Application of Machine Learning in Self-organized Network Management

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Contents

1 DEFINITION

1.1 PICTURES USED

Self-organization as applied to cellular networks is usually referred to Self-organizing Networks (SONs), and it is a key driver for improving Operations, Administration, and Maintenance (OAM) activities. (definition) SON aims at reducing the cost of installation and management of 4G and future 5G networks, by simplifying operational tasks through the capability to configure, optimize and heal itself. (benefit) Machine Learning (ML) has been identified as the key tool to implement autonomous adaptability and take advantage of experience when making decisions. (ML - SOn)

Up to 4G - hardware . 5g software With the advent of these software advancements, and unprecedented levels of computational capacity, the vision of autonomous network management can be put into practice taking advantage of also other cross-disciplinary knowledge advancements in the area of Machine Learning.

Network management: self-awareness, self-configuration, self-optimization, and self-healing,

SON is a common term used to refer to mobile network automation and minimization of human intervention in the cellular/wireless network management.

Benefit: 1) to bring intelligence and autonomous adaptability into cellular networks, 2) to reduce capital and operation expenditures (CAPEX/OPEX), 3) to enhance network performances in terms of network capacity, coverage, offered service/experience, etc.

Problem: 1) mainly based on heuristics, 2) the automated information processing is usually limited to low complexity solutions like triggering, 3) many operations are still done manually (e.g. network faults are usually fixed directly by engineers), 4) SON solutions do not really capi2 talize on the huge amount of information that is available in mobile networks to build next generation network management solutions, and 5) several open challenges are still unsolved, like the problem of coordination of SON functions [15], [16], or the proper solution of the trade-off between centralized and distributed SON implementations

Network Functions Virtualisation (NFV) bring the economy of scale: selforganized network management vision could be extended also beyond the RAN segment and include all the segments of the network, from the access to the core, while fulfilling the requirements of different kind of vertical service instances.

Reason for machine learning: * use of SON and of smart network management policies is crucial and inevitable for operators running multi-RAT, multi-vendor, multi-layer networks, where an overwhelming number of parameters need to be configured and optimized. * We believe that Machine Learning (ML) can be effectively used to allow the network to learn from experience, while improving performance. In particular, big data analytics, through the analysis of data already generated by the network, can pursue the self-awareness by driving the network management from reactive to predictive.

