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AI/ML Enabled Automation System for Software Defined Disaggregated Open Radio Access Networks: Transforming Telecommunication Business

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Abstract: Open Air Interface (OAI) alliance recently introduced a new disaggregated Open Radio Access Networks (O-RAN) framework for next generation telecommunications and networks. This disaggregated architecture is open, automated, software defined, virtual, and supports the latest advanced technologies like Artificial Intelligence (AI) Machine Learning (AI/ML). This novel intelligent architecture enables programmers to design and customize automated applications according to the business needs and to improve quality of service in fifth generation (5G) and Beyond 5G (B5G). Its disaggregated and multivendor nature gives the opportunity to new startups and small vendors to participate and provide cheap hardware software solutions to keep the market competitive. This paper presents the disaggregated and programmable O-RAN architecture focused on automation, AI/ML services, and applications with Flexible Radio access network Intelligent Controller (FRIC). We schematically demonstrate the reinforcement learning, external applications (xApps), and automation steps to implement this disaggregated O-RAN architecture. The idea of this research paper is to implement an AI/ML enabled automation system for software defined disaggregated O-RAN, which monitors, manages, and performs AI/ML-related services, including the model deployment, optimization, inference, and training.

Key words: Open Radio Access Networks (O-RAN); Flexible Radio access network Intelligent Controller (FRIC); Reinforcement Learning (RL); external Applications (xApps); Artificial Intelligence (AI); Machine Learning (ML), sixth generation (6G)

1 Introduction

The upcoming software defined automated networks, called sixth generation (6G), is a revolutionary technology which eliminates bandwidth, latency, energy efficiency, and performance limits on worldwide connectivity. 6G is expected to transform telecommunication networks from the Internet of Everything (IoE) to Intelligent Networks by enabling Artificial Intelligence Machine Learning (AI/ML) applications to connect trillion of sensors, computational devices, and mobile devices and machines. 6G is positioned as a cutting-edge business technology that enhances lifestyles worldwide through innovative applications, like connected autonomous systems, smart grid & energy management, advance remote sensing & imaging, smart healthcare, extended reality, flying vehicles, robotics, and telemedicine. For successful implementation of these use-cases, 6G systems must offer near real-time low latency, wide bandwidth, wide coverage & connectivity, better energy efficiency, wide frequency band (in THz), and

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intelligent automated applications across multivendor devices. A versatile network is required to enable the co-existence of various services by considering all their unique features. The traditional Open Radio Access Networks (O-RAN) do not support all these services, therefore O-RAN optimization is the need of time and new business opportunities. The private sector and academic community are employing virtual and programmable technologies, like Software Defined Network (SDN), to enhance the software orientation, intelligence, and energy efficiency of mobile radio networks. These advancements aim to fulfill the specific service demands. Another approach to increase adaptability and intelligence is to divide the Radio Access Network (RAN) component into functional layers, aligning with the needs of the mentioned services.

The new O-RAN architecture represents a significant paradigm shift with aims to move the telecommunication and network providers towards the AI/ML enabled automation system for software-defined disaggregated O-RAN. The fundamental concept of O-RAN is to pull the key programmable components from the computing hardware and control and manage them through automated software programs. The disaggregated components will communicate and connect via open and standardized interfaces, like E2, A1, O1, etc. In order to accommodate automated programed applications, O-RAN has created a Flexible Radio access network Intelligent Controller (FRIC). In order to improve RAN management, monitoring, orchestration, and performance, and simplify operational tasks, FRICs supports Machine Learning (ML) applications. 6G caters to the demands of future telecommunication and network businesses by implementing real-time operations, such as radio resources selection, like channels, device mobility management, and frequency administration. These processes include device real-time resource allocation and arrangement, energy allocation, and real-time radio link connection, all tailored to encounter the exact requirements of numerous applications.

Programmability, virtual, and openness are the important characteristics of O-RAN, however the key point is to upgrade the existing designs to ones that are smarter and more autonomous. O-RAN is designed to support the latest technologies and data science tools to optimize and automate the O-RAN system. An essential requirement for introducing a high level of intelligence is the development of a robust architecture design that enables algorithms to nonstop understand and effectively utilize system data. In order to support Artificial Intelligence (AI) and ML capabilities, as well as manage the growing complexity of envisioned networks, the O-RAN functionality and building blocks need to be extended beyond traditional manually programmed approaches. The initial step towards allowing AI and ML algorithms to manage advanced RAN functions is the implementation of flexible system disaggregation and open interfaces. These fundamental concepts enable operators to separate RAN elements from distinct manufacturers while maintaining compatibility & interoperability among multiple vendors.

Disaggregated O-RAN results serve as the foundation by handing over management to AI and ML algorithms. The placement of advanced models and the adoption of intelligent agent-based systems are particularly significant for addressing complex problems that demand high levels of security and trust. The near-Real-Time RAN Intelligent Controller (near-RT RIC) and the non-Real-Time RAN Intelligent Controller (non-RT RIC) are crucial entities that show a pivotal role in the new automated system for disaggregated O-RAN. These controllers determine the optimisation justification of O-RAN operations based on their respective decision timescales, with the near-RT RIC focusing on minimizing latency. Additionally, the functionality of the Central Unit (CU) and Distributed Unit (DU) programmable intelligent controllers are complemented by the availability of apps. As these applications are programmable, open, and flexible for implementation and deployment on both the non-RT RIC and near-RT RIC, depending on the use cases. Non-RT RIC monitors long-term trends and patterns for telecommunication resources performance, and employs AI/ML methods to perform corrective actions through Service Management and Orchestration (SMO) reconfiguration via O1 interface or via creation of A1 policies. Non-RT RIC trains relevant AI/ML models deployed at near-RT RIC. On the other hand, near-RT RIC enables optimized RAN actions through execution of deployed AI/ML models in near-real-time by considering both O1 configuration and received A1 policies. Disaggregated O-RAN is, in general, revolutionizing the telecom industry by fostering vendor diversity, flexibility, interoperability, cost effectiveness, automation, innovation, and cooperation. It gives telecom operators the ability to create networks that are more adaptable, scalable, and economical, which ultimately benefits customers by enabling greater connection, quicker and customized services, and more competition in the market. Disaggregated O-RAN enables operators to select hardware and software components from a variety of vendors by utilizing open interfaces, standardization initiatives, a wide-ranging vendor ecosystem, plug-and-play compatibility, and rigorous validation & testing. This multivendor strategy encourages innovation and competition while enabling telecom operators to customize their network architecture to meet their business needs. In the end, it offers operators in the telecom sector greater flexibility, scalability, and cost effectiveness.

This paper introduces the innovative concept of Reinforcement Learning (RL) within the O-RAN framework, wherein intelligent agents interact with the system, receive rewards and penalties, and optimize their actions to enhance network performance. The paper combines RL with the Markov Decision Process (MDP), a well-established technique for simulating complex systems, to create a method for optimizing action selection in O-RAN, and deploy the Deep Q-Network (DQN) algorithm, which utilizes neural networks, enhances the adaptability of O-RAN in complex and large-scale scenarios. Additionally, the use of target and prediction networks within DQN ensures consistent and stable decision-making. Automation in resource allocation and scheduling, achieved through DQN learning, results in efficient resource utilization. Integration of ML Operations (MLOps) principles bridges the gap between machine learning model development and operation, ensuring the continuous and reliable operation of ML models within the dynamic O-RAN environment. The paper also sheds light on the challenges of manual model deployment, emphasizing the need for automation to overcome scalability, consistency, and maintenance issues effectively. Overall, this paper introduces groundbreaking approaches to RL, MDP, and DQN algorithms in O-RAN, promising improved network performance and resource allocation through intelligent automation, while highlighting the significance of MLOps in managing machine learning models in evolving network environments.

Section 2 of this paper shows a literature survey and details of relevant research works. We survey all aspects of O-RAN, FRIC, integration of O-RAN components, and AI/ML technologies. Section 3 discusses the evolution of O-RAN from traditional monolithic methods to a new programable system, and shows the new included features of O-RAN. Sections 4 and 5 discuss the standard AI/ML enabled automated system for software defined disaggregated O-RAN architecture and newly added AI/ML components. Finally, Section 6 depicts and implements the RL for automation system. Section 7 is about the open problems and future scope for further innovation of the system.

