Fifth Generation (5G) networks are envisioned to be fully autonomous in accordance to the ETSI-defined Zero touch network and Service Management (ZSM) concept. To this end, purpose-specific Machine Learning (ML) models can be used to manage and control physical as well as virtual network resources in a way that is fully compliant to slice Service Level Agreements (SLAs), while also boosting the revenue of the underlying physical network operator(s). This is because specially designed and trained ML models can be both proactive and very effective against slice management issues that can induce significant SLA penalties or runtime costs. However, reaching that point is very challenging. 5G networks will be highly dynamic and complex, offering a large scale of heterogeneous, sophisticated and resource-demanding 5G services as network slices. This raises a need for a well-defined, generic and step-wise roadmap to designing, building and deploying efficient ML models as collaborative components of what can be defined as Cognitive Network and Slice Management (CNSM) 5G systems. To address this need, we take a use case-driven approach to design and present a novel Integrated Methodology for CNSM in virtualized 5G networks based on a concrete eHealth use case, and elaborate on it to derive a generic approach for 5G slice management use cases. The three fundamental components that comprise our proposed methodology include (i) a 5G Cognitive Workflow model that conditions everything from the design up to the final deployment of ML models; (ii) a Four-stage approach to Cognitive Slice Management with an emphasis on anomaly detection; and (iii) a Proactive Control Scheme for the collaboration of different ML models targeting different slice life-cycle management problems.
**Keywords** 5G · Mobile communication · Computer network management and control · Computer networks · Machine Learning

1 Introduction

Fifth Generation (5G) mobile networks pose a major paradigm shift, aimed to improve efficiency and flexibility with a service-oriented architecture that delivers networks as-a-service. The underlying concept is to support multiple services and virtual networks over one or more physical network infrastructure, with respect to (wrt) different service definitions and performance requirements. This service-oriented 5G vision can address the vast variety of emerging resource-hungry wireless services, via a cost-efficient network composition and resource sharing model that reduces both Capital Expenditure (CAPEX) and Operating Expenses (OPEX). The later is done by decoupling infrastructure providers (e.g., operators and data center owners), service providers (e.g., operators and verticals) and network function providers (e.g., vendors). Therefore, a 5G service can be built by combining multi-vendor physical network functions and Virtual Network Functions (VNFs), bringing network slicing to the foreground as a key enabler for the envisioned service-oriented 5G.

Slicing enables the composition of multiple logical networks and their delivery-as-a-service or as-a-slice over a shared physical infrastructure. A slice can either be completely isolated from the other slices down to the different sets of spectrum and cellular site, or be shared across all types of resources including radio spectrum and network functions, or be customized for a subset of user plane and control plane processing with an access to a portion of radio resources in a virtualized form. Furthermore, a slice may span across multiple domain-specific resources each with different levels of isolation and sharing to accommodate the needs of both Network Operators (NOs) and slice owners.

But apart from its grand potential, slicing adds further to the already increased complexity of network and traffic management in 5G. The denser and more heterogeneous nature of 5G networks, on the one hand, and the required slice resource provisioning and performance fulfillment, on the other, both call for Zero touch network & Service Management (ZSM). Following a long period of remaining in obscurity, Machine Learning (ML)-based approaches have created a trend towards different aspects of ZSM in the literature such as discussed in [4,6] thanks to breakthroughs made on computational devices, mainly multi-core Central Processor Units (CPUs), Graphical Processing Units (GPUs) and Tensor Processing Units (TPUs). Therefore ML models qualify as an appropriate option for managing multiple coexisting 5G slices on top of physical resources within a unified Cognitive Network & Slice Management (CNSM) system.

1.1 Motivation for an Integrated Methodology

ML algorithms can be trained to learn how to efficiently tackle concrete problems towards (re)organizing network and slice resources straight after online input data. This means that even after their deployment the models can keep learning from feedback such as network statistics. Also, they have to coexist and in most cases cooperate within the wider scope of 5G cognitive management, without the need for a time-consuming human engineering intervention or the use of predefined action rules. This is also supported in the work [8], which discusses the solution of a wide variety of wireless networking problems by deploying ML approaches.

A 5G CNSM system can deploy appropriate ML algorithms against two main causes for increasing runtime costs: unnecessary slice resource overprovisioning and the lack of desirable overprovisioning. While unnecessary slice overprovisioning regards dedicating more resources than needed (e.g., due to lacking an accurate demand model or due to the inability to predict outstanding demand fluctuations), “desired” overprovisioning needs to be clarified. First off, it prevents resource underutilization and may further enhance NOs’ revenue in cases of Service Level Agreements (SLAs) that allow to assign to slices virtually more resources than the available physical ones. Second, it helps to avoid SLA violations and corresponding penalties, which are particularly high for critical slices like eHealth, by taking timely overprovisioning actions. These actions enable to correspond quickly to predicted resource need increases such as when an ambulance is moving fast by quickly changing next Generation NodeB (gNB) on its way to the hospital.

Past work in the literature has identified the need for a well-defined and organized way to manage 5G sliced resources intelligently. The authors of [9] propose a cognitive management architecture with ML techniques following the Monitor, Analyze, Plan and Execute over a shared Knowledge (MAPE-K) control loop.

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1 ZSM is a concept defined by the European Telecommunications Standards Institute: https://www.etsi.org/technologies/zero-touch-network-service-management.
2 Tensor Processing Unit by Google: https://goo.gl/8TZLRS
Along the same lines, the work of [11] introduced an architectural framework based on the MAPE-K loop for 5G network management tools to address requirements such as batch, real-time and joint batch plus real-time. Another interesting work presented in [5] demonstrates how to empower self-organizing networks based on an ML model used to cluster and forecast the network traffic of cells.

The current work takes a different approach and tries to complement efforts such as the ones above by covering a gap of a methodological approach that systematizes, organizes and automates a series of necessary steps for building efficient ML models as components of a unified 5G CNSM system. In essence, we try to design a framework on (i) designing ML models that (ii) can work together in order to identify and apply an appropriate resource provisioning model adaptable to the high network dynamics and demand uncertainties in 5G.

Towards such a methodology, we identify three strongly-coupled dimensions (see Figure 1):

1. **Choosing–training–validating**: A dimension of choosing, training and validating an appropriate ML algorithm targeting a specific problem type.

2. **Identifying/predicting problems**: A dimension for predicting and identifying the exact nature a problem after input from network and slice-logical “sensor readings”.

3. **Runtime life-cycle**: A fully fledged management life-cycle that defines the runtime cooperation of the different ML models that together form a unified 5G cognitive management system.

Accordingly, the current paper poses a novel Integrated Methodology approach to CNSM in virtualized multi-tenant 5G networks. The methodology is built bottom-up, aligned with a concrete eHealth use case by keeping a specific example (5G connected ambulance) in mind along with references to other examples and further use case scenarios. However, it is elaborated towards deriving a generic methodology approach that can cover a plethora of other 5G cognitive slice management use-cases, adding further components as needed.

### 1.2 Contribution

In a nutshell, the main points of contribution of our methodology are:
• **5G Cognitive Workflow Management model**[3] We adopt a Workflow of four phases that serves as a step-wise guideline for abstracting every important aspect for successfully building an appropriate ML model, spanning from specifying the exact type of a problem related to 5G CNSM up to training, deploying and maintaining the model. This component tries to address the previously identified “choosing–training–validating” dimension.

• **Four-stage approach to Cognitive Slice Management (4-CSM):** We identify four stages to managing 5G slices in a cognitive way that span from gathering slice “sensor” readings and identifying a potentially “anomalous” situation, up to taking action(s) against it. Note that each stage follows the Workflow internally. This component tries to address the “Identifying/predicting problems” dimension.

