Interference coordination strategy based on Nash bargaining for small-cell networks

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\textbf{Abstract:} In this study, a distributed scheme based on the Nash bargaining model is designed to coordinate co-channel interference for small-cell networks. The authors consider a scenario that resource blocks can be reused among different small cells. Different to existing works where resource allocation is conducted at the base stations, they propose the scheme where user initiates resource bargaining request to the serving base station once its quality-of-service cannot be satisfied because of the severe co-channel interference from other users. Since the general bargaining problem is a non-linear integer optimisation, the genetic algorithm is utilised to solve it. They also develop a low-complexity bargaining model which only takes into account the strongest co-channel interference. Simulation results show that the proposed distributed scheme can effectively reduce the outage probability of users and improve the system throughput. In addition, the proposed low-complexity bargaining solution can achieve a close performance to the genetic algorithm-based solution.

\section{Introduction}

Recently, exponentially increased mobile users with diverse quality-of-service (QoS) requirement have caused tremendous data traffic growth in wireless communication systems, which will continue to increase greatly. To fulfil such demand, three alternative ways have been proposed: improving the spectral efficiency, finding more usable frequency spectrum and increasing the network density. It has been revealed that network densification can bring more performance improvement than the other two [1]. Therefore a small cell technique has been widely investigated as a promising solution for the next-generation cellular networks [2, 3].

One of the important issues in small-cell networks is the coordination of co-channel interference caused by spectrum reuse, which generally includes inter-tier interference between macro base stations (MBSs) and small cell base stations (SBSs) and intra-tier interference among SBSs. Owing to geographically randomness and unplanned deployment, the SBSs may generate great interference to its neighbour cells using the same spectrum resource, which results in the degradation of users’ QoS, especially in high dense small-cell networks.

To avoid or alleviate interference, several mechanisms have been developed in the literature. The enhanced inter-cell interference coordination has been proposed by the 3rd generation partnership project (3GPP), and some related methods have been designed in [4, 5]. In [6], a beam subset selection strategy has been proposed to reduce interference for a two-tier femtocell network. A distributed signal-to-interference-plus-noise ratio (SINR) adaptation method to alleviate inter-tier interference has been developed in [7].

Another effective method to cope with the interference issue is resource allocation or resource block (RB) allocation in long-term evolution (LTE) systems. Generally, RB allocation can be realised in both centralised and distributed ways. In centralised algorithms, the MBS has to collect all the channel state information (CSI) to design the resource allocation strategy. In [8], an energy-efficient resource allocation algorithm has been developed, taking into account the interference constraint. A graph-based interference coordination scheme has been proposed to maximise the system throughput while guaranteeing that interference is under control, as well as proportional rate fairness among SBSs [9]. In [10], a fine-scale physical RB allocation algorithm has been proposed for effective interference management.

In general, centralised algorithms require tremendous signalling overhead and complex computation, especially in high dense networks [11]. Thus, distributed resource allocation algorithms are much more applicable for small-cell networks, which also have the merits of strong robustness and good expandability. In [12], a distributed resource management framework has been proposed for SBSs to opportunistically determine its available resources to control interference. An adaptive and distributed interference coordination algorithm has been proposed, which decomposes the multi-cell resource allocation problem into distributed single-cell problems [13].

Recently, game theory has been utilised to design interference coordination strategies for small-cell networks. The Stackelberg game model has been applied to design a price-based power allocation algorithm in two-tier femtocell networks [14], and the repeated game has been used to develop the energy-efficient power control mechanism [15]. In [16], the authors have proposed a distributed non-cooperative game to realise sub-channel assignment, adaptive modulation and power control in multi-cell orthogonal frequency division multiple access (OFDMA) networks. In [17], sequential game and Nash bargaining model have been used to design a cooperation framework for mobile operators and fixed-line operators.

