Capacity-and-Energy Efficient Resource Allocation for Emergency Communications

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***Abstract*—Recently, Green Radio, which aims to reduce energy consumption of information and communication technologies (ICTs), has been concerned by telecommunication operators and researchers and can be applied to emergency scenarios. However, the communication system in emergency situation is pursuing not only energy reduction, but the large number of serviced users. In this paper, in order to provide telecommunication services for a great number of clients with low energy consumption in emergency scenarios, a capacity-and-energy efficient radio resource allocation mechanism is proposed, which is modeled as a Sigmoid-based optimization problem. Our simulation results demonstrate that compared with the conventional resource allocation algorithms, the proposed one achieves the largest capacity-and-energy efficiency, i.e., the largest number of serviced users per power unit.**

Keywords—Capacity-and-Energy Efficient; Emergency Communication; Green Radio; Radio Resource Allocation

I. INTRODUCTION

On 11 March 2011, a strong earthquake hit the Tohoku (Northeast) region in Japan, and caused incredibly giant Tsunami, which swept away residents, houses, and the whole social infrastructure. The 50% death took place within two hours after the disaster, so it is very important to set up reliable emergency communication systems rapidly and effectively, which can ensure the government to make disaster rescue plans and take rescue actions. Since all the terrestrial telecommunication systems may be severely damaged, aerial platforms as emergency communication systems have attracted significant interest from government, academia and industry. Captive balloons [1] stationary ranging from about 2 km to 20 km can be used to cover a wide area during disaster relief. This makes them an attractive option for carrying telecommunication equipments obeying diverse wireless standards, including, 3GPP long term evolution (LTE) and LTE-Advanced (LTE-A), Worldwide Interoperability for Microwave Access (WiMAX) or combinations of them. Hence, an aerial platform-based LTE system [2] can be used for providing emergency services in disaster areas.

However, besides the destruction of communication infrastructures other two key problems may appear in the disasters [3]. Firstly, as the electric infrastructure will certainly be damaged in large disasters, the power supply is very difficult for communications in emergency scenarios. Secondly, once disaster happens, survivors will call their families and friends to inform their safety, and also many people not living in disaster areas will make calls to make sure that their friends or families living in disaster areas have survived. So after disasters, the main service is a great deal of voice calls, where quality-of-service (QoS), e.g., short delay and broadband, is not a serious problem. The continuous investment in radio resource allocation for LTE/LTE-A has been aiming at providing a high QoS to territorial clients, and brings about a wealth of theoretical knowledge and practical engineering solutions [4]. However, the relevant context of emergency services is not considered. Therefore, much attention should also be placed on more efficient and effective resource allocation solutions for managing a high tele-traffic with low energy consumption.

In order to solve the above two problems, two basic design principles have to be considered simultaneously.

- Capacity criterion: Define capacity as the number of serviced users. Then the design goal is to maximize the capacity.
- Energy-efficiency criterion: In order to operate effectively in disaster areas, we need to maximize the energy efficiency of emergency communication systems.

In a cell, the most of power is consumed in base stations by which terminals access services from the network. Proper modeling of the energy consumption of base stations has been shown to be an important issue when trying to obtain a clear view of how different radio technologies can reduce energy consumption. Various energy efficient resource allocation algorithms have been discussed in [5]. [2] describes an energy efficient resource allocation algorithm considering only the energy-efficiency criterion. A user-capacity efficient resource allocation algorithm in [6] takes only one basic design principle into consideration, capacity criterion, to maximize the number of serviced users in the system. To the author's

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best knowledge, there is little information available in literature about how to maximize both performance metrics. Moreover, the proposed utility in [6] is only the necessary condition, not the necessary and sufficient condition, of the maximum number of serviced users. Until recently, there is some lack of knowledge about the existence of utility function's optimal solution.

The rest of this letter is organized as follows. After introducing the capacity-and-energy efficient utility function based on the sigmoid function and its mathematical property in section II, a joint time-frequency-power resource allocation algorithm is detailed in section III. In section IV, simulations are carried out to evaluate the performance of the proposed algorithm. Our conclusions are offered in section V.

