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Review

Self-Organizing Networks for 5G and Beyond: A View from the Top

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Abstract: We describe self-organizing network (SON) concepts and architectures and their potential to play a central role in 5G deployment and next-generation networks. Our focus is on the basic SON use case applied to radio access networks (RAN), which is self-optimization. We analyze SON applications' rationale and operation, the design and dimensioning of SON systems, possible deficiencies and conflicts that occur through the parallel operation of functions, and describe the strong reliance on machine learning (ML) and artificial intelligence (AI). Moreover, we present and comment on very recent proposals for SON deployment in 5G networks. Typical examples include the binding of SON systems with techniques such as Network Function Virtualization (NFV), Cloud RAN (C-RAN), Ultra-Reliable Low Latency Communications (URLLC), massive Machine-Type Communication (mMTC) for IoT, and automated backhauling, which lead the way towards the adoption of SON techniques in Beyond 5G (B5G) networks.

Keywords: self-organization; self-optimization; self-healing; SON applications and architecture; SON design and dimensioning; machine learning (ML) and artificial intelligence (AI) for SON; massive Machine-Type Communication (mMTC); IoT; URLLC; backhauling; SON for 3G/4G; 5G and B5G networks

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1. Introduction

Almost all industries shall be digitally transformed and accelerated through the launch of 5G networks, which have already expanded dynamically, the COVID-19 pandemic notwithstanding. The development of 3G (Universal Mobile Telecommunications System (UMTS) and High-Speed Packet Access (HSPA)) networks has been focused on advancements at the physical layer of the radio interface and led to higher capacities, while 4G (Long-Term Evolution (LTE), and Long-Term Evolution Advanced (LTE-A)) networks have provided a new IP-based core network architecture on top of extra efficient radio transmission schemes. Fifth-generation networks aim to extend the existing capabilities of 4G (LTE) networks concurrently in the core and access domains via new techniques, but also through pushing digitalization, automation, and interdependence in many, if not all, vertical domains, industries, and aspects of life.

The expected outcome of 5G development and the basic 5G use cases is the provision of extreme mobile broadband (e-MBB) services, enabling a very high data rate, massive Machine-Type Communication (mMTC) for Internet of Things (IoT), the connectivity of a vast number of low-complexity and low-energy-consumption IoT devices capable of monitoring infrastructure, environmental parameters, and logistics, and, finally, Ultra-Reliable Low Latency Communication (URLLC) services supporting applications with strict and very low latency and reliability requirements, which is perhaps the most tricky part [1–8].

As far as the migration from existing Global System for Mobile communication (GSM)/UMTS and LTE networks to 5G is concerned, key enablers include techniques such as Network Function Virtualization (NFV), aiming to decouple the dependency between hardware and software in terms of network functions and migrate legacy network functions to a virtual or Cloud-based architecture in the core network domain. NFV combined with Software Defined Networking (SDN), with the aim to separate the data and control planes, shall be applied in the radio access network (RAN) part as well through the Cloud-RAN (C-RAN) concept, aiming to virtualize and aggregate the baseband units of the base stations in a central baseband pool [1–8].

Apart from NFV, SDN, C-RAN and techniques applied in the radio access domain, such as massive Multiple Input Multiple Output (MIMO), mmWave technologies, spectrum sharing, network slicing and cognitive radio, the key solution for automatically configuring, optimizing and tuning 5G and B5G network functions is using self-organizing network (SON) platforms, combined with the previously mentioned applications and empowered by intelligent machine learning (ML) algorithms, leading to full RAN automation, self-configuration, self-healing, and self-optimization capabilities [8–23].

The application of self-organization in mobile networks is derived from natural or biological sciences, mainly biology, and a big variety of papers exists in the literature referring to this specific issue; however, we shall not focus on describing the abstract characteristics of self-organization in nature, but describe and analyze the characteristics of SON technology, its benefits, its operation rationale for existing mobile networks, its evolution and the basic application fields in cellular communications networks [24].

1.1. Motivation and Main Drivers for SON Deployment in Next-Generation Networks

The SON concept applied in networking and the telecommunications industry resulted from a long history of original academic research, through industry–academia consortia and standardization organizations, resulting in network automation techniques and leading operators and equipment manufacturers to apply it as the basic solution for automating network functions and optimization processes, especially in the radio access domain. SON platforms are already being used with great success, leading to network performance and Key Performance Indicator (KPI) improvements as well as OPEX/CAPEX benefits in 2G/3G/4G radio access networks of mobile operator networks; interest has been increasing significantly in the last few years as 5G network deployments gradually expand and operators start switching off 2G and 3G networks in order to migrate the frequency usage to 4G and 5G network structures [9–23,25].

The basic trigger point for the development of SON systems is closely related to the automation benefits of ML and artificial intelligence (AI) techniques in order to overcome the manual handling of very complex and real-time aspects of network management, planning, and optimization procedures. As an example, consider the existing scenario for real mobile infrastructures where an operator intends to expand or modernize an existing multi-technology network either in dense urban or rural area cell clusters. During this long process, new base stations (macro, micro, pico, and femto cells and repeaters) enter or leave the network and relocate, and daily issues, such as low-quality channels or interference, must be mitigated manually. Prior to SON, the first step in this process was to manually configure the basic RAN, transport, and core network parameters, while at the same time redesigning the neighboring area network. If we include as a factor the unpredictable user mobility and activity, it is clear that the manual handling of all these procedures has very high complexity and is time consuming and error prone [26].

These challenges can be addressed by SON platforms/systems since network parameter tuning and optimization can be performed automatically through intelligent SON algorithms in real time. This is achieved through decisions made by the SON platform algorithm, which takes real-time network data as input (e.g., network counters collected by various network entities, such as the radio access network controllers—Base Station Controller (BSC), Radio Network Controller (RNC), Mobility Management Entity (MME), and Access and Mobility Management Function (AMF), for 2G, 3G, 4G, and 5G, respectively—at various granularities).

It can be said that as networks evolve following the network deployment lifecycle with procedures starting with their initial planning, network design, installation and commissioning, optimization and finally maintenance, only some sub-procedures such as site survey, selection, licensing, equipment shipment and installation or hardware replacement cannot be substituted by SON platforms [16,27].

Additionally, especially considering the RAN optimization aspect, which is our focus, the following figure depicts the comparison of a traditional, legacy (manual) approach compared to automated optimization through SON. The benefits, as shown in Figure 1, are important since the conventional radio access network optimization process takes approximately 8 weeks, which is slower than the automated approach. More specifically, the conventional optimization rationale includes three basic steps that have to be repeated manually many times until the optimum result is achieved. In order to optimize a RAN, the first step is to collect data from drive tests and measurement campaigns, KPIs, customer complaints and existing configuration. Step 1 is the input to step 2 that includes the reconfiguration and optimization steps so that network performance is improved. Finally, step 3 includes the monitoring of the changes and reconfiguration deployed during step 2 and it provides feedback about how beneficial these are. The process repeats until the optimum result is achieved in a manual manner, leading to a long and time-consuming process. Network automation is the key to eliminating delays and the error-prone nature of manual activities by replacing the prementioned steps with automated procedures performed by ML algorithms [9,28,29].

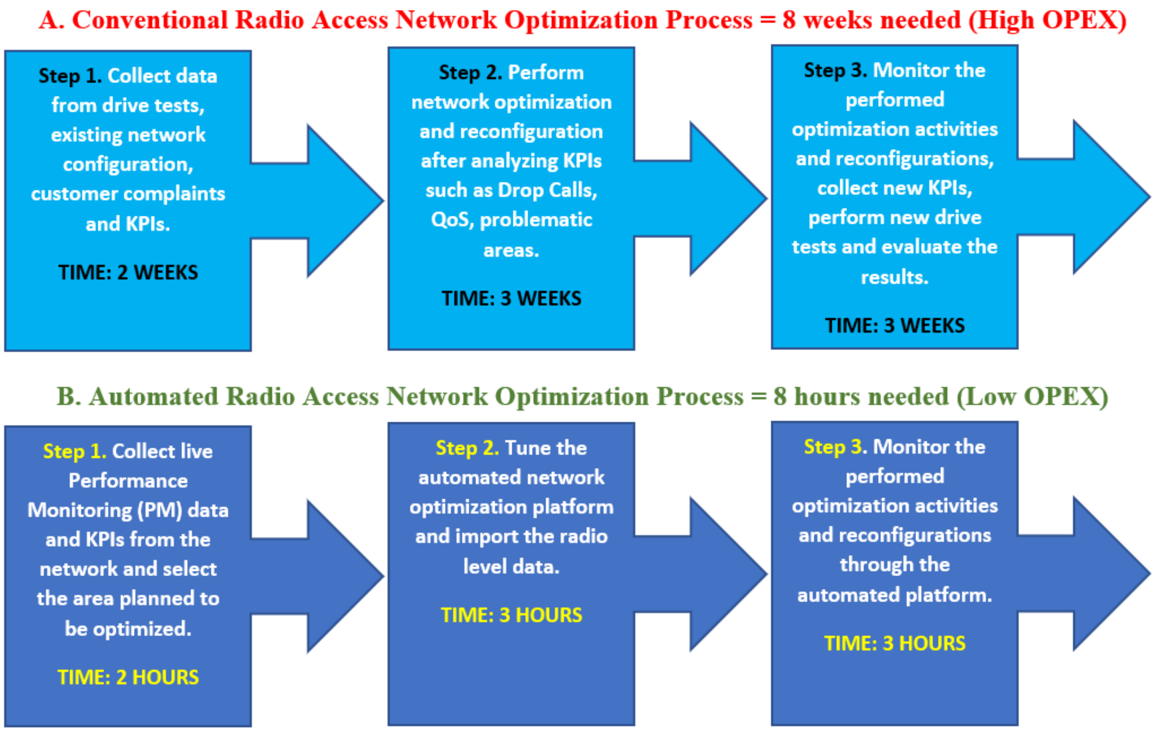

Figure 1. Traditional vs. automated optimization.

