User Association in Cell-less 5G Networks Exploiting Particle Swarm Optimisation

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***Abstract*—In heterogeneous networks (HetNets), users can by default associate with the macro base stations (BSs) while the small cell BSs are underloaded. Biasing user association is a simple and realistic approach to balance the load in HetNets, as well as creating a cell-less architecture where a user does not connect to the closest base station. Most of the existing research focuses on the static biasing scheme which is not the optimal strategy to improve the system performance. In this paper, the biasing factors are generated dynamically by the algorithm of particle swarm optimisation (PSO) with the objective of balancing the load and maximising the cell spectral efficiency (CSE). This work studies two different interference cases: the first case is when each tier uses different radio resources (typical when multiple radio access technologies are used) and a user receives interference only from same-tier base stations, whereas the second interference case is when all tiers use the same radio resources and a user receives interference from the same-tier and other tier BSs. The simulation results show that the dynamic biasing using PSO outperforms the static biasing in terms of balancing the load and maximising the CSE.**

Keywords—cell-less architcture; User association; hetergenoues networks; particle swarm optimisation;

I. Introduction

The deployment of heterogeneous networks is a promising approach towards the success of the 5G era. HetNets can improve spectral efficiency, create hot-spots, eliminate coverage holes, and reduce cost.

User association in heterogeneous networks can improve the system performance by balancing the load and optimising the spectral efficiency as well as energy efficiency. Dense heterogeneous networks in 5G introduce several challenges in designing a user association scheme. As a result, user association has attracted many researchers recently.

The traditional user association scheme that is based on the maximum received signal strength is not a suitable approach in heterogeneous networks since many UEs will be attracted to the macrocell due to its high transmission power while small cells will be lightly loaded [1]. To address the aforementioned problem, 3GPP Release 10 introduced the concept of Cell Range Expansion (CRE). In CRE, a bias is added to the power received by UEs from small cells which attracts more UEs to associate with small cells. CRE is a practical approach that has the ability to achieve load balancing in heterogeneous networks since it only requires a simple uncoordinated decision, i.e., adding a bias to the received power from a small cell [2, 3]. Based on the concept of CRE, the authors in [4] showed that the system capacity is improved by offloading users from macro-BS to small cells BSs. The drawback of CRE is that UEs who are encouraged to connect to small cells due to the added bias suffer from strong interference caused by the nearby macro-cell [5]. To balance between the network throughput and the load balance, the selected bias must be carefully chosen [6].

User association based on the biasing concept forms a cell-less architecture where a user does not necessarily associate with the closest BS or the BS that provides the strongest SINR. In other words, users who are out of a cell boundary can still be associated with that cell. Biasing user association can also be implemented to balance the load in coordinated multipoint transmission (CoMP) networks, which is one form of the cell-less architecture, where a user can associate with more than one BS. In CoMP, most of the users still associate with the macro BS causing the macro BS to be heavily loaded and the small cells under loaded. An easy and practical approach to solve the load imbalance in CoMP is to implement the biasing user association. A recent work has been conducted on a cell-less architecture that decouples the uplink and downlink and it showed that biasing is needed to balance the load and achieve optimal rate coverage probability [7]. It is clear that biasing user association plays an essential role in balancing the load in cell-less architectures with a simple and realistic implementation.

The purpose of this paper is to show how PSO can be applied to dynamically adjust the bias to each small cell BS in order to balance the load and maximise the SE. Several research studies have been carried out on user association in multi-tier networks focusing on various performance metrics such as spectrum efficiency and energy efficiency. In [8], Q-learning was applied in order to find the bias value of each user instead of using a common bias value among all users. In the proposed technique, each user independently learns from historical experience the optimal bias value that can optimise the number of outage users. The proposed scheme outperformed the optimum common bias value in terms of network throughput as well as the number of outage users. In [9], biased user association in multi-tier heterogeneous networks for both uplink and downlink was investigated. The optimum biasing factors were derived analytically with the assistance of stochastic geometry. The obtained results showed that the optimal downlink and uplink biasing factors are not identical. Based on quantum-behaved particle swarm optimisation (QPSO), a dynamic biasing user association approach in heterogeneous networks was presented in [10] to address the problem of load balancing. The role of QPSO is to periodically find the best biasing factors that can achieve load balancing and maximise the throughput. Based on the achieved results, the low complex suboptimal QPSO algorithm outperformed the static biasing scheme in terms of spectral efficiency. However, the authors limited the static biasing value to a maximum of 10dB and, according to the obtained results, the cell spectral efficiency increases as the static basing value increases indicating that the static biasing method has the potential to outperform the proposed dynamic biasing scheme if the biasing value is set to be higher than 10dB. In addition, the authors did not show the PSO parameters such as the swarm size and maximum number of iterations which are essential to understand the convergence speed of the proposed algorithm.

