Risk-Aware Energy Scheduling for Edge Computing with Microgrid: A Multi-Agent Deep Reinforcement Learning Approach

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Abstract—In recent years, multi-access edge computing (MEC) is a key enabler for handling the massive expansion of Internet of Things (IoT) applications and services. However, energy consumption of a MEC network depends on volatile tasks that induces risk for energy demand estimations. As an energy supplier, a microgrid can facilitate seamless energy supply. However, the risk associated with energy supply is also increased due to unpredictable energy generation from renewable and non-renewable sources. Especially, the risk of energy shortfall is involved with uncertainties in both energy consumption and generation. In this paper, we study a risk-aware energy scheduling problem for a microgrid-powered MEC network. First, we formulate an optimization problem considering the conditional value-at-risk (CVaR) measurement for both energy consumption and generation, where the objective is to minimize the loss of energy shortfall of the MEC networks and we show this problem is an NP-hard problem. Second, we analyze our formulated problem using a multi-agent stochastic game that ensures the joint policy Nash equilibrium, and show the convergence of the proposed model. Third, we derive the solution by applying a multi-agent deep reinforcement learning (MADRL)-based asynchronous advantage actor-critic (A3C) algorithm with shared neural networks. This method mitigates the curse of dimensionality of the state space and chooses the best policy among the agents for the proposed problem. Finally, the experimental results establish a significant performance gain by considering CVaR for high accuracy energy scheduling of the proposed model than both the single and random agent models.

Index Terms—Multi-access edge computing (MEC), microgrid, multi-agent deep reinforcement learning, conditional value-at-risk (CVaR), energy scheduling, demand-response (DR).

I. INTRODUCTION

MULTI-ACCESS edge computing (MEC) enables a large amount of computational tasks for massive IoT-applications and background services to be executed by smart devices [2], which requires more energy consumption as compared with normal execution of the wireless networks [3]. To handle the continual growth of energy consumption for wireless networks [4], renewable energy usage is essential for interrupt-free wireless network operation by reducing the dependency on non-renewable energy usage. Furthermore, research shows that a proper combination of energy generation (i.e., renewable, non-renewable, and storage) and distribution can save a significant amount of energy usage for radio access networks [5]. Specifically, a jointly optimized demand-side management mechanism is claimed to save up to 18% of the total energy usage in wireless networks [6]. Therefore, renewable energy aware task scheduling and resource allocation for wireless networks infrastructure are necessary when considering energy consumption [7]. However, risk-aware energy scheduling is overlooked in a microgrid-powered MEC networks, where energy consumption of the MEC network strongly depends on the nature of MEC task fulfillment over time [8]. This paper provides one of the first models for risk-aware energy scheduling of a microgrid-powered MEC network.

In case of the physical deployment of MEC, the technical and business point of view are considered [9]. MEC facilitates various applications such as those are related to smart cities, health care, smart agriculture, automotive, virtual reality (VR), and augmented reality (AR) [2], along with user specific requirements. Consequently, MEC is already included as an essential component in various smart infrastructures such as smart cities and smart factories. Meanwhile, microgrids have been considered prominent in those MEC infrastructures [10] [11]. Thus, microgrid can be an effective energy supplement to MEC.

Uncertain tasks request to MEC compels a volatile energy consumption, while randomness of renewable energy generation admits the volatility in microgrid (as seen in Fig. 1). The volatility [12] of energy consumption-generation possibly induces energy shortfalls between energy demand and supply. This characteristic of energy demand-supply raises a risk toward an efficient energy scheduling of the microgrid-powered MEC network, where the volatility is directly proportional to the risk. Thus, to mitigate this challenge, risk-aware energy scheduling whereby the uncertainties of both MEC energy consumption and microgrid generation are considered is essential. In the literature, conditional value-at-risk (CVaR) [13].
satisfy. We summarize our key contributions as follows:

- First, we formulate a risk-aware energy scheduling problem for the microgrid-powered MEC network, where the objective is to reduce the loss of energy demand-supply estimation such that the CVaR confidence level is satisfied. This optimization problem not only coordinates between MEC energy consumption and microgrid generation, but also considers the expected shortfall in CVaR risk measurement with a long tail distribution, where we show that the formulated problem is NP-hard.

- Second, to achieve optimal scheduling of the formulated problem, we analyze and remodel it with multi-agent deep reinforcement learning (MADRL), which is similar to an N-agent stochastic game with a joint policy. We show that this game not only guarantees at least one Nash equilibrium point in stationary strategies, but also ensures the convergence of the proposed model.

- Third, to derive the solution of proposed model, we apply a MADRL-based asynchronous advantage actor-critic (A3C) algorithm and achieve the optimal policy, in which we employ shared neural networks (weight sharing) for low computational complexity. This MADRL model overcomes the curse of dimensionality for the state-space and accepts the best policy among the other agents toward updating the global policy with less information.

- Finally, we perform an extensive experimental analysis for the proposed risk-aware energy scheduling model, and the experimental results show the proposed approach outperforms the single agent A3C and random-agent A3C solution in terms of energy scheduling and risk measurement, achieving around 92%, 96%, and 92% test accuracy with 4.72%, 5.65%, and 7.46% CVaR for confidence levels of 90%, 95%, and 99%, respectively.

The rest of the paper is organized as follows. We present some related works of current research in Section II. In Section III, we describe the network energy consumption model, microgrid energy generation model, risk assessment model, and problem formulation of the risk-aware energy scheduling problem. We present risk-aware energy scheduling via an N-agent stochastic game and MADRL in Section IV. In Section V, we provide the experimental analysis and discussion regarding the proposed solution. Finally, we conclude the paper in Section VI.

II. RELATED WORKS

In this section, we discuss background of MEC and microgrid, some of the related works, and challenges, which are grouped into four categories: (i) background, (ii) MEC networks with renewable energy, (iii) sustainable demand response (DR) management, and (iv) reinforcement learning in wireless networks.

A. Background

The goal of the MEC technology is to provide computational facilities at the edge of a network by employing low-
latency, high-bandwidth communication with real-time feedback for Internet of Things (IoT) applications and services [2]. Initially, mobile edge computing was referred to as the network edge of a mobile network [3]. However, the MEC function is not only limited to mobile networks but also reflects on non-cellular operators’ requirements. Therefore, the European Telecommunications Standards Institute (ETSI) Industry Specification Group (ISG) officially changed its name from Mobile Edge Computing ISG to Multi-Access Edge Computing ISG [17]. MEC hosts are deployed in a large geographical area such as, at the edge or central data network, where User Plane Function (UPF) manages the user traffic for the targeted MEC applications in the data network [2]. Further, network operators can be responsible for the physical location of the data networks based on the supported applications, available site facilities, and requirements, where they consider technical and business parameters [9]. Nowadays, the necessity of MEC becomes a promising technology to facilitate the smart city, smart factory, smart home, and other smart infrastructures [2], [18]. Meanwhile, microgrid has shown its competence in those smart infrastructures as an energy supplier [10], [11], [19]. Thus, microgrid is capable of supplying energy from its renewable, non-renewable, and storage energy sources (local sources) and also able to sell/buy energy to/from main grid [8], [20], [21]. As a result, microgrid is a suitable candidate to enable sustainable edge computing in the era of next-generation networks.

B. MEC Networks with Renewable Energy

MEC emerges via computational requirements at the edge of wireless networks to handle the massive expansion of IoT applications and services. The amount of computational data will reach 49 exabytes per month by 2021 and MEC will be responsible for computing 63% of the total computational data [22]. Therefore, to operate sustainable MEC function, a microgrid enables facilitation of energy consumption from renewable, non-renewable, and storage sources. Sustainable energy management for renewable energy enabled wireless networks has been a focus of recent years, facilitating seamless edge computing. A study on renewable energy powered base stations (BSs) operation was performed a decade ago in [23], where authors have analyzed the usefulness and effectiveness of usages of renewable energy in the wireless network. Afterward, in [24], small cell networks have facilitated with renewable energy, in which they investigate a network deployment methodology and design the network operation function. Recently, a learning-based scheme has proposed in [7], where user scheduling and network resource allocation have performed of heterogeneous networks by considering hybrid energy supply. To facilitate sustainable MEC, it is essential to study the energy demand for MEC computational tasks as well as the energy generated from renewable energy sources.

In recent years, MEC has faced challenges related to low latency scheduling, scalability, and sustainability, in which proper energy scheduling can solve the sustainability of MEC due to energy failure [25], [26]. To promote energy saving for user devices, energy-efficient task offloading [27] and dynamic task offloading are considered in [28], increasing the energy consumption of MEC networks. Therefore, to enable smart grid powered mobile networks, a joint method was proposed for both BS operation and power distribution, which provides a strong relationship between BS operation power consumption and smart grid power generation [6]. A hybrid energy supply aware user scheduling and resource allocation scheme has developed for HetNets environment, where every small cell base station (SBS) is enabled with renewable energy sources [7]. Further, a wired energy transferred (via energy harvesting and energy load balancing) mechanism for the BSs has been established, with a grid architecture that considers task offloading decisions among the BSs [29]. In [30], a method for energy-efficient wireless data transmission has been proposed that minimizes the power loss for both power generation and wireless network power consumption. However, these studies have overlooked MEC energy consumption with respect to computational tasks. Thus, a computational tasks consume 33% of energy from the total consumed energy of the wireless networks [31].

