the edge server obtains global status information to take appropriate actions for all MDs. Once the decisions are made, the edge server will download the policy to each MD. Due to the extremely small size of data for state information and action decisions, we can ignore the transmission delay and transmission energy for upload of local states and transmission of the policy in the FL network. The CMDP formulation consists of the following components:

- **State:** We define the global state $S(t)$ of the all MDs in the t-th iteration as $S(t) = [h(t), E^{\text{sta}}(t)]$, which is

composed of the current global channel state $h(t) = [h_1(t),...,h_N(t)]$ and the current global remaining battery energy state $E^{\text{sta}}(t) = [E_1^{\text{sta}}(t),...,E_N^{\text{sta}}(t)]$.

- **Action:** Let us denote the global action $A(t)$ of all MDs in the t-th iteration by $A(t) = [b(t), \epsilon(t), P(t)]$, which consists of the number of bits of training data $b(t) = [b_1(t),...,b_N(t)]$, the upload decision $\epsilon(t) = [\epsilon_1(t),...,\epsilon_N(t)]$ and the transmission power $P(t) = [P_1(t),...,P_N(t)]$.

- **Transition probability:** According to the dynamic energy queue given in (1), the global remaining energy $E^{\text{sta}}(t)$ under action $A(t)$ is a controlled Markov chain with the transition probability of

$$\Pr[E^{\text{sta}}(t+1)|E^{\text{sta}}(t), A(t)]$$
$$= \prod_n \Pr\Big[E_n^{\text{arr}}(t) = E_n^{\text{sta}}(t+1) \qquad (7)$$
$$- \big[E_n^{\text{sta}}(t) - \lceil E_n^{\text{com}}(t) + E_n^{\text{cop}}(t)\rceil\big]^+\Big].$$

Since the energy queue dynamic is affected by both the data training energy and communication energy, it is controlled by the actions $A(t) = (b(t), \epsilon(t), P(t))$. Moreover, the global state transition probability is also Markovian, which is given by

$$\Pr[S(t+1)|S(t), A(t))]$$
$$= \Pr[h(t+1)|S(t), A(t))]$$
$$\qquad \times \Pr[E^{\text{sta}}(t+1)|S(t), A(t))] \qquad (8)$$
$$= \Pr[h(t+1)]\Pr[E^{\text{sta}}(t+1)|S(t), A(t))],$$

where the second equation is due to the i.i.d. property of wireless channel.

- **Reward:** The model accuracy of the FL is difficult to quantify, and does not promise a closed-form. In most circumstances, one observes that the accuracy of FL training increases with the total size of local training data at each MD [13], [31]. Hence, we define the reward of the n-th MD by the product of its local training data size and its upload decision, i.e., $\sum_{n=1}^N b_n(t)\epsilon_n(t)$. If the MD is unable to upload the training parameters ($\epsilon_n(t) = 0$), then its reward in the current iteration is 0.

We assume that each training iteration is synchronized across the MDs with the duration of τ. Thus, the total time for data training and transmission should not exceed the duration of one iteration, i.e.,

$$\tau_n^{\text{com}}(t) + \tau_n^{\text{cop}}(t) \leq \tau. \qquad (9)$$

Moreover, the energy used for local training and uploading should not exceed the remaining energy $E_n^{\text{sta}}(t)$ at the beginning of the t-th iteration, which is described by the energy causality constraint of

$$\lceil E_n^{\text{com}}(t) + E_n^{\text{cop}}(t)\rceil \leq E_n^{\text{sta}}(t). \qquad (10)$$

From (9) and (10), we see that there is a tradeoff between the computing and communication phases due to limited time and battery energy in each training iteration. According to (3), if the number of training data bits b_n increases, the computing

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[3]We assume all MDs have the same structures of the local network model and bit precision (typically floating point precision) of the local network parameters, respectively.

energy consumption will increase, which leaves less energy for the communication phase. In the meanwhile, according to (2), by increasing the training bits number b_n, the local training time will increase, which leaves less time for communication. Due to the above tradeoff, each MD needs to allocate time and energy wisely between the computing and communication phases. For example, the probability that the total remaining energy $E_n^{\text{sta}}(t)$ at the n-th MD equals zero can not exceed the energy outage probability constraint Pr_n^{out}, i.e.,

$$\text{Pr}[E_n^{\text{sta}}(t) = 0] \leq \text{Pr}_n^{\text{out}}, \tag{11}$$

Here, $E_n^{\text{sta}}(t) = 0$ does not mean that the MD is completely powered off. We adopt a dedicated battery to support the energy harvesting circuit and the information signaling in each training iteration. The dedicated battery stores the energy that arrives at random in each iteration, and provides energy for information feedback, local training and parameter updates during the FL process. We thus assume that the MDs can exhaust its battery before the next recharge cycle [32]. Furthermore, we assume the subchannels occupied by all MDs in the current iteration cannot exceed the number of channels L in the system, i.e.,

$$\sum_{n=1}^{N} \epsilon_n(t) \leq L. \tag{12}$$

Due to the randomness of states in each iteration and the correlation of states across the iterations, the edge server needs to make sequential decisions on b_n, ϵ_n and P_n along the time horizon. Without much loss of generality, we formulate the problem as an infinite horizon CMDP, resulting in the stationary policies which do not change with time. The definition of stationary control policy is given as follows.

Definition 1: (Stationary Control Policy) *A stationary control policy is a mapping $\boldsymbol{S} \rightarrow \boldsymbol{A}$ from the state space to the action space $\mathcal{S}$, which is given by $\boldsymbol{\Omega}(\boldsymbol{S}) = \boldsymbol{A} \in \mathcal{A}, \forall \boldsymbol{S} \in \mathcal{S}$.*

Hence, we denote the control policy of the all MD by $\boldsymbol{\Omega}(S) = (\boldsymbol{b}, \boldsymbol{\epsilon}, \boldsymbol{P})$. Let $\boldsymbol{\Omega}$ be the stationary feasible control policy which should satisfy constraints (9), (10), (11) and (12).

B. Constrained Markov Decision Process Problem

The formulation of CMDP is given in *Problem 1*. The aim is to find the efficient control policy that optimized the total long-term average utility of all MDs under the energy outage constraints, transmit power constraints, delay constraints, energy causality constraints and channel constraints.

Problem 1: (CMDP Problem)

$$\max_{\boldsymbol{\Omega}} \quad \mathcal{U}(\boldsymbol{\Omega}) = \lim_{T \to \infty} \frac{1}{T} \sum_{t=1}^{T} \mathbb{E}^{\boldsymbol{\Omega}} \left[\sum_{n=1}^{N} b_n(t) \cdot \epsilon_n(t) \right] \tag{13}$$

$$s.t. \quad Pr[E_n^{sta}(t) = 0] \leq Pr_n^{out}, \tag{13a}$$

$$0 \leq P_n(t) \leq P_n^{max}, \tag{13b}$$

$$\epsilon_n(t) \in \{0, 1\},$$

$$(9), (10) \text{ and } (12), \quad \forall n,$$

where the expectation $\mathbb{E}^{\boldsymbol{\Omega}}[\cdot]$ is taken with respect to the steady-state distribution induced by the control policy $\boldsymbol{\Omega}$, and P_n^{max} is the maximum allowable transmit power of the n-th MD. Besides, the constraint (13a) can be redescribed as a long-term description of the energy outage probability constraint, i.e.,

$$\lim_{T \to \infty} \frac{1}{T} \sum_{t=1}^{T} \mathbb{E}^{\boldsymbol{\Omega}} \left[\mathbf{1}[E_n^{\text{sta}}(t) = 0] \right] \leq \text{Pr}_n^{\text{out}}. \tag{14}$$

