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Survey paper

Comprehensive survey on self-organizing cellular network approaches applied to 5G networks

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ABSTRACT

Self-Organizing Network (SON) stands for a key concept characterizing the behavior of the future mobile networks. The evolution of telecom infrastructures towards 5G transforms the network management from the traditional and static processes to automatic and dynamic ones. SON was proposed to offer agile on-demand services to the users through providing self-adaptation capabilities to mobile networks on different categories. This paper presents a detailed and exhaustive survey on SON evolution from 4G towards 5G networks. The central focus of this survey is upon providing a deep understanding of SON mechanisms along with the architectural changes associated with 5G networks. Within this framework, the approaches and trends in self-organizing cellular networks are discussed. Additionally, the main functionalities of SON, namely self-configuration, self-optimization and self-healing are displayed. Our work serves as an enlightening guideline for future research works on SON as far as cellular networks domain is concerned.

1. Introduction

SON and Computer Systems have been a hot area of research among the computer networking scientific community in recent years. Indeed, self-organizing systems are invested in many scientific areas including biology, chemistry, cybernetics, and computer science. The seminal study of self-organizing systems has been conducted since 1953 by Grassé [1], who explored the behavior of insect societies. His study, which has check centered around nature, has shown changing forms of order occurring without any central point of control. As artificial systems, i.e. computer science applications, have become more difficult to adapt and respond to changes in their environment without any external control. Both researchers and industries have inspired by these systems in such a way that they applied their mechanisms as artificial systems.

Particularly, the wireless cellular communication systems have become extremely complex mainly owing to the insatiable demand by users for high-speed data as well as the emergence of new services. SON' importance lies in advancing the use cases of cellular networks. Thus, self-organization is an intrinsic tool for network operators to manage the operations and the maintenance of future networks as well as to reduce the operational expenditures. One of the main objectives of future cellular networks is to make them fully organized systems.

1.1. Problem statement

The hyper-connectivity, diversity of applications and high density of traffics have whetted the interest and drawn the attention towards elaborating a new generation of 5G cellular network, which can not only support more services than 4G but also fulfill the requirements of novel applications. To cater for this new breed of services, several key technologies adopted by 4G need to be integrated into 5G with several improvements involving new further technologies. The integration of these technologies in 5G gives rise to certain challenging problems. To address these challenges, Machine Learning (ML) and big data have the potential to empower intelligent SON operations [2]. Therefore, they are leveraged in the network data analysis for decision-making activities in the network automation process.

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1.2. Motivation and contribution

Several studies [3–11] surveyed SON concept in 4G context. We are basically concerned with not only the basic concept of SON, but also the challenging questions appearing with the implementation of SON legacy in 5G cellular network and how ML design helps meet 5G requirements. Table 1 depicts the relevant works that surveyed the application of SON in 4G and in 5G cellular network. As far as our research is concerned, it is noteworthy that only surveys published between 2010 and 2020 have been considered. Unlike other surveys, we are the pioneer to the best of our knowledge to deeply discuss state-of-the-art works for SON mechanisms including further explorations, as illustrated in Table 2. For instance, the authors in [12] tackled the challenges of Network Management Automation (NMA) in 5G from an ML-perspective. Moreover, they also highlighted the potential enablers for leveraging 5G NMA. Other surveys, such as [13] and [14], handled the need for ML algorithms in different identified SON use cases in 5G. The authors in [10] traced the evolution of SON in 3rd Generation Partnership Project (3GPP), referring to the specific use cases defined by the 3GPP standard. They also provided a guideline of ML solutions along with their applications in network management from 4G to 5G. Survey [8] explored fully and in-depth the SON concept, the definition of SON use cases in cellular networks and how ML techniques can be applied to meet 5G requirements. Survey [15] gave special focus on SON architectures and use cases of SON in 5G.

As in [4–6,8,10,14,15], the survey [16] discussed the different SON categories and the most common use cases. As in [15] and [6], survey [16] exhibited SON architectures. To the best of our knowledge, there is no comprehensive survey paper that encompasses all these points (i) SON definition (ii) SON concept (iii) all SON categories, use cases and architectures (iv) Pros and Cons of SON categories, use cases and architectures, (v) Pros of SON functions application, SON use case in 5G and its challenges that need to be tackled, (vii) Insight to other organizations instead of 3GPP, (viii) released projects and projects in progress on SON application in 5G, (ix) SON challenges to meet 5G requirements, (x) Deep analysis of SON solutions, (xi) Algorithmic aspects of each use cases. The main goal of our work is to provide the reader a deeper insight into of all these points. Basically, we provide a new SON definition and concept. Additionally, we depict an accurate classification of SON categories, use cases, architectures, considering the Pros and Cons of each of them. Furthermore, we report some projects investigating the Pros provided by ML and big data to enhance 5G SON. Moreover, we discuss the proposed works of SON application in the literature highlighting the aspect of each proposed solution. Our main contributions are outlined as follows:

- We provide an overview for future research on SON functions, its definitions, its categories, the basic SON use cases and architectures in 5G.
- We point out the shortcomings and the issues of SON implementation in 5G and discuss the significant benefits from ML and big data to cope with these limitations.
- We categorize the SON functions based on the management in 5G cellular networks.

1.3. Scope and paper organization

In this paper, we intend to provide a basic tutorial and explanation of the main SON categories as well as most popular SON use cases in 5G cellular network, the fundamental SON architecture that meets the 5G requirements in addition to the significant works which used an ML-based approach to implement automation and SON. The rest of our survey is organized as follows. Section 2 introduces a tutorial on the SON background, its definition, its SON standardization efforts, its categories, the most popular SON use cases in 5G, 5G SON architecture and the projects concerning SON application in 5G. Section 3 identifies the proposed ML solutions applied in SON. Section 4 explores some open issues and future trends. This organization is illustrated through Fig. 1.

1.4. List of acronyms

See Table 3.

2. SON background

In this section, we first set forward the basic principles of SON philosophy and then recall its various definitions, drivers, use cases and related architecture challenges.

2.1. SON definitions

The widespread use of Self-Organization (SO) term in a variety of systems makes it difficult to find an exact definition of what SO is about. In literature, there exist numerous definitions of SO in the context of cellular networks. For instance, Serugendo et al. defined it as an adaptive system which can cope with unstructured and complex open environment [18]. Ye et al. considered it as a system that should exhibit the proactive, reactive, and social behavior [19]. Erol G referred to SON as a cognitive network, *"the network that can identify its 'self' by being able to store and then be aware of its past, present and future experience and plans, may then be able to plan new actions under various foreseeable circumstances, and carry out such planned actions whenever it senses that the current or future conditions require that these actions be taken"* [20]. Self-organization is regarded as a mechanism or a process which enables a system to change its organization without explicit command during its execution time.

2.2. Overview of SON standardization efforts

There are multiple industrial organizations and standardization bodies related to network communications, such as 3GPP, 5GNOW, FANTASTIC-5G, 5G Infrastructure Public Private Partnership (5GPPP), FP7, International Telecommunication Union (ITU), National Institute of Standards and Technology (NIST), 4G Americas, 5G Americas, Small Cell Forum, Global System for Mobile Communications (GSMA), Next Generation Mobile Networks (NGMN) Alliance. These bodies have focused on cellular network (i.e., LTE, 5G and beyond) standards and regulations and they are examining the future 6G. NGMN Alliance is associated with 3GPP as a Market Representation Partner to help it ensure a high level of service and to meet the satisfaction of end-users. The organizations 3GPP, NGMN, FP7 and 5GPPP have concentrated on NM area, i.e SON evolution as well as use cases and their application to address cellular network requirements.

2.3. SON concept

SON is an autonomous management network that is considered as a next-generation network architecture in 3GPP standards. SON concept started to appear and to set with Release 8 and NGMN [21] through defining its functionalities regarding self-configuration, initial equipment installation and integration. The main target underlying the use of SON is to meet the expected network performance (i.e., Key Performance Indicator (KPI)). The KPI lies within the perspective of telecommunications operators, including capacity, Quality of Service (QoS), Capital and Operation Expenditures (CAPEX/OPEX) [11]. SON promises operators to enhance the QoS as well as to reduce CAPEX and OPEX costs in an autonomous way. Thus, SON mechanisms allow the easy management of network operations, resources and optimization [4,10,13]. The success of 5G rests upon SON functions deployment in Radio Access Network (RAN) in a coherent manner. SON algorithms operate at coarse timescales and optimize RAN performance via control plane coordination without affecting the fine timescale scheduling decisions in the wireless data plane [22] – [23].

Table 1
Related work on SON in Cellular networks.

SON in 4G		SON in 5G	
Ref+Y	Key vision	Ref+Y	Key vision
[3] 2010	*Self-configuration, self-optimization, Long Term Evolution (LTE)*	[13] 2014	*5G, SON challenges, big data, ML.*
[4] 2012	*Cellular networks, Self-configuration, self-optimization, self-healing.*	[15] 2015	*5G, SON, cloud, cognitive radio, security.*
[5] 2013	*SON, LTE, mobile network, 3GPP, enhanced Node Base station (eNB)*	[12] 2016	*5G, Network Management (NM), SON, cognition, ML, automation.*
[6] 2013	*Self-configuration, self-optimization, LTE-advanced heterogeneous networks*	[8] 2017	*ML, SON, cellular networks, 5G.*
[7] 2016	*SON, SON coordination, routing protocols, wireless sensor networks, 3GPP, LTE, peer to peer, NM, conflict resolution, reinforcement learning, state aggregation.*	[10] 2018	*NM, ML, SON, mobile networks, big data.*
[8] 2017	*ML, SON, Cellular Networks, 5G.*	[14] 2019	*5G mobile communication, Artificial Intelligence (AI) techniques, network optimization, resource allocation, unified acceleration, end-to-end joint optimization*
[9] 2017	*SON, self-configuration, self-optimization, self-healing, SON architecture*	[11] 2020	*SON, big data, 5G*
[10] 2018	*NM, ML, SON, mobile networks, big data.*	[16] 2020	*5G, NM, network automation, SON*
[11] 2020	*SON, big data, 5G*	[17] 2020	*5G, ML, SONs, 5G standalone, AI*

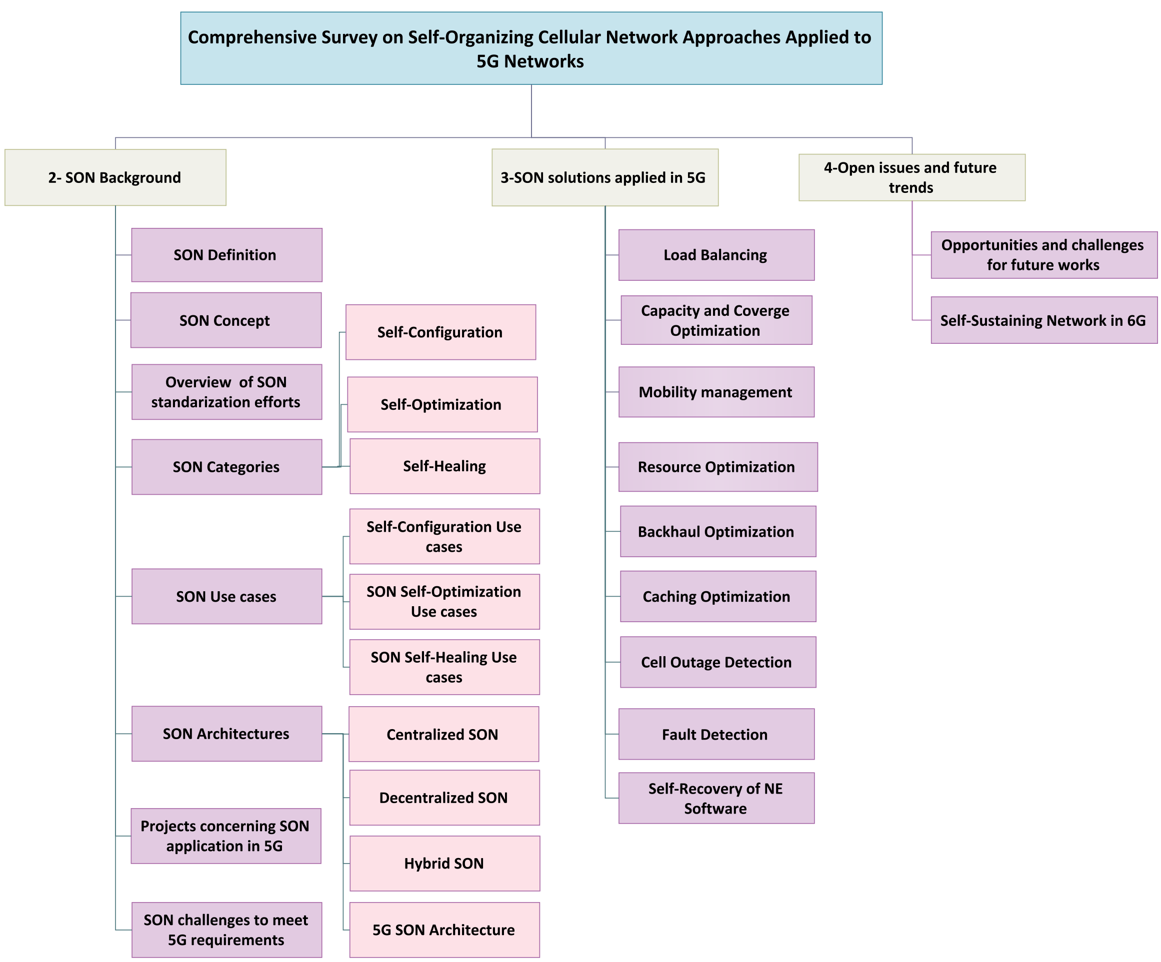

Fig. 1. Paper organization.

