A Distributed Self-healing Mechanism Based on Cognitive Radio and AP Cooperation in UDN

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Abstract. Self-healing is considered as an indispensable function to achieve intelligent network management in future wireless communication systems. However, in ultra-dense networks (UDNs), it's a great challenge to realize efficient self-healing due to the massive and diverse network nodes, as well as complex transmission environment. The failed network access point (AP) may result in sudden traffic outage and severe user service degrading. In this paper, we propose an effective self-healing mechanism for UDNs with complete procedure of intelligent failure detection, diagnosis and recovery. Cognitive technology has been introduced to realize the effective detection of the AP working status. Then the processed information are analyzed based on multi-armed bandit model for possible AP failure judgement. After it is confirmed that an AP is failed, the impacted users, which are served originally by the failed AP, would be accessed to the proper neighbor APs. Furthermore, the corresponding resource allocation based on Non-Orthogonal Multiple Access (NOMA) is proposed. Simulation results show that the proposed mechanism could detect the AP failure effectively and realize quick self-healing for the network.

Keywords: Ultra-dense network · Self-healing · Failure detection · Resource allocation

1 Introduction

Recently, with the rapid development of wireless communications, ultra-dense networks (UDNs) have been considered as an inspiring approach to meet the huge traffic requirements, nearly 1 ms latency and massive devices access in typical scenarios [1]. With densely deployed network access points (APs), traditional manual or semi-automatic network management methods are inefficient

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and costly [2]. Therefore, self-organizing networking (SON) is introduced into UDN to realize the intelligent network parameters self-optimization, possible failure self-healing, and entities self-deployment [3,4]. Relative fields have attracted huge research interests and still need further investigation.

As one of the key technologies of SON, self-healing could detect the AP failure in time, and then efficiently provide service for the impacted users (served originally by the failed AP) automatically, thereby, prevent the network performance degradation. Generally, it contains three parts: failure detection, diagnosis, and recovery [4]. Currently, there are some existing works in relative fields. In [5], a self-healing framework based on cognitive learning is proposed for failure detection and compensation. In [6], the authors propose a self-healing algorithm with the water ripple algorithm and variable transmission power to provide seamless and reliable service despite AP failures.

However, self-healing in UDN is quite different from the traditional conditions and still an open problem. On one hand, the performance of self-healing usually has sensitive time constraint for failure detection. Existing centralized failure detection algorithms are too complicated to be implemented for UDN with a lot of APs. On the other hand, due to the short distance between neighbor APs, the simple increasing transmission power to cover the impacted users may cause severe interference in UDN. Therefore, the traditional failure recovery resource allocation algorithms are not suitable to be adopted in UDN directly.

Recently, there are some self-healing mechanism in small cell networks. In [7], a optimization algorithm considering APs selection and resource allocation is proposed to guarantee the reliable and seamless service for the impacted users. Reference [8] explores a hidden Markov model to automatically capture current states of the BSs and probabilistically estimate a cell outage. In [9], the authors propose a cell outage detection architecture based on the handover statistics in a two-tier heterogeneous network. Reference [10] presents a novel cell outage management framework for heterogeneous networks with split control and data planes. However, these detection methods require the network nodes to send report data to APs frequently, and there are huge costs. Moreover, the possible serious interference among APs are not considered.

Therefore, the self-healing in UDN is an important problem and needs further discussion. In this paper, we propose a self-healing mechanism consisting of intelligent failure detection, diagnosis and recovery. APs are divided into clusters and a leading AP (L-AP) is responsible for detecting their working information by cognitive technology in each cluster. Then these information are analyzed based on multi-armed Bandit Model to judge possible AP failure. Once an AP is confirmed to be failed, the impacted users would be connected to the optimal APs in the cluster. In addition, the corresponding resource allocation based on AP selection and Non-Orthogonal multiple Access (NOMA) is developed to reduce interference.