In most of the work mentioned above, resource allocation algorithm is performed at base stations. However, base stations usually do not know the interference and service condition of users, and tremendous signalling overhead will be required to obtain this information periodically. Therefore, in this paper, we propose the scheme where resource bargaining is initiated at the user side. Once the QoS of the user cannot be satisfied because of the severe co-channel interference from other SBSs, a resource allocation request will be sent to the serving base station to bargain for more resources or reallocating the RBs. We utilise the Nash bargaining model to design the distributed RB allocation.
scheme. Since the bargaining problem is a non-linear integer optimisation, we apply the genetic algorithm to solve it. Moreover, to further reduce the computational burden, we also develop a low-complexity bargaining model, which considers the strongest co-channel interference only. Simulation results show that the proposed resource bargaining scheme can greatly improve the system throughput and reduce the outage probability of users. In addition, the genetic algorithm can achieve almost the same performance as the exhaustive method, and the low-complexity algorithm has a close performance to the genetic algorithm.

The remainder of this paper is organised as follows. In Section 2, we describe the system model. The proposed distributed method is illustrated in Section 3. The low-complexity method is presented in Section 4 and simulation results are shown in Section 5. Finally, Section 6 concludes the whole paper.

2 System model

As shown in Fig. 1, we consider a typical small-cell network, where the MBS is located in the centre and K SBSs are randomly distributed around it according to a Poisson point distribution model. M users are randomly located in the coverage area of SBSs with a uniform distribution. We focus on the downlink case to deal with the co-channel interference among SBSs while the developed algorithms can also be used for uplink after some minor revisions.

To avoid inter-tier interference, we assume orthogonal RB allocation between MBS and SBSs, while a full RB reuse algorithms can also be used for uplink after some minor revisions.

To avoid co-channel interference, we consider RBs reused by SBSs. The co-channel interference among SBSs while the developed algorithms can also be used for uplink after some minor revisions.

To avoid inter-tier interference, we assume orthogonal RB allocation between MBS and SBSs, while a full RB reuse mechanism is adopted for SBSs, as shown in Fig. 2. In this paper, we focus on the coordination of interference among SBSs. Therefore, we only consider the RBs reused by SBSs.

We further assume that N RBs are fully reused among K SBSs. Denote \( x_{k,m,n} \in \{0,1\} \) \( (k \in \{1, ..., K\}, n \in \{1, ..., N\}, m \in \{1, ..., M\}) \) as the association indicator of users, that is, \( x_{k,m,n} = 1 \) means that user \( m \) connects to SBS \( k \) and occupies RB \( n \), and \( x_{k,m,n} = 0 \) otherwise. The transmission power set is denoted as \( P = \{p_1, p_2, ..., p_K\} \) for SBSs. The throughput in RB \( n \) of SBS \( k \) for user \( m \) can be expressed as

\[
R_{k,m,n} = B_n \cdot \log(1 + \text{SINR}_{k,m,n})
\]

where \( B_n \) is the bandwidth of RB \( n \), and \( \text{SINR}_{k,m,n} \) is the SINR of user \( m \) when it connects to SBS \( k \) and occupies RB \( n \), which can be written as

\[
\text{SINR}_{k,m,n} = \frac{p_k \cdot h_{k,m,n}}{I_{k,m,n} + N_{k,m,n}}
\]

where \( h_{k,m,n} \) and \( N_{k,m,n} \) are the channel gain and the noise power of RB \( n \), respectively, and \( I_{k,m,n} \) is the interference that user \( m \) suffers from the neighbour SBSs on channel \( n \)

\[
I_{k,m,n} = \sum_{m' \neq m \neq k} \sum_{n' \neq n} x_{k',m',n'} \cdot p_{k'} \cdot h_{k',m',n'}
\]

User association is according to standardised 3GPP LTE reference signal received power (RSRP) method [18]. Each user measures the RSRP from each SBS, which is calculated as

\[
\text{RSRP} = \text{RSP} - \text{PL} + \text{SL}
\]

where \( \text{RSP} \), \( \text{PL} \) and \( \text{SL} \) are the reference signal power, the path loss and the channel fading, respectively. Then, each user associates to the SBS with the highest RSRP. The details are not provided in this paper due to page limit.