2 Related Work

Numerous research papers have been published by various authors exploring the components of 4G/5G RAN. In a comprehensive analysis of the literature, Polese et al.[1] examined Cloud-RAN (C-RAN), Heterogeneous Cloud-RAN (H-CRAN), Virtualized Cloud-RAN (V-CRAN), Fog-RAN (F-RAN), and presented their findings. Another survey[2] focuses on C-RAN and elaborates the role of advance applications. Similar to this, in Ref. [3], the C-RAN architecture is discussed. More precisely, a thorough analysis of how resources is allocated in such an RAN architecture. Reference [4] utilizes the O-RAN design to propose a machine learning centered approach for enhancing gNodeB (gNB) handovers by optimizing the Self-Organizing Network's (SON) Automatic Neighbor Relation (ANR) function. Chinchilla-Romero et al.[5] delved into team learning and multi-agent systems, showcasing their implementation on the O-RAN design. The development of O-RAN, including architecture, functionality, and implementation, is explored in Ref. [6]. Integration possibilities with Beyond 5G (B5G), scalability, energy efficiency, resource management, and network automation concepts are discussed in Refs. [7, 8]. The challenge of disaggregation of elements in O-RAN is addressed in Refs. [9, 10]. References [11, 12] proposed an advance method related to the RL, where an agent is learning from its behavior and dynamically partitions the jobs in O-RAN, aiming to minimize the ingesting of power in RAN. In Ref. [13], a framework called "New Radio flexibility" (NRflex) is developed to address the slicing challenge in 5G RAN. NRflex enables dynamic allocation of Bandwidth Parts (namely BWP) and wireless resources to system slices and its associated operators[14]. The mapping of O-RAN architecture to the NRflex framework for dynamic BWP sizing is discussed in Refs. [15, 16]. For affordable 5G deployments, Ref. [17] presents a new architecture framework called 5G Non-Public Networks (NPN). References [18–21] explore the development of ML-based closed-loop results related to the O-RAN design and demonstrate preliminary O-RAN lab setup, testing, and validation[22]. The Colosseum network simulator is utilized to deploy O-RAN, manage multiple network slices, and perform experimentation[23]. It should be noted that while several survey articles discuss 4G/5G RAN architectures, they mostly focus on earlier architectures, like C-RAN, H-CRAN, V-CRAN, etc., and do not address innovative O-RAN design principles[24–26]. Furthermore, Deep Learning (DL)-based studies addressing RAN issues in 4G/5G networks exist[27], but they need to be integrated into the emerging O-RAN architecture. Existing survey works on O-RAN provide brief details about its design, modules, advantages, and disadvantages[28, 29]. This review specifically focuses on DL-based techniques addressing resource management in 5G and 5G RAN. The summary of review papers and analysis is given in Table 1.

3 Evolution of O-RAN

3.1 Monolithic to disaggregated

The evolution of O-RAN towards openness and interoperability is achieved by incorporating the theories of both C-RANs and V-RANs to expand the features of the RAN. Traditional cellular network deployment uses an unbreakable, monolithic, and “black box” infrastructure that is unable to separate the network infrastructure’s hardware and software. The design needs 5G and B5G, which are characterized by many network resources, real-time management and configuration, cannot be addressed by this vendor lock-in strategy at this time. The first method to do away with these restrictions is C-RANs, which make use of some of the cloud’s computational power. The C-RAN architecture consists of two main components of O-RAN. One is the Baseband Units (namely BBUs), and the other one is the Remote Radio Heads (RRHs). Finally, C-RANs connect both components using the high speed fronthaul links. The base station is the main component of C-RAN and we mainly divide it into two groups: scattered RRHs and BBUs. In this architecture we place both components on a centralized location[62]. This central location is in the cloud or data center, facilitates sharing of different computing resources, zero delay immediate and scalable scheduling. This setup allows for radio resource sharing among multiple BBUs and efficiently meets fluctuating user demands.

V-RANs have built upon the C-RAN concept by leveraging the two important features of virtualization and programming, called Network Function Virtualization (NFV) and SDN, respectively. To provide interoperability, V-RAN uses a smart concept of programmable controllers. In this method the hardware is simply a forwarding device with very limited functionality. However, all the main functions of the device are in terms of software or applications on the cloud. This allows for the sharing of wireless resources among radio heads based on evolving networks conditions[63]. As a result, new business and technology requirements like virtualization, security, reliability, fault tolerance, service management, orchestration, and scalability of network resources emerged. Hypervisors, which run guest operating systems like OpenStack, and containers, such as Docker, running specific software applications in isolated system settings, are among the popular virtualization methods employed to address these needs.

O-RAN, which is now the practical evolution of traditional RAN methods, introduces the RL for self-network configuration. It incorporates new programmable open APIs to connect different components and open-source applications, which enables small vendors to gradually introduce new services based on their own needs or business requirements. O-RAN also facilitates the rapid and efficient deployment of networks while ensuring compatibility with legacy systems[2]. Achieving this involves a significant degree of system disaggregation to support collaboration between multiple suppliers, although it does introduce complexities in adaptation, implementation, security, and management of critical resources[64]. To address these challenges, AI and ML play a crucial role in O-RAN design, enabling a network automation system to self-configure their resources as per the need of user or business. This facilitates software splitting and network densification.

Table 1 Literature survey analysis.

Number	Reference	Resource management type and issue	Algorithm used	Functional block	O-RAN interface	Module/Layer
1	[30]	Scheduling resource management	RL & DNN	O-RAN O-DU	E2, O1, A1	UL scheduler/NR scheduler
2	[31]	Management of resource	DNN	O-RAN O-DU	E2, O1, A1	Resource allocation/NR-MAC
3	[32]	Radio resource management	LSTM	O-RAN O-DU	E2, O1, A1	Resource assigignment/NR-MAC
4	[33]	Scheduling of radio resource	Deep RL (DRL)	O-RAN O-DU	E2, O1, A1	UL Scheduler/NR scheduler
5	[35]	Radio resource management	DRL	O-RAN O-DU	E2, O1, A1	Resource assigignment/NR-MAC
6	[36]	Resource management: Resource management of radio links	RNN with LSTM	O-RAN O-DU	E2, O1, A1	Resource assignment/NR-MAC
7	[34]	Resource management: Energy management in downlink	RL	O-RAN O-DU	E2, O1, A1	Resource assignment/NR-MAC/PDSCH/high-PHY
8	[37]	Resource management: Energy allocation in downlink	RL	O-RAN O-DU	E2, O1, A1	Resource assignment/NR-MAC/PDSCH/high-PHY
9	[38]	Radio resource management	DRL	O-RAN O-DU	E2, O1, A1	UL scheduler/NR scheduler
10	[39]	Resource scheduling management	RL	O-RAN O-DU	E2, O1, A1	UL scheduler/NR scheduler
11	[40]	Resource management: Uplink power allocation	RL	O-RAN O-DU	E2, O1, A1	Resource assignment/NR-MAC
12	[41]	Scheduling resource management	RL	O-RAN O-DU	E2, O1, A1	UL scheduler/NR scheduler
13	[42]	Resource management: Downlink power allocation	RL	O-RAN O-DU	E2, O1, A1	Allocation of resources/NR-MAC/high-PHY/PDSCH
14	[43]	Mobility management: Issue are related to the handover technique	RL and DNN	O-RAN O-CU-CP	E2, O1, A1	gNB and UE management
15	[44]	Mobility management: Issue of base station power related	RL	O-RAN O-CU-CP	E2, O1, A1	Cell procedure management
16	[45]	Handover mobility management	LSTM	O-RAN O-CU-CP	E2, O1, A1	gNB and UE management
17	[46]	Mobility management: Base station energy related	Q learning and RL	O-RAN O-CU-CP	E2, O1, A1	Cell procedure management
18	[47]	Mobility management: Issue related to the handover technique	LSTM	O-RAN O-CU-CP	E2, O1, A1	gNB and UE management
19	[48]	Mobility management: Issues related to base station	RNN and DNN	O-RAN O-CU-CP	E2, O1, A1	Cell procedure management
20	[49]	Mobility management: Issues related to handover mechanism	DNN	O-RAN O-CU-CP	E2, O1, A1	gNB and UE management
21	[50]	Mobility management: Base station energy related	Actor critic and DRL	O-RAN O-CU-CP	E2, O1, A1	Cell procedure management
22	[51]	Mobility management: Related to User Equipment(UE) and base station power	DRL	O-RAN O-CU-CP	E2, O1, A1	UE and cell procedure
23	[52]	Mobility management: Issues related to handover mechanism	Federated learning	O-RAN O-CU-CP	E2, O1, A1	gNB and UE management
24	[53]	Spectrum management: Channel estimation	DNN	O-RAN O-DU	E2, O1, A1	PUCCH/high-PHY
25	[54]	Spectrum management: Signal encoding and decoding	DNN	O-RAN O-DU	E2, O1, A1	PUCCH/high-PHY
26	[55]	Spectrum management: Channel estimation	DNN	O-RAN O-DU	E2, O1, A1	PU(D)C(S)CH/high-PHY
27	[56]	Spectrum management: Beam selection	DNN	O-RAN O-RU	E2, O1, A1	Low-PHY
28	[57]	Spectrum management: Channel estimation	DNN	O-RAN O-DU	E2, O1, A1	PU(D)C(S)CH/high-PHY
29	[58]	Spectrum management: Feedback and channel estimation	DNN	O-RAN O-DU	E2, O1, A1	PU(D)C(S)CH/high-PHY
30	[59]	Spectrum management: Signal detection at the receiver	DNN	O-RAN O-DU	E2, O1, A1	PU(D)C(S)CH/high-PHY
31	[60]	Spectrum management: Beam selection	RL	O-RAN O-RU	E2, O1, A1	Low-PHY
32	[61]	Spectrum management: Signal classification	LSTM and CNN	O-RAN O-DU	E2, O1, A1	PU(D)C(S)CH/high-PHY

The evolution of RAN is illustrated in Fig. 1.

