Particle Swarm Optimization Based Multi-Objective User Association for LTE-A Heterogeneous Networks

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Abstract Heterogeneous networks (HetNets) are a promising communication paradigm to satisfy the diverse requirements of Long Term Evolution-Advanced (LTE-A). Associating users with different base station tiers using the conventional technique based on the highest received SINR is not viable in HetNets due to its rigid association, which only aims at throughput maximization. Many efforts have been made to tackle the optimization problem of user association with a single objective such as throughput, fairness or energy efficiency. In this paper, we propose a novel multi-objective user association technique using particle swarm optimization (PSO) with the aim of jointly maximizing the throughput and the network balance index (NBI). By incorporating weight factors into the proposed scheme, the system operator has the flexibility to configure the priority levels of throughput and NBI. Numerical results demonstrate that our proposed multi-objective user association technique achieves better performance in terms of fitness values compared to the single-objective user association schemes.

Keywords Cell range expansion · Heterogeneous network · Multi-objective optimization · Particle swarm optimization · User association

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1 Introduction

The continuous surge in capacity demands due to explosive growth of wireless devices and various high-speed multimedia services have spurred the deployment of heterogeneous networks (HetNets) in Long-Term Evolution-Advanced (LTE-A). In a HetNet, the macro cell is overlaid by multiple independent tiers of small cells, e.g. micro cell, pico cell, femto cell, etc. [1]. In general, macro cells have the highest transmission power that ranges from 5W to 40W [2] and a carefully planned and organized deployment is required to maximize their coverages. This is followed by pico cells which have a transmission power of 250mW to 2W and they are widely deployed by the operators to fill the coverage holes [2]. Femto cells can be deployed indoor by consumers or operators as they have a low transmission power [3] and an unplanned deployment manner is sufficient. A user equipment (UE) in a HetNet should be associated with a base station (BS) whether it is a macro cell or any type of small cells.

In LTE homogeneous networks, the 3GPP association is based on the highest signal-to-noise ratio (SINR) or received signal strength (RSS) [4-5]. However, such an association is not viable in HetNets due to the various characteristics and diverse traits of the BSs engaged [6]. The power disparity between the macro cell and the small cells will cause fewer number of users to be associated with the small cells if the conventional association method is used, thereby causing a significant load imbalance among the different tiers of the HetNet [7].

To address the load imbalance issue, 3GPP proposed a user association method known as cell range expansion (CRE) [8]. A bias value is added to the downlink reference-signal-received-power (RSRP) of the small cells in order to attract more users to be associated with them and hence offloading traffics from the macro cells. Adding a fixed bias value to the small cells is known as static biasing, where adding a low bias value only attracts a small number of the UEs to be associated with the small cells. On the contrary, adding a high bias value implies that more users will be associated with the small cells [9]. From the overall perspective of the system, resources in the small cells will either be over-utilized or under-utilized when setting the bias value of the small cells to a high or a low value, respectively. Hence, dynamic biasing methods lead to a better performance compared with static biasing methods [10] because the bias value is adjusted based on the availability of resources in the small cells.

The authors in [11] proposed closed form bias values for HetNets and used stochastic geometry to improve the average throughput rate. In [12], the optimal bias value for a BS is calculated to maximize the energy efficiency. However, the increased mobile data users and their huge traffic demands are leading researchers to focus on methods which are able to dynamically tune the bias value based on certain conditions. This adaptability requires the use of smart solutions such as evolutionary algorithms, fuzzy neural networks, machine learning, bio-inspired methods and artificial intelligence [13].
The user throughput is not the sole requirement of LTE-A network as load imbalance between the macro cell and the small cells lead to performance degradation in terms of fairness, throughput and/or energy efficiency [14]. Therefore, a multi-objective optimization algorithm is deemed necessary to optimize the performance of HetNets in multi-dimensions. Thus, a multi-objective particle swarm optimization based user association (MOPSO-UA) scheme is proposed in this paper.

The work of [15] introduced a heuristic method to jointly maximize the spectral and energy efficiency of HetNet by formulating the problem as a generalized assignment problem. In [16], Niu et al. considered a multi-objective optimization problem by modeling the traffic delay and the power consumption as the performance objectives. Their aim was to obtain suitable control parameters for their proposed user association method which assist in setting control policies for the small cells. The authors in [17] employed a weighted-sum approach to solve a multi-objective optimization problem so that the user experience and the network performance are both improved. More explicitly, they used a multi-objective genetic algorithm to perform user association. Lagrangian dual decomposition and sequential convex programming algorithm are applied in [18] to solve the multi-objective optimization problem with the sum utility and the power consumption as the objective functions.

