

# Self-Organizing Ultra-Dense Small Cells in Dynamic Environments: A Data-Driven Approach

Li-Chun Wang , *Fellow, IEEE*, and Shao-Hung Cheng , *Student Member, IEEE*

**Abstract**—This paper presents a data-driven biadaptive self-organizing network (Bi-SON) for ultra-dense small cells (UDSC), which can improve energy efficiency and reduce interference in dynamic environments, taking account of cell switching ON/OFF, transmission power adjustment, and traffic loads simultaneously. In the first adaptation of Bi-SON, a joint traffic load and interference aware cell ranking mechanism first determines the necessary active small cells based on traffic loads, and then ranks all the active small cells based on their carried traffic load and resulting interference. Top ranked cells will transmit at the maximum power. The last ranked  $K$  cells will adjust the transmission power for interference reduction in the second adaptation function of Bi-SON, while maintaining the required quality of service. According to a polynomial regression learning approach, the total system throughput of UDSC is characterized as a function of  $K$ . Compared to the baseline case when all the cells transmit with the maximum power, our proposed Bi-SON framework can improve the throughput and energy efficiency of UDSC by 73% and 169%, respectively. However, the pure switching ON/OFF approach can only improve the throughput and the energy efficiency of UDSC by 52% and 115%, respectively. As demonstrated, even with a simple power adaptation algorithm, a learning-based Bi-SON framework can improve the performance of UDSC by taking advantage of the pervasive availability of voluminous data.

**Index Terms**—Data-driven, energy efficiency, polynomial regression (PR), self-organizing network (SON), ultra-dense small cells (UDSC).

## I. INTRODUCTION

**D**EPLOYING ultra-dense small cells (UDSC) is an important approach in provisioning broadband data services for the fifth generation (5G) wireless systems. However, energy consumption and interference are the two major performance issues. First, some small cells may be underutilized during the off-peak traffic periods [1], thereby increasing operational expense. Second, intercell interference increases as the cell density grows.

Manuscript received October 11, 2017; revised March 31, 2018 and May 2, 2018; accepted June 23, 2018. Date of publication July 16, 2018; date of current version May 31, 2019. This work was supported in part by the Ministry of Science and Technology (MOST) of Taiwan under Grant MOST 105-2218-E-009-009- and in part by the Science Park Administration, Ministry of Science and Technology of Taiwan under Grant 105A05. (*Corresponding author: Li-Chun Wang.*)

The authors are with the Department of Electrical and Computer Engineering, National Chiao Tung University, Hsinchu 300-10, Taiwan (e-mail: lichun@cc.nctu.edu.tw; locoling@gmail.com).

Digital Object Identifier 10.1109/JSYST.2018.2851755

## Total Interference Power from Cell 3

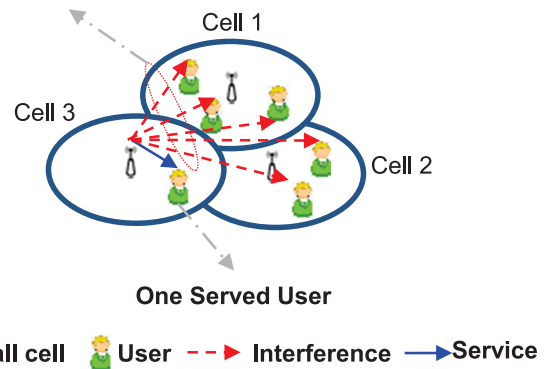


Fig. 1. Illustrative example of cell ranking issue in UDSC, where cell 1 serves most users, cell 2 ranks second, and cell 3 causes the most serious interference and serves the fewest users.

## A. Motivation

Generally, UDSC need to handle frequently changed nonuniformly distributed traffic loads and interference among cells. Therefore, a cell-ranking issue arises in UDSC. As shown in Fig. 1, cells 1, 2, and 3, respectively, serve three, two, and one users, while interfering three, four, and five users in the neighboring cells. Based on the carried traffic load and the resulting interference, these cells can be ranked accordingly. Clearly, Cell 3 causes the most serious interference to neighboring users and serves the fewest users. Therefore, Cell 3 is suggested to adjust transmission power. Because traffic patterns and interference conditions in UDSC change quite dynamically, it is of importance to update cell ranking dynamically.

