Bi-SON: Big-Data Self Organizing Network for Energy Efficient Ultra-Dense Small Cells

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***Abstract*—In this paper, we present a big-data self organizing network (Bi-SON) framework aiming to optimize energy efficiency of ultra-dense small cells. Although small cell can enhance the capacity of cellular mobile networks, ultra-dense small cells suffer from severe interference and poor energy efficiency. The self organizing network (SON) can automatically manage and optimize the system performance. However, current SON-enable mechanisms mostly focus on indoor femtocells. Our proposed Bi-SON suggests a data flow framework from data collection, analysis and optimization to reconfiguration. We adopt the statistics analysis approach to determine the optimal system parameters to improve the energy efficiency of a huge number of outdoor small cells. The Bi-SON mechanism periodically collects the management data of small cells, e.g. transmission power, reference signal receiving power and the number of users per cell. We find that simple sorting and filtering data analysis from huge number of small cells can already effectively find the almost optimal solution. Our simulation results show that Bi-SON can improve throughput and energy efficiency by 50% and 135% respectively, compared to the scheme without energy saving approach.**

***Index Terms*—Big-data; energy efficiency; self organizing network; ultra-dense small cell.**

I. INTRODUCTION

To meet massive mobile data traffic demand in the next decade, the ultra-dense small cell network is an explicit trend in the future network deployment. The network operators deploy small cell densely with almost 100% coverage for serving the huge access demands.

Generally, when ultra-dense small cells deployment is considered, energy consumed and serious co-channel interference in the small cell layer becomes more significant. If there is no intelligent and automated small cells management strategy, users will suffer serious interference and the operators will have high operational expense (OPEX).

Operators can utilize the self organizing network (SON) to automatically manage and optimize the system performance for lower OPEX [1]. In the current SON framework [2], the static analysis model can not dynamically update the decision function according to the variations of active user densities to optimize the system at any time moment. Therefore, the SON framework may need the optimization algorithm with a dynamic analysis model to improve the co-channel cell interference and the energy efficiency.

In the literature, most papers [3], [4] studied SON-enable mechanisms for indoor femtocells. In [3], the authors proposed a novel self-optimization mechanism for femtocells, which can improve indoor coverage and promote energy efficiency of networks. The paper [4] proposed a reinforcement-learning based SON framework for interference management in femtocells networks. However, these papers [3], [4] did not consider outdoor small cells to improve the energy efficiency in the SON framework. In addition, most papers [5], [6] investigated the energy saving schemes with the power switched mechanism. In [5], the authors designed a novel database-aided mechanism to help macro cells control the sleeping mode of small cells for energy saving in the heterogeneous network. The paper [6] proposed a small cell on/off scheme to improve the throughput and energy efficiency of an ultra-dense centralized/cloud radio access network with various densities of small cells. However, these papers [5], [6] did not consider the power adjustment scheme to improve the energy efficiency in the SON framework.

In this paper, we develop a big-data self organizing network (Bi-SON) framework with data-driven dynamic power control scheme to improve energy efficiency of the outdoor ultra-dense small cell network system. The Bi-SON combines a data-driven dynamic analysis (D3A) model and an interference-aware (IA) energy saving algorithm into the data-driven dynamic power control scheme to optimize the energy efficiency and total cell throughput for the ultra-dense small cell network. Simulation results show that the proposed Bi-SON with data-driven dynamic power control scheme can improve 50% higher cell throughput and 135% higher energy efficiency respectively, compared to the approach without any power control in the 5G ultra-dense small cell network.

The remainder of the paper is organized as follows. Section II introduces the system architecture, channel model and performance metrics. The Bi-SON framework and the data-driven dynamic power control scheme are detailed in Section III and IV, respectively. We show the simulation results in Section V. Finally, our concluding remarks are given in Section VI.

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II. System Model

A. System Architecture

We consider a downlink ultra-dense small cell network with a power adjustment mechanism. The cell layout is set according to small cell deployment scenario in 3GPP LTE Release 12 standardization [7], as shown in Fig. 1. ~~We assume that the macro cell and the small cell use different frequency for transmission so that there is no cross-tier interference, and the co-channel interference exists only in the small cell layer.~~ Each small cell and each user is equipped with only one isotropic antenna. As small cells are deployed densely in some typical hot pots in ultra-dense network scenario, small cell clusters are formed in hot spots. We assume three sectors in a macro cell, four clusters in a sector and ten small cells in a cluster. Total 120 small cells are deployed in the macro cell coverage. The radius of each cluster is 50 m and the small cell density in a cluster is 1300 cells/km^2, which is considered for an ultra-dense deployment. On the other hand, users are randomly deployed around the area with the radius of 70 m from cluster center in each cluster. We consider the variations of active user densities over time.

