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# Distributed Resource Scheduling for Large-Scale MEC Systems: A Multi-Agent Ensemble Deep Reinforcement Learning with Imitation Acceleration

Feibo Jiang, Li Dong, Kezhi Wang, Kun Yang and Cunhua Pan

**Abstract**—In large-scale mobile edge computing (MEC) systems, the task latency and energy consumption are important for massive resource-consuming and delay-sensitive Internet of things devices (IoTDs). Against this background, we propose a distributed intelligent resource scheduling (DIRS) framework to minimize the sum of task latency and energy consumption for all IoTDs, which can be formulated as a mixed integer nonlinear programming. The DIRS framework includes centralized training relying on the global information and distributed decision making by each agent deployed in each MEC server. Specifically, we first introduce a novel multi-agent ensemble-assisted distributed deep reinforcement learning (DRL) architecture, which can simplify the overall neural network structure of each agent by partitioning the state space and also improve the performance of a single agent by combining decisions of all the agents. Secondly, we apply action refinement to enhance the exploration ability of the proposed DIRS framework, where the near-optimal state-action pairs are obtained by a novel Levy flight search. Finally, an imitation acceleration scheme is presented to pre-train all the agents, which can significantly accelerate the learning process of the proposed framework through learning the professional experience from a small amount of demonstration data. The simulation results in three typical scenarios demonstrate that the proposed DIRS framework is efficient and outperforms the existing benchmark schemes.

**Index Terms**—Multi-agent reinforcement learning, Distributed deep reinforcement learning, Imitation learning, Resource scheduling, Lévy flight.

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## I. INTRODUCTION

### A. Motivation

Recently, with the rapid increase of resource-intensive tasks, e.g., augmented reality (AR), Internet of things (IoT) applications and autonomous driving, the quality of our life has the potential to be improved greatly. However, due to the limited size and battery life of IoT devices (IoTDs), these applications may be difficult to be implemented in practice. Fortunately, mobile edge computing (MEC) has been proposed recently as a promising technique to liberate IoTDs from computation-intensive tasks by allowing them to offload their high workloads to edge servers [1], [2].

However, due to the large number of IoTDs, one edge server may not be powerful enough to support all the devices at the same time. Thus, multiple MECs may be deployed to support the IoTDs. Then, it is critical to determine the offloading decision and resource allocation between computing and communication resource from different MECs to IoTDs [1]. Unfortunately, the above problem is normally formulated as a mixed integer nonlinear programming (MINLP) problem [3] [4], which involves integer variables (i.e., offloading decision) and continuous variables (i.e., communication and computing resource allocation). This problem is very difficult to solve in general, especially in large-scale IoTD scenarios and dynamic environments.

### B. Background and related works

Some traditional solutions have been applied to solve the above problem, such as game theory [5], branch-and-bound method [6] and dynamic programming [7]. However, these solutions normally need a large amount of computing resource and it is difficult to realize online decision making process. Some other solutions, such as convex relaxation [8] and heuristic local search [9] algorithms are also applied to handle the above problems. However, those algorithms normally need a considerable amount of iterations to achieve a satisfying local optimum, which may not be suitable for dynamic environment. Moreover, with the increase of the number of IoTDs and MEC servers, the complexity of the above-mentioned traditional solutions increases significantly, which makes them very difficult to be applicable in large-scale environment.

Fortunately, the emerging deep reinforcement learning (DRL) approach has shown great potential in solving the above-mentioned joint optimization problem [10], [11]. The

DRL employs deep neural networks for mapping input MEC system parameters to the output resource scheduling decisions directly. After training from the environments, it can output the optimal decisions very quickly without explicitly solving the original mathematical optimization, which is very suitable for the fast varying and large scale MEC environment. However, there are still several challenges yet to be addressed: 1) Value-based DRL (e.g., Q-learning [12], DQN [13] [14] and double DQN [15]) can only work well in a limited action space, which is inefficient in large-scale application scenarios; 2) Although policy-based DRL (e.g., DDPG [16], A3C [17], and MADDPG [18]) can update policy by computing policy gradient for maximizing the expected reward, it is difficult to converge in complicated environment, especially for distributed architecture [18].

### C. Key contributions

In this paper, we aim to develop a distributed intelligent resource scheduling (DIRS) framework, which can be applied to large-scale MEC systems with multiple MECs and IoTs in dynamic environment. To enhance the performance of the framework, centralized training scheme is designed, whereas distributed decision making is proposed to increase the flexibility of the framework. The main contributions are summarized as follows:

- We first formulate an optimization problem and the objective is to minimize the sum of task latency plus energy consumption for all the IoTs. Then, we decompose the proposed MINLP optimization problem into an offloading decision sub-problem and a communication and computing resource allocation sub-problem, which can reduce the complexity of the original problem and guarantee that the solutions meet all the constraints.
- We propose a distributed multi-agent ensemble DRL framework for solving the decision making sub-problem. In this framework, one agent is deployed in each MEC to conduct the distributed decision making for IoT offloading tasks to this MEC. To improve the performance of the whole system, we have a scheduler deployed in the Core-MEC (C-MEC) to conduct the centralized training with the global information in the training stage. Ensemble learning is introduced into this distributed DRL framework to simplify the neural network structure of each agent by partitioning the state space and improve the performance of a single agent by combining decisions of all the agents. Once the centralized training is completed, each agent in MEC can make distributed offloading decision only with local information.
- We present a Lévy flight search as the action refinement to find the best actions for the DRL model according to the current state. Lévy flight search can help the DRL framework to skip the local optimum. In the Lévy flight search, a mutation operator is used to generate mutant vector according to the channel state information, and then the Lévy crossover operator is applied to avoid candidate vector trapping into the local optimum. Finally, greedy selection operator is applied to select the better solution between candidate vector and original solution.

- We propose an imitation acceleration scheme, which combines the DRL and imitation learning to accelerate the training process of all the agents. We first generate a small amount of demonstration data, and then we pre-train all the agents using a novel demonstration loss function, which can reduce the training time and increase the stability of the DRL based framework.

### D. Organization

The rest of this paper is organized as follows. Section II presents a review of related works. Section III describes the system model and problem formulation. Section IV describes the detailed design of the DIRS framework. Section V presents the simulation results, followed by the conclusions in Section VI.

## II. RELATED WORKS

The DRL-based algorithms have attracted extensive attention in the resource scheduling field. In the following, we present the related works from four aspects: Value-based DRL, Policy-based DRL, Distributed DRL, and Hybrid DRL.

Value-based DRL method: In [13], a deep Q-learning based offloading scheme was presented to optimize offloading policy according to the current battery level, the radio transmission rate and the harvested energy in the MEC system. In [14], a deep Q network (DQN) approach was introduced to optimize the networking, caching, and computing resources in the vehicular networks. Moreover, in [19], a deep reinforcement scheduling with experience relay is applied for mobile crowd-sensing in fog computing.

Policy-based DRL: In [16], a deep deterministic policy gradient (DDPG) method was used to design the trajectory of UAVs by jointly considering the communications coverage, fairness, energy consumption and connectivity. In [17], a high performance asynchronous advantage actor-critic (A3C) DRL algorithm is proposed to solve the complex dynamic resource allocation problem in vehicles network.

Distributed DRL: In [20], a novel two-timescale deep reinforcement learning (2Ts-DRL) was presented, which leveraged federated learning to train the 2Ts-DRL model in a distributed manner. In [21], a distributed DQN was applied to search the optimal sub-band and power level for transmission, and each vehicle-to-vehicle link was considered as an agent and trained in a decentralized way. Then, in [22], a decentralized offloading policy learned by DDPG for a multi-user MEC system was proposed, in which each DDPG was adopted to learn the efficient offloading policy interdependently at each mobile user. In [23], a meta-training enhanced multi-agent DRL is introduced to design the trajectory of a team of drone base stations under unpredictable environments. In [24], the recent progress and future challenges of distributed learning in wireless networks are summarized.

Hybrid DRL method: In [25], The task offloading method was proposed based on meta reinforcement learning, which can adapt fast to new environments with a small number of gradient updates and samples. In [26], an A3C deep reinforcement learning algorithm was introduced to obtain

the resource pricing and allocation MEC enabled blockchain systems. In [27], the DRL with Monte Carlo tree learning was introduced to solve the complex resource allocation problem for a collaborative MEC network. In [28], a generative adversarial network-powered deep distributional Q network (GAN-DDQN) was proposed to learn the action-value distribution driven by minimizing the discrepancy between the estimated and the target action-value distribution, which can be used to solve demand-aware resource allocation problem.

