Self-Healing in Emerging Cellular Networks: Review, Challenges, and Research Directions

Ahmad Asghar, *Student Member, IEEE*, Hasan Farooq, *Student Member, IEEE*, and Ali Imran, *Member, IEEE*

***Abstract*—Mobile cellular network operators spend nearly a quarter of their revenue on network management and maintenance. Incidentally, a significant proportion of that budget is spent on resolving outages that degrade or disrupt cellular services. Historically, operators mainly rely on human expertise to identify, diagnose, and resolve such outages. However, with growing cell density and diversifying cell types, this approach is becoming less and less viable, both technically and financially. To cope with this problem, research on self-healing solutions has gained significant momentum in recent years. Self-healing solutions either assist in resolving these outages or carry out the task autonomously without human intervention, thus reducing costs while improving mobile cellular network reliability. However, despite their growing popularity, to this date no survey has been undertaken for self-healing solutions in mobile cellular networks. This paper aims to bridge this gap by providing a comprehensive survey of self-healing solutions proposed in the domain of mobile cellular networks, along with an analysis of the techniques and methodologies employed in those solutions. This paper begins by providing a quantitative analysis to highlight why in emerging mobile cellular network self-healing will become a necessity instead of a luxury. Building on this motivation, this paper provides a review and taxonomy of existing literature on self-healing. Challenges and prospective research directions for developing self-healing solutions for emerging and future mobile cellular networks are also discussed in detail. Particularly, we identify that the most demanding challenges from self-healing perspective are the difficulty of meeting 5G low latency and the high quality of experience requirement.**

***Index Terms*—Self organizing network, self healing, 5G, future mobile cellular networks.**

I. Introduction

At a time when mobile cellular network operators are competing for customers demanding higher data rates and greater data capacity at lower costs, keeping revenue margins up is proving increasingly difficult. Furthermore, the rising network operating expenses add to the stress on network operator revenues. Mobile cellular network expenditures are divided into two primary categories, i.e., capital expenditure which is spent on acquiring and updating network entities, and operational expenditure which is spent on managing and maintaining existing network resources. Based on industry estimates, mobile cellular network operators spend between 23% and 26% of their total revenue on mobile cellular network operation [1], [2]. A breakdown of operational expenses reveals that a significant proportion of it is spent on managing mobile cellular network outages and performance degradations. Such service interruptions require human intervention and may sometimes go unnoticed leading to poor customer experience, and eventually leading to high customer churn. According to one survey estimate [3], mobile cellular network operators worldwide spent nearly $20 Billion in the year 2015 to counter issues caused by network outages and service degradations which accounts for nearly 1.7% of total revenue and nearly 7% of total operational expenses.

The inevitable introduction of 5G technologies for mobile cellular networks brings with it a key challenge of increased load on network resources in terms of network performance management. The primary solution to this challenge proposed by researchers and the mobile cellular network standardization body, 3GPP, is the deployment of Self-Organizing Network (SON) solutions to automate processes that would otherwise require skilled human input. SON are broken down into three key areas: Self-configuration, Self-optimization [4] and Self-healing [5]. Self-configuration is dedicated to solutions that autonomously configure mobile cellular network nodes for plug and play. Self-optimization is related to solutions that target mobile cellular network performance optimization based on operator specifications. Self-healing is focused on solutions that identify performance issues in the mobile cellular network such as cell outages and key performance indicator (KPI) degradations. On top of the three components of SON mentioned above, Self-coordination was also introduced by the 3GPP as part of Release 10 specifications for 4th Generation mobile cellular networks [6] to address the potential conflicts arising between SON solutions that would lead to KPI degradations.

To understand how the four SON components are related, a generalized SON framework is given in Fig. 1. While Self-configuration and Self-optimization represent more implicit areas of operational expenditure reduction, Self-healing provides the clearest quantifiable path towards operational expenditure reduction by minimizing the impact of mobile cellular network outages [3]. These include outages caused due to failure of physical or soft components of the network entities, rendering them non-functional and causing complete or *full outage*, or significant service degradations leading to *partial outage* that may not necessarily generate any system level alarms.

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The authors are with the Department of Electrical and Computer Engineering, University of Oklahoma, Tulsa, OK 74135 USA (e-mail: ahmad.asghar@ou.edu; hasan.farooq@ou.edu; ali.imran@ou.edu).

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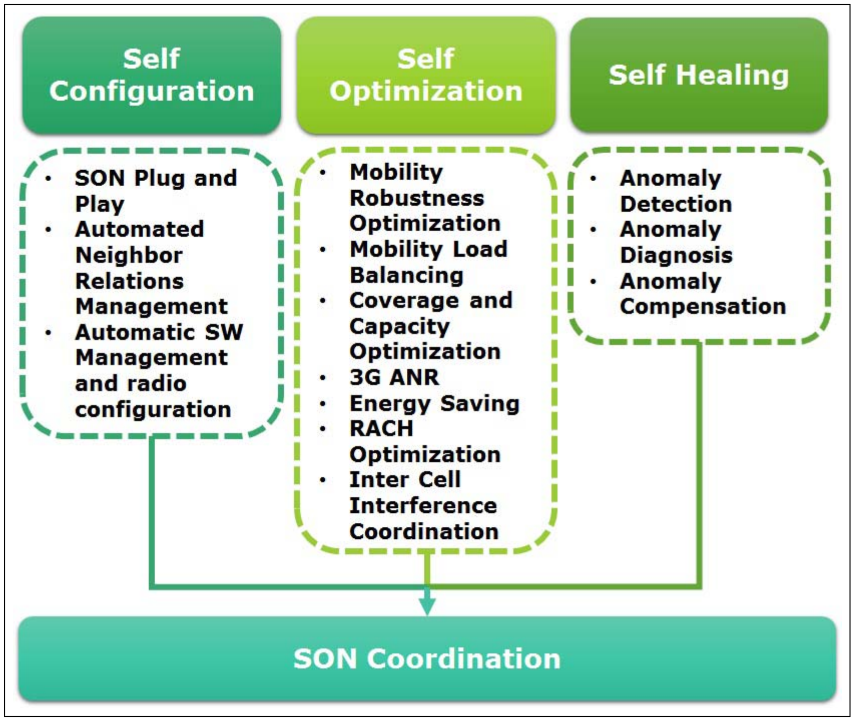

Fig. 1. Self-Organizing Network Framework for Cellular Networks.

An overview of the key research drivers for Self-healing are presented as follows.

A. Reduction of Network Operating Expenses

As mentioned already, mobile cellular network operators can spend as much as 1.7% of the total revenue on fixing issues due to network outages. Network outages have the potential to disrupt service to millions of subscribers, as recently observed in case studies [7] and [8]. Overwhelming reliance on manual outage detection, diagnosis and compensation not only slows down the recovery process, but is also more expensive than autonomous solutions. Thus, autonomous Self-healing solutions are one of the most inviting areas for mobile cellular network operators to cut down their operational costs for managing network outages.

B. Increase in Network Data

The limited capability of human experts to absorb large amounts of network information at the same time and coming to conclusions about the existence of outages or KPI degradations in the mobile cellular network means that as the number of entities in the network grows, the number of experts to monitor the network would grow proportionally. This will put further strain on the operators' already inflated operating expenses. Self-healing can reduce the load on human experts by providing solutions for the detection of service degradations and disruptions.

C. Complexity of Network Architecture

With small cells expected to make up a significant part of future cellular network infrastructure [9], solutions specifically focusing on them must be developed. This concern is further fueled by the fact that small cells are subject to sparse reporting due to the low percentage of users associated with them and a more packed mobile cellular network topology in terms of inter-node distances. This makes it more difficult to identify service disruptions at small cells through traditional means.

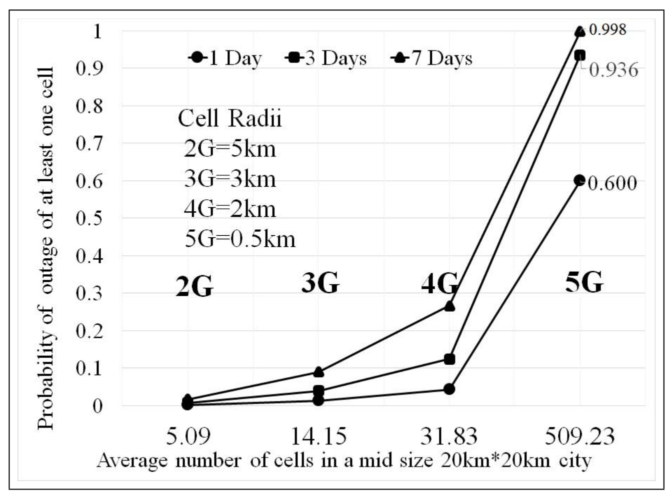

Fig. 2. Outage Probability of One Cell with Increase in Cell Density.

D. Increase in Network Density

The increasing number of radio nodes in the 5G mobile cellular network can result in an increase in node failures [10]. This is demonstrated in Fig. 2, which shows the outage probability of a cell as mobile cellular network density increases, obtained using a Poisson distribution-based method for estimating node failures derived from [10]. Fig. 2 shows the probability of a single node failure in one day (lower line chart), in three days (middle line chart), and seven days (top line chart). We can see that probability of node failures is relatively low in a low density network such as a 2nd Generation mobile cellular network. However, as the network density increases, the probability of node failure increases, so much so that on any given day the probability of node failure could be anywhere between 60% and 99.8%.

Hardware failures are already a significant area of concern for network operators. Turner *et al.* [11] present an analysis of customer complaints over a period of nine months in an enterprise network. The authors conclude that nearly 39% of all customer complaints are due to hardware failures. Therefore, it is safe to assume that if the number of network nodes is increased significantly, the corresponding probability of hardware failure will also increase. In wake of increasing number of nodes per unit area, dealing with such high rates of node failures will be very difficult if mobile cellular network operators continue the practice of manual outage management. In short, Self-healing solutions will be less of a luxury and more of a necessity in future 5G networks.

E. Increase in Network Parameters

With the introduction of 5G services and the associated technologies discussed above, the number of configuration and optimization parameters are expected to grow significantly [12]. The increasing number of network control parameters and entities can raise the probability of parameter misconfiguration significantly. The frequency and impact of parametric misconfiguration have been noted by Yin *et al.* [13]. Based on an analysis of a large number of customer complaints, the authors conclude that nearly 31% of high-severity customer complaints are due to misconfigured parameters. Out of this, 85.5% issues were due to mistakes in parameter configuration and in only 15% of the cases does a misconfiguration lead to an actual alarm. Otherwise, the misconfiguration is only identified when a customer complains about service outage. Though the actual count of customer complaints is not shared in [13], if we assume that there are 2000 parameters in the network and 10,000 complaints are received over a period of two years, the probability of a parametric misconfiguration every 100 days is 1.5%

A quantitative analysis of parameter misconfiguration in 5G mobile cellular networks is presented in Fig. 3 which shows the probability of misconfiguration of one parameter per cell every 100 days as the total number of configurable parameters per cell increases. The parameter misconfiguration probability is also derived using the Poisson distribution-based method of failure estimation presented in [10]. In Fig. 3, three different probabilities, 0.01% (bottom line chart), 0.05% (middle line chart), and 0.1% (top line chart), of parametric misconfiguration per 100 days are assumed. These probabilities are well below the parameter misconfiguration probability estimated from [13]. Furthermore, since the data in [13] comes from an analysis of customer complaints, it is safe to argue that parametric misconfiguration does lead to a disruption of service. From Fig. 3 it is clear that parametric misconfiguration will become a major concern for mobile network operators in 5G networks.

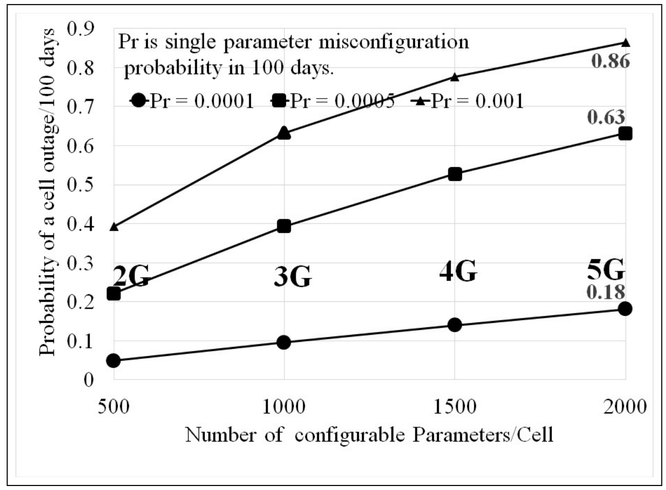

Fig. 3. Probability of Single Parameter Misconfiguration with Increase in Configurable Parameters.

F. Increased Focus on (Quality of Experience) QoE Calls for Increased Focus on Self-Healing

Very high user QoE requirements in 5G mobile cellular networks mean near ubiquitous spatial and temporal network availability for various 5G use cases. State-of-the-art network availability estimation process depends on classic drive test-based methods. However, the process is time and resource consuming while lacking comprehensiveness due to inaccessibility of a major portion of the network, i.e., all areas other than paved roads. Therefore, better methods are needed for network availability estimation and outage detection for 5G networks.

Additionally, low latency requirements for several 5G use cases mean that classic methods of manual outage diagnosis and manual outage compensation will not suffice. To address this challenge autonomous mechanisms to compensate outages quickly and seamlessly need to be developed.

G. Past Work and Contributions

In terms of mobile cellular networks, SON and Self-optimization have received significant attention, with comprehensive studies published highlighting the contributions in both areas. Aliu *et al.* [14] present an overview of the recent studies carried out under the scope of SON for cellular networks, while Peng *et al.* [15] have presented an overview of state-of-the-art in Self-configuration and Self-optimization in mobile cellular networks.

Another area of automation in wireless networks are cognitive radio technologies. Cognitive radio technologies refer to dynamic spectrum access techniques that enable need-based bandwidth allocation to mobile users via heterogeneous physical layer resource usage [16]. A survey of cognitive radio technologies has been presented by Akyildiz *et al.* [17]. Discussion on state-of-the-art and future challenges of cognitive radio technologies has been presented by Akyildiz *et al.* [18] while Akhtar *et al.* [19] have discussed the exploitation of unlicensed and unused spectral resources for dynamic spectrum allocation. Furthermore, Zhang *et al.* [20] have presented a survey of the research studies on Self -optimization for cognitive radio technologies.

