A Network Graph Approach for Network Energy Saving in Small Cell Networks

Tao Chen*, Xianfu Chen*, Roberto Riggio[†]

* VTT Technical Research Centre of Finland, P.O. Box 1100, FI-90571 Oulu, Finland
[†] CREATE-NET, via Alla Cascata 56/D, 38123 Povo, Trento, Italy

Abstract-Small cell networks are key components in 5G networks to boost the network capacity, improve spectrum and energy efficiency, and enable flexible and new services. Due to the flexible spectrum access among and flexible deployment of small cells, the inter-cell coordination becomes critical for the performance of the network. In this paper, based on the key concept in software defined networking (SDN) for Internet, we first introduce the network graph approach as a tool for the control and coordination among small cells. The network graph is constructed from the abstracted network state information extracted from underlying base stations. It shields the logical centralized control unit from implementation details of the underlying physical layer and thus reduces the control overhead in a centralized solution. We use the network graph for network energy saving in small cell networks, in which network graphs are used to decide the optimal set of small cells in the network. For cells outside this set we can switch them off for energy saving. We propose three types of network graphs with different network state details. Based on these graphs, we formulate the energy saving problem as an integer linear programming (ILP) problem, and propose the practical algorithms to solve the problem. The performance of the algorithms are studied by simulation. It shows the potential of the proposed network graph approach for the inter-cell resource coordination in small cell networks.

I. INTRODUCTION

Mobile networks are evolving to the next generation, in which small cells are expected to play an important role [1]. Since 2012 the number of small cell base stations (BS) around the world has surpassed that of traditional cellular BSs. The prevalence of small cells brings higher network capacity, lower energy consumption, more efficient use of spectrum, and lower operational expenditure (OPEX). Meanwhile, the wide and dense deployment of small cells introduces new research challenges. New solutions are demanded for spectrum management, interference coordination, traffic steering, mobility, backhaul technologies and energy efficiency.

Technical challenges regarding small cells are well summarized in [2]. Due to the spectrum reuse with macrocells and among small cells, the interference coordination and joint resource allocation among the network become necessary [3]. This requires efficient coordination among cells. In multitier cellular networks with small cells, traffic offloading is an important means to balance the resource utilization in the network [4]. However, the load coupling in small cells makes the traffic offloading decision a complex optimization problem [5]. In addition to conventional optimization approaches, both centralized and distributed learning algorithms are proposed [4]. Traffic offloading is utilized to improve energy efficiency in multi-tier cellular networks [6].

While many research problems in small cell networks have been intensively studied in recent years, they are based on the current 3G and 4G cellular network architecture. The coupling in small cells with regard to spectrum access, interference and traffic load calls for effective and efficient inter-cell coordination. Similar to software defined networking (SDN) for Internet, the logical centralized control will be a powerful means to solve the cooperation and coordination problem in small cell networks.

The centralized control solution can be tracked back to 2G systems. However the flexibility and scalability are missing therein for large scale small cell networks. New control architecture for next generation mobile networks is needed. We proposed in [7] the software defined (SD) radio access networks (RAN) control architecture to satisfy this need. The key idea is to introduce a logical centralized control and coordination framework for heterogeneous mobile networks, in which network graphs reflecting low layer states of networks are used at central control units for inter-cell resource coordination.

This paper develops coordination algorithms based on the proposed control framework. We focus on the network energy saving problem in small cell networks. Since a user in the network may be covered by multiple cells, by re-associating users in the network, some cells in the network can switch to the energy saving mode. With network awareness by the proposed control framework, we can turn the working cell selection problem to a graph problem and solve it by rich optimization tools. The main contribution of this paper is to propose different network graphs, develop working cell selection algorithms, and study the energy saving performance of different network graphs.

We first introduce the abstract network graph concept. The network graph captures the abstracted network states of the underlying RANs and offer to tune selected parameters for network re-configurations. Based on the proposed network graphs, we develop algorithms to find the optimal cell set, which satisfies the quality of service (QoS) needs of users while minimizing the working cells in the network. Finally we evaluate the performance of the proposed cell selection algorithms.