The remainder of our work is organized as follows. Section 2 gives the system model. In Sect. 3, we introduce the proposed self-healing mechanism. Simulation results and discussions are given in Sect. 4. Finally, we conclude this paper and present some future work in Sect. 5.

2 System Model

2.1 Topology Scene

We consider a typical scenario in UDN, where a series of APs are deployed by network operator with fixed positions. Considering the large number of APs, centralized algorithms require intolerable computation for failure detection, which couldn't meet the sensitive time constraint. Thus, we propose a distributed self-healing mechanism and it's suitable for the clusters that take spatial location as main similarity feature.

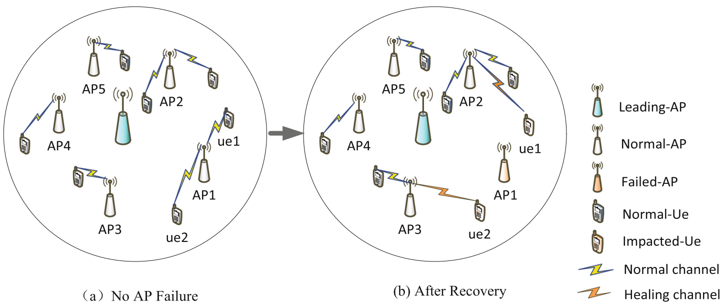

Fig. 1. System model of self-healing mechanism in UDN

In each cluster, the total system bandwidth is equally divided by APs, each AP occupies a sub-band, and the AP would serve different users based on NOMA. Each cluster has a L-AP to monitor the work of other APs by cognitive radio technology (CR).The L-AP has a list that records the users connection tables of all APs, and it would be updated synchronously when users access or disconnect from an AP, therefore, it works well when users move. Then it could schedule the APs and users in the cluster. In addition, we assume that the wireless channel would not vary during the transmission of a packet and the perfect channel quality information (CQI) is available by APs. The detailed system model is shown in Fig. 1.

In a cluster, $\mathbb{M}$ is the set of total APs, $\mathbb{M}_N$ and $\mathbb{M}_F$ are the sets of normal and failed APs respectively. Therefore, $\mathbb{M} \triangleq \mathbb{M}_N \cup \mathbb{M}_F$. Similarly, $\mathbb{U}$ is the set of total users, while $\mathbb{U}_N$ and $\mathbb{U}_F$ are the sets of normal users and impacted users respectively; here $\mathbb{U} \triangleq \mathbb{U}_N \cup \mathbb{U}_F$. $\mathbb{N}_i$ represents the users set of i-th AP. B_i represents the bandwidth allocated to the i-th AP. p_{ij} is the power allocated to the j-th user in the i-th AP. h_{ij} denotes the j-th user's channel gain in the i-th AP. n_0 is the power spectral density of Additive White Gaussian Noise (AWGN), $p_{i,max}$ denotes the maximum transmission power of the i-th AP, $p_{i,min}$ denotes the minimum power of each sub-channel. $r_{j,min}$ indicates the rate requirement of the j-th user, and C_{max} is the constraint of maximum connections of APs.

2.2 Downlink NOMA Channel Model

In this NOMA systems, each AP's spectrum band is orthogonal and no longer divided, then multiple users are served by power-domain NOMA. In addition, successive interference cancelation (SIC) is adopted to decode the different users' information in the same sub-channel. There are $\mathbb{N}_i$ users ($\mathbb{N}_i \leq C_{max}$) in the AP ($\forall i \in \mathbb{M}$). For each user in the same AP, user k is able to correctly decode then remove the interfering signals of other users $g \in \mathbb{N}_i \backslash \{k\}$ with $h_{ig} < h_{ik}$ and treat the interfering signals of other users $g \in \mathbb{N}_i \backslash \{k\}$ with $h_{ig} > h_{ik}$ as interference. Therefore, the interference after SIC for user k could be expressed as [11]:

$$\sum_{\substack{g \in \mathbb{N}_i \backslash \{k\} \\ h_{ig} > h_{ik}}} p_{ig} |h_{ik}|^2, \quad \forall k \in U \tag{1}$$