In terms of Self-healing, a survey of applications from natural systems to software engineering has been presented in [21] where analogies between self-rectifying software systems and natural systems have been studied. Psaier and Dustdar [22] discuss the applications of Self-healing in autonomous systems pertaining to the fields of information technology and communications. Furthermore, Paradis and Han [23] have surveyed studies on Self-healing capabilities in wireless sensor networks.

Self-healing techniques in mobile cellular networks have briefly been discussed in [14] in the larger context of SON. The authors have presented description of Self-healing in mobile cellular networks accompanied by a review of four outstanding works in the area. Since the publication of [14], research on Self-healing techniques for mobile cellular networks has grown significantly and, to the best of our knowledge, this study is the first attempt to provide a consolidated review of these developments. With the efforts to propose and standardize SON solutions for 5G technologies reaching their climax, the need for a comprehensive study on Self-healing highlighting the efforts of research groups, equipment manufacturers and standardization bodies could not be higher. Furthermore, this study aims to go well beyond the limited contributions of [14] towards surveying Self-healing techniques for mobile cellular networks by breaking down the studies in terms of the type of outages, the measurements and methodologies used, and their results.

The primary contributions of this paper are summarized as follows:

- This paper identifies the need for Self-healing solutions in the wake of 5G mobile cellular networks and explains why Self-healing functionality will not remain a luxury but will become a necessity in 5G and beyond.
- The paper provides a brief introduction and tutorial on Self-healing and provides comprehensive review of major contributions from individual projects and collective standardization efforts undertaken so far with respect to Self-healing for mobile cellular networks.
- Following the intrinsic flow of Self-healing in nature and in practical applications, the paper organizes the literature on Self-healing into the three primary areas of Self-healing, i.e., Detection, Diagnosis and Compensation.
- The paper further categorizes the reviewed studies on Self-healing in terms of the network topology, performance metrics, control mechanisms, and methodologies used for detection, diagnosis and compensation of full and partial outages in a mobile cellular network. This allows easy understanding and comparison of studies within each particular area of Self-healing.
- The paper presents comprehensive discussion of challenges in Self-healing and identifies the research directions therein. Notably, it discusses the two primary types of challenges faced by existing Self-healing solutions to adapt to 5G network requirements: 1) challenges that stem from ambitious QoE and low latency requirements in 5G, and 2) challenges that arise from the idiosyncrasies of anticipated 5G technologies, i.e., ultra-dense deployments, millimeter wave cells (in which outage is the norm, not anomaly) and increased rate of emergence of sudden traffic hotspots due to higher data rate per users leading to sudden change in KPIs (partial outage).
- In order to enable the advancement of research in Self-healing solutions for future 5G mobile cellular networks, we also discuss possible solution methodologies for each of the aforementioned challenges.

The organization of this paper is as follows: Section II presents a brief tutorial on SON and Self-healing including possible taxonomies. Section III presents key definitions and terminologies used in the development of Self-healing solutions for mobile cellular networks. Based on the generally accepted trifurcation of Self-healing in literature specific to mobile cellular networks, Sections IV–VI provide a survey of Detection, Diagnosis and Compensation techniques for outages occurring in mobile cellular networks respectively. In Section VII, we identify key challenges faced by Self-healing paradigm to become adaptable by 5G and beyond, along with prospects for future work in the field of Self-healing for mobile cellular networks. Section VIII concludes the key aspects of this survey. For ease of reference, key acronyms are given in Table I.

TABLE I
KEY ACRONYM DEFINITIONS

Acronym	Definition
SON	Self-Organizing Network
KPI	Key Performance Indicator
QoE	Quality of Experience
SINR	Signal to Interference and Noise Ratio
LOF	Local Outlier Factor
kNN	k-Nearest Neighbors
(OC)SVM	(One Class) Support Vector Machines
SOM	Self-Organizing Maps
NBC	Naïve Bayes Classifier
HC	Healing Channel
UAV	Unmanned Aerial Vehicles

II. SELF-HEALING: BACKGROUND STUDY

A. *Self-Organizing Networks in Cellular Mobile Networks*

SON functions gained popularity with the introduction of 4th Generation cellular networks, primarily due to the increased network complexity. The efficacy of a SON function depends on four key design components [24]: *Autonomy:* SON functions must be independent of human input, *Scalability:* Any SON functions deployed in the mobile cellular network must be scalable in terms of both time and space, *Adaptability:*

The functions must be able to adapt to outside influences and internal failures. Additionally, it has been proposed that future SON networks must be *intelligent* [12], i.e., they must be able to learn from the information generated by the users and mobile cellular network entities to become completely independent in terms of adapting network parameters based on the primary goals of the operator.

As described previously, SON functions for cellular networks can be broadly classified into three main categories, i.e., Self-configuration, Self-optimization and Self-healing, with Self-coordination being introduced to manage SON function interactions. Since SON functions in general [14] and Self-optimization in particular [20] have already been the subject of comprehensive studies, this study is aimed at covering the work done in the domain of Self-healing for mobile cellular networks.

B. Self-Healing in Mobile Cellular Networks

Traditionally, mobile cellular network operators employ human experts to detect, diagnose and recover the network from any faults and outages in the network. As per the standard fault management framework defined by the 3GPP [25], faults and outages include issues such as hardware failures of mobile cellular network nodes, software failure issues at the nodes, failures of functional resources in which case no hardware component is responsible for the fault, loss of node functionality due to system overloading, and communication failure between two nodes due to internal or external influence. In such cases, the node will become completely dysfunctional leading to a *full outage*. As per 3GPP specifications, faults must be accompanied by the generation of an alarm that identifies the node and the type of failure that has occurred. The alarm may contain additional information to aid the recovery of the system but that is dependent on the equipment manufacturer.

Conversely, many service affecting issues in mobile cellular networks do not generate alarms or may not specifically be classified as faults or failures. Such issues are labeled *partial outages*. One such example is the degradation of a performance metric due to sudden changes in the mobile cellular network environment. Partial outages may include service degradations due to environmental effects, sudden variations in traffic, or the presence of man-made interference sources that hinder normal operation of the network. Thus, mobile cellular network operators are dependent on human experts to monitor the network data to identify any such anomalies and to execute recovery actions to counter them. However, with the advent of 4G and the growth in network sizes and subscribers, network operators can no longer rely purely on human experts to sift through the vast amounts of network performance data generated consequently in search of anomalies.

1) Research in Self-Healing: Self-healing specifically for cellular networks has been studied as part of several research projects focusing on SON for cellular networks including the EUREKA Gandalf project [26] which explored the parametric interactions in 2G, 2.5G and 3G networks with the environment and studied the impact of automation in wireless networks, especially UMTS and Wi-Fi networks. The key deliverable of the project was Bayesian Networks based fault identification and diagnosis toolkit.

Similarly, the SOCRATES project [27] was aimed at investigating the impact of automation particularly in LTE networks, while the QSON project [28] investigated SON solutions primarily for Self-optimization and Self-healing along with preliminary analysis of the interactions of parameters and metrics as part of SON coordination. The project investigated new techniques, especially the exploitation of big data analytics [12], to empower existing SON solutions. Recently, the SEMAFOUR project [29] has been launched which aims to develop a unified self-management system for heterogeneous radio access networks, comprising multiple radio access technologies and SON solutions including solutions for network anomaly detection, diagnosis and compensation for 4G standards and possible future 5G cellular networks.

2) Self-Healing Framework for Cellular Networks: As the number of physical entities in a network increases, the probability of network outages, both full and partial, increases proportionally as demonstrated in Figs. 2 and 3. In order to respond to these network outages, typical Self-healing solutions employ a 3-stage framework. The first stage is detecting network outages for which *outage detection* algorithms are deployed. For effective Self-healing, the outage detection solution must be able to detect both full and partial outages. In case a network outage is detected, the outage detection solution flags the effected network node for further actions, depending on the outage type. For example, in case a cell experiences hardware failure and is no longer able to send and receive data, it will be flagged for Self-healing.

Once the outage has been detected, diagnostic algorithms will execute routines to identify the exact cause of network outage. For the sample case of hardware failure, the detection algorithm will examine alarms and fault codes to pinpoint the hardware component whose failure led to the outage. This information will then be relayed to the Network Controller which will either command field teams to replace the failed component or activate the redundancy elements to take over operations of failed entity. Conversely, if the outage is partial, the diagnosis algorithm will break down the degraded KPI or KPIs in order to identify the reason for the outage.

Upon completion of outage diagnosis, the information is passed along to the final stage of the Self-healing function, i.e., outage compensation. In the outage compensation stage, the Self-healing function determines the impact of outage on neighboring entities and the subscribers which is then used to execute changes to mitigate the outage. For example, in the case of hardware failure, outage compensation solution will identify the coverage hole created as a result of the outage and execute changes in neighboring cells to provide temporary coverage to affected subscribers. Alternatively, in the case of partial outage, the outage compensation solution may execute emergency parameter changes at either the affected cell or its neighbors or both to recover the degraded KPI or KPIs. The complete Self-healing framework, along with relevant studies is demonstrated in Fig. 4. A taxonomy of studies based on these components is presented in Fig. 5.

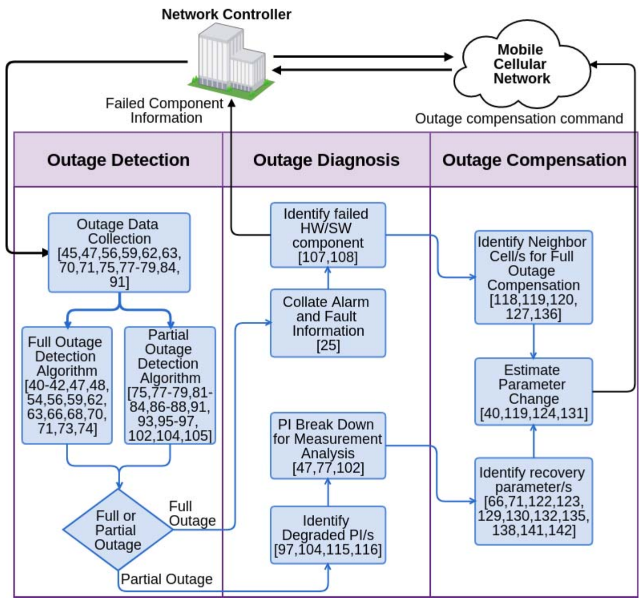

Fig. 4. Self-Healing Framework.

III. Key Components of Self-Healing Techniques for Mobile Cellular Networks

To develop a comprehensive review of the work pertaining to Self-Healing for mobile cellular networks, we present a collection of key definitions that will enable the reader to quickly comprehend the nuances of the reviewed studies. The five core components that constitute the logical structure of these studies are: 1) methodology, 2) network topology, 3) performance metrics, 4) control mechanism, and 5) direction of control.

A. Methodology

Each study presenting a solution for detection, diagnosis or compensation of outages follows an underlying methodology. These can be split into three broad categories: 1) Heuristic, 2) Analytical and 3) Learning-based. *Heuristic* solutions follow a set of pre-defined rules and are built upon intuition or prior knowledge gained from existing literature or experience. Two heuristic solutions commonly found in literature are rule-based algorithms, which follow a set of if-else rules, and frameworks, which mostly consist of guidelines. *Analytical* solutions break down a given problem into its mathematical components which are then solved to achieve an optimal or close to optimal solutions. Analytical solution methodologies include techniques such as convex optimization [30], non-convex optimization such as pattern search [31], genetic algorithms [32], simulated annealing [33] etc., multi-objective optimization [30], and game theory [34]. *Learning-based* solutions are built on machine learning techniques popularized by the field of computer science. These algorithms rely overwhelmingly on user and network data and very little on expert knowledge [35]. Machine learning techniques are generally split into three overarching techniques [36], [37], i.e., supervised, unsupervised and reinforcement learning.

B. Network Topology

The term network topology is defined as the architecture or layout of the network in terms of cell deployments. More specifically, network topology is used to describe the tiered structure of the network. There are two main types of network topologies used in literature. Homogeneous networks consist of only one tier of cells. These cells may be only macro cells with large coverage areas or only small cells which have lower power, and consequently lower coverage. Conversely, a combination of macro and small cells forming a multi-tier cellular network is referred to as a heterogeneous network or HetNet. While most studies on legacy mobile cellular networks employ homogeneous network topology as the baseline, HetNets are quickly gaining popularity due to their flexibility and their potential to achieve the goals set out for 5G cellular networks [38].

C. Performance Metrics

Performance metrics are the benchmark measurements used to evaluate network performance and can be obtained from network entities and user-generated reports. The solutions and algorithms presented in any study rely heavily on the choice of performance metrics employed in the study to construct and evaluate them. The performance metrics most relevant to studies on Self-healing can be classified under the umbrella term *network health*.

Network health is a broad term used to describe the performance of the network in terms of universally accepted KPIs such as Accessibility, Retainability and Mobility [39]. *Accessibility* is the ability of subscribers to access the network resources for data transmission and includes KPIs such as attach success rate, radio resource control setup success rate, connection setup success rate, random access success rate etc. *Retainability* is the ability of the network to carry a data session to its completion without drop and is characterized by the session drop rate KPI. *Mobility* is the ability of the network to allow successful transition of a subscriber from one cell to another with minimal impact on services and is generally represented by handover attempt, success and failure rate KPIs.

Additionally, measurements signifying network coverage including reference signal received power (RSRP), and network quality including spectral efficiency, signal-to-interference and noise ratio (SINR), reference signal received quality (RSRQ), network and user data throughputs, channel quality indicators and data latency are also often employed in the design and analysis of Self-healing solutions.

