Base Station Preference Association with Network Dynamics

Yifei Huang, Salman Durrani and Xiangyun Zhou

Research School of Engineering, The Australian National University, Canberra, Australia.
Corresponding author email: salman.durrani@anu.edu.au

***Abstract*—Increasing densification in future wireless networks means that user association will play an ever more critical role in the network decision process in order to manage the large number of base stations and users. Though conventional user association aims to maximize a sum rate or capacity related objective, user rate fairness could become a more important consideration for dense networks. In this paper, we propose a downlink base station preference association scheme where users connect to the base station where it is most preferred in terms of the maximum received power. We prove analytically that this scheme results in roughly the same number of users associated to each base station regardless of base station transmit power, and will result in high user rate fairness in dense networks. In addition, we study how the associations change with network dynamics, i.e., users entering and exiting the network (e.g., due to users crossing boundaries of small cells) or base stations entering and exiting the network (e.g., due to base station switching ON or OFF to reduce energy consumption). Our results show that there exists a type of user most likely to re-associate, and that a shrinking network leads to more re-association than a growing one.**

***Index Terms*—User association, heterogeneous networks, network dynamics.**

I. Introduction

User association is a critical process in heterogeneous networks (HetNets) and cellular communications that connects users to suitable base stations as a means of accessing the network [1], [2]. In the literature, user association has been studied using many mathematical approaches, including as a matching problem with parallels to the college admissions game in game theory [3], as an optimization problem [4], [5], or modelled as a stochastic game [6]. Future networks with more dense users and base station deployments will require a deeper understanding of user association mechanisms and more complex schemes to provide the best quality of service to each user. In this regard, conventional user association has aimed to improve a system utility, most commonly sum rate or capacity. Fairness is a popular alternative metric to consider, though often as a secondary thought, e.g., imposed as a constraint rather than an objective to maximize. However, high fairness (in terms of a quantitative measure such as Jain's Fairness Index (JFI)) may be beneficial in scenarios where users might be accessing the same information from the network, and therefore may become a primary objective in user association for future networks.

In addition to achieving desirable quantitative metrics such as fairness and sum rate, a study of the effects of network dynamics on user association and network state is particularly important for future networks. For instance, if the number of users in a large network changes slightly, e.g., one user enters or leaves, the new association may be very similar to the previous, and therefore it is unnecessary to recalculate all associations. Predicting or at least determining probabilities of future user associations to decrease computation can be beneficial to large networks. In this regard, sequential or predictive user association was mentioned in [7], and a similar concept was briefly considered in [8] but with a specific and rigid system model. Although game theory seems to be a suitable technique to study the interaction between user and network behaviour and can lead to suitable strategies to achieve an objective [9], current research generally models each instance (i.e., fixed number of players) as a game or Markov decision process, rather than what happens when the number of players change [10]. Further, game theory is not an analytical tool and thus is limited in its ability to explain trends or predict behaviours. A user entering or leaving a base station is studied in [11] and the Nash equilibrium property is proven to hold, though the focus is on user rates.

The number of base stations in the network may also change depending on factors such as energy saving and network load. Base stations can be turned off during off-peak times to save power [12], while ad hoc base stations such as the ones deployed through drones may be used to serve hotspots or bursty traffic [13]. Entering or exiting base stations can dramatically affect the network state, and consequently a study of network behaviour with base station dynamics can bring insight into network design. To the best of our knowledge, the study of user association to guarantee high fairness in dense networks, including network dynamics such as users and/or base stations entering and exiting the network, is an important open problem.

The main contributions of this work as follows:

- We propose a downlink base station preference association rule where users associate with the base station it is ranked highest in. Compared to the max received power association, where users determine which base station the user wants the most, our association associates users to base stations that want the user the most.
- We analytically prove that this association achieves high JFI fairness, and study how network dynamics (users or base stations entering or exiting the network) affect user associations under this rule. Our analysis provides exact re-association probabilities for users, and determines the effects of network size, association strength and user preference ranking on re-association probabilities.
- Our results indicate that there exists a type of user most likely to re-associate, and that a shrinking network has more effect on user association than a growing one.

