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SELF-ORGANIZED NETWORK MANAGEMENT MEETS MACHINE LEARNING AS WE TRANSITION FROM 4G TO 5G

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ABSTRACT

In this research, we analyze self-organized network management from the network's beginning to finish. Self-organization is commonly referred to as Self-organizing Networks (SONs) in cellular networks, and it is a crucial driver for enhancing Operations, Administration, and Maintenance (OAM) tasks. SON seeks to reduce the cost of 4G and future 5G network installation and administration by simplifying operational chores with the capacity to setup, optimize, and heal itself. This autonomous management vision must be extended throughout the end-to-end network to meet 5G network management needs. Machine Learning (ML) has been highlighted as the primary instrument to apply autonomous adaptation and take use of experience when making judgments in the literature and in certain instances of goods available on the market. In this article, we look at how machine learning technologies may help network management. We discuss and offer the fundamental principles and taxonomy for SON, network management, and machine learning. We examine the state of the art in the literature, standards, and the market. We pay special attention to the evolution of the Third Generation Partnership Project (3GPP) in network management, as well as the data that can be extracted from 3GPP networks, in order to gain knowledge and experience in how the network works, and to improve network performance in a proactive manner. Finally, we discuss the major issues connected with this area of study, both in 4G and in how 5G is being developed, while also highlighting new research avenues.

Keywords: Network Management, Machine Learning, Self-Organizing Networks, Mobile Networks, Big Data.

I. INTRODUCTION

Historically, and up to 4G, the transition from one generation of mobile networks to another was driven by breakthroughs in hardware technology. The 5G revolution is unique, and significant advances in software technology, particularly in network management, will be vital. With the introduction of these software improvements and unprecedented levels of processing capability, the goal of autonomous network management may be realized while also benefiting from additional cross-disciplinary knowledge advancements in the field of Machine Learning. This vision correlates with the network management principles of self-awareness, self-configuration, self-optimization, and self-healing. We focus on the access portion of the 4G cellular Long-Term Evolution (LTE) network using the Self-organizing Network (SON) concept. SON is a frequent word for mobile network automation and the reduction of human intervention in the administration of cellular/wireless networks.3GPP established this notion in Release 8 and has expanded it in successive editions. The 3GPP effort is motivated by the operators' Alliance Next Generation Mobile Networks (NGMN).

SON's major goal may be divided into three categories:

1) To introduce intelligence and self-adaptability into cellular networks;

2) To minimize capital and operating expenses (CAPEX/OPEX); and 3) to improve network performance in terms of network capacity, coverage, service/experience delivered, and so on.

Today, SON is regarded as a driving technology with the goal of increasing spectral efficiency, simplifying management, and lowering the operating costs of next-generation Radio Access Networks (RANs). The entire difficult SON problem has been reduced into a number of interesting use cases discovered by 3GPP, NGMN, 5G Infrastructure Public Private Partnership (5GPPP), and many EU initiatives [1]-[6]. In the context of the aforementioned use cases, the academic literature has committed substantial effort to SON algorithms, giving smart solutions to maximize network operator performance, expenditures, and user experience. Many of these works have already been discussed [7].

The market also already provides whole sets of SON solutions (e.g. [8]-[11], among others), and several items were promoted and exhibited during the 2016 and 2017 Mobile World Congress (MWC) [12], [13]. Air Hop's eSON from Jio & Air Hop communications [11], for example, which employs a multi-vendor, multi-technology, real-time SON solution based on a scalable and virtualized software platform, was recently awarded the 2016 Small Cell Forum Heterogenous Network (Het-Net) management software and service award [14]. However, to the best of our knowledge, the SON solutions on the market are 1) primarily based on heuristics, 2) automated information processing is typically limited to low complexity solutions such as triggering, 3) many operations are still done manually (e.g., network faults are typically fixed directly by engineers), and 4) SON solutions do not fully capitalize on the massive amount of information available in mobile networks to build next generation networks.

Furthermore, this self-organized network management concept should be expanded beyond the RAN segment to cover all network segments, from the access to the core, while meeting the requirements of various types of vertical service instances.

To realize this ambition, the networking world is looking in new areas. Network Functions Virtualisation (NFV) is projected to bring the economies of scale of the information technology sector to the telecommunications business. The benefits of programmability and flexibility are highlighted when NFV is combined with Software Defined Network (SDN) concepts. Another factor to consider is that, as we observed in [18], a large amount of data is already generated in 4G networks during normal operations by control and management functions, and more is expected to be generated in 5G networks due to densification [19], heterogeneity in layers and technologies, additional control and management complexity in NFV and SDN architectures, and the introduction of Machine to Machine (M2M) and Internet of Things. Another factor to consider is that, as we observed in [18], a large amount of data is already generated in 4G networks during normal operations by control and management functions, and more is expected to be generated in 5G networks due to densification [19], heterogeneity in layers and technologies, additional control and management complexity in NFV and SDN architectures, and the introduction of Machine to Machine (M2M) and Internet of Things.

Due to hyper dense deployments, heterogeneous nodes, networks, applications, and RANs coexisting in the same environment, 5G network management is projected to provide a whole new set of issues. 2) the need to manage highly dynamic networks in which operators may have little control over the deployment of some nodes (e.g., femto-cells), energy-saving measures are in place, resulting in a changing number of nodes, active antennas are a reality, and so on. 3) the requirement to sustain 1000x traffic and 10x users while also improving energy efficiency 4) the need to improve user experience by allowing Gbps speeds and extremely low latency 5) the requirement for new virtualized architectures to be managed, 6) the requirement to manage heterogeneous spectrum access rights via unique LTEUnlicensed (LTE-U), Licensed Assisted Access (LAA), and MuLTEFire paradigms, as well as the availability of both classic sub-6 GHz bands and above-6 GHz mmWave bands. In this demanding environment, we think that the usage of SON and smart network management policies is critical and unavoidable for operators running multi-RAT, multi-vendor, multi-layer networks with a plethora of factors to design and optimize. The overarching goal is to create networks. 1) more self-aware, by utilizing existing network information to build experience in network management; 2) more self-adaptive, by utilizing intelligent control decision procedures that allow for the automation of decision processes based on experience.

We think that Machine Learning (ML) may be utilized successfully to allow the network to learn from experience and improve performance. Big data analytics, in particular, may seek self-awareness by shifting network management from reactive to predictive by analyzing data already created by the network. Big data analytics are presently garnering a lot of interest in research and in the industry because of their capacity to provide insightful information from the examination of data that operators already have.

In this study, we will not look at these applications of data analytics and machine learning, but rather at the applications to 4/5G network management. Unlike previous surveys on SON [7], [20], or surveys related to 5G network management [21], we focus here on the study and analysis of the available literature on SON and network management from a 5G perspective, using ML as a tool to implement automation and self-organization. In Section II, we examine and explain the fundamental ideas and taxonomy of classical SON and 5G network management. We pay close attention to the progress of 3GPP in this area, adopting its terminology and referring to the specific use cases outlined by the standard.

In Section III, we next present advice for selecting the best relevant ML algorithm and methodology based on the network management issue to be addressed. Section IV examines the primary sources of information important to knowledge-based network management, data created by the network, and the literature on ML-based network management. Section V then highlights potential work issues. Section VI brings the survey to a close.

II. SELF ORGANIZING NETWORK (SON) AND NETWORK MANAGEMENT

SON is a fundamental driver in cellular network total performance optimization. The fundamental goal is to reduce human participation while improving network performance in terms of network capacity, coverage, and service quality. Its capacity to setup, optimize, and heal itself seeks to reduce installation and administration costs by reducing operating duties.

The fundamental reason for the increased interest in SON implementation from operators, standardization organizations, and initiatives is twofold. On the one hand, from a market standpoint, the ever-increasing demand for a variety of supplied services, as well as the need to minimize the time to market of new services, contribute to the pressure to remain competitive through cost reductions. However, because to the multiplicity of adjustable parameters and the deep relationships among them, the complexity and enormous scale of future radio access technologies present major operational issues. Furthermore, the introduction of heterogeneous networks is predicted to significantly expand the number of nodes in this new ecosystem, rendering traditional manual and field trial design methodologies impracticable.

Similarly, manual optimization procedures or expert-performed fault detection and treatment are no longer efficient and must be automated, since this results in time-consuming trials with restricted operational scope, or delayed, manual, and inefficient management of cell/site failures. Key operational tasks, such as radio network planning and optimization, are increasingly separated, resulting in inherent flaws such as the abstraction of access technologies for network planning purposes or the consideration of performance indicators that are of limited relevance to the end user's perception of service. European initiatives such as SOCRATES [2] and Gandalf [1] have addressed these issues using SON. SON has also been addressed in EU FP7 and 5GPPP initiatives. FP7 SEMAFOUR [3], in particular, which develops a unified self-management system to operate complex HetNets.

Among the 5GPPP initiatives, we emphasize SESAME [4], which offers the Cloud-Enabled Small Cell (CESC) idea, i.e., a new multi-operator enabled Small Cell by introducing Network Functions Virtualisation (NFV), enabling sophisticated self-management inside the access network architecture. The article project seeks to enable the application of ML to deliver real-time autonomous 5G network management in SDN and NFV [5]. The project specifically investigates the intelligent integration of cutting-edge technologies in SDN, NFV), SON, cloud computing, and artificial intelligence. The COGNET project [6] has similar goals and attempts to build multiple operators use cases using machine learning methods. 3GPP initially introduced SON as a fundamental component of an LTE network in Release 8, and it has since been expanded to successive releases. Meaningful SON use cases have been defined in SOCRATES [2] and 3GPP [22], which can be classified into three categories based on the phases of a cellular system's life cycle (planning, deployment, maintenance, and optimization), as shown in Figure 1.