• **Proactive Control Scheme (PCS):** PCS models a fully-fledged runtime approach for addressing arising problems, and a complete life-cycle for 5G CNSM. PCS describes the runtime execution of the deployed ML models, hence incarnating the deployment phase of the Workflow model. Moreover, it organizes the functioning, the update actions, the cooperation and –if needed– the redeployment or replacement of running ML models with other ones trained specifically for different scenarios. As it becomes clear, Proactive Control Scheme (PCS) tries to address the “runtime life-cycle” dimension.

As portrayed in Figure 1, the above components integrate into a unified methodology, and of which address a corresponding methodology dimension. The Workflow abstracts the internal process of each step in the 4-CSM, while the 4-CSM guides the steps for addressing runtime slicing issues by PCS, emphasizing on anomaly detection and prediction. Therefore, the three methodology components are intertwined with 4-CSM holding a “linking role” between the Workflow and PCS.

Last, as a by-product of our methodology’s practical assessment, we contribute raw and processed 5G Radio Access Network (RAN) monitoring data[12] from the MAC, RRC and PDCP layers to the Community Resource for Archiving Wireless Data At Dartmouth (CRAWDAD). To our knowledge, this is a rare contribution of real 5G RAN monitoring data to the 5G community.

1.3 Article structure

This article is organized as follows. Section 2 introduces the reader to fundamental concepts such as SLAs and the eHealth use case as a reference for building the methodology. Moreover, it discusses important related works in the literature regarding the use of ML in 5G. We proceed with posing and analyzing all the components that make up our integrated methodology in Section 3, and discuss its applicability beyond the scope of the eHealth use case. In Section 4, we demonstrate the merits of the proposed methodology in a practical assessment based on two different use case scenarios. Finally, we wrap up and outline our future work goals in Section 5.

2 Background and Related Work

This section introduces the reader to the practical problems faced by NOs while trying to respect their SLAs with 5G slice owners. As a first step, we provide a high-level description of the problem of keeping NOs in line with their SLAs by continuously optimizing network resource allocation to address the high network dynamics in 5G. Second, we outline the role of cognition in respecting SLAs.

Next, we discuss use cases in 5G. We focus first on the eHealth use case defined within the context of the EU-initiative H2020 SliceNet project. This discussion is fundamental, as we take a use case-driven bottom-up design approach based on eHealth to derive our methodology. Putting things within a greater perspective, we also discuss two other sample use cases in 5G, namely a strike sample use case and another one on sudden and important events. Note that we return and explain how our approach can be applied to other 5G use cases after presenting our methodology in Section 3.5.2.

Finally, we outline significant works from literature related to how ML can be used in 5G.

2.1 Service level agreements in 5G

The heart of the 5G cognitive slice management problem lies in the continuous effort of NOs to respect their Service Level Agreements (SLAs) with slice owners. Although there is no general “recipe” for SLA contracts,

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For brevity, also simply referred as the “Workflow”.
they are usually along the lines of guaranteeing a particular level of Quality-of-Service (QoS). For instance, giving at least a 2 Mbps download capacity to the User Equipments (UEs) of a 5G slice in 95% of the times. SLA violations translate directly to monetary penalty costs and can even lead to significant revenue losses due to dissatisfied slice owners that can shut down their slices and move them to a competitor NO.

Unless dictated by an SLA, the current trend is for NOs to depart away from the obsolete and inefficient model of overprovisioning of the resources, and rather to adapt a resource multiplexing model for hosting and controlling 5G slices \cite{13,15}. Nevertheless, resource multiplexing can put at stake the SLAs of different 5G slices running in parallel and competing for the same physical resources \cite{16}. Consequently, NOs need to timely predict and address possible SLA violations via continuously monitoring network conditions. Some examples of network conditions include network statistics like traffic congestion in the backhaul (BH), the fronthaul (FH) or the wireless part of RAN slice, throughput and throughput jittering or latency perceived by UEs. Other examples that refer to monitoring network states include the quality of UE connectivity services such as the percentage of cellular attachment failures or cellular handover failures. Last, monitoring can include clearly user-centric metrics like UE battery consumption, which is of particular importance in IoT 5G slicing scenarios.

2.2 The role of Cognition in respecting Service Level Agreements

No matter how quick in predicting and responding ML-based solutions can be, still, there are scenarios in which it is inevitable to violate one or more slice SLAs. Therefore, pragmatically efficient solutions must imply cognitive actions that re-allocate resources among the hosted slices in a way that optimizes a feasible resource utilization by minimizing the induced monetary cost penalties for the NO. Such actions by an ML model could use the cost of the current or predicted utilization of physical operator resources as input. Resources imply their own type of a cost based on some cost function implied by the SLA.

Finally, the cognitive model must avoid wasting resources due to slice overprovisioning \cite{17} (i) prevent resource-wasting bottlenecks in either the Core Network (CN) or RAN, and to (ii) conform to slice SLA requirements \cite{18} during a near-by future time-window. Another example refers to expanding RAN and wireless resources for a particular slice so that the latter can achieve its mobility management and/or wireless scheduling goals that derive from its SLA requirements.

2.3 Use Cases

2.3.1 The eHealth Use Case

We consider an eHealth use case organized around the concept of a “5G connected ambulance” that acts as a mobile edge or hub for emergency medical equipment and wearable sensory devices, enabling to store and to stream real-time video of patients’ data to the awaiting emergency medical professionals at the destination hospital. Real-time streaming video enables the awaiting professionals to remotely monitor the patient and possibly to provide life-saving remote assistance while in the ambulance under the supervision of the remote specialists with access to sensory and video data.

The SLA requirements in the eHealth use case are highly demanding, mainly w.r.t. two aspects:

1. There is a need to support High Definition (HD) and ultra HD video streaming from the 5G connected ambulance to the remote site where professionals reside to serve serious medical emergencies requiring a detailed video made available to remote professionals, e.g. for a serious injury or a stroke. Note, that under extremely stressful network conditions or when an ambulance has to go through a poorly covered area, the HD requirement may be degraded to Standard Definition (SD) video quality.

2. This enhanced and interactive communication between the medical professionals and the remote paramedics requires the continuous and uninterrupted collection and streaming of data, starting from the arrival of the emergency ambulance at the incident point and lasting until the delivery of the patient to the destination hospital. The goal is for all paramedics to have wearable clothing that can provide real-time video feed as well as other sensor-related data pertaining to the immediate environment.

Based on the above, it is clear that the ambulance (i) must remain connected to the 5G network throughout its trip to the hospital, while the required (ii) HD video QoS must remain guaranteed under difficult conditions, falling back to SD only when it cannot be done otherwise. “Difficult” conditions refer to traffic jams impacting the distribution of ambulances to cells and, thus, their share of available physical resources; unexpected network
flashcrows and/or background network traffic; and Massive Emergency Event (MIE) under catastrophic scenarios such as massive injuries or extreme weather conditions where multiple ambulances must be served at any cost, getting the highest possible QoS even at the cost of degrading/shutting down other slices over the same physical infrastructure. Apart from multiplying the needs for network resources in catastrophic scenarios, note that it may be required to serve the ambulances via gNBs along road routes “out of the ordinary” towards the hospital.

Clearly, eHealth slices must be treated with the highest priority compared to other slices in order to have enough resources to deliver the service and to respect the SLA. The HD video requirement, in particular, also raises the QoS standards in terms of the needed amount of resources that satisfy a quite hard Quality-of-Experience (QoE) expectation by medical professionals, who must have a crystal-clear view of the patients’ condition.