978-1-5090-5932-4/17/$31.00

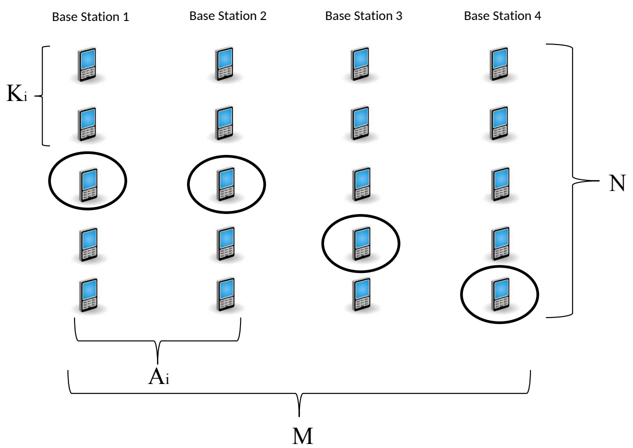

Fig. 1: Illustration of base station preference association and key parameters.

II. System Model and Preference Association

Consider a HetNet with M randomly located base stations, which could be a mixture of macro and small cells. N users are also randomly distributed. Suppose each user calculates the average receive powers from each base station, given by

$$P_j d_{i,j}^{-\alpha}, \tag{1}$$

where P_j is the transmit power of the jth base station, $d_{i,j}$ is the distance in metres between the ith user and jth base station, and α is the pathloss exponent. Each user feeds back the received powers to the corresponding base stations, and the base stations then construct their preference lists, i.e., ranking each user with respect to the received powers. Each list represents the users each base station would most like to associate with.

A. Base Station Preference Association

We define the base station preference association rule as users associating with the base station where it is ranked highest in. The value of this highest rank is termed the *associated rank* of that user. The number of users that are higher than a particular user at its associated rank is $0 \leq K_i \leq N-1$, such that its associated rank is $K_i + 1$.

Note that for a HetNet with small cells and different base station transmit powers, this association rule will be different from the max received power association method, as it is possible for a user to have a smaller received power from a femto than from a macro, but be ranked higher in the femto's preference list. If a user is ranked equal highest in multiple base station lists, the user will randomly pick any of those *tied* base stations to associate with. The number of ties for user i is $0 \leq A_i \leq M$ Fig. 1 illustrates the defined parameters. The circled users are the user appearing in each base station's list.

To define various terminology, we describe a *weakly associated* user as one that has multiple ties for its highest rank (with *more weakly associated* meaning a larger A_i). A *strongly served* user is one where its highest rank is high up in the preference list (small K_i), while a *weakly served* user is one where its highest rank is low in the preference list (large K_i).

III. Fairness Analysis

In terms of Jain's fairness index (JFI) [14], the fairness of user rates is defined as

$$\frac{\sum_{i=1}^{M}(r_i)^2}{M\sum_{i=1}^{M} r_i^2}, \tag{2}$$

where

$$r_i = \log_2\left(1 + \frac{P_j d_{i,j}^{-\alpha}|h_{i,j}|^2}{\sigma^2}\right) \tag{3}$$

is the rate for the ith user without load considerations, $h_{i,j}$ is the Rayleigh channel coefficient and σ^2 is the additive white Gaussian noise power.

Due to the $\log_2$ term, even if the transmit powers are orders of magnitude apart, the actual rate values would be within the same order of magnitude. Therefore, fairness of rates for each user without load considerations would be high, i.e., close to 1.

However, actual rates users experience are dependent on the load of their associated base station, meaning that rates are divided by the number of users also associated with that base station, assuming round robin scheduling of time and frequency resources, i.e.,

$$r_i = \frac{1}{N_j}\log_2\left(1 + \frac{P_j d_{i,j}^{-\alpha}|h_{i,j}|^2}{\sigma^2}\right), \tag{4}$$

with N_j number of users are associated to base station j.