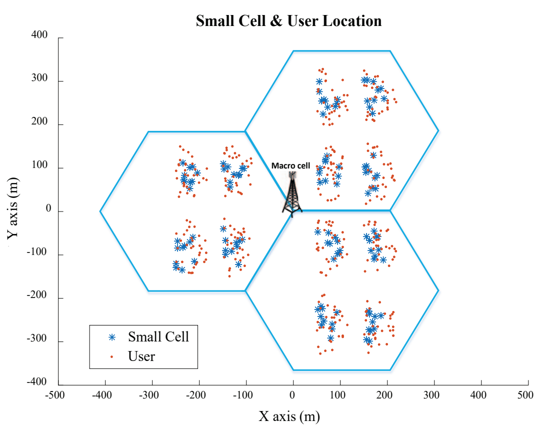

Fig. 1. The downlink heterogeneous network system.

B. Channel Model

We consider the radio propagation effects, including path loss and shadowing, to evaluate the co-channel interference in the ultra-dense small cell network. The receive power of the user n from the small cell q, denoted by $P_{R,q,n} = P_{T,q}\xi d_{q,n}^{-\alpha}$, where $P_{T,q}$ represents the transmission power from a small cell q. α is the path loss exponent and $d_{q,n}$ is the distance between the user n and the small cell q. Shadowing is modelled by a normal distribution $10log_{10}\xi$ with zero mean and standard deviation σ_ξ, where ξ is a random variable with log-normal distribution.

C. Performance Metrics

We assume that there are N users and Q small cells in the ultra-dense small cell network. The downlink signal to interference plus noise power ratio (SINR) from the small cell q to the user n can be expressed as

$$SINR_{q,n} = \frac{P_{R,q,n}}{\sigma^2 + \sum_{l \neq q} P_{R,l,n}} \ , \tag{1}$$

where $P_{R,q,n}$ is the receive power from the small cell q to the user n. $P_{R,l,n}$ is the interference power from the small cell l to the user n in the small cell q. σ^2 is the background noise.

To maximize the sum utility of data rate, we assume that the system uses a full-buffer traffic model [8]. The served users share the total bandwidth of the attached cell. The overall cell throughput R of the system and the data rate r of the user n can be defined as

$$R = \sum_{q}^{Q}\sum_{n} r_{q,n} = \sum_{q}^{Q}\sum_{n} \frac{B}{M_q} log_2(1 + SINR_{q,n}) \ , \tag{2}$$

where M_q represents the number of served users in the small cell q. B is the bandwidth of each small cell. The spectral efficiency of the user n which served by the small cell q can be expressed as $log_2(1 + SINR_{q,n})$.

When no user is connected to a small cell, the small cell can be switched to the sleeping mode for saving power and reducing the interference to adjacent cells. We assume that a small cell q consumes $P_{sleep,q}$ watt under the sleeping mode or $P_{active,q} = P_0 + \frac{1}{\eta}P_{T,q}$ watt under the active mode. P_0 is the basic consumption of circuit depending on the small cell type, and η is the power amplifier (PA) efficiency. The transmission power of the active and the sleeping mode is P_T watt and 0 watt, respectively. In addition, in the dense small cell region, the small cell caused the strongest interference to neighboring cells should give the priority to be reduced transmission power for decreasing interference and energy consumption. The power control decision is made by central controller like a macro cell. Consequently, the total energy consumption of the system can be represented as

$$\begin{aligned} P_{total} &= \sum_q P_q = \sum_q [\alpha_q P_{active,q} + (1-\alpha_q)P_{sleep,q}] \\ &= \sum_q [\alpha_q (P_0 + \frac{1}{\eta}P_{T,q}) + (1-\alpha_q)P_{sleep,q}] \ , \end{aligned} \tag{3}$$

where $\alpha_q \in \{0, 1\}$. If the small cell q is in the sleeping mode, $\alpha_q = 0$, and the small cell q is in the active mode as $\alpha_q = 1$.

