Multi-Agent Meta-Reinforcement Learning for Self-Powered and Sustainable Edge Computing Systems

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Abstract—The stringent requirements of mobile edge computing (MEC) applications and functions fathom the high capacity and dense deployment of MEC hosts to the upcoming wireless networks. However, operating such high capacity MEC hosts can significantly increase energy consumption. Thus, a BS unit can act as a self-powered BS. In this paper, an effective energy dispatch mechanism for self-powered wireless networks with edge computing capabilities is studied. First, a two-stage linear stochastic programming problem is formulated with the goal of minimizing the total energy consumption cost of the system while fulfilling the energy demand. Second, a semi-distributed data-driven solution is proposed by developing a novel multi-agent meta-reinforcement learning (MAMRL) framework to solve the formulated problem. In particular, each BS plays the role of a local agent that explores a Markovian behavior for both energy consumption and generation while each BS transfers time-varying features to a meta-agent. Sequentially, the meta-agent optimizes (i.e., exploits) the energy dispatch decision by accepting only the observations from each local agent with its own state information. Meanwhile, each BS agent estimates its own energy dispatch policy by applying the learned parameters from meta-agent. Finally, the proposed MAMRL framework is benchmarked by analyzing deterministic, asymmetric, and stochastic environments in terms of non-renewable energy usages, energy cost, and accuracy. Experimental results show that the proposed MAMRL model can reduce up to 11% energy usage and by 22.4% the energy cost (with 95.8% prediction accuracy), compared to other baseline methods.

Index Terms—Mobile edge computing (MEC), renewable energy, stochastic optimization, meta-reinforcement learning, self-powered, demand response.

I. INTRODUCTION

Next-generation wireless networks are expected to significantly rely on edge applications and functions that include edge computing and edge artificial intelligence (edge AI) [1]–[7]. To successfully support such edge services within a wireless network with mobile edge computing (MEC) capabilities, energy management (i.e., demand and supply) is one of the most critical design challenges. In particular, it is imperative to equip next-generation wireless networks with alternative energy sources, such as renewable energy, in order to provide extremely reliable energy dispatch with less energy consumption cost [8]–[15]. An efficient energy dispatch design requires energy sustainability, which not only saves energy consumption cost, but also fulfills the energy demand of the edge computing by enabling its own renewable energy sources. Specifically, sustainable energy is the practice of seamless energy flow to the MEC system that emerges to meet the energy demand without compromising the ability of future energy generation. Furthermore, to ensure a sustainable MEC operation, the retrogressive penetration of uncertainty for energy consumption and generation is essential.

To provide sustainable edge computing for next-generation wireless systems, each base station (BS) with MEC capabilities unit can be equipped with renewable energy sources. Thus, the energy source of such a BS unit not only relies solely on the power grid, but also on the equipped renewable energy sources. In particular, in a self-powered network, wireless BSs with MEC capabilities is equipped with its own renewable energy sources that can generate renewable energy, consume, store, and share energy with other BS units.

Delivering seamless energy flow with a low energy consumption cost in a self-powered wireless network with MEC capabilities can lead to uncertainty in both energy demand and generation. In particular, the randomness of the energy demand is induced by the uncertain resources (i.e., computation and communication) request by the edge services and applications. Meanwhile, the energy generation of a renewable source (i.e., a solar panel) at each self-powered BS unit varies on the time of a day. In other words, the pattern of energy demand and generation will differ from one self-powered BS unit to another. Thus, such fluctuating energy demand and generation pattern induces a non-independent and identically distributed (non-iid) of energy dispatch at each BS over time. As such, when designing self-powered wireless networks, it is necessary to take into account this uncertainty in the energy patterns.

A. Related Works

The problem of energy management for MEC-enabled wireless networks has been studied in [16]–[22]. In [16], the authors proposed a joint mechanism for radio resource management and users task offloading with the goal of minimizing the long-term power consumption for both mobile devices and
the MEC server. The authors in [17] proposed a heuristic to solve the joint problem of computational resource allocation, uplink transmission power, and user task offloading problem. The work in [18] studied the tradeoff between communication and computation for a MEC system and the authors proposed a MEC server CPU scaling mechanism for reducing the energy consumption. Further, the work in [19] proposed an energy-aware mobility management scheme for MEC in ultra-dense networks, and they addressed the problem using Lyapunov optimization and multi-armed bandits. Recently, the authors in [21] proposed a distributed power control scheme for a small cell network by using the concept of a multi-agent calibrate learning. Further, the authors in [22] studied the problem of energy storage and energy harvesting (EH) for a wireless network using deviation theory and Markov processes. However, all of these existing works assume that the consumed energy is available from the energy utility source to the wireless network system [16]–[22]. Since the assumed models are often focused on energy management and user task offloading on network resource allocations, the random demand for computational (e.g., CPU computation, memory, etc.) and communication requirements of the edge applications and services are not considered. In fact, even if enough energy supply is available, the energy cost related to network operation can be significant because of the usage of non-renewable (e.g., coal, petroleum, natural gas). Indeed, it is necessary to include renewable energy sources towards the next-generation wireless networking infrastructure.

Recently, some of the challenges of renewable energy powered wireless networks have been studied in [8]–[14], [23], [24]. In [8], the authors proposed an online optimization framework to analyze the activation and deactivation of BSs in a self-powered network. In [9], proposed a hybrid power source infrastructure to support heterogeneous networks (HetNets), a model-free deep reinforcement learning (RL) mechanism was proposed for user scheduling and network resource management. In [10], the authors developed an RL scheme for edge resource management while incorporating renewable energy in the edge network. In particular, the goal of [10] is to minimize a long-term system cost by load balancing between the centralized cloud and edge server. The authors in [11] introduced a microgrid enabled edge computing system. A joint optimization problem is studied for MEC task assignment and energy demand-response (DR) management. The authors in [11] developed a model-based deep RL framework to tackle the joint problem. In [12], the authors proposed a risk-sensitive energy profiling for microgrid-powered MEC network to ensure a sustainable energy supply for green edge computing by capturing the conditional value at risk (CVaR) tail distribution of the energy shortfall. The authors in [12] proposed a multi-agent RL system to solve the energy scheduling problem. In [13], the authors proposed a self-sustainable mobile networks, using graph-based approach for intelligent energy management with a microgrid. The authors in [14] proposed a smart grid-enabled wireless network and minimized grid energy consumption by applying energy sharing among the BSs. Furthermore, in [23], the authors addressed challenges of non-coordinated energy shedding and mis-aligned incentives for mixed-use building (i.e., buildings and data centers) using auction theory to reduce energy usage. However, these works [9]–[14], [23] do not investigate the problem of energy dispatch nor do they account for the energy cost of MEC-enabled, self-powered networks when the demand and generation of each self-powered BS are non-iid. Dealing with non-iid energy demand and generation among self-powered BSs is challenging due to the intrinsic energy requirements of each BS evolve the uncertainty. In order to overcome this unique energy dispatch challenge, we propose to develop a multi-agent meta-reinforcement learning framework that can adapt new uncertain environment without considering the entire past experience.

B. Contributions

The main contribution of this paper is a novel energy management framework for next-generation MEC in self-powered wireless network that is reliable against extreme uncertain energy demand and generation. We formulate a two-stage stochastic energy cost minimization problem that can balance renewable, non-renewable, and storage energy without knowing the actual demand. In fact, the formulated problem also investigates the realization of renewable energy generation after receiving the uncertain energy demand from the MEC applications and service requests. To solve this problem, we propose a multi-agent meta-reinforcement learning (MAMRL) framework that dynamically observes the non-iid behavior of time-varying features in both energy demand and generation at each BS and, then transfers those observations to obtain an energy dispatch decision and execute the energy dispatch policy to the self-powered BS. Fig. 1 illustrates how we propose to dispatch energy to ensure sustainable edge computing over a self-powered network using MAMRL framework. As we can see, each BS that includes small cell base stations (SBSs) and a macro base station (MBS) will act as a local agent and transfer their own decision (reward and action) to the meta-agent. Then, the meta-agent accumulates all of the non-iid observations from each local agent (i.e., SBSs and MBS) and optimizes the energy dispatch policy. The proposed MAMRL framework then provides feedback to each BS agent.
for exploring efficiently that acquire the right decision more quickly. Thus, the proposed MAMRL framework ensures autonomous decision making under an uncertain and unknown environment. Our key contributions include:

- We formulate a self-powered energy dispatch problem for MEC-supported wireless network, in which the objective is to minimize the total energy consumption cost of network while considering the uncertainty of both energy consumption and generation. The formulated problem is, thus, a two-stage linear stochastic programming. In particular, the first stage makes a decision when energy demand is unknown, and the second stage discretizes the realization of renewable energy generation after knowing energy demand of the network.
- To solve the formulated problem, we propose a new multi-agent meta-reinforcement learning framework by considering the skill transfer mechanism between each local agent (i.e., self-powered BS) and meta-agent. In this MAMRL scheme, each local agent explores its own energy dispatch decision using Markovian properties for capturing the time-varying features of both energy demand and generation. Meanwhile, the meta-agent evaluates (exploits) that decision for each local agent and optimizes the energy dispatch decision. In particular, we design a long short-term memory (LSTM) as a meta-agent (i.e., run at MBS) that is capable of avoiding the incompetent decision from each local agent and learns the right features more quickly by maintaining its own state information.
- We develop the proposed MAMRL energy dispatch framework in a semi-distributed manner. Each local agent (i.e., self-powered BS) estimates its own energy dispatch decision using local energy data (i.e., demand and generation), and provides observations to the meta-agent individually. Consequently, the meta-agent optimizes the decision centrally and assists the local agent toward a globally optimized decision. Thus, this approach not only reduces the computational complexity and communication overhead but it also mitigates the curse of dimensionality under the uncertainty by utilizing non-iid energy demand and generation from each local agent.
- Experimental results using real datasets establish a significant performance gain of the energy dispatch under the deterministic, asymmetric, and stochastic environments. Particularly, the results show that the proposed MAMRL model saves up to 22.44\% of energy consumption cost over a baseline approach while achieving an average accuracy of around 95.8\% in a stochastic environment. Our approach also decreases the usage of non-renewable energy up to 11\% of total consumed energy.

