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QoE-Aware Downlink User-Cell Association in Small Cell Networks: A Transfer-matching Game Theoretic Solution With Peer Effects

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ABSTRACT The user-cell association mechanism is one of the important research topics for radio resource management in heterogeneous wireless networks. Existing studies mainly concerned the physical performance such as throughput and SINR, and ignore the upper layer users demand. For avoiding blindness of pursuing higher data rate and achieving more rational user-cell association, a novel method is proposed to associate users with heterogeneous traffic to small cell base stations (SBSs) based on user quality of experience (QoE). The user-cell association problem is formulated as a distributed transfer-matching game between SBSs and users to address the sum-QoE maximization problem. Furthermore, an effective distributed cooperative transfer-matching self-optimizing algorithm, roulette transfer matching algorithm, is designed for exploring the stable point of the game. It is proved that the proposed algorithm can converge to a stable solution and find the optimal two-sided transfer matching. Numerical experiments are presented to validate the proposed scheme and show the improvement for the system performance and fairness.

INDEX TERMS User-cell association, QoE, many-to-one matching, peer effects, transfer matching algorithm.

I. INTRODUCTION

With the rapid growth of demand for various high-speed and high-definition traffic data in 4G and 5G cellular networks [1], the dense deployment of small base stations (SBSs) has emerged as a promising technology to increase the system capacity and improve the network coverage. The SBS provides a cost-effective approach for offloading traffic from the macro-cell networks and brings an improved user experience [2], [3]. Facing the multiple overlapping available networks, designing an efficient user-cell association mechanism is an important research topic for radio resource management (RRM) [4]. In the future heterogeneous wireless networks, mobile terminals need to have the ability to dynamically select and connect to the best network according to their current demand [5]. In the context of the coexistence of different wireless networks and different traffic type users, to exploit the diversity of networks and users for optimal discrimination service solution by user-cell association has always been a challenge for RRM in heterogeneous small cell networks. The different matching criterion can affect the performance of user-cell association in great extent. The currently common criterion for user-cell association mainly relates to application requirements in physical layer, such as bandwidth [6], [7], received signal strength [8], SINR [9], packet loss [9], [10], required throughput [11]. For user-cell association problem, its critical task is to provide user high-quality service to meet their differential demands and requirements at the greatest extent. However, existing studies more concerned the physical performance indexes and ignored the upper layer user demands. Current throughput-centric user-wide optimization do not achieve the user demand diversity gain [12].

In recent years, many enterprises and researchers began to express the tremendous interest for the evaluation index based on quality of experience (QoE) to carry out the better communication products and services [13]. QoE is a subjective assessment of media quality of users and has recently become a hot issue in wireless networks [12], [14], [15]. Owing to the individual application types and user preferences, there will be different QoE for different users with the same data rate. In view of the realistic consideration of user QoE demands, when the user QoE can not be improved anymore, a higher throughput would be meaningless. In other words, the benefit of increasing throughput to a special user is not always as obvious as expected. Furthermore, QoE-driven techniques will bring about the improvement of fairness and efficiency, but it does not add any cost of additional resource investment [16]. Note that the optimized target for maximizing user QoE has its advantages, which will alleviate the situation of pursuing higher data rate blindly and improve radio resources utilization. Accordingly, the approach of user-cell association based on QoE can satisfy more users demands with limited resources. Therefore, we model the problem of user-cell association to improve user QoE instead of throughput or other standards of physical layer, which exist potential performance gains to satisfy the user demands [12]. Mean Opinion Score (MOS) is one of the main subjective service quality evaluation methods to characterize QoE and has emerged as the most popular descriptor of perceived multiple media quality [17]. In this paper, we will adopt the MOS method, which is widely used in many RRM researches [12], [16], [18].

The studies related to user-cell association can be divided into distributed manner and centralized manner [19]. All centralized approaches need a centralized controller, which may lead to unsustainable communication overhead, such as [20] and [21]. However, due to the character of self-organized and self-optimizing for SBS, it is difficult to SBS to acquire global information in a centralized manner. Therefore, the traditional centralized resource allocation method is hard to be applied to the RRM in heterogeneous small cell networks. In this paper, we tend to design a distributed method to solve the user-cell association problem. Game theory is a powerful decentralized optimization approach to analyze the interactions among decision makers [3], [22]. Recently, the matching game theory [23], winning the 2012 Nobel Prize, provides a mathematically tractable distributed method for personnel assignment problem in two distinct sets. The matching models have aroused the researchers' attention in the area of communication and being applied to resource management for wireless networks gradually [31]–[33], [35], [37]. The matching game has many intrinsic attributes, such as the inherently self-organizing mechanism, the fast speed of convergence, and the suitable models for characterizing interactions between two heterogeneous sets that wanted to match. It is suitable to be applied to the RRM in wireless communication systems, such as user-cell association [24].

In this paper, we propose user demand-centric optimization via maximizing QoE to find the most appropriate user-cell association using matching game model. To the best of authors' knowledge, this is the first work to consider the problem of QoE-aware user-cell association based on matching game formulation in small cell networks. In short, the main contributions of this paper are as follows:

- We model the user-cell association framework as a 0-1 integer programming problem in SBS networks. Different from the previous work, the optimization objective is to maximize the cumulative sum of the MOS, which is widely used to provide a generic measure of the user QoE to the network-wide users.
- We formulate the user-cell association problem as a novel distributed transfer-matching game. Furthermore, we prove the proposed transfer matching exists the two-sided exchange-stable matchings.
- We investigate two effective distributed cooperative transfer-matching algorithms to address the sum-QoE maximization issue. Theoretic analysis and simulation results indicate that the proposed greedy transfer matching algorithm (GTMA) can converge to a suboptimal stable matching within a relatively less iterations. Moreover, the proposed roulette transfer matching algorithm (RTMA) can find the optimal two-sided transfer matching solution without exhaustively searching.

The rest of this paper is organized as follows. Section II introduces the related works. In Section III, the system model and the problem formulation are presented. Specifically, we apply a matching game to model the users-cell association process in SBS networks. In Section IV, a transfer-matching framework is proposed and two algorithms are designed for a good association. In Section V, simulation results are given. Finally, the conclusion is drawn in Section VI.

II. RELATED WORK

In this section, some related studies are presented. Several solutions are proposed in the literature [8], [10], [25]–[28] on the user-cell association in heterogeneous cellular networks based on different optimization objects. However, most of them focus only on users' throughput or received signal strength indicator (RSSI), ignoring the user QoE. Specifically, in [10], P. Coucheney *et al.* designed a distributed algorithm to exploit the benefits of vertical handover by finding fair and efficient assignment schemes. In [25], S. Deb *et al.* proposed the mobile operator and technology agnostic access (MOTA) service model with associating each application to a suitable base station to improve the overall spectrum utilization. In [26], E. Aryafar *et al.* formulated the user-cell association problem as a non-cooperative game, in which users only strive to maximize their own throughputs without regarding the others. In [8], S. Quek *et al.* discussed a practical implementation method and its performance based on reference signal received power (RSRP). In [27], Shen *et al.* studied a pricing-based user-cell association scheme for downlink heterogeneous cellular networks.

In [28], Zhou *et al*. proposed a load-aware and quality of service (QoS) aware user-cell association strategy and utilized a gradient descent method to find optimum solutions. Some work discussed QoE-driven RRM using game theory in [12] and [16].