It is easy to see that conventional association rules such as maximum received power or minimum distance may result in unbalanced load distributions. Since the load is a pre-log term, large differences in load will drastically *reduce* rate fairness. In other words, to *maintain* high fairness, it is desirable to have base stations with equal load, e.g., similar number of users associated to them. Mathematically, this is due to the scale invariance property of the JFI - if all rates are scaled by the same factor, JFI will remain the same.

A. Proof of High Fairness for Preference Association

If either base stations or users are randomly distributed, then the probability that a particular user appears in a specific rank on a base station's preference list is $\frac{1}{N}$.

For a particular base station, the probability that a user at rank i will be ranked lower in all other base station lists (i.e., the user is associated to that base station) is

$$\left(\frac{N-i}{N}\right)^{M-1}, \tag{5}$$

since there are $N-i$ positions lower than position i, and $M-1$ other base station lists where this must be true.

Since there are N users, and each user has a $\frac{1}{N}$ chance of being in any of i positions in a base station's list, the expected number of users associated to each base station is therefore

$$\frac{1}{N}N\sum_{i=1}^{N}\left(\frac{N-i}{N}\right)^{M-1} = \frac{1}{N^{M-1}}\sum_{i=1}^{N-1} i^{m-1} \overset{(a)}{=} \frac{1}{N^{M-1}}\times \tag{6}$$

$$\left(\frac{N^M}{M} - \frac{N^{M-1}}{2} + \frac{(M-1)N^{M-2}}{12} + \mathcal{O}(N^{M-4})\right) \tag{7}$$

$$= \frac{N}{M} - \frac{1}{2} + \frac{M-1}{12N} + \mathcal{O}(N^{-3}), \tag{8}$$

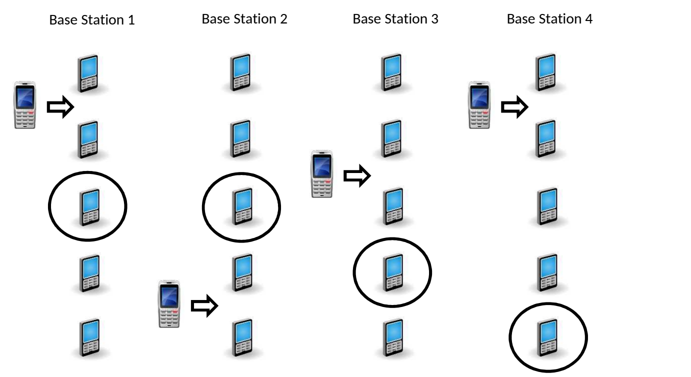

Fig. 2: User entering network. If circled user was initially associated with base station 1, it will now associate with base station 2 since the user in base station 1's list has been pushed down.

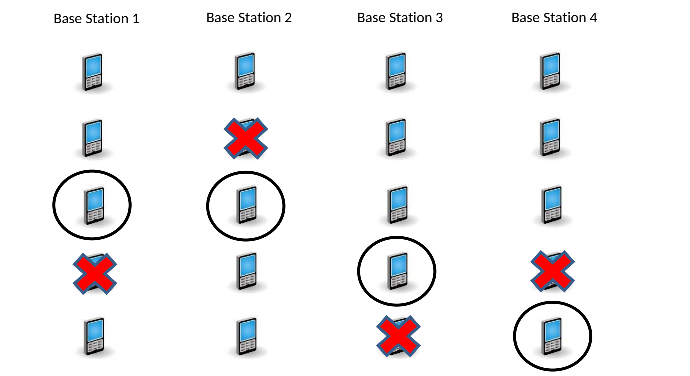

Fig. 3: User exiting network. If circled user was initially associated with base station 1, it will now associate with base station 2 since the user in base station 2's list has been pushed up.

where $\mathcal{O}(N^{-3})$ is a polynomial in N of at most degree -3. The equality (a) is obtained from [15].

For realistic N users and M base stations ($N > M$), $\frac{N}{M}$ will be the dominant term. Thus, users are divided approximately evenly across all base stations, leading to even load distribution and high rate fairness.

B. Distribution of Associated Ranks

The distribution of associated ranks is not uniform, as more users will have a lower-valued associated rank than a higher-valued one.