$\mathbf{1}[\cdot]$ is an indicator function that takes on a value of 1 when the battery energy is exhausted at the n-th MD. The objective function (13) in *Problem 1* is the long-term average total utility of all MDs under the control policy $\boldsymbol{\Omega}$. In the following analysis, we decompose *Problem 1* into two stages. In stage one, we first omit the short term constraints in *Problem 1* and simplify the problem as follows,

Problem 2: (Simplified CMDP Problem)

$$\max_{\boldsymbol{\Omega}} \quad \mathcal{U}(\boldsymbol{\Omega}) \tag{15}$$

$$s.t. \quad \lim_{T \to \infty} \frac{1}{T} \sum_{t=1}^{T} \mathbb{E}^{\boldsymbol{\Omega}} \left[\mathbf{1}[E_n^{sta}(t) = 0] \right] \leq Pr_n^{out}, \forall n, \tag{15a}$$

$$\boldsymbol{\Omega} \in \mathcal{D}(t), \forall t, \tag{15b}$$

where $\mathcal{D}(t)$ means the feasible region of the short term constraints in the learning iteration t. The Lagrange function of *Problem 2* is given by

$$L(\boldsymbol{\Omega}, \boldsymbol{\gamma}) = \lim_{T \to \infty} \frac{1}{T} \sum_{t=1}^{T} \mathbb{E}^{\boldsymbol{\Omega}} \left[g(\boldsymbol{S}(t), \boldsymbol{\Omega}, \boldsymbol{\gamma}) \right], \tag{16}$$

where

$$\begin{aligned} &g(\boldsymbol{S}(t), \boldsymbol{\Omega}, \boldsymbol{\gamma}) \\ &= \sum_{n=1}^{N} \left(b_n(t)\epsilon_n(t) - \gamma_n \mathbf{1}[E_n^{\text{sta}}(t) = 0] \right) + \gamma_n \text{Pr}_n^{\text{out}}. \end{aligned} \tag{17}$$

And, the corresponding Lagrange dual function $G(\boldsymbol{\gamma})$ is given by

$$G(\boldsymbol{\gamma}) = \max_{\boldsymbol{\Omega}} \lim_{T \to \infty} \frac{1}{T} \sum_{t=1}^{T} \mathbb{E}^{\boldsymbol{\Omega}} \left[g(\boldsymbol{S}(t), \boldsymbol{\Omega}, \boldsymbol{\gamma}) \right], \tag{18}$$

There exists Lagrange multipliers $\boldsymbol{\gamma} \succeq 0$ such that $\boldsymbol{\Omega}^*$ maximizes the Lagrange function $L(\boldsymbol{\Omega}, \boldsymbol{\gamma})$. And we can get the following problem as,

Problem 3: (Lagrange Dual Problem)

$$L^* = \min_{\boldsymbol{\gamma}} \max_{\boldsymbol{\Omega}} L(\boldsymbol{\Omega}, \boldsymbol{\gamma}) \tag{19}$$

$$s.t. \quad \boldsymbol{\gamma} \succeq 0,$$

$$\boldsymbol{\Omega} \in \mathcal{D}(t), \forall t.$$

According to [33], there exists an optimal control policy $\boldsymbol{\Omega}^*$ and a series of non-negative Lagrangian multipliers $\boldsymbol{\gamma}^*$ such that $\boldsymbol{\Omega}^*$ maximizes the Lagrange function $L(\boldsymbol{\Omega}^*, \boldsymbol{\gamma}^*)$, and the inequality condition holds:

$$\begin{aligned} L(\boldsymbol{\Omega}, \boldsymbol{\gamma}^*) \leq L(\boldsymbol{\Omega}^*, \boldsymbol{\gamma}^*) \leq L(\boldsymbol{\Omega}^*, \boldsymbol{\gamma}), \\ \forall \boldsymbol{\Omega}, \quad \forall \boldsymbol{\gamma} \succeq 0. \end{aligned} \tag{20}$$

$\boldsymbol{\Omega}^*$ and $\boldsymbol{\gamma}^*$ are the original optimal solution and the dual optimal solution, respectively. *Problem 2* can be regarded as an infinite-dimensional linear programming problem with the feasible region $\mathcal{D}(t)$, which is a special type of convex problem. Thus, the duality gap between the original optimal and the dual optimal are 0. The original optimal solution is obtained by solving the dual problem.

Generally, Bellman equation is a necessary condition for a dynamic programming to be optimized. Given Lagrange multipliers $\boldsymbol{\gamma}$, the classical infinite-horizon average-utility CMDP problem *Problem 2* can be solved by the Bellman equation [28]. Thus, we can obtain the following equation,

$$
G(\boldsymbol{\gamma}) + V(\boldsymbol{S}(t)) = \max_{\boldsymbol{\Omega}} \left\{ g\left(\boldsymbol{S}(t), \boldsymbol{\Omega}, \boldsymbol{\gamma}\right) + \right.
$$
$$
\left. \sum_{\boldsymbol{S}(t+1)} \Pr\left(\boldsymbol{S}(t+1)|\boldsymbol{S}(t), \boldsymbol{\Omega}\right) V(\boldsymbol{S}(t+1)) \right\} \tag{21}
$$
$$
\forall \boldsymbol{S}(t), \quad t > 0,
$$

where $V(\boldsymbol{S}(t))$ is the value function representing the average utility obtained by the control policy $\boldsymbol{\Omega}$ from each global state $[\boldsymbol{h}(t), \boldsymbol{E}^{\text{sta}}(t)]$. According to (8), we know that the channel states possess independent statistical characteristics, which is not affected by the control policy. We can further simplify the Bellman equation by taking the expectation of (21) on the global channel state $\boldsymbol{h}(t)$.

Lemma 1: (Equivalent Bellman Equation) *Given a series of Lagrange multipliers $\boldsymbol{\gamma}$, the objective function (16) can be solved by the equivalent Bellman equation as follows:*

$$
G(\boldsymbol{\gamma}) + V(\boldsymbol{E}^{sta}(t)) = \max_{\boldsymbol{\Omega}(\boldsymbol{E}^{sta})} \left\{ \overline{g}\left(\boldsymbol{E}^{sta}(t), \boldsymbol{\Omega}(\boldsymbol{E}^{sta})\right) + \right.
$$
$$
\left. \sum_{\boldsymbol{E}^{sta}(t+1)} Pr\left(\boldsymbol{E}^{sta}(t+1)|\boldsymbol{E}^{sta}(t), \boldsymbol{\Omega}(\boldsymbol{E}^{sta})\right) V(\boldsymbol{E}^{sta}(t+1)) \right\}
$$
$$
\forall \boldsymbol{E}^{sta}(t), \quad t > 0, \tag{22}
$$

where the expectation of the value function $V(\boldsymbol{h}(t), \boldsymbol{E}^{sta}(t))$ is

$$
V(\boldsymbol{E}^{sta}(t)) = \mathbb{E}_{\boldsymbol{h}(t)}[V(\boldsymbol{h}(t), \boldsymbol{E}^{sta}(t))]. \tag{23}
$$

Similarly, by taking the expectation over the channel state, we have

$$
\overline{g}\left(\boldsymbol{E}^{sta}(t), \boldsymbol{\Omega}(\boldsymbol{E}^{sta})\right)
$$
$$
= \mathbb{E}_{\boldsymbol{h}(t)}\left[g(\boldsymbol{h}(t), \boldsymbol{E}^{sta}(t), \boldsymbol{\Omega}, \boldsymbol{\gamma})\right], \tag{24}
$$

and,

$$
Pr(\boldsymbol{E}^{sta}(t+1)|\boldsymbol{E}^{sta}(t), \boldsymbol{\Omega}(\boldsymbol{E}^{sta})) \tag{25}
$$
$$
= \mathbb{E}_{\boldsymbol{h}(t)}\left[Pr(\boldsymbol{E}^{sta}(t+1)|\boldsymbol{h}(t), \boldsymbol{E}^{sta}(t), \boldsymbol{\Omega}(\boldsymbol{E}^{sta})\right].
$$

Moreover, $\boldsymbol{\Omega}(\boldsymbol{E}^{sta}) = \{\boldsymbol{\Omega}(\boldsymbol{h}(t), \boldsymbol{E}^{sta}(t))|\forall \boldsymbol{h}(t)\}$ is a policy set under a given global energy state $\boldsymbol{E}^{sta}(t)$ for all possible channel states.