As a final remark, we note that the eHealth use case requirements fall within the general class of End-to-End (E2E) slicing requirements. E2E slice users, i.e. medical professional at a fixed point on the one end and paramedics in a mobile environment on the other, must be satisfied based on one or more QoE metrics. At the same time, a series of strict QoS levels must be aligned with the SLA between NOs and slice owners. Ideally, QoE levels should be automatically extracted from quantified QoS metrics, rather than asking users to score their opinion. The latter can be impractical to perform for medical professionals who must quickly treat one incident after another during an emergency shift. This implies the use of further ML techniques that use QoS as part of their input. Nevertheless, this is a problem that is orthogonal to what we discussed here, thus it is left out of the scope of this article.

2.3.2 Strike use case

Let us assume a simple SLA according to which all the UEs of a slice must have a guaranteed access to wireless cellular resources with at least 2 Mbps of throughput. To simplify complexity even more, let us also assume that the SLA requirement must hold with a 100% level of guarantee, i.e: (i) every UE (ii) must always have access to a gNB and (iii) must always enjoy the aforementioned minimum throughput.

A typical working day involves residential area users turning on their UEs and starting to roam to non-residential areas or to hotspots within the residential areas (e.g., students going to schools, people that work in the city center, etc.). These are observations in time and space characterizing a “normal” slice behavior. Thus, the hosting NO expects to have to increase (resp., reduce) the range of its gNBs or to turn on (resp. shutdown) some gNBs following user dynamics. Parallel to such evident actions, a series of other actions must be taken to support traffic dynamics such as increasing (resp. reducing) RAN BH/FH resources (e.g., microwave BH connections to gNBs), all of which map to cost changes for implementing the SLA.

Problems start to arise under a strike scenario or any other equivalent event. This either sudden or scheduled event directly unsettles the ordinary traffic pattern in many ways. For example, users do not use the bus or metro lines, which decreases the expected UE usage during commuting because users that drive their own vehicle do not stream video content as they would do when commuting with mass transportation. Moreover, some users may not even leave home at all.

In such a use case scenario, the NO must take actions in order to continue to respect the SLA, despite the anomaly in the traffic pattern demand. In addition, slice users may be homogeneous such as in the case of a special students slice, which can make the use-case clearly user-centric. In bottom line, addressing the observed traffic pattern anomaly translates to preventing needless overprovisioning of resources for certain gNBs, while allocating more resources to other gNBs for serving users who, e.g. stay at home rather than move.

2.3.3 Sudden and important events

For the sake of a more complete view on possible use-cases and scenarios, here we briefly comment upon sudden, important and/or emergency event scenarios like traffic demand flashcrows that occur after an accident, police incident or a natural disaster (fires, earthquakes, floods, etc.). Note that sudden & important event use case scenarios can coexist with the eHealth use case. Sticking to the SLA can involve prioritizing

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4 The role of ML is to predict ambulance paths (including radio handovers) and side-traffic demand from other slices. Then, based on a given slice priority parameter, special ML models define how resources are given to slices. Shutting down, rather than degrading, other slices is an extreme action (the last resort).

5 Our framework makes no assumption regarding the number of users grouped in a slice. This is up to the slice SLA designers and the developed ML algorithms that manage the slices.
slices, shutting down slices (for security), taking resources from other slices and giving them to eHealth, military or police slices, so as to preserve the desired E2E QoE for users.

2.4 Related Work

The work of [4] identifies the high complexity and OPEX in the upcoming 5G era. The authors focus on Self-Organizing Networks (SONs) as a solution, which falls within the concept of ZSM adopted in our work. To this end, they propose a comprehensive framework for empowering SONs with big data to address the requirements of 5G. Likewise, to some steps and actions in our workflow, they do data characterization and clarify the needed ML tools to transform big data into integrable data forms in a Knowledge Base (KB).

The authors of [9] propose a cognitive management architecture with ML techniques following the Monitor, Analyze, Plan and Execute over a shared Knowledge (MAPE-K) [10] control loop. The work also presents a prototype instantiation for two NO use cases using Long-Short Term Memory (LSTM) and an ML framework for real-time accurate bandwidth prediction for mobile users.

Along the same lines with [9], the authors of [11] build upon the Lambda Architecture [19] by proposing an extended version of it, namely, the Extended Lambda Architecture (ELA). ELA is a generic unified framework solution for new 5G network management tools. It combines together batch and real-time data processing with adaptive ML in a simple Monitor-Analyze-Plan-Execute scheme over a shared Knowledge (MAPE-K) loop [10]. Last, this work provides an experimental tool after the ELA architecture, which tries to address the objectives of mobile operators for cell outage management in 5G.

Another interesting work presented in [5] demonstrates how to empower SONs based on an ML model for traffic management after clustering and forecasting cellular traffic. Despite the idea being designed for older generations (GSM, 3G, 4G), it remains largely contemporary in 5G due to a large number and heterogeneity of cells, as well as a variety of traffic characteristics per different cell types.

All of these works have an important contribution towards ML-based ZSM in 5G. However, they leave an important gap for systematizing, organizing and automating all the necessary steps and actions for building efficient ML models as components of a unified 5G CNSM system. This is where our work comes in place to complement the above.

3 Integrated Methodology for Cognitive 5G Network & Slice Management

In what follows, we present and analyze our novel integrated methodology approach. We start by defining the role of the KB and its various aspects w.r.t. to the methodology components. Then, we provide a detailed description of each methodology component by building our concepts upon the eHealth use case (Section 2.3.1), noting, however, that the methodology is able to cover a broader context of use cases.

3.1 The Knowledge Base

Due to its continuous interaction with a process of analyzing data in Phase 2(b) of the Workflow, an initial Knowledge Base (KB) gets created and then continuously updated and optimized with (i) online monitoring data, (ii) processed/complex data such as labeled data along with desired policies, and (iii) feedback data from the deployed model(s). The result is a continuously-refined KB that interacts with the phases, stages and components of the Workflow, the 4-CSM and PCS, respectively. Therefore, the KB as a common abstraction component spanning every part of our methodology. As it becomes clearer after discussing Workflow’s Phase 4, the KB is an “integration” point between the training data fed to the ML model and the “knowledge” learned by the runtime of the ML model itself, an aspect which we present in the Proactive Control Scheme of Section 3.4. Also, the KB can be further enriched with logical network data “sensors”, an aspect which we cover later as the first stage of our 4-CSM (see “Pre-phase” on pg. 11).

Finally, there are two dimensions regarding the policies included in the KB:

1. First, there are policies on both raw and augmented/structured data, which dictate how to share data between stakeholders (i.e., slice owners and NOs) via filters that secure privacy restrictions such as for NOs which do not want to share all/parts of their monitoring information and setup/configuration logs with other NOs or even the slices that they host.
2. On the other hand, there are 5G policies in the KB that are orthogonal to data. Such policies can be used to train ML models or to complement their decisions, e.g. by posing handover restrictions between gNBs or by posing rules and restrictions w.r.t. hosting 5G slices across different NOs.

3.2 5G Cognitive Workflow Management model

Figure 2 portrays the 5G Cognitive Workflow Management model, which is composed of a step-wise series of four phases including two fallback loops marked as the “Validation Fallback” and the “Runtime feedback”. There is also an initial knowledge base built upon history data, which remains neither static nor composed of only raw data, getting eventually evolved to a Knowledge Base. In what follows, we discuss the KB first, and then every phase in detail.

Phase 1 - Problem Specification:

This first phase involves the proper identification of the 5G target problem. Some representative examples of 5G problems in the context of eHealth include anomaly detection (e.g., the ambulance moves too slow/fast or via areas with poor resource availability); regression, clustering or categorization (e.g., for discovering the statistical relationship between ambulance connectivity and/or route behavior to past performance data); prediction (e.g., ambulance connectivity will drop after a while or QoS will be degraded); or any other problem from a selection of well known ML problem categories.

