IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received June 19, 2017, accepted July 20, 2017, date of publication August 2, 2017, date of current version September 19, 2017.

Digital Object Identifier 10.1109/ACCESS.2017.2734925

Multi-Cell Cooperative Outage Compensation in Cloud-RANs Based 5G Public Safety Network

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This work was supported in part by 863 Program under Grant 2015AA01A705 and in part by the National Natural Science Foundation of China under Grant No. 61271187.

ABSTRACT Cell outage compensation is a crucial way for public safety network (PSN) to recover network communication independently during disasters. As a significant technology for 5G, a cloud-radio access network (C-RAN) plays an important role in a PSN. C-RAN can better achieve multi-cell cooperative outage compensation under dense network coverage because of the characteristics of densification and centralization. Therefore, we propose an efficient multi-cell cooperative outage compensation convergence for the scene where more than one radio remote units (RRUs) are destructed in C-RAN-based PSN. This scheme compensates the network using both cooperative transmission and power adjustment. First, RRUs are selected to participate in the compensation according to the topology structure. Then, the problem model is built aiming at optimizing system outage probability. At the same time, the constraints of resources and service quality are considered. In addition, an enhanced immune-genetic algorithm is proposed innovatively to solve this NP-hard problem and to get the results of RRU transmit power parameters. Finally, simulation results demonstrate that the proposed algorithm convergences rapidly and our scheme reduces the PSN system outage probability effectively with the guarantee of users received power and the restriction of interference effects. The outage probability of the PSN system using the proposed method is 17.8% of the only cooperative transmit method and 3.9% lower than the only adjust power method.

INDEX TERMS Public safety network (PSN), cloud radio access network (C-RAN), outage probability, cooperative transmission, immune-genetic algorithm.

I. INTRODUCTION

Public Safety Network (PSN) is a kind of wireless communication network which can provide efficient and reliable communication during disasters [1]. Researchers and standards organizations want to further enhance the performance of PSN through 5G emerging technology such as D2D, Massive MIMO and C-RAN etc. [2]. Cloud Radio Access Network (C-RAN), an architectural concept of 5G, is regarded as one of the core technology solutions for service demand of 5G [3]. After introduced centralized network construction and management of C-RAN in PSN, the network's ability of resource sharing and dynamic on-demand configuration can make the utilization of resources becoming more effective and flexible [4], [5]. In the event of a disaster, the communication network in some area will arise a temporary communication outage due to accidental failure or energy-saving closure. The ability of rapid outage compensation is needed by the PSN to meet users' real-time communication requirement. In 5G C-RAN, the characteristic of resource sharing brings new possibilities to network recovery. Meanwhile, the new communication technologies proposed by LTE-A are matured to be used in compensation scenarios. Therefore, how to achieve network outage compensation by utilizing network characteristic and new communication technology become the critical point of our study. So this paper dedicates to find a C-RAN based PSN outage compensation strategy, which can effectively improve the independent management ability of network and the user experience.

C-RAN based PSN can use a variety of outage compensation technologies, such as transmit power adjustment, cooperative transmission and so on. In previous studies, the outage compensation usually takes the measure of adjusting the parameters of neighboring base stations until reaching the demand of users' service quality and network performance. Reference [6] changed the user association and adjusted antenna tilts to restore some of the users' communication. But this strength is not strong enough to support a larger network failure. In [7], the joint optimization of power and tilt improves the network coverage effectively, but it cannot solve the interference problem. Reference [8] deployed mobile facilities in edge area to deal with network failure flexibly. While the attendant consequence is the network expenditure and resource utilization problems. With the development of network, we hope the network compensation can be integrated by existing technologies. On one hand, coordinated multi-point transmission technology (CoMP) [9], proposed in LTE-A, improves the received power and simultaneously reduces the interference by turning the interference signal into the useful signal. When we use it to transmit multiple identical resources to one mobile terminal, the resources shortage problem may occur. C-RAN based PSN has the characteristics of resource sharing and concentrated distribution, which can solve the resource reuse problem and avoid resource scarcity problem after outage compensation [10], [11]. On the other hand, in order to ensure the strength of received signal of users, RRUs' transmit power adjustment is also a common compensation scheme. But this scheme will increase interference at the same time. Based on the analysis above, both compensation technologies have their advantages and weakness. And a single parameter adjustment may cause several issues like high network cost, intensity interference, and low network performance. The network needs to synthesize more than one compensation methods to achieve a better compensation effect. So we combine these characteristics together in C-RAN architecture. We do improve users' receive power by transmit power adjustment. Then, the interference can be converted to useful signal by cooperative transmission.

The optimization goal of problem model is to minimize the system outage probability. Meanwhile, constraints of resources and users' service quality will be taken into consideration. Intelligent optimization algorithms are commonly used in previous studies, such as particle swarm optimization algorithm [12], immune algorithm [13] and genetic algorithm [14]. But the results are always unstable, and the convergence ability of these algorithms is poor. In order to solve this math problem, we use Adaptive Chaos Immune-Genetic Algorithm (ACIGA), an Enhanced Immune-Genetic Algorithm. Where, Chaos optimization algorithm has the features of randomness, ergodicity and intrinsic relation [15]. Some studies introduce the chaos optimization algorithm into PSO, GA and other intelligent optimization algorithms [16]–[18]. Therefore, ACIGA uses chaos optimization algorithm to optimize the population initialization, which can effectively balance the global search capabilities and local search capabilities [19]. In addition, standard genetic algorithm or immune algorithm is prone to cause premature and local convergence phenomenon [20], [21]. In order to solve these problems, adaptive crossover probability and mutation probability are used to maintain population diversity and accelerate convergence in ACIGA. Therefore, ACIGA is designed based on the model's characteristics.

Article contributions are as follows:

- Outage compensation problem and its characteristics under C-RAN based PSN architecture are analyzed. And the technology of jointing collaborative transmission and power adjustment are used to solve the compensation problem in the intensive and centralized network.
- On the basis of composite channel model, the system outage probability of the compensation area is modeled as the optimization goal to achieve the C-RAN based PSN universal compensation model. ACIGA is designed to solve the problem.

The rest of paper is organized as follows: Section II describes the C-RAN based PSN multi-cell cooperative outage compensation mechanism. In section III, system models are presented, including Channel model, outage probability and problem model. Section IV is the method of application of ACIGA. Simulation environment with results are described in section V and the conclusion is provided in section VI.

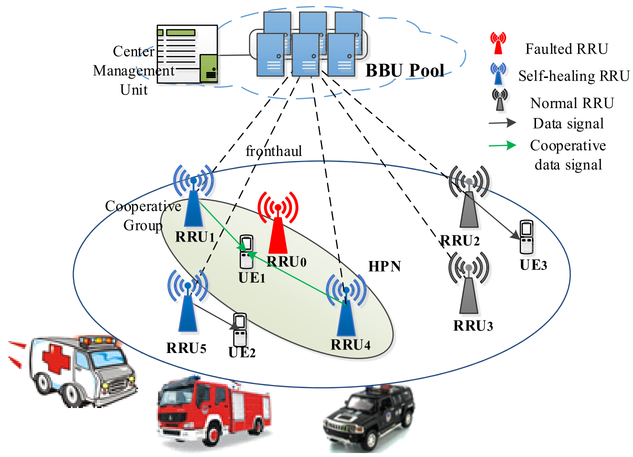

FIGURE 1. Outage compensation in C-RAN based PSN.

II. C-RAN BASED PSN MULTI-CELL COOPERATIVE OUTAGE COMPENSATION MECHANISM

The architecture of C-RAN based PSN applied for PSN is shown in Fig.1 consists of radio remote units (RRU), base band units (BBU) and center management units (CMU). All the network resources are centralized in BBU Pool and regulated by CMU. CMU administrate and allocate resources to each RRU directly instead of considering the connection details between users and RRU or between RRUs and BBU. The ability of resource sharing and dynamic on-demand configuration of H-CRAN can make networks performing more effective and flexible. If an e-NB is under outage in LTE or LTE-A network, resources of this node will be wasted. But in C-RAN based PSN, BBUs are correlative, and RRUs share all resources. That is, resources continued to be available for other network nodes even if RRU interruption occurred.

Fig.1 indicates the situation with RRU_0 in outage. Depending on topology information, RRU_1, RRU_4, RRU_5 are selected to take part in the compensation. RRU_1 and RRU_4 transmit the same resources to UE_1 simultaneously, and the UE received power is strengthened. Then the transmit powers of RRU_1, RRU_4 and RRU_5 are increased to recover the outage area.