D. Control Mechanism

Control mechanism is defined as the method of controlling SON solution functionality and can be categorized by the following methods: 1) Centralized, 2) Distributed, and 3) Hybrid. *Centralized* control implies that the SON functions are controlled from one central controller connected to every node in the network, whereas *distributed* control implies that the control of SON functions resides within the network nodes. *Hybrid* control is a combination of central and distributed control and implies that while some SON functions may reside

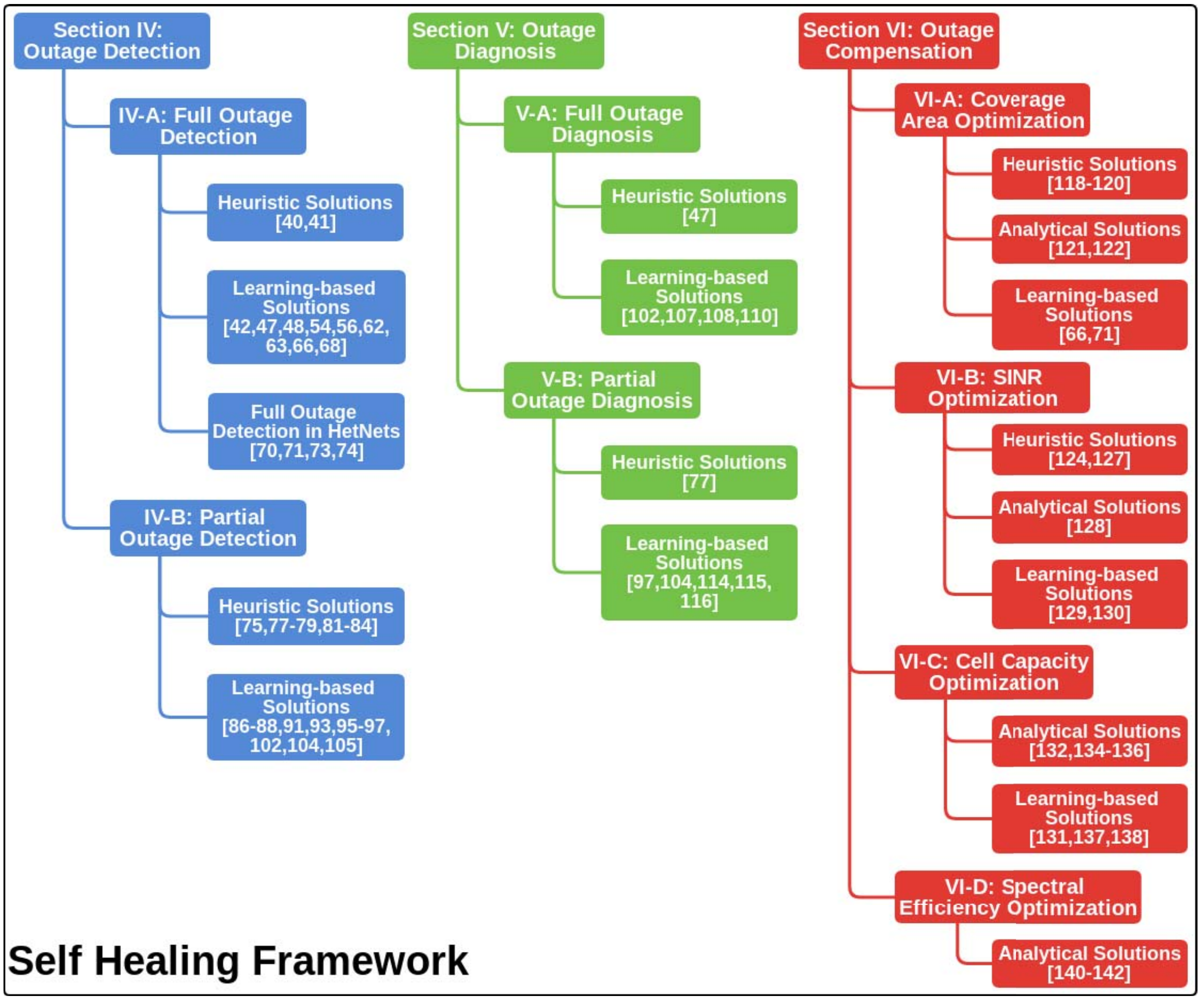

Fig. 5. Proposed Taxonomy.

inside a centralized SON controller, other less computationally heavy functions which do not directly impact neighboring nodes, can be distributed to the nodes.

E. Direction of Control

Direction of control defines whether a SON function is designed to optimize the node-to-user link, user-to-node link, or both. Solutions designed to optimize the node-to-user link are *downlink* controlled, whereas the solutions optimizing the user-to-node link are *uplink* controlled. Some solutions optimize both downlink and uplink and thus, offer *bidirectional* control of network performance.

IV. Outage Detection in Cellular Mobile Networks

While the standardized Self-healing framework [5] does present a roadmap to a fully integrated Self-healing framework, the precise inner workings of each component have been deliberately left open-ended. This has allowed researchers and network equipment manufacturers to come up with proprietary algorithms to suit the needs of evolving mobile cellular networks. In this and the following sections, we describe the research done in each of the Self-healing framework components, beginning with a review of outage detection techniques. The studies in this section are ordered based on the type of outage and methodology employed within.

A. Full Outage Detection in Mobile Cellular Networks

The following subsections describe techniques and methodologies proposed for full outage detection in mobile cellular networks. The studies included in this section have been summarized in Table II in terms of techniques, network architectures, measurements and tools used within them.

1) Heuristic Solutions for Full Outage Detection: Heuristic algorithms and frameworks for cell outage detection are heavily reliant on pre-existing knowledge of domain experts which makes them extremely useful for deployment in existing mobile cellular networks. One such framework has been proposed by Amirijoo *et al.* [40] which employs rule-based decision tree algorithm for full outage detection in mobile cellular networks. The framework derives its rules from expert knowledge to create full outage detection trigger thresholds for performance metrics such as cell load, radio link failures, handover failures, user throughputs and cell coverage. A more comprehensive approach to rule-based outage detection has

TABLE II
QUALITATIVE COMPARISON OF CELL OUTAGE DETECTION ALGORITHMS

Solution	Reference	Methodology	Sub-Method	Network Topology	Performance Metrics	Control Mechanism	Direction of Control
Full Outage Detection	[40]	Heuristic	Rule-Based	Homogeneous	Retainability, Mobility, Quality	Centralized	DL
	[41]				Accessbility, Quality		
	[42]	Learning Based	Supervised Learning		Coverage		
	[45]				Retainability, Mobility, Quality		UL/DL
	[73]			HetNet	Coverage	Hybrid	DL
	[48]		Unsupervised Learning	Homogeneous	Accessibility, Mobility, Coverage	Centralized	
	[56]				Coverage		
	[59,62,63,66]				Mobility, Coverage		
	[68]				Retainability, Mobility		
	[54]				Coverage	Distributed	
	[71]			HetNet	Coverage	Centralized	
	[74]				Retainability		
	[70]				Coverage	Hybrid	

been proposed by Liao *et al.* [41] that uses variations in user performance metric distributions to detect outages. The authors propose the construction of a weighted cost function composed of channel quality indicator distribution, the time correlation of channel quality differential and radio resource connection re-establishment requests. The cost function is treated as a hypothesis of normal cell performance. A cell is considered in outage if its neighboring cells fail this hypothesis, i.e., their targeted KPIs deviate from normal. The authors demonstrate that, using measurements from cell edge users, the proposed algorithm can detect neighbor cell outages almost instantaneously.

2) Learning-Based Solutions for Full Outage Detection: Beyond the heuristic methodologies of identifying outages in the network, machine learning based algorithms have been the prevailing method for full outage detection in research. Most of the studies on full outage detection that employ learning based algorithms can be split into two categories, i.e., supervised learning techniques for full outage detection solutions and unsupervised learning techniques for full outage detection.

a) Supervised learning techniques for full outage detection: Supervised algorithms are a popular choice in terms of full outage detection due to their reliance on pre-classified data. In the study by Mueller *et al.* [42] have compared the performance of a rule-based heuristic algorithm against a decision tree algorithm [43] and a linear discriminant binary classification function [44] to identify complete cell outages. The algorithms use user reports containing downlink signal power measurements to detect when a cell stops featuring in neighbor cell lists due to outage. The results show that the expert system is faster but less successful in detecting neighbor cell outages while the linear discriminant binary classification function performs the best in terms of true positive detection rate.

Another supervised learning approach for full outage detection is developing cell profiles for outage detection. Alias *et al.* [45] have proposed to develop performance profiles of cells in mobile cellular networks using hidden Markov chains [46] which track the state progression of network nodes that undergo outages. The proposed framework requires execution of controlled outages to build state profiles using signal quality and signal strength measurements of the outage affected cell and its neighbors. These measurements are then used to identify cell performance in real-time to predict if a cell has experienced an outage. The results show that the proposed approach can reach an accuracy of up to 90% in low fading environments.

Since the idea of executing controlled outages to build cell profiles may be prohibitive for live mobile cellular networks, Szilágyi and Novaczki [47] have proposed to construct default activity profiles of cells using simulated network data to detect when a cell faces an outage. The proposed algorithm uses level functions which continuously monitor downlink signal metrics such as channel quality, call drop rate and handover timing advance to detect when a cell falls below the acceptable threshold set by human experts. The authors have demonstrated that the proposed approach can act in near-real time by detecting outages within a few minutes of occurrence, which is a significant improvement over the detection time by human experts, especially in very large networks.

b) Unsupervised learning techniques for full outage detection: The unique ability of unsupervised learning algorithms to cluster data into distinct groups without any pre-classification makes them highly popular in outage detection applications. A major application of unsupervised learning is the detection of cells that are in outage but do not generate any alarms, otherwise known as *sleeping cells*. Detection of such cells is not immediately possible manually due to the lack of alarms accompanying the outage which makes their detection a highly useful application of unsupervised learning.

An extensive comparison of clustering algorithms for sleeping cell detection has been presented by Chernov *et al.* [48] where they have compared the performance of k-Nearest Neighbors (kNN) [49], Self-Organizing Maps (SOM) [50], Local-Sensitive Hashing [51] and Probabilistic Anomaly Detection. The authors use random access channel access failure measurements in addition to the high-dimensional minimization-of-drive-test (MDT) data [52] as input data for clustering algorithms. To compare the performance of individual clustering algorithms, receiver operating characteristics and precision-recall curves are used. The results show that Probabilistic Anomaly Detection has the best receiver operating characteristics out of the four algorithms and a higher precision-recall curve compared to the other algorithms. Additionally, the authors have compared the training time of the four clustering algorithms which shows that Local Sensitivity Hashing has a training time of linear order, whereas Probabilistic Anomaly Detection takes the least amount of time to detect sleeping cells compared to the other algorithms.

Another clustering algorithm, Dynamic Affinity Propagation [53], has been utilized for sleeping cell detection by Ma *et al.* [54]. The proposed algorithm uses Dynamic Affinity Propagation to calculate user clusters based on received power values of neighboring and serving cells reported by users, while Silhouette index [55] is used as clustering quality criterion to estimate the number of significant user clusters. The resultant clustering is mapped to physical data including user location to identify cells in outage. While the approach clearly succeeds in identifying sleeping cells using simulated outages, it is possible that in a live network, some users suffering deep fade may be wrongly clustered.

Dimensionality Reduction for Unsupervised Learning: While the above unsupervised learning solutions have a high degree of accuracy, their computational cost is equally high because network and user data can have very high dimensions. In addition to being resource hungry, the highly dimensional network and user data may cause increased detection latency as well as over-fitting. As the implications of these caveats are likely to surface in large scale real network, they are not exclusively addressed in above studies that rely on simulated small-scale network and user population for performance evaluation.

To tackle high dimensional network and user data, Chernogorov *et al.* [56] have proposed to construct diffusion maps [57] of user handover attempts and successes data. These diffusion maps are obtained through Eigen decomposition of Markov matrix obtained from the diffusion maps of network and user data. The resulting low-dimensional data is used to create cell coverage dominance maps which are then used to detect sleeping cells through k-means clustering [58] of cells into normal and sleeping cell clusters. Alternatively, Chernogorov *et al.* [59] have employed principal component analysis [60] to reduce the dimensionality of network and user data. The lower dimension data is then used to identify sleeping cell using the FindCBLOF algorithm [61] which separates clusters of normal cells from sleeping cells. Although a direct comparison of the results of the approaches in [56] and [59] has not been presented, the authors separately demonstrate that the proposed algorithms in [56] and [59] can identify sleeping cells and the affected neighboring cells as a result of the outage with high level of accuracy and also quantify the impact of the outages in terms of failed handover and call events.

Alternatively, Zoha *et al.* [62], [63] have addressed the challenges posed by high dimensionality through multi-dimensional scaling [64]. Multi-dimensional scaling allows easy visualization of the high dimensional network and user data by translating it into fewer dimensions using kernel transformations. This reduces the convergence time of clustering algorithms. In [62], the resulting low dimensional data is passed to Local Outlier Factor (LOF) [65] algorithm for sleeping cell identification, whereas kNN and LOF are compared with each other in [63]. It is observed that kNN outperforms LOF in terms of speed and reliability since LOF can sometimes misclassify normal cells.

The concepts from [62] and [63] are further extended by Zoha *et al.* [66] to include comparison of LOF with One-class Support Vector Machine (OCSVM) algorithm [67] under different shadowing scenarios. The results show that like kNN, OCSVM algorithm also outperforms LOF. Since LOF is limited to identifying localized outliers to cell clusters, the algorithm is prone to identifying normal cells as sleeping cells. This is avoided in both kNN and OCSVM because of the global approach adopted by both algorithms which only identifies global outliers. However, OCSVM takes significantly longer to train compared to either k-NN or LOF algorithms.

3) Full Outage Detection in HetNets: In the studies described above, the target topology for outage detection was invariably a homogeneous mobile cellular network of macro cells. Due to the large serving radii of macro cells and high subscriber count associated with them, generating measurements for full outage detection is not a primary concern.

a) What makes outage detection in HetNets different than homogeneous networks?: Cell outage detection in HetNets differs compared to homogeneous networks due to the architectural difference between the two topologies. The low computational ability of small cells, sparse network information due to fewer connected users and proposed future 5G solutions such as network densification means that outage detection algorithms for HetNets must be designed separately. The influences of sparse network data on outage detection algorithms plays an extremely important role in the accuracy of the algorithm. Less data can mean less accurate outage detection and an increase in false positive rate.