2.4. SON categories

3GPP Release 8 classified SON into three main categories: self-configuration, self-optimization and self-healing [8,24]. The SON functions are mostly divided and located in different nodes. Self-configuration functions are located in eNB, e.g. macro- pico- and heterogeneous communication entities, e.g. relay, femtocell Access Point (AP). The self-optimization functions are located in NM systems and/or in eNB [6]. Table 4 foregrounds the advantages and limitations of SON categories.

Table 2
Surveys compared to our contribution.

Ref+Y			[3] 2010	[4] 2012	[5] 2013	[6] 2013	[13] 2014	[15] 2015	[7] 2016	[12] 2016	[8] 2017	[9] 2017	[10] 2018	[14] 2019	[11] 2020	[16] 2020	[17] 2020	Our Contribution
SON Background	Definition																	✓
	Overview of SON standardization efforts		✓	✓	✓			✓	✓		✓		✓					✓
	Concept			✓	✓			✓	✓			✓	✓	✓	✓			✓
	Categories		✓	✓	✓	✓		✓			✓	✓	✓	✓	✓	✓		✓
	SON Use Cases	OPC		✓		✓			✓		✓		✓		✓			✓
		NCLC		✓	✓	✓		✓			✓		✓		✓			✓
		RAPC				✓					✓		✓		✓	✓		✓
		LB	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓		✓	✓	✓	✓
		IC		✓		✓		✓					✓		✓		✓	✓
		MM		✓	✓			✓			✓		✓					✓
		HPO				✓			✓		✓	✓	✓			✓		✓
		RACHO		✓				✓					✓					✓
		CCR		✓	✓	✓		✓			✓	✓	✓		✓	✓	✓	✓
		BO						✓			✓		✓					✓
		CO						✓			✓		✓					✓
		RO		✓		✓		✓	✓		✓		✓	✓		✓		✓
		CSONF		✓	✓				✓		✓		✓					✓
		SR-NES											✓					✓
		SH-BF											✓					✓
		COM		✓				✓			✓		✓		✓			✓
	SON Architectures	C-SON				✓		✓		✓		✓	✓			✓		✓
		D-SON				✓		✓		✓		✓	✓			✓		✓
		H-SON				✓		✓			✓	✓				✓		✓
		V-SON						✓										✓
	Projects concerning SON application in 5G	Previous Projects		✓				✓	✓	✓			✓					✓
		Current Projects																✓
	SON challenges to meet 5G requirements						✓			✓	✓		✓		✓	✓		✓
General guidelines for each ML algorithm according to SON use cases											✓		✓		✓		✓	✓

Table 3
List of acronyms.

Symbol	Description
SON	Self-Organizing Network
ML	Machine learning
LTE	Long Term Evolution
3GPP	3rd Generation Partnership Project
eNB	enhanced Node Base station
AI	Artificial Intelligence
NM	Network Management
SO	Self-Organization
5GPPP	5G Infrastructure Public Private Partnership
ITU	International Telecommunication Union
NIST	National Institute of Standards and Technology Partnership
GSMA	Global System for Mobile Communications
NGMN	Next Generation Mobile Networks
KPI	Key Performance Indicator
QoS	Quality of Service
CAPEX	Capital Expenditures
OPEX	Operation Expenditures
RAN	Radio Access Network
AP	Access Point
NE	Network Element
BS	Base station
ANR	Automatic Neighbor Relations
PCI	Physical Cell Identity
O&M	Operation and Maintenance
IP	Internet Protocol
aGW	access GateWay
HO	HandOver
CCO	Coverage and Capacity Optimization
MLB	Mobility Load Balancing
MRO	Mobility Robustness/Handover Optimization
ICIC	Inter-Cell Interference Coordination
RACH	Random Access Channel
COD	Cell Outage Detection
COC	Cell Outage Compensation
NCL	Neighbor Cell List
OPC	Operational Parameters Configuration
NCLC	Neighbor Cell Lists Configuration
CID	Cell IDentity
NR	New Radio
gNB	generation NodeB
NF	Network Function
NRT	Neighbor Relation Table
NDF	Neighbor Detection Function
NRF	Neighbor Removal Function
RAPC	Radio Access Parameters Configuration
LB	Load Balancing
IC	Interference Control
MM	Mobility Management
HPO	Handover Parameters Optimization
RACHO	Random Access Channel Optimization
CCR	Coverage and Capacity via Relaying
BO	Backhaul Optimization
CO	Caching Optimization
RO	Resource Optimization
CSONF	Coordination of SON Functions
RAT	Radio Access Technology
UE	User Equipment
E2E	End-to-End
SDN	Software Defined Networking
RLF	Radio Link Failure
TTT	Time To Trigger
RRH	Remote Radio Head
BBU	BaseBand Unit
CPRI	Common Public Radio Interface
ES	Energy Saving
QoE	Quality of Experience
SR-NES	Self Recovery of Network Element Software
SH-BF	Self Healing of Board Faults
COM	Cell Outage Management
AAS	Active Antenna Systems
D-SON	Distributed SON
C-SON	Centralized SON
H-SON	Hybrid SON
EM	Element Management
Itf-N	Northbound Interface connection
V-SON	Virtual-SON
NFV	Network Function Virtualisation
URLLC	Ultra-Reliable Low Latency Communications
MIMO	Multiple Input Multiple Output
IoT	Internet of Things
CoMP	Coordinated Multi-Point
SINR	Signal to-Interference-Noise-Ratio
RSS	Received Signal Strength
KNN	K-Nearest Neighbor
GA	Genetic Algorithm
LSTM	Long-Short-Term Memory model
MLP	MultiLayer Perceptron
D3A	Data-Driven Dynamic Analysis model
IA	Interference Aware
CREO	Cell Range Extension Offset
RSSI	Received Signal Strength Indicator
RSRQ	Reference Signal Received Quality
RSRP	Reference Signal Received Power
MEC	Mobile Edge Computing
CIO	Cell Individual Offset
SSN	Self-Sustaining Network
NWDAF	Network Data Analytic Function
NAMO	Network AI Management and Orchestration

(continued on next page)

2.4.1. Self-configuration

Self-configuration is defined as a process of incorporating a new Network Element (NE) into a service requiring minimal human operator intervention [25]. In fact, this concept started with 4G in order to replace the conventional process of manual configuration through self-configuration without the need for any human intervention. The configuration started locally at each node. The Base Stations (BSs) or eNBs, relay stations, and femtocells are configured during deployment/extension/upgrade of network terminals, or during a modification occurring in the system. Then, they become autonomously configured especially with the huge increase in the number of nodes and scale of the system [4]. Self-configuration uses several functions such as Automatic Neighbor Relations (ANR), automated configuration of Physical Cell Identity (PCI). Article [3] portrayed some detailed steps that are needed to achieve self-configuration process in eNBs, which can also be extended to the femtocells impromptu deployment scenario. The steps are as follows: eNB is powered on to be self-configured. It scans the neighbor cells and generates the neighbor cell list. It chooses a neighbor from the list which has a backhaul link with the Operation and Maintenance (O&M) center. The new eNB checks the security to the network and sends its authentication information to the selected neighbor which will forward it to the O&M center. Next, the O&M sends the Internet Protocol (IP) addresses of new eNB, the access GateWay (aGW) and the configuration server to the sponsor eNB which will transmit them subsequently to the new eNB. Using the IP addresses, the new eNB connects the configuration server in order to make itself in operational mode. After that, it downloads the essential softwares and operational parameters and configures itself. It chooses autonomously other parameters based on configuration parameters in neighboring nodes. Finally, it establishes a backhaul link with both of the neighbor eNBs and the core network, which achieves and delivers a status report to the NM node [10].

The self-configuration process is still facing several challenges owing to the steady increase in the number of BSs which results in a similar rise in the number of parameters e.g., thousands of different parameters need to be configured; in addition to corruption likelihood in the existing BS, begetting the disappearance of neighboring lists [8].

Table 4
Advantages and limitations of SON categories.

SON category	Advantages	Limitations
Self-configuration	Autonomous bringing of a new NE into service	Corruption occurs in the existing BS due to the configuration of intensive and different parameters.
Self-optimization	Network parameters optimization during operation and after the initial self-configuration	Dependencies between parameters.
Self-healing	Correct NE performance to satisfy users	Self-healing solutions weakness due to change from reactive to proactive scenarios in current networks.

2.4.2. Self-optimization

3GPP Release 9 [26] inserted another category, namely self-optimization, which autonomously optimizes the parameters of the system after the initial self-configuration. The network provides some measurements that help optimize the network parameters during operation. It intelligently optimizes the coverage and capacity, HandOver (HO) and interference in cellular networks. To accomplish this purpose, this concept uses several functions such as Coverage and Capacity Optimization (CCO), Mobility Load Balancing (MLB), Mobility Robustness/Handover Optimization (MRO), Inter-Cell Interference Coordination (ICIC) and Random Access Channel (RACH) optimization [4,10]. MRO, MLB, ICIC, CCO and others are defined based on NGMN standard and 3GPP releases [27]. The self-optimization process is still facing challenges of dependencies between parameters. Indeed, any change in one of them can modify the operation of the network altogether [8].

2.4.3. Self-healing

Autonomously, it solves or reduces the faults in cellular network by triggering appropriate recovery actions, especially the fault management in the RAN. In fact, if the NE (i.e., smartphones and tablets, eNBs) does not correctly perform their tasks, the network performances will be degraded with dissatisfaction of users.

However, the self-healing solutions face several challenges due to the change from reactive to proactive scenario in current cellular networks. Indeed, the solutions must cope with this change by leaning on previously gathered data in order to predict faults in the network [8]. Release 9 defined self-healing concept. Then, Release 10 added new self-healing functions: Cell Outage Detection (COD) and Cell Outage Compensation (COC) [10,15,28,29].

2.5. SON use cases

SON use cases define situations in which the self-organizing algorithms are implemented. Each SON category is classified into self-configuration use cases, self-optimization use cases and self-healing use cases. 3GPP has proposed divers SON functions that automate the network operations and achieve the goals of SON use cases designing [4,30]. In addition, NGMN outlines the important SON use cases for LTE, which are foreseen by standardization bodies and operators [31] – [32]. Fig. 2 and Table 5 summarize the major use cases of each SON category.

2.5.1. Self-configuration use cases

The basic steps of self-configuration process in eNBs can be outlined in three main stages: configuration of operational parameters, Neighbor Cell List (NCL) creation with neighbor eNB selection, and configuration of existing radio parameters and setting of network topology.

These stages involve three major use cases of self-configuration such as Operational Parameters Configuration (OPC) which describes the self-configuration of all initial eNB parameters (including IP addresses), Neighbor Cell Lists Configuration (NCLC) and Radio Access Parameters Configuration (RAPC) [4,8].

- Operational Parameters Configuration: is the configuration of basic operational parameters in eNB such as IP address, aGW, Cell IDentity (CID) and PCI. In fact, it learns the parameters of BSs in order to make them operable [8]. In order to distinguish the signals received by each cell, it is necessary to identify each cell by configuring its physical layer signature, called PCI. There are several approaches [33] – [34] that focus on PCI assignment problem. The work [6] was elaborated to set up the basic parameters configuration. In 5G network, the configuration consists in automatically assigning the PCI to New Radio (NR) in next generation NodeB (gNB) (typically eNB in LTE-advanced) by central system management [10,35]. There are 1008 unique PCIs for identifying gNBs [36]. PCI must be unique. A confusion or collusion can occur if the PCI is not unique. The central NM system can detect the confusion/collusion with reassigning a new PCI [37]. In addition, PCI can aid to produce the NCL. In fact, neighboring cells can use NCL to communicate with each other and uncover the new neighbors [5]. Mwanje et al. [38] investigated the performance of PCI allocation strategies and determined their limits.
- Neighbor Cell Lists Configuration: is based on the autonomous NCL algorithm performance. It aims at discovering the neighbor cells, introducing the new station to the neighbors and adding it to their list. In order to detect the nearest neighbors and connect them, several basic Network Functions (NF) can be invested. Therefore, 3GPP Release 8 defined ANR function related to self-configuration. ANR is located in eNB. It can reduce the manual work, the provision and management of NCL and the update of neighbor relation function in new deployed eNB. This automation can minimize the time of eNB installation. Furthermore, ANR can manage the conceptual Neighbor Relation Table (NRT). It uses both functions which are located in ANR, Neighbor Detection Function (NDF) and Neighbor Removal Function (NRF). In fact, NDF can discover the new neighbors and add them to NRT whereas NRF can remove outdated Neighbor Relation [5,10]. Natural Disasters, attacks, accidents must be thoroughly addressed. Thus, disaster-resilient heterogeneous small cell networks based on SON were proposed by [39] to autonomously enhance the performance of small cell networks in disaster scenarios management. To fulfill reliability, scalability and robustness of 5G network, ANR exerts a direct impact on these requirements but with certain enhancements. In fact, blacklisting and whitelisting eX2 or/and eS1 policies are the evolved versions of the LTE protocols X2 and S1. They are introduced to 5G NCLC. eX2 or/and eS1 rely on two transmission/reception BSs points, which can increase both the scalability and the robustness of M2M communications in 5G network [40] – [41].
- Radio Access Parameters Configuration: the new eNB must configure other parameters after the NCLC [4,8]. These parameters should be adjusted through:
  - the reconfiguration of the backhaul when adding a new eNB in 5G small-cells, can optimize the network's connections and minimize the latency [42].
  - the configuration of transmit power parameters in the new eNB using the data generated by neighboring cells, can minimize the interference between neighboring cells [6,43].
  - the self-configuration of HO parameters [44].
  - the transmit power parameters adjustment in each femtocell can improve indoor coverage and energy efficiency of the network [45].
  - Antenna azimuth configuration.
  - Self-configuration of frequency allocation can minimize the interference between existing nodes.

Bajzik et al. [46] tackled the application of SON in mobile backhaul. SON can autonomously evaluate the network status, simplify its configuration process and minimize the configuration cost.

