International Journal of Technology 10(7): 1407-1415
ISSN 2086-9614

IMPROVED LOAD BALANCING FOR LTE-A HETEROGENEOUS NETWORKS USING PARTICLE SWARM OPTIMIZATION

Mhd Amen Summakieh[1*], Chee Keong Tan[2], Ayman A. El-Saleh[3], Teong Chee Chuah[1]

[1]*Faculty of Engineering, Multimedia University, Persiaran Multimedia, 63100 Cyberjaya, Selangor, Malaysia*
[2]*School of Information Technology, Monash University Malaysia, Selangor, 47500, Malaysia*
[3]*College of Engineering, A'shraqiyah University, Ibra, 400, Oman*

(Received: November 2018 / Revised: Desember 2018 / Accepted: September 2019)

ABSTRACT

Heterogeneous networks (HetNets) are a promising means of meeting the requirements of Long Term Evolution-Advanced (LTE-A) in terms of data traffic, coverage and capacity. In HetNets, power disparities arise between base stations in different tiers. The use of existing user association schemes will lead to load imbalances between these base stations, thus affecting network performance. Biased user association has been widely studied to improve load balancing in HetNets. Static biasing has been the focus of most existing work but this approach does not yield optimized performance because the optimal biasing values vary with user location. In this paper, we investigate the use of the Particle Swarm Optimization (PSO) algorithm to conduct dynamic user association by finding the optimal bias values. The simulation results demonstrate that the proposed scheme achieves better load balancing performance in terms of the network balance index compared to a baseline scheme.

Keywords: Heterogeneous network; Load balancing; Particle swarm optimization; User association

1. INTRODUCTION

The introduction of LTE-A HetNets aims to improve spectral efficiency per coverage area (Suryanegara, & Asvial, 2018). Using a mixture of macro and small cells (e.g., micro, pico, and femto cells), HetNets enable flexible and low-cost deployments (Mohamed et al., 2017) while providing a uniform broadband experience to users anywhere in the network (Wang et al., 2011). These small cells can be distinguished from macrocells based on physical size, transmission power, cost and deployment (Ye et al., 2013). In a HetNet, users need to be associated to a macrocell or a small cell. In 3GPP LTE networks, a user is associated to the base stations (BSs), based on the highest received signal (Sheikhidris et al., 2018). Nonetheless, this association is not practical in an LTE-A HetNet because of the transmission power disparity between the macrocell and the small cells (Corroy et al., 2012). As a result, a small number of users will be connected to the small cells, thus leading to load imbalance between the macrocell and small cells. A technique called cell range extension (CRE), which is a modified user association method has been proposed by 3GPP, whereby a fixed bias value is added to the small cells to attract more users with lower signal strengths to them, hence leading to a higher offload from the macrocells (Borst et al., 2013). Even though the fixed bias value added to the user association process could result in better load balancing, it does not necessarily lead to a lower signal-to-interference-plus-

*Corresponding author's email: amens1994@gmail.com, Tel. +60-17-6674094, Fax. +60-3-83125300
Permalink/DOI: https://dx.doi.org/10.14716/ijtech.v10i7.3253

noise ratio (SINR) because of the added interference level (Corroy et al., 2012).

Moreover, a static bias may not improve the user experience; however, in order to avoid excessive sacrifice in the user rates, dynamic biasing is necessary (Chou et al., 2015). When there are limited resources available at a BS, there will be fewer available resources for certain users, leading to reduced aggregate throughput. For this reason, attaining load balancing among BSs during user association is essential (Boostanimehr & Bhargava, 2015).