2 DEFINITION

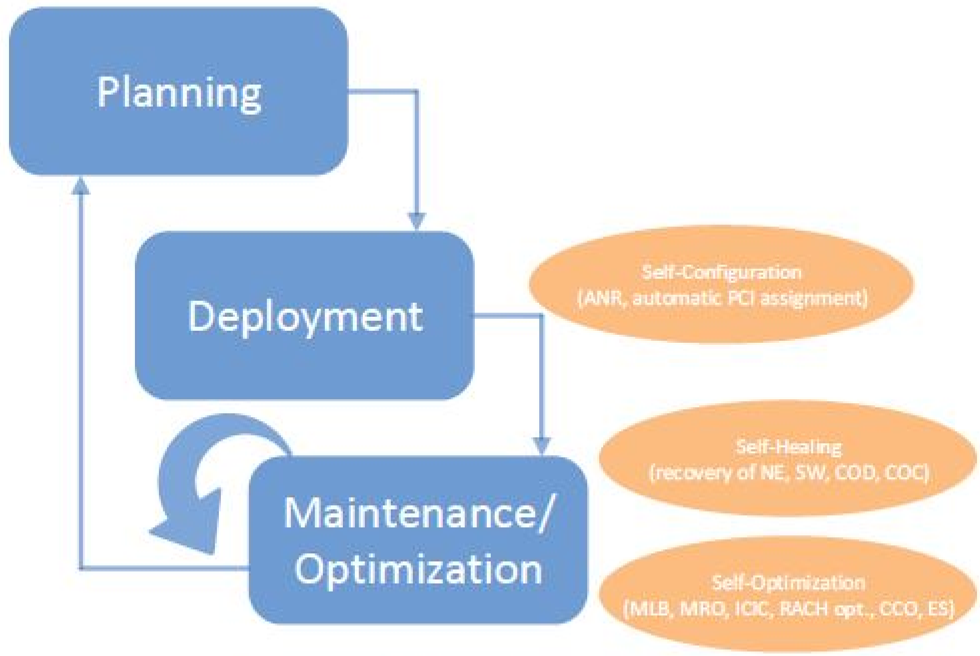

Fig. 1: Self-organizing networks

A Self-Organizing Network (SON) is an automation technology designed to make the planning, configuration, management, optimization and healing of mobile radio access networks simpler and faster.

Self-organizing network functionalities are commonly divided into three major sub-functional groups, each can be used in most phases of the life cycle of a cellular systems (planning, deployment, maintenance and optimization) into: self-configuration, self-healing and self-optimization, as depicted in Figure 1.

2.1 SELF-CONFIGURATION

Self-configuration strives towards the "plug-and-play" paradigm in the way that new base stations shall automatically be configured and integrated into the network. This means both connectivity establishment, and download of configuration parameters are software. Self-configuration is typically supplied as part of the software delivery with each radio cell by equipment vendors. When a new base station is introduced into the network and powered on, it gets immediately recognized and registered by the network. The neighboring base stations then automatically adjust their technical parameters (such as emission power, antenna tilt, etc.) in order to provide the required coverage and capacity, and, in the same time, avoid the interference.

2.2 SELF-OPTIMIZATION

Every base station contains hundreds of configuration parameters that control various aspects of the cell site. Each of these can be altered to change network behavior, based on observations of both the base station itself and measurements at the mobile station or handset. One of the first SON features establishes neighbor relations automatically (ANR) while others optimize random access parameters or mobility robustness in terms of handover oscillations. A very illustrative use case is the automatic switch-off of a percent of base stations during the night hours. The neighboring base station would then re-configure their parameters in order to keep the entire area covered by the signal. In case of a sudden growth in connectivity demand for any reason, the ”sleeping” base stations ”wake up” almost instantaneously. This mechanism leads to significant energy savings for operators.

2.3 SELF-HEALING

When some nodes in the network become inoperative, self-healing mechanisms aim at reducing the impacts from the failure, for example by adjusting parameters and algorithms in adjacent cells so that other nodes can support the users that were supported by the failing node. In legacy networks, the failing base stations are at times hard to identify and a significant amount of time and resources is required to fix it. This function of SON permits to spot such a failing base stations immediately in order to take further measures, and ensure no or insignificant degradation of service for the users.

3 ML

Class of problem can be addressed with ML when managing the network autonomously are:

- Variable estimation or classification: The tasks belonging to this class of problem aim at e.g. estimating the QoS or the QoE of the network, at predicting performances or behaviours of the network, by learning from the analysis of data obtained from past behaviours of the network. NM and SON functions where these tasks are useful are QoS 8 estimation and other MDT use cases, the prediction of behaviours to optimize network parameters, etc. Solutions to these problems can be translated into finding the relationship between one variable and some others, or Identifying which class of a set of predefined classes the data belongs to. Solutions are then to be found in the SL literature, with both regression and classification tasks.

- Diagnosis of network faults or misbehaviours: The tasks belonging to this class of problems aim at detecting issues ongoing in the network, which may be associated to faults and anomalous setting of network parameters. This kind of problems relates to self-healing issues and solutions can be found in UL literature, and in particular in the anomaly detection solution.