To meet 5G requirements, a new configuration of parameters can be injected to produce a dynamic system. The update of configuration is grounded on an online method that guarantees low latency compared to SON legacy [28].

To settle the problems related to the self-configuration of the new site in 4G, each node aims at simplifying the configuration of all its initial parameters including IP addresses, neighbor lists, Radio Access Parameters [4].

2.5.2. Self-optimization use cases

The most prominent self-optimization use cases are: Load Balancing (LB), Interference Control (IC), Mobility Management (MM), HO Parameters Optimization (HPO), Random Access Channel Optimization (RACHO), Coverage and Capacity via Relaying (CCR), Backhaul Optimization (BO), Caching Optimization (CO), Resource Optimization (RO), Coordination of SON Functions (CSONF).

- Load Balancing: eNB may initiate an HO owing to the congestion of traffic demand load in cell. In fact, cellular networks aim to intelligently balance the load among cells or shift a part of traffic from a congestion cell to neighboring cells which have spare resources through self-optimizing the cell reselection. It aims also to minimize the number of HOs by self-optimizing HO parameters (optimizing the intra- Radio Access Technology (RAT) and inter-RAT mobility parameters in 5G network) [47]. This optimization can improve the capacity of cells and their neighbor cells and end-user experience [26,35]. MLB function is used for managing cells' congestion by redistributing cell load. MLB operates based on the load estimation and resource status exchange procedures [8,10,13]. To accomplish an excellent load balancing, HO parameters (and cell border) are modified in both cells to guarantee that User Equipment (UE) does not return to the congested cell. In the inter-RAT case, RAN Information Management protocol is responsible for transferring the information to the load of cells among BSs. O&M sets cell capacity class values to compare and weigh the capacities between different technologies radio [24]. However, improper HO decisions can degrade the load balancing performance, which yields inefficient usage of resources and service degradation [48]. To overcome the HO decision problem, Mohajer et al. [49] elaborated an effective mobility-aware load balancing approach that optimizes the configuration of HO parameters and learns the possibilities to distribute the excess load throughout the network. In view of the required time to observe and diagnose the load problem, the application of LB in reactive SON cannot achieve the zero latency required by 5G [13].
- Interference Control (IC): since the inter-cell interference is the cause of the spectral efficiency and system capacity weakness, the capacity needs to be improved through the interference minimization between cells. Therefore, cellular networks use the ICIC function aiming to self-optimize the management of radio resources in order to control interference. It was introduced by 3GPP Release 9 to reduce the interference among cells using the same spectrum. In fact, it coordinates the physical resources in order to reduce the interference between neighboring cells [10,50] – [51]. This function can be used by SON 5G [35]. The inter-cell interference is mitigated for UEs at the cell edge by using ICIC in eNBs communication via the X2 interface. Indeed, eNBs communication is thought of as a load information message which is sent from eNB to inform the neighboring eNBs about uplink interference level per physical resource block in order to optimize scheduling for UEs at cell edges [52]. Témoa et al. [53] identified a full dynamic ICIC scheme to optimize the joint resource allocation to users and dynamic power control. For 5G network, coordinated scheduling, coordinated beamforming, and joint transmission are considered as significant components of ICIC techniques. Despite cell-edge UEs throughput improvement provided by these components, 5G still faces many different challenges (i.e., SON must provide higher data rates, higher End-to-End (E2E) performance, and lower energy consumption). Moreover, several practical issues in 5G interference management must be settled to achieve real implementations (i.e., realistic interference condition, practical receiver architecture, channel state information reporting for advanced interference management, practical issues with joint scheduling, prospective gains) [54].
- Mobility Management: cellular networks aim to predict users' movement and label users' placement in order to automatically optimize the cell resource management and reduce the HO cost. MM is classified into two components: location management and HO management. The cellular network uses the location management process to effectively and accurately identify the location of user and HO management process to optimize the HO performance between neighboring BSs cells. The HO optimization tries to minimize the likelihood of dropped calls and unnecessary HOs. [8,55] – [56]. Alhammadi et al. [57] set forward a weighted fuzzy self-optimization approach to optimize the parameters of HO control. The application of Software Defined Networking (SDN) technology in 5G can solve the MM problems that face 4G network. Indeed, SDN controller has a global view on 5G network which can optimally handle HO problems by using clustering solutions. The MM in 5G still faces various challenges even with SDN utilization (e.g., network devices limitations when applying SDN service functions) [58]. The increase in deployment of small BS in 5G network will deepen the HO management problems (i.e., high HO probability, more Radio Link Failure (RLF) and unnecessary HOs).
- Handover Parameters Optimization: two main HO parameters govern HO performance: Time To Trigger (TTT) and HO Hysteresis value. Setting HO parameters affects several measures determining a proper network performance such as ping-pong (unnecessary HOs) rate, call blocking probability, call dropping probability and early or late HOs. In fact, incorrect HO parameter settings raise multiple mobility problems such as radio link connection failures and ping-pong HOs (unnecessary HOs) that degrade user experience and produce wasted network resources [8,26]. Release 9 3GPP defined MRO function which is used to detect and minimize the HO-related radio link connection failures. Indeed, eNB can communicate to neighboring cells to detect HO failure cases or can receive a report from the user at the time of failure containing radio measurements [7,59]. In addition, MRO is used to minimize the inefficient use of network resources generated by the unnecessary HOs [26]. Alhammadi et al. [60] introduced dynamic HO control parameters in HetNets adjusting TTT and HO margin parameters. These issues can be intensified with the increase of ultra-dense small cells deployment in 5G. SON MRO algorithm must be enhanced to keep abreast of changes and automatically detect and solve five 5G mobility problems such as failure due to too early HO, failure due to too late HO, failure due to HO to wrong cells, unnecessary HO and ping-pong HO [35,57].
- Random Access Channel Optimization: to have a quick access to the network, the RACH must be well configured. Incorrect configuration increases the access time as well as the number of accesses failures. Furthermore, it affects call setup performance. To achieve a better performance for UE random access, a set of RACH parameters must be automatically configured. This configuration reduces the network access time and minimizes the accesses failures: RACH configuration (resource unit allocation),

RACH attempts split, RACH back-off parameter value, RACH transmission power control parameters. This use case rests upon two main functions: RACH management and control function that collects the performance measurements to supervise the performance and RACH optimization function that adjusts RACH parameters. Indeed, RACH optimization function aims to minimize the number of attempts on the RACH channel, which causes the interference in order to optimize the RACH performance. This use case can be applied in 5G network (e.g., 5G NR cells) using RACH management and control function as well as RACH optimization function. After connection, 5G NR BS uses RACH management and control function to query UEs about the number of attempts sent until successful access and the number of conflict resolution failures in order to minimize the accesses failures on the RACH channel. The accesses failure minimization offers a better performance by minimizing the interference. In addition, it collects measurements about the time division needed for UEs in order to achieve the synchronization [10,35,47,61]. 3GPP Release 16 defined a new feature: Two-step RACH that can be applied in 5G NR. This feature presents several challenges: preamble allocation problem, resource mapping between preamble IDs of a specific RACH Occasion and a PUSCH Resource Units problem as well as a detected collision problem [62].

To improve the interoperability between small-cells and macro-cells, 3GPP Release 10 [61] introduced new functions to each use case like CCO, Energy Saving, MLB enhancement and enhanced ICIC.

- Coverage and Capacity via Relaying: cellular networks aim to self-optimize the network parameters to provide an optimal capacity and an optimal coverage [26]. It uses a CCO function that aims to achieve the best trade-offs between capacity and coverage. To reach this goal, CCO implements self-optimizing algorithms that ameliorate the coverage, cell throughout and edge cell throughput [10]. A set of parameters can be optimized in cellular networks e.g., antenna parameters. Dreifuerst et al. [63] proposed to optimize the transmit power and downtilt settings in each sector in order to maximize the coverage and minimize the interference in a multi-cell network. CCO can be adopted in 5G taking into account the functions specific to 5G radio technology such as beam management [35,47]. In industry application, 5G is absolutely beam-centric which is slightly new for operators and engineers. In addition, 5G is expected to improve the enhanced Mobile Broadband service which requires powerful beamforming and improved time-synchronization [64].
- Backhaul Optimization: The backhaul is the connection between the BSs and the core of the network. In LTE, a radio controller node is designed for backhaul aggregation but it is not exploited. This node can manage all backhaul connections from all radio stations towards the core. In Cloud RAN 5G architecture, the backhaul directly connects the Remote Radio Head (RRH) to BaseBand Unit (BBU) or to aggregation node (e.g., fronthaul). Common public radio is the interface that separates the RRU from the BBU. The basic fronthaul performs over this interface. To overcome the strict requirements of Common Public Radio Interface (CPRI)-based basic fronthaul in 5G network, researchers sought other interface solutions such as next-generation fronthaul interface, fronthaul-lite and xHaul. Chitimalla et al. [65] suggested encapsulating CPRI over Ethernet to overcome CPRI challenges by using Ethernet technology. The current backhaul is completely incapable to satisfy specific user needs in 5G network, especially with the incorporation of new wireless technologies. The backhaul needs more intelligence to meet 5G user requirements. The SON aims to intelligently optimize the communication between cells core network providing different requirements such as high capacity, flexible end-to-end connectivity, reliability and low latency [66].
- Caching Optimization (CO): the duplication of popular content requests generates a high content request concentration. To avoid the frequent transmission of duplicate content and reduce the network load, the same content will be cached at BS [8,67] – [68]. To optimize the hit-ratio of caching content, the caching decision must be based on reasonable information such as content type, its caching placement and steps. Therefore, the analysis of user behavior can assist the caching solutions to opt for the best decision [67]. Tanzil et al. [69] predicted content popularity by using users' behavior, content and request statistics features. Through using AI solutions, the 5G caching optimization aims to predict not only the type of content, that can be required by users, but also the path loss/link budget. Resting on the observable channel, AI can facilitate the deduction of the unobservable channel state information [70].
- Resource Optimization: energy expenses stand for a typical critical cost for the operator. It emerges with the continuous densification of network. The minimization of energy consumption is considered as a primary problem in the resource optimization. The network must offer a capacity corresponding to the required traffic demand at any one time. Energy Saving (ES) mechanism is implemented to save the energy expenses by allowing cells to go into sleep mode, resulting in low energy consumption [7,8,10,26]. Mwanje et al. [71] identified a distributed solution which provides an individual decision of cell deactivation or reactivation taking into account the amount of network-wide traffic and signaling minimization among cells. In 5G network, the ES mechanism is classified into: intra-RAT 5G ES and inter-RAT ES. In intra-RAT 5G ES, some functions of an NR or an NF are powered-off in an off-peak-traffic situation as well as coverage and capacity of ES cell or NF would be operated by other NR cells or NFs. The same intra-RAT ES scenario was adopted by inter-RAT 5G ES, provided that the coverage and capacity of ES cell or NFs will be operated by cells or NFs of other RAT [35,47]. Legacy ES ON solutions are foregrounded to reactively switch the OFF/Sleep states of BS. Due to the sharp dynamics of traffic and high densification in 5G, the switching among states requires a certain amount of time which can degrade the Quality of Experience (QoE) of users [72].
- Coordination of SON Functions (CSONF): Self-Coordination among SON functions was identified by 3GPP Release 11 [73] in order to improve network operational stability. In fact, some self-optimization use cases share the same parameters with different functions and goals. The coordination operates in the situations when SON function affects the other SON functions triggering the degradation in their performances [74]. Cellular networks aim to guarantee a coordination between two and more distinct functions without interference or conflicts. For example, LB and HO parameters optimization use cases share the same parameters e.g., HO backup, with different functions: MLB and MRO, and different goals: balance the load between cells and reduce ping-pong HO effects. Thus, a suitable SON algorithm must be performed to coordinate MLB as well as MRO and combine both conflicting goals in order to avoid MLB and MRO conflicts. This algorithm can reach load balancing between cells with ping pong minimization [8,74]–[75]. FP7 SOCRATES project focused on the SON functions conflict problem and proposed to classify the selected inter-related parameters of parametric conflict into basic groups in order to ensure well coordination [76]. Hard classification approach proposed by Lateef et al. [74] is based on five main categories: parameter conflicts, network topology mutation conflicts, KPI conflicts, logical dependency conflict, and measurement conflict. In [77], Lateef et al. analyzed the different conflicts between different kinds of SON functions and proposed to classify these conflicts into two principle soft categories: measurement and logical dependency conflicts. Based on hard and soft classifications, a hybrid self-coordination mechanism is developed. It rests on two essential architectures:

– Hybrid self-coordination mechanism based on centralized architecture: the resolution of SON function conflicts is determined by the centralized server. The work [77] handled MRO and Energy Efficiency functions conflict problem. Indeed, two eNB communicate with each other to check whether there is any active conflicting SON function. The two eNBs perform root cause evaluation procedure. Then, the evaluation results will be exchanged to the $O\&M$ server in order to resolve the logical dependency conflict between two functions.
– Hybrid self-coordination mechanism based on distributed architecture: the same steps of the centralized self coordination mechanism are kept, but the conflict resolution performs at eNBs rather than at the centralized $O\&M$ server.

In 5G, the SON legacy solutions may raise trust and robustness problems which need an efficient coordination scheme solutions [78].

2.5.3. Self-healing use cases

Release 11 [29,79] defined a set of self-healing use cases such as Self-Recovery of Network Element Software (SR-NES), Self-Healing of Board Faults (SH-BF), Cell Outage Management (COM). These use cases can be applied in 5G NE [35].