PSO is used in the literature to optimize various objectives, mainly tackling single-objective problems, such as energy efficiency, power and throughput. The authors in [19] used PSO to maximize the cell spectral efficiency, while the authors in [20] used PSO to maximize the number of the users that meet their downlink requirements. Less work has been done in terms of tackling multi-objective problems using PSO particularly for cellular wireless HetNets.

The key feature of the proposed MOPSO-UA algorithm is that the users are associated to the BSs based on a flexible setting of priority by the system operator, where the priority can be given to the throughput, the network balance index or equally for both objectives. In this work, the bias values of the small cells are adjusted dynamically by using a novel PSO approach which jointly enhances the throughput and network balancing index in a multi-objective optimization scenario.

The remainder of this paper is structured as follows. The system model and the problem formulation are presented in Section 2. The proposed algorithm is outlined in Section 3. Section 4 illustrates and discusses the evaluation of the proposed scheme under different scenarios. Finally, Section 5 concludes the paper and recommends some directions of future work.

2 Methodology

2.1 System Model

The downlink of a three-tier wireless HetNet is considered in this paper. In this multi-tier HetNet, small cells, specifically pico and femto cells, are deployed
within the coverage area of a macro cell. Users would be associated to any of the three tiers based on the proposed user association mechanism. Figure 1 illustrates the three-tier wireless HetNet considered in this work, where the association of a UE to a BS is indicated by a communication link.

As shown in Figure 1, the BSs can serve more than one user but each user is only associated with a single BS. An association indicator, denoted by $\xi_{uj}$, is used to identify the association status between a user $u$ and a BS $j$ where $\xi_{uj} = 1$ if a user $u$ is associated with a BS $j$ and $\xi_{uj} = 0$, otherwise.

2.2 Channel Model

In this paper, the 3GPP channel model in [21] as summarized in Table 1 is adopted, where $d$ is the distance in km between a UE and its associated BS. The channel model takes into account the pathloss and shadowing closed-form expressions and figures. The downlink SINR at the receiver of UE $u$ from BS $j$ can be expressed as
### Table 1 Channel Model of A LTE Heterogeneous Networks

| Parameter                     | Description                  |
|-------------------------------|------------------------------|
| Macro cell pathloss          | $128.1+37.6\log d$           |
| Pico cell pathloss           | $140.7+36.7\log d$           |
| Femto cell pathloss          | $127+30\log d$               |
| Macro cell shadowing standard deviation | 8dB                      |
| Pico cell shadowing standard deviation | 10dB                   |
| Femto cell shadowing standard deviation | 10dB                  |

\[
\phi_{uj} = \frac{p_j g_{uj}}{\lambda_u + \delta^2} \tag{1}
\]

where $p_j$ is the transmission power of BS $j$, $g_{uj}$ represents the gain of the channel between UE $u$ and BS $j$ which incorporates the path loss and the shadowing, $\lambda_u$ signifies the interference that UE $u$ receives from BSs other than the one it is associated with and $\delta^2$ is the additive white Gaussian noise (AWGN) power which includes the noise spectral density and the noise figure.

In this work, the bias value is adjusted dynamically for each BS rather than for each tier. The bias value for BS $j$ is denoted by $\beta_j$. Thus, after biasing the SINR expressed in Equation (1), the biased SINR can be written as

\[
\phi_{uj}^{biased} = \beta_j \frac{p_j g_{uj}}{\lambda_u + \delta^2} \tag{2}
\]

It is noteworthy that the bias values are added to the BS of the small cells only, not to the BS of the macro cell.

### 2.3 Problem Formulation

In this paper, two single objectives, i.e., throughput and network balance index, are aggregated to form a multi-objective problem. Both objectives are to be maximized and thus the overall multi-objective function denoted by $F(x)$ is a maximization problem [22]. The weighted sum approach described in Equation (3) is used. A Pareto-optimal solution is obtained for the two objective functions after combining them together into a single objective function.

\[
\max_{\xi_{uj}} F(x) = \sum_{i=1}^{N} w_i f_i(x) \tag{3}
\]

where $N$ is the number of the objectives, $w_i$ is the weight coefficient of the function $f_i(x)$. In this paper, $N = 2$, $f_1$ and $f_2$ represent the throughput objective and the network balance index respectively. The corresponding weightage coefficients for $f_1$ and $f_2$ are $w_1$ and $w_2$, respectively, and $w_1 + w_2 = 1$. In this paper, several weightage combinations have been considered. The solution to Equation (3) is Pareto optimal when all the weightage values are set to positive values. The main benefit of using the proposed formulation is the flexibility
that can be granted to the LTE-A system to drive the focus of Equation (3) to any of the objectives by adjusting its corresponding weightage value based on the operator’s desire.