This fact is demonstrated by Chernov *et al.* [68] who compare the performance of several learning-based outage detection algorithms using radio link and handover failure metrics under different subscriber density levels. The results demonstrate that as the number of subscribers per cell, and consequently samples of performance metric report, starts to decrease, the area under the curve of true positive rate plot decreases exponentially. The authors also demonstrate that this result is true regardless of the outage detection algorithm,

TABLE III
QUALITATIVE COMPARISON OF PARTIAL OUTAGE DETECTION ALGORITHMS

Solution	Reference	Methodology	Sub-Method	Network Topology	Performance Metrics	Control Mechanism	Direction of Control
Partial Outage Detection	[75]	Heuristic	Rule-Based	Homogeneous	Mobility	Centralized	DL
	[78,84]				Quality		
	[79]				Retainability	Distributed	UL
	[77]		Framework		Accessibility, Retainability, Quality	Centralized	DL
	[81]				Quality		
	[82]				Retainability, Mobility		
	[83]				Retainability, Mobility, Quality		
	[86]	Learning Based	Supervised Learning		Retainability, Quality		
	[87,88]				Accessibility, Retainability, Mobility, Quality		
	[91,93]		Unsupervised Learning		Quality		
	[95]				Accessibility, Retainability, Coverage, Quality		DL/UL
	[96]				Quality	Distributed	DL
	[97]				Retainability, Mobility	Coverage	
	[102,104]				Accessibility, Retainability		
	[105]				Retainability		

which makes it a universal issue. Similar evidence is also implicit in the results presented in [45], [62], [63], and [66].

b) Outage detection in sparse data environment: In a sparse data environment such as a HetNet with control-data separation architecture [69], Onireti *et al.* [70], [71] have proposed to use Grey first order one variable prediction model [72] to predict downlink received power of the cell at locations where no such data is reported. Outage detection is triggered when sudden changes in user associations are observed. The Grey prediction model predicts the downlink received power of the cells if user associations had remained the same. The predicted information is then compared to actual downlink measurement reports to identify cells in outage. For this purpose, the authors use k-NN and LOF algorithms with k-NN demonstrating higher prediction accuracy just as it did for the case of homogeneous networks [63]. The choice of Grey prediction models in this study stems from the fact that these models have been shown to have higher prediction accuracy in sparse data environments compared to other prediction algorithms such as linear regression.

The algorithm proposed by Wang *et al.* [73] also refers to a HetNet with control-data separation and outages in small cells are detected through a comparison of predicted versus actual measurements. Measurement prediction is made using collaborative filtering where data collected during normal circumstances from highly correlated users is used to generate predictions for normal cell performance. The predicted data is then passed through sequential hypothesis testing which measures the likelihood of a hypothesis being true and returns the hypothesis with maximum likelihood to be true, i.e., whether a cell is in outage or not. The proposed algorithm is accurate nearly 75% of the time even in very low user density (1 user per 10000m^2) and very high fading (8 dB).

Finally, Xue *et al.* [74] have proposed to use simulated radio link failure data of normal and outage-hit cells to overcome the lack of data generated per cell in an ultra-dense HetNet. The authors propose to use kNN clustering to detect outages in HetNets using simulated outages in the network to train the algorithm.

B. Partial Outage Detection in Cellular Networks

Partial outage detection has historically been the domain of network optimization experts since, unlike full outage, KPI degradation generally does not generate network alarms. Degradation of network performance can lead to poor user QoE and may go unnoticed not only because no alarms are generated, but also because unlike full outage, the effect of partial outage may not manifest itself right away in the form of customer complaints. Therefore, it is integral to include partial outage detection in the autonomous Self-healing framework. In this sub-section, we discuss the recently proposed solutions for partial outage detection in mobile cellular networks, while Table III presents a qualitative comparison of the studies included in this sub-section. Before presenting techniques for partial outage detection, it is clarified that the terms partial outage and performance degradation are used interchangeably in this sub-section.

1) Heuristic Solutions for Partial Outage Detection:

a) Heuristic solutions leveraging large-scale network data for partial outage detection: Karatepe and Zeydan [75] have proposed a heuristic rule based algorithm for network misconfiguration detection due to its scalability and speed of operation compared to learning-based approaches especially when dealing with large-scale network data. The authors deploy a Hadoop [76] based data processing cluster to process large amounts of customer call detail record data which contains timestamps, handover attempts and successes, and all the cells a user is associated with during the call. After data processing, the information is forwarded to a heuristic algorithm that matches user location with the associated cells and returns any misconfigurations observed during the call. The authors claim that the proposed algorithm can detect misconfigured cells over 82% of the time.

Similarly, Shafiq *et al.* [77] have proposed to compare cell profiles during routine network operation with performance during heavy traffic situations to identify partial outages. The authors use data from a large mobile cellular network operator to study the trend of several network performance metrics including radio link setup failures, user counts, dropped calls, blocked calls, data session count, data session duration and the average time between consecutive data sessions of a user. The resulting time series profiles of cells during routine operation is compared with their operation during an unusual traffic activity period such as a sporting event. The authors demonstrate that if the normal cell performance during routine operations is known, it is possible to predict the level of cell performance degradation during non-routine events with a high degree of accuracy.

b) Comparative analysis-based heuristic solutions for partial outage detection: In order to facilitate partial outage detection through comparative analysis of normal and degraded cell behavior, Novaczki and Szilagyi [78] propose construction of faultless network performance profiles by fitting network performance metrics such as channel quality to a β-distribution. The detection algorithm compares the α and β parameters of real time cell performance distribution with the faultless performance distribution parameters. In case the real-time parameters differ from faultless profile parameters by a threshold decided by experts, the cell is considered to be suffering partial outage.

Comparison of time-series distribution has also been explored by D'Alconzo *et al.* [79] who propose to construct univariate probability distribution functions of performance metrics including number of synchronization packets and number of distinct network addresses contacted. The baseline distribution functions are constructed for different temporal resolutions to avoid false detections. The approach in [79] differs from that in [78] since the proposal is to identify partial outages using the Kullback-Leibler divergence [80] or relative entropy of current behavior distribution from baseline behavior distribution, while the behavior distribution modeling is not limited to β-distributions.

Correlational comparison of time-series is an alternative methodology of comparative analysis-based techniques for partial outage detection. An example of correlational comparison has been presented by Asghar *et al.* [81] who have proposed to utilize *Pearson's correlation factor* to match cells based on cell load estimated through the number of active users associated with the cell. The algorithm states that if a cell falls below an arbitrary correlation threshold with multiple cells with which it was previously well correlated, it is considered to be degraded. The authors demonstrate that not only is the proposed method effective for detecting slow partial outages, it is also effective for full outage detection. However, the performance of this algorithm is highly dependent on correlated cells, i.e., if multiple correlated cells suffer same degradation, it may go undetected. To avoid this pitfall, Muñoz *et al.* [82] have proposed to correlate successful handover count and call drop count time series of a cell with a synthesized data series that represents partial outage and a reference data series of the cell itself during normal behavior as a preventive measure for false flags. High correlation with synthesized data and low correlation with reference data signifies partial outage. The authors advocate use of time-series correlations over cumulative data correlations since cumulative correlation may hide any short-term degradations in cell performance. However, time-series correlation requires higher and faster computations especially if more performance metrics are included in the comparison process.

c) Other heuristic solutions for partial outage detection: In their work on partial outage detection, Sanchez-Gonzalez *et al.* [83] propose a decision tree based solution to identify partial outages in a mobile cellular network. The proposed algorithm applies a set of expert-defined rules separating normal and degraded behavior on the uplink and downlink received power measurements, handover failures, and radio link failures to categorize the performance of each cell. If a cell fails said rules, it is considered to be in partial outage and diagnostic functions are initiated. The solution is validated using real-network data where it is able to effectively identify the degraded cells.

Merging heuristic and learning-based methodologies, Kumpulainen *et al.* [84] have proposed a hybrid solution for partial outage detection. The proposed solution evaluates channel quality measurements of a cell over one day and categorizes the quality samples as good, medium and bad based on a heuristic algorithm developed using expert knowledge. Additionally, the solution utilizes fuzzy C-means clustering [85] to generate cell clusters based on the commonality of their profiles in terms of channel quality data distribution over a day [84, Fig. 7]. Based on the similarity of channel quality measurement distribution of a cell over a day with fuzzy clusters, the solution decides if it is degraded. The authors have demonstrated that the proposed solution can not only identify degraded cell performance but also the amount of time it spends as degraded. However, scalability of the solution requires further investigation since the proposed approach is limited to evaluation of one performance metric over a period of a whole day.

2) Learning-Based Solutions for Partial Outage Detection: One of the application areas of machine learning is the estimation of network reliability explored by Sattiraju *et al.* [86]. The authors capture long-term reliability data such as link availability and apply semi-Markov transition process to construct renewal models for normal and degraded network link states. Link reliability is defined as the amount of time network links spend in normal states and two transition actions, i.e., failure and repair exist in the network. The authors find that lower reliability states are highly absorbing states, i.e., once a link is sufficiently degraded, its recovery probability approaches zero.

Ciocarlie *et al.* [87], have also explored the feasibility of deploying time-series averaging based anomaly detection algorithms over variable window lengths. However, unlike the heuristic approaches presented in [78] and [79], the proposed algorithm uses autoregressive integrated moving average to compute predicted KPI values for a cell which are then compared with an ensemble of models for different unspecified KPIs. The authors propose to construct normal and anomalous KPI models using different techniques including empirical cumulative distribution function and SVM with radial basis function kernel. The proposed solution is validated against human experts using visualization tools. Results show that while the proposed approach is able to accurately predict a partial outage, the detection delay between outage occurring and being detected was never less than five hours. Another important concern raised by the authors is the exponential training time of the machine learning algorithms which can make the proposed methodology prohibitive in live networks. The authors have provided further refinement of this approach in [88] by including the utilization of the Kolmogorov-Smirnov test [89] to identify the sliding window size for data streams used to train the SVM models. Another key distinction of [88] over [87] is that the authors use seasonal trend decomposition based on Loess [90] to identify and remove outliers from the original training data to create true performance models.

A key commonality among [78], [79], [87], [88] is the use of individual data streams for input to outage detection algorithms. However, Barreto *et al.* [91] postulate that using single variable data streams for anomaly detection, though simple, is not always effective. Therefore, the authors have proposed a joint neural network that takes univariate and multivariate data containing channel quality measurements, traffic loads and user throughputs from the network as inputs to generate global and local network performance profiles which are used to detect anomalous cells via percentile-based confidence intervals computed over global and local network profiles. The authors demonstrate the efficacy of training a multivariate neural algorithm by presenting a comparison with a single-threshold neural algorithm using several neural network-based algorithms including winner-take-all, frequency sensitive competitive learning [92], Self Organizing Map (SOM) and neural gas algorithm. Results show that the proposed multivariate partial outage detection algorithm consistently outperforms single-threshold method in terms of false positive alarm rate by 0.6% to over 5.5%.

Frota *et al.* [93] have presented an extension to the work in [91] where the authors combine the originally proposed multivariate neural networks with Gaussian distribution based SOM clustering algorithm to create a partial outage detection algorithm. The authors use network core traffic statistics to train the Gaussian distribution based SOM clustering algorithm which is compared with multivariate heuristic anomaly detection methods. It is demonstrated that the proposed technique can lower false partial outage detection rate by nearly 30% when trained over 10% of dataset compared to the algorithm proposed in [94] for fault diagnosis in rotating machines. However, the solution proposed in [93] builds on an underlying assumption that network performance metrics such as user count, throughput, noise levels and interference levels are normally distributed which may not hold always true in typical real networks.

a) Partial outage detection using self-organizing maps: Self-Organizing Maps are a popular neural networks based clustering technique. SOMs work by projecting input vectors of large size onto a 2-dimensional space using weights obtained by training the underlying neural network. A number of studies have proposed SOM-based algorithms for partial outage detection including [91], [93], [95]–[97].

As already discussed, Barreto *et al.* [91] and Frota *et al.* [93] have used SOMs for comparison-based partial outage detection. On the other hand Lehtimäki and Raivio [95] harness the capability of SOMs to arrange similar input vectors of network measurements including call request blocking, traffic channel availability, channel quality, voice call traffic, and uplink/downlink signal strength together. The authors use this arrangement to identify cells with partial outage through k-means clustering algorithm. The proposed scheme is compared with principal component analysis and independent component analysis [98] to detect partial outages in control signaling and traffic channel statistics of a real 2G network. Results show that SOM and principal component analysis performed equally well while outperforming independent component analysis.

Kumpulainen and Hätönen [96] also use SOM based clustering to detect localized partial outages compared to the general global partial outage detection models. The proposed algorithm first creates SOM which is then used to identify best matching units for each node in the map and distance (quantization error) between the two units is calculated. A cell is considered in partial outage if its best matching unit is also in outage and the distance between the two is less than a pre-defined threshold. The authors compare the usage of local partial outage detection model using SOM with Gaussian Mixture Models and k-means clustering with results showing that the local anomaly detection scheme not only detects all the outages but also whenever the activity level of a cell changes.

Gómez-Andrades *et al.* [97] employ a similar approach to [96] in their work where SOM is used to arrange the cells based on signal strength, quality, call drop and handover failure metrics, and then clustered using Ward's hierarchical clustering [99]. The authors use the Davies-Bouldin index [100] and the Kolmogorov-Smirnov test [101] to set the number of clusters to be created in the SOM. The clusters are labeled as normal or faulty based on expert knowledge. A comparison of the proposed methodology with a rule-based algorithm and a Bayesian network classifier shows that the proposed approach outperforms them by 31% and 12% respectively.

b) Partial outage detection using clustering techniques: Apart from SOMs, other unsupervised clustering technique such as k-means, density based and hierarchical clustering, topic modeling and LOF clustering have also been explored in literature for partial outage detection. Rezaei *et al.* [102] have presented a comparison of several supervised partial outage detection schemes in a 2G network. The study uses input data including call blocking and drops, as well as signal quality measurements. Classification techniques explored by the authors for partial outage detection include chi-squared automatic interaction detection [103], quick unbiased efficient statistical tree, Bayesian networks, SVM, and classification and regression trees. The authors find that SVM has the best detection rate among supervised learning techniques (94%) but requires from longer training time while quick unbiased efficient statistical tree has the shortest training time with relatively high accuracy (93%).

Ciocarlie *et al.* [104] use topic modeling to detect partial outages in a cellular network. The method resembles other clustering techniques with the difference that it assigns a probability to the presence of commonality within the cluster of cells. Once the clusters have been developed, the framework uses domain knowledge to identify which cluster represents anomalous behavior. The approach is tested on real-network data with verification of results performed using visual analysis of data by experts. Alternatively, Dandan *et al.* [105] have used kernel-based LOF anomaly detection which is simply LOF with kernel based distance calculation. The authors propose using kernel-based LOF to identify cells in partial outage by associating a degree of anomaly to each cell in a density map for LOF based on kernel Gaussian distance (kGD). Normal cells are characterized by having a kGD of 1 and any cells with kGD above are outliers. The authors also suggest that kernel-based LOF can better deal with non-uniform distributions of cells in real datasets compared to typical LOF algorithm. The proposed method has a 91% success rate in detecting outages compared to 70% for normal LOF.