- Self-Recovery of Network Element Software: the NE must remain in operation, even if NE software fails due to loading the previous software version or configuration. Thus, the process of Self-healing is triggered to heal the fault by removing the fault software and re-configuring or restoring the incorrect configuration data [10,29].
- Self-Healing of Board Faults: cellular networks aim to automatically detect and solve the board faults. The process of self-healing is triggered to heal the fault. In fact, if a failed board in a system does not function appropriately, it will be blocked and the system automatically switches to a stand-by board that is in working order, then the failed board will be restarted. If the stand-by board is not in working order, the failed system board will also be blocked [29,80].
- Cell Outage Management (COM): Referring to the exponential increase in cell number, manual solutions for detection of cell outage like sleeping and out-of-service, will be insufficient. Therefore, several auto-detection and auto-compensation solutions have been developed to overcome the outage scenario and avoid the disruptions in the network [8]. This use case is divided into two main functions: COD and COC. COD helps automatically identify the cell outage using input parameters such as KPIs and alarms. Once the parameters satisfy the COD condition, the cell outage will be detected. For instance, the value of one KPI arrives at a threshold or alarm rings during cell outage [29]. COC automatically compensates for a cell outage to continue cell operations. In fact, the neighboring cells detect the fault, classify its type and take a compensation decision. The compensation can be a relay assisted HO, power compensation or reconfiguration of their antenna tilt [4]. Sleeping cell remains a challenge for SON legacy. It leads to the degradation of the coverage and capacity gap as well as the increase of the congestion in neighboring cells. In addition, the NM cannot directly detect the cell outage if the configurations are wrong. Moreover, the cell outage detection can take hours and days, which degrades further the QoE of users. From this perspective, ML is regarded as the best and most intelligent solution to enhance SON especially for 5G management network [28]. Ping et al. [81] displayed a cell outage detection method based on ML solution to fix the above issues.

The autonomous troubleshooting process provided by self-healing category is composed of several phases. Among the most outstanding ones, we mention the diagnosis system phase [82]. The diagnosis is also called root cause analysis which ensures the fault identification of cause on the basis of symptoms (i.e., KPIs and alarms) [83]. The fault identification confronts both the no labeled symptoms with the causes of fault and the analysis tasks of each fault cause without expert knowledge [14]. To surmount these challenges, Gómez-Andrades et al. [82] exhibited an automatic diagnosis system based on AI aiming to identify new faults and to help the system diagnose without considering historical reports of solved cases and expert knowledge.

In addition to self-healing use cases and SON functions coordination introduction, Release 11 focused also on MRO enhancement and inter-RAT HO optimization. Release 12 explored the use of LTE technology for emergency and security services. Moreover, it examined the Active Antenna Systems (AAS) Base Station feasibility specifications, the NM enhancements in centralized CCO, Multi-vendor plug and play eNB connection to the network, SON enhancements for ULTRAN/EUTRAN and especially ES enhancement in EUTRAN [84] – [85].

2.6. SON architectures

According to 3GPP Release 8, SON architecture is classified into three main categories: Distributed SON (D-SON), Centralized SON (C-SON) and Hybrid SON (H-SON) which corresponds to a combination of centralized and distributed architectures. The efficiency of self-coordination among SON functions depends on the architecture selection [86].

2.6.1. Centralized SON

In C-SON architecture, the SON algorithms work on a central NM system or in a central SON server (O&M in 3GPP LTE-advanced) that manages all edge radio nodes without human intervention [86] – [87]. This central NM system uses the management data to monitor the network (especially eNB), then analyzes the monitoring information and takes decisions on the actions of SON. By analyzing the historical and current monitoring information, it monitors and evaluates the results which will be then executed on the network [6,35]. 3GPP defined two management levels in C-SON [59,88]:

- Network Management-Centralized SON: SON algorithms are performed at the NM level.
- Element Management-Centralized SON: SON solutions are performed at the Element Management (EM) level.

All SON functions in C-SON are implemented by the central NM system. Simultaneous operations of the conflicts SON functions may beget network instability. Therefore, C-SON is the most robust solution that controls all SON functions in a centralized way, which facilitates their coordination in central NM [89]. In order to specify the decision parameters, the SON functions must request a permission to the SON coordinator before changing the setting of its parameters. This operation can take a long time especially as Operations, Administration, and Maintenance messages have the highest priority in central NM system [10]. C-SON is characterized by its high computational capacity which executes powerful optimization algorithms including several variables or cells. However, this execution can take a long time [10]. Introducing a new eNB node gives rise to another challenge that obstructs the operation of C-SON [84]. The C-SON architecture with NM or EM is depicted in Fig. 3.

2.6.2. Distributed SON

In D-SON architecture, the SON algorithms perform at the NFs which are located in NE (typically eNBs). NE locally makes autonomous decisions and communicates their decisions to neighbor NEs through the X2 interface. According to 3GPP, SON algorithms in D-SON are executed at the NE level [59,88]. NF monitors the network and analyzes the network data. Then, it takes decision on the SON actions and executes them in NE [35,37,90]. D-SON is used in cases where real-time response, frequent or sudden changes and a fast automation cycle

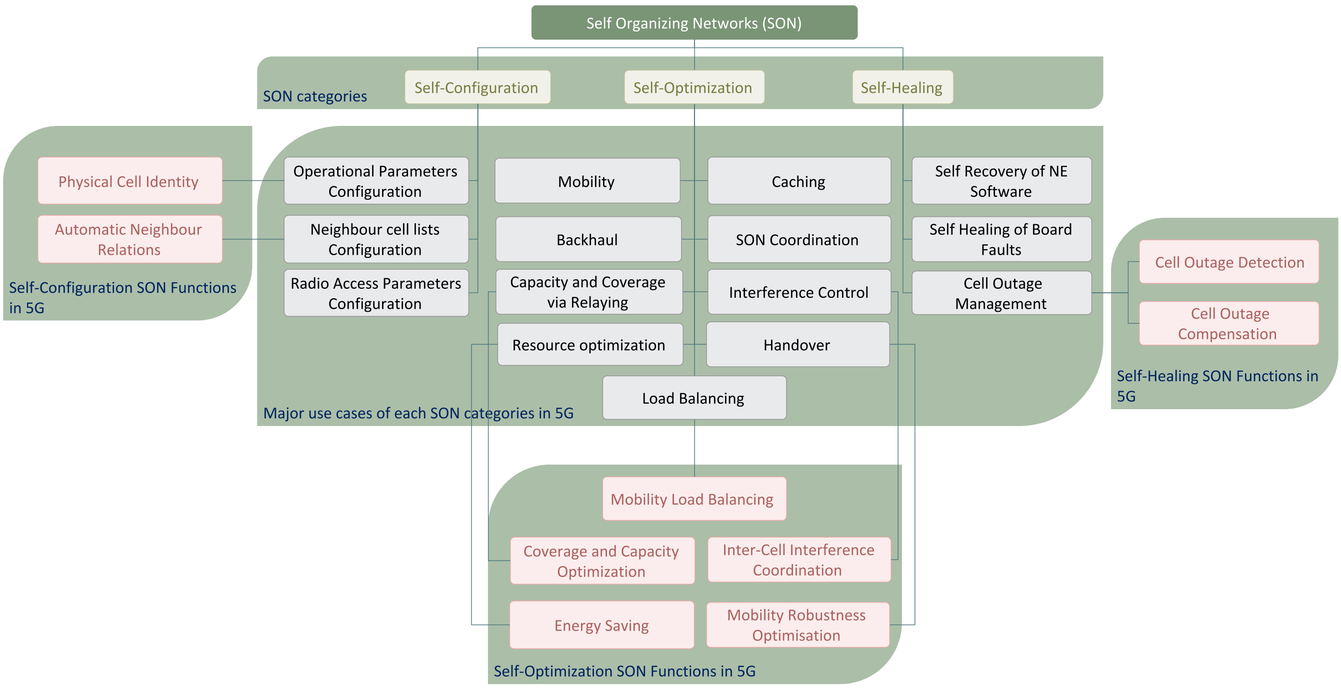

Fig. 2. SON categories, use cases and functions in 5G.

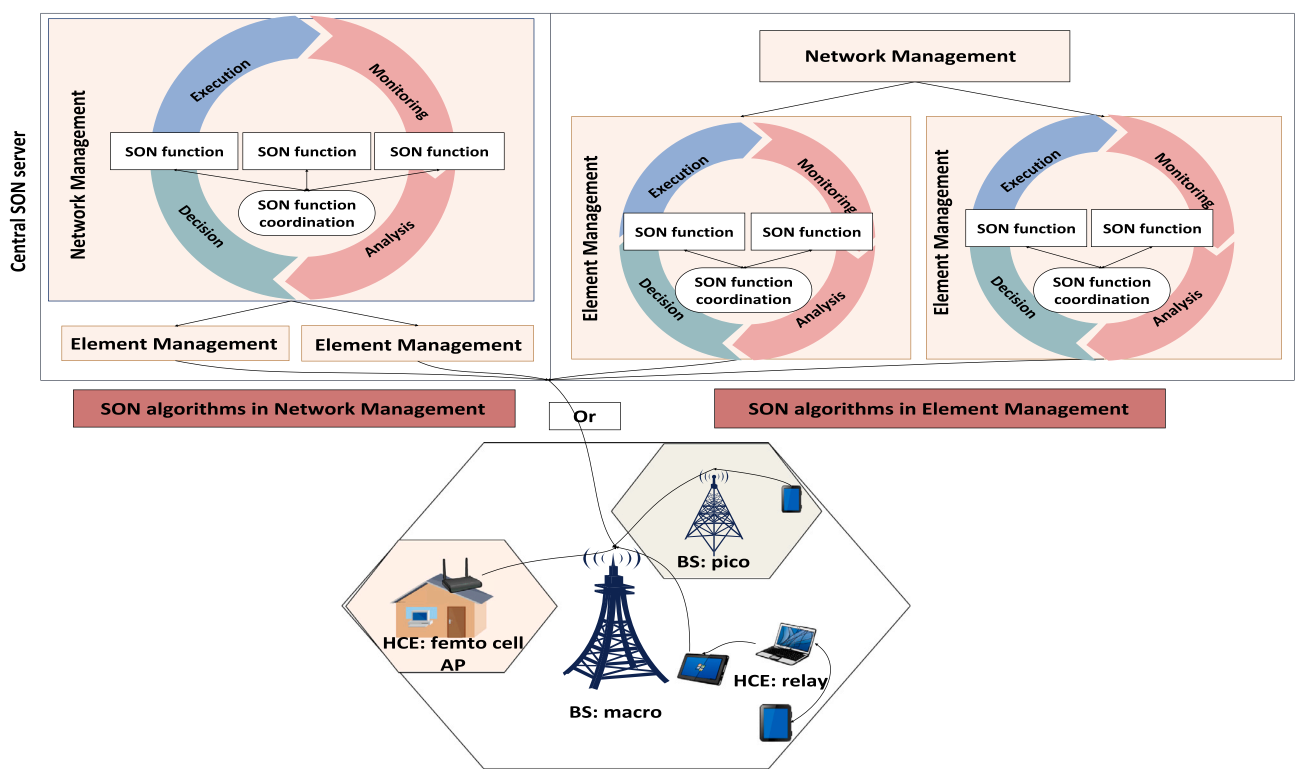

Fig. 3. Centralized SON architecture.

are required. In fact, this architecture offers fast and easy optimization and makes the SON functions much more dynamic than C-SON.

D-SON is generally adopted in small geographic scope, each NE has its SON functions that can be coordinated by the local SON coordinator with lower latency characteristics [10]. Despite all these features, D-SON does not provide efficient and consistent operations and cannot execute powerful optimization algorithms. In addition, this architecture is vulnerable compared to C-SON [15,86,91]. D-SON architecture is illustrated in Fig. 4. Release 13 introduced Operations, Administration, and Maintenance enhancements in centralized and distributed architectures (especially in distributed MLB and centralized CCO). It studied SON effectiveness on AAS deployments, and investigated the effectiveness of the continuity and adaptation of connection between SON and MRO without affecting radio resource management mechanism [84].

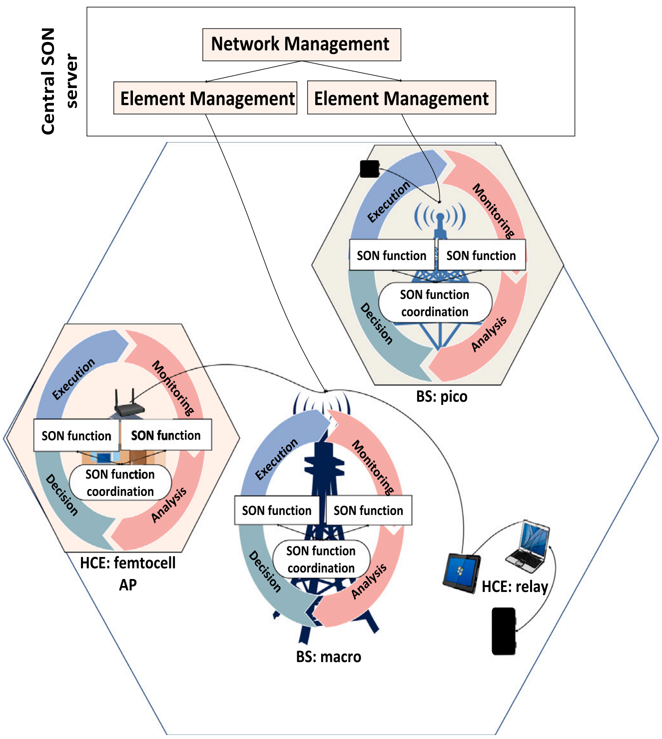

Fig. 4. Distributed SON architecture.