However, none of the above contributions considered the application of distributed DRL in online resource scheduling for large-scale MEC systems, which can be seen as a complex MINLP problem. Traditional value-based and policy-based DRLs are hard to be applied in large scale MEC systems directly. For example, the value-based DRL can only work well in a limited action space, thus it may not be suitable for large-scale offloading decision making environment. The advantage of policy-based DRL is that the outputs can be continuous, but it is easy to fall into the local optimal for the large action space and it is normally difficult to converge in dynamic environments [18]. Distributed DRL has a great potential in addressing the above-mentioned issues by conducting distributed learning and dynamic decision in large-scale application scenarios [22].

### III. SYSTEM MODEL AND PROBLEM FORMULATION

#### A. System model

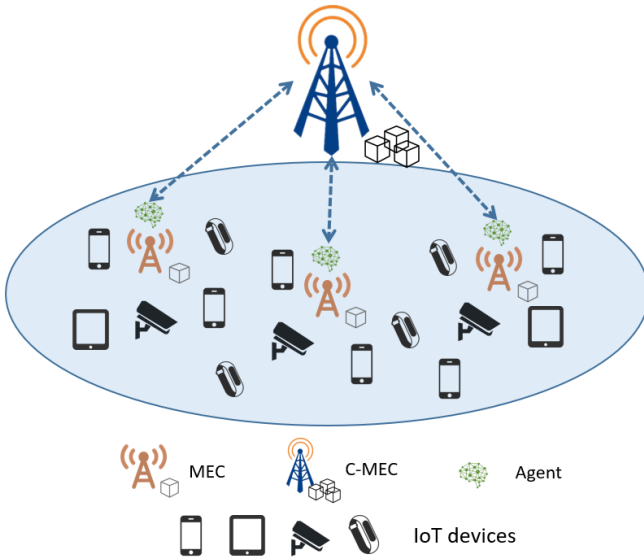


Fig. 1: Proposed MEC system.

Fig. 1 shows our proposed system with one C-MEC and  $M$  normal MECs, denoted as the set of  $\mathcal{M} = \{1, 2, \dots, M\}$ . C-MEC is deployed at the macro base station, whereas the other edge servers are installed in each small base station. We assume there are  $N$  IoT devices, denoted as the set of  $\mathcal{N} = \{1, 2, \dots, N\}$ . Each IoT device has a computation task to be executed, which can be either offloaded to the MECs or processed locally.

We define the computing task in each IoT device as  $U_i$ , where  $U_i = (F_i, D_i)$ ,  $\forall i \in \mathcal{N}$  [29],  $F_i$  denotes the total number of the CPU cycles and  $D_i$  describes the data size transmitting to the MEC if offloading action is conducted.  $D_i$  and  $F_i$  can be obtained by using the approaches provided in [30] [31].

Then, the overall time consumption of completing a task can be given by

$$T_{ij} = T_{ij}^{Tr} + T_{ij}^C = \frac{D_i}{r_{ij}} + \frac{F_i}{f_{ij}}, \forall i \in \mathcal{N}, \forall j \in \mathcal{M} \quad (1)$$

where  $T_{ij}^{Tr}$  is time consumed for data offloading from the  $i$ -th IoT device to the  $j$ -th MEC,  $T_{ij}^C$  is execution time in an MEC server if the  $i$ -th IoT device offloads task to the  $j$ -th MEC server,  $f_{ij}$  is the computation capacity of the  $j$ -th MEC allocating to the  $i$ -th IoT device and  $j = 0$  if IoT device executes the task locally. Also,  $r_{ij}$  denotes the offloading data rate from the  $i$ -th IoT device to the  $j$ -th MEC, which can be given by

$$r_{ij} = B \log_2 \left( 1 + \frac{p_{ij} h_{ij}}{\sigma^2} \right), \forall i \in \mathcal{N}, \forall j \in \mathcal{M} \quad (2)$$

where  $p_{ij}$  is the transmission power from the  $i$ -th IoT device to the  $j$ -th MEC server and  $B$  is the channel bandwidth,  $\sigma^2$  is the noise spectral density and  $h_{ij}$  is the channel gain which is given by

$$h_{ij} = \frac{\beta_0 l_{ij}}{(X_j - x_i)^2 + (Y_j - y_i)^2}, \forall i \in \mathcal{N}, \forall j \in \mathcal{M} \quad (3)$$

where  $\beta_0$  denotes the channel power gain at the reference distance,  $l_{ij}$  describes the small-scale fading factor,  $(x_i, y_i)$  is the coordinate of the  $i$ -th IoT device, and  $(X_j, Y_j)$  is the coordinate of the  $j$ -th MEC.

We consider a binary offloading strategy as

$$a_{ij} = \{0, 1\}, \forall i \in \mathcal{N}, \forall j \in \mathcal{M} \quad (4)$$

where  $a_{ij} = 1$  denotes that the  $i$ -th IoT device decides to offload the task to the  $j$ -th MEC, while  $a_{ij} = 0$  denotes that the  $i$ -th IoT device decides not to offload the task to the  $j$ -th MEC. We assume that one IoT device can access to at most one edge server, which is formulated as follows:

$$\sum_{j \in \mathcal{M}} a_{ij} + a_{i0} = 1, \forall i \in \mathcal{N}. \quad (5)$$

Also, assume that the computing resource of each MEC is constrained by

$$\sum_{i=1}^N a_{ij} f_{ij} \leq F_{j, \max}^{MEC}, \forall j \in \mathcal{M} \quad (6)$$

where  $F_{j, \max}^{MEC}$  is the computational capability of the  $j$ -th MEC.

Then, define  $P_{i, \max}^{IoT D}$  as the maximum transmission power that each IoT device can apply and then one has

$$\sum_{j=1}^M a_{ij} p_{ij} + a_{i0} p_i^E \leq P_{i, \max}^{IoT D} \quad (7)$$

where  $p_i^E$  is the execution power of the  $i$ -th IoT device which is given by  $p_i^E = \kappa_i (f_{i0})^{v_i}$ ,  $\forall i \in \mathcal{N}$ , and  $f_{i0}$  is the local computing capacity and is a fixed value in this paper,  $\kappa_i \geq 0$

is the effective switched capacitance and  $v_i \geq 1$  is the positive constant. To match the realistic measurements, we set  $\kappa_i = 10^{-27}$  and  $v_i = 3$  [29].

### B. Problem Formulation

For each IoTD, the time consumption is

$$T_i = \sum_{j \in \mathcal{M}} a_{ij} T_{ij} + a_{i0} \frac{F_i}{f_{i0}}. \quad (8)$$

Also, for each IoTD, the energy consumption is given by

$$E_i = \sum_{j \in \mathcal{M}} a_{ij} (p_{ij} T_{ij}^{Tr}) + a_{i0} \frac{F_i}{f_{i0}} p_i^E. \quad (9)$$

Then, define  $\Phi_i$  as

$$\Phi_i = \phi_T T_i + \phi_E E_i. \quad (10)$$

where  $\phi_T$  and  $\phi_E$  are weighted coefficients. The weighted coefficients are determined by the specific application scenarios [32]. If the task is a time-sensitive task, one can set  $\phi_T > \phi_E$ . If the task is energy-sensitive, then  $\phi_T < \phi_E$  can be set. The weighted coefficients  $\phi_T$  and  $\phi_E$  regarding computational energy and time can be determined by applying the multiple criteria decision making theory [33].