In this paper, a downlink multi-tier network is considered. PSO as an optimisation tool is used to generate dynamic biasing factors in heterogeneous networks with the objective of balancing the load as well as maximising the CSE. The performance of dynamic biasing approach is compared with the static approach in terms of balancing the load and maximising the CSE.

The organisation of this paper is as follows. Section II describes the system model. In Section III, the methodology of generating the dynamic basing factors using PSO is explained. Section IV presents the results and discussion. Finally, Section V concludes this work.

II. System Model

A downlink three-tier heterogeneous network with x BSs is considered in this work. Tier 1 represents conventional macrocells whereas tier 2 and tier 3 denote picocells and femtocells, respectively. BSs in each tier have the same transmission power, coverage area, and density. The small cell BSs are randomly distributed in the area. The BS set is denoted as $N = \{1, 2, \dots, n\}$ where the macrocell is represented by the first element and the rest of the elements represent the small cells.

This work studies two different interference cases: a user receives interference only from BSs that belong to the same tier, a user receives interference from all BSs in the same tier as well as from BSs in other tiers. The received signal to interference noise ratio (SINR) by user i from BS j in the first and second interference cases can be calculated, respectively as follows:

$$SINR_{ij} = \frac{p_j g_{ij}}{\sum_{l \in A, i \neq j} p_l g_{il} + \sigma^2} \quad (1)$$

$$SINR_{ij} = \frac{p_j g_{ij}}{\sum_{l \in B, i \neq j} p_l g_{il} + \sigma^2} \quad (2)$$

where p_j is the transmit power of BS j, g_{ij} is the channel gain between user i and BS j which includes path loss and shadowing, A is the set of all BSs in the same tier except BS j, B is the set of all BSs in all tiers except BS j, and $\sigma^2$is the noise power.

The truncated Shannon bound (TSB) model is used to model the transmission rate as follows:

$$Th = \begin{cases} 0, & SINR > SINR_{min} \\ \alpha log_2(1 + SINR), & SINR_{min} < SINR < SINR_{max} \\ Th_{max}\ , & SINR > SINR_{max} \end{cases} \quad (3)$$

where Th is the achieved throughput in bps/Hz, $SINR_{min}$ is the minimum SINR value that is required to guarantee satisfactory QoS, α is the attenuation factor, $SINR_{max}$ is the maximum value of SINR to achieve the highest throughput, Th_{max}. The TSB parameters [11] are $\alpha = 0.65$, $SINR_{min} =$ 1.8dB, $SINR_{max} = 21$dB, $Th_{max} = 4.5$bps/Hz.

Based on the SINR biased concept, a user is attracted to the BS that provides the maximum biased $SINR'$ and is calculated based on the following:

$$SINR' = S_j SINR \quad (4)$$

where S_j is the biasing value for BS j. It is noteworthy that no bias is added for the macro BS, i.e. $S_{1=1}$. Each small cell BS j can have a bias value of $S_j > 1$. The biasing values must be selected carefully in order to optimise the CSE and balance the load.

III. Dynamic Biasing Using PSO

The selection of the biasing values clearly affects the performance of the overall system in terms of the achievable throughput and load balance. Dynamic biasing is a promising solution to find the optimal biasing values; however, this approach proves to be a NP hard problem. An optimal yet prohibitively complex solution to generate the biasing values is to perform exhaustive search. Taking the advantage of its low complexity, robustness, and fast convergence speed, PSO [12] is used in this work to dynamically generate the biasing factors for the picocells and femtocells.