First, we will provide a summary of the evolution of SON in 3GPP. We walk over the self-configuration, optimization, and healing functions, introducing the use cases for each. We examine the self-coordination problem in order to deal with any conflicts that may arise from the concurrent execution of various SON functions. The Minimization of Drive Tests (MDT) feature is demonstrated. Finally, we focus on an end-to-end vision by applying SON ideas to the core, and we address the importance of virtualized and software-defined networks in 5G Network Management. It is important to note that we do not focus on academic literature here because it has previously been evaluated in other fascinating studies [7]. We concentrate on the 3GPP taxonomy, the associated roadmap, and market penetration.

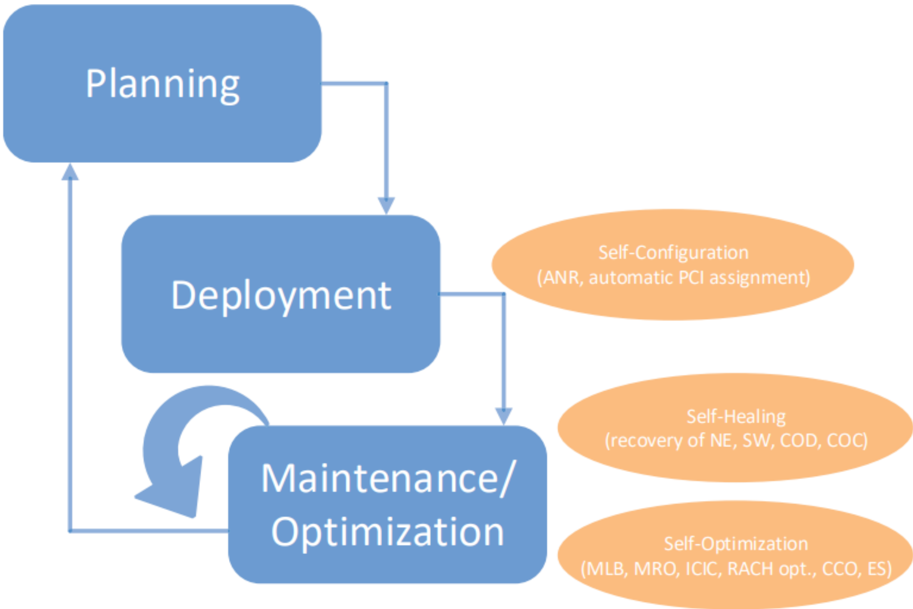

Fig. 1: Self-organizing networks

A. SON evolution in 3GPP

3GPP Release 8 has begun to define LTE and has already established the foundation for ideas and specifications, as well as SON functionalities for self-configuration, initial equipment installation, and integration. The ANR capability is added here to lessen the amount of administrative labour involved in setting the neighbouring list in freshly installed eNBs. In the context of Release 9, the concepts of self-optimization are defined. Coverage, capacity, handover, and interference are all optimized. Mobility Load Balancing (MLB), Mobility Robustness/ Handover Optimisation (MRO), Inter-Cell Interference Coordination (ICIC), and Random-Access Channel (RACH) optimization are the functionalities introduced (and will be explained in the next sections). Release 10 focuses on improvements to previously defined SON functions to improve interoperability between small cells and macro-cells, as well as NGMNs recommendations, such as new functionalities such as Coverage and Capacity Optimization (CCO), enhanced ICIC, and it defines all concepts related to self-healing, such as Cell Outage Detection (COD) and Cell Outage Compensation (COC). Finally, in Release 11, the ideas of MDT and Energy Saving (ES) are introduced and then expanded.

The automated administration of heterogeneous networks is one of the Release 11 SON functionalities. It improves mobility robustness optimization and inter-radio access technology Handover (HO). Release 12 includes small cell optimization and upgrades, as well as deployments in crowded regions. Unlicensed LTE ideas were added in Release 13. Aside from that, Release 13 investigated OAM upgrades in terms of centralized and distributed architecture. Specifically focuses on distributed MLB, as well as improved NM and centralized CCO. Finally, Release 14 is focused on addressing 5G criteria such as latency reduction, fair use of unlicensed spectrum, carrier aggregation support, energy efficiency at the OAM level, SON for active antennas, and so on. The development of SON in 3GPP is summarized on Table 1. Other publications of note include the protocol-neutral SON policy Network Resource Model (NRM) Integration Reference Point (IRP), including the Information Service (IS) [31], [41], and Solution Sets (SS) [42], [43].

B. Self-Configuration

The process of bringing a new network part into operation with little human operator interaction is referred to as self-configuration [24]. This includes the planning and deployment phases of the cellular system life cycle. All parts of the Enhanced Node Base Station (eNB) setup are handled by self-configuring algorithms. When you turn on the eNB, it recognizes the transport link and connects to the main network parts. Following that, the eNB is ready to establish OAM, S1 and X2 connections before entering operational mode. Following configuration, the eNB does a self-test to provide a status report to the network management node. ANR and Automated Configuration of Physical Cell Identity (PCI) application cases have been studied since Release 8 [75, 76]. The ANR function handles the conceptual Neighbour Relation Table (NRT) in the eNB. The Neighbour Detection Function, which is located inside ANR, searches for new neighbours and adds them to the NRT. The Neighbour Removal Function in ANR also eliminates obsolete NRs. The Neighbour Detection and Removal Functions are implementation dependent [77]. The PCI is a physical layer signature used to differentiate signals from various eNBs. It works on the basis of synchronization signals. Because the total number of PCIs in LTE is 504, reuse is unavoidable, particularly in dense installations. The Automatic PCI assignment strives for cell identification that is devoid of conflict and confusion [78]. [79] provides recommended procedures for both use scenarios.

TABLE I: Evolution of SON in 3GPP

Release	WI	Feature	TS or TR
Rel.8	SA5-SON concepts and requirements	SON concepts and requirements	[23]
Rel.8	SA5-Self establishment of eNBs	Self configuration	[24]–[29]
Rel.8	SA5-SON Automatic Neighbour Relation (ANR) list management	ANR, PCI	[30]–[33]
Rel.9	SA5: Study of SON related OAM Interfaces for HeNBs	SON related OAM Interfaces for HeNBs	[34]
Rel.9	SA5: Study of self-healing of SON	Self-healing management	[35]
Rel.9	SA5:SON OAM aspects: Automatic radio network configuration data preparation	Automatic radio network configuration data preparation	[24]–[26]
Rel.9	SA5:SON OAM aspects self-organization management	Self-optimization (MRO, MLB, ICIC)	[36]
Rel.9	RAN3: Self-organizing networks	CCO, MRO, MLB, RACH opt.	[37]–[40]
Rel.10	SA5: SON self-optimization management continuation	Self-coordination, self-optimization (MRO, MLB, ICIC, RACH opt.)	[31], [36], [41]–[43]
Rel.10	SA5: Self-healing management	CCO, COC	[44]
Rel.10	SA5: OAM aspects of ES in radio networks	ES	[31]–[33], [36], [45]–[47]
Rel.10	RAN2-3: LTE SON enhancements	CCO, ES, MLB, MRO enhancements	[38]–[40], [48]
Rel.11	SA5: ULTRAN SON management	SON management	[23], [41], [42], [49]–[52]
Rel.11	SA5: LTE SON coordination management	SON coordination [53]	[23], [31], [36], [41], [42], [51]
Rel.11	SA5: Inter RAT ES management	OAM aspects of ES management	[41], [42], [47], [49], [52], [54]
Rel.11	RAN3: Further SON enhancements	MRO, MDT enhancements	[37]–[40], [48], [55]–[58]
Rel.12	SA5: Enhanced NM centralized CCO	Enhanced NM centralized CCO	[36], [59]–[64]
Rel.12	SA5: Multi-vendor plug and play eNB connection to the network	Multi-vendor plug and play eNB connection to the network	[24], [65], [66]
Rel.12	SA5: Enhancements on OAM aspects of distributed MLB	OAM aspects of distributed MLB	[67]
Rel.12	SA5: Energy efficiency related performance measurements	Energy efficiency related performance measurements	[36]
Rel.12	SA5: Het-Nets management/OAM aspects of network sharing	Het-Nets/network sharing	[68], [69]
Rel.12	RAN2-3: Next generation SON for ULTRAN/EUTRAN	SON per UE type, active antennas, small cells	[70]
Rel.12	RAN2-3: ES enhancements for EUTRAN	ES	[71]
Rel.13	RAN2-3: Enhanced Network Management centralized CCO	CCO	[61]
Rel.13	SA5: Study on Enhancements of OAM aspects of Distributed Mobility Load Balancing SON function	MLB	[72]
Rel.14	RAN: OAM (SON for Active Antenna Systems (AAS)-based deployments)	Energy efficiency	[73], [74]

C. Self-Optimization

Self-optimization refers to the collection of techniques that optimize network settings during operation based on network measurements. Following is a quick description of the primary self-optimization functions implemented in the various recent versions [78]. Work on:

1. MLB:

The MLB is the SON function in charge of reducing cell congestion by transferring load to neighbouring cells. The primary goal is to improve end-user experience while increasing system capacity by dispersing user traffic among system radio resources. The load estimation and resource status exchange method facilitate the implementation of this function. Messages with important information for this SON function (resource status request, response, failure, and update) are sent over the X2 interface [40]. MLB can be enabled by adjusting the Cell Individual Offset (CIO). The offsets of the serving and neighbour cells that all UEs in this cell must apply in order to meet the A3 handover requirement are stored in the CIO [80].

