Toward a Smart Resource Allocation Policy via Artificial Intelligence in 6G Networks: Centralized or Decentralized?

Ali Nouruzi, Atefeh Rezaei, Graduate Student Member, IEEE, Ata Khalili, Member, IEEE, Nader Mokari, Senior Member, IEEE, Mohammad Reza Javan, Senior Member, IEEE, Eduard A. Jorswieck Fellow, IEEE, and Halim Yanikomeroglu, Fellow, IEEE

Abstract—In this paper, we design a new smart software-defined radio access network (RAN) architecture with important properties like flexibility and traffic awareness for sixth generation (6G) wireless networks. In particular, we consider a hierarchical resource allocation framework for the proposed smart soft-RAN model, where the software-defined network (SDN) controller is the first and foremost layer of the framework. This unit dynamically monitors the network to select a network operation type on the basis of distributed or centralized resource allocation architectures to perform decision-making intelligently. In this paper, our aim is to make the network more scalable and more flexible in terms of achievable data rate, overhead, and complexity indicators. To this end, we introduce a new metric, throughput overhead complexity (TOC), for the proposed machine learning-based algorithm, which makes a trade-off between these performance indicators. In particular, the decision making based on TOC is solved via deep reinforcement learning (DRL), which determines an appropriate resource allocation policy. Furthermore, for the selected algorithm, we employ the soft actor-critic method, which is more accurate, scalable, and robust than other learning methods. Simulation results demonstrate that the proposed smart network achieves better performance in terms of TOC compared to fixed centralized or distributed resource management schemes that lack dynamism. Moreover, our proposed algorithm outperforms conventional learning methods employed in other state-of-the-art network designs.

Index Terms—SDN controller, 6G, smart network, soft actor-critic method, DRL.

I. INTRODUCTION

The evolution from fifth-generation (5G) to sixth-generation (6G) wireless networks has proceeded along two main lines, which consist of evolving network architecture and evolving communications technologies. As 5G and beyond networks continue to evolve, it will be possible for network architecture and communication technologies to be dynamically adapted in relation to the changing needs of the network. In such a flexible architecture, a huge amount of signaling and computational resources are needed to manage the network resources efficiently.

Due to discrepancies between the mathematical tractability and the exponentially greater complexity of wireless networking, conventional convex optimization approaches are unfortunately ineffective and may not be able to fulfill the precise quality of service (QoS) requirements of emerging applications. To tackle this issue, artificial intelligence has been identified as a promising solution for automatic and autonomous network management. Adopting intelligent resource allocation for wireless networks not only has the potential to replace the manual intermediation needed for current network management tasks, but also presents novel optimization possibilities to ameliorate performance gains in real-time. Since future dense wireless networks will involve high complexity algorithms, machine learning (ML) has emerged as a key enabler to manage high complexity for real-time implementation. In this regard, reinforcement learning (RL) as a type of ML has been employed to learn from an environment by trial and error, which promotes improvements over time. Also, deep reinforcement learning (DRL) has been investigated for comprehensive inputs as well as more accurate results in comparison to RL algorithms [1]. Furthermore, to enable a real-time scheduler for stochastic environments, it has been shown that learning via multiple agents can solve complicated stochastic optimization problems more practically [2]. Although DRL methods have been applied to several resource allocation problems, they have two major challenges: high sample complexity and sensitivity to hyper-parameters [3]. To address these issues, the soft actor-critic algorithm with a maximum entropy objective can be leveraged to provide more accurate and stable solutions for scalable networks in dynamic environments.

With the development of 6G, the baseband function placement in cloud radio access network (C-RAN) can be performed by the software-defined networking (SDN) control/management plane based on a complete knowledge of the network. Also, in the open RAN architecture, this controller could be implemented as a RAN intelligent controller (RIC), which is responsible for controlling and optimizing RAN functions. However, since the aggregation nodes in the access network evolve over time, the knowledge of the network state requires frequent interactions between the controller and network’s entities. It may be desirable to have latency insensitive tasks performed by a centralized unit, while relatively more stringent latency constraints can be performed at edge nodes. Additionally, centralized approaches are not scalable enough to satisfy computational requirements of networks with huge dimensions. To address this, distributed algorithms can be adopted that provide more scalable solutions when adding or removing virtual or physical baseband resources. The high level of flexibility envisioned for 6G can be exploited by designing algorithms that activate baseband functions on demand. As a result of the architectural evolution and flexibility requirements, future network should be able to dynamically adopt the proper resource management strategy, whether it be centralized or distributed. In addition, the choice of transmission technology adopted could take into account
the dynamics of the environment as well as user density and their traffic volume. Consequently, to guarantee real-time services, it is more beneficial to consider both centralized and distributed frameworks depending on network status and QoS requirements. To illustrate this, this paper proposes a new learning based resource allocation framework that considers network status, resource budget, and loads to determine the allocation policy. In fact, in the literature, resource management is typically either centralized or decentralized by default, and software-defined networking decisions have not been investigated to determine the best operation mode. Our research therefore considers the implications for performance of a 6G network that can dynamically and intelligently switch between centralized and distributed network operations.