Once a user is associated with an SBS, the SBS will allocate certain RBs for it. As mentioned before, the SBS has to cost tremendous signalling overhead to design a centralised optimal resource allocation scheme. Even if the SBS can get all the information, it will cause great computational burden. To avoid overwhelming signal overhead and computational burden, we design a two-step RB allocation algorithm. In the first step, the SBS allocates RBs according to the signal-to-noise ratio (SNR) information without considering the interference at the user side. Specifically, the SBS determines the number of RBs for each user according to the channel capacity and the data rate requirement. In the second step, we focus on interference coordination with the RB bargaining to handle the co-channel interference arisen from the first step. In the following section, we will describe in detail the proposed Nash bargaining scheme.

3 Proposed resource block bargaining method

In this section, we will propose the distributed RB bargaining method to alleviate the co-channel interference among SBSs based on the Nash bargaining model. The utility function in the bargaining plays an important role in the game design, which can also be regarded as the system objective. Since the RBs can be reused among base stations, it is of great importance to efficiently use the limited RBs while carefully coordinating intra-tier interference, especially in high dense small-cell networks. Therefore we define the average data rate per RB as the utility function in the bargaining game, as in (6) and (7).

The details of the proposed scheme can be described in the flowchart shown in Fig. 3. After users associate with the corresponding SBS, the SBS will allocate RBs to users in its coverage, according to the SNR information and the QoS of users. Once the interference from other SBSs causes great degradation so that the QoS of the user cannot be satisfied, a bargaining request is sent to its serving SBS. Assume SBS \( k \) receives \( \gamma \) bargaining requests at a certain time, it will first rank these users. Since we aim to achieve high RB utilisation, the RB utility of each user is used to calculate the rank, \( \beta_i, i \in \{1, ..., \gamma\} \). These users are temporarily waiting for RB bargaining in a queue. Then, SBS \( k \) starts the bargaining game to decide the RB reuse policy.

First, SBS \( k \) selects the user with the highest rank, \( m = \arg \max \beta_i \). Assume that the set of the RBs used by user \( m \) is \( R_{S, m} \), and the RBs in

![Fig. 1 System model for small-cell networks](image1)

![Fig. 2 RB allocation mechanism for MBS and SBS](image2)
set $\text{RS}_m$ are reused by others. The sum rate on the RBs, which are not reused, is a constant during the bargaining game and can be calculated as

$$r_m = \sum_{n \in \text{RS}_m} x_k, n, m \cdot \log \left(1 + \frac{p_k \cdot h_{k, n, m}}{\bar{N}_{k, m}}\right)$$  (5)

SBS $k$ then finds the other SBSs who partially or totally reuse the RBs of user $m$, and treats them as the bargaining targets. After that, SBS $k$ begins to collect the necessary information, including the data rate requirement of user $m$ and the channel gain from SBS $k$ to user $m$ on each RB in $\text{RS}_m$. In addition, SBS $k$ will interact with those SBSs who reuse the same RBs to know the interference information. After all these information are collected, SBS $k$ begins to solve the RB bargaining problem.

First, we define the profit of SBS $k$ on RB set $\text{RS}_m$ as (see (6)) where $x$ is the RB allocation vector containing $x_{k,n,m}$ ($n \in \{1, \ldots, N\}$). Similarly, the profit of other SBSs is (see (7)). The

$$U_{k,m}(x) = \frac{\sum_{n \in \text{RS}_m} x_{k,n,m} \cdot \log \left(1 + \left(p_k \cdot h_{k,n,m}/(\sum_{k' \neq k} \sum_{n' \neq m} x_{k',n',m} \cdot p_{k'} \cdot h_{k',n',m} + \bar{N}_{k,n,m})\right)\right)}{\sum_{n \in \text{RS}_m} x_{k,n,m}}$$  (6)
The bargaining problem on set $RS_b^m$ can be formulated as

$$\max_{x'} (U_{k,m}(x') - U_{k,m}(x)) (U_{\text{other}}(x') - U_{\text{other}}(x)) \quad (8)$$

(see equation at the bottom of the page) where $x'$ is the RB allocation vector after bargaining, $U_{k,m}(x')$ and $U_{\text{other}}(x')$ are, respectively, the profits of SBS $k$ on RB set $RS_b^m$ and those SBSs who reuse these RBs after bargaining, which can be calculated similarly to (6) and (7), and $\alpha_m$ is the data rate requirement of user $m$.

