

# RADIO RESOURCE MANAGEMENT (RRM) IN 5G NETWORKS USING BIG DATA ANALYTICS

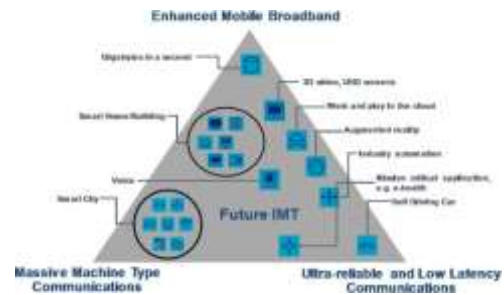
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**Abstract**—In the fifth generation (5G) of mobile broadband systems, Radio Resources Management (RRM) will reach unprecedented levels of complexity. To cope with the ever more sophisticated RRM functionalities and with the growing variety of scenarios, while carrying out the prompt decisions required in 5G, this manuscript presents a lean 5G RRM architecture that capitalizes on recent advances in the field of machine learning in combination with the large amount of data readily available in the network from measurements and system observations. The architecture relies on a single general-purpose learning framework conceived for RRM directly using the data gathered in the network. The complexity of RRM is shifted to the design of the framework, whilst the RRM algorithms derived from this framework are executed in a computationally efficient distributed manner at the radio access nodes. The potential of this approach is verified in a pair of pertinent scenarios and future directions on applications of machine learning to RRM are discussed. Big data analytics can process large amounts of raw data and extract useful, smaller-sized information, which can be used by different parties to make reliable decisions. We conduct a survey on the role that big data analytics can play in the design of data communication networks

(also referred to as mission-critical communications).



A succinct characterization of these services can be put forward as follows:

- eMBB supports stable connections with very high peak data rates, as well as moderate rates for cell-edge users.
- mMTC supports a massive number of Internet of Things (IoT) devices, which are only sporadically active and send small data payloads
- URLLC supports low-latency transmissions of small payloads with very high reliability from a limited set of terminals, which are active according to patterns typically specified by outside events, such as alarms.

**Index Terms**—Data Analytics, Radio Resource Management, 5G, Self Optimizing Networks(SON).

## 1. INTRODUCTION

### 1. 5G

5G mobile telecommunication standards stand for fifth-generation advancements made in the mobile communications field. These comprise packet switched wireless systems using orthogonal frequency division multiplexing (OFDM) with wide area coverage, high throughput at millimeter waves (10 mm to 1 mm) covering a frequency range of 30 GHz to 300 GHz, and enabling a 20 Mbps data rate to distances up to 2 km. The millimeter-wave band is the most effective solution to the recent surge in wireless Internet usage. These specifications are capable of providing 'wireless world wide web' (WWW) applications.

During the past few years, there has been a growing consensus that 5G wireless systems will support three generic services, which, according ITU-R, are classified as enhanced mobile broadband (eMBB), massive machine-type communications (mMTC), and ultra-reliable and low latency communications (URLLC)

### 2. RRM

Radio Resource Management (RRM) in Radio Access Networks (RANs) is a large-scale control problem encompassing numerous network functionalities operating at different time-scales ranging from sub-millisecond to seconds. The architecture governing RRM in today's RANs is the result of incremental engineering, with new RRM functionalities constantly being added to follow the system evolution. While this approach has stimulated rapid development of the 3GPP LTE system, ten years down the road of system evolution lead to an increasingly fragmented RRM architecture founded on an ever growing number of parameters.

The complexity of an RRM task depends on the dimensionality of the problem at hand and the available execution time. With the fifth generation (5G) of mobile broadband systems, which shall integrate new technology components (e.g. massive MIMO, mm-Wave