C. Summary and Insights

Outage detection is one of the most labor intensive process in a mobile cellular network. Researchers have devoted a lot of attention to autonomous full and partial outage detection solutions. Majority of these solutions attempt to detect outages based on coverage metrics such as received signal strength. For outage detection in future 5G networks with millimeter wave cell deployment, researchers will need to consider additional metrics. This is because millimeter wave cells have a very high pathloss leading to natural loss of coverage even at a distance of a few hundred meters [106]. A challenge for future studies is to come up with solutions that can detect outages in spite of the coverage limitations of millimeter wave cells.

A common theme among the studies for full and partial outage detection is the growing use of machine learning techniques in general, and unsupervised clustering techniques in particular, for outage detection. This reduces the chances of outages due to unconventional reasons, such as weather anomalies, to be missed. This is not the case for heuristic and supervised machine learning based solutions since they are only trained to look for evidence of outage based on human expert knowledge. This does not mean that unsupervised learning solutions for outage detection can become industry standard as is. Some of the major issues concerning unsupervised learning solutions include:

1 Machine learning techniques in general are prone to errors due to noise in the recorded dataset, as demonstrated in [45], [62], [63], and [66]. This means that unsupervised learning solutions deployed for outage detection in areas with high shadowing and multipaths, such as metro hubs, can result in higher false negatives. Future solutions for outage detection must address this issue before they can become practically viable.

2 Majority of techniques for outage detection discussed above only consider spatial data for outage detection purposes. This means that the KPI data used for outage detection is gathered over a set of spatial points representing user locations for one time instance. Therefore, outages detected by these solutions are instantaneous. This raises the issue of outages that are extremely short-lived, have little impact on subscriber QoE, and may be gone by the time they can be compensated. To address this issue, future solutions for outage detection must consider the temporal dimension as well as the spatial dimension of user reported data to differentiate between temporary and long-term outages.

3 Most of the approaches for outage detection reviewed above require a secondary analysis by human expert to confirm the existence of the outage which can add some delay before outage compensation is triggered. This can be an issue in 5G networks where low latency and high QoE requirements mean that the outages would have to be detected and compensated as quickly as possible.

In addition to addressing the above issues, future studies for outage detection must also incorporate the effects of millimeter wave propagation and capacity enhancement solutions such as massive MIMO. Additionally, detecting partial outages in massive MIMO cells such as failure of some beams will also need to be addressed. Based on the review of existing literature, there are no current studies that expressly include either of these two features which makes them prime candidates for future research in outage detection.

V. Outage Diagnosis in Cellular Mobile Networks

Once a network outage (full or partial) is detected, the next phase is to diagnose the underlying cause of the outage. In this section, we analyze the literature on Outage Diagnosis. Some full outages can trigger fault alarms, thus eliminating the need for full outage detection in those particular cases. However, the exact cause of the failure still needs to be diagnosed. Conversely, the key difficulty in diagnosis with partial outage is the lack of fault alarms associated with the

TABLE IV
QUALITATIVE COMPARISON OF OUTAGE DIAGNOSIS ALGORITHMS

<table>
<tr><th>Solution</th><th>Reference</th><th>Methodology</th><th>Sub-Method</th><th>Network Topology</th><th>Performance Metrics</th><th>Control Mechanism</th><th>Direction of Control</th></tr>
<tr><td rowspan="4">Full Outage Diagnosis</td><td>[47]</td><td>Heuristic</td><td>Rule-Based</td><td rowspan="10">Homogeneous</td><td>Retainability, Mobility, Quality</td><td rowspan="10">Centralized</td><td rowspan="2">UL/DL</td></tr>
<tr><td>[107]</td><td rowspan="3">Learning Based</td><td rowspan="2">Supervised Learning</td><td>Accessibility, Retainability, Mobility, Quality</td></tr>
<tr><td>[108,110]</td><td>Retainability</td><td rowspan="7">DL</td></tr>
<tr><td>[102]</td><td>Unsupervised Learning</td><td>Accessibility, Retainability</td></tr>
<tr><td rowspan="6">Partial Outage Diagnosis</td><td>[77]</td><td>Heuristic</td><td>Framework</td><td>Accessibility, Retainability, Quality</td></tr>
<tr><td>[104]</td><td rowspan="5">Learning Based</td><td rowspan="3">Supervised Learning</td><td>Accessibility, Retainability</td></tr>
<tr><td>[114]</td><td>Accessibility, Retainability, Mobility, Quality</td></tr>
<tr><td>[115]</td><td>Retainability</td></tr>
<tr><td>[97]</td><td rowspan="2">Unsupervised Learning</td><td>Retainability, Mobility</td></tr>
<tr><td>[116]</td><td>Quality</td><td>UL</td></tr>
</table>

anomalies which makes their diagnosis more difficult, thus requiring sophisticated diagnostic techniques. Table IV provides the qualitative comparison of studies describing full and partial outage diagnosis techniques.

A. Diagnosis of Full Outages in Cellular Networks

A starting point towards full outage diagnosis is building the knowledge-base of possible faults. A quite extensive description of standard faults in cellular networks has been presented in [25] which are applicable to 2G, 3G and 4G networks. The standard documentation also provides alarm descriptions for faults associated with hardware failure, software failure, functionality failure or any other faults that cause the network node to stop performing its routine operations. However, outage diagnostics have remained in the domain of human experts who use their knowledge to identify outage causes. While this method is effective, it cannot remain as the method of choice going forward towards ultra-dense networks.

To this end, some studies have proposed techniques combining expert knowledge with mobile cellular network data to create autonomous outage diagnosis algorithms. One such approach has been demonstrated by Szilágyi and Novaczki [47] which utilizes expert knowledge to create targets for network performance such as channel quality, dropped calls and handover failures. The solution uses weighted sums of the difference of actual KPI value to the target value to calculate a diagnostic score. The algorithm then uses expert knowledge to associate a range of scores with different fault causes to complete the diagnosis process. The proposed technique is validated using real data, with results showing that the algorithm was able to diagnose each outage correctly.

1) Learning-Based Solutions for Full Outage Diagnosis: Solutions for outage diagnosis using stationary KPI targets derived from expert knowledge can become obsolete quickly in the face of changing network dynamics. Khanafer *et al.* [107] argue this point and propose an alternate learning-based solution using Naïve Bayes Classifier (NBC) to predict possible causes of hardware faults and KPI degradations in the network given the symptoms (failures). The algorithm uses discretized value ranges for various KPIs including blocked calls, dropped calls, connection request failures, and HO failures to indicate normal and faulty performance states. The authors compare two different techniques of KPI value discretization namely percentile-based discretization and entropy minimization discretization. Results show that outage diagnoses are over 10% more accurate when entropy minimization discretization is used compared to percentile-based discretization.

Barco *et al.* [108] compare the performance of a NBC for outage diagnosis with a modified NBC which assumes the independence of causal influence [109]. The two methods are compared using data from a live network containing faults such as call drops, handover failures and call blocking with results showing modified NBC to be more efficient in terms of simplicity with the same level of accuracy as regular NBC. However, in order for modified NBC to diagnose outages accurately, it needs knowledge of prior KPI distributions in the event of an outage. Barco *et al.* [110] have discussed the process of developing this knowledge using a knowledge acquisition tool. The tool combines past diagnoses performed by experts with fault data from the mobile cellular network. The tool takes faults such as high network congestion or high call drops, possible causes such as high interference, observed performance metrics at the time of the fault such as handovers due to high interference, and cell parameter settings. Combining this information, the tool outputs the prior probabilities of different diagnoses.

Unlike other techniques for full outage diagnosis, Rezaei *et al.* [102] propose to use unsupervised clustering techniques for fault diagnosis and present a comparison of several such techniques including expectation minimization, density-based spatial clustering of applications with noise [111], agglomerative hierarchical clustering [112], X-means and k-means clustering. The authors use clustering algorithms to split cells based on their call drops and blocking values. Diagnosis is done by comparing cells in clusters to faulty cells with known diagnosis. Validation is done using expert knowledge to confirm the result of fault diagnosis through clustering. The clustering results are verified using the Silhouette Coefficient [113] and show that expectation minimization is the most successful technique in terms of data clustering with clearest cluster divisions between different sets of faulty cells.

B. Partial Outage Diagnosis in Cellular Networks

Diagnostic techniques are primarily needed in mobile cellular network for performance degradations scenarios, i.e., partial outages which generally do not generate any alarms. The operators can define thresholds for KPI values to generate customized alarms; however, apart from being useful only for KPI degradation detection, this technique cannot help in diagnosis or root cause analysis. For this reason, partial outage diagnosis carries great importance in autonomous Self-healing solutions for SON.

Shafiq *et al.* [77] have presented an analysis of real-time measurements from some cells of a large mobile cellular network before, during and after two abnormally high traffic events. The results have been used to present heuristic detection and diagnosis schemes for network congestion and dropped calls during such events along with suggestions on how to rectify these problems. The authors analyze network performance measurement for call connections, link performance and data service performances, and suggest that major issues in terms of call drops and congestion occur when users access the network without coordination. While this would not pose problems during routine network operations since the network is designed to handle such traffic, it becomes an issue during major events or gatherings if additional capacity is not deployed. The analysis presented in the paper solely relies on expert knowledge to derive diagnostic inferences from the real data.

1) Partial Outage Diagnosis Using Learning-Based Techniques: Other than heuristic techniques, learning-based techniques have also been exploited in [97], [104], and [114]–[116] for KPI degradation diagnosis.

a) Supervised learning techniques for partial outage diagnosis: Ciocarlie *et al.* [104] propose to use Markov Logic Networks and Principal Component Analysis to diagnose weather-related and parameter misconfiguration-related partial outages from real network data. The proposed technique generates clusters of degraded cells using Principal Component Analysis which are then passed through a Markov Logic Network for diagnosis. The Markov Logic Network generates a sequence of events that would lead to a degradation in call drop rate, throughput or handover failures, thus leading to the diagnosis. Weights for each sequence of events in the Markov Logic Network leading to a diagnosis are initialized using expert knowledge and updated with each successful and unsuccessful diagnosis. The diagnostic results of the proposed approach have been validated against expert diagnoses. The proposed approach also relies heavily on expert knowledge to generate the event sequences used in the Markov Logic Networks.

Barco *et al.* [114] present a comparison of the impact of continuous versus discretized data models for auto-diagnostic systems in cellular network using Bayesian network classifier. The authors use β-distributions to construct continuous models from KPI data streams, and selective entropy minimization discretization [117] to construct discrete KPI models. The study uses dropped call rate, blocked call rate, handover blocking, throughput, and active neighbor set update rate KPIs to generate probability of degradation in the network given a set of symptomatic KPI distributions. The results show that continuous models exhibit nearly 10% higher diagnosis accuracy when the training set size is sufficiently large ($\sim$2000 examples) while the discrete models are more accurate ($\sim$20%) when the training data is sparse ($\sim$50 examples).

The results from [114] have been used by Barco *et al.* [115] to propose a hybrid KPI modeling methodology called Smoothed Bayesian Networks which can decrease the sensitivity of diagnosis accuracy to imprecision in the model parameters. The posterior probabilities of the causes follow a smoother transition near the boundaries between states given their related symptoms in Smoothed Bayesian Networks than in traditional Bayesian networks. The authors compare the accuracy of diagnoses for both Smoothed Bayesian Networks and Discrete Bayesian Networks on real network data for diagnosis of call drop rate. The results suggest that Smoothed Bayesian Networks perform better by almost 10% when there was a certain degree of inaccuracy in the model brought about by sparseness in data. However, Discrete Bayesian Networks perform better on a larger dataset resulting in a more accurate KPI model.

b) Unsupervised learning based solutions for partial outage diagnosis: SOMs have been used frequently not only to detect KPI degradations [93], [95]–[97], but also to diagnose them [97], [116]. Gómez-Andrades *et al.* [97] have used SOM based clustering cell in 4G networks based on call drop rate, channel interference, handover failures, received signal strength, channel quality, and throughput to diagnose the possible cause of performance degradations in the eNBs. The clustering algorithm arranges cells based on their degree of association with other degraded cells by finding the best matching unit for each cell. If a cell is experiencing KPI degradations, it will be clustered with pre-existing degraded cells with known diagnosis. The authors demonstrate that the proposed scheme can outperform rule-based algorithms and Bayesian Network Classifiers by $\sim$32% and $\sim$12% respectively but takes longer to train compared to the other two techniques. Laiho *et al.* [116] have proposed a similar solution

TABLE V
QUALITATIVE COMPARISON OF COVERAGE OPTIMIZATION ALGORITHMS FOR COMPENSATION

Solution	Reference	Methodology	Sub-Method	Network Topology	Performance Metrics	Control Mechanism	Direction of Control
Coverage Optimization	[118]	Heuristic	Framework	Homogeneous	Retainability, Coverage, Quality	Centralized	DL
	[119]				Coverage, Quality		UL/DL
	[120]				Coverage, Quality		DL
	[121]	Analytical	Non-convex Optimization		Coverage, Quality		UL/DL
	[122]						DL
	[66]	Learning Based	Reinforcement Learning		Coverage		
	[71]			HetNet			

to diagnose degradations in channel quality and frame error rate in 3G networks with the exception that the cells are clustered using k-means clustering. Cells are diagnosed by taking the diagnosis of the nearest known degraded cell and the results are validated using real-network data and comparing expert diagnoses with the diagnoses generated by the technique.

C. Summary and Insights

Outage diagnosis is a relatively under-explored aspect of Self-healing in mobile cellular networks compared to outage detection and compensation techniques. Part of the reason for this are the standardized fault and alarm codes that are automatically generated in the event of a full outage due to hardware/software failure. However, no such standardized diagnostics exist for partial outages. This is because the same partial outage may be caused by two different sets of circumstances. For this reason, majority of studies on outage diagnosis use supervised learning solutions such as Bayesian networks and Markov logic networks which can associate a probability with each known cause leading to an outage. However, the use of such solutions can be challenging in practical networks since training them would require constructing a database of every root cause resulting in an outage.