The consequent two phases and, particularly, Phase 3 about the model definition on pg. 9 imply high costs w.r.t. human experts effort, computational load, and the corresponding time cost. Therefore, a wrong decision at this stage leads to a significant waste of time and resources until realizing that the problem specification needs to be revisited, forcing to loop back from Phase 3 to Phase 1, as denoted by the “Validation fallback” loop in Fig. 2. Not only that but also an added time cost has to be suffered for revising the ML model in an effort to address an unsatisfactory learning performance. Last, a revision to the problem specification and the ML model implies a further high cost for repeating the process of selecting the types and amount of raw and/or processed training data needed to train again the revised model (see Phase 2 next).

Phase 2 - 5G monitoring & History Data:

This phase embodies to strongly coupled sub-phases: first, for collecting new (raw) data from 5G sources such the RAN or the 5G CN, or for utilizing existing history data from past 5G recordings; followed by a process of analyzing the former input data into semantic information (i.e., useful/meaningful/valuable processed data) to be integrated to the KB.
(a) Collecting New or Utilizing History Data: This sub-phase implies the use of network traffic traces, network performance logs and/or online statistics from 5G sources. Thus, the discussions here as well as later in Section 3.4 about PCS are interdependent w.r.t. collecting both offline and online data, including performance monitoring feedback from the deployed runtime model. Depending on the exact nature of the problem we can utilize data from different network layers such as packet-level or MAC layer flow traces labeled with some 5G service or application class. Using RAN throughput as an example, we could use spectral efficiency data and data rate(s). Spectral efficiency can itself be the output of raw data processing like Channel Quality Indicator (CQI) or rank indicator metrics. In a likewise manner, the data rate can be the output of considering the number of active users, packet size(s) and rates, and/or cellular bandwidth. As previously mentioned, collecting raw and processed data can be done either (i) offline or (ii) online from different network 5G sensors. These “sensors” are logical entities specially crafted for monitoring 5G events (telemetry readings, topology-related, etc.), raw or processed networking information like network statistics. Whereas offline data involve history data extracted from a repository, online data collection takes place after model deployment during a perpetual data monitoring process parallel to the runtime ML model instance. Therefore, online data implies the use of real-time network information used either as input or feedback for updating the learning model (see “Runtime Feedback” loop in Fig. 2). Feeding data back to the ML model such as for mobile attachment or handover failures helps to maintain (keep training and improving) the deployed model. Note that online collected 5G data can be merged to a “dump/raw” repository of history data, or get later processed and used to update the 5G KB. Last, to put things into the perspective of eHealth, this sub-phase covers the need to provide the ML model that allocates resources to the eHealth slice with sanitized essential data or features like the statistical distribution of 5G connected ambulances in space (i.e., per gNBs) and time (during day or night, weekday or weekend, public holiday or season, etc.). Other key feature examples include the QoE reported by paramedics and remote medical professionals or the recorded QoS measurements.

(b) Processing, Structuring & Semantic Analysis: Evidently, the sub-phase of Semantic Analysis requires a problem-specific insight by combining knowledge from both 5G domain experts and service domain experts, e.g. in the context of the eHealth use case for video QoE optimization and/or for guaranteeing seamless transmission of sensory patient data. Raw data and statistics must be analyzed to extract the required key features from data samples, which will next further enrich the KB. This presupposes the pre-processing of raw data stemming from both monitoring and history data repositories, which includes: value normalization and discretization; data sanitization, as needed; detecting and correcting or clearing out corrupt/inaccurate records; possibly replacing absolute timestamps with relative times between 5G data recordings; performing dimensionality reduction, i.e. feature selection and feature extraction; and so forth. As a result, the KB gets to also include augmented/structured data. The manipulation of online data can take also place in real-time by special applications running in the 5G monitoring system. These applications can span from simple ones such as for calculating average bandwidth consumption per connected UE or slice, to more complex ones such as a ML model.

Phase 3 - Model Definition: This step happens in two separate but strongly coupled sub-phases: “Training & Harmonization” and “Validation & Optimization”. The goal within context of the eHealth use case is to come up a fine-tuned slice maintenance ML model that guarantees ambulance connectivity and a desired level of QoS. This, also, involves to both train and to validate a candidate ML model, where validation refers to the hard requirements of not falsely recognizing a need for reallocating network resources and to not assign resources sub-optimally to the eHealth slice. Notice that the two sub-phases are connected with a double-sided arrow, validation testing may imply the need to step back and repeat Phase 3(a), and then returning back to 3(b), as many times as needed.

(a) Training & Harmonization: As briefly mentioned on Sec 3.2 it is necessary to undergo a (most often time-consuming) offline training step based on analyzed history data and policies (e.g., NO policies on resource allocation priorities between slices, or slice QoS/QoE requirements) from the 5G KB, which yields an initial model. In addition, a painful harmonization takes place for model parameter tuning. This involves human effort based on accumulated ML training experience and w.r.t. the particular ML model, the level of understanding of the problem and of the input data. As a result, parameter harmonization may involve searching in a large space in seek for a “good” setup parameter approximation.

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6See the discussion on pg. 12 on output data dimensioning in Stage 3 of 4-CSM.
(b) Validation & Optimization: Offline validation is indispensable in order to evaluate whether the candidate ML model works sufficiently after its initial learning phase. It involves testing the output initial model to understand if it avoids over-fitting and under-fitting, both of which lead to poor performance during the final “Deployment & Runtime” Phase. Over-fitting, on the one hand, adapts “too much” to the details and noise in the training data, hence the model has ultimately adapted its decisions to noise and outlier data that prevents its ability to generalize to new data during runtime. On the other extreme, under-fitting causes the model to neither to fit training data nor to generalize. For example, when dealing with a sparse city area in a real-time deployment scenario, training data from dense city areas should not trigger actions analogous to the ones aimed for a massive emergency accident. And vice-versa, data from a sparse area should not lead to ignoring an emergency. The earlier would waste resources (hence, harm other, less-prioritized 5G slices); whereas the latter would fail to provide ambulances with guaranteed connectivity, HD video streaming and sensory data transmission during a massive emergency event that involves multiple ambulances in an otherwise sparsely inhabited area.

Based on the above, a candidate ML model can be optimized in the sense of lowering model complexity to tackle over-fitting, altering the data volumes fed to the model and examining wrong samples to discover flaws in the model and/or the KB. In addition, different parts of the KB can be utilized to train different versions of the same or another ML algorithm in order to tackle the different needs per use case scenario (e.g., the sparse versus dense area eHealth slice above). Finally, if the model fails to pass the validation sub-phase due to over-fitting, under-fitting or use of corrupt/inaccurate data, then the flow falls back to repeating Phase 2. Likewise, if the model fails to pass the validation sub-phase because of a wrong problem definition and corresponding model selection, then the flow needs to fall back to problem model Phase 1. We refer to the former as the Validation Fallback. Also, we remind the reader that if Phase 2(a) concludes that there is a need to redefine the model by re-harmonizing its parameters and re-training, then there is an internal step back to repeat Phase 3(a) and then returning back to 3(b), as many times as needed.

Phase 4 - 5G Deployment & Runtime Model: At first, a model may work in a best-effort way. Assessing its performance in practice involves tradeoff decisions that depend on the nature of the problem. Having the 5G networking and slicing concepts in mind, as well as the eHealth use case, this refers to the cost of resources (e.g., gNB energy consumption), accuracy versus overhead and response times (e.g., for ambulance attachment), and the frequency of handovers.

