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User-Centric Approaches for Next-Generation Self-Organizing Wireless Communication Networks Using Machine Learning

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***Abstract*—With the ever-increasing rise of a wide range of data-driven applications and services, as well as the synergies of gigabit wireless connectivity and pervasive broadband connectivity, there is a need for a paradigm shift in network methodologies to develop and deploy networks, such as 5G wireless. User-centric approaches to implementing self-organizing networks (SON) using machine learning (ML) have the potential to address the above challenges for 5G wireless communications networks and provide a seamlessly connected eco-system with superior user experience. This paper focuses on the potential performance improvements that can be achieved by integrating self-organizing networks and machine learning using user-centric approaches, with a focus on self-healing and self-optimizing SON functions.**

***Index Terms* — 5G, ML, SON, User-centric approach**

I. Introduction

The next generation wireless communication network vision is to build a seamlessly connected eco-system with superior user experience that can be evaluated using metrics such as QoS (Quality of Service) and QoE (Quality of Experience). Emerging 5G technologies takes us one step closer towards realizing this vision. By supporting new types of applications and the flexible use of spectrum, including never before used millimeter wave (mmWave) frequencies in cellular systems, 5G will provide the communications foundation for a future world of augmented and virtual reality, autonomous cars, smart cities, wearable computers, and innovations that are not yet conceived [1]. Cisco's projection of global mobile data consumption through 2021 depicted in Fig. 1 shows that the overall mobile data traffic is expected to grow to 49 exabytes per month by 2021 [2]. Network operators are under constant pressure of deploying denser networks that can sustain the tremendous growth in connected devices, types of services and applications, and mobile data traffic volume at acceptable levels of capital expenditures (CAPEX), operational expenditures (OPEX), and energy consumptions. Consequently, network automation has gained significant momentum. Network automation of ultra-dense networks would require tools that are highly intelligent and scalable to manage the complexities of such networks and consistently enhance the network performance to achieve end-user satisfaction. User-centric approaches to implementing self-organizing networks using machine learning have the potential to redefine the art of the possible and design a future network that could meet the above-mentioned challenges and is the basis for this research. This paper focuses on the potential performance improvements that can be achieved by integrating self-organizing networks and machine learning using user-centric approaches, with a focus on self-healing and self-optimizing SON functions. This paper is organized as follows: Section II provides an overview of the research domain. Section III covers application and methodologies to illustrate the initiatives taken by the authors towards integrating SON and ML using user-centric approaches. The paper ends with concluding remarks in Section IV.

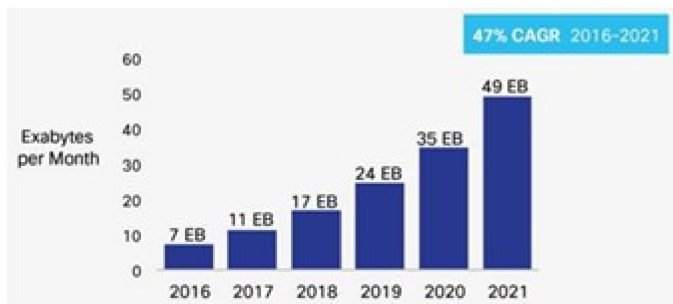

Fig.1 Global mobile data projection from 2016 to 2021. (CAGR – compound average growth rate) [2].

II. Overview of SON, ML, and User-Centric Approaches

A. Self-Organizing Networks

The concept of a self-organizing network (SON) for wireless mobile communication was first introduced in 3GPP Release 8 and is further developed in the current standardization of 3GPP Release 16. The main drivers were reducing the large number and complex structure of network parameters, quick evolution of wireless networks that has led to parallel operations of 2G, 3G, 4G and now 5G technologies, and the rapidly expanding number of network nodes (base stations/eNodeBs/gNodeBs) that need to be configured and managed with the least possible human interaction [3]. Automation of network planning, configuration, and optimization processes via the use of SON functions can help network operators to reduce OPEX by reducing manual involvement in such tasks [4]. Based on the location of the SON algorithm, SON architecture can be centralized (C-SON), distributed (D-SON) or a hybrid (H-SON) solution as shown in Fig. 2(a), Fig. 2(b), and Fig. 2(c) where NFs are the Network Functions, CN is the core network, and RAN is the Radio Access Network [5].