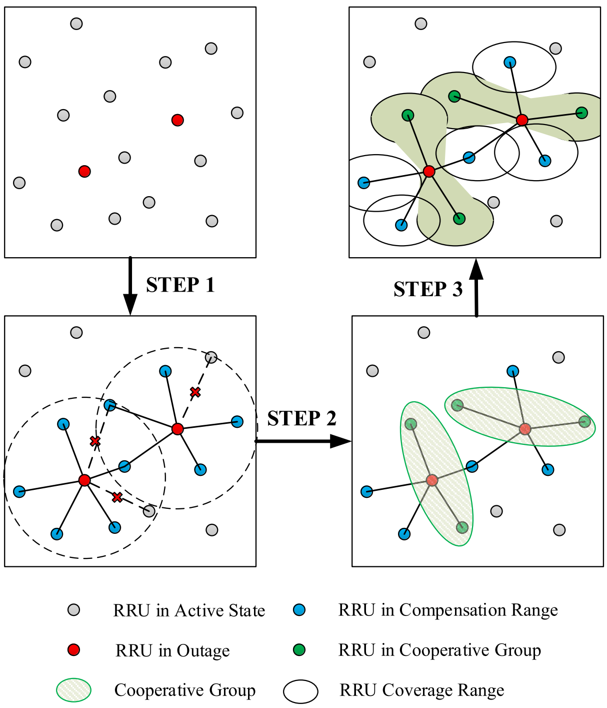

FIGURE 2. C-RAN multi-cell cooperative outage compensation mechanism.

In addition, C-RAN based PSN multi-cell cooperative outage compensation mechanism can also figure out complex scenes with irregular network topology or more than one broken-down RRUs. This mechanism incorporates three steps as shown in Fig.2: Filter compensatory RRUs, Select RRU cooperative group, Compute RRU transmit power appreciation. Table I lists the notation of required parameters of the mechanism.

There are two faulted RRUs in the initial scenario of Fig.2. C-RAN based PSN outage compensation processes are described as follows:

A. STEP 1 FILTER COMPENSATORY RRU

The network deployment is more intensive and irregular depending on complex geographical environment. In addition, there may be more than one RRU malfunctions in one BBU Pool. So we select compensating RRUs by

TABLE 1. Units for magnetic properties.

Notation	Description
$\mathbf{K}=\{1, 2, \cdots, K\}$	A set of BBUs with cardinality of K. BBU $k\in\mathbf{K}$.
$\mathbf{J}=\{1, 2, \cdots, J\}$	A set of RRUs with cardinality of J. RRU $j\in\mathbf{J}$.
$\mathbf{Jc}=\{j_1,\cdots, j_s\}$	A set of cooperative RRUs with cardinality of s.
$\mathbf{I}=\{1, 2, \cdots, I\}$	A set of UEs with cardinality of I. UE $k\in\mathbf{K}$.
$\mathbf{I'}=\{i\}$	A set of UEs in outage area.
$\mathbf{M}=[M_1,M_2,\cdots,M_J]$	A vector of RRU antennas. M_j stands for the antenna numbers of RRU_j.
$\mathbf{G}=[G_1, G_2,\cdots,G_J]$	A vector of RRU transmit power appreciation. G_j stands for the transmit power appreciation of RRU_j.
$\mathbf{Q}=[Q_1, Q_2,\cdots,Q_J]$	A vector of RRU status. Q_j is the state of RRU_j. 1 is participation cooperation. 0 is in outage. -1 is nonparticipating cooperation.

topology information to build an adaptive model and to reduce the amount of computation [22]. If RRU_j is a compensatory RRU, it needs to meet two conditions. 1) Within the scope of interrupt RRU. d_m is the maximum coverage range of RRU. So the RRUs within 2 d_m distance from interrupt RRU can do compensation. Otherwise, RRU is too far to compensate. 2) Low occlusion between compensatory RRUs. When two RRUs are both in the compensatory scope of interrupt RRU, it is needed to determine whether their coverage is obscured. At this point, the peripheral RRU not only is weak to compensate but also creates a strong interference.

We set $\mathbf{Q}=[Q_1, Q_2 \cdots Q_J]$ as RRU running status vector. When RRU_j is in outage, Q_j is set as 0. After selecting compensation RRUs, $Q_X = 1$ only if RRU_x is judged to compensate. Else, $Q_X = -1$.

B. STEP 2 SELECT RRU COOPERATIVE GROUP

On the premise of enough resource, we choose RRUs to participate in cooperative transmission. Because this is not the focus of this paper, the mechanism traversals the RRU cooperative group.

Each RRU cooperative group is indicated by $\mathbf{Jc}=\{j_1, \cdots, j_s\}$.

C. STEP 3 COMPUTE RRU TRANSMIT POWER APPRECIATION

Aiming at the lowest system outage probability, we calculate RRU transmit power appreciation $\mathbf{G} = [G_1, G_2, \cdots, G_J]$ through ACIGA. Specific algorithmic descriptions and applications are described in section IV.

Finally, after traversing all the collaboration patterns, RRU transmit power appreciation with lowest system outage probability is the result of the mechanism.

III. SYSTEM MODEL

A. CHANNEL MODEL

Signal fading during transmission is indeterminacy. Generally, the fading value used to be calculated by a distance-related empirical parameter in traditional channel transmission model. In order to adapt to a more complex network environment, this paper establishes a composite fading channel model embarking on the practical channel property. Based on the channel model, we can calculate the user received power. It is also a standard to determine whether the user can accept the RRU service by comparing the user's received power with the threshold P_{th}.

In the process of downlink transmission, there can be many causes which lead to random variation of the amplitude of received signals. In the channel model, the calculation of the transmission loss LL from RRU_j to user i can be divided into three parts, path loss $L_p\text{L}_\text{P}$, shadow fading L_s and fast fading $L_f\text{L}_\text{f}$. Thus the overall path loss can be computed as (1).

$$L\left(i,j,M_j\right)=L_p\left(i,j\right)L_sL_f\left(M_j\right)\tag{1}$$

1) L_p: In traditional model, path loss L_P (i, j) L_p decreases according to the exponentiation of distance $d_{i,j}^{-\alpha}$ between a user i and its corresponding serving RRU j as $L_p(i,j)=d_{i,j}^{-\alpha}$. The empirical value of path loss exponent α is [3, 5].
2) L_s: Slow fading L_s [23], the shadow caused by obstacles and terrain structure, shows as slow fading and fits lognormal distribution. And the probability density function of $f_{L_s}(u)$ is formulized with (2). The expectation and variance of shadow fading variable is $\mu_s=0$, $\sigma_s=1.5$.

$$f_{L_s}(u)=\begin{cases}\dfrac{1}{\sqrt{2\pi}\sigma_s u}e^{-\frac{(\ln u-\mu_s)^2}{2\sigma_s^2}}, & u>0\\ 0, & u\le 0\end{cases}\tag{2}$$

3) L_f: Fast fading L_f is caused by the local scattering from users surrounded [24]. Fast fading $L_f(M_j)$ from RRU_j to its users is formulized as

$$L_f\left(M_j\right)=\sum_{m=1}^{M_j}\left|h_{jm}\right|^2\tag{3}$$

h_{jm} is fast fading diversity gain from the m^{th} antenna of RRU_j. h_{jm} can be modeled as a complex Gaussian distribution, i.e. $h_{jm}\sim CN(0,1)$. Thus, when $j>1$, $L_f(M_j)$ follows the gamma distribution, i.e. $L_f(M_j)\sim\Gamma(M_j,1)$. The probability density function is shown as (4).

$$f_{L_f}\left(v\right)=\frac{v^{M_j-1}e^{-v}}{\left(M_j-1\right)!}\tag{4}$$

Finally, based on the above channel fading models, for each RRU transmit process the receive power P_r^{ij} of user i from RRU j with the consideration of transmit power appreciation G_j can be written as (5). And when considering the cooperative transmission, all the RRUs in cooperative group $\mathbf{Jc}$ transmit useful signal to the user as (6).

$$P_r^{ij}=P_t^jG_jL_p\left(i,j\right)L_sL_f\left(M_j\right)\tag{5}$$

$$P_r^{i\mathbf{J_c}}=\sum_{j\in\mathbf{J_c}}P_t^jG_jL_p\left(i,j\right)L_sL_f\left(M_j\right)\tag{6}$$

