A QEE-Oriented Fair Power Allocation for Two-tier Heterogeneous Networks

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Abstract

In future wireless network, user experience and energy efficiency will play more and more important roles in the communication systems compared to their roles at present. Quality of experience (QoE) and Energy Efficiency (EE) become the widely used metrics. In this paper, we study a combinatorial problem of QoE and EE and investigate a fair power allocation in heterogeneous networks. We first design a new metric, QoE-aware EE (QEE) to reflect the relationship of QoE and energy. Then, the concept of Utopia QEE is introduced, which is defined as the achievable maximum QEE in ideal conditions, for each user. Finally, we transform the power allocation process to an optimization of ratio of QEE and Utopia QEE and use invasive weed optimization (IWO) algorithm to solve the optimization problem. Numerical simulation results indicate that the proposed algorithm can get converged and efficiently improve the system energy efficiency and the QoE for each user.

Keywords: QEE, power allocation, two-tier heterogeneous networks, IWO

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1. Introduction

Network isomerization is becoming one of the architectural shifts towards the emerging 5G wireless networks to support the ever-increasing need of data and services from users [1,2]. The paradigm shift towards heterogeneity brings many new challenges to wireless network design [3,4]. In future wireless network, a wide range of services can be offered to mobile users and the capacity of today's network is far away from satisfaction, which will finally affect the QoE for users. Thus, one of the main challenges is to promote the QoE of users with limited resource [5,6]. On the other hand, from the operator's perspective, macro-cells and small cells would be ultra-dense because of the huge traffic load in future, which will cause lots of problems (e.g. high energy cost). Considering these financial and environmental problems, energy efficiency is also necessary to be paid attention to [7,8]. In this paper, how to properly realize power allocation to improve the energy efficiency (EE) and QoE under such environment is our primary goal.

A Related Work

Nowadays, a substantial amount of work focuses on the areas of power allocation. The main purpose of these literatures is to improve the spectrum or energy utilization [9,10]. To improve the spectrum utilization, the literatures address the optimality of system capacity [11-17]. The authors in [11] propose a power allocation scheme to maximize the sum-rate of network. The scheme formulates a standard non-convex quadratically constrained quadratic problem (QCQP) and uses a distributed algorithm to solve it. In [12], the authors also propose an optimal power allocation to maximize the capacity of network. It assumes that the single cell power is constrained and formulates the optimal problem to get the optimal power allocation scheme. However, the interference among small cells is ignored in a dense environment [13,14]. The authors in [13] use game theory to promote the transmission rate of edge users. However, these literatures fail to pay attention to the energy efficiency problem in a wireless environment.

Nowadays, with the densification of the network, there have been extensive researches on energy efficiency (EE)-oriented problems [18-22]. The system energy efficiency is studied in [18], in which a resource allocation scheme is proposed where base stations jointly process the data of all users to maximize the system EE. In [19], the authors not only consider the energy efficiency, but also consider to maintain the quality of service (QoS) level and formulate the power allocation scheme as a tractable convex optimization problem, which is solved by iterative algorithm. Non-cooperative game-theoretic approaches are also employed in [20] and [21] to handle the energy efficient power allocation problems in wireless networks.

As one of the common points, research works (and the references therein) only care for the EE of system and do not consider the EE of the individual users. This is called network EE-optimal problems (NEPs). The system would bring benefit to good channel condition users, and thus, the improvement in network EE is gained at the cost of benefit of users in the bad channel conditions. As result, the NEPs ignore the fairness of users in terms of EE. Therefore, the authors in [23] explore a max–min EE-optimal problem to ensure the EE of the worst-case user and propose a general EE-based update algorithm to tackle the max–min EE-optimal problem. However, the users' quality of experience is not considered in aforementioned work.

In future wireless system, users will not only consider the EE but also pursue the QoE. Actually, there have been some attempts on QoE-oriented. The authors propose lots of QoE models of users with different services [24]. In [25], the authors also investigate the optimal the sum of QoE and the proportional fair of users' QoE in [26]. However, these works all ignore to take consideration of algorithm design related to the EE and QoE. Since, different users will have different QoE and EE requirements, the QoE and EE for each user should be individually considered, rather than as a whole. So, in this paper, we investigate the power allocation in heterogeneous network to improve the QoE and EE of each user. We also design a metric called QoE-aware energy efficiency to measure the QoE and EE of each user.

B Contribution

In this work, our aim is to improve the EE and QoE of each user in a fair manner by power allocation. The main contribution of our work is summarized as follows.

- We investigate the user experience and formulate the different QoE functions for various type of users. The QoE function reflects the user satisfaction to the network.
- A new model called QEE is formulated in this paper, which is used to measure the QoE and EE of each user.
- We propose a metric to measure the user's proximity degree to the ideal value i.e., utopia QEE and formulate an optimal problem using it to avoid discriminating to bad users in power allocation.
- The IWO algorithm is proposed to solve the problem, and the performance of our proposed algorithm is verified by simulations.

