Intelligence and Learning in O-RAN for Data-driven NextG Cellular Networks

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Abstract—Next Generation (NextG) cellular networks will be natively cloud-based and built upon programmable, virtualized, and disaggregated architectures. The separation of control functions from the hardware fabric and the introduction of standardized control interfaces will enable the definition of custom closed-control loops, which will ultimately enable embedded intelligence and real-time analytics, thus effectively realizing the vision of autonomous and self-optimizing networks. This article explores the disaggregated network architecture proposed by the O-RAN Alliance as a key enabler of NextG networks. Within this architectural context, we discuss the potential, the challenges, and the limitations of data-driven optimization approaches to network control over different timescales. We also present the first large-scale integration of O-RAN-compliant software components with an open-source full-stack softwarized cellular network. Experiments conducted on Colosseum, the world’s largest wireless network emulator, demonstrate closed-loop integration of real-time analytics and control through deep reinforcement learning agents. We also show the feasibility of Radio Access Network (RAN) control through xApps running on the near real-time RAN Intelligent Controller, to optimize the scheduling policies of co-existing network slices, leveraging the O-RAN open interfaces to collect data at the edge of the network.

I. INTRODUCTION

The fifth (5G) and sixth generations (6G) of cellular networks will undoubtedly accelerate the transition from inflexible and monolithic networks to agile, disaggregated architectures based on softwarization and virtualization, as well as on openness and re-programmability of network components [1]. These novel architectures are expected to become enablers of new functionalities, including the ability to: (i) Provide on-demand virtual network slices that, albeit sharing the same physical infrastructure, are tailored to different mobile virtual network operators, network services and run-time traffic requirements; (ii) split network functions across multiple software and hardware components, possibly provided by multiple vendors; (iii) capture and expose Key Performance Indicators (KPIs) and network analytics through open interfaces that are not available in old architectures, and (iv) control the entire network physical infrastructure in real time via third party software applications and open interfaces.

A. Disaggregation and Programmability in O-RAN

The O-RAN Alliance—a consortium of industry and academic institutions—is working toward realizing the vision of Next Generation (NextG) cellular networks, where telecom operators use standardized interfaces to control multi-vendor infrastructures and deliver high performance services to their subscribers [2]. To achieve this goal, the Alliance proposes an architectural innovation based on two core principles. First, O-RAN embraces and promotes the 3rd Generation Partnership Project (3GPP) functional split, where Base Station (BS) functionalities are virtualized as network functions and divided across multiple network nodes, i.e., Central Unit (CU), Distributed Unit (DU) and Radio Unit (RU) [1]. This facilitates the instantiation and execution of diverse networking processes at different points of the network. Specifically, CUs implement functionalities at the higher layers of the protocol stack operating over larger timescales, while DUs handle time-critical operations at the lower layers. Finally, the RUs manage Radio Frequency (RF) components and lower Physical (PHY) layer parts.

The second core innovation—which is likely to be even more impactful—is the Radio Access Network (RAN) Intelligent Controller (RIC), a new architectural component that provides a centralized abstraction of the network, allowing operators to implement and deploy custom control plane functions. In both its non and near real-time versions, the RIC facilitates RAN optimization through closed-control loops, i.e., autonomous action and feedback loops between RAN components and their controllers. O-RAN envisions different loops operating at timescales that range from 1 ms (e.g., for real-time control of transmission strategies) to thousands of milliseconds (e.g., for network slicing and traffic forecasting). For instance, the non real-time RIC performs operations with a time granularity higher than one second, such as training of Artificial Intelligence (AI) and Machine Learning (ML) models. The near real-time RIC instead handles procedures at timescales above 10 ms, hosts third party applications (xApps) that communicate with the CU/DU through standardized open interfaces, and implements intelligence in the RAN through data-driven control loops.
Figure 1 illustrates one of the possible disaggregated deployments specified by O-RAN, where different network components are connected by open interfaces.

In this deployment ("Scenario B", deemed the most common), the RICs are deployed in the cloud. They interact with each other via the A1 and O1 interfaces, and control specific parameters of the RAN defined through the so-called Service Models (SMs). The CU and DU are deployed at the network edge, interconnected through the F1 interface and controlled by the near real-time RIC via the E2 interface. The RU is located at the operator cell site, and controlled by the DU through the Open Fronthaul interface. Finally, CU, DU and RU are connected to the non real-time RIC through the O1 interface for periodic reporting. Other deployment options allow to instantiate RICs and CUs in the edge or regional cloud (Scenarios A and C-F, respectively); the DU in the edge cloud (A-D); and the RU at the operator cell site (A-D) or in the cloud cell site, possibly co-located with the DU (E, F).