Given our 5G slicing context, we also include a Runtime Feedback loop from this runtime phase to the KB via the steps of Phase 2. The ML model takes real-time input like the current distribution of ambulances to gNBs, their scheduled routes towards incident sites and the current QoS demand for video streaming resources (HD or SD). Then, it retrains itself and yields (i) online ML model decisions based on which runtime phase provides (ii) performance output for enriching the KB.

3.3 Four-stage Cognitive Slice Management Approach

Figure 3 portrays a Four-stage approach to Cognitive Slice Management (4-CSM), as part of our integrated methodology. 4-CSM is composed of a (i) Pre-phase for measuring logical “sensor readings” from slices; a stage of (ii) Anomaly Detection based on input parameters, which may signify the need to address a situation “out of the ordinary”; a stage of (iii) Clustering or Categorization to identify the exact nature of the anomaly; and a final stage of taking appropriate (iv) Actions and (potentially) Updating the ML model. Notice that the depicted KB in the Pre-phase is shared among stages. Also, the Workflow model of Section 3.2 is internally followed by the later three stages of 4-CSM, which in turn pose the basis of the components of the Proactive Control Scheme (PCS) to be discussed latter in Section 3.4. Notice that the KB in the Pre-phase is later on shared among the consequent stages, as the pre-phase holds a preparation role for A/U, C/C, and A.D. by collecting and placing network measurements in the KB. The 4-CSM does not imply direct message flows between the stages. However, there is an implicit exchange of input/output data between the stages via the KB. Finally, we note that stages A/U, C/C, and A.D. share the same internal structural template presented in the Workflow model of Section 3.2 and that these stages pose in turn the basis of all components in the PCS discussed in Section 3.4.
Figure 3: 4-CSM: (i) Pre-phase; (ii) Anomaly Detection (A.D.); (iii) Clustering and Categorization (C/C); and (iv) Actions and Update model (A/U). The Pre-phase is operated by both slice owners and underlying NOs, and has a special preparation role for A.D., C/C and A/U that follow after. The rest of the stages are operated only by NOs, and are internally structured in line with the 5G Workflow of Fig. 2. Message flows between the stages can happen via the KB.

3.3.1 Pre-phase

A series of network measurements are collected via logical network “sensors” and placed to the KB. Such measurements can refer to (traces of) raw data like the description of an ambulance network attachment attempt at a certain point in time and space along with a failure/success bit; or they can refer to processed network information such as the percent of connection failures per slice, gNB region, etc. The ultimate goal of slice monitoring is to gather data about the current conditions in a slice and to place them in a repository as history data. As we analyzed in sub-phase 2(a) of our Workflow, the purpose here is to provide the necessary input for learning normal system behavior via some ML model, yet under the series of important considerations in the context of 5G slicing. Note that the questions posed below as well as the discussion that follows cover how our framework’s 4-CSM can be applied under both single- and multi-tenant 5G network scenarios, without a need to adopt any changes in the framework:

1. **Who owns training data?** NOs need access to QoS data, the *ownership* of which, however, belongs to slices. Likewise, QoE information can be valuable for training NO-run models, yet again owned by slices. Also, ML algorithms may need combined input information with sensitive data such as patients’ medical background, etc.

2. **Who pays the cost of resources to collect network data?** Sensors imply a significant system load for resource telemetry and traffic capturing (e.g., sFlow⁷).

3. **How and where is data stored?**

4. **How is data processed?**

5. **Who manages data?** What are the potential implications to *security* and *privacy* for sensitive patients’ medical data?

Besides the above, complexity raises further in E2E slicing scenarios, as 5G slices can be composed of resources from multiple NOs, of different types, using (un)licensed radio bands, etc. Fortunately, the adaptation of Software-Defined Networking (SDN)/VNFs allows each NO to expose its own VNF to the slice owner who can in turn use the VNFs to exchange signals with the NOs. Such “signals” can be either raw data or processed

⁷http://www.sflow.org/sFlowOverview.pdf
statistics. This concept is adapted via Virtual Network Applicationss (VNAs) \[22,23\] in response to an SLA, leaving room for interaction between NOs and slices, with mutual benefits: efficient resource multiplexing from the NOs’ perspective and desired runtime conditions for slices. For example, specially crafted VNFs can allow an eHealth slice to have the highest possible priority over less critical or best-effort slices.

Regarding security and privacy, using user mobility tracking data as our example, it becomes clear that slices cannot be expected to willingly share such sensitive data with NOs. eHealth slices, as well as public security slices (police, military, fire department, etc.), would probably not trust NOs to share where their vehicles can be statistically found more often. Existing literature solutions like Bloom filter data structures Bloom filters \[24\] enable slices to, e.g., pass information about UEs (ambulances) handed over to another gNB without exposing their ID. Particularly counting filters can be used to multiplex UE routes or higher-level information such as resource needs per route.

**3.3.2 Anomaly Detection (A.D.)**

Anomaly detection lies at the heart of the cognitive management of 5G slices. It is based on input parameters from the pre-phase such as the use of multi-signal input reading, which are fed to a model that responds with an anomaly score output for short-term prediction. For example, the score can be a difference-based metric that refers to the next time-window, computed after the algorithmically predicted data against the observed data. LSTM is a good example of an anomaly detection model that can be combined to recurrent Artificial Neural Networks (ANNs) \[25\] to capture network dynamics. For example, in eHealth LSTM can detect an arising anomaly in the routes taken by ambulances or their demanded QoS level. Irrespective of the ML model, it has to be continuously updated after each time-window. The input must refer to data from the current and/or a recent window to predict an anomaly in the next window. We return and discuss model retraining on Section 3.2.

**3.3.3 Clustering/Categorization (C/C)**

This is a bridging stage between anomaly detection and that of treating the predicted problem. Therefore, its purpose is two-fold. First, to interpret the anomaly so as to select a specially crafted ML model (possibly by replacing the running model) to address the issue or to provide information to the running model. As previously referred, one example within the context of eHealth involves using different resource allocation models for sparse and dense network areas. Another example refers to the use a different model under public emergencies that can lead to even shutting down other slices. The second purpose is to perform dimension reduction on data for the purposes of feature selection and extraction. Apart from reducing the cost of gathering data and maintaining the KB, dimensioning is necessary for passing the appropriate size and kind of input to the ML model running at the next stage. For instance, the ML model may simply need to learn (or get better trained by learning) from the number of ambulances or the frequency of their handovers in a greater area of gNBs, rather than per each gNB or a sector of an gNB.

Whereas dimensioning is straightforward with known mathematical models, understanding the anomaly and its cause(s) implies to perform either i) clustering or classification. The earlier refers to assigning the detected anomaly to an algorithmically discovered cluster of anomalies using an algorithm like K-Means. The latter refers to identifying with a predefined class of anomalies based on a ML probabilistic classifier algorithm, e.g. within the context of eHealth a massive incident like a building collapse, a natural disaster or a casual incident increase during vacation times. By definition, clustering needs further interpretation compared to classification. Labeling clusters can be more difficult, even painful, based on injecting test traffic in slices and then “following” that traffic to label clusters.

**3.3.4 Actions and model Update (A/U)**

This stage contains the appropriate actions taken by a ML-based cognitive slice management model tailored specifically for addressing the problem stemming from the previously identified type of anomaly. The result of these actions is a change in the performance of the slice, e.g. more ambulances can be supported with HD video QoS, causing training feedback to the running model. In essence, the model is continuously being updated with performance feedback as a result of its own actions. More details are provided in our PCS model discussion.
3.4 Proactive Control Scheme

Figure 4 portrays our proposed Proactive Control Scheme (PCS) as a graph of perpetually interacting components during the runtime of a fully fledged CNSM system. Each component has a specific role. Note that the context of this scheme is not bound only to models for addressing an already identified anomaly like an upcoming congestion in the CN or the RAN of a slice; but it can also apply to anomaly detection itself with the use of multiple ML techniques.