C. Sustainable Demand Response Management

A sustainability issue arises for MEC networks, where the computations of MEC are directly proportional to energy consumption [2]. The energy consumption of MEC network is nondeterministic in nature [8]. Therefore, efficient energy supply can fulfill the requirements of sustainable MEC operation. The reliability and stability of the MEC network not only depend on MEC energy consumption, but also on energy generation of renewable (e.g., solar, wind, biofuels, etc.) and non-renewable (e.g., diesel generator, coal power, and so on) sources [32]. A microgrid can manage those challenges by providing proper demand response (DR) management, in which a microgrid controller is essential [33]. Competence of the proper DR management is already shown in the field of residential [34], [35], commercial [36], and cloud data center [37], [38] energy management. In [39], a risk management scheme was introduced for optimizing the midterm power portfolio in energy market, where reliability of energy pricing is increased since risk measurement has included. Volatility of energy demand and supply induces a risk of energy failure, indicating the significance of energy scheduling of the microgrid-powered MEC networks. As a result, to ensure a sustainable energy scheduling, we discretize the risk under a CVaR [13], [14], where the risk of energy shortfall is characterized by a long-tail distribution.

D. Reinforcement Learning in Wireless Network

A variety of reinforcement learning (RL) approaches have been used to solve complex problems such as user tasks offloading, software-defined network (SDN) management, strategic planning of energy markets, and SBS network resources allocation [7], [40], [44]. Multi-agent reinforcement learning is used to solve spatio-temporal resource assignment problems [40]. An ε-greed-based RL method has been applied to SDN-based smart city service management [41], and a single agent
Q-learning model has studied for energy market analysis in [42]. Furthermore, deep Q-networks (DQN) have been employed for green resource management in content-centric IoT networks [43]. A DQN-based single agent A3C model has been proposed for task scheduling in renewable energy powered heterogeneous networks [7], and a data-driven model has developed for the BS energy saving mechanism in [45]. However, these approaches are very expensive with respect to computation, whereas multi-agent deep reinforcement learning with shared neural networks is one possible way to obtain a low computational complexity solution. In order to solve the risk-aware energy scheduling problem with optimal results and fast convergence, a MADRL-based asynchronous A3C model has developed for the BS energy saving mechanism in [45]. The fast convergence, a MADRL-based asynchronous A3C model has developed for the BS energy saving mechanism in [45].

In this paper, we tackle the risk-aware energy scheduling problem for the microgrid-powered MEC networks by considering both energy consumption and generation under risk measurement. The detail discussion of the system model and problem formulation are given in the following section.

III. SYSTEM MODEL AND PROBLEM FORMULATION

The multi-access edge servers are capable of performing heterogeneous computational tasks (e.g., smart health, VR, emergency monitoring and so on) and these tasks are associated with SBSs as shown in Fig. 2. The energy demand of this MEC network is fulfilled by the microgrid energy sources (e.g., renewable, non-renewable, and storage), and a microgrid controller can communicate with the macro base station (MBS) for managing the energy supply based on MEC network energy demand. All the SBSs are physically connected with the MBS and controlled by the same network operator. Here, the risk of energy failure is a fundamental challenge for sustainable edge computing [25] in existing microgrid-powered MEC networks, where the energy consumption of edge computing is random over time and renewable energy generation is nondeterministic in nature [8], [26]. Therefore, the microgrid-powered MEC network system model can be decomposed into three parts, the network energy consumption model, microgrid energy generation model, and risk assessment model, which are discussed in the later subsections in detail.

A. Network Energy Consumption Model

In the network energy consumption model, we consider a set of SBSs \( B = \{1, 2, \ldots, B\} \) that are deployed under a macro base station (MBS), where each SBS \( i \) has a set of MEC heterogeneous active servers \( C_i = \{1, 2, \ldots, C_i\} \) and these MEC servers are physically deployed with SBS \( i \) [48]. We consider one energy consumption cycle as a set \( T = \{1, 2, \ldots, T\} \) of a finite time horizon, where the length of a discrete time slot \( t \) is a 15-minute duration (i.e., one observational period), in general, the total duration of each cycle is one month [20]. In the typical wireless networks [49], [50], the per-user channel and traffic variation period is up to 0.1 second and traffic aggregation demand variation is 0.1 minute. In fact, we can predict the user association and network status variations by the duration of several minutes, hours, and days [6], [49], [50]. On the other hand, the microgrid (i.e., renewable, non-renewable, and storage) energy generation and supply model belongs to several time slot durations correspondingly up to 15 minutes, 1 hour, 6 hours, 1 day, several days and so on [8], [10], [16], [20], [21]. The observation of a time slot \( t \) is ended at the 15-th minute and capable of capturing the changes of network dynamics for entire 15 minutes duration. Therefore, 15 minutes time slot is reasonable for the proposed scenario. Let us consider a smart city scenario, where the SBS \( i \) can serve a set of heterogeneous user tasks \( K = \{1, 2, \ldots, K\} \) (e.g., video surveillance, emergency health care, smart transportation and so on.) at time slot \( t \). The user association between SBS \( i \in B \) and task \( k \in K \) is denoted as \( \Omega_{ik}(t) \). We assume \( \Omega_{ik}(t) = 1 \) if task \( k \) is assigned to SBS \( i \) at time \( t \), and 0 otherwise. Moreover, SBSs are considered as up and running to anticipate those user requests. The main parameters used in this work is represented in Table 1.

1) Network Operation Energy Consumption: We consider a task arrival rate \( \lambda_i(t) \) for SBS \( i \) with an average traffic size \( \chi_{i}(t) \) at time slot \( t \), where the task arrival rate follows a Poisson process and \( \lambda_i(t)\chi_i(t) \) is the average traffic load. The capacity of SBS \( i \in B \) to receive the user tasks \( \forall k \in K \) is as follows [8], [51], [52]:

\[
\varphi_i(t) = \sum_{k\in K} \Omega_{ik}(t) w_{ik} \log_2 \left( 1 + \frac{p_{ik} g_{ik}(t)}{\sigma^2 + \sum_{j\in B, j\neq i} I_j(t)} \right), \forall i \in B, \tag{1}
\]
where \( w_{ik} \) is the fixed channel bandwidth assigned to \( k \in \mathcal{K} \), \( p_{ik} \) is the transmission power between task \( k \in \mathcal{K} \) and SBS \( i \in \mathcal{B} \), \( \delta_{ik}(t) \) determines the channel gain, the variance of the Additive white Gaussian noise (AWGN) is denoted by \( \sigma_{ik}^2 \), and \( I_{l}(t) \) is the channel interference with other SBSs. Therefore, the average service rate for SBS \( i \) is calculated as follows:

\[
\mu_i(t) = \frac{\varphi(t)}{\chi(t)},
\]

(2)

The SBS \( i \in \mathcal{B} \) data rate is considered as constant and the traffic size is already known, so the service rate follows an exponential distribution. As a result, the M/M/1 queuing model can be considered as an appropriate choice \cite{8, 53, 54}. At time slot \( t \), tasks \( \forall k \in \mathcal{K} \) are uniformly distributed under SBS \( i \) and the overall server utilization rate is as follows \cite{6}:

\[
\rho_i(t) = \sum_{k \in \mathcal{K}} \Omega_{ik}(t) \frac{\lambda_i(t)}{\mu_i(t)},
\]

(3)

where \( \sum_{k \in \mathcal{K}} \Omega_{ik}(t) \frac{\lambda_i(t)}{\mu_i(t)} \) is the total amount of served tasks at time slot \( t \) by SBS \( i \).

The energy consumption of each SBS \( i \in \mathcal{B} \) is comprised of SBS general operation (i.e., up and running) and data transfer through the network (i.e., payload communications). In which, the general operation energy and payload communication energy consumptions are considered as static energy \( E_{\text{net}}(t) \) and dynamic energy, respectively \cite{6, 55}. Thus, a linear energy model is suitable to estimate the network operation energy consumption of SBS \( i \) and the network operation energy consumption is determined as follows \cite{6}:

\[
E_{\text{net}}^i(t) = \eta_{\text{net}}(t) \rho_i(t) + E_{\text{net}}^t(t),
\]

(4)

where \( \eta_{\text{net}}(t) \) represents the energy coefficient and the value of \( \eta_{\text{net}}(t) \) depends on psychical components of SBS as well as transferred payload size \cite{6, 55}.

2) MEC Server Computational Energy: MEC server energy consumption depends on the number of CPU cores, activity ratio, and processor architecture. Each MEC server consists of \( L \) number of homogeneous CPU cores with \( M \) numbers of CPU component (i.e., FE: frontend; INT: integer units, FP: floating point units, BPU: branch prediction unit, L1: L1 cache, L2: L2 cache, and MEM: FSB and main memory) \cite{57}. Therefore, the dynamic energy consumption for core \( l \) with \( M \) components is determined by \( \sum_{m \in M} \eta_{lmu}(t) \delta_{ml}(t) \), where \( \eta_{lmu}(t) \) is the weight of component \( m \) and \( \delta_{ml}(t) \) represents the activity ratio at time slot \( t \) and \( \sum_{c \in C_l} \sum_{l \in L} \sum_{m \in M} \delta_{ml}(t) \approx \frac{1}{n_{cpu}} \). The general operation (e.g., signal messaging, idle state) of the MEC server consumes a static energy \( E_{\text{st}}(t) \). Thus, the total energy consumption for the multi-core MEC server is defined as follows \cite{57}:

\[
E_{\text{mec}}^i(t) = \sum_{c \in C_l} \left( \sum_{l \in L} \sum_{m \in M} \eta_{lmu} \delta_{ml}(t) + E_{\text{st}}^i(t) \right).
\]

(5)

In \cite{5}, since the activity ratio \( \delta_{ml}(t) \) of the each core depends on the server capacity, this ensures variability of the MEC servers energy consumption.