Key drivers for SON deployment in existing and next generation networks:

- B5G networks further increase the complexity of network planning and optimization processes since the former must coexist and cointeract with the existing networks (2G/3G/4G/5G) in parallel. The network parameter design, tuning, and management lead to a high complexity in terms of smooth coordination among all existing networks, and it is obvious that as more complex architectures and B5G evolve, network management shall not be feasible without the use of automated SON functions operating in real time and taking direct feedback from the network [8–23].

- The standardization of network traffic characteristics and parameters in order to support the basic 5G use cases (i.e., e-MBB, URLLC and MTC) should be embedded in SON systems and applications so that already set targets for 5G, such as low latency and high reliability, can be achieved.
- The benefits of AI and ML for the operation of next-generation networks should be applied as the basic building blocks for B5G intelligent operation. SON platform advancements and network automation are clearly dependent on advanced ML algorithms and their implementations [8–23,30]. Simplistic automation solutions do not enable a distributed approach and they are not effective and efficient in complex environments.
- Academia and the telecommunications industry to combine 5G use cases and intelligent techniques, such as C-RAN, mmWave, cognitive radio (CR), network slicing, spectrum sharing, NFV/SDN, mm-Wave (Millimeter-Wave), automated backhauling and massive MIMO (massive multiple-input and multiple-output). with next-generation SON platforms for maximum performance.

1.2. Paper Structure and Contribution

The goal of this paper is to provide an extensive review of self-organizing network (SON) technologies, explain their rationale and operation with a focus on self-optimization functions, describe in detail the flow of SON systems design, analyze basic issues that should be resolved as we move towards SON adoption in 5G networks and beyond, and discuss the latest research directions in this field. In Section 2, we describe the basic SON architectures and provide a detailed guide to the design and dimensioning of SON systems. In Section 3, we analyze the operation of basic self-optimizing applications. We provide a brief description of ML algorithms applied to SON systems in Section 4, and in Section 5 we discuss and comment on the latest research directions for the application of SON technology in different domains of B5G networks. Finally, in Section 6, we provide a summary and conclude the paper.

2. SON Operation Rationale, Use Cases, Standardization, Architectures and Dimensioning

2.1. Manual RAN Planning and Optimization Activities Replaced by SON

As already mentioned, SON applications were developed to provide network automation and fully replace the RAN optimization process as a main aim and the planning process as a secondary aim, in terms of initial RAN nodes and core/backhaul network configuration, since some steps of network planning such as site location selection and coverage planning cannot be fully automated. The basic steps of the planning lifecycle are depicted in Figure 2 [22,23,28].

The following figure describes the planning process from the early stage of detecting the need for a new site to the activation of an LTE site. As a very first step, the need of a new site is recognized based on known coverage holes or the capacity advancement needs for specific areas. After the radio propagation environment is examined and simulated and exact capacity needs are identified, a coverage simulation is deployed and the initial RAN parameters are designed by taking into account any neighboring sites. A configuration file is created and planned to be committed by the OSS to the RAN, and then the activation takes place. As a last step, real-time network KPIs are monitored and drive testing takes place so that the whole coverage area is examined and a clear outcome about any possible optimization actions needed is extracted. Apart from the initial steps of understanding the need for a new site due to poor coverage or capacity needs and coverage simulation, the configuration procedure can be substituted by SON self-configuration applications that are able to eliminate human errors since the interaction with neighboring sites is what creates complexity.

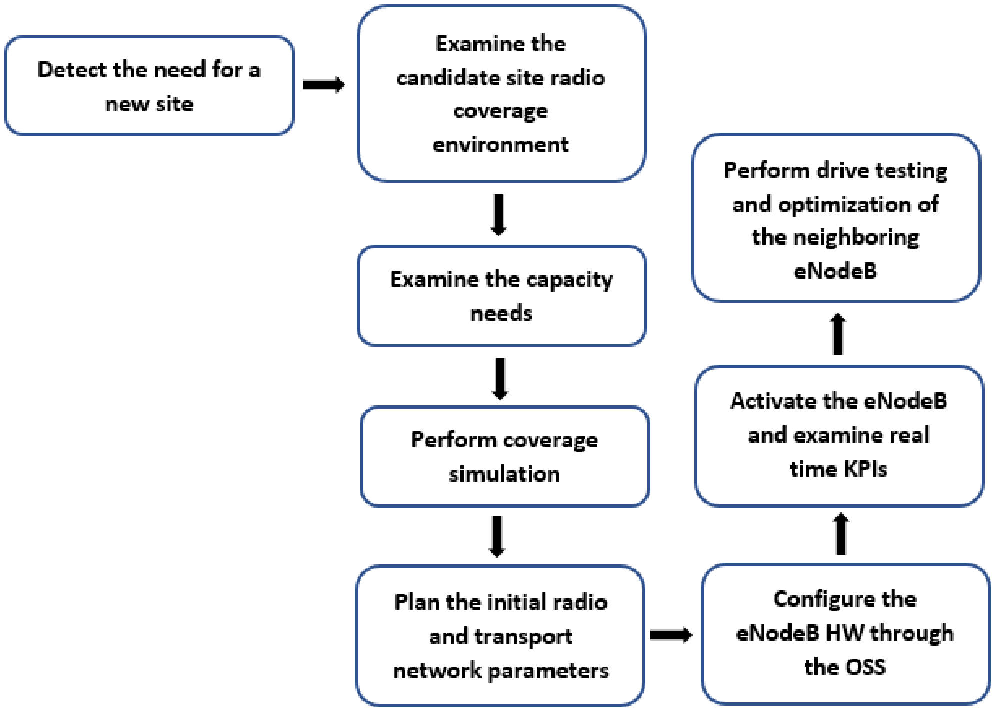

Figure 2. RAN planning and configuration lifecycle.

SON system intervention, no matter the technology (2G/3G/4G/5G), starts from the configuration phase (preoperational state of a node/cell) and expands to network optimization, which is the basic field of SON applications as well as healing. Optimization and healing take place in the operational state, while both preoperational and operational states can migrate from a manual to fully automated status, as depicted in Figure 3, through a SON orchestrator that monitors and organizes SON applications.

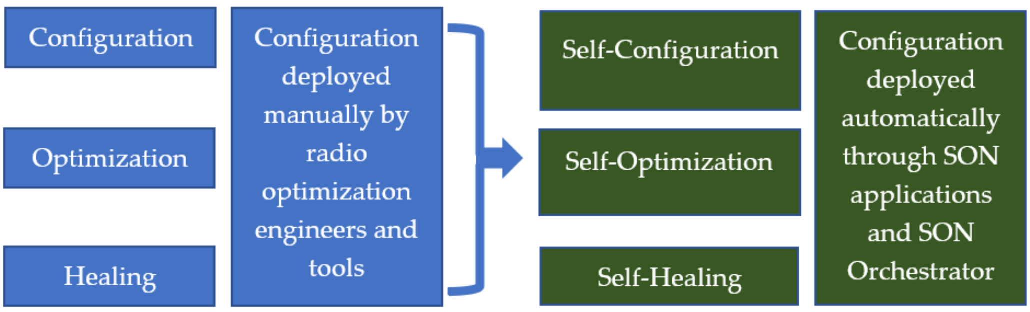

Figure 3. Replacing manual operations with SON.

Healing activities regard the automated maintenance handling in case nodes fail and existing SON systems follow a reactive approach; however, a proactive approach is more efficient. Typical healing cases that lead to a reduction in operational expenses include interference mitigation, the detection of KPI degradation, outage detection, diagnosis and compensation [31].

2.2. SON EU Research Programs, the NGMN Alliance and 3GPP Standards

Since SON seem to be the optimum automation technique for mobile networks, academy, industry, alliance and standardization bodies started analyzing potential scenarios and use cases.

Organizations such as 5GPPP and European research programs such as SOCRATES, SEMAFOUR, SESAME, COGNET, Gandalf, and BeFEMTO describe and propose SON architectures [32–39], while the NGMN alliance, founded by leading international mobile network operators in 2006 as an industry organization to provide innovation platforms for next-generation mobile networks, was the first to propose SON use cases and prerequisites for deployment in modern mobile networks [27,40,41].

During 2017, NGMN proceeded with the analysis of SON use cases for 5G networks since industry adopted SON solutions for 2G/3G/4G networks with great success in terms of network KPI improvement and CAPEX/OPEX savings [21,42–56]. Based on the former NGMN recommendations for SON applicability in 2G/3G/4G networks, NGMN proceeded by proposing SON functions for 5G networks [20].

Just after NGMN, 3GPP started working towards standardizing self-optimizing and self-organizing network use cases for 3G/4G networks, starting from Release 8 up to Release 12. The specific standards are described in detail in network automation and management features. 3GPP releases added enhancements in the prementioned configuration and optimization processes, while proposals allowing inter-radio access technology operation, enhanced inter-cell interference coordination, coverage and capacity optimization, energy efficiency, and the minimization of operational expenses through the minimization of drive tests were added [57–63].

As expected, 3GPP has been working on 5G SON recommendations by further expanding the specific use cases proven to be successful in 2G/3G/4G networks [8,21,64].

2.3. Essential SON Use-Cases

According to 3GPP and NGMN, SON use cases are classified into three basic categories with each category including subcategories of SON applications. The three basic ones and key pillars are:

- Self-optimization.
- Self-configuration.
- Self-healing.

Self-optimization includes activities such as coverage and capacity optimization, interference handling, Mobility Load Balancing and cell neighbor relation setting; self-healing relates mainly to maintenance issues such as cell outage detection; and self-configuration enables auto-connectivity and automated initial parameter configuration [23,27,31].

Especially for the cases of self-optimization and self-configuration, it should be noted that the specific procedures introduced in 3GPP TS 36.300 version 9.4.0 Release 9, as a capability of Evolved Universal Terrestrial Radio Access Network (E-UTRAN), were further developed up to their applicability in 5G [58,64].

2.4. SON Systems Basic Architectures and Operation Rationale

In terms of SON system architectures, the 3GPP consortium defines the following three types of SON architectures that can be applied in 2G/3G/4G and 5G networks [57–64]:

- Centralized (C-SON).
- Distributed (D-SON).
- Hybrid (H-SON).