B. Contributions

While the O-RAN architectural vision is gaining momentum among researchers, the challenges of implementing it for data-driven, open, programmable and virtualized NextG networks are still largely to be dealt with. Important architectural questions are yet to be answered, including (i) the exact functionalities and parameters to be controlled by each network component; (ii) where to place network intelligence; (iii) how to validate and train data-driven control loop solutions, and (iv) how AI agents can access data and analytics from the RAN while minimizing the overhead of moving them from the RAN to the storage and inference locations. To answer these questions, we provide the following contributions.

- We discuss how data-driven, closed-control loop solutions can be implemented in NextG RANs. We focus on the opportunities offered by the O-RAN architecture, including functional split and open interfaces, and on their role in advancing intelligent and programmable networks.
- Different from prior work [1], [4], we investigate the limitations of the current O-RAN specifications and the challenges associated with deploying data-driven policies at different nodes of the RAN.
- We discuss how large-scale experimental testbeds will play a key role by providing researchers with heterogeneous and large datasets, critical to the success of data-driven solutions for cellular networks. We focus on the three PAWR platforms, i.e., POWDER [5], COSMOS [6], and AERPAW [7], and on Colosseum and Arena [8], which can all be used to generate massive datasets under a variety of network configurations and RF conditions.
- We provide the first demonstration of an O-RAN data-driven control loop in a large-scale experimental testbed using open-source, programmable RAN and RIC components. We deploy O-RAN on the Colosseum network emulator and use it to control multiple network slices instantiated on 4 Software-defined Radio (SDR) BSs serving 40 SDR User Equipments (UEs).
- We develop a set of Deep Reinforcement Learning (DRL) agents as RIC xApps to optimize key performance metrics for different network slices through data-driven closed-control loops. Experimental results show that our DRL approach outperforms other control strategies improving spectral efficiency by up to 20% and reducing buffer occupancy by up to 37%. We released the DRL agents and the 7 GB dataset used to train them [1].

The remainder of this article is organized as follows. We first discuss how intelligent control schemes can be embedded in the O-RAN architecture. We then present how experimental testbeds can foster the development of data-driven solutions. Finally, we present our experimental evaluation and draw our conclusions.

II. INTELLIGENT WIRELESS ARCHITECTURES

Openness, programmability, and disaggregation are key enablers of data-driven applications. However, they are only the first step toward the seamless integration of AI and ML-based control loops in cellular networks. Typically, data-driven approaches involve several steps, ranging from data collection and processing, to training, model deployment and closed-loop control and testing.

This section illustrates how O-RAN is steering 5G deployments to bring intelligence to the network, by defining a practical architecture for the swift execution of data-driven operations, and discusses extensions to control procedures not currently considered by O-RAN.

Data Handling and Training Procedures. The effectiveness of data-driven approaches heavily depends on how data is handled, starting from data collection and aggregation at the RAN (where data is generated) to the point where it is processed for model training and inference. However, collecting and moving large amounts

https://github.com/wineslab/colosseum-oran-commag-dataset
of data might result in significant overhead and latency costs. Hence, data-driven architectures must cope with tradeoffs between centralized approaches—providing a comprehensive view of the state of the network at the cost of overhead and latency—and distributed ones—which operate at the edge only, gather data from a small number of sources while enjoying low latency [9].

In this context, the O-RAN ML specifications introduce standardized interfaces (e.g., O1) to collect and distribute data across the entire infrastructure as well as operational guidelines for the deployment of ML and AI solutions in the network [10]. These include practical considerations on how, where and when models can be trained, tested and eventually deployed in the network. First, AI/ML models are made available to operators via a marketplace system similar to that of the well-established Network Function Virtualization (NFV) Management and Orchestration (MANO) architecture, where models are stored in a catalog together with details on their control objectives, required resources, and expected inputs and outputs. Second, data-driven solutions must be trained and validated offline to avoid causing inefficiencies—or even outages—to the RAN. Indeed, since AI/ML techniques usually rely upon a randomized initialization, O-RAN requires all ML models to be trained and validated offline before their deployment [10]. As we will discuss next, albeit shielding the network from unwanted behavior, this requirement also limits the effectiveness of such approaches, especially the online ones. Online AI/ML techniques could still be used in O-RAN compliant architectures by allowing models to be trained with offline data in the non real-time RIC, and then perform online learning in the near real-time RIC. The smaller time-scale of the control loops of the latter would in fact allow the online training pipeline to be fed with data collected in real time.