In the above, $C1$ and $C2$ guarantee that both two sides in the bargaining game can get positive benefits from the game, respectively. $C3$ guarantees the QoS of the game promotor, that is, user $m$. The problem in (8) is a non-linear integer optimisation problem, which is hard to solve in general. In this paper, we adopt the genetic algorithm to solve it [19].

A genetic algorithm is a stochastic search technique, which mimics the natural selection process to solve optimisation problems. Genetic algorithm has many excellent and attractive characteristics. For example, it is capable of global stochastic search, and can be applied to many problems; it searches from the community with potential parallelism; the evaluation of each solution is based on the adaption value, which is easy to calculate; in addition, it has good expandability and robustness.

In the genetic algorithm, each variable is coded into a sequence called chromosomes. A set of some chromosomes, which are the solutions of our bargaining problem, is firstly initialised. These chromosomes will evolve through some generations by being applied with some adaptations, including mutation and crossover.

In the mutation operator, some bits of a current chromosome will generate variation, specifically, from '0' to '1' and '1' to '0' in a binary sequence. In the crossover operator, two current chromosomes will exchange some bits, and generate a new chromosome. Then, the adaptation values of all chromosomes are calculated, which are used to guide the selection of the next generation. Fitter chromosomes with higher adaptation values will have a higher probability to be selected. After some generations, the genetic algorithm will converge to the best chromosome, which is the optimal or suboptimal solution of the optimisation problem.

After the optimal or suboptimal solution is obtained, RBs in $RS_b^m$ will be reallocated, and user $m$ will be deleted from the waiting queue by setting its rank value as 0. However, in some cases, no satisfactory solution could be found. In this situation, since the RB

Algorithm 1

```plaintext
Begin
1: User association.
2: The SBS allocates resource blocks according to SNR information.
3: Users with poor QoS propose the bargaining request.
4: Calculate $\gamma$ and the rank value.
5: count = 1;
6: while count $\leq \gamma$ then
7: Pick the highest ranked user, user $m$.
8: if QoS of user $m$ is satisfied then
9: count = count + 1.
else
10: Solve the bargaining problem (8) with genetic algorithm.
11: if find a solution then
12: count = count + 1.
13: Reallocate the resource blocks according to the solution.
14: Set the rank value of user $m$ 0.
15: else
16: if $\text{count} < \gamma$ then
17: Pick the lowest ranked user, user $j$
18: Set the rank value of user $j$ 0.
19: Disconnect user $j$ and release the resource blocks used by him, go to step 18.
else
20: count = count + 1.
21: end if
22: end if
23: end if
24: end if
25: end while
End
```

Fig. 4 Distributed RB bargaining algorithm for SBS $k$
The utilisation of user $m$ is the highest in the waiting queue, we design the following mechanism to guarantee its QoS.

SBS $k$ will first checks whether it has any unallocated RBs. If it has, it will allocate one more RB to user $m$ to restart the bargaining game. If there is no RB remained, SBS $k$ will check whether there is another user waiting in the queue. If there is, the bargaining game will go on. The worst case is that SBS $k$ has no more RBs remained, and there is no other user in the waiting queue. In this case, the bargaining game has to be terminated, and an outage event happens.

There is a special case that needs to be carefully considered in solving bargaining problem (8). If the resource bargaining problem does not have any solution due to violation of constraints C1 or C2, which means that the bargaining result cannot benefit both sides simultaneously. Then, SBS $k$ will allocate one more RB to user $m$, and the bargaining game goes on. If the newly allocated RB is not reused by any other SBS, it will not be added to $R_{S_b}$. In this case, the bargaining problem is the same as before, and still no satisfactory solution can be found. If this process repeats continually, the RB bargaining problem will be keeping unsolved while redundant RBs will be allocated to user $m$ even its QoS is satisfied. Therefore we must terminate the bargaining game for user $m$ if constraint C2 is satisfied after user $m$ is allocated one more RB, and starts the bargaining game for the next user waiting in the queue. The implementation process of the proposed scheme for SBS $k$ is summarised in Algorithm 1 (see Fig. 4).