We define that the energy efficiency $E(Mbits/J)$ is the ratio of the total cell throughput R to the total power consumption P_{total}, which can be represented as

$$E = \frac{Overall\ cell\ throughput}{Total\ power\ consumption} = \frac{R}{P_{total}}. \tag{4}$$

III. The Framework of Big-Data Self Organizing Network (Bi-SON)

Figure 2 shows the block graph of our proposed Bi-SON framework. In the following, we illustrate the block of the framework step by step:

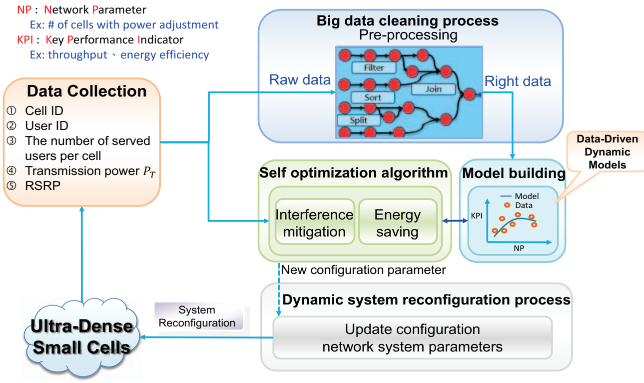

Fig. 2. The framework of energy efficient Bi-SON.

1) Data collection: This step is set to gather massive management data from the ultra-dense small cell network. The data include the number of users per cell, transmission power, reference signal receiving power (RSRP), and so on.
2) Big data cleaning process: Unprocessed massive management data are called big raw data. This block performs data pre-processing via underlying data analytics (e.g., sort, filter) to extract useful right data from big raw data. The right data contain key performance indicator (KPI) (e.g., throughput, energy efficiency) with the corresponding network parameter (NP) (e.g., the number of cells with power adjustment).
3) Model building: The right data are used by this block which employs statistics analysis approach to derive the functional relationship, known as model, between the KPI and the NP. The statistics analysis approach used in this work is polynomial regression (PR). The model can dynamic update the polynomial coefficients to fit data distribution at the moment. Due to periodically collecting management data, the model is called a data-driven dynamic analysis (D3A) model.
4) Self optimizing algorithm: Massive management data are injected into this block to calculate the energy efficiency of the ultra-dense small cell network. When the energy efficiency is less than a preset threshold, our proposed interference-aware (IA) energy saving algorithm is triggered and this block extracts the most appropriate NP from the D3A model to make the optimal decision. Consequently, this block determines new configuration parameters for system reconfiguration to achieve improving network performance.
5) Dynamic system reconfiguration process: The new configuration parameters are injected into the source cellular network to update configuration parameters and improve the system performance.

We propose a promising framework for empowering SON with big data to implement intelligent procedure and to satisfy the performance requirements of 5G. In the next section, we illustrate data-driven dynamic power control scheme which is considered for the core technique of the Bi-SON framework.

IV. Data-Driven Dynamic Power Control Scheme

A. Interference-Aware (IA) Algorithm

The data-driven dynamic power control scheme includes both data-driven dynamic analysis (D3A) model and interference-aware (IA) energy saving algorithm. In the IA estimation method, we calculate the total interference power caused by each active small cell in each dense district. The total interference power I_q caused by the small cell q can be expressed as

$$IA_q = I_q = \sum_{n \notin U_q} P_{R,q,n} \ , \tag{5}$$

where $P_{R,q,n}$ is the received power of user n from the small cell q. Denote U_q as the served user set of the small cell q and $n \notin U_q$ as the non-served user set of the small cell q. The small cells which cause stronger interference (i.e., larger IA value) should be turned down the transmission power to decrease the co-channel interference and to improve the energy efficiency.

Under the described above, we calculate the IA value of each small cell and then sort the values in the descent order. For the given sorted small cells, we filter the first k cells which be turned down the transmission power to reduce severe interference and effectively improve energy efficiency. We define k as the number of cells with power adjustment. The proper k value is provided by D3A model. The detail D3A model is described in the next subsection.