The rest of this paper is organized as follows. In section 2, we introduce the system model and design the QoE and utopia QEE of each user with different services. In section 3, the problem is formulated and solved by IWO. Section 4 presents simulation experiments and analyzes the performances of the proposed algorithm. Finally, we draw the conclusion in Section 5.

2. System model and QoE

In this section, we firstly describe the model of two-tier heterogeneous networks, and then the QoE is proposed.

A System and Channel model

As shown in **Fig. 1**, we consider two-tier heterogeneous networks with a macro-cell and M small-cells. The set of cells can be denoted by $\mathcal{M} = \{1, 2, ..., M+1\}$. We also define $\mathcal{N} = \{1, 2, ..., N\}$ and $\mathcal{K} = \{1, 2, ..., K\}$ as the set of users and sub-channel, respectively. All users randomly distribute in the two-tier heterogeneous network. A sub-channel in each cell would be allocated to a user for transmission. We assume that; (i) $N = K(M+1)$, i.e., there are K users per cell and sub-chann el; (ii) the nth user accesses to the mth cell in kth sub-channel for both macro-cell and small-cell. These assumptions are solely for the sake of notational simplicity. Our work can be extended to the case of arbitrary values M, N, K. The bandwidth of the sub-channel is B and the transmission power of the sub-channel in mth cell in kth sub-channel is p_m^k.We also assume that the users would use different applications which transmit different services. In this paper, assuming that there is a central controller in two-tier heterogeneous networks, the controller can allocate the power for all users. The central controller has all the channel side information (CSI) and achieves good performance.

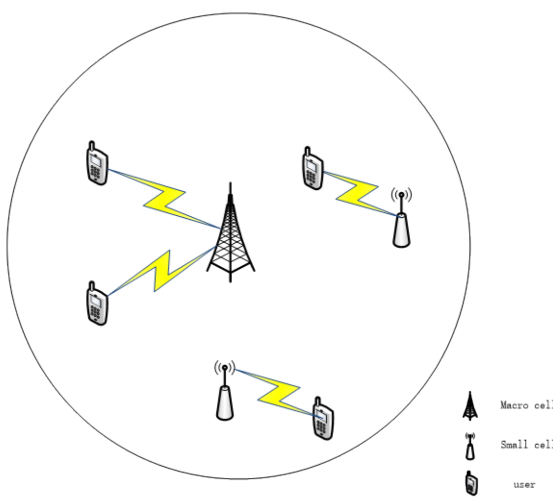

Fig. 1. System model

B QoE with Different service

In wireless networks, QoE assessment is a challenge which draws a lot of interests from both academia and industry. The Mean Opinion Score (MOS) model is widely used to characterize QoE whose value can reflect users' opinions on services, which ranges from totally unacceptable to fully satisfied [5]. We denote the QoE with C type and S type service.

Traditionally, the main C type service is voice service which usually measured by Perceptual Evaluation of Speech Quality (PESQ) recommended by International Telecommunication Union (ITU). However, it is still not suitable for dynamic real-time system because of the computationally complexity and requirement of the original speech signal. In [27], the QoE model for voice service is described as the function of transmission rate. We assume that the transmission rate of C type service is R_C, and its QoE will increase with the increasing transmission rate but the increasing rate will slow down. Thus, the function of the service can be denoted as:

$$MOS = \begin{cases} 0 & , R < R_{\min}^{req} \\ a\log\left(R/b\right) & , R_{\min}^{req} \le R < R_{\max}^{req} \\ 5 & , R \ge R_{\min}^{req} \end{cases} \tag{1}$$

where, $R_{\min}^{req}$ and $R_{\max}^{req}$ are the minimum and the maximum requirement transmission rates of C type service, respectively. a and b are the constant value.

The S type services include real-time and non-real-time ones, such as video service which is a real-time service with adaptive coding and file download service which is a non-real-time service. As described in [28], these services can use S-shaped function to reflect the satisfaction degree of users. The QoE value will not decrease to zero directly when the transmission rate is smaller than the required rate. We assume that the transmission rate of S type service is R_S. The obtained QoE of it can increase with the increasing of transmission rate and the increase speed gets faster firstly and slow down lately. Thus the function of the S type service is:

$$MOS = \begin{cases} \begin{array}{c} p^2 a\log\left(R_{\tan\_1}/b\right) \\ where\ R = 2p(1-p)R_{\mathrm{int}\_1} + p^2 R_{\tan\_1} \end{array} & ,if\ R < R_{\tan\_1} \\ a\log\left(R/b\right) & ,if\ R_{\tan\_1} \le R < R_{\tan\_2} \\ \begin{array}{c} (1-p)^2 a\log\left(R_{\tan\_2}/b\right) + 10p(1-p) + 5p^2 \\ where\ R = (1-p)^2 R_{\tan\_2} + 2p(1-p)R_{\mathrm{int}\_2} + p^2 R_{\max} \end{array} & ,if\ R_{\tan\_2} \le R < R_{\max}^{req} \\ 5 & \text{, otherwith} \end{cases} \tag{2}$$

where, $R_{\tan\_1}$ and $R_{\tan\_2}$ are the points of contact in the curve $MOS = a\log\left(R/b\right)$. p is a variate value.