communication, network slicing, vehicular networks, more and broader frequency bands, etc.) with larger optimization domains and tighter latency requirements, RRM is expected to reach unprecedented complexity. Thus, optimizing such large-scale RRM problems with traditional rule-based algorithms is particularly challenging. RANs are data-rich environments, where data is continuously gathered in the form of radio measurements or other system observations by thousands of user devices and network entities. Nonetheless, RRM nowadays derives little insight from such data. On the one hand, data is utilized as input to run rule-based algorithms then swiftly discarded either upon aging (e.g., after few milliseconds) or when a user moves across radio cells. On the other hand, the decisions taken using such data are circumscribed in time and space. As a result, RANs currently treat data as a short-lived and localized commodity. The rapid advances in the Machine Learning (ML) field, however, combined with the recent technology leap in hardware specialized to handle large data sets, present an opportunity to give data a more central role in wireless networking. The contributions of this manuscript are twofold: A logical architecture to enable an efficient implementation of ML based solutions in RANs and a general purpose learning framework capable of autonomously generating, directly from data, algorithms specialized for the RRM functionality at hand. Thus, the learning framework treats data available in the RAN as a growing source of information from which RRM algorithms are derived (i.e., learned) and refined over time. We consider a framework broadly based on Reinforcement Learning (RL), a branch of ML suitable for solving control problems such as the ones arising in RRM. Although basic RL formulations have been successfully applied to specific RRM functionalities, a general-purpose application of RL to RRM poses additional challenges beyond the scope of these studies. Starting from such challenges, we discuss architectural and algorithmic approaches that can overcome the challenges and enable general purpose learning for RRM in RANs. Although the ideas proposed in this manuscript are described in the context of radio cellular networks, with 5G being the natural application scenario, the concepts extend to any RAN technology where one can conceive the idea of a central unit gathering data from the edge nodes. For instance, a proprietary Wi-Fi network deployed by a network operator, could collect data from the access network and learn to adjust several parameters of the MAC or PHY layer, such as the contention window, the thresholds for user association, transmission power, etc.

## 2. ROLE OF BIG DATA ANALYTICS IN CELLULAR NETWORK DESIGN

In this section, we review the research done on the use of big data analytics for the design of cellular

networks. Compared to other network design topics, we observed that the wireless field has received the most attention, as measured by its share of research papers. These papers can be classified according to the application or area under investigation. Consequently, we have classified those papers into the following:

**Counter-failure-related:** This includes fault tolerance (i.e. detection and correction), prediction, and prevention techniques that use big data analytics in cellular networks.

**Network monitoring:** This illustrates how big data analytics can be beneficial as a large-scale tool for data traffic monitoring in cellular networks.

**Cache-related:** Investigates how big data analytics can be used for content delivery, cache node placement and distribution, location-specific content caching, and proactive caching.

**Network optimization:** Big data analytics can be involved in several topics including predictive wireless resource allocation, interference avoidance, optimizing the network in light of Quality of Experience (QoE), and flexible network planning in light of consumption prediction.

### Failure prediction, detection, recovery, and prevention

Inter-technology failed handover analysis using big data:

One of the most frustrating encounters happens when a mobile subscriber gets surprised by a sudden call drop. Many of these incidents occur when the user is at the edge of a coverage area and moving towards another, technologically-different area, e.g., moving from a 3G Base Station (BS) to a 2G BS. The common solutions to address such shortcomings are by either conducting drive tests or performing network simulation. However, another solution that leverages the power of big data was proposed by the authors in [1]. The proposed solution uses big data analytics (Hadoop platform) to analyze the Base Station System Application Part (BSSAP) messages exchanged between the Base Station Subsystem (BSS) and Mobile Switching Center (MSC) nodes. Location updates (only those involved in the inter-technology handover) are identified and the geographic locations where the 3G-service disconnections occur are identified by relying on the provided target Cell ID.

The results of the above method were then compared with a drive test (which is an expensive and time-consuming approach) results, where coherence between the two results was demonstrated. Another comparison was conducted with the Key Performance Index (KPI)-based approach and the results were in favor of the proposed approach.

By utilizing the combination of all around signaling and user and wireless environment data, combined with Self-Organized Network technologies (SON), full-scale automatic network optimization could be realized.

The authors of [2] developed an intelligent cellular network optimization platform based on signaling data. This system involves three main stages: Providing best practice solutions: Identified and solved problems can provide an optimization experience. As a consequence, a variety of network problems can be verified. For example, when a cell has a low handover success rate, according to the definition of the associated indicators, the reason is suggested to be the low success rate of the handover preparation. The solution would be to adjust the overlapping coverage areas formed between the source and the target cells and the parameters (e.g., the decision threshold offset and the handover initiation).

A recommended solution can be provided when a deteriorating indicator surfaces, and this is simply done by clicking the index query that caused the deterioration.

### **Anomaly detection in cellular networks**

When a certain problem occurs in the cellular network, the user would usually be the first who feels the service disruption and suffers the impact. An abnormal and disrupted service may be identified by examining the Call Detail Record (CDR) of the users in a specific area. CDR files are generated upon making a call, and include, among other information, the caller and called numbers, the call duration, the caller location, and the cell ID where the call was initiated or received.