In a wireless cellular network, achieving the requirements of different load scenarios with the supplies of the BSs resources is known as load balancing (Feng et al., 2014). When traffic is offloaded from highly loaded BSs to lowly loaded ones, and the load distribution amongst the base stations is reasonable, then load balancing will be achieved. Consequently, better user experience and good network performance will be maintained (Mishra & Mathur, 2014). Different solutions for load balancing have been proposed, which can generally be classified into two types (Zhou et al., 2014). In the first type, the solutions are based on the number of resources used; heavily loaded cells offload extra traffic to other cells nearby by cell breathing techniques (Bejerano & Han, 2009) or by using a specific cell offset (Siomina & Yuan, 2012). Bejerano and Han (2009) presented a cell breathing technique to provide fairness based on finding the global optimal solution. They reduced the size of the congested cells by decreasing the transmission power and hence forcing the users of these cells to shift to less congested adjacent cells. Siomina and Yuan (2012) performed load balancing by optimizing the cell specific offset range of the low power nodes. They aimed to reach a fair load distribution by considering Jain's fairness index as an objective function.

In the second type, the solutions are based on the number of connected users, including several kinds of utility functions, the overall rate maximization (Ye et al., 2013), alpha optimal user association (Kim et al., 2010) and biasing methods (Cho & Choi, 2013; Tang et al., 2013). Ye et al. (2013) investigated a utility maximization problem considering the overall rate as an objective function and showed that a load-aware association reduces the congestion of heavily loaded macro base stations. Kim et al. (2010) studied load balancing in a wireless network under spatially inhomogeneous traffic distributions. By taking the base station's load into consideration, Tang et al. (2013) proposed a load-aware model based on stochastic geometry and associated users determined by the strongest average long-term biased received power. Cho and Choi (2013) used repulsive cell activation and showed that the minimum separation distance between the base stations affects the load balancing of the cells. However, the metric used to determine their objective was average user throughput. In order to quantify a metric for load balancing, Chiu and Jain (1989) introduced a balance index to measure the balance of resources in a system (Ganco & Correia, 2015). Limitations were identified for this metric due to the chances that a certain user might generate several added loads based on the BS it is connected to (Ganço & Correia, 2015).

In this paper, we propose a particle swarm optimization-based user association (PSO-UA) scheme for load balancing. PSO is an algorithm that mimics the foraging of a flock of birds or the navigation of fish (Baskoro et al., 2011). It has few parameters that need adjusting and hence is easy to be implemented. PSO shows good performance, together with fast convergence speed and low complexity. Shami et al. (2018) used PSO to control the load with the objective of maximizing the cell's spectral efficiency, in which a spread control parameter was used to ensure that the number of users assigned to any base station neither exceeded nor went below a specific boundary. In this paper, we propose the use of a load balancing metric proposed by Huang et al. (2017). We show that the proposed PSO-UA leads to a more balanced network compared to the currently used association scheme and that the proposed metric is more suitable for measuring the load balancing of HetNets. The novelty of the current work is a new PSO-based technique for improving the network balancing index via dynamic adjustment of the small cell bias values.

The remainder of the paper is organized as follows: Section 2 describes the system model, presents the problem formulation and the proposed algorithm is discussed. In Section 3, performance evaluation of the proposed technique is presented. Finally, the paper is concluded in Section 4.

2. METHODS

2.1. System Model and Objective Function

In this paper we consider the downlink of a multi-tier wireless HetNet; specifically, a three-tier HetNet in which users are associated to the macrocell or to the picocells and femtocells, whereby small cells are deployed within the macrocell coverage area, as shown in Figure 1. The communication link shows that the user equipment is associated with the corresponding basestation. In this system model, each user's equipment is associated with only one base station, as presented in Figure 1. There are several BSs, and the number of macrocells, picocells and femtocells are denoted by M, P and F respectively.