3.2 Advancement of O-RAN

To construct a comprehensive 5G/B5G system architecture, it is essential to incorporate various well-known or cutting-edge technologies, such as AI/ML alongside the cloud, programmable, virtual, and interoperable facilities provided by O-RAN.

These additional technologies include Network Automation (NA), Cloud Access Computing (CAC), Resource Optimization (RO), Network Sharing and Slicing (NSS), Multiple Mobile Network Operator (MMNO), and more. While these characteristics often exhibit interdependencies and synergies, some functions can be effectively shared and reused. However, integration needs to consider the impact of functional block redundancy on system latency and performance. Nevertheless, O-RAN-based 5G and B5G designs encompass several significant enabling principles, as outlined below:

Network automation: The O-RAN's automation, intelligence, self-configuration, self-fault tolerance are examples of NA principles. NAs must add newly installed nodes and alarm-triggered reconfiguration of all active devices in networks, and finally self-optimization of network resources. The optimization of resources includes interference management, mobility management, radio management, handover of connections, and power management. However, the Third Generation Partnership Project (3GPP) does not provide any specific documentation for the NA architecture, the O-RAN intelligent controllers that are installed as iApps in FRIC, xApps in near-RT RIC, and rApps in non-RT RIC are primarily responsible for NA functionality.

Cloud access computing: In recent times, there has been a notable shift in data generation from the network core to the cloud edge, specifically in environments like manufacturing. This paradigm emphasizes the significance of processing data at the edge, as it offers numerous benefits, such as reduced telecommunication network latency (zero delay), wireless congestion, and enhances reliability, and improves availability using caching. To effectively address these requirements, the concept of CAC has emerged. This enables the provision of data centers or cloud computing capabilities at the network edge, bringing computational resources closer to the data source. This proximity minimizes network traffic by processing data locally, resulting in reduced latency and improved overall network performance. Furthermore, CAC facilitates flexible deployment of applications and services, enabling efficient resource utilization and enhancing the scalability and agility of the network. By leveraging CAC, organizations can leverage the power of edge computing to optimize data processing, enhance real-time decision-making, and deliver a wide range of innovative applications and services to end-users.

Network sharing and slicing: NSS involves the process of parallelizing the network infrastructure while minimizing costs. It enables the division of tasks among multiple logical networks or slices, each task is specialized in handling specific services, based on the business needs. This allows for efficient allocation of network resources, ensuring optimal performance and customization for each service type. By leveraging NSs, operators can effectively manage and deliver diverse services over a shared infrastructure, providing enhanced flexibility and scalability in meeting the unique demands of various 5G use cases.

Multiple mobile network operator: Network densification can be significantly enhanced through the implementation of neutral hosting, which enables MMNOs to share the same infrastructure and access the radio access network. This is a cost-effective and shared wireless infrastructure accessible to multiple operators. Neutral Hosting (NH) facilitates the delivery of services to customers who have contracts with multiple hosted operators, offering increased flexibility and choice. By collaborating with an MMNO, O-RAN can provide the B5G and 6G services at very low cost, enabled by open APIs and virtualization concepts of cloud and networks. This integration allows MMNO to combine their services with other distinct offerings while ensuring seamless connectivity within the

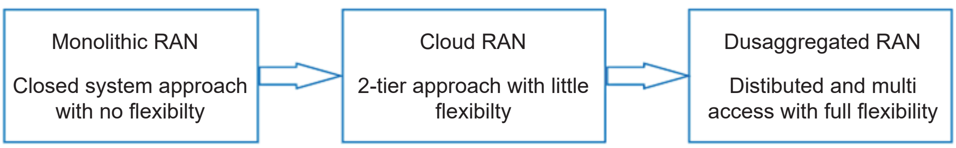

Fig. 1 Evolution of RAN.

coverage area provided by the neutral host. NH enables the efficient utilization of resources and promotes collaboration among operators, ultimately leading to enhanced service availability, improved network performance, and a more diverse range of service options for end-users.

4 Intelligent O-RAN Architecture & Components

The O-RAN alliance focuses on enhancing the RAN domain by introducing openness, flexibility, virtualization, interoperability, innovation, and intelligence. It achieves this by adopting a fundamental concept of separating software from hardware and establishing open APIs connection between the disaggregated components. This approach enables operators to embrace APIs and standardized advance practices, fostering MMNO collaborations and interoperability while avoiding vendor lock-in. The reference new framework of the O-RAN, as illustrated in Fig. 2, demonstrates its support for AI/ML capabilities and open interfaces, showcasing its commitment to advancing intelligent and open RAN solutions. Through the O-RAN initiative, the industry is empowered to drive innovation, enhance network efficiency, and enable seamless integration among diverse network elements.

The introduction of SDN and NFV technologies in this new architecture enables the inclusion of innovative service models and redefines the old methods of communications. It allows the implementation of new applications, like xApp and rApp, to automate the service model. The deployment of such applications (xApp, rApp, and iApp) and service models on top of the RAN infrastructure is the best possible solution. It is important to note that Fig. 2 illustrates a specific functional split scenario known as the three-tier architecture, where you can implement the controllers at separate locations. If you focus on the architecture, the non-RT RIC is placed at the top with

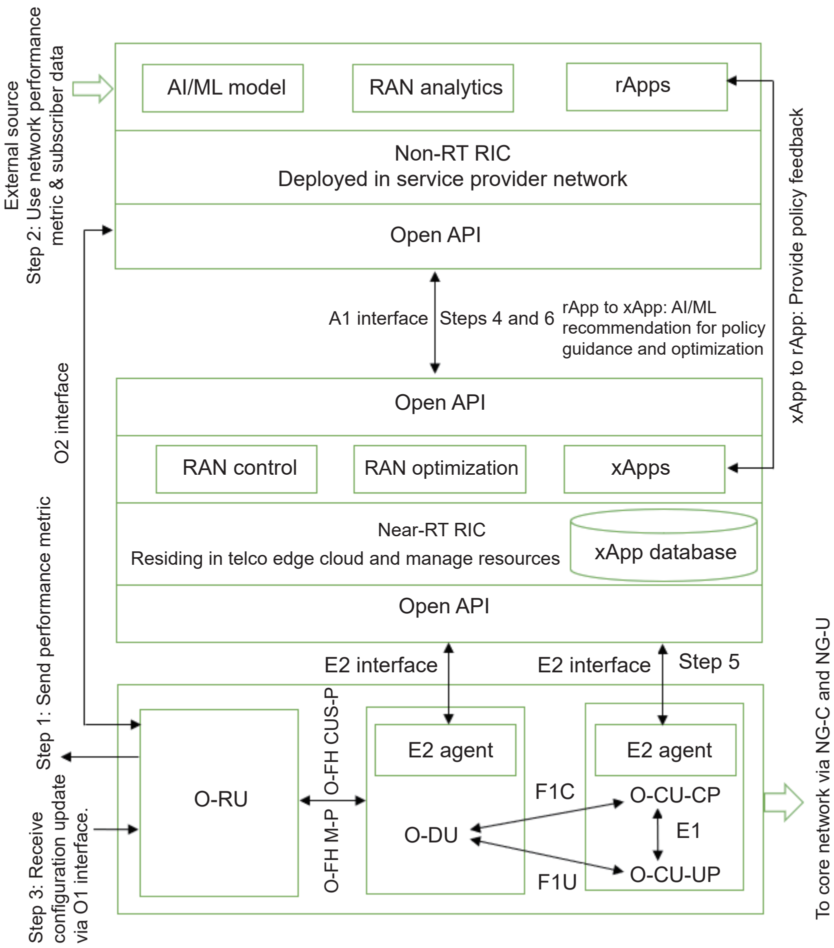

Fig. 2 Architecture disaggregated O-RAN.

AI/ML components, near-RT RIC with external Apps is at the middle and bottom O-CU Control Plane (O-CU-CP), O-CU User Plane (O-CU-UP), O-Distributed Unit, (O-DU), and O-Radio Unit, (O-RU). These components work together to enable efficient and flexible management of the RAN, supporting the implementation of advanced functionalities and enabling the integration of diverse functions and provisions within the network.