From the equivalent Bellman equation (22), we notice that the equation is composed by a series of linear equations, where

the dimensions of these equations depend on the number of value functions $V(\boldsymbol{E}^{\text{sta}}(t))$. Hence, for any global energy state $\boldsymbol{E}^{\text{sta}}(t)$ and the global channel state $\boldsymbol{h}(t)$, the optimal control policy $\boldsymbol{\Omega}^*$ in (16) can be obtained by maximizing the right-hand side of the equation (22).

IV. APPROXIMATE MARKOV DECISION PROCESS AND STOCHASTIC LEARNING

In this section, we use approximate MDP and stochastic learning methods to analyze and simplify the resource scheduling problem, and design online algorithms to obtain the resource scheduling policy for the FL system.

A. Approximate Markov Decision Process

According to (22), the global energy state value function $V(\boldsymbol{E}^{\text{sta}}(t))$ is unknown, which holds a great difficulty for solving the control policy in the FL system. Due to the existence of the huge state-action space, we are unable to get the value function with the conventional value iteration method. However, we can obtain the value function and develop a solution of the *Problem 1* by the value approximation and online stochastic learning. Assumed that we have obtained the value function $V(\boldsymbol{E}^{\text{sta}}(t))$ through value approximation and online stochastic learning. Thus, the MDP problem can be solved as follow.

Problem 4: (Optimal Partitioned Actions) *For a given value function $V(\boldsymbol{E}^{sta}(t))$, find the optimal partitioned actions $\boldsymbol{\Omega}^*(\boldsymbol{E}^{sta}(t))$, which is satisfied to the Equivalent Bellman's equation in (22). The optimal control policy can be rewritten as*

$$
\boldsymbol{\Omega}^*(\boldsymbol{E}^{sta}(t)) = \arg \max_{\boldsymbol{\Omega}(\boldsymbol{E}^{sta}(t))} \mathbb{E}_{\boldsymbol{h}(t)} \{ g(\boldsymbol{S}(t), \boldsymbol{\Omega}(\boldsymbol{E}^{sta}(t)), \boldsymbol{\gamma})
$$
$$
+ \sum_{\boldsymbol{E}^{sta}(t+1)} \Pr\left(\boldsymbol{E}^{sta}(t+1)|\boldsymbol{h}(t), \boldsymbol{E}^{sta}(t), \right.
$$
$$
\left. \boldsymbol{\Omega}(\boldsymbol{E}^{sta}(t))\right) V(\boldsymbol{E}^{sta}(t+1)) \},
$$
$$
s.t. \quad 0 \le P_n(t) \le P_n^{max},
$$
$$
\epsilon_n(t) \in \{0, 1\},
$$
$$
(9), (10) \text{ and } (12), \quad \forall n. \tag{26}
$$

Given the global state value function $V(\boldsymbol{E}^{\text{sta}}(t))$ and the realization of the global channel state $\boldsymbol{h}$, the *Problem* 4 then becomes a static optimization problem.

B. Stochastic Learning

By the feature-based method, the energy state value function $V(\boldsymbol{E}^{\text{sta}})$ can be approximated by a linear form of the state value function of the n-th MD $V_n(E_n^{\text{sta}})$. The global energy state value function $V(\boldsymbol{E}^{\text{sta}})$ and a series of Lagrange multipliers $\boldsymbol{\gamma}$ will be updated according to the current energy state and channel state information. Then the proposed linear approximation architecture for the global energy state value function $V(E_n^{\text{sta}})$ is obtained by

$$V(\boldsymbol{E}^{\text{sta}}) = V(E_1^{\text{sta}}, ...E_n^{\text{sta}}, ...E_N^{\text{sta}})$$
$$\approx \sum_{n=1}^{N} \sum_{l \in \boldsymbol{Q}_n} V_n(l) \boldsymbol{I}[E_n^{\text{sta}} = l] = \boldsymbol{W}^T \boldsymbol{F}(\boldsymbol{E}^{\text{sta}}), \quad (27)$$

where $\boldsymbol{Q}_n$ means energy state set of the n-th MD, that is $\boldsymbol{Q}_n = \{0, 1, 2, ..., E_n^{\text{max}}\}$. The parameter vector $\boldsymbol{W}$ and the feature $\boldsymbol{F}(\boldsymbol{E}^{\text{sta}})$ can be elaborated as,

$$\boldsymbol{W} = [V_1(0), ...V_1(E_1^{\text{max}}), ...V_N(0), ...V_N(E_N^{\text{max}})]^T, \quad (28)$$

and

$$\boldsymbol{F}(\boldsymbol{E}^{\text{sta}}) = \big[\boldsymbol{I}[E_1^{\text{sta}} = 0], ...\boldsymbol{I}[E_1^{\text{sta}} = E_1^{\text{max}}],$$
$$...\boldsymbol{I}[E_N^{\text{sta}} = 0], ...\boldsymbol{I}[E_N^{\text{sta}} = E_N^{\text{max}}] \big]^T. \quad (29)$$

Thus, we can calculate the global energy state value function by the linear form of all MDs. According to the local energy state E_n^{sta}, the value function of global energy state $\boldsymbol{E}^{\text{sta}} = \{E_1^{\text{sta}}, ..., E_N^{\text{sta}}\}$ can be expressed as

$$V(\boldsymbol{E}^{\text{sta}}) \approx \sum_{n=1}^{N} V_n(E_n^{\text{sta}}) \quad E_n^{\text{sta}} \in \boldsymbol{Q}_n. \quad (30)$$

The global energy state value function $V(\boldsymbol{E}^{\text{sta}})$ is the same as the cardinality of the global energy state $\boldsymbol{E} = [E_1, ..., E_N]$, and its number is $\prod_{n=1}^{N}(E_n^{\text{max}}+1)$. However, the number of the linear approximation energy state value function of all MDs is $\sum_{n=1}^{N}(E_n^{\text{max}} + 1)$. Through linear approximation architecture, we exploit the state value function of each MD $V_n(E_n^{\text{sta}})$ with a small state space to represent the global energy state value function $V(\boldsymbol{E}^{\text{sta}})$ with huge state space.