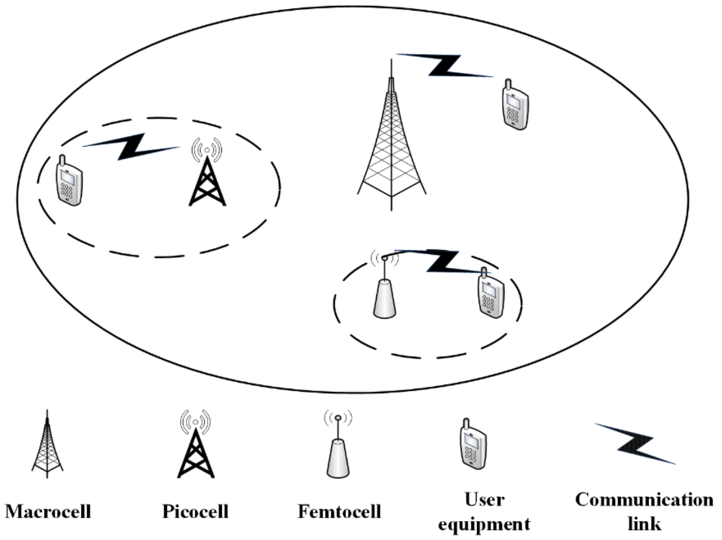

Figure 1 Illustration of a three-tier wireless heterogeneous network

The BSs set is denoted by *B*, where the macrocell is the first element, followed by the picocells and the femtocells. The user equipment (UE) set is denoted by *U*, with *Uj* denoting the total number of users associated with BS *j*.

2.2. Channel Modelling

The path loss models and the shadowing standard deviation values used in this paper are based on 3GPP (3GPP, 2013), as shown in Table 1, where *d* is the distance between the BS and the UE in km.

Table 1 Model details

Parameter	Description
Macrocell pathloss	128.1+37.6 log *d*
Picocell pathloss	140.7+ 36.7 log *d*
Femtocell pathloss	127 + 30 log *d*
Macrocell shadowing standard deviation	8dB
Picocell shadowing standard deviation	10dB
Femtocell shadowing standard deviation	10dB
Noise figure	9 dB
Noise spectral density	-174 dBm
Bandwidth	20 MHz

The received SINR denoted by Ψuj, of a UE *u* from a BS *j*, is expressed as:

$$\Psi_{uj} = \frac{t_j g_{uj}}{I_u + \sigma^2} \quad (1)$$

where t_j is the transmission power of BS *j*; g_{uj} is the channel gain between UE *u* and BS *j*, which is a value that includes shadowing and path loss; *Iu* is the interference received from other BSs; and σ^2 is the additive white Gaussian noise power, which includes the noise figure and the noise spectral density.

After biasing, the UE will be associated to the BS with the highest biased SINR (Shami et al., 2017) which is denoted as:

$$\Psi_{ujbiased} = \propto_j \Psi_{uj} \quad (2)$$

where $\propto_j$ is the bias value added to BS *j*. The bias values are added to all small cells (i.e., picocells and femtocells) and no bias value is added to the macrocell.

2.3. Load Balancing Metric

The network balance index (NBI) proposed by Huang et al. (2017) is used as shown in equation (3). Before determining the load balancing of the network, both the actual load of the cell and the predicted load should be determined. The predicted load denoted by *pl* is the load that can be supported by a BS which is directly proportional to its transmission power, while the actual load denoted by *al* is the load of each cell after user association has been performed.

$$\mathrm{NBI} = 1 - \frac{\sqrt{(pl - al)^2}}{2 \times U} \quad (3)$$

where NBI is the deviation between the predicted and the actual load distributions (Huang et al., 2017) that can have any value in the range of [0, 1], where 0 denotes no load balancing and 1 denotes the best load balancing.

2.4. Proposed User Association Scheme for Load Balancing

In this section, the proposed PSO-UA scheme is presented in Table 2. In this scheme, users are first distributed randomly among random BSs within their receiving ranges. Thereafter, user association is performed to associate users with BSs to maximize the load balancing of the network. In this scheme, the bias values for the small cells are dynamically chosen for each BS to fulfill load balancing by increasing the NBI. In order to dynamically set the bias values, a PSO algorithm is proposed to find the best bias values, as it has been proven to be a low complexity scheme with a fast convergence speed (Al-Dujaili et al., 2015).