II. NETWORK GRAPH APPROACH

The network graph approach introduced in this paper is based on the SD-RAN control architecture proposed in [7]. Similar to the idea in the SDN concept for Internet, the proposed approach aims to enable a logical centralized control solution for large scale heterogenous mobile networks. It can be used to improve spectrum management, network energy saving, mobility management, and other middle to long term network re-configurations in mobile networks.



Fig. 1. An example of heterogenous mobile network and three derived network graphs.

The network graph approach could be realized by additional control interfaces, protocols and control units within current cellular and wireless local area network (WLAN) network architecture. With necessary extensions, BSs and access points (AP) are functioned to report abstracted network states to logically centralized control units so that network graphs reflecting the underlaying radio network reality are formed at these control units, updated and used to tune necessary network parameters according to network performance targets.

Fig. 1 provides an example of network graphs used in this paper. In a network graph, an edge presents a feasible connection between a BS/AP and use equipment (UE). While we focus on long term evolution (LTE) networks in this study, instead of using the terms eNodeB and home eNodeB for macrocell and small cell BS, we use macrocell BS (MBS) and small cell BS (SBS) through the paper. The general term BS stands for both MBS and SBS. Moreover, we mix the use of the term cell, BS and AP.

According the details of reported state information, different types of network graphs may be generated. For instance, Fig. 1(a) only shows feasible connections between BS and UEs; Fig. 1(b) includes the path loss between BS and any potential UE, and therefore the interference-free link rate to a reachable BS; Fig. 1(c) contains channel states among BSs and UEs, which allow to estimate inter-cell interference in the network graph. Incorporating additional information like power, traffic load, spectrum and QoS requirements in the network graph, different algorithms can be developed to get the optimal set of working BSs for network energy saving.

Centralized solutions for large scale networks normally suffer from the scalability and overhead problem. One key idea in the proposed SD-RAN control framework [7] is to extract abstracted and only necessary network state information from the physical and MAC layer of RANs to the logical central control unit. The abstraction here means that the central control unit needs not to know physical layer implementation details of underlying radio access technologies (RAT) but just necessary information to construct the abstracted view of underlying networks for inter-cell resource coordination and control. Therefore it is critical to understand the principles to abstract low layer states for this control purpose. We do not provide details on this subject in the paper.

III. SYSTEM MODEL

We study in this paper the network energy saving performance of different types of network graphs depicted in Fig. 1. The objective is to determine a minimal set of BSs in the network with coverage and capacity satisfying the QoS needs of UEs. We assume the above-mentioned SD-RAN architecture is available. We will develop BS selection algorithms based on available network graphs to obtain the minimal BS set.

More specifically, assume in a given region we have K regularly deployed MBSs, N ad-hoc deployed SBSs, and M' UEs which have low mobility. SBSs provide the open access to UEs. A UE only connects to one BS at a time. The MBSs and SBSs share the spectrum of the total bandwidth W. The spectrum access among MBSs and SBSs is flexible. They can use the spectrum partition method to avoid inter-cell interference when the network traffic load is low, or otherwise the spectrum sharing to improve the network capacity. We assume the central control unit will decide the proper spectrum access method for individual cells according to the network traffic conditions.

We study the downlink traffic in this paper. But the work can be easily extended to the uplink and mixed cases. We assume the perfect neighbor discovery of a UE. A UE u_i is able to accurately estimate channel gain h_{ij} to the neighboring cell B_j . Therefore the average channel gain h_{ij} is available in the network graph. For simplicity, we assume same type of BSs use the same transmission power. The transmission power for the MBS is P_M , and for the SBS is P_H . With the transmission power and channel gain available, a UE can find with which BSs it can associate by evaluating the signal to noise ratio (SNR). Each UE has its minimal data rate requirement. For simplicity, we assume all UEs have the same rate requirement R. In our study, a BS tries to satisfy that rate to UEs. With the SNR and assigned bandwidth the interference-free link rate between a BS and UE is estimated in the network graph. Assuming the UE takes all bandwidth W, the link rate between the UE u_i and the BS B_j is r_{ij} . The share of resource allocated by B_j to u_i is R/r_{ij} . The load of B_j , denoted by L_j , is the sum of R/r_{ij} from all associated UEs. We assume a BS will serve the load L_j and then turn to the idle mode. That means no extra data rate is provided for UEs. Note that those are assumptions used in the network graph to decide the working BS set. The actual data rate of a UE depends on the scheduling algorithm by the BS and inter-cell interference.