3. The Proposed Power Allocation Algorithm

In this section, we develop a power allocation algorithm to achieve the optimal QoE-aware energy efficiency in a fair allocation manner.

A Utopia QEE

Before formulating the problem, we first discuss the Utopia QEE and the method to calculate the Utopia QEE for each individual user.

Definition 1 (Utopia QEE): The Utopia QEE for each user can be defined as the maximal QEE it can be achieved in ideal conditions (without interference).

Accordingly, the following optimization problem can be formulated for *n*th user to obtain the Utopia QEE of *n*th user.

$$\begin{aligned} &\max \eta_n = MOS_n^{IN} / (\varepsilon_m p_m^k + p_n^{fix} + p_{m,k}^I) \\ &subject\ to \\ &\qquad C_1 : p_m^k \le p_{m,\max} \\ &\qquad C_2 : p_m^k > 0 \end{aligned} \tag{3}$$

where, η_n is Utopia QEE of *n*th user, p_n^{fix} is the fix power of *n*th user when accessing to the *m*th cell, p_m^I is the fixed power consumption of *k*th sub-channel in *m*th cell. ε_m denotes the inverse of power amplifier efficiency of *m*th cell. In ideal conditions, the *n*th user can make full use of power resource of *m*th cell, so the constraint can be formulated as C_1. MOS_n^{IN} is the QoE of *n*th user in ideal conditions which is only related to the transmission rate according to the formulation (1) and (2). The transmission rate in ideal conditions when the *n*th user accesses to the *m*th cell can be calculated by:

$$R_n^{IN} = B\log\left(1 + p_m^k g_{m,n}^k / (N_0 B)\right) \tag{4}$$

where, R_n^{IN} is the transmission rate in ideal conditions , $g_{m,n}^k$ is the channel power gain between *n*th user and *m*th cell in *k*th sub-channel. N_0 is the power spectral density (PSD) of the additive white Gaussian noise (AWGN). To simplify the formulation (3), we assume that $\mathcal{P}_n$ is the power consumption of the *n*th user when access to *m*th cell in *k*th sub-channel, which can be calculated by

$$\mathcal{P}_n = \varepsilon_m p_m^k + p_n^{fix} + p_{m,k}^I \tag{5}.$$

Thus, the optimization problem above can be transformed and the objective function can be rewritten as:

$$\begin{aligned} &\max \eta_n = MOS_n^{IN} / \mathcal{P}_n \\ &subject\ to \\ &\qquad C_1 : p_m \le p_{m,\max} \\ &\qquad C_2 : p_m > 0 \end{aligned} \tag{6}$$

The optimization problem above is a convex-concave fractional programming. To find its global optimum, we define

$$q(\eta_n) = MOS_n^{IN} - \eta_n \mathcal{P}_n \tag{7}$$

Then we have the following theorem, which can be proved by directly following a similar approach as that in [29].

Theorem 1: The Utopia QEE is achieved if

$$\max_{R_n^{IN}} q\left(\eta_n^0\right)=0 \tag{8}$$

Note that $q\left(\eta_n\right)$ only has a single variable, therefore, its maximum can be easily achieved by derivation methods, the detailed procedures to achieve the Utopia QEE are shown in the **Table 1**.

Table 1. The algorithm to achieve the Utopia QEE for *n*th user

Algorithm 1 The Algorithm to Achieve the Utopia QEE for User n
1: Initialize Δ and η_n
2: While
3: $p^* = \arg\max\left(MOS_n^{IN} - \eta_n \mathcal{P}_n\right)$
4: if $\left\|MOS_n^{IN*} - \eta_n \mathcal{P}_n^*\right\| \le \Delta$
5: $\eta_n^0 = MOS_n^{IN*} / \mathcal{P}_n^*$
6: break
7: else
8: update $\eta_n = MOS_n^{IN*} / \mathcal{P}_n^*$
9: end
10: end

B Problem Formulation

In section 2, the Utopia QEE of each user has been achieved. In this section, we formulate our optimal problem. Our goal is to assign users to cells in a fair manner; i.e., the assignment allocates each user sufficient power without unduly restricting the amount of power available to others. To achieve the goal, we define a proximity degree for each user.

Definition 2 (proximity degree): The proximity degree for each user can be defined as the ratio of the actual QEE and the Utopia QEE.