B. The Joint IA Algorithm and Data-Driven Dynamic Analysis (D3A) Model

We propose the D3A model which can dynamically update the polynomial coefficients based on continuously collecting the management data form the ultra-dense small cell network. We assume that each small cell can be controlled by the central controller like the macro cell. The central controller can periodically collect the management data for data pre-processing to be transformed into the useful right data. The data pre-processing includes sorting the IA value and calculating the cell throughput, and so on. The right data can form the data sets of the cell throughput and the corresponding k value. The D3A model is built for the reliable functional relationship between the cell throughput and the corresponding k value by the statistics analysis approach, such as polynomial regression (PR) [9]. We fit the right data by using a PR function of the form

$$y(x, W) = w_0 + w_1 x + w_1 x^2 + ... + w_M x^M = \sum_{j=0}^{M} w_j x^j \ , \tag{6}$$

where M is the order of the polynomial, x^j denotes x raised to the power of j, x is independent variable which represents

k value, and y is corresponding variable (i.e., predictive value) which represents cell throughput. The polynomial coefficients $w_0, ..., w_M$ are collectively denoted by the vector W. The values of the coefficients will be determined by fitting the polynomial to the right data. After verification, the third order ($M = 3$) polynomial gives the best fit to the right data.

The D3A model is used to choose the most appropriate k value that meets the expected cell throughput. After choosing appropriate k value, we put it in algorithm to have an optimal decision making. Figure 3 is the flow chart of our proposed data-driven dynamic power control scheme with the joint IA algorithm and D3A model. In the following, we illustrate more detail of the scheme step by step:

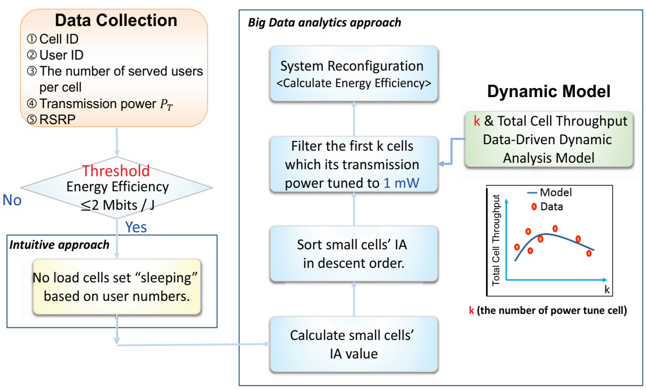

Fig. 3. The data-driven dynamic power control scheme flow chart.

1) The ultra-dense small cells generating massive management data are injected into the computing platform for data processing and analysis.
2) Calculate the energy efficiency of overall network. If the energy efficiency is less than a presetting threshold (i.e., 2 Mbits/J), the power control scheme is triggered to improve network performance.
3) Users choose serving cells based on the RSRP. When the small cell without any active user attached, it will be switched to the sleeping mode in order to decrease power consumption of the overall network. This small cell switching strategy is known as the intuitive approach.
4) For each small cell, we can sum the total interference (i.e., IA value) to the users outside the served region.
5) Sort the small cells based on IA value in descent order.
6) Filter the first k cells which tune down the transmission power to 1 mW (milliwatt). The proper k value is provided by D3A model.
7) New power configuration parameters for system reconfiguration achieves network performance improvement.

V. Simulation Results

In this section, we show performance improvements of the Bi-SON with data-driven dynamic power control scheme for the ultra-dense small cell network. The simulation environment is shown in Fig 1. Assume that the maximum transmission power $P_T = 1$ W, the basic circuit power consumption $P_0 = 6.8$ W, the sleeping mode power consumption $P_{sleep} = 4.3$ W, and the power amplifier (PA) efficiency $\eta = 0.25$ [10]. The downlink ultra-dense small cell system parameters are list in Table I [8]. We compare our proposed data-driven dynamic power control scheme (i.e., ISA algorithm with D3A model) with no energy saving approach, the intuitive scheme (i.e., the small cell would be switched to sleeping mode if no user is connected), and IA with static analysis model. The static analysis model can not update the polynomial coefficients with the density variations of active users, while the D3A model can periodically update the polynomial coefficients every three hour.

TABLE I
The Downlink Ultra-Dense Small Cell System Parameters

Parameters	Value/Mode
System bandwidth	10 MHz
Density of cell	1300 $cells/km^2$
Transmission power, P_T	1 W
P_0	6.8 W
P_{sleep}	4.3 W
The power amplifier (PA) efficiency, η	0.25
Path loss coefficient, α	3.67
Shadowing standard deviation, σ_ξ	4 dB
Service type	Full buffer

TABLE II
The Variations of Active User Densities Over Time.