PSO is a low complex search algorithm that is inspired by observing the social behavior of birds flocking and fish schooling. The advantage of using PSO is that it has few controlling parameters and it has a fast convergence speed. PSO consists of a number of particles called a swarm where each particle represents a potential solution. During the searching process of PSO, each particle flies in the searching space to improve its position and find a better solution. Each particle in the swarm provides a better solution by updating its velocity and position based on the following equations:

$$v_{id} = wv_{id} + c_1 r_1 (Pbest_{id} - x_{id}) + c_2 r_2 (gbest_d - x_{id}) \quad (5)$$

$$x_{id} = x_{id} + v_{id} \quad (6)$$

where $w, c_1,$ and c_2 are the three main controlling parameters of PSO known as inertia weight, cognitive acceleration coefficient and social acceleration coefficient, respectively. r_1 and r_2 are two uniform random variables in the range of [0,1], $Pbest_i$ is the best historical position of particle i and $gbest$ is the best particle in the whole swarm.

In this work, the role of PSO is to search for the best particle that can maximise the cell spectral efficiency provided in equation 8. The cell spectral efficiency is calculated based on the following:

$$System\ throughput = \sum_{k=1}^{N}\sum_{j=1}^{M} D_{ki}\, Th_{ki} \qquad (7)$$

$$CSE = \frac{System\ throughput/BW}{N} \qquad (8)$$

where

$$D_{ki} = \begin{cases} 1 & \text{, if a user } i \text{ is connected to BS } k \\ 0 & \text{, if a user } i \text{ is not connected to BS } k \end{cases}$$

N is the number of total BSs, $M$is the number of users, BW is the bandwidth.

The procedure of using PSO to generate the dynamic biasing values as explained as follows. The PSO algorithm initially generates a random swarm of particles in the search space where the dimension of each particle is the total number of BSs. A particle i can be denoted as $S_i = \{S_1, S_2 \ldots, S_N\}$ where $S_1 = 1$ indicates no biasing is needed for the macrocell and $S_2 \ldots S_N$ are the bias values for pico and femto cells. Each particle i updates its velocity position in each iteration based on equations 5 and 6 in order to find a better solution.

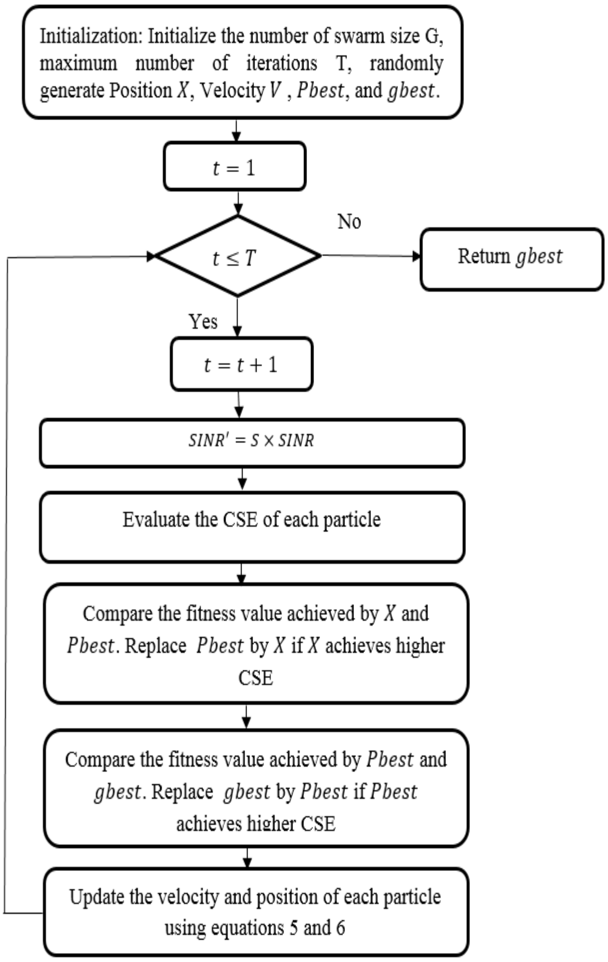

Fig. 1. The PSO process to generate dymanic biasing values

The fitness of each particle is evaluated by calculating the cell spectral efficiency according to equation 8. PSO records its best historical particles as $Pbest$ and the best particle that has achieved the best results so far as $gbest$. The PSO process continues till the maximum number of iteration is reached. At the end of the PSO process, $gbest$ is returned which denotes the best achieved biasing values. Fig. 1 illustrates how PSO is used to find the biasing values that can maximise the CSE and balance the load.