For a user at rank $K_i + 1$, there is a $\left(\frac{N-K_i}{N}\right)^{M-1}$ probability that its rank in the other $M-1$ base stations will be equal or lower to it. Thus, with M base stations, there are

$$M\left(\frac{N-K_i}{N}\right)^{M-1} \tag{9}$$

users should have $K_i + 1$ as their associated rank.

IV. Association Probabilities with Entering or Exiting Users

If we consider how the associations will change with entering or exiting users, we note that with a single entering or exiting user, the rankings of an existing user will change by at most one position. Therefore, we can deduce that only users that are weakly associated, i.e., have ties where their highest ranking belongs to multiple base stations, will have to switch associations.

A current user's ranking will only change if an entering or exiting user is ranked above, since an entering or exiting user ranked below would not change the ranks of any users above and hence have no effect on the association decision.

A. Entering User

If an entering user is ranked above user i in its associated base station's list, user i will be pushed down from rank $K_i + 1$ to $K_i + 2$, meaning that it may re-associate to one of its tied base stations, provided that in *none* of them is the entering user also ranked above. Thus, the probability that user i will have to change its association due to an entering user is

$$X_{enter} = \frac{K_i+1}{N+1}\left(1-\left(\frac{K_i+1}{N+1}\right)^{A_i-1}\right). \tag{10}$$

The first term $\frac{K_i+1}{N+1}$ is the probability that user i is pushed down in its current associated base station list ($N+1$ because there are that many positions in the list a new user can enter into), while the second is the probability that at least one tied rank out of $A_i - 1$ base station lists retains its position.

B. Exiting User

A current user i will only need to re-associate to another tied base station if an exiting user ($N-1$ possible users) from its associated base station list exists from the last $N - K_i - 1$ ranks (user i maintains its rank), and at least one other tied base station has the exiting user exit from their first K_i ranks (such that at least one tied base station rank gets pushed up). The probability of this occurring, and hence forcing user i to re-associate, is

$$X_{exit} = \frac{N-K_i-1}{N-1}\left(1-\left(\frac{N-K_i-1}{N-1}\right)^{A_i-1}\right). \tag{11}$$

The first term $\frac{N-K_i-1}{N-1}$ is the probability that user i retains its current associated base station rank, while the second is the probability that at least one tied position out of $A_i - 1$ tied base station lists is pushed up.

Verifying when $K_i = 0$, $X_{exit} = 0$, meaning that user will never have to change associations.

C. Effect of A_i, K_i, and N on Association Probability

Plotting each of the parameters while keeping the others fixed shows both expected and unexpected trends.

1) Varying A_i: Increasing the number of ties for a particular user i, i.e., more weakly associated, increases the probabilities of changing association in (10) and (11). This is expected as weakly associated users have more options to re-associate, and are more likely to do so if there is a change in the network.

2) Varying K_i: Interestingly, there exists a value of K_i where a user of that position is more likely to re-associate than any other. This position is neither a strongly nor a weakly served user, but an average served user. The value of this K_i is different for (10) and (11), and can be determined as shown in the Appendix.

This observation can be explained as follows. Strongly served users will not likely need to re-associate, as they have little to benefit from a single entering or exiting user. Weakly served users would also not likely to re-associate as they are likely to receive the same perceived benefits from any re-association, meaning that they are still more likely to have their highest ranking with their current base station.

We note that this finding makes intuitive sense, as it parallels with real life college admissions. Strong candidates will likely to be preferred by most or all colleges, and therefore have little incentive to change their own preferences, as will weak candidates who will stay unpreferred even if some new candidates appear. However, average candidates, who might be preferred by some colleges but not by others, are most volatile in terms of their decision, and will be most affected by any change in the process.

3) Varying N: Increasing the number of users in the whole network decreases the probabilities of changing association in (10) and (11). This is expected since larger networks appear more similar to each other than smaller networks, meaning that associations are more likely to remain unchanged.