In this paper, we aim to jointly optimize the offloading selection, computing resource allocation, and power allocation to minimize the weighted sum of task latency and energy consumption of all tasks. Specifically, we formulate the optimization problem as follows:

$$\begin{aligned} P0 : \min_{\mathbf{a}, \mathbf{f}, \mathbf{p}} \sum_{i \in \mathcal{N}} \Phi_i \\ \text{s.t. (4) - (7)} \end{aligned} \quad (11)$$

where  $\mathbf{a} = \{a_{ij} | i \in \mathcal{N}, j \in \mathcal{M}'\}$ ,  $\mathbf{f} = \{f_{ij} | i \in \mathcal{N}, j \in \mathcal{M}'\}$ ,  $\mathbf{p} = \{p_{ij} | i \in \mathcal{N}, j \in \mathcal{M}'\}$  are vectors for offloading decisions, computing resource allocation and transmission power from each IoTD, respectively. One can see that this problem includes both integer and continuous variables. If IoTD conducts the task itself, the energy consumption can be expressed as  $p_{i0} = p_i^E$ . Also assume that  $\mathbf{h} = \{h_{ij} | i \in \mathcal{N}, j \in \mathcal{M}\}$  are time-varying input values, whereas other parameters are fixed.

### C. Problem transformation

One can see that Problem P0 is an MINLP, which is very difficult to address in general. This problem becomes even more complex if it involves large-scale variables. To obtain the low complexity solution, we first decompose this problem into two sub-problems: 1) Offloading decision making sub-problem and 2) Resource allocation sub-problem.

Firstly, we propose a distributed DRL framework to obtain optimal offloading decision  $\mathbf{a}$  from the interaction between distributed agent and global environment. Once the offloading

variable  $\mathbf{a}$  is obtained, the resource allocation sub-problem can then be expressed as follows:

$$\begin{aligned} P1 : \min_{\mathbf{f}, \mathbf{p}} \sum_{i \in \mathcal{N}} \left( \phi_T \left( \sum_{j \in \mathcal{M}} a_{ij} \left( \frac{D_i}{r_{ij}} + \frac{F_i}{f_{ij}} \right) + a_{i0} \frac{F_i}{f_{i0}} \right) + \right. \\ \left. \phi_E \left( \sum_{j \in \mathcal{M}} a_{ij} p_{ij} \frac{D_i}{r_{ij}} + a_{i0} \frac{F_i}{f_{i0}} p_i^E \right) \right) \\ \text{s.t. (6)(7)}. \end{aligned} \quad (12)$$

Then, we can decouple the above problem into the following optimization to facilitate the distribute decision making in each MEC as

$$\begin{aligned} \min_{f_j, p_j} \sum_{i \in \mathcal{N}} \left( \phi_T \left( a_{ij} \left( \frac{D_i}{r_{ij}} + \frac{F_i}{f_{ij}} \right) + a_{i0} \frac{F_i}{f_{i0}} \right) + \right. \\ \left. \phi_E \left( a_{ij} p_{ij} \frac{D_i}{r_{ij}} + a_{i0} \frac{F_i}{f_{i0}} p_i^E \right) \right), \forall j \in \mathcal{M} \\ \text{s.t. (6)(7)}. \end{aligned} \quad (13)$$

where  $p_j = \{p_{1j}, \dots, p_{Nj}\}$  and  $f_j = \{f_{1j}, \dots, f_{Nj}\}$ .

The above problem only includes the continuous variables and therefore can be easily addressed using heuristic optimization methods (e.g., Lévy flight search).

## IV. DISTRIBUTED INTELLIGENT RESOURCE SCHEDULING (DIRS) FRAMEWORK

In this section, we will introduce the proposed DIRS framework, which focuses on joint computation offloading decision and resource allocation in dynamic environment. Distributed model-free DRL is introduced to address the offloading decision making problem, as it is a goal-oriented method which can learn the optimal policy through the interaction between agent and environment. In a large-scale MEC system with multiple users, there are several challenges to be addressed as follows: (1) The policy is randomly distributed and the experience replay buffer is sparse at the beginning of the learning process, so that the interaction process is inefficient and the DRL framework is difficult to converge, especially in dynamic situations. (2) Because of the large number of users, the state space of the DRL is extremely large, which increases the difficulty of policy learning. (3) The action exploration is very challenging because of the complex optimization problem such that the DRL is difficult to explore the optimal action and the search is prone to trap into local minimum. These challenges prohibit the DRL from being directly applied in the real environment. To tackle the large-scale decision problems, Google proposed an improved DRL with KNN as the action refinement in large discrete action spaces [34], and leveraged the demonstration data to accelerate the large-scale learning of DQN [35]. Inspired by the previous works, we present a DRL-based DIRS framework with centralized training and distributed inference. Next, we give a brief introduction of the proposed framework.

### A. The framework outline

The DIRS framework is illustrated in Fig. 2, which includes local agents and a global scheduler. Specifically, the local agents are deployed on each MEC to conduct the independent decision making, and a global scheduler is deployed on the resource-abundant C-MEC to conduct the centralized training, which involves local information exchange of all the agents, generation of demonstration data by using imitation acceleration scheme and refinement of the actions with the aid of Lévy flight search. In online inference stage, each MEC only needs to perform some simple algebraic calculations with the help of local agent enhanced by DRL instead of solving the original optimization problem.

The workflow of the DIRS framework is presented in **Algorithm 1**. Firstly, we initialize parameters of all deep neural networks (DNNs) in  $M$  agent with the parameters  $\theta^0 = \{\theta_1^0, \dots, \theta_M^0\}$  randomly generated and we also initialize an empty replay buffer  $\mathcal{D}$ . Then, we pre-train all the agents using demonstration data produced by the imitation acceleration scheme (i.e., **Algorithm 2**) and obtain the pre-trained parameters of all the agents  $\theta^D = \{\theta_1^D, \dots, \theta_M^D\}$ , and then keep all the demonstration data in the replay buffer  $\mathcal{D}$ . Next, the online training stage and online distributed inference stage are executed. Particularly, the online distributed inference stage is performed continuously, where each agent  $j$  generates an offloading action  $a_{j,t} = \{a_{1j,t}, \dots, a_{Nj,t}\}$  for  $N$  IoTs according to the channel state information  $h_{j,t} = \{h_{1j,t}, \dots, h_{Nj,t}\}$  and policy  $\pi$  with parameters  $\theta_{j,t}$  at time slot  $t$ , and obtains  $p_{j,t} = \{p_{1j,t}, \dots, p_{Nj,t}\}$  and  $f_{j,t} = \{f_{1j,t}, \dots, f_{Nj,t}\}$  by solving Problem (13) independently. The online training stage is performed at every interval  $\phi$  by multi-agent ensemble algorithm (i.e., **Algorithm 3**) and Lévy flight search algorithm (i.e., **Algorithm 4**), and then the learned parameters of all  $M$  agents  $\theta = \{\theta_1, \dots, \theta_M\}$  are updated.  $\phi$  is the training interval. These two stages are alternately performed and the offloading policies of all the agents can be gradually improved in the iteration process.

In general, the DIRS includes three work stages: (1) Offline pre-training stage is applied to accelerate the DRL training for the large-scale application scenarios; (2) Online training stage is introduced to track the variations of the real scenarios in dynamic environments; (3) Online distributed inference stage is presented to make real-time decisions. Moreover, there are three key improvements of the DIRS framework compared to traditional DRL: (1) An imitation acceleration scheme is presented to generate demonstration data and initialize the parameters of distributed agents rather than initializing them randomly to accelerate the learning speed of the distributed DRL (i.e., Subsection-V-B). (2) Multi-agent ensemble algorithm is proposed in Subsection-V-C for large state space partition and decision consolidation, in which the original channel state information  $\mathbf{h}$  is regarded as the current state  $s$  of DRL and it is divided into smaller subsets  $\{h_1, h_2, \dots, h_M\}$  according to the ownership of MECs. Finally, the maximum vote approach is applied to integrate the results of all distributed agents, and obtain the ensemble offloading decision  $\mathbf{a}^e$  according to the maximum vote. This method can realize dimensionality

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### Algorithm 1 DIRS framework

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**Input:**  $h_{j,t}, \phi$ .

