Energy Efficient Resource Allocation for 5G Heterogeneous Networks using Genetic Algorithm

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ABSTRACT The energy efficient resource allocation scheme based on genetic algorithm (GA) for the downlink orthogonal frequency division multiple access (OFDMA) heterogeneous networks (HetNets) is developed in this paper. To maximize the spectrum efficiency for the fifth generation (5G) mobile networks, frequency reuse-1 is employed. Thus, advanced inter-cell interference coordination techniques are required to mitigate the inter-cell interference for 5G HetNets. In this paper, the energy efficient optimization problem based on coordinated scheduling is formulated, which is a mixed-integer nonlinear fractional programming problem and is intractable to solve directly. To tackle this, a two-step GA based scheme is proposed to solve the optimization problem. In the first step, the resource blocks matrix is solved by normal GA in the spectral efficiency aspect with fixed power distribution matrix, and then the power distribution matrix is obtained in the second step by non-dominated sorting genetic algorithm II (NSGA-II) with obtained resource blocks allocation matrix. Finally, the system level numerical evaluation process is provided to illustrate the effectiveness of the developed scheme.

INDEX TERMS Energy efficiency, resource allocation, heterogeneous networks, genetic algorithm.

I. INTRODUCTION

In the rapidly evolving field of communication accompanied with continuous advancements of science and technology, there is a consensus that the number of devices connected to the wireless communication system as well as the communication traffic of entire wireless system will continue to increase exponentially. To meet traffic demand and support trillions of devices, the next generation wireless networks are calling for quantum jump in energy and spectral efficiency of wireless systems. As wireless communication systems have been developed from the first generation (1G) to fourth generation (4G), the main objective was to increase the spectral efficiency (SE) based on the Shannon formula to make sure the reliable delivery and the quality of services (QoS) [1]. For the fifth generation (5G) systems, the connection equipment, and the transmission rate are expected to be 10-100 times higher [2]. It is also envisaged that the energy consumption of 5G systems could be extremely high. Nowadays, most power is produced by consuming fossil fuels and a lot of greenhouse gas is emitted. Due to the environmental concern, reducing the consumed power while maintaining the same QoS is worth to investigate. Therefore, instead of SE, one important performance aspect of 5G is the energy efficiency (EE) for 5G design as reported by international telecommunications union (ITU).

The earliest research results show that EE maximization and SE maximization conflict with each other, that is to say, if one of them is maximized, the other will be compromised [3]. For instance, in order to maximize the SE, the water filling method was proposed, and the EE was reduced when such method is adopted [4]. Hence, many green communication schemes were proposed to alleviate the compromise between SE and EE such as [5], [6], and resource allocation in EE perspective has become the main objective.

To cope with the requirements of high transmission rate and QoS for 5G systems, several potential technologies have been emerged, such as massive multiple inputs multiple outputs (mMIMO) [7], millimeter wave (mmWave) [8], and heterogeneous networks (HetNets) [9], [10]. HetNets, which is constructed by deploying small cells (e.g., picocell or femtocell) base stations (SBSs) inside the conventional microcell, is recently emerged as the most promising technique to satisfy the requirements like network capacity and QoS [11]–[13] for 5G. In HetNets structure, the microcell cov-
erage is overlapped by several SBSs services range, which is possible to achieve high SE performance. However, with huge number of SBSs deployed to construct the HetNets, more circuit power needs to consume to meet the operation of BSs equipment. Therefore, it is essential to investigate efficient and intelligent resource allocation schemes in order to improve the EE of 5G systems.