Table 2 Proposed PSO-UA scheme for improved load balancing

Algorithm 1 Proposed PSO algorithm for improved load balancing

Input: Initialize the system model settings.
Input: Initialize the PSO control parameters.
Input: Initialize the population of N particels.
Initialize the variables to zero:
Calculate the load balancing index of each cell.
while the number of maximum iterations is not reached yet **do**
for N = 1 to $nb_{particles}$ **do**
Calculate the load balancing index of the particle
if $PBEST > PBEST_{initial}$ **then**
update PBEST
end if
if $GBEST > GBEST_{initial}$ **then**
update GBEST
end if
end for
update the inertia weight
for N = 1 to $nb_{particles}$ **do**
update the velocity
update the position
end for
return GBEST as the best estimation of the global optimum
end while

In the proposed scheme, every single bias value for each small-cell BS is considered as one particle within the overall swarm of particles. Since the particles move in the search space, their positions must be updated depending on two formulas: position and velocity, as shown in Equations 4 and 5, respectively.

$$X_i^{t+1} = X_i^t + V_i^{t+1} \tag{4}$$

$$V_i^{t+1} = wV_i^t + c_1 r_1 \left(P_i^t - X_i^t\right) + c_2 r_2 \left(G^t - X_i^t\right) \tag{5}$$

Equation 4 demonstrates the position of the particles in the search space, where X_i^t is the current position of the nth particle at the tth iteration and $V_i^{t+1}$is the velocity of the nth particle in the next iteration. Equation 5 shows the direction and the intensity of the movement, where the first term wV_i^t is the inertia which maintains the current velocity and the current direction of the movement. The second term, $c_1 r_1 \left(P_i^t - X_i^t\right)$, is called the cognitive component and considers the distance between the personal best and the current location of each particle individually. The final term, $c_2 r_2 \left(G^t - X_i^t\right)$, is known as the social component, because the distance is calculated between the current position and the best position found by the entire swarm of particles.

The position and velocity equations are updated in each iteration based on Equations 4 and 5. Subsequently, each particle will have a fitness function calculated based on Equation 3. The algorithm in Table 2 stores the best fitness value for each particle from the swarm under a term known as personal best (PBEST). The fitness values for all the particles in the swarm are compared with each other and the best particle that has the highest fitness value will be stored as a term known as the global best (GBEST). In this work, the fitness function to be maximized is the NBI, while the particles in the swarm represent possible bias values for the small cells. Upon convergence, this stochastic process is guaranteed to find the best bias value for each small-cell

BS, because each particle involved maintains the best bias value in the search space so this space becomes smaller and the search process becomes faster.

3. RESULTS AND DISCUSSION

In this section, we present the results of the proposed user association scheme for load balancing using PSO-UA. A three-tier wireless HetNet is considered, consisting of one macrocell with a transmission power of 46 dBm, overlaid with 19 small cells, four of which are picocells and the remaining 15 femtocells, with transmission power of 30 dBm and 20 dBm, respectively. The number of resource blocks is fixed to 100 as per a channel bandwidth of 20 MHz, based on 3GPP specifications (3GPP, 2011). For the proposed PSO algorithm, the swarm size is set to 30, with a maximum number of iterations of 100. The inertia coefficient *w* is set to 0.9, and the acceleration coefficients *c1* and *c2* are set to 2 (Clerc & Kennedy, 2002). All the results in this section are shown as the average of 100 simulation runs. First, we analyze and compare the NBI of the proposed PSO user association with an SINR association, which associates users to BSs based on the maximum received SINR (Dhillon et al., 2012). Figure 2 demonstrates the NBI comparison, with the number of users varying from 100 to 1000. We notice that in all cases the NBI of the proposed PSO-UA scheme is higher than the SINR-based scheme association. The proposed PSO-UA scheme outperforms the SINR-based one in terms of NBI because the former takes the load balancing into consideration when performing user association.

