AI-driven Closed-loop Automation in 5G and beyond Mobile Networks

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ABSTRACT

The 5th Generation (5G) mobile networks support a wide range of services that impose diverse and stringent QoS requirements. This will be further exacerbated with the evolution towards 6th Generation mobile networks. Inevitably, 5G and beyond mobile networks must provide stricter, differentiated QoS guarantees to meet the increasing demands of future applications, which cannot be satisfied with traditional human-in-the-loop service orchestration and network management approaches. In this paper, we lay out our vision for closed-loop service orchestration and network management of 5G and beyond mobile networks. We extend the MAPE (*i.e.*, monitor, analyze, plan, and execute) control loop to facilitate closed-loop automation, and discuss the quintessential role of Artificial Intelligence/Machine Learning in its realization. We also instigate open research challenges for closed-loop automation of 5G and beyond mobile networks.

CCS CONCEPTS

• **Networks → Network management**; **Mobile networks**.

KEYWORDS

5G; artificial intelligence; machine learning; closed-loop orchestration and management

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1 INTRODUCTION

The 5th Generation (5G) mobile networks are poised to support a wide range of services that go well beyond traditional voice and data. These include services with diverse QoS requirements, such as enhanced mobile broadband (eMBB) (*e.g.*, ultra-HD video streaming), ultra-reliable low-latency communications (URLLC) (*e.g.*, remote surgery), and massive machine-type communications (mMTC) (*e.g.*, smart cities) [13]. Services envisioned for 6th Generation mobile networks will impose even more stringent QoS requirements (*e.g.*, <1 millisecond end-to-end (E2E) latency, 1 Tb/sec throughput, and seven-nines reliability). These include new services, such as human-centric service (HCS) (*e.g.*, brain-computer interaction), converged compute, communication, control, sensing, and localization (3CSL) (*e.g.*, autonomous control of industrial processes), and fusion of classical 5G services, such as mobile broadband reliable low latency communication (MBRLLC) (*e.g.*, multi-sensory extended-reality communications) and massive URLLC (mURLLC) (*e.g.*, connected robotics) [14, 15, 17, 21, 23], as shown in Figure 1. Inevitably, 5G and beyond mobile networks must provide stricter QoS guarantees to meet the demands of future disruptive services and applications.

Network slicing, facilitated by network softwarization and virtualization, is a key enabling technology to accommodate different QoS requirements on the same physical infrastructure. It enables on-demand deployment of right-size virtualized network functions (VNFs) at the appropriate location, to meet the stringent requirements imposed by the 5G and beyond services. Effectively, the physical network can be partitioned into multiple network slices, each supporting the tailored QoS requirement of an application [13]. For example, emergency response services could operate a network slice independent from others with a specific QoS, increased security and privacy to accommodate their operational needs.

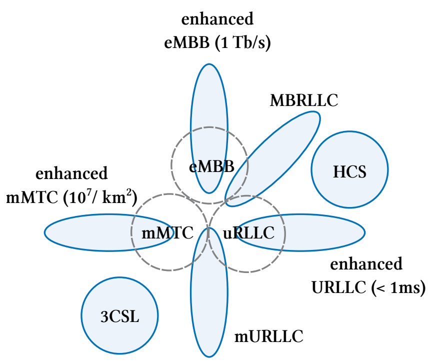

Figure 1: Services in 5G and beyond mobile networks

As network operators are rolling out 5G networks, effective life-cycle management of E2E network slices is becoming increasingly important for meeting applications' QoS requirements, on a dynamic and evolving infrastructure. However, managing virtualized networks can be challenging, as anomalies, *e.g.*, faults and performance degradation, can unfold in various levels, such as the virtualized infrastructure and the VNFs. Furthermore, softwarization and virtualization broaden the surface for faults and performance degradation, such as degradation specific to hypervisor and network controller. Moreover, heterogeneity of infrastructure devices and operating environments makes it difficult to manually track error propagation. This necessitates data-driven orchestration and management approaches to support the diverse, demanding, and stringent QoS guarantees expected from 5G and beyond networks, which cannot be satisfied with traditional reactive human-in-the-loop orchestration and management approaches.

Artificial Intelligence (AI) and Machine Learning (ML) offer techniques for extracting knowledge from data [5, 8]. They can play a vital role in facilitating closed-loop orchestration and management, to realize zero-touch, data-driven 5G and beyond network life-cycle management. For example, maintenance of network equipment is crucial to ensure seamless network operation. Traditionally, this is achieved based on a static maintenance schedule, which is non-trivial to predetermine. AI/ML-enabled predictive maintenance of network equipment is an alternate to scheduled maintenance, which can minimize downtime and maintenance costs.