**Control Loops.** Figure 2 portrays how intelligence can be embedded at different layers and entities of a disaggregated cellular network together with the challenges and limitations of doing so. Each closed-control loop optimizes RAN parameters and operations by running at different timescales, with different number of UEs, and using different sources for the input data. The O-RAN Alliance is also looking into how to standardize the data-driven workflows for these control loops. As of this writing, O-RAN only considers non and near real-time loops, while real-time loops are left for future studies. Figure 2 also depicts the additional inference timescale below 1 ms to process raw I/Q samples and perform AI-driven PHY layer tasks, currently not part of O-RAN as it would require device- and/or RU-level standardization.

To better highlight the potential and limitations of the approach proposed by O-RAN, in the following we analyze each control loop individually, highlighting the role of each network component. Finally, we discuss how the current O-RAN architecture can be extended to realize the control loops and applications illustrated in Fig. 2.

**A. Non Real-time Control Loop**

The O-RAN Alliance defines non real-time any control loop that operates on a timescale of at least one second. As shown in Fig. 2 this involves the coordination between the non real-time and near real-time RIC through the A1 interface. This control loop manages the orchestration of resources at the infrastructure level, making decisions and applying policies that impact thousands of devices. These actions can be performed using data-driven optimization algorithms processing data from multiple sources, and inference models deployed on the non real-time RIC itself.

Practical examples of non real-time data-driven control include instantiating and orchestrating network slices, as well as selecting which pre-trained inference models in the catalog should be deployed to accomplish operator intents, and deciding in which near real-time RIC these models should be executed. Said decisions can be made according to a variety of factors, ranging from computational resources and data availability to minimum
performance requirements to comply with service level agreements. Moreover, since the non real-time RIC is endowed with service management and orchestration capabilities, this control loop can also handle the association between the near real-time RIC and the DUs/CUs. This is particularly useful in virtualized systems where DUs and CUs are dynamically instantiated on-demand to match the requests and load of the RAN. However, non real-time loops are challenging to actuate in practice because of the very many interactions among the non real-time RIC and the network elements, which require tight coordination, data collection and orchestration capabilities.

B. Near Real-time Control Loops

Near real-time control loops operate on a timescale between 10 ms and 1 s. As shown in Fig. 2, they run between the near real-time RIC and two components of the Next Generation Node Bases (gNBs): The CU and the DU. Because one near real-time RIC is associated to multiple gNBs, these control loops can make decisions affecting up to thousands of UEs, using user-session aggregated data and Medium Access Control (MAC)/PHY layer KPIs. ML-based algorithms are implemented as external applications, i.e., xApps, and are deployed on the near real-time RIC to deliver specific services such as inference, classification, and prediction pipelines to optimize the per-user quality of experience, controlling load balancing and handover processes, or the scheduling and beamforming design. Challenges of near real-time control loops include the need to promptly make decisions in a matter of tens or hundreds of milliseconds for each of the several CUs and DUs controlled by the RIC.

C. Real-time Control Loops

A crucial component of the operations of a cellular network involves actions at a sub-10 ms—or even sub-ms—timescale. In O-RAN, these operations are labeled as real-time control loops, and mainly concern interactions between elements in the DU. Control loops at a similar timescale could also be envisioned to operate between the DU and the RU, or at the UEs. However, as deploying ML solutions at the DU is not currently supported, these loops are left for future extensions of the O-RAN specifications.

Finally, data-driven approaches at the lower layers of the protocol stack or at the device, i.e., involving sub-ms timescales, are extremely powerful and can be used for data-driven scheduling decisions [1] and for feedbackless detection of PHY layer parameters (e.g., modulation and coding scheme, and interference recognition) [2]. Overall, the fact that device-/RU-level standardization is required for sub-ms loops makes it very challenging to realize them in practice, thus limiting their applicability.