4 Low-complexity resource block bargaining method

In high dense small-cell networks, RB will be frequently reused, which makes the interference scenario very complex. Thus, it is impractical to analyse the interference cancellation problem. We assume the number of the RBs in the set $R_{S_b}$ is $H$, and the length of chromosomes in the genetic algorithm equals to the amount of the reused RBs, $S$, which is clearly more than twice of $H$. The number of SBSs participating in the original bargaining game is $T$. Since the genetic algorithm only needs a very small set of initial chromosomes, we randomly generate some sequences and select those sequences which satisfy the constraints as the initial chromosomes of the bargaining game. The number of random sequences cannot be set too large to avoid high complexity, but should be enough to find the initial chromosomes. In our method, $T < S$ steps are used for the utilisation step. Moreover, the computational complexity of crossover, mutation, adapting and selection has the same order as the number of chromosomes.

Therefore, in the first generation, the computational complexity is $O(T \cdot S)$, and in the following generations the complexity is $O(S^2)$. With both the number of users and SBSs increase, $T$ and $S$ may become very large. In addition, the number of initial chromosomes increases correspondingly. In this case, the computational complexity of solving the bargaining method becomes extremely high.

Therefore, in this section, a low-complexity RB bargaining method is presented to save computation for high dense small-cell networks. The main idea of the low-complexity method is that we aim at only eliminating the strongest interference. This is reasonable since generally the highest interference is dominating.

As shown in Fig. 5, a virtual SBS is introduced as the game participant together with SBS $k$, which is defined as the SBS with the strongest interference to user $m$ on each RB. On RB $n$ in $R_{S_b}$, the SBS with the strongest interference is

$$k' = \arg \max_{k \neq k} I_{k', n}$$

In this way, the RB bargaining algorithm will be executed only between SBS $k$ and the virtual SBS. Furthermore, assuming that user $m'$ is associated with SBS $k'$ which uses RB $n$, then the SINR of user $m$ on RB $n$ in SBS $k$ can be expressed as

$$\text{SINR}_{k, m} = \frac{p_k \cdot h_{k, m}}{\sum_{j \neq k} p_j \cdot h_{j, m} + N_{k, m}}$$

where the interference does not include the one from SBS $k'$ since after bargaining, RBs are orthogonally divided between SBS $k$ and the virtual SBS. Similarly, the SINR on RB $n$ of the virtual SBS can be calculated as

$$\text{SINR}_{k, n} = \frac{p_k \cdot h_{k, n}}{\sum_{j \neq k} p_j \cdot h_{j, n} + N_{k, n}}$$

Denote $y_n \in \{0, 1\}$ as an indicator, where $y_n = 1$ means RB $n$ is used by SBS $k$, otherwise it is used by the virtual SBS. Now, the profit of SBS $k$ can be calculated as

$$U'_y(y) = \sum_{n \in R_{S_b}} y_n \cdot \log (1 + \text{SINR}_{k, n})$$

where $y$ is a vector consisting of $y_n$, and the profit of the virtual SBS is

$$U'_y(y) = \sum_{n \in R_{S_b}} (1 - y_n) \cdot \log (1 + \text{SINR}_{k, n})$$

Then, the RB bargaining problem in this model can be formulated as

$$\max_{y'} U'_y(y') - U'_y(y')$$

subject to

$$\begin{align*}
C1: U'_y(y') \geq U'_y(y) \\
C2: U'_y(y') \geq U'_y(y) \\
C3: \gamma'_n + \sum_{n \in R_{S_b}} y'_n \cdot \log (1 + \text{SINR}_{k, n}) \geq \alpha_n \\
C4: y'_n \in \{0, 1\}, \forall n \in R_{S_b}
\end{align*}$$

where $y'$ is a vector containing the newly obtained $y'_n$.