2. MRO:

The MRO is a SON function that ensures proper mobility, that is, correct handover in connected mode and cell re-selection in idle mode. Among the particular aims of this function are the reduction of call dropouts, the reduction of Radio Link Failures (RLFs), the elimination of superfluous hand-overs, ping-pongs, and the reduction of idle issues. It is widely used. The messages that include useful information are as follows:

The S1AP handover request or X2AP handover request, the handover report, and the RLF indication/report are all examples of such requests. Release 11 concentrated on several handover optimization improvements [81]. MRO acts on the characteristics of the connected mode and the idle mode. It adjusts significant handover trigger parameters in connected mode, such as the event A3 offset (when referring to intra-RAT, intra-carrier handovers), Time to Trigger (TTT), and Layer 1 and Layer 3 filter coefficients.

It adjusts the offset values, such as the Qoff-set for the intra-RAT, intra-carrier scenario, in idle mode.

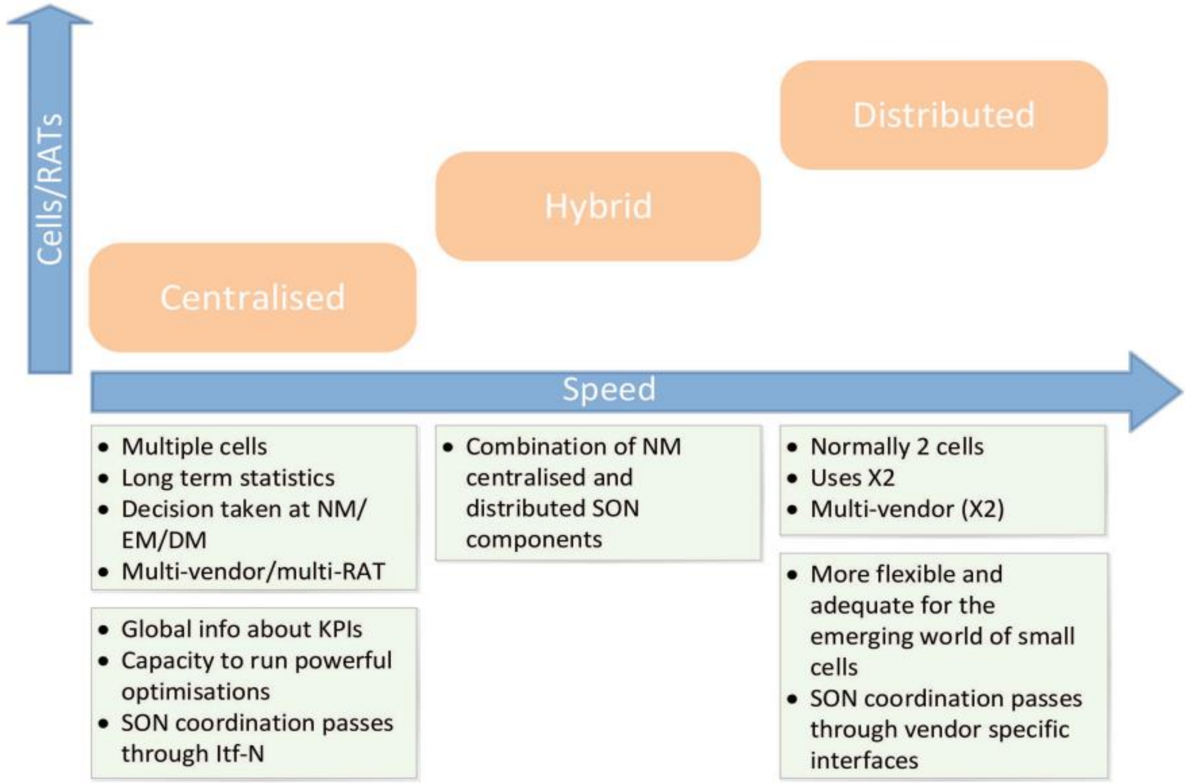

Fig. 2: SON implementations.

3. Inter-Cell Interference Coordination (ICIC):

The goal of ICIC is to reduce interference between cells that use the same wavelength. It entails coordinating physical resources among neighboring cells in order to prevent interference from one cell to the next. For the data channels Physical Downlink Shared Channel (PDSCH) and Physical Uplink Shared Channel (PUSCH), as well as the uplink control channel Physical Downlink Control Channel (PDCCH), ICIC can be done in both uplink and downlink. It is possible for ICIC to be static, semi-static, or dynamic. Dynamic ICIC is based on frequent parameter modifications, which are aided by cell-to-cell communication via the X2 interface. High Interference Indicator (HII) and Relative Narrowband Transmit Power (RNTP) indicators have been established to promote proactive coordination across cells, while the Overload Indicator (OI) has been introduced to provide reactive coordination [40].

4. RACH:

RACH optimization seeks to improve random access channels in cells based on UE feedback and knowledge of the RACH configuration of neighbouring eNBs. To achieve the desired access latency, RACH optimization can be accomplished by altering the Power control (Pc) parameter or changing the preamble structure [82].

D. Self-healing

Self-healing [44] focuses on the cellular network's maintenance phase. The RAN is the most crucial sector for fault control in wireless cellular networks. With little or no redundancy, each eNB is responsible for serving a specific area. If a NE is unable to execute its tasks, it causes a period of performance deterioration during which users do not receive adequate service. The operator suffers a significant revenue loss as a result of this.

Self-healing was first investigated in Release 9 [35], but it is in Release 10 that the majority of the work has been completed and features for detection and parameter modification have been described [83]. Release 11 [44] includes additional updates to these specs.

The main defined use cases are the following:

a. NE Software self-recovery. If the NE software failed because it was loaded with an older software version and/or configuration, the most essential step is to guarantee that the NE functions normally by deleting the faulty software and restoring the settings.

b. Board Fault Self-Healing. The goal of this use case is to resolve hardware faults in the NE [84].

c. Handling Cell Outages. This use case is divided into two parts:

1. Detection of cell outages. The key goal here is to detect a cell outage using monitor performance indicators that are compared to thresholds and profiles, and then to compensate for the outage. This use case tries to mitigate the downtime induced by the failure of a cell [44].

2. It refers to the automated mitigation of the outage's degrading effect by modifying necessary radio parameters, such as pilot power and antenna characteristics of adjacent cells.

E. Self-Coordination:

SON features are frequently developed as stand-alone functionalities through control loops. The impact of these interactions is difficult to anticipate whether they are conducted concurrently in the same or separate network components, and undesirable effects may even arise among instances of the same SON function when implemented in neighbouring cells. As the number of SON functions increases, so does the danger of intolerable oscillations of setup parameters or bad performance consequences.

3GPP has suggested several SON implementation designs, ranging from centralized C-SON to distributed DSON. The architecture chosen has a significant influence on the self-coordination framework's efficiency. If C-SON is employed, SON functionalities are implemented in the OMC or the Network Management Centre.

Systems (NMS) as a component of the Operation and Support System (OSS). This solution takes advantage of global data on metrics and Key Performance Indicators (KPIs), as well as processing capability to conduct complex optimization algorithms involving several variables or cells. It does, however, suffer from extended time scales. To avoid decision parameter oscillations, 3GPP mandates [53] that each SON function request permission before modifying any configuration parameter. This means that a request from the SON function must be sent to the SON coordinator, and a response must be returned.

All of these requests must flow via the Interface-N in Centralized SON (C-SON), which is not designed for real-time communication, therefore SON coordination messages cannot be prioritized above other OAM communications. If distributed coordination is implemented, the contact between the SON function and the local SON coordinator will take place via internal vendor-specific interfaces with substantially reduced latency. This makes the Distributed SON (D-SON) architecture far more adaptable and suitable for small cell networks, which have strong responsiveness to propagation and traffic circumstances due to their high transient traffic loads.

Figure 3 shows an example of how iterations across various SON functions deployed in a centralized and distributed way might cause network problems. This figure focuses specifically on the SON output parameter conflict, which occurs when two or more SON functions seek to optimize the same output parameter with distinct actions requests, and where at least three potential conflicts might arise: 1) a resource conflict between MRO and MLB; 2) a resource conflict between CCO and ICIC; and/or 3) a resource conflict between COC and ICIC use cases. We can identify output parameters that are influenced by two opposing decisions made by two separate functions that are each attempting to attain their own goals. As a result, it is deemed necessary to create and implement a self-coordination framework [2], [85], [86].

C-SON market implementations are provided by vendors such as Celcite (acquired by AMDOCS), Ingenia Telecom, and Intucell (acquired by Cisco), whereas D-SON solutions have traditionally been more difficult to implement and vendor specific, not allowing for easy interaction of products from different vendors, so that a supervisory layer is frequently still required to coordinate the various instances of D-SON across a much broader scope and scale. D-SON has just recently been proposed as a mainstream SON by suppliers like as Qualcomm and Airhop, as tiny cells and Het-Net require the millisecond reaction times of D-SON.

F. Minimization of Drive Tests:

MDT allows operators to gather measurements from User Equipments (UEs) as well as location information, if available, in order to optimize network management while decreasing operational impacts and maintenance costs.

3GPP has been researching this feature since Release 9 [87], with goals including standardization of solutions for coverage optimization, mobility, capacity optimization, parametrization of shared channels, and QoS verification [84]. Because operators are also interested in predicting QoS performance, MDT capability has been extended in Release 11 by gathering metrics showing throughput and connection concerns to appropriately design and plan the network [88]. These MDT features were expanded in Release 11, while Release 12 incorporated particular upgrades in terms of information correlation, as documented in the research on enhanced network management centralized CCO. [23] contains these additions and expansions of SON enhancements delivered up to Release 13.