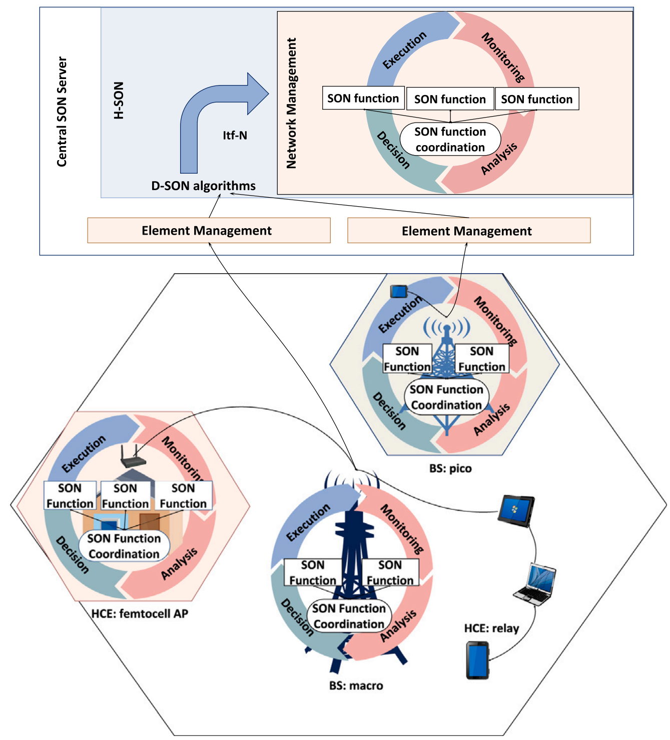

Fig. 5. Hybrid SON architecture.

2.6.3. Hybrid SON

In H-SON architecture, the SON algorithms perform both at NFs and central SON server. The server provides the initial parameters and NF can then update and refine these parameters. This architecture is a combination of the best of both C-SON and D-SON. In fact, NFs coordinate with the server to create a complete SON algorithm. Then, the decision on the SON actions can be taken by the eNB or SON server according to the use cases [35]. According to 3GPP, SON algorithms in H-SON are executed at two or more levels of the following levels: NE, EM or NM [59,88].

H-SON ensures an eNBs communication without using an interface counter to D-SON. In addition, it provides a load balancing to multiple technologies. It enables the power management optimization which minimizes the small cells interference including pilot pollution [15,37,86]. H-SON architecture with NM or EM is depicted in Fig. 5.

2.6.4. 5G SON architecture requirements

In the current networks, SON legacy systems rely on H-SON architecture. In fact, this architecture is grounded on the best of both C-SON and D-SON. C-SON algorithms operate several cells in the network controller level and D-SON uses various fast-reacting D-SON algorithms which perform in each eNB with low scope. To combine both approaches, a coordination between the C-SON cells algorithms and the input/output of D-SON algorithm is established through a Northbound Interface connection (Itf-N). With the emergence of 5G, SON architecture needs to be improved in order to meet 5G requirements and overcome the high densification of small cells and the heterogeneity in RATs challenges. Virtualization is introduced into H-SON architecture in order to offer an open and scalable network architecture and to handle the large volume of cells and the variety of radio interfaces as well as the required configuration. Basically, the Virtual-SON architecture (V-SON) deals with two basic 5G technologies: Network Function Virtualisation (NFV) and SDN. Their algorithms operate on Virtual Machines that locate close or at eNB. V-SON optimizes the interfaces organization between the radio resources, provides a fast and coordinated SON that enhances the reconfiguration of RAT and cell layers and takes heed of demands [15]. Fig. 6 depicts the V-SON architecture.

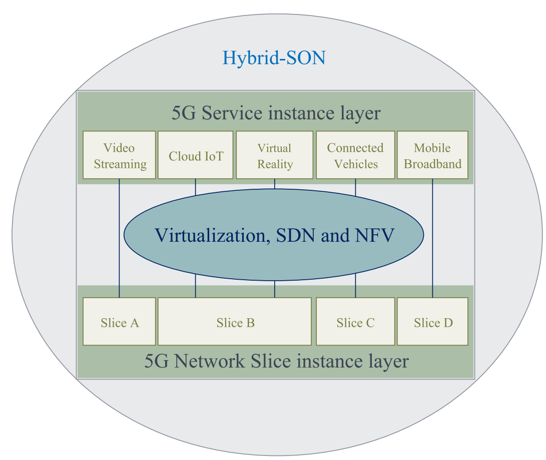

Fig. 6. Virtual-SON architecture.

2.7. SON challenges to meet 5G requirements

In the future, the network is expected to be more and more densified. Indeed, the node parameters in 5G network are expected to be higher than 4G, with nearly 2000 parameters per a node, which leads to operational tasks complexity. Besides, the heterogeneity progression in layers and technologies, the complexity of NFV and SDN management as well as increasing diversity of 5G applications and services deepen the management complexity and obstruct 5G requirements implementations [10,13]. From this perspective, the management and orchestration SON is developed by 3GPP as an advanced automation solution to manage the volume and diversity of services in 5G. Release 15 corroborated the use of SON solution to enhance the 5G

Table 5
SON use cases.

SON use cases	Objectives	SON functions	Problems in use cases	Proposed works	SON use case applied in 5G
OPC	Configure the basic operational parameters in eNB	PCI, CID	PCI assignment problem.	[33]–[34],[38]	-Automatically assigning PCI to NR. -Confusion/collusion detection with reassigning a new PCI.
NCLC	Discover the neighbor cells, introduce the new station to the neighbors and adds it to their list	ANR, NDF, NRF, NRT	Natural Disasters, attacks and accidents problems.	[39]	New blacklisting and whitelisting eX2 or/and eS1 policies which increase both the scalability and the robustness of M2M.
RAPC	Other parameters configuration		Problems in mobile backhaul.	[46]	-Injection of new configuration of parameters to give a dynamic system. -Online method to guarantee the low latency in 5G.
LB	Intelligently balance the load among cells	MLB	Load balancing performance degradation due to improper HO decisions	[49]	LB in reactive SON cannot achieve the zero latency required by 5G.
IC	Reduce the interference among cells that use the same spectrum	ICIC	Poor interference coordination degrades both resource allocation to users and power control	[53]	SON 5G challenges: Realistic interference condition, practical receiver architecture, channel state information reporting for advanced interference management, practical issues with joint scheduling, prospective gains.
MM and HPO	Automatically optimize the cell resource management and reduce the HO cost	MRO	HO-related radio link connection failures	[57,60]	High ultra-dense small cell deployment increases 5G problems: failure due to too early HO, failure due to too late HO, failure due to HO to wrong cell, unnecessary HO, ping-pong HO.
RACHO	Minimize the number of attempts on the RACH channel	RACH	Incorrect configuration increases the access time and number accesses failures		New features: Two-step RACH which presents: preamble allocation problem, resource mapping between preamble IDs of a specific RACH Occasion and PUSCH Resource Units problem, detected collision problem.
CCR	Self-optimize the network parameters to provide an optimal capacity and an optimal coverage	CCO	Transmit power and downtilt settings optimization problem	[63]	5G Enhanced Mobile Broadband service improvement thanks to powerful beamforming and improved time-synchronization.
BO	Ensure the connection between the BSs and the core of the network	–	No radio controller node use in LTE	[65]	-The basic fronthaul performs over the CPRI. -Incorporation of new wireless technologies to overcome the use of basic fronthaul in 5G.
CO	The same content is cached at BS	–	Analysis of user behavior	[69]	-AI solutions for type of content and path loss/link budget prediction. -Deduction facilitation of unobservable channel state information.
RO	Minimize the energy consumption by offering a capacity corresponding to the required traffic demand.	ES	Saving the energy expenses	[71]	-Intra-RAT and inter-RAT ES mechanism in 5G. - Certain amount of time requirement in 5G.
CSONF	Guarantee coordination between two and more distinct functions without conflict.	All functions	Classification of the selected inter-related parameters of parametric conflict.	[74,77]	Trust and robustness problems with SON legacy in 5G.
COM and autonomous troubleshooting process	-Overcome the outage scenario and avoid the disruptions in network using auto-detection and auto compensation solutions. -Ensure the fault identification of cause on the basis of symptoms.	COD, COC	Sleeping cell problem, fault identification problem.	[81]–[82]	Cell outage detection and new faults identification based on ML solutions.

management and introduced the 5G NR with standalone operation enhancements and basic Ultra-Reliable Low Latency Communications (URLLC) functionality.

Release 16 exhibited several enhancements of URLLC and various major enhancements and extensions to NR using SON specific to LTE [92] – [93]. Furthermore, it introduced SON functions enhancements such as RACH report, RLF report and ANR for network resource optimization [94]. Consequently, current SON becomes insufficient and needs to be improved to enhance the NM capabilities and fulfill 5G requirements detailed in 3GPP Release 14 [95], e.g., very low latency and higher data rate than 4G. Several SON breakthroughs in 5G must be covered by providing:

- More transparent SON to gain user trust
- More coherent SON by adding new technology elements that enable SON functions integration in RAN and Core Network [96].
- The architecture of 5G is more complex than 4G. The analysis of conflict between SON functions and the autonomous coordination algorithms used in the 4G framework will be inefficient with 5G. New self coordination approaches compatible with 5G must be incorporated to minimize the potential conflicts in 5G SON functions.
- More intelligence SON for 5G end-to-end visibility needs to be elaborated to gather all the spatio-temporal information about problems in network such as HO ping pong zone, congestion and coverage gap locations [13,96].
- Large Timescale SON

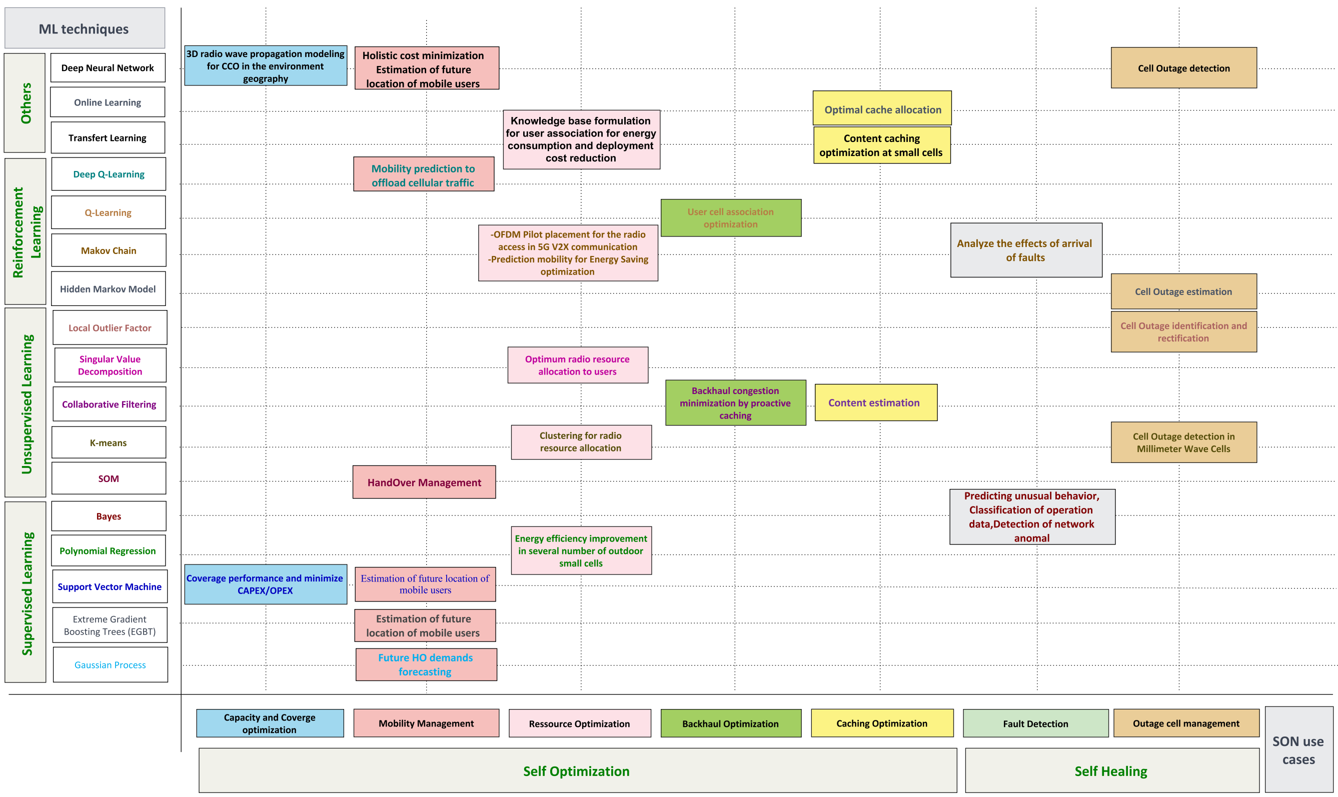

Fig. 7. SON applied in ML.

- New set SON solutions need to be set forward to settle 5G energy-efficiency and multi-RAT) interoperation problems [13,96].
- New KPI is needed to exploit the full potential of SON functions in 5G.
- Faster and proactive SON: the current classical SON, such as MLB, is reactive when a problem occurs. It waits to observe and spot the problem. To meet 5G real time requirements, the SON mode has to be transformed to a proactive one so as to observe the situation and predict the problem before it occurs.
- Other SON enhancements need to be undertaken like SON for 5G mmWave[97], SON for 5G MMIMO, SON for 5G NFV-based networking and the addition of new Self-Protection use case for 5G.

Big data using ML tools can empower the reactive SON through transforming it to a proactive SON in order to meet 5G requirements. In fact, it can integrate three main skills to 5G network: full intelligence, prediction of user behavior and dynamically organization between network response and the Network Parameters [13].

Release 16 and Release 17 started to consider the integration of ML for the upcoming versions of 5G in order to empower storage and computing capability of new RAN and to enhance the SON through the use of big data. In addition, Release 17 includes various features enhancements related to Release 16, such as massive Multiple Input Multiple Output (MIMO), unlicensed access and Integrated Access Backhaul enhancements. Release 17 is attempting to introduce reduced capability devices support for specific Internet of Things (IoT) use cases [93,98] – [99]. Release 17 is still on decision and Release 18 is not yet considered. Thus, there will be several discussions about Release 18 details. As a matter of fact, Release 18 features are likely to be approved of by the end of 2021 [100]. (See Table 6.)