In the rest of the paper, we first delineate our vision for closed-loop orchestration and management of 5G and beyond mobile networks in § 2. We extend the MAPE (*i.e.*, monitor, analyze, plan, and execute) control loop [25], and discuss the crucial role of AI/ML in its every aspect. In § 3, we instigate open research challenges that need to be addressed to realize closed-loop automation in 5G and beyond mobile networks.

2 CLOSED-LOOP ORCHESTRATION AND MANAGEMENT

In this section, we first present an overview of next generation mobile networks, followed by our vision for AI-driven closed-loop orchestration and management.

2.1 Overview of 5G and beyond Networks

Supporting multi-faceted requirements of 5G and beyond mobile networks warrant a highly flexible network architecture, enabling E2E network slices spanning from the Radio Access Network (RAN) to the mobile core. In this new architecture, traditional RAN functionality is decoupled into Remote Radio Unit (RRU), Distributed Unit (DU), and Central Unit (CU) [4]. Different RAN functions (*e.g.*, Radio Resource Control (RRC), Radio Link Control (RLC), Medium Access Control (MAC), and Baseband Unit (BBU)) can be disaggregated and hosted on RRU/DU/CU to support a highly flexible functional split that is tailored to support specific use-cases. Fronthaul network carries radio signals from RRUs to DUs using Common Public Radio Interface (CPRI) or e-CPRI protocols. Midhaul (between DU and CU) and backhaul (connecting CUs to the core) networks carry IP traffic and can leverage SDN principles.

In the same way, Next Generation (NG) core separates the current Evolved Packet Core (EPC) functions into finer-grained Network Functions (NFs) (*e.g.*, Access and Mobility Management Function (AMF), Session Management Function (SMF), Policy Control Function (PCF), User Plane Function (UPF), and Unified Data Management (UDM)) and interfaces with the Internet [4]. Both RAN and core NFs can be deployed as VNFs on commodity servers using virtual machines (VMs), containers, or unikernels. Virtualizing RAN and core NFs enable flexibility in creating, operating, and managing NFs by hosting them on distributed computing facilities, including multi-access edge computing (MEC) data centers. Another key feature of this new architecture is to use open interfaces to enable integration of hardware and software from a diverse collection of vendors. This will also facilitate the use of white box hardware and open source software to take full advantage of the economies of scale offered by an open computing platform approach.

2.2 Closed-loop Automation

A network slice is a virtual network that is composed of a collection of virtual nodes representing VNFs and their interconnecting virtual links [4]. An E2E network slice extends the virtual network into multiple technological and potentially administrative network segments (*e.g.*, RAN, transport network, MEC, cloud and NG core) [9]. Manually managing E2E network slices that involve heterogeneous resources can be cumbersome and time-consuming, and may lead to QoS violations. Hence, Closed-loop Automation (CLA) is necessary to realize zero-touch orchestration and management of network slices [24]. Although CLA aims to reduce human intervention, it still allows interactions with human operators in the form of specifying policies, defining objectives, as well as approval/rejection of actions taken by CLA. In the rest of this section, we extend the MAPE control loop [25] to present our view of CLA in 5G and beyond mobile networks, which is depicted in Figure 2. Note that each component (*e.g.*, Network Controller) of CLA in Figure 2 can adopt AI/ML techniques to provide intelligent, data-driven, and automated orchestration and management.

2.2.1 Intelligent Monitoring. The intelligent algorithms that form the basis of CLA rely on large amounts of data collected from the network infrastructure and constituent NFs. As such, the first function of CLA is an intelligent monitoring framework (similar to *Monitor* function in the MAPE loop) that collects metrics at an adaptive rate to maintain the predictive validity and efficacy of the AI/ML algorithms being used. Given this constraint, it is infeasible to use traditional monitoring frameworks, such as those present in OpenStack [19] and Open Source MANO [12]. These monitoring frameworks rely on pull-based mechanisms to gather metrics from agents running on the corresponding node. Furthermore, both OpenStack and OSM only provide support for *fixed-frequency* monitoring, where metrics are collected once during a specified, fixed time interval for every element in the network. Such a naïve approach to monitoring leads to the collection of redundant metric values, particularly in the case where the variance of the metric time-series is significantly different across the various network slices. Therefore, an intelligent monitoring framework must leverage adaptive algorithms to determine the optimal monitoring frequency for particular slices and metrics.

