Machine Learning Aided Context-Aware Self-Healing Management for Ultra Dense Networks With QoS Provisions

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***Abstract*—The self-organizing network is envisioned as a key technology to future wireless networks, especially for densely deployed small cell scenarios. Self-healing (SH) is an essential functionality to allow the networks to automatically detect and compensate for cell outages, which typically occur when unexpected network failures arise. In this paper, reaping the benefits of machine learning, we propose a novel SH framework in ultra dense small cell networks for meeting the demands of low-cost and fast network operation, quality of service (QoS), and energy efficiency. The proposed SH scheme comprises small cell outage detection (SCOD) and small cell outage compensation (SCOC) to enable self-healing in ultra dense small cell networks. Based on the context information of the partial key performance indicator (KPI) statistics, we propose a novel SCOD algorithm to detect the outage by applying support vector data description (SVDD) approach. The SCOD algorithm detects a small cell outage efficiently considering two situations: KPIs available situation and non-KPIs available situation. Furthermore, in order to compensate the small cell outage, SCOC is formulated as a network utility maximization problem to optimally compensate for the outaged zone in small cell network. A distributed compensation algorithm with low computational complexity is developed to balance the load of small cell networks, considering the QoS provision for users. Simulation results demonstrate that the proposed SH scheme can detect the small cell outage efficiently and can achieve an optimized QoS performance when compensating for the detected small cell outage.**

***Index Terms*—Self-organizing network (SON), self-healing (SH), cell outage, machine learning, key performance indicator (KPI), load balancing, ultra dense networks.**

Manuscript received May 16, 2018; revised September 12, 2018; accepted September 27, 2018. Date of publication October 24, 2018; date of current version December 14, 2018. This work was supported in part by National Natural Science Foundation of China under Grant 61471287, in part by 111 Project (B08038), in part by the National Research Foundation of Korea (MSIP) under Grant NRF-2014K1A3A1A20034987, and in part by the Natural Sciences and Engineering Research Council (NSERC), Canada. The review of this paper was coordinated by Dr. A.-C. Pang. *(Corresponding author: Qinghai Yang.)*

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Digital Object Identifier 10.1109/TVT.2018.2877910

I. Introduction

THE exponential growth of wireless data services driven by mobile Internet and smart devices, which leads to dense deployment of small cell networks, has triggered the investigation of the network planning, the management and the performance optimization for a better user quality of service (QoS) in future wireless networks, especially for 5G cellular networks [1], [2]. It is notable that the complexity of operations, capital expenditure (CAPEX) and operational expenditure (OPEX), is the major challenge for operators of future cellular networks [3], [4]. Particularly, with increasing scale of 5G networks especially for ultra dense small cell scenarios, new approaches of automatic detection and compensation with high efficiency are required to cope with the risks of outage owing to various kinds of hardware or software failures in wireless networks and to reduce the operation cost due to a mass of configuration operation parameters, which is a great challenge to manage 5G network efficiently.

Self-organizing network (SON) has recently been recognized as an attractive paradigm for the 5G networks, which enables autonomic features, including self-configuration, self-optimization and self-healing (SH) [5]. The main task of SH functionality is twofold, i.e., autonomous cell outage detection and cell outage compensation. Cell outage detection aims to autonomously detect outaged cells, and cell outage compensation adjusts the parameters of nearby cells to recover the service of users in the outage cells. The main advantage of SH functionality is that SH significantly reduces the time to detect and compensate the cell outage automatically, which could take hours for manual operations. This is especially important with the ultra dense small cell deployment in 5G networks, where manual operations are highly costly due to the huge amount of unplanned network deployment [6]–[9].

There are extensive research works focusing on SH in wireless networks [10]–[18]. The cell fault identification algorithms are designed based on monitoring of Reference Signal Received Power (RSRP) and Channel Quality Indicator (CQI) measurements in [10], [11]. Minimization of drive test (MDT) measurements are used to both profile network behavior and detect sleeping cells in [12], [13], which have been studied in Release 9 by the 3GPP in order to reduce the operation cost for drive test. Owing to the key advantages of artificial intelligence, researchers have applied methods from the machine learning such as clustering algorithms and Bayesian networks to automate the detection of faulty cell behavior [14]–[18]. A genetic algorithm is proposed for learning the outage rules in [14]. An automated cell outage detection mechanism based on dynamic affinity propagation clustering algorithm is introduced in [15]. Furthermore, the cell outage compensation is performed during the time period when the network fault happens. The problem of cell outage compensation is studied in [16]–[18]. A cell outage compensation methodology is proposed by adapting different outage compensation strategies to different cell outage situations. In [17], a framework for mitigating the adverse impact of dynamic outages is proposed while taking into account both the channel characteristics and eNodeB's residual resources. In [18], a novel pre-planned reactive cell outage compensation approach is presented to mitigate the effects of fronthaul failure. Furthermore, contextual information (e.g., user location and network state information) is introduced for improving management of wireless networks [19].

Although SH is extensively studied in the literature, there are still some challenges, especially for the ultra dense small cell networks. First, cell outage detection and cell outage compensation algorithms have been independently presented. However, it is necessary to jointly consider the cell outage detection and cell outage compensation processes for quick and flexible response to the network operation management. Such a complete SH framework is still missing. Second, the evolving 5G networks will be featured by ultra densely deployed small cells, with the benefits of covering holes, offloading traffic, and increasing energy efficiency [20], [21]. Small cells are particularly prone to failures due to its unplanned massive deployment, more hardware, and plenty of configuration parameters. Thereby, typical SH solutions in macrocell cannot be directly applied in ultra dense small cell scenario due to that small cell networks have reduced monitoring functions and limited computing capabilities. Moreover, it is very common in SH management that no KPI information (e.g., alarm or performance degradation information) may be reported to network operation and management (OAM) system in ultra dense small cell networks, due to unplanned deployment and limited reporting capability. The difficulty that knowing the effects of each outage cause when the KPIs are not available, not only impacts the design of SH scheme but also limits the outage detection efficiency under realistic conditions. Hence, an efficient SH scheme is urgently needed to deal with the outage situation that no KPIs are available. In addition, the outage compensation algorithms in the literature, were developed for optimizing the capacity and coverage of the identified outage cell zone but ignoring the optimal load balance and different users' QoS requirements, which is of vital importance to small cell network performance. Therefore, the SH mechanism with partial KPI information needs further investigation, considering the load balancing and users' QoS requirements.

There have been several research works that study the SH scheme in small cell networks. The authors investigated the problem in small cell networks without considering the context of MDT reports in [10]–[18]. Research works in [22]–[24] mainly focus on outage detection, which require fairly large network measurement data of users, leading to high computational cost. However, to the best of our knowledge, there has not been a comprehensive SH scheme that is designed for the ultra dense small cell networks with low computational complexity, and can deal with the partial KPI situation.

In this paper, we investigate the SH problem in SON-based ultra dense small cell networks, where KPI information of some small cells may not be available. We propose a comprehensive SH scheme including both small cell outage detection mechanism and small cell outage compensation mechanism, and is capable of dealing with partial KPI situations. Specifically, the proposed SH scheme includes SCOD stage and SCOC stage, where in SCOD stage the outage is detected, followed by the SCOC stage to compensate the users in the outage zones. For the SCOD stage, we propose a SCOD algorithm by applying support vector data description approach (SVDD), considering partial KPIs statistics. An effective SVDD algorithm with low computational complexity is developed to detect and locate the outaged small cells with the context of KPIs and user position information. The proposed SVDD algorithm has the time complexity and space complexity of $O(k^3)$ and $O(k^2)$, respectively, with k being the sample number. For the SCOC stage, to compensate the users in detected outage zone, we propose a novel distributed resource allocation algorithm that aims to optimize load balancing of the detected outage small cells area. The SCOC scheme is designed to allocate resources of neighboring small cells to the outage users, considering the dynamics and density of small cell environments. Specifically, we formulate resource allocation as a mixed integer optimization problem, solved by Lagrangian dual theory to guarantee both load balancing and QoS requirements of users.