B. OUTAGE PROBABILITY

The outage probability of PSN system, a vital index of wireless network, reflects the performance of the whole PSN network directly. At the same time, it can also guide the network detection, optimization and recovery processing. Thus, the study of PSN system outage probability has great theoretical and applied value. In this paper, received power of a user i is regarded as the assessment criteria to judge whether the RRU_j can serve that user. So the user outage probability is counted by the probability that the received power is lower than a threshold P_{th}. Because the RRUs is far enough from each other, the received powers from different RRUs are independent. Therefore, the outage probability of user i can be expressed as (7). We assume that the user is served by the RRU with lowest outage probability.

$$P_{out}\left(i\right)=\min_{j\in\mathbf{J}\cup\mathbf{J_c}}P\left(P_r^{ij}<P_{th}\right)\tag{7}$$

Where, $P\left(P_r\left(i,j,G_j,M_j\right)<P_{th}\right)$ stands for the outage probability of user i from RRU_j as (8). We assume that the RRU initial transmit power is P_t.

$$\begin{aligned}&P\left(P_r^{ij}<P_{th}\right)\\&=P(P_tG_jL_p\left(i,j\right)L_sL_f\left(M_j\right)<P_{th})\\&=1-P\left(L_sL_f\ge\frac{P_{th}}{P_tG_jd_{i,j}^{-\alpha}}\right)\\&=1-\int_{\frac{P_{th}}{P_tG_jd_{i,j}^{-\alpha}}}^{+\infty}\int_0^{+\infty}\frac{1}{u}\frac{1}{\sqrt{2\pi}\sigma_su}e^{-\frac{(\ln u-\mu_s)^2}{2\sigma_s^2}}\frac{\left(\frac{w}{u}\right)^{M_j-1}e^{-\left(\frac{w}{u}\right)}}{\Gamma\left(M_j\right)}dudw\end{aligned}\tag{8}$$

Gauss–Hermite quadrature [25] is a Gaussian quadrature method which can calculate the approximating integrals value with the following kind:

$$\int_0^{+\infty}g(y)e^{-y^2}dy\cong\sum_{i=1}^{n}\omega_ig(y_i)\tag{9}$$

Where n is the number of sample points used. The y_i are the physical roots of the Hermite polynomial $H_n(y)$, and the associated weights ω_i are given as (10)

$$\omega_i=\frac{2^{n-1}n!\sqrt{\pi}}{n^2[H_{n-1}(y_i)]^2}\tag{10}$$

By using the Gauss–Hermite integral formula, the complex integral expression (8) can be converted to simpler closed expression (11). $P\left(L_sL_f \geq P_{th}/P_tG_ad_{i,j}^{-\alpha}\right)$ is the service probability. H_{n-1} is n-1order Hermite polynomial, and y_h is the h^{th} root of n order Hermite polynomial. In this paper, $\gamma(a,b) = \int_0^a x^{b-1}e^{-x}dx$.

$$P\left(L_sL_f \geq \frac{P_{th}}{P_tG_jd_{i,j}^{-\alpha}}\right) \cong \sum_{h=1}^{n} \frac{2^{n-1}n!}{n^2\left[H_{n-1}(y_h)\right]^2} \times \left[1-\gamma\left(\frac{P_{th}}{e^{\left(\mu_s+\sqrt{2}\sigma_s y_h\right)}P_tG_jd_{i,j}^{-\alpha}}, M_j\right)\right] \tag{11}$$

$$P_{out}(i) \cong \min_{j\in\mathbf{J}\cup\mathbf{J_c}} \left\{1-\sum_{h=1}^{n} \frac{2^{n-1}n!}{n^2\left[H_{n-1}(y_h)\right]^2} \left[1-\gamma\left(\frac{P_{th}}{e^{\left(\mu_s+\sqrt{2}\sigma_s y_h\right)}P_tG_jd_{i,j}^{-\alpha}}, M_j\right)\right]\right\} \tag{12}$$

The outage probability related to the location of the user. To analysis the overall situation of the PSN system, we need to consider the communication quality of all users within the compensation area. The outage probability of PSN system is the expectation of all users' outage probability which is shown as

$$P_{out}^{sys} = \mathrm{E}(P_{out}(i)) = \mathrm{E}(\min_{j\in\mathbf{J}\cup\mathbf{J_c}} P\left(P_r^{ij} < P_{th}\right)) \tag{13}$$

C. PROBLEM MODELS

The problem models are constructed in this section. First, RRUs are selected to compensate according to topology situations. And then we establish the problem model with the optimal objective of minimizing the system outage probability. To reduce the outage probability of system, we adjust the RRUs transmit power and the involvement of cooperative transmission. Thus, we need to consider the constraints of users' access situation and total resources. On one hand, in order to avoid the interference enhancement for users causing by excess power adjustment and the waste of power resources, signal interference and noise ratio (SINR) for each user need to be constrained. On the other hand, we need to use existing resources as much as we can with the limitation of total resources when considering cooperative transmission mode.

We use SINR as the constraint to ensure the communication quality of users who are in compensation situation. Users may choose to access to the RRU or RRU cooperative group with the strongest signal. As the users' receive power will be affected by the decline process, the choice of RRU cannot be determined. So we use probability SINR (PSINR) to express the same character (14). $\mu(x)$ stands for the service probability of RRU_x (15). RRU with higher service rate has a higher probability to be selected.

$$PSINR(i) = \sum_{x\in\mathbf{J}\cup\mathbf{J_c}} \mu(x)\frac{P_r^{ix}}{\sum_{j\in\mathbf{J}\cup\mathbf{J_c},j\neq x} P_r^{ij} + N_0} \tag{14}$$

$$\mu(x) = \frac{P\left(P_r^{ix} \geq P_{th}\right)}{\sum_{j\in\mathbf{J}\cup\mathbf{J_c}} P\left(P_r^{ij} \geq P_{th}\right)} \tag{15}$$

Although cooperative transmission can increase the service proportion, it can cause resource consumption repeatedly at the same time. So it is necessary to find an applicable size of $\mathbf{J_c}$ according to customer's request and remaining resources. Resources relation in system are as shown in (16)-(17). The maximum available resources of BBU pool λ_p^{max} is the sum of each BBU's resource $\lambda_B^{max}(k)$. And the remaining resources of BBU pool λ_P^{re} is the difference between λ_p^{max} and the sum of used resources in RRUs $\lambda_R^{max}(j)$.

$$\lambda_p^{max} = \sum_{k\in\mathbf{K}} \lambda_B^{max}(k) \tag{16}$$

$$\lambda_P^{re} = \lambda_p^{max} - \sum_{j\in\mathbf{J}} \lambda_R^{max}(j) \tag{17}$$

Due to resources constraints, the total resources assigned to RRUs $\sum_{j\in\mathbf{J}} \lambda_R^{max}(j)$ shall not exceed the total resources in BBU pool λ_p^{max}.

$$\sum_{j\in\mathbf{J}\cup\mathbf{J_c}} \lambda_R^{max}(j) \leq \lambda_p^{max} \tag{18}$$

Set $\lambda_u(i)$ to be the user resources requirements, and $\mathbf{I'}$ stands for the set of users in compensation area. So s should meet the condition (19) to ensure enough resources available.

$$s \leq \lambda_P^{re} / \sum_{i\in\mathbf{I'}} \lambda_u(i) \tag{19}$$

There are many models in RRU collaboration. The cooperative group scale $s = |J_c|$ is restricted by resources constrain. For example in Fig.1 situation, if $s = 2$, then the possible collaboration may be $\text{RRU}_1, \text{RRU}_4$. If $s = 3$, then the possible collaboration may be RRU_1, RRU_4 and RRU_5. If J_c do not meet the resource constraints, skip it and move on to the next one.