II. PROBLEM FORMULATION

A. Capacity-and-energy efficient Utility Function

Assume that there are N user equipments (UEs) in a given cell. In order to optimize both capacity-and-energy efficiency, the utility of the n-th UE (UE_n) is defined as $U_n=u_n/P_n$, where u_n represents whether UE_n is serviced or not, and P_n is its allocated transmission power. If the attainable data rate r_n of UE_n is larger than its minimal required data rate $r_{n,min}$, then u_n=1; otherwise, u_n=0. Hence, the sum of u_n's is the total number of serviced UEs, and the system's utility indicates the capacity and energy efficiency, or the average number of serviced UEs per power unit. Hence, the capacity-and-energy efficient resource allocation can be modeled as the following optimization problem:

$$\max\sum_{n=1}^{N}U_n=\max\sum_{n=1}^{N}\frac{u_n}{P_n}=\max\sum_{n=1}^{N}\frac{\operatorname{sgn}(r_n-r_{n,\min})}{P_n}. \quad (1)$$

As we can see from the above definition of capacity u_n that the value of u_n jumps from 0 to 1 when the data rate condition is satisfied, resulting in that the derivative of the jumping point is infinite and that it is difficult to mathematically solve.

According to utility theory, which is borrowed from micro-economics, we can get that utility functions are used to quantify the benefit of usage of certain resources. In communication networks, utilities of service flows are monotonically increasing functions of effective serving rate. So we can use a function whose property approaches the capacity function's and the derivative of the jumping point is not infinite, to replace the capacity function u_n. The utility function is often approximated by the sigmoid function as:

$$sigmoid(\mathrm{x})=\frac{1}{1+e^{a(x-b)}} \quad (2)$$

where a and b determine, respectively, the steepness and the center of the curve. Both of them can be tuned to customize the utility for a given user as demonstrated in Fig. 1.

Hence, we choose sigmoid function in this letter as:

$$u_n(r_n)=sigmoid(r_n-r_{n,\min})=\frac{1}{1+e^{a(r_n-r_{n,\min}-b)}}, \quad (3)$$

where a and b are the parameters of sigmoid function. With proper parameters (e.g., a=-10, b=0 in this letter), the value of sigmoid function approaches 1 when r_n is larger than or equal to $r_{n,min}$ and 0 when r_n is smaller than $r_{n,min}$, and the derivative of the jump point is not infinite. Hence, the capacity-and-energy efficient resource allocation can be modeled as the following optimization problem:

$$\max\sum_{n=1}^{N}U_n=\max\sum_{n=1}^{N}\frac{sigmoid(r_n-r_{n,\min})}{P_n}. \quad (4)$$

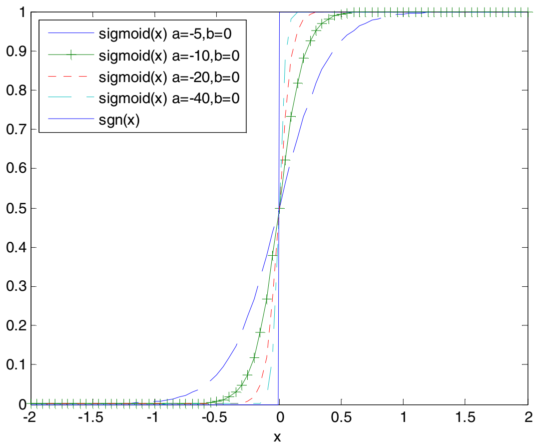

Fig. 1 *S-shaped sigmoidal utility function vs. sgn function.*

Obviously, as the data rate of voice is much lower than that of multimedia services, the more voice users are serviced, the larger system's utility is, and the voice service gets a higher priority than the other services based on this utility function.

B. Mathematical property of utility function

Definition: The α-super-level set of any function f(x) in a non-empty open convex set D is defined as:

$$C_\alpha=\{x\in D\,|\,f(x)\geq\alpha\}, \quad (5)$$

where α is a given integer.