The concept of a self-organizing network (SON) was introduced to manage cellular networks in an intelligent, adaptive, and automotive fashion [2]. However, the current SON-based interference avoidance and energy-saving mechanisms [3]–[6] are more suitable for a quasi-static system, rather than for dynamic environments. In the dynamic environments of UDSC, the SON shall be designed to take into account cell switching ON/OFF, power control, and time-varying nonuniform traffic loads simultaneously [7]. To our knowledge, this is still an open research issue.

## B. Contributions

The main contribution of this paper is to develop a biadaptive self-organizing network (Bi-SON) framework based on the

operation data of small cells, aiming to enhance throughput and energy efficiency for UDSC in a dynamic environment by taking the nonuniform traffic loads and the complicated intercell interference into account. Our proposed data-driven Bi-SON framework consists of two adaptation functions and one learning-based approach for predicting the total system throughput of UDSC. The first adaptation functions involve the switching ON/OFF power control and the resulting signal-to-interference (SIR) cell ranking. The second adaptation aims to adjust the transmission power of the inefficient small cells that deliver low traffic loads and cause huge interference. The contributions of this work are described by the following three aspects.

- 1) Develop a network-assisted interference measurement approach based on the collections of the received signals of each user from the serving cells and neighbor cells. Cell identification (ID) can help a user equipment to distinguish the desired signal from the interference, which is much easier than to execute the process of SIR measurement in the physical layer [8].
- 2) Design a fast cell-ranking scheme based on carried traffic load and resulting interference. This cell-ranking scheme can help UDSC in Bi-SON quickly identify the cells whose transmission power should be adjusted to reduce the interference in a dynamic environment, rather than relying on the exhaustive search approach or the complicated power control algorithms.
- 3) Propose a system throughput prediction model as a function of the last ranked  $K$  cells. The total throughput of UDSC is the sum of throughput from the top ranked active cells with the maximum transmission power and those from the last ranked  $K$  cells with a lower transmission power. We develop a learning-based polynomial regression (PR) approach [9] to establish a prediction model based on the historical data of  $K$  and the total throughput of UDSC.

From our simulation results, we will show that the proposed data-driven Bi-SON with downlink power control can achieve the state-of-the-art performance of the UDSC in a dynamic environment, which can significantly improve cell throughput and energy efficiency compared with the existing approach.

### C. Organization

The remainder of this paper is organized as follows. Section II gives a brief review of related works. In Section III, we discuss the considered cell architecture, radio propagation model, power consumption model, and performance metrics. The data-driven Bi-SON framework and its downlink power control mechanism are presented in Sections IV and V, respectively. Simulation results are given in Section VI. Finally, we give our concluding remarks in Section VII.

## II. RELATED WORK

Table I summarizes the energy saving and interference reduction for small cell networks according to the following conditions: 1) Switching ON/OFF, 2) transmission power adjustment, 3) time-varying nonuniform traffic loads, 4) dual connectivity,

TABLE I  
SUMMARY OF ENERGY SAVING AND INTERFERENCE REDUCTION  
FOR SMALL CELL NETWORK

	Reference
Switching On/Off	[5] [10-17]
Transmission Power Adjustment	[3-7] [15] [18-21]
Time-Varying Nonuniform Traffic Loads	[6] [10-14] [16-18] [20-21]
Dual Connectivity	[15-17]
Self Organizing Network	[3-6]
Ultra-Dense Network	[5] [7] [10] [17-18] [20-21]

5) SON, and 6) ultra-dense network. In terms of energy saving, turn ON or OFF of the transmission power of base stations is proposed in [10]–[14]. Wu *et al.* suggested a greedy small cells ON/OFF strategy depending on the current and estimated traffic load, network topology, and user requirements. In [11], the optimal densities of active small cells were analyzed. In [12], the authors proposed a dynamic cluster-based ON/OFF mechanism for small cells while striking a balance between throughput and energy consumption. In [13], the authors developed a simple energy-saving scheme without changing any 3rd Generation Partnership Project (3GPP) defined message flows among the macrocell, small cells, and users. This simple yet novel solution can turn OFF small cells when they are not serving users and wake them up when the macrocell has a heavy traffic load. Using a stochastic geometry-based network model in [14], the authors proposed an approach to achieve a better energy-throughput tradeoff under the quality of service (QoS) constraints of coverage probability and average wake-up time. In [15]–[17], the dual connectivity heterogeneous networks were investigated by sending the control signals from the macrocell and user data to the small cells. For the dual connectivity heterogeneous networks, Esmaeel *et al.* [15] proposed downlink traffic scheduling schemes to reduce the overall power consumption of the network. In [16], the authors proposed the energy-efficient offloading scheme for the dual connectivity heterogeneous network environment. In [17], a novel database-aided mechanism was designed to help the macrocells control the sleeping mode of small cells for energy saving. A self-organizing resource allocation technique for UDSC was proposed in [5] and [6]. In [5], a joint partner selection and power allocation method for UDSC was proposed by exploiting matching theory, nonlinear fractional programming, and Lagrange dual decomposition, where the matching theory provided a decentralized self-organizing solution to the two-sided matching problem. In [6], an energy-saving self-organizing small cell network was designed based on the noncooperative game theoretical power control scheme.