Being one of the most important metrics in a wireless system, the throughput is considered as the first objective function to be maximized in this paper. The throughput of the system can be expressed as:

\[ T_{u_j} = B \log_2 (1 + \phi_{u_j}) \] (4)

where \( B \) is the system bandwidth. The formulation of the performance objective of maximizing the system throughput is formulated as:

\[ \max_{\xi_{u_j}} T_{u_j} \] (5)

subject to

\[ \sum_{j \in J} \xi_{u_j} = 1 \] (6)

\[ \beta_{j}^{\text{min}} < \beta_j < \beta_{j}^{\text{max}} \] (7)

where constraint (6) ensures that each UE associates only with one BS and constraint (7) guarantees that the bias value falls within a certain range.

The second objective considered in this paper is the load balancing and the metric chosen is the network balance index which represents the standard deviation between the actual load, \( L_{\text{act},j} \) of a BS \( j \) and its predicted load, \( L_{\text{pred},j} \). The system network balance index (NBI) can be expressed as

\[ NBI = 1 - \frac{\sum_{j \in J} |L_{\text{pred},j} - \sum_{u \in U} \xi_{u_j}|}{2U} \] (8)

where \( \sum_{u \in U} \xi_{u_j} \) is considered as the actual load of the BS \( j \) demonstrating the total number of users associated with BS \( j \). The formulation of the performance objective of maximizing the NBI is formulated as:

\[ \max_{\xi_{u_j}} NBI \] (9)

subject to

\[ \sum_{j \in J} \xi_{u_j} = 1 \] (10)

where constraint (10) ensures that each UE associates only with one BS.
Table 2 Symbols of the PSO equations

| Parameter | Description |
|-----------|-------------|
| $X^t_i$   | Current position of particle $n$ at iteration $t$ |
| $V^{t+1}_i$ | Velocity of particle $n$ in the next iteration |
| $wV^t_i$ | Responsible to maintain the current direction of movement and current velocity, called inertia |
| $c_1r_1(P^t_i - X^t_i)$ | The distance between the personal best and the current location of each particle, known as the cognitive component |
| $c_2r_2(G^t - X^t_i)$ | The distance between the current position and the best position found by all the particles, referred to as the social component |

3 Proposed PSO-Based Algorithm

Figure 2 illustrates the flowchart of the proposed scheme. Firstly, users are distributed randomly within the small and macro cells. Subsequently, users are associated to specific BSs based on the decisions made by the MOPSO-UA algorithm. In the proposed MOPSO-UA algorithm, particles are initiated in the beginning. Then, the fitness function is computed for each particle based on predefined objectives and the best fitness value is selected. After that, the position and velocity equations are updated in each iteration based on equations (11) and (12), respectively.

$$X^{t+1}_i = X^t_i + V^{t+1}_i$$ (11)

$$V^{t+1}_i = wV^t_i + c_1r_1(P^t_i - X^t_i) + c_2r_2(G^t - X^t_i)$$ (12)

Equation (11) represents the position of the swarm particles within the search space and Equation (12) demonstrates the intensity of the movement and its direction. Table 2 clarifies each term in the previous equations:

In every iteration, the best value for each particle $p_{best}$ and the best value of all the $p_{best}$ values called $g_{best}$ are defined by equation (13) and equation (14), respectively. Each particle in the swarm will have an evaluation of the fitness function representing the objective function.

$$p_{best}(i, t) = \max(f(\psi_i))$$ (13)

$$g_{best}(i, t) = \max(p_{best}(i, t))$$ (14)

where $f(\psi_i)$ represents the fitness function value for particle $i$.

For each particle, the best value is selected and compared with $p_{best}$ and $g_{best}$ values. Finally, the previous steps will be repeated till the stopping criteria is met which in this work is reaching the maximum number of iterations. Upon convergence, this stochastic process is guaranteed to find the best bias value for each small cell because each particle involved maintains the best bias value in the search space so the search space becomes smaller and the search process becomes faster.
Fig. 2 Flowchart of the proposed MOPSO-UA
4 Results and Discussion

The results of the proposed MOPSO-UA scheme are presented in this section. MATLAB 8.2 software is used to simulate the wireless HetNet, which is a three-tier network with a total of 20 cells, where the first tier consists of 1 macro cell, the second and the third tier consist of 4 pico cells and 15 femto cells, respectively. The channel bandwidth is set to 20MHz and the number of resource blocks is 100 as specified in [23].