According to the above definition, the α-super-level set of the UE_n's utility function U_n can be expressed as:

$$S_\alpha=\{r_n\geq r_{n,\min},B_n\geq B_{n,\min}|U_n\geq\alpha\}, \quad (6)$$

where B_n and $B_{n,min}$ are UE_n's bandwidth and the required minimal bandwidth, respectively. In the real telecommunications scenarios, as the UE_n's utility function U_n is always greater than zero, we only consider $\alpha \geq 0$. By substituting Eq. (4) into Eq. (6), S_α can be re-expressed as:

$$S_\alpha=\{r_n\geq r_{n,\min},B_n\geq B_{n,\min}|\,u_n-\alpha P_n\geq 0\}. \quad (7)$$

Based on the Shannon-Hartley theorem, the attainable data rate of UE_n can be expressed as:

$$r_n=B_n\log\left(1+\frac{G_nP_n}{n_0B_n}\right), \quad (8)$$

where G_n is UE_n's channel gain, and n_0 is the noise power spectral density. By solving the above equation, we get UE_n's transmission power, which is the function of r_n and B_n,

$$P_n(r_n,B_n)=\frac{n_0B_n}{G_n}\left(e^{r_n/B_n}-1\right)=\frac{n_0}{G_n}h(r_n,B_n)-\frac{n_0B_n}{G_n}, \quad (9)$$

where $h(r_n,B_n)=B_ne^{r_n/B_n}$. And then we obtain that

$$\begin{aligned}&h(\theta r_{n1}+(1-\theta)r_{n2},\theta B_{n1}+(1-\theta)B_{n2})\\&=(\theta B_{n1}+(1-\theta)B_{n2})e^{\frac{\theta r_{n1}+(1-\theta)r_{n2}}{\theta B_{n1}+(1-\theta)B_{n2}}}\\&=(\theta B_{n1}+(1-\theta)B_{n2})e^{\left(\frac{\theta B_{n1}}{\theta B_{n1}+(1-\theta)B_{n2}}\frac{r_{n1}}{B_{n1}}+\frac{(1-\theta)B_{n2}}{\theta B_{n1}+(1-\theta)B_{n2}}\frac{r_{n2}}{B_{n2}}\right)}\end{aligned}, \quad (10)$$

where θ is any given parameter and $0\leq\theta\leq1$.

By taking $\mu=\frac{\theta B_{n1}}{\theta B_{n1}+(1-\theta)B_{n2}}$, the above equation can be re-expressed as:

$$e^{\left(\frac{\theta B_{n1}}{\theta B_{n1}+(1-\theta)B_{n2}}\frac{r_{n1}}{B_{n1}}+\frac{(1-\theta)B_{n2}}{\theta B_{n1}+(1-\theta)B_{n2}}\frac{r_{n2}}{B_{n2}}\right)}=e^{\left(\mu\frac{r_{n1}}{B_{n1}}+(1-\mu)\frac{r_{n2}}{B_{n2}}\right)}, \quad (11)$$

where μ varies obviously between 0 and 1. As an exponential function is a convex function, based on the Eq. (11), we obtain

$$\begin{aligned}e^{\left(\mu\frac{r_{n1}}{B_{n1}}+(1-\mu)\frac{r_{n2}}{B_{n2}}\right)}&\leq\mu e^{\frac{r_{n1}}{B_{n1}}}+(1-\mu)e^{\frac{r_{n2}}{B_{n2}}}\\&=\frac{\theta B_{n1}}{\theta B_{n1}+(1-\theta)B_{n2}}e^{\frac{r_{n1}}{B_{n1}}}+\frac{(1-\theta)B_{n2}}{\theta B_{n1}+(1-\theta)B_{n2}}e^{\frac{r_{n2}}{B_{n2}}}\end{aligned} \quad (12)$$

By substituting the above equation into Eq. (10), we have

$$\begin{aligned}&h(\theta r_{n1}+(1-\theta)r_{n2},\theta B_{n1}+(1-\theta)B_{n2})\\&\leq\theta B_{n1}e^{\frac{r_{n1}}{B_{n1}}}+(1-\theta)B_{n2}e^{\frac{r_{n2}}{B_{n2}}}\\&=\theta h(r_{n1},B_{n1})+(1-\theta)h(r_{n2},B_{n2})\end{aligned} \quad (13)$$

Hence, $h(r_n, B_n)$ is a convex function of r_n and B_n. Also, $P_n(r_n, B_n)$ is still a convex function of r_n and B_n, as n_oB_n/G_n is a linear function of B_n.

Moreover, when $r_n\geq r_{n,min}$, it is very known that the sigmoid function $u_n(r_n)$ is a strictly concave function of r_n. Hence, we could get that $u_n - \alpha P_n$ is also a concave function of r_n and B_n.

Theorem 1: C_α is a convex set if f(x) is a concave function for any value of α.

Based on Theorem 1 and Eq. (7), we can get that S_α is a convex set.