**Output:**  $a_{j,t}, p_{j,t}, f_{j,t}$ .

- 1: Initialize  $M$  agents with policies randomly parameterized by  $\theta^0$ .
  - 2: Initialize an empty replay buffer  $\mathcal{D}$ .
  - Offline pre – training stage**
  - 3: Train all agents using demonstration data by **Algorithm 2**, and obtain the demonstrated parameters of all agents  $\theta^D$ .
  - 4: Keep all demonstration data in the replay buffer  $\mathcal{D}$ .
  - Online distributed inference stage**
  - 5: Set iteration number of online inference  $T_{DRL}$ .
  - 6: **while**  $t < T_{DRL}$  **do**
  - 7:   **for** each agent  $j$  **do**
  - 8:     Obtain the channel state information  $h_{j,t}$  according to the environment.
  - 9:     Generate the offloading action  $a_{j,t} = \pi(h_{j,t}|\theta_{j,t})$  independently.
  - 10:    Obtain  $p_{j,t}$  and  $f_{j,t}$  by solving Problem (13) independently.
  - 11:   **end for**
  - Online training stage**
  - 12:   **if**  $t \bmod \phi = 0$  **then**
  - 13:     Train all agents using **Algorithm 3** and **Algorithm 4**.
  - 14:   **end if**
  - 15: **end while**
- 

reduction for the DNN in each agent and simplify the policy learning in each sub-state space. (3) A novel Lévy flight search is introduced in Subsection-V-D for action refinement, which can enhance the action exploration of DRL. Then the optimal offloading action  $\mathbf{a}^*$  is achieved by maximizing the reward which is cached into the replay buffer  $\mathcal{D}$ . One can see that the DIRS framework is a model free DRL which can provide distributed decision making and resource allocation without solving the original MINLP problem. We describe the implementation details of each module in the following subsections.

### B. Imitation acceleration scheme

In large-scale scenarios, distributed DRL typically requires to learn a huge amount of data before they reach reasonable performance, which is very time-consuming by trial and error. This is the major drawback of the DRL to solve the large-scale optimization problem. Recently, imitation learning has been shown to help address this difficult exploration problems in DRL [35], [36].

Imitation learning focuses on imitating human learning or expert demonstration for controlling the behaviour of the agent, which can help DRL reduce the time required to learn by an agent to a great extent through reducing the number of trials [37]. In DRL, imitation learning can help an agent to achieve better performance in complex environment by pre-training it with the demonstration data.

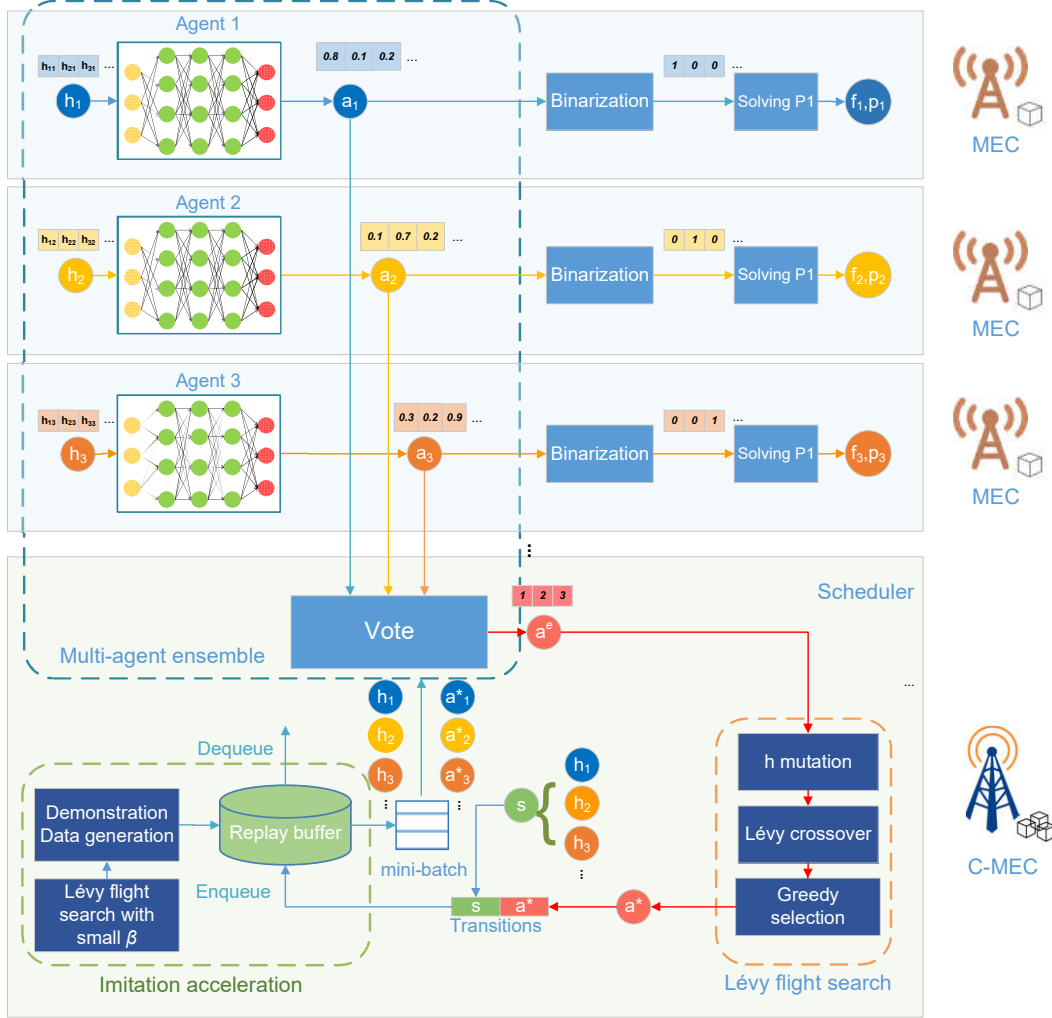


Fig. 2: The DIRS framework.

In the proposed DRL, we propose an imitation acceleration scheme combined with DRL and imitation learning. The imitation acceleration algorithm leverages relatively a small amount of demonstration data to pre-train the agents in our framework, which can significantly accelerate the learning process of the distributed DRL. The details of the imitation acceleration scheme are described as follows.

Firstly, we collect demonstration data by leveraging the optimization algorithm for solving the problem in Eq. (11). In general, the algorithm can be divided into three categories: (1) If the action space is small, we can use the exhaustive search approach to obtain the optimal decision. (2) If the action space is medium, we can use some mixed integer programming solver (e.g., CPLEX). (3) If the action space is large, we can use some global heuristic algorithms to obtain suboptimal decisions [38]. In our study, the demonstration data is generated from the Lévy flight search with small value of parameter  $\beta$  (to be introduced in Appendix) which is suitable for solving large-scale MINLP problems and can possibly

achieve globally optimal solutions [39]. Then the channel state information as well as its optimal offloading actions solved by the Lévy flight search are stored into the replay buffer  $\mathcal{D}$ .

Secondly, we redefine the demonstration loss function from [35]. Because our DRL is not a standard DQN network, so we ignore the DQN loss terms in the original loss function. Then the simplified demonstration loss function has two losses:

$$L_1(\theta) = L_D(\theta) + \lambda_1 L_{L2}(\theta) \quad (14)$$

where  $L_D(\theta) = -\frac{1}{K} \sum_{k \in \mathcal{K}} \left( (a_k^*)^T \log(\pi(h_k|\theta)) + (1 - a_k^*)^T \log(1 - \pi(h_k|\theta)) \right)$  is the demonstration data loss which is the cross-entropy for demonstration data and  $K$  is the number of demonstration data in the batch, whereas  $L_{L2}(\theta) = \|\theta\|^2$  is the  $L_2$ -norm of  $\theta$ , which can increase the generalization of DNN in each agent.

Thirdly, we initialize the pre-training process of all the agents solely on the demonstration data before starting any interaction with the environment.

Finally, once the offline pre-training phase is complete, all the agents start to act in the environment. Then the online training stage and distributed inference stage are alternately executed. We describe the whole process of **Algorithm 2** as follows.

---

**Algorithm 2** Imitation acceleration algorithm

---

**Input:**  $K$ .

**Output:** pre-trained parameters  $\theta^D$ .

- 1: Generate demonstration data and record them in the replay buffer  $\mathcal{D}$ .
  - 2: Set iteration number of imitation learning  $T_D$ .
  - 3: **while**  $t < T_D$  **do**
  - 4:   Sample a minibatch of  $K$  transitions from replay buffer  $\mathcal{D}$ .
  - 5:   Train all agent and update the offloading policy  $\pi_t$  with parameters  $\theta^D$  using the demonstration loss in Eq. (14).
  - 6: **end while**
- 

*C. Multi-agent ensemble based distributed DRL algorithm*

In the proposed large-scale MEC systems with a large number of IoTDS, the traditional DRL suffers from the challenge that the state space is also extremely large, and therefore it is difficult to train a steady policy because of the partial observability of the large state space. To address this, we introduce ensemble learning to enhance the distributed DRL as follows.