The rest of the paper is organized as follows. Section II presents the system model of self-powered edge computing. The problem formulation is described in Section III. Section IV provides MAMRL framework for solving energy dispatch problem. Experimental results are analyzed in Section V. Finally, conclusions are drawn in Section VI.
for receiving packet from users, and the energy for wired network dynamics [11], [12], [31]. A set \( J \) of \( J \) heterogeneous MEC application task requests from users will arrive to BS \( i \) with an average task arrival rate \( A_i(t) \) (bits/s) at time \( t \). The task arrival rate \( A_i(t) \) at BS \( i \in B \) follows a Poisson process at time slot \( t \). BS \( i \) integrates \( K_i \) heterogeneous active MEC application servers that has \( u_i(t) \) (bits/s) processing capacity. Thus, \( J \) computational task requests will be accumulated into the service pool with an average traffic size \( S_i(t) \) (bits) at time slot \( t \). The average traffic arrival rate is defined as \( A_i(t) = \frac{1}{\lambda_i} \). Therefore, an \( M/M/K \) queuing model is suitable to model these \( J \) user tasks using \( K_i \) MEC servers at BS \( i \) and time \( t \) [32], [33]. The task size of this queuing model is exponentially distributed since the average traffic size \( S_i(t) \) is already known. Hence, the service rate of the BS \( i \) is determined by \( \mu_i(t) = \frac{1}{\sum_{j \in J_i} u_i(t)} \). At any given time \( t \), we assume that all of the tasks in \( J \) are uniformly distributed at each BS \( i \). Thus, for a given MEC server task association indicator \( Y_{jk}(t) = 1 \) if task \( j \) is assigned to server \( k \) at BS \( i \), and 0 otherwise, the average MEC server utilization is defined as follows [11]:

\[
\rho_i(t) = \sum_{j \in J_i} \frac{A_i(t)}{\mu_i(t)} \text{ if } Y_{jk}(t) = 1, 0, \text{ otherwise.}
\]

1) MEC Server Energy Consumption: In case of MEC server energy consumption, the computational energy consumption (dynamic energy) will be dependent on the CPU activity for executing computational tasks [16], [17], [34]. Further, such dynamic energy is also accounted with the thermal design power (TDP), memory, and disk I/O operations of the MEC server [16], [17], [34] and we denote as \( \eta_d^{\text{MEC}}(t) \). Meanwhile, static energy \( \eta_s^{\text{MEC}}(t) \) includes the idle state power of CPU activities [16], [18]. We consider, a single core CPU with a processor frequency \( f \) (cycles/s), an average server utilization \( \rho_i(t) \) (using [11]) at time slot \( t \), and a switching capacitance \( \tau = 5 \times 10^{-17} \text{ farad} \) [17]. The dynamic power consumption of such single core CPU can be calculated by applying a quadratic formula \( \tau \rho_i(t)f^2 [18], [35] \). Thus, energy consumption of \( K_i \) MEC servers with \( L \) CPU cores at BS \( i \) is defined as follows:

\[
\xi_i^{\text{MEC}}(t) = \sum_{k \in K_i} \sum_{l \in L} \sigma_{kl} \rho_i(t) f^2 \eta_s^{\text{MEC}}, \text{ if } \rho_i(t) > 0, \eta_d^{\text{MEC}}, \text{ if } \rho_i(t) = 0,
\]

where \( \sigma_{kl} \) denotes a scaling factor of heterogeneous CPU core of the MEC server. Thus, the value of \( \sigma_{kl} \) is dependent on the processor architecture [36] that assures the heterogeneity of the MEC serves.

2) Base Station Energy Consumption: The energy consumption needed for the operation of the network base stations (i.e., SBSs and MBS) includes two types of energy: dynamic and static energy consumption [37]. On one hand, a static energy consumption \( \eta_s^{\text{BS}}(t) \) includes the energy for maintaining the idle state of any BS, a constant power consumption for receiving packet from users, and the energy for wired transmission among the BSs. On the other hand, the dynamic energy consumption of the BSs depends on the amount of data transfer from BSs to users which essentially relates to the downlink [38] transmit energy. Thus, we consider that each BS \( i \in B \) operates at a fixed channel bandwidth \( W_{ij} \) and constant transmission power \( P_i \) [38]. Then the average downlink data of BS \( i \) will be given by [11]:

\[
R_i(t) = \sum_{j \in J_i} W_{ij} \log_2 \left( 1 + \frac{P_i g_{ij}(t)}{\sigma_i^2 + I_{ij}(t)} \right)
\]

where \( g_{ij}(t) \) represents downlink channel gain between user \( j \) to BS \( i \), \( \sigma_i^2 \) determines a variance of an Additive White Gaussian Noise (AWGN), and \( I_{ij}(t) \) denotes the co-channel interference [39], [40] among the BSs. Here, the co-channel interference \( I_{ij}(t) = \sum_{t \in B \setminus i} P_t g_{ij}(t) \) relates to the transmissions from other BSs \( i' \in B \) that use the same subchannels of \( W_{ij}, P_t \) and \( g_{ij}(t) \) represent, respectively, the transmit power and the channel gain of the BS \( i' \neq i \in B \). Therefore, downlink energy consumption of the data transfer of BS \( i \in B \) is defined by \( P_i R_i(t) \) [watt-seconds or joule], where \( S_i(t) \) [seconds] determines the duration of transmit power \( P_i \) [watt]. Thus, the network energy consumption for BS \( i \) at time \( t \) is defined as follows [19], [37]:

\[
\xi^{\text{net}}_i(t) = \sum_{j \in J_i} \left( \delta_i^{\text{net}} P_i S_i(t) R_i(t) + \eta_d^{\text{net}} I_{ij}(t) \right)
\]

where \( \delta_i^{\text{net}} \) determines the energy coefficient for transferring data through the network. In fact, the value of \( \delta_i^{\text{net}} \) depends on the type of the network device (e.g., \( \delta_i^{\text{net}} = 2.8 \) for a 6 unit transceiver remote radio head [37]).

3) Total Energy Demand: The total energy consumption (demand) of the network consists of both MEC server computational energy (in \( \xi_i^{\text{MEC}} \)) consumption, and network the operational energy (i.e., BSs energy consumption in \( \xi_i^{\text{BS}} \)). Thus, the overall energy demand of the network at time slot \( t \) is given as follows:

\[
\xi_d^i = \sum_{i \in B} \left( \xi_i^{\text{net}}(t) + \xi_i^{\text{MEC}}(t) \right)
\]

The demand \( \xi_d^i \) is random over time and completely depends on the computational tasks load of the MEC servers.

B. Energy Generation Model

The energy supply of the self-powered wireless network with MEC capabilities relates to the network’s own renewable (e.g., solar, wind, biofuels, etc.) sources as well as the main grid’s non-renewable (e.g., diesel generator, coal power, and so on) energy sources [8], [41]. In this energy generation model, we consider a set \( R = \{ R_0, R_1, \ldots, R_B \} \) of renewable energy sources of the network, with each element \( R_t \) representing the set of renewable energy sources of BS \( i \in B \). The amount of renewable energy generation is defined by \( \xi^{\text{ren}}_i(t) \). The total renewable energy generation at time \( t \) is defined as \( \xi^{\text{ren}} = \sum_{i \in B} \sum_{t \in R} \xi^{\text{ren}}_i(t) \). Further, the self-powered wireless network is able to get an additional non-renewable energy amount \( \xi^{\text{net}}_i(t) \) from the main grid at time \( t \). The per unit renewable and non-renewable energy cost are defined by \( c^{\text{ren}}_i \) and \( c^{\text{net}}_i \).
and $c_{\text{ren}}^{\text{non}}$, respectively. In general, the renewable energy cost only depends on the maintenance cost of the renewable energy sources \cite{42, 43, 44}. Therefore, the per unit non-renewable energy cost is greater than the renewable energy cost $c_{\text{ren}}^{\text{non}} > c_{\text{ren}}$. Additionally, the surplus amount of the energy $\xi_{\text{sto}}$ at time $t$ can be stored in energy storage medium for the future usages \cite{43, 44} and the energy storage cost of per unit energy store is denoted by $c_{\text{sto}}$.

1) Non-renewable Energy Generation Cost: In order to fulfill the energy demand $\xi_{\text{d}}$ when it is greater than the generated renewable energy $\xi_{\text{ren}}$, the main grid can provide an additional amount of energy $\xi_{\text{non}}$ from its non-renewable sources. Thus, the non-renewable energy generation cost $c_{\text{non}}$ of the network is determined as follows:

$$
c_{\text{non}} = \left\{ \begin{array}{ll}
    c_{\text{non}}^{\text{non}}[\xi_{\text{d}} - \xi_{\text{ren}}], & \text{if } \xi_{\text{d}} > \xi_{\text{ren}}, \\
    0, & \text{otherwise},
\end{array} \right. \quad (6)
$$

where $c_{\text{non}}^{\text{non}}$ represents a unit energy cost.

2) Surplus Energy Storage Cost: The surplus amount of energy is stored in a storage medium when $\xi_{\text{d}} < \xi_{\text{ren}}$ (i.e., energy demand is smaller than the renewable energy generation) at time $t$. We consider the per unit energy storage cost $c_{\text{sto}}$. This storage cost depends on the storage medium and amount of the energy store at time $t$ \cite{43, 45, 46}. With the per unit energy storage cost $c_{\text{sto}}^{\text{non}}$, the total storage cost at time $t$ is defined as follows:

$$
c_{\text{sto}} = \left\{ \begin{array}{ll}
    c_{\text{sto}}^{\text{non}}[\xi_{\text{d}} - \xi_{\text{ren}}], & \text{if } \xi_{\text{d}} < \xi_{\text{ren}}, \\
    0, & \text{otherwise},
\end{array} \right. \quad (7)
$$

3) Total Energy Generation Cost: The total energy generation cost includes renewable, non-renewable, and storage energy cost. Naturally, this total energy generation cost will depend on the energy demand $\xi_{\text{d}}$ of the network at time $t$. Therefore, the total energy generation cost at time $t$ is defined as follows:

$$
Q(\xi_{\text{ren}}, \xi_{\text{d}}) = c_{\text{ren}} \xi_{\text{ren}} + c_{\text{non}}[\xi_{\text{d}} - \xi_{\text{ren}}] + c_{\text{sto}}^{\text{non}}[\xi_{\text{d}} - \xi_{\text{ren}}], \quad (8)
$$

where the energy cost of the renewable, non-renewable, and storage energy are given by $c_{\text{ren}}^{\text{ren}}$, $c_{\text{non}}[\xi_{\text{d}} - \xi_{\text{ren}}]$, and $c_{\text{sto}}^{\text{non}}[\xi_{\text{d}} - \xi_{\text{ren}}]$, respectively. In \cite{43}, energy demand $\xi_{\text{d}}$ and renewable energy generation $\xi_{\text{ren}}$ are stochastic in nature. The energy cost of non-renewable energy $\xi_{\text{d}}$ and storage energy $\xi_{\text{d}}$ completely rely on energy demand $\xi_{\text{ren}}$ and renewable energy generation $\xi_{\text{ren}}$. Hence, to address the uncertainty of both energy demand and renewable energy generation in a self-powered wireless network, we formulate a two-stage stochastic programming problem. In particular, the first stage makes a decision of the energy dispatch without knowing the actual demand of the network. Then we make further energy dispatch decisions by analyzing the uncertainty of the network demand in the second stage. A detailed discussion of the problem formulation is given in the following section.