G. Core networks:

Self-organizing features can be used to manage basic network operations. Reduced human intervention and lower operating expenses are also advantages in this instance. Self-organization in the core network enables self-adaptation of traffic loads and the avoidance of bottlenecks. Furthermore, Core self-organization allows the core network to handle signalling more effectively. Nokia [89] already automates fundamental network operations using SON technology in this area.

The goal is to automatically and quickly assign core network resources to satisfy unanticipated broadband behaviours and needs. It should be noted that SON use cases for core networks are not confined to LTE networks; many of them may also be used to other types of networks, such as 2/3G.

H. Virtualized and Software defined networks:

The wireless industry is presently preparing to handle a 1000x increase in data traffic. Users are unlikely to want to pay more for the service than they do now, posing a significant issue for both mobile operators and manufacturers, namely how to upgrade infrastructure 1000 times without raising CAPEX and OPEX. Aside from SON, another trend in this direction, initiated by an ETSI industrial study group in 2012, is NFV, which allows the IT industry to capitalize on economies of scale by shifting traditional network functions away from specialized hardware and toward general purpose computation, storage, and memory pools distributed throughout the network and in data centers. NFV virtualizes network functional parts, instantiating matching functionalities as programs that operate on commercial off-the-shelf (COTS) and less costly hardware. This concept is offered in conjunction with an SDN architecture to reduce the cost of mobile network deployments. [21], [90].

The basic goal behind these innovative designs is to provide a framework capable of supporting network operators in resolving management issues such as cyber assaults, network failures, network performance optimization, and user QoE, among others. SON may help accomplish real-time autonomous network management in this circumstance.

In this novel softwerized vision, we can leverage all of the opportunities provided by centralized, distributed, and local SON implementations proposed at the RAN level to extend this view beyond the radio access border, by proposing a SON over NFV architecture, in which SON functions aimed at addressing the main radio access and backhauling challenges of extremely dense deployments are virtualized and run over generic purpose hardware. As envisioned in the ETSI design, the NFV infrastructure will be administered by an orchestrator entity. This is the brain of the NFV architectural entities, with the most comprehensive perspective of the vertical service characteristics and network resource availability.

As a result, it coordinates function assignment throughout the many portions of the dense, heterogeneous network. At the methodological level, the orchestrator can use machine learning-based methodologies to use the massive quantity of information flowing across the network in terms of measurements, signaling information, QoS and QoE indicators, and so on.

There are already start-ups in the market promoting the notion of C-SON in the cloud. SON over NFV reduces software and hardware dependencies, as well as system scale constraints, and enables cost savings via automated operations. One of these is Cellwize [12]. They are proposing a cloud-based platform that would

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function smoothly across multiple suppliers, spectrum, and technologies. This study area is highly unique, with little previous work. However, we emphasize the ongoing work in the article and COGNET projects [5], [6].

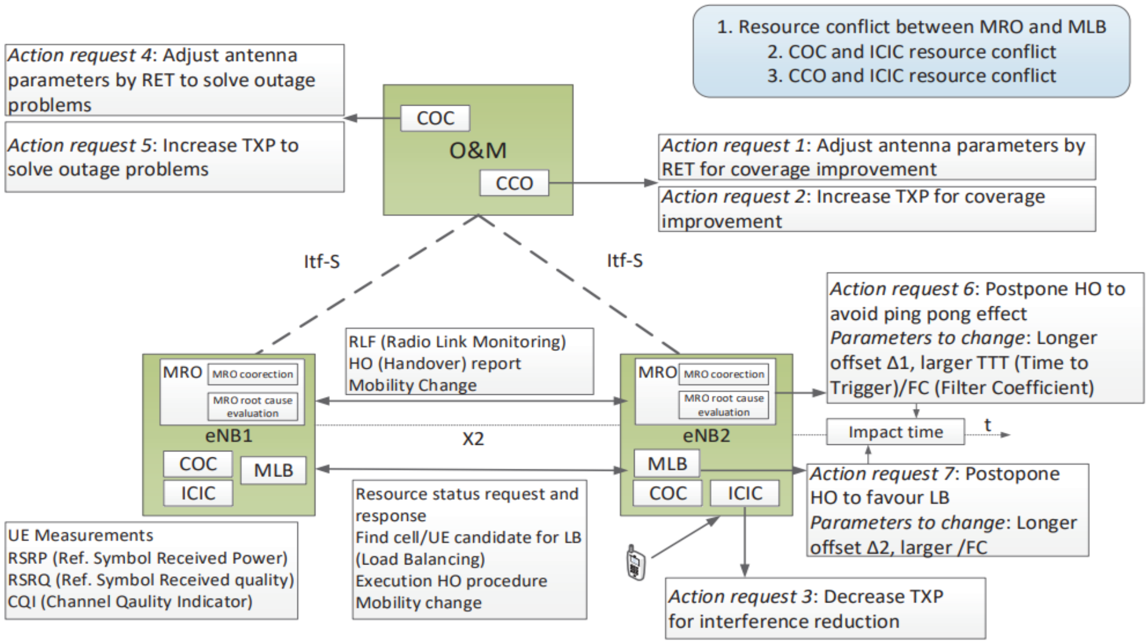

Fig. 3: High-level example of how the iterations of multiple SON functions may interfere.

III. HOW TO ADDRESS SON AND NM THROUGH ML

In this part, we categorize the many network management classes of challenges that one may encounter when attempting to manage the network in a self-organized manner. We identify the machine learning technologies that can be employed for each issue class. The goal of ML is to enhance the performance of a certain set of tasks by developing a model that aids in the discovery of patterns using learning techniques. TheA taxonomy of machine learning is generally divided into three categories: 1. Supervised Learning (SL), 2. Unsupervised Learning (UL), and 3. Reinforcement Learning (RL). New ML trends have recently gained traction, owing to advancements in software engineering, computing capability, and memory availability. Deep learning has been shown to be viable and extremely successful in a variety of applications, including language, video, and voice recognition, as well as object and audio identification.

The most notable example is AlphaGo's victory against the world champion in the Chinese board game Go. The creation of a deep reinforcement learning system capable of self-learning contributed to AlphaGo's win. Keeping in mind the SON and NM functions presented in the preceding section, the following issue classes must be addressed when operating the network autonomously:

- **Variable estimate or classification:**

The tasks in this class of issue aim at measuring the QoS or QoE of the network, anticipating network performances or behaviours, and learning from data collected from past network behaviours. QoS estimation and other MDT use cases, behaviour prediction to optimize network settings, and so on are examples of NM and SON functions where these activities are beneficial. Finding the link between one variable and others, or identifying which class of a collection of pre-defined classes the data belongs to, are solutions to these difficulties. Then, for both regression and classification problems, solutions are to be found in the SL literature.

- **Network fault or misbehaviours diagnosis:**

This class of challenges' tasks are aimed towards discovering difficulties in the network that may be caused by failures or incorrect network parameter settings. This type of issue is related to self-healing concerns, and answers may be found in UL literature, namely in the anomaly detection solution.

- **Dimensionality reduction:**

The network continuously creates a massive amount of data. It is convenient to reduce the noise existing in the data base by lowering the dimensionality of data for suitable processing and extraction of important information. This problem has solutions in the UL literature, notably among the dimensionality reduction techniques.

- **Pattern recognition and grouping:**

The activities in this class try to find patterns and groups of nodes with similar properties based on some form of criterion. One goal may be to apply comparable optimization methodologies to them. Self-configuration use cases are a natural solution to these problems. Solving these challenges entails understanding which classes the data belongs to. The UL literature provides solutions for clustering.

- **Online parameter adjustment challenges involving sequential decision making:**

This type of challenge is highly widespread in the field of autonomous management, where we encounter control decision problems to alter network parameters live in order to fulfil specified performance objectives. This type of choice issue, in which we learn the best suitable option live depending on the environment's reaction to the network's activities, may be solved via RL methods. These methods can solve all self-optimization use cases, as well as COC difficulties.

In the next part, we tie each type of NM problem to the ML literature that may be used to address it. The following review of ML literature is far from comprehensive. Many approaches and strategies will not be detailed since the goal of this paper is to present a helpful taxonomy for addressing NM and SON problems, as well as to study and comprehend the associated literature utilizing ML solutions. The reader is directed to explore particular literature for a fuller grasp of ML solutions.

- **Supervised Learning (SL)**

This ML approach might be quite effective when the NM function to be addressed includes variable estimation, prediction, and classification. SL is a machine learning approach that uses training data (organized into an input vector (x) and a desired output value (y)) to build a predictive model by inferring a function f(x), which returns the predicted output y. This necessitates the creation of a dataset. The dataset is often partitioned into two sets that comprise training samples (rows) and features (columns). The training set and the test set are used to train the model and ensure that the predictions are correct. The training model's purpose is to reduce the difference between predicted and actual values. As a result, we want to evaluate how effectively a learning algorithm generalizes beyond the samples in the training set by using ML.

A n-dimensional input vector x = (x (1),...,x(n)) T Rn represents the input space. Each dimension is a variable in the input. Furthermore, a training set has m training samples ((x1, y1),...,(xm, ym)). Each sample is made up of an input vector xi and an output vector yi. Hence The value of the input variable x (j) in training sample i is denoted by x (j) i, and the error is often determined using |yi yi |. The classification and regression applications of the SL approach are the most common. On the one hand, classification is used when y, the output value we are attempting to predict, is discrete, as when we want to predict whether a cancer is benign or malignant based on a dataset constructed from medical records and containing many features, such as tumour size, age, uniformity of cell size, and uniformity of cell shape. When y is a real number, on the other hand, a regression issue is used.