On the other hand, in [7], [18]–[21], the authors proposed to adjust the transmission power of small cells to reduce the co-channel cell interference. In [18], the interference aware power control problem was formulated as a mean field game. The authors formulated the interference mitigation mean field game to

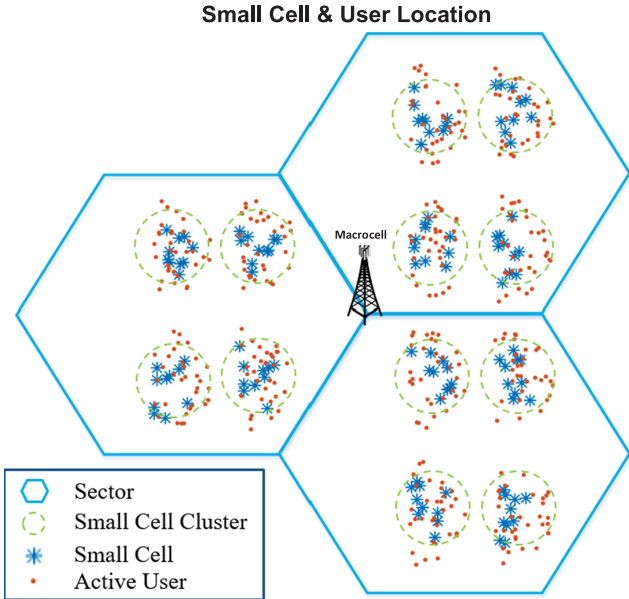


Fig. 2. Deployment scenario of the 5G UDSC with the assumption that macrocell and small cells utilize different frequency bands for transmission.

reduce requirements of complete interference-related information. In [19], the authors designed an interference control scheme to dynamically adjust the transmission power of femtocells and the QoS class identifiers. In [20], a novel joint power control and user-scheduling mechanism was proposed to reduce interference and to lower outage probabilities. In [21], a semiclustering of victim-cells approach was presented to address the co-tier interference issue in ultra-dense femtocell networks. Finally, a novel game theoretical approach to manage the power of UDSC was proposed in [7]. As per the related work for SON in the literature, [3], [4] presented a SON-enabled inter-cell interference coordination technique. For interference avoidance, Lima *et al.* provided a statistical analysis of the SON and a distributed antenna system with consideration of range expansion bias and almost blank subframe. In [4], a cooperative self-organizing optimal control approach was proposed to calculate the transmission power of a set of femtocells aiming to minimize the proposed cost index, which weighed the indoor signal to noise ratio and the interference to neighboring femtocells. Therefore, the femtocells can set the transmission power to guarantee signal quality and to manage the interference among femtocells.

However, the small cell resource allocation techniques in the literature, such as [3]–[7], [10]–[17], [19]–[21], did not simultaneously consider dynamic small cell switching ON/OFF, transmission power adjustment, and time-varying nonuniform traffic loads in the UDSC. Our proposed Bi-SON framework can allow small cells to adjust the transmission power in such a dynamic environment by frequently observing the cell operation data.

### III. SYSTEM MODEL

#### A. Cell Architecture

Fig. 2 shows the UDSC scenario considered by 3GPP [22], in which a few clusters of small cells coexist with an overlaying

macrocell. Each small cell is equipped with an isotropic antenna, and the macrocell is equipped with three-directional antennas. Each cluster of small cells will select one cluster head to collect the data of its cluster members and then send these data to the macrocell via the user data plane. The resource management functions of our proposed Bi-SON framework for the UDSC will be implemented in the macrocell.

For the users covered by both a macrocell and a cluster of small cells, the control signaling data and user data are designed to transmit in a dual connectivity manner. The macrocell is responsible for sending control signals, while the small cells are responsible for sending user data. For this purpose, the macrocell and small cells use different frequency bands. Thus, the cross-tier interference between the macrocell and small cells is not to be considered in our UDSC system. In this paper, we focus on examining the effects of the cochannel interference among small cells. In a more complicated coexisting scenario when the macrocell and the underlying small cells use the same frequency band, the cross-tier interference can be resolved by certain interference cancellation techniques, such as the enhanced intercell interference cancellation technique in 3GPP [23].