The main contributions of this paper are summarized as follows.

- We propose a novel self-healing framework for ultra dense small cell networks based on machine learning approach that jointly considers outage detection and compensation, even when only partial KPI information is available.
- We develop a low-complexity SCOD algorithm to detect and locate the outage small cells with the context information of KPIs and user position, in which both misconfigurations and sleeping cells can be accurately detected.
- We propose a distributed compensation algorithm for outaged small cells guaranteeing load balancing in small cell networks, which is very practical and can be applied in real systems.

The remainder of this paper is organized as follows. Section II presents the system model. In Section III, the proposed SCOD algorithm based on SVDD approach is illustrated, and we analyze its effectiveness. Section IV presents a novel resource allocation algorithm for outage compensation. Section V presents the simulation results. Finally, Section VI concludes the paper.

II. System Model

We consider the ultra dense small cell networks scenario with partial KPI information. In this section, we present the system

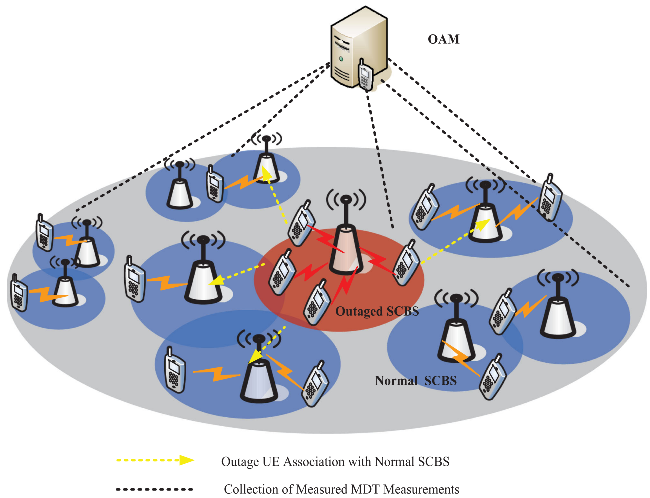


Fig. 1. SON-based small cell system model.

model of the paper, including the self-healing architecture, network model, and channel model.

A. Comprehensive SH Architecture

We consider a scenario with a set of small cells, and focus on SH in SON-based small cell networks, where small cells are connected to a centralized unit (for OAM) as shown in Fig. 1. The small cell base station (SCBS) which may experience cell outage with a certain probability in the process of operation, can share information for cooperation through OAM. The SCBS transmits reference signals periodically on downlink. The reference signals, which facilitate users' channel measurements (e.g., the RSRP and reference signal received quality (RSRQ) measurements), are sent back to the SCBS as feedback messages [23]. Particularly, the outaged SCBS cannot transmit or receive any signals.

A comprehensive SH architecture including both SCOD and SCOC is proposed, as shown in 2, i) In the SCOD stage, the OAM collects MDT reports from cells to build a MDT database, and the SCOD algorithm monitors KPIs profiled by MDT reports to determine if the small cells experience problems or failures. Then, the problems can be located based on the contextual information of small cell locations if there are failures occurred. ii) In the SCOC stage, the SCOC algorithm is executed to compensate the affected users by normal small cells and produce optimal compensation policy for the small cell networks. Based on this architecture, the SCOD phase and the SCOC phase are elaborated in detail in Section III and Section IV, respectively.

B. Network Model

We consider a set of small cells $\mathcal{S} = \{1, 2, \ldots, S\}$ and a set of users $\mathcal{N} = \{1, 2, \ldots, N\}$ in small cell networks. We assume that perfect CQI is acquired via OAM and the identities of users previously served by each SCBS are recorded in OAM. The assumption is reasonable since the overhead of reporting CQI and user information is necessary to guarantee the network performance [16]–[18]. Therefore, the users can be identified for compensation when the serving SCBS becomes faulty. We also

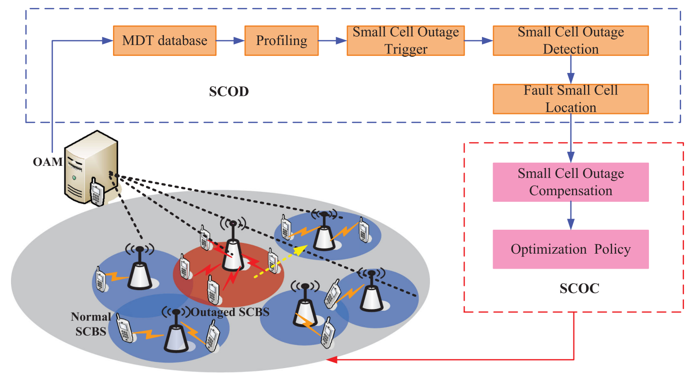


Fig. 2. The self-healing framework of SON-based small cells.

assume that users whose services are disconnected should find the preamble or pilot of a neighboring SCBS. In this situation, they can obtain the information about cooperative resource allocation, and can be served continuously by normal SCBS.

C. Channel Model

In the small cell network scenario, the channel gain of user u to SCBS s is determined based on the model described in [26]:

$$g_{u,s} = \left(\frac{d_0}{d_{u,s}}\right)^q e^{X_{u,s}} e^{Y_{u,s}}, \tag{1}$$

where d_0 is the reference distance, $d_{u,s}$ is the distance between the SCBS and user u, and q denotes the path loss exponent. $e^{X_{u,s}}$ and $e^{Y_{u,s}}$ are the shadow fading factor and multi-path fading factor, respectively. The shadowing fading follows a Gaussian distribution described by $X_{u,s} \sim N(0, \delta)$. The multi-path fading is modeled by Rayleigh fading with zero mean[1] [23].

III. The SCOD Scheme With Context Information of MDT Measurements

In this section, we propose a small cell outage detection framework considering the partial KPIs[2] measured on every SCBS by neighboring small cells, using the MDT report acquired from a fault-free operating scenario to profile the behavior of the small cell network. Particularly, each MDT report is tagged with the context of the location and the time information, which is regarded as contextual information. The goal of the proposed outage detection is to detect the cells' outage accurately and efficiently. To this end, two stages are involved: a trigger stage with no inter-cell communication, and a cooperative detection stage with high accuracy and low delay. In the trigger stage, each small cell collects the MDT measurements reported by users, and the OAM server initiates the detection stage to make a final decision. In the detection stage, the detection algorithm is executed to detect outages in small cells. The procedure is illustrated in Fig. 2.

[1]As shown in [23], shadowing fading effects are assumed to be independent of each other over time. With this assumption, the RSRP statistics of a user are independent random variables and can be characterized by (1).

[2]The OAM monitors the values of different KPIs for each cell, including the situation that the lack of KPIs for a certain cell, so we collect partial KPIs.

TABLE I
KEY PERFORMANCE INDICATORS

KPI Measurements	KPI Description
Load	The load of small cells
RSRP	Reference signal received power
RSRQ	Reference signal received quality
CDR	Call dropping rate
CBR	Call blocking rate
Location	Longitude and latitude information

A. Small Cell Outage Profiling and Triggering

Users can report measurements like RSRP and RSRQ to small cells, which could primely reflect the system performance. All KPIs are collected by virtue of the MDT reporting scheme, which has been defined in LTE Release 10 [27]. The MDT configuration report procedure consists of configuration, measurements, report and storing phase, and the scheme flow has shown in [25]. In the outage profiling stage, we obtain KPIs information (as shown in Table I) from the reference small cell scenarios to build the database, which is used to learn the small cell network's profile (the performance of small cell networks).