Resource allocation optimization schemes have been investigated for many years to improve the SE and EE of the wireless cellular systems. In [14], the resource allocation scheme was investigated for two-tier HetNets to improve the SE with both microcell base station (MBS) and SBSs sharing the same spectrum resource. A subchannel and power allocation model with QoS and interference constraints was constructed and then an iterative method was proposed. The authors in [15] studied the sum capacity maximization problem of two-tier HetNets with joint cell association and wireless backhaul allocation. The mixed-inter nonlinear optimization problem was modeled with backhaul constraint involving and a two-level hierarchical decomposition scheme was proposed. The energy efficiency resource management scheme was investigated for multi-cell orthogonal frequency division multiple access (OFDMA) based network in [16]. Then a centralized method to achieve the global optimal EE solution and a distributed method to maximize the EE for each BSs were proposed. The work in [17], studied the power distribution problem, and the wireless backhaul bandwidth allocation problem from the EE maximization perspective. By decomposing the original non-convex nonlinear programming problem into two convex sub-problems, an iterative resource allocation method, and a suboptimal low-complexity algorithm were developed.

The EE, as defined in [18] is the quotient of the sum throughput divided by the total power consumption required and expressed as bits/watt. Therefore, the optimization problem of EE is fractional programming (FP) problem which is non-convex and impossible to solve directly. In [19], the authors investigated the EE optimization problem for the downlink multi-cell mMIMO networks. In order to address the non-convex FP problem, Dinkelbach method was adopted to transform the original FP objective into several sub-problems which are convex. Then a centralized iterative water filling method was proposed to solve these convex sub-problems. In [20], the EE optimization problem was first transformed into multi-objective optimization problem (MOOP), and then the MOOP was solved by using $\epsilon$-constraint method. For multiple objective functions, one objective function is selected as the main objective function, and all other objective functions are used as constraint conditions. The authors in [21] investigated the EE of downlink non-orthogonal multiple access (NOMA) enabled HetNets with maximum transmit power and minimum rate constraints. The non-convex FP problem was initially transformed into two sub-problems and then an iterative method and a closed-form method were proposed to solve power distribution and bandwidth allocation, respectively. The EE maximization problem for downlink multi-cell NOMA networks was investigated in [22]. The formulated maximization problem is mixed-integer non-convex and NP-hard. In order to tackle this, it is firstly decomposed into two sub-problems, and then binary whale optimization algorithm (BWOA) and successive pseudo-convex approximation (SPCA) were proposed to solve the two sub-problems, respectively.

From the above discussion, for the mixed-integer nonlinear SE maximization problems, schemes like iterative or decomposition were applied to solve it. In general, for the non-convex FP of EE maximization problem, the original problem was transformed into several sub-problems or subtractive forms and then different schemes were developed. The commonly proposed schemes that rely on transforming the original problem into convex form and then solving it result in high computational complexity. Some low complexity schemes have also been proposed by many research articles. However, both the EE and SE performances are obviously compromised. The bio-inspired optimization methods have been developed to solve complex problems for reality fields for decades. The genetic algorithm (GA) which is developed from the theory of natural evolution proposed by Charles Darwin is shown to converge to the optimal or near-optimal solution for very hard optimizations problems [23].

In this paper, the EE maximization problem for the downlink OFDMA HetNets is formulated. It is an FP and mixed-integer nonlinear programming that cannot be solved directly. Therefore, deviating from existing methods, a GA based resource allocation method is proposed in this paper that is comprised of two steps: i) RBs allocation with fixed power distribution; ii) power distribution with obtained RBs allocation. The main contributions can be summarized as follows.

1) In contrast to existing methods, we propose a two-step GA based resource allocation scheme to solve the EE maximization problem. The RBs allocation matrix is first solved with normal GA depending only on the channel gain matrix by fixing the power distribution matrix. Then, a MOOP is formed, and NSGA-II is used to solve the power distribution matrix with obtained RBs allocation matrix.

2) One common perception of GA is that the optimization result has high correlation with the setting of population, iteration, crossover rate and variation rate and the computational complexity of GA has functional relationship with the number of population and iterations. In order to obtain better performance and reduce computation time simultaneously, the relationship between the number of variables and the setting of population, iterations, crossover rate and variation rate is investigated. Moreover, we find the relation between the size of the wireless communication system and the values of population and iterations.