2.8. Projects concerning SON application in 5G

Like 3GPP releases, there are various projects elaborated by different organizations seeking to investigate the SON implementation in cellular network. Table 7 plots 5G projects in each SON use cases.

AIMM, IEoT, AI-NET, AI-instorage are Celtic European projects which focus on AI incorporation in SON-5G cellular networks.

- AIMM [101]: AI-enabled Massive MIMO enhancements to improve existing 5G RAN and beyond. It started in October 2020 and is supported to finish towards September 2022. This project can be classified under RAPC use case.
- IEoT [102]: AI-integrated into edge computing frameworks to build intelligent edge for dynamic, adaptive edge maintenance and management and full potential utilization of each tier of the IoT Edge architecture to meet different application requirements. This project can be classified under CO use case. It started on March 2020 and will finish in February 2023.
- AI-NET [103]: AI is used to complement traditional optimization algorithms in order to not only minimize energy consumption of edge-centric compute, but also provide high-performance services which are deployed and operated at the network edge. This project can be classified within the framework of RO use case. It was brought to life in June 2020 and will finish in August 2024.
- AI-instorage [104]: AI – enabled smart storage services for future renewable district energy networks. This project can be classified under RO use case. It started in January 2021 and will finish in December 2023.

SELFNET, COGNET, SESAME, COHERENT, ONE5G AI@EDGE, TeraFlow and ARIADNE are outstanding projects developed by 5GPPP. They are selected from several proposals received by the European Commission Horizon 2020 Programme in response to 5G-PPP.

- SELFNET [105]: corresponds to SON management framework for 5G. It uses AI technology to combine virtualized and SDN infrastructure. It addresses several SON categories i.e., Self-protection

Table 6
Evolution of SON in 3GPP.

Year	Releases	Description
2008	*Rel.8*	SON concepts and requirements, self-configuration category, ANR and PCI functions, SON architecture
2009	*Rel.9*	Self-optimization and self-healing categories, MLB, MRO, ICIC and RACH functions
2011	*Rel.10*	Self-healing functions: COD, COC, MLB and MRO enhancement, enhanced ICIC, ES, CCO
2012	*Rel.11*	New self-healing use cases: SR-NES, SH-BF, COM, CSONF, MRO enhancements, inter-RAT HO optimization, SON coordination
2015	*Rel.12*	LTE utilization for emergency and security services enhancements, AAS feasibility, NM in centralized CCO, ES enhancement in EUTRAN
2016	*Rel.13*	Operations, Administration, and Maintenance enhancements in distributed MLB and centralized CCO, SON/MRO connection continuity, SON effectiveness on AAS deployment
2017	*Rel.14*	5G requirements, the new 5G system architecture
2018	*Rel.15*	5G management enhancement using SON, 5G NR with standalone operation enhancements, basic URLLC functionality
2020	*Rel.16*	ML integration for the upcoming versions of 5G
2021–2022	*Rel.17*	MIMO, unlicensed access and Integrated Access Backhaul enhancements, reduced capability devices support for specific IoT use cases
2021–2022	*Rel.18*	Features will be approved by the end of 2021

capabilities against distributed cyber-attacks, self-healing capabilities against network failures and self-optimization to improve QoS and QoE of users. This project started in July 2015 and lasted for three years.

- COGNET [106]: rests upon applying ML research to achieve a high level of NM automation in 5G. It addresses different domains related to SON use cases: usage prediction, recognizing error conditions, security conditions and energy efficiency. This project was launched in July 2015.
- SESAME [107]: relies on Cloud-Enabled Small Cell CESC concept. It supports Small cells that integrate a virtualized execution platform by providing powerful self-x management and executing novel applications and services. This project emerged in July 2015.
- COHERENT [108] framework can control and manage load balancing task through the use of such abstracted network graphs [109]. It started in July 2015.
- ONE5G [110]: addresses E2E-aware optimizations and advancements for the network edge of 5G NR. It uses the novel E2E and context-aware approaches to enhance mobility optimization and provide fast agile load balancing mechanisms. Furthermore, it operates on the interference management with D2D networks. It started in June 2017.
- AI@EDGE [111]: focuses upon ensuring a secure and reusable AI Platform for Edge Computing Beyond 5G Networks. This project can be classified under CO use case. It was developed in January 2021.
- TeraFlow [112] creates new architecture of secure cloud-native SDN controller to enhance beyond 5G. New SDN controller provides revolutionary SON automation features for flow management and optical/microwave network equipment integration and will use ML to secure autonomic traffic management. This project can be classified under RAPC use case. It emerged in January 2021.
- EU-funded ARIADNE project [113] handles management problems in 5G when using scale and complex NR attributes in the new frequency ranges. ARIADNE applies ML and AI to manage NR communication technologies using D-Band frequency ranges. This project can be classified under RAPC use case. It started in November 2019 and will finish in October 2022.

Artificial AI/ML Driven Multi-Layer SON for 5G era systems [114] stands for a research challenge project associated with the transformational Canada-Québec-Ontario partnership *ENCQOR 5G*. It seeks to develop and verify AI/ML driven approaches for automated design, planning and operations of full stack 5G era systems investing the principles of self-organization and self-optimization. This project can be classified under self-optimization category.

SONNET [115] corresponds to an MSCA-RISE-2020 project. It aims to amplify further the coverage zone of SON within the network. SON can enhance network sharing and Coordinated Multi-Point (CoMP) technologies to reduce cost and energy per bit in legacy and future emerging mobile technologies in 5G. It focuses also on the use of SON in network slicing. It was introduced in January 2017 and will finish in June 2021. This project can be classified under LB use case.

Table 7
SON Projects.

SON use case	5G projects
RAPC	AIMM, TeraFlow, EU-funded ARIADNE
CO	IEoT,AI@EDGE
RO	AI-NET,AI-instorage
Self-healing and self-optimization	SELFNET
Usage prediction, recognizing error conditions, security conditions and energy efficiency.	COGNET
Self-x management	SESAME
LB	COHERENT, ONE5G, SONNET
Self-optimization	Artificial AI/ML Driven Multi-Layer SON for 5G era systems

3. SON solutions applied in 5G

In this section, we are basically interested in works that apply SON solutions in 5G network. Most of them rely on ML algorithms to fulfill 5G requirements. The comparison between solutions reveals the addition offered by ML and big data features to SON which is meant to enhance QoS and QoE for users in 5G. This section is divided according to SON use cases with description of the proposed solution for each case.

3.1. *Load balancing*

Basically, SON aims to autonomously adjust the load balancing among cells network. To fulfill this objective, article [116] used a user-centric CoMP clustering algorithm and a novel re-clustering algorithm to minimize the high load on cells. The idea rests on two stages. In the first stage, the proposed CoMP SO clustering algorithm is used to maximize the cluster size of small groups of cells in order to enhance the spectral efficiency. The CoMP SO solution can also provide better Signal to-Interference-Noise-Ratio (SINR) gains and additional backhaul capacity. In the second stage, the novel re-clustering algorithm is introduced to distribute the load from the highly loaded cell to neighbor cells with a fewer load. A trade-off between the two SON use cases, namely LB and IC yield the emergence of the trade-off between two significant 5G requirements: user satisfaction and high QoS (i.e., high spectral efficiency). User centric CoMP SO clustering solution serves to maximize the spectral efficiency in order to enhance the QoS in 5G network, i.e., high system throughput according to high number of loaded cells, high SINR and high backhaul capacity. Based on load balancing SON solution, the re-clustering algorithm manages to minimize the number of unsatisfied users, especially when cell load exceeds 80%, but fails to keep the high system throughput.

Authors in [117] set forward a proactive load balancing method called OPERA to solve the imbalance issue between macro and small cells. From this perspective, Farooq et al. used a semi-Markov ML technique to predict the mobility of users then the future cell load in order to proactively optimize key antenna parameters and cell individual offsets, preempting congestion before it happens. Unlike [116], Farooq et al. [117] proposed a proactive load balancing solution by predicting the future cells load. This prediction can maximize the capacity better than the reactive mode and estimate the unsatisfied users percentages in order to quickly optimize the QoS and achieve better QoE. OPERA can reduce the percentage of unsatisfied users to 0.35% compared to the previous work which can reduce the percentage by 73.6%.

3.2. *Coverage and capacity optimization*

In order to optimize the capacity and the coverage in cells, several works based on ML solutions were elaborated to accomplish a good performance. Considering the constraints and limitations of traditional channel modeling methods, article [118] displayed a scalable solution to variation in geography environment. Deep Neural Network ML based 3D propagation model solution helps to accurately estimate the path loss in order to optimize the radio propagation in modern wireless communication systems. In fact, this realistic propagation model results in a 25% increase of prediction accuracy better than the state-of-the-art empirical propagation models. ML can pre-identify idiosyncrasies of various propagation environments so as to estimate the path loss or the Received Signal Strength (RSS) as opposed to the empirical propagation models. Moreover, it does not extremely consume time and money compared to ray-tracing based solutions. Deep Neural Network can reach 12× decrease in prediction time compared to ray tracing. Although the Deep Neural Network outperforms Decision Tree and linear solutions in terms of error prediction even with sparse training data, it presents the same prediction error as K-Nearest Neighbor (KNN) for 1% training data.

The deployment of BSs is expected to be more difficult with the increasing densification of small cells. Indeed, the unreasonable layout of densely BSs affects the coverage performance, CAPEX and OPEX. In this context, Dai et al. [119] identified a predictive Received Signal Strength (RSS) solution in order to minimize the number of deployed BSs. The solution is composed of two steps: First, predicting the RSS through the extraction of the main features of the strength of RSS and mapping the relationship between the extracted features and RSS values. Second: using Genetic Algorithm (GA) solution to optimize the coverage performance of the BS deployment taking into account the geographical types and operating parameters of BS constrains.

3.3. *Mobility management and handover parameters optimization*

In order to provide seamless mobility and autonomously manage HO demands especially with the emergence of 5G, SON MRO solution is adopted to rapidly minimize the HO failures (i.e ping pong HO and radio link failure HO) as low as possible. Unlike other works, Nguyen et al. [120] focused on simultaneously minimizing these two failures and eliminating the trade-off between them. Based on Apollonian circle of mathematical tool resting upon modeling the wireless network as geometry, Nguyen et al. proved the existence of optimal HO settings to minimize both ping pong rate and RLF.

Predicting the users' movement allows to rapidly manage HO demands and proactively reduce the energy consumption, balance the load among cells, detect the abnormal behaviors HO and satisfy more users. For this reason, SON needs to be reinforced by using ML solutions. Article [121] proposed a practical process based on big data and multiple linear and nonlinear ML models. This process intelligently manages and forecasts the future HO demands in a huge number of cells and detect abnormal behaviors HO. Tung et al.invested ML solutions to successfully extract some observations on hourly number attempted HO patterns from big data in order to evaluate the performance of the network mobility. The work demonstrates the efficiency of ML solutions in HO clustering, HO forecasting and abnormal HO detection. In HO clustering, the addition of ML into SON ensures an intelligent collection of the most similar HO behavior by exploration and detection of the complex pattern of regularities in data. In HO forecasting and abnormal HO detection, ML empowers SON by making it in the proactive mode. As a matter of fact, SON becomes able to forecast future HO decisions and detect the abnormal cells in order to proactively minimize the HO failures. Despite the reinforcement added to SON by the proposed Gaussian process ML solution, numerous other ML solutions could not offer the desired efficiency. In fact, the results indicate that Auto-Regressive, both linear regression and polynomial regression, Neural networks are less efficient than Gaussian process ML with a high root mean square error, especially in rapid changes and at an increasing period of HO demand. Additionally, the difference between the mean absolute error and the root mean square error of normalized and real values results is high with respect to all proposed ML forecasting solutions.

Article [122] proposed a recurrent deep learning architecture solution for mobility prediction. This solution is included in the holistic HO cost evaluation function in order to minimize the holistic cost. The holistic cost involves different parameters such as signaling overhead, latency, user dissatisfaction and resource wastage. This paper corroborates the effectiveness of the prediction solution to minimize the holistic cost. HO has been predicted using Deep Learning ML solution, (i.e., stacked Long-Short-Term Memory model (LSTM)) and MultiLayer Perceptron (MLP). The results are suggestive that LSTM outperforms MLP for all users and displays the same computational complexity compared to MLP. The increase in number of hidden neurons and the LSTM size leads to validation accuracy increase, but the further increase in these parameters can yield over-fitting, which influences the validation accuracy.

In order to provide an efficient offloading of cellular traffic to small BSs, article [123] exhibited a scheme based on deep Q network which predicts the traffic demand.

Caching the future contents leads to settle load issues and provide a load balancing between cells. In order to maximize the QoE and minimize the load, article [124] offered a Semi-Markov renewal process ML solution to proactively cache future contents through predicting the users mobility.

Article [125] analyzed and compared four mobility predictors, namely Deep Neural Network, Extreme Gradient Boosting Trees, Semi-Markov and Support Vector Machine in order to select the optimal solution that grants a high prediction of future location of mobile users. This analysis is governed by realistic synthetic human traces generated by a Self-similar Least Action Walk mobility model. The results reveal that Extreme Gradient Boosting Trees has the best accuracy with 90%, which would offer a high energy saving gain and lower execution time. Despite its high prediction accuracy, Extreme Gradient Boosting Trees displays a high time of prediction compared to Semi-Markov model and Deep Neural Network.

3.4. *Resource optimization*

This section is divided into ES optimization and resource allocation optimization. The solutions correspond to GA for ES optimization, polynomial regression for energy efficiency, Singular Value Decomposition for blocks allocation, k-means for resource allocation, Polynomial Regression for sub-channel allocation optimization and Markov decision for pilot pattern determination and Transfer learning for spectrum assignment. Article [72] exhibited an AUtonomous pROactive eneRgy sAving framework. This solution rests on Semi-Markov model-based Spatio-temporal mobility prediction framework. The mobility prediction can determine future cell loads and proactively schedule small cell sleep cycles. Grounded on the mobility prediction results, AUtonomous pROactive eneRgy sAving framework would proactively optimize energy saving in order to minimize the energy consumption in Ultra Dense Heterogeneous Network by using GA solution. GA is considered as the most suitable choice as it improves the chance to find the global solution especially for highly nonlinear objective functions with a large variable count and an enormous search space. The results disclose that the solution grants a high mean prediction accuracy in 1 min of time prediction interval. However, this accuracy decreases with the increase of the prediction time interval which can influence the convergence time of GA.