In addition, for the profiling phase, the tracing KPI database is processed to extract the feature vector $\mathcal{D}_{KPI}$, by storing the embedded measurements that represent the normal operation of the small cell networks, which is expressed in (2), shown at the bottom of this page. In (2), subscript s indicates the serving small cell, and subscript $c1 \cdots cn$ denotes n neighboring cells of the serving cells. This reference database is used in the cell outage detection algorithm to learn the "normal" small cell network profile. The goal of the SCOD algorithm is to define an anomaly detection rule that can differentiate between normal and abnormal MDT measurements by computing a threshold. At first, the KPI data set is pre-processed to be normalized, and then it is taken as input parameters for cell outage detection algorithm. The algorithm named SCOD is proposed on the basis of a machine learning technique, called SVDD algorithm, which is inspired by Support Vector Machine (SVM). SVM is a powerful data-driven approach for fault detection and diagnosis, which can use a hypothesis space of linear functions in a high dimensional feature space and can be trained with a learning algorithm from optimization theory [28].

The SVDD algorithm is able to form a decision boundary around the learned KPI data domain with very little (or even zero) information from outside the boundary, which is considered as outliers. The SVDD method originates from the idea of finding a sphere with minimal volume to contain all target data (the normal KPIs) [28], in which the sphere (the sphere means the domain consisting of the normal KPIs in small cell area) described as the objective function is characterized by center ϖ and radius Φ. The outaged cell detection problem is transformed to find an optimal sphere by minimizing Φ^2 based on the collected KPI data samples as follows.

$$\begin{aligned} \min \quad & \Phi^2 \\ \texttt{s.t.} \quad & \|x_i - \varpi\| \leq \Phi^2, i = 1, \ldots n \end{aligned} \tag{3}$$

where $x_i, i = 1, 2, \ldots, n$ is the i-th example in the MDT measured KPI data set $\mathcal{D}_{KPI}$, and the constraint in (3) indicates that all of the sampled KPI data should be contained by the sphere. To ensure the possibility of outliers in the training set based on the collected KPIs data samples, the distance from x_i to center ϖ should not be strictly smaller than Φ^2, and a larger distance for $\mathcal{D}_{KPI}$ should be penalized. Hence, we introduce the slack variables $\xi_i \geq 0$ to rewrite the problem as

$$\begin{aligned} \min \quad & f(\Phi, \varpi, \xi) = \Phi^2 + C \sum_{i=1}^{n} \xi_i, \\ \texttt{s.t.} \quad & \|x_i - \varpi\| \leq \Phi^2 + \xi_i, \\ & \forall x_i \in S, \xi_i \geq 0, \end{aligned} \tag{4}$$

where C is a particular constant parameter, which aims to control the trade-off between the volume of the sphere and the errors that namely the fraction false positives (outliers accepted) and the fraction false negatives (targets rejected). Hence, the outaged small cell detection problem is formulated as a convex quadratic optimization problem with convex constraints, and we introduce Lagrange multipliers in (5), shown at the bottom of this page. $\alpha_i \geq 0$ and $\gamma_i \geq 0$ are Lagrange multipliers. Then, setting partial derivatives to zero gives the constraints as

$$\begin{aligned} & \frac{\partial L}{\partial \Phi} = 2\Phi - \sum_{i=1} \alpha_i \cdot 2\Phi = 0 \Rightarrow \sum_{i} \alpha_i = 1, \\ & \frac{\partial L}{\partial \varpi} = \sum_{i=1} \alpha_i (2x_i - 2\varpi) = 0 \Rightarrow \varpi = \frac{\sum_i \alpha_i x_i}{\sum_i \alpha_i} = \sum_i \alpha_i x_i, \\ & C - \alpha_i - \gamma_i = 0, \forall i = 1, \ldots\ldots, N, \\ & 0 \leq \alpha_i \leq C. \end{aligned} \tag{6}$$

$$\begin{aligned} D_{KPI} = [& RSRP_s, RSRP_{c1}, \ldots RSRP_{cn}, RSRQ_s, RSRQ_{c1}, \ldots RSRQ_{cn}, \\ & Load_s, Load_{c1}, \ldots Load_{cn}, CBR_s, CBR_{c1} \cdots CBR_{cn}, CDR_s, CDR_{c1} \cdots CDR_{cn}, CQI] \end{aligned} \tag{2}$$

$$L(\Phi, \varpi, \xi, \alpha, \gamma) = \Phi^2 + C \sum_{i=1}^{n} \xi_i - \sum_{i=1}^{n} \alpha_i [\Phi^2 + \xi_i - (\|x_i\|^2 - 2\varpi \cdot x_i + \|\varpi\|^2)] - \sum_{i=1}^{n} \gamma_i \xi_i \tag{5}$$

Then, we can generalize the Lagrange dual function as

$$L(\Phi, \varpi, \xi, \alpha, \gamma) = \sum_{i=1}^{n} \alpha_i (x_i \cdot x_i) - \sum_{i=1,j=1}^{n} \alpha_i \alpha_j (x_i \cdot x_j). \tag{7}$$

By solving (7), we obtain the optimal solution $\alpha^* = \{\alpha_i^*, i = 1, \ldots\ldots N\}$, and the vectors with coefficient $\alpha_i^* \neq 0$ are called as support vectors (SVs).[3] The values of ϖ and Φ^2 depend on the support vectors illustrated as

$$\Phi^2 = (x_k, x_k) - 2\sum_{i=1}^{n} \alpha_i (x_i, x_k) + \sum_{i=1,j=1}^{n} \alpha_i \alpha_j (x_i, x_j). \tag{8}$$

Then, we build an optimal sphere for the outaged cell detection based on the collected normal KPIs data sample, by solving the convex quadratic optimization problem. We define the cell outage detection rule whereby the new collected KPI data sample ν in small cell network can be treated as normal when it satisfies the following:

$$\|\nu - \varpi\|^2 = (\nu \cdot \nu) - 2\sum_{i=1}^{n} \alpha_i (\nu \cdot x_i) + \sum_{i=1,j=1}^{n} \alpha_i \alpha_j (x_i, x_j) \leq \Phi^2. \tag{9}$$

Support objects with $\alpha_i = C$ will occur when $C < 1$ is satisfied. These objects are outside of the sphere which are considered outliers (which means the abnormal KPIs in this paper). The rest of the training data is within the description (which means the normal KPIs in this paper). Then, the small cell outage can be detected by using the cell outage detection rule of KPIs data domain description.

B. Small Cell Outage Detection and Localization

In the detection and outage localization phase, each MDT report is tagged with location and time information. We can obtain the normal area of the small network based on the SVDD algorithm and the new MDT KPIs are then tested by checking if they fall in the optimal normal area. If not, the small cell outage algorithm is triggered, and we can locate the outaged small cell based on the location information. However, there are also other situations in which the cell is sleeping or switched off by the operator for maintenance tasks or due to energy saving reasons. Hence, we introduce the concept of incoming handovers (Ξ_{in}), which are measured on a per small cell basis by neighboring small cells. Specifically, the small cell monitors the number of Ξ_{in} during measurement time period T, to determine the time period between two executions of the outage detection algorithm. If this number becomes zero for a certain small cell, that cell should be considered as an outaged small cell, and no KPIs can be measured in this situation as discussed in [29]. We define Ξ_a as the number of Ξ_{in} in the last period for T and define Ξ_b as the number of Ξ_{in} in the previous period for T. The measurement period time T is a configurable parameter, which has an effect on the execution time of outage detection algorithm. The smaller the measurement period T is, the faster the outage detection is. During this period T, the KPIs are collected statistically and updated the KPIs in the OSS periodically.

Then, we propose a novel SCOD algorithm that considers KPIs available situation and non KPIs available situation based on SVDD, taking advantage of localization information as well as monitoring KPI data obtained by user equipments. The proposed SCOD algorithm is shown in Algorithm 1.

[3]Generally, when the training set involves a large amount points, SVs is a small proportion, most of the training points are non-support vectors. That is to say, most components of the Lagrange Dual solution are zero [28].