As RRU status is $\mathbf{Q}$, cooperative group is $\mathbf{J_c}$, We set RRU transmit power appreciation as the decision variables in outage compensation process. And the problem model is established by setting minimizing system outage probability as the optimization goal (20)-(23).

$$\min_{\mathbf{G}} \mathrm{E}(\min_{j\in\mathbf{J}\cup\mathbf{J_c}} P\left(P_r^{ij} < P_{th}\right)) \tag{20}$$

$$S.t.\ \forall i \in \mathbf{I'},\quad \exists j \in \mathbf{J}\cup\mathbf{J_c},\ P_r^{ij} > P_{th} \tag{21}$$

$$\forall i \in \mathbf{I'},\quad \sum_{x\in\mathbf{J}\cup\mathbf{J_c}} \mu(x)\frac{P_r^{ix}}{\sum_{j\in\mathbf{J},J_c,j\neq x} P_r^{ij} + N_0} \geq SINR_{th} \tag{22}$$

$$\forall j \in \mathbf{J},\quad G_j|(Q_j \neq 1) = 0 \tag{23}$$

(21): To guarantee the communication effectiveness, there should be at least one RRU or a cooperative group $\mathbf{J_c}$ which can make each user's received power greater than the threshold P_{th}. This constraint will increase transmit power to enhance the user's reception power. (22): To guarantee the communication quality, the PSINR of each user should be greater than SINR threshold $SINR_{th}$. This constraint can avoid excessive interference from power adjustment or cooperative transmission. (23): Only compensatory RRUs take transmit power appreciation. The other RRUs keep the transmit power unchanged.

IV. ADAPTIVE CHAOS IMMUNE-GENETIC ALGORITHM

Transmit power appreciation $\mathbf{G}$ is continuous with countless results. So problem (20)-(23) is an NP-hard problem. Therefore, we try to solve it on the basis of immune algorithm. When establishing a mathematical model, using immune-genetic algorithm needn't consider the inner nature of the problem. It can deal with any form of objective functions and constraints, no matter linear or nonlinear, discrete or continuous. Immune-genetic algorithm has the following advantages: convenient application, strong robustness, easily to parallel processing and it can restrain degradation phenomena purposefully. ACIGA can reinforce initial population dispersion degree with chaos optimization algorithm. Meanwhile, it can optimize immune-genetic operators with self-adaptive crossover and mutation rate. On the basis of the immune-genetic algorithm, ACIGA can avoid the situation of stuck in local optimal situation and increase converge speed rapidly.

In the scene of compensation, the trigger to start the compensation algorithm is the change of RRU running status. Therefore, we set RRU running status vector $\mathbf{Q} = [Q_1, Q_2 \cdots Q_J]$ as immune antigen in immune algorithm. After the interruption occurred, RRUs participated in compensation do the restore work by increasing transmit power. We set transmit power appreciation vector $\mathbf{G} = [G_1, G_2 \cdots G_{J}a]$ as immune antibody where J_a is the number of RRUs taking part in compensation. G_j is the j^{th} active RRU transmit power appreciation. And the whole population $\boldsymbol{popu} = [\mathbf{G}]_{N*Ja}$ has N antibodies.

A. ANTIGEN INITIAL RESPONSE

The diversity factor between antigens $\mathbf{Q}^x$ and $\mathbf{Q}^y$ is shown as (24), which is calculated by Hamming Distance. Two antigens are identical only when the same RRUs are in outage. That means $D_q(\mathbf{Q}^x, \mathbf{Q}^y) = 0$.

$$D_q(\mathbf{Q}^x, \mathbf{Q}^y) = \sum_{j=1}^{J} \delta \begin{cases} \delta = 1 & Q_j^x \neq Q_j^y \\ \delta = 0 & Q_j^x = Q_j^y \end{cases} \tag{24}$$

When detecting the current antigen $\mathbf{Q}^o$, it should be compared with all antibodies in memory unit $\boldsymbol{memo} = [\mathbf{Q}]_{Nm*J}$. The diversity degree of $\mathbf{Q}^o$ is $D_{q,m}$ (25). $D_{q,m} > 0$ means it is the first time to meet this antigen. Otherwise, $D_{q,m} = 0$.

$$D_{q,m} = \min D_q(\mathbf{Q}^o, \mathbf{Q}^m) \tag{25}$$

B. AGGREGATION FITNESS FUNCTION

Immune-genetic algorithm optimize selection strategy through concentration regulation. The antibody with high fitness and low concentration will be easily selected. Meanwhile, an antibody will be hardly chosen when it has lower fitness function and higher concentration value. The concentration regulation can help to avoid the blindness of crossover and mutation in Immune-genetic algorithm. So it can maintain the population diversity, reduce repetitive operations and improve the algorithm efficiency.

First, we calculate the degree of approximation between antibodies through diversity degree function. Then, the antibody concentration can be calculated according to the proportion of approximate antibodies in population. Finally, aggregation fitness, the final gist of selection, is computed synthetically between concentration value and fitness function. The diversity degree between antibodies $\mathbf{G}^x$, $\mathbf{G}^y$ is calculated by Euclidean Distance computing method which is shown as (26). And the calculation of similarity degree is shown as (27). So concentration of the k^{th} antibody in $\boldsymbol{popu}$ is computed as (28). $\varepsilon(x)$ is step function. If $x \geq \gamma/\varsigma$, $\varepsilon(x) = 1$; otherwise, $\varepsilon(x) = 0$. γ is the threshold of antibodies' resemblance.

$$D_{\mathrm{g}}(\mathbf{G}^x, \mathbf{G}^y) = \sqrt{\sum_{j=1}^{J} (G_j^x - G_j^y)^2} \tag{26}$$

$$S_{\mathrm{g}}(\mathbf{G}^x, \mathbf{G}^y) = \frac{1}{1 + D_{\mathrm{g}}(\mathbf{G}^x, \mathbf{G}^y)} \tag{27}$$

$$C_{\mathrm{g}}(k) = \frac{\sum_{i=1}^{N} \varepsilon(S_{\mathrm{g}}(popu(k), popu(i)))}{N} \tag{28}$$

In the outage compensation mechanism, optimization objective is to minimize the system outage probability P_{out}^{sys}. So we set antibody affinity A_{g} as (29). A higher system outage probability leads to a higher antibody affinity. And the overall valuation of antibodies are based on aggregation fitness function (30).

$$A_{\mathrm{g}} = \frac{1}{1 + P_{out}^{sys}} \tag{29}$$

$$F_{fit}^{\mathrm{g}} = \frac{A_{\mathrm{g}}}{C_{\mathrm{g}}} \tag{30}$$

C. POPULATION INITIALIZATION BASED ON CHAOS OPTIMIZATION ALGORITHM

Chaos optimization algorithm has features of randomness, ergodicity and regularity. So it can help us to traverse all the status efficaciously within limits. Utilizing Chaos Optimization Algorithm in generating initial antibodies population can effectively avoid falling into local optimal solution. We use

Logistic Mapping to create chaos variables with the following expression:

$$x_{n+1} = \varpi x_n(1 - x_n), \quad 0 < x_n < 1 \tag{31}$$

ϖ is fractal parameter, $1 \le \varpi \le 4$. When $3.570 \le \varpi \le 4$, $\{x_n\}$ is in a chaotic status. And we set $\varpi = 4$ to create chaotic variables. The sequence of x_n is chaotic, and it has the following features:

1) Randomness. The value of x_n are derived base on an unstable motion of Logistic Mapping within [0, 1].
2) Regularity. After confirming the value of ϖ and x_1, each x_n is well-determined by (31).
3) Initial condition sensitiveness. The tiny change of x_1 will produce the immense amount of difference among x_n. And the difference will increase significantly with the process of iteration.
4) Ergodicity. Three chaos sequences $\{x_n\}$, $\{y_n\}$ and $\{z_n\}$ iterate with different initial values respectively. Then (x_i, y_i, z_i) will traverse all positions without repetition.

Therefore, initialize population $\left[G_j^n\right]_{N\times Ja}$ can be generated through (32). Where ς stands for the maximum appreciation of transmit power.

$$\begin{cases} G_j^n = \varsigma \cdot x_n^j & 0 < j < J_a \\ x_{n+1}^j = \varpi x_n^j(1 - x_n^j), & 0 < x_n^j < 1 \\ x_1^j = \mathrm{rand}(\cdot), & x_1^j \notin \{0.25, 0.5, 0.75\} \end{cases} \tag{32}$$

D. ADAPTIVE CROSSOVER AND MUTATION

Crossover rate R_c and mutation rate R_m are crucial to immune operators' performance and they influence the convergence effect of the algorithm directly. The generation of new individuals is speeded up and the heredity degree of a formal population is reduced by the influence of a higher R_c. On the contrary, the search process will be held back or even stagnated with a lower R_c. The new individuals are generated uncomfortably with a lower R_m, which reduce system's diversity. On the contrary, the search process will be transformed from intelligence algorithm to stochastic search with a higher R_m. R_c and R_m are changed according to separate requirements of various system environments or diverse stages of iteration. As system iteration keep on performing, constant values of R_c and R_m are inappropriate. Therefore, R_c and R_m should be altered based on the change of system aggregation fitness, which named adaptive crossover and mutation.