The proximity degree is the metric to measure the benefit of *n*th user. When the proximity degree is higher, the user will get closer to the ideal condition. Our aim is to get the maximum proximity degree of all users which can also maximize the total QEE in a fair manner. The optimal problem can be formulated as:

$$\begin{aligned} &\max \sum_{n=1}^{N} \left(QEE_n / \eta_n \right) \\ &\textit{subject to} \\ &\qquad C_1 : \sum_{k \in \mathcal{K}} p_m^k < p_{m\max}, \forall m \in \mathcal{M} \\ &\qquad C_2 : \frac{h_{mn} p_m^k}{\sum_{j \in \mathcal{N}, j \neq n} h_{jn} p_j^k + N_0 B} \geq \gamma_{n\min}, \forall n \in \mathcal{N} \\ &\qquad C_3 : p_m^k > 0 \end{aligned} \tag{9}$$

In formulation (9), C_1 and C_3 are the power constraints: The power cannot exceed the maximum power $p_{m\max}$. $p_{m\max}$ not only controls the out-cell interference, but also restricts the power amplifier to linear region which corresponds to the constant amplifier efficiency. C_2 is the QoS constraint: The SINR at received terminals should meet the requirement to maintain its performance. $\gamma_{n\min}$ is the recognition SINR of receiving set. QEE_n can be calculated by :

$$QEE_n = MOS_n / (\varepsilon_m p_m^k + p_n^{fix} + p_{m,k}^I) \tag{10}$$

where MOS_n is the QoE of nth user which is related to the transmission rate with interference R_n. It can be described by:

$$R_n = B \log \left(1 + \frac{h_{mn} p_m^k}{\sum_{j \in \mathcal{M}, j \neq m} h_{jn} p_j^k + N_0 B} \right) \tag{11}$$

where, h_{mn} and h_{jn} are the channel gain between mth and jth base-station to nth user, respectively. For macro-cell users, the interferences are between small-cells and macro-cell users, and for small-cell users, the interferences have two parts, one is between other small-cells and small-cell user and the other is macro-cell and small-cell user.

C The Proposed Algorithm

Above all, our target is to maximize the total QEE in a fair manner, thus, the problem is formulated as formulation (9), considering that the feasible solution space of this optimization problem is huge, it is difficult to find the optimal solution using enumeration method. So the practical algorithm should have fast convergence speed to get the optimal solution. In this paper, we use the Invasive Weed Optimization (IWO) to solve the optimal problem. The IWO has strong robustness to achieve the optimal value. The key methods can be summarized as follows:

1 Initialization

Set the generation counter $t=1$ and generate the initial location of invasive weed which represents the transmission power in *t*th iteration. The coordinate of location is the transmission power. The location can be denoted by

$$P(t)=\left\{p_1^1(t),\ldots,p_1^K(t),\ldots p_m^k(t),\ldots,p_M^K(t)\right\} \tag{12}$$

2 Reproduction

According to the object value in formulation (9), the number of seeds has a positive relationship with the object value. The seed number of each invasive weed can be calculated by:

$$w=\left(f-f_{\min}\right)(s_{\max}-s_{\min})/\left(f_{\max}-f_{\min}\right)+s_{\min} \tag{13}$$

where, $f_{\max}$ and $f_{\min}$ are the maximum and minimum object value, respectively, $s_{\max}$ and $s_{\min}$ are the maximum and minimum seed number of one invasive weed can generate, respectively.

3 Spatial Diffusion

The seed will grow into a weed which will distrust around the father invasive weed according to the Normal distribution with zero mean. The standard deviation should decrease with the increase of iteration. The standard deviation value can be generated by:

$$\sigma_t=\left(t_{\max}-t\right)^x\left(\sigma_{inital}-\sigma_{final}\right)/t_{\max}+\sigma_1 \tag{14}$$

where, $t_{\max}$ is the maximum iteration, σ_{inital} and σ_{final} are the initial and final standard deviation value, respectively. x is the nonlinear harmonic factor.

4 Selection

When the weed number get equal to the maximum number $Num_{\max}$, we select the $Num_{\max}$ weed with roulette method. The detail description is displayed in **Fig. 2.**