A large number of SL algorithms for classification can be found in the literature, and [91] has research that evaluates the performance of some of them. The most prevalent algorithms are briefly introduced here.

1. For classification and regression, k-Nearest Neighbours (k-NN) can be utilized. k-NN is a non-linear approach that uses the k nearest training samples in the input space as input. The expected output is the average of its k nearest neighbours' values. The Euclidean distance is a popular distance measure for continuous variables. The k-NN approach has the benefit of being simple to understand, quick to train, and requires little parameter adjustment. However, the prediction's precision is often restricted.
2. GLM stands for Generalized Linear Model. The linear model defines a linear connection between the output and one or more input variables, and the approximation function translates from xi to yi as shown below.

yi = 0 + 1x (1) i +.... + nx (n) i (1)

where i are the variables that are unknown. The goal is to select i in such a way that yi minimizes the loss function.

Typically, we assume that the samples in each dataset are independent of one another and that the training and testing sets are distributed similarly.

It should be noted that if the connection is not linear, the model should be extended in order to represent it [92].

3. Bayesian naivety. The approach is used for classification and is based on the Bayes theorem, which states that probabilities should be calculated based on prior probabilities. The primary responsibility is to categorize new data items as they arrive. When the dimensionality of the input is high, an NB classifier is preferred since it assumes that all characteristics are conditionally independent [93]. Because NB assumes independent variables, estimating the variables' means and variances takes just a little quantity of training data.

4. The Artificial Neural Network (ANN) is a statistical learning model inspired by the structure of the human brain, in which the linked nodes represent neurons that provide appropriate responses. Classification and regression methods are both supported by ANN. The primary concept is to train and verify a neural network in an effective manner. The trained network is then utilized to predict the test set. The parameters in charge of modifying the data in the computations in this approach are the weights.

The most critical characteristics to train are the interconnection pattern between various layers of neurons, the learning method for updating the weights of the interconnections, and the activation function that translates a neuron's weighted input to its output activation [97].

5. Support Vector Machines (SVMs) can be used for classification and regression. SVMs are inspired by statistical learning theory, which is a strong technique for estimating multidimensional functions [94], [95]. This strategy may be expressed as a mathematical optimization problem that can be addressed using well-known techniques. The purpose of this problem is to learn the parameters of a function that best suit the data given m training samples ((x1, y1),...,(xm, ym)). It examines hyperplanes. As a result, the hyperplane with the greatest distance from the sample points is preserved.

6. Decision Trees (DT) are flow-chart models in which each internal node represents an attribute test.

The branch represents the test result, and each leaf node represents a response [98]. DTs may be used for classification and regression, and they include annoying factors like the desired depth and number of leaves in the tree [99]. They also do not need any prior knowledge of the data, are resilient (i.e., do not suffer from the curse of dimensionality since they focus on the relevant qualities), and perform well on noisy data. DTs, like many classifiers, are dependent on the coverage of the training data. Furthermore, they are prone to overfitting.

7. The Hidden Markov Model (HMM) may be utilized for classification as well as other tasks. They may be used as a Bayesian classification framework, with the data described by a probabilistic model.

- **Unsupervised Learning (UL)**

When the NM function includes finding aberrant behaviours, recognizing patterns, or decreasing data dimensionality, this type of learning can be quite beneficial.

UL is a machine learning approach that accepts unlabelled input patterns and attempts to detect a pattern in them. In this scenario, we let the computer learn on its own without offering the proper solution to the problem. The objective is to build input representations that may be used to predict future inputs without providing the algorithm with the correct answer, as we do in supervised learning [105]. Clustering algorithms, dimensionality reduction methods, and anomaly detection algorithms are the three most essential groups of algorithms.

There are several instances of UL applications in our daily lives, such as news.google.com, genomics comprehension, computer cluster organization, social network analysis, astronomical data analysis, market segmentation, and so on. UL algorithms are typically used in the context of SON for self-optimization and self-healing use cases.

- **Clustering:**

The goal of this approach is to find groupings of data in order to generate a representation of the input. Non-overlapping, hierarchical, and overlapping clustering algorithms are the most commonly used for creating clusters by grouping data. Non-overlapping clustering algorithms include K-means [106] and Self-organizing Maps (SOMs) [107]. A hierarchical clustering approach [108] is used when clusters at one level are connected as clusters at the next level (cluster-tree). When an observation exists in more than one cluster at the same time, this is referred to as overlapping or fuzzy clustering. This method includes fuzzy C-means and Gaussian mixture models [106, 109]. Clustering can also be accomplished using HMM. This type of algorithm has been proposed in a variety of domains, including robotics, wireless systems, and routing algorithms for mobile ad hoc networks.

- **Reducing Dimensionality:**

High-dimensional datasets provide several difficulties. One issue is that not all of the measured variables are required to grasp the topic of interest in many circumstances. There are several algorithms available now that can predict models with great performance from high-dimensional data. Many situations, however, benefit by reducing the dimension of the original data. For example, in [110], [111], the authors address the problem of the system's large number of possible characteristics as input, and they propose that regression analysis performs better in a smaller area. The most prevalent approaches in this context are: Feature Extraction (FE) and Feature Selection (FS) [112]. Both approaches aim to minimize the amount of characteristics in the dataset. FE approaches do this by generating new feature combinations (for example, principal component analysis (PCA)), which project the data into a reduced dimensional subspace by recognizing linked characteristics in the data distribution. They keep the PCs with the most variation and eliminate the others in order to save as much information as possible while minimizing repetition [113]. Correlation-based FS approaches incorporate and omit data aspects without affecting them. Sparse Principal Component Analysis (SPCA), for example, extends the traditional PCA approach for reducing data dimensionality by imposing a sparsity requirement on the input features.

- **Detection of Anomalies:**

Anomaly detection detects occurrences that do not follow a predictable pattern. The system identifies a group of unexpected occurrences by modelling the most typical behaviours [114]. Self-healing is one of the primary functions for which these approaches are used; examples include [115], [116]. The two most popular methods are:

• Rule-based systems: similar to DTs, but more adaptable because new rules may be introduced without conflicting with current ones [114].

• Pruning techniques: they seek to discover outliers in any combination of variables.

- **Models with latent variables:**

This type of method allows for the development of a model in which an unknown variable aid in the simplification and description of data. The nonnegative matrix factorization is one example.

C. Reinforcement Learning (RL)

This group of ML techniques may be utilized to address NM functions that need network parameter control.

In contrast to SL, RL seeks to learn how to attain a certain objective through interactions. It is not practical to offer explicit supervision to the training (i.e. the correct answer to the issue) in many real-world applications, particularly in sequential decision and control problems. In these circumstances, we can only give a reward/cost function that tells the algorithm when it is performing well and when it is performing poorly. Many real-world applications, including as autonomous helicopters, network routing, robot legged automation, and so on, have previously demonstrated the effectiveness of RL [117]-[119].

The agent is the learner or decision maker who constantly interacts with the so-called environment. The agent chooses actions, and the environment responds by evolving into new circumstances. The environment, in particular, reacts to activities through rewards, which are numerical values that the agent attempts to maximize over time.

In order to get a good reward, the agent must utilize what it already knows, but it must also investigate in order to conduct better actions in the future. Learning might take place in a single agent or across numerous agents. ML techniques in single agent systems are capable of determining optimum choice policies in dynamic circumstances with only one decision maker. Distributed choices are made by several intelligent decision makers in multi agent systems, and optimum solutions or equilibria are not always guaranteed [120].

The problem is then specified using a Markov Decision Process (MDP) S, A, T, R,, where S denotes the set of alternative environmental conditions. S = s1, s2,..., sn, A represents the collection of potential actions. A = a1, a2,..., aq from which each decision maker may select, T (s ′ |s, a) is a transition function that denotes the probability of getting s ′ when performing action an in state s, R(s, a) is a reward function that specifies the expected immediate return obtained by performing action an in states, and 0 1 is a discount factor that prioritizes immediate rewards over future rewards [121].

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The MDP is the theoretical foundation of the RL framework [121]. The agent implements a mapping from states to probability of choosing each feasible action at each time step. The agent's policy is represented by this mapping.

IV. MACHINE LEARNING ENABLED NETWORK MANAGEMENT

As stated in the introduction of this study, mobile networks are a massive source of data that may be evaluated with the right tools in order to make better educated judgments about how to manage the overall 4G or 5G network. In this context, machine learning (ML) is a fantastic potential owing to its capacity to provide insightful information from the study of data that is already available to operators, which can be utilized to make improvements or modifications. In this part, we will look at how ML may be used especially for SON and innovative network management ideas.

First, we provide all of the important information sources that may be derived from a mobile network. All of these data are available to operators and may contain sensitive information about the privacy of users. Some useful data, however, can be extracted from open databases or sniffed from unencrypted control channels such as the PDCCH. We shall then deliberate on these alternatives. Third, we will go over the main SON and network management functions once more and provide a classification of the main inputs and outputs that we would need in the form of data when designing an appropriate ML algorithm to target the specific use case, as well as the KPI indicators that we would need to monitor. Finally, we present an overview of relevant work in SON and network management where ML approaches have been used, categorizing this work based on the desired use case, the specific high-level challenge to tackle, and the ML methodology that the authors have chosen to handle the problem.

a) Data generated by mobile cellular networks

According to [18], a massive quantity of data is already created in mobile networks during routine operations by control and management services. This type of data may be used to identify trends and extract relevant information. This enables more informed decisions to be made in order to efficiently control network performance. Table II details some instances of the many types of information created by mobile networks, as well as the type of usage currently offered by operators and associated references of relevance.