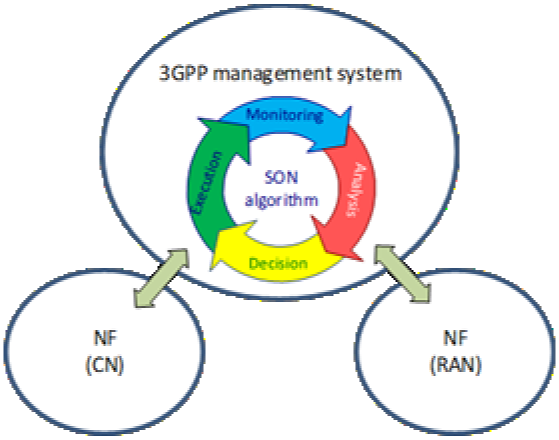

Fig. 2(a) C-SON view

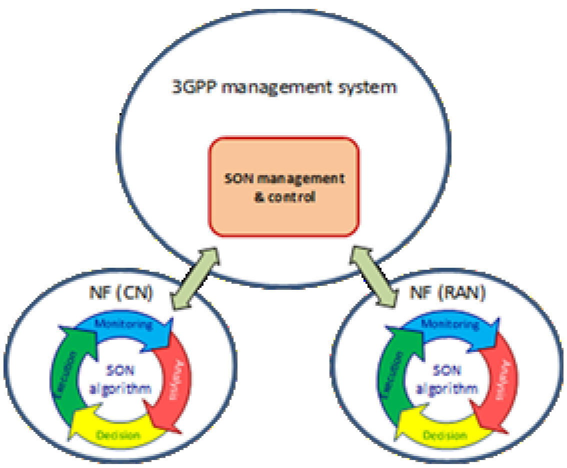

Fig. 2(b) D-SON view

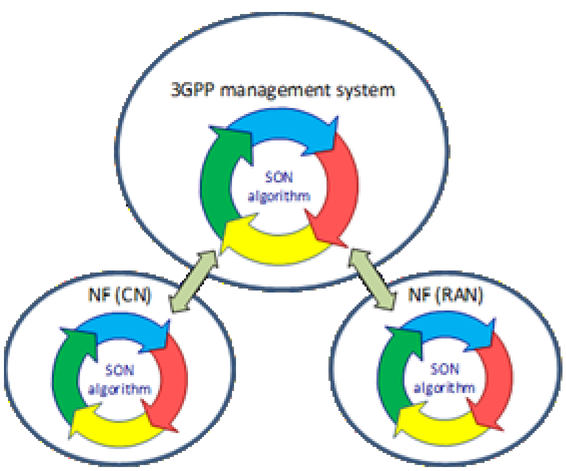

Fig.2(c) H-SON view

SON solutions, which have been standardized by 3GPP, can be divided into three categories: Self-Configuration, Self-Optimization, and Self-Healing each of which can be described as follows [5-7].

Self-configuration is the process of automatically configuring network nodes and parameters including dynamic plug-and-play configuration of newly deployed network nodes where a network node will, by itself, configure operational parameters, radio parameters, and neighbor relations. This includes dynamic configuration and assignment of physical cell identity (PCI), transmission frequency, transmission power, X2 and S1 interfaces, IP addresses, connections to IP backhaul, and automatic neighbor relations (ANR) and other such functions that are required for a newly deployed network node to become fully operable. This initial configuration of network parameters may successfully be able to manage a network in a static environment, but since the real-world environment is not static, there is a need for further optimization.