The matching game is a good method to pair each element for two sets with different target preferences. Individual preferences represent how a player would choose among different alternatives. In this paper, the users' objective is to select a serving SBS, which can optimize a certain QoE requirement. For the SBSs, the goal is not only to find the maximum level of users' QoE requirements, but also to realize load balance. The matching game model can be divided into two categories in existing applications: canonical matching and matching with externalities [24]. The canonical matching is relatively simple and can be solved by the deferred acceptance (DA) algorithm [33] based on fixed individual preference. For example, in [31], A. Leshem *et al*. presented a one-to-one matching in cognitive spectrum access about second user (SU) accessing to the frequency band of a primary user (PU). In [32], matching theory is extended to the resource allocation using the basic model of one-to-one and many-to-one matching markets. There exist some works on user-cell association in the downlinks of small-cell networks. In [33], Semiari *et al*. proposed a scheme based on many-to-one matching game considering rate and fairness for cell-edge users. In [34], Zhou *et al.* proposed a cooperative matching approach based on the diversity of secondary users' demands.

The matching with externalities (or peer effect) is significantly challenge owing to its variability of individual preferences [24]. In [35], Pantisano *et al*. took device-specific QoS characteristics, which extracted from the context features, as the preference and build a many-to-one matching game with externalities model to solve the problem of user-cell association. In [37], Saad *et al*. proposed a many-to-one matching scheme with peer effects to solve the problem of uplink user-cell association in small-cell networks, regarding packet success rate and transfer delay as the preference function. For the user-cell association using many-to-one matching, peer effects often play an important role. That is, the preference of any user not only cares about the information available for itself, but also cares about other users matched to the same SBS. Unfortunately, there is no general existence method to obtain the stable solution of matching with externalities [35]. In addition, the previous studies on matching theory for wireless resource management only focus on the relationship of preferences, because the value of each user's throughput is usually different, it is easy to build them. The stable matching does exist when the preferences are different from one to another for object selection, which can be strictly distinguished according to user's individual utility. This paper adopts the mean opinion score (MOS), which build effective QoE control mechanisms onto measurable QoS parameters. However, the strict preferences based on QoE can not usually exist due to the limited level of MOS. Different from our preliminary work in [36], rigorous theoretical proofs and performance analysis are provided in this paper. In addition, we add a distributed optimal two-sided transfer matching solution. Finally, extensive simulations are conducted to verify the effectiveness of the proposed schemes.

In fact, prior works by means of matching game do not address the problem of maximizing user's satisfaction. In fact, it is a great challenge to solve the matching problem considering the peer effect and the indistinguishable preference list [24]. Moreover, there is not a kind of matching algorithm can obtain the optimal system user-cell association with good fairness. So the differences between the proposed scheme and the existing schemes mentioned above are summarized as follows:

(i) From the user demand-centric perspective, we propose a novel distributed user-cell association framework for maximizing the QoE in terms of classical MOS in a multiple users case.

(ii) The proposed matching game is a many-to-one matching game with peer effects, in which the choice of each user is influenced by the other users who matched to the same SBS. Moreover, the unfixed quota and the non-strictly distinguishability of the utility metric (i.e., infinite MOS level) make the problem more complicated. Specifically, we will employ the idea of coalition to address the major issues identified above and give out the optimum user-cell matching algorithm with good fairness.

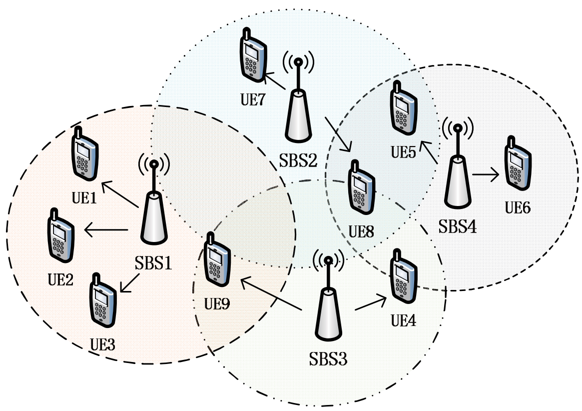

FIGURE 1. An exemplary user-cell association in downlink scenario.

III. SYSTEM MODEL AND PROBLEM FORMULATION

A. SYSTEM MODEL

1) NETWORK MODEL

We consider the downlink transmission of an orthogonal frequency division multiple access (OFDMA) small-cell network consisting of N SBSs and M users[1] as shown in Fig.1. Let $\mathbf{N} = \{1, 2, ..., N\}$ denote the SBS set and $\mathbf{M} = \{1, 2, ..., M\}$ denote the user set needing to be served in the SBS networks. The total number of SBSs and users are

[1] We can easily extend our method to the scenario considering the impacts of macro cell. For convenience, we consider a simple scenario only consisting of SBS networks in this paper.

denoted by $N = |\mathbf{N}|$ and $M = |\mathbf{M}|$, respectively, where $|\bullet|$ is the cardinality of the set. We assume that neighboring SBSs are able to interchange information such as though X2 interface or high data rate optical fiber backhaul, thus their information exchange is easy to obtain. Each user has a set of available SBSs, i.e., the available SBSs set of user m is denoted by $A_m \subseteq \mathbf{N}$. We assume that one user can only access one SBS at a given time slot. Based on each SBS's loading and location, each SBS can service a varying number of wireless device users in its coverage area with qualities assurance. Due to the overlap of service coverage among different SBSs, users located in the overlapping areas of networks can access any one of the available SBSs set. In conventional cell networks [38], each user typically accesses the base station with the highest RSSI, i.e., serviced by the nearest base station. Despite its simplicity, this approach suffers from several drawbacks. Specifically, a user's throughput is not only about the physical layer data rate, but also about the load condition and resource allocation policy of the associated network. For resource allocation policy on the network side, we assume that the proportional fairness and soft-QoS based on the differentiation of the multilevel service are adopted, which are widely used in cellular networks including LTE-A networks. In this paper, based on the idea of system model in [12] and [25], the average throughput of user m associated with SBS n is

$$\theta_{m,n} = \frac{\omega_m R_{m,n}}{W_n}, \qquad m \in \mathrm{SBS}_n, \tag{1}$$

where $R_{m,n}$ is the practically physical layer data rate of user m associating with SBS n, i.e., Shannon capacity. For given scheduled users in SBSs, ω_m denotes the weight of user m in SBS n; $W_n = \sum_{m \in SBS_n} \omega_m$ is the total weight of users in SBS n, which can indicate the load of the network. The throughput model in Eq. (1) reflects the actual scene multi-features. First, $R_{m,n}$ abstracts the physical characteristics such as modulation and channel condition. Second, the proportional factor ω_m/W_n reflects the occupancy of resources by user m associated with SBS n. Third, for soft-QoS, the weight associated with each user can reflect its relative priority and different application types. Meanwhile, Eq. (1) shows that if SBS n broadcasts the current total weights to all associated users associated with it, all users can timely estimate their own achieved throughput (using channel measurements).

2) QoE-CENTRIC APPROACH

Although the selection criterion of throughput-centric optimization is commonly used for network selection, it only reflects the physical layer characteristics. However, blindly pursuing individual user's throughput maximization is not always preferred for the whole system. In view of customer satisfaction, taking up too much system resources may imply a waste for some users. Therefore, to improve the user satisfaction is more rational than to optimize the system performance simply. In this section, we present an idea to maximize users' QoE in application layer.