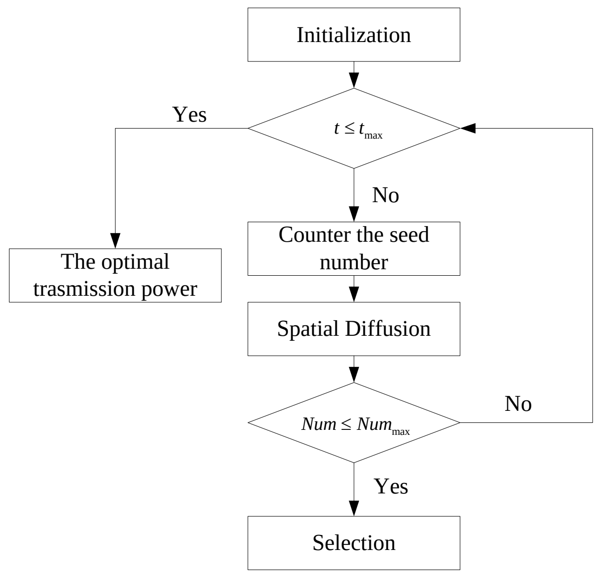

Fig. 2. The algorithm for maximum total proximity degree

4 Simulation Experiment and Result Analysis

The previous section is based on an analysis of the optimization problem in theory. In this section, the accuracy of the analysis is evaluated experimentally. To solve the optimization problem, we choose the invasive weed optimization algorithm. Here, the performance of the proposed algorithm is compared with that of other algorithms.

All the experiments are performed in the same simulation scenario shown in **Fig. 1**. The coverage radius of the macro-cell is 500m, and LPN is 10m. Each user is randomly distributed in the network. The experiment parameters are showed in **Table 2** [30-32]

Table 2. Simulation parameters

Parameter	value
Sub-channel Bandwidth(B)	200KHz
Number of sub-channels(K)	10
the PSD of AWGN(N_0)	-174dBm/Hz
Maximum transmit power of macro cell $p_{1\max}$	10w
Maximum transmit power of small cell $p_{m\max}$	1w
the inverse of power amplifier efficiency ε_m	1
The covering radio of macro-cell	500m
The covering radio of small cell	10m
The fixed power of macro-cell $p_{1,k}^{I}$	0.2w

The fixed power of small cell $p_{m,k}^{I}$	0.05w
The fixed power of user p_{n}^{fix}	30mw
Maximum seed number of one invasive weed $s_{\max}$	5
Minimum seed number of one invasive weed $s_{\max}$	0
Initial standard deviation value σ_{inital}	0.5
Final standard deviation value σ_{final}	0.05
Maximum number of weed	100

A Performance of IWO

Fig. 3 shows the variation of object value with the iteration increasing, it is obvious that when the iteration comes to 5, the IWO falls into local optimization trap and gets converged when the iteration is around 15.

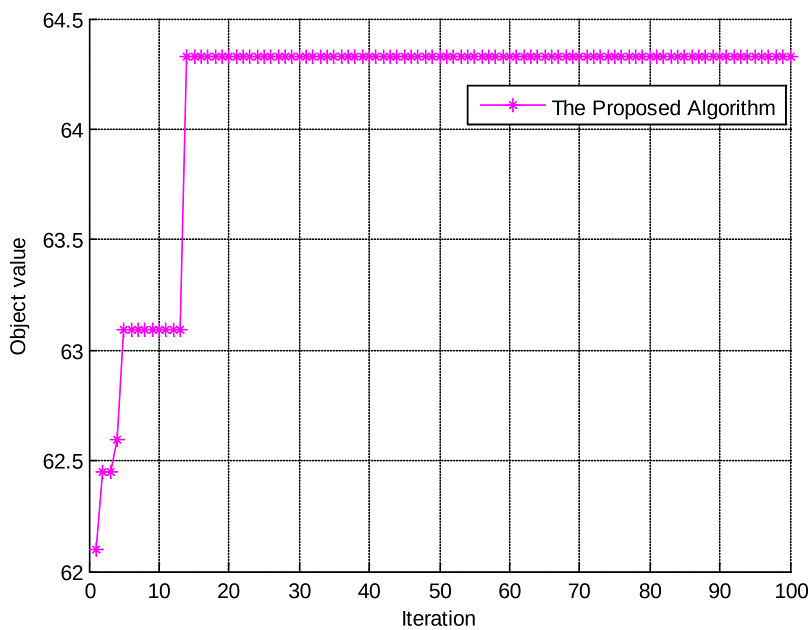

Fig. 3. The convergence of the proposed algorithm

B Energy Efficient

In **Fig. 4,** a performance evaluation of the total network energy efficient versus the number of base-station is depicted. It is obvious that the proposed algorithm can achieve higher energy efficient than other two algorithms. The EEUA considers to get the energy efficiency fairness of users but it would decrease the total energy efficiency because it sacrifices large resource to improve the poor users' performance. EPAS can improve the transmission rate of edge users by improving the transmission power which would bring serious interference which will reduce the total energy efficiency.