Self-optimization can be defined as a function that constantly monitors the network parameters and its environment and updates system parameters in order to guarantee that the network performs as efficiently as possible and optimizes coverage, capacity, handover, and interference management. Self-optimization involves functions such as mobility load balancing (MLB) where network nodes exchange information about load level and available capacity by means of radio resource status reports in order to transfer load from congested cells to other cells, mobility robustness optimization (MRO) that performs mobility management and handover parameter optimization for automatic detection and correction of errors in the mobility configuration, random access channel (RACH) optimization where a UE can be polled by a network node to obtain RACH statistics that can be used to minimize the number of attempts on the RACH channel reducing interference, interference coordination to keep inter-cell interference under control by managing radio resources, and energy efficiency to enable a greener network where some network nodes can be switched off during off-peak-traffic situations when capacity is not needed. While these optimization strategies can help improve network performance, partial or full outages may occur due to various faults and failures that can degrade the overall performance of the network and require self-healing.

Self-healing is activated whenever a fault or failure occurs, and its objective is to continuously monitor the network in order to ensure a fast and seamless recovery by automatic detection and removal of failures so that the network can return to proper functioning. Self-healing includes functions such as anomaly detection that is automatically able to detect faults and failures that have occurred in the network, fault diagnosis or classification that can determine the causes of the problems to find the correct solution, and cell outage management to implement compensation mechanisms in order to minimize the disruption caused in the network until the completion of recovery operations. The self-healing function in future networks is expected to proactively predict the faults and anomalies to take necessary measures to mitigate network degradation before a fault or failure actually happens. The SON categories and functions are summarized in Fig. 3.

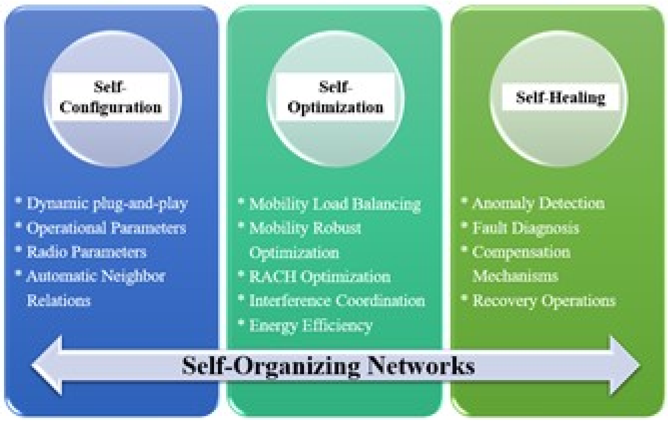

Fig. 3 Taxonomy of self-organizing networks

The full automation of SON is desirable to maximally reduce the OPEX of the networks, and to achieve the fastest reaction to the network issues but in order to prevent any major negative network impact due to improper SON actions, it is critical that the network operators build the confidence about the SON functions step by step before allowing the SON process to run fully autonomously, thus human intervention of the SON process needs to be allowed [5]. In accordance to this, SON process can be categorized as open loop or closed loop. Network operators have the flexibility to stop, resume, and cancel the SON process and make adjustments to the network as needed in an open loop SON process. Once the network operators have built adequate confidence, they may convert the open loop SON process to a closed loop SON process that will be completely autonomous. This can be achieved with the help of machine learning such that the SON networks can not only achieve the fastest reaction to the network issues but also be able to take proactive measures based on ML-based predictions.

B. Machine Learning

Machine learning (ML) is the ability of systems to acquire their own knowledge, by extracting patterns from raw data to address problems involving knowledge of the real world and make decisions that appear to be subjective [8]. ML algorithms can be categorized into supervised, unsupervised and reinforcement learning which are described as follows [7]: Supervised learning, as the name implies, requires a supervisor in order to train the system. This supervisor tells the system, for each input, what is the expected output and the system then learns from this guidance. Unsupervised learning, on the other hand, does not have the luxury of having a supervisor. This occurs, mainly when the expected output is not known, and the system will then have to learn by itself. Reinforcement Learning (RL) works similarly to the unsupervised scenario, where a system must learn the expected output on its own, but a reward mechanism is applied. If the decision made by the system was good, a reward is given; otherwise, the system receives a penalty. This reward mechanism enables the RL system to continuously update itself, while the previous two techniques provide, in general, a static solution. The block diagram in Fig. 4 [9] describes the basic structures of each of these ML categories.