Algorithm 1: The Proposed SCOD Algorithm.

Input: MDT measured KPIs: RSRP, RSRQ, CDR, CBR, Load, Ξ_{in} and T
Output: small cell outage detection
For each small cell take the following steps:
1: Collect the KPIs from SCBS, users and OAM periodically during measurement time T;
2: Calculate Ξ_a and Ξ_b;
3: **If** $\Xi_a == 0, \Xi_b > 0$, and KPIs are available, then, follow these steps:
3.1: KPI data preparation to obtain a measurement of N dimensions space, $x_{iT} = \{x_{iT}(1), x_{iT}(2), \cdots x_{iT}(N)\}$ (the KPI data that are collected in i-th T period);
3.2: Calculate the values of ϖ and Φ for the normal KPIs' objective based on (6) and (8) by using the collected KPI data; collect the new KPI sample from SCBS, and set the label of the new KPIs as $\nu = x_m + 1$;
3.3: If $\|\nu - \varpi\|^2 \leq \Phi^2$, then we set $F = 1$, which indicates that KPIs of the small cell are normal, and we also set the outage counter $L = 0$; else, we set $F = 0$ which represents that the KPIs are abnormal, and the outage counter $L++$;
3.4: If the outage counter satisfies $L > M$, the small cell is selected as an outaged small cell, in which M is introduced as an outage threshold value;
Else
The small cell is selected as an outaged small cell;
4: Generate the outage warning;
End;

IV. Distributed Small Cell Self-Healing Scheme

Once the outaged cell problem is detected by the proposed SCOD algorithm, a novel compensation mechanism is required to compensate the users in the outage cells to improve the overall network performance.

We propose a novel resource allocation scheme for self-healing, which aims to compensate for an abrupt cell outage in small cell networks. In particular, we consider a scenario with a set of small cells, and some of these small cells have already been detected as outages by the proposed the SCOD algorithm. Then, we optimize the resource allocation to balance the load in the identified outage zone whilst guaranteeing coverage and users' QoS requirements. To implement this approach, we propose a decentralized algorithm for small cell outage compensation.

We assume that the whole bandwidth of the small cell network is split into two parts: normal bandwidth and SH bandwidth. Particularly, normal bandwidth is used to transmit data for normal users, and SH bandwidth is used to serve users in the outaged small cells [30]. The whole SH bandwidth W is allocated to outaged small cells for compensation. Let $\mathcal{U}_F \in \mathcal{N}$ be the set of users previously served by the outaged small cells, namely compensated users, whom should be served by a set of normal cells and denote $\mathcal{M} = \{1, 2, \ldots\ldots M\} \in \mathcal{S}$ as the set of normal SCBS. The binary assignment indicator $a_{u,m} \in \{0, 1\}$ takes the value 1 if user $u \in \mathcal{U}_F$ is assigned to SCBS $m \in \mathcal{M}$, otherwise it is 0. A user of the outaged small cell can be assigned to exactly one normal small cell, and the assignment indicator in the assignment matrix $A = \{a_{u,m}\}_{\mathcal{M}\times\mathcal{U}_F}$ satisfies

$$\sum_{m=1}^{M} a_{u,m} = 1, \forall m \in \mathcal{M}, \forall u \in \mathcal{U}_F. \tag{10}$$

The bandwidth that SCBS m allocates to user u is denoted by $w_{u,m}$. Since all SCBSs share the same SH bandwidth, intra-cell interference arises when two or more neighboring SCBSs use the same SH bandwidth. Hence, the rate of a compensated user $u \in \mathcal{U}_F$ when served by SCBS $m \in \mathcal{M}$ is expressed as

$$r_u = \log_2\left(1 + \frac{\sum_{m\in M} a_{u,m} p w_{u,m} |g_{um}|^2}{\sigma^2 + \sum_{m\in M}(1 - a_{u,m}) p w_{u,m} |g_{um}|^2}\right), \tag{11}$$

where p is the fixed value per unit of frequency and measured in [Joule/sec/Hz], $pw_{u,m}$ is the transmit power on bandwidth $w_{u,m}$ allocated by SCBS m. g_{um} is the channel gain related to SCBS m and compensated user $u \in \mathcal{U}_F$ and σ^2 is the corresponding noise power.

For a unit of bandwidth, the signal to interference plus noise ratio $(SINR)$ [31] of compensated user u in (11) can be rewritten as

$$SINR_{u,m} = \frac{p|g_{um}|^2}{\sum_{s\neq m} p|g_{um}|^2 \left(\frac{\sum_{j=1}^{\mathcal{U}_F} w_{j,s}}{W}\right) + \sigma^2}. \tag{12}$$

Particularly, the traditional spectral efficiency for SCBS m is defined as $\mathcal{L}_m = \sum_{n=1}^{N} a_{u,m} \frac{r_m}{w_{u,m}}$, which represents SCBS load and the value of spectral efficiency becomes unbounded when $w_{u,m} \to 0$. Additionally, we simplify the spectral efficiency function. For SCBS m to a linear equation defined as

$$\mathcal{L}_m = \sum_{n=1}^{N} (a_{u,m} r_u - \kappa w_{u,m}), \forall m, u \in \mathcal{U}_F, \tag{13}$$

where we use the context of information about the minimum rate requirement r_u^{req} instead of the actual rate, and κ is a tuning parameter (the larger the value of κ, the higher the cost of the bandwidth resource).

A. Problem Statement

We consider a scenario where some small cells have already been detected as outaged through SCOD approach. Under this scenario, our objective is to find an optimal user association and resource allocation policy to compensate the users in the outaged small cells. We formulate the compensation problem to maximize the utility $\mathcal{U}_m(\mathcal{L}_m)$, which reflects the level of load balancing and users' satisfaction, considering the diverse users' rate requirement r_u^{req}. As shown in [32], a logarithmic utility function $\mathcal{U}_\mathrm{m} = \log(\mathcal{L}_m)$ can naturally achieve load balancing and a certain level of fairness among users. Therefore, we use a logarithmic utility function as an objective utility.

To optimally compensate users while balancing the load under the small cell outage scenario, we formulate the aggregate utility function maximization problem $\mathcal{P}1$ as

$$\begin{aligned}
\mathcal{P}1:\ &\max_{\mathbf{L},\mathbf{A},\mathbf{w}} \sum_{m=1}^{M} \mathcal{U}_m(\mathcal{L}_m)\\
\text{s.t. } \mathtt{C1}:\ &\sum_{m=1}^{M} a_{mu} = 1,\\
\mathtt{C2}:\ &\sum_{u=1}^{\mathcal{U}_F} w_{u,m} \le W,\\
\mathtt{C3}:\ &0 \le w_{u,m} \le a_{u,m} \min\left\{\frac{r_u}{\kappa}, W\right\},\\
\mathtt{C4}:\ &w_{u,m}\log_2(1 + SINR_{u,m})\\
&\ge a_{u,m} r_u^{req}, \forall m, \forall u,\\
\mathtt{C5}:\ &a_{u,m} \in \{0, 1\}, \forall m, u \in \mathcal{U}_F,
\end{aligned} \tag{14}$$

where $\mathbf{L} = \{\mathcal{L}_1, \mathcal{L}_2, \ldots \mathcal{L}_m\}$ is the load vector of SCBSs in small cells network, $\mathbf{A}$ denotes the association matrix between users and SCBSs, and $\mathbf{w} = \{w_1, w_1, \ldots, w_{u_F}\}$ denotes the allocated bandwidth vector for outaged users. Constraints C1 and C5 guarantee that the outaged user $u \in \mathcal{U}_F$ can be assigned to only and exactly to one normal SCBS, C2 denotes the limits of the bandwidth allocation for all the SCBSs, and C3 specifies the users' QoS requirements. C4 restricts the maximum bandwidth for outaged user $u \in \mathcal{U}_F$, which is a nonlinear constraint, leading to great difficulty solving this problem. Hence, we propose Theorem 1 to facilitate solving our problem.