Our self-adaptive rule is projected as follows: When antibodies have high fitness and the population has less convergence, R_c and R_m should be reduced to promote the opportunity of antibodies to enter the next generation. When antibodies have high fitness and the population has high convergence, R_c and R_m should be increased to accelerate the generation of new individuals. And when antibodies have low fitness,R_c and R_m should be increased to eliminate the poor solutions.

Therefore, we use aggregation fitness to measure convergence, and the adaptive R_c, R_m are counted as (33)-(34).

$$R_c = \begin{cases} k_c, & f_c < \bar{f} \\ k_c + \dfrac{(k_c' - k_c)(f_c - \bar{f})^2}{(f_{\max} - \bar{f})^2}, & \bar{f} \le f_c \le wf_{\max} \\ k_c', & wf_{\max} < f_c \le f_{\max} \end{cases} \tag{33}$$

$$R_m = \begin{cases} k_m + \dfrac{(k_m' - k_m)(f_m - \bar{f})^2}{(f_{\max} - \bar{f})^2}, & f_m \ge \bar{f} \\ k_m, & f_m < \bar{f} \end{cases} \tag{34}$$

Where, when two antibodies are going to do crossing, f_c stands for the aggregation fitness of antibody with higher value. f_m stands for the aggregation fitness of antibody which is going to mutate. $f_{\max}$ is the maximum aggregation fitness value of population. And $\bar{f}$ is the average aggregation fitness value. $f_{\max} - \bar{f}$ indicates the degree of convergence. k_c, k_c', k_m and k_m', which are numbers between (0, 1), respectively represent upper limit and lower limit of R_c, R_m. w is the lower boundary of aggregation fitness of high quality antibodies. When $wf_{\max} < f_c$, R_c is steadily equal to k_c'.

E. IMMUNE-GENETIC OPERATORS

In each generation, two antibodies are chosen at first in the selecting part. Then they are determined whether to cross by the crossover rate R_c. The final variation of new antibody is generated variably according to the mutation rate R_c. Θ_{slct}, Θ_{crss}, Θ_{muta} are the random numbers of above three operations.

1) SELECTION

Roulette mechanism is used in selecting the antibodies, where N_k is stand for the probability of k^{th} antibody to be selected. The higher aggregation fitness is, the greater selected probability is. When the random number Θ_{slct} satisfies $N_{k-1} < \Theta_{slct} < N_k$, then N_k^{th} antibody is selected.

$$N_k = \sum_{t=1}^{k} F_{fit}^{g} / \sum_{t=1}^{N} F_{fit}^{g} \tag{35}$$

2) CROSSOVER

We use the two antibodies chosen by selection to breed the new antibody of the next generation. When the random number $\Theta_{crss} \ge R_c$, these two selections inherit directly to the next generation. When $\Theta_{crss} < R_c$, the selected antibodies $\mathbf{G} = [G_1, G_2 \cdots G_{Ja}]$ and $\mathbf{G}' = [G_1', G_2' \cdots G_{Ja}']$ are randomly positioned by rg for exchanging to produce next generation antibody. The new result is $\mathbf{G}'' = [G_1 \cdots G_{rg}, G_{rg+1}' \cdots G_{Ja}']$.

3) MUTATION

There is no variation if $\Theta_{muta} \ge R_m$ after judging each crossover result. According to (36), new antibody should be changed slightly when $\Theta_{muta} < R_m$. The ψ_g stands for the value of fine-tuning. On the basis of same probability, each

G_j is changed randomly. In addition, value G_j transforms in range [0, 6] dB.

$$\mathbf{G}''(k) = \begin{cases} \mathbf{G}''(k) + \psi_g, & rand > 0.5 \\ \mathbf{G}''(k) - \psi_g, & rand \leq 0.5 \end{cases} \tag{36}$$

F. ALGORITHM PROCEDURE

The detailed procedure of ACIGA is summarized in Algorithm 1. Specific steps described as below:

Algorithm 1 ACIGA for Problem (20)

Step	
1	Initialize $N, T, k_c, k_c', k_m, k_m', w$, Set t = 1
	If $\mathbf{Q}^o \in \boldsymbol{memo}$, $\boldsymbol{popu} = \boldsymbol{memo} \cup [\mathbf{G}]_{N/2*Ja}$;
	Otherwise, $\boldsymbol{popu} = [\mathbf{G}]_{N*Ja}$.
	For $j = 1 \dots J$, $x_1^j = \text{rand}()$
2	For $n = 1 \dots N$, $x_{n+1}^j = \varpi x_n^j(1 - x_n^j)$,
	$G_j^n = \varsigma \cdot x_n^j$
	Update $\mathbf{G}$ and $\boldsymbol{popu}$
	Repeat
3	Set $A_g = 1/1 + P_{out}^{sys}$
4	For $n = 1 \dots N$ Obtain D_g, S_g, C_g and
	$F_{\text{fit}}^{\text{g}} = A_g/C_g$
	Update R_c and R_m from (33) − (34)
5	Repeat
	For $k = 1 \dots N$, Set $\Theta_{\text{slct}}, \Theta_{\text{crss}}, \Theta_{\text{muta}}$,
	count N_k from (35)
	if $N_{k-1} < \Theta_{\text{slct}} < N_k$, $\mathbf{G} = \mathbf{G}(k)$, $\mathbf{G}' = \mathbf{G}(k')$
	if $\Theta_{\text{crss}} < R_c$, rg =rand(),
	Update $\mathbf{G}'' = [G_1 \cdots G_{rg}, G'_{rg+1} \cdots G'_{Ja}]$
	if $\Theta_{\text{muta}} < R_m$, Update $\mathbf{G}''$ from (36)
	Until $\boldsymbol{popu}$ converges
6	Update $\boldsymbol{popu}$, $\boldsymbol{memo}$
7	t = t + 1
	Until $F_{\text{fit}}^{\text{g}}$ converges or t = T

Step1. Initialization and Antigen Recognition. We judge if the outage event happens for the first time by $D_{q,m}$ which is the diversity between new antigen $\mathbf{Q}^o$ and history memory antigens $\boldsymbol{memo} = [\mathbf{Q}]_{Nm*J}$. **Step2.** Generation of Initial Population. Initial antibody population $\boldsymbol{popu} = [\mathbf{G}]_{N*Ja}$ is generated according to the judgment of step1. If it is not the primary response, $N/2$ antibodies will consist of memory antibodies, the other $N/2$ antibodies are created by chaos optimization algorithm randomly. Otherwise, all the antibodies generated randomly through chaos optimization algorithm. **Step3.** Calculate the Antibody Affinity. Evaluate each antibodies in initial population by affinity A_g, which stands for the matching rate between antibody and antigen. Affinity also representatives the degree of excellence for feasible solutions in the process of iteration. **Step4.** Facilitation and Inhibition based on antibody concentration. The higher value of antibody affinity is, the higher probability of antibodies to enter the next iteration. These singularizes population evolution and leads to local optimization. Therefore, we need to get aggregation fitness $F_{\text{fit}}^{\text{g}} = A_g/C_g$ by utilizing antibody concentration C_g to promote or restrain A_g. Then update crossover rate R_c and mutation rate R_m by (33)-(32). **Step5.** Immune-Genetic Operators. New individuals are generated through selection, crossover and mutation. **Step6.** Updating the Population and Memory Unit. The population is updated by step5. And the better individuals are stored into the memory unit to ensure the reservation of good solutions. **Step7.** Determine Termination Conditions. Loop and output the optimal solution will be ended as the final result when aggregation fitness converges or t = T. Otherwise, the algorithm will jump to step3 and continues the iterations.

V. MATH SIMULATION RESULTS

In this paper, MATLAB is used as the simulation platform to do the performance verification. This section is composed of parameters setting, algorithms effects and the comparison of different outage compensation tactics. We compare the method provided in this paper, Joint Cooperative Transmission and Adjust Power (CTAP), with different compensation strategies to verify its validity. Strategies participating in comparison include: pre-compensation (Outage), Only Adjust Power (OAP), and Only Cooperative Transmit (OCT). The parameters used in the simulation process for comparison are as follows: PSN system outage probability, resource usage, total transmit power and PSINR.

TABLE 2. Simulation parameters.