According to *Lemma* 1 and the linear approximation architecture, we can obtain the following equations,

$$\mathbb{E}_{\boldsymbol{h}} \Big\{ \sum_{\boldsymbol{E}^{\text{sta}}(t+1)} \Pr \big(\boldsymbol{E}^{\text{sta}}(t+1) | \boldsymbol{h}(t), \boldsymbol{E}^{\text{sta}}(t) ,$$
$$\boldsymbol{\Omega}(\boldsymbol{h}(t), \boldsymbol{E}^{\text{sta}}(t)) \big) V(\boldsymbol{E}^{\text{sta}}(t+1)) \Big\},$$
$$= \mathbb{E}_{\boldsymbol{h}} \Big\{ \sum_{\boldsymbol{E}^{\text{sta}}(t+1)} \Big(\prod_{n=1}^{N} \Pr(E_n^{\text{sta}} | \boldsymbol{h}(t), \boldsymbol{E}^{\text{sta}}(t),$$
$$\boldsymbol{\Omega}(\boldsymbol{h}(t), \boldsymbol{E}^{\text{sta}}(t))) \sum_{n=1}^{N} V_n(E_n^{\text{sta}}(t+1)) \Big) \Big\},$$
$$= \mathbb{E}_{\boldsymbol{h}} \Big\{ \sum_{n=1}^{N} \sum_{E_n^{\text{sta}}(t+1) \in \boldsymbol{Q}_n} \Pr(E_n^{\text{sta}}(t+1) | \boldsymbol{h}(t), \boldsymbol{E}^{\text{sta}}(t),$$
$$\boldsymbol{\Omega}(\boldsymbol{h}(t), \boldsymbol{E}^{\text{sta}}(t))) V_n(E_n^{\text{sta}}(t+1)) \Big\},$$
$$= \mathbb{E}_{\boldsymbol{h}} \Big\{ \sum_{n=1}^{N} \sum_{A_n(t)} \Pr(A_n(t)) V_n(E_n^{\text{sta}}(A_n(t), \Omega_n(\boldsymbol{S}(t)))) \Big\},$$
$$(31)$$

where the post-action energy state of the n-th MD $E_n^{\text{sta}}(A_n(t), \Omega_n(\boldsymbol{S}(t)))$ can be defined as

$$E_n^{\text{sta}}(A_n(t), \Omega_n(\boldsymbol{S}(t))) =$$
$$\min \Big\{ \big[E_n^{\text{sta}}(t) - \lceil E_n^{\text{com}}(t) + E_n^{\text{cop}}(t) \rceil \big]^{+} + A_n(t), E_n^{\text{max}} \Big\}. \quad (32)$$

The equation (31) holds due to the state transition probability in (7) and the state update in (32). Thus, we can get the following optimal policy by (31),

$$\boldsymbol{\Omega}^*(\boldsymbol{E}(t)) = \arg \max_{\boldsymbol{\Omega}(\boldsymbol{E}(t))} \mathbb{E}_{\boldsymbol{h}} \Big\{ g(\boldsymbol{S}(t), \boldsymbol{\Omega}(\boldsymbol{S}(t)), \boldsymbol{\gamma})$$
$$+ \sum_{n=1}^{N} \sum_{A_n(t)} \Pr(A_n(t)) V_n(E_n^{\text{sta}}(A_n(t), \Omega_n(\boldsymbol{S}(t)))) \Big\}. \quad (33)$$

According to the linear value approximation structure (30) and (33), the control policy problem can be re-written as the following problem.

Problem 5: (Equivalent control policy problem)

$$\max_{\boldsymbol{\Omega}^*} \mathbb{E}_{\boldsymbol{h}} \Big\{ g(\boldsymbol{S}(t), \boldsymbol{\Omega}(\boldsymbol{S}(t)), \boldsymbol{\gamma})$$
$$+ \sum_{n=1}^{N} \sum_{A_n(t)} \Pr(A_n(t)) V_n(E_n^{sta}(A_n(t), \Omega_n(\boldsymbol{S}(t)))) \Big\},$$
$$s.t. \quad 0 \le P_n(t) \le P_n^{max},$$
$$\epsilon_n(t) \in \{0, 1\},$$
$$(9), \ (10) \ and \ (12), \forall n. \quad (34)$$

Since $E_n^{\text{sta}}(A_n(t), \Omega_n(\boldsymbol{S}(t)))$ represents the update of the local energy state, we need to calculate the objective function of (34) for each local energy state, and derive the objective function over all local energy states. To solve (34), we expand $V(E_n^{\text{sta}}(A_n(t), \Omega_n(\boldsymbol{S}(t))))$ in (34) using Taylor expansion as follows [34], [35]:

$$V(E_n^{\text{sta}}(A_n(t), \Omega_n(\boldsymbol{S}(t)))) = V(E_n^{\text{sta}}(t))$$
$$+ (A_n(t) - \lceil E_n^{\text{com}}(t) + E_n^{\text{cop}}(t) \rceil) V'(E_n^{\text{sta}}(t)), \quad (35)$$
where
$$V'(E_n^{\text{sta}}(t)) = \big[V(E_n^{\text{sta}}(t) + 1) - V(E_n^{\text{sta}}(t) - 1) \big] / 2.$$

The optimization objective in (34) can be expressed as follow,

$$\max_{\boldsymbol{\Omega}} \quad \mathbb{E}_{\boldsymbol{h}} \Big\{ g(\boldsymbol{S}(t), \boldsymbol{\Omega}(\boldsymbol{S}(t), \boldsymbol{\gamma})$$
$$+ \sum_{n=1}^{N} \sum_{A_n(t)} \Pr(A_n(t))(V(E_n^{\text{sta}}(t)) + (A_n(t)- \quad (36)$$
$$\lceil E_n^{\text{com}}(t) + E_n^{\text{cop}}(t) \rceil) V'(E_n^{\text{sta}}(t))) \Big\}.$$

In this way, we can obtain the equivalent optimization problem at the current iteration shown as follow, which is equivalent to (34),

$$
\begin{aligned}
\max_{\boldsymbol{b},\boldsymbol{\epsilon},\boldsymbol{P}} \quad & g(\boldsymbol{S}(t),\boldsymbol{\Omega}(\boldsymbol{S}(t)),\boldsymbol{\gamma}) + \sum_{n=1}^{N}\sum_{A_n(t)}\Pr(A_n(t)) \\
& \times (A_n(t) - \lceil E_n^{\mathrm{com}}(t) + E_n^{\mathrm{cop}}(t)\rceil)V'(E_n^{\mathrm{sta}}(t)), \quad (37) \\
\text{s.t.} \quad & (9),\ (10)\ \text{and}\ (12), \\
& \epsilon_n(t) \in \{0,1\}, \\
& 0 \le P_n(t) \le P_n^{\max}, \quad \forall n,t,
\end{aligned}
$$

where (37) is a static mixed variable optimization problem, in which $\boldsymbol{b}$ and $\boldsymbol{P}$ are continuous variables, while $\boldsymbol{\epsilon}$ are discrete variables. Besides, the ceiling operator $\lceil \cdot \rceil$ is difficult to handle, which brings great difficulties to the optimization problem. In order to solve the problem caused by the ceiling operator $\lceil \cdot \rceil$, we introduce a series of auxiliary variables $\Delta E_n(t), \forall n$ to simplify the optimization problem. The optimization problem can be further described as follow:

$$
\begin{aligned}
\max_{\boldsymbol{b},\boldsymbol{\epsilon},\boldsymbol{P}} \quad & g(\boldsymbol{S}(t),\boldsymbol{\Omega}(t),\boldsymbol{\gamma}) + \sum_{n=1}^{N}\sum_{A_n(t)}\Pr(A_n(t)) \\
& \times (A_n(t) - \Delta E_n(t))V'(E_n(t)) \\
\text{s.t.} \quad & (9)\ \text{and}\ (12), \quad\quad\quad\quad\quad\quad\quad (38)\\
& E_n^{\mathrm{com}}(t) + E_n^{\mathrm{cop}}(t) - \Delta E_n(t) \le 0, \\
& \Delta E_n(t) \in \{0,1,2,...,E_n(t)\}, \\
& \epsilon_n(t) \in \{0,1\}, \\
& 0 \le P_n(t) \le P_n^{\max}, \quad \forall n,
\end{aligned}
$$

where the auxiliary variable is

$$
\begin{aligned}
\Delta E_n(t) &= \lceil E_n^{\mathrm{com}}(t) + E_n^{\mathrm{cop}}(t)\rceil \\
&= \left\lceil \alpha b_n(t)C_n f_n^2 + \frac{\epsilon_n(t)P_n(t)d}{R_{n,s}(t)} \right\rceil. \quad (39)
\end{aligned}
$$