It is obvious that this resource bargaining problem is an integer optimisation problem with a relatively small scale. Therefore it can be efficiently solved by the branch-and-bound method [20], in which a rooted tree with the full set is formed first, and the algorithm searches the best solution by exploring and discarding those branches. The implementation process is the same as the original RB.
bargaining algorithm shown in Fig. 4 except that step 11 is replaced by solving the bargaining problem (14) with the branch-and-bound method, instead of solving problem (8) using the genetic algorithm. In the following, we will compare the computational complexity of the algorithms developed in Sections 3 and 4. The low-complexity algorithm is based on the branch-and-bound method, whose computational complexity will be no more than $O(2^H)$, as analysed before, the genetic algorithm has a complexity of $O(T \cdot S^2)$ in the first generation. Note that $H$ is the number of RBs in $RS_m$, and $S$ is the total number that these RBs being reused. Since each RB is reused at least once, we can obviously get $S \geq 2H$. $T$ is the number of base stations that participate in the bargaining game. For one RB in $RS_m$, it is reused by at least two base stations. Therefore $T \geq 2$. Therefore we have $T \cdot S^2 \geq 8H^2 \geq 2^H$ when $H$ is no more than 9. In practical systems, each user will only occupy a few number of RBs, which means $H$ is generally a small value. In addition, the total complexity in the following generations of genetic algorithm is generally much larger than the complexity in the first generation. Hence, we can conclude that the algorithm proposed in this section has a lower computational complexity than the genetic algorithm. Moreover, as the density of SBSs increases, $S$ will become even larger while $H$ still keeps the same. In this case, the computational complexity can be further reduced by the low-complexity algorithm.

We now analyse the signalling overhead of the proposed algorithms. In the centralised method, the signalling overhead mainly comes from the information collection, such as the service demand, CSI and interference. Assume that $X$ bits are required to represent the service demand for a user and $Y$ bits are required to represent the RSRP information on each RB from one SBS. Then, for one user, the signalling overhead is $O(X + K \cdot N \cdot Y)$ in the centralised method and the total overhead is $O(X + K \cdot N \cdot Y) \cdot M$. However, in the distributed method, only those users who reuse the RB of the bargaining proposer needs to transmit their information to the SBS. Assuming that the number of users reusing the same RB in $RS_m$ is $M'$ and $Z$ bits are required to represent the interference level, then the total signalling overhead is $O((Y + Z) \cdot M')$ in the distributed algorithm. Typically, $Z$ can be set equal to $Y$ and $M'$ is much smaller than $M$. Therefore, the signalling overhead can be significantly reduced in the distributed method.

5 Simulation results

In the simulations, we assume a small-cell network with four SBSs randomly distributed. As the RBs are orthogonally used between MBS and SBSs, inter-tier interference between MBS and SBSs is not considered. User association is according to standardised 3GPP LTE RSRP method [18]. Once the association is established, the serving SBS will allocate RBs according to the SNR information. The outage of users occurs in two cases: the association fails due to not enough RBs or the QoS cannot be satisfied after RB bargaining. Twenty RBs are reused among SBSs, and the bandwidth of each RB is 5 MHz. The service demand of the user obeys uniform distribution, with the intervals $[5, 30]$ Mbps. Table 1 summarises all the parameters used in the simulation.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Settings</th>
</tr>
</thead>
<tbody>
<tr>
<td>radius</td>
<td>2 km</td>
</tr>
<tr>
<td>band width of each RB</td>
<td>5 MHz</td>
</tr>
<tr>
<td>path loss</td>
<td>$128 + 4 \cdot \log(d[\text{km}])$</td>
</tr>
<tr>
<td>shadowing std</td>
<td>4 dB</td>
</tr>
<tr>
<td>number of RBs</td>
<td>20</td>
</tr>
<tr>
<td>length of frame</td>
<td>10 ms</td>
</tr>
<tr>
<td>signal power of SBS</td>
<td>21 dBm</td>
</tr>
<tr>
<td>background noise</td>
<td>$-174 \text{ dBm}$</td>
</tr>
</tbody>
</table>

Table 1 Simulation parameter setting

$\alpha_m$ [5, 30] Mbps, with uniform distribution

represent the interference level, then the total signalling overhead is $O((Y + Z) \cdot M')$ in the distributed algorithm. Typically, $Z$ can be set equal to $Y$ and $M'$ is much smaller than $M$. Therefore, the signalling overhead can be significantly reduced in the distributed method.