3) The system level simulation is performed to verify the effectiveness of proposed GA based resource allocation scheme. The energy efficiency and sum throughput performance from EE and SE perspectives, respec-
TABLE 1. Notations

| Symbol | Description |
|--------|-------------|
| S, U, V | Number of BSs, UEs, and RBs |
| g_{s,u,v} | Path gain on channel v between BS s and user u |
| p_{s,u,v} | Power assigned from BS s to user u over channel v |
| \alpha_{s,u,v} | Binary value to indicate channel v send by BS s to user u or not |
| G, A, P | Channel gain, RBs indication, and power distribution matrices |
| N_0 | Power spectral density of AWGN |
| R_{u,R} | Throughput of user u, and total throughput |
| P_t, P_c, P_s, P_t | Transmit, circuit, static, and total power |
| \varepsilon | Coefficient of power consumed per unit throughput |
| \sigma | Drain efficiency of power amplifier |
| P_{th} | Total power consumed by \( s \)th BS |
| R_{th}^u | Threshold rate of user u |
| V_{Total} | Total number of RBs |
| N, L, I | Population size, length of chromosome, and iteration steps of GA |
| T, Q | Number of objectives, number of variables of MOOP |

...tively, are illustrated for different scenarios.

The remainder of this paper is maintained section-wise as follows: the system model together with the EE maximization problem of the downlink OFDMA HetNets is formulated in Section II. In Section III, two-step GA based resource allocation scheme for the formulated optimization problem is developed. In Section IV, the setting of parameters for GA based scheme is investigated. Numerical evaluation for the proposed GA based scheme is presented in Section V, and finally, the conclusions and future research directions are given in Section VI. The notations used in the paper are described in Table 1.

II. SYSTEM MODEL AND PROBLEM FORMULATION

In this section, we consider an OFDMA based two-tier HetNets which is depicted in Fig. 1. As can be seen from Fig. 1, the HetNets has one MBS and the microcell range is overlapped by s SBSs, and u user equipments (UEs) are distributed randomly inside the microcell range. We do not artificially designate the UEs that belong to microcell or small cell users. Both MBS and SBS share the same bandwidth or spectrum resource and the spectrum is separated into V sub-channels where \( v \in \{1, 2, \ldots, V\} \) is used to represent the set of resource blocks (RBs). The sets of users and base stations are indicated as \( u \in \{1, 2, \ldots, U\} \) and \( s \in \{0, 1, 2, \ldots, S\} \), respectively, where \( s = 0 \) denotes the MBS and \( 1 \leq s \leq S \) denotes the \( s \)th SBS. Let \( g_{s,u,v} \) denotes the path gains on sub-channel v between BS s and user u, and \( p_{s,u,v} \) denotes the power that is assigned from BS s to user u over sub-channel v.

Let \( G = [g_{s,u,v}]_{(S+1) \times U \times V}, A = [a_{s,u,v}]_{(S+1) \times U \times V}, \) and \( P = [p_{s,u,v}]_{(S+1) \times U \times V} \) be the channel gain matrix, RBs indication matrix, and power distribution matrix, respectively. We identify the user u as the microcell user or the small cell user according to the matrix G. For a particular user u, we compare the channel gain between the user u and all the BSs over all sub-channels v and identify the BS which has the best channel gain as the serving BS and all other BSs as the interference BSs. Thus, the received signal to interference plus noise ratio (SINR) of user u over channel v based on coordinated scheduling can be obtained as

\[
\gamma_{uv} = \frac{a_{i,u,v}p_{i,u,v}g_{i,u,v}|i \in S}{\sum_{j \neq i} a_{j,u,v}p_{j,u,v}g_{j,u,v}|j \in S + N_0 B},
\]

where \( B \) is the bandwidth of each RB, \( a_{s,u,v} \) takes on binary value 1 if \( \forall s \in S, \forall u \in U, \forall v \in V \), which means that the BS s sends the RB v to the user u, and 0 otherwise. The symbol \( N_0 \) represents the power spectral density of additive white Gaussian noise (AWGN). Thus, the throughput of user u can be obtained as

\[
R_u = B \sum_{v=1}^{V} \log_2 (1 + \gamma_{uv}),
\]

where the summation is due to multiple resource blocks assigned to the single user to meet its data requirements. Therefore, the total throughput for all the users of the system is given by

\[
R = \sum_{u=1}^{U} R_u.
\]