A. Resource Allocation for Wireless Communication

Let us start by introducing the candidate transmission strategy and the resource allocation frameworks in conventional network architectures. The idea of improving the performance of RAN architecture in 5G and beyond has been considered in the literature, where power domain non-orthogonal multiple access (PD-NOMA) is one of the best candidates for resource allocation policies. Furthermore, several works have tried to model the structure and efficiency of the network and the structure and efficiency of the network by centralizing functionality in a baseband unit (BBU) pool [4], [5]. In [6], a distributed structure was proposed to improve the latency and proficiency of a network.

1) Centralized Resource Allocation: In such architectures, BS information is supposed to be gathered in the centralized controller to perform the overall resource management. In fact, in this scheme, the baseband signals of the distributed units are processed by the central processor for the purpose of effective interference management. In [5], a multi-agent DRL based algorithm was employed for sum-rate maximization in a centralized network. In [7], the authors proposed a DRL based resource allocation policy to enhance the network performance of the multi-carrier NOMA system. However, these works employed a centralized architecture, which entails more signaling between BSs and the centralized controller.

2) Distributed Resource Allocation: In this scheme, resource allocation and management are performed in a distributed manner on the basis of information available locally. The authors in [6] developed a multi-agent DRL based resource allocation policy for the heterogeneous QoS requirements in vehicular networks. In [8], the authors proposed an iterative algorithm for subcarrier assignment and power allocation by using a DRL based method that considered the impact of SIC errors. However, in this scheme, BSs performed local signal processing which degrades the performance of the dense networks due to incorporating interference.

3) Combination of Centralized and Distributed Resource Allocation: In [2], a multi-access edge computing technique was considered that reduced the core network congestion. More specifically, cooperative computation offloading policy was designed for MEC technology using the soft actor-critic (SAC) method for both the centralized and distributed offloading. In [9], a DRL algorithm for vehicular-to-everything (V2X) communication was proposed that determined resource block allocation and performed power control. The DRL algorithm also selected the transmission mode (i.e., vehicle-to-infrastructure [V2I] or vehicle-to-vehicle [V2V]) communications. The authors in [10] performed functional splits of control and data planes between the cloud and edge nodes in C-RAN while taking the fronthaul delay into account. The authors in [11] considered a semi-centralized framework for the resource allocation problem by using matching theory and a successive convex approximation (SCA) approach. Similarly, the authors in [4] proposed a semi-centralized resource allocation scheme to maximize the weighted matching (MWM) problem for integrated access and backhaul (IAB) networks. The authors in [12] compared both centralized and distributed algorithms regarding the BBU hotel location problem in C-RAN where their proposed solution is based on a distributed heuristic algorithm. Moreover, in [13], the authors compared the energy efficiency of their proposed distributed and centralized user association algorithms by sequentially minimizing the power consumption of the heterogeneous network they considered. In each of the aforementioned works, resource allocation was performed in either a centralized or distributed framework; none of the works considered the possibility of dynamically changing the framework. A summary of these works is shown in Table I.

B. Contribution

This paper proposes an intelligent approach approach for determining an effective resource allocation policy in a downlink PD-NOMA network. We consider a network that can switch between centralized and distributed operations for resource management on demand. To the best of our knowledge, a smart network architecture configuration such as this has not been studied yet. Previous works have not considered the changing environmental conditions of networks, and thus are not appropriate for real-world scenarios. Besides, the complexity, overhead, and achievable data rate performance metrics are not considered jointly in the other existing works in the literature while it is important to consider them jointly in selecting the resource management. The capacity of networks to learn autonomously and change their architectures to boost performance will be a critical enabler of next-generation intelligent wireless networks. The main contributions of this paper are summarized as follows:

- In contrast to the conventional approaches that employed a framework for the resource allocation based on the analytical models, an intelligent approach based on the learning methods is exploited for solving the SDN decision and resource allocation problems in a centralized or distributed manner. This approach allows a network to adapt to the environment and perform more effectively in real-world scenarios.
- We introduce a novel algorithm for the SDN controller. This algorithm chooses the best resource allocation policy
In the centralized scheme, we consider the single-agent SAC algorithm at the centralized unit that designates the appropriate actions based on the collected information. Additionally, in the distributed scheme, we consider that there is no information exchange between agents, and that the BSs (as RRSs) locally perform resource allocation tasks based on a multi-agent actor-critic algorithm. This algorithm can be applied to the more complex environments and it provides stable solutions for the network compared to the other learning methods.