4 algorithms are compared:

- No bargaining: SBSs allocate RBs according to the SNR information independently.
- Algorithm 1: the Nash bargaining algorithm proposed in Section 3, based on the genetic algorithm.
- Algorithm 2
- Exhaustive algorithm

Fig. 6 System performance with the different number of users

a) System throughput
b) Average throughput per user

Fig. 7 Outage probability of users

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**Algorithm 2:** the low-complexity algorithm proposed in Section 4.

**Exhaustive method:** the algorithm to solve (8) using the exhaustive method.

**The algorithm in [21]:** RBs are first allocated to different SBSs using the Tabu search algorithm and then each SBS determines its resource allocation to maximise the number of users whose QoS is satisfied.

Fig. 6a shows the overall system throughput of all SBSs with the different number of users. From the figure, the system throughput will increase slightly with the number of users without bargaining. With the proposed algorithms (Algorithm 1 and Algorithm 2), the system throughput will be greatly improved. It is also observed that the scheme based on the genetic algorithm achieves almost the same performance as the optimal scheme with exhaustive searching. However, the computational complexity can be dramatically decreased. Moreover, Algorithm 2 has a close performance as Algorithm 1, which demonstrates that it is reasonable to consider the strongest interference only. From the figure, we can see that the proposed Algorithm 1 always performs better than the algorithm in [21]. When the number of users is small, the proposed low-complexity algorithm (Algorithm 2) can efficiently deal with the interference since in this case interference is not strong. Therefore it achieves a better performance than the algorithm in [21]. However, as the number of users goes large, interference cannot be effectively cancelled by the low-complexity algorithm since it only considers the user with the strongest interference. Therefore, in this case, the algorithm in [21] has a better performance.

The average throughput per user with the different number of users is plotted in Fig. 6b. It is obvious that the average throughput decreases with the number of users because of the co-channel interference. However, with the proposed Nash bargaining scheme, the decreasing rate is much more slight than the algorithm without bargaining.

Fig. 7 shows the outage probability of users. We see that outage probability increases with the number of users. The outage probability will be very high without bargaining, however, it can be controlled within a small region for the proposed bargaining schemes.

In Fig. 8, we change the signal power of SBS 1 during the bargaining game to investigate the impact of signal power. As the signal power of SBS 1 increases, the data rate on each RB increases simultaneously in SBS 1. Therefore the profit (defined as the average data rate on each RB) of SBS 1 increases with the signal power while the profit of other SBSs decreases slightly due to stronger interference from SBS 1.

In Fig. 9, the outage probability under different signal power is investigated. Since the RB utilisation of SBS 1 improves with its signal power increases, more RBs will be allocated to users in SBS 1 in the bargaining game. Thus, the QoS of users in SBS 1 are more likely guaranteed, which leads to the decreasing of the outage probability.
outage probability. On the contrary, the outage probability in other SBSs will increase slightly.

6 Conclusions

In this paper, we have proposed a distributed scheme based on the Nash bargaining model for interference coordination by changing the RB reuse policy among SBSs in small cell networks. We aim to alleviate the co-channel interference to improve the QoS of users and achieve high RB utilisation. The genetic algorithm has been utilised to solve the integer optimisation problem. Furthermore, a low-complexity RB bargaining method is proposed, in which the strongest interference on each RB is taken into account only. Numerical simulation results have validated the performance of both methods, which show that the performance gap between the low-complexity method and the genetic algorithm based one is very close. We have focused on the throughput improvement in this paper. As a future work, we will consider the fairness among users in the RB bargaining algorithm.

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8 References