To address this issue, future studies on outage diagnosis should focus on how this database of root causes can be created without creating artificial outages. In addition, causes of full and partial outages in future 5G networks with millimeter wave cells, massive MIMO and ultra-dense cell deployment must also be explored since they are an uncharted territory as yet.

VI. OUTAGE COMPENSATION IN CELLULAR MOBILE NETWORKS

Outage compensation forms the core element of the Self-healing framework; therefore, it is no surprise that, among the three components of Self-healing, outage compensation has received the most attention from the research community. Compensation actions and algorithms are designed specifically to provide temporary service to users in case of a full outage or partial outage since both events are not immediately recoverable. While detection and diagnosis of full outage and partial outage in a mobile cellular network require different methodologies, compensatory actions for both events involve similar techniques. The majority of studies on compensation algorithms are presented as a solution for full outage but lend themselves seamlessly to compensation for partial outages.

The key principle of outage compensation is to leverage resources from neighboring cells of outage-affected cells to provide temporary services in affected area. These resources include cell bandwidth and user associations which can be modified using primary parameters such as cell/user equipment transmit powers, and antenna parameters as well as secondary parameters such as neighbor lists and cell selection parameters [40]. In the following subsections, compensation algorithms are presented based on the optimization objective with description of their methodology of optimization along with parameters of choice and other taxonomically significant insights.

A. Coverage Area Optimization for Outage Compensation

One of the key consequences of network outages and KPI degradations is the loss of network coverage near effected network entity. Several studies [66], [71], [118]–[122] have presented outage compensation algorithms that focus on coverage optimization. A list of these studies along with their proposed techniques is presented in Table V.

1) Choosing the Right Neighboring Cells, Optimization Parameters, and Recovery Action: Choice of neighboring cells, optimization parameters, and recovery action plays an important role in the effectiveness of an outage compensation solution and has been investigated in [118], [119], and [120] respectively. The Self-healing framework proposed by Asghar *et al.* [118] defines an outage compensation algorithm that uses received power measurements from users of outage-affected cell to create coverage polygons for neighboring cells. The algorithm then iterates through different antenna configurations of key neighboring cells with potential coverage overlap to outage cell until coverage constraints of all users are met. Additionally, the algorithm monitors downlink throughputs and radio link failures of the neighboring cells to benchmark network recovery. A demonstration of the algorithm by the authors on real network outages shows it can effectively compensate for outages within 2 hours of their occurrence.

The outage compensation framework proposed by Amirijoo *et al.* [119] compares compensation potential of different control parameters suggested in [40], i.e., reference signal power, uplink target received power level P0 and antenna tilt in mitigating outage-induced performance degradations. An iterative algorithm is used to update the parameters of neighboring cells and their results are benchmarked. Results in terms of cell coverage and user throughput indicate that uplink target received power level P0 and antenna tilt are the most effective parameters for improving coverage, while P0 is most effective for improving throughput.

Frenzel *et al.* [120] discuss choice of optimal recover action based on three inputs, i.e., the probability of effectiveness of a solution which depends on the outage cause, the preference of the network operator for a recovery action, and the preference of the network operator for a degradation resolution. The authors propose a weighted-sum function which returns the cost of selecting a solution, action and resolution tuple. The proposed framework is flexible to changing network technology as more tuples can be added for future networks; however, the determination of probabilities and preferences requires manual input by experts.

2) Non-Convex Coverage Optimization Techniques for Outage Compensation: Several studies have explored the use of non-convex optimization methods for outage compensation based on the analysis that in a large network with a diverse set of optimization parameters, outage compensation can be a NP-hard non-convex problem. Conversion of the outage compensation problem into a convex problem requires too many generalizations and assumptions which can make the result unsuitable for practical implementation. Jiang *et al.* [121] and Wenjing *et al.* [122] base their solutions on this premise and use non-convex optimization techniques to solve the problem of coverage optimization.

Jiang *et al.* [121] have proposed a cost function minimization approach which uses weighted sum of downlink channel quality and received signal strength. The authors state that the problem is a large scale non-convex optimization problem. Outage compensation is carried out by calculating the optimal uplink target received power P0 using a non-convex optimization technique called immune algorithm [123] for cost function maximization. The authors show that the immune algorithm improves both coverage and channel quality after optimization and can converge in a very short time period. The results, compared against two other techniques [124], [125], show that the proposed methodology can significantly improve coverage post-optimization by 10% without significantly sacrificing cell edge throughput. However, it is observed that the immune algorithm is highly sensitive to initial parameters, i.e., it may not be able to escape the infeasible solution set if initial parameters are not set correctly.

Similarly, Wenjing *et al.* [122] propose that the minimization of coverage holes and pilot pollution using downlink pilot powers of neighboring cells for outage compensation is also a non-convex problem. In this study, the authors propose to use a non-convex optimization technique called particle swarm algorithm [126]. Results on the analysis of the algorithm indicate that it is highly efficient in terms of execution time while also recovering over 98% of the coverage area in terms of signal strength without significantly degrading link quality. However, like immune algorithm, the particle swarm algorithm is also highly dependent on initialization parameters for convergence.

3) Learning-Based Coverage Optimization Solutions for Outage Compensation: Examples of learning-based algorithms for outage detection and diagnosis covered in the previous sections mostly employed classification and clustering techniques. However, reinforcement learning [37] represents the most effective learning-based solution for outage compensation algorithms, primarily due to its ability to identify maximum reward strategies over a learning period. One reinforcement learning-based solution for outage compensation has been proposed by Zoha *et al.* [66] within a complete learning-based Self-healing framework. The outage compensation component of the framework is built upon fuzzy-logic based reinforcement learning which adjusts antenna tilts and cell transmit powers to achieve the desirable compensated performance in terms of cell coverage. The compensation algorithm makes incremental or decremental step changes in optimization parameters after an outage using exploration of new rewards or exploitation of past rewards. The resulting network state from the reinforcement learning database is interpreted through the fuzzy-logic regulator as better or worse than the previous state which then dictates the next step of the reinforcement learning algorithm. The authors demonstrate that the proposed solution can improve post-outage cell edge coverage by 5 dB while also helping to regain mean data rate to pre-outage levels.

A similar approach to [66] has been presented by Onireti *et al.* [71] for heterogeneous networks with the difference that the fuzzy logic component has been replaced with an actor-critic module for enabling reinforcement learning. The actor-critic module executes an exploratory or exploitative actions such as changing antenna tilt or transmit power of a neighboring cell based on probability of reward learned over time. The critic then evaluates the reward associated with the action taken and updates past rewards and probabilities. The solution is compared against the one presented in [66] with results showing it improves cell coverage and channel quality, particularly for cell edge users, and brings them closer to pre-outage levels.

B. *SINR Optimization for Outage Compensation*

A secondary consequence of outage compensation can be the degradation of SINR of existing users in neighboring cells due to parameter reconfiguration. Therefore, some studies [124], [127]–[130] use SINR as the objective to be optimized while including the existing and outage-affected users into the optimization process. This allows them to avoid or minimize the degradation of SINR in areas not affected by outage. Table VI lists a qualitative comparison of the studies targeting SINR optimization for outage compensation.

TABLE VI
QUALITATIVE COMPARISON OF SINR OPTIMIZATION ALGORITHMS FOR COMPENSATION

Solution	Reference	Methodology	Sub-Method	Network Topology	Performance Metrics	Control Mechanism	Direction of Control
SINR Optimization	[124]	Heuristic	Rule Based	Homogeneous	Coverage, Quality	Centralized	UL/DL
	[127]			HetNet	Quality	Distributed	DL
	[128]	Analytical	Convex Optimization				
	[129]	Learning Based	Supervised Learning			Centralized	
	[130]			Homogeneous		Distributed	

1) Heuristic SINR Optimization Solutions for Outage Compensation: Wang *et al.* [127] present a distributed heuristic outage compensation algorithm for SINR optimization in HetNets. The proposed algorithm minimizes the number of neighboring cells to be reconfigured to achieve desired post-outage SINR. This is done by calculating an inner group of femtocells that can recover the outage-affected femtocell through reconfiguration of transmit powers, and by creating a second outer group of femtocells beyond which no further outage compensation actions can be propagated to prevent the effects of reconfigurations from rippling outwards. The authors demonstrate that the proposed technique requires fewer neighboring cells for SINR optimization compared to other solutions such as [131] while also reducing the number of cells with negative differential SINR compared to pre-outage values. However, the authors also show that as the density of the mobile cellular network increases, the grouping algorithms takes longer to converge.

While the solution in [127] endeavors to find the optimal set of compensating neighbors, the solution put forth by Amirijoo *et al.* [124] focuses on optimization parameters of the neighboring cells for outage compensation. The algorithm iterates through values of uplink target received power P0 and the antenna tilts of neighboring cells in a homogeneous network. The optimal set is obtained when cell coverage can no longer be improved without affecting SINR. Results indicate that the algorithm can regain pre-outage SINR and coverage values in low network load scenario. Moreover, the compensation potential of the solution in terms of SINR improves as the network load decreases while quality degradation is most visible for high and medium loads.

2) Convex SINR Optimization Solution for Outage Compensation: Lee *et al.* [132] present an outage compensation solution using the concept of collaborative resource allocation strategy. The solution is based on reallocation of dedicated bandwidth called Healing Channels (HCs) to provide physical channel resources to users affected by an outage. The concept has been used in associated studies for outage compensation, such as the one by Lee *et al.* [128] who use a fairness-aware collaborative resource allocation algorithm with the objective of maximizing the sum of logarithmic user rates. The maximization process guarantees user fairness in terms of resource allocation while maximizing user throughput which is directly related to bandwidth and user SINR. Use of log-rate removes the possibility of outage facing users not being allocated any resources and ensures that the rate maximization algorithm treats all users fairly. The proposed scheme is compared with a number of competing resource allocation solutions for outage compensation including regular collaborative resource allocation [128], non-cooperative resource allocation, and the outage compensation solution for wireless sensor networks proposed in [133]. Results show that even though regular collaborative resource allocation offers nearly 10% more mean throughput gains, those gains are overshadowed by large disparity between maximum and minimum throughput levels. On the other hand the fairness aware-collaborative resource allocation algorithm offers a fairer throughput distribution between users.

3) Learning-Based SINR Optimization Algorithms for Outage Compensation: Saeed *et al.* [129], and Moysen and Giupponi [130] employ reinforcement learning techniques to optimize SINR for outage compensation. Saeed *et al.* [129] propose a fuzzy Q-learning algorithm for compensation of SINR loss due to outage. The algorithm configures transmit power and antenna tilts of neighboring cells iteratively using fuzzy logic control and records the rewards in terms of change in downlink SINR of affected users. The rewards are used by the reinforcement learning algorithm for learning future actions which might lead to better outage compensation in terms of overall DL SINR. Simulation results indicate around 40% of effected users are restored to their original SINR under low load conditions. Similarly, Moysen and Giupponi [130] propose reinforcement learning technique for adjusting neighbor cell coverage using antenna tilt and the downlink transmission power. The approach differs from the one in [129] such that the actions and rewards are calculated using the actor-critic approach discussed previously in [71] for coverage optimization instead of fuzzy logic. To make the algorithm in [130] work, each cell reserves a certain amount of frequency bandwidth for users effected by the outage. Neighboring cells are informed of this bandwidth through the inter-cell interface so that a distributed and cooperative outage compensation solution can be achieved. The algorithm modifies cell power and antenna tilts in fixed step sizes to exploit the reward of each change which is based on the SINR of users effected by outage. Simulation results indicate that compensation delay is around 500 ms and the approach can compensate 98% of outage users.

One key observation regarding reinforcement learning solutions is that solutions such as the ones presented in [66], [71], [129], and [131] require considerable number of training examples, or outages, before their actions can

TABLE VII
QUALITATIVE COMPARISON OF CAPACITY OPTIMIZATION ALGORITHMS FOR COMPENSATION

Solution	Reference	Methodology	Sub-Method	Network Topology	Performance Metrics	Control Mechanism	Direction of Control
Cell Capacity Optimization	[132,134]	Analytical	Convex Optimization	HetNet	Accessibility, Quality	Distributed	DL
	[135]		Non-convex Optimization	Homogeneous		Centralized	
	[136]			HetNet		Distributed	
	[137]	Learning Based	Supervised Learning			Centralized	
	[131,138]			Homogeneous			

become effective. This can make effective deployment of such solutions a challenge for mobile cellular network operators.

C. Cell Capacity Optimization for Outage Compensation

Like degradation in SINR, cell overloading is another consequence of network outages resulting from re-association of affected users to neighboring cells. Moreover, compensatory actions to achieve another objective, such as coverage optimization, can also result in overloading of neighboring cells. This can lead to users being blocked and service requests being discarded, which affects subscriber QoE. To circumvent these problems, some studies [131], [132], [134]–[138] have focused on outage compensation solutions that focus on optimizing user associations so that the load is fairly distributed among neighboring cells. Table VII presents a qualitative comparison of these studies.

1) Convex Capacity Optimization Solution for Outage Compensation: As mentioned previously, Lee *et al.* [132] have proposed an outage compensation solution for HetNets based on collaborative resource allocation. The authors state that users in faulty femtocells cannot be served reliably by the macro cells due to power imbalance between macro cell and small cells, and cell edge performance limitations of macro cells. Therefore, only normal small cells can support users in a faulty small cell. To this end, the reserved HCs of healthy small cells are allocated cooperatively to users of the outage-affected cell. The proposed scheme finds adaptable set of HCs, subchannels and power allocation to maximize network capacity through convex optimization implemented via an iterative gradient descent algorithm. The solution is quick and improves the total capacity utilization of neighboring cells by nearly 30% while also ensuring fairness in terms of user throughputs.

The collaborative resource allocation solution [132] is further extended by Lee *et al.* [134] to include collaborative beamforming strategy along with HC allocation for outage compensation. The proposed cooperative beamforming strategy can be performed without power cooperation between nodes, and is also the optimal transmission strategy under individual power constraints. The proposed algorithm performs HC selection through convex optimization based on maximizing system capacity in outage scenario, and then carries out sub-channel allocation and power allocation based on an iterative algorithm. The proposed solution is compared against several resource allocation schemes including regular collaborative resource allocation, equal power allocation [133] and multi-user iterative water filling [139] schemes, with the results showing that for 10 HCs, the proposed algorithm improves the average cell capacity by 5% and user fairness by 10%.

