Deep-Reinforcement-Learning-Based Scheduling with Contiguous Resource Allocation for Next-Generation Cellular Systems

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Abstract—In this work, we propose a novel scheduling algorithm with contiguous frequency-domain resource allocation (FDRA) based on deep reinforcement learning (DRL) that jointly selects users and allocates resource blocks (RBs). The scheduling problem is modeled as a Markov decision process, and a DRL agent determines which user and how many consecutive RBs for that user should be scheduled at each RB allocation step. The state, action, and reward sets are delicately designed to train the DRL network. More specifically, the originally quasi-continuous action space, which is inherent to contiguous FDRA, is refined into a finite and discrete action space to obtain a tradeoff between the inference latency and system performance. Simulation results show that the proposed DRL-based algorithm outperforms other representative baseline schemes while having lower online computational complexity.

Index Terms—Deep reinforcement learning (DRL), frequency-domain resource allocation (FDRA), next generation, scheduling.

I. INTRODUCTION

RESOURCE allocation is an indispensable ingredient in wireless systems with multiple user equipments (UEs), in order to meet certain quality of service (QoS) requirements such as throughput, fairness, latency, and/or reliability. The 3rd Generation Partnership Project (3GPP) has specified two types of downlink frequency-domain resource allocation (FDRA), type 0 and type 1, for the fifth-generation (5G) and beyond-5G (B5G) wireless communications [1], [2]. There exist two essential discrepancies between type-0 and type-1 FDRA: (1) Type 0 is on the resource block group (RBG) level, where an RBG contains a number of consecutive resource blocks (RBs), while type 1 is on the RB level; (2) The resources (RBGs or RBs) assigned to each UE can be non-contiguous for type 0, while they must be contiguous for type 1.

The contiguous-RB constraint in type-1 FDRA renders it extremely difficult to find an optimal UE and resource allocation strategy except using brute-force search, whose computational complexity is prohibitively high. Consequently, it is necessary and preferred to propose sub-optimal scheduling algorithms with contiguous FDRA that have reasonable complexity hence implementable in practice. A plethora of contiguous FDRA scheduling approaches have been proposed previously (for instance, [3], [4] and references therein). Specifically, three practical scheduling algorithms with contiguous FDRA have been presented in [4], wherein one of the algorithms, joint allocation with dual ends (JADE), yields the best performance and outperforms a contiguous FDRA method representative in the industry [4], [5]. Nevertheless, albeit its relatively low complexity compared with existing algorithms, JADE still incurs considerable complexity when UEs abound since its complexity scales with the square of the number of UEs. On the other hand, artificial intelligence (AI) has found various applications in the field of wireless communications [6], which can help solve problems difficult to handle using conventional non-AI methods, improve efficiency/performance of existing solutions, or reduce instantaneous computation time while offering comparable performance, among other advantages. Therefore, it will be beneficial and valuable if AI techniques can be leveraged to schedule UEs and resources that yields performance comparable to or even better than JADE while inducing much lower online computational complexity.

Given the fact that UE and resource scheduling can be modeled by a Markov decision process [6], [7], deep reinforcement learning (DRL), an important branch of machine learning belonging to AI, can be adopted to train an agent to offer optimal or superhuman performance while requiring significantly less instantaneous computational effort. In this work, we propose a novel algorithm that jointly schedules UEs and contiguous frequency-domain resources based on DRL, named STAR (Superhuman-level Type-1 Allocation based on Reinforcement learning). Specifically, the DRL-based algorithm makes decisions on which UE and how many RBs for that UE shall be scheduled jointly at each allocation step. Major merits of the proposed algorithm are two-fold: (1) it can yield remarkable performance which is even superior to JADE, and (2) it enjoys significantly reduced online computational complexity as compared to JADE.