From user demand perspective, we assume that users can tolerate throughput variation within a certain degree, because the user experience is insensitive. Inspired by the user's QoE metric, in this paper, an ordinal qualitative MOS is used as a measure to reflect the satisfaction for different applications, such as web browsing, file downloading and video streaming. The value of MOS is generally classified into five levels, 1 to 5, which represent 'Excellent', 'Good', 'Fair', 'Poor' and 'Bad' for users' QoE, respectively. For example, MOS = 1 reflects that the perceived quality drops to an unacceptable level and MOS = 5 implies that the user has feasted the most satisfied experience.

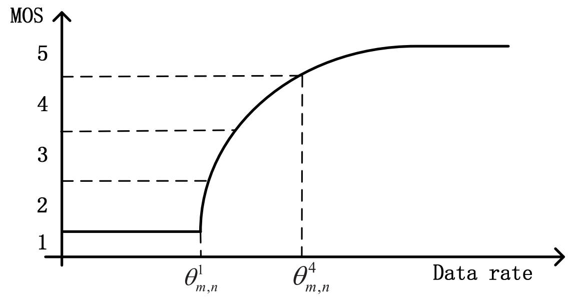

FIGURE 2. Generic application model of mean opinion score.

Different from the traditional definition of continuous MOS, this paper presents a discrete MOS model with limited grades. According to [39] and [40], the relationship between data rate and MOS can be written as a bounded logarithmic relationship function as illustrated in Fig. 2:

$$\mathrm{MOS}_{m,n}(\theta_{m,n}) = \begin{cases} 5, & \theta_{m,n} > \theta^4_{m,n} \\ 4, & 3 < a \log \dfrac{\theta_{m,n}}{b} \le 4 \\ 3, & 2 < a \log \dfrac{\theta_{m,n}}{b} \le 3 \\ 2, & 1 < a \log \dfrac{\theta_{m,n}}{b} \le 2 \\ 1, & \theta_{m,n} \le \theta^1_{m,n} \end{cases}$$
$$a = 3.5/\log(\theta^4_{m,n}/\theta^1_{m,n}),$$
$$b = \theta^1_{m,n}\left(\theta^1_{m,n}/\theta^4_{m,n}\right)^{\frac{1}{3.5}},$$
$$0 \le \theta^1_{m,n} < \theta^4_{m,n}, \forall n \in \mathbf{N}, \tag{2}$$

where θ denotes the average throughput of a user; a, b are parameters dependence on the specific satisfaction and the minimal acceptable date rate of a user, which is classified by different applications. Each user application characteristics can be parameterized by two parameters $\{\theta^1_{m,n}, \theta^4_{m,n}\}$. This means that users with different types have different MOS standards. For example, for the general video calling user in Skype [41], the required minimal throughput is 128 kbps and the recommended throughput is 500 kbps, so 128 kbps, 500 kbps correspond to $\{\theta^1_{m,n}, \theta^4_{m,n}\}$.

B. QoE MATCHING GAME FORMULATION

For associating users to SBSs, our goal is to maximize the cumulative sum MOS of total users in the network. The satisfaction of user m associated with SBS n is classified into five levels based on MOS, denoted as $\mathrm{MOS}_n^m \in \{1, 2, 3, 4, 5\}$. We define a utility function for user m under matching μ is

$$U_m(\mu) = \mathrm{MOS}_{\mu(m)}^m(\theta_{m,\mu(m)}), \tag{3}$$

where $\mu(m)$ denotes the matching result of m, i.e., the SBS accessed by user m. MOS_n^m is the satisfaction score for user m accessing SBS n. For the whole system, our main goal is to assign each user $m \in M$ to the best fit SBS $n \in N$ through a matching method $\mu : \mathbf{M} \rightarrow \mathbf{N}$. In this paper, to obtain the globally optimal solution, we consider the 'social welfare', which reflects the satisfaction degree of entire network and the 'efficiency loss' caused by enforcing stability of assignments in matching markets. We define it as follows:

$$\begin{aligned} \max W(\mu) &= \max \sum_{m\in\mathbf{M}} U_m(\mu) \\ &= \max \sum_{n\in\mathbf{N}} \sum_{\mu(m)=n} a_{m,n} \times \mathrm{MOS}_{m,n}(\theta_{m,n}) \qquad (4) \\ &\quad s.t.\ a_{m,n} \in \{0,1\}, m \le |\mathbf{M}|, n \le |\mathbf{N}| \qquad (4.1) \\ &\quad \sum_{\mu(m)\in\mathbf{N}} a_{m,\mu(m)} = 1, m \le |\mathbf{M}| \qquad (4.2) \end{aligned}$$

The constraint (4.1) ensures that the status of associating a user to one of the SBS set only includes one of the two cases: accessible or inaccessible. $a_{m,n}$ denotes the matching index, i.e., $\mu(m) = n \Leftrightarrow a_{m,n} = 1$. The constraint (4.2) guarantees each user can only access to one SBS.

To solve the user-cell association problem and avoid combinatorial complexity, we propose a novel approach on the framework of many-to-one matching games referring to the model of assigning housing to college students [42]. A matching game model offers a valid tool for matching players in two distinct sets depending on the individual information and preference. In this paper, one user is matched to only one SBS, while one SBS can be matched to multiple users with a quota restriction, i.e., the maximal quota of SBS n is expressed as q_n. The definitions of a matching μ are given below:

Definition 1: A matching μ is a pair, where $\mu \in \mathbf{M} \otimes \mathbf{N}$ such that $|\mu(m)| = 1$ and $|\mu(n)| = q_n$, where $\mu(m) = \{m \in \mathbf{M} : (m, n) \in \mu\}$, $\mu(n) = \{n \in N : (n, m) \in \mu\}$ and $\otimes$ denotes the set of matching agents.

Definition 2: An agent in matching μ must be individually rational, where there don't exist that one user is unacceptable to any SBS nor one SBS is unacceptable to any user. Such a matching is said to be unblocked.

Definition 3: A matching μ is blocked by the user-SBS pair $(m, \mu(m))$ if $\mu(m) \neq n$ and $n \succ_m \mu(m)$ for user m, or by the user-SBS pair $(\mu(n), n)$ if $\mu(n) \neq m$ and $m \succ_n \mu(n)$ for SBS n. Here, the preference relation $\succ$, ranked by an agent based on the preference of matching object, is defined as a complete and transitive relation between the agent in $\mathbf{M}$ and $\mathbf{N}$. If one agent in matching pair prefers another than present assignment, the present pair is blocked.

Definition 4: A matching μ is stable if it is not blocked by any individual agent or any user-SBS pair.