III. PROBLEM FORMULATION WITH A TWO-STAGE STOCHASTIC MODEL

We now consider the case in which the non-renewable energy cost is greater than the renewable energy cost, $c_{\text{ren}}^{\text{non}} > c_{\text{ren}}$ that is often the case in a practical smart grid as discussed in \cite{42, 43, 44, 47}. Here, $\xi_{\text{ren}}$ and $\xi_{\text{d}}$ are the continuous variables over the observational duration $t$. The objective is to minimize the total energy consumption cost $Q(\xi_{\text{ren}}, \xi_{\text{d}})$. $\xi_{\text{ren}}$ is the decision variable and the energy demand $\xi_{\text{d}}$ is a parameter. When the energy demand $\xi_{\text{d}}$ is known, the optimization problem will be:

$$
\chi = \min_{\xi_{\text{d}} \geq \xi_{\text{ren}}} Q(\xi_{\text{ren}}, \xi_{\text{d}}). \quad (9)
$$

In problem (9), after removing the non-negativity constraints $\xi_{\text{ren}} \geq 0$, we can rewrite the objective function in the form of piecewise linear functions as follows:

$$
Q(\xi_{\text{ren}}, \xi_{\text{d}}) = \max_{\xi_{\text{ren}}} \left\{ (c_{\text{ren}} - c_{\text{non}})\xi_{\text{ren}} + c_{\text{non}}^{\text{non}} \xi_{\text{d}}, \right. \left. (c_{\text{ren}} + c_{\text{sto}})\xi_{\text{ren}} - c_{\text{sto}}^{\text{non}} \xi_{\text{d}} \right\}. \quad (10)
$$

Where $(c_{\text{ren}} - c_{\text{non}})\xi_{\text{ren}} + c_{\text{non}}^{\text{non}} \xi_{\text{d}}$ determine the cost of non-renewable (i.e., $\xi_{\text{d}} > \xi_{\text{ren}}$) and storage (i.e., $\xi_{\text{d}} < \xi_{\text{ren}}$) energy, respectively. Therefore, we have to choose one out of the two cases. In fact, if the energy demand $\xi_{\text{d}}$ is known and also the amount of renewable energy $\xi_{\text{ren}}$ is the same as the energy demand, then problem (10) provides the optimal decision in order to exact amount of demand $\xi_{\text{d}}$. However, the challenge here is to make a decision about the renewable energy $\xi_{\text{ren}}$ usage before the demand becomes known. To overcome this challenge, we consider the energy demand $\xi_{\text{d}}$ as a random variable whose probability distribution can be estimated from the previous history of the energy demand. We can re-write problem (9) using the expectation of the total cost as follows:

$$
\min_{\xi_{\text{ren}} \geq 0} \mathbb{E}[Q(\xi_{\text{ren}}, \xi_{\text{d}})] \quad (11)
$$

The solution of problem (11) will provide an optimal result on average. However, in the practical scenario, we need to solve problem (11) repeatedly over the uncertain energy demand $\xi_{\text{d}}$. Thus, this solution approach does not significantly affect when large variations (i.e., non-iid) of the energy demand that are generated by $B + 1$ BSs over the observational period of $t$.

We consider the moment of random variable $\xi_{\text{d}}$ that has a finitely supported distribution and takes values $\xi_{\text{d}}^{1}, \ldots, \xi_{\text{d}}^{B}$ with respective probabilities $p_{0}, \ldots, p_{B}$ of BSs $B + 1$. The cumulative distribution function (CDF) $H(\xi_{\text{d}})$ of energy demand $\xi_{\text{d}}$ is a step function and jumps of size $p_{t}$ at each demand $\xi_{\text{d}}$. Therefore, the probability distribution of each BS energy demand $\xi_{\text{d}}$ belongs to the CDF $H(\xi_{\text{d}})$ of historical observation of energy demand $\xi_{\text{d}}$. In this case, we can convert problem (11) into a deterministic optimization problem and the expectation of energy usage cost $\mathbb{E}[Q(\xi_{\text{ren}}, \xi_{\text{d}})]$ is determined by $\sum_{t \in B} p_{t} Q(\xi_{\text{ren}}, \xi_{\text{d}})$. Thus, we can re-write the problem (9) as a linear programming problem using the representation in (10) as follows:

$$
\min_{\xi_{\text{ren}}, \chi} \chi \quad (12)
$$

s.t. $\chi \geq (c_{\text{ren}} - c_{\text{non}})\xi_{\text{ren}} + c_{\text{non}}^{\text{non}} \xi_{\text{d}},$ \quad (12a)

$\chi \geq (c_{\text{ren}} + c_{\text{sto}})\xi_{\text{ren}} - c_{\text{sto}}^{\text{non}} \xi_{\text{d}},$ \quad (12b)

$\xi_{\text{ren}} \geq 0.$ \quad (12c)
For a fixed value of the renewable energy \( \xi_{\text{ren}} \), problem (12) is an equivalent of problem (10). Meanwhile, problem (12) is equal to \( Q(\xi_{t}^{\text{ren}}, \xi_{t}^{\text{d}}) \). We have converted the piecewise linear function from problem (10) into the inequality constraints (12a) and (12b). We consider \( p_{i} \) as the highest probability of energy demand at each BS \( i \in B \). Therefore, for \( B + 1 \) BSs, we define \( p_{0}, \ldots, p_{B} \) as the probability of energy demand with respect to BSs \( i = 0, \ldots, B \). Thus, we can rewrite the problem (11) for \( B + 1 \) BSs \( \xi_{t} \) = \( (\xi_{t}^{D_{0}}, \ldots, \xi_{t}^{B}) \) as follows:

\[
\min_{\xi_{t}^{\text{ren}}, \xi_{t}^{\text{non}}, \xi_{t}^{\text{sto}}} \sum_{i \in B} p_{i} x_{i}, \tag{13}
\]

s.t. \( x_{i} \geq (c_{i}^{\text{ren}} - c_{i}^{\text{non}})\xi_{t}^{\text{ren}} + c_{i}^{\text{non}}\xi_{t}^{D_{i}}, \forall i \in B, \tag{13a}\)

\( x_{i} \geq (c_{i}^{\text{ren}} + c_{i}^{\text{sto}})\xi_{t}^{\text{ren}} - c_{i}^{\text{sto}}D_{i}, \forall i \in B, \tag{13b}\)

\( \xi_{t}^{\text{ren}} \geq 0, \tag{13c}\)

where \( p_{i} \) represents the highest probability (close to 1) of energy demand at BS \( i \in B \) and estimates a probability distribution from \( i \)-quantile of empirical CDF \( H(\xi_{t}^{D_{i}}) \) of the historical demand observation. Thus, for a fixed value of \( \xi_{t}^{\text{ren}} \), this problem is almost separable. Therefore, we can decompose problem (13) with a structure of two-stage linear stochastic programming problem [48], [49].

To find an approximation for a random variable with a finite probability distribution, we decompose problem (13) in a two-stage linear stochastic programming under uncertainty. The decision is made using historical data of energy demand, which is fully independent from the future observation. As a result, the first stage of self-powered energy dispatch problem for sustainable edge computing is formulated as follows:

\[
\min_{\xi_{t}^{\text{ren}}, \xi_{t}^{\text{non}}, \xi_{t}^{\text{sto}}} \sum_{i \in T} \left( (c_{i}^{\text{ren}})^{T}\xi_{t}^{\text{ren}} + \mathbb{E}[Q(\xi_{t}^{\text{ren}}, \xi_{t}^{D})] \right), \tag{14}
\]

s.t. \( \xi_{t}^{\text{ren}} \geq \xi_{t}^{\text{non}} \geq 0. \tag{14a}\)

where \( Q(\xi_{t}^{\text{ren}}, \xi_{t}^{D}) \) determines an optimal value of the second stage problem. In problem (14), the decision variable \( \xi_{t}^{\text{ren}} \) is calculated before the realization of uncertain energy demand \( \xi_{t}^{D} \). Meanwhile, at the first stage of the formulated problem (14), the cost \( (c_{i}^{\text{ren}})^{T}\xi_{t}^{\text{ren}} \) is minimized for the decision variable \( \xi_{t}^{\text{ren}} \) which then allows us to estimate the expected energy cost \( \mathbb{E}[Q(\xi_{t}^{\text{ren}}, \xi_{t}^{D})] \) for the second stage decision. Constraint (14a) provides a boundary for the maximum allowable renewable energy usage. Thus, based on the decision of the first stage problem, the second stage problem can be defined as follows:

\[
\min_{\xi_{t}^{\text{ren}}, \xi_{t}^{\text{non}}, \xi_{t}^{\text{sto}}} \left( (c_{i}^{\text{non}})^{T}\xi_{t}^{\text{non}} - (c_{i}^{\text{sto}})^{T}\xi_{t}^{\text{sto}}, \tag{15}\right)
\]

s.t. \( \xi_{t}^{\text{sto}} = |\xi_{t}^{\text{ren}} - \xi_{t}^{\text{non}}|, \tag{15a}\)

\( 0 \leq \xi_{t}^{\text{non}} \leq (\xi_{t}^{D})^{T}, \tag{15b}\)

\( \xi_{t}^{\text{non}} \geq 0. \tag{15c}\)

In the second stage problem (15), the decision variables \( \xi_{t}^{\text{non}} \) and \( \xi_{t}^{\text{sto}} \) depend on the realization of the energy demand \( \xi_{t}^{D} \) of the first stage problem (14), where \( \xi_{t}^{\text{ren}} \) determines the amount of renewable energy usage at time \( t \). The first constraint (15a) is an equality constraint that determines the surplus amount of energy \( \xi_{t}^{\text{sto}} \) must be equal to the absolute value difference between the usage of renewable \( \xi_{t}^{\text{ren}} \) and non-renewable \( \xi_{t}^{\text{non}} \) energy amount. The second constraint (15b) is an inequality constraint that uses the optimal demand value from the first stage realization. In particular, the value of demand comes from (5) that is the historical observation of energy demand. Finally, the constraint (15c) protects from the non-negativity for the non-renewable energy \( \xi_{t}^{\text{non}} \) usage.