3) Total Energy Consumption: The energy consumption of MEC enabled SBS \( i \) includes the static energy \( E_{\text{st}}^i(t) \) and the dynamic energy \( E_{\text{mec}}^i(t) \) \cite{55}. Equations (4) and (5) provide the dynamic energy consumption for the SBS network’s operation and MEC servers usages, respectively. Here, the total dynamic energy consumption of SBS \( i \) for time slot \( t \) is as follows:

\[
E_{\text{dyn}}^i(t) = E_{\text{mec}}^i(t) + E_{\text{net}}^i(t).
\]

(6)

Therefore, the total energy demand for SBS \( i \) is as follows \cite{55}:

\[
E_{\text{dem}}^i(t) = E_{\text{st}}^i(t) + E_{\text{mec}}^i(t),
\]

(7)

where \( \eta_{\text{dyn}}(t) \) is the energy coefficient for dynamic energy consumption and \( E_{\text{st}}(t) \) determines the idle operation energy consumption for SBS \( i \) at time slot \( t \). Therefore, the total energy demand for \( B \) SBSs under the MBS is as follows:

\[
E_{\text{dem}}^B(t) = \sum_{i \in B} \left( E_{\text{st}}^i(t) + E_{\text{mec}}^i(t) \right).
\]

(8)

In \cite{8}, \( \eta_{\text{dyn}}(t) \) is an energy coefficient parameter for SBSs that follows a linear energy model \cite{55}. The value of parameter \( \eta_{\text{dyn}}(t) \) is known and depends on the types of SBSs.

B. Microgrid Energy Generation Model

The microgrid can supply both renewable energy (e.g., solar, wind, biofuels, etc.) and non-renewable energy (e.g., diesel generator, coal power, and so on). Here, \( E_{\text{ren}}^t(t) \) and \( E_{\text{non}}^t(t) \) denote the amount of renewable energy generation and non-renewable energy generation at time slot \( t \), respectively. Let \( E_{\text{gen}}^t(t) \) denote the maximum energy generation capacity and \( E_{\text{gen}}^t(t) \leq E_{\text{gen}}^t \) denote total amount of energy generation. The total energy generation \( E_{\text{gen}}^t(t) \) includes both renewable and non-renewable generated energy at time slot \( t \), which can be calculated as follows:

\[
E_{\text{gen}}^t(t) = E_{\text{ren}}^t(t) + E_{\text{non}}^t(t).
\]

(9)

The microgrid can obtain additional energy from the main grid for meeting extra demand \cite{8, 20, 55}. Therefore, for the energy demand \( E_{\text{dem}}^t(t) \), the additional amount of energy is calculated as,

\[
E_{\text{buy}}^t(t) = E_{\text{dem}}^t(t) - E_{\text{gen}}^t(t).
\]

(10)

Furthermore, the microgrid has energy storage capacity \( E_{\text{sto}}^t(t) \) \cite{21, 58} to preserve the extra amount of generated energy \( E_{\text{sto}}^t(t) \leq E_{\text{sto}}^t \) for future use and is determined as follows:

\[
E_{\text{sto}}^t(t) = E_{\text{gen}}^t(t) - E_{\text{dem}}^t(t).
\]

(11)

Hence, using \( \text{(10)} \) and \( \text{(11)} \), we can define the following binary decision variable:

\[
a_t = \begin{cases} 
1, & \text{if } E_{\text{sto}}^t(t) \geq E_{\text{buy}}^t(t), \forall t \in \mathcal{T}, \\
0, & \text{otherwise},
\end{cases}
\]

(12)

where \( a_t = 1 \) if the microgrid is able to fulfill energy demand from its own sources, and 0 otherwise.
C. Risk Assessment with Conditional Value-at-Risk (CVaR)

Let us consider a $p = 2$ dimensional decision (i.e., store and buy) vector $a_t \in \mathbb{R}^p$ that stands for energy storage and buying decision. Therefore, a set of decision vectors $A_t$ holds the available decision $a_t \in A_t$ at time slot $t$ and the decisions are affected by uncertainties of the energy demand $E^\text{dem}(t)$, renewable energy generation $E^\text{ren}(t)$, non-renewable generation $E^\text{non}(t)$, and storage energy $E^\text{sto}(t)$. Considering a $q = 4$ dimensional random vector $s_t \in \mathbb{R}^q$ (i.e., $s_t := (E^\text{dem}(t), E^\text{ren}(t), E^\text{non}(t), E^\text{sto}(t)) \in \mathbb{R}^q, s_t \in S_t$), where $s_t$ represents state information at time slot $t$ and loss function $\Upsilon(a_t, s_t)$. Since the decision $a_t$ is involved with the characteristics of $s_t$, the energy shortfall (loss) is also affected by the uncertainties of $s_t$. Hence, we define the total supplyable energy at time slot $t$ as $E^\text{tot}(t) = E^\text{dem}(t) + E^\text{ren}(t) + E^\text{non}(t) + E^\text{sto}(t)$ and the loss function $\Upsilon(a_t, s_t)$ is determined as follows:

$$
\Upsilon(a_t, s_t) = \min_{a_t \in A_t} \mathbb{E}_{a_t \sim s_t} \left[ \sum_{i \in T} (a_t(i) - \min(1 - a_t(i), (E^\text{dem}(t) - E^\text{tot}(t))^2) \right].
$$

(13)

We characterize the risk of energy shortfall (i.e., $\Upsilon(a_t, s_t)$) by employing CVaR, which catches up with the tail end of energy demand $E^\text{dem}(t)$ and generation $E^\text{tot}(t)$ (i.e., state $s_t$). For each $a_t \in A_t$, the energy shortfall $\Upsilon(a_t, s_t)$ is a random variable and the probability distribution is bounded by the distribution of $\xi$. Thus, the probability distribution of $\Upsilon(a_t, s_t)$ is denoted by $\psi(a_t, \xi)$, where $\psi(a_t, \xi) = P\{s_t \in \mathbb{R}: \Upsilon(a_t, s_t) \leq \xi\}$. Hence, $\Upsilon(a_t, s_t)$ is continuous in decision $a_t$ and measurable in $s_t$, in which for each decision $a_t \in A_t$, the expectation of energy shortfall belongs to $\mathbb{E}[|\Upsilon(a_t, s_t)|] < \infty$.

Let us consider $\xi$ is a left limit of probability distribution $\psi(a_t, \xi)$ at $\xi$, where $\psi(a_t, \xi) = P\{s_t \in \mathbb{R}: \Upsilon(a_t, s_t) < \xi\}$. Therefore, there exits a probability atom in $\xi$ since $\psi(a_t, \xi) - \psi(a_t, \xi^-) = P\{s_t \in \mathbb{R}: \Upsilon(a_t, s_t) = \xi\}$ is positive. In literature [13], [14], [59]–[61], the measurement of CVaR is derived from value at risk (VaR) one of the suitable ways for our scenario, where CVaR is also capable of capturing the shortcoming of VaR by quantifying tail risk of the distribution of possible decisions. We define a confidence range $\alpha \in (0, 1)$, any specified probability range $\alpha \in (0, 1)$ (e.g., empirically used $\alpha = 0.90$, $\alpha = 0.95$, or $\alpha = 0.99$ [59]–[61]) and the VaR $\xi_a(a_t)$ is defined as follows:

**Definition 1. (VaR $\xi_a(a_t)$):** The risk of energy shortfall is associated with a decision of $a_t$ such that $\xi_a(a_t) = \min_{\xi \in \mathbb{R}} \{\xi \in \mathbb{R}: \psi(a_t, \xi) \geq \alpha\}$, where value of $\xi_a(a_t)$ belongs to $\xi$ since $\psi(a_t, \xi)$ is nondecreasing and continuous in $\xi$. Thus, the value at risk $\xi_a(a_t)$ for decision $a_t$ is defined as follows:

$$
\xi_a(a_t) = \arg \min_{\xi \in \mathbb{R}} \psi(a_t, \xi) \geq \alpha,
$$

(14)

where $\xi_a(a_t)$ determines the value $\xi$ such that $\psi(a_t, \xi) = \alpha$.

To capture the extreme risk of energy shortfall which exceeds from VaR cutoff point, we define CVaR $\Phi_a(a_t)$ as the expectation of worst outcomes of decision $a_t$ for $\alpha \in (0, 1)$ as follows:

**Definition 2. (CVaR $\Phi_a(a_t)$):** Considering $\Phi_a(a_t)$ is the conditional expectation with the energy shortfall associated with the variable $a_t$, and the energy shortfall is at least $\xi_a(a_t)$. Thus, the CVaR $\Phi_a(a_t)$ is defined as follows:

$$
\Phi_a(a_t) = \min_{\xi \in \mathbb{R}} \frac{1}{(1 - \alpha)} \mathbb{E}_{\xi_a(a_t)}[\Upsilon(a_t, s_t)],
$$

(15)

where the probability of energy shortfall $P(\Upsilon(a_t, s_t)) \geq P(\xi_a(a_t))$ is equal to $1 - \alpha$.

To characterize both VaR $\xi_a(a_t)$ (in Definition [1]) and CVaR $\Phi_a(a_t)$ (in Definition [2]) in terms of a function $H_a(a, \xi)$ on $A_t \times \mathbb{R}$, we define as follows:

$$
H_a(a, \xi) = \min_{\xi \in \mathbb{R}} \xi + \frac{1}{(1 - \alpha)} \mathbb{E}_{\xi - \psi(a_t, \xi)}[\Upsilon(a_t, s_t) - \xi^+],
$$

(16)

where $E[\Upsilon(a_t, s_t) - \xi^+]$ is positive and as a function of $\xi$, $H_a(a, \xi)$ is continuous and differentiable [59]–[61]. Therefore, we represent the risk assessment of risk-aware energy scheduling problem as follows:

$$
\min_{\xi \in \mathbb{R}} H_a(a, \xi).
$$

(17)

In later section, we will provide an optimization problem for the microgrid controller so that the energy scheduling of the MEC network can be calculated efficiently.