Thus, the result of a stable matching is a bilateral assignment to all agents. Specifically, the users build their preferences based on the MOS level of accessing different SBS. For any user m and any two SBSs $n, n' \in \mathbf{N}, n \neq n'$, two matchings $\mu, \mu' \in \mathbf{M} \otimes \mathbf{N}$, $n = \mu(m)$, $n' = \mu'(m)$, there are the following properties:

$$\begin{aligned} n \succ_m n' &\Leftrightarrow U_m(n) > U_m(n') \\ &\Leftrightarrow \mathrm{MOS}_n^m(\theta_{m,n}) > \mathrm{MOS}_{n'}^m(\theta_{m,n'}) \end{aligned} \tag{5}$$

Similarly, for any SBS n and any two users $m, m' \in \mathbf{M}, m \neq m'$, two matchings $\mu, \mu' \in \mathbf{M} \otimes \mathbf{N}$, $m = \mu(n)$, $m' = \mu'(n)$, there are the following properties:

$$\begin{aligned} m \succ_n m' &\Leftrightarrow U_n(m) > U_n(m') \\ &\Leftrightarrow \mathrm{MOS}_n^m(\theta_{m,n}) > \mathrm{MOS}_n^{m'}(\theta_{m',n}) \end{aligned} \tag{6}$$

From (5) and (6), the preferences of all agents for matched object are related to their utilities. Thus, the date rate in (1) and the value of MOS in (2) depend on the interaction (the current total weights of the SBS) produced by the other users who are matched to the same SBS. So the preferences of relevant agents about the average throughput are interdependent, i.e., they are influenced by the existing matching.

Our proposed matching model, in which agentąŕs preferences depend on the identity and number of other users matched to the same resource, is classified into matching with peer effects [24]. The matching method is challenging when peer effects are considered. There is no guarantee that a stable many-to-one matching will exist [43]. While most literatures about matching games, such as [23] and [44], assume that the preferences of agents are not related with the other agents' choices. So the traditional methods based on independent preference sorts, such as the deferred acceptance algorithm used in [31] and [32], cannot fit our problem owing to the sort of the preference changing with the matching process. For a certain user in the matching game, the user not only considers preferences overall SBSs, but also takes into peer-effect account. It is clear that how to find the stable matching is a key goal of this user-cell assignment problem in our game model.

In addition, for each SBS, in conventional notation for many-to-one matching, there exists a positive integer quota q_n, which indicates the largest number of users provided by SBS n. In former literatures [23], [33], SBSs all have the same fixed quota. However, in this paper, we assume that the initial load of SBS is random. Because of the different quality requirements for different types of users, the value of load of each SBS is metabolic in the process of the game. So it implies that the quota of each SBS is different from one another, which is related to the initial condition of SBS loading and the types of access user. Therefore, we must utilize new methods to find the stable solution of the matching game with peer effects and unfixed quota.

IV. TRANSFER-MATCHING ALGORITHM

In this section, we will develop two Transfer-matching algorithms to address the user-cell association problem and show that our proposed schemes always have a stable matching solution. In this paper, the problem of matching users to SBSs in the network with peer effects can be formulated by the model of assigning housing to college students as [42]. We first define the concept of transfer matching $\mathcal{T}^{(m_n)}_{n'/(m'_{n'})}$, in which user m (accessing to SBS n) and user m' (accessing to SBS n') swap their SBSs or user m switch itself from original SBS n to SBS n' directly while keeping all other users assignments unchanged.

Definition 5: A transfer matching

$$\mathcal{T}^{(m_n)}_{n'/(m'_{n'})} = \mathcal{T}^{(m_n)}_{(m'_{n'})} \text{or} \mathcal{T}^{(m_n)}_{n'},$$

$$\text{therein, } \mathcal{T}^{(m_n)}_{(m'_{n'})} = \{[\mu \backslash ((m,n),(m',n'))] \cup [(m,n'),(m',n)]\},$$
$$\mathcal{T}^{(m_n)}_{n'} = \{[\mu \backslash (m,n)] \cup [m,n']\}. \tag{7}$$

Note that the word 'transfer' has two transformation forms, $\mathcal{T}^{(m_n)}_{(m'_{n'})}or\mathcal{T}^{(m_n)}_{n'}$, i.e., swapping two users accessed to different SBSs or switching one user to other available SBS.

Definition 6: A transfer matching μ is two-sided stable (2ST) if and only if there does not exist any transformation such that:

$$\begin{aligned}&(1)\ \forall i \in \{M\},\ U_i(\mathcal{T}^{(m_n)}_{n'/(m'_{n'})}) \geq U_i(\mu), \text{ and}\\ &(2)\ \exists i \in \{m, m' \in M\},\ U_i(\mathcal{T}^{(m_n)}_{n'/(m'_{n'})}) > U_i(\mu)\end{aligned} \tag{8}$$

Lemma 1: Any transfer matching $\mathcal{T}^{(m_n)}_{n'/(m'_{n'})}$ for which

$$\begin{aligned}&(1)\ \forall i \in \{M\},\ U_i(\mathcal{T}^{(m_n)}_{n'/(m'_{n'})}) \geq U_i(\mu), \text{ and}\\ &(2)\ \exists i \in \{m, m' \in M\} with U_i(\mathcal{T}^{(m_n)}_{n'/(m'_{n'})}) > U_i(\mu)\end{aligned} \tag{9}$$

has $W(\mathcal{T}^{(m_n)}_{n'/(m'_{n'})}) > W(\mu)$.

Proof: The following proof procedure refers to the idea of proof given in [42] and [45]. We define the social welfare function as the potential function. Due to the difference between the two transfer patterns, $\mathcal{T}^{(m_n)}_{(m'_{n'})}$ and $\mathcal{T}^{(m_n)}_{n'}$, we have to split up two cases to prove. In case $\mathcal{T}^{(m_n)}_{(m'_{n'})}$, we discuss the situation where two users in different SBS swap places from their respective SBSs. We begin by calculating the difference in the social welfare function for a transfer matching using Eq. (4):

$$\begin{aligned}W(\mathcal{T}^{(m_n)}_{(m'_{n'})}) - W(\mu) = &\sum_{i/m' \in n'} U_i(\mathcal{T}^{(m_n)}_{(m'_{n'})}) - \sum_{i/m' \in n'} U_i(\mu)\\ &+ \sum_{i/m \in n} U_i(\mathcal{T}^{(m_n)}_{(m'_{n'})}) - \sum_{i/m \in n} U_i(\mu)\\ &+ U_{m'}(n) + U_m(n') - U_m(n) - U_{m'}(n')\end{aligned} \tag{10}$$

where $W(\mu) = \sum_{i \in n'} U_i(\mu) + \sum_{i \in n} U_i(\mu) + \sum_{i \in N/n',n} U_i(\mu)$ is the value of social welfare before the transfer matching. $W(\mathcal{T}^{(m_n)}_{(m'_{n'})}) = \sum_{i/m' \in n'} U_i(\mathcal{T}^{(m_n)}_{(m'_{n'})}) + \sum_{i/m \in n} U_i(\mathcal{T}^{(m_n)}_{(m'_{n'})}) + U_m(n') + U_{m'}(n) + \sum_{i \in N/n',n} U_i(\mu)$ is the value of social welfare after the transfer matching. Due to that only SBS n, n' are affected by the swap, the utility of the user in other SBS except for SBS n, n' is unchanged. So $\sum_{i \in N/n',n} U_i(\mu)$ stays the same before and after the transfers.