III. OPEN WIRELESS DATA FACTORIES

Data-driven approaches aim at autonomously managing the network requiring little to no human intervention. Training and testing algorithms and data-driven closed-control loop policies require large amounts of data gathered in diverse scenarios, with varying traffic patterns, requirements and user behaviors, so that the resulting policy is effective when deployed in real networks.

Access to the massive amounts of data needed for training, however, is usually a privilege that only telecom operators enjoy. Owing to privacy and competition concerns, operators seldom share such data openly with the research community. As a consequence, researchers and practitioners are often constrained to rely on datasets collected in small laboratory setups, which seldom capture the variety and scale of real cellular deployments. In the context of intelligent networking for NextG cellular systems, large-scale wireless testbeds are needed for developing, training and testing new data-driven solutions, serving as open wireless data factories for the community. Such open platforms would facilitate massive data collection in realistic and diverse wireless deployments [1].

The city-scale platforms of the U.S. National Science Foundation PAWR program promise to be a valuable tool to provide the community with the desired diversity of scenarios and scale. The program is currently supporting three open testbeds representative of a variety of wireless use-cases, ranging from state-of-the-art SDRs and massive Multiple Input, Multiple Output (MIMO) communications (POWDER, in Salt Lake City, UT [5]), to ultra-high capacity and low-latency wireless networks (COSMOS, in New York City [6]), and to aerial wireless communications (AERPAW, in the Research Triangle of North Carolina [7]). All three platforms provide users with data generation and analysis tools [1]. Arena is a SDR ceiling testbed that allows to study MIMO, cellular and Internet of Things (IoT) applications with up to 64 antennas deployed in an 8 × 8 grid in an office space [8].

Another instrument for wireless research at scale is Colosseum, the world’s largest wireless network emulator with hardware-in-the-loop. Colosseum includes 128 compute nodes, called Standard Radio Nodes (SRNs), equipped with USRP X310 SDRs that can be used to run generic protocol stacks. These are connected in a mesh topology through 128 additional USRPs X310 of the Massive Channel Emulator (MCHEM) for emulating realistic RF scenarios. The wireless channel between each pair of devices is modeled through complex-valued finite impulse response filter taps. In this way, scenarios are able to capture effects such as path loss, multi-path and fading as if the SDRs were operating in a real RF environment.
Colosseum is also equipped with an edge datacenter, with 900 TB of storage and the capability of processing RF data at a rate of 52TB/s, enabling massive data collection and testing of ML algorithms on heterogeneous networks.

IV. USE CASE: SCHEDULING CONTROL IN SLICED 5G NETWORKS THROUGH THE O-RAN RIC

This section showcases an example of a data-driven closed-loop control implemented using the O-RAN Software Community near-real-time RIC and an open cellular stack on Colosseum (Fig. 3). We demonstrate the feasibility of a closed-control loop where DRL agents running in xApps on the near real-time RIC select the best-performing scheduling policy for each RAN slice.

**Experimental Scenario.** We have emulated a 5G network with 4 BSs and 40 UEs (Fig. 3, left) in the dense urban scenario of Rome, Italy. The locations of the BSs have been extracted from OpenCelliD (a database of real-world cellular deployments) and cover an area of 0.11 km². Downlink and uplink frequencies have been set to 0.98 and 1.02 GHz, respectively; the channel bandwidth to 3 MHz. While these parameters might be atypical for 5G, their choice depends on the Colosseum environment. We note, however, that this does not affect our findings on how data-driven solutions improve the RAN performance.

We consider a multi-slice scenario in which UEs are statically assigned to a slice of the network and request three different traffic types, i.e., high capacity Enhanced Mobile Broadband (eMBB), Ultra Reliable and Low Latency Communication (URLLC), and Machine-type Communications (MTC). This reflects the case, for instance, of telecom operators providing different levels of service to different devices (e.g., MTC service to IoT-enabled devices, or URLLC to devices for time-critical applications). The BSs serve each slice with a dedicated—and possibly different—scheduling policy, selecting among Proportionally Fair (PF), Waterfilling (WF), and Round Robin (RR) [12]. We also consider the case where the number of Physical Resource Blocks (PRBs) allocated to each slice varies over time [14], [15].