Then the signal to interference noise ratio (SINR) of user k in the AP is described as following

$$SINR_k = \frac{p_{ik}|h_{ik}|^2}{\sum\limits_{\substack{g \in \mathbb{N}_i \backslash \{k\} \\ h_{ig} > h_{ik}}} p_{ig}|h_{ik}|^2 + n_0 B_i}, \quad \forall k \in U \tag{2}$$

Thus, the achievable rate of user k in i-th AP is

$$R_k = B_i \log_2(1 + SINR_k) \tag{3}$$

3 Algorithm Design

Our proposed self-healing mechanism includes the complete procedure of failure detection, diagnosis and recovery. Firstly, a distributed failure detection algorithm is developed based on CR to reduce the detection time. Then the intelligent judgement of whether an AP is normal would be decided by our proposed algorithm based on multi-armed bandit model. Finally, we optimize the system energy consumption and consider possible inter-interference during recovery and resource allocation.

3.1 Failure Detection Based on CR

In the aspect of failure detection, the traditional methods require AP to report their work status periodically. Due to large number of APs in UDN, this might lead to "signal storm", resulting in degradation of network performance. Therefore, we set up a L-AP in each cluster, and adopt CR to sense other APs' working status in the cluster, as shown in Fig. 1(a). Every L-AP have a detection cycle T, which is determined by the number of APs (i.e. $\|\mathbb{M}\|$) and its computation ability. Meanwhile, L-AP builds a vector $V = \{v_1, v_2 \ldots v_m\}$, where $v_i \in \{0, 1\}, \forall i \in \mathbb{M}$ represents whether i-th AP's spectrum is occupied. An AP is considered as working when $v_i = 1$, otherwise it's idle or failed. If AP's spectrum isn't occupied, we will use the multi-armed Bandit Model to judge the AP's status according to collected information, then return the judgment result. If the result is idle, no further action needs to be taken. Otherwise, the L-AP needs to send a inquiry signaling to this AP. If the reply comes back in time, this AP is judged as normal, otherwise it is considered as failed.

3.2 Diagnostic Model Based on Multi-armed Bandit

In order to analyze the actual status of the APs, we introduced multi-armed bandit model to set up the proposed diagnose model. The multi-armed Bandit Model comes from a realistic problem of maximizing revenue [12]. There are K rocker arms in a gambling machine, μ_1, $\mu_2 ... \mu_K$ represent the return function of each arm. The gambler presses one of the rocker arms after puts a coin, then this rocker gives the corresponding revenue, and the gambler's goal is to get the best benefit.

In this paper, we set the number of arms as 2, representing the idle or failed statuses respectively. Considering that the probability of an AP failure is usually low, we use the Upper Confidence Bound Algorithm (UCB) to achieve this model. This algorithm not only focuses on the reward of each arm, but also considers the number that each arm is chosen. Then we need to record the information of each arm, with the following format:

$$S = (m, c, v) \tag{4}$$

Here, m is the identification of each arm, c is the number that each arm is selected and v is the average reward value of this arm.

The understanding degree of an arm is denoted as:

$$bonus = \frac{\sqrt{2 \times \ln(tc)}}{S_i.c} \tag{5}$$

tc is the sum that all arms are selected, and $S_i.c$ is the number that i-th arm is selected. $bonus$ is a indicator showing the degree that an arm is understood. If we have little knowledge about the arm, its v has a low confidence at this time, and we need to choose the arm to get more information. So its $bonus$ is big, then we are more probably to select this arm.