D. Problem Formulation

The goal of the risk-aware energy scheduling problem is to minimize the loss of the energy shortfall of the MEC network while satisfying the CVaR confidence level subject to the energy supply, which is imposed by the microgrid energy sources. Hence, the problem is formulated as follows:

$$
\min_{a_t, \xi} \sum_{t \in T} \sum_{i \in B} \sum_{j \in C_i} \sum_{k \in K} \Omega_k(t) \Upsilon(a_t, s_t),
$$

(18)

s.t. $P(H_a(a_t, \xi)) \leq \omega, \forall t \in T,
$$

(18a)

$$(a_t - 1)E^\text{demand}(t) \leq a_t E^\text{ren}(t), \forall i \in B, \forall j \in C_i, t \in T,
$$

(18b)

$$a_t E^\text{sto}(t) + (1 - a_t) E^\text{non}(t) \geq 0, \forall i \in B, t \in T,
$$

(18c)

$$a_t E^\text{sto}(t) \leq E^\text{max}_t, \forall i \in B, t \in T,
$$

(18d)

$$\sum_{t \in T} a_t \leq T,
$$

(18e)

$$a_t \in \{0, 1\}, \forall t \in T,
$$

(18f)

$$a_t E^\text{sto}(t) \leq E^\text{max}_t, \forall \xi \in \mathbb{R}.
$$

(18g)

In problem (18), the objective function contains multiplication of the task association indicator $\Omega_k(t)$ and loss function $\Upsilon(a_t, s_t)$, where $\Omega_k(t)$ is given for task $k$ and is associated with SBS $i$. Constraint (18a) states inequalities for any $\xi \in \mathbb{R}$, $P(\Phi_a(a_t)) \leq P(H_a(a_t, \xi)) \leq \omega$, where $\omega$ denotes the risk tolerance and takes a small value. As a result, the probability of energy scheduling loss satisfies the maximum tolerable risk $P(\Upsilon(a_t, s_t)) \leq \omega$. Therefore, maintaining the relationship between energy demand and supply is very crucial due to the nondeterministic nature of both energy consumption and generation. Hence, constraint (18b) ensures coupling between the energy demand $E^\text{demand}(t)$ and generation $E^\text{ren}(t)$, where the energy demand is derived from the linear energy model [4] considering both network energy consumption [4] and MEC network efficiency.
server computational energy consumption \( E \). The amount of energy storage \( E^{sto}(t) \) and buying \( E^{bas}(t) \) depends on a decision of the binary decision variable \( a_t \), which is defined in \((12)\). Therefore, constraint \((18c)\) takes into account the renewable energy generation \( E^{ren}(t) \) on the microgrid side for deciding energy buying and storing. The amount of storage energy \( E^{sto}(t) \) is calculated based on the availability of non-renewable energy store/buy decision for the entire time horizon \( T \) and constraint \((18f)\) assures that the decision variable \( a_t \) is a binary variable, where constraint \((18c)\) guarantees the energy store/buy decision for the entire time horizon \( T \) and constraint \((18f)\) assures that the decision variable \( a_t \) is a binary variable. Finally, constraint \((18g)\) ensures that the total storage energy does not exceed the limit of maximum capacity.

Since formulated problem \((18)\) is a mixed-integer programming problem with the corresponding constraints \(18a\) through \(18l\), this problem can be reduced to a 0/1 multiple-knapsack problem as a base problem [62], which is NP-Complete \[63\]. Similar to the 0/1 multiple-knapsack problem, problem \((18)\) is combinatorial in nature, which can be used to determine the feasible energy scheduling of the network by the microgrid; however, the complexity of problem \((18)\) leads to an exponential complexity \(O(2^{T\times V\times C})\). In fact, constraint \((18g)\) exhibits stochastic properties due to uncertainties in energy consumption and generation. Note that there is no known polynomial algorithm that can solve problem \((18)\) with the optimal results. As a result, we can infer that problem \((18)\) is NP-hard, similar to the multiple-knapsack problems \[64\].

To obtain a solution of problem \((18)\), we model an \(N\)-agent stochastic game with multi-agent deep reinforcement learning approaches. This model consists of two parts: 1) global agent (i.e., critic), and 2) virtual agents (i.e., actors). The global agent works for exploration which guides the virtual agents to correct the policy estimation by aggregating the each virtual agent’s outcome (i.e., observation including current state, reward, action, and next state). Thus, virtual agents learn environment (i.e., \(s_t\)) in parallel (asynchronous way) and explore with the suggestions (i.e., temporal difference among the value functions) of global agent. Each virtual agent interdependently explores and predicts the next state (i.e., \(s_{t+1}\)) by following the exploration suggestions from the global agent, this mechanism amplifies the learning process with more diverse information. As a result, global agent is capable of choosing the best energy schedule policy by employing a joint decision for determining the decision \(a_t\) of the problem \((18)\). In this solution, we employ shared neural networks (weight sharing) for low computational complexity among the virtual agent and global agent. The MADRL model accepts the best policy among the other agents toward updating the global energy schedule policy with less information. A detailed discussion of the solution to the risk-aware energy scheduling problem is given in the following section.

IV. RISK-AWARE ENERGY SCHEDULING VIA AN \(N\)-AGENT STOCHASTIC GAME AND MADRL

In this section, first we devise an \(N\)-agent discounted rewards stochastic game model for the risk-aware energy scheduling problem in \((18)\), where we show that this game has at least one Nash equilibrium thus ensuring an optimal energy scheduling policy. Second, we solve this game using the MADRL-based Asynchronous A3C approach. The overall solution approach is shown in Fig. 3 and a detailed discussion of the \(N\)-agent stochastic game and MADRL-based risk-aware energy scheduling are explained later in this section.

A. \(N\)-Agent Stochastic Game with MADRL for Risk-Aware Energy Scheduling

First, we convert the objective of risk-aware energy scheduling problem \((18)\) from a loss minimization problem to a reward maximization problem. To do this, we consider a multi-agent reinforcement learning setting with a set of virtual agents \( \mathcal{N} = \{1, 2, \ldots, N\} \) defined by a set of states \( \mathcal{S} = \{1, 2, \ldots, S\} \), a set of agent actions \( \mathcal{A} = \{\mathcal{A}_1, \mathcal{A}_2, \ldots, \mathcal{A}_N\} \), and a set of observations \( \mathcal{O} = \{O_1, O_2, \ldots, O_N\} \) for each agent \[65\]. From now on in the entire paper, virtual agents are represented as agents. The state-space at time slot \( t \) is redefined by a tuple \( s_t := (E^{dem}(t), E^{sto}(t), P(H_d(a_t, \xi))) \in \mathcal{S} \), where \( E^{dem}(t), E^{sto}(t), P(H_d(a_t, \xi)) \) are the demand, renewable energy, stored energy, and probability of CVaR, respectively. To calculate \( P(H_d(a_t, \xi)) \), we use the normal linear model as shown in Algorithm 1. In Algorithm 1 first, we calculate VaR (lines 3 and 4), while satisfying \( P(\xi(a_t)) \geq 1 - \alpha \) (constraint \(23a\)). Second, using the distribution of the calculated VaR, we determine the probability of CVaR \( P(H_d(a_t, \xi)) \) (lines 5 and 6 in Algorithm 1) and update the state-space information in line 8. Finally, this algorithm returns the updated state-space (in line 10) for further use. The action space \( a_t \in \mathcal{A} \) is comprised of \( (\xi^l, \xi^h) \), where \( \xi^l \) and \( \xi^h \) are discrete variables such that \( \xi^l \) determines the action
Algorithm 1 CVaR Calculation Using Normal Linear Model

Input: $E^{dem}(t), E^{en}(t), E^{non}(t), E^{stor}(t), T, \alpha, \xi$

Output: $\forall s_t \in S$

Initialization: $\mu, \sigma, \text{volatility}$

1: for $\forall t \in T$ do
2: for Until: $P(\xi, a_t(\xi)) \geq 1 - \alpha$, Constraints: $23a$ do
3: $\sigma = \text{volatility} \cdot \frac{1}{\sqrt{T}}$
4: $\text{VaR} = \text{norm.ppf}(1 - \alpha) \cdot \sigma - \mu$
5: $\text{CVaR} = \frac{1}{(1 - \alpha)} \cdot \text{norm.pdf}(\text{VaR}) \cdot \sigma - \mu$
6: Assign: $P(H_s(\alpha, \xi)) = P(\text{CVaR})$
7: end for
8: Update: $s_t \leftarrow \langle E^{dem}(t), E^{en}(t), E^{stor}(t), P(H_s(\alpha, \xi)) \rangle$
9: end for
10: return $\forall s_t \in S$, $\forall t \in T$

regarding energy storage for the microgrid and $\xi^0$ decides the action for energy buying from the main grid at time slot $t$.

The energy storage/buying action for each agent $n \in N$ with parameter $\theta_n$ is determined by a stochastic policy $\pi_{\theta_n}$, where $\pi_{\theta_n} : O_n \times A_n \rightarrow [0,1]$. A state transition function $\Gamma : S \times A_1 \times A_2 \times \cdots \times A_N \rightarrow S$ determines the next state according to policy $\pi_{\theta_n}$. Each agent $n$ determines the reward as a function of the state and its action $r_n : S \times A_n \rightarrow \mathbb{R}$, which is an element of the observation tuple $o_n$ for agent $n$, where $o_n := (s_t, a_t, r_t, s_{t+1})$. This observation correlates with the state space $S$ such that $o_n : S \rightarrow O_n$. The agent follows a discrete time slot $t \in \{1,2,\ldots,T\}$, and the objective of each agent $n$ is to maximize the total expected reward defined by

$$r_n(a_t, s_t) = \max_{a_t \in A_n} \mathbb{E}_t \sum_{t'=t}^{\infty} \gamma^{t'-t} r_t(a_t, s_t),$$

where $\gamma \in (0,1)$ is a discount factor.