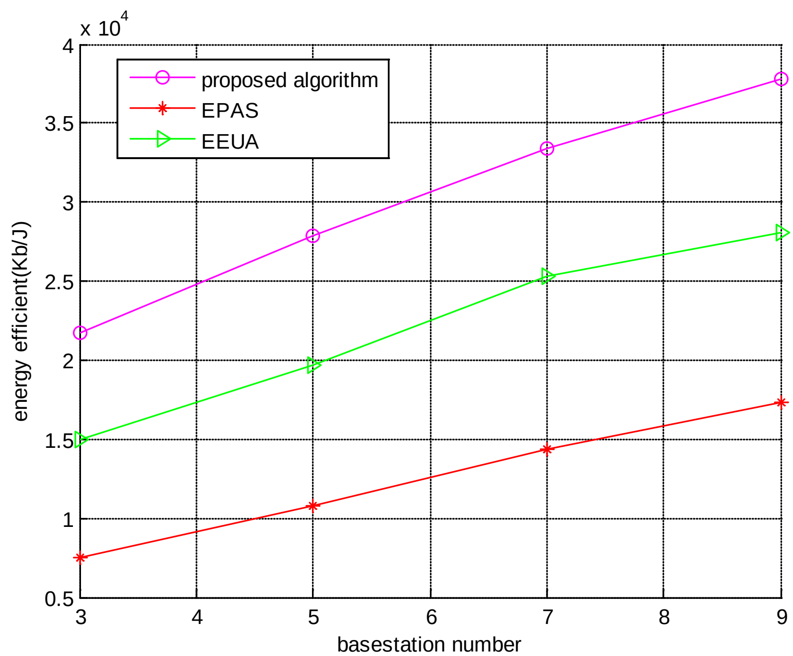

Fig. 4. Energy efficiency of system

C The average MOS

Fig. 5 demonstrates the average MOS in different algorithms with the variation of base-station number. With the increase of base-station number, users will get the higher quality of experience. However, the average MOS will increase slowly because of the serious interference. As shows in **Fig. 5**, we also can see that the average MOS of the proposed algorithm will be higher than that of other two algorithms since the proposed algorithm consider the users' quality of experience instead of transmission rate.

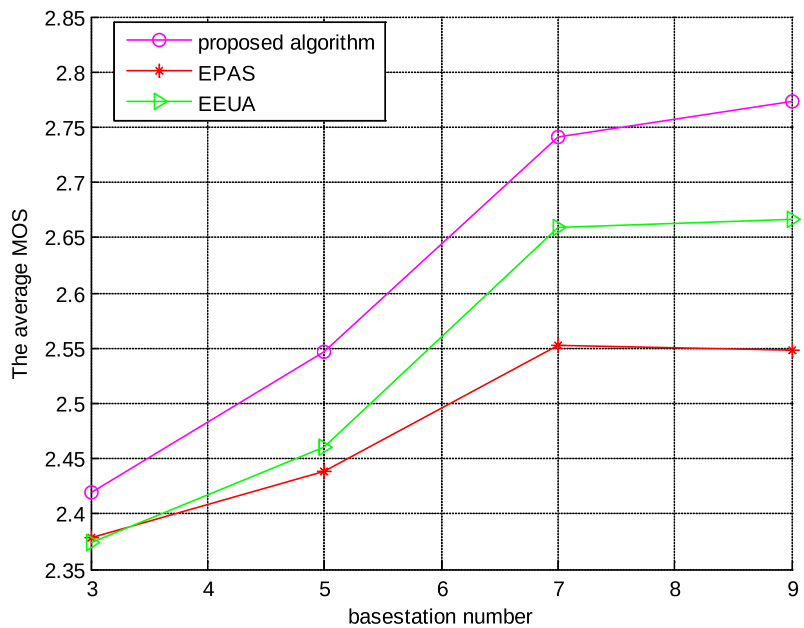

Fig. 5. The average MOS of users versus network number

Fig. 6 and **Fig. 7** show the average MOS for different services in these three algorithms. It can be seen the average MOS of C type is lower than that of S type for its restriction of minimization transmission rate.