According to condition (1) in Lemma 1, we can obtain

$$\begin{aligned}&\sum_{i/m' \in n'} U_i(\mathcal{T}^{(m_n)}_{(m'_{n'})}) - \sum_{i/m' \in n'} U_i(\mu)\\ &\quad + \sum_{i/m \in n} U_i(\mathcal{T}^{(m_n)}_{(m'_{n'})}) - \sum_{i/m \in n} U_i(\mu) \geq 0\end{aligned} \tag{11}$$

According to condition (2) in Lemma 1, we can have

$$\begin{aligned}&U_{m'+m}(\mathcal{T}^{(m_n)}_{(m'_{n'})}) - U_{m'+m}(\mu)\\ &\quad = U_{m'}(n) + U_m(n') - U_m(n) - U_{m'}(n') > 0\end{aligned} \tag{12}$$

From inequalities(11) and (12), we obtain the following:

$$W(\mathcal{T}^{(m_n)}_{(m'_{n'})}) - W(\mu) > 0 \tag{13}$$

Similarly, in case $\mathcal{T}^{(m_n)}_{n'}$, where single user moves to other available SBS, we can get the same conclusions. First, we get the value of social welfare after the transfer matching:

$$\begin{aligned}W(\mathcal{T}^{(m_n)}_{n'}) = &\sum_{i/m \in n'} U_i(\mathcal{T}^{(m_n)}_{n'}) + \sum_{i/m \in n} U_i(\mathcal{T}^{(m_n)}_{n'})\\ &+ U_m(n') + \sum_{i \in N/n',n} U_i(\mu)\end{aligned} \tag{14}$$

According to conditions (1) and (2) in Lemma 1, we have

$$\begin{aligned}&\sum_{i/m \in n'} U_i(\mathcal{T}^{(m_n)}_{n'}) - \sum_{i/m \in n'} U_i(\mu)\\ &\quad + \sum_{i/m \in n} U_i(\mathcal{T}^{(m_n)}_{n'}) - \sum_{i/m \in n} U_i(\mu) > 0\end{aligned} \tag{15}$$

$$U_m(\mathcal{T}^{(m_n)}_{n'}) - U_m(\mu) = U_m(n) - U_m(n') > 0 \tag{16}$$

From inequalities(15) and (16), we can obtain

$$\begin{aligned}&W(\mathcal{T}^{(m_n)}_{n'}) - W(\mu)\\ &\quad = \sum_{i/m \in n'} U_i(\mathcal{T}^{(m_n)}_{n'}) - \sum_{i/m \in n'} U_i(\mu) + \sum_{i/m \in n} U_i(\mathcal{T}^{(m_n)}_{n'})\\ &\qquad - \sum_{i/m \in n} U_i(\mu) + U_m(n) - U_m(n') > 0.\end{aligned} \tag{17}$$

Due to the symmetry of the social network, it can be seen from (12), (13) and (16), (17) that an arbitrary player is affected by the swap and the change in its utility is non-negative and strictly increasing, which is the same as the change in the potential function W. As there is a finite set of matches, the global maximum of the potential function must be two-sided exchange-stable. therefore, a two-sided exchange stable matching will always exist. Lemma 1 is proved. ∎

Theorem 1: All local maxima of $W(\mu)$ are two-sided stable transfer.

Proof: Let matching μ be the local maximum of $W(\mu)$. Using proof by contradiction, we assume that μ is not two-sided stable transfer. Lemma 1 shows that any transfer matching that is acceptable to all parties (i.e. satisfies conditions (1) and (2) in Lemma 1) strictly increases $W(\mu)$. But this contradicts with the assumption that μ is a local maximum. Thus, μ must be two-sided stable transfer. Hence, Theorem 1 is proved. ∎

Based on the arguments from [39], we can conclude that all stable points of the transfer matching game are the extreme points of the potential function $W(\mu)$, either locally or globally. Fortunately, according to Eq. (4), we know that the potential function which is defined as sum-QoE of users coincides with the total network. Therefore, the maximum sum-QoE of users is a stable solution of the proposed game and the best solution acts as the global optimum of the network utility W_{opt}, which can achieve the highest system level QoE.

According to **Theorem 1**, we can design an effective algorithm by searching the best two-sided transfer stable point to achieve the global optimal solution of problem (4). In particular, two natural algorithms follow immediately from our analysis.

A. GREEDY TRANSFER MATCHING ALGORITHM (GTMA)

In the above section, we have proved that the transfer matching stable point will always exist. Moreover, under certain assumptions, the stable transfer matching is the socially optimal matching. Due to this project involves the user(s) transferring between two SBSs, how to represent the transferring is a first issue. This motivates us to use a list of user service to mitigate the problem. The list contains two parts, i.e. current and prospective users. To better representation to these two parts, we create an concept of dummy for these users with multiple accessed SBSs. Every dummy inherits the location information and traffic types of the original user. Given an original user m, denote $DU = [du_m^1, du_m^2, ..., du_m^{|A_m|}]$ as the dummy set of user m, where du_m^l denotes the l-th dummy buyer; the $A_m \subseteq \mathbf{N}$ is the available SBSs set of user m. For each dummy user, his state can be classified into two states: active or inactive. We introduce the state of index $DUS_{m,n}^l$ to reflect the current state of the l-th dummy buyer of original user m in SBS n as follows:

$$DUS_{m,n}^l = \begin{cases} 1, & \text{active} \\ 0, & \text{inactive} \end{cases} \tag{18}$$

The 'active' state means this dummy buyer has access to SBS n, the state of user m equal to 1 in the list of SBS n. Similarly, if dummy user's state is 'inactive', it means that user m located in the coverage of the serving SBS n but not access. That way, all SBSs have a dynamic list of user service to show the current situation of user-cell association and the potential transferring users.

We first present a greedy transfer matching algorithm (GTMA) in Algorithm 1 to find a two-sided transfer stable. GTMA consists of two phases: the initial arrangement of users and the transfer matching process. In a real scenario, transfer matching algorithm can be used to resolve the

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Algorithm 1 Greedy transfer matching algorithm (GTMA)

Step1: Initial arrangement of users and Information Computation

(1)Each user m discovers all SBSs within the scope of cell it covers.

(2)Each user is initially associated to a randomly selected SBS n,

and report the location and traffic types information to all available SBSs.

(3)Each SBS calculates networks performance metrics in (1), (2)

according to practical access situation and creates own list of user service.

Step2: Transfer matching process

Repeat (polling mode)

Select one SBS, i.e. SBS n

Generate a random number rand $\in (0, 1)$

If rand<0.5

Select one active user m from the list of SBS n randomly

if $U_n(\mathcal{T}_{n'}^{(m_n)}) - U_n(\mu) > 0$,

SBS n sends transferring application to neighboring SBS n'

if $U_{n'}(\mathcal{T}_{n'}^{(m_n)}) - U_{n'}(\mu) > 0$

$\{\mu(n')\} \leftarrow \{\mu(n')\} \cup m$;

SBS n' agrees the transfer proposal of SBS n.

else

SBS n' refuses the transfer proposal of SBS n.

else

SBS n keeps silent and miss a turn.

Else

Select a pair of active user $\{m, m'\}$ from the list of SBS n and SBS n' randomly.

if $U_n(\mathcal{T}_{(m'_{n'})}^{(m_n)}) - U_n(\mu) > 0$

SBS n sends transferring application to neighboring SBS n'

if $U_{n'}(\mathcal{T}_{(m'_{n'})}^{(m_n)}) - U_{n'}(\mu) > 0$

$\{\mu(n')\} \leftarrow \{\mu(n')/m'\} \cup m$, $\{\mu(n)\} \leftarrow \{\mu(n)/m\} \cup m'$

SBS n' agrees the transfer proposal of SBS n.

else

SBS n' refuses the transfer proposal of SBS n.

else

SBS n keeps silence and miss a turn.