1) Chargeable Data Records (CDR). They are specified in [122] and give a detailed set of data at the service, bearer, and IP Multimedia System (IMS) levels.

Typically, these records are saved for offline processing by the operator. However, the granularity of this information in the temporal domain is rather coarse, as records are created in response to high-level service events (for example, the commencement of a conversation).

2) Functionality for performance management. This data source [123] [36] provides network performance data and covers, among other things, radio resource control and utilization, performance of the various bearers (both radio and backhaul), idle and connected mode mobility.

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TABLE II: Information elements relevant for ML enabled SONs

Source	Data	Usage	TS
Charging Data Records (CDR)	Includes statistics at the service, bearer and IP Multimedia Subsystem (IMS) levels.	These records are typically stored, but only used by customer service. The network operation departments typically do not leverage this information and do not have access to it, as much as customer service does not leverage network management data.	TS 32.298 [122]
Performance management (data on network performance)	It covers long-term network operation functionalities, such as Fault, Configuration, Accounting, Performance and Security management (FCAPS), as well as customer and terminal management. An example is that defined for Operations, Administration, and Management (OAM), which consists of aggregated statistics on network performance, such as number of active users, active bearers, successful/failed handover events, etc. per BS, as well as information gathered by means of active probing.	The data is currently mostly used for fault identification, e.g., triggering alarms when some performance indicator passes some threshold, so that an engineer can investigate and fix the problem. Typically, the only automatic use of this info is threshold-based triggering, which can be done with very low computational complexity.	TS32.401 [123], TS32.425 [36]
Minimization of Drive Tests (MDT)	Radio measurements for coverage, capacity, mobility optimization, QoS optimization/verification	This data is used for identified use cases such as coverage, mobility and capacity optimization, and QoS verification	TS37.320 [125]
E-UTRA Control plane protocols and interfaces	Control information related to regular short-term network operation, covering functionalities such as call/session set-up, release and maintenance, security, QoS, idle and connected mode mobility, and radio resource control.	A This information is normally discarded after network operation purposes have been fulfilled. Some data can be gathered via tracing functionality or used by SON algorithms which normally discards the information after usage	TS36.331 [48], TS36.413 [39], TS36.423 [40]

TABLE III: SON inputs, outputs and KPIs

SON function	Inputs	Output actions	KPIs
Mobility Load Balancing (MLB)	X2 resource status and load estimation information.	Tuning the CIO, i.e. offsets of serving and neighbour cells to satisfy handover conditions.	Improved QoS and capacity
Mobility Robustness/Handover Optimisation (MRO)	S1AP and X2AP handover requests, handover reports, RLF reports and indications.	A3 offsets, TTT, L1 and L3 filter coefficients, in connected mode, and Qoffset in Idle mode.	Minimized call drops, RLFs and ping pong effects.
Coverage and Capacity Optimization (CCO)	UE measurements	Transmission power, pilot power, antenna parameters, coordinated Almost Blank Subframes (ABS)	Maximized coverage and cell and edge throughput
Inter-Cell Interference Coordination (ICIC)	HII, RNTP, OI, UE Measurements.	Transmission power, pilot power, antenna parameters, coordinated ABS	Minimized Intercell interference.
Cell Outage Compensation (COC)	UE Measurements.	Transmission power, antenna parameters of neighbouring cells	Minimized outage.
Energy Saving (ES)	Resource status, UE Measurements.	Switch ON and OFF policies	Minimized energy consumption.

3) Drive test minimization (MDT). This data pertains to radio measurements of both idle and connected mode mobility, coverage elements like as power measurements, and radio connection failure events, and can be correlated with the UE conducting the measurement's position. More information on these statistics is available in section II-F.

4) E-UTRA Control plane protocols and interfaces, such as Radio Resource Control (RRC), S1-AP, and X2-AP protocols, are another rich source of data, particularly on topics such as cell coverage, user connectivity, mobility in idle and connected mode, intercell interference, resource management, and load balancing.

5) Data plane traffic flow data are also a valuable resource of data that may be acquired at various places network, such as the eNB or the PDN Gateway (PGW) and SGW (Serving Gateway). One example is the Internet Protocol Flow Information Export (IPFIX) defined format for exchanging this type of data [124].

b) Overview of ML based Network management's relevant literature

This section examines SON and Network Management's most current ML work. We will go through each primary function and use case, as well as explore relevant literature and the ML technique utilized to address the problem. Table IV highlights the major studies in this field and categorizes them according to the 3GPP use case, approach, and particular algorithm used by the authors.

1) Use case: The 3GPP-targeted use case is indicated.

2) Reference: Indicates the relevant work's reference.

3) Technique: The ML approach used (Supervised Learning, Unsupervised Learning, Reinforcement Learning) is indicated.

4) Problem: Indicates the overall issue to be resolved.

5) Algorithms: The exact ML algorithm used to analyze the data (see Table 4).

1) Mobility Load Balancing: The literature provides various instances of how ML approaches have been used to the MLB use case. The majority of applications fall under the purview of RL, since the basic challenge to be solved is a sequential decision problem concerning how to establish configuration settings that improve network performance and user experience. [135] contains an example of an RL application for the MLB use case.

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The authors offer a distributed Q-learning technique that learns the optimum MLB action to take at each load level while also reducing HO metrics degradation.

Approaches that combine fuzzy logic with RL capabilities have the benefit of capturing the uncertainty that exists in real-world complicated settings, whereas schemes that just include learning approaches may be constrained by the fixed variable specification. When fuzzy logic is combined with RL, the learning's modifying skills transcend the subjectivity with which the fuzzy variable may be described.

Alternatively, in [138], a centralized system is proposed, in which a central server in the cellular network uses a dynamic programming approach to calculate all HO margins across cells. In this area, in addition to RL, clustering algorithms have been developed to group cells with comparable features and supply them with similar configuration settings [139].

2) Mobility Robustness Optimization: In the instance of MRO, we discover many techniques based on RL to handle a control decision issue in the literature. The writers of [141], [142] concentrate on improving the user experience and the HO performance. In [141], the authors use the Q-learning approach to effectively reduce call drop rates, whereas in [142], the authors, unlike other solutions that assume general constant mobility, adjust the HO settings in response to network mobility changes using distributive cooperative Q-learning. In contrast to [141], [142], the authors of [143] also make use of fuzzy logic capabilities. Because these solutions are based on the control optimization of HO parameters using RL, they suggest solutions that are comparable to those reported in MLB literature. In this scenario, we may make the same arguments regarding the benefits of embracing fuzzy logic in order to obtain flexibility in the unpredictable and complicated actual network setting. Different techniques, in turn, address the challenge by recognizing successful HO occurrences using solutions based on unsupervised learning. The works of [144] and [145], in particular, present a strategy to HO management based on UL and SOM research.

TABLE IV: Related work

	Reference	ML technique	Problem	Algorithm
Self-configuration				
PCI	[134]	UL	Planning	Clustering
Self-optimization				
MLB	[135]	RL	Control optimization	Q-learning
	[136]	RL	Control optimization	Q-learning
	[137]	RL	Control optimization	Fuzzy Q-learning
	[138]	RL	Control optimization	Dynamic Programming
	[139]	UL	Grouping	K-means clustering
	[140]	SL	Prediction	Multivariate polynomial regression
MRO	[141]	RL	Control optimization	Q-learning
	[142]	RL	Control optimization	Q-learning
	[143]	RL	Control optimization	Fuzzy control
	[144], [145]	UL	Pattern identification	SOM
	[146]	UL	Prediction	Semi-Markov model
	[147]–[150]	SL	Prediction	ANN
CCO	[151]	RL	Control optimization	Fuzzy Q-learning
	[152]	RL	Control optimization	Fuzzy Q-learning
	[153]	RL	Control optimization	Fuzzy Q-Learning
	[154]	UL, RL	Control optimization	Fuzzy ANN/Q-learning
ICIC	[155]	RL	Control optimization	Q-learning
	[156]	RL	Control optimization	Fuzzy Q-learning
	[157], [158]	RL	Control optimization	Q-learning
ES	[159]	RL	Control optimization	Q-learning
	[160]	UL	Decision making	Fuzzy logic
	[161], [162]	UL	Grouping, pattern identification	Clustering
Self-healing				
COC	[163]	RL	Control optimization	Actor Critic
	[164]	RL	Control optimization	Actor-Critic
	[165]	SL	Control optimization	Fuzzy logic
COD	[166]	UL	Anomaly detection	Diffusion Maps
	[167]	SL	Anomaly detection	Fuzzy logic
	[168]	SL/UL	Diagnosis	Naive Bayesian
	[169]	SL	Anomaly detection	SVM, Ensemble methods
	[164]	SL/UL	Anomaly detection	*k*-NN, local-outlier-factor
	[170]	UL	Grouping, pattern identification	Hidden Markov Model
	[171]–[173]	SL	Fault Detection	*k*-NN
	[174], [175]	SL	Diagnosis	Naive Bayesian
Self-coordination				
	[176]	SL	Classification	Decision Trees
	[177]	RL	Control optimization	Actor Critic
	[178]	RL	Control optimization	Q-learning
	[179]	RL	Control optimization	Actor Critic
Minimization Drive Tests				
	[180], [181]	SL	Verification/estimation	Linear correlation
	[110]	SL	Prediction	Regression models
	[182]	SL/UL	Prediction/curse of dimensionality	Regression models/Dimensionality reduction
	[111], [183]	SL	Prediction	Bagged-SVM/Dimensionality reduction
Core Networks				
	[184]	SL	Prediction	Adaboost, SVM

3) Coverage and Capacity Optimization: Different techniques in the literature for CCO rely on RL solutions based on continuous interactions with the environment, targeted to online modifying antenna tilts and transmission power levels using TD learning methodologies. A fuzzy Qlearning strategy to optimizing the complicated wireless network by learning the best antenna tilt control policy is suggested in [151] and [152], and a similar approach is followed in [153] and [154]. They also propose combining fuzzy logic with Q-learning to cope with continuous input and output variables. [153] also presents a central control system for initiating and terminating the learning optimization process of each learning agent deployed in each eNB.