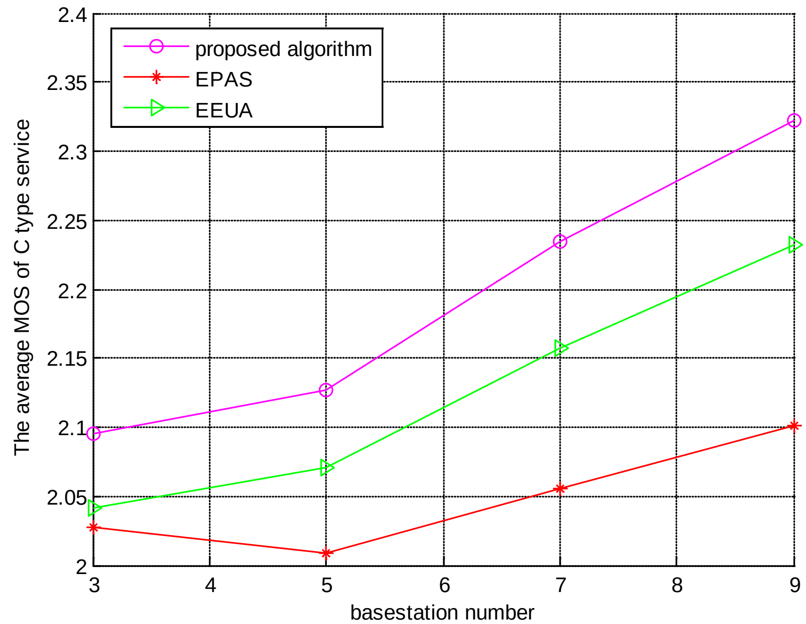

Fig. 6. The average MOS of user with C type service

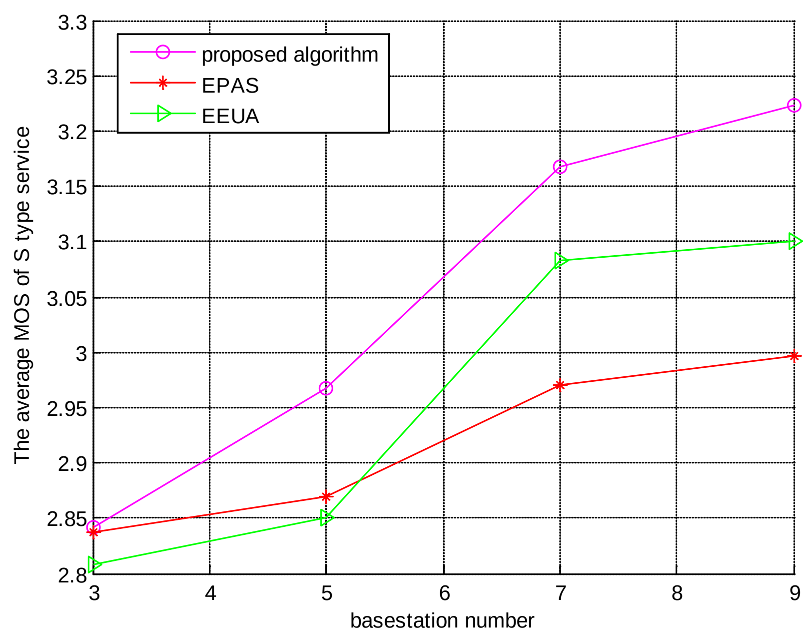

Fig. 7. The average MOS of users with S type service

Fig. 8 shows the average MOS in different cells. From the figure, the macro-cell (base-station ID is 1) can get lower average MOS than small cells (base-station ID is 2-9). The reason is that the users in the macro-cell can receive the serious interference from small cells, while the macro-cell to small-cell user's interference is tiny. The users in small cells can get better quality of experience than users in macro-cell.

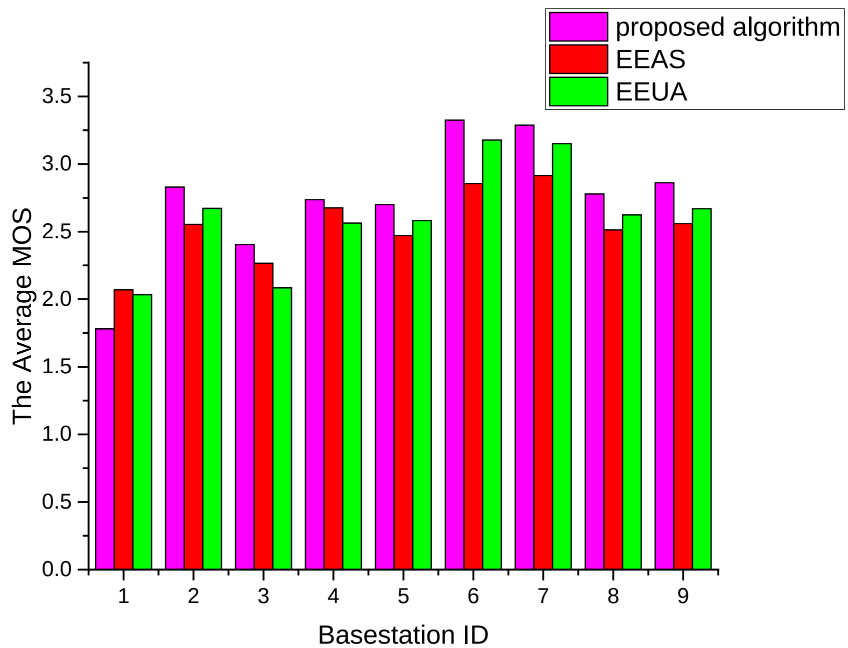

Fig. 8. The average MOS of different basestation

D Fairness Analysis

In the sub-section, we use Jain's Index to measure the fairness of three algorithms. The average MOS of proposed algorithm is superior to the others but the Jain's fairness of EPAS is the highest among three algorithms in **Table 3.** It is because that the EPAS consider to maximize the minimization EE of users which will balance the users MOS. However, the proposed algorithm consider to promote the users MOS to near the Utopia MOS which leads to decreasing the fairness.