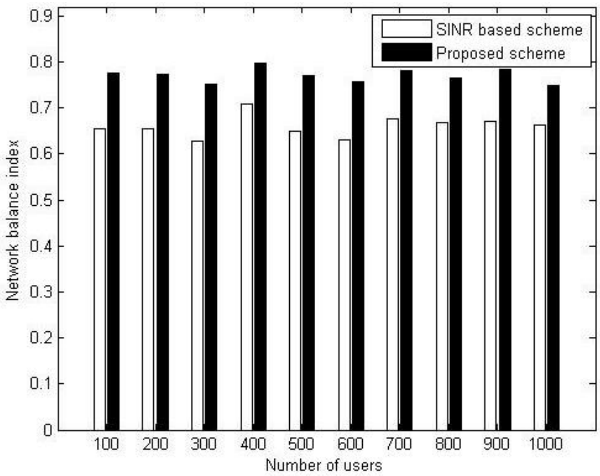

Figure 2 Network balance index of the proposed scheme and existing scheme

By varying the number of users from 100 to 1000 in increments of 100, the proposed PSO-UA scheme still outperforms the SINR-based one, even though the user locations and small cell locations vary in all the scenarios. This is due to the dynamic association performed by the proposed scheme to find the optimal bias values to improve load balancing. As shown in Figure 2, in the 400 user scenario, the proposed scheme NBI 0.7972 is higher than the SINR based scheme NBI value of 0.7094. Overall, in all the different scenarios with varying numbers of users, there is an average improvement of 16% in terms of the NBI when using the proposed scheme compared to the SINR-based one.

The number of users connected to each tier in the HetNet is then investigated. It can be seen that the number connected to the small cells increases when using the PSO-UA. In a 100 user scenario, as demonstrated in Figure 3, the SINR-based association scheme leads to 38 users being associated with the macrocell, 17 with the picocells and 45 with the femtocells. Using the proposed PSO-UA scheme, 25 users are attracted to the macrocells, 23 to the picocells and 52 to the femtocells. The proposed PSO-UA association results in a 13% improvement in offloading users to the small cells. Therefore, since more users are offloaded to the small cells when using the proposed PSO-UA scheme, compared to the SINR-based one, the load balancing of the network improves and hence the NBI increases accordingly. The results shown in Figure 3 are grouped per tier; all the users connected to the four picocells are grouped in the pico tier, and all those associated with the 15 femtocells are grouped in the femto tier.

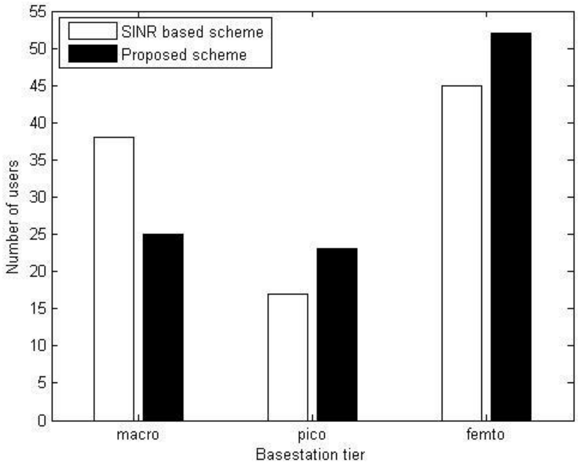

Figure 3 Number of users connected using the proposed scheme and existing scheme for different tiers

Furthermore, the NBI metric is shown along with the load balancing index (LBI) metric from Ganco and Correia (2015). Even though the LBI may seem to be a simple metric compared to the NBI, the computational time of the latter is slightly shorter. Furthermore, the LBI metric is maximized when all the base stations in the network have an equal load, regardless of which tier the base station belongs to. The percentage of users connected to each tier is presented in Fig. 4 as an average per tier; i.e., for the macro tier there is a single macrocell, while the pico and femto tiers reflect the average of the total number of users connected to each tier from the four picocells and 15 femtocells. The main difference between these two metrics is that the NBI takes the predicted load into consideration, rather than the actual load, as in LBI. Hence, 11% more users are connected to the macro tier when using NBI compared to LBI and 2% fewer users are connected to small cells when using NBI compared to LBI, as the macrocell can handle more load than the small ones.