#### B. Users and Cells Distribution Model

We adopt a two-dimensional Poisson point process (PPP) to characterize the locations of distributed users [24]. Denote the random variable  $G$  as the number of active users in each cluster of small cells. Given the user density  $\lambda_u$  and an area  $A$ , it follows that:

$$\text{Prob}\{G = g|A\} = \frac{(\lambda_u A)^g}{g!} e^{-\lambda_u A}. \quad (1)$$

The spatial distribution of small cells can be modeled by the two-dimensional PPP with a cell density  $\lambda_c$ . The historical cell operation data of these cells are collected for decision making in our Bi-SON framework. We compare the performance of the PPP-generated users on the PPP-generated cells with that of uniform-process-generated cells and find that the performance difference between the two is insignificant.

#### C. Radio Propagation Model

In our considered scenario, the new power level parameters of the data-driven power control management scheme are periodically reconfigured in the scale of several seconds to minutes. According to [25], the small-scale fading is the level of milliseconds and the shadowing (i.e., a medium-scale propagation) normally lasts several seconds or minutes. Hence, path loss and shadowing are the two radio propagation effects that are considered in this paper [26], [27]. The reference signal received power (RSRP) and the received signal strength (RSS) of user  $n$  at cell  $q$  can be expressed as

$$\text{RSRP}_{q,n} = P_{q,r} \xi d_{q,n}^{-\alpha} \quad (2)$$

$$\text{RSS}_{q,n} = P_{q,d} \xi d_{q,n}^{-\alpha} \quad (3)$$

where  $P_{q,r}$  is the transmission power of reference signal,  $P_{q,d}$  is the transmission power for user data, the shadowing component is modeled by a log-normal distributed random variable  $\xi$ , i.e.,

$10\log_{10}\xi$  is a Gaussian random variable with zero mean and the standard deviation of  $\sigma_\xi$ ,  $d_{q,n}$  is the distance from user  $n$  to small cell  $q$ , and  $\alpha$  is the path loss exponent. For simplicity, the transmission power for reference signals are assumed to be the same in all the small cells.

#### D. Power Consumption Model

Small cells can have two operation modes, i.e., active mode and sleeping mode [28]. Denote  $P_{\text{sleeping},q}$ ,  $P_{\text{active},q}$ , and  $P_q$  as the consumed power in the sleeping mode, the consumed power in the active mode, and the total consumed power for cell  $q$ , respectively. Then, it follows that:

$$P_q = \alpha_q P_{\text{active},q} + (1 - \alpha_q) P_{\text{sleeping},q} \quad (4)$$

where  $\alpha_q = 1$  if cell  $q$  is in the active mode; otherwise,  $\alpha_q = 0$ .

First, we consider the light sleeping mode for small cells, meaning that the radio frequency transceiver and the power amplifier are deactivated to save energy [14]. The ON/OFF process will cause extra power consumption and addition time. However, the transient time of the cell ON/OFF process in a light sleeping mode is much shorter than the steady-state time in the active mode or sleeping mode [29]. Thus, the power consumption of the switch ON/OFF process is not considered in this work.

Second, in the active mode, we need to consider the load-dependent power consumption [30]. Let  $P_0$  be the load-independent connection parameter, and  $\Delta$  be the slope of the load-dependent power consumption. Then we can express  $P_{\text{active},q}$  as

$$P_{\text{active},q} = P_0 + \zeta \Delta P_{q,d}, \quad \text{if } 0 \leq \zeta \leq 1 \quad (5)$$

where  $\zeta$  is the load scaling parameter. Note for a fully loaded system  $\zeta = 1$  (i.e., transmitting at full power and full bandwidth), while for an idle system  $\zeta = 0$ .

By substituting (5) into (4), the total consumed power of  $Q$  small cells  $P_{\text{total}}$  can be written as

$$\begin{aligned} P_{\text{total}} &= \sum_q^Q P_q \\ &= \sum_{q=1}^Q [\alpha_q (P_0 + \zeta \Delta P_{q,d}) + (1 - \alpha_q) P_{\text{sleeping},q}]. \end{aligned} \quad (6)$$

#### E. Performance Metrics

In the UDSC, the downlink SIR plus noise power ratio (SINR) from cell  $q$  to user  $n$  can be expressed as

$$\text{SINR}_{q,n} = \frac{\text{RSS}_{q,n}}{\sum_{l \neq q} \text{RSS}_{l,n} + \sigma^2} \quad (7)$$

where  $\sigma^2$  is the thermal noise.