In centralized SON (C-SON) architectures, a SON platform that resides in a server cluster handles all network elements centrally through the interaction with the OSS (Operations Support System) of each RAN technology. C-SON is the most widespread solution for mobile operators; however, it might present single point of failure characteristics. On the other hand, the basic advantage is that the overall network status information/KPIs are collected and processed centrally, and thus the SON platform has a better insight regarding the network health status. In Distributed SON (D-SON) cases, SON functions run locally at the base stations, while Hybrid SON (H-SON) is a combination of the prementioned cases that is not widely used.

Moreover, in terms of infrastructure, SON platforms reside on server clusters which host the SON applications running per radio access technology (GSM/UMTS/LTE/5G), the database of the system, the orchestrator, which is the entity managing the applications, and the API (Application Programming Interface). The system interacts directly and in real time with all basic radio access network controllers (BSC/RNC/MME/AMF) and the OSS and collects live performance counters and KPIs, which are analyzed by the running algorithm of each SON application. The outcome is the automated creation of an executable script executed with no manual intervention through the OSS. More specifically, each script is executed through a dedicated privileged SON OSS account and then an evaluation period/timeframe starts where the SON application algorithm decides to revert the action/script created and executed [27]. A high-level LTE SON system design is proposed in Figure 4 and since 5G SON systems derive from LTE, the same design rationale applies to 5G as well and the only difference is that MME is replaced by AMF [13]. A SON platform consists of the hardware part, including the servers and RAN database, the management of SON applications and orchestration module, which handles SON applications and APIs, providing the ability to handle and manage the RAN database. A SON server cluster interacts with the LTE OSS system of each RAN vendor and uses the latter to commit configuration plans that include the changes that each SON application decides. Configuration plans are committed to the OSS of each vendor in case more than one exists and through the MME to the base stations.

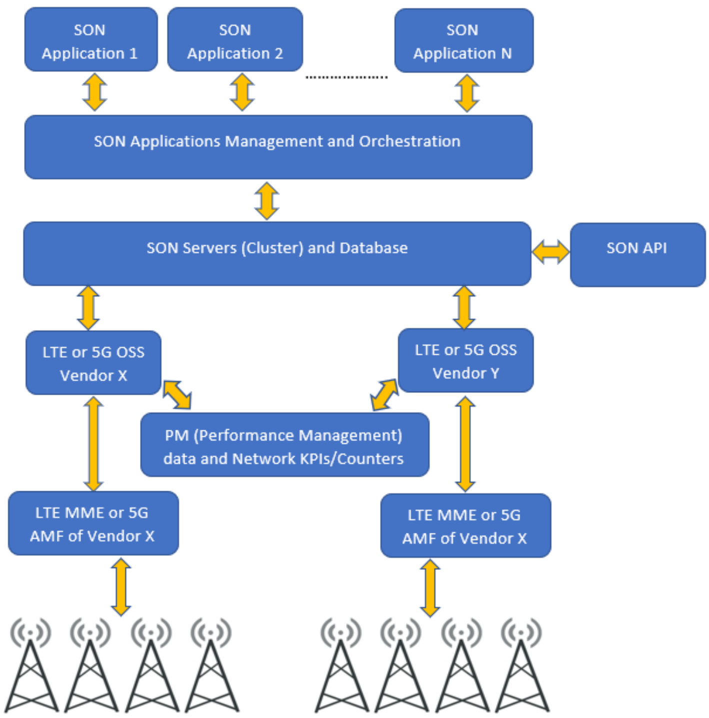

Figure 4. High-level SON system architecture.

As far as the applications are concerned, the rationale that rules all applications is divided into three phases. As depicted in Figure 5, the snapshot period concerns the evaluation of the current state of the network according to the counters of KPI collection prior to any SON actions taken, the action phase concerns the creation and execution of a script for the OSS through SON applications, and the feedback period concerns the evaluation of the action phase and a decision to keep a specific action in the network or revert it to the initial pre-SON operation status [55,65].

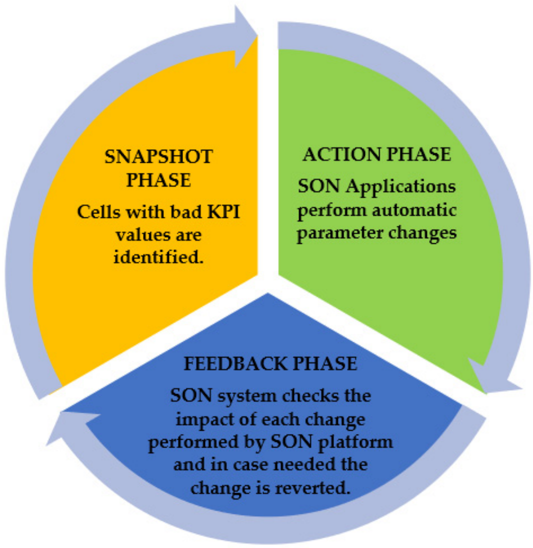

Figure 5. SON loop, basic phases, and lifecycle.

2.5. Principles of Dimensioning and Designing a SON System

SON systems' initial dimensioning is based on the collection of existing RAN characteristics through a RAN audit providing key information about the existing policies followed, while it is the most important activity and the basic factor to decide the system architecture and the applications that should be applied. More specifically, in order to decide on the system architecture, we must receive an initial input and define the basic needs no matter what the network technology is that we want to apply SON to (2G/3G/4G/5G). Essential information that must be collected from the network for the needs of system dimensioning and architecture design can be found in the following:

1. Network features applied in the RAN per vendor.
2. RAN parameter settings/values. Key points include:
   - Handover and reselection policy.
   - Admission control policy (admission control is the process that evaluates the existing resources to check if these are sufficient, prior to the establishment of a new connection).
   - Load balancing policy (load balancing aims to transfer the load from overloaded cells to the neighboring less loaded ones so that end-user experience and network performance is improved).
   - Scrambling codes planning strategy in UMTS and Physical Cell ID (PCI) planning strategy in LTE and 5G.
   - Neighbor relation planning strategy (unidirectional/bidirectional) for Intra-Frequency/Inter-Frequency and Inter-RAT and number of maximum neighbors per cell for all technologies.
   - Number of maximum number of cells supported per BSC/RNC/MME/AMF.
   - Inter-carrier Layer Management Strategy (LMS).
   - Frequency bands and number of carriers used per technology (UMTS 2100 MHz, LTE 900 MHz, 1800 MHz, 2600 MHz, etc., according to the spectrum usage acquisition and spectrum refarming policy for 5G).
3. Radio Frequency (RF) hardware equipment in the network (antenna types, Remote Electrical Tilt (RET) types).
4. Pre-SON network KPIs and the expected result after SON deployment.
5. Performance Monitoring (PM) counters activated per vendor.
6. Desired IP planning information for SON platform by considering all needed interconnections and ports that must be open.

7. Current and expected OSS dimensioning information. (Moreover, full read/write execution rights to the OSS assigned to the SON orchestrator should be ensured.)
8. The geolocation information (latitude and longitude) of the cells as well as antenna azimuth information.
9. Possible network expansion and site rehoming plans from a BSC/RNC/MME/AMF to a neighboring one, or the use of new RAN technologies.
10. Network size in terms of the number of subscribers and number of active cells per technology, number of network controllers (BSCs, RNCs, MMEs, and AMFs) and number of OSS systems per vendor. A typical real case scenario for a medium-sized operator in Europe prior to 5G commercial launch might include 6,000,000 subscribers in total, 60,000 GSM cells, 90,000 UMTS cells, 80,000 LTE cells, 25 BSCs and RNCs and 5 MMEs. The number of OSS subsystems depends on the different vendors an operator might use.

Table 1 can be used as input to the SON dimensioning and design process for a real network including 2G/3G and LTE technologies and correlates the applied handover, admission control, and load balancing policies with specific SON applications. The same rationale applies in 5G networks as well, leading to the outcome that IRAT policies, admission control and load balancing parameters are the initial factors to consider.

Table 1. Correlation of basic radio access parameters with SON applications.

LTE to 3G layer IRAT handover rules	SON-related application according to 3GPP defined use cases
Circuit Switching (CS) fallback to 2nd carrier	ANR (Automatic Neighbor Relations)
Packet Swiching (PS) redirection to 2nd carrier	
Cell reselection to 1st carrier	
GSM to 3G layer IRAT handover rules	SON-related application according to 3GPP defined use cases
GSM to UMTS: Cell reselection only (no handover)	ANR (Automatic Neighbor Relations)
UMTS to GSM: Cell reselection and no handover	
Define the value of admission control parameters (UMTS)	SON-related application according to 3GPP defined use cases
Power admission control settings: 1st carrier: 85%; 2nd and 3rd carriers: 75%	MLB (Mobility Load Balancing)
Codes admission control: 90%	
UL/DL channel elements admission control: 95%	
Describe the load balancing features activated	SON-related application according to 3GPP defined use cases
Example: Intrafrequency load sharing	MLB (Mobility Load Balancing)

Through using the RAN audit and information collection as the dimensioning input, the equivalent output regards the optimum architecture design of a 2G/3G/4G/5G SON system. Basic system design decisions include:

1. Decision regarding the hardware infrastructure needs of the SON system to be deployed and prediction for possible hardware expansion (mainly based on the input collected regarding the number of cells per technology as well as existing network controllers (BSC/RNC/MME/AMF).
2. Decision about the needed SON applications and tuning of the latter according to the current network planning and optimization strategy.
3. Decision and prediction about the expected KPI improvement.

Technoeconomic decisions such as system pricing, human resources and system deployment project time plans are taken as well but these are out of the scope of this paper.

In terms of hardware infrastructure, the prementioned input shall lead to the decision of the servers' cluster (number/type of servers) hosting the platform and applications and providing disaster recovery, database replication, system orchestration and load balancing capabilities.

We suggest that SON platforms interact with a geolocation database including all needed cell antenna directions, antenna type, cell name, site ID, operating frequency, BSC/RNC/MME/AMF hosting the cell, latitude, longitude and location parameters instead of the manual loading of such information since the latter might be error prone. Especially for the 5G case, static information about the equipment served in specific areas (either UEs or IoT sensors) can be added as well.