4) Inter-cell Interference Coordination: As with the CCO instance, ML has been offered as a legitimate solution in the literature of the ICIC use case, where RL is the primary employed technique, with specific focus on TD approaches, in order to target the optimization of control parameters. Several publications [155]-[158] address the challenge of minimizing cell interference by employing the most widely used TD learning approach, Q-learning. Control inter-cell interference in a diverse femto-macro network is the focus of [155]. The work integrates information handled by multi-user scheduling with judgments made by a learning agent based on Q-learning, which attempts to control cross-tier interference per resource block. Based on a Fuzzy Q-learning implementation, [156] provides a distributed solution for ICIC in OFDMA networks. The suggested method provides joint improvement for all users, i.e., gains for low-quality users do not come at the price of high-quality users. Furthermore, in this paper, a decentralized Q-learning architecture for interference control in tiny cells is provided. The authors concentrate on a use scenario in which tiny cell networks attempt to reduce disturbance to the macro-cell network.

5) Energy Savings: In the past, energy-saving strategies for wireless cellular networks were developed, allowing cells to enter a sleep state in which they consume less energy. Several publications connected to ML approaches can be discovered in order to minimize the energy consumption of eNBs. [159] is an example of this, in which the authors use RL to propose a decentralized Qlearning strategy to allow energy savings by learning a policy via iterations with the environment, taking into consideration changing elements over time, such as daily sun irradiation.

In addition, the authors of [160] turn off certain underused cells during off-peak hours. The suggested method maximizes energy savings by optimizing the number of base stations in dense LTE pico cell installations. They employ a combination of Fuzzy Logic, Grey Relational Analysis, and Analytic Hierarchy Process tools to trigger the switch off operations, and they examine several choice inputs for each cell at the same time.

6) Cell Outage Compensation: The literature already has a variety of articles that address the issue of COC. Because this is a continuous decision making/control problem, RL has been demonstrated to be a viable solution for this use case. In this regard, [163], [164] provide a contribution in the domain of self-healing, in which the authors propose a full solution for the automated mitigation of the degrading impact of the outage by correctly modifying necessary radio parameters of the surrounding cells. The approach involves maximizing the coverage and capacity of the detected outage zone by changing the antenna gain due to electrical tilt and the downlink transmission power of the neighboring eNBs.

7) Cell Outage Detection: As previously said, COD tries to automatically detect cells that are not performing properly owing to potential faults. Anomaly detection methods provide an intriguing answer for this type of problem by identifying outlier data, which might indicate a hidden fault in the network. [166] and [167] provide solutions to this problem. [166] in particular proposes a method based on diffusion maps and clustering schemes that is capable of recognizing anomalous behaviors induced by a sleeping cell. [167] proposes a fuzzy logic-based technique for autonomous troubleshooting system diagnostics.

8) SON Conflict Coordination: As the number of stand-alone SON functions deployed grows, so does the amount of conflicts and dependencies between them. As a result, an organization has been proposed to coordinate such conflicts. Several studies based on ML are included in the existing literature in this regard. The authors of [176] concentrate on the classification of possible SON conflicts as well as the tools and methods for implementing an effective self-coordination framework. Q-learning has been presented as an RL approach in [177] in order to lessen the uncertainty connected with the influence of SON coordinator decisions while choosing one action over another to settle conflicts. The authors of [178] employ Q-learning to resolve a disagreement between two SON instances. To correctly regulate Remote Electrical Tilt (RET) and transmission power, decision trees have been presented in [186]. Furthermore, in [179], the authors present a functional architecture that may be

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utilized to cope with conflicts caused by the concurrent execution of numerous SON functions. They demonstrate that the suggested technique is broad enough to represent all SON functions and their associated conflicts. They begin by introducing various SON functions within the context of the overall SON architecture, followed by high-level illustrations of how they may interact.

9) Drive Test Minimization: The vast bulk of research that uses MDT capability to target MDT use cases employs supervised and unsupervised learning approaches to give different solutions for the various use cases. In [180], [181], the authors address QoS estimate by picking multiple KPIs and correlating them with common node metrics to determine if a UE is happy with the received QoS. [110] pursues a similar goal, however unlike prior research, the authors focus on multilayer heterogeneous networks, resulting in a more complicated and realistic situation than the classic macrocell scenario. They offer, in particular, a regression-based technique for predicting QoS in heterogeneous networks for UEs, regardless of the UE's physical location. This work is expanded in [182] by considering not just the most promising regression models, but also dimensional reduction strategies. The number of random variables under consideration is minimized by performing PCA/SPCA on the input features and supporting solutions in which just a limited number of input features capture the majority of the variation.

10) Core Networks: As noted in section II, the operational characteristics of core network elements can be improved by, for example, automating the neighbor cell interactions function. The concept of using ML to this function is not novel in this sense. The authors of [184] investigate the advantages of utilizing ML to do root-cause analysis of session drops as well as drop prediction for specific sessions. They provide an offline Adaboost and SVM technique for developing a predictor that is in charge of eliminating/reducing session dropouts by utilizing actual LTE data.

V. CHALLENGES FOR FUTURE WORKS

This section focuses on several outstanding issues that must be addressed before ML-based network management becomes a reality.

- Real data
- Big Data and Deep Learning
- Theoretical research
- Network management of multi-technologies networks and of future New Radio.
- Network management of novel softwarized and virtualized architectures.

VI. CONCLUSION

In this paper, we argue that machine learning should be regarded as a critical and unavoidable instrument for dealing with automation, self-awareness, and self-organization in present and future mobile networks. The SON capabilities have been regarded vital in LTE definition and have been included in this technology since its inception in Release 8. We believe that the predicted complexity of future 5G network management will exacerbate the demand for automation. Furthermore, we have demonstrated that current cellular networks generate a massive amount of data, which, if properly stored and managed, can provide new insights into how networks work as well as new challenges for improving network management by taking into account the experience gained from these data. We discussed the major taxonomies of machine learning and the emerging developments that might enable this data exploitation to get network insight a reality. We also explored open data choices, as well as ways for obtaining data from networks that would otherwise be unavailable to the academic community. With these goals in mind, we began by analyzing the basic ideas and taxonomy of SON, network management, and ML, as well as major academic publications in the domain of network management, focusing only on ML-based solutions. The paper examined the state of this fascinating research area while also emphasizing outstanding issues that must be addressed in order for future autonomous network management to become a reality.

VII. REFERENCES

[1] Gandalf. Monitoring and self-tuning of RRM parameters in a multisystem network. [Online]. Available: http://www.celtic-initiative.org/

[2] SOCRATES. Self-Optimisation and self-ConfiguRATion in wirelEss networkS. [Online]. Available: http://www.fp7-socrates.org/

[3] SEMAFOUR. Self-Management for Unified Heterogeneous Radio Access Networks. [Online]. Available: http://fp7-semafour.eu/
[4] SESAME. Small Cells Coordination for Multi-tenancy and Edge services. [Online]. Available: https://5g-ppp.eu/sesame/
[5] SELFNET. Framework for Self-Organised Network Management in Virtualised and Software Defined Networks. [Online]. Available: http://www.cognet.5g-ppp.eu/cognet-in-5gpp/
[6] COGNET. Cognitive Networks. [Online]. Available: https://5g-ppp.eu/
[7] O. Aliu, A. Imran, M. Imran, B. Evans, "A Survey of Self Organization in Future Cellular Networks," IEEE Communications Surveys & Tutorials, no. 99, pp. 1–26, 2012.
[8] Sistelbanda. SN4G SON. [Online]. Available: http://sistelbanda.es/
[9] Qualcomm. Self managing and enabling seamless roaming. [Online]. Available: https://www.qualcomm.com/videos/qualcomm-wi-fi-son
[10] Huawei. Huawei's Innovative Single SON Solution. [Online]. Available: http://www1.huawei.com/en/solutions/broader-smarter/
[11] A. communications. Powering 4G networks. [Online]. Available: http://www.airhopcomm.com [
[12] Cellwize. Driving value through SON. [Online]. Available: http://www.cellwize.com
[13] AVIAT. Wireless products for small cell applications. [Online]. Available: https://startupgenome.co/aviat-networks
[14] S. C. Forum. Small cell industry award. [Online]. Available: http://www.smallcellforum.org/events/awards
[15] 3GPP, "Technical Specification Group Services and System Aspects; Telecommunication Management; Self-Organizing Networks (SON); Concepts and requirements (Release 13)," 3GPP, TS 32.500, v13.0.0, 2016.
[16] A. Imran, A. Zoha, A. Abu-Dayya, "Challenges in 5G: How to Empower SON with Big Data for Enabling 5G," IEEE Network, vol. 28, no. 6, pp. 27–33, 2014.
[17] NOKIA, "Intelligent Self-Organizing Networks: Increased automation for higher network performance with lower costs," White paper, 2013.
[18] N. Baldo, L. Giupponi, J. Mangues-Bafalluy, "Big Data Empowered Self Organized Networks," 20th IEEE European Wireless, 2014.
[19] B. Romanous, N. Bitar, A. Imran, H. Refai, "Network Densification: Challenges and Opportunities in enabling 5G," 20th IEEE International Workshop on Computer Aided Modelling and Design of Communication Links and Networks (CAMAD, Special Session: Dense and Elastic Big Data Empowered SON, pp. 129–134, 2015.
[20] D. Falko, "A Study of Self-Organization Mechanisms in Ad Hoc and Sensor Networks," Elseiver Computer Communications, pp. 3018– 3019, 2008.
[21] D. Kreutz, F. M. V. Ramos, P. E. Verissimo, C. E. Rothenberg, S. Azodolmolky, S. Uhlig, "Software-Defined Networking: A Comprehensive Survey," Proceedings of the IEEE, vol. 103, no. 1, pp. 14–76, Jan 2015.
[22] 3GPP, "Evolved Universal Terrestrial Radio Access Network (EUTRAN); Self configuring and self optimizing network uses case and solutions (Release 9)," 3GPP, TR T36.902, v9.2.0, 2010.
[23] "Telecommunication management; Self-Organizing Networks (SON); Concepts and requirements (Release 11)," 3GPP, TS 32.500, v11.1.0, 2011.
[24] 3GPP, "Self Configuration of Network Elements; Concepts and Requirements, Release 9," 3GPP, TS 32.501, 2010.
[25] 3GPP, "Self-configuration of network elements Integration Reference Point (IRP); Information Service (IS) (Release 10)," 3GPP, TS 32.502, v10.1.0, 2010.
[26] "Self-Configuration of Network Elements Integration Reference Point (IRP); Common Object Request Broker Architecture (CORBA) Solution Set (SS)(Release 8)," 3GPP, TR 32.503, 2008.
[27] "Software Management (SWM); Software and Integration Reference Point (IRP) Requirements (Release 10)," 3GPP, TR 32.531, 2010.
[28] "Software management Integration Reference Point (IRP); Information Service (IS) (Release 8)," 3GPP, TR 32.532, 2009.