4.1 Non-RT RIC

The top layer of the O-RAN alliance architecture is called Service Management and Orchestration (SMO), which is made up of a platform and several microservices that serve as the intelligence. It implements the non-RT RIC as an interface or module to handle the service management and orchestration functions in an open RAN ecosystem, complementing the real-time control capabilities of the RT-RIC. The fundamental principles to design the non-RT RIC are moved around the AI/ML model, accessing to information, user level assurance, dynamic optimization, and innovation for openness. The roles of R1, A1, O1, and O2 open interfaces are very important here, and this framework uses R1 to provides the essential services to rApps and A1 to connect to the near-RT RIC with latency above 500 ms. The non-RT RIC applications, on the other hand, make use of SMO services, including provisioning services and checking via the O1. It enables RAN elements and resources to be intelligently optimised on a non-real-time basis, often at intervals longer than one second. The goal is to advance the industry towards an architecture that sends an intelligent RAN policy across the A1 interface. This policy is predominantly centered on network performance metrics, AI/ML training, AI/ML inference, and subscriber data. The information flow between the different components can be observed in Fig. 2, illustrating the interplay between different components of the architecture in achieving intelligent RAN optimization and control. Non-RT RIC, in our opinion, will benefit the industry the most by enabling new services and enhancing user performance. It can affect RAN behavior by opening up a wide range of new use cases and capabilities that are not currently possible in existing telecommunication networks.

4.2 Flexible-RIC

The FRIC has been implemented, and the repository is accessible on GitHub. The repository includes many xApps developed in C/C++ and Python, O-RAN alliance compliant E2 node agent emulation, patches for the 4G srsRAN and 5G Open Air Interface (OAI), as well as patches to integrate FRIC with disaggregated RAN. It implements several service models and an integrated emulator also. The service models are tested and validated with Radio Frequency (RF) simulator also. The tested and validated service models are NG/GTP, PDCP, RLC, MAC, KPM v2, SLICE, and TC. We also validate the xApps and service models with real Universal Software Radio Peripheral (USRP) hardware, and results are visible in Figs. 3 and 4. We have tested the three encoding schemes ASN.1, flatbuffer, and plain. These encoding schemes are developed depending on the service type. We use sqlite3 database to store the xApps indication messages and data. Anyone can retrieve useful data from this database through the APIs, and also can perform AI/ML operations. The list of features included in this version is provided in Table 2, according to component and service model.

By executing the service model unit test and the three nodes test, we have tested and validated the integration. This test mimics a situation including an xApp, a near-RT RIC, and E2 nodes. Data are filled out at random.

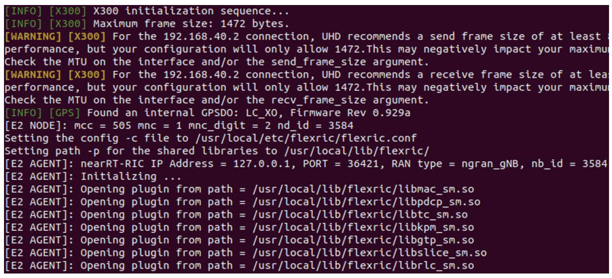

Fig. 3 FRIC integration and xApp results with disaggregated RAN.

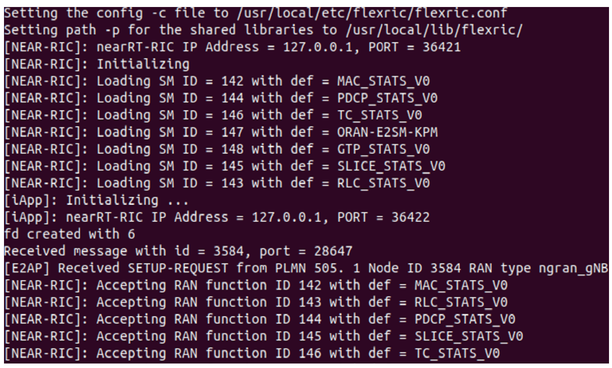

Fig. 4 Near-RT RIC results with disaggregated RAN.

Table 2 Testing and validation service models.

Testing service model	4G	5G	E2 emulator	xApp Python	xApp C/C++	Near RT-RIC	O-RAN standard	Tested and validated with USRP
KPM	No	Yes	Yes	No	Yes	Yes	Yes	Yes
TC	No	No	Yes	No	Yes	Yes	No	Yes
RLC	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes
GTP	No	Yes	Yes	Yes	Yes	Yes	No	Yes
MAC	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes
SLICE	Yes	No	Yes	Yes	Yes	Yes	No	Yes
PDCP	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes

To enable the multi-language feature (i.e., C/C++ and Python) for the xApps, we employ SWIG as an interface generator. The majority of tests can also be started by using the ctest automation framework. Researchers can expand on this work in the future by adding ctest as a new dependency.

We fetch statistics from the E2 agents using Python xApps xapp_gtp_monipy, at the same time in another window we start a second xApp developed in c xapp_mac_rlc_pdcp_moni. FRIC is currently functioning properly on an Ubuntu 20.04 PC, and its multi-agent, multi-xApp, and multi-language features have all been put to the test. Wireshark is used to watch the flow of the E2AP messages as we also test and confirm the same. The latency from the E2 agent to the near-RT RIC and xApp is the delay that we have noticed in our monitor xApp. The maximum near-RT RIC latency of 10 ms stipulated by O-RAN should be 50 times faster than the latency on contemporary computers, which should be less than 200 ms. The xApp has written all the data in xapp_db database and researcher can use this database to further investigate and analyse through the machine learning or artificial intelligence applications.

The FRIC operates within a control loop with a response time ranging from 10 ms to 100 ms. Its primary responsibility is to manage and optimize the O-RAN nodes, including O-CU-CP, O-CU-UP, and O-DU, along with their associated resources, utilizing the E2 interface. To enhance the performance of the O-RAN nodes, the near-RT RIC incorporates various primitives, such as monitoring, stop, suspend, control, and override. This layer applications known as intelligent xApps, leverage these primitives and monitor real-time RAN data from RUs. These xApps utilize the policy data obtained from the non-RT RIC through the A1 interface to deliver value-added services. These services include the management of frequencies, different radio resource allocations, energy efficiency, services configuration, mobility control, and other functionalities provided by xApps. Through this integration and utilization of near-real-time data and policies, the FRIC enhances the overall performance and efficiency of the architecture. Command to invoke the gNB is: sudo.nr-softmodem -O../../../targets/PROJECTS/GENERIC-NR-5GC/CONF/gnb.band78.sa.fr1.106PRB.usrpn310.conf–sa–usrp-tx-thread-config 1–thread-pool 0,2,4,6.

4.3 O-RU, O-DU, O-CU-CP, and O-CU-UP

The intelligent controller O-RU serves as a logical node responsible for handling the cellular spectrum processing and low-level physical (namely low-PHY) layer tasks within the new disaggregated O-RAN framework. The physical layer functionalities are split into two components: high-level physical (namely high-PHY) residing in the intelligent controller O-DU and low-PHY residing in the intelligent controller O-RU. This split architecture adopts the open front-haul interface, as defined in the O-RAN design, for communication between the O-DU and O-RU. The O-DU, on the other hand, functions as a logical node composed of three primary layers: high-PHY, Medium Access Control (MAC), and Radio Link Control (RLC). Through the F1 interface, the O-DU interacts with the O-CU to provide a range of functionalities related to these layers.

5 Enhanced AI/ML Enabled Framework O-RAN

Now, our focus is on the potential of intelligent applications to enhance the productivity of O-RAN. We begin by providing an overview of existing applications of advanced technology in the field of communications. As per the specifications outlined by the standard organizations, we categorize intelligent applications into three groups based on their expected latency requirements. These categories include non-real-time applications, near-real-time applications, and real-time controllers that operate on the DU. Throughout this section, we explore how AI is utilized in O-RAN across different network levels. We delve into the specific applications of AI, taking into consideration their latency needs. Furthermore, we offer detailed insights into their historical context, practical implementation, and associated complexities. By examining these aspects, we aim to provide a comprehensive understanding of the applications of AI within the O-RAN ecosystem. Very soon, the O-RAN Software Community (SC) is planning to introduce the next official software release. In this new release the more components to AI/ML framework will also be included, and this framework will introduce the basic modules and functions necessary for the next generation telecommunication. As shown in Fig. 5, the O-RAN alliance has widely defined the components, elements, and functions linked to the AI/ML workflow. The following major stages and functions are included in the standard AI/ML lifecycle procedure and interface framework:

- Host's capacity to query and discover,
- Generation, training, and selection,
- Deployment and inference of ML models,
- Monitoring the performance, and
- Optimization, termination, reselection, and retraining of ML models.

When creating a new architecture for the AI/ML based O-RAN project, it is necessary to consider the features, terminologies, and components given in Fig. 5. The new AI/ML architectures components and modules are given in Fig. 6. The two main computing platforms−AI training host and AI inferences platforms are introduced in the architecture. AI training host uses Training Platform Service (TPS) to execute the model training, and AI inference performs model inference results with a trained model, and AI management functions. The best way for implementing this is to use Kubeflow to deploy the ML models on Kubernetes. We may use the docker images also as the other option. This Kubeflow pipeline represents the workflow of ML modules related to the training, from data pre-processing to the validation phase. We can deploy and execute the pipeline without any complexity, as model training is performed according to the predefined order.