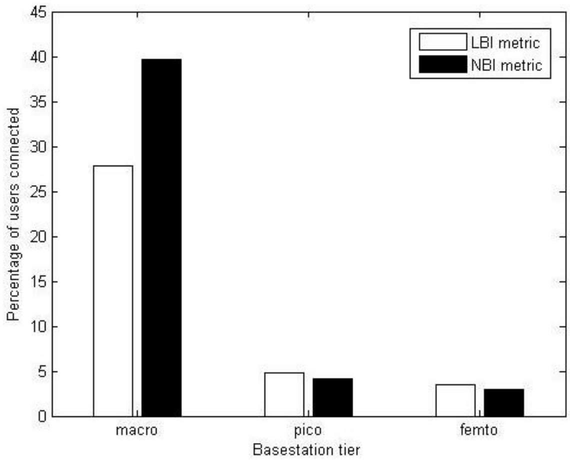

Figure 4 Comparison between the network balance index metric and load balance index using the proposed scheme

As shown in Figure 4, the percentage of users connected to the macrocell increases from 27.83 to 39.66 when using the NBI instead of the LBI. However, the percentage of users associated with the small cells decreases from 4.83 to 4.20, and from 3.52 to 2.9, for the pico and macro tiers respectively. This difference does not show a decrease in the metric performance. In contrast, it shows the advantage of using the NBI metric over the LBI one. Different base station tiers are considered in the model and consequently different transmission powers for each tier; therefore considering the capability of each base station when using the NBI metric displays its benefit compared to the LBI metric.

4. CONCLUSION

In this paper, we have proposed the use of a PSO algorithm to perform a dynamic biasing user association and have chosen the network balancing index as the maximization objective function. The results show that the proposed PSO-UA scheme leads to higher NBI performance compared to the SINR-based UA.

5. ACKNOWLEDGEMENT

This work was supported by Telekom Malaysia Research and Development, under grant RDTC/160915.

6. REFERENCES

Al-Dujaili, A., Tanweer, M.R., Suresh, S., 2015. On the Performance of Particle Swarm Optimization Algorithms in Solving Cheap Problems. *In*: Computational Intelligence, 2015 IEEE Symposium Series on, pp. 1318–1325

Baskoro, A.S., Masuda, R., Suga, Y., 2011. Comparison of Particle Swarm Optimization and Genetic Algorithm for Molten Pool Detection in Fixed Aluminum Pipe Welding. *International Journal of Technology*, Volume 2(1), pp. 74–83

Bejerano, Y., Han, S.J., 2009. Cell Breathing Techniques for Load Balancing in Wireless LANs. *IEEE transactions on Mobile Computing*, Volume 8(6), pp. 735–749

Boostanimehr, H., Bhargava, V.K., 2015. Unified and Distributed QoS-Driven Cell Association Algorithms in Heterogeneous Networks. *IEEE Transactions on Wireless Communications*, Volume 14(3), pp. 1650–1662

Borst, S., Hanly, S., Whiting, P., 2013. Throughput Utility Optimization in HetNets. *In:* Vehicular Technology Conference (VTC Spring), 2013 IEEE 77th, pp. 1–5

Chiu, D.M., Jain, R., 1989. Analysis of the Increase and Decrease Algorithms for Congestion Avoidance in Computer Networks. *Computer Networks and ISDN systems*, Volume 17(1), pp. 1–14

Cho, S.R., Choi, W., 2013. Energy-Efficient Repulsive Cell Activation for Heterogeneous Cellular Networks. *IEEE Journal on Selected Areas in Communications*, Volume 31(5), pp. 870–882

Chou, G.T., Liu, K.H.S., Su, S.L., 2015. Load-based Cell Association for Load Balancing in Heterogeneous Cellular Networks. *In:* Personal, Indoor, and Mobile Radio Communications (PIMRC), 2015 IEEE 26th Annual International Symposium on, pp. 1681–1686

Clerc, M., Kennedy, J., 2002. The Particle Swarm-explosion, Stability, and Convergence in a Multidimensional Complex Space. *IEEE transactions on Evolutionary Computation*, Volume 6(1), pp. 58–73

Corroy, S., Falconetti, L., Mathar, R., 2012. Cell Association in Small Heterogeneous Networks: Downlink Sum Rate and Min Rate Maximization. *In:* 2012 IEEE Wireless Communications and Networking Conference (WCNC), pp. 888–892

Dhillon, H.S., Ganti, R.K., Baccelli, F., Andrews, J.G., 2012. Modeling and Analysis of K-Tier Downlink Heterogeneous Cellular Networks. *IEEE Journal on Selected Areas in Communications*, Volume 30(3), pp. 550–560