Assume each active user can use all the available spectrum and each used channel is fully loaded (i.e., full-buffer traffic model) [31]. The total cell throughput  $R$  of  $Q$  small cells is

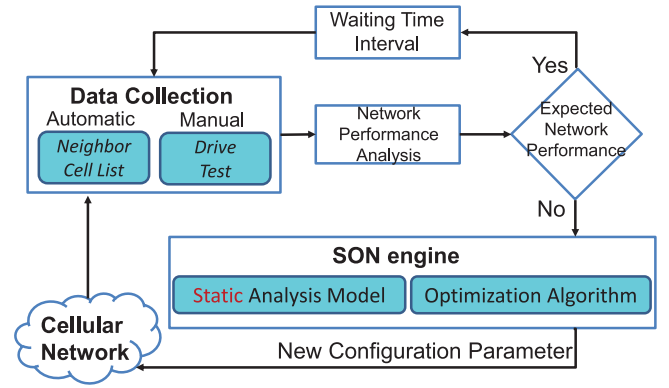


Fig. 3. 4G SON-enabled management scheme.

written as

$$R = \sum_{q=1}^Q \sum_{n=1}^{G_q} r_{q,n} = \sum_{q=1}^Q \sum_{n=1}^{G_q} \frac{B}{G_q} \log_2(1 + \text{SINR}_{q,n}) \quad (8)$$

where  $G_q$  is the number of active users in cell  $q$ ,  $r_{q,n}$  is the data rate of the user  $n$  in cell  $q$ , and  $B$  is the channel bandwidth. According to the type of the small cells [32], a suitable value of  $G_q$  can be determined. In practice,  $G_q$  is not unbounded. Therefore,  $B/G_q$  shall be larger than the minimum required bandwidth for each active user.

The energy efficiency  $E$  (Mb/J) is defined as the ratio of the total cell throughput  $R$  to the total power consumption  $P_{\text{total}}$ , which can be expressed as

$$\begin{aligned} E &= \frac{\text{Total cell throughput}}{\text{Total power consumption}} = \frac{R}{P_{\text{total}}} \\ &= \frac{\sum_{q=1}^Q \sum_{n=1}^{G_q} \frac{B}{G_q} \log_2(1 + \text{SINR}_{q,n})}{\sum_{q=1}^Q [\alpha_q (P_0 + \Delta P_{q,d}) + (1 - \alpha_q) P_{\text{sleeping},q}]} \end{aligned} \quad (9)$$

## IV. SON FOR SMALL CELL MANAGEMENT

### A. Quasi-Static SON

In general, SON aims to automatically adjust transmission strategies for performance enhancement by learning the system states from the operational environments. As specified in 3GPP LTE systems [2], SON shall consist of three kinds of capability: 1) self-configuration, 2) self-optimization, and 3) self-healing. Fig. 3 shows a SON-enabled management scheme [33]. The operational procedures of SON are described as follows.

- 1) The data collection module gathers the data from the automatic neighbor cell list and manual drive test.
- 2) The network performance analysis module estimates the system performance based on the observed data.
- 3) The SON engine will be triggered if the default system performance cannot be achieved.
- 4) The SON engine combines the static analysis model and the optimization algorithm to output the new configuration parameters.
- 5) The new system parameters are reconfigured to improve the performance.



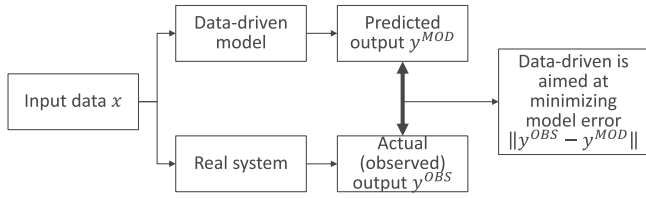


Fig. 4. Data-driven concept.

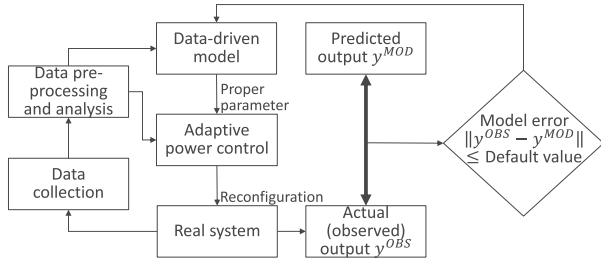


Fig. 5. Data-driven Bi-SON concept for improving energy efficiency.