The inter-cell interference in a spectrum sharing network is a complex problem, mainly due to the coupling of inter-cell interference. In this paper we use a simple interference model in the network graph. We will use more realistic models as in [3][8] in our future work. We define two cells are neighbors when at least one UE can connect both. If the sum load of two neighboring cells is less than one, we assume a perfect intercell scheduling among them and thus no inter-cell interference. Otherwise, the UEs covered by both cells may suffer inter-cell interference and the amount is determined by the total load of both cells. In reality the inter-cell interference is worse and unpredictable. Therefore the actual data rate of an UE may be less than the required R.

Following the power consumption model of LTE home eNodeB in [9], we assume it will consume 10 watts if switching on and 0 watt otherwise. Since the MBS needs to be always on in order to ensure the coverage, we assume it consumes the constant power and then leave it out in the computation of the minimal BS set. In the future study, we will take into account the load dependent power consumption model of the MBS and jointly consider MBSs and SBSs in the algorithms. Since we assume the SBSs consumes the same amount of power, the problem turns to find the minimal dominating set of small cells with the QoS constraints of UEs.

Three network graph models are used in the algorithm development. All network graphs have the incident matrix $A_{[N \times M]}$, indicating $A_{ij} = 1$ if u_i can associate with B_j , and otherwise $A_{ij} = 0$. Note that we only consider the SBSs in the network graph. UEs have the priority to connect to SBSs for high data rates. In the case of the first network graph shown in Fig. 1(a), the QoS constraint of the UE is not considered so the algorithm will obtain the minimal BS set. The case of the second network graph considers the data rate requirement of the UE and the capacity limit of the SBS, but inter-cell interference is not considered. The third case considers inter-cell interference on top of the second case. The afore-mentioned simplified inter-cell interference model is applied.

IV. PROBLEM FORMULATION BASED NETWORK GRAPH

Given the set of UEs $\{u_i : i = 1 \cdots M'\}$ in which M of them are covered by SBSs, the set of BSs $\{B_j : i =$

 $1 \cdots K + N$ in which N of them are SBSs, the average power consumption P_j^e for the MBS B_j and P_j^h for the SBS B_j , the incident matric A from the network graph, the data rate requirements of UEs as R, the channel gain between BS and UE in network graph, and the transmission power of BSs as P_M and P_H for MBS and SBS respectively, the original problem is to minimize the total average power consumption of the network as:

$$\min \sum_{j=1}^{K} P_j^e + \sum_{j=1}^{N} y_j P_j^h$$
(1)

where y_j is the indicator variable, while $y_j = 1$ if the SBS B_j is in the working BS set or otherwise 0.

As we discussed in Section III, the problem in Eqn. (1) can be reduced to:

$$\min \sum_{j=1}^{N} y_j \tag{2}$$

subject to:

$$y_j \ge x_{ij} \tag{3}$$

$$\sum_{j=1}^{N} x_{ij} = 1$$
 (4)

$$A_{ij} \ge x_{ij} \tag{5}$$

and the QoS constraints:

$$\sum_{i=1}^{M} \alpha_{ij} \le 1 \tag{6}$$

$$\alpha_{ij} = R/r'_{ij} \tag{7}$$

where $x_{ij} = 1$ if $u_i \in B_j$ or otherwise $x_{ij} = 0$; α_{ij} is the portion of resource taken by u_i from B_j , and $L_j = \sum_{i=1}^M \alpha_{ij}$; r'_{ij} is the link rate between u_i and B_j . In this study, we get α_{ij} from Eqn. (7) where r'_{ij} is estimated by assuming u_i takes all bandwidth W for its transmission. Depending on the algorithm, r'_{ij} may or may not take into account the intercell interference. If no inter-cell interference is considered, $r'_{ij} = r_{ij}$.