2.2.2 Data Processing Pipeline. The *Analyze* function in the proposed CLA includes a data processing pipeline for ingestion, cleaning, indexing, enrichment, and storage, as well as visualization of the data collected from different elements of 5G and beyond mobile network. This includes metrics and operational logs collected from different VNFs, compute resources, and network elements. To scale to the voluminous amount of operational data, the pipeline may use distributed cluster (*e.g.*, Hadoop) to house the software stack (*e.g.*, Apache Spark) needed for data processing and storage. The data processing pipeline is also responsible for calculating Key Performance Indicators (KPIs) and metrics based on the collected data.

2.2.3 Data Analytics. Our proposed CLA in 5G and beyond mobile networks leverages AI/ML techniques to extract knowledge and inference from operational data gathered in the data processing pipeline, and realize the *Analyze* function. Examples of inference include forecasting traffic volume changes, estimating user mobility patterns, predicting future network events such as throughput drop and network congestion, and early detection of anomalous behavior that can lead to device/link failures. These inferences will be leveraged by the Plan function to take more informed orchestration and management decisions.

2.2.4 Slice Orchestrator. This component is central to the *Plan* function in CLA, as it is responsible for provisioning, run-time operation, and decommissioning of network slices based on their QoS requirements. The provisioning tasks include instantiation, configuration, and activation of RAN NFs, core NFs and virtual links corresponding to a network slice. Operational and maintenance tasks such as scaling or adaptation to changes in requirements are at the core of run-time operation. Finally, decommissioning phase re-optimizes resources after departure of one or more network slices. Slice orchestration decisions can be dynamically adapted by taking advantage of the AI/ML-based estimation and predictive models in the Data Analytics component.

2.2.5 Performance and Fault Management. This is a critical component of the *Plan* function, which is responsible for monitoring slice performance and network state, handling slice performance degradation, and managing faults, failures, and alarms in network infrastructure. Guaranteeing performance while ensuring resource efficiency in a multi-tenant environment is challenging, where a number of network slices co-exist with heterogeneous requirements. Similarly failures and faults, if not treated properly, may disrupt the services and applications hosted on network slices, incurring high penalties in terms of revenue losses and Service Level Agreement (SLA) violations. This component benefits from early detection of performance degradation and fault prediction provided by Data Analytics component, and accordingly devises corrective action plan and mitigation workflow.

2.2.6 Radio Intelligence Controller (RIC). The proposed CLA relies on RIC, introduced and standardized by the O-RAN alliance [11], for carrying out orchestration and management in the RAN. RIC plays an analogous role to the Network Controller for transport segments and the NF Orchestrator for compute resources to realize the *Execute* function in the CLA. As per O-RAN alliance, RIC has two modules:

Near real-time RIC: The near real-time RIC is co-located with the CU and performs many of the Radio Resource Management (RRM) tasks that are carried out by traditional eNBs and gNBs. In addition to legacy RRM tasks, such as resource block management and interference detection, the near real-time RIC will also leverage