ML will play a pivotal role in implementing SON network functions described in Fig. 3. ML-based 5G SON platforms will be able to leverage the extensive amount of data generated across the network creating new opportunities for data monetization. Current SON solutions lack massive intelligence required for end-to-end network visibility, self-coordination required in SON functionalities to create a conflict-free reliable SON, a certain degree of transparency to network operators without compromising the degree of automation, network ability to adapt to long-term dynamics by developing solutions for longer timescales to improve system-efficiency, network strategies that are more energy-efficient, a holistic approach to define the right Key Performance Indicators (KPIs) that can reflect user experience with high accuracy and quantify the interests of the network stakeholders, and solutions that are not just reactive but also proactive [10]. ML-based SON solutions can help overcome these challenges.

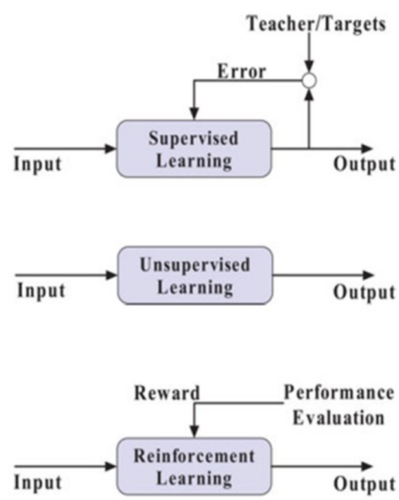

Fig. 4 Basic structures of ML categories

C. User-Centric Approaches

A user-centric approach is one where the network design and strategies will be developed with the end-user as the point of focus, and network solutions will be tailored per the needs and feedback of the end-users. Network operators have witnessed a gradual decline in the average revenue per user (ARPU) over the years and the end-users have got accustomed to the flat rate tariffs. The network operators are expected to deliver significantly increased operational performance (e.g. increased spectral efficiency, higher data rates, low latency), as well as superior user experience (approaching that of wireline, fixed networks but offering full mobility and coverage) and the need to deploy massive deployments of Internet of Things networks, while still offering acceptable levels of energy consumption, equipment cost and network deployment and operation cost [11]. Therefore, it is extremely significant that 5G developments are based on use-cases that are more user-centric opening up new revenue streams for network operators. A user-centric approach is at the heart of 5G, where connectivity, computing, and content all come together, close to the user, be it a human, a vehicle, a machine, or a "thing," where users will no longer be mere end-points, rather they will be integral parts of the network, creating edgeless connectivity [12]. There are multiple network-centric approaches taken in the state-of-the-art literature, but user-centric approaches are still rare [13] and need more attention as 5G mobile networks evolve to new architectures and modes that will include densely deployed network nodes, cell-less architectures, dynamic coordinated multi-point techniques, enhanced mobile broadband, Internet of Things, ultra-reliable low latency connections, vehicle-to-X communication, multi-access edge computing, and spatial computing (e.g., virtual and augmented reality) as shown in Fig. 5.

Fig. 5 5G usage scenarios [11]

III. Applications and Methodologies

User-centric, ML-based SON solutions would have the capability to support 5G requirements and features such as network densification and heterogeneity, dynamic network optimization and troubleshooting, organization of 5G network topology that would involve end-to-end network slicing and cell-less architectures, flexible spectrum management and resource allocation based on ML predictions, and security management by self-protection against digital threats. 5G aims to go beyond the needs of what humans can currently perceive and empower new types of services and user experiences with lower latency, cost, and energy consumptions that cannot be achieved by conventional non-user centric approaches [12]. Given the importance of SON, ML, and user-centric approaches in developing the next generation wireless communications eco-system, it is crucial that future research directions emphasize on exploring user-centric approaches to realize next generation self-organizing networks using machine learning. Following are some recent research initiatives of our team in this direction that focus on user-centric, ML-based solutions for anomaly detection and load balancing and optimization in 5G SON networks.