Ensemble learning is a machine learning method that generates and combines multiple inducers to solve the complex optimization problem. The intuitive explanation behind ensemble learning stems from human nature and the tendency to gather different opinions and combine them to make a complicated decision [40]. There are many advantages to introduce ensemble learning into our DIRS framework as follows.

(1) Global optimization: a single agent that conducts local inference may get stuck in a local optimum. By combining several agents, ensemble methods can decrease the risk of obtaining a locally minimal solution.

(2) Dimensionality reduction: each agent can be constructed and trained using a selected subset of all the features (i.e., its own channel gains), which can reduce the impact of the curse of dimensionality by reducing the state space for each agent.

(3) Output manipulation: the original offloading decision can be seen as a multi-class classification problem for multiple MECs, but each agent is a binary classifier. By applying ensemble learning, many binary classifiers can be combined into a multi-class classifier, which can simplify the decision process of each agent.

To this end, we propose a multi-agent ensemble algorithm to support the distributed DRL, in which the basic components are redefined as follows.

(1) State space: The overall channel state information is  $\mathbf{h} = \{h_{ij}\}, \forall i \in \mathcal{N}, \forall j \in \mathcal{M}$ . We also assume that each agent in each MEC can only obtain its own related channel state information, and therefore the state of agent  $j$  is denoted as  $h_j = \{h_{1j}, \dots, h_{Nj}\}$ .

(2) Action space: We define two kinds of action, i.e., global action and local action for each agent. Specifically, global action is applied in the training stage, whereas local action is generated in each agent for the distributed decision making. The global action is defined as  $\mathbf{a}^e = \{a_i\}, \forall i \in \mathcal{N}$ , where  $a_i = 0$  means the  $i$ -th IoTDS decides to execute the task itself, whereas  $a_i = j$  means that the  $i$ -th IoTDS decides to offload the task to the  $j$ -th MEC, where  $j \in \mathcal{M}$ . The local decision in the  $j$ -th agent is defined as  $a_j = \{a_{1j}, \dots, a_{Nj}\}$ , where  $a_{ij} = 1$  means that the  $i$ -th IoTDS decides to offload the task to the  $j$ -th MEC, while  $a_{ij} = 0$  means the  $i$ -th IoTDS decides not to offload the task to the  $j$ -th MEC. One can see that each agent can make distributed decision according to its own local information.

(3) Reward: The global reward is defined as the reciprocal of the objective function in Eq. (11).

(4) Policy: The policy  $\pi_j(h_j|\theta_j)$  of each agent  $j$  is implemented by applying a DNN, where  $\theta_j$  is the parameters of the DNN at the  $j$ -th agent.

(5) Vote: The output of each agent can be combined by voting solutions. The final solution is chosen based on the highest value of the decisions of all the agents. Here we give an example to illustrate the proposed voting process. Suppose there are three MECs and the outputs of three agents for the  $i$ -th IoTDS are  $a_{i1}=0.7$ ,  $a_{i2}=0.8$  and  $a_{i3}=0.2$ , respectively. Since the second value  $a_{i2}$  is the highest number, we can have the global ensemble action of the  $i$ -th IoTDS  $a_i^e$  as 2, which means this IoTDS will offload the task to the second MEC. If all the values of the  $i$ -th IoTDS are lower than 0.5, then we set the corresponding ensemble action  $a_i^e$  of the  $i$ -th IoTDS as 0.

(6) Prioritized experience replay: The scheduler in C-MEC refines the global action by applying Lévy flight search (to be introduced in Subsection-V-D) and adds the self-generated data to its replay buffer  $\mathcal{D}$ . Data will be added to the replay buffer until it is full, and then the agent starts to overwrite old data in this buffer during the online training stage. Prioritization batch is also used in the replay buffer. The probability of sampling transitions  $i$  is defined as

$$P_i = \frac{w_i^\tau}{\sum_{k \in \mathcal{K}} w_k^\tau} \quad (15)$$

where  $w_i = |\Delta\delta_t| + \epsilon$  and  $\epsilon$  is small positive constant that guarantees that all the transitions can be sampled. Two different  $\epsilon_A$  and  $\epsilon_D$  can be applied to control the relative sampling of the agent generated data versus the demonstration data.  $\Delta\delta_t$  is the average loss function variation of all the agents. The exponent  $\tau$  determines the intensity of prioritization.

(7) Loss function: The loss function of the DNN in the agent is proposed as follows:

$$L_2(\theta) = L_1(\theta) + \lambda_2 L_A(\theta) \quad (16)$$

where  $L_1(\theta)$  is the demonstration loss function defined in Eq. (14) and  $L_A(\theta)$  is the agent generated data loss which is given by

$$L_A(\theta) = -\frac{1}{S} \sum_{k \in \mathcal{S}} \left( (a_k^*)^T \log(\pi(h_k|\theta)) + (1 - a_k^*)^T \log(1 - \pi(h_k|\theta)) \right) \quad (17)$$



where  $S$  is the number of agent generated transitions in the batch.

When we initialize the environment and obtain the state, the offline training stage is performed, in which each agent  $j$  generates the offloading action  $a_{j,t}$  according to the policy  $\pi_{j,t}(h_{j,t}|\theta_{j,t})$  at the time slot  $t$ . Then, we obtain the global offloading decision  $a_t^e$  according to the maximum vote of all the agents. To increase efficiency of action exploration, we search the best  $a_t^*$  by applying **Algorithm 4**, and then we append the state-action pairs  $\{h_t, a_t^*\}$  to the replay buffer  $\mathcal{D}$  as training samples of all the agents. Next, we sample a batch of transitions by applying priority strategy discussed before, and then we train all the agents using the Adam algorithm [41] and update all the offloading policies  $\pi_t = \{\pi_{1,t}, \dots, \pi_{M,t}\}$  by minimizing the loss function defined in Eq. (16). We describe the whole process of **Algorithm 3** as follows.

---

**Algorithm 3** Multi-agent ensemble algorithm

---

**Input:**  $h_t, a_t, \mathcal{D}$ .

**Output:**  $\theta_t$ .

- 1: Integrate the global  $a_t^e$  by voting form all agents.
  - 2: Find the best  $a_t^*$  by **Algorithm 4**.
  - 3: Append the state-action pair  $\{h_t, a_t^*\}$  to the replay buffer  $\mathcal{D}$ .
  - 4: Sample a random minibatch of transitions by priority strategy using Eq. (15) from replay buffer  $\mathcal{D}$ .
  - 5: Feed these transitions to all agents.
  - 6: Set iteration number of distributed learning  $T_D$ .
  - 7: **for** each agent  $j$  **do**
  - 8:   **while**  $t < T_M$  **do**
  - 9:     Update agent parameters  $\theta_{j,t}$  by minimizing the loss function in Eq. (16) in distributed way.
  - 10:   **end while**
  - 11: **end for**
- 

#### D. Lévy flight search

Action exploration is an important part in DRL. Traditional DRL normally uses random process for action exploration (e.g.,  $\epsilon$ -greedy), which is blind and inefficient in large action space [18]. Some local search methods are also applied for action exploration which can achieve the suboptimal offloading policy  $\pi$  [34], [42]. However, these local search methods are easily stuck in local optimum and the right offloading policy cannot be guaranteed, especially in large-scale MEC systems [42]. To address this problem, we introduce a novel Lévy flight search, which can jump out of local optimum with high efficiency, to find the best offloading action  $a_t^*$  according to  $a_t^e$  in DRL. After Lévy flight search, the newly generated state-action pairs  $\{s_t, a_t^*\}$  at time slot  $t$  are appended to the replay buffer as training transitions of all the agents.

Traditional Lévy flight is used to generate a new solution in the heuristic search as follows:

$$x_i(G) = x_i(G-1) + \eta d_i \quad (18)$$

where  $x_i(G)$  is the solution at iteration  $G$ ,  $d_i$  is a Lévy flight step, and  $\eta$  is a scale weight.