Although appealing, it is a challenging task to apply the SON for saving energy and managing interference in UDSC. The current 4G SON is a knowledge-driven approach, for which the system parameters are configured based on the reports of operation and maintenance center, guidelines, and experts' opinions [34]. The static analysis model for 4G SON cannot quickly adapt its system parameters to deal with the changes of active user density and interference scenario at each small cell.

### B. Data-Driven SON

In this section, we introduce a data-driven SON, called Bi-SON. Data-driven approaches are utilized for inferring the system decision-making under an unknown network status that relies on learning processes from the observed data [35]. The main part of data-driven modelling is learning which includes the unknown dependencies between a system's inputs and its outputs from the available data, as shown in Fig. 4. As such, a dependence (i.e., model) is discovered, which can be used to effectively predict the future system's outputs from the known input values [36]. For our considered system, the inputs and outputs are considered as cell operation parameters (e.g., the number of inefficient cells with transmission power adjustment) and key performance indicators (e.g., the throughput of the system), respectively. The differences between the observed outputs of the real system and the predicted outputs of the prediction model are taken as feedback to adjust the parameters in the performance prediction model, as shown in Fig. 5. In this figure, the power control of small cells is managed on top of the proposed Bi-SON framework. Fig. 6 further shows the function blocks of Bi-SON when it is applied to manage small cell transmission power for energy saving and interference reduction. In general, the operational procedures of Bi-SON consist of six phases: 1) data collection, 2) data preprocessing, 3) environmental sensing and cognition, 4) data-driven performance modeling ( $D^2PM$ ) process, 5) adaptive power control process, and 6) dynamic system reconfiguration.

- 1) *Data collection*: Operation data from small cells are collected, including the number of serving users, transmis-

sion power per cell, physical resource block usage per cell, and RSRP from user's devices. Based on the data-driven network-assisted approach, the macrocell with a central server can synchronously collect operation data from all small cells.

- 2) *Data preprocessing*: This process involves the function of data cleaning to remove irrelevant data, and the function of reporting system status regarding the total system throughput and energy efficiency. Substituting the information of the number of users and RSRP into (8) and (9), the total system throughput and energy efficiency can be estimated.
- 3) *Environmental sensing and cognition*: When the network energy efficiency is lower than the default threshold, Bi-SON starts to evaluate traffic load and interference in each cell. There are two important steps in this phase. First, a coarse ON/OFF power control is executed based on the existence of the active users. If a user is detected by the surrounding neighboring cells, the cell with the highest RSRP will serve this user. Accordingly, this serving cell enters the active mode. If not serving any active users, a cell will enter the sleeping mode. Second, Bi-SON will calculate the sum of RSRP of the served users from cell  $q$  (i.e.,  $S_q$ ) and the resulting interference from cell  $q$  to the users of other cells (i.e.,  $I_q$ ). All the active small cells are sorted in descending order by  $S_q/I_q$ . A cell with small  $S_q/I_q$ , delivering low throughput and causing high interference, will be classified as the inefficient cell.
- 4)  *$D^2PM$  process*: As the user density varies above a predefined range, Bi-SON enters the  $D^2PM$  process to retrain the performance prediction model as follows:
  - a) adjust transmission power of the last  $K$  cells in the  $S_q/I_q$  list based on the transmission power adaptation (TPA) scheme which will be described in Section V;
  - b) calculate the total cell throughput based on (8) for each  $K$  value;
  - c) infer the relationship between  $K$  and the total cell throughput via a learning-based approach, such as PR.
- 5) *Adaptive power control process*: In order to achieve the expected total cell throughput, the adaptive power control process can extract the appropriate  $K$  from the performance prediction model. The selected  $K$  cells are adjusted to their transmission power according to the TPA scheme.
- 6) *Dynamic system reconfiguration*: The system is reconfigured with the new transmission power to achieve the predicted total cell throughput. Once the difference between the measured and predicted total cell throughput exceeds the predefined threshold, Bi-SON will enter the  $D^2PM$  process to retrain the prediction model.