In the algorithm, if there is an arm with its c as 0, that is, the arm has never been selected, then choose it first (ie, each arm will be selected once at the beginning). If all arms have been selected, this algorithm will calculate the sum of $bonus$ and v for each arm, and selects the arm with maximum sum. Then, the reward of the selected arm is updated. For example, i-th arm is selected, and its v is updated as follows:

$$S_i.v = \frac{S_i.v \times S_i.c + res}{S_i.c + 1} \tag{6}$$

res is the reward after choosing the i-th arm.

The details are shown in Algorithm 1, and it will be triggered when an AP's spectrum isn't occupied.

3.3 Recovery Model Based on Optimizing Energy Consumption

When an AP is detected to be failed, the L-AP acquires the failed AP's user connection table, and manages these users to access nearby normal APs. The L-AP informs other normal APs about this failure, and every AP sends a beacon frame to detect the impacted users near it. Then the L-AP asks each AP to report the CQI between itself and these impacted users, and it verifies whether all the users are found. If not, it notifies the nearby APs to increase the detection range until all impacted users are found. After that, every user is accessed to the AP that its CQI is optimal under the scheduling of L-AP, and if this AP has reached the maximum connections, impacted users are scheduled to access the suboptimal AP, and so on. As shown in Fig. 1(b), when AP1 failed, the impacted users UE1 and UE2 are connected to AP2 and AP3 respectively.

Algorithm 1 Multi-armed Bandit Model Based on UCB Algorithm

1: Initialization:
2: (a) Create a record structure for each AP, containing the following data:
- S defined in Eq. (4): the two S are marked with 0 and 1 respectively, their v and c are set to 0.
- tc is set to 0.
- Set the reward function for each state.

(b) $Id = 0$, $maxB = 0$
3: **for** $i = 1, 2$ **do**
4:     **if** $S_i.c == 0$ **then**
5:         Set $Id = i$ then jump to line 11
6:     **else**
7:         Calculate this state's *bonus* according to Eq. (5)
8:         **if** $S_i.v + bonus \geq maxB$ **then**
9:             $maxB = S_i.v + bonus$; $Id = i$
10: Update $S_{Id}.v$ based on this state's return function
11: $S_{Id}.c = S_{Id}.c + 1$
12: $tc = tc + 1$
13: **if** $S_{Id}.m == 0$ **then**
14:     L-AP send inquiry signaling to this AP
15:     **if** Receive response from this AP **then**
16:         The judgement result is incorrect, and punish this state (i.e. Cut down its v).
17:     **else**
18:         This AP has failed, and call Algorithm 2.

When all impacted users are connected to the assigned AP, we begin to allocate power. Firstly, the AP sorts user connection table in the descending order of CQI, then calculates the power that should be assigned for each channel to meet the user's rate requirements. For example, the demanding power of user k in the i-th AP is denoted as:

$$p_{ik} = \frac{(2^{\frac{B_i}{r_{k,min}}} - 1)(\sum_{g \in \mathbb{N}_i \setminus \{k\}; h_{ig} > h_{ik}} p_{ig}|h_{ik}|^2 + n_0 B_i)}{|h_{ik}|^2} \tag{7}$$

We need to guarantee that the allocated sum power is less than the maximum power of this AP. If this AP couldn't meet the power requirements of some users, other AP would be assigned for these users.

Hence the system energy consumption is formulated as

$$\begin{aligned} &\min_{p_{ij}} \sum_{i \in \mathbb{M}_N} \sum_{j \in N_i} p_{ij} + (M - M_F) \cdot P_C \\ \texttt{s.t.}\ \ & C1: \sum_{j \in \mathbb{N}_i} p_{ij} \leq p_{i,max} \quad \forall i \in \mathbb{M}_N, j \in \mathbb{N}_i \\ & C2: p_{ij} \geq p_{i,min} \quad \forall i \in \mathbb{M}_N, j \in \mathbb{N}_i \\ & C3: 0 \leq j \leq C_{max} \quad \forall i \in \mathbb{M}_N, j \in \mathbb{N}_i \end{aligned} \tag{8}$$

Here, P_C is the circuit power consumption at each AP.