V. Association Probabilities with Entering or Exiting Base Stations

Because the addition or removal of a base station does not affect the ordering of existing preference lists, base station dynamics is simpler to analyse than user dynamics.

A. Entering Base Station

With the inclusion of an additional base station, the chance of any particular user switching association to the new base station is $\frac{K_i}{N}$, since there are K_i positions in the new base station's preference list that the i user can be ranked in and switch association to. Therefore, the total number of expected users that may re-associate to the new base station is

$$\sum_{i=1}^{M} \frac{K_i}{N}. \quad (12)$$

B. Exiting Base Station

If the number of base station reduces by one, all users associated with the exiting base station would simply associate with the base station where it was ranked second highest in, or with one of the $A_i - 1$ tied base stations.

VI. Simulation Results

In our simulations, we uniformly randomly distribute $M = 5$ base stations and $N = 100$ users. The base stations are randomly chosen to be either a macro, pico or femto, and all transmit at their maximum powers of 40, 30 and 20 dBm respectively. We set the pathloss exponent to $\alpha = 2$. Channels are Rayleigh fading with mean 0 and noise power $\sigma^2 = -174$ dBm/Hz. We average over 5000 Monte Carlo simulation runs.

Fig. 4 plots the simulated and theoretical distribution of associated ranks. The two plots match almost perfectly, confirming that associated ranks are concentrated towards lower rank values.

Fig. 5 compares the JFI of all user rates from different user association schemes, including maximum received power, nearest base station, and a dynamic range heuristic from [16]. As discussed in Section III, rates without load consideration naturally have a high fairness value. Once load is taken into consideration, our proposed preference association maintains a high JFI, while other associations significantly decrease fairness. If fairness is an important factor, preference association is a much more suitable method compared to conventional associations.

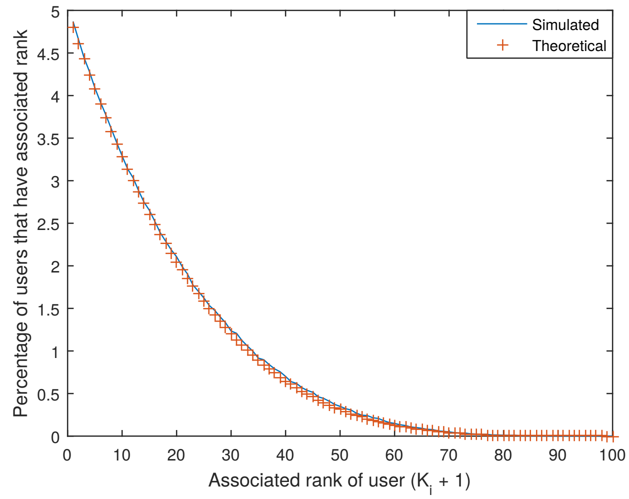

Fig. 4: Distribution of associated ranks as given by (9). Ranks are more concentrated towards lower values.

Fig. 6 plots the percentage of times a user of a particular associated rank will change associations with a single entering or exiting user. Both scenarios show that there exists a rank where users are most likely to re-associate. The results shown here are generated with no fixed A_i, and therefore do not correspond exactly to (10) and (11). However, we observe that the peak of exiting user probability occurs to the right of (i.e., higher valued associated ranks) the peak of entering user probability. This can be explained by jointly considering the findings from Sections III-B and IV.

Our analysis shows that the most likely K_i is generally larger for exiting users than entering users, and hence one would expect a negative skew shape for exiting users, and a positive skew shape for entering users. However, Fig. 6 shows a positive skew for both, which is a result of multiplying individual associated ranks by (9). Since there are more users with a smaller valued associated rank, the final shape of exiting user probabilities will be weighted towards the lower valued ranks, and therefore still be positively skewed. The sum of these probabilities (i.e., area under the plot) multiplied by the total number of users gives the expected number of re-associations due to a single entering or exiting user.

In addition, Fig. 6 shows that exiting users have more of an effect on the network than entering users, which agrees with our intuitions. Larger networks look and behave more similar to each other than smaller networks, since when a network is small each additional user represents a larger percentage of the network. Also, as indicated by (11), no re-associations can occur for users with associated ranks of 1.