However, there are two disadvantages that avoid Lévy flight from being directly applied to our distributed DRL algorithm. Firstly, the search step  $d_i$  output from Lévy flight is a continuous real number, but the offloading decision  $a_i$  in our problem is an integer value. Secondly, it does not take advantage of the channel state information in the search process. To tackle these issues, we propose a novel Lévy flight search, in which the solution can be represented as:

$$x = [a_1, \dots, a_N, f_1, \dots, f_N, p_1, \dots, p_N] \quad (19)$$

where  $N$  is the number of IoTDS,  $a_i$ ,  $f_i$  and  $p_i$  denote the offloading decision, allocated computation resource and transmission power of the  $i$ -th IoTDS, respectively.

The Lévy flight search consists of three operations: h mutation, Lévy selection and greedy selection. We introduce each of them as follows.

(1) h mutation: channel state information  $\mathbf{h}$  provides the prior information to create a mutant vector  $a_i^m(G)$ . The h mutation is applied by comparing the normalized  $h_{ij}$  with a Lévy flight step, which represents that the IoTDS that offloads the task to the MEC with higher  $h_{ij}$  has a higher stability. Thus, the h mutation for the integer part of the solution can be represented as follows:

$$a_i^m(G) = \begin{cases} randm & \text{if } \gamma d_i > \frac{h_{i,a_i}}{\sum_{j \in \mathcal{M}} h_{ij}} \\ a_i(G-1) & \text{otherwise} \end{cases} \quad (20)$$

where  $randm \in \mathcal{M}'$  is a randomly generated integer to ensure that the  $i$ -th IoTDS will offload the task to an MEC or execute the task itself,  $\gamma$  is a decreased weight calculated as follows:

$$\gamma = 2 - 2G/G_{max} \quad (21)$$

where  $G_{max}$  is the maximum iteration number.

The rest part of the solution (e.g.,  $f_i^m(G)$  and  $p_i^m(G)$ ) is generated by Eq. (18).

2) Lévy crossover: the Lévy crossover is carried out to produce a candidate vector  $x_i^c(G)$  by combining the mutant vector  $x_i^m(G)$  and a target vector  $x_i(G-1)$ , which is achieved by comparing the weighted Lévy flight step with a threshold  $th$ . Thus, the Lévy crossover is represented as follows:

$$x_i^c(G) = \begin{cases} x_i^m(G) & \text{if } \gamma d_i > th \\ x_i(G-1) & \text{otherwise} \end{cases} \quad (22)$$

3) Greedy selection: The selection operator determines whether the candidate vector  $x_i^c(G)$  or the target vector  $x_i(G-1)$  survives into the next iteration. Greedy selection is used to select the vector with the better fitness as follows:

$$x_i(G) = \begin{cases} x_i^c(G) & \text{if } f(x_i^c) < f(x_i(G-1)) \\ x_i(G-1) & \text{otherwise} \end{cases} \quad (23)$$

where  $f(\cdot)$  denotes the objective function in Eq. (11).

In a word, the Lévy flight search employs the channel state information to guide the mutation of solution, and introduces Lévy steps to avoid solution trapping into the local optimum,

so it is an efficient action exploration method. The detailed description of the Lévy flight search algorithm is provided in **Algorithm 4**.

---

**Algorithm 4** Lévy flight search algorithm

---

**Input:**  $a_t^e, \beta, th$

**Output:**  $a_t^*$

- 1: Initialize  $x(0)$  with ensemble offloading decision  $a_t^e$ , and random computation resource and energy resource allocation.
  - 2: **while**  $G \leq G_{max}$  **do**
  - 3:   Generate Lévy search step  $d_i$ .
  - 4:   Generate a mutant vector  $x_i^m(G)$  with  $a_i^m(G)$  by Eq. (20)-Eq. (21), and  $f_i^m(G)$  and  $p_i^m(G)$  by Eq. (18) in h mutation.
  - 5:   Obtain a candidate vector  $x_i^c(G)$  by Lévy crossover in Eq. (22).
  - 6:   Calculate the fitness of  $x_i^c(G)$  and  $x_i(G-1)$  by solving the objective function in Eq. (11).
  - 7:   Select the subsequent solution  $x_i(G)$  by greedy selection in Eq. (23).
  - 8:   Update  $\gamma$  according to Eq. (21).
  - 9: **end while**
- 

In addition, variation factor  $\beta$  (to be introduced in Appendix) is the key parameter of Lévy flight to balance global and local search. If  $\beta$  value is large, the step size of Lévy flight will be restricted in a small search range, which can really focus on the local search and occasionally global search. Therefore, larger  $\beta$  value implies the faster convergence speed and slightly lower solution accuracy. If the  $\beta$  value is small, the search length of walking distance of Lévy flight is long so that the global search can be enhanced and the optimal solution is achieved with slow convergence speed. For these above reasons, we use Lévy flight search with large  $\beta$  value in online training stage (i.e., Ensemble learning at **Algorithm 3**) and apply Lévy flight search with small  $\beta$  value in offline pre-training stage (i.e. Imitation acceleration at **Algorithm 2**).

#### E. Time complexity analysis of DIRS framework

There are two key elements which will influence the time complexity of our DIRS framework. They are the DNN learning and the Lévy flight search. The time complexity of DNN learning is  $O(K \times I_{DNN} \times T_N)$ , where  $K$  denotes the number of samples,  $T_N$  is the iteration number of DNN learning, and  $I_{DNN}$  indicates the time complexity of one iteration, which depends on the number of parameters in DNNs. The time complexity of Lévy flight search is  $O(P \times I_{LF} \times G_{max})$ , where  $P$  denotes the population size,  $G_{max}$  is the maximum iteration number, and  $I_{LF}$  indicates the time complexity of the update of one feasible solution, which depends on the dimension of the feasible solution and the evaluation complexity of the feasible solution [43].

So, in our DIRS, the time complexity of the offline pre-training stage (Imitation learning) is  $O(M \times K \times I_{DNN} \times T_D)$ , where  $M$  indicates the number of MECs,  $T_D$  is the maximum iteration number for imitation learning. The offline pre-training

TABLE I: Simulation parameters.

Parameters	Assumptions
Data size of task $D_i$	100kB
Required CPU cycles of task $F_i$	$10^9$ cycles
Bandwidth $B$	1MHz
Local Computational Capability $f_{i0}$	$10^9$ cycles/s
Maximum transmission power $P_{max}^{IoT D}$	1.5W
Noise Spectral Density $\sigma^2$	$10^{-12}$ W/Hz

stage is carried out in the core MEC or the remote cloud with abundant resources. In multi-agent ensemble learning, the time complexity of the online training stage for the core MEC is  $max(O(K \times I_{DNN} \times T_M), O(P \times I_{LF} \times G_{max}))$ , while the time complexity of the online training stage for the normal MEC is  $O(K \times I_{DNN} \times T_M)$ . Considering the MEC system with limited resources, the  $K$  and  $T_M$  of the DNN and the  $P$  and  $G_{max}$  of the Lévy flight in online training stage are set with very small values. The time complexity of the online distributed inference stage is  $O(I_{DNN})$  for each MEC, which is a low time complexity and is suitable for IoT and MEC system.

## V. SIMULATION RESULTS AND NUMERICAL ANALYSIS

### A. Simulation environment settings

We first present experimental settings of the MEC system in Table I. The proposed DIRS framework is implemented on the Python 3 platform. The parameters of the DIRS framework are chosen as follows: replay buffer size=1024, minibatch size=256 and training interval  $\phi=10$ . The parameters of the imitation acceleration scheme are chosen as follows:  $T_D=500$ ,  $\lambda_1=10^{-4}$ . The parameters of the multi-agent ensemble algorithm are chosen as follows:  $T_M=2$ ,  $\lambda_2=0.5$ ,  $\epsilon_A=0.08$  and  $\epsilon_D=0.02$ . The parameters of the Lévy flight search are chosen as follows:  $P=5$ ,  $G_{max}=10$ ,  $\beta=1.5$  and  $th=0.4$ . All simulations are carried out in Tensorflow 2.2 environment running on a i7-6500U CPU with 16GB RAM and 512GB SSD. The Agents of the DRL are designed by Keras using dense layer and Adam optimizer. Next, we present two different evaluations to verify the performance of the DIRS framework.