The formulated problems (14) and (15) can characterize the uncertainty between network energy demand and renewable energy generation. Particularly, the second stage problem (15) contains random demand \( \xi_{t}^{D} \) that leads the optimal cost \( \mathbb{E}[Q(\xi_{t}^{\text{ren}}, \xi_{t}^{D})] \) as a random variable. As a result, we can rewrite the problems (14) and (15) in a one large linear programming problem for \( B + 1 \) BSs and the problem formulation is as follows:

\[
\min_{\xi_{t}^{\text{ren}}, \xi_{t}^{\text{non}}, \xi_{t}^{\text{sto}}} \left\{ \sum_{i \in T} \left( (c_{i}^{\text{ren}})^{T}\xi_{t}^{\text{ren}} + \sum_{i \in B} p_{i}[(c_{i}^{\text{non}})^{T}\xi_{t}^{\text{non}} - (c_{i}^{\text{sto}})^{T}\xi_{t}^{\text{sto}}] \right) \right\}, \tag{16}
\]

s.t. \( \xi_{t}^{\text{sto}} = |\xi_{t}^{\text{ren}} - \xi_{t}^{\text{non}}|, \forall i \in B, \tag{16a}\)

\( 0 \leq \xi_{t}^{\text{non}} \leq (\xi_{t}^{D})^{T}, \forall i \in B, \tag{16b}\)

\( \xi_{t}^{\text{ren}} \geq 0, \forall i \in B, \tag{16c}\)

\( \xi_{t}^{\text{non}} \geq 0, \forall i \in B. \tag{16d}\)

In problem (16), for \( B + 1 \) BSs, energy demand \( \xi_{t}^{D_{0}}, \ldots, \xi_{t}^{B} \) happens with positive probabilities \( p_{0}, \ldots, p_{B} \) and \( \sum_{i \in B} p_{i} = 1 \). The decision variables \( \xi_{t}^{\text{ren}}, \xi_{t}^{\text{non}} \) and \( \xi_{t}^{\text{sto}} \), which represent the amount of renewable, non-renewable, and storage energy, respectively. Constraint (16a) defines a relationship among all of the decision variables \( \xi_{t}^{\text{ren}}, \xi_{t}^{\text{non}}, \) and \( \xi_{t}^{\text{sto}} \). In essence, this constraint discretizes the surplus amount of energy for storage. Hence, constraint (16b) ensures the utilization of non-renewable energy based on the energy demand of the network. Constraint (16c) ensures that the decision variable \( \xi_{t}^{\text{non}} \) will not be a negative value. Finally, constraint (16d) restricts the renewable energy \( \xi_{t}^{\text{ren}} \) usages in to maximum capacity \( \xi_{t}^{\text{max}} \) at time \( t \). Problem (16) is an integrated form of the first-stage problem in (14) and the second-stage problem in (15), where the solution of \( \xi_{t}^{\text{ren}} \) and \( \xi_{t}^{\text{sto}} \) completely depends on realization of demand \( \xi_{t}^{D_{i}} \) for all \( B + 1 \) BSs. The decision of the \( \xi_{t}^{\text{ren}} \) comes before the realization of demand \( \xi_{t}^{D_{i}} \) and, thus, the estimation of renewable energy generation \( \xi_{t}^{\text{ren}} \) will be independent and random. Therefore, problem (16) holds the property of relatively complete recourse. In problem (16), the number of variables and constraints is proportional to the numbers of BSs, \( B + 1 \). Additionally, the complexity of the decision problem (16) leads to \( O(2^{[\xi_{t}^{D_{i}}]} \times |B|) \) due to the combinatorial properties of the decisions and constraints [48]–[50].

The goal of the self-powered energy dispatch problem (16) is to find an optimal energy dispatch policy that includes amount of renewable \( \xi_{t}^{\text{ren}}, \) non-renewable \( \xi_{t}^{\text{non}}, \) and storage \( \xi_{t}^{\text{sto}} \) energy of each BS \( i \in B \) while minimizing the energy consumption cost. Meanwhile, such energy dispatch policy relies on an empirical probability distribution \( H(\xi_{t}^{D_{i}}) \) of historical demand at each BS \( i \in B \) at time \( t \). In order to solve problem (16), we choose an approach that does not rely on the conservativeness of a theoretical probability distribution.
of energy demand in problem \((\ref{prob})\), and also will capture the uncertainty of renewable energy generation from the historical data. A data-driven approach that can vanish the conservativeness of theoretical probability distributions as historical data goes to infinity. Eventually, non-iid energy demand and generation will also be captured at each BS \(i \in \mathcal{B}\). To prevalence the aforementioned contemporary, we propose a multi-agent meta-reinforcement learning framework that can explore the Markovian behavior from historical energy demand in problem (16), and also will capture the time-varying features of both energy demand and generation are characterized by the Markovian properties of the historical data. To prevalence the aforementioned contemporary, we propose a multi-agent meta-reinforcement learning framework that can explore the Markovian behavior from historical energy demand and generation of each BS \(i \in \mathcal{B}\). Meanwhile, the meta-agent can cope with such time-varying features to a globally optimal energy dispatch policy for each BS \(i \in \mathcal{B}\).

We design an MAMRL framework by converting the cost minimization problem (16) to a reward maximization problem that we then solve with a data-driven approach. In the MAMRL setting, each agent works as a local agent for each BS \(i \in \mathcal{B}\) and determines an observation (i.e., exploration) for the decision variables, renewable \(\xi_{i,t}^{\text{en}}\), non-renewable \(\xi_{i,t}^{\text{non}}\), and storage \(\xi_{i,t}^{\text{sto}}\) energy. The goal of this exploration is to find time-varying features from the local historical data so that the energy demand \(\xi_{i,t}^{\text{d}}\) is satisfied. Furthermore, using these observations and current state information, a meta-agent is used to determine a stochastic energy dispatch policy. Thus, to obtain such dispatch policy, the meta-agent only requires the observations (behavior) from each local agent. Then, the meta-agent can evaluate (exploit) behavior toward an optimal decision for dispatching energy. Further, the MAMRL approach is capable of capturing the exploration-exploitation tradeoff in a way that the meta-agent optimizes decisions of the each self-powered BS under uncertainty. A detailed discussion of the MAMRL framework is given in the following section.

**IV. ENERGY DISPATCH WITH MULTI-AGENT META-REINFORCEMENT LEARNING FRAMEWORK**

In this section, we developed our proposed multi-agent meta-reinforcement learning framework (as seen in Fig. 3) for energy dispatch in the considered network. The proposed MAMRL framework includes two types of agents: A local agent that acts as a local learner at each self-powered with MEC capabilities BS and a meta-agent that learns the global energy dispatch policy. In particular, each local BS agent can discretize the Markovian dynamics for energy demand-generation of each BS (i.e., both SBSs and MBS) separately by applying deep-reinforcement learning. Meanwhile, we train a long short-term memory (LSTM) 53, 54 as a meta-agent at the MBS that optimizes 53 the accumulated energy dispatch of the local agents. As a result, the meta-agent can handle the non-iid energy demand-generation of the each local agent with own state information of the LSTM. To this end, MAMRL mitigates the curse of dimensionality for the uncertainty of energy demand and generation while providing an energy dispatch solution with a less computational and communication complexity (i.e., less message passing between the local agents and meta-agent).

**A. Preliminary Setup**

In the MAMRL setting, each BS \(i \in \mathcal{B}\) acts as a local agent and the number of local agents same as the number of BSs \(B + 1\) (i.e., 1 MBS and \(B\) SBSs) in the network. We define a set \(\mathcal{S} = \{S_0, S_1, \ldots, S_B\}\) of state spaces and a set \(\mathcal{A} = \{A_0, A_1, \ldots, A_B\}\) of actions for the \(B + 1\) agents. The state space of a local agent \(i\) is defined by \(s_{i,t}: (\xi_{i,t}^{\text{d}}(t), C_{i,t}^{\text{sto}}, C_{i,t}^{\text{non}}) \in S_i\), where \(\xi_{i,t}^{\text{d}}(t), C_{i,t}^{\text{sto}}\), and \(C_{i,t}^{\text{non}}\) represent the amount of energy demand, renewable generation, storage cost, and non-renewable energy cost, respectively, at time \(t\). We execute Algorithm 1 to generate the...
state space for every BSs $i \in B$, individually. In Algorithm [1] lines 3 to 6 calculate the individual energy consumption of the MEC computation and network operation using (2) and (4), respectively. Overall, the energy demand of the BS $i$ is computed in line 7 and the self-powered energy generation is estimated by line 8 in Algorithm [1]. Non-renewable and storage energy costs are calculated in lines 9 and 10 for time slot $t$. Finally, line 11 creates state space tuple (i.e., $s_{ti}$) for time $t$ in Algorithm [1].

**B. Local Agent Design**

Consider each local BS agent $i \in B$ that can take two types of actions $a_{ti}: (\xi^{sto}(i), \xi^{non}(i)) \in A_i$ which is the amount of storage energy $\xi^{sto}(t)$ and the amount of non-renewable energy $\xi^{non}(t)$ at time $t$. Since the state $s_{ti}$ and action $a_{ti}$ both contain a time varying information of the agent $i \in B$, we consider the dynamics of Markovian and represent problem (16) as a discounted reward maximization problem for each agent $i$ (i.e., each BS). Thus, the objective function of the discounted reward maximization problem of agent $i$ is defined as follows [51]:

$$r_i(a_{ti}, s_{ti}) = \max_{a_{ti} \in A_i} \mathbb{E}[a_{ti}-s_{ti}|\sum_{t'=t}^{\infty} \gamma^{-t'}r_i(a_{ti}, s_{ti})]$$

(17)

where $\gamma \in (0, 1)$ is a discount factor and each reward $r_i(a_{ti}, s_{ti})$ is considered as,

$$r_i(a_{ti}, s_{ti}) = \begin{cases} 1, & \text{if } \frac{\xi^{sto}}{\xi^{non}} > 1, \\ 0, & \text{otherwise.} \end{cases}$$

(18)

In (13), $\frac{\xi^{sto}}{\xi^{non}}$ determines a ratio between renewable energy generation and energy demand (supply-demand ratio) of the BS agent $i \in B$ at time $t$. When renewable energy generation-demand ratio $\frac{\xi^{sto}}{\xi^{non}}$ is larger than 1 then the BS agent $i$ achieves a reward of 1 because the amount of renewable energy exceeds the demand that can be stored in the storage unit.

Each action $a_{ti}$ of BS agent $i \in B$ determines a stochastic policy $\pi_{\theta_i}$, $\theta_i$ is a parameter of $\pi_{\theta_i}$ and the energy dispatch policy is defined by $\pi_{\theta_i}: S_i \times A_i \mapsto [0, 1]$. Policy $\pi_{\theta_i}$ decides a state transition function $\Gamma: S_i \times A_i \mapsto S_{t'}$ for the next state $s_{t'} \in S_i$. Thus, the state transition function $\Gamma$ of BS agent $i \in B$ is determined by a reward function (17), where $r_i(a_{ti}, s_{ti})$: $S_i \times A_i \mapsto \mathbb{R}$. As a result, for a given state $s_{ti}$, the state value function with a cumulative discounted reward will be:

$$V^{\pi_{\theta_i}}(s_{ti}) = \mathbb{E}[\pi_{\theta_i}(a_{ti}|s_{ti})|\sum_{t'=t}^{\infty} \gamma^{-t'}r_i(a_{ti}, s_{t'})|s_{ti}, a_{ti}]$$

(19)

where $\gamma^{-t'}$ is a discount factor and ensures the convergence of state value function $V^{\pi_{\theta_i}}(s_{ti})$ over the infinity time horizon. Thus, for a given state $s_{ti}$, the optimal policy $\pi_{\theta_i}^*(a_{ti}|s_{ti})$ for the next state $s_{t'}$ can be determined by an optimal state value function while a Markovian property is imposed. Therefore, the optimal value function is given as follows:

$$V^{\pi_{\theta_i}^*}(s_{ti}) = \max_{a_{ti} \in A_i} \mathbb{E}[\sum_{t'=t}^{\infty} \gamma^{-t'}r_i(a_{ti}, s_{t'})|s_{ti}, a_{ti}]$$

(20)