3.4.1 Monitor & State

The monitoring component continuously queries the current state in order to extract raw data about the slice such as ambulance to gNB link quality based on Received Signal Strength (RSS) or BackHaul (BH)/FrontHaul (FH) conditions like bandwidth and delay. “Monitor” can compute and submit processed data to “Predict” in the form of network statistics, e.g. average throughput per user or aggregated per cell. The monitoring level can be (re)configured to produce more (resp. less) stats or detailed/frequent stats, depending on the needs of the cognition loop and with a corresponding monitoring cost increase (resp. decrease).

3.4.2 Predict

This component feeds predictions to “Action” that depend on the current monitoring and status, as well as input about slice behavior under normal conditions. For instance, an ML algorithm can learn normal behavior, hence predict the expected load of ambulances, their location and the needed amount of resources based on, e.g., SLA-tailored re-enforcement learning. Example predictions include average throughput per ambulance or per cell during some next time window. Additionally, “Predict” cluster or categorize anomalies so that appropriate actions can be decided by “Action”.

Regarding eHealth in particular, PCS must reserve some resources in advance, which cannot be allocated fast enough upon demand. This implies giving the highest priority to allocating resources for the 5G connected ambulances even at the cost other traffic.

![Proactive Control Scheme Diagram](image)

Figure 4: Proactive Control Scheme. The scheme represents the runtime version of all Workflow phases and particularly phase 5. Likewise, it represents the runtime of 4-SCA with steps like the pre-phase being incarnated by the “State” and “Monitor”, or Anomaly Detection being identified with every component apart from “Action”. Last, the steps of Clustering/Categorization and Action/Update are identified more with the “Action” component.

3.4.3 Action

Actions in a 5G cognitive management system do not only control the network status. This component has a dual role as both an internal (i) ML control loop and a (ii) network control loop for network actions. The ML control loop can imply actions such as (re)validating a ML model in use and then replacing one ML
model with another one. Other possible actions include instructing to change monitoring level, to (re)start learning, etc. Note that all of these actions are intertwined, therefore they affect each other. Regarding the network control loop, example actions include readjusting transmission power from gNBs, handing over UEs to other gNB, turning on/off gNBs, altering the current status of cell breathing (i.e., the range of coverage of gNBs), adding or reducing CN resources (CPU cycles for serving packet queues, bandwidth), changing the BH capacity in the RAN, and so forth. Notice that some of these actions can affect one slice in particular or even all slices such in the case of altering cell breathing. Last, the changes caused by actions are fed back to the prediction component along with raw data (e.g. logs) and processed statistics from the state and monitor components, respectively, to always update the ML-based KB.

3.5 Applicability beyond eHealth

Next, we brief how our methodology is aligned to eHealth and how it gets generalized to virtually all use cases in 5G.

3.5.1 Aligned with the eHealth use case

The root goal is to identify an ordinary functioning pattern of an eHealth slice based on sanitized key data or features. This allows to build a ML model for the allocation of HD video resources under ordinary conditions as well as to identify in due time an anomaly w.r.t. the casually exhibited pattern. An anomaly can be caused by, e.g., a strike that forces ambulances to move via alternative routes (thus, to connect to different gNBs), or due to, e.g., a massive incident that puts more ambulances in streets and increases the demand for HD video streaming resources. Pattern anomalies are identified by Anomaly Detection models. Assuming as an example that an unusually high number of ambulances starts to move towards a forest area during a summer period, what follows is that this anomaly is classified by another special ML model for Clustering/Categorization to a particular type of a problem, in this case a massive incident of a forest fire. Last, the ML model trained for (re)allocating resources under normal conditions can be replaced in real-time with a specialized model for emergencies and, more specifically, for emergencies in network areas with a poor infrastructure such as a forest area. In this particular case example, an appropriate model would not only aggressively provision resources in favor of the eHealth slice, but may even completely shutdown some other slices.

3.5.2 Applicability to other 5G use cases

Our methodology can successfully address the needs of 5G use cases beyond eHealth, as its integral parts can be extend with further components as needed. Every Workflow phase is universal to crafting ML models for targeted 5G cognitive management scenarios by (i) treating every ML problem differently, (ii) creating and (iii) maintaining a special KB, and by (iv) training and validating a ML model that is targeted for the needs of a particular slice. Each 4-CSM stage can be applied beyond eHealth starting from a common need for “sensing” data as a pre-phase to learning normal slice behavior within the context of any use case. Then, continuing with detecting pattern anomalies, which signify a change and a potential problem such as content demand flash-crowds or unusual UE movement and/or concentration in an urban environment. What follows is anomaly detection as well as Clustering/Categorization as cornerstones for cognitive 5G slice management in all use-cases. Last, we remind the reader that PCS incarnates the runtime of virtually every 5G use case.

4 Methodology in Practice

In what follows, we demonstrate the merits of systematizing, organizing and automating all necessary steps and actions in our methodology towards building and deploying efficient ML models as components of a unified CNSM system. To achieve this, we present a practical assessment using two different use case scenarios both of which are related to wideband CQI (wbCQI). In general, CQI is an important 4-bit integer metric that denotes how good or bad the communication channel quality is, based on the observed signal-to-interference plus noise ratio (SINR) that is reported back to the gNB by a UE to indicate a suitable downlink transmission data rate. wbCQI, in particular, represents an effective SINR over the entire channel bandwidth.

Before we proceed with defining the scenarios below, we stress upon the fact that we do not propose nor intend to produce a realistic ML model as part of an integrated CNSM system. Our goal is to provide the reader with a Proof-of-Concept (PoC) evaluation of our methodology via posing two different use case problems and exemplifying how it can be necessary to (i) loop back to Phase 1 in our Workflow for redefining the 5G problem (in Scenario 1), or to (ii) loop back to Phase 2 for repeating sub-phase 2(a) (in Scenario 2).
Upon finishing with exemplifying the Workflow, we discuss how our trained regression model for the Scenario 2 can fit in the contexts of the 4-CSM and PCS, and comment on how it can be combined with other cognitive models in an integrated CNSM system.

4.1 Proof of Concept Use Case Scenarios

Scenario 1 – Estimating wbCQI in sleeping Internet-of-Things (IoT) device scenario: This first scenario regards the ability to maintain the desired QoS level for an IoT sensory device when the serving gNB has no knowledge of the device’s contemporary wbCQI because the sensory device goes periodically to sleep; thus, when it wakes up it starts to receive data with either old or unknown channel information.

Scenario 2 – Estimating wbCQI: This second scenario falls in the context of eHealth and regards the ability to maintain the desired QoS level for a service that allows the doctor to stream his video from the hospital to the ambulance or remotely control medical devices to treat a patient inside a moving ambulance. In eHealth it is important to guarantee the seamless mobility of ambulances, which gives priority to frequently tracking Radio Resource Control (RRC) metrics like Reference Signal Received Power (RSRP) and Reference Signal Received Quality (RSRQ) with the highest granularity on a per ms basis. However, Medium Access Control (MAC) metrics like wbCQI can be monitored in the order of tens of ms, as frequent monitoring implies significant costs per slice in 5G, with the amount of monitoring data becoming huge w.r.t. using online or for storing offline for future uses. Nonetheless, wbCQI is important for inferring information about the downlink quality of the ambulance, hence for maintaining HD video quality or for a critical Ultra-Reliable Low-Latency Communication (URLLC) medical remote control service.