Feng, L., Yin, M., Xiang, N., Li, W., Qiu, X., 2014. Load-balancing based on Base-station CoMP with Guaranteed Call Blocking Rate. *In*: International Symposium on Wireless Personal Multimedia Communications (WPMC), pp. 271–276

Gança, P., Correia, L. M., 2015. Load Balancing in Heterogeneous Networks with LTE. Master's Sc. Thesis, Instituto Superior Técnico, Lisbon, Portugal

Huang, Y., Durrani, S., Dmochowski, P., Zhou, X., 2017. A Proposed Network Balance Index for Heterogeneous Networks. *IEEE Wireless Communications Letters*, Volume 6(1), pp. 98–101

Kim, H., de Veciana, G., Yang, X., Venkatachalam, M., 2010. Alpha-optimal user Association and Cell Load Balancing in Wireless Networks. *In*: INFOCOM, 2010 Proceedings IEEE, pp. 1–5

Mishra, S., Mathur, N., 2014. Load Balancing Optimization in LTE/LTE-A Cellular Networks: A Review. arXiv preprint arXiv: 1412.7273. pp. 1–7

Mohamed, K.S., Alias, M.Y., Roslee, M.B., 2017. Investigation and Improvement of Maximum Likelihood Channel Estimator in Ofdm Systems. *In:* 2017 International Conference on Platform Technology and Service (PlatCon), pp. 1–4

Shami, T.M., Grace, D., Burr, A., 2017. User Association in Cell-less 5G Networks Exploiting Particle Swarm Optimisation. *In:* International Symposium on Wireless Communication Systems (ISWCS)

Shami, T.M., Grace, D., Burr, A., 2018. Load Balancing and Control using Particle Swarm Optimisation in 5G Heterogeneous Networks. *In:* 2018 European Conference on Networks and Communications (EuCNC), pp. 1–9

Sheikhidris, K., Alias, M.Y., Roslee, M., Alam, M.J., 2018. Throughput Maximization based on User Association in Heterogeneous Networks. *In:* 2018 6th International Conference on Information and Communication Technology (ICoICT), pp. 34–37

Siomina, I., Yuan, D., 2012. Load Balancing in Heterogeneous LTE: Range Optimization Via Cell Offset and Load-coupling Characterization. *In:* Communications (ICC), 2012 IEEE International Conference, pp. 1357–1361

Suryanegara, M., Asvial, M., 2018. The Patterns of Innovation Agendas on 5G Mobile Technology. *International Journal of Technology*, Volume 9(5), pp. 876–887

Tang, H., Peng, J., Hong, P., Xue, K., 2013. Offloading Performance of Range Expansion in Picocell Networks: A Stochastic Geometry Analysis. *IEEE Wireless Communications Letters*, Volume 2(5), pp. 511–514

Technical specification group radio access network; evolved universal terrestrial radio access (E-UTRA); physical channels and modulation," TS 36.211, (3GPP). Available Online at https://www.3gpp.org/ftp/Specs/archive/36_series/36.211/

Technical specification group radio access network; small cell enhancements for e-utra and e-utran - physical layer aspects," TR 36.872, (3GPP). Available Online at https://www.3gpp.org/ftp/Specs/archive/36_series/36.872/

Wang, J., Liu, J., Wang, D., Pang, J., Shen, G., 2011. Optimized Fairness Cell Selection for 3GPP LTE-A Macro-pico HetNets. *In:* Vehicular technology conference (VTC Fall), 2011 IEEE, pp. 1–5

Ye, Q., Rong, B., Chen, Y., Al-Shalash, M., Caramanis, C., Andrews, J.G., 2013. User Association for Load Balancing in Heterogeneous Cellular Networks. *IEEE Transactions on Wireless Communications*, Volume 12(6), pp. 2706–2716

Zhou, T., Huang, Y., Huang, W., Li, S., Sun, Y., Yang, L., 2014. QoS-Aware user Association for Load Balancing in Heterogeneous Cellular Networks. *In:* Vehicular Technology Conference (VTC Fall), 2014 IEEE 80th, pp. 1–5