As stated in [1], the total power consumed can be separated into two parts, the transmit power and the system’s circuit power. The transmit power, which is represented by \( P_t \), can be obtained as follows:

\[
P_t = \sum_{s=0}^{S} \sum_{u=1}^{U} \sum_{v=1}^{V} a_{s,u,v}p_{s,u,v}.
\]

The circuit power, which is represented by \( P_c \), can be further classified into two parts: the static part \( P_s \), to satisfy the basic operation of the hardware and the throughput related dynamic part, which is related to the total throughput, namely

\[
P_c = P_s + \varepsilon R,
\]
where $\varepsilon$ represents the coefficient to denote the power consumed per unit throughput. Therefore, the total consumed power $P$ can be written as

$$P = \sigma P_t + P_a + \varepsilon R,$$

(6)

where $\sigma$ represents the drain efficiency of the power amplifier. Based on equations (3) and (6), the EE is given by

$$EE = \frac{R}{P} = \frac{R}{\sigma P_t + P_a}.$$

(7)

Accordingly, optimization problem, to maximize the EE in (7), can be formulated as follows:

$$\text{maximize} \quad EE,$$

subject to:

C1: $\sum_{u=1}^{U} a_{s,u,v} \leq 1, \forall s \in S, \forall u \in V$

C2: $\sum_{u=1}^{U} \sum_{v=1}^{V} a_{s,u,v} p_{s,u,v} \leq P_s^{max}, \forall s \in S$

C3: $R_u \geq R^{th} u, \forall u \in U$

C4: $p_{s,u,v} \geq 0, \forall s \in S, \forall u \in U, \forall v \in V$

C5: $a_{s,u,v} \in \{0,1\}, \forall s \in S, \forall u \in U, \forall v \in V$

Here C1 is the orthogonality constraint to ensure that one RB can only be assigned to at most one user by the same BS. C2 is total power constraint where $P_s^{max}$ represents the total power that can be consumed by the BS $s$. C3 is QoS constraint of the user $u$ where $R^{th} u$ is the threshold rate to ensure the QoS requirement and C4 ensures that the power assigned on each sub-channel cannot be non-negative.

Obviously, the objective in (8) is in FP form, which is non-convex and mixed integer since the binary variables $a_{s,u,v}$ and real variables $p_{s,u,v}$ are involved in the optimization problem. Therefore, the direct solution is not feasible. The GA is population-based search optimization method where the evolution procedures include selection, crossover, and mutation. The objective function value can be used directly as the search information, and the fitness function value as a measure the goodness of the individual. Many operators for each evolution process have also been developed and GA has shown immense success for hard optimization problems [23]. For this reason, we pursue GA based resource allocation method to solve the optimization problem (8).

III. GA BASED RESOURCE ALLOCATION

Clearly, the optimization problem in (8) has to be solved for two matrices i.e., $A$ and $P$. For the sake of simplicity, we first tackle RBs allocation $A$ by fixing the matrix $P$, and then solve the power distribution matrix $P$ with the known matrix $A$. In such case, the solution of (8) can be regarded as the suboptimal solution. In this section, we are going to solve the RBs allocation and power distribution separately using the GA based method.

A. GA BASED RBs ALLOCATION

In this subsection, we first determine the RBs allocation matrix $A$. Assume that the power is uniformly distributed to each RB by both MBS and SBS, i.e., the elements of the fixed power distribution matrix $P$ can be written as

$$p_{s,u,v} = \frac{P_{max}}{V_{total}}, \forall s \in S, \forall u \in U, \forall v \in V,$$

where $V_{total}$ is the total number of RBs. With fixed matrix $P$, we can solve the RBs allocation matrix $A$ according to channel gain matrix $G$ in spectral efficiency aspect, i.e., maximization the capacity of the system. Thus, the optimization problems to obtain the RBs allocation matrix can be written as