In this setting, the policy of energy dispatch is determined by choosing an action in (20) that can be seen as an actor of BS agent $i$ while the estimated value function (19) plays the role of a critic. Thus, the critic criticizes actions made by the actor using a temporal difference (TD) error [52] that determines an energy dispatch policy. The TD error is considered as an advantage function and the advantage function of agent $i$ is defined as follows:

$$\Lambda^{\pi_{\theta_i}}(s_{ti}, a_{ti}) = (r_i(a_{ti}, s_{ti}) + \sum_{t'=t}^{\infty} \gamma^{-t'}V^{\pi_{\theta_i}^*}(s_{t'})) - V^{\pi_{\theta_i}}(s_{ti}).$$

(21)

Thus, the policy gradient is determined as,

$$\nabla_{\theta_i} \Lambda^{\pi_{\theta_i}}(s_{ti}, a_{ti}) = \mathbb{E}[\sum_{t'=t}^{\infty} \gamma^{-t'}\nabla_{\theta_i} \log \pi_{\theta_i}(a_{ti}|s_{ti}, a_{ti})\Lambda^{\pi_{\theta_i}}(s_{ti}, a_{ti})].$$

(22)

Using (22), we can discretize the energy dispatch decision $a_{ti}: (\xi^{sto}(i), \xi^{non}(i))$ for each self-powered BS $i \in B$ in the network. In fact, we can achieve a centralized solution for $\forall i \in B$ when all of the BSs state information (i.e., demand and generation) are known. The space complexity for computation increases as $O(2^{S_i} \times A_i \times |B|^2 \times T)$ and also the computational complexity becomes $O(S_i \times A_i \times |B|^2 \times T)$ [21]. Further, the solution does not meet the exploration-exploitation dilemma since the centralized (i.e., single agent) method ignores the interactions and energy dispatch decision strategies of other agents (i.e., BSs) which creates an imbalance between exploration and exploitation. Next, we propose an approach that not only reduces the complexity but also explores alternative energy dispatch decision to achieve the highest expected reward in (17).

**C. Multi-Agent Meta-Reinforcement Learning Modeling**

We consider a set $O = \{O_0, O_1, \ldots, O_B\}$ of $B + 1$ observations [27], [50] and for an BS agent $i \in B$, a single observation tuple is given by $O_i \in C_i$. For a given state $s_{ti}$, the observation $O_i$ of the next state $s_{t'}$ consists of $O_i: (r_i(a_{ti}, s_{t'}), r_i(a_{ti}, s_{ti}), a_{ti}, a_{t'}, t^i, \Lambda^{\pi_{\theta_i}}(s_{ti}, a_{ti})), \Lambda^{\pi_{\theta_i}}(s_{ti}, a_{ti})$ are next-state discounted rewards, current state discounted rewards, next action, current action, time slot, and TD error, respectively. Here, a complete information of the observation $O_i$ is correlated with the state space $O_i: S_i \mapsto O_i$ while observation $O_i$ does not require the complete state information of the previous states. Thus, the space complexity for computation is $O((2^{O_i} \times T) + (O(O_i^2 \times T)$ is the communication complexity of each agent $i$.

In the MAMRL framework, the local agents work as an optimizer and the meta-agent performs the role of optimizer.
To model our meta-agent, we consider an LSTM architecture \cite{53, 54} that stores its own state information (i.e., parameters) and the local agent (i.e., optimizer) only provides the observation of a current state. In the proposed MAMRL framework, a policy \( \pi_0 \) is determined by updating the parameters \( \theta_i \). Therefore, we can represent the state value function \( (20) \) for time \( t \) as follows: \( V^\pi_{\theta_i}(s_{ti}) \approx V^\pi_{\theta_i}(s_{ti}; \theta_i) \). and the advantage (temporal difference) function \( (21) \) is presented by, \( \Lambda^\pi_{\theta_i}(s_{ti}, a_{ti}; \theta_i) \). As a result, the parameterized policy is defined by, \( \pi_0(a_{ti}|s_{ti}) \approx \pi_0(a_{ti}|s_{ti}; \theta_i) \). Considering all of the BS agents \( B + 1 \) and the advantage function \( (21) \) is rewritten as,
\[
\Lambda^\pi_{\theta_i}(s_{ti}, a_{i0}, \ldots, a_{iB}; \theta_i) = \gamma \sum_{t'=t}^{\infty} \gamma^{t'-t} \Gamma(s_{t'}, a_{t'}, s_{ti}, a_{i0}, \ldots, a_{iB}) V^\pi_0(s_{t'}, \pi_{a_0}, \ldots, \pi_{a_B}) - V^\pi_{\theta_i}(s_{ti}, \pi_{a_0}, \ldots, \pi_{a_B}),
\]
(23)
where \( \pi_{a_0}^*; (\pi_{a_0}, \ldots, \pi_{a_B}) \) is a joint energy dispatch policy and \( \Gamma(s_{t'}, a_{t'}, s_{ti}, a_{i0}, \ldots, a_{iB}) \rightarrow [0, 1] \) represents state transition probability. Using (23), we can get the value loss function for agent \( i \) and the objective is to minimize the temporal difference \( (22) \).
\[
L(\theta_i) = \min_{\pi_0} \frac{1}{|B|} \sum_{t \in B} \frac{1}{2} \left( r_i(s_{ti}, a_{ti}) + \gamma \sum_{t'=t}^{\infty} \gamma^{t'-t} V^\pi_{\theta_i}(s_{t'}, \pi_{a_0}, \ldots, \pi_{a_B}) - V^\pi_0(s_{ti}, \pi_{a_0}, \ldots, \pi_{a_B}) \right)^2.
\]
(24)
To improve the exploration with a low bias, we consider an entropy regularization \( \beta h(\pi_{a_0}(a_{ti}|s_{ti}; \theta_i)) \) that cope with the non-iid energy demand and generation for all of the BS agents \( \forall i \in B \). Here, \( \beta \) is a coefficient for the magnitude of regularization and \( h(\pi_{a_0}(a_{ti}|s_{ti}; \theta_i)) \) determines the entropy of the policy \( \pi_{a_0} \) for the parameter \( \theta_i \). Additionally, a larger value of \( \beta h(\pi_{a_0}(a_{ti}|s_{ti}; \theta_i)) \) encourages the agents to have a more diverse exploration to estimate the energy dispatch policy. Thus, we can redefine the policy loss function as follows:
\[
L(\theta_i) = -E_{s_{ti}, a_{ti}} [\pi_{a_0}(a_{ti}|s_{ti}; \theta_i) + \beta h(\pi_{a_0}(a_{ti}|s_{ti}; \theta_i))].
\]
(25)
Therefore, the policy gradient of the loss function \( (25) \) is defined in terms of temporal difference and entropy. The policy gradient of the loss function is defined as follows:
\[
\nabla_\theta L(\theta_i) = \frac{1}{|B|} \sum_{t \in B} \frac{1}{2} \sum_{t'=t}^{\infty} \nabla_{\theta_i} \log \pi_{a_0}(a_{ti}|s_{ti}) \Lambda^\pi_{\theta_i}(s_{ti}, a_{ti}; \theta_i) \\
+ \beta h(\pi_{a_0}(a_{ti}|s_{ti}; \theta_i)).
\]
(26)
To design our meta-agent, we consider meta-agent parameters \( \phi \) and optimized parameters \( \theta^* \) of the optimizer (i.e., local agent). The meta-agent is defined as \( M_i(O_i; \phi) \equiv M_i(\nabla_{\theta_i} L(\theta_i); \phi) \), where \( M_i(\cdot) \) is modeled by an LSTM. To design meta-agent, we employ 2 layers of fully connected LSTM unit with 48 cells in each unit. Consider an observational vector \( O_{it'} \in O \) of a local BS agent \( i \in B \) at time \( t' \) and each observation is \( o_i; \{r_i(s_{ti}, a_{ti}), s_{ti}, a_{ti}, r_{i'}(s_{ti}, a_{ti}), a_{ti}, a_{ti}, \lambda^\pi_{\theta_i}(s_{ti}, a_{ti})\} \in O_{it'} \). The LSTM-based meta-agent takes the observational vector \( O_{it'} \) as an input. Meanwhile, the meta-agent holds long-term dependencies by generating its own state with parameters \( \phi \). To do this, the LSTM model creates several gates to determine an optimal policy \( \pi^*_0 \) and advantage function \( \Lambda^\pi^*_0(s_{ti}, a_{ti}, \ldots, a_{iB}; \theta_i) \) for the next state \( s_{ti'} \). As a result, the formulation of meta-agent is similar to the LSTM model \cite{53, 54}. Therefore, the meta-agent consists of four gate layers such as forget gate \( F_i \), input gate \( I_i \), cell state \( \hat{C}_i \), and output \( Z_i \). The cell state gate \( \hat{C}_i \) uses a tanh activation function and other gates are used sigmoid function \( \sigma(\cdot) \) as an activation function. The meta-agent formulation is as follows:
\[
M_i(O_i; \phi) = \text{softmax}(H_i),
\]
(27)
where \( F_i = \sigma(\phi_{FO}(O_i)^\top + \phi_{FH}(H_i)^\top + b_F) \),
(27a)
\( I_i = \sigma(\phi_{IO}(O_i)^\top + \phi_{IH}(H_i)^\top + b_I) \),
(27b)
\( \hat{C}_i = \tanh(\phi_{EO}(O_i)^\top + \phi_{EH}(H_i)^\top + b_E) \),
(27c)
\( Z_i = \sigma(\phi_{ZO}(O_i)^\top + \phi_{ZH}(H_i)^\top + b_Z) \),
(27d)
\( H_i = \tanh(E_i) \cap Z_i \).
(27e)
In the meta-agent formulation \( (27) \), the forget gate vector \( (27a) \) determines what information is needed to throw away. Input gate vector \( (27b) \) helps to decide which information is needed to update, the cell state \( (27c) \) is used to create a vector of new candidate values using tanh(\( \cdot \)) function, and updates the cell state information by applying \( (27d) \). The output layer \( (27e) \) determines what parts of the cell state are going to output and calculate the cell outputs using the equation \( (27f) \). Further, the cell state through the tanh(\( \cdot \)) will restrict the values between -1 and 1. This entire process is followed for each LSTM block and finally, \( (27) \) determines the meta-policy for \( \pi^*_0 \) of the state \( s_i \). Thus, the loss function \( L(\phi) = \mathbb{E}_{L(\theta_i)}[L(0^*; L(\theta_i); \phi)] \) of meta-agent depends on the distribution of \( L(\theta_i) \) and the expectation of the meta-agent loss function is defined as follows \cite{55}:
\[
L(\phi) = \mathbb{E}_{L(\theta_i)}[\sum_{t=1}^{T} L(\theta_i)].
\]
(28)
Algorithm 2 Local Agent Training of Energy Dispatch of BS $i \in B$ in MAMRL Framework