The detailed steps are shown in Algorithm 2.

Algorithm 2 Self-healing Power Allocation Algorithm

1: Initialization:
2: Create a record structure for each AP, containing the following data:
3:
- A *list* records the users' CQI connecting to this AP. $list = \{h_{i1}, h_{i2}...h_{i,C_{max}}\}$
- A *Plist* records the power allocated to these users, and the initial values are set to 0. $Plist = \{p_{i1}, p_{i2}...p_{i,C_{max}}\}$
- Set $P_{i,max}$ for i-th AP.

4: L-AP asks normal APs to detect $\mathbb{U}_F$
5: **while** $\mathbb{U}_N \cup \mathbb{U}_F < \mathbb{U}$ **do**
6:     All APs increase the detection range
7: L-AP acquires the CQI between APs and impacted users, then determine the optimal AP (i.e. i-th AP) for each user by comparing CQI
8: **if** length($AP_i.list$)$\leq C_{max}$ **then**
9:     L-AP schedules this user to access the AP
10: **else**
11:     L-AP selects a sub-optimal AP for this user, then jump to line 8
12: *list* is sorted in the descending order of channel quality
13: Calculate the subchannel power p_{ik} assigned for each user according to Eqs. (1), (7)
14: **if** $p_{i,max} - \sum Plist \leq p_{ik}$ **then**
15:     The user will access a new AP that can provide service

In this algorithm, the self-healing mechanism is achieved without affecting the operation of other normal APs in the cluster as far as possible, and it is compatible with manual maintenance. If the AP fails, then its spectrum is allocated, other normal APs need to divide the spectrum again. And the failed AP will not have available spectrum when it is repaired. Therefore, the corresponding spectrum of failed AP is no longer allocated.

4 Simulation Results and Discussions

In this section, simulation results are presented to illustrate the performance of the proposed mechanism. We consider a circular area with a radius of 26 m in the square. The L-AP is deployed in the center of this area, and there are $4 \sim 10$ APs as well as 16 users. The wireless channel is modeled as rayleigh fading channel including pathloss, where the channel coefficient is ${h_{ij}}^2 = {h_{0j}}^2 L_{ij}^{-\kappa}$, in which L_{ij} is the distance between AP i and user j. h_{0j} is the complex Gaussian channel coefficient [7].

Figure 2 illustrates the average time to find AP failure as AP number changes in a cluster. In order to ensure that the result is more accurate, we take the average of multiple outcomes, and find that detection time for each AP failure is small. As the number of APs increases in the cluster, the detection time becomes longer, this is because the L-AP needs to detect more APs each cycle and performs more operations (Table 1).

Figures 3, 4, 5 and 6 are from the same simulation. Figure 3 shows the APs' throughput changes in this simulation. When an AP failed, it can't continue to provide services and its throughput (i.e. AP3) drop to 0. After a period of time, L-AP finds this failure, and schedules neighboring APs service for these impacted users. In order to save the transmission power, these impacted users are accessed to the AP with the best channel gain. In this simulation, AP3 serves two users originally, and the users are connected to AP1 and AP4 respectively after AP3 fails, therefore the throughput of AP1 and AP4 increases. And the added throughput of AP1 and AP4 is exactly equal to the original throughput of AP3.

Table 1. The simulation parameters

Simulation parameters	Value
Carrier center frequency	2.5 GHz
The system bandwidth	$W = 30$ MHz
AP radius	10 m
Path loss exponent κ	4
Power spectral density of noise	-100 dBm/Hz
The maximum transmission power of AP	5 W
The detection threshold at SIC receiver	10 dBm
Users' minimum rate	$5 \sim 15$ Mbps
Monitoring time interval of L-AP (Iteration time interval)	10 ms