$$\text{maximize} \quad R,$$

with the constraints C1, C5 and

C6: $\sum_{s=0}^{S} \sum_{v=1}^{V} a_{s,u,v} \geq 1, \forall s \in S, \forall u \in V$

where constraint C6 ensures that at least one RB is sent by any BS to any user to fulfill the QoS constraint. Note that the optimization problem (9) involves two inequality constraints. In order to solve the optimization problem with inequality constraint by using GA method, an efficient method was proposed in [24]. Specifically, we consider the optimization problem of the form,

$$\text{maximize} \quad f(x),$$

(10)

subject to $M$ constraints as:

$$g_m(x) \geq 0, m = 1, 2, \ldots, M,$$

where $x = [x_1, \ldots, x_k, \ldots, x_q]$ and $x^l_k \leq x_k \leq x^u_k$, $x^l_k$ and $x^u_k$ are the lower and upper bound of $k^{th}$ element of $x$. The fitness can be calculated as [24],

$$F(x) = \begin{cases} f(x) & \text{if } g_m(x) \geq 0, \\ f_{min} - \sum_{m=1}^{M} g_m(x) & \text{otherwise}, \end{cases}$$

(11)

where $f_{min}$ is the value of an objective function with the population which has the worst feasible solution, operator $\{ \}$ represents the absolute value of $g_m(x)$, and returns zero if $g_m(x)$ is negative. It means if one population satisfies all the constraints of problem (10), the fitness of this population is the objective function value, otherwise, the fitness calculates as the subtraction of the worst feasible solution by the summation of the absolute value of violation. Based on this, the procedure of using GA method to solve the optimization problem (9) is described in Algorithm 1.

Since $a_{s,u,v}$ of the RBs allocation matrix $A$ is a binary value and the size of $A$ is $(S + 1) \times U \times V$, we can reformulate the matrix $A$ into a binary string of length $(S + 1)UV$. Therefore, the length of the chromosome in line 1 of Algorithm 1 can be set to $(S + 1)UV$ and the values of population size, iteration steps, crossover rate, selection rate, and variation rate are also given as well. In line 2, the initial
population is generated with given number of population and length of chromosome. Thus the initial population set has \( N \) individuals and each individual is a \((S+1)UV\) length binary string. Next, the evolution process is started. First the fitness of each population is calculated in line 5 according to the method shown in (11). The selection process is performed in line 5 with obtained fitness values and selection rate, and Rank method is adopted for the selection mode, i.e., the population having better fitness can be selected as parent population. Then, the crossover and mutation process of the selected parent population are shown in line 6 with crossover and mutation rates given in line 1 to get children population. The parent population together with obtained children population are used to form the new generation population for the next evolution step. Finally, the optimal matrix \( A \) is obtained after all iteration steps are over.

**B. GA BASED POWER DISTRIBUTION**

After the RBs allocation matrix \( A \) is solved, we are going to solve the power distribution problem to get power distribution matrix \( P \). It is clear that the FP problems (8) can be rewritten as the equivalent MOOP form given by

\[
\text{minimize} \quad \left\{ \begin{array}{l}
\text{Function 1:} \quad -R, \\
\text{Function 2:} \quad \sigma P_t + P_e,
\end{array} \right. \tag{12}
\]

subject to the constraints C2 and C4. For MOOP, a set of solutions (Pareto optimal solutions) can be obtained. Many multi-objective evolutionary algorithms have been developed [25] and in [26] the NSGA-II was proposed. Moreover, to solve the constrained MOOP, a binary tournament selection method was introduced. The steps needed to solve the optimization problem (12) based on NSGA-II method are detailed in Algorithm 2.