- Simulation results indicate a performance gain by employing the SAC methods relative to other ML based (i.e., DDPG and DQN approaches). Furthermore, results demonstrate performance gaps between fixed centralized or fixed distributed schemes with the proposed smart algorithm in which the time complexity, overhead, data rate are considered, simultaneously.

II. System Model and Problem Statement

As shown in Fig. 1, we consider that the RAN network consists of two major units, which we refer to as the access network outer (AN-O) and the access network inner (AN-I). The AN-O is the cloud network, and the AN-I includes $B$ reconfigurable radio systems (RRSs) as local units. The RRSs provide signaling and data coverage for the users. As a result of considering an intelligent network, it is necessary to obtain some efficient feedback about network status to operate the network in a real-time manner. Furthermore, it is assumed that the information can be fed back from the BSs to the AN-O through the control links. Here we consider downlink PD-NOMA network. Also, we assume that all RRSs and users are equipped with single antennas. The AN-O consists of a BBU pool which performs centralized baseband processing, and a centralized SDN controller, which controls the network operation by programming the network’s element functionalities properly. By monitoring the network, the SDN controller determines whether the network would operate in a centralized or distributed manner. We formulate the problem in terms of maximizing the functionality of the network. As we will see, there are two sides to this problem: decision making and resource allocation.

A. Decision-Making Optimization Problem

We consider a comprehensive framework in which the SDN controller switches between centralized and distributed network operations by considering the total data rate and the amount of data exchanged in terms of overhead and complexity.

1) Overhead: As a key performance indicator overhead is a critical key performance indicator at the considered smart network. The overhead is a function of the number of information bits needed to feed back the data of the channel status, subcarrier indicators, and the transmission power of a specific user over a subcarrier. Also, the total number of RRSs, users, and subcarriers in each RRS and in each time slot can affect overhead.

In the centralized mode, the resource allocation task is performed at the BBU, and thus the information needs to be transmitted from the RRSs to the centralized unit. In the distributed mode, by contrast, all tasks related to resource allocation are performed independently by the RRSs without any data exchange.

2) Computational Complexity: The computational complexity of RL-based methods depends on the number of neu-
rons, the DNN layers, the state size, and the action space which is described in [14]. It should be noted that the soft actor-critic method has two DNN layers and the computational complexity of each agent as $O_{agent}$ is a function of the complexity of both DNNs, the number of episodes, and the minibatch size. In this structure, the complexity of each RRS is a linear function of $O_{agent}$, the size of the subcarrier, and the users set in the RRS coverage area.

3) Achievable Data Rate: We define two integer decision making parameters for the centralized and distributed scenarios as $x^{(t)}_{Cnt}$ and $x^{(t)}_{Dst}$, respectively, where $x^{(t)} = \{x^{(t)}_{Cnt}, x^{(t)}_{Dst}\}$. To make a trade-off between data rate, overhead, and complexity, we introduce a new metric as TOC to perform mode selection by considering the data rate, overhead, and complexity functions. Consequently, the decision-making structure for the SDN controller is shown at the top of Fig. 1. In this framework, we consider that in each transmission time slot $t$ only one operation scheme can be selected. More specifically, this algorithm aims to select the best action $a^{(t)}_{SDN}$ as the operation mode based on the network’s traffic, where $a^{(t)}_{SDN}$ determines which of $x^{(t)}_{Cnt}$ and $x^{(t)}_{Dst}$ are more appropriate. It should be noted that this action is based on the determined states $S^{(t)}_{SDN}$ and rewards $r^{(t)}_{SDN}$ in the network. In Fig. 2, we define the states, actions, and rewards for the proposed resource management structure in details.

B. Proposed Solution for the SDN

Here, we provide an efficient algorithm for deciding between the centralized and distributed schemes. The DRL framework for the decision-making problem at the SDN is employed whose states, actions, and rewards are described in Fig. 2. In the SDN algorithm, based on the given state $S^{(t)}_{SDN}$ in each time slot, the SDN selects an action $a^{(t)}_{SDN}$. By taking the action at each time slot, the agent gets a reward $r^{(t)}_{SDN}$ that is defined on the basis of the objective function in $P^{(t)}_{SDN}$. After observing $S^{(t+1)}_{SDN}$, the SDN stores $S^{(t)}_{SDN}, a^{(t)}_{SDN}, r^{(t)}_{SDN}$ and $S^{(t+1)}_{SDN}$ and using Adam [15], a method for efficient stochastic optimization, it minimizes the loss function and updates its decision.