A. QoE driven Anomaly Detection in SON

Anomaly detection in SON involves detection of dysfunctional network nodes to ensure fast and seamless recovery. The state-of-the-art approaches for detecting failing network nodes include alarm monitoring, routine checks of configuration parameters and counters, collection of traffic data to profile the behavior of the network, RSRP and SINR measurements, incoming handover measurements from neighboring cells, keeping track of customer complaints, and analyzing other KPIs to detect any degradation. Although the above-mentioned approaches are useful techniques for anomaly detection, they have a few limitations. Alarm monitoring and configuration parameter checks may not be able to detect sleeping cells. Drive test data, RSRP, and SINR measurements can get affected by poor RF conditions due to temporary reasons like ducting or external interference that may not be due to faulty network nodes. The number of handover attempts made could be less or more affecting the results of the detection method based on handover measurements. Customer complaints may provide limited information. KPI analysis is crucial in anomaly detection and needs more user-centric KPI's such as Quality of Experience (QoE) to evaluate and detect dysfunctional nodes.

The use of QoE-driven anomaly detection for SON using ML methodology to learn and predict the QoE has been proposed [14-15] where the QoE scores are predicted for all the end-users of a network and these scores are further used to detect dysfunctional network nodes in that network. This method is evaluated using the LTE-EPC network simulator of *ns-3* [16] that creates an end-to-end network scenario generating representative data that is fed to a supervised ML program whose labels are generated using a parametric QoE model for FTP services given the type of application run in the *ns-3* simulation is FTP. The ML model learns how to predict QoE scores (range: 0 to 5) of all the users in the network after being trained by an ML algorithm. If the maximum number of users connected to a network node have poor QoE scores (range: 0 to 1), then such a node is identified as a dysfunctional node.

The performance of three different ML algorithms, *support vector machine*, *k-nearest neighbors* and an optimized version of *decision tree* was investigated, whose accuracy results for QoE prediction for the given dataset are summarized in Fig. 6. Subsequent to QoE prediction, the QoE scores obtained using each of the three ML algorithms could successfully detect dysfunctional network nodes with near certainty.

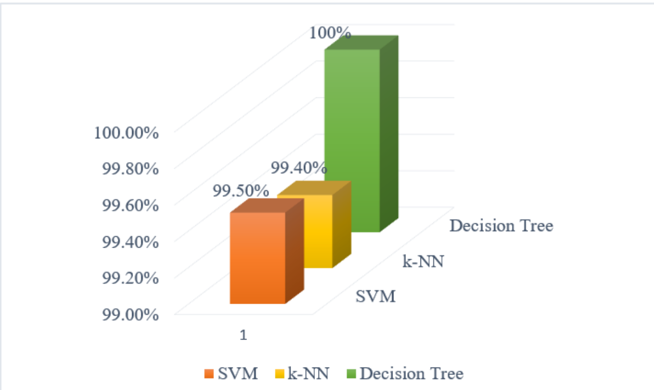

Fig. 6. ML-based performance comparison for QoE prediction

Additionally, the performance and scalability of the ML algorithms are further evaluated by creating different network scenarios by embedding three different propagation path loss models (Friis propagation, Log-Distance propagation, and Cost 231 propagation [16]) in the *ns-3* simulation. The accuracy results for QoE predictions are shown in the Fig. 7.