4.2 5G Workflow

4.2.1 Phase 1; Regression model for wbCQI

We specify that both scenario problems fall in the well-known category of regression analysis for “predicting” wbCQI as a dependent value from other independent monitoring metric values. A proper wbCQI regression model will become part of our CNSM system, being responsible for assessing the contemporary status of QoS in either of our PoC use case scenarios.

4.2.2 Phase 2; 5G monitoring & History Data

Collecting New Data For the purposes of this PoC, we collected new and raw 5G RAN monitoring data using our prototype version of ElasticMon v0.1, a novel elastic monitoring 5G framework built over the FlexRAN for OAI-RAN and OAI-CN. The collected raw data contain over a 100 metric categories from the MAC, RRC and Packet Data Convergence Protocol (PDCP) layers as exposed by the FlexRAN controller recorded for 1 UE in a JSON format. These raw data are organized in 5 different raw datasets recorded for one gNB, each of which corresponds to one out of 5 different UE mobility scenarios by following different motion and distance patterns.

Note, that we have contributed these raw as well as processed versions of the datasets from Phase 2(b) to CRAWDAD. To our knowledge, this is still a rare contribution of realistic 5G RAN monitoring data to the 5G community.

Processing & Structuring Analysis It was necessary to process, structure and, in general, to clear up these raw datasets in two steps:

– Step 1; Pre-processing: Pre-processing takes place to sanitize raw recordings and to reduce the number of metrics per measurement from over a 100 to 42. Pre-processing is necessary for a series of reasons:

  • Adding a timestamp: Exact dates in raw measurements do not give useful information. It is necessary to add timestamps inside the recorded JSON tree of each measurement. This is needed for computing the time elapsed between consecutive measurements.
  • Cleaning out static values: Omitting specific metric fields that do not change over time. Such metrics maintain a constant value across measurements regardless of the UE being in motion or not.

8https://gitlab.eurecom.fr/mosaic5g/elasticmon/tree/develop. For more information on how to access the code and resources, visit the Mosaic5G web site: http://mosaic-5g.io/membership/.
9https://snapcraft.io/oai-ran, https://snapcraft.io/oai-cn.
Therefore, they offer no valuable information for prediction. Note that the remaining 'dynamic' metrics after this step drops to 42.

- **Adjusting corrupt/inaccurate metric values:** There were some measurements with corrupt/inaccurate values. The problem was addressed based on the type of the metric and number of consecutive corrupt/inaccurate values in two different ways by replacing evident corrupt/inaccurate values with (i) the median value of their neighboring rows, or (ii) the mean value over a period of time (e.g., past 100 ms) out of a series of neighboring rows.

- **Step 2: Dimensionality reduction & Feature extraction:** In this step, the number of metric features got further reduced from 42 to 15 according to the following:

  - **Correlation analysis:** We produced a correlation matrix[10] that enabled us to proceed with a corresponding appropriate feature extraction based on the level of correlation against wbCQI. In further, this process allowed us to reduce the dimension of the training input and testing datasets that would be used next for the model definition phase.

  - **Feature exclusion:** We excluded MAC statistic metrics like “mcs1Dl”, which are directly calculated based on wbCQI, as the purpose of the envisioned regression model is to predict the dependent wbCQI out of independent metric values.

The resulting analyzed datasets got ready-to-use for training and testing, being composed of recordings taken in approximately 30000 scenarios.

### 4.2.3 Phase 3 – Model Definition

We considered the following candidate regression model approaches in our effort to find a best-fitting regression model for predicting wbCQI:

- **LASSO:** Least Absolute Shrinkage and Selection Operator (LASSO) is a regression method that penalizes the absolute size of predictor coefficients. It is a good approach when dealing with highly correlated predictors.

- **Elastic Net:** Elastic Net is a linear combination of the penalties of both LASSO and ridge regression (a.k.a. weight decay). Note that Elastic Net encourages a grouping effect among highly correlated predictors, which enables better control of the impact of each predictor on the wbCQI prediction.

- **Random forest and XGBoost:** These are tree-based models. A random forest uses an ensemble learning method for regression by constructing multiple decision trees at training time and outputting the mean regression of the individual trees. Extreme Gradient Boosting (XGBoost) on the other, grows a tree with a “boosted” training approach according to which it learns each variable-to-variable relation and grows a tree accordingly.

**Training & Harmonization** We considered the $x_1^2$, $x_2^3$, $\sqrt{x}_i$, and $\sqrt[3]{x}_i$.p of the best 15 features $\{x_1, x_2, \cdots x_{15}\}$ from Phase 2 alongside those 15 features in our training data frames. This causes a x5 increase in the number of features (from 15 to 75), which adds up to the level of training complexity for all of our candidate models. However, it helps to capture any polynomial relations between the independent feature metrics and wbCQI. We chose not to get into the details of harmonizing the parameters of each candidate regression model, as this would imply many details orthogonal to showcasing the steps of our methodology.

**Validation** We chose to make a scenario-based split, where the training set includes data corresponding to all mobility patterns and the validation set includes its own patterns. By doing so, we aim to provide more insight on where and why the models fail to predict or become less accurate. Using a k-fold cross validation split, as it is common to do, would have not enabled us to discover the exact data series in time and space (due to the motion pattern) that cause performance to drop. Still, we tried to keep a 90% to 10% ratio between training and validation data set sizes, yielding a training set of 26082 data frames and a validation set that consists of 2959 data frames.

In what follows, we first explain why for Scenario 1 we need to loop back to Phase 1. Then, we explain why for Scenario 2 we need to also loopback, this time to Phase 2(a). Note that from that point and on, we stop referring to Scenario 1 for the rest of this PoC methodology assessment, and continue only with Scenario 2.

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[10] Based on DataFrame_Corr: https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.corr.html.
• **Scenario 1: Loop back to Phase 1:** Regarding Scenario 1, specifying the problem falls into the category of regression is **wrong**, thus we must fall back to Phase 1. The reason is that a regression model would need to use RRC metrics like RSRP, RSRQ and Power Headroom Report (PHR). But just like wbCQI, these metrics are normally reported back to the gNB, which means that when the IoT device is put on a sleep mode, none of these data would be available as input to the deployed model at runtime. In fact, according to LASSO the most important 6 fields are √RSRP, RSRQ, √PHR, √√RSRP, RSRP and PHR. A similar conclusion applies to the case of the other models too.

• **Scenario 2: Loopback to Phase 2(a) and repeat Phase 3:** We notice a pattern w.r.t. the highest prediction errors observed for all models. For example, in the case of LASSO, the highest errors are presented in Table 1. Similar errors about actual values '3' are observed with the rest of the models as well. Driven by this, we returned to the training and test sets and observed that there are wbCQI values, as continuous series with values such as 14, 13, 10 or 8 where interrupted in parts by a small series of values equal to 3. These value recordings stand easily out as disrupted because of the consistency and accordance of the data series with the mobility pattern of the user in time and space. Based on an expert’s view it is impossible for wbCQI to suddenly and ephemerally drop to a such a lower value. The latter is not consistent with the specific point in time and space-distance from the gNB, in an environment without any interference sources (other gNBs or UEs). Note that is a prominent example to remind the reader that the quality of all steps and stages in the process of designing, training and deploying ML models depends on human expertise.