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[29] "Software Management (SWM) Integration Reference Point (IRP): Common Object Request Broker Architecture (CORBA) Solution Set (SS) (Release 9)," 3GPP, Tech. Rep. 32.533, 2009.

[30] Tech. Rep.

[31] "Evolved Universal Terrestrial Radio Access Network (EUTRAN) Network Resource Model (NRM) Integration Reference Point (IRP); Information Service (IS) (Release 11)," 3GPP, TS 32.762, v11.7.0, 2014.

[32] "Evolved Universal Terrestrial Radio Access Network (EUTRAN) Network Resource Model (NRM) Integration Reference Point (IRP): CORBA solution set (Release 9)," 3GPP, TR 32.763, 2009.

[33] "Evolved Universal Terrestrial Radio Access Netwrok (EUTRAN) Network Resource Model (NRM) Integration Reference Point (IRP): eXtensible Markup Language (XML) definitions (Release 9)," 3GPP, TR 32.765, v9.6.0, 2004.

[34] "Study of Self-Organizing Networks (SON) related Operations, Administration and Maintenance (OAM) for Home Node B (HNB) (Release 9)," 3GPP, TR 32.821, v9.0.0, 2004.

[35] "Telecommunication management; Self-Organizing Networks (SON); Study on self-healing (Release 9)," 3GPP, TR 32.823, 2010.

[36] 3GPP, "Performance measurements Evolved Universal Terrestrial Radio Access Network (E-UTRAN)(Release 10)," 3GPP, TS 32.425, v10.6.0, 2012.

[37] 3GPP, "Universal Mobile Telecommunications System (UMTS); UTRAN Iu Interface RANAP Signalling," 3GPP, TS 25.413, v3.4.0, 1999.

[38] "Radio Access (E-UTRA) and Evolved Universal Terrestrial Radio Access Network (E-UTRAN); Overall description; Stage 2 (Release 12)," 3GPP, TS 36.300, 2015

[39] "LTE; Evolved Universal Terrestrial Radio Access Network (EUTRAN); S1 Application Protocol (S1AP) (Release 9)," 3GPP, TS 36.413, v9.4.0, 2010.

[40] 3GPP, "Technical Specification Group Radio Access Network; Evolved Universal Terrestrial Radio Access Network (EUTRAN); X2 Application Protocol (X2AP) (Release 11)," 3GPP, TS 36.423, v10.7.0, 2013.

[41] 3GPP, "Self-Organizing Networks (SON) Policy Network Resource Model (NRM) Integration Reference Point (IRP); Information Service(IS), 3rd Generation Partnership Project (3GPP), (Release 10)," 3GPP, TS 32.522, 2011.

[42] "Self-Organizing Networks (SON): Policy Network Resource Model (NRM) Integration Reference Point (IRP); Information Service(IS); Solution Set (SS) definitions, (Release 10)," 3GPP, TS 32.526, 2011.

[43] "Evolved Universal Terrestrial Radio Access Network (EUTRAN); Network Resource Model (NRM) Integration Reference Point (IRP); Solution Set(SS) definitions, (Release 10)," 3GPP, TS 32.766, 2011.

[44] "Telecommunication management; Self-Organizing Networks (SON); Self-healing concepts and requirements (Release 12)," 3GPP, TS 32.541, v12.0.0, 2014.

[45] "Technical Specification Group Services and System Aspects; Telecommunication Management; Study on Energy Savings Management (ESM) (Release 10)," 3GPP, TR 32.826, 2010.

[46] "Technical Specification Group Services and System Aspects; Study on Operations, Administration and Maintenance (OAM) aspects of inter-Radio-Access-Technology (RAT) energy saving (Release 11)," 3GPP, TR 32.834, 2012.

[47] "Universal Mobile Telecommunications System (UMTS); LTE; Telecommunication management; Energy Saving Management (ESM); Concepts and requirements (Release 10)," 3GPP, TS 32.551, v10.1.0, 2011.

[48] "Technical Specification Group Radio Access Network; Evolved Universal Terrestrial Radio Access (E-UTRA); Radio Resource Control (RRC); Protocol Specification (Release 10)," 3GPP, TS 36.331, v10.7.0, 2010.

[49] "Performance Management (PM); Performance Measurements UTRAN (Release 9)," 3GPP, TS 32.405, 2009.

[50] "Automatic Neighbor Relation (ANR) management, Concepts and Requirements, (Release 11)," 3GPP, TR 32.511, 2011.

[51] 3GPP, "Technical Specification Group Services and System Aspects; Telecomunications Management; Self-Organizing Networks (SON) Policy Network Resource Model (NRM) Integration Reference Point (IRP)(Release 10)," 3GPP, TR 32.521, v10.2.0, 2009.

[52] 3GPP, "Configuration Management (CM); UTRAN network resources Integration Reference Point (IRP); Network Resource Model (NRM)(Release 9)," 3GPP, TS 322.642, 2009.
[53] "TSG SA WG5 (Telecom Management) Meeting 85; Study of implementation alternative for SON coordination," 3GPP, Tech. Rep. S5-122330, 2012.
[54] "Configuration Management (CM); UTRAN network resources Integration Reference Point (IRP); Solution Set (Release 10)," 3GPP, Tech. Rep. 32.646, v10.3.0, 2011.
[55] "Radio Resource Control (RRC); Protocol specification (Release 10)," 3GPP, TS 25.331, v10.6.0, 2011.
[56] "UTRAN overall description (Release 10)," 3GPP, TS 25.401, 2011.
[57] "UTRAN Iu Interface: General Aspects and Principles (Release 10)," 3GPP, TS 25.410, 2011.
[58] "UTRAN Iur interface Radio Network Subsystem Application Part (RNSAP) signalling (Release 9), institution = 3GPP," TS 25.423, 2010.
[59] "Study on Network Management (NM) centralized Coverage and Capacity Optimization (CCO) Self-Organizing Networks (SON) function," 3GPP, TS 32.836, 2013.
[60] "Integration Reference Point (IRP) overview and usage guide (Release 10)," 3GPP, TS 32.103, v10.0.0, 2011.
[61] "Self-Organizing Networks (SON) Policy Network Resource Model (NRM) Integration Reference Point (IRP); Requirements (Release 11)," 3GPP, TS 28.627, v11.1.0, 2012.
[62] "Self-Organizing Networks (SON) Policy Network Resource Model (NRM) Integration Reference Point (IRP); Information Service (IS) (Release 11)," 3GPP, TS 28.628, v11.4.0, 2014.
[63] "Evolved Universal Terrestrial Radio Access Network (EUTRAN) Network Resource Model (NRM) Integration Reference Point (IRP); Information Service (IS) (Release 11)," 3GPP, TS 28.658, v11.0.0, 2012.
[64] "Evolved Universal Terrestrial Radio Access Network (EUTRAN) Network Resource Model (NRM) Integration Reference Point (IRP); Solution Set (SS) definitions (Release 11)," 3GPP, TS 28.659, 2012.
[65] "Gap analysis between 3GPP SA5 specifications and NGMN Top Operational Efficiency (OPE) Recommendations (Release 12)," 3GPP, TS 32.508, 2013.
[66] "Data formats for multi-vendor plug and play eNodeB connection to the network (Release 12)," 3GPP, TS 32.509, 2013.
[67] "Gap analysis between 3GPP SA5 specifications and NGMN Top Operational Efficiency (OPE) Recommendations (Release 12)," 3GPP, TR 32.838, 2013.
[68] "Study of heterogeneous networks management (Release 12)," 3GPP, TR 32.835, v12.0.0, 2014.