End

Until $i \in \{m, m' \in M\} with U_n(\mathcal{T}_{n'/(m'_{n'})}^{(m_n)}) > U_n(\mu), n \in \mathbf{N}$

or reach max-iterations.

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problem user scheduling to improve the accumulative utility. In initial phase, users are associated to the closest or a random SBS. Next, the information of the user is exchanged among the neighboring SBSs. Each SBS create own the list of user service. The neighboring SBSs are able to interchange information though X2 interface, thus their information exchange is easy to obtain. In most of the aforementioned works, small cell is modeled as selfish and only aims at maximizing its own performance metrics such as achievable rate. In this paper, we propose an local altruistic framework referring to the idea of [46]. In the transfer matching phase, all SBS will be attempted orderly to send the application of user transferring through polling mode based on the list of user service. Every SBS must abide by a common rule, which the SBS will agree with transferring application if its utility does not reduce for the transferring. Because the neighboring relationship among SBSs co-exist over a long period of time in a given geographical region, setting this common rule make sense from long term profit for each SBS. When polling to a certain SBS, the SBS will send transferring application to neighboring SBSs for implement a transfer match if the utility of the SBSs can be increased while swapping a 'inactive' user or switching a 'inactive' user from oneself to neighboring SBS. Then, the neighboring SBS may accept or reject the application based on the change of its own utility by transferring. Fig.3 shows the illustration of transfer matching process.

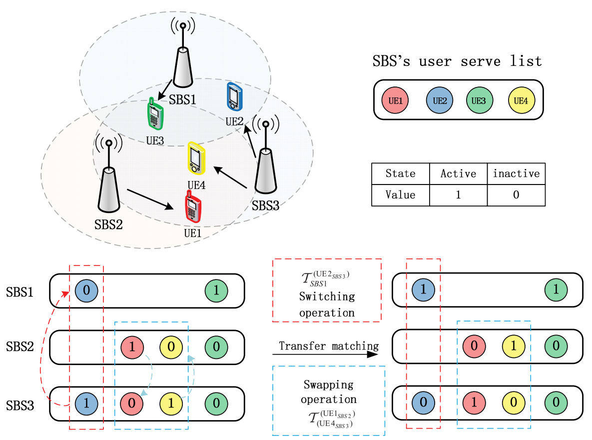

FIGURE 3. Illustration of transfer matching process with two transformation forms.

By greedily considering transfer of selected users, GTMA proceeds with improving the social welfare from initial arrangement. The transfer matching algorithm can be completed in a distributed manner, where only local information of neighboring SBSs exchange is required for the distributed manner. From Lemma 1 and Theorem 1, it is clear that our proposed algorithm will converge to a stable transfer matching point because of the social welfare strictly improving in each iteration. Moreover, all local maxima of social welfare W are two-sided stable transfer-matching. However, GTMA is not guaranteed to converge to the socially optimal stable matching, i.e., it will be likely to find the local maximum W. For GTMA, in each iteration, there are many users accessed to different SBSs for an approved transfer. This diversity of transfer, which is the number of users approved transfer, will gradually decline with the iteration.

These early users who are selected to transfer will introduce a bias and may cause a premature convergence and diversity loss. Due to the monotonicity of GTMA, it has little room to maneuver, an initial user will quickly dominate the whole load margin of SBSs and prevent the SBS from exploring other potentially better transfer of users. In this situation, first impressions are firmly transferred, which may cause a high diversity loss of transfer. So GTMA generally does not get the global optimum.

B. ROULETTE TRANSFER MATCHING ALGORITHM (RTMA)

In algorithm 2, namely RTMA, we seek the optimal social welfare by using the idea of Roulette Wheel Selection [49]. In proportional roulette wheel, the transfers of users are selected with a probability that is directly proportional to their change in local social welfare (only contains two neighboring SBSs with transfer relation), i.e., $W(\mathcal{T}^{(m_n)}_{n'/(m'_{n'})}) - W_{best}$. Obviously, those users with the larger social welfare have more probability of being chosen to transfer, while all users have a chance. Similar to GTMA, the RTMA also has two phases. However, the most basic difference is that the diversity of transfer in the agent is preserved in a much greater degree, that is, the transfer of user from an absolute one to a comparative one based on a probability that depends on the change in social welfare, so it gives a chance for all users to transfer. A positive change of social welfare, yields a probability of transferring larger than 1/2. Therefore, the RTMA can keep tracking the best matching solution and jump out of the local maximum, even as it sinks into worse matching.

Theorem 2: The RTMA converges to a stable state of the matching game. When the stable state is unique, RTMA converges to the optimal solution (4).

Proof: The process of the proposed transfer-matching can be seen as an irreducible periodic Markov chain. We define the set of transition probability $P_{\mathcal{T}}$ and the result of transfer matching μ in each iteration as the transition matching matrix and state space, respectively. Based on the convergence theorem of Markov chain [47], from arbitrary initial transfer-state $\mathcal{S}^{(0)}$, for any state, i.e., $\mathcal{S}^{(n)}$, which is stationary for the transition matrix μ, we have $\mathcal{S}^{(n)} \rightarrow \mathcal{S}^{(optimal)}$. ∎

From the Markov chain convergence theorem [47], we can see that if we run a Markov chain for a sufficiently long time, then, regardless of what the initial state was, the distribution will be close to the stationary state. Obviously, the globally optimal solution $\mathcal{S}^{(optimal)}$ is stationary. If the stable state is unique, we get RTMA converges to the optimal solution. Hence, Theorem 2 is proved. From Theorem 2, we can know that a good performance may signify long conver-

Algorithm 2 Roulette transfer matching algorithm (RTMA)