II. SYSTEM MODEL AND PROBLEM FORMULATION

We investigate a downlink cellular system comprising of one next-generation nodeB (gNB) and K UEs indexed by the set \( K = \{0, ..., K-1\} \), where the UEs’ traffic types can be diverse with distinct QoS requirements. The transmission bandwidth part (BWP) \( W \) is orthogonally divided into \( B \) RBs indexed by the set \( B = \{0, ..., B-1\} \). The payload for UE \( k \) is denoted by \( L_k \). Two constraints in type-1 FDRA in 3GPP 5G and B5G specifications [1], [2]: (1) exclusivity, i.e., an RB can only be allocated to at most one UE in the same time resource; (2) contiguity, indicating that the RBs assigned to each UE must be contiguous.

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For UE \( k \) on RB \( b \), given the estimated channel \( H_{k,b} \) and precoding matrix codebook [1], the rank indicator (RI), precoding matrix indicator (PMI), and modulation and coding scheme (MCS) [1] can be obtained via Algorithms 1 and 2 in [8], after which the transport block size (TBS), TBS\(_{k,b}\), is computed via the aforementioned strategy. The achievable rate of UE \( k \) on RB \( b \) in each slot is \( r_{k,b} = \text{TBS}_{k,b} \). Let \( B_k \) denote the set of RBs allocated to UE \( k \), the achievable rate of UE \( k \) is \( r_k = \sum_{b \in B_k} r_{k,b} \). The scheduling metric (e.g., sum-rate, proportional fairness (PF) [9], among others) can be selected as the scheduling metric as an example. The optimization problem is formulated as

\[
(P1): \quad \max_{\{B_0, \ldots, B_{K-1}\} \subseteq \mathcal{D}} \sum_{k \in K} \sum_{b \in B_k} r_{k,b} \quad \text{subject to} \quad B_k \cap B_{k'} = \emptyset, \forall k \neq k', k', k \in K
\]

where \( \mathcal{D} \) is the set of all possible RB allocations satisfying the contiguity constraint. The optimal solution to (P1) requires \( D \) is the set of all possible RB allocations satisfying the contiguity constraint. The optimal solution to (P1), which is proved to provide satisfactory complexity. In [4], a sub-optimal algorithm JADE has been put forth to solve (P1), which is proved to provide satisfactory performance based on simulation results. The procedures of JADE is detailed in Algorithm 1. The main design principle of JADE is to jointly prioritize the UE and RB(s) in each allocation step that produces the largest scheduling metric with the minimum number of RBs, where the RB selection is performed and compared between both ends of the active BWP to exploit frequency diversity.

Algorithm 1 Joint Allocation with Dual Ends (JADE)

**Require:** Initialize \( K^* = \emptyset, B^* = \emptyset \).

1. while \( K \neq \emptyset \) and \( B \neq \emptyset \) do
2.  \textbf{for } \forall k \in K \textbf{ do}
3.  \quad Calculate the number of RBs needed, \( n_{k,\text{start}} \), to transmit \( L_k \) starting from the first remaining RB in \( B \) and going forward, until \( r_{k,\text{start}} \geq L_k \) or \( B = \emptyset \). Denote the selected RB set as \( B_{k,\text{start}} \).
4.  \quad Calculate the number of RBs needed, \( n_{k,\text{end}} \), to transmit \( L_k \) starting from the last remaining RB in \( B \) and going backward, until \( r_{k,\text{end}} \geq L_k \) or \( B = \emptyset \). Denote the selected RB set as \( B_{k,\text{end}} \).
5.  \quad If \( n_{k,\text{start}} \leq n_{k,\text{end}} \), store \( B_{k,\text{start}} \) and \( r_{k,\text{start}} \) as \( B_k \) and \( r_k \), respectively; otherwise store \( B_{k,\text{end}} \) and \( r_{k,\text{end}} \) as \( B_k \) and \( r_k \), respectively.
6.  \quad Calculate \( \sum_{b \in B_k} \mu_{k,b} \).
7. \textbf{end for}
8. \quad \text{if } k^* = \arg \max_{k} \sum_{b \in B_k} \mu_{k,b} \text{ then}
9.  \quad \text{Calculate MCS}_{k^*}, \text{the final MCS for UE } k^* \text{ over } B_{k^*} \text{.}
10. \quad \text{If } B_{k^*} = k^* \cup \{k^*\}, B^* \leftarrow B^* \cup B_{k^*} \text{.}
11. \text{If } \text{the state is updated, } \text{then } K \leftarrow K \setminus \{k^*\}, B \leftarrow B \setminus B_{k^*} \text{.}
12. \text{end if}
13. \text{return } K^*, B^*, \text{ and } \text{MCS}_{k}, \forall k \in K^* \text{.}