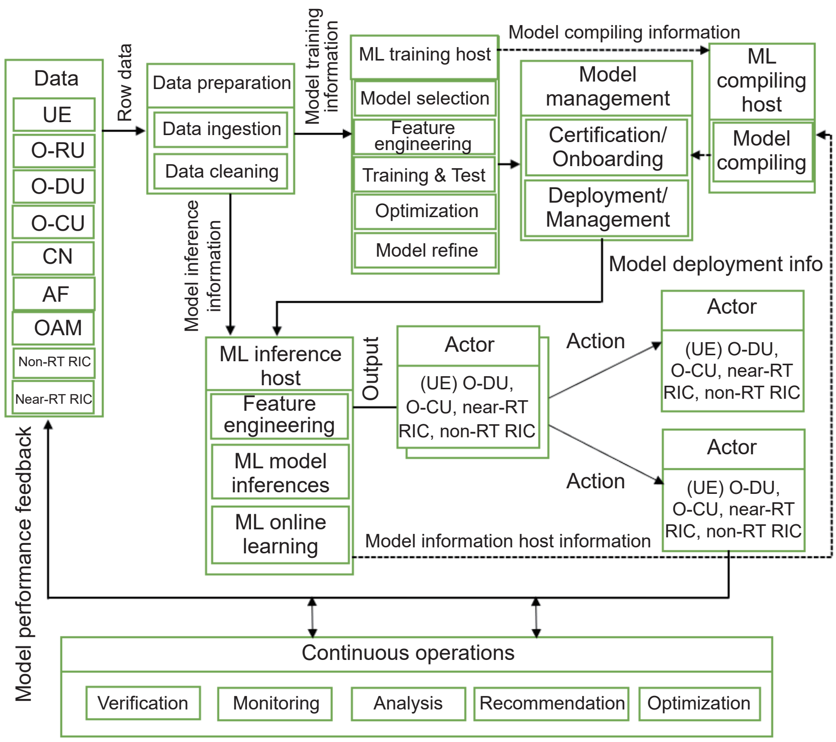

Fig. 5 O-RAN alliance specified ML components (the abbreviations "CN", "AF", and "OAM" stand for Centralized Unit, Application Function, and Operations, Administration, and Maintenance, respectively).

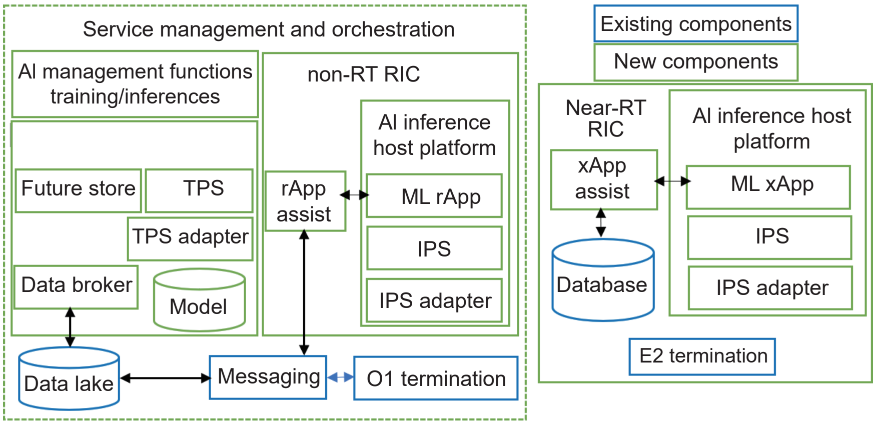

Fig. 6 Newly added AI/ML components.

Now we can use this model to train wherever we need. Training host stores data broker and features to deliver the necessary data for training to the pipeline. After the execution of the pipeline, we must store the trained model.

The overarching aspiration of advanced algorithms like AI/ML is to feed insights, predictions, or recommended actions for unidentified system scenarios. These algorithms aim to establish a relationship between system input and output in the form of features and dependent variables, in order to achieve specific objectives. In this pursuit, three primary categories are identified which are suitable for network scenarios: Supervised Learning (SL), UnSupervised Learning (USL), and Reinforcement Learning (RL). These categories are differentiated based on the methodologies employed to discover this mapping between inputs and outputs. SL involves training the model on labeled data, where the desired outputs are known, enabling the model to learn from examples and make predictions on unseen data. USL, on the other hand, explores unlabeled data to identify patterns, relationships, or clusters without any predefined target outputs. RL entails an interactive learning process where an agent learns through trial and error by receiving feedback from the environment, aiming to maximize a reward signal. By leveraging these AI/ML categories, with aim to trigger alerts, predictions, or suggested actions pertaining to various network scenarios, such as traffic forecasting, cell congestion warnings, and power configuration for maximizing throughput. These techniques play a crucial role in enabling intelligent decision-making and optimization within the network environment. The first two branches of AI and ML completely rely on previously gathered samples that link inputs and outcomes. Regression problems and classification problems are examples of problems where the outputs might either be numerical values or categorical values. This new architecture is specifically engineered to leverage the power of AI and ML, which is playing a critical role in various cross-layer aspects. One such area is automating the management of radio frequencies. To enable this functionality, an AI or ML model is hosted at an edge component of O-RAN, such as the O-DU. The models are trained using the principles of advanced learning algorithms, such as SL, USL and RL, and take charge of controlling O-RU parameters. This includes dynamically managing power levels and allocating bandwidth in resource blocks. By analyzing real-time data and making intelligent predictions, the AI or ML models within the O-RAN architecture optimize the utilization of radio resources, enhancing overall system performance and efficiency. Conversely, tasks that involve beamforming parameter configuration, dynamic resource assignment in network slices, and the installation of virtual network functions, which are typically less time-sensitive but computationally intensive, can be allocated to higher layers within the O-RAN architecture, such as the non-RT RIC or SMO. By distributing these processes to higher layers, which can handle higher computational loads and offer greater flexibility, the O-RAN architecture ensures efficient resource utilization and system scalability. This enables the deployment of advanced functionalities and services while maintaining optimal performance and responsiveness in the overall network.

5.1 Newly added AI/ML components in standard O-RAN framework

To support automated and intelligent administration features, separate AI/ML-specific processes and standardized modules have been built. The key components of O-RAN along with their interconnected interfaces, facilitate both online and offline training and inference while hosting AI and ML capabilities across network domains. Offline training, which involves time-consuming processes to train a model, is essential in O-RAN. On the other hand, online learning involves real-time agents that interact with their environment, learn from their experiences, and adapt accordingly. In order to make timely decisions, O-RAN relies on pre-trained models, underscoring the significance of offline training support. There are two crucial building blocks which are responsible for executing the ML workflow within the new architecture. The main point in the newly added feature is to note that, at the time of employing SL and USL algorithms, we must deploy the ML training node in the non-RT RIC module. However, it is up to the researcher to deploy the ML models as per the need in any module. In contrast to this if you are using reinforcement learning, it is necessary to deploy the ML training host and ML inference host or actor within the same module. The same module means either in non-RT RIC or the near-RT RIC. This ensures effective coordination and execution of the reinforcement learning process within O-RAN.

5.2 Deployment of AI/ML module

SL: it can be implemented in centralized or distributed (federated) manners. O-RAN can use federated learning because it is also built on a split architecture. This mechanism permits agents to construct an intelligent module utilizing their correct data without sharing them to the cloud. Once the model is ready, the weights of the local models are sent to the cloud for aggregation of all models at the centralized system. Then, this final aggregated model is forwarded to the learners. Using this method, we can reduce the congestion on the network as we are sharing only the weights of the model instead of entire model data. In the context of O-RAN, various SL techniques are employed to address different challenges and applications. Basically, security concerns, intrusion detection, and mitigating DDOS attacks are tackled using algorithms, such as logistic regression. These SL methods play a crucial role in ensuring the robustness and effectiveness of O-RAN systems across a range of security and performance-related tasks. We can use algorithms like linear regression, logistic regression, K Nearest Neighbor (KNN), Classification and Regression Tree (namely CART), SVM, Naïve Bayes, and extreme gradient boosting. We have two deployment options: Option 1: Non-RT RIC (ML training host and ML inference host), Option 2: Non-RT RIC (ML training host) and near-RT RIC (ML inference host).

USL: It is a type of learning that does not need labelled input data. In contrast to the SL approach, this learning method’s issue set is much more limited. This group includes standard data processing algorithms, like K-means clustering and PCA, which are used as steps in various machine learning processes. We have two options to deploy USL: Option 1: Non-RT RIC (ML training host and ML inference host), Option 2: Non-RT RIC (ML training host) and near-RT RIC (ML inference host).

RL: By interacting with its environment, an agent can learn patterns and decision-making techniques through RL. As opposed to SL, it does not require labelled data. To obtain the necessary precision, however, accurate environment modelling and occasionally more repetition than SL is needed. Many communications use cases, including packet routing, beamforming, handover optimization, and others, have made use of RL.