Parameter	Value(Unites)
Original transmit power P_n	40 dBm
BBU amount K	6
Simulative user amount I	600
Outage area user amount I'	53
Active RRU amount J	16
RRU antenna amount M_j	2
Path loss exponent α	5
Expectation of shadow fading μ_s	0
Variance of shadow fading σ_s	1.5
Rank of Hermite polynomial n	5
Power threshold P_{th}	-105 dBm
RRU coverage range d_m	700m
SINR threshold $sinr_{th}$	-3dB
BBU resource extent $\lambda_B^{max}(k)$	100RB
User resource requirement $\lambda_u(i)$	1 RB

A. SIMULATION PARAMETERS

The key parameters of the simulation scene are shown in TABLE 2. Original transmit power of each RRU P_t^j is 43 dBm, and the adjustment range is 1-6 dB. Degree 5 Gauss–Hermit polynomial is used to simplify the calculation of outage probability. TABLE 3 shows parameters

TABLE 3. ACIGA parameters.

Parameter	Value(Unites)
Population size N	100
Maximum number of Generation T	200
Fractal parameter ϖ	4
Maximum appreciation ς	6
High quality fitness percentage w	0.85
Upper limit of crossover rate k_c	0.7
Lower limit of crossover rate k'_c	0.4
Upper limit of mutation rate k_m	0.5
Lower limit of mutation rate k'_m	0.2
Antibody resemblance threshold γ	0.8
Fine-tuning value ψ_g	0.1

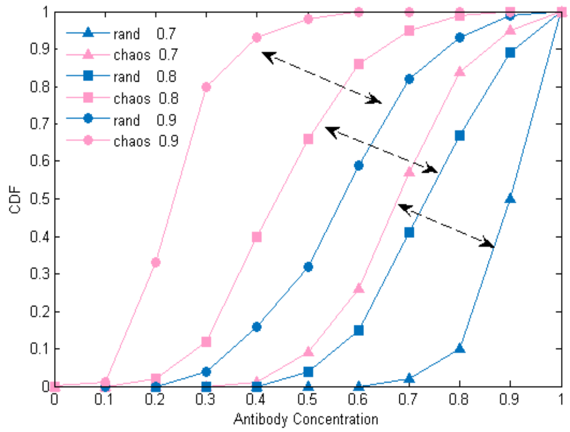

FIGURE 4. Antibody concentration CDF of initial population.

of ACIGA. The outage compensation problem model is solved by ACIGA, and the RRU power adjusting values are finally obtained and used for the compensation scheme.

B. ALGORITHMS EFFECTS

The ACIGA has been optimized on the basis of IGA in two respects: population initialization based on chaos optimization, adaptive crossed operator, and adaptive mutation operator. The initial population distribution of the ACIGA and the iteration of different algorithms are compared in the process of algorithm verification.

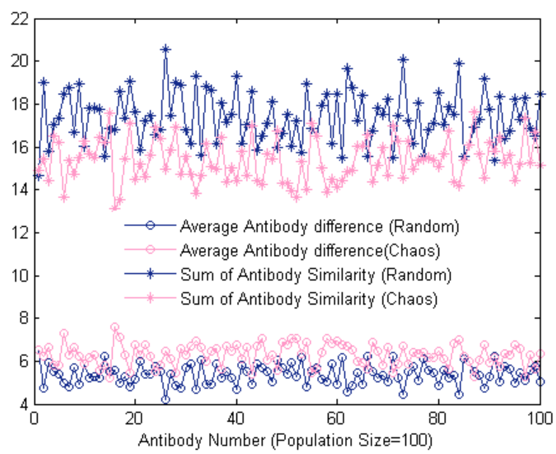

FIGURE 3. Antibody distribution of initial population.

Fig. 3 contrasts diversity and similarity of the initial population between initial population produced by the chaotic system and the randomly generated one. The scene is a single RRU interrupts, compensation RRU number $J_a = 5$ and population size $N = 100$. The average antibodies difference in the population produced by the chaotic optimization system is higher than that in randomly generated population. This is due to the chaotic optimization algorithm has characteristics of randomness, ergodicity and regularity, so that population can traversal all states more effectively in a certain range. It avoids the situations of antibody aggregation and duplication produced by randomly initialized population. Correspondingly, the overall distribution of antibody similarity in the population of chaotic optimization system was lower than that in random initialized population due to the large difference among the antibodies. Fig.4 is the CDF comparison chart of initial population antibody concentration when γ is 0.7, 0.8 or 0.9. It shows that at the same value of γ, the proportion of the low concentration antibody in chaos population is higher than that in the random population. That means antibody reproducibility of chaos initialized population is low. Meanwhile, randomly initialized antibodies are mostly concentrated in the high concentration region, which indicates a large number of similar antibodies are repeatedly present in the initial population. In addition, a higher antibody similarity threshold γ means a higher requirement of antibody approximate degree, and can also make the proportion of high-concentration antibodies decreased gradually. Uniform concentration distribution of the antibody can reduce the fluctuation of the aggregation fitness. So we set $\gamma = 0.8$ in later scenarios.

The iteration situations of following algorithms are compared in Fig.5: Immune-Genetic Algorithm (IGA), Adaptive Immune-Genetic Algorithm (AIGA), Chaos Immune-Genetic Algorithm (CIGA) and Adaptive Chaos Immune-Genetic Algorithm (ACIGA). The conclusions can be seen from the change of the maximum polymerization fitness function and the average polymerization fitness function, which showing as follows: a) IGA: The optimal solution found after iterating 103 times when the maximum fitness remains unchanged. While the average fitness value continues increasing, and the whole antibody population is developed in the direction of optimization. b) AIGA: Adaptive optimization is used in the crossover and mutation probability. After finding the optimal solution, the fitness of the population will still fluctuate to avoid sticking local optimization. The adaptive operator accelerates the generation of new antibodies when the population has high fitness and strong convergence. c) CIGA: In the initial iteration,

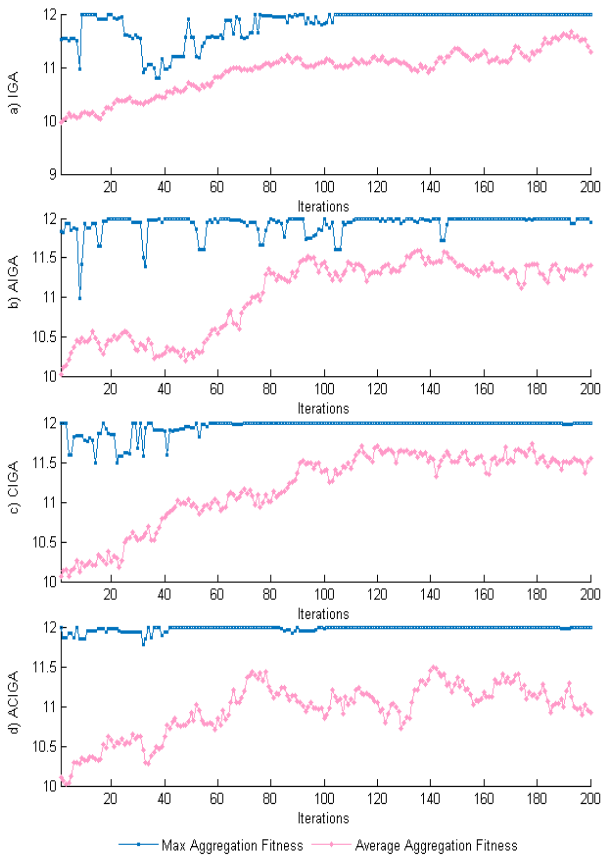

FIGURE 5. IGA, AIGA, CIGA, ACIGA iteration situations.

CIGA has higher maximum aggregate fitness and average aggregate fitness, and also converge quickly. Chaos initial population has strongly ergodic characteristic which leads to better solutions and optimal distributions. At the same time, it speeds up the overall convergence. d) ACIGA: It takes the fluctuation of adaptive crossover operators into consideration during optimizing initial distribution. These will accelerate convergence rate of overall iteration results and avoids sticking in local optimal solutions. In summary, ACIGA, which used in this paper, can solve the problem quickly and efficiently.

C. OUTAGE COMPENSATION EFFECTS

The adjustment scheme after outage compensation and the system status can be obtained through ACIGA according to the problem optimization target and related constraints. In order to evaluate the performance, we compare CAPT with pre-compensation (Outage), OAP and OCT in system outage probability, resource usage, total transmit power and user communication quality.