(1)Each user m discovers all SBSs within the scope of cell it covers.
(2)Each user is initially associated to a randomly selected SBS n, and
report the location and traffic types information to all available SBSs.
(3)Each SBS calculates networks performance metrics in (1), (2)
according to practical access situation and creates own list of user.
Calculate the social welfare of every SBS:
$W(\mu) = \sum_{\mu(m)\in n} \mathrm{MOS}_{m,n}(\theta_{m,n})$ and $W_{best} = W(\mu)$.
Step2: Transfer matching process
Repeat (polling mode)
Select one SBS, i.e. SBS n
Generate a random number rand $\in (0, 1)$
If rand<0.5
Select one active user m from the list of SBS n randomly, and pick an switch objective SBS n'. Calculate
$P_{\mathcal{T}} = \frac{1}{1+e^{-\sigma(W_n(\mathcal{T}_{n'}^{(m_n)})+W_{n'}(\mathcal{T}_{n'}^{(m_n)})-W_{best}^{n}(\mu)-W_{best}^{n'}(\mu))}}$
SBS n sends transferring application to neighboring SBS n' with
probability $P_{\mathcal{T}}$, where σ is learning step.
if $U_{n'}(\mathcal{T}_{n'}^{(m_n)}) - U_{n'}(\mu) > 0$,
$\{\mu(n')\} \leftarrow \{\mu(n')\} \cup m$.
SBS n' agrees the transfer proposal of SBS n.
else
SBS n' refuses the transfer proposal of SBS n.
Else
Select a pair of active user $\{m, m'\}$ from the list of SBS n and
SBS n' randomly.
SBS n send transferring application to neighboring SBS n'. Calculate
$P_{\mathcal{T}} = \frac{1}{1+e^{-\sigma(W_n(\mathcal{T}_{(m'_{n'})}^{(m_n)})+W_{n'}(\mathcal{T}_{(m'_{n'})}^{(m_n)})-W_{best}^{n}(\mu)-W_{best}^{n'}(\mu))}}$
SBS n send transferring application to neighboring SBS n' with
probability $P_{\mathcal{T}}$, where σ is learning step.
if $U_{n'}(\mathcal{T}_{(m'_{n'})}^{(m_n)}) - U_{n'}(\mu) > 0$
$\{\mu(n')\} \leftarrow \{\mu(n')/m'\} \cup m$, $\{\mu(n)\} \leftarrow \{\mu(n)/m\} \cup m'$
SBS n' agrees the transfer proposal of SBS n.
else
SBS n' refuses the transfer proposal of SBS n.
End
If $W(\mathcal{T}_{n'/(m'_{n'})}^{(m_n)}) > W(\mu)$, **then** $W_{best} = W(\mathcal{T}_{n'/(m'_{n'})}^{(m_n)})$;
End if.
Until $i \in \{m, m' \in M\} with U_n(\mathcal{T}_{n'/(m'_{n'})}^{(m_n)}) > U_n(\mu), n \in \mathbf{N}$
or reach max-iterations.

gence time. Hence, it is important to find a good trade-off between exploration (i.e., transfers with less or no improvements of social welfare must have chance) and exploitation (i.e., transfers with better improvements have more chances) within the mechanism of the transfer. Therefore, we must strike a compromise between speed and performance according to a variety of performance requirements.

Remark: Our proposed two kinds of algorithms possess with simple structure, nice commonality and strong expansibility. The proposed two algorithms have respective advantages in the field of the convergence speed and the optimality of matching results. We can make a choice according to actual use requirement. Moreover, in the proposed model, the definition of social welfare can be a multi-perspective view and modification based on the optimization goal. For example, we assume that the satisfied level for MOS is 3 for all users. Accordingly, if our goal is to maximize the number of satisfied users, the social welfare can be defined as

$$W(\mu) = \sum_{m\in M} U_m(\mu) = \sum_{n\in N} \sum_{\mu(m)\in n} \mathrm{MOS}_{m,n}(\theta_{m,n}), \quad (19)$$

where

$$U_m(\mu(m) = n) = \begin{cases} 1; & \mathrm{MOS}_{m,n} \geq 3 \\ 0; & \text{otherwise} \end{cases}$$

V. PERFORMANCE EVALUATION

In simulation section, a small cell wireless network deployment scenario is considered. We deploy N=4 SBSs and M users randomly in a L-by-L square meter area. The coverage of every SBS is a circle with the same radius, 20m. The simulation parameters are shown in Table I.

TABLE 1. Simulation parameter.

Parameter	Value
size L of the hotspot	60m
Carrier frequency	1.0MHz
Thermal noise density	-174dBm/Hz
Transmission power of SBS	20dBm
Coverage radius of SBS	20m
Pathloss model(dB) [50]	18.7∗lg(d[m]) + 46.8 + 20∗lg(2.7/5)

TABLE 2. Typical QoS requirements of video calling application [41].

Application(video calling)	Minimal throughput	Recommended
The group video	512kbps	2Mbps
HD video calling	1.2 Mbps	1.5 Mbps
The general video calling	128 kbps	500 kbps

We take three types of video calling users in Skype as examples of user demand model. Typical QoS requirements as shown in Table II. Corresponding to the Eq. (2), the minimal throughput and the recommended throughput are $\theta_{m,n}^2$ and $\theta_{m,n}^4$, that is, the output MOS values are 2 and 4, respectively. On the basis of these two MOS values, we can obtain the explicit QoE function of each user type. Each SBS has different initial load and is set as $\mathbf{W}_{inital} = (3, 5, 7, 9)$, which reflects that different SBSs possess different quotas. The weight in Eq. (1) of each user is denoted as $\mathbf{w} = (\omega_1, \omega_2, \omega_3)$.

It can be flexibly set according to the actual requirement such as equal weights $\mathbf{w} = (1, 1, 1)$ for simplicity and unequal weights $w = (1, 3, 4)$ for the difference of traffic. Since similar results can be found regardless of type of weights, we only consider the unequal weights $\mathbf{w} = (1, 3, 4)$ case in this paper. These parameters are fixed unless expressively stated. For convenience, we define the system-level QoE as the accumulated sum of all user satisfaction MOS in the total network. We can define the system level throughput similarly.

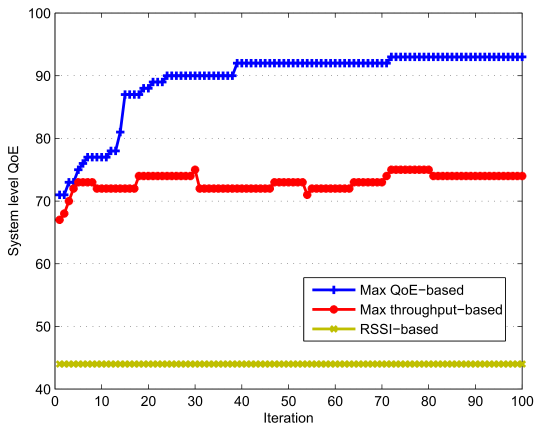

FIGURE 4. **The system-level QoE in a network with 20 users under the considered scheme.**

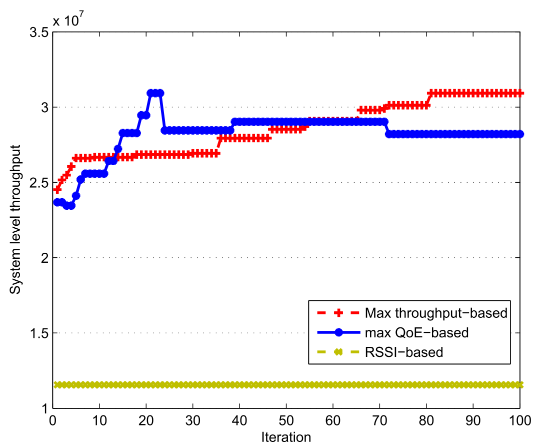

FIGURE 5. **The system-level throughput in a network with 20 users under the considered scheme.**

Fig.4 and Fig.5 show the system-level MOS and system-level throughput in a network with 20 users (M=20) accessed to 4 SBSs (N=4). In Fig.4, we compare the proposed demand centric user-cell association with the performance of the conventional association in system-level QoE and throughput performance based on the highest receive RSSI in [38] and based on throughput [8] under the same network configuration. Obviously, the system-level QoE based on MOS yields significant performance gains relative to the maximum throughput-based and RSSI-based criteria.