- Dimensionality reduction: The network generates continuously a huge amount of data. For an appropriate processing and to extract useful information, it is convenient to eliminate the noise present in the data base, by reducing the dimensionality of data. Solutions to this problem are to be found in the UL literature, and specifically among the dimensionality reduction solutions.
- Pattern identification, grouping: The tasks belonging to this class aim at identifying patterns, group of nodes with similar characteristics, according to some kind of criteria. An objective may be to apply to them similar optimization approaches. Self-configuration use cases are intuitive application for these issues. Solutions to these problems can be translated into learning the set of classes the data belongs to. UL literature offers solutions in the area of clustering.
- Sequential decision problems for online parameter ad- justment: This class of problems is extremely common in the area of autonomous management, where we face control decision problems to online adjust network parameters, with the objective to meet certain performance targets. This kind of decision problems, where we learn the most appropriate decision online, based on the reaction of the environment to the actions the network is taking, can be addressed through RL solutions. All selfoptimization use cases can be addressed through these solutions, as well as COC problems.

4 ADDRESS SON AND NM THROUGH ML

a huge amount of data from normal operations of mobile network can be exploited to find patterns and extract useful information:

TABLE II: Information elements relevant for ML enabled SONs

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

Table IV summarizes the main use cases of ML in each SON and Network management function and classifies them per 3GPP use case, technique and specific algorithm

- Mobility Load Balancing:The majority of applications fall in the area of Reinforcement learning (RL), as the main problem to solve is a sequential decision problem about how to set configuration parameters, which optimize network performance and user experience. An example of a RL application for MLB use case can be found in [135]. Here the authors present a distributed Q-learning approach that learns for each load state the best MLB action to take, while also minimizing the degradation in HO metrics. Another option to take advantage also of fuzzy logic capabilities of dealing with heterogeneous sources of information is provided in [136], where fuzzy logic is combined with Q-learning in order to target the load balancing problem. For similar reasons, fuzzy logic is also proposed in [137] to enhance the network performance by tuning HO parameters at the adjacent cells. Approaches incorporating fuzzy logic with RL capabilities have the advantage to capture the uncertainty existing in real world complex scenarios, while schemes considering only learning approaches may be limited by the fixed variable definition. When combining fuzzy logic with RL, also the subjectivity with which the fuzzy variable may be defined is overcome by the adjusting capabilities of the learning. Alternatively, a centralized solution is approached in [138], where a central server in the cellular network determines all HO margins among cells by means of a dynamic programming approach. Besides RL, also clustering schemes have been proposed in this area, to group cells with similar characteristics and provide for them similar configuration parameters [139]. Considering clustering in large realistic scenarios is an added value to reduce computational complexity and take advantage of what is learnt in other regions of the network where we observe similar environment characteristics.

- Mobility Robustness Optimization: Also for the case of MRO, we find in literature different solutions based on RL to solve a control decision problem. In [141], [142], the authors focus on the optimization of the users' experience and of the HO performance. In [141] the authors take advantage of the Q-learning approach to effectively reduce the call drop rates, whereas in [142], unlike other solutions that assume a general constant mobility, the authors adjust the HO settings in response to the mobility changes in the network by means of a distributive cooperative Q-learning. Differently from [141], [142], in [143], the authors take advantage also of fuzzy logic capabilities. These solutions are based on control optimization of HO parameters through RL, so they propose similar solutions to those found in the literature of MLB. In this case we can do the same considerations about the advantages of considering fuzzy logic in order to gain in flexibility in the uncertain and complex real network context. Different approaches in turn, address the problem by identifying successful HO events, through solutions based on unsupervised learning. In particular, the works of [144] and [145] propose an approach to HO management based on UL and SOM analysis. The idea is to exploit the experience gained from the analysis of data of the network based on the angle of arrival and the received signal strength of the user, to learn specific locations where HOs have occurred and decide whether to allow or forbid certain handovers to enhance the network performance. The solutions enable self-tuning of HO parameters to learn optimal parameters' adaptation policies. Similarly, in [146] the authors exploit the huge amount of information generated in the network to predict user traffic distribution. In particular, they take advantage of semi-Markov model for spatiotemporal mobility prediction in cellular networks. Finally, the works in [147]–[150], propose schemes to make predictions about UE's mobility, which allows to anticipate smart HO decisions.