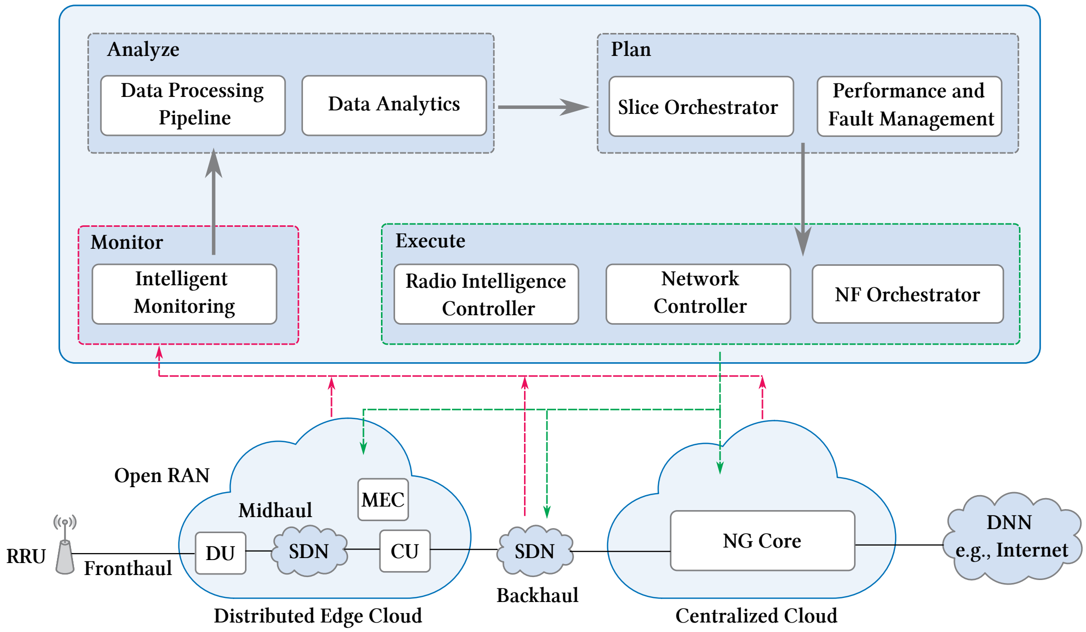

Figure 2: Closed-loop orchestration and management

embedded AI algorithms to carry out more nuanced tasks, such as UE-centric QoS management.

Non real-time RIC: The non real-time RIC interacts with the near real-time RIC to apply policy and configuration that influences the behavior of the RAN. Policy and configuration could include new applications developed in-house by Telecom operators or by third-parties. It is also envisioned that the non real-time RIC will host RAN analytics and model training, with the trained models and analytic insights deployed to the near real-time RIC to realize the policy defined by the network tenants.

The RIC is a crucial component to realize a flexible, softwarized RAN that provides the interfaces necessary to create on-demand E2E network slices.

2.2.7 Network Controller. Given the dynamicity required to support CLA, it is essential to incorporate a component that can set up virtual links tailored to particular use-cases at run-time. This role is fulfilled by the Network Controller as part of the the *Execute* function. In particular, the Network Controller is responsible for instantiating E2E network paths that span across midhaul and backhaul networks, since the NF Orchestrator may not be able to provision such paths. The Network Controller is also responsible for realizing QoS policies pertaining to the transport network as defined by the *Plan* components. This can be accomplished by incorporating state-of-the-art techniques for routing optimization and fault tolerance in transport networks, many of which also leverage AI/ML techniques.

2.2.8 NF Orchestrator. The NF Orchestrator is responsible for managing the Network Functions Virtualization Infrastructure (NFVI) and executing the plans computed by the Slice Orchestration, and Performance and Fault Management components of the proposed CLA. In practice, this often involves provisioning, scaling, migrating, or tearing down compute resources in the form of VMs or containers subject to the constraints imposed by the orchestration components. It is often the case that the NF Orchestrator will be able to provide connectivity between the constituent NFs of a given slice. However, in more complex cases, intervention from the Network Controller may be required to provision connectivity between slice NFs.

3 RESEARCH CHALLENGES

We conclude this paper by outlining some open research challenges that need to be addressed to realize CLA in 5G and beyond mobile networks.

3.1 Slice Requirement Translation

A network slice is specified with its intent or desired functionality, including customer facing QoS requirements such as throughput, latency, and Bit Error Rate. Depending on the application or service, each slice customer may have its unique set of QoS parameters. The first step in slice orchestration is to map the high-level slice QoS requirements into appropriate infrastructure resource requirements, including RAN and core NF requirements such as their location, required compute, memory, and storage resources, and the level of isolation with other slices, as well as network requirements such as slice topology and bandwidth requirement. Representing resource needs as a function of slice QoS requirements is non-trivial, since their relationship is not linear and various factors such as network condition, the level of isolation between slices, and traffic load influence the perceived QoS for end users. In this context, we need a deeper understanding of how infrastructure parameters influence perceived slice QoS and devise mechanisms for translating customer facing slice QoS requirements into infrastructure resource requirements.

3.2 Dynamic Function Splitting in RAN

Legacy RAN and even virtualized RAN solutions make use of closed-box functions and proprietary interfaces, which makes it difficult to flexibly control radio resources and impedes the realization of E2E slicing. The Open RAN paradigm, which combines RAN disaggregation, virtualization, radio network intelligence, and open interfaces, provides the necessary flexibility to realize the vision of E2E slicing[18]. The open-interfaces and embedded intelligence of Open RAN can enable AI/ML-driven dynamic function splitting, where RAN NFs are split between the CU and DU depending on the traffic type. This enables different functional splits for different slices, allowing the network to be tailored to support specific use-cases.

A key challenge in this regard is the orchestration of disaggregated NFs, potentially from different vendors, using a common orchestration platform. The problem of orchestrating these disaggregated NFs becomes especially difficult when considering the need for highly flexible traffic steering solutions in the midhaul and backhaul segments. In this context, a better understanding of the appropriate functional splits for various slices is needed, which is adapted to the requirements of different use-cases and the limitations of transport delay budget and bandwidth. Another crucial challenge involves energy-aware placement of the disaggregated NFs, to optimize the energy usage in the RAN and realize the concept of energy-efficient network slices.