In the above formulated problem, the constraint in (3) only allows a UE to associate with one BS in the selected working BS set; the constraint in (4) limits a UE to connect only with one BS; the constraint in (5) associates a UE only with reachable BSs; the constraint in (6) adds the capacity limit of a BS to the problem.

In the following we refine the problem in three network graphes as described in Section III.

A. Network graph case I

We have no QoS constraints in this type of network graph. The problem takes the simplest form, which is formulated by Eqn. (2-5). It is an integer linear programming (ILP) problem, which can be effectively solved.

The solution provides the lower bound of the problem in Eqn. (2). However the solution may end up with no realistic

result as the cell capacity and interference are not considered. We will use the case I as the reference model to the other algorithms.

B. Network graph case II

In this type of network graph, we do not consider the interference from other cells. Therefore we have $r'_{ij} = r_{ij}$, which is the interference-free link rate for $u_i \in B_j$ in Eqn. (7). The problem is formulated by Eqn. (2-7), which remains an ILP problem. Due to the QoS constraint, the problem may have no solution. In this case we will use other association method, for instance, a UE associates with a BS with the best SNR. Therefore, the outcome may result in more cells than that of the case I.

C. Network graph case III

The inter-cell interference is considered in this network graph. However, as far as the load coupling is concerned, the change of load and association in one cell will affect the interference to other cells and thus the achievable rate of UEs. The problem is not any more a linear programming problem. It involves the complex interference calculation and even demands the power control at BSs to find the minimal working BS set .

To simplify the problem, we use a simple interference model to calculate r'_{ij} in Eqn. (7). For $u_i \in B_j$, it has a number of neighbor cells, defined in $S = \{B_q : q = 1 \cdots Q\}$. Then the probability of collision with a neighboring cell in S is

$$p_{iq}^{c} = \begin{cases} 0, & \text{if } L_{j} + L_{q} \le 1\\ L_{j} + L_{q} - 1, & \text{otherwise} \end{cases}$$

The probability that u_i will have a successful transmission is then: $p_{ij}^s = \prod_{q \in S} (1 - p_{iq}^c)$. We can get the r'_{ij} as $r'_{ij} = p_{ij}^s r_{ij}$.

It turns the problem to an ILP problem. However, the interference model will underestimate the real interference in the network, making the actual data rate of u_i less than R. Moreover, the ILP problem may have no solution due to the QoS constraint. We use the same approach as in the case II to find the working BSs.

V. WORKING BS SELECTION ALGORITHM

This section describes the proposed algorithm. Since the computation overhead of the ILP problem is proportional to the size of the network and the number of UEs, we first explore the structure of the network graph to reduce the computation complexity.

For all BSs in the graph, two BSs are connected if they are neighboring BSs. In a connected BS set, any two BSs are connected directly or through other BSs. A connected BS set and the UEs covered by them form a sub-graph. While it depends on the network topology, normally an ad-hoc deployed network can be decomposed to several small size subnetworks. By applying well established graph decomposition methods, e.g. DulmageMendelsohn decomposition [10], we can easily obtain the set of sub-graphs. We apply the algorithm

on the sub-graphs. The combined results from all sub-graphs give the solution for the all network.



Fig. 2. Flow chart of algorithm.

The flow chart of the algorithm is shown in Fig. 2. Note that all three network graph cases use the same flow chart. First, the network graph is created by using the reported states from low layers. The graph decomposition will then break down the network graph into several sub-graphs. For each sub-graph, the ILP problem is set up and solved. We get the new working BS set by the results from all sub-graphs. The new result is compared with the previous result, and the new configuration will send to the underlying BSs if two results are different.

VI. SIMULATION STUDY

The performance of the algorithms is studied by simulation based on MATLAB. We deploy one MBS in the middle, and a number of SBSs and UEs uniformly distributed in a playground of size 500m \times 500m. The SBS has the transmission power of 15dBm, and the coverage of 40m. As not all UEs are covered by the SBSs, the uncovered UEs will be served by the MBS. We assume the spectrum partition between MBS and SBS and thus no interference between the MBS and SBSs. The simplified spectrum access model allows us to focus on the network graph approach for SBSs. In the future work we will study more realistic spectrum sharing models.