- Coverage and Capacity Optimization: In case of CCO, different approaches in literature focus on RL solutions based on continuous interactions with the environment, oriented to online adjusting antenna tilts and transmission power levels through TD learning approaches. In [151] and [152] a fuzzy Qlearning approach to optimize the complex wireless network, by learning the optimal antenna tilt control policy has been proposed, and a similar approach is followed also in [153] and [154]. In addition, they also propose to combine fuzzy logic with Q-learning, in order to deal with continuous input 15 and output variables. [153] also proposes a central control mechanism, which is responsible to initiate and terminate the learning optimization process of every learning agent deployed in each eNB. Finally, [154] innovates with respect to other approaches since in order to adjust the antenna tilt and transmission power parameters, it considers the load distribution of the different cells involved in the optimization process, and introduces novel mechanisms to facilitate cooperative learning among the different SON entities.

- Inter-cell Interference Coordination: Similarly to the CCO case, ML has been proposed in the literature of ICIC use case as a valid solution, where RL is the principle used tool, with special emphasis to TD methods, in order to target the optimization of control parameters. Several works target the problem to minimize the interference among cells by using the most common TD learning method, Q-learning [155]–[158]. The work in [155] is related to control inter-cell interference in a heterogeneous femto-macro network. The work combines information handled by the multi-user scheduling with decisions taken by a learning agent based on Q-learning, which tries to control the cross-tier interference per resource block. [156] proposes a distributed solution for ICIC in OFDMA networks based on a Fuzzy Q-learning implementation. The proposed solution achieves joint improvement for all users, i.e., the improvements of users with bad quality does not come at the expense of users with good quality. Moreover, a decentralised Q-learning framework for interference management in small cells is proposed in [157]. The authors focus on a use case in which the small cell networks aim to mitigate the interference caused to the macro-cell network, while maximizing their own spectral efficiencies. Finally, in [158] also a decentralized Qlearning approach for interference management is presented. The goal is to improve the systems performance of a macrocellular network overlaid by femto-cells. In order to improve the time of convergence, a mitigation approach has been introduced, allowing them to have significant gains in terms of throughput for both, macro and femto users. Interesting trade-offs can be studied to compare centralized vs. distributed solutions. In the novel context of small cells distributed solutions to interference management are to be preferred over more complex centralized solutions, but convergence and instability approaches may appear to affect the TD learning schemes, compromising system performances [155].

- Energy Savings: Energy savings schemes for wireless cellular systems have been proposed in the past, enabling cells to go into a sleep mode, in which they consume a reduced amount of energy. In order to reduce the energy consumption of the eNBs, we can found several works related to ML techniques. An example of that can be found in [159], where the authors take advantage of RL to propose a decentralized Qlearning approach to allow energy savings by learning a policy by the iterations with the environment taking into account different aspects over time, such as the daily solar irradiation. Also, in [160], the authors switch off some underutilized cells during off peak hours. The proposed approach optimizes the number of base stations in dense LTE pico cell deployments in order to maximize the energy saving. For the purpose, they use a combination of Fuzzy Logic, Grey Relational Analysis and Analytic Hierarchy Process tools to trigger the switch off actions, and jointly consider multiple decision inputs for each cell. This last work uses smart decision theory approaches, which though are not able to take advantage of the previous decisions made in the same environment, as in turn does the work proposed in [159], as a result of the TD learning approach. This allows that the work in [159] offers a more solid solution, considering also past information in the decision. Also for HetNets, we find several works, such as, [161], [162], where the authors take advantage of KPIss available in the network for the construction of different kind of databases to analyse the potential gains that can be achieved in clustered small cell deployments.