C. Resource Allocation Problem

After the decision-making stage, the resource allocation problem (RAP) is solved using two different schemes. In particular, we formulate the resource allocation problem to maximize the throughput of the network while taking into account the subcarrier allocation and power control based on the downlink PD-NOMA. To solve the problem, we propose a soft actor-critic based resource allocation for the centralized and decentralized scenarios. In what follows, we explain how we solve the resource allocation problem.

1) Centralized Scheme: In the case where $x^{(t)}_{Cnt} = 1$, the RAP is solved on the basis on a single agent soft actor-critic at the BBU pool as shown in Fig. 1. Specifically, in this scheme RRSs act as RRHs in which the radio frequency tasks and the resource allocation process are performed at the BBU pool. Each RRH collects related information and forwards
it to the BBU pool. Drawing on the received information at time slot $t$, the agent chooses action $a_{\text{Cnt}}$. Then, the actions are sent to the RRHs based on the resource allocated in the BBU pool unit. Moreover, the reward $r_{\text{Cnt}}$ and new states $S_{\text{Cnt}}$ are collected and forwarded to the BBU pool through fronthaul links.

2) Decentralized Scheme: In the decentralized scheme (i.e., $x_{\text{Cnt}} = 1$), resource allocation would be done by the RRSs using an independent multi-agent actor critic method. To reduce the overhead, we consider that RRS $b$ in the distributed mode cannot access to the others’ information and just performs the resource allocation tasks by using its own information. The main and target DQNs are implemented at the RRS and each agent computes the power control and subcarrier allocation locally. As we can see in Fig. 2, each RRS $b$ at time slot $t$ observes state $S_{b}(t)$ and takes the action $a_{b}(t)$ individually. Also, it receives the results of its own behavior as the reward $r_{b}(t)$ without knowing the actions of other agents. The proposed algorithm for each actor-critic agent is detailed in Fig. 3.

III. NUMERICAL RESULTS AND DISCUSSION

We consider a coverage area of radius 500 m with four BSs distributed, each covering a radius of 100 m. The maximum transmit power of the BSs are set to 40 dBm, and the total bandwidth is divided into 32 orthogonal subcarriers. The path-gain between a specific user and a BS for RF communication follows the Rayleigh distribution with path loss. The noise power at each subcarrier is assumed $-174$ dBm/Hz.

A. Overhead & Complexity

Fig. 4 illustrates the overhead and complexity of the network based on the different policies (i.e., centralized, distributed, and smart). We assume the set $\{16, 4, 4\}$ as the number of information bits to transmit channel status, subcarrier indicators, and the transmission power in the feedback process. As we can see, the network overhead and complexity for the centralized structure is too high, which leads to numerous difficulties in the network, such as the high delay and low reliability. The overhead and complexity in the distributed network are lower, which makes the distributed architecture preferable for real-time reliable networks. Fig. 4 also shows that the complexity and overhead of the centralized structure are greater in the ultra-dense networks, which makes the centralized policy inefficient for a dense network. This is due to the fact that in the centralized scheme, the complexity and overhead grow linearly due to resource management being performed over all the transmission nodes of the network with information being exchanged between all nodes. In contrast, the complexity and overhead of the distributed scheme are inferior. This indicates that the complexity gap between the two schemes is much more sensible in dense networks with many users. On the other hand, the overhead and complexity of the smart framework closely follow those of the centralized and distributed structures in low and ultra-dense networks, respectively. We remark that although for a single instance
the smart decision selects one of the centralized/distributed approaches, as a result of the existence of different channels that are variable over the time, the overhead and complexity of the smart network on average would occur between two different strict centralized or distributed architecture.

C. New Performance Metric: Throughput Overhead Complexity (TOC)

In this section, we introduce a new metric for evaluating system performance as Throughput Overhead Complexity (TOC) which considers the effect of overhead and complexity in the network. Fig. 6 presents a comparison of TOC values for the centralized, distributed, and proposed smart network frameworks. It is assumed that the number of users in the network varies depending on the level of traffic, from low to heavy. As we can see in Fig. 6, the centralized network shows a moderate performance increase in terms of TOC when the traffic status is low while it experiences a sharp decrease in a dense network. In the distributed network, there is a moderate increase of performance in terms of TOC by increasing the load of the network. At $|K| = 160$ the throughput of the distributed structure exceeds that of the centralized one, and thus the decision-making algorithm here plays a vital role in the network. Another interesting observation in this figure is that the performance gain in terms of the TOC through the learning-based approaches is more efficient than that of DDPG method. This means that although the achieved data rate through the DDPG is higher than that of the ML solutions, the complexity of the DDPG in the centralized manner is very high, which deteriorates the performance gain in terms of TOC.