VII. Conclusion

We have proposed a new base station preference association scheme where users associate with the base stations who prefer it the most. Our analysis and simulation results confirm that it leads to high fairness compared to conventional association schemes. Using this preference association, we have studied the effects

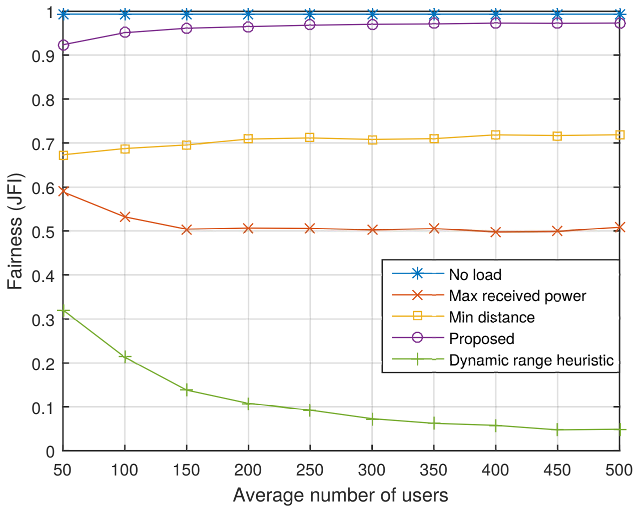

Fig. 5: Fairness of user rates for various association rules with random base station locations and PPP users.

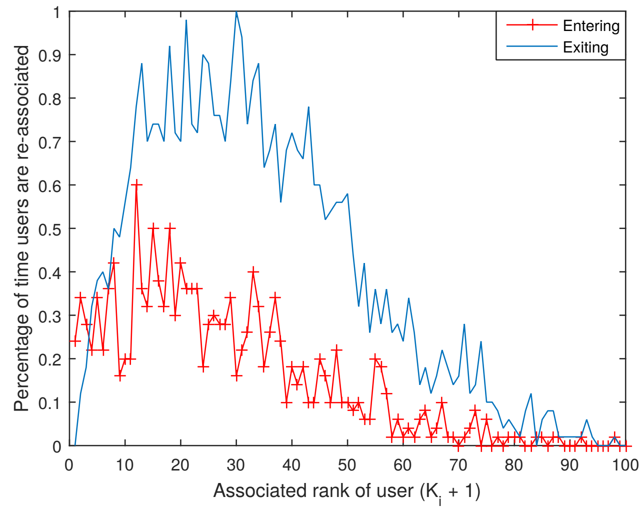

Fig. 6: Percentage of times user of a particular associated rank re-associated due to a single entering or exiting user. Exiting users induces more change in user association than entering users.

of network dynamics, namely entering and exiting single users and base stations, on the user association state. Re-association probabilities and associated rank distributions are derived and verified by simulations. Our results indicate that a typical weakly associated user is mostly likely to re-associate given a network dynamic, and that shrinking network size has more effect on user association than a growing network.

Appendix - Most likely positioned user to re-associate

For fixed and given N, M and A_i, we can find the most likely position where a user may have to re-associate by differentiating (10) and (11) with respect to K_i.

For entering users,

$$\frac{\mathrm{d}X_{enter}}{\mathrm{d}K_i} = \frac{1}{N+1} - \frac{A_i(K_i+1)^{A-1}}{(N+1)^{A_i}}. \tag{13}$$

Setting the above to 0,

$$K_i = \sqrt[A-1]{\frac{(N+1)^{A_i-1}}{A_i}} - 1. \tag{14}$$

For exiting users,

$$\frac{\mathrm{d}X_{exit}}{\mathrm{d}K_i} = \frac{A_i(N-K_i-1)^{A-1}}{(N+1)^{A_i}} - \frac{1}{N+1}. \tag{15}$$

Setting the above to 0,

$$K_i = N - 1 - \sqrt[A-1]{\frac{(N+1)^{A_i-1}}{A_i}}. \tag{16}$$

Thus, the most likely position for a user to re-associate with entering or exiting users is K_i+1, rounded to the nearest integer. Generally, (14) is a smaller value than (16).