Time (Hour)	0	3	6	9	12	15	18	21	24
User Density ($users/km^2$)	1500	700	500	900	1100	1300	1700	1900	1500

Table II shows the typical daily variation of active user density against the time [11]. From the table, the minimal user density and the maximal user density are 500 $\mathrm{users/km^2}$ and 1900 $\mathrm{users/km^2}$, and occur at 6 o'clock and 21 o'clock, respectively. The largest difference of user density can reach 1400 $\mathrm{users/km^2}$. For the sharp variation of active user density, our proposed D3A model is more suitable than the static analysis model to optimize the system performance, because the D3A model can dynamically update the polynomial coefficients according to the density variation. For simplification, we assume that the static analysis model can generate the polynomial coefficients based on 1200 $\mathrm{users/km^2}$ only.

Figure 4 shows that the total cell throughput against the time. From the figure, we have the following observations:

1) For the IA algorithm, the static analysis model has the same total cell throughput as the D3A model with a high active user density. However, the static analysis model has lower total cell throughput than the D3A

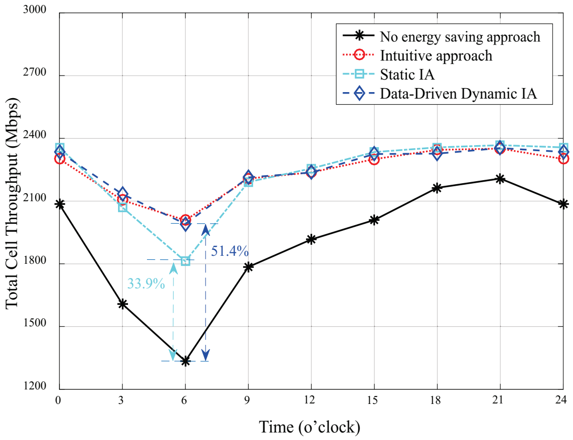

Fig. 4. The total cell throughput in varied time. There are three schemes for comparison with our proposed ISA algorithm with D3A model, including the no energy saving approach, the intuitive scheme, and the IA with static analysis model.

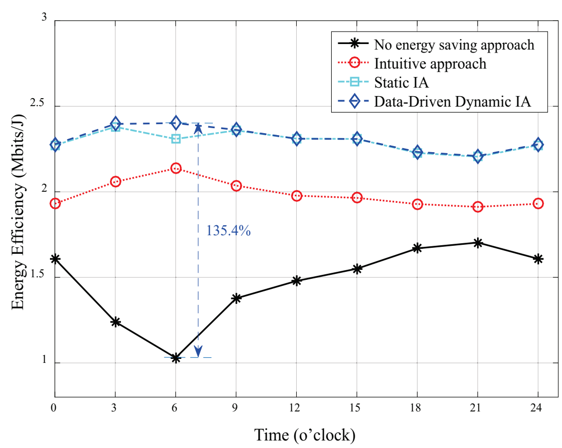

Fig. 5. The energy efficiency in varied time.

model in a low user density because the static analysis model can not dynamically update the decision function to optimize the system.

2) In this case, the IA method with the D3A model can improve 50% higher total cell throughput than the no energy saving approach.

Figure 5 shows that the energy efficiency against the time. From the figures, we have the following observations:

1) The IA algorithm has better energy efficiency than the intuitive approach. This is because the IA algorithm can significantly reduce co-channel interference and power consumption in the high density region of active small cells to improve the energy efficiency.
2) Compared with no energy saving approach, the IA method with D3A model can provide the 135% energy efficiency.

VI. Conclusion

In this paper, we proposed the Bi-SON framework with the data-driven dynamic power control scheme to improve the total cell throughput and energy efficiency of the ultra-dense small cell network. The power control scheme includes both data-driven dynamic analysis (D3A) model and interference-aware (IA) energy saving algorithm. With collecting the management data from the small cells, our proposed IA algorithm can estimate and sort the cells with large interference to neighboring users, and decrease the transmission power of the cells for reducing interference and power consumption. The fitting amount of these cells with the transmission power adjustment can be provided by our proposed D3A model, according to the statistics analysis approach. With the effective cooperation between the D3A model and the IA algorithm, the Bi-SON can produce the new configuration parameter for the network reconfiguration, thus improving the total cell throughput and energy efficiency for the ultra-dense small cell network system. We showed that our proposed Bi-SON can achieve the highest total cell throughput and the energy efficiency for the ultra-dense small cell network. Compared with no energy saving approach, our proposed Bi-SON can improve the total cell throughput and the energy efficiency by 50% and 135% respectively.

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