The recently launched 5G is more complicated and complex compared to the previous generation in terms of range, bandwidth, network architecture, base station, number of physical layer parameters, and distribution of components. Manual management and monitoring of such complex systems is not feasible to improve the quality of experience. Therefore, now there is a need for an automated network system to increase the user experience and to reduce the operational costs. RL is the best approach to solve complex network problems and to service automation. RL aims to identify the optimal strategies for complex network systems in dynamic environments by learning from interactions between system resources and their surroundings. It possesses the capability to handle intricate scenarios, like cellular systems and their interactions with users in diverse conditions. However, RL necessitates extensive trial-and-error experiences to effectively learn, which highlights the importance of generating a substantial amount of cost-efficient experience data. While an RL agent can directly interact with real systems for training, this approach may lead to system instability and negative user experiences during the exploration phase, where the agent takes unexplored paths to understand the system. To address these challenges, simulation environments are commonly employed to provide a large volume of experience without risking real systems and user services. Nevertheless, simulations have their limitations as they may not fully capture the complex interactions found in real-world systems and environments. Bridging the gap between simulations and real-world phenomena is therefore a crucial task in order to train and deploy AI/ML models effectively in such complex systems. We have two deployment options for reinforcement learning: Option 1: Non-RT RIC (ML training host and ML inference host), Option 2: Non-RT RIC (ML training host) and near-RT RIC (ML inference host). Table 3 shows the references included in this paper to provide the AI/ML enabled automations system for software defined disaggregated O-RAN.

6 Proposed Reinforcement Learning & Automation

Intelligent agents, or a group of such agents, can be deployed in interactive environments to learn through their own behavior by utilizing feedback from their actions and experiences, and training itself according to the rewards, penalty, and error. Intelligent agents in O-RAN communicate with other modules of the system, such as O-RAN Controller (ORC), to exchange information and receive high-level instructions. They leverage standardized interfaces and protocols, such as the E2 interface, to communicate with the ORC and other network entities, enabling seamless coordination and collaboration among different components. This RL intelligent agents interact with system, receive rewards and penalties based on the outcomes of its events. The objective of RL is to enable agents to select appropriate action strategies that maximize their cumulative rewards. To achieve this, we use a process called MDP in the first step and RL in the second step. The MDP is commonly employed to simulate the studied systems, and RL is then used to control the best action plan. The MDP involves a set of actions ($a \in A$), a set of states ($s \in S$), a transition function ($P\ (s; a; s')$) that describes the state transitions once taking an action on the state, and a reward function ($R\ (s; a)$) that assigns rewards for actions performed at a given state. In the context of O-RAN, deep deterministic policy gradient, trust region policy optimization, Dyna-Q, Monte-Carlo tree search, Q-learning, DQN, and multi-armed bandit learning algorithms can be applied. However, this paper specifically focuses on the deployment of the DQN algorithm. Q-learning is suitable for finite MDPs with small state and action spaces, aiming to identify correct module based on the rewards earned. It works on a simple principle: maximizing total reward leads to the best policy. On the other hand, DQN, which utilizes a neural network, is employed when the application complexity is high, and the state and action matrix table is in large volume. To enhance the performance of operating xApps, the intelligent agents are placed at FRIC module of O-RAN as depicted by Step 1 in Fig. 7. When the performance of operating xApps is enhanced, it is observed that there is an increased in efficiency with higher scalability and better utilization of network resources, which leads to reduced network congestion,

Table 3 Papers related to the O-RAN AI/ML algorithm.

Number	Algorithm	Algorithm type	Research papers
1	Safe, associative, and inverse	Reinforcement	[10–15, 17, 19, 23, 48, 53]
2	Clustering algorithms	Unsupervised	[20]
3	Data mining algorithms	Unsupervised	[3]
4	Logistic regression	Supervised	[21]
5	Random forest	Supervised	[46]
6	SVM security and time series	Supervised	[54]
7	Naïve Bayes	Supervised	[58]
8	Neural network	Supervised	[60]
9	Decision tree	Supervised	[63]
10	KNN	Supervised	[65]

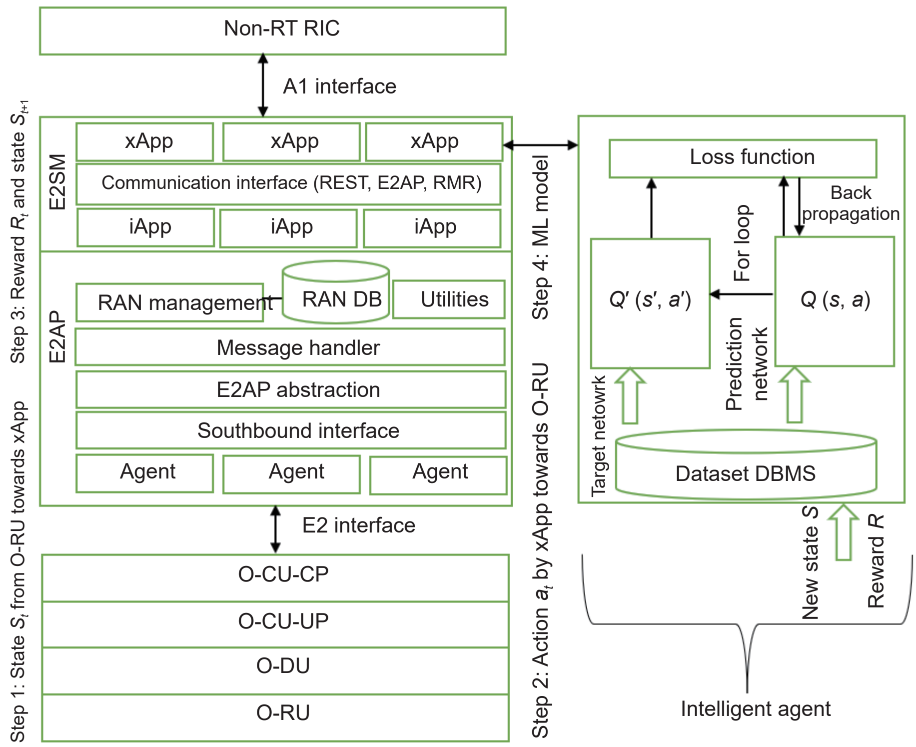

Fig. 7 Network automation reinforcement learning framework.

optimized data transmission, and improved overall network performance. It benefits not only the xApps themselves, but also other applications and services running on the network. These intelligent agents will interact with the intelligent O-RU, intelligent O-DU, intelligent O-CU-CP, and intelligent O-CU-UP, which are placed in the external environment. These agents will regularly use the E2 interface as an AI/ML enabled automated system for software defined disaggregated O-RAN to optimise the RAN performance. The agent enabled xApp performs actions through the E2 interface and controls the network resources in real time as depicted in Step 2 of Fig. 7. To address challenges related to the lower layer resource radio channel allocation and management, an intelligent agent can modify the resource allocation and scheduling strategy of the MAC layer in the O-DU to meet business requirements, as shown in Step 2 of Fig. 7. After performing an action, the intelligent agents collect the information (reward and updated state) of the intelligent system through the open O1 API through non-RT RIC, as depicted as Step 3 in Fig. 7. In that scenario, the reward is calculated according to the user's behavior, and the updated system state is represented by the total resources (bandwidth and number of users). By utilizing RL, an automated and optimal resource allocation and scheduling strategy can be developed, thereby improving the overall user experience.

In the case of DQN, we are using Neural Network (NN), which works on the concept of current state as an input, and in output it generates Q-values (rewards), enabling intelligent agents to make informed decisions on dynamically allocating network resources based on real-time observations and rewards for each possible action. DQN learning specifically incorporates the use of two neural networks to facilitate the learning process. The first NN is Target Network (TN) and represented by states and actions like Q' (s'; a'; $'$) and the other NN is Prediction Network (PN) and represented by Q (s; a;). During each iteration of the learning loop, the prediction network Q (s; a;) is updated, allowing it to continuously assess the current state of actions within the network. Meanwhile, the target value is generated by employing the target network Q' (s'; a'; $'$), which plays a vital role in the learning process. In Step 4, the DQN algorithm is highlighted. The TN and PN enable intelligent agents to make informed resource allocation decisions based on real-time observations and rewards. The TN is periodically synchronized with the PN to maintain stability and reliability, and a loss formula is used for efficient learning. This step contributes to optimizing system performance and resource allocation in O-RAN. This synchronization process ensures that the target network remains consistent and provides a reliable baseline for assessing the effectiveness of actions taken. By utilizing these two neural networks and their synchronization through cloning, DQN learning in O-RAN enables intelligent agents to make informed decisions regarding resource allocation based on real-time observations and rewards. This approach contributes to the optimization of system performance, efficient sharing of manageable and controllable intelligent resources within the O-RAN ecosystem.

We use a loss formula given in Eq. (1) to minimize the loss function between the outputs of the two NNs, DQN seeks to do the following:

$$L = (r + \lambda \max Q'(s', a', \theta') - Q(s, a, \theta))^2 \qquad (1)$$

where $a' \in A$, λ is the discount factor, r is the reward, and θ is the learning weight of the DQN. θ is updated for every iteration.