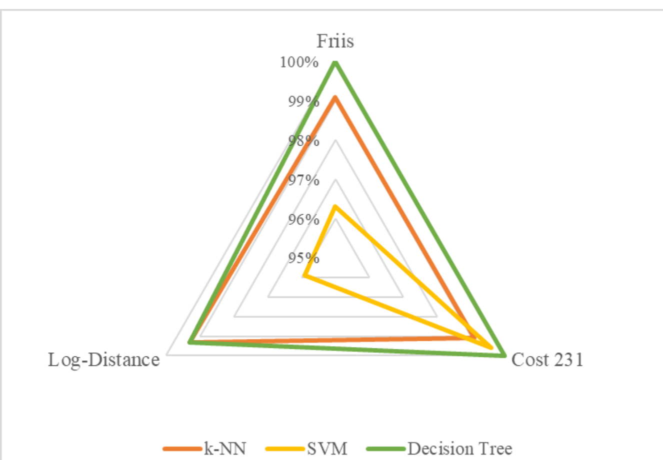

Fig 7. QoE prediction accuracy with different propagation models

This ML-based QoE-driven anomaly detection method for SON is a resource-efficient method that has the potential to support the future green communications network design as it would be able to distinguish between dysfunctional network nodes from partially switched off nodes in energy saving mode and should be further enhanced to support a wide range of applications. Combining this method with the existing techniques of KPI analysis for anomaly detection can provide highly robust and reliable methods for anomaly detection supporting the ultra-dense 5G networks with the expected benefits of an improved understanding of end-users' perspective, and resource-efficiency by effectively prioritizing recovery operations supporting high-density network.

B. Optimal-Capacity Shortest Path Routing for Mobility Load Balancing and Optimization in SON

Mobility Load Balancing (MLB) in SON is critical to efficiently deliver the required user capacity over the available spectrum resources. MLB is a function where cells suffering congestion can transfer the load to other cells that have spare resources [6]. The state-of the-art approaches for load balancing and optimization include strategies such as a channel borrowing mechanism [17] where a cell can borrow a fixed number of channels from adjacent cells, handover-based approaches where UEs are handed off between serving and neighboring cells [18-20], and remote electrical tilt [RET] optimization [21]. While these are some very useful techniques that can be applied for load balancing and capacity optimization, there are some limitations and challenges. If the adjacent cells in the channel borrowing mechanism do not have enough resources to share, it can lead to even more congestion. Handover parameter changes to offload traffic from the congested cell can lead to instability and handover drops due to the ping-pong effect. RET controllers may have a limited range to perform tilt adjustments. If a RET is broken, the electrical tilt changes cannot be made until the RET is fixed which can take several days, especially in the cases where antennas are mounted on the top of a tower. These network-centric approaches can be further enhanced by implementing a user-centric approach, where the shortest path with optimal capacity available is pre-determined and recommended to the end-user given its source and destination.

A user-centric methodology for MLB and capacity optimization in SON networks called User Specific, Optimal Capacity and Shortest Path (US-OCSP) is proposed [22] that performs user-specific dynamic routing to find the shortest path with optimal capacity, given source and destination. The primary metrics and tools implemented in this methodology include determination of available nodal capacity per gNodeB/eNodeB by calculating Physical Resource Blocks (PRB) utilization followed by determination of the shortest path via implementation of *Q-learning*, an ML reinforcement learning technique. The methodology was tested in a simulated environment where the optimal-capacity shortest path was recommended in an *ns-3* based LTE-EPC network scenario created where PRB utilization was calculated for every network node to identify which of the network nodes are congested vs. the ones that have available capacity. This information was then fed to the ML program based on *Q-learning*. The recommended path given by the methodology was the optimum path discarding any path that goes via congested network nodes and all other paths that may be longer than the recommended path. This way, the network can be operated in a more efficient manner by reducing congestion in the network and meeting the capacity requirements of the end-users.

US-OCSP can create a win-win situation for end-users as well as the network, since the end-users will be served with good capacity throughout the route and the network will be less congested, as the users' path will avoid already or almost congested network nodes. An in-built application for navigation based on this methodology can play a significant role in future networks where a network layout provided by US-OCSP can be overlapped with topography recommending the shortest path with optimal capacity to end-users.

IV. Conclusions

This paper makes the case that a paradigm shift in the deployment, performance, and optimization of wireless communications networks by the integration of user-centric approaches, SON, and ML is required in order to meet the complex requirements of the next generation 5G wireless communications networks. The paper also proposed research methodologies for SON functions to enhance anomaly detection, load balancing and capacity optimization. ML-based user-centric approaches for next generation SON networks are quite promising and are expected to be further explored to realize the vision of creating and developing a seamlessly connected eco-system with superior user experience.

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