In RSSI-based scheme, each user tends to access to the closest SBS. In such cases, due to the lack of coordination, the traffic load can increase rapidly leading to a great reduce of transmission performance. User's throughput is far from guaranteed, not to mention users' QoE. In throughput-based scheme, the optimum rule of the user-network association is maximizing the total throughput of users. Obviously, it can be seen that the throughput optimum rule is worse than the QoE-based scheme in system level QoE cases due to the unawareness of user demand. From Fig.4 and Fig.5, we can see the system-level QoE does not increase as the growth of the system-level throughput based on the maximizing throughput scheme. On the contrary, the system-level QoE based on maximizing QoE scheme get higher value despite the fall in the system-level throughput. These results imply that increasing throughput is meaningless sometimes, such as the satisfied users, even though their MOS is reached to 5. So the QoE-based scheme can obtain the better user experience and satisfaction of resources allocation.

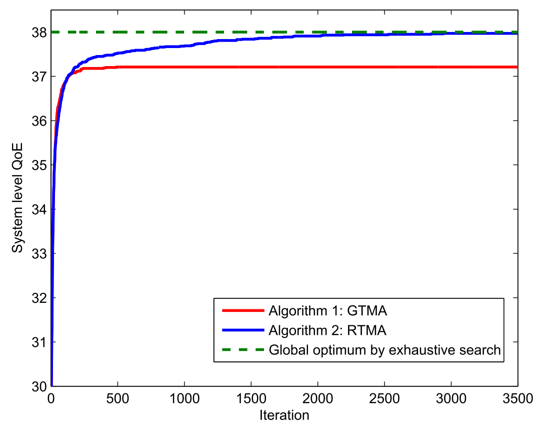

FIGURE 6. **Convergence behavior of two algorithms (M = 8).**

Next, we show the convergence comparison for the proposed GTMA and RTMA for the transfer-matching game based on QoE in Fig.6. The simulation results are obtained through running 100 independent trials and compare the average system level QoE. Because the global optimum is hardly to find by existing computing techniques in large scale networks, Fig.6 studies a small network with 8 users (M=8) accessed to 4 SBSs. In this case, 4 users are group video users and 4 users are HD video calling users. We set the initial load as $W_{inital} = (6, 10, 14, 16)$ and the step size σ as 1.5. The global optimum is obtained by using the exhaustive search method, which can achieve the upper bound of system-level QoE. As shown in Fig. 6, the system-level QoE of the two algorithms is updated at each iteration. It is noted that the GTMA converges faster than RTMA, since the GTMA only obtains a local optimum. However, RTMA can achieve the global optimum. Moreover, simulation results obviously show the superiority of RTMA to GTMA in terms of the system-level QoE at the expense of an increase in the number of computations.

We calculate the average numbers of user in different MOS under the condition of randomly generated different user

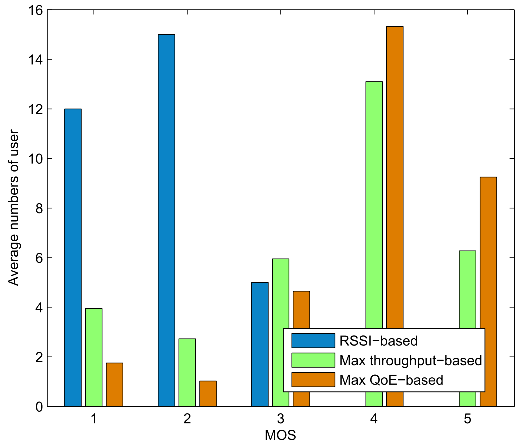

FIGURE 7. Average numbers of user in different MOS.

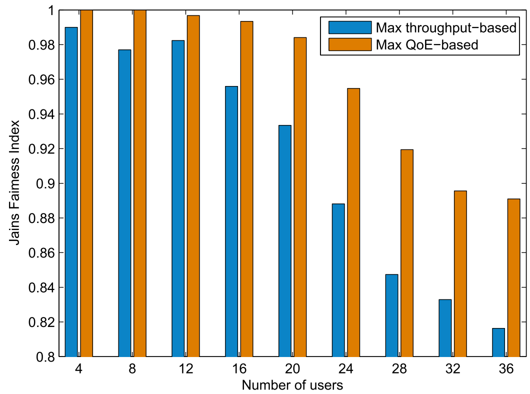

FIGURE 9. Comparison results of the JFI between QoE-based and throughput-based scheme with different network size.

locations in Fig.7. We set a network with 32 users and fix user type distributions including 12 general video calling users, 12 HD video calling users and 8 group video calling users. The Monte Carlo simulations are conducted with 500 runs. From Fig.7, we can see the number of high score users using the QoE-based scheme is more than the other two schemes. All users with RSSI-based schemes cannot get good QoE score, i.e., MOS <4.

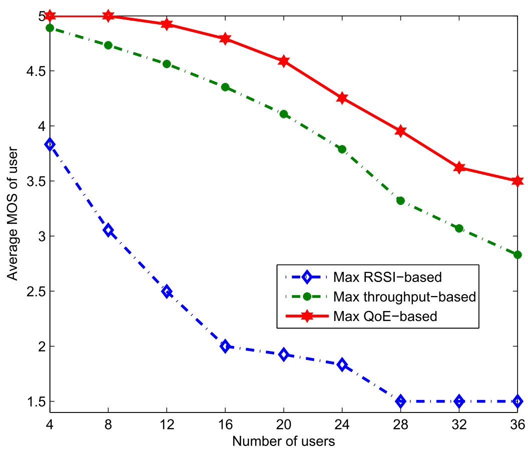

FIGURE 8. Average MOS with different network load.

Fig.8 shows the average MOS per user as the number of users increases in the network. The proportion of three user types, video calling users, general video calling users and HD video calling users, is set as 1:2:1 for networks with different scales. The average MOS of user within the proposed QoE-based scheme achieves the perfect QoE level (MOS=4) in different network scales, i.e. ($M \approx 28$). For larger networks, the average achievable MOS decreases for all the three other schemes due to the increased interaction, and the proposed QoE-based scheme yields significant performance gains for all network sizes.

In the following, we investigate the fairness of the transfer-matching game based on two scheme using Jains fairness index (JFI) [48]. JFI is an important indicator of measuring resource allocation in fairness, which is defined as follows:

$$J_{\mathrm{QOE}}(\mu) = \frac{\left(\sum\limits_{m \in M} \mathrm{MOS}(\mu)\right)^2}{M \sum\limits_{m \in M} [\mathrm{MOS}(\mu)]^2} \tag{20}$$

Fig.9 shows the fairness comparison of the JFI for the throughput-based scheme and the QoE-based scheme. It is noted that the QoE-based scheme achieves better fairness with different scales. The values of JFI within the proposed QoE-based approach achieves perfect fairness ($J \approx 1$) in small network scales, i.e. ($M < 12$). Meanwhile, the proposed approach is robust with the increase of the number of users.

VI. CONCLUSION

In this paper, the scheme of user-cell association based on user demand-centric in small cell wireless networks is proposed to maximize usersąŕ QoE. A novel transfer-matching game formulation for optimal user assignment was formulated to address the system-level QoE maximization problem, which provides us a new perspective in wireless networks resource management. To exploit the stable point of the game, two kinds of effective cooperative transfer-matching self-optimizing algorithms are designed. Moreover, the convergence performance of the two proposed algorithms is analyzed. Last but not the least, the proposed RTMA can find the optimal transfer matching solution. The simulation results indicated that the propose algorithms can effectively improve the system-level QoE and fairness comparing to other existing methods.

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