**Input:** $s_{t_i} = (\xi_i^{\text{act}}(t), C_i^{\text{to}}(t), C_i^{\text{con}}(t), \forall s_{t_i} \in S_i, \forall t_i \in T$  
**Output:** $a_i = (r_i(a_{t_i}, s_{t_i}), r_i(a_{t_i}, s_{t_i}), a_i, a_{t_i}, a_{t_i}^t, \Lambda_i(s_{t_i}, a_{t_i})), O_i$, $\nabla_{\theta_i} L(\theta_i)$  
**Initialization:** LocalLSTM($\cdot$, $\theta_i$, $i \in B$, $\mathcal{O}$, $\text{lstmS}$)  
1: for episode = 1 to maximum episodes do  
2: initialization: epcBuf[]  
3: for each $t \in T$ do  
4: for step = 1 to MaxStep do  
5: Calculate: $r_i(s_{t_i}, a_{t_i})$ using eq. (17)  
6: Calculate: $V_{\theta_i}^{\pi_{\theta_i}}(s_{t_i})$ using eq. (19)  
7: Choose Action: $a_{t_i} \sim \pi_{\theta_i}(a_{t_i}|s_{t_i})$  
8: Append: epcBuf[$a_{t_i}, r_i(s_{t_i}, a_{t_i})$, $t$, step, $V_{\theta_i}^{\pi_{\theta_i}}(s_{t_i})$]  
9: end for  
10: LocalLSTM($r_i(a_{t_i}, s_{t_i}), a_{t_i}, a_{t_i}^t, \text{lstmS}$))  
11: \{  
12: Evaluate: $\Lambda_{\theta_i}^{\pi_{\theta_i}}(s_{t_i}, a_{t_i})$ using eq. (21)  
13: Local agent policy gradient: $\nabla_{\theta_i} \Lambda_{\theta_i}^{\pi_{\theta_i}}(s_{t_i}, a_{t_i})$ using eq. (22)  
14: \}  
15: Append:  
16: $a_i = (r_i(a_{t_i}, s_{t_i}), r_i(a_{t_i}, s_{t_i}), a_i, a_{t_i}, a_{t_i}^t, \Lambda_{\theta_i}(s_{t_i}, a_{t_i})), O_i \in \mathcal{O}_i$  
17: Get Meta-agent policy gradient: $M_i(\nabla_{\theta_i} L(\theta_i); \phi)$ using Algorithm [3]  
18: Update: $\theta_i' = \theta_i + M_i(\nabla_{\theta_i} L(\theta_i); \phi)$  
19: end for  
20: return new_state($s_{t_i}$ = argmax $\pi_{\theta_i}(a_{t_i})), i \in B$  

Estimated policy $\pi_{\theta_i}(a_{t_i}|s_{t_i})$ (in line 7), episode buffer is generated and appended in line 8. Advantage function $\phi_{\theta_i}(s_{t_i})$ in line 12 and the policy gradient $\nabla_{\theta_i} L(\theta_i)$ is calculated in line 13 using an LSTM-based local neural network. Algorithm [2] generates observational tuple $a_i = (r_i(a_{t_i}, s_{t_i}), r_i(a_{t_i}, s_{t_i}), a_i, a_{t_i}, a_{t_i}^t, \Lambda_{\theta_i}(s_{t_i}, a_{t_i})), O_i \in \mathcal{O}_i$ in line 15. Here, we transfer the knowledge of local BS agent $i \in B$ to the meta-agent learner (deployed in MBS) in Algorithm [3] so as to optimize the energy dispatch decision (in Algorithm [2] line 16). Hence, the observation tuple $a_i$ of local BS agent $i$ consists of only the decision from BS $i$, where does not require to send all of the state information to meta-agent learner. Employing the meta-agent policy gradient, each local agent is capable of updating the energy dispatch decision policy in line 17 in Algorithm [2]. Finally, the energy dispatch policy is executed in line 20 at the BS $i \in B$ by local agent $i$.

The meta-agent learner (Algorithm [3] in MBS) receives the observations $O_i \in O_i$ from each local BS agent $i \in B$ asynchronously. Then the meta-agent asynchronously updates the meta-policy gradient of the BS agent $i \in B$. In Algorithm [3] entropy loss $\nabla_{\theta_i} L(\theta_i)$ and gradient of the loss $\nabla_{\theta_i} L(\theta_i)$ are estimated in lines 6 and 7, respectively. The meta-agent (i.e., LSTM) utilizes the observations of the local agents and determines its own state information in lines 9 and 10 which helps to estimate energy dispatch policy of the meta-agent.

Algorithm 3 Meta-Agent Learner of Energy Dispatch in MAMRL Framework

**Input:** $a_i = (r_i(a_{t_i}, s_{t_i}), r_i(a_{t_i}, s_{t_i}), a_i, a_{t_i}, a_{t_i}^t, \Lambda_{\theta_i}(s_{t_i}, a_{t_i})), O_i \in \mathcal{O}_i, \forall i \in B, \forall t_i \in T$  
**Output:** $\phi$  
**Initialization:** MetaLSTM($\cdot$, $\phi$, $\gamma$)  
1: for each $t_i \in T$ do  
2: for each $i \in B$ do  
3: $a_i = (r_i(a_{t_i}, s_{t_i}), r_i(a_{t_i}, s_{t_i}), a_i, a_{t_i}, a_{t_i}^t, \Lambda_{\theta_i}(s_{t_i}, a_{t_i})), O_i \in \mathcal{O}_i$  
4: MetaLSTM($O_i, \pi_{\theta_i}$)  
5: \{  
6: Entropy Loss: $L(\theta_i)$ using eq. (25)  
7: Gradient loss: $\nabla_{\theta_i} L(\theta_i)$ using eq. (26)  
8: \}  
9: Execute: (27a) to (27c)  
10: Calculate: $M_i(\nabla_{\theta_i} L(\theta_i); \phi)$ using eq. (27)  
11: Get meta policy loss $L(\phi)$ using eq. (28)  
12: end for  
13: end for  
14: return $M_i(\nabla_{\theta_i} L(\theta_i); \phi)$  

Finally, the meta policy loss $L(\phi)$ is calculated in line 11 (in Algorithm [3]). To this end, a meta-agent learner deployed at center node (i.e., MBS) in the considered network and sends the learning parameters of the optimal energy dispatch policy to each local BS (i.e., MBS and SBS) through the network.

The proposed MAMRL framework established a guarantee to converge with an optimal energy dispatch policy. In fact, the MAMRL framework can be reduced to a $|B|$-player Markovian game [59], [60] as a base problem that establishes more insight into convergence and optimality. The proposed MAMRL model has at least one Nash equilibrium point that ensures an optimal energy dispatch policy. This argument is similar to the previous studies of $|B|$-player Markovian game [59], [60]. Hence, we can conclude with the following proposition:

**Proposition 1.** $\pi_{\theta_i}$ is an optimal energy dispatch policy that is an equilibrium point with an equilibrium value $V_{\pi_{\theta_i}}(s_{t_i}, \pi_{\theta_0}, \ldots, \pi_{\theta_B})$ for BS $i$ [see Appendix A].

We can justify the convergence of MAMRL framework via the following Proposition:

**Proposition 2.** Consider a stochastic environment with a state space $s_{t_i} \in S_i, \forall i \in \mathcal{B}$ $|B|$ BS agents such that all BS agents are initialized with an equal probability of 0.5 for a binary actions, $P(\xi_i^{\text{act}}(t)) = P(\xi_i^{\text{con}}(t)) = \theta_i \approx 0.5$, where $a_{t_i} = (\xi_i^{\text{act}}(t), \xi_i^{\text{con}}(t)) \in \mathcal{A}_i, \forall i \in \mathcal{B}$, and $r_i(s_{t_i}, a_{t_i}, \ldots, a_{t_B})$. Therefore, to estimate the gradient of loss function $\nabla_{\theta_i} L(\theta_i)$, we can establish a relationship among the gradient of approximation $\nabla_{\theta_i} L(\theta_i)$ and true gradient $\nabla_{\theta_i} L(\theta_i)$.

$$P \left( \nabla_{\theta_i} L(\theta_i), \nabla_{\theta_i} L(\theta_i) > 0 \right) \propto (0.5)^{|B|}. \quad (29)$$

[See Appendix B].
TABLE II: Summary of experimental setup

| Description                          | Value                                      |
|--------------------------------------|--------------------------------------------|
| No. of SBSs (no. of local agents)    | 9                                          |
| No. of MEC server in each SBS        | 2                                          |
| No. of MBS (meta-agent)              | 1                                          |
| Channel bandwidth                    | 180 kHz [57]                               |
| System bandwidth                     | 20 MHz [17]                                |
| Transmission power                   | 27 dB [16]                                 |
| Channel gain                         | $140.7 + 36.7 \log d$ [17]                 |
| A variance of an AWGN                | $-114 \text{ dBm/Hz}$ [57]                 |
| Energy coefficient for data transfer | $\delta^\text{net}_i$ $2.8$ [37]           |
| MEC server CPU frequency $f_0$       | 2.5 GHz [16]                               |
| Server switching capacitance $\tau$  | $5 \times 10^{-27}$ (farad) [17]           |
| MEC static energy $\eta^\text{MEC}_i(t)$ | $[7.5, 25] \text{ Watts}$ [58]             |
| Task sizes (uniformly distributed)   | $[31, 1546060]$ bytes [61]                 |
| No. of task requests at BS $i$       | $[11, 10000]$ [111]                        |
| Unit cost renewal energy $c^\text{ret}_i$ | $50 \text{ per MW-hour}$ [57]             |
| Unit cost non-renewal energy $c^\text{non}_i$ | $102 \text{ per MW-hour}$ [47]           |
| Unit cost storage energy $c^\text{sto}_i$ | $10\%$ additional [46]                    |
| Discount factor $\gamma$             | 0.9                                        |
| Initial action selection probability | $[0.5, 0.5]$                               |
| No. of LSTM layer                    | 2                                          |
| No. of LSTM cell                     | 48                                         |

Fig. 4: Histogram of energy demand and renewable energy generation for 9 SBSs and each SBS consists of 96 time slots after preprocessing using Algorithm 1.

Fig. 5: Reward value achieved for proposed Meta-RL training of the meta-agent alone with other SBS agents.

Fig. 6: Reward value achieved of proposed Meta-RL, single-agent centralized, and multi-agent centralized methods.

Three environments are as follows: 1) In the deterministic environment, both network energy consumption and renewable generation are known, 2) network energy consumption is known but renewable generation is unknown in the asymmetric environment, and 3) the stochastic environment contains both energy consumption and renewable generation are unknown. To benchmark the proposed MAMRL framework intuitively, we have considered a centralized single-agent deep-RL, multi-agent centralized A3C deep-RL with a same neural networks configuration as the proposed MAMRL, and a pure greedy model as baselines. We implement our MAMRL framework using multi-threading programming in Python platform, along with TensorFlow APIs [63]. Table II shows the key parameters of this experiment setup.