Article [126] elaborated big data-SON framework that optimizes the energy efficiency in Ultra Dense network. It uses big data with polynomial regression of supervised learning to improve energy efficiency in several numbers of outdoor small cells. The idea lies in collecting, analyzing, optimizing and re-configuring data of huge number of outdoor small cells in order to reduce the co-channel interference and the power consumption. This solution is based on Data-Driven Dynamic Analysis (D3 A) model and Interference Aware (IA) energy saving algorithm. It can periodically collect the management data of small cells, estimate cells neighbor with high interference and decrease its transmission power in order to improve energy efficiency. This solution offers good performance in terms of energy efficiency as well as throughput. In fact, it provides 135% of energy efficiency and evolves throughput more than the scheme without energy saving approach. However, it presents a similar throughput to intuitive approach and similar energy efficiency to static IA since it is used to optimize the energy saving in this framework.

Article [127] invested GA in order to minimize the energy consumption and optimize the average download latency of the Mobile Edge Computing (MEC) through developing an effective caching placement strategy.

Article [128] attempted to extract the information on user behavior from a large quantity of log files, configuration files, database entries/updates and monitoring alarms. The extraction of information can solve the resources allocation problem to users in RANs. Singular Value Decomposition solution is used to identify the physical resource blocks that will be allocated to users.

Article [129] used k-means to cluster the mobile station in order to solve the radio resource allocation problem to users. Then, it uses a greedy algorithm in order to pick a number of mobile stations from each cluster and locate them into Space-Division Multiple Access schemes groups.

Article [130] attempted to solve the sub-channel allocation optimization and power control problems, especially, sharing the same spectrum between D2D links problem in order to optimize the energy efficiency, spectral efficiency and delay.

To boost the pilot placement for the radio access in 5G vehicle to everything communications, article [131] proposed the Markov decision process in order to determine a pilot pattern from different candidate pilot configurations.

To create an insight base for user association, article [132] applied cognitive radio engines and proposed a Transfer Learning to transfer the expertise knowledge determined intelligently from spectrum assignment.

3.5. Backhaul optimization

SON serves to optimize the offloading backhaul congestion in order to offer a flexible end-to-connectivity and low latency.

Article [133] adopted a user-centric backhaul solution that enables users to associate with cells in order to satisfy their requirements from RAN and backhaul network. This solution uses Reinforcement Learning to optimize the Cell Range Extension Offset (CREO) value that influences end-to-end network capabilities. This optimization aims to maximize the user's QoE with respect to three joint radio/backhaul capabilities and constraints: throughput, latency and resilience. The low transmitted power presented by small cells compared to the high transmitted power of macro cell leads users to turn first the macro cell then neglect the extra capacity provided by small cells. To motivate users to rank and select first the small cells, cell range extension mechanism is used to broadcast the CREO for the small cells to bereave their positions and appeal users to opt for them. The solution provides a high user satisfaction with low degradation in cumulative throughput compared to state-of-the-art user-cell association schemes, especially with SINR-based scheme. SINR-based scheme can satisfy users with respect to latency and resilience, but not for cumulative throughput because of macro-cell saturation and reluctance of users to select small cells.

3.6. Caching optimization

Basically, caching content technique refers to the possibility of caching the same contents in BS in order to reinforce the computation capability close to Users Equipment. In order to optimize the caching content intelligently, several works tend to use ML solution.

Article [134] proposed a proactive networking paradigm which uses Singular Value Decomposition based Collaborative Filtering ML solution. It helps to proactively cache files during off-peak demands so as to reduce the backhaul congestion. The authors compared the proactive to reactive low traffic load and proactive to reactive high traffic load. The proactive mode satisfies requests more than reactive mode. In addition, the very small users' requests in the reactive mode influence the backhaul load. Indeed, the reactive approach causes a low generation of load on the backhaul. This influence does not help the Collaborative filtering to draw any inference owing to a non-sufficient amount of information about the popularity matrix. On the other side, most of requests are satisfied when the traffic load is low. When the contents are hidden, the requests are satisfied for low traffic load more than high traffic load until they reach 80% of cache size. If they exceed 80%, the same satisfaction is obtained. The backhaul load keeps going down until it reaches 100% of caching. Thus, it will not be loaded. In fact, it decreases regarding the number of requests. For the impact of popularity distribution, the backhaul load with reactive caching outperforms the proactive caching when the popularity distribution exceeds 50%.

Article [135] offered a context/trend-aware caching solution. It uses Online Learning algorithm to predict the popularity information investing users' context in order to decide the caching content replacement.

Article [136] recorded a proactive caching scheme to handle the huge amounts of big data and to exploit them for content popularity estimation using ML techniques.

Article [137] advocated a clustering based on GA to identify the influential users in order to proactive cache their generated contents and minimize the backhaul traffic load.

Article [138] proposed Transfer Learning algorithm to cache contents in order to maximize the offload of the backhaul gains. Transfer Learning algorithm helps transfer the hidden latent features from the domain source to the target domain.

3.7. Cell outage detection

Article [139] developed a cell outage detection solution. Based on Hidden Markov Model, this solution captures the current states of different BSs in order to estimate the Cell Outage.

Article [140] focused on cell outage detection in 5G H-CRAN. This solution applies the modified Local Outlier Factor unsupervised anomaly detection algorithm to identify cells outage and rectify it immediately. The proposed solution is more efficient. In fact, Local Outlier Factor considers 12% of normal cells as outage cells, while the proposed solution only considers 6%. However, the proposed solution presents a low percentage of false negative rates. In fact, only 3% of abnormal cells are considered as outage cells.

Article [141] reported a cell outage detection solution based on Artificial Neural Network like the autoencoder. It uses simulated data that are provided by SON simulator and compares the results to Nearest Neighbor ML technique results.

To detect the cell outage with high accuracy in Millimeter-Wave communication, article [142] used Entropy Field Decomposition technique which yields a higher true positive results compared to the k-means clustering solution.

3.8. Fault detection

The self-healing function in SON is expected not only to solve eventual failures that might occur, but also to perform fault detection, diagnosis and trigger automatically the corresponding compensation mechanisms. The root cause analysis is a task fulfilled by operators in order to provide customers with necessary QoS and keep them satisfied. In this respect, authors in [143] foregrounded a fault detection solution based on Bayesian network theory which minimizes the root causes of faults.

3.9. Self-recovery of NE software

To analyze the effects of faults arrival, article [144] elaborated an adaptive fault predictive framework based on Continuous Time Markov Chain. It learns from past database in order to reduce the network recovery time.

3.10. Synthesis

In this section, the previous discussed works are synthesized in terms of ML solutions. Table 8 and Fig. 7 display a summary of ML techniques and their respective SON use cases. Table 9 portrays the taxonomy of SON Algorithmic Aspects in 5G.

The self-configuration function is designed to automate the configuration of quasi-static parameters such as cell ID and neighbor lists. Recall that self-configuration includes operational parameters, a neighbor cell list, and radio parameters. In terms of ML technique, OPC use case is typically invested by applying self-organizing maps and miscellaneous learning methods [6,145]. Regarding self-optimization, the deployed functions are devoted to optimize dynamic network parameters during operation based on the measurements received from the network. The most popular use case in this category is load balancing function which manages the congestion by redistributing the load between cells. For load balancing function, a relevant work is stated above [116] incorporating an unsupervised clustering algorithm in a high dense deployment scenario. It transfers the traffic from highly loaded cells to neighbor cells in order to manage uneven traffic distributions. It can be more suitable for future cellular networks. Despite the 5G QoS enhancements achieved by using user-centric dynamic CoMP clustering SO algorithm, the proposed solution still requires certain improvements to achieve a high user satisfaction through keeping high QoS (i.e trade-off between spectral efficiency losses and load balancing gains). Based on averaged receive power levels, the decisions of clustering are updated in longer time intervals. Besides, the system model consists of one macro BS. These two points are considered as limitations of applied methodologies and considered as assumptions. Another solution OPERA [117] also focused on minimization in number of unsatisfied users and achieves a maximum residual capacity in ultra dense heterogeneous network. This work confirms the necessity for ML to operate SON in proactive mode. In fact, the proactive mode in [117] contributes to meet 5G user satisfaction and QoS requirements better than the reactive in [116]. But, the use of deep neural network instead of Semi Markov can enhance the prediction accuracy to provide better optimization. The proposed mobility traces used to predict mobility of pedestrians cannot be applied for vehicles. In fact, the vehicles take a direction of the trajectory which is more deterministic and regular. In CCO subsection, the work [118] attempted to optimize the system propagation in order to boost the capacity and the coverage in the environment geography. In [119], Dai et al.used ML to predict RRS, as in [118], in order to enhance CCO SON. In fact, ML can intelligently extract relevant feature information about strength of RSS from the rich cellular data, and rapidly optimize the deployed BSs by predicting the relations between these features and RSS values in order to enhance the coverage performance and minimization CAPEX/OPEX. Based on [118] – [119], the prediction idea gives certain SON improvement to optimize the coverage and capacity in cells. In addition, the use of ML can intelligently provide a high accuracy prediction and offer a low prediction error better than empirical propagation models. This high prediction reinforces the CCO SON results. Despite the effectiveness of ML solutions, it is necessary to choose the best ML that maintains the lower error prediction. Moreover, these works exhibit other solutions instead of features extraction such as the raw geographical image [146] or extract further RSS information such as Received Signal Strength Indicator (RSSI), Reference Signal Received Quality (RSRQ) and Reference Signal Received Power (RSRP) to better improve the prediction process [63]. In mobility management subsection, the work [120] purported to reactively manage HO in small cell network by minimizing the HO failures simultaneously. The linear path movement of users is considered as an assumption limitation because users move in different directions. Compared to [120], the work [121] elucidated the necessity to ML to manage the huge number of cells generating huge data. ML can forecast the future HO and predict the huge abnormal failures, in order to proactively heal them and make 5G network more transparent and more coordinated. Unlike the reactive mode, ML solutions can be implemented in SON to learn intelligently the variation of collected HO behavior over the course of the day. Based on the performance evaluation of the collected HO pattern, ML can rapidly and intelligently minimize HO problems to reach the best mobility management which ensures both user satisfaction and high QoS. In spite of the effectiveness of the proposed proactive mode, it will be better to apply other ML solutions that result in a lower difference error percentage between normalized and real rather than the proposed ML solution. The evaluation of the performance of each model is quite thorny owing to limitations of calculated parameters number. In [122], the HO prediction is also reported to assess and minimize the holistic HO cost. Holistic HO cost includes signaling overhead, latency, call dropping, and radio resource wastage. LSTM ML solution proved its efficiency and accuracy to solve mobility management problems based on mobility prediction despite the over-fitting risk. Limited real-world data sets and necessity to examine the trade-offs between computational cost and real time decision-making stand for two obvious limitations applied methodologies and considered assumptions. In addition to the merits offered by ML solution in terms of enhancing SON mobility management and solving HO problems, the mobility prediction using ML can ensure also an efficient and proactive SON Load Balancing and Caching Content as reported in the works [123] – [124]. The work [125] provided another insight on the use of ML and data collection in mobility prediction. Based on data traces collection, the mobility prediction can efficiently promote the SON Energy Saving

Table 8
SON solutions applied in 5G network.

SON use cases	Ref+Y	Proposed solutions	Advantages	Drawbacks	Limitations of applied methodologies and considered assumptions	Objectives
Load balancing	[116] 2016	-CoMP SO clustering algorithm -Novel re-clustering algorithm	-System throughput, SINR and backhaul capacity maximization. -Unsatisfied users Minimization	-Some improvements are required to reach a high user satisfaction with keeping high QoS -Trade-off is needed between spectral efficiency losses and load balancing gains	-One Macro BS in the system model -Decisions of clustering are updated in longer time intervals	- Spectral efficiency enhancements - Minimization of unsatisfied users number using reclustering algorithm
	[117] 2020	Proactive LB based on Semi-Markov and GA	-Minimization in number of unsatisfied users and maximization in residual capacity better than the reactive - SON LB and CCO conflicts free operation	Deep learning is being investigated heavily for cellular networks optimization instead of the proposed Semi-Markov	-Proposed mobility traces cannot be applied for vehicles.	Meeting 5G user satisfaction and QoS requirements
Coverage and Capacity Optimization	[118] 2019	*Deep Neural Networks*	-Path loss estimation to optimize the radio propagation - Use of realistic propagation model	Necessity to select an ML solution that outperforms other ML solutions in all cases	Using other RSS measurements (such as RSSI, RSRQ, RSRP), height of BS.	3D radio wave propagation modeling to enhance the capacity and coverage in the environment geography.
	[119] 2020	Predictive received signal strength solution using KNN, Random Forest, SVM, MLP	High accuracy prediction and low prediction error reinforcing CCO SON	Necessity to select ML solution that outperforms other ML solutions in all cases	Using other RSS measurements (such as RSSI, RSRQ, RSRP), BS Tilt angle, BS Frequency, BS antenna type, UE Measurements	Coverage performance and minimization CAPEX/OPEX
Mobility management	[120]2020	Apollonian circle mathematical tool	Both ping pong rates and RLF failures minimization	Less efficient solution than proactive mode	Users moving on a linear path	Autonomous Reactive management of HO
	[121] 2017	Practical process based on big data and diversity linear and nonlinear ML models.	Efficient HO clustering, HO forecasting and abnormal HO detection.	High difference between mean absolute error and root mean square error of normalized and real values results for all proposed ML forecasting solutions.	-Limited numbers of calculated parameters -No comparison with Deep Learning solution	Future HO demands prediction and proactive abnormal behaviors HO detection
	[122] 2019	Deep Learning	ML efficiency to provide high prediction accuracy that enhances SON mobility management and solves HO problems	Over-fitting risk	-Limited real-world data sets -Studying the trade-offs between computational cost and real time decision-making	Holistic cost minimization
	[125] 2019	Deep Neural Network, Extreme Gradient Boosting Trees, Semi-Markov and Support Vector Machine comparison	Extreme Prediction using Gradient Boosting Trees provides: -High energy saving gain and lower execution time -True performance generated by predictors when using SLAW model	High time of prediction	Lower predictability rate caused by the variations in the number of BSs visited by users	Estimation of future location of mobile users