Theorem 2: If any α-super-level set C_α is convex, f(x) is a quasi-concave function.

Based on Theorem 2 and Eq. (6), the UE_n's utility function U_n is a quasi-concave function of r_n and B_n, as S_α is a convex set for any real value of α.

Theorem 3: If any function $f_i(x)$ is a concave function in D, $\sum_{i=1}^{N}f_i(x)$ is also a concave function.

Hence, the system's objective function, $\sum_{n=1}^{N}U_n$, is a two dimensional quasi-concave function of r_n and B_n., i.e., there is one optimal value at least. The optimal result can be obtained based on joint radio resource allocation.

III. JOINT TIME-FREQUENCY-CODE-POWER RESOURCE ALLOCATION

A typical Aerial LTE scenario includes the aerial NodeBs (aNBs), each of which supports a traffic cell, and the user equipment (UEs) randomly distributed on the ground. According to the LTE standard, the system relies on orthogonal frequency division multiplexing (OFDM) in the DL and single carrier frequency division multiple access (SC-FDMA) in the UL, and the radio resources include the resource blocks (RB), the specific modulation and coding schemes (MCS), and the power allocation schemes, which correspond to three resource categories at the time-frequency, code, and power domains, respectively. In this letter, we can schedule the resources at the three domains simultaneously, which is modeled as:

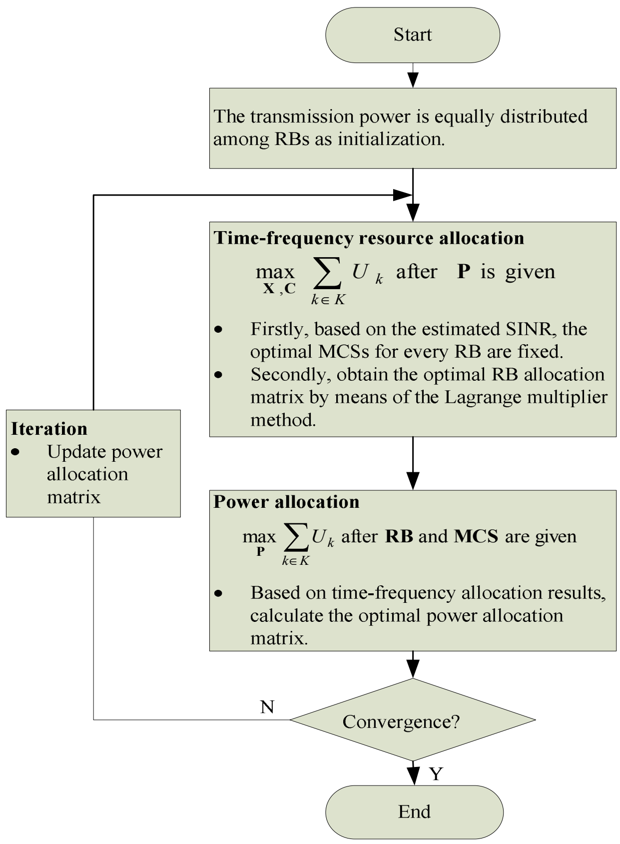

Fig. 2 *Joint Radio Resource Allocation.*

$$\max_{\mathbf{X},\mathbf{C},\mathbf{P}}\sum_{n}U_n=\max_{\mathbf{X},\mathbf{C},\mathbf{P}}\sum_{n=1}^{N}\frac{sigmoid(r_n-r_{n,\min})}{P_n}, \quad (14)$$

subject to:

$$\begin{aligned} & p_{n,k,t} \ge 0, \quad \forall n,k,t \\ & x_{n,k,t} = \{0,1\}, \quad \forall n,k,t \\ & \sum_{n=1}^{N} x_{n,k,t} \le 1, \quad \forall k,t \\ & r_n \ge r_{n,\min}, \quad \forall n \\ & \sum_{n=1}^{N} P_n \le P^{total} \end{aligned} \tag{15}$$

where $\mathbf{X}=\{x_{n,k,t}\}$, $\mathbf{C}=\{C_{n,k,t}\}$, and $\mathbf{P}=\{P_{n,k,t}\}$ denote the RB allocation, MCS and power allocation matrix, respectively. If RB at the k-th row and t-th column of resource grid is assigned to UE_n, then we have $x_{n,k,t}$=1 and its assigned MCS and power is $C_{n,k,t}$ and $P_{n,k,t}$, respectively. The optimal $C_{n,k,t}$ and $P_{n,k,t}$ are calculated based on the estimated signal-to-interference-plus-noise-ratio (SINR) on the give RB. Otherwise, we have $x_{n,k,t}$=0. Since a RB in each aerial NodeB can be assigned to one and only one UE, so we have $\sum_{n=1}^{N} x_{n,k,t} \le 1$.Furthermore, the sum of the assigned transmission power is less than the maximum transmission power P^{total} of aNBs.