After having installed the servers, the database and the SON platform software modules must proceed with the final IP planning of the system, ensure connectivity to the operators' data network, and enable connectivity with the OSS assigned to handle each technology, as depicted in Figure 6. This figure is an extension of Figure 4 and includes the coexistence of a UMTS and an LTE network. In case a 5G network is included, the design rationale is identical to an AMF interacting with the gNBs, the 5G OSS and the 5G KPIs database (db). Finally, the initial tuning of the platform and applications according to the desired policy must be performed before starting the system.

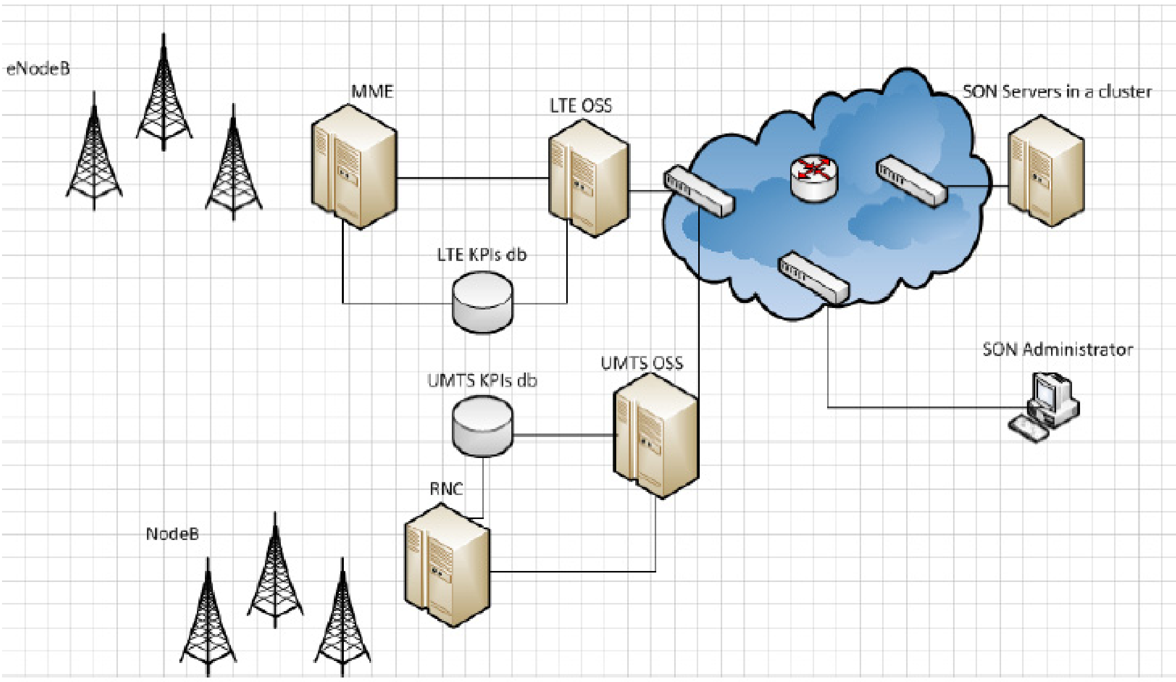

Figure 6. Interconnection of SON server cluster with UMTS and LTE OSS (centralized architecture).

3. SON Applications

3.1. Basic SON Applications in 2G3G/4G/5G Networks and Operation Rationale

As far as the key applications for existing mobile networks are concerned, 3GPP and NGMN overlap in some of them; however, the major ones are the following [21–23,27,40,41,57–64]:

1. Automatic neighbor relation (ANR).
2. Automatic radio network configuration (initial radio and core parameters setting).
3. Mobility Load Balancing optimization (MLB).
4. Coverage and capacity optimization (CCO).
5. Mobility Robustness Optimization (MRO).
6. Automated configuration of physical cell identity (Cell ID (CI) and PCI optimization).
7. Interference reduction.
8. Minimization of drive testing (MDT).
9. Energy saving (ES).

10. RACH (Random Access Channel) optimization.
11. Inter-cell interference coordination (ICIC).

We believe that the most popular applications are ANR, MLB and CCO; thus, we explain their operation rationale, the factors that led to the need for them, and the issues that they resolve.

Before the development of SON systems, configuration, optimization, and healing processes were performed manually based on a time-consuming and error-prone lifecycle. As an example, problems such as interference, capacity, and coverage holes mitigation were identified through KPIs monitoring, CM/PM data collected from the OSS, alarms collection, drive test campaigns or even subscriber complaints. The next step was the manual analysis of KPIs and drive test results, and as a last step the network parameters reconfiguration and the monitoring of the new KPIs after the changes were committed to the network. In some cases, drive testing repetition was needed as well for a new evaluation.

As expected, these procedures frequently led to time-consuming and error-prone actions, especially in the cases of optimization and healing since capacity, coverage, and interference must be faced in real time and with a holistic approach. Moreover, the results after manual network parameter changes cannot be regarded as beneficial in all scenarios since they trigger a chain reaction of additional needed network changes for the neighboring cells, especially in dense areas. As expected, OPEX spending occurs as well.

As explained earlier, all SON applications are ruled by the Snapshot–Action–Feedback lifecycle. At this point, it should be noted that we can configure and tune the trigger thresholds of the snapshot phase so that the frequency of SON activities in the OSS is increased or decreased. Very frequent activities lead to system and OSS load, while rare activities do not have a fast outcome; thus, trigger balance is a key point.

3.2. The Key SON Applications Leading to Full Automation

3.2.1. SON (ANR/Handover Success Rate) and NCL (The Need behind ANR)

Prior to SON applications, academy and industry proposed solutions for automating key optimization activities for network performance KPI advancement, mainly related to the handover success rate and load balancing. The handover success rate enables continuous connection for User Equipment (UE) while subscribers are moving and it is one of the most critical KPIs for all mobile networks radio access technologies. A neighbor cell list (NCL) includes handover candidate cells and all UEs connected to a specific cell are informed about this candidate list [66]. More specifically, NCL includes interactions among:

- Intra-frequency (same technology and same frequency) cells of the serving and neighbor cells.
- Inter-frequency (same technology and different frequency) cells of the serving and neighbor cells.
- Inter-RAT (different radio access technology) cells of the serving and neighbor cells.
- All the above cell interactions of the serving and neighbor cells in the same Base Transceiver Station (BTS)/NodeB/eNodeB/gNB.

Before SON, neighbor cell lists (NCL) were manually configured by radio network planning and optimization engineers, by using data from the current and real-time status of the network (OSS) combined with data from coverage simulation tools to extract the optimal list. Apart from being time consuming and the need for operational expenses, this manual process includes multiple drawbacks, since it is very difficult to predict the radio propagation environment (at the microcell level) and predict all the actions that might take place such as the operation of new cells not activated during the manual NCL creation process or the non-operational status of specific cells at that time [67,68]. In [69], the authors propose an automatic optimization algorithm based on base station coordinates and cell direction, but the disadvantage was that large lists of candidate cells were created, while the authors of [70,71] were focused on finding potential neighbors based on cell coverage overlap.

The prementioned proposals had a key contribution to the road towards self-optimization and their common disadvantage was that static network information data were mainly used as input (coordinates and cell coverage according to simulation tools). This creates difficulties in adapting in a constantly changing and dynamic network environment; thus, the authors of [68] further included live measurements for the creation of an NCL.

The authors of [66] proposed a method for the self-configuration and self-optimization of NCLs. In the former case, the serving cells of the base stations collect signal quality information about the neighboring cells, while in the latter case real-time reports regarding neighboring cell quality measurements are collected from UEs and reported back to the serving cell. One of the key findings for the self-configuration scenario was that the neighbor's pilot signal quality cannot be measured in the whole serving cell coverage area since a sectorized antenna is used; thus, live measurements from the moving UEs are needed. A simulation deployed predicted an 85% call success rate for self-configuration and 97.3% for self-optimization. We believe that this result is optimistic; however, said paper is an excellent contribution to the explanation of self-optimizing and self-organizing rationale and a prelude to SON ANR applications.

Figure 7 depicts the rationale of the self-configuration and self-optimization as discussed prior to the official launch of SON ANR applications.

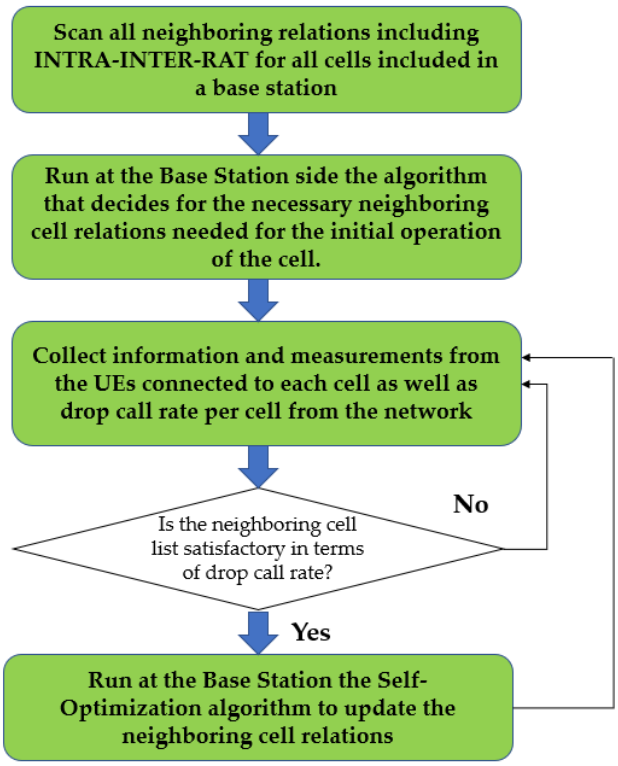

Figure 7. Self-configuration and self-optimization process.

3.2.2. SON—ANR

Possibly the most common self-optimization application is ANR (Automatic Neighbor Relations), which replaces the manual process of neighbor cell configuration and handover optimization previously described by creating automatically and in real time the most optimal neighbor relation list for a cell operating in either technology (2G/3G/4G/5G) and in relation to either technology as well. The application runs both for operational and new cells added into the network and it is a key use case for B5G development since recent publications analyze and propose hybrid solutions for ANR implementation in 5G networks [64,72].