- Cell Outage Compensation: The literature already offers different works targeting the problem of COC. For this use case RL has been proven as a valid solution since it is a continuous decision making/control problem. In this context a contribution in the area of self-healing has been presented in [163], [164], where the authors present a complete solution for the automatic mitigation of the degradation effect of the outage by appropriately adjusting suitable radio parameters of the surrounding cells. The solution consists of optimizing the coverage and capacity of the identified outage zone, by adjusting the gain of the antenna due to the electrical tilt and the downlink transmission power of the surrounding eNBs. To implement this approach, the authors propose a RL based on actor-critic theory to take advantage of its capability of making online decisions at each eNB, and of providing decisions adapting to the evolution of the scenario in terms of mobility of users, shadowing, etc., and of the decisions made by the surrounding nodes to solve the same problem. A COC contribution also based on ML is targeted in [165], where fuzzy logic is proposed as the driving techniques to fill a coverage gap. The authors show performance gains by using different parameters, such as, the power transmission, the antenna tilt, and a combination of the two schemes. These two works are compared in [163] and the work in [163] is proven superior thanks to the ability to learn from the past experience introduced by the RL actor-critic approach.

- Cell Outage Detection: As we already mentioned, COD aims to autonomously detect cells that are not operating properly due to possible failures. For this kind of problem, anomaly detection algorithms offer an interesting solution that allows to identify outliers measurements, which can be highlighting a hidden problem in the network. Proposals of solutions for this problem can be found in [166] and [167]. In particular, [166] presents a solution based on diffusion maps, by means of clustering schemes, capable of detecting anomalous behaviours generated by a sleeping cell. [167] presents a solution based on fuzzy logic for the automatic diagnosis of a troubleshooting system. In order to determine if there is a failure, the authors propose a controller, which receives as an inputs a set of representative KPIs. A similar approach is presented by [168], where the authors present an automated diagnosis model for Universal Mobile Telecommunications System (UMTS) networks based on Naive Bayesian classifier, and where the model uses both network simulator and real UMTS network measurements. In the context of this king of 16 classifiers , the works in [174], [175], also take advantage of NB for automated diagnosis based on different inputs network performances. The work in [169] addresses both the case of outage and the one where in turn the cell can provide a certain level of service, which though does not allow to fulfil the expected UEs requirements. The approach relies on ensemble methods to train KPIs extracted by human operators to make informed decisions. In [185], the authors consider large data sets to identify anomaly behaving base station. They proposed an algorithm consisting of preprocessing, detection and analysis phases. The results show that by using dimensionality reduction and anomaly detection techniques irregularly behaving base stations can be detected in a self-organized manner. In [164] data gathered through MDT reports is used for anomaly detection purposes. Furthermore, the works of [171]–[173] take advantage of k-NN algorithm to propose a self-healing solution, in particular to tackle the fault detection domain. Finally, in [170], the authors consider a HetNet and they take advantage of HMM to automatically capture the dynamic's of four different states and probabilistically estimate if there exist a possible failure.

- SON Conflicts Coordination: As the deployment of stand-alone SON functions is increasing, the number of conflicts and dependencies between them also increases. Hence, an entity has been proposed for the coordination of this kind of conflicts. In this context, current literature includes several works based on ML. In [176] the authors focus on the classification of potential SON conflicts and on discussing the valid tools and procedures to implement a solid self-coordination framework. Q-learning, as a RL method, has been proposed in [177] to take advantage of experience gained in past decisions, in order to reduce the uncertainty associated with the impact of the SON coordinator decisions when picking an action over another to resolve conflicts. In [178], the authors use Q-learning to deal with the conflict resolution between two SON instances. Decision trees have been proposed in [186] to properly adjust Remote Electrical Tilt (RET) and transmission power. Additionally, in [179] the authors provide a functional architecture that can be used to deal with the conflicts generated by the concurrent execution of multiple SON functions. They show that the proposed approach is general enough to model all the SON functions and their derived conflicts. First they introduce these SON functions in the context of the general SON architecture, together with high-level examples of how they may interfere. Second, they define the state and action spaces of the global MDP that models the self-optimization procedure of the overall RAN segment. Finally, they show that the global self-optimization problem can be decomposed onto as many Markov decision sub-processs (subMDPs) as SON functions.