In order to reduce the complexity imposed, the optimization problem is divided into two sub-problems, namely separate time-frequency and power allocation, with a lower complexity, as shown in Figure 2. In order to obtain the optimal resource allocation results, we first obtain the RB, and MCS assignment based on the power allocation, then update the power allocation based on the RB assignment, and finally substitute the power allocation results obtained in the second step into the first step to update the RB, and MCS assignment, and this iteration will continue until the result converges. Using iterations, system utility keeps increasing and approaches the optimal value [2].

IV. Simulation Results

In order to evaluate the performance of the proposed resource allocation algorithm, the following simulations are carried out under the aerial LTE system [2], and the key parameters are listed in Table I. We consider a rectangular area of 50km×50km on ground, which is serviced by seven aNBs installed on captive balloons of 2km in height. Each UE randomly opts for one of the four services.

TABLE I
SYSTEM PARAMENTS

Parameters	Value
Carrier frequency	2.6 GHz
System Bandwidth	20 MHz
Transmission time interval	1 ms
Antenna gain	15 dBi
Maximum transmission power of aNBs	46 dBm
Maximum transmission power of UEs	23 dBm
Noise power	-106 dBm
Propagation model	Free space propagation

Four different types of service requirements are considered, which are VoIP, web-browsing, file-download and video, which are supported at data rates of 64kbps, 128kbps, 384kbps and 1024kbps, respectively. Each UE opts for one service evenly.

For comparison, the well-established maximum carrier-to-interference (Max-C/I), round robin (RR), proportional fairness (PF), energy efficient resource allocation algorithm [2], user-capacity efficient resource allocation algorithm [6], and our proposed capacity-and-energy resource allocation algorithm are evaluated. The user fairness function used in the paper is defined as:

$$\beta = \frac{\left(\sum_{n=1}^{N} r_n\right)^2}{N\sum_{n=1}^{N} r_n^{\,2}} \tag{16}$$

where β is a number between 0 and 1,with no unit. UEs benefit from an increased fairness as β approaches 1.