IV. Conclusion

In this paper, we proposed a hierarchical network management framework that adopts the best resource allocation policy in relation to changes in network status. The proposed intelligent framework is density aware, which guarantees the
network’s performance on the basis of the DRL algorithm. We investigated three different scenarios (i.e., fixed centralized, fixed distributed, and dynamic) for different levels of network traffic. Simulation results showed that the proposed algorithm not only performs better than conventional learning methods in terms of TOC, but that it also outperforms both fixed centralized and distributed resource allocation policies.

REFERENCES

[1] W. Lee, O. Jo, and M. Kim, “Intelligent resource allocation in wireless communications systems,” IEEE Communications Magazine, vol. 58, no. 1, pp. 100–105, 2020.

[2] C. Sun, X. Wu, X. Li, Q. Fan, J. Wen, and V. C. Leung, “Cooperative computation offloading for multi-access edge computing in 6G mobile networks via soft actor critic,” IEEE Transactions on Network Science and Engineering, Early Access, 2021.

[3] T. Haarnoja, A. Zhou, K. Hartikainen, G. Tucker, S. Ha, J. Tan, V. Kumar, H. Zhu, A. Gupta, P. Abbeel, and S. Levine, “Soft actor-critic algorithms and applications,” 2018.

[4] M. Pagin, T. Zagno, M. Polese, and M. Zorzi, “Resource management for 5G NR integrated access and backhaul: a semi-centralized approach,” IEEE Transactions on Wireless Communications, 2021.

[5] A. A. Khan and R. Adve, “Centralized & distributed deep reinforcement learning methods for downlink sum-rate optimization,” IEEE Transactions on Wireless Communications, vol. 19, no. 12, pp. 8410–8426, 2020.

[6] J. Tian, Q. Liu, H. Zhang, and D. Wu, “Multi-agent deep reinforcement learning based resource allocation for heterogeneous QoS guarantees for vehicular networks,” IEEE Internet of Things Journal, p. Early Access, 2021.

[7] C. He, Y. Hu, Y. Chen, and B. Zeng, “Joint power allocation and channel assignment for NOMA with deep reinforcement learning,” IEEE Journal on Selected Areas in Communications, vol. 37, no. 10, pp. 2200–2210, 2019.

[8] S. Wang, T. Lv, W. Ni, N. C. Beaulieu, and Y. Guo, “Joint resource management for MC-NOMA: A deep reinforcement learning approach,” IEEE Transactions on Wireless Communications, vol. 20, no. 9, pp. 5672–5688, 2021.

[9] X. Zhang, M. Peng, S. Yan, and Y. Sun, “Deep-reinforcement-learning-based mode selection and resource allocation for cellular V2X communications,” IEEE Internet of Things Journal, vol. 7, no. 7, pp. 6380–6391, 2019.

[10] W. Xia, T. Q. S. Quek, J. Zhang, S. Jin, and H. Zhu, “Programmable hierarchical C-RAN: From task scheduling to resource allocation,” IEEE Transactions on Wireless Communications, vol. 18, no. 3, pp. 2003–2016, 2019.
[11] A. Rezaei, P. Azmi, N. Mokari, M. R. Javan, and H. Yanikomeroglu, “Robust resource allocation for cooperative MISO-NOMA-based heterogeneous networks,” IEEE Transactions on Communications, vol. 69, no. 6, pp. 3864–3878, 2021.

[12] B. Khorsandi, F. Tonini, and C. Rafaelli, “Centralized vs. distributed algorithms for resilient 5G access networks,” Photonic Network Communications, vol. 37, no. 3, pp. 376–387, 2019.

[13] M. J. Kalbasi and S. Valae, “Centralized and distributed algorithms for energy and spectrum efficient user association in small cell networks,” IEEE Transactions on Green Communications and Networking, vol. 5, no. 4, pp. 1781–1790, 2021.

[14] A. Khalili, E. M. Monfared, S. Zargari, M. R. Javan, N. Mokari, and E. A. Jorswieck, “Resource management for transmit power minimization in uav-assisted ris hetnets supported by dual connectivity,” IEEE Transactions on Wireless Communications, pp. 1–1, 2021.

[15] D. P. Kingma and J. L. Ba, “Adam: A method for stochastic optimization,” in Proc. Int. Conf. Learn. Represent, pp. 1–41, 2015.