6.1 Automation process implementation

O-RAN places a strong emphasis on the widespread deployment of advanced techniques, like ML based deep learning to promote automation and make intelligent RAN applications possible. However, creating ML models with consistent performance over the course of their lifetimes is a huge issue. In order to ensure the reliable operation of RAN applications, efforts must be taken to prevent ML models from degrading as a result of changing data profiles. To address this, there is an urgent need for automation at all stages of DL development, such as data preparation from raw data, training a good model, assessment, validation, continuous monitoring of data profiles and actual model performance. In order to connect the development (Dev) and operation (Ops) parts of machine learning systems, or MLOps, this section examines how DevOps principles might be applied. MLOps enables seamless integration and deployment of machine learning models within the O-RAN ecosystem. The intensity of automation always directly impacts the performance of existing models based on input data profiles, streamlines the development, testing, and deployment processes. MLOps facilitates the continuous monitoring and management of ML models in O-RAN automation. With new practices in place, operators can check real-time processes, detect anomalies, and implement necessary updates or improvements. The subsequent sections delve into the fundamental aspects of MLOps, outlining the levels of automation across all ML processes.

6.1.1 Manual deployment of ML models in O-RAN

At this time of development, an entire ML process, including development and deployment of learning models, is carried out manually. The key steps involved in this process, which take place within the non-RT RIC layer, are illustrated in Fig. 6. Each step, from data collection, cleaning, preparation to model training, testing and deployment, is performed manually. The manual approach entails progressing from one action to the next, relying on source code that is interactively executed until an executable model is generated and deployed. We deploy this executable model using the A1 to the near-RT RIC layer. However, this approach is equivalent to infrequently updating ML models, which is not suitable for serval reasons First, due to the complexity of the network, managing scalable resources is very challenging. Second, dynamic changes inherent in wireless RAN environments. Adjustments in the dynamic radio access states or modifications in the input data representing the states can lead to a decline in the performance of the system. Therefore, it is imperative to introduce automation into the ML system within the RAN section to address these challenges effectively.

6.1.2 Automation ML models in O-RAN

To enable the automation, the upper layer module continuously monitors the effectiveness of ML models through the A1 interface. The A1 interface serves as a communication link between different RIC modules within the system architecture, facilitating the exchange of control information and enabling coordination between these modules. The monitoring process in O-RAN involves real-time collection of metrics, data, and feedback from the FRIC module. The upper layer module analyzes behavior, accuracy, efficiency, and overall performance of deployed ML models. This monitoring enables informed decision-making and appropriate actions based on observed results, ensuring correct functionality and expected outcomes of the ML models. It detects performance issues, anomalies, and deviations from desired behavior, safeguarding optimal operation within the O-RAN ecosystem. Figure 8 illustrates the automated

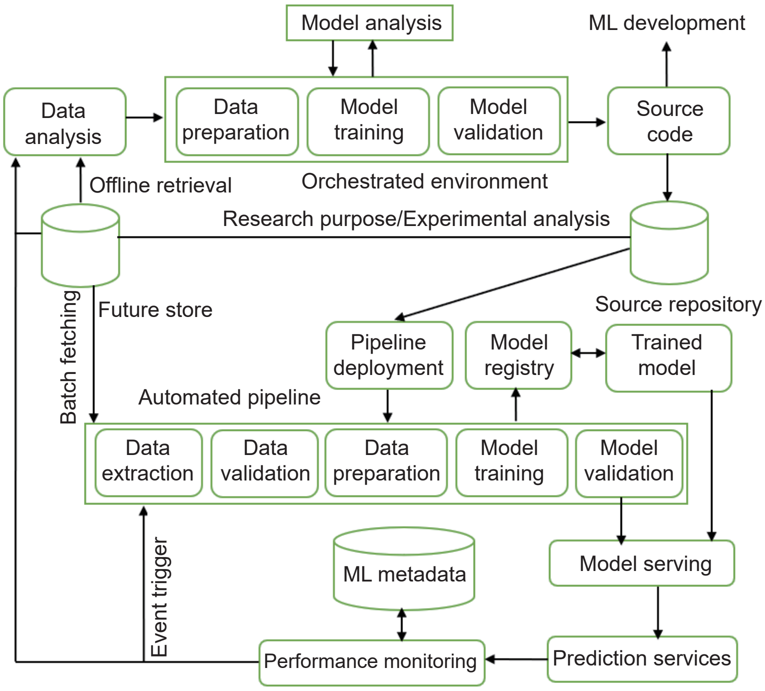

Fig. 8 Non-RT RIC AI/ML component steps.

machine learning process. The subsequent description outlines the key features and components of this level:

• **Models undergo automatic Continuous Training (CT) based on triggers from the ML pipeline and fresh data.**

• **Continuous Delivery (CD) of models:** The machine learning pipeline ensures continuous delivery of prediction services. It is a twofold process, Firstly, it ensures that the O-RAN ecosystem remains updated with the most accurate and relevant models, keeping pace with the changing dynamics of the network environment. By integrating newly trained models seamlessly, operators can leverage the predictive capabilities to optimize network performance, intelligent resource allocation, and overall user experience. Secondly, the automation of the deployment process eliminates manual intervention and saves time. This streamlined delivery mechanism enhances efficiency, allowing operators to focus on analyzing the outcomes and refining the ML models, ultimately leading to improved network operations within the O-RAN framework.

• **Continuous Integration/Continuous Development (CI/CD) pipeline:** As of now we are using the manual level of trained model, which is utilized to provide prediction services. However, at the automated levels, CI/CD training pipeline is deployed, to deliver prediction services. The deployment process can be easily replicated and scaled to accommodate changing data volumes or evolving requirements. It allows operators to handle larger datasets, train models on more powerful hardware, and incorporate new features or algorithms into the pipeline without significant manual effort. This automated deployment ensures a streamlined process for consistently delivering accurate prediction services.

• **Testing and validation of model:** Once the ML pipeline is established, it operates automatically in response to triggers. To leverage recent data for creating new models, automated data and model validation become necessary. Data validation ensures that the pipeline’s execution is either halted or the models are retrained. Retraining is crucial in two main scenarios: (1) Data schema skews refer to situations where the training pipeline receives data that do not conform to the expected schema or structure which occur when the pipeline receives unexpected data, such as new features, missing expected features, or unforeseen feature values. For example, if a new data source is integrated into the pipeline, it may introduce additional features that are not previously considered. To address these concerns, the ML pipeline needs to be temporarily paused and updated. The development team needs to modify the pipeline’s configuration, data processing steps, and feature handling to accommodate the new data schema. This ensures that the pipeline can effectively handle and process unexpected data, maintaining the integrity of the ML models being trained. (2) Data value skews occur when there are changes in the statistical characteristics and patterns of the data used for training. This can happen due to various factors, such as shifts in user behavior, network conditions, or external factors impacting the data. When data value skews occur, it is crucial to retrain the ML models to adapt to these modifications. By retraining the models with the updated data, they can capture the new patterns and make accurate predictions in the current context. Additionally, the validation process takes place after training the new models to thoroughly test and validate them before deploying them.

• **Data about management:** In order to facilitate troubleshooting of faults and anomalies, metadata management is employed. The metadata encompasses comprehensive details about each execution of the ML pipeline. This includes information such as the parameters and arguments used by the executor and pipeline, timestamps for each step's execution, references to the outputs of each step, indications for potential rollbacks to previous models, and other relevant information.

• **Trigger steps of ML pipeline:** The execution of the ML pipeline can be automated based on various use cases. These triggers determine when the models should be updated or retrained. The triggers can be categorized as follows:

(1) On-demand: It enables manual execution of the ML pipeline as needed. It allows users to initiate the pipeline when specific conditions or requirements arise.

(2) Scheduled: The pipeline trigger automates the execution of the ML pipeline on a regular basis. It ensures that the pipeline is refreshed with fresh and readily available data at predetermined intervals.

(3) Ad hoc data availability: The pipeline is triggered when new data become accessible.

(4) Deterioration of model performance: The pipeline is activated when the performance of the models starts to decline due to changes in data distribution.

Overall, metadata management and the selection of appropriate triggers enhance the efficiency and effectiveness of the ML pipeline, ensuring that models are updated and retrained when necessary.

6.1.3 Decision-making and control

Finally, the outputs are utilized for decision-making, monitoring and controlling the system environment. This process involves actions, such as resource allocation, traffic optimization, interference management, or network configuration. Automated decision-making processes leverage the predictions or recommendations of the AI/ML models to guide and automate network operations in real time.

6.2 Enhancing energy efficiency in O-RAN through AI and DRL optimization

Energy consumption is always a big challenge for any computing system, in 5G and B5G networks also. Now, AI can play a crucial role to save the energy in such systems by applying different approaches, like intelligent task allocation and resource optimization. Proposed algorithms in recent research optimize the offloading selection in computing systems, while autonomous control methods are designed to reduce energy consumption. These AI applications enable efficient resource utilization, reduce redundancy, and contribute to green wireless networking. In O-RAN, an Energy-Efficient (EE) method employs a multi-agent DRL model. It jointly optimizes throughput and power consumption by providing a power allocation technique for active Radio Units (RUs) and their physical resource blocks. DRL's suitability for optimization, effortless model inference and deployment, and trial-and-error interactions without extensive training data make it an ideal approach for EE optimization in O-RAN. By integrating AI-driven energy efficiency techniques, O-RAN can significantly reduce energy consumption, enhance resource utilization, and create a greener wireless networking ecosystem. Further advancements in RF devices, RAN components, and AI algorithms will contribute to greater energy conservation and sustainability in telecommunications.