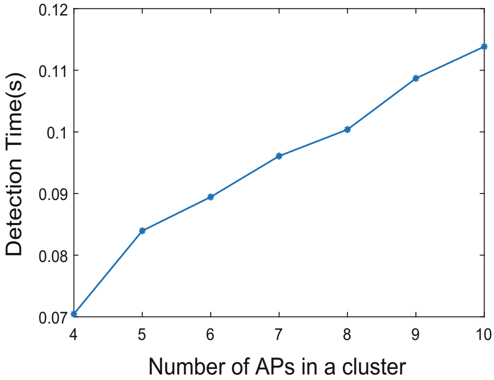

Fig. 2. Detection time with different number of APs

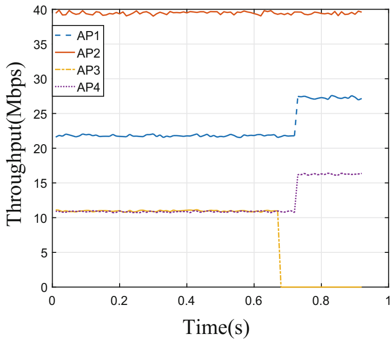

Fig. 3. APs' throughput change in self-healing process

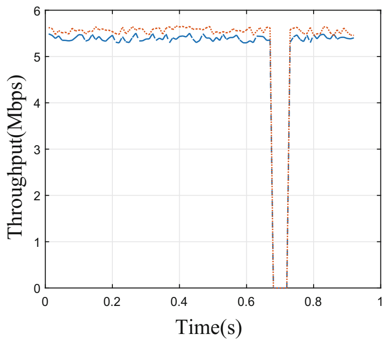

Fig. 4. UEs' throughput change in self-healing process

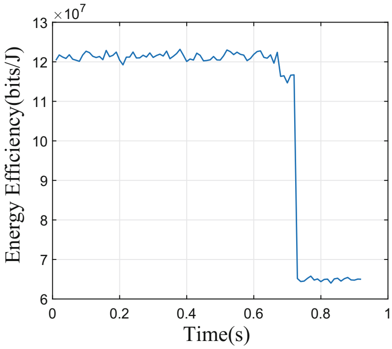

Fig. 5. System energy efficiency change

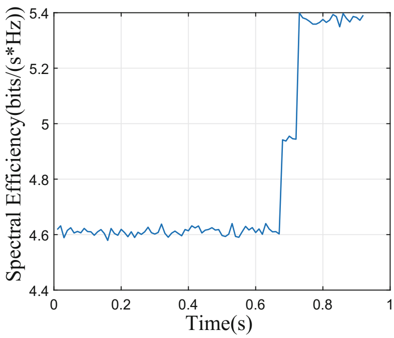

Fig. 6. System spectral efficiency change

Figure 4 illustrates the impacted users' throughput change in the process of self-healing. Initially, the UE normally receives data from AP3. When an abrupt failure occurs in AP3, they can't be served by AP3, and their throughput drop to 0. After L-AP detects the failure, these impacted users access nearby normal APs, and each user can be served as before. It shows that our proposed mechanism can eliminate the impact of a sudden failure effectively.

Figures 5 and 6 illustrate entire system's energy efficiency (EE) and spectrum efficiency (SE) changes in self-healing process. Because of the sub-channels allocated by NOMA, the power consumed by each added sub-channel increases significantly. Thus, the more sub-channels an AP has, the lower its EE is generally, but its SE may be higher. When AP3 fails, due to its sub-channels less, its EE is relatively high, thus entire system EE reduces a little. And its throughput is lower than other APs, its SE is also relatively low, thus system SE increases after AP3 fails. When these impacted users are connected to nearby APs, they require greater transmission power to achieve the original rate, thus the system EE further decreases. However, the system SE increases because an AP failure results in a reduction in system bandwidth yet the system throughput remains unchanged.

We simulate the channels' changes in reality, and CQI can't be obtained immediately, thus simulation results fluctuate.