### B. Performance evaluation for different modules of DIRS

In this section we consider the performance for different modules of DIRS in a medium-scale IoT scenario. There are two MEC servers and 30 IoTs randomly distributed in the squared area with size 50m×50m. We assume that the coordinates of two MEC servers are (10 m, 10 m) and (40 m, 40 m). The remote computational capability of MEC  $F_{max}^{MEC}$  is set to  $15 \times 10^9$  cycles/s. The 4-layer fully-connected DNNs are applied as the agents, which includes 30, 80, 60 and 30 neurons in each layer, respectively. We collect 3000 environment data as the state inputs of DRL and  $T_{DRL}$  is set to 3000.

Imitation learning is used as a pre-training tool in our DIRS framework, and the amount of demonstration data will

TABLE II: The performance comparison of imitation learning.

Data quantity	$L_1(\theta)$		$L_D(\theta)$	
	Training accuracy	Testing accuracy	Training accuracy	Testing accuracy
64	90.8%	90.1%	90.3%	85.5%
128	92.4%	91.8%	92.2%	89.8%
256	96.7%	96.3%	96.6%	93.4%
512	96.7%	96.5%	96.6%	94.3%

influence the performance of pre-training. We compare the performance of imitation learning with various quantities of demonstration data using different loss functions in TABLE II. It can be stated that, the DNNs may not improve its learning performance significantly when demonstration data quantity is above 256. Moreover, the proposed loss function  $L_1(\theta)$  can achieve better training and testing accuracy than  $L_D(\theta)$ . The reason behind this is when demonstration data quantity is above 256, the over-fitting issue may happen. Therefore, the  $L_2$  regularized term is added in  $L_1(\theta)$  and it can ensure the generalization of DNN, which can lead to a higher learning accuracy, especially for the testing process.

Multi-agent ensemble learning assisted DRL is the core part of DIRS framework, which uses multi-agent learning and decision consolidation. Fig. 3 shows the convergence curves of all the agents in different MECs. One can see that the loss values of agent 1 and agent 2 all converge to 0.2 after around 300 iterations, which means all the agents in our DIRS framework can work properly and the over-fitting does not happen in ensemble learning.

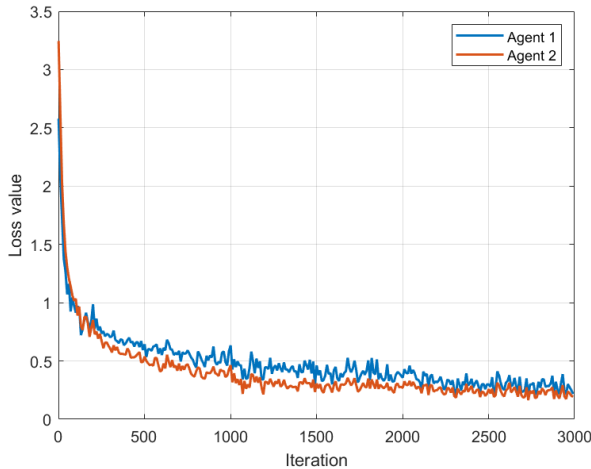


Fig. 3: Comparison of loss values for Agent1 and Agent2.

Moreover, Lévy flight search is applied to refine the action in the proposed framework. Fig. 4 characterizes the action refinement performance using classic Lévy flight search and our proposed Lévy flight search. It can be observed from Fig. 4 that the proposed Lévy flight search achieves better performance with lower fitness value than classic Lévy flight

search. The reason of higher accuracy of the proposed Lévy flight search is that the channel state information is applied to guide the action exploration and the Lévy flight crossover is applied to jump out from the local optimum during the search process.

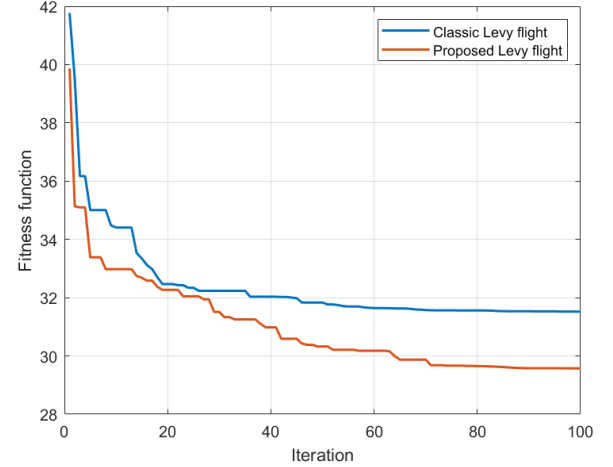


Fig. 4: Action refinement using different Lévy flight searches.

Next, we analyze the benefits of Lévy flight search and imitation acceleration for the whole DIRS framework by using the performance metric of the average reward during the training process. One can see from Fig. 5 that the ensemble DRL with Lévy flight search converges to a higher average reward than the ensemble DRL with  $\epsilon$ -greedy search. This is due to the fact that the Lévy flight search is a heuristic local search which can refine the action and jump out of the local optimum by Lévy steps. One can also see that the DIRS with imitation acceleration converges faster than the ensemble DRL without imitation acceleration in Fig. 5.

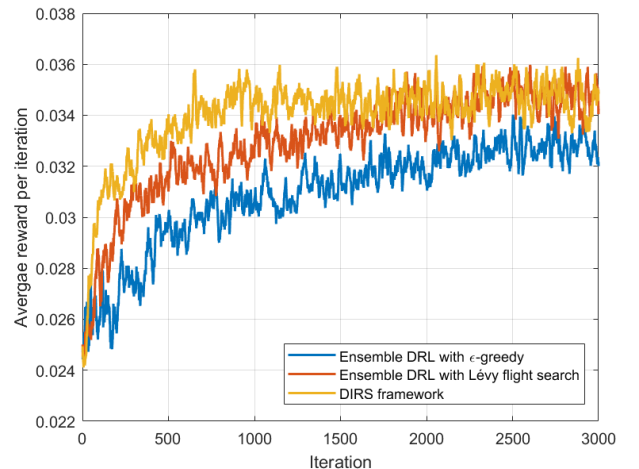


Fig. 5: The comparison of average reward curve.

### C. Performance evaluation for the large-scale IoT scenario with different parameters

In this section, we consider the performance of DIRS in a large-scale IoT scenario. Assume that there are 8 edge servers and 180 IoTDs, randomly distributed in the squared area with size 50m×50m. The coordinates of 8 edge servers are obtained by the k-means algorithm for all the IoTDs at the first time. The remote computational capability of MEC  $F_{max}^{MEC}$  is set to  $10 \times 10^9$  cycles/s. The 4-layer fully-connected DNNs are applied for the agents, which includes 180, 260, 200 and 180 neurons in each layer, respectively. We collect 4000 environment data as the state inputs of DRL and  $T_{DRL}$  is set to 4000.

We first evaluate the performance of DIRS framework with different weighted coefficients in Eq. (10). We define three different tasks: Time-sensitive task ( $\phi_T=1.5$  and  $\phi_E=0.5$ ), Normal task ( $\phi_T=1$  and  $\phi_E=1$ ) and Energy-sensitive task ( $\phi_T=0.5$  and  $\phi_E=1.5$ ). Fig. 6 characterizes the energy and time consumption of all the tasks. It can be observed that the time consumption decreases gradually when the  $\phi_T$  increases. Additionally, the energy consumption decreases with the increase of  $\phi_E$ , as expected.

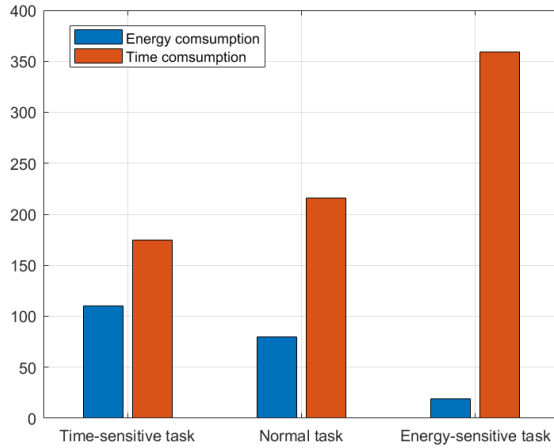


Fig. 6: The comparison of the DIRS framework with different weighted coefficients.