SON ANR applications are mainly used to create intra-frequency (same technology and same frequency) and inter-frequency (same technology and different frequency) neighbor lists since these are of high importance; however, Inter-RAT (Radio Access Technology, different technology and different frequency) relations can be optimized too. ANR applications act by deleting existing redundant neighbor relations that either are not used or exist with cells out of the coverage area and they add important neighbor relations according to the status of the network at a given time. This means that even if a neighbor relation is deleted because it has low usability rates, the same one might be added again after a certain period since subscribers moving around the coverage area of a cell might need this relation again so that handovers in either technology are successful. All cells have a maximum allowed number of neighbor relations that can be set and ANR applications are initially tuned during the initial SON system tuning process to keep the specific rule according to the policy that each network operator demands. The ANR operation is repeated multiple times until the neighbor list is perfectly optimal according to real-time metrics and according to the subscriber's mobility and distribution.

3.2.3. Input for ANR and Triggering

The following thresholds and parameters are set as input to the SON ANR algorithm, which evaluates the existing neighbor list and creates a candidate list for deletion and addition actions [66–72]:

- DCR (Drop Call Rate) for a defined sample period or bad quality (SNR ratio).
- Minimum number of calls served (low or high usability of a cell).
- Importance and usability of existing neighbor relations according to the ratio of handovers for a specific neighbor relation compared to the total number of handovers of the cell.
- Missing neighbor events (collection of network counters reporting missing neighbors).
- Intersection (coverage pattern of each cell and overlap among them).
- Cell coverage including propagation delay counters collected from the OSS.
- Layer Management Strategy (LMS): Policy followed by the operator regarding the inter-frequency relations (i.e., three carriers are used (F1, F2, and F3) if a handover is allowed).

3.2.4. Mobility Load Balancing (MLB) and Traffic Steering (TS)

In a similar manner, Mobility Load Balancing (MLB) or traffic steering (TS) is one of the key optimization activities applied either independently, or in case multiple radio access technologies coexist. The target of MLB is to forward voice and data traffic to the most appropriate frequency/carrier or hierarchy cell layer or radio technology according to the radio parameters policy followed by the network operator. MLB can be applied either in idle or in connected mode states of a UE (inter-/intra-frequency or Inter-RAT scenarios).

In GSM/UMTS networks, static load balancing procedures usually take place while in LTE and 5G mechanisms for MLB are embedded in 3GPP standardized SON functions, leading to autonomous operation based on network counters' feedback [57–64,73]. Basic parameters that affect traffic steering/load balancing concern neighbor cell level parameters related to intra-/inter-frequency or inter-system relations or cell parameters that concern only a specific cell [22,23]. Currently, key mechanisms for traffic steering include the tuning of inter- or intra-frequency handover or reselection parameters, absolute priorities (AP) (the UE is informed in idle mode about the priority of a candidate camp frequency or candidate RAT) and Basic Biasing (BB) (triggering cell selection or reselection in idle mode).

As a definition, network load can be described by the following scenarios with the first one being the most common [8,22,23,64,73]:

- Radio resource load related to blocking due to a lack of resources.
- BTS/NodeB/eNodeB/gNB hardware resource load.
- Transport/backhaul network resource load.

3.2.5. Scenarios and Impairments That Trigger MLB Operation

Depending on the optimization scenario that must be deployed, load balancing and traffic steering aim to resolve the following impairments [8,22,23,64,73]:

- Offload loaded cells towards non-loaded ones, achieve a better UE throughput and QoS (Quality of Service), and ensure optimum cell capacity while users are moving within an area of interest, as a scenario assumes that an operator uses three carriers for one radio access technology. When a high load is observed in one of the three carriers, load balancing is achieved by forwarding traffic from one of the three carriers to the other through a reselection or handover.
- Offload higher power/capacity macro cells towards low-power/capacity micro/pico or femto cells. This scenario is deployed through the decreasing or increasing cell coverage by adjusting cell power. The same stands in a case where cells operate at high power, but traffic is low.
- Ping pong effects limitation (cases where handovers take place constantly). This phenomenon is seen especially in cases such as highways with fast moving UEs trying to camp on lower cells.

3.2.6. SON MLB and TS Applications—Conflicts among MLB and MRO (Mobility Robustness Optimization)

As expected, the manual handling of load balancing and setting of optimum handover and reselection parameters in real time is extremely difficult due to the constant mobility of users that cannot be predicted. The only exception concerns the cases of mass event handling such as planned concerts or athletic events where operators can approximately predict the load/capacity demands of the network and plan/tune the network accordingly by using specific network features or by adding extra equipment (mobile base stations). Based on these factors, SON MLB applications are considered as one of the most critical SON functions, while their impact has been regarded as one of the most basic for UMTS and LTE networks [22,23]. The same stands for 5G as well. MLB operation can overcome load balancing issues but needs careful tuning since rapid MLB parameter changes increase the Physical Uplink Shared Channel (PUSCH) interference level in the uplink channel and decrease average the Channel Quality Indicator (CQI) in the downlink for the LTE case [74].

Furthermore, SON MLB goes hand in hand with another application called SON MRO (Mobility Robustness Optimization), an application that aims to optimize cell reselection in idle mode and handovers in connected mode. However, it has been noticed that MRO operation creates conflicts with MLB and vice versa, since the same mobility parameters are handled by both SON functions. As an example, after MLB changes, handover performance degradation might be noticed and, as expected, the MRO application finds that user mobility problems exist [22,23,75]. Figure 8 depicts the conflicts that might be created in mobility thresholds (idle and connected modes) through MLB and MRO applications since both applications interact with idle and connected mode thresholds, and thus conflicts can easily occur.

The authors of [76] proposed a solution so that these conflicts are avoided through a scheme where MLB is based only on cell reselection instead of handover since there is no conflict between the cell reselection parameters changed by MRO and MLB. Instead of changing mobility thresholds, an alternative approach for MLB applications which is widely followed by SON vendors is based on the changing of the antenna tilt (either down-tilt or up-tilt) since this action affects the coverage area of cells and traffic can be shifted to a neighbor cell that is less loaded. Additionally, the authors of [77] approached MLB operation through antenna tilt changes and concluded on the importance of antenna vertical beamwidth and the addition of an extra handover offset so that a minimum difference in the received power between the serving and neighbor cells is ensured before handover. No matter which technique is used, the aim is to enable subscribers to move and camp in non-congested cells.

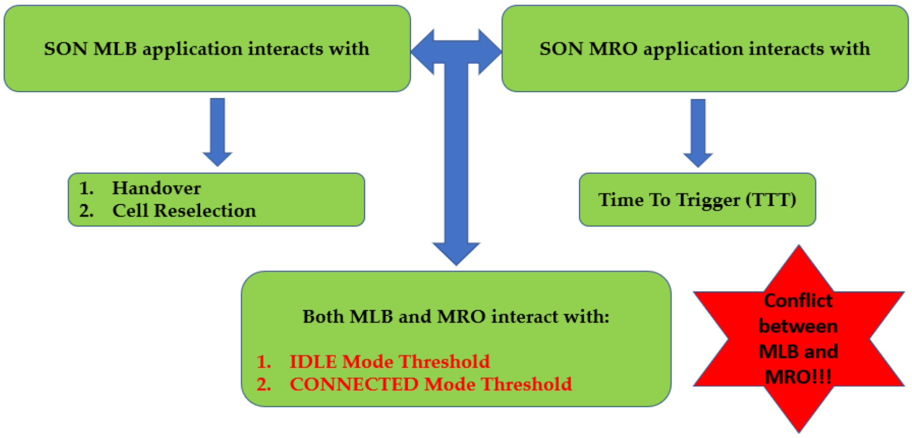

Figure 8. Conflicts between MLB and MRO.

Future research for 5G includes the determination of load by considering the backhaul state as well. A variety of MLB and MRO algorithms have been proposed; however, the former might fail in case backhaul capacity limitations occur. This is very critical for future 5G networks where base station backhaul limitations might lead to low rates for bandwidth intensive services [78]. Finally, the authors of [79] presented a SON load balancing algorithm that considers the backhaul restrictions and proposes the future consideration of backhaul restriction in SON MRO algorithms.

3.2.7. SON Coverage and Capacity Optimization (CCO), Interference Management and Adaptive Antennas

SON Coverage and Capacity Optimization (CCO) and Interference Management applications were developed to ensure uniform coverage and capacity in problematic areas where continuous coverage cannot be ensured, signal quality is not satisfactory, and interference is a key issue that cannot be handled easily manually in real time. The aim of this is to extend a desired cell's coverage, mitigate coverage holes, and avoid interference at the same time. Triggered mainly by the high drop call rate, low handover success rates, and deteriorated QoS KPIs such as SINR (Signal to Interference Ratio), the specific applications operate mainly through antenna electrical tilt adjustments (adjusting azimuth and main or side lobes) centrally through the network OSS by controlling the Remote Electrical Tilt (RET) installed in each antenna [22,23]. Antenna tilt changes (either down-tilting or up-tilting) must be performed very carefully since they affect coverage boundaries, while an interference issue might be triggered after such a change.

- When electrical tilt is decreased (uptilt), the coverage area of the cell might overlap with a neighboring cell, and thus interference is created together with capacity issues. This specific case creates the so-called "over-shooting cells".
- On the other hand, when electrical tilt is increased (down-tilt), the coverage area of the cell is reduced, leading to interference mitigation towards the neighbor cells, traffic offloading because of capacity limitations, and the elimination of over-shooting cells. This tradeoff must be constantly monitored, and operators must perform such changes in a central manner through SON CCO application.

Antenna parameter optimization needs constant monitoring; thus, it can be said that electrical tilt changes through SON and the algorithms supporting the specific applications need to react very fast in frequent load cases. Alternative methods include changes related to cell output power or reference/pilot signal power.