We preprocess both of the datasets (61) and (62) using Algorithm 1 that generates the state space information. The histograms of the network energy demand (in 4(a)) and a renewable energy generation (in 4(b)) of the deterministic environment are shown in Fig. 4. To the best of our knowledge, there are no publicly available datasets that comprises both of energy consumption and generation of a self-powered network with MEC capabilities. In fact, if we use other datasets, the performance of the proposed MAMRL framework will not be affected, only the numerical value of the decisions will be different. As a result, the above experiment setup is reasonable for the benchmarking of the proposed MAMRL framework. Fig. 5 illustrates the reward achieved by each local SBS.
along with a meta-agent, where we take an average reward for each 50 episodes. In the MAMRL setting, we design a maximum reward of 96 (15 minute slot for 24 hours), where meta-agent converges with a high reward value (around 90). Hence, all of the local agents converge with around 80–85 reward value except the SBS 6 that achieves a reward of 70 at convergence because its energy consumption and generation vary more than the others. In fact, this variation of reward among the BSs is leading to anticipate the non-iid energy demand and generation of the considered network as well as densification of the exploitation and exploration tradeoff for energy dispatch.

We compare the achieved reward of proposed MAMRL model with single-agent centralized and multi-agent centralized methods in Fig. 6. The single agent centralized (diamond mark with red line) model converges faster than the other two models but it achieves the lowest reward due to the lack of exploitation as it has only one agent. Further, the multi-agent centralized (circle mark with blue line) model converges with a higher reward than the single agent method. The proposed MAMRL (cross mark with green line) model outperforms the other two models while converges with the highest reward value. In addition, multi-agent centralized needs the entire state information. In contrast, meta-agent requires only the observation from local agents, and it is also optimized the neural network parameters by its own state information.

We analyze the relationship among the value loss, entropy loss, and policy loss in Fig. 7 where the maximum policy loss of the proposed MAMRL (in 7(a)) model is around 0.06 whereas single-agent centralized (in 7(b)) and multi-agent centralized (in 7(c)) methods gain about 1.88 and 0.12, respectively. Therefore, the training accuracy increases due to more variation between exploitation and exploration. Thus, our MAMRL model is capable of incorporating the decision of each local BS agent that solves the challenge of non-iid demand-generation for the other BSs.

In Fig. 8 we examine the testing accuracy of the proposed Meta-RL, single-agent centralized, and multi-agent centralized methods with deterministic, asymmetric, and stochastic environments of the 9 SBSs.

Fig. 8: Testing accuracy of the proposed Meta-RL, single-agent centralized, and multi-agent centralized methods with deterministic, asymmetric, and stochastic environments of the 9 SBSs.

The prediction results of renewable, storage and non-renewable energy usage for a single SBS (SBS 2) for 24 hours (96 time slots) under the stochastic environment are shown in Fig. 9. The proposed MAMRL outperforms all other baselines and achieves an accuracy of around 95.8%.
and 93.7% for the single-agent centralized and multi-agent centralized, respectively.

In Figs. 10 and 11 we validate our approach with two standard regression model evaluation metric, explained variation and mean absolute error (MAE) [64], respectively. Fig. 10 shows that the explained variation score of the proposed MAMRL method almost the same as the multi-agent centralized. However, in the case of renewable energy generation, MAMRL method significantly performs better (i.e., 1% more score) than the multi-agent centralized solution. In particular, the proposed MAMRL model has pursued the uncertainty of renewable energy generation by the dynamics of Markovian for each BS. Further, meta-agent anticipates the energy dispatch by other BSs decisions and its own state information. We analyze the MAE for the three environments (i.e., deterministic, asymmetric, and stochastic) among the proposed MAMRL, single-agent centralized, and multi-agent centralized methods in Fig. 11. The MAE of the proposed MAMRL is 11%, 15%, and 4% for deterministic, asymmetric, and stochastic, respectively since meta-agent has the capability to adopt the uncertain environment very fast. This adaptability is enhanced by the exploration mechanism that is taken into account at each BS, and exploitation that performs by capitalizing the non-iid explored information of all BSs.

Fig. 12 investigates the benefit of knowledge transfer of the proposed MAMRL by showing the empirical cumulative distribution function (ECDF) for non-renewable energy estimation for all 9 SBSs. The proposed MAMRL (circle mark with green line) outperforms the three baselines with respect to non-renewable consumption. Fig. 12 shows that the proposed MAMRL will be saved up to 11%, 6%, and 4% of non-renewable consumption as compared to pure greedy, single-agent centralized, and multi-agent centralized, respectively.

Fig. 13 analyzes the overall energy consumption cost of
Fig. 14: Competitive cost ratio of the proposed Meta-RL method for 24 hours (96 time slots) under the deterministic, asymmetric, and stochastic environments.

the proposed MAMRL framework under deterministic, asymmetric, and stochastic environments for 24 hours. Fig. 13 shows that the proposed method significantly reduce the energy consumption cost (around 22.4%) for all of the three environments. In contrast, pure greedy can execute only in the deterministic environment due to the lack of complete information on energy consumption and generation in asymmetric and stochastic environments.

Finally, in Fig. 14 we examine the competitive cost ratio of the proposed MAMRL framework. From this figure, we observe that the proposed MAMRL framework effectively minimizes the energy consumption cost for each BS under deterministic, asymmetric, and stochastic environments. In fact, Fig. 14 ensures the robustness of the proposed MAMRL framework that is performed a tremendous performance gain by coping with non-iid energy consumption and generation under the uncertainty. Furthermore, in MAMRL training, each local agent has captured the time-variant features of energy demand and generation from the historical data while meta-agent optimizes energy dispatch decisions by obtaining those features with its own parameters of LSTM. In the case of testing, a generalized MAMRL trained model is employed that makes a fully independent and unbiased energy dispatch from an unknown environment. To this end, the proposed MAMRL framework shows the efficacy of solving the energy dispatch of a self-powered wireless network with MEC capabilities with a higher degree of reliability.

VI. Conclusions

In this paper, we have investigated an energy dispatch problem of a self-powered wireless network with MEC capabilities. We have formulated a two-stage stochastic linear programming energy dispatch problem for the considered network. To solve the energy dispatch problem in a semi-distributed manner, we have proposed a novel multi-agent meta-reinforcement learning framework. In particular, each local BS agent obtains the time-varying features by capturing the Markovian properties of the network’s energy consumption and renewable generation for each BS unit, and predict its own energy dispatch policy. Meanwhile, a meta-agent optimizes each BS agent’s energy dispatch policy from its own state information, and it transfers global learning parameters to each BS agent so that they can update their energy dispatch policy into an optimal policy. We have shown that the proposed MAMRL framework can capture the uncertainty of non-iid energy demand and generation for the self-powered wireless network with MEC capabilities. Our experimental results have shown that the proposed MAMRL framework can save a significant amount of non-renewable energy with higher accuracy prediction that ensures the energy sustainability of the network. In particular, the performance of energy dispatch over deterministic, asymmetric, and stochastic environments outperform other baseline approaches, where average accuracy achieves up to 95.8% and reduces the energy cost about 22.4% of the self-powered wireless network.

Appendix A

Proof of Proposition

Proof. For a BS agent \(i\), energy dispatch policy \(\pi_{\theta_i}^*\) is the best response for the equilibrium responses from all other BS agents. Thus, the BS agent \(i\) can not be improved the value \(V^{\pi_{\theta_i}^*}(s_{t_i})\) any more by deviating of policy \(\pi_{\theta_i}^*\). Therefore, (24) holds the following property,

\[
V^{\pi_{\theta_i}^*}(s_{t_i}) \geq r_i(s_{t_i}, a_{t_0}, \ldots, a_{t_B}) + \sum_{s'_{t,t'} \in S_{t,t'}} \gamma^{t'-t} \Gamma(s_{t_i}, a_{t_0}, \ldots, a_{t_B}) V^{\pi_{\theta_i}^*}(s_{t'_{t,t'}}, \pi_{\theta_0}^*, \ldots, \pi_{\theta_B}^*).
\]

Hence, the meta-agent \(M_i(\Omega; \phi)\) of the \(|B|\)-agent energy dispatch model (i.e., MAMRL) reaches a Nash equilibrium point for policy \(\pi_{\theta_i}^*\) with parameters \(\theta_i\). As a result, the optimal value of BS agent \(i \in B\) can be as follows:

\[
V^{\pi_{\theta_i}^*}(s_{t_i}) = M_i(\nabla \theta_i, L(\theta_i); \phi).
\]

(31) implies that \(\pi_{\theta_i}^*\) is an optimal policy of energy dispatch decisions. Thus, the optimal policy \(\pi_{\theta_i}^*\) belongs to a Nash equilibrium point and holds the following inequality,

\[
V^{\pi_{\theta_i}^*}(s_{t_i}) \geq E_{L(\theta)}[L(\theta^*(L(\theta); \phi))]
\]

Appendix B

Proof of Proposition

Proof. A probability of action \(a_{t_i}\) of BS agent \(i \in B\) at time \(t\) can be presented as follows:

\[
P(a_{t_i}) = \theta_i^{a_{t_i}}(1 - \theta_i)^{1-a_{t_i}} = a_{t_i} \log \theta_i + (1 - a_{t_i}) \log(1 - \theta_i).
\]

(33)
We consider a single state, and a policy gradient estimator can be defined as,
\[
\frac{\partial}{\partial \theta_i} L(\theta_i) = r_i(s_{t_i}, a_{t_0}, \ldots, a_{t_B}) \frac{\partial}{\partial \theta_i} \log P(a_{t_0}, \ldots, a_{t_B})
\]
\[
= r_i(s_{t_i}, a_{t_0}, \ldots, a_{t_B}) \frac{\partial}{\partial \theta_i} \sum_{i \in B} a_{t_i} \log \theta_i + (1 - a_{t_i}) \log(1 - \theta_i)
\]
\[
= r_i(s_{t_i}, a_{t_0}, \ldots, a_{t_B})(a_{t_i} \log \theta_i + (1 - a_{t_i}) \log(1 - \theta_i))
\]
\[
= r_i(s_{t_i}, a_{t_0}, \ldots, a_{t_B})(a_{t_i} \theta_i - (1 - a_{t_i}) \theta_i)
\]
\[
= r_i(s_{t_i}, a_{t_0}, \ldots, a_{t_B})(2a_{t_i} - 1), \text{ for } \theta_i = 0.5.
\]
Thus, an expected reward for $\mathcal{B}$ BS agents can be represented as,
\[
\mathbb{E}[r_i] = \sum_{i \in B} (2a_{t_i} - 1) \mathbb{E}((2a_{t_i} - 1) | \theta_i = (0.5)^{\mathcal{B}}).
\]
Now, we can define an expectation of a gradient estimation as,
\[
\mathbb{E}\left[\frac{\partial}{\partial \theta_i} L(\theta_i)\right] = \mathbb{E}\left[\frac{\partial}{\partial \theta_i} L(\theta_i)\right]\theta_i - \mathbb{E}\left[\frac{\partial}{\partial \theta_i} L(\theta_i)\right]
\]
\[
= (0.5)^{\mathcal{B}} - (0.5)^{2\mathcal{B}}.
\]
Now, we can analyze the step of gradient for $P((\tilde{\nabla}_{\theta_i} L(\theta_i), \nabla_{\theta_i} L(\theta_i)) > 0)$ (in (29)), where
\[
P((\tilde{\nabla}_{\theta_i} L(\theta_i), \nabla_{\theta_i} L(\theta_i)) > 0) = (0.5)^{\mathcal{B}}\sum_{i \in B} \frac{\partial}{\partial \theta_i} L(\theta_i).
\]
As a result, $P((\tilde{\nabla}_{\theta_i} L(\theta_i), \nabla_{\theta_i} L(\theta_i)) > 0) = (0.5)^{\mathcal{B}}$ implies that the gradient step not only moves in the correct direction but also decreases exponentially with an increasing number of BS agents.