Remark 1: The logarithm function $U_m = \log(\mathcal{L}_m)$ is concave and widely employed in other works [32, 35]. The property of this function can encourage load balancing efficiently. This is consistent with the resource allocation philosophy in real systems, where allocating more resources for a well-served user is considered low priority, whereas providing more resources to users with low rates is considered desirable [32].

Theorem 1: Constraint C4 is equivalent to (15) in solving problem $\mathcal{P}1$,

$$p|g_{u,m}|^2 w_{u,m} \ge r_u^{req}\left[\sum_{s\neq m} p|g_{u,s}|^2 \left(\frac{\sum_{j=1}^{\mathcal{U}_F} w_{j,s}}{W}\right) + \sigma^2\right]. \tag{15}$$

Proof: Please refer to Appendix A. ■

According to Theorem 1, we replace constraint C4 with (15), and thus problem $\mathcal{P}1$ can be reformulated into a problem with linear constraint set, which is easy to handle.

Furthermore, constraint C3 actually states that $w_{u,m} = 0$ when $a_{u,m} = 0$, otherwise

$$0 \le w_{u,m} \le \min\left\{\frac{r_u}{\kappa}, W\right\}. \tag{16}$$

For better understanding, we replace C3 with (16), which is equivalent to C3 in the context of $\mathcal{P}1$.

Problem $\mathcal{P}1$ is a mixed integer programming problem. By linearly relaxing the binary user assignment indictors into a continuous value within [0, 1], problem $\mathcal{P}1$ becomes a convex problem with a concave objective function and can be solved by known techniques, although with high computational complexity [33], based on Theorem 1 and (16). To directly solve the optimization problem $\mathcal{P}1$ with the aid of convex programming [33], [34], global network information is required, which necessitates a centralized controller for user association and coordination. Additional issues with centralized mechanisms include excessive computational complexity and low reliability, as any disabling of the centralized control operation will disrupt load balancing [35]–[37]. In small cell networks, it is usually difficult to coordinate small cells, some of which (e.g. a femtocell) are deployed by either operators or users [37]. Therefore, a low-complexity distributed algorithm without coordination is desirable. In this section, we propose a distributed algorithm via Lagrangian dual decomposition approach.

We proceed by relaxing with each equality a real Lagrange multiplier, $\lambda_m \in R$, and with each inequality a real non-negative Lagrange multiplier, $\mu_{u,m} \in R_+$. Adding them to the objective function, we reformulate problem $\mathcal{P}1$ to problem $\mathcal{D}$ in (17), shown at the bottom of this page, in which $\psi = p|g_{u,s}|^2(\frac{\sum_{j=1}^{\mathcal{U}_F} w_{j,s}}{W})$.

By further analyzing problem $\mathcal{D}$, we find that there is no terms coupling among $\mathbf{L}$, $\mathbf{A}$, and $\mathbf{w}$ in the objective for constraints. Hence, in order to further reduce the computational complexity, the dual decomposition method is employed to solve problem $\mathcal{D}$. It is based on the decomposition of the Lagrangian dual problem [38], and it can decompose the original large problem into distributively solvable subproblems. Then, they are easy to handle and can be solved separately on the users' side and SCBSs' side respectively [31].

With the dual analysis, we observe that the solution for the assignment variables will not be influenced by solving $\mathcal{D}$ from (17). Hence, the sub-problems are presented and solved independently as follows:

- Utility Distribution: the optimal utility per small cell is given by solving (18) over $l_m, \forall m$

$$\max_{\mathbf{L}} \sum_m [\mathcal{U}_m(\mathcal{L}_m) - \lambda_m \mathcal{L}_m]. \tag{18}$$

- User Association Distribution: the optimal user association distribution is derived by maximizing the overall network utility and is given by solving the problem below

$$\max_{\mathbf{A}} \sum_m \left[\lambda_m r_u a_{u,m} + \mu_{u,m}(1 - a_{u,m}) r_u \times \left[\sum_{s \ne m} \psi_{u,s}^{\max} + \sigma_u^2\right]\right]$$
$$\text{s.t.} \sum_{m=1}^{M} a_{u,m} = 1, \forall m, \forall u \in \mathcal{U}_F. \tag{19}$$

- Bandwidth Allocation: the optimal bandwidth allocation is derived by solving

$$\max_{\mathbf{w}} \sum_{u,m} \left(w_{u,m}\left(\mu_{u,m} p |g_{u,m}|^2 - \kappa_u \lambda_m\right) - \mu_{u,m} r_u \left(\sum_{s \ne m} \psi_{u,s}^{\max} + \sigma_u^2\right)\right)$$
$$\text{s.t.} \sum_{u=1}^{\mathcal{U}_{\mathcal{F}}} w_{u,m} \le W,$$
$$0 \le w_{u,m} \le \min\left\{\frac{r_u}{\kappa}, W\right\}, \tag{20}$$

where the constraint actually states that when the user is not connected to small cell m, then necessarily, bandwidth $w_{u,m} = 0$, otherwise $0 \le w_{u,m} \le \min\{\frac{r_u}{\kappa}, W\}$. We simplify the constraints by assuming that the total bandwidth available is sufficiently large $W \gg 1$, so that the constraint can be always satisfied with strict inequality.

In particular, given Lagrange multipliers (λ, μ), called from now on as price, we have the following solutions by solving problems (18)–(20).

Theorem 2: a) Given Lagrange multipliers for the relaxed problems (18)–(20), the optimal utility value of SCBS m is the solution to

$$\lambda_m = \frac{d\mathcal{U}_m(\mathcal{L}_m)}{d\mathcal{L}_m}. \tag{21}$$

$$\mathcal{D} : \mathrm{D}(\lambda, \mu) = \max_{\mathcal{L}_m} \sum_m [U_m(\mathcal{L}_m) - \lambda_m \mathcal{L}_m]$$
$$+ \max_{\mathbf{A}} \sum_m \left[\lambda_m r_u a_{u,m} + \mu_{u,m}(1 - a_{u,m}) r_u \left[\sum_{s \ne m} \psi^{\max} + \sigma_u^2\right]\right]$$
$$+ \max_{\mathbf{w}} \sum_{u,m} \left[\mu_{u,m} p h_{u,m} w_{u,m} - \kappa_u \lambda_m w_{u,m} - \mu_{u,m} r_u \left[\sum_{s \ne m} \psi + \sigma_u^2\right]\right] \tag{17}$$

b) Furthermore, each outaged user u is assigned to SCBS m satisfying

$$m_u{}^* = \arg\max_m \left\{ \lambda_m - \mu_{u,m} \left(\sum_{s \neq m} \psi^{\max} + \sigma_u^2 \right) \right\}. \quad (22)$$

c) The outaged users in small cells can find an optimal compensation small cell based on (22). The optimal bandwidth allocation for outaged user u is constrained by the following conditions

$$\begin{cases} w_{u,m} \in \left(0, \min(\frac{\gamma_u^{req}}{\kappa}, W)\right). \\ \sum_{u=1}^{\mathcal{U}_{\mathcal{F}}} w_{u,m} \leq W. \\ u_{u,m} p |g_{u,m}|^2 \geq \lambda_m \kappa + \sum_{s \neq m} \sum_j u_{j,s} \gamma_j \frac{p|g_{j,m}|^2}{W}. \end{cases} \quad (23)$$

Proof: Please refer to Appendix B. ■

Note that there may be a certain inconsistency between the assignment of a user to a single SCBS whilst satisfying (23) and the allocation of positive bandwidth to possibly more than one station. The reason for this is the change of the constraint from C3 to (16). In the following, we will conclude that the optimal solution derived from C3 is the same as that from (16).