### C. Complexity Analysis

The computational complexity of the proposed operational procedures of Bi-SON is discussed as follows. The computational complexity of the data-driven Bi-SON framework is

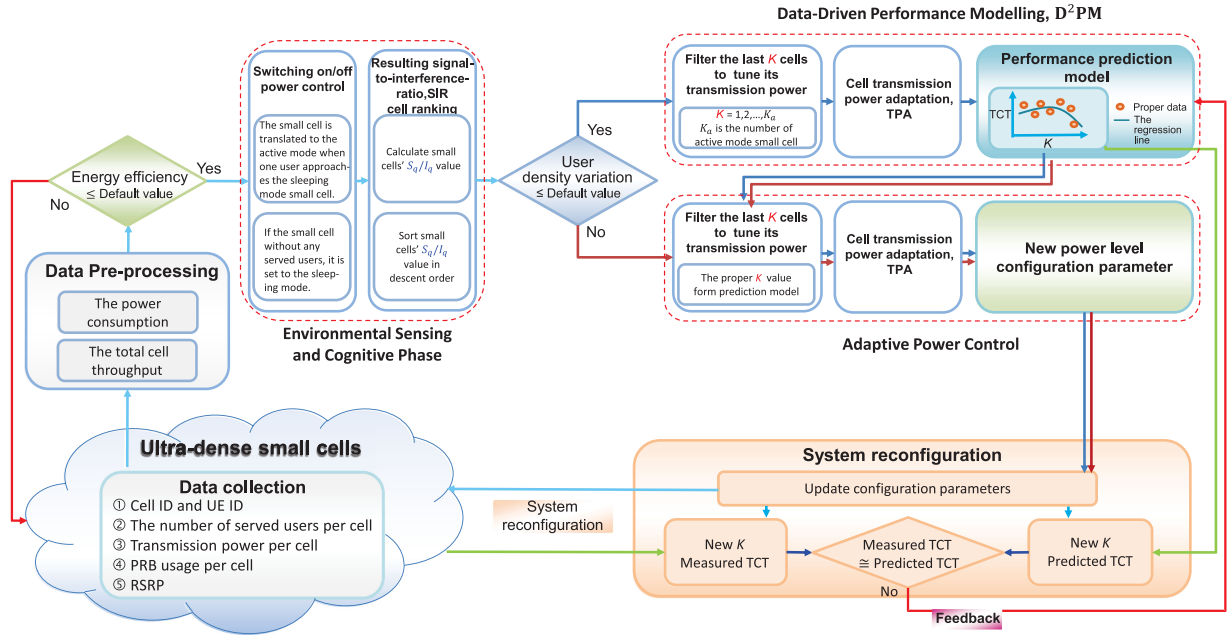


Fig. 6. Framework of Bi-SON, in which the data collection, the data preprocessing, environmental sensing and cognition, the data-driven performance modeling ( $D^2PM$ ) process, the adaptive power control process, and dynamic system reconfiguration.

mainly influenced by merge sort with  $S_q/I_q$  and adaptive power control process. Merge sort in descending order according to  $S_q/I_q$  for  $Q$  cells requires an operation of  $O(Q \times \log Q)$ . For the total  $G$  users in the system, the complexity of calculating  $S_q/I_q$  in cell  $q$  is  $O(G)$  operation. An adaptive power control process requires  $O(Q)$  operation to adjust the transmission power of the last  $K$  cells in the  $S_q/I_q$  list. As a result, the overall computational complexity of the proposed Bi-SON is  $O(G + Q \times \log Q + Q)$ , which is low computational complexity and is easy for implementation in a dynamic environment.

## V. DATA-DRIVEN POWER CONTROL

The data-driven power control in the proposed Bi-SON framework consists of three key elements: 1) environment sensing and cognition, 2)  $D^2PM$ , and 3) adaptive power control process.

### A. Environmental Sensing and Cognition

The environmental sensing and cognition process in the Bi-SON framework consists of three steps: 1) the switching ON/OFF power control, 2) the resulting SIR cell ranking, and 3) selection of the appropriate  $K$ .

1) *Switching ON/OFF power control*: Depending on whether there exists an active user, a simple and effective small cell ON/OFF method [37] is adopted in Bi-SON to achieve high energy efficiency. In [38], the effect of void cell probability was shown to be significant for UDSC. The existence of the optimal cell density for UDSC was further shown in [39] based on the stochastic geometry analysis. In addition to the cell-OFF mode, Bi-SON further classifies the cell-ON mode into the high transmission power mode and the low transmission power mode.