2) Non-Convex Capacity Optimization Solutions for Outage Compensation: As already discussed, a diverse set of problem constraints and parameters can result in the outage compensation problem becoming non-convex. To solve these problems researchers must resort to non-convex optimization methods. One such solution presented by Xia *et al.* [135] uses genetic algorithm [32] to solve the capacity optimization problem for outage compensation. The problem objective is to minimize the sum of squared difference between capacity utilization of a compensated cell and average network capacity utilization in a homogeneous network. In this study, the genetic algorithm searches over the user association sets including users affected by the outage to find the set that minimizes the capacity utilization objective. Results show that the proposed methodology can improve average resource utilization by at least 5% compared to non-optimized cell capacity utilization. The key advantage of using genetic algorithms is their immunity to initialization point and their ability to get out of the non-feasible zones in the solution set. However, as the size of a system grows larger, the genetic algorithm takes longer to converge.

Rohde and Wietfeld [136] propose to use probabilistic network performance estimation to compensate network outages through ad-hoc deployment of unmanned aerial vehicles (UAVs) mounted relays. Aerial relays can help to exploit unused local capacities of nearby macro cells which cannot be used optimally for connectivity by users or ground based relays when no line of sight link is available. The proposed algorithm builds probabilistic estimation models of interference and throughputs through iterative modification of relay positions to achieve stable cell loads. The authors have compared results using 1 to 6 aerial relays at different distances from outage cell under stationary user locations with results showing that as the number of relays increases and distance from outage cell center decreases, average resource utilization on neighboring cells decreases.

3) Learning-Based Capacity Optimization Solutions for Outage Compensation: Aráuz and McClure [137] utilize probabilistic graphic models derived from Bayesian Networks to detect sleeping cells in HetNets and compensate for their outage. Probabilistic graphic models are used to predict user distribution in the outage-affected cell as well. It also allows the categorization of incoming load based on the user distribution and the active cell load without the need to store lengthy baseline data. Each neighboring cell of the faulty cell arranges

TABLE VIII
QUALITATIVE COMPARISON OF SPECTRAL EFFICIENCY OPTIMIZATION ALGORITHMS FOR COMPENSATION

Solution	Reference	Methodology	Sub-Method	Network Topology	Performance Metrics	Control Mechanism	Direction of Control
Spectral Efficiency Optimization	[140]	Analytical	Convex Optimization	HetNet	Quality	Distributed	DL
	[141]		Game Theory				
	[142]		Multi-objective Optimization			Centralized	

the predicted load probabilities in increasing order and decides the expansion of its coverage. The authors report that the probabilistic graphic model can successfully predict the expected user distribution and incoming loads for majority of the cases which results in 91.1% of the cases in total coverage recovery with just two sectors cooperating by expanding their footprint. Total recovery is reported for 96% of the cases with three sectors cooperating. The key advantage of proposed approach is that instead of using all neighboring sites or sectors it can yield substantial recovery using only two or three neighboring sectors.

In another study based on supervised learning, Tiwana *et al.* [131] use statistical learning with constrained optimization for outage compensation. The study utilizes logistic regression to extract the functional relationships between the noisy KPIs including file transfer time, block call rate and drop call rate, and cell resource utilization. These relationships are then processed by an optimization engine to calculate the optimized resource allocation which improves the KPIs of a degraded cell. The process is iterative and converges to the optimum value in few iterations, which makes it suitable for large mobile cellular networks. Results using Monte Carlo simulations indicate 44% improvement in blocked call rate and $\sim$26% improvement in file transfer time.

The algorithm in [131] has been extended by Tiwana [138] to utilize α-fair packet scheduling for radio resource allocation at neighboring cells for outage compensation. At $\alpha = 0$, the scheduler acts as max-throughput scheduler, whereas at $\alpha = 1$, the scheduler becomes proportional fair. Changing the value of α allows compromise between higher capacity (higher throughput for its mobile users) and greater coverage (serving higher number of users concurrently). The results indicate that for $\alpha = 1.3$, the average blocked call rate decreases by 61%, which is a gain of 17% compared to the scheme in [131], while average bit rate falls by 4%. However, for $\alpha = 0.8$, the average bit rate increases by 3% while blocked call rate falls by 5%.

D. Spectral Efficiency Optimization for Outage Compensation

Spectral efficiency is the ratio of data rate to the used bandwidth and depends on factors which include user distribution, interference, neighboring cell load, geographical SINR distribution, topology, spectrum reuse, modulation schemes, and the number of data links between the communicating nodes, among others. Therefore, spectral efficiency is heavily dependent on the outage compensation actions and has been used as the optimization objective in several studies [140]–[142] which are presented below while their qualitative comparison is given in Table VIII.

The physical implementation of HCs, described in [132], has been discussed by Lee *et al.* [140] for outage compensation. The study assumes that indoor base stations or small cells can support scalable bandwidths which can be used to compensate users affected by outage in neighboring small cells. Furthermore, it is shown that the maximum spectral efficiency in the event of an outage is achieved when the minimum number of HCs, predetermined by an indoor central unit, is assigned to support users covered by the outage-affected cell. The proposed technique achieves the largest average cell capacity and user fairness in terms of spectral efficiency when compensating cells can be selected by affected users opportunistically for each HC, which is called the multi-cell diversity effect.

Fan and Tian [141] employ game theory to address outage compensation in HetNets. The authors propose a resource allocation scheme in which data transmission can be done cooperatively by the cells. Similar to the approach in [134], channel allocation and cooperation is done at sub-channel level, i.e., by splitting the bandwidth of healthy cells for the purpose of compensating users affected by the outage. The problem is formulated as a rate maximization coalition game with weights for individual users and is solved using equal power allocation strategy. Once coalitions are formed between users and compensating cells, the authors use Lagrangian multipliers to solve for the optimal power set with the objective function of maximizing rate over a coalition. The approach requires users to go through multiple iterations of cell coalitions until the Pareto-optimal coalition is found which may require significant time expense.

Finally, He *et al.* [142] present a multi-objective optimization based approach for outage compensation in Cloud-RAN architecture. The optimization objective is the weighted sum of spectral efficiency of edge users of outage-affected remote radio units, and average spectral efficiency of users in outage and compensating remote radio units. Optimization parameters, i.e., antenna tilt of adjacent remote radio units, are adjusted to expand the coverage in an online-iterative manner. The algorithm is designed to maximize spectral efficiency of compensating cells and users affected by the outage but does not guarantee global maximization. Results show that the solution can recover spectral efficiency of users affected by an outage by 90%.

E. Summary and Insights

A review of techniques for outage compensation in Self-healing mobile cellular networks suggests four basic metrics are targeted in the event of an outage. These are: 1) coverage area, 2) SINR, 3) cell capacity/load, and 4) spectral efficiency. The optimization of these metrics is suitable for legacy mobile cellular networks. However, future 5G cellular networks will be more complex and QoE-focused. This means that outage compensation solutions of the future will have to focus on more than just these basic metrics. Some examples of potential metrics which will be important in 5G cellular networks include energy efficiency, service latency, and throughput fluctuations [38].

Ensuring service latency by itself will be a major challenge for network operators in 5G mobile cellular networks due to the complex nature of these networks. A review of outage compensation studies suggests that the most popular techniques for outage compensation are convex and non-convex optimization. Both of these techniques are computationally tedious and require far more time than would be acceptable in a 5G network. Furthermore, as these networks become denser, and the number of tunable parameters increases, the optimization process will get slower and more complex. Thus, one of the foremost challenges for future outage compensation solutions will be to reduce the time it takes for an optimization algorithm to reach its solution. Exploring trade-offs between different metrics for outage compensation in 5G networks will also be an interesting future area of study.

Another important research area in terms of outage compensation solutions is their integration into the larger SON framework. The SON framework includes technique for Self-optimization which oftentimes use the same parameters as outage compensation techniques. For example, coverage and capacity optimization solutions use transmit powers, antenna tilts and beamforming parameters which are also key for outage compensation techniques, as evidenced by the review of studies above. To avoid this issue, network operators will need to incorporate a Self-coordination entity to resolve such conflicts. Additionally, coordination will be important to avoid the triggering of Self-optimization as a result of some outage compensation action. For example, changing the azimuth of a cell to provide coverage to subscribers of a cell affected by a full outage might trigger coverage and capacity optimization in a neighboring cell. This could, in turn, trigger a cascade of changes in neighboring cells. While some studies have proposed the use of exclusion zones to reduce the impact of outage compensation on other cells [127], this area needs further research.

Finally, like existing outage detection and outage diagnosis techniques, outage compensation techniques do not incorporate technologies such as massive MIMO and millimeter spectrum utilization. To enable Self-healing in 5G networks, more solutions must be explored which focus on these technologies, making this a key area of research.

VII. Challenges and Future Prospects in Self-Healing for 5G and Beyond

In order for future 5G mobile cellular networks to achieve the desired gains laid out by the research and standardization community [38], SON solutions must play a far greater role than ever before [12]. This means that future mobile cellular networks must be intelligent, proactive, knowledge-rich and interactive at the same time. To achieve this goal, researchers must develop solutions which enable the network to achieve self-reliance, and harness the power of vast quantities of data generated by the users and network nodes to empower such solutions. However, Self-healing in future mobile cellular networks must cope with several research challenges which have been discussed below.

A. Challenge 1: Coping With Increased Number of Conventional Undetectable Outages Arising From SON Conflicts

SON functions deployed independently can potentially come into conflict with each other. A list of potential parametric SON conflicts has been presented in [143]. Similarly, [144] identifies the types of potential SON conflicts that may occur in the network when multiple SON functions are deployed concurrently. A consequence of these conflicts is parametric misconfiguration which can lead to degradation in user QoE. While a number of studies, including but not limited to [143] and [144], have proposed solutions for coordination of SON functions, the general approach utilized for coordination is reactive rather than proactive in nature. While this may be feasible in existing 4G and legacy networks, it cannot be the way forward in 5G mobile cellular networks.

Possible Solution and Future Research Direction: In order to proactively overcome outages due to parametric misconfigurations in 5G mobile cellular networks, the Self-healing framework may benefit from the ability to predict when a parametric misconfiguration might occur and take preventive measures to rectify it. One method of doing that is to explore the probabilistic reliability behavior of SON functions. This can be done by exploring techniques such as hidden Markov prediction models, as explored in [46].

Using hidden Markov models we can calculate the stationary probability of a parameter being misconfigured given a sequence of parametric reconfigurations. This allows us to analyze the long-term reliability behavior of SON-enabled mobile cellular networks to estimate the time of first occurrence of misconfigurations and the fraction of time the network spends in outage. Fig. 6 shows a Markovian SON coordination framework that can project the effect of activation of SON functions on the overall performance of the network. Such a solution can also be used to identify the selection priorities of proactive SON functions as well as their network parameters.

B. Challenge 2: Coping With Increased Outages Due to Increased Network Density

Network densification, driven by the need to meet capacity and data rate requirements of 5G mobile cellular networks,

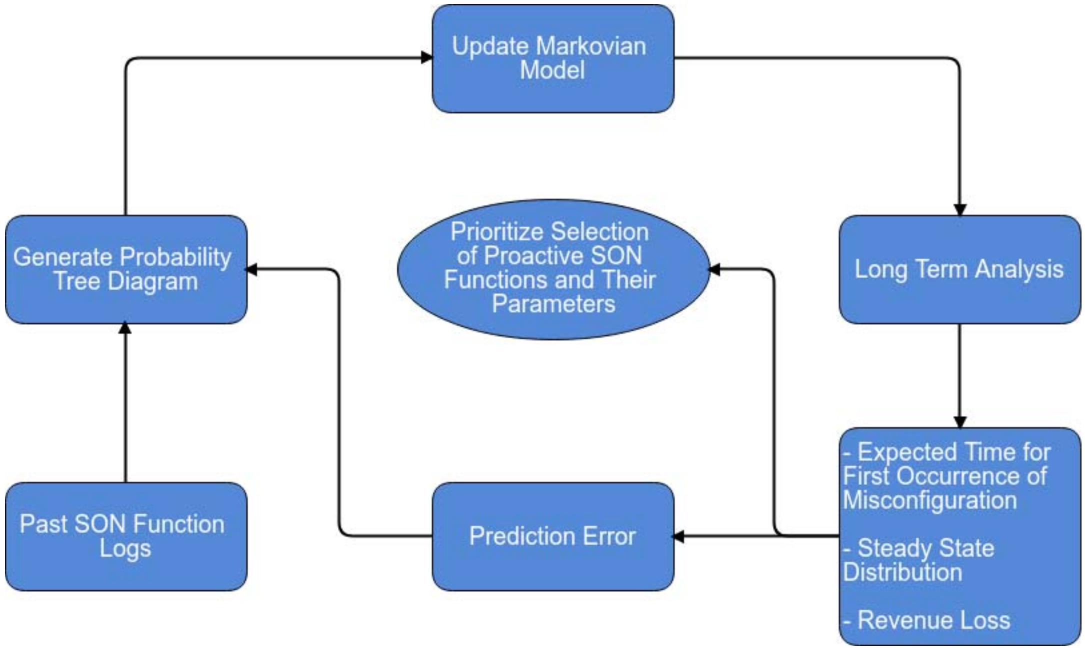

Fig. 6. Markovian SON coordination framework.

means that future mobile cellular networks will have to handle far more network nodes than before. Higher cell densities coupled with technologies such as millimeter wave spectrum utilization, and more configurable parameters will result in frequent network outages driven by both parametric misconfigurations and routine equipment failures as demonstrated in Figs. 2 and 3.

1) Possible Solution and Future Research Direction: A number of research areas have been highlighted in recent studies that can aid in dealing with network outages quickly and efficiently, especially in the context of dense and ultra-dense HetNets. One such approach is the control-data separation architecture (CDSA) [69] where the control functionality lies with macro cells while data transmission is handled by small cells. This adds redundancy to the network architecture. For example, in the event of a small cell failure, the macro cell can handle both control and data transmissions to the affected users.

Furthermore, with the development of UAV technology for enabling 5G mobile cellular networks, UAV-based outage compensation techniques, such as the one presented in [136], can become ubiquitous. Additionally, decreasing cost of small cell deployment will mean network densification itself can be used to create redundancies within the network such that the UE-to-cell ratio becomes less than 1. This will mean that in the event of a small cell failure, there will be additional small cells ready to serve the users without effecting their QoE. Network densification will play an especially significant role in the context of millimeter wave cells where coverage will be limited to line of sight links and outages due to link obstruction will be frequent.