Table 3. Performance comparison under Jain's Fairness factor

	3	5	7	9
Proposed algorithm	0.8756	0.8930	0.8904	0.9084
EPAS	0.9077	0.9107	0.9141	0.9170
EEUA	0.8606	0.8836	0.8805	0.8870

Fig. 9 is 10th percentile MOS (the average of the lowest 10% MOS of users). The EPAS is outperformances in three algorithms and the proposed algorithm is second to the EEUA. The reason is the proposed algorithm does not only consider to promote the fairness but also considers to improve the average MOS, so the performance in terms of average MOS is inferior to EPAS. But as shown in **Fig. 10**, the EEPA sacrifices the good users' QoE to improve the poor users' QoE (The QoE in 0-1 and 4-5 is lowest in three algorithms), the proposed algorithm also can guarantee the highest good users' QoE.

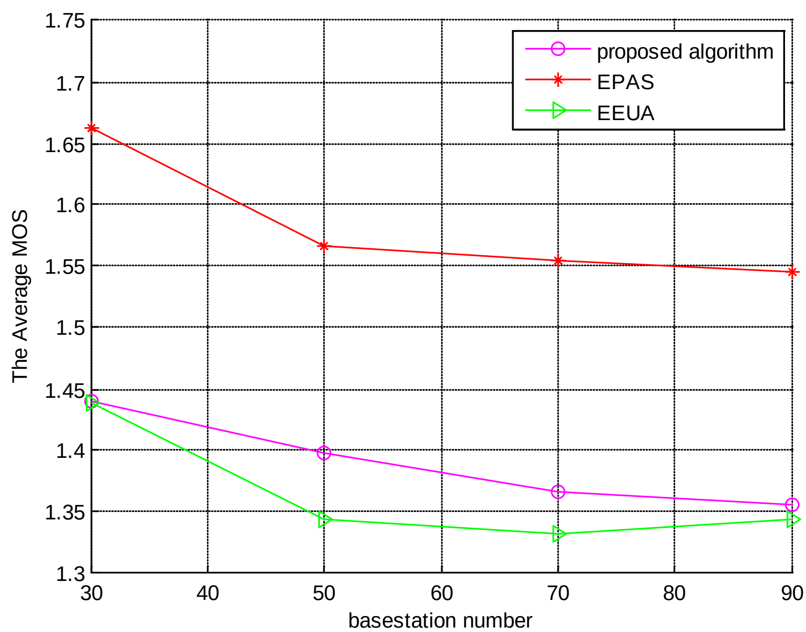

Fig. 9. 10th percentile MOS versus network number

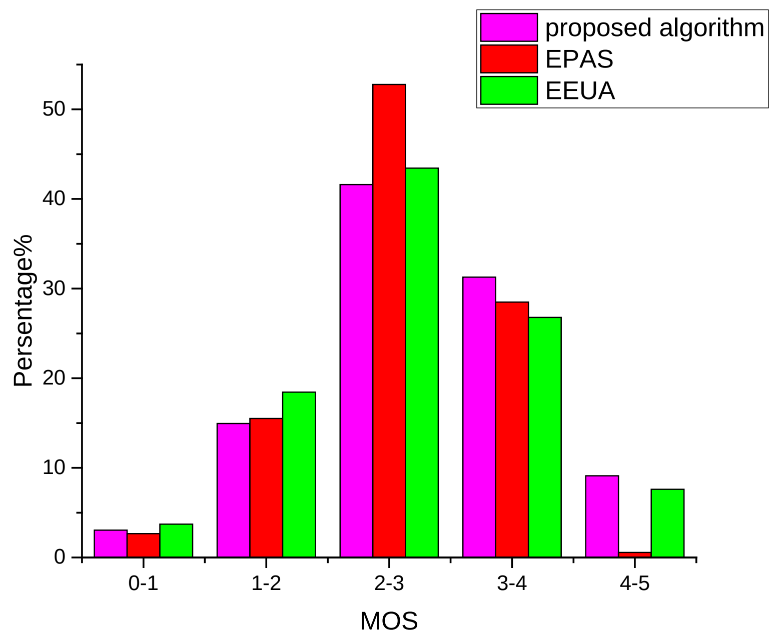

Fig. 10. The percentage of users versus the MOS

5. Conclusions

In this paper, we have investigated power allocation in heterogeneous networks. Our object is to improve the QEE for each user. Therefore, we formulate the optimal problem in fair manner. To find the optimal value, we use IWO to solve it. Simulation results demonstrate that the proposed algorithm can improve the QoE and EE, and achieve high QoE fairness among users. In future, we will extend our work to the scenario where there exists much relay nodes in each cell.

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