Theorem 3: Constraints C3 and (16) are equivalent in terms of solving problem $\mathcal{P}1$. Moreover, if $a_{u,m}^* = 1$, then $w_{u,m}^* \in \left(0, \min\{\frac{r_u}{\kappa}, W\}\right)$, else $a_{u,m}^* = 0$, then $w_{u,m}^* = 0$.

Proof: Theorem 3 is derived directly according to the complementary slackness condition related to (15) and Theorem 2. The detail derivation is omitted due to lack of space, and interested readers can refer to [31] for details. ■

From Theorem 3, once the user assignment variables are acquired, we can determine the bandwidth allocation for outaged users. Therefore, we derive Corollary 1 to acquire the user assignment scheme. Particularly, since we aim at providing an algorithm possible to implement in small cell networks, in the following sections, we will explain how the users in the outaged SCBS are compensated by normal SCBS.

Corollary 1: Choosing an appropriate SCBS for the outaged users is based on the following rules with the load price and interference cost. We choose the small cell with the maximum utility equal to the load price and the minimum interference cost towards the neighboring SCBSs that can satisfy

$$m^* = \arg\max_m \left(\underbrace{\lambda_m}_{\text{Load price}} - \underbrace{\zeta \sum_{j \notin N_m} \sum_{s \neq m} u_{j,s} r_j \frac{p|g_{j,m}|^2}{W}}_{\text{Interference cost}} \right), \quad (24)$$

where ζ is a tuning factor giving higher or lower weight on the interference cost. Based on the above, we present the algorithm for the optimal load balancing among SCBSs of small cell networks.

Based on Theorems 1–3 and Corollary 1, we develop a greedy ascend algorithm to acquire the user assignment. Considering the information of the outaged users set $\mathcal{U}_F$ and measured MDT data of SCBSs, the outline of the SCOC scheme procedures is detailed in Algorithm 2.

Algorithm 2: The Proposed SCOC Algorithm.

Input: The outaged SCBS user association and resource allocation vector $\pi^0 = \{\mathbf{L}, \mathbf{a}, \mathbf{w}\}$, where all users can gain information over the channel through RSRP measurements. Afterwards they communicate their channel quality vectors $\mathbf{G}_n = [g_{u,1}, \ldots\ldots g_{u,M}]$. Set K as the number of algorithm iteration.

Output: the adequate reconfiguration of SCBS user association and resource allocation

For *i=1:K*

1: Each SCBS calculates the current load $\mathcal{L}_m^i$ using (13), the current load price λ_m^i using (21), and the interference cost I_m^i using (24);

2: SCBSs exchange the current values of load and interference cost with their neigbors which are listed in its neighbors list.

3: Based on information over the other load and interference cost of SCBSs, each small cell can decide whether it's a target small cell for its neighborhood to load balancing.

4: The outaged small cell users $\mathcal{U}_F$ are defined as candidate users, then calculate the possible change in load of the other cells and get the utility;

5: The user set which maximize the utility is chosen;

6: Update $\pi^{i+1} \leftarrow \pi^i$;

7: When $\lambda^i = \lambda^{i-1}$ and $I^i = I^{i-1}$, stop;

End;

B. Complexity Analysis

The proposed SH management algorithm for SON-based small cell networks consists of two main phases: the SCOD phase and the SCOC phase. In SCOD phase, the computational complexity of cell outage detection process is determined by the SVDD algorithm, and the time and space complexity of obtaining the decision boundary using SVDD are $\mathcal{O}(k^3)$ and $\mathcal{O}(k^2)$, respectively (k is the sample number of KPIs). In particular, the main idea of SVDD algorithm is transmitted to solve a quadratic programming problem, which needs to compute a sphere around the data in the input space, and it is stated completely in terms of inner products between vectors as shown in (7). Based on the characteristics of computer dealing with linear and quadratic optimization problems, we can achieve the complexity of the detection algorithm in the SCOD phase. Furthermore, in SCOC phase, the outaged users are properly served based on resource allocation. In each iteration of this phase, the complexity of the proposed distributed SCOC algorithm is $\mathcal{O}(|\mathcal{U}_F||\mathcal{M}|)$, where $|\mathcal{U}_F|$ denotes the number of compensation users and $|\mathcal{M}|$ is the number of SCBSs. Thus, the proposed SH scheme can reduce the computational complexity compared with the optimal solution which has exponential computational complexity.

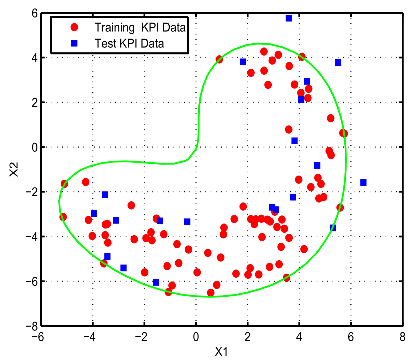
V. Simulation Results

A. Simulation Setup

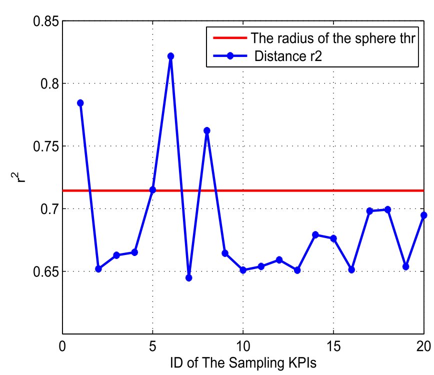
In the simulation, we consider a small cell network with 10 small cells and 50 users uniformly distributed within a 50 m ×

TABLE II
SIMULATION PARAMETERS

Parameters	Value
Number of Small cells	10
Number of Users	50
Bandwidth	0.5 MHz
Maximum transmission power	30 dBm
Standard deviation of showing factor	$\delta_{dB} = 8$dB
Thermal noise power density	-174 (dBm/Hz)



(a) SCOD based normal KPIs



(b) Test KPIs Classification

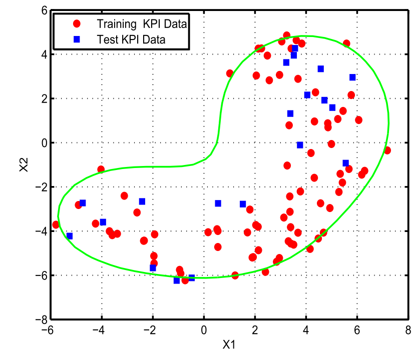
Fig. 3. The outage detection of SCOD based on normal KPIs.

50 m area. The propagation model is determined based on the ITU and COST231 model described in [23]. The standard deviation of shadowing factor $\delta_{dB} = 8$ dB, where $\delta_{dB} = 10\,\delta/\ln(10)$. The simulation parameters are given in Table II.

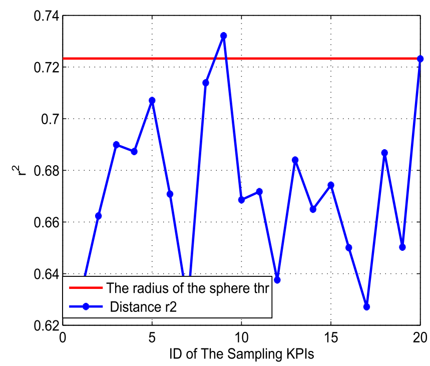
B. Simulation Performance

In this section, simulation results are provided to validate our theoretical performance analysis. Different faults which lead to the emergence of cell outages can be detected separately as we described in Section II. In the simulation, different antenna gain reductions are configured to represent different degrees of failures for cell outages. As detailed in Section III, the preprocessed MDT measurements data set is used as the input data for SH scheme.