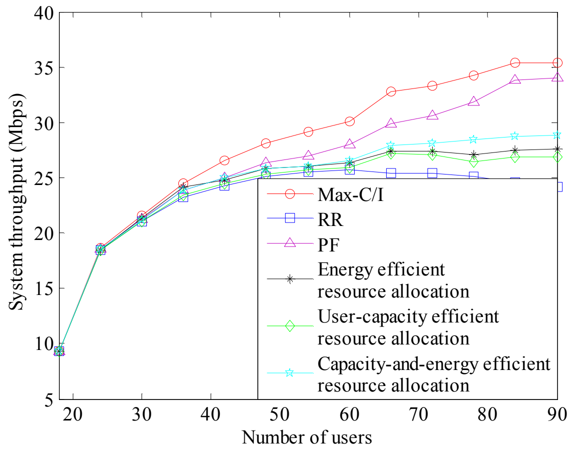

Fig. 3 *System throughput.*

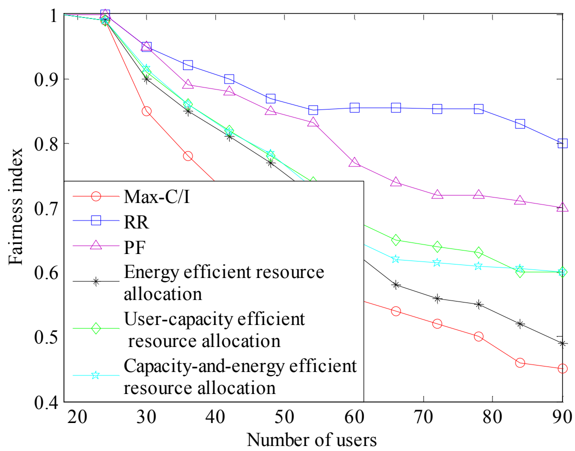

Fig. 4 *User fairness.*

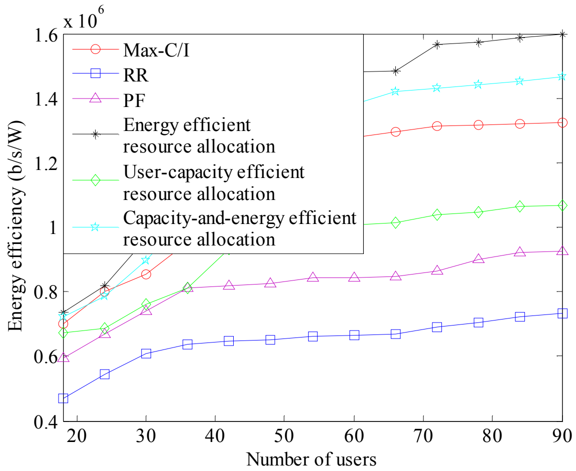

Fig. 5 *Energy efficiency.*

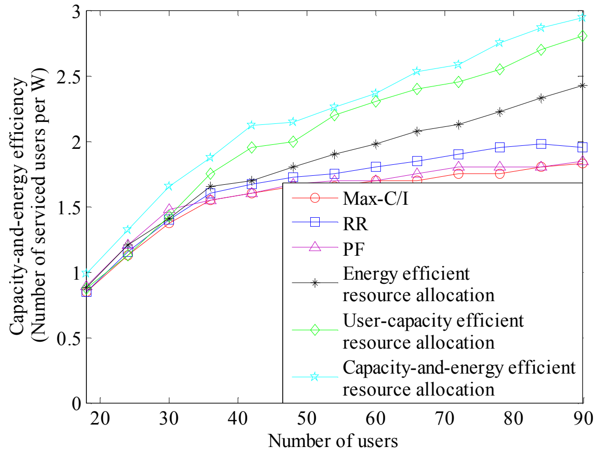

Fig. 6 *Capacity-and-energy efficiency*

Fig. 3, 4 and 5 show the system's throughput, fairness, and energy efficiency for different number of UEs, respectively. In the Max-C/I algorithm, in order to achieve the maximum throughput, resources are allocated to the specific UEs having the best channel conditions. Hence, its throughput represents the upper bound of all the algorithms considered, as shown in Fig. 3. However, its lower fairness and reduced power efficiency is an obvious impediment, as shown in Fig. 4 and Fig. 5. Fairness is quantified in terms of the fairness index β in (16).

Because of taking turn to allocate resources to each UE and ignoring the change of instantaneous channel conditions, the RR algorithm can hardly make use of the time varying of wireless mobile channels, so its throughput represents the lower bound of all the algorithms considered. However, its fairness represents the upper bound of all the algorithms.

The PF algorithm defines priority level of every user which decreases when achieving better throughput during a specified time interval and allocates more subchannels to users of high priority level. Hence, it guarantees a user with better channel condition will not possess channel all the time and thus achieves a better trade-off between throughput and fairness, as shown in Fig. 3 and 4.

The energy efficient resource allocation algorithm and the user-capacity efficient resource allocation algorithm, the resources are both proportionally allocated according to each UE's channel conditions while satisfying the minimum requirement, and then the resources are allocated to maximize energy efficiency and the number of serviced users in the system, respectively. Thus, both algorithms have a tradeoff between throughput and fairness to achieve their targets by sacrificing its throughput.

In the proposed capacity-and-energy resource allocation algorithm, the resources are proportionally allocated according to each UE's channel conditions while satisfying the minimum requirement. By sacrificing its throughput, the algorithm obtains an attractive tradeoff between the achievable throughput and ensuring fairness among users.

Fig. 6 illustrates the capacity-and-energy efficiency of the six resource allocation algorithms. The proposed capacity-and-energy resource allocation algorithm's objective is to maximize the number of system serviced user per power unit. It achieves the largest capacity-and-energy efficiency of all the algorithms with this objective to allocate the resources.

V. CONCLUSIONS

In this paper, in order to accommodate a great number of users with low energy consumption during disasters, we proposed capacity-and-energy efficient resource allocation algorithm that achieve a good tradeoff among different performance metrics, i.e., system throughput, user fairness, energy efficiency.

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