The convergence criteria for the proposed MOPSO-UA algorithm is set to the maximum number of iterations of 100 and the swarm consists of 30 particles. The acceleration coefficients are set to 2 and the inertia coefficient is set to 0.9 [24].

The multi-objective optimization problem presented in Section 2.3 is employed for user association. The corresponding weight coefficient is multiplied by each objective function and the weighted sum is then computed. The setting of these weighting values determines the impact of the objectives in the overall performance of the system.

In the multi-objective function, it is required to specify the maximum value for every objective function. Since the NBI values fall in the range of [0, 1], the maximum value for the load balancing objective is naturally 1. On the other hand, the throughput objective is normalized in order to have a maximum value of 1 as that of the load balancing. In this work, different weightage settings are studied which simulate the case of the operator to decide which objective to prioritize. The weightage values considered \((w_1 - w_{11})\) range from 1 to 0 with a decrement of 0.1 for the throughput and from 0 to 1 with an increment of 0.1 for the NBI. At any time, the sum of the weightage values is equal to 1. Figure 3 shows the corresponding values of the fitness function for different weightage settings. The throughput fitness values start from the maximum normalized value which is 1 and decreases as the corresponding weightage decreases. On the other hand, the load balancing fitness values start from its minimum value and increases as the corresponding weightage increases.

In the following, a comparative performance study between the proposed MOPSO-UA scheme and the existing single-objective user association techniques based on throughput and NBI is carried out. For the proposed MOPSO-UA scheme, three different settings for the priority levels of the objective functions are considered in the simulations, namely balanced, throughput and NBI importance scenarios.

The balanced importance scenario imitates the case when the operator aims to realize a balanced performance of the HetNet over the two objectives; the throughput and the NBI. In Figure 4, it can be observed that the achievable fitness of the multi-objective function is positioned between the other two curves of the throughput and the NBI. Under this scenario, the proposed MOPSO-UA algorithm grants a fair amount of throughput to the associated users and achieves fairness of load balancing across the BSs. The multi-objective function has a normalized value of 0.8577 which falls between
Fig. 3  Fitness function values corresponding to different weightage values

the normalized throughput and NBI function values of 1 and 0.7189, respectively.

Under the throughput importance scenario, the multi-objective function is configured to provide a high user throughput while maintaining a fair NBI. The achievable fitness of the multi-objective function is closer to the high throughput values as shown in Figure 5. The multi objective function has a normalized value of 0.9755, which is closer to the normalized throughput function value of 1. This setting can be invoked by the network operator when a better-throughput performance is desired.

Lastly, in a NBI importance scenario, the multi-objective function prioritizes the NBI objective while offering a fair throughput performance for the associated users. As shown in Figure 6, the achievable fitness of the multi-objective function has a normalized value of 0.7912 which is closer to the high NBI curve with a normalized value of 0.7718. This operational mode can be exploited by the HetNet operator when aiming to prioritize load balancing between the BSs.

The convergence speed of the proposed MOPSO-UA algorithm is quite satisfactory. Although the multi-objective function converges within a different number of iterations in every scenario, however, less than 50 iterations are needed for all scenarios. The performance of the MOPSO-UA while optimizing the multi-objective function under the three aforementioned scenarios is
Fig. 4 Multi-objective function with balanced priority for objectives

Fig. 5 Multi-objective function with throughput priority
justifiable and its effectiveness is verified by observing the performance trends as a result of the objectives being prioritized.

Figures 4-6 reveal that the proposed MOPSO-UA algorithm is capable of controlling the priorities of the multi-objective function by adjusting the weightage parameters. The proposed multi-objective weightage setting is useful whether it is desired to prioritize the throughput, the load balancing, or both of them.

5 Conclusion

There are several aspects to be considered regarding user association in HetNets. In this paper, the performance of HetNet is steered and optimized by adjusting the weightage coefficients towards the user throughout or network load balancing, thus both the users’ and the operators’ perspectives are taken into account. The best bias values for the pico cells and femto cells are found by exploiting the MOPSO algorithm. The results reveal that the proposed MOPSO-UA scheme provides flexibility for the operators to focus on their desired objective in comparison with single-objective based association. Future directions of this work might include and are not limited to adopting it in a self-organizing network or an improved mobility perspective.
Conflict of interest

The authors declare that they have no conflict of interest.

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