The bandwidth used by the SBSs is 1MHz. The path loss model from [11] is used in the small cell path loss calculation, i.e. $L(dB) = 37 + 32 \log_{10}(d)$, where L(dB) is the path loss in dB, d is the distance between the SBS and UE.

To test the performance of algorithms under different QoS requirements, three data rate requirements are set for UEs, standing for very low, moderate, and very high data rate requirements compared to the capacity of the SBS. We assume the normal number of UEs in a SBS is 6. Under the system parameters listed above, 6 UEs at the edge of an SBS can each achieve 2.7Mbit/s. This is the moderate rate set in our simulation. The other two rates are then set as 2.7Kbit/s and 6Mbit/s.

We develop the bestRate algorithm as a reference to compare the performance. In this algorithm, UEs simply associate



Fig. 3. The number of working SBSs under different number of UEs in the network. Network setting: 5 and 65 SBSs. Data rate requirement of UEs: 2.7Mbit/s.



Fig. 4. The number of working SBSs under different number of UEs in the network. Network setting: 5 and 65 SBSs. Data rate requirement of UEs: 6Mbit/s.

with the SBSs with highest SNR. The data rate requirement of UEs is not considered in this reference algorithm.

Firstly we compare the number of working BS set obtained from each algorithm. Note that since each working SBS has the fix power consumption of 10W, the number of working BS reflects the total power consumption of SBSs. Therefore we only show the SBS number in the simulation results.

Fig. 3-4 show the results of bestRate and three developed algorithms under different QoS requirements and different SBS settings. ILP, ILP-QoS and ILP-intf in the figures are the algorithms from the network graph case I-III, respectively. We can see from the 5 SBSs case, the performance of all algorithms in both figures are similar. It is because the UEs have less cells in the network to associate. When the SBSs in the network increase to 65, the best result is achieved by the

ILP algorithm in both Fig. 3-4. If the QoS requirement are taken into account, since the SBS in Fig. 3 has the sufficient capacity to support nearby UEs, ILP, ILP-QoS and ILP-intf have the similar performance. However, when the data rate requirement increases to 6Mbit/s, ILP-QoS and ILP-intf will need more SBSs being switched on as the number of UEs in network increasing. But they still out-perform the bestRate algorithm when the data rate requirement of UEs is 6Mbit/s.

The performance of all proposed algorithms under different data rate requirements is compared in Fig. 5. When the data rate requirements is small, as in the case of 27Kbit/s, all algorithms produced the same results under all network settings. When the data rate requirement is moderate, i.e. 2.7Mbit/s, the differences of all algorithms are very small at the low UE numbers, but increase with the UE numbers. As expected, ILP results in the smallest number of SBSs. ILP-



Fig. 5. The number of working SBSs under different number of UEs and different data rate requirements in the network. Network setting: 35 SBSs.



Fig. 6. Actual data rate by UEs under different number of UEs in the network. Network setting: 65 SBSs. Data rate requirement of UEs: 2.7Mbit/s.



Fig. 7. Actual data rate by UEs under different number of UEs in the network. Network setting: 65 SBSs. Data rate requirement of UEs: 6Mbit/s.

QoS outperforms ILP-intf because the interference considered in ILP-intf leads to more working SBSs to offer the QoS support. When the data rate requirement is as high as 6 Mbit/s, which make a cell to easy out of the capacity to support UEs, ILP-QoS and ILP-intf need more working SBSs than ILP, and the difference increases quickly as the number of UEs in the network grows. ILP-QoS and ILP-intf have the similar results because even no interference is considered, ILP-QoS needs more working SBSs to support the QoS of UEs.