5 Conclusion

In order to facilitate management and reduce calculation in UDN, we propose a distributed self-healing mechanism including complete procedure of intelligent failure detection, diagnosis and recovery. A L-AP is set to monitor other APs' status in each cluster, and their working information are collected by cognitive technology. When some spectrum is perceived to be unoccupied, the processed information of corresponding APs are analyzed based on multi-armed Bandit Model for possible failure AP judgement. If an AP is confirmed to be failed, the impacted users would be accessed to the optimal neighbor APs under the scheduling of L-AP. Furthermore, the corresponding resource allocation based on AP selection and NOMA is proposed, which considers inter-interference. Simulation results prove this mechanism can find AP failure quickly and realize effective self-healing for the network. However, there are some shortages in the mechanism. On the one hand, the current failure detection algorithm considers less about the AP status parameters, so that couldn't reflect the AP status accurately, thus more AP information should be considered. On the other hand, the proposed self-healing mechanism doesn't consider the case of L-AP failure, and this will reduce the detection sensitivity, therefore L-AP failure detection should be considered in the future.

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References

1. Rakshit, S.M., Banerjee, S., Hempel, M., Sharif, H.: Towards an integrated approach for distributed 5G cell association in UDN under interference and mobility. In: 2018 International Conference on Computing, Networking and Communications (ICNC), March 2018, pp. 810–814 (2018)
2. Jiang, W., Strufe, M., Schotten, H.D.: Intelligent network management for 5G systems: the SELFNET approach. In: 2017 European Conference on Networks and Communications (EuCNC), June 2017, pp. 1–5 (2017)
3. Nagarajan, D.R., Thiagarajah, S.P., Alias, M.Y.: Robust son system with enhanced handover performance system. In: 2017 IEEE 13th Malaysia International Conference on Communications (MICC), Nov 2017, pp. 276–281 (2017)
4. Moysen, J., Giupponi, L.: A reinforcement learning based solution for self-healing in LTE networks. In: IEEE 80th Vehicular Technology Conference (VTC2014-Fall), Sept 2014, pp. 1–6 (2014)
5. Chernogorov, F., Repo, I., Räisänen, V., Nihtilä, T., Kurjenniemi, J.: Cognitive self-healing system for future mobile networks. In: 2015 International Wireless Communications and Mobile Computing Conference (IWCMC), Aug 2015, pp. 628–633 (2015)
6. Lin, F. Y.-S., Tsai, M., Wen, Y., Hsiao, C.: Adaptive power ranges and associations for self-healing in multiple types of Wi-Fi networks. In: 2017 13th International Wireless Communications and Mobile Computing Conference (IWCMC), June 2017, pp. 1084–1089 (2017)
7. Liu, Y., Li, X., Ji, H., Wang, K., Zhang, H.: Joint APS selection and resource allocation for self-healing in ultra dense network, July 2016, pp. 1–5 (2016)
8. Alias, M., Saxena, N., Roy, A.: Efficient cell outage detection in 5G HetNets using hidden Markov model. IEEE Commun. Lett. **20**(3), 562–565 (2016)
9. Zhang, T., Feng, L., Yu, P., Guo, S., Li, W., Qiu, X.: A handover statistics based approach for cell outage detection in self-organized heterogeneous networks. In: 2017 IFIP/IEEE Symposium on Integrated Network and Service Management (IM), May 2017, pp. 628–631 (2017)
10. Onireti, O., et al.: A cell outage management framework for dense heterogeneous networks. IEEE Trans. Veh. Technol. **65**(4), 2097–2113 (2016)
11. Lei, L., Yuan, D., Ho, C.K., Sun, S.: Joint optimization of power and channel allocation with non-orthogonal multiple access for 5G cellular systems. In: 2015 IEEE Global Communications Conference (GLOBECOM), Dec 2015, pp. 1–6 (2015)
12. Zhou, Z.: Machine Learning. Tsinghua University Press (2016)