Apart from central control through RET, another option is the usage of Active Antenna Systems (AAS), which are able to perform antenna beam forming or MIMO with spatial multiplexing, while the key behind the operational rational of AAS is to create spatial beamforming patterns [80]. This approach is expected to be a key technique for 5G networks due to the importance of massive MIMO for 5G development. Finally, the authors of [81] further analyzed the role of ML algorithms in antenna tilt changes and more specifically the role of reinforcement learning (RL) algorithms for obtaining the optimum result. The role of specific algorithms not only in the CCO case but SON as a system seems to present an ideal application scenario according to the upcoming conferences during 2022 on the issue, but in our opinion the use of deep reinforcement learning seems even more challenging and can bring even better results [82].

4. Machine Learning Algorithms for SON

The application of ML and AI techniques in future wireless networks constitutes a separate and very wide research field, but to address this we must refer briefly to the key algorithms applied in SON systems. In this section, our target is to briefly describe the main machine learning (ML) algorithm taxonomy applied in SON systems. Machine learning (ML) as a subset of artificial intelligence (AI) is a key enabler for SON systems since all related applications are based on intelligent ML algorithms that use real network data (counters and KPIs) as input to make decisions about the action needed for each optimization issue and create executable scripts for the OSS.

Future research on SON systems for 5G networks includes the development of new ML algorithms that can adapt in a variety of scenarios and provide cognitive behavior and intelligence in past and present network statuses, so that full end-to-end automation through SON can be achieved [30]. Table 2 describes the suggested ML technique and possible algorithm that can be used per SON application.

Table 2. ML technique and possible algorithm used per SON application.

SON Application	Machine Learning Technique	Algorithms That Can Be Used
Mobility Load Balancing (MLB)	RL or DRL, UL, SL	Q-learning
		Fuzzy Q-learning
		Dynamic Programming
		K-means clustering
		Polynomial regression
Mobility Robustness Optimization (MRO)	RL or DRL, UL, SL	Q-learning
		Fuzzy control
		Pattern identification SOM
		Semi-Markov model
		ANN
Coverage and Capacity Optimization (CCO)	RL or DRL, UL	Fuzzy Q-learning
		ANN

4.1. ML Algorithms Taxonomy

ML taxonomy in computer science is usually split into supervised learning (SL), unsupervised learning (UL) and reinforcement learning (RL). According to the approach of the authors in [15], SON systems' learning algorithms can be classified into supervised and unsupervised learning, similarly to humans, who learn something independently or with the help of a teacher. Figure 9 depicts the taxonomy based on SL, UL, and RL.

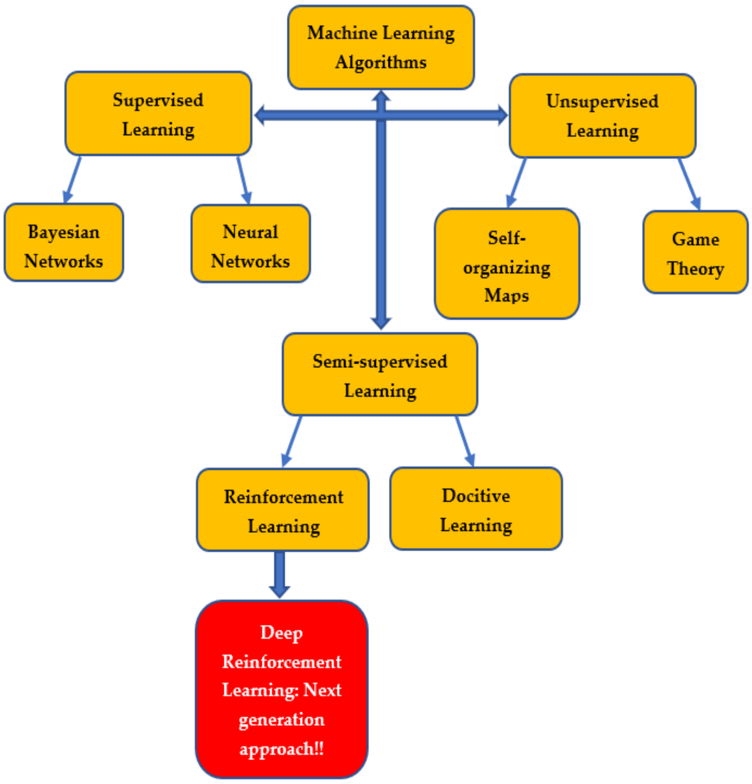

Figure 9. ML Algorithms taxonomy.

4.1.1. Supervised Learning (SL)

Supervised learning is an ML technique based on training data used as input and test data leading to an output prediction close to reality [9]. A huge number of algorithms proposed can be found in the literature; however, the most common ones related to self-optimizing network functions are the following:

- Bayesian: Bayesian algorithms are based on Bayes theorem and their aim is to calculate probabilities according to pre-existing probabilities. Additionally, they do not require a large training sequence.
- Neural networks: This specific category comes from biology (brain neural networks). Neural networks are trained by taking examples and generating identification characteristics from the training input that they are given. A neural network consists of a set of interconnected nodes, while the processing ability of the nodes' network is described through the node connection weights, created by the adaptation of a learning process obtained by training patterns provided as input [83].

Additional SL algorithms categories include:

- Decision trees (DT).
- Hidden Markov Models (HMM).
- Support Vector Machines (SVMs).
- K-nearest neighbors (k-NN).

4.1.2. Unsupervised Learning (UL)

Unsupervised learning does not involve any training input or sample contrary to supervised learning. The key rationale of unsupervised learning is to recognize a pattern among the input data that the algorithms receive so that future inputs can be predicted. Typical examples include social networks analysis while in SON applications. Unsupervised learning algorithms are used mainly for self-healing and self-optimizing use cases [9]. The most common cases are the following:

- Self-organizing maps (SoM): A SoM intends to identify groups of data so that a representation of the input data is created. This technique is called clustering. The main idea behind SoM is to group cells with similar network parameter settings and trigger changes for the specific group uniformly.
- Game theory: Known since the 1950s and applied later in biology, social science and economy/political sciences during 1970s game theory have been used for network systems modelling. According to game theory, several players, nodes or artificial agents (in the case of computer science) perform actions that affect each other while the target is to get a zero-sum result by subtracting the losses of one player and adding the gains of the winning player [83]. According to the authors of [15], operators can avoid zero human interaction by using game theory approaches in mobile networks but limited literature concerning game theory applicability in LTE networks exists.

4.1.3. Reinforcement Learning (RL)

This specific subcategory has been already proven as effective for autonomous vehicles, network elements routing, and other applications, including self-optimization. The basic rationale is based on learning through interactions with neighbor nodes. In more detail, the specific algorithms receive as input a reward function indicating that they work as expected [9,15]. Reinforcement learning is tightly coupled with Markov Decision Processes (MDP) in terms of defining a possible set of network states and a possible set of actions for each state. Possibly the most common examples are Q-learning and Fuzzy Q-learning. The specific algorithms are based on the rationale that for any finite Markov decision process (MDP), an optimal policy for awarding or maximizing the expected value of each step is identified. Deep reinforcement learning is the evolution of RL that seems to be an even more promising technique for 5G and beyond networks [84–88].

Reinforcement learning (RL) and deep reinforcement learning (DRL) as an advancement of RL is a very promising approach in the field of machine learning for B5G networks dealing with sequential decision making. The difference between the two relates to the fact that the former is based on dynamic learning with a trial-and-error method, while the latter is learning from existing knowledge and applies it to a new data set. However, the operation rationale is very similar and they are expected to have a key role in future telecommunication systems.

RL is vital due to the ability that can be provided to the agents to learn in real time with no previous knowledge of the environment and continuously interact with it, contrary to the other legacy ML techniques that require full knowledge of the environment and a training set as input, provided by an external resource to the algorithm. The main rationale is that an agent, which in our case might be a UE or a base station (BTS/NodeB/eNodeB/gNB), learns the optimum behavior by collecting information in real time and tries to obtain the maximum reward at each algorithm step [12,84–88]. The key terms related to RL algorithms are the following:

- Environment (e): A real-life scenario that an agent must interact with.
- Agent: An entity or a node that performs specific actions in an environment in order to gain some reward.
- State (s): The current situation in the environment.
- Reward (R): A return provided to the agent when a specific action is taken.
- Policy (π): The rationale that the agent follows in order to decide on the next action according to the current state.
- Value (V): The long-term reward to the agent compared to the short-term reward.
- Value Function: The value of a state as a total amount of reward gained by the agent.
- Q value (Q) or Action Value: An estimation of how good it is to take the action at each state.

Figure 10 depicts the interaction between the environment and the agent and correlates the action, state, and reward terms related with RL.

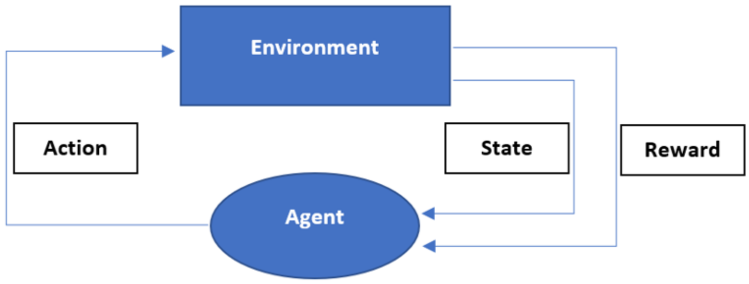

Figure 10. Environment and agent interaction.

Apart from the fact that the agent interacts with an uncertain environment and must face it in a holistic manner, one of the key challenges related to reinforcement learning is the exploitation and exploration tradeoff. This specific tradeoff is related to the selection of the actions already selected in the past from the agent proven to provide a beneficial reward and at the same time explore the environment so that even better actions are selected.

We cannot avoid referring to the ancestor of RL, the Bellman equation, which is a functional equation that describes the behavior of a dynamically changing environment over time and led to the development of dynamic programming methods that try to handle optimal control scenarios in such environments [88]. The Bellman equation describing the values received by an agent during the process use for trying to find the most optimal action to take at each step can be written as:

$$V(s) = \max\,[R(s,a) + \gamma V(s')] \tag{1}$$

The key terms of the equation are:

- Action performed by the agent is "a".
- State instance by performing an action by the agent is "s".
- The reward received for each beneficial action or not is "R".
- The discount factor is Gamma "γ".
- V(s): Corresponds to the value calculated at a specific point.
- R(s,a): The reward at a particular state after an action is performed.
- γ = Corresponds to the discount factor that determines if the agent as regards the beneficial the rewards received in the near future compared to those in the immediate future.
- $V(s')$ = The value obtained at the previous state.