III. PROPOSED SCHEDULING ALGORITHM BASED ON DRL

Note that in JADE, the number of TBS and scheduling metric calculation is proportional to \( K^2 \) due to the iteration for each remaining UE and RB. To reduce the online computational complexity and further enhance performance, we propose using a DRL-based scheduling approach, STAR, to smartly allocate RBs to multiple UEs. A deep Q-network is utilized for the training of STAR. The input and output relationship per slot incorporating DRL is illustrated by Fig. [1] where the green shaded modules represent the environment, and the blue module depicts the DRL agent.

![Fig. 1: Input and output relationship per slot for multi-UE Type-1 FDRA based on DRL. The green shaded modules represent the environment, and the blue module denotes the DRL agent.](image)

A. State Design

In this work, DRL is utilized to determine which UE and how many RBs for the selected UE should be scheduled at each allocation step. The state design is closely related to the scheduling metric used in the scheduling algorithm. Since the scheduling metric employed herein is sum-rate, or equivalently, sum-TBS, both RB-related channel state information (CSI) and the metric related to sum-TBS, i.e., remaining payload, should be reflected in the state. Detailed methodology for the acquisition of the current state \( s \) at each RB allocation step is given by Algorithm 2. It is worth noting that if the next UE scheduling and resource allocation takes place in the current slot, the next state \( \hat{s} \) is the state after the current UE scheduling and resource allocation in the current slot. If the next UE scheduling and resource allocation takes place in the next slot, \( \hat{s} \) takes the first state in the next slot, which reflects both the decision made in the current slot and new packet information and CSI in the next slot. This way, the state transition is always continuous and Markovian for both intra-slot and inter-slot cases.

B. Action Design

For contiguous FDRA, the action consists of two aspects: UE selection and RB allocation, which leads to a quasi-continuous action space \( \mathcal{A} \) due to potentially large number
Algorithm 2: State Design for STAR

1: for ∀k ∈ K do
2: for ∀b ∈ B do
3:     \( g_{k,b} = \text{MCS}_{k,b} \times \text{RI}_{k,b} \)
4: end for
5: if \( L_k > 0 \) then
6:     \( s_k = \left[ L_k, g_{k,0}, g_{k,1}, \ldots, g_{k,B-1} \right] \)
7: else
8:     \( s_k = \{-1, -1, -1, \ldots, -1\} \)
9: end if
10: end for
11: \( s = [s_0, s_1, \ldots, s_K-1] \)
12: return \( s \)

Table I: Actions and the Corresponding Physical Meanings

| \( a/5 \) | \( k \) | \( n_k \) | \( n_k,\text{WB} \) |
|----------|-------|--------|---------------|
| 0        |       | -2     |               |
| 1        |       | -1     |               |
| 2        |       | \( n_k,\text{WB} \) + 1 |               |
| 3        |       | \( n_k,\text{WB} \) + 2 |               |
| 4        |       | \( n_k,\text{WB} \) + 3 |               |