We used srsLTE to implement our softwarized cellular network. This open-source framework, which has recently been renamed “srsRAN” to reflect a new focus toward 5G NR, provides a full-stack implementation of BSs and UEs, as well as a lightweight core network. Although this framework is not yet fully compliant with the NR specifications, we are confident that our DRL-based approach enabled by O-RAN can be easily extended to future NR-compliant versions of this (or of any other) software where BSs expose control interfaces to the network. For ease of prototyping, we co-located the core network on the same SRN that also runs the BS application. For the purposes of our work, this setup is equivalent to deploying the core network on a dedicated SRN (see Fig. 3). We extended the BS implementation to include network slicing capabilities and additional scheduling policies [15]. The scenario we considered concerns pedestrian user mobility with time-varying path-loss and channel conditions. Traffic among BSs and UEs is generated through the Colosseum Traffic Generator (TGEN), configured to send different traffic types to UEs of different slices, i.e., eMBB (1 Mbps constant bitrate traffic), URLLC (Poisson traffic, with 10 pkt/s of 125 bytes) and MTC (Poisson traffic, with 30 pkt/s of 125 bytes). For each BS, the UE-slice allocation is as follows: eMBB and URLLC slices serve 3 UEs each, while MTC slices serve 4 UEs. We embedded the DRL agents into xApps running in the near real-time RIC (right of Fig. 3), for a total of 12 DRL agents running in parallel and making decisions with a time granularity of 500 ms. Agents connect with the network BSs through the O-RAN E2 interface. This interface is composed of two
elements: The application protocol, and the SM [3]. The former defines the set of messages that the near real-time RIC and the RAN nodes can exchange, and the procedures for the RAN node subscription to the RIC. The SM, instead, defines which parameters of the RAN nodes can be controlled by the RIC to achieve a given closed-loop control objective. Specifically, the E2 interface exposes analytics and the scheduler policy selection using a custom SM. As shown in Fig. 3, xApps interface with the BSs through the O-RAN E2 manager, which ultimately connects with the BSs via the E2 interface. Other components of the RIC include the RIC database, which keeps entries on the connected BSs, the training engine, and the ML model catalog, which deploys the DRL model chosen by the telecom operator on the near real-time RIC. Finally, messages internal to the RIC are managed by the RIC Message Router, a library which associates message types to destination endpoints.

**DRL Agent Training.** To train our DRL agents we generated some 7 GB of training data of various performance metrics (e.g., throughput and bit error rate), system state information (e.g., transmission queue size, signal-to-interference-plus-noise ratio, and channel quality information) and resource allocation strategies (e.g., slicing and scheduling policies) by running a total of 89 hours of experiments on Colosseum. Each DRL agent has been trained via the Proximal Policy Optimization (PPO) algorithm to manage a single slice for fine-grained and flexible control of the whole cellular network. Agents have been trained under network configurations obtained by varying the distance between BSs and UEs and the mobility of the UEs. Testing has been performed in the most challenging setup, which includes the random mobility of the UEs. Although the training is performed with the same topology configuration, we notice that our agents are topology-independent, as each of them controls a single slice for a given BS. Specifically, agents process the performance metrics received by the BS they are controlling—which possibly expresses the performance of several UEs—through an encoder. This allows them to cast the dimensionality of the input data to a fixed size and to process it regardless of the number of active UEs of the slice. As a consequence, the DRL agents do not need to be aware of the number of UEs and BSs in the network, which makes our approach general and scalable. Through the RIC Indication messages sent via the O-RAN E2 interface (Fig. 3), the agent is fed real-time performance measurements of the slice it controls. These messages generate an overhead of 72 bytes/s per UE. Data goes through an encoder for dimensionality reduction and is then used by the agent to identify the state of the system. The agent uses a fully connected neural

![](image1)

**Experimental Results.** Figure 4 shows the Cumulative Distribution Function (CDF) of the downlink spectral efficiency of the eMBB slice. We compare the performance of the network when DRL agents dynamically select the best scheduling strategy among RR, PF and WF against the case where scheduling strategies are fixed over time. Our results clearly indicate that data-driven optimization outperforms fixed policies by delivering gains in spectral efficiency that are up to 20% higher than that of the best performing static policy. This is due to the fact that eMBB traffic requires high data-rates and DRL agents are capable of dynamically adapting scheduling decisions to the current network state and traffic demand.

![Fig. 5: Downlink buffer size of the URLLC slice for different scheduling policies and with DRL control.](image2)
buffer size indicates timely data delivery to requesting UEs; higher buffer size results in higher latency due to packets waiting in the queue. Results show that DRL agents serve the UEs faster than the static policies, resulting in a lower latency. Particularly, the average buffer size of the URLLC slice when using DRL control is 37%, 5% and 17% smaller than that of the RR, WF and PF scheduling policies, respectively. The DRL agent also significantly outperforms the WF policy between the 50th and 90th percentiles.