A CDR based Anomaly Detection Method (CADM) was proposed by the authors in [3]. CADM was used to detect the anomalous behavior of user movements in a cellular network. This was done, first, with the CDR data being collected from the network nodes and stored in a mediation department. Then, the second phase starts by distributing the collected CDRs to the relevant departments (e.g., data warehouse, billing, and charging departments). After that, the Hadoop platform is used to detect the anomalies. The discovered

anomalies are then fed-back to the mediation department for adequate actions. The use of big data analytics was essential in this case. Large datasets that require distributed processing across computer clusters were processed by the Hadoop Platform. The result was an improved system that is able to detect location based anomalies and improve the cellular system's performance.

### **Self-healing in cellular networks**

The idea to develop a system that is capable of monitoring itself, detecting the faults, performing diagnoses, issuing a compensation procedure, and conducting a recovery is very appealing. However, the self-healing process has another factor to keep in mind, which is time. The process should be carried out within a reasonable amount of time so it would not degrade the quality of the delivered services.

Self-healing process in cellular networks: Detecting Sleeping Cells: Cell outage or sleeping cells is a common problem in mobile networks. Users are directed to neighboring cells instead of the nearest and optimal cell.

### **Cell site equipment failure prediction**

A sudden outage of services might have serious consequences, and this is why keeping communication equipment, like cell sites, in a good working state is of high importance. The challenge identified by the authors in [6] is to analyze the user's bandwidth on the cell level. Equipment(s) failure and infrastructure faults can be predicted by analyzing the bandwidth trends in a particular cell.

Due to the size and diversity of the collected data, it is essential to use big data analytics to process it. Thus, the customers' received bandwidth can be acquired over a particular time period (i.e., month or year, etc.). Next the data from diverse data sources are integrated and then analyzed to know the bandwidth trends.

### **Network monitoring**

Large-scale cellular network traffic monitoring and analysis

Large cellular networks have relatively high data rate links and high requirements to meet. Usually these networks use a high-performance and large capacity server to perform traffic monitoring and analysis. However, with the continuous expansion in data rates, data volumes, and the requirements for detailed analysis, this approach seems to have a limited scalability. Hence, the authors of [4] proposed a system

to undertake that task, utilizing the Hadoop MapReduce, HDFS, and HBase (a distributed storage system that manages the storage of structured data and stores them in a key/value pair) as an advanced distributed computing platform. They exploited its capability of dealing with large data volumes while operating on commodity hardware. The proposed system was deployed in the core side of a commercial cellular network, and it was capable of handling 4.2 TB of data per day supplied through 123 Gbps links with low cost and high performance.

**QoE modelling for the support of network optimization:** The authors of [5] believed that the management of services and applications needed more than just relying on the QoS parameters. Instead, they suggested taking the quality (i.e., QoE), as perceived by the end users, to be regarded as the optimization objective. Accurate and automatic real time QoE estimation is important to realize the optimization objective. In addition to the technical factors, non-technical factors (e.g., user emotions, habit, and expectations, etc.) can affect the QoE. A profile for each particular user comprising the above non technical factors would help in the QoE evaluation. Since answering the questions that would lead to a clear profile is not a task that would be fancied by a typical user, the authors suggested installing a profile collection engine on the users' mobile devices. User activities are compared and tracked to recognize differences and similarities, and then they are stored in a database for additional processing. After profiling, the following step constitutes the use of machine learning to identify the relationship between QoE and the influencing factors.

Data analytics can be used to discover what impacts the QoE in users' devices, as well as the services and network resources. The next step is for network optimization functions to react to determining what caused the problem and select the optimal action accordingly.

### 3. CLASSIFICATION OF RRM STRATEGIES

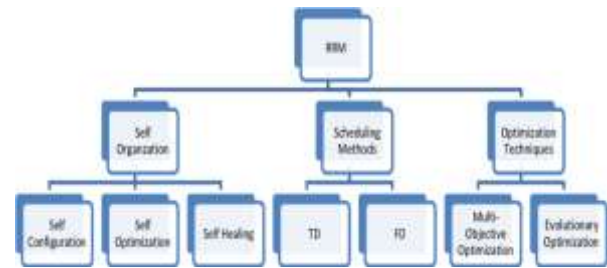
The self-organizing capabilities are divided into the following three activities:

**Self configuration:** It is the process carried out by the base station (BS) as soon as it is powered on. It's based on two parts: connecting to the backbone network and setting up radio configurations.

**Self-optimization:** It is majorly related to any operations carried out in case of system changes. It tries to self-optimize various QoS control parameters.