Actual received data rate per UE is shown in Fig. 6-7. That is the data rate taken into account the simple interference model described in Section IV. When the number of UEs increases, the actual data rate decreases. In both figures, the ILP algorithm produces the minimal number of working SBSs. But the UEs suffer more inter-cell interference and the actual data rate is compromised. When the data rate requirement is moderate as in Fig. 6, bestRate, ILP-QoS and ILP-intf have the similar actual data rate. Under the high data rate requirement as in Fig. 7, ILP-intf has the same data rate results as bestRate, because in most cases no optimal solutions will be found for the ILP-intf problem due to the QoS constraints. The UEs have to use the bestRate approach to find their associations. ILP-QoS provides the best actual data rate.

VII. CONCLUSION

In this paper, we introduce a network graph approach to offer efficient centralized network coordination for large scale heterogeneous mobile networks. Based on the proposed network graph, we study the BS switch on/off problem for network energy saving in small cell networks. We propose a simple inter-cell interference model to simplify the working cell selection problem and formulate the problem as an ILP problem. The simulation study shows the impact of the QoS requirement on the optimal number of cells to serve the network. Since in small cell networks the load is normally coupled, the network graph approach could be a very useful tool to optimize resource allocation among small cells and improve network energy efficiency. In the future work, we will consider more realistic interference models and study the joint spectrum allocation and traffic steering for the trade off between network capacity and energy efficiency.

REFERENCES

- J. G. Andrews, S. Buzzi, W. Choi, S. V. Hanly, A. Lozano, A. C. Soong, and J. C. Zhang, "What Will 5G Be?" *IEEE Journal On Selected Areas In Communications*, vol. 32, no. 6, pp. 1065–1082, 2014.
- [2] J. G. Andrews, H. Claussen, M. Dohler, S. Rangan, and M. C. Reed, "Femtocells: Past, Present, and Future," *Selected Areas in Communications, IEEE Journal on*, vol. 30, no. 3, pp. 497–508, 2012.
- [3] S. Singh and J. G. Andrews, "Joint Resource Partitioning and Offloading in Heterogeneous Cellular Networks," *Wireless Communications, IEEE Transactions on*, vol. 13, no. 2, pp. 888–901, 2014.
- [4] X. Xianfu, J. Wu, Y. Cai, H. Zhang, and T. Chen, "Energy-Efficiency Oriented Traffic Offloading in Wireless Networks: A Brief Survey and A Learning Approach for Heterogeneous Cellular Networks," *Selected Areas in Communications, IEEE Journal on*, vol. 33, no. 4, pp. 627–640, 2015.
- [5] C. K. Ho, D. Yuan, and S. Sun, "Data Offloading in Load Coupled Networks: A Utility Maximization Framework," *IEEE Transactions on Wireless Communications*, vol. 13, no. 4, pp. 1921–1931, Apr. 2014.
- [6] Ł. Budzisz, F. Ganji, G. Rizzo, M. Ajmone Marsan, M. Meo, Y. Zhang, G. Koutitas, L. Tassiulas, S. Lambert, B. Lannoo *et al.*, "Dynamic Resource Provisioning for Energy Efficiency in Wireless Access Networks: a Survey and an Outlook," *IEEE Communications Surveys & Tutorials*, no. 99, 2014.
- [7] T. Chen, H. Zhang, X. Chen, and O. Tirkkonen, "SoftMobile: Control Evolution for Next Generation Heterogeneous Mobile Networks," *Wireless Communications, IEEE*, vol. 21, no. 6, pp. 70–78, 2014.
- [8] Y. S. Soh, T. Q. Quek, M. Kountouris, and H. Shin, "Energy Efficient Heterogeneous Cellular Networks," *Selected Areas in Communications*, *IEEE Journal on*, vol. 31, no. 5, pp. 840–850, 2013.
- [9] M. Imran and E. Katranaras, "ICT-EARTH Project, Deliverable D2. 3, EC-IST Office, Brussels, Belgium (January 2011)."
- [10] A. L. Dulmage and N. S. Mendelsohn, "Coverings of Bipartite Graphs," *Canadian Journal of Mathematics*, vol. 10, no. 4, pp. 516–534, 1958.
- [11] D. Cichon and T. Kurner, "EURO-COST 231 Final Report," Tech. Rep., Tech. Rep., 1998.