The expectation of the action value function for agent $n$ taking action $a_t$ in state $s_t$ is defined as follows:

$$Q^{\pi_{\theta_n}}(s_t, a_t) = \mathbb{E}_{\pi_{\theta_n}} \sum_{t'=t}^{\infty} \gamma^{t'-t} r_t(a_t, s_t),$$

where $\gamma^{t'-t}$ ensures convergence of the action value function $Q^{\pi_{\theta_n}}(s_t, a_t)$ estimation by controlling the discount factor over the infinity time horizon. Thus, the expectation of the state value function for agent $n$ is given below:

$$V^{\pi_{\theta_n}}(s_t) = \mathbb{E}_{\alpha \sim \pi_{\theta_n} | a_t, s_t} [Q^{\pi_{\theta_n}}(s_t, a_t)],$$

where the action value function $Q^{\pi_{\theta_n}}(s_t)$ is determined by (20). In this case, the environment of the RL problem is non-trivial and in general, the transition probability between the two consecutive states $s_t$ and $s_{t+1}$ (for simplicity, we change the notation of next state from $s_{t+1}$ to $s_{t'}$ with some action is unknown. The model-free reinforcement learning approach is appropriate to learn the dynamics of the problem environment [47].

To solve the RL problem, the goal is to find the optimal policy $\pi^{*}_n(a_t | s_t)$ for value function (21), where the optimal state value is as follows:

$$V^{\pi^{*}_{\theta_n}}(s_t) = \max_{a_t \in A_n} \mathbb{E}_{\pi^{*}_{\theta_n}} \left[ \sum_{t'=t}^{\infty} \gamma^{t'-t} V^{\pi^{*}_{\theta_n}}(s_{t'}, a_{t'}) \right].$$

Consequently, problem (18) can be rewritten as follows:

$$\max_{a_t \in A_n, \pi_{\theta_n}} \sum_{t'=t}^{\infty} \sum_{s_{t'=t}} \sum_{a_{t'=t}} \Omega_{t'} V^{\pi_{\theta_n}}(s_{t'}),$$

s.t. $P(\pi_{\theta_n} | a_t, s_t) \geq (1 - \alpha)$, (23a)

(18b) to (18g).

In problem (23), we admit a new constraint (23a), for a given probability $\alpha$, state $s_t$ and action $a_t$ this constraint satisfies the CVaR confidence level of loss function (13). Further, $a_t \in A$ and $\pi_{\theta_n}$ are two decision variables, where $a_t$ decides energy storing or buying decision and $\pi_{\theta_n}$ represents the energy scheduling policy with parameters $\theta$. The constraints from (18b) to (18g) remain the same as in problem (18). All though the objective has changed in problem (23), the complexity is the same as the base problem (18). Therefore, we discretize the risk-aware energy scheduling problem (23) using the $N$-agent stochastic game. The definition of the game is as follows:

**Definition 3. (N-agent Stochastic Game):** An N-agent (player) stochastic game $\mathcal{G}$ consists of a tuple $\langle S, A_1, A_2, \ldots, A_N, r_1, r_2, \ldots, r_N, \Gamma \rangle$, where $S$ is the state space, $A_n$ determines the action space of agent $n \in N$, the reward (payoff) is defined by $r_n : S \times A_1 \times A_2 \times \cdots \times A_N \rightarrow \mathbb{R}$, and $\Gamma \rightarrow [0,1]$ is the state transition probability of agent $n$ at state space $S$.

For a state $s_t \in S$ at time $t$, all agents $n \in N$ independently choose their own actions $(a_{t_1}, a_{t_2}, \ldots, a_{t_N})$ and determine the rewards $(r_1(s_t, a_{t_1}), r_2(s_t, a_{t_2}), \ldots, r_N(s_t, a_{N}))$. After that, for a fixed transition probability, the current state $s_t \in S$ transit to the next state $s_{t'} \in S$ and satisfies the following property:

$$\sum_{s_{t'} \in S} P(s_{t'} | s_t, a_{t_1}, a_{t_2}, \ldots, a_{t_N}) = 1.$$ (24)

In this game, we determine a policy $\pi_{\theta_n}$ by updating the parameters $\theta_n$, where for time slot $t$, parameter $\theta_t$ is derived via an N-agent stochastic game $\mathcal{G}$, and action value function (20) can be represented as follows:

$$Q^{\pi_{\theta_n}}(s_t, a_t) \approx Q^{\pi_{\theta_n}}(s_t, a_t; \theta_t).$$ (25)

Hence, state value function (22) can be rewritten as follows:

$$V^{\pi_{\theta_n}}(s_t) \approx V^{\pi_{\theta_n}}(s_t; \theta_t).$$ (26)

Moreover, the parameterized policy is represented as follows:

$$\pi_{\theta_n}(a_t | s_t) \approx \pi_{\theta_n}(a_t | s_t; \theta_t).$$ (27)

Thus, if $\pi_{\theta_n}$ is the parameterized policy for agent $n$ at current state $s_t$ then the value function can be redefined as follows:

$$V^{\pi_{\theta_n}}(s_t, \pi_{\theta_1}, \pi_{\theta_2}, \ldots, \pi_{\theta_N}) = \max_{a_t \in A_n} \sum_{t'=t}^{\infty} \gamma^{t'-t} \mathbb{E}_{\pi_{\theta_n}} \left[ r_n(a_t, s_t) | O_n \right].$$ (28)
where $O_n = (s_t, \pi_{\theta_a}, \pi_{\theta_b}, \ldots, \pi_{\theta_N})$, $\forall n \in N$ and policy definition is given as follows:

**Definition 4. (Game Policy):** The policy (strategy) $\pi_{\theta_a}$ of the $N$-agent stochastic game is defined by $\pi_{\theta_a}: O_n \times \mathcal{A}_n \mapsto [0,1]$. Here, we consider a stationary policy such that state $s_t \in \mathcal{S}$ remains unchanged during time $t$ and the policy is determined by $\pi_{\theta_a} = (\pi_{\theta_1}, \pi_{\theta_2}, \ldots, \pi_{\theta_N})$.

In the $N$-agent stochastic game $\mathcal{G}$, a Nash equilibrium determines a joint strategy, where each agent achieves the best response to the other agents. The policy (strategy) of each agent is defined over time $t \in \mathcal{T}$ and the definition of policy Nash equilibrium is as follows:

**Definition 5. (Policy Nash Equilibrium):** In game $\mathcal{G}$, for the state space $s_t \in \mathcal{S}$, a Nash equilibrium contains a tuple of $\forall n \in N$ policies $(\pi_{\theta_1}, \pi_{\theta_2}, \ldots, \pi_{\theta_N})$, and for agent $n$,

$$V^{\pi_{\theta_n}}(s_t, \pi_{\theta_1}^*, \pi_{\theta_2}^*, \ldots, \pi_{\theta_N}^*)$$

(29)

The (22) determines optimal state value function, which is equivalent to the Nash equilibrium for an agent $n$ with the Nash equilibrium policy $\pi_{\theta_n}^*$. A joint policy Nash equilibrium of the $N$-agent stochastic game $\mathcal{G}$ is as follows:

**Definition 6. (Joint Policy Nash Equilibrium):** For a joint policy Nash equilibrium of agent $n$, the state-action value function is defined over $(s_t, a_{t1}, a_{t2}, \ldots, a_{tN})$, where the state-action value function is the sum of agent $n$’s current reward addition with future rewards, and is defined as follows:

$$Q^{\pi_{\theta_n}}(s_t, a_{t1}, a_{t2}, \ldots, a_{tN}) = r_n(s_t, a_{t1}, a_{t2}, \ldots, a_{tN}) + \sum_{s_{t'}, a'_{t1}, s_{t'}, a'_{t2}, \ldots, a'_{tN}} \gamma^{t-t'} P(s_{t'}, a'_{t1}, a'_{t2}, \ldots, a'_{tN})V^{\pi_{\theta_n}}(s_{t'}, a'_{t1}, a'_{t2}, \ldots, a'_{tN})$$

(30)

In (30), $(\pi_{\theta_1}^*, \ldots, \pi_{\theta_N}^*)$ determines the joint policy Nash equilibrium. The current reward for agent $n$ is defined by $r_n(s_t, a_{t1}, a_{t2}, \ldots, a_{tN})$, and the total discounted reward for state space $s_t \in \mathcal{S}$ with the joint action $(a_{t1}, a_{t2}, \ldots, a_{tN})$ is represented by $V^{\pi_{\theta_n}}(s_t, \pi_{\theta_1}^*, \ldots, \pi_{\theta_N}^*)$. As a result, (30) follows a joint policies (strategies) Nash equilibrium, in which the optimal state-action value (payoff) is determined by all the actions $(a_{t1}, a_{t2}, \ldots, a_{tN})$ from other agents in the state space $s_t \in \mathcal{S}$. In the multi-agent RL environments, agent $n$ not only observes its own reward, however also needs to know about the others observations as well. For state-action value function $Q^{\pi_{\theta_n}}(s_t, a_{t1}, a_{t2}, \ldots, a_{tN})$, the joint policy is determined by $(a_{t1}, a_{t2}, \ldots, a_{tN}) \sim \pi_{\theta_n}(a_{t1}, a_{t2}, \ldots, a_{tN})|s_t = \arg \max Q^{\pi_{\theta_n}}(s_t, a_{t1}, a_{t2}, \ldots, a_{tN})$, where the chosen action represents the action of the original problem [15]. Thus, the game $\mathcal{G}$ can be decomposed by $N$-agent stage game and the definition is as follows:

**Definition 7. (N-agent Stage Game):** The $N$-agent (player) stochastic game $\mathcal{G}$ is represented with an $N$-agent stage game $(M_1(O_n, a_1), M_2(O_2, a_2), \ldots, M_N(O_N, a_N))$, $\forall i \in \mathcal{T}$, under the state space $s_t \in \mathcal{S}$. For a single stage, the reward (payoff) of agent $n$ is determined by $M_n(O_n, a_1)$ and the reward consists of the joint action and agent $n$’s own reward $r_n$. The reward of agent $n$ is defined as follows:

$$M_n(O_n, a_1) = \mathbb{E}_{O_n,a_1\sim M_n}[r_n(a_1, \ldots, a_N)|(a_1 \in \mathcal{A}_1, \ldots, a_N \in \mathcal{A}_N)].$$

(31)

We define $\theta_{\theta_n}$ as the product of all agents policies (strategies) except for agent $n$, i.e.,

$$\theta_{\theta_n} = (\theta_{\theta_1}, \ldots, \theta_{\theta_{n-1}}, \theta_{\theta_n}, \ldots, \theta_{\theta_N}).$$

Hence, Nash equilibrium of $N$-agent stage game is defined as follows:

**Definition 8. (N-agent Stage Game Nash Equilibrium):** For the $N$-agent single stage game $(M_1(O_1, a_1), M_2(O_2, a_2), \ldots, M_N(O_N, a_N))$, a Nash equilibrium is discretized by a joint strategy, $(\theta_{\theta_1}, \ldots, \theta_{\theta_N})$, such that

$$\theta_{\theta_n} \theta_{\theta_n} M_n(O_n, a_1) \geq \theta_{\theta_n} \theta_{\theta_n} M_n(O_n, a_1), \forall \theta_{\theta_n} \in \hat{\theta}_{\theta_n}(\mathcal{A}_n)$$

(32)

From Definitions 5 and 8 we determine the Nash equilibrium with policy $\pi_{\theta_n}^*$ for agent $n$ of the discounted reward stochastic game, and the joint strategy Nash equilibrium $\theta_{\theta_n}$ of the stage game, respectively. We conclude with the following theorem:

**Theorem 1.** Every $N$-agent (player) discounted stochastic game consists of at least one Nash equilibrium point in stationary strategies [66].

Using Theorem 1 we can derive the following proposition:

**Proposition 1.** $\pi_{\theta_n}^*$ is the optimal policy, which is an equilibrium point with the equilibrium rewards (payoffs) $V^{\pi_{\theta_n}^*}(\pi_{\theta_1}^*, \ldots, \pi_{\theta_N}^*)$ for the discounted reward stochastic game (see Appendix [4]).

Proposition 1 not only confirms the Nash equilibrium of the $N$-agent (player) stochastic game $\mathcal{G}$, but also restrains strong evidence of the similar arguments from the previously studied $N$-player stochastic games [66], [67].

### B. Solution with Asynchronous Advantage Actor-Critic (A3C)

To solve problem (25) with fast and efficiently, we use the A3C model with shared neural networks (as seen in Fig. 4). This approach determines the best policy estimation among the other agents, and is also capable of handling the curse of dimensionality.
of dimensionality of the state space, which is convenient for solving our formulated problem \(23\).

In the A3C method, in order to learn the action value function \(Q^\pi_n(s_t, a_t)\), and find the optimal policy \(\pi^*_n\) using a deep Q-networks (DQN), the objective is to minimize the loss \(68\):

\[
L(\theta_n) = \mathbb{E}_{o_n \in O_n} [(Q^\pi_n(s_t, a_t|\theta) - y)^2],
\]

and the ideal target is represented as follows:

\[
y_t = r_n(a_t, s_t) + \gamma \max_{a_t' \in A} Q^\pi_n(s_t, a_t'),
\]

where \(o_n: (s_t, a_t, r_t, s'_t)\) is the observation with the current state \(s_t\) and \(Q^\pi_n(s_t, a_t)\) represents the target value function. Both are important components for achieving a stable DQN learning process and parameters \(\theta_n\) are periodically updated with the recent values.

In multi-agent reinforcement learning settings, policy \(\pi_\theta\) is independently updated for each agent \(n\) and this non-stationary nature violates the convergence characteristics of the learning process. The observations from the experience cannot be used for the general environment settings. To overcome these challenges, we use a policy gradient method to directly adjust parameters \(\theta\) for policy \(\pi_\theta\) to maximize the expected reward \(\mathbb{E}[r_n]\).

We consider a set of policies \(\pi_\theta = \{\pi_\theta_1, \pi_\theta_2, \ldots, \pi_\theta_N\}\) with the parameter set \(\theta = \{\theta_1, \theta_2, \ldots, \theta_N\}\) for \(N\) agents and the expected return for policy \(n\) as defined is follows:

\[
J(\theta_n) = \mathbb{E}_{\pi_\theta_n}[r_n].
\]

The gradient of (35) can be defined as follows:

\[
\nabla_{\theta_n} J(\theta_n) = \mathbb{E} \left[ \nabla_{\theta_n} \log \pi_\theta_n(a_n|o_n) Q^\pi_\theta_n(O, a_1, \ldots, a_N) \right],
\]

where \(Q^\pi_\theta_n(O, a_1, \ldots, a_N)\) is the centralized action-value function, \(a_1, \ldots, a_N\) determine all the actions for \(N\) agents, and \(O\) represents all the observations \(O = \{o_1, \ldots, o_N\}\) for the \(N\) agents. The gradient from equation (36) generates high bias and lower variance due to the deterministic observations.

However, this model cannot be directly applied to this risk-aware energy scheduling scenarios because the risk of energy scheduling is highly dependant on uncertainties in both the energy consumption of the MEC networks and the renewable energy generation. To execute this energy scheduling model, we have approximated using \(N\) continuous policies \(\theta_n\) with respect to the parameters \(\theta_n\), such that the policy gradient function can now be presented as follows:

\[
\nabla_{\theta_n} J(\theta_n) = \mathbb{E}_{O,a - M_n} \left[ \nabla_{\theta_n} \log \pi_\theta_n(a_n|o_n) Q^\pi_\theta_n(O, a_1, \ldots, a_N) | a_n = \theta_n(o_n) \right],
\]

where according to Definition \(7\) \(M_n\) represents the experiences for all the agents \((O, O', a_1, \ldots, a_N, r_1, \ldots, r_N)\) which includes both the previous and current observations, \(O\) and \(O'\), respectively. The centralized action value function for all agents can be represented as follows \(69\):

\[
L(\theta_n) = \min_{\theta} \mathbb{E}_{o_n, a_n} \left[ \frac{1}{2} (Q^\pi_n(O, a_1, \ldots, a_N) - y)^2 \right],
\]

and

\[
y = r_n + \gamma Q^\pi_n(O', a'_1, \ldots, a'_N) | a'_j = \theta_n(o'_j),
\]

where for parameters \(\theta_n\), the set of target polices is determined by \(\theta' = \{\theta_1', \theta_2', \ldots, \theta_N'\}\). Therefore, to execute centralized action value function \(33\), the actions for all agents need to know, whereas the nature of environment is stationary as the policies are changing. In this scenario, we can efficiently learn the other agents’ polices from the observations. Let us consider parameters \(\phi\) for each agent \(n\) that can maintain an approximation policy \(\hat{\pi}_n\) from the observed policy \(\pi_j\) of agent \(j\). Thus, the loss function is defined as follows:

\[
L(\phi_n) = -\mathbb{E}_{o_j, a_j} \left[ \hat{\pi}_n(a_j) + \beta h(\hat{\pi}_n) \right],
\]

where \(\beta\) is a coefficient for the magnitude of regularization for solving the bias problem and \(h()\) determines the entropy for the policy distribution \(\hat{\pi}\). Now, we can rewrite \(39\) using this approximation, where \(\hat{\pi}_n\) determines the target policy networks for the policy \(\hat{\pi}_n\) and redefined as follows \(40\):

\[
y = \hat{y} = r_n + \gamma Q^\pi_n(O', \hat{\pi}_n(a_1), \ldots, \hat{\pi}_n(a_N)).
\]

Hence, the objective function for the policy \(\hat{\pi}\) looks as follows:

\[
L(\phi_n) = \min_{\phi_n} \mathbb{E}_{o_j, a_j} \left[ \frac{1}{2} (Q^\pi_n(O, a_1, \ldots, a_N) - \hat{y})^2 \right],
\]

and the policy gradient is as follows:

\[
\nabla_{\phi_n} L(\phi_n) = \frac{1}{N} \mathbb{E}_{O,a - M_n} \left[ \sum_{n \in \mathbb{N}} \nabla_{\phi_n} \log \pi_n(a_n|o_n) \nabla_{\theta_n} Q^\pi_n(O, a_1, \ldots, a_N) | a_n = \theta_n(o_n) \right].
\]

The Adaptive Moment Estimation (ADAM) optimizer has been widely used for function approximation \(70\). This method employs both first and second moments of the gradients and computes the individual adaptive learning rates for different batches of observations with different parameters. Hence, the first and second moment of gradients from \(42\) are as follows:

\[
\frac{\delta v_n^w}{\delta t} = v_1 \frac{\delta v_n^w}{\delta t} + (1 - v_1) \nabla w L(\phi_n),
\]

\[
\frac{\delta v_n^{\delta w}}{\delta t} = v_2 \frac{\delta v_n^{\delta w}}{\delta t} + (1 - v_2) (\nabla w L(\phi_n))^2,
\]

where \(v_1\) and \(v_2\) are the decay rates. As a result, the ADAM optimizer can compute a bias correction (hyper-parameters correction) for both first and second order moments before a weight change calculation. This is important for the first few steps of training to tackle biasness. Thus, the corrected bias estimation functions are as follows:

\[
\frac{\delta v_n^w}{\delta t} = \frac{\delta v_n^w}{1 - (v_1)^t},
\]

\[
\frac{\delta v_n^{\delta w}}{\delta t} = \frac{\delta v_n^{\delta w}}{1 - (v_2)^t},
\]
Algorithm 2 Risk-Aware Energy Scheduling MADRL Model Based on Asynchronous Advantage Actor-Critic (A3C)