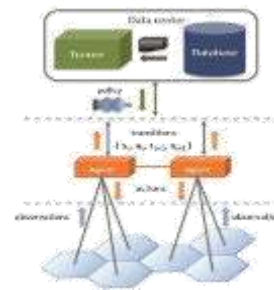
**Self-healing:** Its primary concern is detection and

recovery from failure.



Depicts various techniques commonly used in 4G with reference to resource sharing.

### LEARNING ARCHITECTURE FOR RRM



Learning architecture to enable centralized training and the distributed execution at the agents in RANs.

More powerful computer hardware technology, more efficient data storage technology, and more advanced machine learning tools present an opportunity to radically rethink the design of RRM algorithms. The leap in Graphical Processing Units (GPUs) and multi-core Central Processing Units (CPUs) technology made massive parallel computing widely available at relatively low cost. This gives the opportunity to consider the abundance of data continuously gathered in radio networks as the source of RAN's intelligence from which RRM algorithms can be derived and progressively updated, as opposite to today's approach of generating data to run RRM functionalities and discarding it soon thereafter. Data can therefore be reused both spatially (between cells) and in time. For instance, data associated to users that left the network is still valuable as it encodes system experience which can be reused at a later time or in other parts of the network. Another opportunity is the drive towards extensive radio measurements, e.g. originating from user centric uplink beaconing sensed with large antenna arrays at the network side, enabling more exact positioning and radio finger printing. Radio Environment Maps (REM) can offer convenient ways of representing such data. Additionally, the networks gather data related to both user mobility and to traffic

patterns, or more generally as to how/when/what the user acts in the network, at much higher rate than ever before.

#### 4. CONCLUSION

There are many areas in which big data analytics can be utilized in the network design process. The concept of gathering network data and correlating them with user trends and service requirements can indeed create an adaptive and user-centric network design. Throughout our paper, we noticed a lot of focus on the field of wireless communication networks design using big data. Delving deeper reveals that the field of 5G is getting the majority of the researchers' attention due to the new opportunities it has to offer. The optical networking, inter-DC and SDN fields, on the other hand, have yet further research challenges to tackle. We also note that the integration of SDN and big data analytics would facilitate the perfection of the design cycle. The field of network security also has its share where big data analytics is utilized to detect security threats. Industrial efforts toward optimizing networks based on big data analytics reflect the increasing trend toward employing AI-like approaches, such as pattern recognition and machine learning for network design. Some of the considered solutions handle big data in a batch manner while others are capable of performing real-time processing. Handling big data in a batch mode can offer more accurate information at the expense of delayed results due to the size of the processed data, while real-time processing offers fast results at the expense of accuracy. Hence, it would be an application-dependent decision whether to choose the former or the latter option. We predict that the field of network design based on big data analytics will continue to flourish in the near future as more data are collected from the networks and processed to extract useful information regarding network behaviour. In the far future, or maybe quite soon, as some claim, employing quantum computing for machine learning purposes could help in dethroning Moore's law and provide more processing space per unit time. This extra space can be harnessed for big data analytics employed in network design.

The abundance of data and significant improvements in capabilities of modern hardware and ML algorithms make the time ripe for introducing a fundamentally different RRM architecture, where individual rule-based RRM algorithms are replaced by a general-purpose learning framework capable of autonomously generating, directly from data, complex algorithms specialized for the RRM functionality at hand. The advantages of this approach are multi-fold. Firstly, the experience (i.e. data) gathered by an access node can be reused to improve the behaviour of other nodes. Secondly, improving the single learning

framework leads to an improvement across all RRM tasks, resulting in a compounded RRM performance gain. Thirdly, a new node installed in the operator's network will be promptly equipped with a near optimal policy by benefiting from the experience gathered by existing nodes. Moreover, changes in the non-stationary wireless environment are automatically taken into account by continuous learning at the network side. These benefits naturally result in significant Capital Expenditure (CAPEX) and Operating Expense (OPEX) reductions, while enhancing the system performance. The proposed learning NFQ-iteration combined with transfer learning and ensemble learning is an example of framework capable of improving the performance against the state-of-threat for a variety of RRM functionalities. Nonetheless, the fast pace of advances in the ML field regularly brings about more powerful techniques that can enrich or replace parts of the framework without affecting the overall architecture, which is intended to be future-proof. One such extension, given the recent successes of deep learning, is to directly learn features from raw measurements. While this approach requires significantly more data samples, naturally available in modern RANs, than the current feature-engineered solutions, the resultant features would certainly be more accurate. Another interesting and more involved extension is to jointly solve multiple RRM tasks with the aid of a single learned algorithm by extending the number of actions the agent has access to.

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