As far as 5G networks are concerned, recent approaches and proposals involving RL algorithms regard power and interference control and they can be a perfect match for the development of intelligent B5G SON platforms [12,84–87]. The UEs and RAN nodes can run RL and DRL algorithms so that real-time network optimization activities can be fully automated and able to be effective in real-time and continuously changing radio propagation environments.

4.2. Docitive Learning (DL)

Docitive learning algorithms (from the word docere = to teach or transfer information) are mature ML algorithms based on the rationale that a decentralized network of nodes can exhibit a better performance in case nodes exchange information among themselves. Studies have shown that docitive learning can be effectively applied in cognitive radio (CR) networks as well [89].

5. Future SON Research Directions for B5G

Currently, SON research and development is spread over many different domains. Academy, industry, and worldwide standardization bodies such as 3GPP/ITU have evolved so that SON is fully embedded in future B5G solutions [8–14,20–23,30,56,64,72,73].

Interesting cases include:

- The development of Virtual SON (V-SON) platforms since NFV and SDN architectures have been suggested as one of the key drivers for SON deployment in 5G networks as well as the binding of SON with C-RAN.
- The development of new ML algorithms and the binding of SON with big data and deep learning technologies.
- The binding of SON with key 5G eMBB enablers such as mmWave.
- The application of SON in IoT network infrastructures, and massive Machine-Type Communication (mMTC).
- The backhaul network management through SON.
- The risk assessment and the development of security solutions and policies related to SON systems in 5G networks.
- The development of hybrid SON solution targeting in URLLC services.

Figure 11 depicts the key entities of a non-roaming 5G architecture as defined by 3GPP in [73]. The basic ones depicted in the figure are the following:

- Network Slice Selection Function (NSSF).
- Network Exposure Function (NEF).
- Network Repository Function (NRF).
- Policy Control Function (PCF).
- Unified Data Management (UDM).
- Application Function (AF).
- Network Slice Specific Authentication and Authorization Function (NSSAAF).
- Authentication Server Function (AUSF).
- Access and Mobility Management Function (AMF).
- Session Management Function (SMF).
- Service Communication Proxy (SCP).
- User Equipment (UE).
- (Radio) Access Network ((R)AN).
- User Plane Function (UPF).
- Data Network (DN), e.g., operator services, Internet access or third party services.

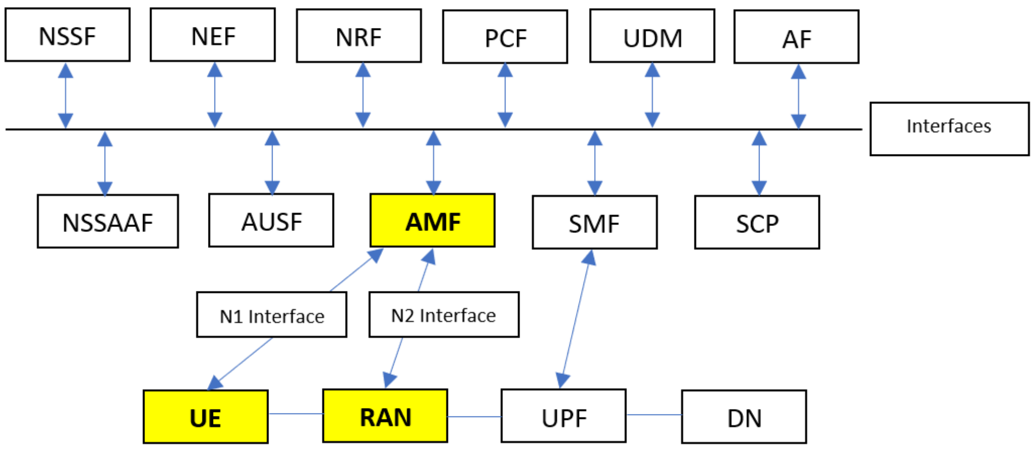

Figure 11. Non-roaming 5G architecture.

Among the key elements depicted in Figure 11, the ones directly interacting with 5G SON platforms shall be AMF, UE (Might Include UEs or IoT sensors), and RAN, including the gNBs.

5.1. NFV and SON (vSON) for 5G Networks—RAN Virtualization/C-RAN Architectures and SON

The telecommunications industry managed to develop critical network function entities such as Evolved Packet Core (EPC) in the case of LTE which is an indication that it can be applied in 5G network entities as well [90,91]. An example is the migration from virtual Evolved Packet Core (vEPC) the Stand-alone for 5G core (SA) [92]. Since very critical parts of a network can be virtualized and legacy hardware tends to be replaced by virtualized solutions, SON platform virtualization over NFV seems to be intelligent, cost effective and fast in terms of deployment; however, performance metrics must be carefully examined since the interaction of a SON system with the OSS of a mobile network in real time and in terms of time response is very critical. Companies such as Cellwise have already deployed virtualized SON solutions [93].

Virtual SON (V-SON) as an extension of the NFV and SDN architecture has been suggested as one of the key drivers for SON deployment in B5G networks. This can occur either in a centralized or in a distributed/hybrid architecture approach, enabling the provision of SONaaS (SON as a service) [8,11,94,95].

The basic architectural functional blocks of an NFV architecture are the following [96]:

- Virtualized Network Function (VNF): VNF refers to a standard network function, non-virtualized prior to NFV introduction, which can be fully or partially virtualized. Typical examples might be the MME or AMF, the SGW (Serving Gateway), or even the eNodeB/gNB. In our case, SON might be one of the VNFs [95].
- Element Management (EM): Refers to the management operations strategy of the VNFs.
- NFV Infrastructure (NFVI): VNFI refers to the common hardware resources (servers and storage) that host the NVFs. Routers, switches and wireless links interconnecting the main servers can be regarded as part of the NFV infrastructure as well.

Moreover, C-RAN (Cloud-RAN), or Centralized-RAN, was first proposed as an architecture by China Mobile Research Institute in April 2010 providing a unified, centralized, and cloud computing solution, leading to the virtualization of the RAN part of 2G, 3G, 4G, and 5G networks [97].

Network operators can benefit from C-RAN since it can provide higher spectrum efficiency, interference, and capacity management, load balancing/traffic peaks handling, energy consumption, and CAPEX/OPEX savings [97–100]. The former is the outcome of the centralized or partially centralized operation of a Base Band (BB) pool gathering basic RAN functions and serving multiple radio units. The possible architectures are initially based on the assignment and sharing of the functionalities of the BBU (Baseband Unit) and Remote Radio Head (RRH) (referred as Remote Radio Unit (RRU) as well).

There are two basic approaches: In the first approach full centralization is provided, since the baseband unit provides layer 1, layer 2, and layer 3 functionalities, while in the second approach (partial centralization) the RRH provides the BBU functionalities leading to partial centralization [97–100]. The traditional strong relation of the BBU with the RRU where the latter coexist in the same site does not exist anymore since an RRU might belong to different BBUs and the functionality of a "Virtual BTS" is introduced. This is the key correlation point of C-RAN with Network Function Virtualization (NFV).

In our opinion, the combination of C-RAN with C-SON is a key enabler for future B5G networks, while with the rise of C-RAN it is possible that additional scenarios and use cases for C-SON systems might appear. The rationale behind this is that C-SON systems shall be able to monitor in a more centralized manner metrics and parameters related to the Baseband Units hardware operation and possibly new SON applications focusing on hardware management can be developed. An example might be the efficient hardware resource allocation assignment through C-SON applications running on the BBU pool which is a well-known issue for operators [91,101].

Finally, since network slicing allows the creation of multiple logical networks in the NFV domain able to simultaneously run on top of a shared physical network infrastructure, end-to-end virtual networks that include both networking and storage functions can be created. Network resources are partitioned and scenarios with 5G verticals with different latency and throughput demands can be created. In our opinion, this discrimination can be combined with SON functions per scenario.

5.2. Empowering SON for 5G with Big Data and New ML Algorithms

As we move towards 5G, the amount of training data needed for algorithms increases exponentially; thus, we conclude in dig data structures that must be handled. New ML algorithms must be developed so that SON systems are able to have an end-to-end vision of the network and conflicts among different SON applications handling the same or similar network parameters are resolved. The performance of ML algorithms depends on the representations that it learns to output. This is the point where recent approaches in deep learning such as "Representation learning" provide an efficient solution by transforming input data and defining if input training data such as specific network parameters represent a specific set mapped directly to the output. The core idea of representation learning is that the same representation may be useful for multiple tasks as an output while training sequences are classified in a more efficient manner as far as the output is concerned in this way [102].

The authors of [10] note that existing SON systems lack end-to-end network knowledge, and thus they proposed a big data framework (BSON) as a holistic approach including, apart from the already used network KPIs and performance counters, user/subscriber level data and user application-based data (social media and smartphone sensors).

The authors of [103] proposed an application-characteristics-driven SON system (APP-SON) already applied in a tier-1 operator for next-generation 5G networks. By combining a Hungarian Algorithm Assisted Clustering (HAAC) approach and a deep learning assisted regression algorithm, cell application characteristics were identified and used for SON optimization, leading to a better classification of useful KPIs per cell and a better QoE [103]. The experimental results prove that cell traffic can be profiled according to the applications used per user case. As a next step, weather conditions affecting the propagation environment shall be included.

In our opinion, the prementioned proposals could further evolve by combining information coming from geo-location systems already deployed in network operators [104].

5.3. SON, mmWave and Massive MIMO Technologies for 5G Networks

Compared with 3G and 2G technologies, 4G-LTE was revolutionary, but currently LTE networks are running out of bandwidth; thus, the spectrum usage of the millimeter-wave frequency range is a solution for 5G bandwidth requirements. mmWave is a part of the 5G standard and combined with 3D beamforming techniques, where multiple-element base station antennas use multiple antenna elements to form directional beams for transmission, and it is the key solution for providing low latency and high data speeds [8]. Furthermore, the propagation nature of mmWave leads to shorter communication distances, and thus base stations must be positioned closer if compared with existing mobile networks, leading to even more dense network clusters.