IV. Results and Discussion

A MATLAB snapshot based simulation is considered in this work to implement the presented system model. One macro BS, 4 picocells, and 15 femtocells are deployed the area. The simulation parameters are summarised in Table I. The PSO parameters including the swarm size, controlling parameters, and maximum number of iterations are specified in Table II.

Table 1: Simulation Paramters

Parameter	Value
Bandwidth	20MHz
Tx Power (macro, pico, femto)	(46dBm, 30dBm, 20dBm)
Macro pathloss [13]	$128.137.6\log_{10}(\text{R})$, R in km
Pico pathloss [13]	$140.736.7\log_{10}(\text{R})$, R in km
Femto pathloss [13]	$127 + 30\log_{10}(\text{R})$, R in km
Shadowing std. dev.	8dB (macro), 10dB (pico), 10dB (femto)
Noise power level	-174 dBm/Hz
Scheduler	Round robin
Traffic model	Full buffer

Table 2: PSO Parameter Settings

Parameter	Setting
Swarm size	30
Maximum number of iterations	30
c_1	2
c_2	2
w	0.9-0.4

The performance of the static biasing scheme for values starting from 0dB to 60dB is compared with the dynamic biasing using PSO in terms of maximising the CSE and balancing the load for the two interference cases mentioned in Section II. For the two interference cases, the maximum static biasing value is set to be high enough with a value of 60dB to ensure that an optimal static value is included in the comparison. Fig. 2 shows the performance of the static and dynamic biasing schemes in terms of the CSE for different number of users in the first interference case where each tier uses different frequency band. This figure shows that the CSE increases as the static biasing value increases from 0dB to 15dB and it decreases as the static biasing value goes above 20dB. The reason this occurs is because when there is no bias added, some small cells are not associated with any user causing the CSE to decrease. In other words, when a bias is added to the small cells, the small cells that were not associated with any user are now loaded with some users. It can be concluded that an optimal static value is between 15dB and 20dB. Fig. 2 also shows that the dynamic biasing values generated by PSO achieves the highest CSE as compared with the static biasing values.

Fig. 3 shows the number of users associated with macro, pico, femto BSs for the static and dynamic biasing in the first interference case. As can be seen from the Figure, when no bias is added (0dB), most of the users are associated with the macro BS while the picocells and femtocells are underloaded. This happens because macro BSs transmit at a higher power than