Note that the constraints (12) describes the sub-channel constraints of all MDs, we ignore the constraints for the time being to simplify the optimization problem. Given a typical MD n, we can obtain the following optimization problem by further analysis and simplification of (37),

$$
\begin{aligned}
\max_{b_n,\epsilon_n,P_n} \quad & \frac{\Delta E_n(t) - E_n^{\mathrm{com}}(t)}{\alpha C_n f_n^2}\epsilon_n(t) - \Delta E_n(t)V'(E_n(t)), \\
\text{s.t.} \quad & T_n^{\mathrm{com}}(t) + T_n^{\mathrm{cop}}(t) \le \tau, \\
& \Delta E_n(t) \in \{0,1,2,...,E_n(t)\}, \\
& \epsilon_n(t) \in \{0,1\}, \\
& 0 \le P_n(t) \le P_n^{\max}, \quad \forall n. \\
& \quad\quad\quad\quad\quad\quad\quad\quad\quad\quad\quad\quad (40)
\end{aligned}
$$

From (40), we can draw the following conclusion obviously: if $\Delta E_n(t) \le E_n^{\mathrm{th}}(t)$, then $P_n(t) = 0$ and $\epsilon_n(t) = 0$, in which $E_n^{\mathrm{th}}(t)$ means the threshold energy of the n-th MD at the current iteration, and it can be expressed as,

$$
E_n^{\mathrm{th}}(t) = \frac{\tau\sigma^2}{h_n(t)}\left(2^{\frac{d}{W\tau}} - 1\right). \quad (41)
$$

When $\Delta E_n(t) \le E_n^{\mathrm{th}}$, the energy consumed by the n-th MD at the current iteration is insufficient to support uploading model parameters to the edge server within the iteration duration τ.

Due to the first constraint of (40), we obtain the upper bound of energy consumption by the n-th MD at the iteration t, that is,

$$
\Delta E_n(t) \le (\tau - T_n^{\mathrm{com}}(t))\alpha f_n^3 + T_n^{\mathrm{com}}(t)P_n(t). \quad (42)
$$

When $\frac{1}{\alpha C_n f_n^2} - V'(E_n(t)) \le 0$, the energy consumption $\Delta E_n(t)$ is 0 obviously. Correspondingly, the transmission power $P_n(t)$ of the n-th MD, the transmission decision $\epsilon_n(t)$ of the n-th MD and the batch size of local training data $b_n(t)$ are all 0. When $\frac{1}{\alpha C_n f_n^2} - V'(E_n(t)) > 0$ and $\Delta E_n(t) > E_n^{\mathrm{th}}(t)$, since the value of $P_n(t)$ is related to the value of $\Delta E_n(t)$ and $\Delta E_n(t) \le (\tau - T_n^{\mathrm{com}}(t))\alpha f_n^3 + T_n^{\mathrm{com}}(t)P_n(t)$, the energy consumption $\Delta E_n(t)$ of the n-th MD take the maximum value, i.e.,

$$
\Delta E_n(t) = \left(\tau - \frac{d}{R_{n,s}(t)}\right)\alpha f_n^3 + \frac{d}{R_{n,s}(t)}P_n(t). \quad (43)
$$

Since $P_n(t) \in (0, P_n^{\max}]$ and $\Delta E_n(t)$ increases monotonically as $P_n(t)$ increases, there is a maximum value of $\Delta E_n^{\max}(t)$ as a function of $P_n(t)$, which can be expressed as,

$$
\Delta E_n^{\max}(t) = \left(\tau - \frac{d}{R_{n,s}^{\max}(t)}\right)\alpha f_n^3 + \frac{d}{R_{n,s}^{\max}(t)}P_n^{\max}. \quad (44)
$$

Thus, when $\Delta E_n(t) > \Delta E_n^{\max}(t)$, the transmit power $P_n(t)$ is $P_n^{\max}$, $\epsilon_n(t) = 1$ and the batch size $b_n(t)$ for local training can be expresses as following,

$$
b_n(t) = \frac{\Delta E_n^{\max}(t) - E_{n,\max}^{\mathrm{com}}(t)}{\alpha C_n f_n^2}, \quad (45)
$$

where,

$$
E_{n,\max}^{\mathrm{com}}(t) = \frac{dP_n^{\max}}{W \log_2\left(1 + \frac{P_n^{\max} h_n(t)}{\sigma^2}\right)}. \quad (46)
$$

Then for $E_n^{\mathrm{th}}(t) < \Delta E_n(t) \le \Delta E_n^{\max}(t)$, according to the relationship between $\Delta E_n(t)$ and $P_n(t)$, we can express $P_n(t)$ by $\Delta E_n(t)$, which has shown as follow,

$$
P_n(t) = \frac{\mathrm{lambertW}\left(\frac{B_n(t)}{Z_n(t)}e^{\frac{C_n(t)}{Z_n(t)}}\right)}{\frac{B_n(t)}{Z_n(t)}h_n(t)} - \frac{\sigma^2}{h_n(t)},
$$

where,

$$
\begin{aligned}
B_n(t) &= -\frac{d}{h_n(t)}, \quad\quad\quad\quad\quad\quad\quad\quad (47)\\
C_n(t) &= \frac{W(\Delta E_n(t) - \alpha f_n^3\tau)}{\ln 2}\ln\sigma^2 - \frac{d\sigma^2}{h_n(t)} - \alpha f_n^3 d, \\
Z_n(t) &= \frac{W(\Delta E_n(t) - \alpha f_n^3\tau)}{\ln 2}.
\end{aligned}
$$

And $\epsilon_n(t) = 1$, lambertW means Lambert W Function, which is the inverse function of $f(w) = w \cdot \exp(w)$. And it is a special function that cannot be represented by an expression.

From this, we get the objective function of the variable of ΔE_n by substituting $P_n(t)$ into the objective function in (40),

$$
\begin{aligned}
F_n(t) = \max_{\Delta E_n(t)} \frac{1}{\alpha C_n f_n^2} \Big(& \min\{\Delta E_n(t), \Delta E_n^{\max}(t)\} \\
& - \frac{dP_n(\Delta E_n(t))}{R_{n,s}(\Delta E_n(t))} \Big) \epsilon_n(t) - \Delta E_n(V_n'(E_n(t))) \\
\text{s.t.} \quad & \Delta E_n(t) \in \{0, 1, ..., \min\{E_n^{\text{sta}}(t), \lceil \Delta E_n^{\max}(t) \rceil\}\}.
\end{aligned}
$$
(48)

Algorithm 1: The pseudocode of the proposed static mixed variable optimization problem of all MDs

---

Input: input $\boldsymbol{E}^{\text{sta}}(t), \boldsymbol{h}(t), f_n, P_n^{\max}, V_n'(t), \forall n$;
Output: output result $\boldsymbol{P}^*(t), \boldsymbol{b}^*(t), \boldsymbol{\epsilon}^*(t)$;