The binding of SON with mmWave and beamforming techniques is a recent very interesting concept and the authors of [13] proposed a use case related to directional cell search based on the rationale that the simultaneous transmission of broadcast signals reduces the amount of the needed cell search resources including latency during the process of recognizing neighboring cells. The tradeoff for this includes Radio Link Failures (RLFs) due to SINR deterioration (related to handover measurements) and smaller coverage. However, a centralized SON coordinator might improve the former.

Future research related to SON usage for directional cell search is also related energy savings in case beamforming is applied only in required areas so that coverage overlapping is avoided and with concepts such as the self-optimization of beam direction and transmission power.

Apart from mmWave, massive MIMO is also one of the key components of 5G networks and a key enabler for the provision of high-speed data rates in indoor and outdoor propagation environments operating either in mmWave frequencies or below 6 GHz [8]. ML algorithms can empower massive MIMO, leading to "Intelligent massive MIMO" solutions, and typical examples include massive MIMO power control and user positioning [105].

This means that ML based SON systems can be combined with massive MIMO and might be an interesting research scenario since beamforming can be controlled by SON platforms.

5.4. SON for Backhaul Management in 5G

As already mentioned, the authors of [79] identified the backhaul restrictions and proposed a SON load balancing MRO algorithm considering the backhaul state. Since the application of SON in RAN proved to be very beneficial, academy and industry started working on the application of it in wireless backhaul so that self-configuring, self-optimizing, and self-healing capabilities are adopted in this domain as well. Even if radio access and backhaul technologies impose different handlings and have different characteristics, the operational challenges are closely related [106,107].

As an example, a self-optimization use case might enable cooperation with neighboring backhaul radios and interference mitigation, while the self-healing use case can adjust a link's transmission parameters in order to overcome a possible failed link or a new link addition [107,108]. In terms of self-healing, the key point is to automatically identify proactive rerouting needs in cases of performance degradation due to bottlenecks in the backhaul network. Inputs to backhaul SON might include QoS KPIs collected both from radio and backhaul networks [106].

Finally, the authors of [109] demonstrated a SON solution for mobile backhaul networks, leading to a 31% increase in traffic in case microwave link capacity degradation is detected and a 12% increase in case a link failure is detected.

5.5. SON for IoT

SON applied in IoT infrastructures is a necessity as well and a key enabler for mMTC (massive Machine-Type Communications). IoT networks must be treated as large distributed systems and in this case, apart from neighbor sensor discovery, path establishment and service recovery, the key point is to apply SON functions for sensor energy management. The authors of [110] introduced a new IoT paradigm called Fog of Things (FoT), including FoT-Devices, FoT-Gateways and FoT-Servers, where IoT services have different profiles (FoT-Profiles) and they are offered in a distributed manner. Moreover, they proposed a platform called SOFTIoT enabling SON capabilities for FoT-Profiles, devices, and gateways.

Another very interesting work is described in [111], where the authors introduced a resilient, self-organizing middleware for IoT applications called SORRIR. The rationale of the system is to decouple resilience from business logic, monitor the applications operation, react to failures, and trigger automatically needed reconfigurations.

The authors of [112] investigated self-organization for low-power IoT networks through a lightweight distributed learning approach instead of legacy centralized optimized approaches implemented in the IoT devices. The aim was to reduce signaling between IoT nodes, which leads to decreased energy consumption and minimizes possible collisions.

Finally, in [113], industrial IoT load balancing through the scope of self-organization was investigated through a proposed load balancing scheme that considers wireless link quality, the congestion of the wireless channel, and the amount of data that need to be sent or received. The outcome is that through the specific scheme, reliability can be significantly improved since the packet drop rate is reduced by up to 85%.

5.6. SON Platforms Risk Assessment and Security Concerns

Fifth-generation networks are exposed to the threats identified in 4G networks; however, the attack mitigation measures cannot be performed manually in a central manner due to the heterogeneity of the serving environment with M2M, D2D, and multi-equipment environments. Moreover, virtualization deployments raise trust issues between the operator and a Cloud service provider [114].

As far as SON platforms are concerned, some additional issues must be considered. The fact that a SON platform has full read/write execution rights to the OSS of each RAN technology needs very careful consideration and monitoring, since the damage that might be created to the network infrastructure due to inappropriate and non-legitimate account usage can be irreversible.

The same stands for cases where a non-verified SON system manufacturer developers' code/script is imported into the system, since limited SON vendors enable through their APIs such actions and non-certified personnel, or small firms try to benefit from developing their own scripts due to the APIs provided with the system.

In our opinion, the latter might be acceptable in case of small and non-critical distributed SON architectures, but in case of centralized ones, a misconfiguration might be a complete disaster. Consider the case where wrong scripting is applied centrally in a SON system by non-certified developers by the manufacturer. The outcome shall be a vast number of OSS commands committed to the network which do not lead to the expected KPI advancement and are difficult to revert in real time, manually or by the SON system.

Finally, since SON systems are attached directly to the OSS, they must be completely isolated and reside behind all possible network security infrastructure such as anti-DDoS (Distributed Denial of Service), and NGFW (Next-Generation Firewalls) systems even if, typically, no web traffic (inbound or outbound) enters or leaves the SON system.

5.7. SON for 5G Key Use Cases—The URLLC Use Case

Possibly the most difficult part to ensure and implement in 5G networks will be the URLLC use case. URLLC will be the key enabler for emerging applications and services including tactile internet, mobile factory automation, and inter-vehicular communications for improved safety such as autonomous driving. In order to achieve a successful deployment of the former applications, stringent requirements such as reliability, latency, and availability must be met [115].

Existing SON systems are mostly service agnostic; thus, the authors of [12] proposed SON usage as an approach for the successful implementation of the strict low-latency and reliability requirements through the selection of specific parameter sets as input to the system. The focus of this specific paper is on the Device to Device (D2D) technique, which regards mainly direct short-range communication MTC applications such as Wi-Fi Direct, Bluetooth Low Energy (BLE) or Near Field Communication (NFC).

On the other hand, Machine to Machine (M2M) communications regard mainly long-range Low-Power Wide-Area (LPWA) networks such as SigFox, Long-Range Wide-Area Networks (LoRaWAN) and Narrowband-IoT (NB-IoT), with applicability in smart cities, supply chain management, smart metering, security and surveillance, automotive communications, and e-healthcare scenarios, and it is expected that M2M traffic shall occupy around 45% of the total traffic of the Internet. Thus, currently operators focus on the deployment of M2M networks such as NB-IoT [116–119]. Based on these factors, we believe that future research on SON application in M2M applications is an interesting scenario that should be investigated.

5.8. SON for 6G Networks

In the 6G era, energy efficiency, ultra-low latency, and high reliability shall be key issues to handle in standard mobile communication networks. Apart from this fact, in special cases, such as vehicular communications, the nodes must be able to perform self-organizing functions; thus, SON functions and network automation shall keep evolving [120,121]. As far as the next move towards 6G networks is concerned, and we are at the very early stages of research and standardization, SON systems must embed self-coordination capabilities to manage the complex relations between the different applications that are running, so that slow reactions in real-time situations are avoided. According to the authors of [122], hybrid SONs (H-SONs) combined with feedback from multiple feedback loops might be the ideal case. Virtualized, containerized, multi-tenant architectures as well as federated transfer learning and collective intelligence based on conventional AI techniques can improve the landscape as we move towards 6G architectures.

Another key technique as we move towards 6G regards O-RAN. O-RAN (Open RAN) is another key technique based on the rationale of splitting the centralized unit (CU), distributed unit (DU), and remote unit (RU). Intelligence in O-RAN architectures relies on the separation of the RAN Intelligent Controller (RIC) and allows one to gather radio resource management (RRM) and self-organizing network (SON) applications, controlling the radio resources and network. In addition to this fact, RIC is separated from the processing units and allows us to gather radio resource management (RRM) and self-organizing network (SON) functions, which control the radio resources and network. In the O-RAN concept, intelligence resides in the RIC, employing AI and ML models for radio network automation [123].

Finally, the prominent benefits of network slicing techniques are expected to be blended with SON functions as we move towards 6G infrastructures. As an example, a SON-based network management architecture spread across RAN and core network shall be necessary for controlling networks in a holistic manner with SON functions operating at the user and control plane and cooperating with others running at the core level [124].

6. Conclusions

Self-organizing network (SON) technologies constitute one of the key enablers for B5G network deployment and operation since network management, optimization, and maintenance processes are expected to become even more complicated because of the diversity of services and equipment and the escalation of the number of devices in the network. Without SON, these tasks will become unfeasible. Academia and industry managed to make network automation a reality through SON and embedded machine learning (ML) and artificial intelligence (AI) technologies in mobile networks, while the adoption of SON platforms by many operators worldwide over the last few years has yielded impressive results in terms of KPI advancement and tremendous changes in terms of network management processes.

In this paper, we presented and analyzed in detail the rationale of operation of SON systems and their evolution across generations, and proposed design methodologies for SON applications in B5G environments. We described in detail the design and the components of a C-SON system able to handle 4G and 5G networks and the dimensioning principles that must be considered prior to a SON system deployment in a RAN, including 2G/3G/4G/5G technologies. As far as the applications are concerned, we provided a deep insight into ANR, MLB, MRO, and CCO and explained their operation rationale.

Moreover, we described the key AI and ML algorithms needed for successful SON deployment and described the most recent related research directions such as RL and DRL. These specific algorithms are ideal for B5G SON systems due to their ability to interact with the environment and collect information about the next steps without the need for previous knowledge or training information. Finally, we highlighted the most important points that SON research should focus on in order to guarantee the successful application of SON solutions in future networks such as B5G or 6G. Key points regard the interaction of SON functions with NFV, Big Data, backhaul management, IoT infrastructures, important B5G technology enablers such as mmWave and massive MIMO, and finally the interaction with basic 5G use cases such as URLLC.

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