We take 100 available KPIs (MDT measurement reports, which are all normal data), which contain 80 training samples and 20 test samples to verify the performance of the proposed algorithm. Fig. 3(a) shows that the proposed SCOD algorithm obtains a spherically shaped boundary for small cell outage



(a) SCOD based abnormal KPIs



(b) Test KPIs Classification

Fig. 4. The outage detection of SCOD based on abnormal KPIs.

detection (This boundary can cover the class of objects (e.g., normal KPIs) represented by the training set, and ideally should reject all other possible objects (e.g., abnormal KPIs) in the object space.). The measured KPIs data that are covered in the boundary indicates that the small cell operates normally, and the KPIs data outside the boundary denotes that the small cell is outaged, requiring compensation for this small cell. We further use the collected RSRP values to detect the small cell outage in Fig. 3(b). The horizontal line in Fig. 3(b) represents the radius of the sphere (sphere thr represents the optimal threshold value of the optimal sphere), and we see that an outage (the distance of data which is larger than the radius) has occurred in a small cell. Furthermore, we also take 100 KPIs, which contain normal KPIs and abnormal KPIs to verify the performance of the SCOD algorithm. Fig. 4(a) and 4(b) show that the algorithm can also detect the small cell outage efficiently. Particularly, we detect the situation that the small cell is also outaged, when there is lack of availability of KPIs based on SCOD algorithm, which is also treated as a small cell outage. Furthermore, we take SVM-aided cell outage scheme as the benchmark to verify the performance of SCOD scheme from the two aspects of runtime and accuracy, and the simulation results in Table III show that the proposed SCOD scheme has much lower complexity with high detection accuracy. Thus, the proposed SCOD algorithm can be very practical and robust in real system implementations.

Fig. 5 shows the small cell network performance of the proposed SCOC algorithm when changing tuning parameter κ (the higher the value of κ, the higher the cost of the bandwidth

TABLE III
RUNTIME AND ACCURACY SIMULATION RESULTS

Number of KPI data	SCOD runtime(s)	SVM runtime(s)	SCOD accuracy (100%)	SVM accuracy (100%)
100	2.6926	4.0243	91.00	91.00
200	2.8220	4.3328	92.50	93.50
300	2.9226	6.3784	93.67	94.67
400	3.1352	8.3784	94.50	95.25
500	3.5734	8.4011	95.60	96.40

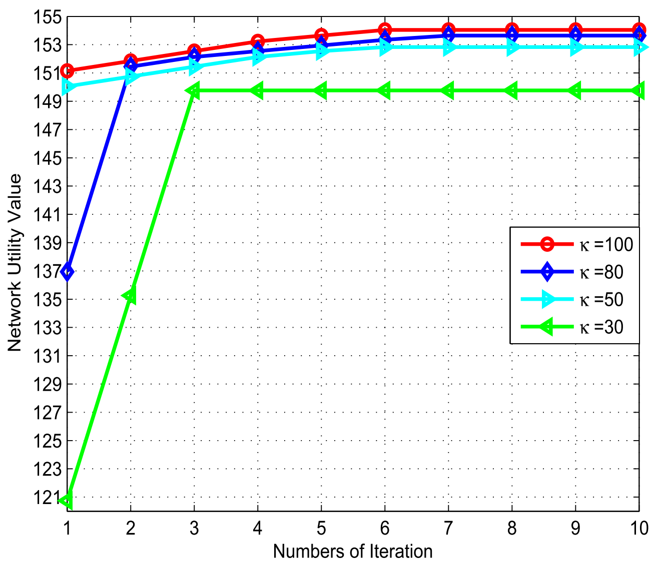


Fig. 5. Network utility vs. number of iterations.

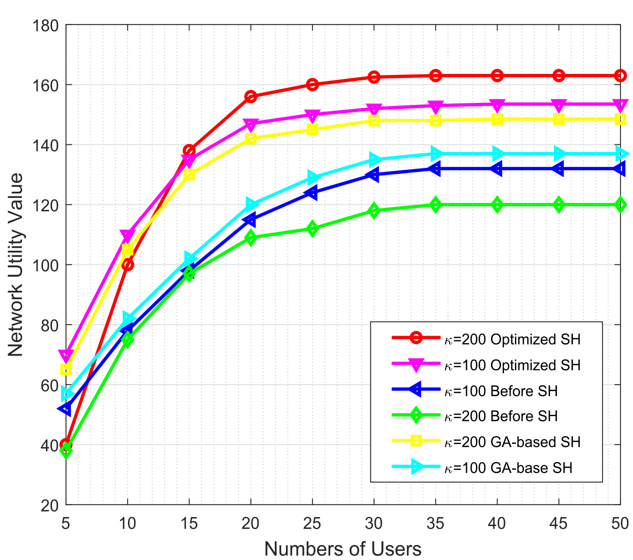


Fig. 6. Network utility vs. number of users.

resource.). This is reasonable because more resources in each small cell will be occupied by compensation users in order to improve the rate to satisfy their QoS requirements according to (12) and (13). Fig. 5 also shows that the proposed SCOC algorithm converges quickly in just a few iterations, because the algorithm operates in a distributed manner, and small cells can make decisions locally without communication with operation centers compared with traditional centralized algorithms.

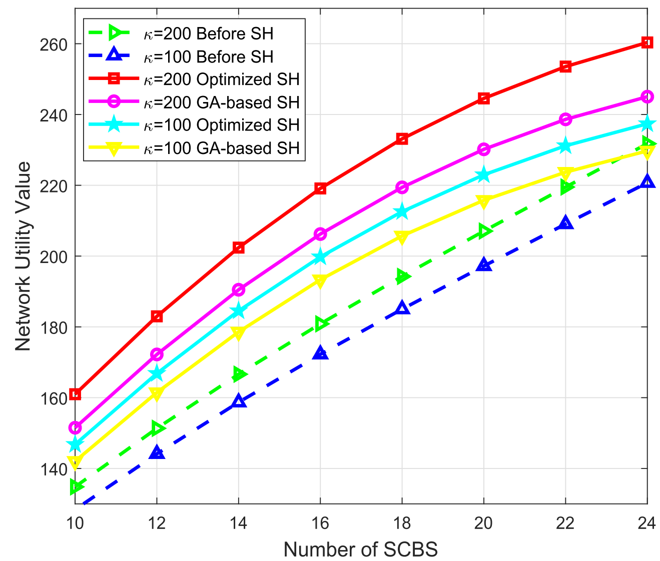


Fig. 7. Network utility vs. number of SCBS.

Fig. 6 shows the network utility of small cell network performance in terms of the number of users, compared to the case where non-SCOC scheme is implemented. The coalition game based resource allocation self-healing algorithm (GA-based SH) is used as the benchmark to verify the performance of SCOC scheme enabling self-healing and compensating abrupt cell outage in small cell networks. We can see that the performance of the SCOC scheme is much better than that of non-SCOC option in outaged small cell networks. Moreover, we can see that higher network utility will be achieved by the proposed SCOC scheme compared with the GA-based scheme. In particular, from Fig. 6, it can be concluded that the SCOC scheme can also achieve much better network utility under different users' QoS requirements. Most importantly, the proposed SH scheme can operate in an automatic manner, which is expected in the future network management with a SON functionality.

Fig. 7 shows the network utility of small cell networks performance in terms of the number of SCBSs and investigates the impact of the density of small cells. As expected, it shows that the proposed SCOC scheme provides better results than GA-based scheme in outaged dense small cell networks. In addition, the proposed scheme also achieves better performance than the non-SCOC scheme in small cell networks. The reason is that we take the interference cost into consideration, which is an important factor in dense small cell networks.

Fig. 8 further shows the load distribution in dense small cell networks. We see that the load of the small cells changes with the number of iterations and converges to a balanced load distribution, which denotes that the small cell network can obtain efficient improvement on load balancing with a QoS provision. Furthermore, as users in outaged small cells become compensated users, which are served by normal small cells, the algorithm converges quickly and will be very practical and robust in real wireless network's system implementations.