References

[1] D. Liu, L. Wang, Y. Chen, M. Elkashlan, K. Wong, R. Schober, and L. Hanzo, "User association in 5G networks: A survey and an outlook," *IEEE Commun. Surveys Tuts.*, vol. 18, no. 2, pp. 1018–1044, 2016.

[2] T. Zhou, Y. Huang, W. Huang, S. Li, Y. Sun, and L. Yang, "QoS-aware user association for load balancing in heterogeneous cellular networks," in *Proc. IEEE VTC Fall*, Sep. 2014, pp. 1–5.

[3] W. Saad, Z. Han, R. Zheng, M. Debbah, and H. V. Poor, "A college admissions game for uplink user association in wireless small cell networks," in *Proc. INFOCOM 2014*, April 2014, pp. 1096–1104.

[4] Q. Ye, B. Rong, Y. Chen, M. Al-Shalash, C. Caramanis, and J. Andrews, "User association for load balancing in heterogeneous cellular networks," *IEEE Trans. Wireless Commun.*, vol. 12, no. 6, pp. 2706–2716, June 2013.

[5] D. Fooladivanda and C. Rosenberg, "Joint resource allocation and user association for heterogeneous wireless cellular networks," *IEEE Trans. Wireless Commun.*, vol. 12, no. 1, pp. 248–257, Jan. 2013.

[6] X. Tang, P. Ren, Y. Wang, Q. Du, and L. Sun, "User association as a stochastic game for enhanced performance in heterogeneous networks," in *Proc. IEEE ICC*, Jun. 2015, pp. 3417–3422.

[7] J. Andrews, S. Singh, Q. Ye, X. Lin, and H. Dhillon, "An overview of load balancing in hetnets: old myths and open problems," *IEEE Wireless Commun. Mag.*, vol. 21, no. 2, pp. 18–25, April 2014.

[8] B. Rengarajan and G. de Veciana, "Practical adaptive user association policies for wireless systems with dynamic interference," *IEEE/ACM Trans. Netw.*, vol. 19, no. 6, pp. 1690–1703, Dec 2011.

[9] D. Liu, Y. Chen, K. K. Chai, and T. Zhang, "Joint uplink and downlink user association for energy-efficient hetnets using nash bargaining solution," in *Proc. IEEE VTC-Spring, 2014*, May 2014, pp. 1–5.

[10] D. Bethanabhotla, O. Y. Bursalioglu, H. C. Papadopoulos, and G. Caire, "Optimal user-cell association for massive mimo wireless networks," *IEEE Trans. Wireless Commun.*, vol. 15, no. 3, pp. 1835–1850, Mar. 2016.

[11] E. Aryafar, A. Keshavarz-Haddad, M. Wang, and M. Chiang, "Rat selection games in hetnets," in *Proc. IEEE INFOCOM*, Apr. 2013, pp. 998–1006.

[12] J. Wu, Y. Zhang, M. Zukerman, and E. K. N. Yung, "Energy-efficient base-stations sleep-mode techniques in green cellular networks: A survey," *IEEE Commun. Surveys Tuts.*, vol. 17, no. 2, pp. 803–826, Second quarter 2015.

[13] E. Kalantari, H. Yanikomeroglu, and A. Yongacoglu, "On the number and 3D placement of drone base stations in wireless cellular networks," in *Proc. IEEE VTC-Fall*, Sep. 2016.

[14] T. Lan, D. Kao, M. Chiang, and A. Sabharwal, "An axiomatic theory of fairness in network resource allocation," in *Proc. IEEE INFOCOM*, March 2010, pp. 1–9.

[15] A. Beardon, "Sum of powers of integers," *American Mathematical Monthly*, pp. 201–213, March 1996.

[16] S. Corroy, L. Falconetti, and R. Mathar, "Dynamic cell association for downlink sum rate maximization in multi-cell heterogeneous networks," in *Proc. IEEE ICC*, Jun. 2012, pp. 2457–2461.