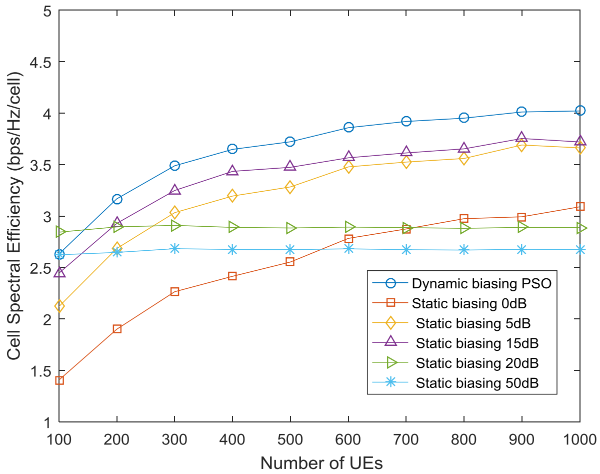

Fig. 2. CSE for different users in the first interference case

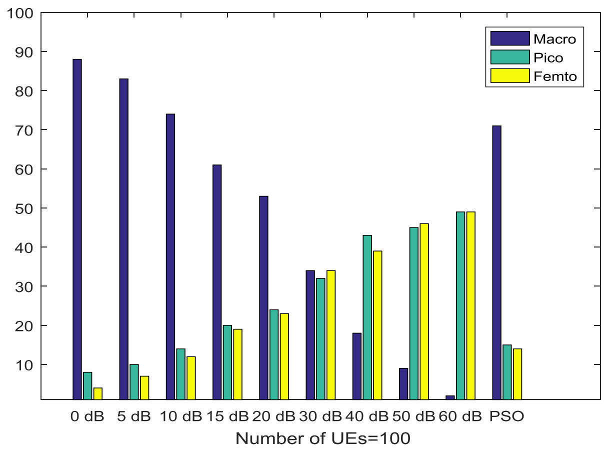

Fig. 3. Number of users associated with each tier in first interference case

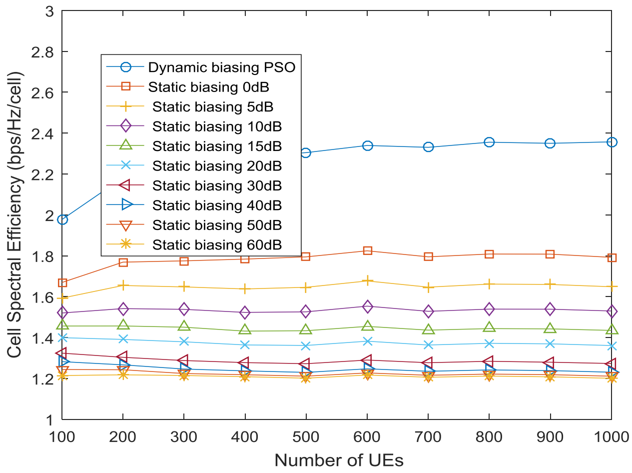

Fig. 4. CSE for different users in the second interference case

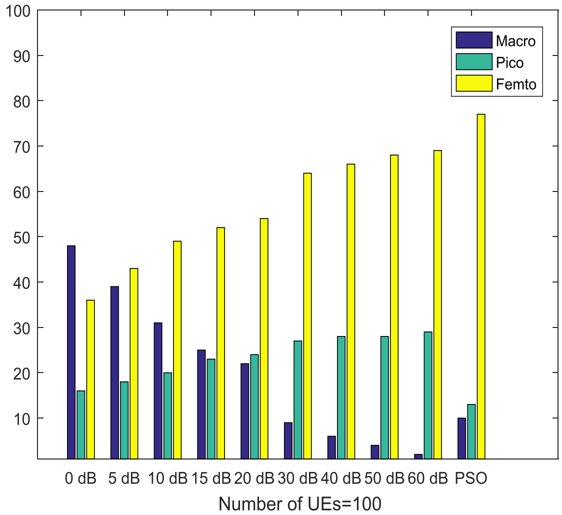

Fig. 5. Number of users associated with each tier in second interference case

picocells and femtocells. Another reason is that users do not receive interference from the other tiers since each tier uses a different frequency and also users do not receive interference from the same tier since there is only one macrocell. Fig. 3 also shows that users are attracted more to small cells as the static biasing value increases. When the static biasing value is set to be 60dB, most users are associated with the small cells. Although a static biasing value of 60dB can attract most of users to small cells, it makes the macro cell nearly unloaded. The static biasing values of 30dB and 40dB show a good load balance among the macro and small cells; however, these two values show a low CSE as can be seen in Fig. 2. The performance of PSO in terms of load balancing is similar to the 10dB static biasing where the number of users associated with the macro BS is slightly reduced.

A comparison between the static and dynamic biasing for the second interference case is shown in Fig. 4. Unlike the first interference case, Fig. 4 shows that the CSE decreases as the static biasing value increases from 0dB to 60dB. This is an expected result since the users that are forced to associate with the picocells and femtocells suffer from strong interference from the macro BS. From Fig. 4, it is clear that the dynamic biasing achieves higher CSE than the static biasing. The number of users associated to each tier for the static and dynamic biasing is illustrated in Fig. 5. From Fig. 5, the number of users associated with the macrocell is less as compared with the first interference case because the macrocell and small cells transmit at the same frequency causing the SINR received by a user from the macrocell to be lower. Nevertheless, a lot of users are still attracted to the macro BS. Similar to the first interference case, as the biasing value increases, more users are forced to associate to the small cells while the macrocell gets underloaded. The dynamic biasing shows that it can attract more users to associate with small cells while some users are still associated with the macrocell.

V. CONCLUSION

This work compared the performance of static biasing and dynamic biasing under two different interference cases. PSO is used to dynamically determine the biasing factor that can improve the overall system by balancing the load and maximising the CSE. The simulation results show that increasing the static biasing value offload users from the macrocell to the small cells at the expense of CSE. Overall, according to the obtained results, dynamic biasing can achieve higher CSE and balance the load better than static biasing.

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