7 New Research Area & Future Scope

Disaggregated O-RAN architecture is still in the early phases of development. Although this design offers a variety of novel features and capabilities, there are important issues that must be resolved before it is widely adopted. We will talk about some of these challenges and possible future research trajectories in this conversation.

7.1 Enhancing RAN models for robust RAN slice service level agreement assurance in 5G networks

In 5G networks, network slicing is a crucial feature that enables the creation and management of customized networks to meet specific service requirements. This flexibility allows different services and applications to have tailored functionality, performance, and user groups. To ensure the quality of service, Service Level Agreements (SLAs) are established for each network slice. However, the existing RAN models face several challenges in effectively supporting RAN slice SLA assurance use cases, necessitating further research and development.

- **Inadequate performance measurements:** The current RAN performance measurement frameworks and information models are insufficient to meet the diverse requirements of different RAN slices. They do not provide the necessary granularity and customization needed to monitor and control the performance of individual slices. This limitation hampers the ability to ensure SLA compliance for RAN slices. Future research should focus on developing enhanced performance measurement mechanisms specifically tailored for RAN slice SLA assurance.
- **Dynamic configuration challenges:** The dynamic nature of RAN slices poses a challenge for existing RAN models in terms of dynamically configuring and adapting RAN behavior to meet slice-specific performance requirements. The current models lack the capability to adjust and fine-tune RAN behavior in real time based on changing network conditions and slice-specific needs. Addressing this challenge requires research and development efforts to enable dynamic configuration mechanisms that ensure continuous SLA compliance for RAN slices.
- **Standardization efforts:** Interoperability and seamless operation of RAN slices from different vendors are essential for effective RAN slice management and SLA assurance. However, the lack of standardized frameworks, protocols, and interfaces hinders the consistent enforcement of SLAs across heterogeneous RAN deployments. Future research should focus on standardization efforts to define common specifications and guidelines that enable interoperability and harmonization of RAN slice management and assurance mechanisms.
- **Integration of AI/ML techniques:** The integration of AI/ML techniques has the potential to enhance RAN slice SLA assurance. AI/ML algorithms can enable proactive decision-making, dynamic optimization, and adaptive behavior based on performance information and slice-specific requirements. However, the current RAN models lack the necessary AI/ML capabilities to support RAN slice SLA assurance. Further research is needed to explore the integration of AI/ML techniques into RAN models, specifically focusing on RAN slice performance management and SLA enforcement.

7.2 Unsolved issues in RAN sharing

RAN sharing is a collaborative approach in the telecommunications industry where multiple network operators join forces to optimize the deployment of wireless communication services. By sharing infrastructure components like base stations, antennas, and spectrum resources, operators can reduce costs, increase network capacity, and accelerate the implementation of advanced technologies such as 5G. Challenges and unsolved issues are as follows:

- **Feasibility of sharing RAN functions:** One of the key challenges in RAN sharing is determining which specific RAN functions should be shared among operators. Ensuring effective coordination between these functions when multiple operators control the same physical layer remains an unsolved issue. Resolving this challenge requires defining standardized protocols and mechanisms to facilitate seamless coordination and efficient resource utilization among participating operators.
- **Implementation challenges:** Implementing RAN sharing involves overcoming various technical and operational hurdles. A significant challenge lies in developing a common interface that enables effective communication between shared network nodes, regardless of the hardware manufacturer or vendor. Achieving interoperability and smooth data exchange among diverse devices and vendors remains an open issue. Addressing this challenge requires establishing industry-wide standards and protocols to ensure seamless integration and efficient communication in multi-vendor environments.
- **Security aspects:** Security is a critical concern when sharing RAN resources among operators. Granting external actors access to the hosting operator's resources and allowing them to orchestrate the partner operator's resources pose security risks. Addressing

these risks and ensuring secure access to shared resources are ongoing challenges. Robust security frameworks, authentication mechanisms, and access control protocols need to be developed to protect against unauthorized access and safeguard the integrity of the shared RAN infrastructure.

7.3 Sharing non-RT RIC data with 5G core

The challenges and future research scope in sharing non-RT RIC data with the 5G core are significant. Non-RT RIC, or non-real-time RAN intelligent controller, plays a crucial role in managing and optimizing the radio access network in 5G. However, integrating non-RT RIC with the 5G core poses certain obstacles.

• Need for mapping the analytic information content from the "generally useful" data structures published across R1 into the specific data structures expected by the 5G core Network Functions (NFs). This mapping process ensures compatibility and effective utilization of the analytics data.

• Establishment of a suitable framework to enable the sharing of non-RT RIC data with the 5G core. The passage presents two options: one with the SMO/non-RT RIC acting as an NetWork Data Analytics Function (NWDAF) and another with a separate NWDAF. Further investigation is necessary to determine the optimal approach.

Future research scope in the area is as follows:

• Refining the mapping mechanisms between non-RT RIC and the 5G core NFs to ensure seamless integration and efficient data exchange.

• Exploring alternative architectures and protocols for sharing non-RT RIC data, such as the proposed options of SMO/non-RT RIC as an NWDAF or a separate NWDAF.

By addressing these challenges and conducting further research in these areas, researchers can unlock the full potential of non-RT RIC in enhancing the performance and capabilities of the 5G network.

7.4 Advancing O-RAN: Challenges in inter-vendor standardization, management frameworks, security, performance optimization, and seamless integration

• **Inter-vendor standardization:** Collaborative efforts among vendors and standardization bodies are needed to establish common interfaces, protocols, and standards to enhance interoperability and compatibility in disaggregated O-RAN.

• **Management and orchestration frameworks:** Research should focus on developing efficient and scalable management and orchestration frameworks tailored for disaggregated O-RAN architectures. This includes automation, network slicing, and intelligent resource allocation mechanisms.

• **Security enhancements:** Future research should address security concerns specific to disaggregated O-RAN, including threat detection, prevention, and mitigation techniques. Robust authentication, encryption, and access control mechanisms need to be developed.

• **Performance optimization techniques:** Investigating advanced optimization techniques for resource allocation, load balancing, and traffic management in disaggregated O-RAN can enhance network efficiency and quality of service.

• **Seamless integration strategies:** Research should explore strategies for seamless integration of disaggregated O-RAN with existing infrastructure, such as legacy base stations and core networks. This includes defining migration paths and compatibility frameworks.

7.5 Scope of multi-agent platform

To enhance network performance and coordination across numerous agents, virtualized O-RAN can benefit from the application of the Multi-Agent Team Learning (MATL) concept. Base stations, virtual network functions, and centralized controllers are only a few of the parts and organizations that collaborate to administer the network in virtualized O-RAN.

• **Decentralized decision-making:** With MATL, agents in virtualized O-RAN can make decentralized decisions based on local observations and interactions with the network environment. Each agent can learn and adapt its decision-making process using techniques, such as RL or game theory. The decentralized decision-making allows agents to respond to network dynamics and optimize their actions for improved network performance.

• **Adaptation to changing network conditions:** Virtualized O-RAN networks are subject to varying network conditions and requirements. MATL enables agents to adapt their behaviors and policies in response to changing network dynamics. Agents can learn from their own experiences as well as from interactions with other agents, allowing for continuous adaptation and optimization in dynamic network environments.

• **Knowledge sharing and transfer:** MATL enables agents to share knowledge and experiences with each other. Agents can exchange information about their learned policies, observations, and rewards to facilitate collective learning. This knowledge sharing helps in the transfer of valuable insights and enables agents to make informed decisions based on shared knowledge.

8 Conclusion

In conclusion, this paper demonstrates an adoption of software-defined disaggregated O-RAN, presents a compelling opportunity for the implementation of next-generation multi-vendor networks. This study has provided an overview of the key architectural concepts underpinning disaggregated O-RAN, with a specific concentration on integration of advanced components within the architecture. This paper explores all the steps of FRIC integration with O-RAN, and tests successfully with emulation, simulation, and real USRP hardware. We also test the FRIC multi-agent, multi-xApp, and multi-language features by running C++ and Python xApps simultaneously. Additionally, we have explored previous works in deep learning based RAN with network automation reinforcement learning framework and discussed their potential integration into the newly developed AI/ML-enabled automation system for software-defined disaggregated O-RAN. To ensure the effectiveness of deployed learning models, case studies on the deployment of reinforcement learning in O-RAN have been presented along with insights into automation steps of implementation and automating key elements of the RL process. The design of the AI/ML-enabled automation system for software-defined disaggregated O-RAN and the application of RL within this architecture have been discussed in detail. Furthermore, we have touched upon emerging research aspects and the future scope related to enhancing RAN models for robust RAN slice SLA assurance in 5G networks, unsolved issues in RAN sharing and sharing non-RT RIC data with 5G core.

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