of RBs to be allocated. Considering the tradeoff between training/inference overhead and performance, we transform the quasi-continuous action space into a discrete and finite training/inference overhead and performance, we transform the action index over 5 equals the UE index, i.e., \( a/5 \) = \( k \). In particular, the size of the action space herein is devised to be \(|A| = 5K\), where the actions are indexed by 0, 1, \ldots, 5K – 1. The quotient produced by the division of the action index over 5 equals the UE index, i.e., \( a/5 \) = \( k \), where \( a \) denotes the action index. For example, Actions 0 to 4 refer to selecting UE 0, Actions 5 and 9 indicate selecting UE 1, so on and so forth. In order to determine how many RBs should be allocated to each UE, the number of RBs needed to transmit \( L_k \), denoted as \( n_k,\text{WB} \), is first calculated based on the wideband (WB) channel quality indicator (CQI) of each UE, where the procedure for obtaining WB CQI is explained in Section II of [4]. The number of RBs allocated to UE \( k \), \( n_k \), is given by

\[
 n_k = n_k,\text{WB} + a \% 5 - 2
\]  

(2)

where \( a \% 5 \) represents the remaining resultant from the division of \( a \) over 5. Intuitively, the five actions associated with UE \( k \) are related to the number of RBs to be allocated based on \( n_k,\text{WB} \). The overall actions and their meanings are detailed in Table I.

Note that variants of the action design described above can also be considered in practice according to specific overhead and/or performance requirements. For instance, the range of actions per UE can be smaller or larger than \( 5K \), i.e., \( n_k \) can be within \( \pm 1 \) with respect to \( n_k,\text{WB} \) to accelerate training and inference processes, or \( \pm 3, \pm 4, \ldots \) with respect to \( n_k,\text{WB} \) to improve scheduling performance. Furthermore, the range of actions per UE can be asymmetric with respect to \( n_k,\text{WB} \).

C. Reward Design

As the scheduling metric is sum-TBS per slot, the reward should incarnate the allocated total TBS in a slot. Therefore, at each allocation step \( i \), the allocated TBS per UE is first calculated, denoted as \( \text{TBS}_k \) for UE \( k \). Next, a temporary quantity \( p_i \) for allocation step \( i \) is computed as

\[
p_i = \min \left( \frac{\sum_{k=0}^{K-1} \text{TBS}_k - \sum_{k=0}^{K-1} L_k}{\sum_{k=0}^{K-1} L_k} \right)
\]  

(3)

The ultimate reward at allocation step \( i \), \( r_i \), is the summation of \( p_j \)’s associated with all the allocation steps up to allocation step \( i \), i.e.,

\[
r_i = \sum_{j=1}^{i} p_j
\]  

(4)

Thus, the reward is always between 0 and 1, which facilitates the training of the deep Q-network.

D. Complexity Analysis

The most prominent advantages of the proposed STAR algorithm over JADE is its superior performance (to be shown later in this work) and its significantly reduced online computational complexity. Assuming each UE needs \( M \) RBs on average, then the total computational complexity of JADE is around \( 3MK^2/2 \) [4], since it necessitates the calculations of the TBS from both ends of the BWP for each UE, the scheduling metric for each UE, as well as repetitions of the above procedure after each UE and resource allocation stage. In contrast, by using STAR, the computational complexity at each allocation step is only 1, since it directly determines which UE and how many RBs should be scheduled without the need to calculate any scheduling metrics and with only one-time TBS calculation, hence substantially reducing the complexity. Therefore, STAR can provide about \( 3MK^2/2 \) times, which can be up to four orders of magnitude, of complexity reduction as compared to JADE. A brief analysis and comparison of the computational complexity of the two algorithms is provided in Table II.

| Algorithm | JADE | STAR |
|-----------|------|------|
| Number of TBS calculation | \( MK^2 \) | 1 |
| Number of scheduling metric calculation | \( 3MK^2 \) | 0 |
| Sum complexity | \( \mathcal{O}(3MK^2) \) | 1 |
| Sum complexity for the case of | | |
| \( K = 30 \), \( B = 270 \), \( M = 10 \), \( M_{\text{RB}} = 4 \) | \( \mathcal{O}(1e4) \) | 1 |