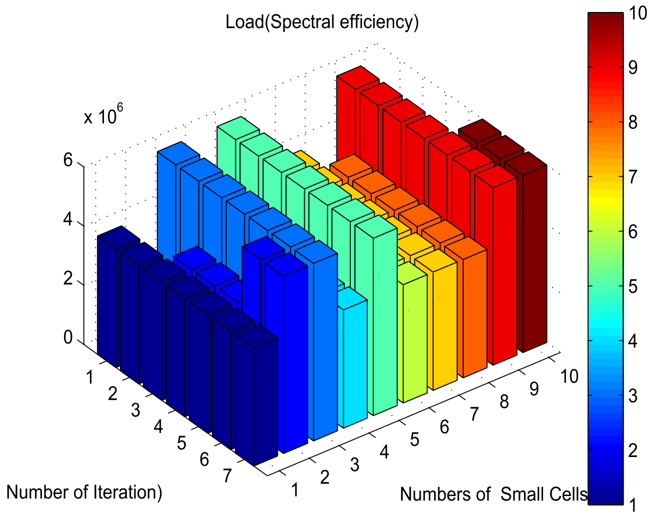


Fig. 8. Load distribution of SCBS vs. number of iterations.

VI. Conclusions and Future Works

In this paper, a self-healing scheme to deal with cell outages in SON-based small cell networks has been investigated. We have proposed a SCOD algorithm using machine learning approach based on partial KPI statistics that are a large scale collection of MDT reports. We also have proposed a novel SCOC algorithm to fairly allocate resources to outaged users for compensation, considering the dynamic and dense deployment of small cells environment. Simulation results demonstrate that the proposed SH scheme can detect the small cell outage efficiently and can achieve an optimized QoS performance when compensating for the detected small cell outage. In addition, the complexity of operation and management can become the biggest challenge in 5G, a comprehensive framework for empowering SONs with big data to address the management requirements of 5G is urgently needed. We will explore from the domain of machine learning to create self-organized end-to-end intelligence of 5G networks.

Appendix A
Proof of Theorem 1

In this paper, we set a minimum rate requirement for each user u, denoted by r_u^{req}. The constraint $w_{u,m}\log_2(1+SINR_{u,m}) \geq a_{u,m}r_u^{req}$ can be satisfied when guaranteeing different users' QoS requirements based on Shannon capacity formulation. We make an approximation $\log_2(1+SINR_{u,m}) \approx SINR_{u,m}$ for simplicity in small cell networks, which was proved valid in [31]. So the constraint can be rewritten as

$$w_{u,m}SINR_{u,m} \geq a_{u,m}r_u^{req}. \tag{25}$$

We substitue the $SINR_{u,m}$ expression from (12) into (25) and have

$$w_{u,m}\frac{p|g_{u,m}|^2}{\sum_{s\neq m}p|g_{u,m}|^2\left(\frac{\sum_{j=1}^{\mathcal{U}_F}w_{j,s}}{W}\right)+\sigma^2} \geq a_{u,m}r_u^{req}. \tag{26}$$

Then, we transform (26) to the form that

$$p|g_{u,m}|^2 w_{u,m} \geq a_{u,m}r_u^{req}\left[\sum_{s\neq m}p|g_{u,m}|^2\left(\frac{\sum_{j=1}^{\mathcal{U}_F}w_{j,s}}{W}\right)+\sigma^2\right] \tag{27}$$

and (28) is the expansion of (27).

$$\begin{aligned}&(1-a_{u,m})r_u^{req}\left(\sum_{s\neq m}\left[p|g_{u,m}|^2\left(\frac{\sum_{j=1}^{\mathcal{U}_F}w_{j,s}}{W}\right)\right]^{\max}+\sigma^2\right)\\&+p|g_{u,m}|^2w_{u,m} \geq r_u^{req}\left[\sum_{s\neq m}p|g_{u,m}|^2\left(\frac{\sum_{j=1}^{\mathcal{U}_F}w_{j,s}}{W}\right)+\sigma^2\right]\end{aligned} \tag{28}$$

Furthermore, we transform the constraint set into a set of linear inequalities, and get the inequalities as shown in (15). This completes the proof of Constraint C4.

Appendix B
Proof of Theorem 2

Given Lagrange multipliers for the relaxed problem $\mathcal{P}1$, we can find the optimal values for utility distribution, user assignment and bandwidth allocation by solving each one of the sub-problems respectively.

- For utility distribution in the problem, the optimal solution is given by solving the utility distribution sub-problem, which satisfies the expression
$$\max_{l_m}\sum_m\left[\mathcal{U}_m(\mathcal{L}_m)-\lambda_m\mathcal{L}_m\right] \tag{29}$$
and the solution is $\mathcal{L}_m=\lambda_m^{-1}$.
- Clearly, the variable a_m is decoupled in the constraints set of (10), and we can separate the optimization in (17) into sub-problems employing the primary decomposition approach. At the lower level, the sub-problems, one for each user u, can be written as
$$\begin{aligned}\max_{\mathbf{A}}\sum_m\Bigg[&\lambda_m r_u a_{u,m}+\mu_{u,m}(1-a_{u,m})r_u\\&\times\left[\sum_{s\neq m}\psi_{u,s}^{\max}+\sigma^2\right]\Bigg]\\ \text{s.t.}&\sum_{m=1}^{M}a_{u,m}=1.\end{aligned} \tag{30}$$
Furthermore, we observe that each outaged user u is assigned to SCBS m in user association problem satisfying
$$m_u{}^*=\arg\max_m\left\{\lambda_m-\mu_{u,m}\left(\sum_{s\neq m}\psi^{\max}+\sigma_u^2\right)\right\}. \tag{31}$$
The outaged users in small cells can find an optimal compensation small cell based on (31).
- Considering the bandwidth allocation problem, we simplify the constraints by assuming that the total available

bandwidth is sufficiently large. We can obtain the optimal resource allocation by solving over $\mathbf{w}$ as

$$\max_{\mathbf{w}} \sum_{u,m} \left(w_{u,m} \left(\mu_{u,m} p \left| g_{um} \right|^2 - \kappa_u \lambda_m \right) \right.$$

$$\left. -\mu_{u,m} r_u \left(\sum_{s \neq m} \psi_{u,s}^{\max} + \sigma_u^2 \right) \right)$$

$$\text{s.t.} \sum_{u=1}^{\mathcal{U}_F} w_{u,m} \leq W,$$

$$0 \leq w_{u,m} \leq \min \left\{ \frac{r_u}{\kappa}, W \right\}, \tag{32}$$

where $a_{u,m}$ and $w_{u,m}$ are related, the constraint actually states that when the user is not connected to small cell m, bandwidth $w_{u,m} = 0$, otherwise $0 \leq w_{u.m} \leq \min\{\frac{r_u}{\kappa}, W\}$. And we simplify the constraints by assuming that total bandwidth available is sufficiently large such as $W >> 1$, so that the constraint can always be satisfied with strict inequality. Then, the optimal resource allocation is equal to

$$w_{u,m} \in \left(0, \min \left\{ \frac{r_u}{\kappa}, W \right\} \right), \tag{33}$$

when ensuring that each SCBS with channel quality above the threshold $u_{u,m} p |g_{u,m}|^2 \geq \lambda_m \kappa + \sum_{s \neq m} \sum_j u_{j,s} \gamma_j \frac{p|g_{j,m}|^2}{W}$.

The optimal value of problem $\mathcal{P}1$ is determined by solving the dual problem of (17). We can find the optimal values on load, user association and resource allocation by solving each one of the above subproblems respectively. Given a Lagrange multipliers (λ, μ), we use a line search method to find the optimal solution for problem $\mathcal{P}1$, which can increase the value of the objective by searching from a feasible direction.

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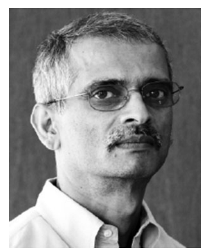

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