With given RBs allocation matrix \( A \), only \((S+1)\times U \times V\) dimensional power distribution matrix \( P \) need to be solved. The number of objectives \( T \) is set to 2 and the number of variables is set to \((S+1)UV\) in line 1. The number of population \( N \) and iteration \( I \) are using the same values as in Algorithm 1. Both the lower bound matrix \( LB \) and the upper bound matrix \( UB \) of size \((S+1)\times U \times V\) are used to produce the initial population. The elements of matrix \( LB \) are set to 0 while the elements of matrix \( UB \) are set to

\[
\frac{P_{\text{max}}}{V_{\text{total}}}, \forall s \in S, \forall u \in U, \forall v \in V.
\]

The initial population is generated according to \( N, LB, \) and \( UB \). Thus each individual is \((S+1)\times U \times V\) size matrix and the elements are generated randomly with \( LB \) and \( UB \) as the bounds. The values of two objectives in problem (12) and the error vector violating constraints C2 and C4 are calculated for each population in line 3. The normalization of the error vector is considered in line 4. A new population is constructed by comprising the initial population together with its corresponding objective value and the normalization error in line 5 for the following evolution process. The non-dominated sorting and crowding distance assignment procedure are performed in lines 6 and 14. Next, the evolution process is started. The binary tournament selection method is adopted for parent population selection in line 8 and
the children population is generated from selected parent population through crossover and mutation process in line 9. The values of two objectives and the error vector for children population are calculated in line 10. Next generation population is formed according to the non-dominated sorting and crowding distance in lines 13 to 15. Finally, the optimal matrix $P$ is obtained after all iteration steps are completed.

IV. PARAMETERS SETTING AND COMPLEXITY
We know that the optimization results of GA algorithm have high correlation with the parameters such as the setting of population, iteration, crossover rate and variation rate. In this section, we are going to present the trend between the optimization results and the values of population, iteration, crossover rate and variation rate. Moreover we find the relation between the size of wireless communication system and the values of population and iteration. Two different systems’ sizes are used to display the results: the HetNets with one MBS, one SBS, two users, and 6 or 8 RBs, i.e., $S = 1, U = 2, V = 6$ or 8. The simulation parameters are shown in Table 2.

A. THE SETTING OF POPULATION
In this part, we perform the numerical evaluation of energy efficiency and sum throughput from EE and SE perspective, respectively, against the number of populations that increases from 10 to 300. In order to observe the relationship between energy efficiency and sum throughput results against different population size we set the number of iterations to 50, the crossover rate of 0.7, and the variation rate of 0.001.

Fig. 2 shows the energy efficiency and sum throughput results with changing population size. The terms “EE: 226” and “SE: 226” represent the results with EE perspective and SE perspective, respectively, with system size $S = 1, U = 2, V = 6$ and so on for other terms. From Fig. 2, the energy efficiency and sum throughput results for the two systems are increasing with the population size increases and reach the optimal values at the end. However, for the system with higher size, a greater population size is needed to reach optimal solutions as evident from comparison between the curves of $S = 1, U = 2, V = 6$ and $S = 1, U = 2, V = 8$ size systems. Thus, to obtain better energy efficiency and sum throughput, a greater number of population is needed for the evolution process, however, the runtime is also increased.

B. THE SETTING OF ITERATION
To observe the relationship between energy efficiency and sum throughput with the number of iterations increasing from 10 to 70, we set the number of population to 200, the crossover rate to 0.7, and the variation rate to 0.001.

The energy efficiency and sum throughput results with changing number of iterations are shown in Fig. 3. As we can see from Fig. 3, the energy efficiency and sum throughput for two systems increase with the number of iterations and reach the optimal values around 30 iterations. However, for the system with higher size, a greater number of iterations is needed to reach the optimal solution. Thus, in order to obtain better energy efficiency and sum throughput, more iterations are needed for the evolution process, however,
C. THE SETTING OF CROSSOVER RATE

In this part, we perform numerical evaluation of energy efficiency and sum throughput under EE and SE perspective, respectively, against the value of crossover rate that increases from 0.1 to 0.9. In order to observe the relationship between energy efficiency and sum throughput against different values of crossover rate, we set the number of populations to 100, the number of iterations to 30, and the variation rate to 0.001.