Then, we evaluate the performance of the DIRS framework with different position distributions of IoTDs. We select three different random functions to generate the positions of IoTDs, which are uniform distribution, Gaussian distribution and Lévy distribution. Table III characterizes the objective function values of the DIRS framework under different distributions of IoTDs. For evaluating the influence of the different position distributions of IoTDs, we define the normalized reward rate (NRR), which is equal to that the inferred reward dividing the optimal reward [44]. In NRR, the inferred reward in the numerator is calculated from the output of the DIRS framework, and the optimal reward in the denominator is obtained from the particle swarm optimization (PSO) algorithm which is always applied to solve large-scale MINLP problems with high quality but low efficiency [44].

TABLE III: Performance of the DIRS framework with different position distributions of IoTDs.

Metric	Uniform distribution	Gaussian distribution	Lévy distribution
Objective function	295.27	291.07	290.38
Time consumption	215.84	203.76	201.83
Energy consumption	79.43	87.31	88.55
NRR	0.9536	0.9528	0.9574

TABLE IV: Performance of the DIRS framework with different  $D_i$  and  $F_i$ .

Metric	$D_i$		$F_i$	
	50kB	1000kB	$0.5 \times 10^9$ cycles	$2 \times 10^9$ cycles
Objective function	290.54	304.89	147.11	587.99
Time consumption	200.37	225.52	107.77	395.72
Energy consumption	90.17	79.37	39.34	192.27
NRR	0.9517	0.9519	0.9524	0.9508

From Table III, one can see that the IoTDs with non-uniform distributions (e.g., Gaussian distribution and Lévy distribution) obtain lower objective function values. One can also find that all the distributions achieve similar NRR values, which means the DIRS framework can work efficiently under different position distributions.

Next, we evaluate the influence of different data size  $D_i$  and required CPU cycles  $F_i$  in the DIRS framework. We select two different  $D_i$  when  $F_i=10^9$  cycles, and two different  $F_i$  when  $D_i=100$ kB. Table IV characterizes the objective function values and NRRs of the DIRS framework with different  $D_i$  and  $F_i$ . It can be observed that when  $D_i$  or  $F_i$  increase, the time to complete the task and the energy consumption also increase, as expected. Moreover, the DIRS framework achieves good performance for different  $D_i$  and  $F_i$ , which means the DIRS framework is insensitive to the task parameters if it has been trained adequately.

### D. Performance evaluation for the large-scale IoT scenario with different benchmarks

In this section we consider the performance of DIRS in a large-scale IoT scenario. There are 10 MEC servers and 200 IoTDs randomly distributed in the squared area with size 50m×50m. The coordinates of 10 MEC servers are obtained by the k-means algorithm for all IoTDs at the first time. The remote computational capability of MEC  $F_{max}^{MEC}$  is set to  $10 \times 10^9$  cycles/s. The 4-layer fully-connected DNNs are applied as the agents, which includes 200, 300, 250 and 200 neurons in each layer, respectively. We collect 5000 environment data as the state inputs of DRL and  $T_{DRL}$  is set to 5000.

TABLE V: The offloading performance comparison of different offloading scheduling strategies.

Metric	Training time	Inference time	Average time consumption	Average energy consumption
DIRS	434.23	0.0163	292.8779	40.5198
AC	489.64	0.017	322.7262	53.4802
DDPG	517.17	0.0198	302.8238	47.2354
PSO	-	1.8565	293.3282	40.8271
DE	-	1.8699	293.7273	40.6938

We first compare the DIRS framework with 2 well-known DRL algorithms and 2 heuristic algorithms:

- Actor-Critic (AC) is a combination of the actor-only DRL and the critic-only DRL. The critic uses an critic's DNN and simulation to learn a value function, which is then used to update the policy of the actor's DNN.
- Deep Deterministic Policy Gradient (DDPG) is a state-of-the-art AC, which includes two critic's DNNs and two actor's DNNs for performance enhancement.
- PSO is a heuristic search which is suitable for solving large-scale MINLP problems for offloading optimization and can normally achieve near-optimal global solutions but with long computation time [45].
- Differential evolution (DE) is another latest heuristic search for task scheduling optimization in large-scale MEC systems [46].

TABLE V characterizes the Training time, Inference time and Average time and energy consumption of all offloading methods for online joint resource scheduling. It can be observed that the DIRS framework achieves the lowest average time consumption and average energy consumption while consuming the least training time. The superiority of the DIRS framework can be attributed to three aspects: (1) Imitation learning from the demonstration data accelerates the training process of DIRS; (2) Ensemble learning simplifies the structure of DNN by state space partition, which leads to less learning time of each agent, while decision consolidation according to the global information improves the reward of DIRS; (3) Lévy flight search refines the action and enhances the exploration, which leads to efficient search and fast convergence. It can also be seen the DIRS framework has the shortest inference time, which can be explained for the following reasons: (1) The DIRS is a distributed DRL framework, in which the trained agents can make offloading decisions in a parallel way; (2) Each agent just needs to solve the local optimization problem in Eq. (13), which is simpler than the original optimization problem. Moreover, the DIRS framework provides almost the same average energy and time consumption as PSO and DE, while PSO and DE takes 113.89 and 114.72 times longer inference time than the DIRS framework, respectively.

The inference performance of the DIRS framework is compared with the following benchmark methods for real-time decisions:

- Random offloading (Random) denotes that the offloading

decision is decided randomly for each IoTD. If the computational resource of the allocated MEC is insufficient, IoTD executes the task locally.

- All offloading (Remote) denotes that all the IoTDs offload the tasks to the nearest MEC. If the computational resource is insufficient, the IoTDs who need more computing resources execute the task locally.
- Local execution (Local) denotes that all IoTDs decides to execute the task locally.
- Multi-agent deep deterministic policy gradient (MADDPG) is a celebrated multi-agent DDPG.

In Fig. 7, we compare sum of energy and time consumption for all UEs (Objective function) between the proposed framework, MADDPG, All offloading, Random offloading and Local execution. As shown in Fig. 7, the proposed method achieves the lowest value of the objective function when the number of IoTDs is large, which implies that the DIRS framework is suitable for the large-scale IoT scenario. Moreover, one can see that the MADDPG also obtains better performance than Remote, Random and Local strategies.

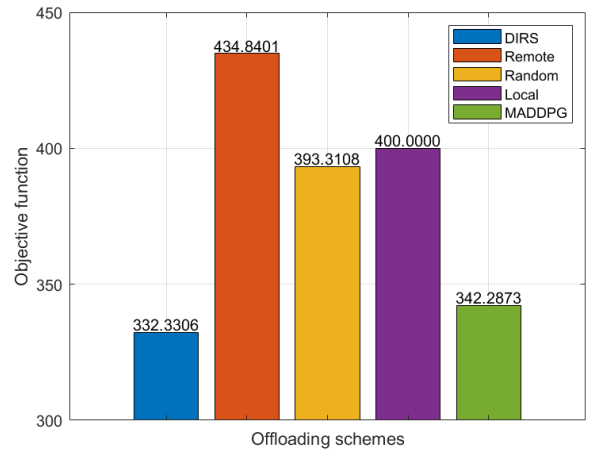


Fig. 7: The comparison of the object function with different offloading schemes.

## VI. CONCLUSION

In this paper, a novel DIRS framework has been proposed for large-scale MEC systems. This framework adopts a distributed DRL to jointly optimize computation offloading, transmission power and resource allocation, with the objective of minimizing the sum of task latency and energy consumption for all the IoTDs. Overall, the proposed DIRS framework has the following three advantages:

- (1) The proposed DIRS framework consists of a multi-agent ensemble assisted DRL architecture for centralized learning and distributed inference.
- (2) A Lévy flight search is proposed as the action refinement module of DRL for more efficient exploration in large action space.
- (3) An imitation acceleration is presented to help agents to achieve better performance in complex environment by pre-training with the demonstration data.

The simulation results demonstrate that the DIRS framework has better performance than the existing benchmarks, and it exhibits enormous potential in the large-scale application scenarios.

In the future, we plan to apply our proposed framework to more complex environment, for instance, in the scenario where unnamed aerial vehicle (UAV) is served as the edge computing node [3]. Additionally, we plan to propose the prediction model to predict the moving pattern of the mobile users based on the historical data. Then, we can integrate the prediction result to our proposed solution to further improve the scalability of the framework.

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