3.3 Data-driven Orchestration Algorithms

Network slice orchestration refers to the allocation of resource and bandwidth to NFs and virtual links, respectively, in different network segments to satisfy given QoS requirement. Contemporary slice orchestration strategies are oblivious to the future network conditions and changes in traffic volume [6]. These strategies usually over-provision resources to circumvent worst-case network behaviors or to accommodate peak traffic demand. Such over-provisioning results in inefficient use of resources and blocking of future network slices. This gap in research literature mandates investigating dynamic slice orchestration algorithms where resource allocation decisions will be adapted time-to-time by taking advantage of data-driven predictive models and the QoS requirements of the slices. Devising such predictive models also pose non-technical challenges, such as obtaining ground truth data from operational networks while complying with local and national policies.

3.4 KPI and Infrastructure Monitoring

KPIs are quantitative measures used for evaluating if services are meeting the agreed upon QoS parameters. For 5G services, the standardization bodies such as 3GPP as well as the research community have defined several KPIs [2, 3, 16]. However, network slice KPI monitoring research is still in preliminary stages and only a handful of works propose an architecture for a KPI monitoring system [20]. A key challenge in KPI monitoring is the non-trivial difficulty in computing these KPIs for E2E network slices. Many of these KPIs are composite, *i.e.*, require measuring multiple infrastructure and NF related metrics for computing their values. A detailed understanding of how different infrastructure and NF related metrics impact the network slice KPIs is still missing.

Traditionally, infrastructure monitoring has been a polling-based approach where a logically centralized control plane or management system polls the counters or probes from the infrastructure. However, polling-based approaches work at coarse time granularity that may be inadequate for providing service assurance to mission critical URLLC services. More recently, push-based streaming telemetry [1, 22] is gaining traction in both academia and industry because of its capability to stream network telemetry data directly from the devices to the collection and analysis engines in near real-time. Indeed, streaming telemetry is a promising approach to be used in 5G and beyond networks, however, it comes with drawbacks such as increased data plane overhead to piggyback telemetry data on live network traffic [7, 10]. Sampling can reduce some of the overhead at the expense of reducing accuracy, which can be unacceptable for some 5G and beyond services.

3.5 Predictive Maintenance

Maintenance of network equipment is crucial to ensure seamless network operation. Typically, network operators rely on a recurring pre-determined maintenance schedule. However, it is non-trivial to choose the optimal maintenance schedule to minimize maintenance contract costs and ensure undisrupted services that are offered via E2E network slices. Predictive maintenance of network equipment is an alternate to scheduled or periodic maintenance, which can minimize downtime and maintenance costs. In this paradigm, prediction models for network equipment failures give early notification of events (*e.g.*, link/device failure) that may lead to performance degradation (*e.g.*, QoS violations). In this way, network operators can proactively take preventive measures (*e.g.*, reroute traffic, migrate NFs) and plan ahead for maintenance. A key challenge in this aspect is the collection and labeling of network operational data. In operational networks, device logs are typically collected without any labels and often miss failure data. Consequently, it becomes difficult to associate failures and alerts from network equipment to their physical meaning.

3.6 Fault and Performance Management

Fault and performance management of E2E network slices can be addressed via a two-pronged approach: (i) proactive, and (ii) reactive. Identification of faults and performance degradation is crucial to ensure the QoS requirements for E2E slices in 5G and beyond mobile networks. Proactive fault and performance management can alleviate the impact of QoS violations, while reducing operational cost. Once a fault or a performance degradation has been identified, it is quintessential to localize its root cause, which pertains to reactive management. Root cause analysis is crucial to isolate alarms and extract meaningful dependencies between them, leading to subsequent stages of mitigation and healing.

Once a fault or performance degradation is detected, mitigation workflows (*e.g.*, reconfiguring E2E slice, resource reallocation, service migration, traffic re-routing) must be executed to alleviate failure impact on services and to prevent failure re-occurrence. However, the challenge lies in determining the appropriate workflow that should be taken when faults and performance degradation are detected. With the complexity of 5G and beyond networks, it is impractical to hand-craft *if-this-then-that* policies for triggering mitigation workflow in the face of failures. In this context, Reinforcement Learning is a promising approach for enabling networks to learn the best mitigation workflow for different scenarios over time.

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