Fig. 4 shows the energy efficiency and the sum throughput results with changing value of crossover rate, and we can see that the both are increasing with the value of crossover rate from 0.1 to 0.9. As the size of system increases, the values of energy efficiency and sum throughput are further increased, this is because with higher value of crossover rate, there is greater possibility for the parent population to do crossover, which results in increasing the number of population from another perspective. So, it’s better to set the value of crossover rate high.

D. THE SETTING OF VARIATION RATE

We numerically evaluate the energy efficiency and the sum throughput from EE and SE perspective against different values of variation rate, such as 0.00001, 0.0001, 0.001, 0.01, and 0.1, respectively. For the sake of simplify, we take the Log values of the variation rate, i.e., \( \log_{10}(\text{variation rate}) \) on the horizontal axis. For other parameters, we set the number of populations to 100, the number of iterations to 30, and the crossover rate to 0.9. From Fig. 5, we can observe that the trend of energy efficiency and sum throughput is not changing under both EE and SE perspective against considered range of the variation rate.

E. COMPLEXITY AND TIME CONSUMED

The total time consumed by the proposed algorithms against different parameters are shown in Fig. 6. The top figure shows the time consumed against different number of populations and we observe a liner relationship between the time consumed and the number of populations. In other words, the computational complexity of GA is linear with the population size. The figure at bottom shows the time consumed against different number of iterations and we also observe the linear computational complexity of GA with iterations. The numerical results show that the computational complexity of GA based method is of the order \( O(NI) \). Generally, as the size of the system increases, more population and iterations are needed for the GA to reach an optimal energy efficiency and sum throughput, therefore, more time need to be consumed. From the numerical results, we can conclude that the performance of energy efficiency and sum throughput can reach more than 80 percent of the optimal values (the GA based method can achieve with the number of population large enough) if the number of populations is two times the variables and more than 95 percent if the number of populations is five times the variables. Also, the GA based method converges within 100 iterations for the simulations considered in this paper.
V. SIMULATION RESULTS

In this section, we numerically evaluate the performance of GA based resource allocation method proposed in Section III. The performance of the proposed GA GA based scheme is also compared with the existing benchmark scheme [27], which uses Dinkelbach and branch-and-bound methods to tackle the formulated mixed-integer nonlinear FP problem. The parameters $\sigma$, $P_S$, and $\varepsilon$ are set to 3, 20 Watt and 2 Watt/Mbps as considered in [27], respectively. The crossover rate, selection rate, and mutation rate in Algorithm 1 are set to 0.9, 0.5, and 0.001, respectively. The distribution index for crossover, mutation constant, and mutation probability in Algorithm 2 are given as 20, 100, and $1/Q$, respectively. The number of populations is set to four times the number of variables, i.e., $4(S + 1)UV$, and the number of iterations is set to 100. The system level parameters are listed in Table 2.

Fig. 7 shows the Pareto-optimal set of problem (12) solved by Algorithm 2 against a scenario with $S = 1$, $U = 2$ and $V = 2$. The abscissa and ordinate represent the results of Function 1 and Function 2 in (12), respectively. The curve shown in Fig. 7 can be seen as the functional relationship between the values of two objective functions. The SE maximization result can be obtained when the value of Function 1 is minimized which is shown in Fig. 7. The EE maximization result falls inside the ellipse shown in the figure.

Fig. 8 plots the average energy efficiency of GA based resource allocation scheme for the downlink OFDMA HetNets. The system has one MBS, one SBS, two users, i.e., $S = 1$, $U = 2$, and the number of RBs increases from 2 to 8. The terms “EE: Benchmark” and “SE: Benchmark” represent the energy efficiency under EE and SE perspectives, respectively, for the existing scheme developed in the benchmark paper [27]. From Fig. 8, we can observe that the energy efficiency is increasing as the number of RBs increases from 2 to 8 due to frequency selection diversity gain. Obviously, the energy efficiency results using the proposed GA scheme outperform the benchmark scheme [27]. Also, the energy efficiency results under EE perspective are better than that under SE perspective for all cases. Fig. 9 shows the average sum throughput corresponding to the energy efficiency results shown in Fig. 8. We can see from Fig. 9, the sum throughput is also increasing as the number of RBs increases from 2 to 8, however, the sum throughput under EE perspective is still lower than that under SE perspective. It means that there is a tradeoff between improving the energy efficiency performance and the sum throughput to some extent.