C. Challenge 3: Coping With Sparsity of Data Due to Smaller Number of Users Per Cell

With network densification, another challenge arises in the form of data sparsity due to fewer users per cell. This will make full outage detection and partial outage detection extremely difficult since there will not be enough measurements to accurately distinguish between cell edge users and outage scenarios. Moreover, even though the expected throughput per user will increase, decreasing user density per cell will mean fewer users will consume more data, hence data sparsity will stay an issue for Self-healing in 5G mobile cellular networks.

1) Possible Solution and Future Research Direction: As we saw in Section IV, the overwhelming majority of full outage detection and partial outage detection solutions relied on machine learning techniques. However, unlike analytical or heuristic techniques, learning based algorithms are overwhelmingly dependent on data from the network, which can be sparse especially in the case of ultra-dense small cell deployment. To improve the accuracy of learning-based outage detection solutions and to counter data sparsity in future mobile cellular networks, measurement prediction techniques can be used. Predictive techniques such as Grey prediction model [72], and smoothing techniques such as Witten-Bell smoothing [145] and Good-Turing smoothing [146] can be used to remove knowledge gaps in the measurement data.

D. Challenge 4: Meeting 5G Latency Requirements in Self-Healing

5G mobile cellular networks are expected to have end-to-end data latency of 1 ms. This means that any Self-healing solution deployed in the network must be able to detect, diagnose and compensate any outage in far less time than state-of-the-art solutions.

1) Possible Solution and Future Research Direction: Given the nature of detection and compensation tasks within the Self-healing framework, future Self-healing solutions must be proactive in nature. This implies that the Self-healing framework will predict when and where an outage might occur with some probability, and execute changes in neighboring cells

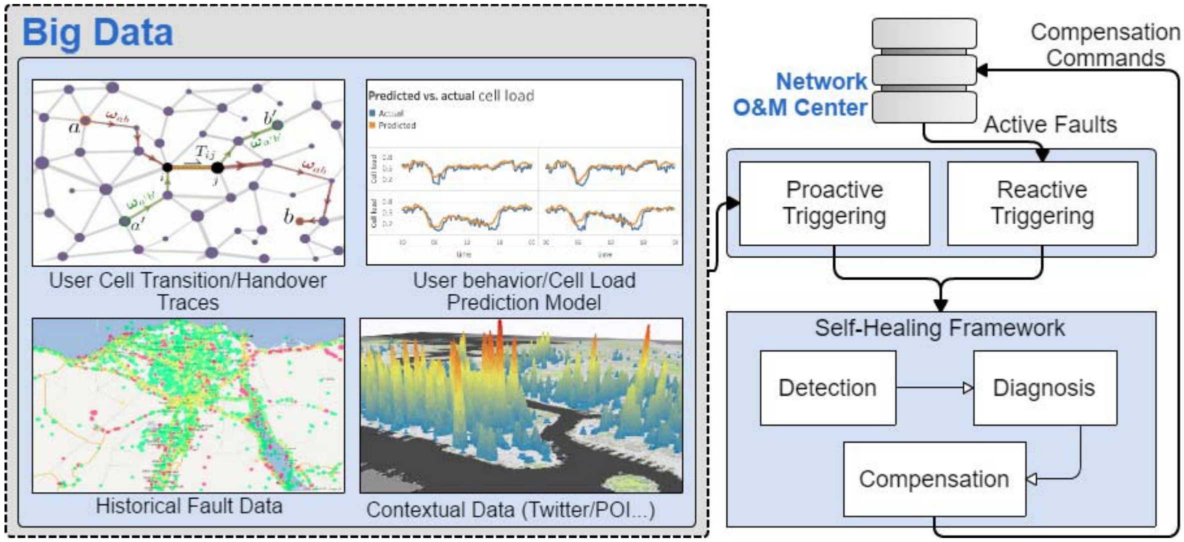

Fig. 7. Proactive Self-Healing Framework for Future Cellular Networks.

proactively. Despite the seemingly random nature of outages, especially full outages, outage prediction is possible and has been demonstrated by Kumar *et al.* [147] who have used different machine learning techniques such as neural networks, NBC and SVM to predict the next fault from real network data. Similarly, Kogeda and Agbinya [148] have predicted fault occurrences by collecting the past data and calculating maximum likelihood of next fault location using Bayesian Network prediction models.

All of the above-mentioned techniques rely on exploitation of big data [12] to identify key patterns in cell and user performance data and associating the information with previous outage information and data. This will allow the proactive Self-healing algorithms to identify changes in network performance that lead to a failure or an outage. Fig. 7 illustrates the concept of exploiting big data resources for prediction of faults in a future mobile cellular network. The definition of big data in the context of Self-healing framework includes historical fault data, user transition and handover data, network traffic and cell load data, and contextual data mined from sources such as social media.

E. Challenge 5: Meeting QoE Requirements in Self-Healing

The combination of requirements for 5G mobile cellular networks including low latency, high capacity, high throughput and low energy consumption means 5G networks will be user QoE centric compared to legacy networks which were user quality of service centric. This implies that meeting user QoE requirements will be the utmost priority in future mobile cellular networks, even in the event of an outage. Given that outages due to failures and parameter misconfigurations are likely to increase, meeting user QoE will be a key challenge for Self-healing solutions.

1) Possible Solution and Future Research Direction: The solution to meeting user QoE requirements despite outages is to deploy intelligence-rich proactive Self-healing framework such as the one shown in Fig. 7. The user-centricity of the framework will be driven by spatio-temporal user activity models. These include user mobility models derived from user transition data in the form of MDT reports [52] along with user location information which can easily be harvested from the positioning sensors inside modern cell phones. Additionally, user behavior load prediction models can be generated using machine learning techniques shown in Fig. 8 while contextual data from social media sources such as Twitter and Facebook can be mapped to network topology which would help to identify potential traffic hotspots and failures. Historical fault data collection can be done by setting up databases that would include network failure records as well the KPI data immediately preceding the failure. All this information will be fed to the proactive fault prediction algorithms which would sit alongside a reactive Self-healing triggering algorithm which monitors fault data from live network.

F. Challenge 6: Coping With Bandwidth Constraints for Self-Healing

Bandwidth constraints are one of the greatest limiting factors for mobile cellular network capacity. Limited bandwidth means extra capacity can only be added by adding more cells into the network. However, as discussed previously, network densification can lead to a rise in network outages itself. Furthermore, bandwidth limitation becomes even more acute in the event of an outage when already strained neighboring cell resources can become completely choked causing partial outages.

1) Possible Solution and Future Research Direction: While millimeter wave spectrum utilization has been promoted as the primary solution to bandwidth limitation [106], it is still in exploratory phases. In addition, the limited range of millimeter wave cells does not make them the ideal candidates for outage compensation solutions unless they are deployed in very high densities. One possible solution to the issue of bandwidth limitation for Self-healing is to deploy spectrum sensing or cognitive radio solutions [18], [19]. Some outage

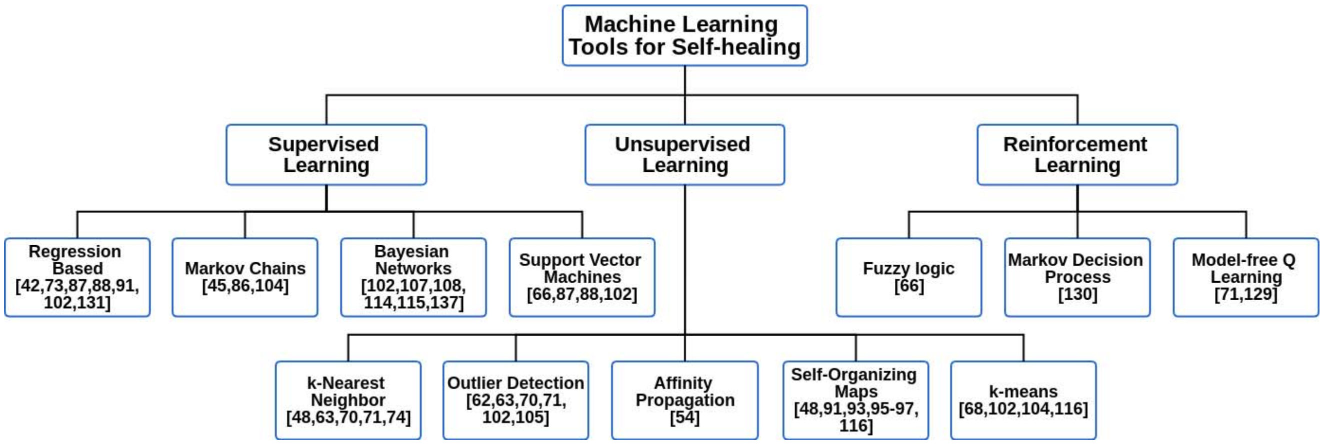

Fig. 8. Machine Learning Tools to Enable Proactive Self-Healing Framework for Future Cellular Networks.

compensation solutions based on spectrum splitting have been proposed in [132], [134], [140], and [141] but these solutions propose to reserve special bandwidth called Healing Channels (HCs) specifically for outage compensation. Given that mobile cellular networks are already facing bandwidth shortage, this approach may not be suitable especially when there are no outages. To avoid dedicating bandwidth for outage compensation, cognitive radio technologies can be explored to split the spectrum between HCs and normal bandwidth specifically in the event of an outage. Not only would this improve radio resource utilization under normal circumstances, it can also improve the service provided to outage-affected users by assigning them low interference resources.

G. Challenge 7: Enabling Self-Healing With Future 5G Services

Future 5G mobile cellular networks will be a combination of a multitude of services including legacy call, text and data services as well as Internet of Things services such as connected homes and smart grids. Each of these services has its own requirements. For example, providing wireless connectivity to smart grids does not require very high data rates but data security and robustness is highly important [149]. As discussed in Section VI, existing studies on Self-healing only address how legacy services such as data transmission and call connectivity would be restored in the event of an outage and do not tackle other services expected to be part of 5G networks.

1) Possible Solution and Future Research Directions: Self-healing for future services such as Internet of Things connectivity is still an open research topic despite being flagged as one of the primary challenges to the technology [150]. Similarly, Self-healing with respect to smart grids has been raised as a key issue [151]. Use of mobile cellular networks to empower smart grids has been a long standing concept [149]. However, due to the differences in performance level requirements for different services, the task of coming up with unified Self-healing solution is very difficult. Some studies have proposed to use cognitive radio technologies to provide the required performance levels in smart grids [152] which means they can also be a potentially useful tool in restoring performance levels in the event of an outage in the mobile cellular network within the unified Self-healing framework.

VIII. Conclusion

Self-healing is potentially the most powerful SON component in terms of reducing mobile cellular network operational expenses, especially in future networks. However, to this date, a comprehensive study on the existing literature on Self-healing techniques for cellular networks was not carried out. This study is an attempt to rectify this issue through a complete background review of Self-healing in terms of mobile cellular networks along with a description of the complete Self-healing framework. Moreover, we have presented methodologies, topologies, design metrics and control mechanisms along with their descriptions which are employed in the reviewed studies. We have also surveyed the studies in each of the three Self-healing framework components, i.e., outage detection, diagnosis and compensation in the event of a failure or KPI degradation.

In addition to the review of existing literature supporting Self-healing for mobile cellular networks, this study presents and elaborates the challenges faced by Self-healing functions in terms of future 5G mobile cellular networks while also presenting possible solutions and future research directions. It is hoped that this survey and the prospective research areas presented within it will empower and encourage researchers to create Self-healing solutions for future mobile cellular networks that can address the limitations of existing research.

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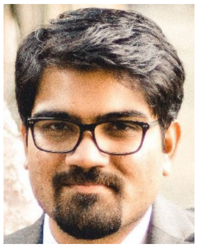

Ahmad Asghar (GS'17) received the B.Sc. degree in electronics engineering from the Ghulam Ishaq Khan Institute of Science and Technology, Pakistan, in 2010 and the M.Sc. degree in electrical engineering from the Lahore University of Management and Technology, Pakistan, in 2014. He is currently pursuing the Ph.D. degree in electrical and computer engineering with the University of Oklahoma, USA as well as contributing to multiple NSF funded studies on Fifth Generation Cellular Networks. His research work includes studies on self-healing and self-coordination of self-organizing functions in future big-data empowered cellular networks using analytical and machine learning tools.

Hasan Farooq (GS'14) received the B.Sc. degree in electrical engineering from the University of Engineering and Technology, Lahore, Pakistan, in 2009 and the M.Sc. degree (Research) in information technology from Universiti Teknologi Petronas, Malaysia, in 2014, wherein his research focused on developing adhoc routing protocols for smart grids. He is currently pursuing the Ph.D. degree in electrical and computer engineering with the University of Oklahoma, USA. His research area is big data empowered proactive self-organizing cellular networks focusing on intelligent proactive self-optimization and self-healing in HetNets utilizing dexterous combination of machine learning tools, classical optimization techniques, stochastic analysis, and data analytics. He has been involved in multinational QSON project on self organizing cellular networks (SON) and is currently contributing to two NSF funded projects on 5G SON. He was a recipient of the Internet Society First Time Fellowship Award toward Internet Engineering Task Force 86th Meeting held in USA, 2013.

Ali Imran (M'15) is the Founding Director of Big Data Enabled Self-Organizing Networks Research Laboratory, University of Oklahoma. His current research interests include self-organizing wireless networks (SON) functions design for enabling 5G, big data enabled SON, artificial intelligence enabled wireless networks, new RAN architectures for enabling low cost human-to-human as well as IoT and D2D communications. On these topics, he has published over 70 refereed journal and conference papers. He has given tutorials on these topics at several international conferences including IEEE ICC, WF-IoT, PIMRC, WCNC, CAMAD, and European Wireless and Crowncom. He has been a principle investigator on several multinational research projects focused on next generation wireless networks, for which he has secured research grants of over $3 million. He is an Associate Fellow of Higher Education Academy, U.K., the President of ComSoc Tulsa Chapter, a member of Advisory Board for Special Technical Community on Big Data at IEEE Computer Society, the Board Member of ITERA, and an Associate Editor of the IEEE ACCESS special section on heterogeneous networks.