REFERENCES

[1] W. Saad, M. Bennis, and M. Chen, “A Vision of 6G Wireless Systems: Applications, Trends, Technologies, and Open Research Problems,” IEEE Network (Early Access), doi: 10.1109/MNET.001.1900287, October 2019.

[2] J. Park, S. Samarakoon, M. Bennis, and M. Debbah, “Wireless Network Intelligence at the Edge,” arXiv:1812.02858 [cs.IT] (https://arxiv.org/abs/1812.02858), September 2019.

[3] E. Dahlman, S. Parkvall, J. Peisa, H. Tullberg, H. Murai and M. Fujioka, “E. Dahlman, S. Parkvall, J. Peisa, H. Tullberg, H. Murai and M. Fujioka,” 6G Wireless Systems: Applications, Trends, Technologies, and Open Research Problems,” IEEE Communications Magazine, vol. 56, no. 5, pp. 144-150, May 2018.

[4] N. H. Tran, S. Akin, and M. C. Gursoy, “On the Energy and Data Storage Manage- ment in Energy Harvesting Wireless Communications,” IEEE Transactions on Wireless Communications, vol. 19, no. 9, pp. 5625-5637, September 2020.

[5] M. S. Munir, S. F. Abedin, N. H. Tran, and C. S. Hong, “Incentivizing Energy Demand Response in Multi-Tenant Mixed-Use Buildings,” IEEE Transactions on Smart Grid, vol. 9, no. 4, pp. 3701-3715, July 2018.

[6] Y. Wu, Z. Zhang, C. Jiao, C. Li and T. Q. S. Quek, “Learn to Sense: A Meta-Learning Based Sensing and Fusion Framework for Wireless Sensor
T. Rauber, G. Runger, M. Schwind, H. Xu, and S. Melzner, "Energy G. Auer et al., "How much energy is needed to run a wireless network?," R. Bertran, M. Gonzalez, X. Martorell, N. Navarro and E. Ayguade, A. Ndikumana, N. H. Tran, T. M. Ho, W. Saad, D. Niyato, and S. Chang, Z. Zhou, T. Ristaniemi, and Z. Niu, "Energy Efficient S. F. Abedin, A. K. Bairagi, M. S. Munir, N. H. Tran and C. S. Hong, Y. Gu, W. Saad, M. Bennis, M. Debbah and Z. Han, "Matching R. Bertran, M. Gonzalez, X. Martorell, N. Navarro and E. Ayguade, T. Han and N. Ansari, "Network Utility Aware Traffic Load Balancing in Backhaul-Constrained Cache-Enabled Small Cell Networks with Hybrid Power Supplies," in IEEE Transactions on Mobile Computing, vol. 16, no. 10, pp. 2819-2832, I Oct. 2017. S. F. Abedin, A. K. Bairagi, M. S. Munir, N. H. Tran and C. S. Hong, "Fog Load Balancing for Massive Machine Type Communications: A Game and Transport Theoretic Approach," IEEE Access, vol. 7, pp. 4204-4218, December 2018. Z. Chang, Z. Zhou, T. Ristaniemi, and Z. Niu, "Energy Efficient Optimization for Computation Offloading in Fog Computing System," IEEE Global Communications Conference, Singapore, December 2017, pp. 1-6. A. Ndikumana, N. H. Tran, T. M. Ho, Z. Han, W. Saad, D. Niyato, and C. S. Hong, "Joint Communication, Computation, Caching, and Control in Big Data Multi-access Edge Computing," IEEE Transactions on Mobile Computing, (Early Access), March, 2019. T. Rauber, G. Runker, M. Schwind, H. Xu, and S. Melzner, "Energy measurement, modeling, and prediction for processors with frequency scaling," The Journal of Supercomputing, vol. 70, no. 3, pp. 1454-1476, 2014. R. Bertran, M. Gonzalez, X. Martorell, N. Navarro and E. Ayguade, "A Systematic Methodology to Generate Decomposable and Responsive Power Models for CMPs," IEEE Transactions on Computers, vol. 62, no. 7, pp. 1289-1302, July 2013. Firstquarter 2016. G. Auer et al., “How much energy is needed to run a wireless network?”, IEEE Wireless Communications, vol. 18, no. 5, pp. 40-49, October 2011. ETSI TS, “5G; NR; Physical layer procedures for data”, [Online]: http://www.etsi.org/deliver/etsi_ts/138200_138299/138214/15.03.00_60/ts_138214v150300p.pdf, 3GPP TS 38.214 version 15.3.0 Release 15, October 2018 (Visited on 18 July, 2019). Y. Gu, W. Saad, M. Bennis, M. Debbah and Z. Han, "Matching theory for future wireless networks: fundamentals and applications," IEEE Communications Magazine, vol. 53, no. 5, pp. 52-59, May 2015. F. Fantisano, M. Bennis, W. Saad, S. Valentin and M. Debbah, “Matching with externalities for context-aware user-cell association in small cell networks,” 2013 IEEE Global Communications Conference (GLOBECOM), Atlanta, GA, 2013, pp. 4483-4488. C. Li et al., “Towards sustainable in-situ server systems in the big data era,” ACM/IEEE 42nd Annual International Symposium on Computer Architecture (ISCA), Portland, OR, 2015, pp. 14-26. N.L. Panwar, S.C. Kaulshik, and S. Kothari, "Role of renewable energy sources in environmental protection: a review," Renewable and Sustainable Energy Reviews, vol. 15, no. 3, pp. 1513-1524, April, 2011. F. A. Chacra, P. Bastard, G. Fleury and R. Clavreul, “Impact of energy storage costs on economical performance in a distribution substation,” IEEE Transactions on Power Systems, vol. 20, no. 2, pp. 684-691, May 2005. H. Kanchev, D. Lu, F. Colas, V. Lazarov and B. Francois, "Energy Management and Operational Planning of a Microgrid With a PV-Based Active Generator for Smart Grid Applications," IEEE Transactions on Industrial Electronics, vol. 58, no. 10, pp. 4583-4592, Oct. 2011. A. Mishra, D. Irwin, P. Shenoy, J. Kurose and T. Zhu, "GreenCharge: Managing RenewableEnergy in Smart Buildings," IEEE Journal on Selected Areas in Communications, vol. 31, no. 7, pp. 1281-1293, July 2013. X. Xu, Z. Yan, M. Shahidehpour, Z. Li, M. Yan and X. Kong, “Data-Driven Risk-Averse Two-Stage Optimal Stochastic Scheduling of Energy and Reserve with Correlated Wind Power,” IEEE Transactions on Sustainable Energy ( Early Access ), January 2019. Business Insider, “One simple chart shows why an energy revolution is coming”, [Online]: https://www.businessinsider.com/solar-power-cost-decrease-2018-5, May 2018 (Visited on 23 July, 2019). Y. Liu, and N. K. C. Nair, “A Two-Stage Stochastic Dynamic Dispatch Model Considering Wind Uncertainty,” IEEE Transactions on Sustainable Energy, vol. 7, no. 2, pp. 819-829, April 2016. D. Zhou, M. Sheng, B. Li, J. Li and Z. Han, “Distributionally Robust Planning for Data Delivery in Distributed Satellite Cluster Network,” IEEE Transactions on Wireless Communications, vol. 18, no. 7, pp. 3642-3657, July 2019. S. F. Abedin, M. G. R. Alam, S. M. A. Kazmi, N. H. Tran, D. Niyato and C. S. Hong, “Resource Allocation for Ultra-reliable and Enhanced Mobile Broadband IoT Applications in Fog Network,” IEEE Transactions on Communications, vol. 67, no. 1, pp. 489-502, January 2019. R. Lowe, Y. Wu, A. Tamar, J. Harb, P. Abbeel, and I. Mordatch, “Multi-agent actor-critic for mixed cooperative-competitive environments," In Advances in Neural Information Processing Systems, pp. 6379-6390. 2017. V. Mnih, A. P. Badia, M. Mirza, A. Graves, T. Lillicrap, T. Harley, D. Silver, and K. Kavukcuoglu, “Asynchronous Methods for Deep Reinforcement Learning,” Proceedings of The 33rd International Conference on Machine Learning, vol. 48, pp. 1928-1937, Jan. 2016. S. Hochreiter, and J. Schmidhuber., “Long short-term memory,” Neural Computation, vol. 9, pp. 1735-1780, 1997. Z. M. Fadlullah et al., “State-of-the-Art Deep Learning: Evolving Machine Intelligence Toward Tomorrow's Intelligent Network Traffic Control Systems," IEEE Communications Surveys & Tutorials, vol. 19, no. 4, pp. 2432-2455, Fourthquarter 2017. M. Andrychowicz et al., “Learning to learn by gradient descent by gradient descent,” Advances in Neural Information Processing Systems 29 (NIPS 2016), 2016. M. L. Litman, “Markov games as a framework for multi-agent reinforce ment learning,” In Proceedings of the eleventh international conference on machine learning, pp. 157-163, 1994. A. K. Bairagi, N. H. Tran, W. Saad, Z. Han and C. S. Hong, “A Game-Theoretic Approach for Fair Coexistence Between LTE-U and Wi-Fi Systems," IEEE Transactions on Vehicular Technology, vol. 68, no. 1, pp. 442-455, Jan. 2019. Inte l, “Intel Core i7-6500U Processor,” [Online]: https://ark.intel.com/content/www/us/en/ark/products/88194/intel-core-i7-6500u-proces sor-4m-cache-up-to-3-10-ghz.html, (Visited on 17 August, 2019). A. M. Fink, “Equilibrium in a stochastic n-person game,” Journal of Science of the Hiroshima University, Series A-1 (Mathematics), vol. 28, no. 1, pp. 89-93, 1964. P. J. Herings, and R. J. A. P. Peeters, "Stationary equilibria in stochastic games: structure, selection, and computation," Journal of Economic Theory, Elsevier, vol. 118, no. 1, pp. 32-60, September, 2004. S. Fu, and Y. Zhang, “CRAWDAD dataset due/packet-delivery (v. 2015-04-01),” downloaded from https://crawdad.org/duel/packet-delivery/20150401, Apr 2015 (Visited on 3 July, 2019). Online：“Solar panel dataset,” UMass TraceRepository http://traces.cs.umass.edu/index.php/Smart/Smart, (Visited on 3 July, 2019). Online: “All symbols in TensorFlow,” TensorFlow, https://www.tensorflow.org/api_docs/python/ (Visited on 3 July, 2019). 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