Input: $s_t = (E^{dem}(t), E^{ren}(t), E^{stor}(t), P(H_o(a_t, \xi))) \in S$
Output: Trained Model: madrl

Initialization: all agents $N$, $\gamma$, $\ell$, maxEpisodes, $T$, DQN
1: for Until: maxEpisodes do
2: Constraints: (18b), (18c) and (18d)
3: for $\forall t \in T$ do
4: for $\forall n \in N$ do
5: Constraints: (18e) and (18g)
6: Initialization: $o_n = (s_t, a_t, r_t, s_{t'}) \in O_n$
7: for Until: $E_{a_n \in O_n} [d_n = \gamma^n \sum_{t' = t}^{\infty} \gamma^{t'-t} E_{a_{n'}} [r_{n}(a_{t'}, s_{t'}) | O_n]]$
8: Calculate: max $\sum_{t' = t}^{\infty} \gamma^{t'-t} E_{a_{n'}} [r_{n}(a_{t'}, s_{t'}) | O_n]$
9: Using: eq. (49), (50), and (51)
10: Action: $a_t \sim \pi_n(a_t | s_t)$
11: Receive: $o_n = (s_t, a_t, r_t, s_{t'})$
12: Evaluate: $L(\phi_n)$ using eq. (42)
13: Calculate: $\nabla_{\phi_n} J(\phi_n)$ using eq. (43)
14: Update: $\theta_n = \theta_n + \nabla_{\theta_n} J(\theta_n)$
15: end for
16: Update: $\phi_n = \phi_n + \nabla_{\phi_n} J(\phi_n)$
17: Calculate: $\nabla_{\theta_n} J(\theta_n)$ using eq. (37)
18: end for
19: Append: $o_t \in O$
20: Update: Policy $\pi_{\theta_n}$, Value $V_{\pi_{\theta_n}}(s_t)$
21: end for
22: Update MADRL model: model
23: end for
24: return madrl

where the bias correction for first and second moments are determined by (46) and (47), respectively. Therefore, the weight change $\Delta w_t$ of $L(\phi_n)$ is defined follows:

$$\Delta w_t = -\ell \frac{\hat{\theta}^n}{\sqrt{\hat{\theta}^n + \kappa}}, \quad (48)$$

where $\ell$ is the learning rate and a very small value of $\kappa$ prevents division by zero. As a result, the updated weight for the next time slot $t'$ is as follows:

$$w_{t'} = w_t + \Delta w_t. \quad (49)$$

To design shared neural networks for the proposed multi-agent A3C model for risk-aware energy scheduling, we use a rectified linear unit (ReLU) activation function [71], which is able to handle nonlinearity and provides good approximations for various combinations of nonlinearity at a smaller computational cost. The ReLU activation function is defined as follows:

$$f(a_t) = \max(0, a_t), \quad (50)$$

where, $a_t$ is the action for energy storage and buying. To determine the output from the neural networks, in this model we use the Softmax activation function [72], which is appropriate for a cross-entropy cost function [40]. This function has the properties of a negative log probability and a very large gradient, which is suitable for estimating the gradient (43) of problem (23). The Softmax function is defined as follows:

$$P(a_t) = \frac{L(\phi_n)/\tau}{\sum_{\forall a \in A} L(\phi_n)/\tau}, \quad (51)$$

where $L(\phi_n)$ is the cost function from (42), $\tau$ determines the temperature parameter, and $P$ is the number of activated neurons. For a large value of $\tau \to \infty$, $P(a_t)$ is near to zero and a lower value of $\tau$ provides the highest expectation of the action probability $P(a_t)$ (tends to 1).

The proposed risk-aware energy scheduling MADRL model in Algorithm 2, which is run by the microgrid controller. Additionally, the microgrid controller receives the necessary information regarding energy demand of each time slot intervals of the MEC network from the MBS. Therefore, this algorithm verifies constraints from (18b) to (18g) (represents as (23b) to (23e) in problem (23)) from lines 2 to 5, where line 2 ensures constraints (18b), (18c) and (18d). Line 5 provides an assurance of binary decision (storing/buying) $a_t \in \{0, 1\}$ for each time slot $t$ in the time horizon $T$. The DQN of the proposed MADRL is developed through lines 7 to 15, where each agent $n$ (the actor) calculates the loss (33) (in line 7) using the DQN and evaluates by critic (42) (in line 12) to update the gradient of the loss function (45) (in line 13). Therefore, the weight of local policy updates in line 16 and the gradient of the global agent (37) is determined in line 17. Finally, the observation of each time slot $o_t$ is appended into the observational set $O$ (in line 19) and updates the parameterized policy $\pi_{\theta_n}$ and value $V_{\pi_{\theta_n}}(s_t)$ (in line 20) for the further use of the MADRL model. Hence, Algorithm 2 provides a risk-aware energy scheduling MADRL model (in line 24) for the microgrid-powered MEC network.

The convergence of Algorithm 2 is discretized via N-agent RL settings, where we consider an action space $a_n \in A$ with two actions $c^r$ and $c^b$ at time slot $t$. To determine the gradient step, we use a probabilistic model, where the gradient step moves toward the correct direction and decreases exponentially with an increasing number of agents. We investigate the convergence via the following Proposition:

**Proposition 2.** Consider an unknown environment with state space $s_t \in S$ with $N$ agents such that all agents are initialized
an equal probability of $\frac{1}{2}$ for the binary actions, $P(a_n = \zeta^1) = \theta_n = \frac{1}{2}, \forall n \in N$, where $r_n(a_1, \ldots, a_N) = 1|a_1 = \cdots = a_N|$. If we estimate the gradient $\hat{\nabla}_{\theta_n} J(\theta_n)$ of the cost function (35), then we get the following relationship with the true gradient $\nabla_{\theta_n} J(\theta_n)$:

$$P \left( \left( \nabla_{\theta_n} J(\theta_n), \nabla_{\theta_n} J(\theta_n) \right) > 0 \right) \approx \left( \frac{1}{2} \right)^N. \quad (52)$$

[See Appendix B].

Proposition 2 justifies that for a single observation the proposed multi-agent risk-aware energy scheduling model achieves convergence, which implies that this model is able to converge toward the multiple observations.

To forecast the risk-aware energy scheduling of the microgrid-powered MEC network, we propose Algorithm 3 where this algorithm uses the trained model of Algorithm 2. In Algorithm 3, line 2 decomposes the trained MADRL model for the current state $s_t$. An action (buying/storing) $a_{t'}$ is taken through the lines 3 and 4 for the next state $s_{t'}$ (energy scheduling) forecasting. Line 5 determines the next state information $s_{t'}$ based on the action $a_{t'}$, which includes the MEC energy demand $E_{dem}(t')$, renewable energy generation $E_{ren}(t')$, storage energy $E_{sto}(t')$, and the CVaR risk for next time slot $t'$.

We analyze CVaR and make a reflection on the learning model. To do this, we generate the state-space information before anticipating the learning model, and the computational complexity belongs to $O(|S|^3)$. In order to accelerate the learning process with a low complexity deep learning model, we design a policy network in shared neural networks (weight sharing) manner among the virtual agents and global agent. The goal of all virtual agent $N$ is always the same and the policy gradient increases linearly with respect to the number of iteration (i.e., the total number of weight $\theta_n$ updates in each time slot $t$). Thus, the overall computational complexity of the policy networks leads to $O(|S|^2|A|(|N|)$ where a single virtual agent complexity goes in $O(|S|^2|A|)$ since learning time is decreasing at a rate $O(\frac{1}{k}), \forall n \in N$. The experimental analysis and insightful discussion of the risk-aware energy scheduling are given in the later section.

V. EXPERIMENTAL ANALYSIS AND DISCUSSION

In this section, we evaluate the proposed model using extensive experimental analyses. We implement the risk-aware energy scheduling model via Python, along with TensorFlow and APIs. We run the simulated model using a core i7 processor with a speed of 2.6 GHz along with 8 GB of RAM as a microgrid controller. To evaluate this model, we used the well-known UMass solar panel dataset [15] for renewable energy generation information, as well as the CRAWDAD nyupoly/video dataset [15], for estimating the energy consumption of the MEC networks. We consider the network parameters are same as the dataset in [15]. Further, we divided both datasets into 70% and 30% for training and testing, respectively [8]. The energy consumption parameters are considered using Raspberry Pi 3 Model B [73] as a baseline for each multi-access edge server. In addition, we prepossess both datasets to extract the state-space information $\forall s_t := (E_{dem}(t), E_{ren}(t), E_{sto}(t), P(H_m(a_t, \xi))) \in S$, where we determine the value of $P(H_m(a_t, \xi))$ using Algorithm 1 and Table II describes the important parameters of the experiment setup. To the best of our knowledge, the literature does not provide similar analogy of the risk-aware energy scheduling for microgrid-powered MEC networks. However, to provide more concrete results, we compared our proposed MADRL model with single agent A3C and random-agent A3C model.

| Description | Value |
|-------------|-------|
| No. of SBSs | 10    |
| No. of servers in each SBS | 5    |
| No. of CPU cores in one server | 4 with 1.2 GHz [73] |
| No. of solar units | 40 [18] |
| Task sizes | 31,1546004 bytes [15] |
| One time slot $t$ | 15 minutes [8] |
| No. of tasks request at each SBS | [1,100000] [8] |
| CVaR confidence levels | [90%, 95%, 99%] |
| Maximum number of episodes | 1000 |
| No. of agents $N$ | 4 |
| Learning rate $\gamma$ | $10^{-2}$ |
| Discount factor $\gamma$ | 0.99 |
| No. of hidden layers and neurons | 2, 100 |

![Fig. 5: Training scores and losses illustration for 95% CVaR confidence.](image-5)

![Fig. 6: Training validation error analysis for the proposed risk-aware energy scheduling for 95% CVaR confidence.](image-6)
Fig. 7: Risk-aware energy scheduling training model validation with 95% CVaR confidence for one day with a 15-minute time slot, as baseline models.