Figure 6 depicts how often DRL agents select specific scheduling policies as a function of the number of PRBs of each slice. The bigger the circle, the higher the probability of selecting a given policy. We observe that MTC and eMBB DRL agents select WF with 99% probability. Also, eMBB agents select RR with 4% probability when only a few PRBs are allocated to the slice. On the contrary, URLLC DRL agents are likely to select both PF and WF scheduling policies even when more PRBs are available. These results show that adapting control strategies to current network state and traffic requirements is essential to achieve remarkable performance improvements (Fig. 4 and 5). DRL agents dynamically select the best performing scheduling strategy based on available resources and current network state, providing performance gains simply unattainable with static scheduling policies.

V. CONCLUSIONS

In this article we provide a path and a demonstration of the feasibility of integrating closed-control loops in cellular networks. We first review key enablers, namely, virtualization, disaggregation, openness and reprogrammability of NextG cellular networks, using O-RAN as an exemplary technology. We then discuss which data-driven control loops can be implemented, their timescale, and whether the current O-RAN architecture supports them. We finally show how large-scale experimental testbeds can be used to develop and validate data-driven algorithms by deploying a DRL-based O-RAN RIC on Colosseum. Our results show that using closed-control loops can provide a strong foundation toward the full realization of future generation, data-driven, autonomous, and self-optimizing cellular networks.

REFERENCES

[1] L. Bonati et al., “Open, Programmable, and Virtualized 5G Networks: State-of-the-Art and the Road Ahead,” Computer Networks, vol. 182, pp. 1–28, Dec. 2020.
[2] O-RAN Working Group 1, “O-RAN Architecture Description - v2.00,” Technical Specification, 2020.
[3] O-RAN Working Group 3, “O-RAN Near-real-time RAN Intelligent Controller Architecture & E2 General Aspects and Principles - v1.01,” Technical Specification, 2020.
[4] S. Niknam et al., “Intelligent O-RAN for Beyond 5G and 6G Wireless Networks,” arXiv:2005.08374 [eess.SP], May 2020.
[5] J. Breen et al., “POWDER: Platform for Open Wireless Data-driven Experimental Research,” in Proc. of ACM WiNTECH, London, UK, Sept. 2020.
[6] D. Raychaudhuri et al., “Challenge: COSMOS: A City-Scale Programmable Testbed for Experimentation with Advanced Wireless,” in Proc. of ACM MobilCom, London, UK, Sept. 2020.
[7] M. Sichitiu et al., “AERPAW Emulation Overview,” in Proc. of ACM WiNTECH, London, UK, Sept. 2020.
[8] L. Bertizzolo et al., “Arena: A 64-antenna SDR-based Ceiling Grid Testing Platform for Sub-6 GHz 5G-and-Beyond Radio Spectrum Research,” Computer Networks, vol. 181, Nov. 2020.
[9] M. Polese et al., “Machine Learning at the Edge: A Data-Driven Architecture with Applications to 5G Cellular Networks,” IEEE Transactions on Mobile Computing, pp. 1–16, June 2020.
[10] O-RAN Working Group 2, “O-RAN AI/ML Workflow Description and Requirements - v1.01,” Technical Specification, 2020.
[11] S. Chinchali et al., “Cellular Network Traffic Scheduling With Deep Reinforcement Learning,” in AAAI, 2018, pp. 766–774.
[12] T. O’Shea and J. Hoydis, “An Introduction to Deep Learning for the Physical Layer,” IEEE Transactions on Cognitive Communications and Networking, vol. 3, no. 4, pp. 563–575, Oct. 2017.
[13] L. Bonati et al., “Celios: Zero-touch Softwarized Open Cellular Networks,” Computer Networks, vol. 180, pp. 1–13, Oct. 2020.
[14] S. D’Oro, F. Restuccia, and T. Melodia, “The Slice is Served: Enforcing Radio Access Network Slicing in Virtualized 5G Systems,” in Proc. of IEEE INFOCOM, Paris, France, May 2019.
[15] S. D’Oro et al., “SI-EDGE: Network Slicing at the Edge,” in Proc. of ACM Mobihoc, Virtual Event, Oct. 2020.

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