1 **for** *The n-th MD, $n \in 1, ..., N$* **do**
2   Calculate threshold energy $E_n^{\text{th}}(t)$ and the maximum energy consumption $\Delta E_n^{\max}(t)$ for calculation and communication in the t-th iterartion from input parameters;
3   **for** $\Delta E_n(t) \in \{0, 1, ..., \min\{E_n(t), \lceil \Delta E_n^{max}(t) \rceil\}\}$ **do**
4   **if** $\Delta E_n(t) \le E_n^{th}(t)$ **then**
5              $P_n(t) = 0, b_n(t) = 0, \epsilon_n(t) = 0$;
6   **else if** $\frac{1}{\alpha C_n f_n^2} - V_n'(E_n(t)) \le 0$ **then**
7              $P_n(t) = 0, b_n(t) = 0, \epsilon_n(t) = 0$;
8   **else if** $E_n^{th}(t) < \Delta E_n(t) \le \Delta E_n^{max}(t)$ **then**
9   The solution of $P_n(t)$ and $b_n(t)$ can refer to the formula (47) and $\epsilon_n(t) = 1$;
10   **else**
11              $P_n(t) = P_n^{\max}$ and the solution of $b_n(t)$ can refer to the formula (45) and $\epsilon_n(t) = 1$;
12   **end if**
13   Substituting the values of $P_n(t)$ and $\epsilon_n(t)$ that have been obtained into the objective function of (40) ;
14   By searching in the $\{0, 1, ..., \min\{E_n(t), \lceil \Delta E_n^{\max}(t) \rceil\}\}$, the optimal energy consumption value $\Delta \hat{E}_n(t)$ of the n-th MD for the maximum value of the objective function in (48) can be found, and $\hat{P}_n(t), \hat{b}_n(t), \hat{\epsilon}_n(t)$ can be calculated.
15 **if** $\| \hat{\boldsymbol{\epsilon}} \|_1 \le L$ **then**
16   The global optimal solution is equal to the solution obtained by the respective MD, i.e., $\boldsymbol{P}^*(t) = \hat{\boldsymbol{P}}(t), \boldsymbol{b}^*(t) = \hat{\boldsymbol{b}}(t)$.
17 **else**
18   The edge server will select L MDs with the largest $F_n(t)$ for FL training. If the n-th MD is selected by the server, then $P_n^*(t) = \hat{P}_n(t), \epsilon_n^*(t) = \hat{\epsilon}_n(t)$ and $b_n^*(t) = \hat{b}_n(t)$, otherwise $P_n^*(t) = 0, \epsilon_n^*(t) = 0$ and $b_n^*(t) = 0$.
19 **end if**

By searching in the $\{0, 1, ..., \min\{E_n(t), \lceil E_n^{\max}(t) \rceil\}\}$, we can find the optimal energy consumption value $\Delta \hat{E}_n(t)$ of the n-th MD for the maximum value of the objective function

in (48). For convenience, we assume $0/0 = 0$ for the term of $\frac{dP_n(\Delta E_n(t))}{R_{n,s}(\Delta E_n(t))}$ in this paper. Recalling the sub-channel constraint (12) that we ignored earlier, we will analyze it. According to (48), we get the optimal objective function $F_n(t)$ of each MD in the current iteration. If $\| \hat{\boldsymbol{\epsilon}} \|_1 \le L$, the global optimal solution is equal to the solution obtained by the respective MD, i.e., $P_n^*(t) = \hat{P}_n(t), b_n^*(t) = \hat{b}_n(t)$. Then, when $\| \hat{\boldsymbol{\epsilon}} \|_1 > L$, the edge server will select L MDs with the largest $F_n(t)$ for FL training. If the n-th MD is selected by the edge server to upload parameters, then $P_n^*(t) = \hat{P}_n(t), \epsilon_n^*(t) = \hat{\epsilon}_n(t)$ and $b_n^*(t) = \hat{b}_n(t)$, otherwise $P_n^*(t) = 0, \epsilon_n^*(t) = 0$ and $b_n^*(t) = 0$. Algorithm 1 reports the pseudocode of the proposed static mixed variable optimization problem.

In the previous section, we assumed that the state value function $V(\boldsymbol{E}^{\text{sta}})$ has been given. However, we need to know the state value function of each MD accurately so that we can make efficient control decisions in the FL process. We utilize stochastic learning and propose a distributed online algorithm to estimate the value function $V(\boldsymbol{E}^{\text{sta}})$ and the Lagrange multipliers $\boldsymbol{\gamma}$ based on the current state. The updates of the value function V at the end of the iteration t can be given by (49).

Algorithm 2: The specific flow of the stochastic learning

---

1 Initialize the respective energy state value function vectors $\boldsymbol{V}^0$ and the Lagrange multiplier vectors $\boldsymbol{\gamma}^0$ of all MDs ;
2 Based on the observed local states, a series of parameters and the local energy value functions $\boldsymbol{V}^t$ of each MD, the control action can be calculated by Algorithm 1 at the beginning of the iteration t;
3 Based on the observed local states, the control actions and the instantaneous rewards of the system, the energy state value function $\boldsymbol{V}^{t+1}$ and Lagrange multiplier vectors $\boldsymbol{\gamma}^{t+1}$ can be updated by (49), (50) and (51);
4 If $\| \boldsymbol{V}^{t+1} - \boldsymbol{V}^t \| < \delta_v$ and $\| \boldsymbol{\gamma}^{t+1} - \boldsymbol{\gamma}^t \| < \delta_\gamma$, stop; otherwise, set $t = t + 1$ and go back to step 2.

$$
V_n^{t+1}(l) =
\begin{cases}
(1 - \epsilon_v^t)V_n^t(l) + \epsilon_v^t \Delta V_n^{t+1}(l) & \text{if } \boldsymbol{E}_n^{t+1} = l \\
V_n^t(l) & \text{if } \boldsymbol{E}_n^{t+1} \ne l
\end{cases}
$$
(49)

where $\Delta V_n^t(l)$ is expressed in (50),

$$
\begin{aligned}
\Delta V_n^{t+1}(l) = {} & b_n(t)\epsilon_n(t) - \gamma_n^t \mathbf{1}[l = 0] \\
& + \sum_{A_n} \{ \Pr(A_n)(V_n^t(l(\Delta E_n^{t+1}, A_n)) - V_n^t(l(A_n))) \}
\end{aligned}
$$
(50)

Moreover, the Lagrange multipliers updates at per MD are given by

$$
\gamma_n^{t+1} = [\gamma_n^t + \epsilon_\gamma^t (\mathbf{1}[E_n^{t+1} = 0] - \Pr_n^{\text{th}})]^+
$$
(51)

In the above equations, $\left(\{\epsilon_v^t\}, \{\epsilon_\gamma^t\}\right)$ are the sequences of iteration size, which satisfy,

$$\sum_{t=0}^{\infty} \epsilon_v^t = \infty, \ \epsilon_v^t > 0, \ \lim_{t \to \infty} \epsilon_v^t = 0,$$

$$\sum_{t=0}^{\infty} \epsilon_\gamma^t = \infty, \ \epsilon_v^\gamma > 0, \ \lim_{t \to \infty} \epsilon_v^\gamma = 0, \qquad (52)$$

$$\sum_{t=0}^{\infty} \left[(\epsilon_v^t)^2 + (\epsilon_\gamma^t)^2\right] < \infty, \ \text{and} \ \lim_{t \to \infty} \frac{\epsilon_\gamma^t}{\epsilon_v^t} = 0.$$

The specific process of stochastic learning can refer to Algorithm 2.

C. Convergence Analysis

We need to provide effective analysis for the convergence of the online stochastic learning algorithm, which is shown in Algorithm 2. From the previous section, we notice that there are two different step size sequences $\{\epsilon_v^t\}$ and $\{\epsilon_\gamma^t\}$ in the stochastic learning process, which are used for the update of state value functions of MDs and Lagrange Multipliers respectively. Since the update of the Lagrangian multiplier γ and the update of the value function V occur simultaneously and $\epsilon_\gamma^t = o(\epsilon_v^t)$, we can obtain $\gamma^{t+1} - \gamma^t = o(\epsilon_v^t)$. Therefore, we consider that the Lagrangian multipliers does not change when the state value function is updated. Therefore, we assume that the Lagrangian multipliers γ^t keep static when the value functions of the mobile devices are updated in (49).