Firstly, the changes of the PSN system outage probability under different interrupt RRU numbers are shown in Fig.6. The PSN system outage probability of CTAP which using collaborative transmission is always better than OCT and OAP. The overall C-RAN based PSN network compensation ability is poorer with more RRUs breakdown. And then users' received power becomes lower. Therefore, the PSN

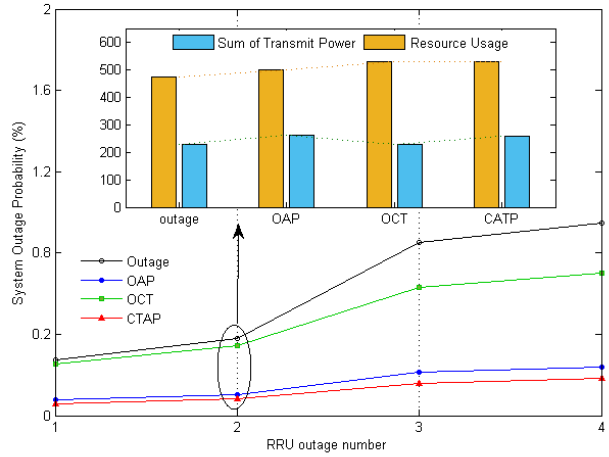

FIGURE 6. Performance comparison of different schemes. System outage probability with different amount of RRU in outage. Resource usage and RRU total transmit power when 2 RRUs in outage.

system outage probability rises when the amount of RRU in outage increases. Here we take detailed comparison on different outage compensation strategies in the scene of 2 outage RRUs. The PSN system outage probability of CTAP is 17.8% of OCT and decreases 3.9% than OAP. The PSN system resource usage and the total transmit power are not only important constraints of problem model, but also important indicators to evaluate the system energy consumption. Comparing with other strategies, CTAP sacrifices resources and the total transmit power in order to reduce PSN system outage probability. The amount of resources used by OCT is 5.6% more than CTAP and OAP. The fluctuation of transmission power in various schemes is within 5%. The sacrifices of resource usage and RRU total transmit power are all within acceptable limits.

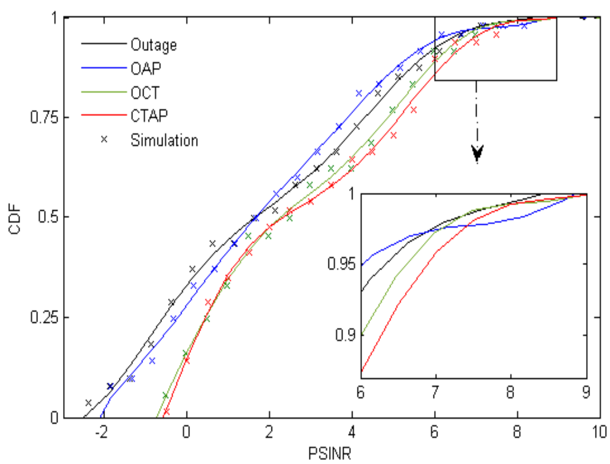

FIGURE 7. CDF of PSINR.

Finally, in order to avoid interference caused by excessive power increment and cooperative transmission, CATP restrains PSINR for each user. We can observe the user's PSINR cumulative distribution in Fig.7. The communication quality of OCT and CTAP users are higher than pre-compensation and OAP users. That's because the cooperative transmission converts the interference signal into useful signal, which enhances the user's received signal quality and also reduce interference. The low PSINR users of CTAP and OCT are significantly reduced because of the collaborative transmission coverage of PSN interrupt area. PSINR in 6-9dB of CTAP is more stable, and high-quality users are distributed more equilibrium.

Above all, CTAP can adapt to different resources distribution PSN network scenarios. Comparing with other strategies, CTAP can improve the C-RAN based PSN network outage probability under the premise of the user experience.

VI. CONCLUSION

Based on the trait of resource sharing, this paper put forward a network outage compensation scheme for C-RAN based PSN. This scheme used the method of cooperative transmission and transmit power adjustment, and set the minimization of PSN system outage probability to be the objective. First, select RRUs taking part in compensation according to RRUs topological information. Then choose cooperative transmission mode on the basis of resource usage. Finally, power adjustment results can be derived by ACIGA. The simulation results verify that this schema can improve PSN users' quality of service and optimize the whole PSN network under limited resources.

In this paper, ACIGA is proposed to find the solution of RRU power adjustment in outage compensation schema. ACIGA, an enhanced immune-genetic algorithm, where chaos initialization and adaptive operators are introduced into immune-genetic algorithm. It uses chaos optimization algorithm to improve the distribution of initial population. The features of randomness, ergodicity and regularity can accelerate the convergence process. ACIGA uses self-adaption to optimize crossover operator and mutation operator for different system environment or different stages. Adaptive crossover and mutation guarantees the rate of convergence, and as well avoid local optimization situation. The simulation results prove that ACIGA has considerable effects on the convergence and accuracy.

Future work could surround heterogeneous dense deployment network in 5G based PSN. 5G based PSN scenario possess the nodes of micro-station, macro-station, Wi-Fi and so on. Furthermore, millimeter wave and D2D technology are introduced into PSN network management. The directional transmission capacity of mm-Wave and the user service expanding ability of D2D can be used as better compensatory devices for signal enhancement. Therefore, we hope to define a new outage compensation problem model in 5G based PSN. And we are looking forward to finding a better problem-model with quicker convergence rate and higher accuracy algorithm. In addition, it is necessary to study outage compensation problem in Internet of things (IoT), Internet of Vehicles (IoV), and Cognitive Radio (CR) as well. So that we can expand the research field to these diversiform network scenarios.

APPENDIX A
PROOF OF FORMULA (11)

To compute $P\left(L_sL_f \geq P_{th}/P_tG_jd_{i,j}^{-\alpha}\right)$ in formula (8), the solution procedure of closed form expression is as follows. First, we command $z = w/u$. So $P\left(L_sL_f \geq P_{th}/P_tG_jd_{i,j}^{-\alpha}\right)$ is transformed into

$$\begin{aligned} P&\left(L_sL_f \geq \frac{P_{th}}{P_tG_jd_{i,j}^{-\alpha}}\right) \\ &= \int_0^{+\infty} \frac{1}{u}\frac{1}{\sqrt{2\pi}\sigma_s u} e^{-\frac{(\ln u-\mu_s)^2}{2\sigma_s^2}} \Gamma\left(M_j\right)^{-1} u \\ &\quad\times \int_{\frac{P_{th}}{uP_tG_ad_{i,j}^{-\alpha}}}^{+\infty} (z)^{M_j-1} e^{-z} dz du \end{aligned} \tag{37}$$

Then, integral z. The integral representation is as (38). Where, x = −z, $\gamma(a, b) = \int_0^a x^{b-1}e^{-x}dx$

$$\begin{aligned} &\int_{\frac{P_{th}}{uP_tG_ad_{i,j}^{-\alpha}}}^{+\infty} (z)^{M_j-1} e^{-z}\Gamma\left(M_j\right)^{-1} dz \\ &= (-1)^{M_j} \int_{-\infty}^{-\frac{P_{th}}{uP_tG_ad_{i,j}^{-\alpha}}} (x)^{M_j-1} e^{x} dx \\ &= 1 - \int_0^{\frac{P_{th}}{uP_tG_ad_{i,j}^{-\alpha}}} (z)^{M_j-1} e^{-z} dz = 1 - \gamma\left(\frac{P_{th}}{uP_tG_ad_{i,j}^{-\alpha}}, M_j\right) \end{aligned} \tag{38}$$

Put the result (39) back to the original formula (37), $P\left(L_sL_f \geq P_{th}/P_tG_jd_{i,j}^{-\alpha}\right)$ is transformed into:

$$\begin{aligned} P&\left(L_sL_f \geq \frac{P_{th}}{P_tG_jd_{i,j}^{-\alpha}}\right) \\ &= \int_0^{+\infty} \frac{1}{\sqrt{2\pi}\sigma_s u}\left[1-\gamma\left(\frac{P_{th}}{uP_tG_ad_{i,j}^{-\alpha}}, M_j\right)\right] e^{-\frac{(\ln u-\mu_s)^2}{2\sigma_s^2}} du \end{aligned} \tag{39}$$