TABLE 2. Simulation parameters

| Parameter                  | Value/Mode |
|----------------------------|------------|
| Microcell radius           | 250m       |
| Small cell radius          | 20m        |
| Carrier frequency          | 4.0 GHz    |
| Bandwidth                  | 20 MHz     |
| Total number of RB         | 50 RBs     |
| Channel model              | i.i.d Rayleigh |
| Pathloss exponent          | 3.5        |
| Minimum distance between UEs and MBS | 15 m |
| Power of MBS               | 46 dBm (40 W) |
| Minimum distance between UEs and SBS | 5 m |
| Power of SBS               | 30 dBm (1 W) |
| Shadowing                  | 8 dB       |
| White noise power density  | -174 dBm/Hz|
The average energy efficiency results of the proposed GA based resource allocation scheme against varying number of users under EE and SE perspective are depicted in Fig. 10. There is one MBS, one SBS, fifteen or twenty RBs, i.e., $S = 1, V = 15$ or $20$, to form the simulation setup, and number of users increases from 2 to 10. From Fig. 10, we can observe that the energy efficiency under both EE and SE perspective is decreasing since more interference is generated as more users are distributed inside the coverage region. In case of massive users in 5G system, the energy efficiency for HetNets could be a disaster due to the inter-cell interference. Thus, inter-cell interference coordination techniques need be used to alleviate the inter-cell interference; however, the backhaul traffic will be large.

Fig. 11 and Fig. 12 show the average energy efficiency results and sum throughput results, respectively, against changing number of SBS. The system scenario involves one MBS, ten users, ten or fifteen RBs, i.e., $U = 10, V = 10$ or $15$, and the number of SBS increases from 1 to 5. Both the energy efficiency and sum throughput are increasing as the number of SBS increases. It means that deploying SBS inside the range of microcell to form HetNets can improve the energy efficiency and spectral efficiency simultaneously. In Fig. 11, the energy efficiency results under EE perspective are better than that under SE perspective. However, the sum throughput under EE perspective is lower than that under SE perspective which is shown in Fig. 12. This again demonstrates the trade-off between the energy efficiency and the sum throughput.

Fig. 13 shows the average energy efficiency results of GA based resource allocation scheme under EE and SE perspective against changing power of MBS. The system scenario has one MBS, two SBS, ten users, and ten or fifteen RBs, i.e., $S = 2, U = 10, V = 10$ or $15$. The corresponding sum throughput results are shown in Fig. 14. In Fig. 13, the energy efficiency results under both EE and SE perspective are same and increasing as the power of MBS $P_{0 \max}$ increases from
In order to solve this, a two-step GA based resource allocation scheme was proposed. First, we fixed the power distribution matrix and solved the RBs allocation matrix according to the channel gain matrix under spectral efficiency perspective. Then the FP problem was transformed into a MOOP and the power distribution matrix was solved by NSGA-II with obtained RBs allocation matrix in the first step. The setting of parameters for GA based scheme was tested and then, the proposed scheme was numerically evaluated under different scenarios. The simulation results revealed that there is a tradeoff between the energy efficiency and the sum throughput, however, by deploying small cells to form HetNets both can be improved simultaneously. Moreover, the power of MBS can also be set accordingly for different purposes. In future works, the use of different operators in the evolution steps: selection, crossover, and mutation are worth investigating and comparing the energy efficiency and sum throughput performance with this paper. And the possibility of solving the RBs allocation matrix and power distribution matrix simultaneously with a single multi-objective GA is worth considering.

VI. CONCLUSIONS

In this paper, we formulated the EE maximization problem for the downlink OFDMA HetNets with coordinated scheduling CoMP. The EE maximization problem turned out to be a mixed-integer nonlinear FP problem, and in order to solve this, a two-step GA based resource allocation

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