(*continued on next page*)

better than the reactive one. In fact, predicting future cell load with ML can intelligently save a certain latency time to wake up from sleep cycle. Moreover, the best selection of ML can reach highest QoS and user satisfaction levels. A trade-off between the prediction accuracy and predicted time can emerge despite the ML benefits offered to proactive SON Energy saving. Compared to [125], the work [72] used one of the ML solutions proposed by [125] for mobility prediction in order to discern the necessity to predict future load in SON Energy Saving enhancements. In addition to solving obstructions of reactive SON to meet 5G Energy Saving requirements, Farooq et al.focused on solving SON functions conflict i.e coordination between LB and CCO functions. The GA AI corresponds to the most suitable choice that multiplies the chance to find the global solution. The authors can take into account the constraints of backhaul with cell loads and use D-SON. Li-Chun et al. [126] used big data to enhance the current SON mechanisms which are allowed only to indoor femtocells. This enhancement can boost the energy efficiency of huge number of outdoor small cells. The addition of both big data and ML can improve the energy efficiency and achieve the highest total cell throughput despite the same performance occasionally offered by intuitive approach. The work [127] presented another branch of resource optimization, namely caching placement optimization for MEC which contributes also to minimize energy consumption. The near optimal caching offers a good performance in terms of energy consumption optimization, especially with the high

Table 8 (*continued*).

SON use cases	Ref+Y	Proposed solutions	Advantages	Drawbacks	Limitations of applied methodologies and considered assumptions	Objectives
Resource optimization	[72] 2018	Semi-Markov model-based Spatio-temporal mobility prediction and GA	Solving obstructions of reactive SON -Coordination between LB and CCO functions	Accuracy decreases with the increase in the prediction time interval	-C-SON architecture -Backhaul constraints taking into account cells load	Mobility prediction to optimize Energy saving
	[126] 2016	Big data-SON framework based on Polynomial Regression	SON mechanisms enhancements with a huge number of outdoor small cell -Energy efficiency and total cell throughput improvements	Similar throughput to intuitive approach and similar energy efficiency to static IA	120 small cells are densely incorporated in one macro cell coverage	Energy efficiency improvement in several number of outdoor small cells
	[127] 2017	Joint optimization framework based on GA	Caching offers -Good performance in term of energy consumption optimization High capacity of backhaul -Average download latency optimization	Inefficient content caching: -Excessively caching of a lot of unpopular content -Average delay cost and Energy efficiency gains degradation	MECs share the same power supply in the cell site	Caching placement optimization to minimize the energy consumption
Backhaul optimization	[133] 2016	User-centric backhaul solution based on Q-learning	-Intelligent association of users with small cells considering the offered capabilities of the backhaul. -High user satisfaction	Low degradation in cumulative throughput	-One macro-cell with three sectors and 21 small cells in fixed locations -Only three joint radio/backhaul capabilities	User-cell association optimization
Caching optimization	[134] 2014	Proactive caching based on Collaborative Filtering	-Amount of satisfied requests for low and high traffic load enhancements backhaul load minimization when the requests of users increase	-More than 80%, the requests have the same satisfaction for low and high traffic loads -Backhaul load with reactive caching outperforms the proactive caching when the popularity distribution exceeds 50%	Limited capacity backhaul links	Backhaul congestion minimization
	[135] 2016	Context-Aware Proactive Content Caching based on Online Learning	Predicting the popularity information to ensure a proactive optimal placement of content caching	Coordination between caching entities or central planner deciding on the caching content must be performed	Multiple caching entities in real caching content placement systems	Caching content replacement decision
Self-Healing	[140] 2018	Cell outage detection in 5G H-CRAN based on modified Local Outlier Factor	Cells outage identification and rectify it immediately	Presence of error percentage	Only RSRP, RSRQ, SINR Channel quality information	Cells Outage identification and rectification
	[144] 2015	Adaptive fault predictive framework based on Continuous Time Markov Chain	-Diagnosis and compensation times minimization -More reliability and high user satisfaction	High passage time from state 1 to state 3	No comparison with more intelligent learning models Time for failure is exponentially distributed	Effects analysis of faults arrival in a cellular network

capacity of backhaul. Otherwise, the system consumes a high energy consumption when the capacity of backhaul is lower. In fact, it gathers the maximum of hidden contents in BSs to minimize the overload on the backhaul. This does not prevent the delay average cost reduction. The inefficient content caching leads to the excessive caching of a lot of unpopular content which effectively influences the average delay cost as well as the energy efficiency gains. Among the most prominent constraints in applied methodologies and considered assumptions, the same power is shared by MECs in the cell site. In backhaul optimization subsection, the work [133] proposed a Reinforcement Learning solution to optimize the user-cell association taking into consideration the corresponding dynamic radio and backhaul conditions respecting users' requirements. The use of Q-learning ML solution in distributed SON can intelligently associate users with small cells through considering the offered capabilities of the backhaul. Unlike the traditional SINR- based scheme, the cooperation between Q-learning and distributed SON enables the improvement at the level of user satisfaction as well as QoS in spite of the low degradation in cumulative throughput. The algorithms in distributed SON generally perform in small BSs, which offers a low latency of transmission compared to centralized SON. Using Q-Learning to promote SON ICIC mechanisms and CREO values generates the enhancement in terms of users' throughput. Using one macro-cell with

Table 9
Algorithmic aspects of proposed works.

Ref+Y	SON type	Architecture	SON function	ML category	Big data	Data-sets type	Multi-objective	Optimization Algorithms method
[116]	Reactive	Centralized	Spectral Efficiency	Unsupervised Learning	–	-	✓	–
[117]	Proactive	Centralized SON	LB, COO, CIO	Reinforcement Learning	–	SLAW-model-generated mobility traces	–	–
[118]	Proactive	SON for 3D Propagation Model	–	Deep Neural Network	–	BS, Geographic Information, UE Measurements data-sets	–	–
[119]	Proactive	Architecture of network planning tool	CCO	Supervised Learning	–	Real-world networks of multiple locations	✓	Heuristic GA
[120]	Reactive	Distributed SON	MRO, CIO		–	RLF related data	–	–
[121]	Proactive	–	–	Unsupervised Learning	✓	Real dataset that collected HO KPI of more than 6000 cells		
[122]	Proactive	Centralized or Control/Data Separation	–	Non-predictive and Predictive Deep Learning	–	Benchmark Real-world dataset	–	Stochastic gradient-decent algorithm and Adam optimizer
[125]	Proactive	Centralized SON	ES	Supervised learning	–	Realistic SLAW mobility model	–	–
[72]	Proactive	Centralized SON	ES, CIO	Markov Model	–	Realistic SLAW mobility model	–	Heuristic GA
[126]	Proactive	Centralized SON	ES	–	✓	–	–	IA energy saving algorithm and D3A Model
[127]	Reactive	Hybrid SON in MEC servers' caching system	–	–	–	MEC servers	–	Heuristic GA
[133]	Reactive	Distributed SON	CREO values, ICIC mechanism	Reinforcement Learning	–	–	–	Q-learning
[134]	Proactive	Distributed SON	ICIC	Supervised Learning	–	–		
[135]	Proactive	Hybrid SON	–	Online Learning	–	MovieLens dataset	–	Heuristic m-CAC
[140]	Reactive	Centralized SON	COD	Unsupervised Learning	–	User, RRH/ACE, NodeC, Drive Test Data-set	–	–
[144]	Proactive	Ultra Dense Heteroge-neous Complex Cellular Network	–	Reinforcement Learning	–	Database of network failures	–	–

three sectors and 21 small cells in fixed locations and focusing only on three joint radio/backhaul capabilities stand for the basic shortcomings of applied methodologies and considered assumptions. To offload the backhaul links and optimize their capacity, the work [134] highlighted a proactive content caching in small cell network based on popular estimation. Compared to [133], Ejder et al. [134] and Kader et al. [136] attempted to optimize backhaul load through proactive SON caching. Compared to reactive mode, the proactive content caching reinforces the amount of satisfied requests for low and high traffic loads in addition to the decrease on the backhaul load when the requests of users increase. The proactive mode is also developed in [135]. It aims to estimate the popularity information using Online Learning solution in order to cache the contents proactively. The proposed online algorithm outperforms the state-of-the-art solutions. In fact, it regularly learns the context-specific connected user, then it ensures an optimal placement of content caching. In real caching content placement systems, the proposed solution needs to be applied in multiple caching entities. To achieve more optimal cache contents, coordination between caching entities or central planners deciding on the caching content needs to be carried out. In self-healing subsection, the cell outage management is a key factor proposed in SON. The work [140] invested modified Local Outlier Factor to detect cells outage in H-CRAN architecture. Peng et al.set forward a centralized self-organized COD architecture. Modified Local Outlier Factor ML algorithm makes the SON COD more accurate and intelligent despite the existence of multiple errors in cell outage consideration. In Self healing context, the work [144] dealt with Self-recovery of NE software. It proposed Continuous Time Markov Chain solution to analyze and evaluate the cells behavior and the effects of faults on them. Thanks to proactive diagnosis, the proposed solution can minimize the diagnosis and compensation times, which will provide more reliability and high users' satisfaction.

4. Open issues and future trends

This section is devoted to highlight the opportunities and trends related to SON functions implementations beyond 5G. We address the new paradigm of *Self-Sustaining Network (SSN)* and the surrogate of SON in 6G. The scale of 5G beyond deployments will trigger new challenges in terms of higher autonomous configuration capabilities. The SON architectures in 5G retain the support of Network Data Analytic Function (NWDAF) to empower AI using centralized cloudification [147]. While 6G networks introduce a new vision of an intelligent plane providing native AI support for the whole mobile communication system, this vision can be fulfilled by moving intelligence to the edge computing resources with embedded ML capabilities. In [147], the authors incorporated a clean slate approach to define 6G E2E system architecture providing native support for intelligence inclusion. Network AI Management and Orchestration (NAMO) is the key design for intelligent plane inclusion, which is responsible for orchestrating and managing heterogeneous and distributed resources as well as defining a universal mechanism to provide diversified AI services. However, further research need to be conducted in order to enable a collaborative ecosystem with all kinds of AI applications as envisioned by 6G architecture.

4.1. Opportunities and challenges for future works

Even though SON stands for a promising tool enabling autonomous and intelligent cellular networks, there are still enormous challenges to tackle and overcome. According to [148], in order to fulfill the aspirations of fully intelligent and autonomous beyond-5G network, five major challenges are addressed: (i) training issues, (ii) lack of Bounding Performance, (iii) lack of Explainability, (iv) uncertainty in generalization and (v) lack of interoperability. The training overhead needs to be investigated and reduced in order to maintain the viability of PHY/MAC layer applications, through applying new training algorithms and neural network architectures. The second challenge is related to exploring the adoption of tolerable and graceful degradation in a worst-case scenario. Third challenge is associated with the lack of explainability of the correctness and the behavior of AI tools. This refers essentially to the fact that they behave as black boxes and represent a stumbling block when AI is applied for real-time decision making.

The fourth challenge corresponds to the uncertainty of the data-set for training the model. In order to minimize uncertainty in generalization, a canonical requirement could involve the comparison of the AI model output against a well-understood theoretical performance bound, such as a maximum likelihood. However, the fifth challenge tends to mitigate the increasingly complex dependencies of AI-based cellular networks by investigating the interoperability and hence the consistency among AI-modules from different vendors.

4.2. Self-sustaining network in 6G

5G beyond and 6G will require a paradigm shift from classical SON to SSN. The strict spectral efficiency, reliability, and latency requirements associated with 6G imply an increasingly autonomous network. Pervasive AI is quite helpful in building up sustainable networks. To accomplish this target, AI needs to be integrated with a game theory to create a distributed learning mechanism where AI agents interact to teach and learn from each other [149]. To autonomously achieve the perpetuity of 6G KPI, SSN must be able to maintain their resources usage and management through gathering energy, efficiently exploiting spectrum and adjusting their functions with the use of the recent revolution in AI solutions [150].

5. Conclusion

This research paper elaborates a comprehensive and exhaustive overview on SON paradigm, its different definitions, its three main categories and its most prominent use cases applied in 5G cellular network, the SON architectures and the addition of virtualization to H-SON architecture in order to make it more scalable, flexible, open and to provide more intelligence to 5G network. Furthermore, this survey illustrates the challenges that SON needs to face in order to be applied in 5G cellular networks. It elucidates the necessity to use ML techniques in order to take decisions intelligently and empower the SON legacy to efficiently meet 5G requirements. In addition, it exhibits a few works that handle some use cases of SON in 5G and ML solutions to face SON challenges.

At this stage of analysis, we would assert that this synthesis would be valuable in terms of opening further fruitful lines of investigation and offering promising research directions. Indeed, our work is a step that may be built upon, extended and taken further as it paves the way and lays the ground for future works to enact more promising applications in the area in a way that 5G Beyond and 6G would transcend SON and would use a new paradigm SSN to perpetuate the 6G KPIs.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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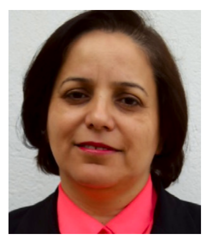

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