E. Training of Deep Q-Network

In the DRL framework of this work, a deep Q-network acts as the agent. The environment incorporates channel models as well as transmission and reception procedures based on the 3GPP standards such as [1], [2], [10], among others. In each training step, the following processes take place (as shown by Fig. 1): (1) The environment generates the current state \( s \) and passes it to the agent; (2) The agent generates an action \( a \) and feeds it back to the environment; (3) The environment yields the reward \( r \) and the next state \( s' \) based on \( a \), and passes them to the agent; (4) The sequence of state, action, reward, and next state, \( [s, a, r, s'] \), is used to train the deep Q-network, i.e., the
TABLE III: Simulation Settings

| Configuration              | Value          |
|----------------------------|----------------|
| Transmit power             | 23 dBm         |
| Number of gNB antennas     | 4              |
| Cell radius                | 250 m          |
| UE distribution            | Uniform        |
| Number of antennas per UE  | 4              |
| Number of UEs per gNB      | 5              |
| Channel                    | EPA (Extended Pedestrian A model) |
| Numerology                 | 30kHz sub-carrier spacing, 100MHz bandwidth |
| CSI feedback delay         | 1 slot         |
| Traffic model              | remoteDrivingDl, powerDist2 |

IV. NUMERICAL RESULTS

System-level simulations are conducted to evaluate the performance of the proposed algorithm. Table III lists the simulation settings, where the traffic models are remoteDrivingDl and powerDist2 which represent the downlink remote driving scenario and the second type of power distribution grid fault and outage management [11], respectively, both of which belong to URLLC (Ultra-Reliable Low-Latency Communications). The total number of UEs in our simulations is $K = 5$, thus yielding 25 actions. Table IV details the parameters for the traffic models used in our simulations. A three-layer fully-connected neural network is used as the deep Q-network. Besides JADE, we also compare the performance of STAR against a variant of STAR without DRL, i.e., randomly selecting which UE and how many RBs to be scheduled at each allocation step. Performances of the aforementioned three algorithms are illustrated in Fig. 2 where the ratio of powerDist2 and remoteDrivingDl UEs is 1:4. Furthermore, Fig. 3 and Fig. 4 show the performance with different UE ratios, using exactly the same offline-trained DRL model for the case in which the ratio of powerDist2 and remoteDrivingDl UEs is 1:4. The following key observations can be drawn from Figs. 2-4:

1) STAR yields obviously higher TBS than both JADE and random scheduling, demonstrating its superior performance to the two schemes.
2) Applying exactly the same offline-trained RL model to different UE ratios, STAR still yields the best TBS performance, which shows its robustness to UE distributions.
3) STAR surpasses JADE in terms of sum-TBS while having significantly lower computational complexity, thus substantially outperforming JADE considering both system-level performance and computational complexity.

V. CONCLUSION

We have proposed a DRL-based algorithm that jointly schedules UE and contiguous frequency-domain resources. In the proposed method, a deep Q-learning agent module is trained offline to determine which UE and how many RBs for that UE should be scheduled at each allocation step. We design the state, action, and reward sets which are suitable for both the UE/resource allocation problem and DRL implementation/realization. System-level simulations demonstrate that compared to a contiguous FDRA algorithm named JADE proposed in [4], the proposed algorithm enjoys both better performance and significantly lower online computational complexity.

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Fig. 2: Performance of JADE, STAR, and random-scheduling approaches. The ratio of powerDist2 and remoteDrivingDl UEs is 1:4.

Fig. 3: Performance of JADE, STAR, and random-scheduling approaches. The ratio of powerDist2 and remoteDrivingDl UEs is 0:5, and the RL model used for the simulation is with a ratio of powerDist2 and remoteDrivingDl UEs of 1:4.
Fig. 4: Performance of JADE, STAR, and random-scheduling approaches. The ratio of powerDist2 and remoteDrivingDl UEs is 5:0, and the RL model used for the simulation is with a ratio of powerDist2 and remoteDrivingDl UEs of 1:4.