Finally, we use Gauss-Hermite quadrature (9)-(10) to simplifying $P\left(L_sL_f \geq P_{th}/P_tG_jd_{i,j}^{-\alpha}\right)$. And the formula (11)'s consequence is obtained.

$$\begin{aligned} &\int_0^{+\infty} \frac{1}{\sqrt{2\pi}\sigma_s u}\left[1-\gamma\left(\frac{P_{th}}{uP_tG_ad_{i,j}^{-\alpha}}, M_j\right)\right] e^{-\frac{(\ln u-\mu_s)^2}{2\sigma_s^2}} du \\ &\xrightarrow{y=\frac{\ln u-\mu_s}{\sqrt{2}\sigma_s},\, u=e^{\left(\mu_s+\sqrt{2}\sigma_s y\right)}} \int_0^{+\infty} g\left(y\right) e^{-y^2} dy \end{aligned}$$

$$= \int_{0}^{+\infty} \frac{1}{\sqrt{\pi}} \left[1 - \gamma \left(\frac{P_{th}}{e^{\left(\mu_s + \sqrt{2}\sigma_s y\right)} P_t G_a d_{i,j}^{-\alpha}}, M_j \right) \right] e^{-y^2} dy$$

$$\int_{0}^{+\infty} g(y) e^{-y^2} dy \cong \sum_{i=1}^{n} \omega_i g(y_i) \xrightarrow[\omega_i = \frac{2^{n-1} n! \sqrt{\pi}}{n^2 \left[H_{n-1}(y_i)\right]^2}]{} \sum_{i=1}^{n} \omega_i g(y_i)$$

$$= \sum_{i=1}^{n} \frac{2^{n-1} n!}{n^2 \left[H_{n-1}(y_i)\right]^2} \times \left[1 - \gamma \left(\frac{P_{th}}{e^{\left(\mu_s + \sqrt{2}\sigma_s y\right)} P_t G_a d_{i,j}^{-\alpha}}, M_j \right) \right] \tag{40}$$

REFERENCES

[1] R. Favraud, A. Apostolaras, N. Nikaein, and T. Korakis, "Toward moving public safety networks," *IEEE Commun. Mag.*, vol. 54, no. 3, pp. 14–20, Mar. 2016.

[2] A. P. Avramova, S. Ruepp, and L. Dittmann, "Towards future broadband public safety systems: Current issues and future directions," in *Proc. IEEE Int. Conf. Inf. Commun. Technol. Converg.*, Jeju, South Korea, Oct. 2015, pp. 74–79.

[3] M. Peng, C. Wang, V. Lau, and H. V. Poor, "Fronthaul-constrained cloud radio access networks: Insights and challenges," *IEEE Wireless Commun.*, vol. 22, no. 2, pp. 152–160, Apr. 2015.

[4] L. Feng *et al.*, "An enhanced OFDM resource allocation algorithm in C-RAN based 5G public safety network," *Mobile Inf. Syst.*, vol. 2016, pp. 1–14, 2016.

[5] M. Peng, Y. Yu, H. Xiang, and H. V. Poor, "Energy-efficient resource allocation optimization for multimedia heterogeneous cloud radio access networks," *IEEE Trans. Multimedia*, vol. 18, no. 5, pp. 879–892, May 2016.

[6] A. J. Fehske, H. Klessig, J. Voigt, and G. P. Fettweis, "Concurrent load-aware adjustment of user association and antenna tilts in self-organizing radio networks," *IEEE Trans. Veh. Technol.*, vol. 62, no. 5, pp. 1974–1988, Jun. 2013.

[7] L. Wen-Jing, Y. Meng-Jun, Y. Peng, and X. Nan, "A cell outage compensation mechanism based on joint optimization of power and tilt," *J. Electron. Inf. Technol.*, vol. 37, no. 5, pp. 1207–1213, 2015.

[8] H. Mahboubi, K. Moezzi, A. G. Aghdam, K. Sayrafian-Pour, and V. Marbukh, "Distributed deployment algorithms for improved coverage in a network of wireless mobile sensors," *IEEE Trans. Ind. Informat.*, vol. 10, no. 1, pp. 163–174, Feb. 2014.

[9] C. Choi, L. Scalia, T. Biermann, and S. Mizuta, "Coordinated multipoint multiuser-MIMO transmissions over backhaul-constrained mobile access networks," in *Proc. IEEE 22nd Int. Symp. Pers. Indoor Mobile Radio Commun. (PIMRC)*, Toronto, ON, Canada, Sep. 2011, pp. 1336–1340.

[10] M. Peng, Y. Li, Z. Zhao, and C. Wang, "System architecture and key technologies for 5G heterogeneous cloud radio access networks," *IEEE Netw.*, vol. 29, no. 2, pp. 6–14, Mar./Apr. 2015.

[11] M. Gerasimenko *et al.*, "Cooperative radio resource management in heterogeneous cloud radio access networks," *IEEE Access*, vol. 3, pp. 397–406, 2015.

[12] L. Wenjing, Y. Peng, J. Zhengxin, and L. Zifan, "Centralized management mechanism for cell outage compensation in LTE networks," *Int. J. Distrib. Sensor Netw.*, vol. 8, pp. 1–8, Jan. 2012.

[13] Z. Jiang, Y. Peng, Y. Su, W. Li, and X. Qiu, "A cell outage compensation scheme based on immune algorithm in LTE networks," in *Proc. Netw. Oper. Manage. Symp.*, Hiroshima, Japan, 2013, pp. 1–6.

[14] Y. Mengjun, F. Lei, L. Wenjing, Y. Peng, and Q. Xuesong, "Cell outage compensation based on CoMP and optimization of tilt," *J. China Univ. Posts Telecom*, vol. 22, no. 5, pp. 71–79, 2015.

[15] S. L. Ho and S. Yang, "A fast robust optimization methodology based on polynomial chaos and evolutionary algorithm for inverse problems," *IEEE Trans. Magn.*, vol. 48, no. 2, pp. 259–262, Feb. 2012.

[16] L.-G. Chen, H.-D. Chiang, N. Dong, and R.-P. Liu, "Group-based chaos genetic algorithm and non-linear ensemble of neural networks for short-term load forecasting," *IET Generat., Transmiss. Distrib.*, vol. 10, no. 6, pp. 1440–1447, Apr. 2016.

[17] M. You and T. Jiang, "New method for target identification in a foliage environment using selected bispectra and chaos particle swarm optimisation-based support vector machine," *IET Signal Process.*, vol. 8, no. 1, pp. 76–84, Feb. 2014.

[18] P. Li, D. Xu, Z. Zhou, W.-J. Lee, and B. Zhao, "Stochastic optimal operation of microgrid based on chaotic binary particle swarm optimization," *IEEE Trans. Smart Grid*, vol. 7, no. 1, pp. 66–73, Jan. 2016.

[19] L.-Y. Chuang, C.-H. Yang, J.-H. Tsai, and C.-H. Yang, "Operon prediction using chaos embedded particle swarm optimization," *IEEE/ACM Trans. Comput. Biol. Bioinf.*, vol. 10, no. 5, pp. 1299–1309, Sep. 2013.

[20] Y. Hou, N. Wu, M. Zhou, and Z. Li, "Pareto-optimization for scheduling of crude oil operations in refinery via genetic algorithm," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 47, no. 3, pp. 517–530, Mar. 2017.

[21] X. Zuo, C. Chen, W. Tan, and M. Zhou, "Vehicle scheduling of an urban bus line via an improved multiobjective genetic algorithm," *IEEE Trans. Intell. Transp. Syst.*, vol. 16, no. 2, pp. 1030–1041, Apr. 2015.

[22] Y. Mengjun, L. Wenjing, Y. Peng, F. Lei, and Q. Xuesong, "Self-healing based on cooperative transmission via Bender's decomposition in cloud radio access network," *China Commun.*, vol. 12, no. 11, pp. 1–10, 2015.

[23] F. Han, Z. Safar, and K. J. R. Liu, "Energy-efficient base-station cooperative operation with guaranteed QoS," *IEEE Trans. Commun.*, vol. 61, no. 8, pp. 3505–3517, Aug. 2013.

[24] M. Peng, S. Yan, and H. V. Poor, "Ergodic capacity analysis of remote radio head associations in cloud radio access networks," *IEEE Wireless Commun. Lett.*, vol. 3, no. 4, pp. 365–368, Aug. 2014.

[25] G. J. Proakis, *Digital Communications*, 4th ed. New York, NY, USA: McGraw-Hill, 2001.

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