The relationship between the the global value function vector V and the parameter vector W can be expressed as,

$$V = MW \qquad \text{and} \qquad W = M^\dagger V, \qquad (53)$$

in which $M \in \mathbb{R}^{|I_S| \times \sum_{n=1}^{N}(E_n^{\max}+1)}$ with the kth row ($k = 1, 2, ..., |I_S|$) equal to $F(E^k)$, where E^k is the kth global energy state and $|I_S|$ is the cardinality of the system state. In addition, $M^\dagger \in \mathbb{R}^{\sum_{n=1}^{N}(E_n^{\max}+1) \times |I_S|}$ means the mapping matrix from V to W, which is the inverse mapping of the first equation of (53). We then have the following convergence lemma on the local state value function for each MD in the stochastic learning.

Lemma 2: (Convergence of State Value Function of each MD): *The convergence performance of the state value function can be expressed mathematically as follows.*

1) *The update of the state value function vector converge almost surely for any given initial parameter vector W^0 and Lagrange multiplier γ, which can be expressed as*

$$\lim_{t \to \infty} W^t(\gamma) = W^\infty(\gamma). \qquad (54)$$

2) *The local steady-state value function vector W^∞ satisfies the vector form of the following steady equivalent Bellman equation,*

$$\theta I + W^\infty(\gamma) = M^\dagger T\left(\gamma, MW^\infty(\gamma)\right), \qquad (55)$$

where I is a $\sum_{n=1}^{N}(E_n^{max}+1) \times 1$ vector whose elements are all equal to 1, T represents a function mapping, which can be defined as,

$$T(\gamma, V) = \max_{\Omega} \{\overline{g}(\gamma, \Omega) + P(\Omega)V\} \qquad (56)$$

where $\overline{g}(\gamma, \Omega)$ is a $\sum_{n=1}^{N}(E_n^{max}+1) \times 1$ vector of function $\overline{g}(E, \Omega(E))$, which is defined in (22). $P(\Omega)$ is the matrix form of transition probability $Pr(E^{t+1}|E^t, \Omega)$ defined in (22).

Proof: *Following [35], we briefly explain the Lemma. Since we consider the stochastic channels, where the channel gain varies within the interval, it is easy to see that each state will be updated comparably often in the asynchronous learning algorithm. Quoting the conclusion in [35], the convergence property of the asynchronous update and synchronous update is the same. Therefore, we just consider the convergence of related synchronous version for simplicity in this proof. According to the definition of parameter vector W and the bounded per-MD value function V_n, it is clearly that the update on the per-MD value function vector is equivalent to the update on the parameter vector and to prove the convergence of the Lemma is equivalent to prove the convergence of update on the parameter vector W. The proof of details can refer to [35].*

Due to $\epsilon_\gamma^t = o(\epsilon_v^t)$, the ratio of step sizes between state value function and Lagrange Multiplier can be expressed as $\frac{\epsilon_\gamma^t}{\epsilon_v^t} \to 0$ during the Lagrange Multiplier update in (51), and the updates of the local state value function are much faster than the Lagrange Multiplier. Thus, the Lagrange Multiplier can be consider as quasi-invariant during the update of the local state value functions of each MD, and the update of the Lagrange Multiplier will trigger another update process of the local state value function of each MD. According to [36], we can obtain that $\lim_{t \to \infty} ||V_n^t - V_n^\infty(\gamma^t)|| = 0$, in which $V_n^\infty(\gamma^t)$ means the converged local state value function of nth MD with Lagrange Multiplier γ^t. Therefore, the update of the local state value function can be considered as almost constant during the Lagrange Multipliers update. Then, we need to the convergence lemma of the Lagrange Multipliers.

Lemma 3: (Convergence of the Lagrange Multipliers): *The iteration on the Lagrange Multipliers γ converges almost surely to the set of minimum of $G(\gamma)$ in (18). Supposing that the Lagrange Multipliers converge to γ^*, then γ^* satisfies the average energy outage constraint in (11).*

Proof: *Quoting to [37, Lemma 4.2], $-G(\gamma)$ is a concave and continuously differentiable except at finitely many points where both right and left derivatives exist. Thus, $G(\gamma)$ is a convex function of γ. Since the energy consumption policy of each MD is discrete, we can obtain that $\Omega^*(\gamma) = \Omega^*(\gamma + \Delta_\gamma)$, i.e., $\nabla_\gamma = (\Omega^*(\gamma + \Delta_\gamma) - \Omega^*(\gamma))/\Delta_\gamma = 0$. Thus, $\partial G(\gamma^t)/\partial \gamma^t$ can be expressed as $\partial G(\gamma^t)/\partial \gamma^t = \mathbb{E}^{\Omega^*(\gamma^t)}\{Pr_n^E - \mathbf{1}[E_n(t) = 0]\}$, where $\Omega^*(\gamma^t) = \arg\max_\Omega G(\gamma^t)$. By the standard stochastic approximation theorem [38], the dynamics of the Lagrange Multiplier update can be represented by ordinary differential equation (ODE). According to [39], we know that that the ODE equals to $\partial G(\gamma^t)/\partial \gamma^t$. Thus, the aforementioned ODE will converge to $\partial G(\gamma^t)/\partial \gamma^t = 0$, i.e., the the average energy outage constraints are satisfied.* ∎

According to Lemma 2 and 3, the iteration on local state value function and the Lagrange Multipliers in Algorithm 2 will converge.
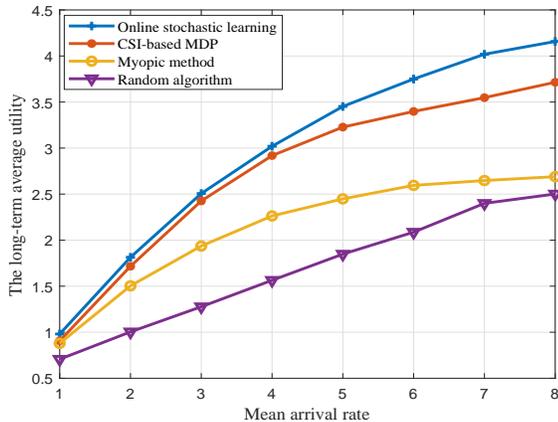
Fig. 2. The long-term average utility $\mathcal{U}$(MB) v.s. the mean arrive rate λ(J)of the random new arrived energy with $E^{\mathrm{max}} = 6$J.
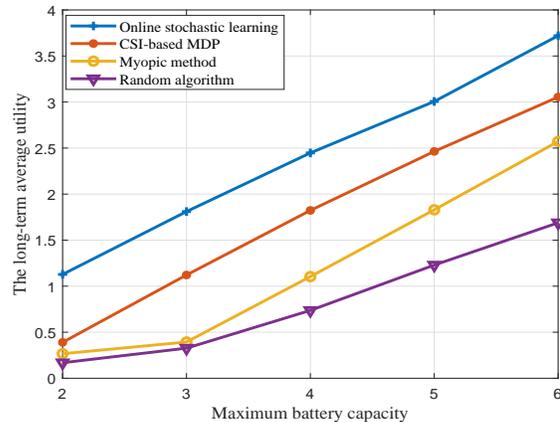
Fig. 3. The long-term average utility $\mathcal{U}$(MB) v.s. the maximum battery capacity E^{max}(J) of MD.

V. SIMULATION AND DISCUSSION

In this section, we evaluate the performance of the proposed algorithm using numerical results. In the simulations, all MDs are randomly distributed in a fixed region. We set the bandwidth of channel between each MD and the edge server as 0.1MHz. The number of CPU cycles C for each MD to perform local model training of unit data sampling takes range from 10^{10}cycle/unit to $1.9 * 10^{10}$cycle/unit. The simulation parameters are detailed in Table II.