- Minimization of Drive Tests: The great majority of literature using the MDT functionality to target MDT use cases, takes advantage of supervised and unsupervised learning techniques to provide different solutions for the different use cases. An example of that can be observed in [180], [181], where the authors address the QoS estimation by selecting different KPIs and correlating them with common nodes measurements, to establish whether a UE is satisfied with the received QoS. A similar objective is targeted in [110], however, differently from the previous works, here the authors focus on multi layer heterogeneous networks, so in a more complex and realistic scenario than the traditional macrocell one. In particular, they present an approach, based on regression models, which allows to predict QoS in heterogeneous networks for UEs, independently of the physical location of the UE. This work is extended in [182] by taking into account the most promising regression models, but also analysing dimensional reduction techniques. By doing PCA/SPCA on the input features, and promoting solutions in which only a small number of input features capture most of the variance, the number of random variables under consideration is reduced. Based on previous results, in [111], [183] the same authors define a methodology to build a tool for smart and efficient network planning, based on QoS prediction derived by proper data analysis of UE measurements in the network. Moreover, the work in [187] presents a system based on a fuzzy logic controller to improve network performances by adjusting antenna tilts values in a LTE system. Differently from previous works, the authors consider the use of call traces to identify the level of coverage, overshooting and overlapping problems, which are the inputs to the algorithm. Also, in [188], the same authors take advantage of connection traces (signal strength, traffic, and resource utilization measurements) to improve the network infrastructure in terms of spectral efficiency. The proposed method is designed to be integrated in commercial network planning tool. Finally, in [189] the authors take advantage of the MDT measurements to build a Radio Environment Map (REM) by applying spatial interpolation techniques (Bayesian kriging). The REM (Radio Environmental Map) is then used to detect coverage holes and predict the shape of those areas.

- Core Networks: As we already mentioned in section II, the operational aspects of core networks elements can be enhanced through, for example, the automatic configuration of the neighbour cell relations function. In this regard, the idea of applying ML to this function is not new. In [184] the authors study the benefits of using ML to root-cause analysis of session drops, as well as drop prediction for individual sessions. They present an offline Adaboost and SVM method to create a predictor, which is in charge of eliminating/mitigating the session drops by using real LTE data.

- Virtualized and Software Define Networks: Also when we go beyond the RAN and we focus on the network in general, ML concepts have already been proposed in different works to build cognitive based techniques to operate the network. An example of these proposals is well summarized by [190]. In this work, a Knowledge Plane is advocated, which would bring many advantages to the networks in terms how the network is operated, automated, optimized and troubleshooted. Conceptually this vision is aligned with different others proposals in other areas, such as the black-box optimization [191], the autonomic self-x architectures [192], or the work presented in [193]. In this context, the work in [194] analyzes the reasons why the vision proposed in [190] has still not been brought to reality, and the main reason that they find is in the challenges that appear when it comes to autonomously manage a network 17 in a distributed fashion. In particular, the work argues that the emerging trend of centralization in control brought by the novel SDN vision, will significantly reduce this complexity and favour the realization of the ML vision in the network. As a result, in [194] some initial experimental results based on the vision defined in [190] are brought into reality in the context of a SDN based architecture. Further work in this area is carried put in the context of different European H2020 projects [6]. The work in [195] presents a novel cognitive management architecture that manages multiple use cases, like the Service Level Agreement (SLA) and the Mobility Quality Predictor. Both use cases are tackled using machine learning approaches, the Long Short Term Memory, and a per user bandwidth predictor. The work in [196] implements SLA through ML approaches. It uses an ANN for evaluation of cognitive SLA enforcement of networking services involving Virtualized Network Functions and SDN controllers.

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