A. MADRL-based Risk-Aware Energy Scheduling Training Validation

In order to validate the training model, first we analyze the convergence of the proposed MADRL Algorithm 2 and compare it with the single agent A3C and random-agent A3C models. Training scores and losses for the single agent A3C (cross mark with yellow line), random-agent A3C (diamond mark with red line), and proposed multi-agent asynchronous A3C (circle mark with a green line) models are shown in Fig. 5. Reward in Fig. 5 illustrates the convergence of proposed model with the high score than the other two models. Even though, at the beginning of training the single agent model gains the higher score than that the other two, whereas for the long term energy profiling estimation proposed MADRL perform better. Consequently, the training losses (in Fig. 5) of the proposed model is more stable than the others.

Second, we present the training validation errors of the proposed MADRL model along with the other two baseline models in Fig. 6, where the Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Root Mean Absolute Error (RMAE) are smaller than for the single agent A3C and random-agent A3C models. Here, the random-agent A3C model achieves a high error because the agents are executed randomly so that the policy does not achieve the high reward value, whereas the proposed model updates the policy by achieving a high score (reward), which generates small loss during training due to the shared information between the agents.

Third, we illustrate one-day energy scheduling with a 15-minute duration time slot for training model validation (in Fig. 7) with a 95% CVaR confidence level, in which the action selection accuracy for the energy storing and buying decision of the proposed model gain around 97%, which is a feasible outcome in terms of training validation. However, the single agent and random agents models have accuracies of 82% and 67%, respectively. Although the number of training episodes (1,000) is the same for all of the three models. Thus, the proposed MADRL model achieves a higher accuracy than that the others due to the nature of information (observations) sharing among the agents of Algorithm 2.

B. MADRL-based Risk-Aware Energy Schedule Testing Validation

To illustrate the performance of the trained model, first we analyze the confusion matrix and receiver operating characteristic (ROC) as shown in Fig. 8 and Fig. 9, respectively. Fig. 8 represents the confusion matrix of test result validation with 95% CVaR confidence, where the proposed model makes 9% incorrect decision to determine the energy buying action (in Fig. 8). However, both the single-agent (in Fig. 8) and random-agents (in Fig. 8) models choose 12% of incorrect
actions for energy buying decision. On the other hand, in the case of storing decisions of the random-agents model, all (100%) are incorrect decisions. Thus, confusion matrix (in Fig. 8) illustrates the significant perform gain of the proposed MADRL model under nondeterministic environment of microgrid-powered MEC networks. In Fig. 9, the random-agent A3C encompasses below 50% for energy storing/buying decisions, while the single agent A3C covers around 91% area of the ROC curve. However, the proposed model captures around 96% of the area in the ROC curve, which assures that the proposed model performs significantly better than the other models.

Second, we validate the forecasting accuracy of Algorithm 3, where Fig. 10 demonstrates the action selection of the one-day energy supply plan with a 15-minute duration for CVaR confidence levels of 90%, 95%, and 99%. This figure illustrates that the testing accuracy is 92%, 96%, and 92% for CVaR confidences of 90%, 95%, and 99%, respectively. Fig. 11 presents the overall energy scheduling for the proposed model. Fig. 11(a) represents the total amount of energy consumption forecasting using CVaR confidences of 90%, 95%, and 99%. Similarly, Fig. 11(b) and Fig. 11(c) present the energy forecast for renewable and stored energy, respectively. The negative values of the stored energy are determined by the amount of energy that needs to be bought from the main grid at that time slot. Therefore, the difference between foretasted and actual energy are negligible, since for 95% CVaR confidence the forecasting accuracy achieves around 96%.

Finally, we investigate the tail of the CVaR in Fig. 12 of the proposed risk-aware energy scheduling model. We analyze two types of distribution, the first is normal and the second is the student’s t-distribution. The normal CVaR distribution is represented as blue dashed line, where we observe CVaR values of 4.72%, 5.65%, and 7.46% with confidence levels of 90%, 95%, and 99% (zoomed-in part in Fig. 12), respectively. Consequently, the student’s t-distribution (red dotted line) achieves CVaR values of 4.65%, 5.60%, and 7.50% with the confidences levels of 90%, 95%, and 99%

VI. CONCLUSIONS

In this paper, we have introduced a conditional value-at-risk based energy scheduling model for a microgrid-powered MEC network using an N-agent stochastic game. We have mitigated the issue of volatilities for both the wireless network’s energy consumption and the microgrid generation while considering uncertainties between demand and supply. Furthermore, we have achieved a joint policy Nash equilibrium, which determines the optimal energy scheduling policy of the proposed model. We solve this model by applying a multi-agent deep reinforcement learning approach, where we have admitted
a shared neural networks with the asynchronous advantage actor-critic algorithm, thus ensuring high-accuracy energy scheduling with fast execution. Our extensive experimental results demonstrate a significant performance gain of the proposed approach, with this model providing up to 96% accurate energy scheduling with 5.65% risk for a 95% CVaR confidence level, as compared with the single-agent and random-agents A3C models. Finally, our experimental results have established a risk-aware sustainable MEC network with respect to energy consumption and generation.

APPENDIX A
Proof of Proposition 1
Proof. For agent \( n \), policy \( \pi_{\theta_n}^* \) is the best response for the equilibrium responses from all other agents. The agent \( n \) is unable to improve reward (payoff) \( V^{\pi_{\theta_n}}(s_t, \pi^*_{\theta_n}) \) by deviating from policy \( \pi_{\theta_n}^* \). Using (30), we can write the following:

\[
V^{\pi_{\theta_n}}(s_t, \pi^*_{\theta_n}) \geq r_n(s_t, a_1, \ldots, a_N) + \sum_{s_{t+1} \in S} \gamma^{t+1} P(s_{t+1}|s_t, a_1, \ldots, a_N) V^{\pi_{\theta_n}}(s_{t+1}, \pi^*_{\theta_1}, \ldots, \pi^*_{\theta_N}).
\]

(53)

Therefore, according to Definition 4 the N-agent (player) stochastic game \( G \) is a multi-periods stage game, which has the properties of a joint strategy Nash equilibrium. Now, using (32), we have

\[
V^{\pi_{\theta_n}}(s_t, \pi^*_{\theta_n}) = \hat{\theta}_n \theta_0M_n(O_n, a_t).
\]

(54)

Equation (54) implies the inequality of (32), which shows that \( \pi^*_{\theta_n} \) is the equilibrium point of single-stage game and is denoted as follows:

\[
V^{\pi_{\theta_n}}(s_t, \pi^*_{\theta_n}) \geq \hat{\theta}_n \theta_0M_n(O_n, a_t), \forall \hat{\theta}_n \in \hat{\theta}_n(\mathcal{A}_n).
\]

(55)

Proof of Proposition 2
Proof. Here, we can write the probability of action \( a_n \) at time slot \( t \) as follows:

\[
P(a_n) = \theta_n^{a_n}(1 - \theta_n)^{1-a_n}
\]

\[= a_n \log \theta_n + (1 - a_n) \log(1 - \theta_n).
\]

(56)

Now, for a single sample the policy gradient estimator is defined as follows:

\[
\frac{\partial}{\partial \theta_n} J(\theta_n) = r_n(a_1, \ldots, a_N) \frac{\partial}{\partial \theta_n} \log P(a_1, \ldots, a_N)
\]

\[= r_n(a_1, \ldots, a_N) \frac{\partial}{\partial \theta_n} \sum_{a_{n+1}} a_{n+1} \theta_n + (1 - a_n) \log(1 - \theta_n)
\]

\[= r_n(a_1, \ldots, a_N) (a_n \log \theta_n + (1 - a_n) \log(1 - \theta_n))
\]

\[= r_n(a_1, \ldots, a_N)(a_n \theta_n - (1 - a_n))
\]

\[= r_n(a_1, \ldots, a_N)(2a_n - 1), \text{ for } \theta_n = \frac{1}{2}.
\]

(57)

Now, the expected reward for the \( N \) agents is defined by \( \mathbb{E}[r_n] = \sum_{a_1, \ldots, a_N} r_n(a_1, \ldots, a_N) \frac{1}{2^N} \), and using \( r_n(a_1, \ldots, a_N) = 1[a_1 = \cdots = a_N] \), we get \( \mathbb{E}[r_n] = \left(\frac{1}{2}\right)^N \). Therefore, the expectation of the gradient estimation is \( \mathbb{E}\left[\frac{\partial}{\partial \theta_n} J(\theta_n)\right] = \frac{\partial}{\partial \theta_n} J(\theta_n) = \left(\frac{1}{2}\right)^N \). The variance of the estimated gradient can be calculated as follows:

\[
\mathbb{E}\left[\frac{\partial}{\partial \theta_n} J(\theta_n)\right] = \left(\frac{1}{2}\right)^N \left(\frac{1}{2}\right)^{2N}.
\]

(58)

From (52), we can analyze \( P((\hat{\theta}_n, a_n, \theta_n, J(\theta_n)) > 0) \) and get

\[
P((\hat{\theta}_n, a_n, \theta_n, J(\theta_n)) > 0) = \left(\frac{1}{2}\right)^N, \text{ which implies that the gradient step moves in the correct direction and decreases exponentially with an increasing number of agents.}
\]

APPENDIX B
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