To address this problem, we **fall back to Phase 2**. We do not need to take actions in Phase 2(a), yet in Phase 2(b) we replace the corrupted wbCQI values with the median value of their neighboring 100 recorded rows, i.e. the preceding 50 ones and the succeeding 50 ones.

| Actual | Predicted | Error |
|--------|-----------|-------|
| 3      | 14.17     | 11.17 |
| 3      | 14.16     | 11.16 |
| 3      | 14.19     | 11.19 |
| 3      | 12.88     | 9.88  |
| 3      | 7.88      | 4.88  |
| 6      | 9.82      | 3.82  |

Table 1: Highest prediction errors for LASSO.

After repeating the validation, we get the results presented in Table 2, showing a performance comparison between all models and a combined model (about which we comment later on) against the testing set. Apart from the prediction accuracy, the table contains the Root Mean Square Error (RMSE) and the Mean Absolute Percentage Error (MAPE). As denoted by its name, RMSE measures the differences between predicted values and actual values, whereas MAPE measures prediction accuracy and can be used as a loss function for our models’ performance. Both RMSE and MAPE express average model prediction error and are negatively-oriented scores (i.e., the lower, the better). Their main difference is that RMSE gives a relatively higher weight to large errors, which important w.r.t. to large-quality deviations based on wbCQI.

| RMSE   | MAPE (%) | Accuracy (%) |
|--------|----------|--------------|
| Lasso  | 0.153    | 10.99        | 76.71        |
| ElasticNet | 0.171    | 11.91        | 72.45        |
| Random Forest | 0.137    | 6.71        | 83.67        |
| XGBoost | 0.125    | 6.3         | 88.34        |
| Combined Model | 0.124    | 6.08        | 88.5         |

Table 2: Performance comparison of all models.

All evaluation results in Table 2 indicate that XGBoost clearly outperforms the rest of the models. It is more accurate parallel to having less RMSE and MAPE error scores. Random Forest ranks as a
second best option, with LASSO and Elastic Net following next. Nevertheless, a closer look to the distribution of errors across all valid wbCQI values from 1 to 15 is not uniform. This means that there is no single model which has a globally optimal performance across all wbCQI index classes. To provide HD video, the choice of the appropriate model has to be based on the ability of the model to be more accurate concerning service/scenario-specific wbCQI index values. Alternatively, we can create a model that combines all of the above regression models in seeking for an optimal prediction of wbCQI.

For this reason, we step back to sub-phase (a) and create, harmonize and retrain a Combined Model (see last row in Tables 2). The Combined Model is comprised of the weighted average of all models after trying all possible weight combinations and assessing the resulting performance of each weighted combination against the testing set. Specifically, LASSO does not contribute at all, whereas ElasticNet, RandomForest and XGBoost contribute with 1%, 21% and 78%, respectively. Notice that apart from having the highest accuracy, the combined model achieves in principal better error performance figures as well.

We are now ready to proceed to Phase 4. We assume that we select to deploy the Combined Model.

4.2.4 Phase 4 – Deployment

The Combined Model will be deployed in our system to predict the wbCQI of UEs in real-time. What follows is to describe how this ML model fits to the 4-CSM and PCS methodology components.

4.3 Four-stage Cognitive Slice Management

4.3.1 Pre-phase

This is an important stage in the 4-CSM for scenario 2. We remind the reader that the combined regression model needs input such as RSRP, RSRQ and PHR among others for the eHealth slice. The first question that needs to be answered is “Who owns training data?”. Given that these are RRC layer metrics it is more likely that their ownership belongs to slices than to NOs, yet access to the measurements or the estimated wbCQI is needed by the NOs in order to proceed with the necessary actions for offering the promised QoS level and respecting the SLA. Regarding “who pays the cost to collect such network data?”, recall the possibility of involving more than one NO at the physical level to guarantee the very strict requirements of this use case and to always deliver the eHealth slice. This means that measurement collection, as well as the corresponding costs, should be taken over the corresponding NOs, again as part of their obligation to respect the QoS promised in the SLA.

The remaining important questions are subject to the SLA agreement with the eHealth slice, referring specifically to (i) “how and where is data stored?”, (ii) “how is data processed?”, (iii) “who manages data?” and, last, (iv) “what are the potential implications to security & privacy?” noting for (iv), however, that this does not have privacy implication on sensitive patients’ medical data. In fact, it covers accountability about for the QoE, i.e. the perceived medical care in the ambulance, rather than privacy.

4.3.2 Anomaly Detection (A.D.) & Clustering/Categorization (C/C)

Our regression model is orthogonal to anomaly detection as well as to clustering and categorization. However, in the context of scenario 2, other models like LSTM or “k-nearest neighbors” can be fed with the same input as our combined regression model and the predicted values by our combined regression model. As a starting point, we can use the features extracted for the explored regression models which compose the combined model, included further or other features as needed.

4.3.3 Actions and model Update (A/U)

Actions refer to trying to adjust all parameters need after the predicted wbCQI such as slice bandwidth to maintain the desired QoS. Continuous updates of the models underlying the combined model are based on actual wbCQI values and predicted ones per composing model. This is more convenient to do offline, as there is more than one underlying model involved in this case.
4.4 Proactive Control Scheme

Finally, our regression model has, clearly, two potential placements in either the “Predict” and/or “Monitor” components of Proactive Control Scheme (PCS) (see Fig. [1]), which depends on a more high-level design approach to CNSM for this use case and for capturing scenario 2. To avoid confusion, wbCQI prediction by the combined regression model does not strictly refer to the (future) prediction of the QoS or QoE, but rather to the estimation (a.k.a. “prediction”) of a specific metric from other metric measurements. If wbCQI is directly used to take actions, then the combined model underlies “Predict”, hence continuously feeding with wbCQI estimations the “Action” component. Alternatively, if the combined regression model is used to estimate wbCQI for other models (anomaly prediction or for classifying the current network state), then in such a case it underlies the “Monitor” component, feeding with wbCQI estimations the “Predict” component.

5 Conclusion and Future Work

We propose a novel unified Methodology approach to Cognitive Network & Slice Management in virtualized multi-tenant 5G networks with the application of ML. Covering a gap in the 5G literature, our methodology eases the complexity of all the necessary actions for crafting and deploying efficient ML models. It follows a bottom-up approach that stresses upon the role of anomaly detection as a cornerstone for cognitive management, and it is comprised of three intertwined components, namely, (i) a 5G Cognitive Workflow design model, (ii) a Four-stage approach to Cognitive Slice Management and (iii) a Proactive Control Scheme. Last, we note our contribution [12] with raw as well as processed 5G monitoring datasets to CRAWDAD, as a rare contribution of real 5G RAN monitoring data to the 5G community.

Future work includes applying and testing our methodology in a greater number of realistic use case scenarios within and beyond the context of the SLibeNet project, leveraging further real network slice data, OpenAirInterface (OAI), and our Mosaic-5G constellation of 5G platforms [26]. One direction is to explore Q-learning such as in our most recent work of [27]. There, we follow our CNSM methodology to study, design, test and deploy an adaptive reinforcement model model as part of a PCS for VNF placement in a realistic city-wide 5G testbed and use case hosted by the University of Bristol. Such an example exhibits the ability of reinforcement learning and other online models like recurrent ANNs to be developed with our methodology as PCS components for controlling end-to-end slices from the CN to the RAN segment. The goal is to optimize the concurrent allocation of different types of resources in end-to-end and Multi-access Edge Computing (MEC) slicing scenarios, rather than studying the simplified cases of slicing a particular resource type in a particular network segment (e.g., only RAN) or a “narrow” problem like interference control [28]. In general, PCS fits well to the reinforcement learning concept due to the interplay between “Action” and “Predict” that resembles the actions of a Q-learning “agent”. Finally, we intend to investigate how congestion pricing models such as in [29,30] can enhance reward assessment schemes for Q-learning-based PCS algorithms.

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