TABLE II
PARAMETERS IN SIMULATIONS

Nations	Values
The number of MDs N	10
The number of channels in FL system L	5
Channel bandwidth W	0.1MHz
The number of CPU cycles C per unit data sampling	$[10^{10}, 1.9 \times 10^{10}]$ cycles/unit
Each iteration duration τ	10s
Computation capacity f_n of the MD	$[2 \times 10^9, 4 \times 10^9]$ cycles/s
The size of local parameter for each MD	10^6bit
The effective capacitance parameter α	10^{-28}
The coefficient determined by machine learning model ζ	1
The upper limit value of the average energy outage $\mathrm{Pr}_n^{\mathrm{th}}$	4%

We compare our proposed approximate MDP solution with online stochastic learning with three other reference control algorithms. One is the CSI-based MDP algorithm, where the edge server takes corresponding decisions based on the channel state only at the current iteration so as to optimize average utility of all MDs. The second reference control algorithm is myopic method, which is a method that only considers the current utility. In myopic method, the edge server never considers long-term utilities. The last reference control algorithm is a random resource scheduling method, where the edge server takes random actions in the feasible regions. The performance of the proposed algorithm is evaluated by averaging over 5000 experiments.

Fig. 2 illustrates the long-term average utility $\mathcal{U}$ v.s. the mean arrival rate λ of the random new arrived energy with $E^{\mathrm{max}} = 6$J. It can be observed that the performance of the online stochastic learning algorithm is better than the other reference algorithms for all the investigated average arrival rate λ. When the value of the mean arrival rate λ is relatively small, the performance of online learning is close to that of other reference algorithms, especially the CSI-based MDP algorithm. The cause of this phenomenon is twofold. First, the small mean arrival rate λ of energy will result in a limited energy level in the battery of the MD. Due to insufficient battery energy, MDs are constrained with a small space of actions compared with those with sufficient battery power. The second reason is that a large amount of battery energy is used for uploading local parameters. When the battery energy of MD is insufficient, the energy for local training of FL is smaller, which leads to smaller long-term average utility. In contrast, when the battery level is high, MD's actions will become more diverse, and more energy will be used for local training in FL process.

Fig. 3 illustrates the long-term average utility $\mathcal{U}$ v.s. the maximum battery capacity E^{max} of MD. We observe that the long-term average utility increases as the maximum battery capacity E^{max} of MD increases in all algorithms, although the mean arrival rate λ of the arrival energy has never changed. It indicates that the long-term average utility $\mathcal{U}$ increases approximately linearly with the maximum battery capacity E^{max} in our proposed algorithm.

Fig. 4 shows the impact of the number of CPU cycles for MD to perform local model training of unit data sampling C on the long-term average utility $\mathcal{U}$. It is obvious that the long-term average utility decreases as the number of CPU cycles for unit training data sampling C. In addition, as the number of CPU cycles for unit training data sampling C continues to increase, performance differences among different algorithms also decrease. Fig. 5 depicts the long-term average utility $\mathcal{U}$ v.s. the computation capacity f of MD. Intuitively, the MDs with more computing capacity will lead to a higher long-term average utility $\mathcal{U}$. However, the opposite is true, it is caused
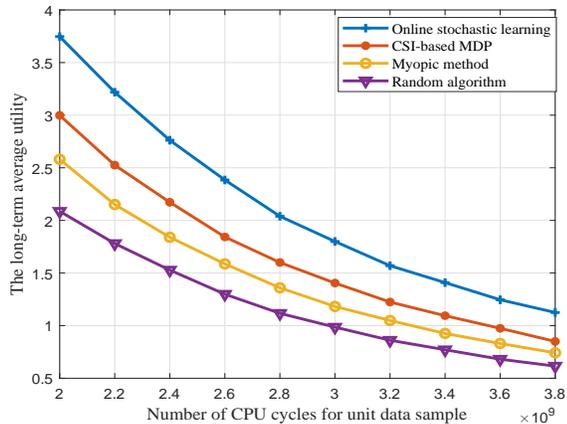
Fig. 4. The long-term average utility $\mathcal{U}$(MB) v.s. the number of CPU cycles for MD to perform local model training of unit data sampling C(cyc/MB).
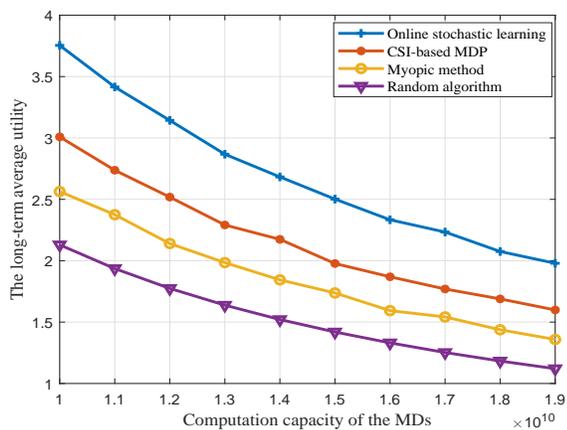
Fig. 5. The long-term average utility(MB) $\mathcal{U}$ v.s. the computation capacity f(Hz) of MD.

Fig. 6. The transmission power(W) v.s. the wireless channel state and the energy state of MD.
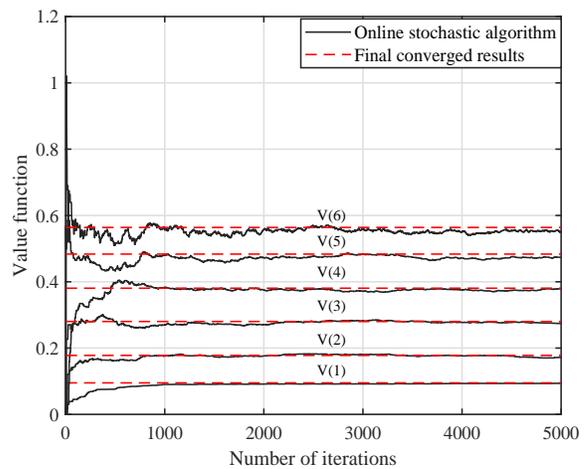
Fig. 7. Convergence property of the proposed online stochastic learning algorithm.

by (3) and the limited energy of MD in each iteration. In other words, a more powerful computing capacity requires more computing energy. Due to the limited amounts of energy available to MDs in each iteration, MDs can only reduce the size of sampling data used for local training.

Fig. 6 describes the relationship among the wireless channel state, the energy state of MD and the transmission power policy. In our simulation settings, H_1 represents the worst channel state, while H_5 represents the best channel state in our system. From the figure, we can see that the MD avoids data transmission to save battery energy when the MD is in a very poor channel state (H_1). In addition, we find that for a given channel state the transmission power monotonously increases with the energy state of the MD.

Fig. 7 illustrates the convergence property of the proposed distributed online learning algorithm. It can be seen that the online stochastic algorithm converges quite fast and after 1500 iterations, the values are close to the final converged results. Moreover, it is clear that the value functions calculated online quickly approach the the final converged results when the number of iterations grows.

VI. Conclusion

In this paper, we study a constrained MDP problem of FL with a MEC sever, where each MDs send local model updates trained on their local sensitive data iteratively to the edge server, and the edge server aggregates the parameters from MDs and broadcasts the aggregated parameters to MDs. We first model the resource scheduling problem in the synchronous FL process as a constrained MDP problem, and we use the size of the training samples as the performance of FL for analysis. Due to the coupling between iterations and the complexity of the state-action space, we cannot directly solve the constrained MDP problem. Thus, we analyze the problem by equivalent Bellman equations and use approximate MDP and stochastic learning methods to simplify the constrained MDP problem so as to approximate the state value function. Then we design static algorithm to obtain the static policy for each MD based the approximate state value function. Finally, we provide theoretical analysis for the convergence of the online stochastic learning algorithm. The simulation results

show that the performance of the stochastic leaning is better than various benchmark schemes.

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