2) *Resulting SIR cell ranking*: To identify the inefficient cells that cause high interference to the non-served users and

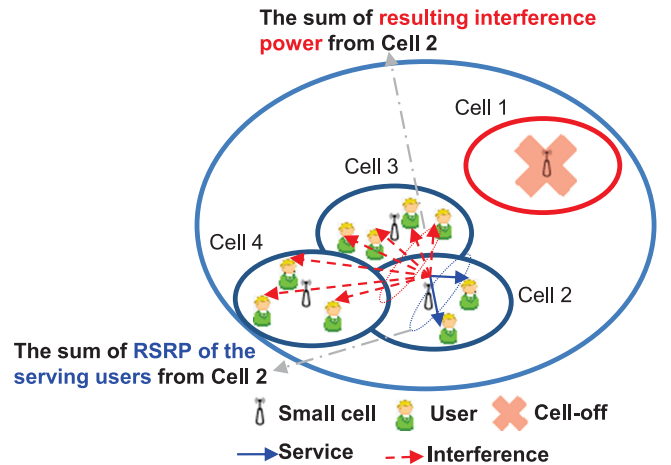


Fig. 7. Resulting SIR cell-ranking scheme identifies the inefficient cell 2 that causes high interference to the nonserved users and results in low signal power to the served users.

result in low signal power to the served users, a resulting SIR cell-ranking scheme is proposed. In Fig. 7, cell 2 serves two users and causes interference to seven users in cells 3 and 4. Compared to cells 3 and 4, cell 2 is the most inefficient; cell 3 is more efficient than cell 4. Hence, we propose a resulting SIR cell-ranking mechanism as follows.

- 1) Calculate the sum of RSRP of the serving users ( $S_q$ ) in cell  $q$

$$S_q = \sum_{n \in U_q} \text{RSRP}_{q,n} \quad (10)$$

where  $U_q$  represents the set of the served users in cell  $q$ .

- 2) Calculate the sum of the resulting interference power ( $I_q$ ) from cell  $q$

$$I_q = \sum_{n \notin U_q} \text{RSRP}_{q,n}. \quad (11)$$

- 3) Sort the total  $Q$  cells according to  $S_q/I_q$  in the descending order, i.e.,  $C_Q, C_{Q-1}, \dots, C_k, C_{k-1}, \dots, C_1$ . With respect to the delivered throughput and the resulting interference,  $C_Q$  is the most efficient, and  $C_1$  is ranked the last. The cells with smaller  $S_q/I_q$  are classified as the inefficient cells. The inefficient cells with low  $S_q/I_q$  will be selected to reduce its transmission power.

3) *Selection of appropriate  $K$* : Let  $K$  be the number of cells to reduce the transmission power. Intuitively, as  $K$  increases, the throughput of UDSC will increase due to the lower interference. However, if  $K$  keeps increasing, the throughput will turn to decrease because of the decrease of high power cells. Hence, there exists an optimal range of  $K$  in terms of the total system throughput. In the next section, we will discuss a learning approach to determine  $K$ .

### B. $D^2$ PM Process

Because 4G SON is not designed for the environment with dynamic interference and frequent changes of active user density, it is of importance to develop a performance prediction model driven by the sensing information learning from the dynamic UDSC. We adopt a PR prediction model to relate the total cell throughput (denoted by  $y$ ) with the number of the cells to reduce transmission power [9]. Specifically, for a  $J$ th degree polynomial in  $K$  and the fitting parameter vector  $W = [w_0, \dots, w_J]$ , we can express  $y(K, W)$  as

$$\begin{aligned} y(K, W) &= w_0 + w_1 K + w_2 K^2 + \dots + w_J K^J \\ &= \sum_{j=0}^J w_j K^j. \end{aligned} \quad (12)$$

Consider  $M$  data points in the training phase and denote the observed total cell throughput  $T_m$ . Our goal is to determine  $W = [w_0, \dots, w_J]$ , so that the sum of the square of the error between  $y(K, W)$  and  $T_m$  can be minimized [9]

$$E(W) = \sum_{m=0}^M \{y(K_m, W) - T_m\}^2. \quad (13)$$

Note that  $J$  shall be designed to avoid the overfitting issue, so that the root-mean-square (RMS) error  $E_{\text{RMS}}$  can be minimized as well for the testing data [9]

$$E_{\text{RMS}} = \sqrt{\sum_{m=0}^M \{y(K_m, W^*) - T_m\}^2 / M}. \quad (14)$$

The performance prediction model of Bi-SON will be updated to find a new  $K$  for the energy-efficient UDSC when the condition of (15) is satisfied. It follows that:

$$\left| \frac{\lambda_u(t) - \lambda_u(t_{\text{update}})}{\lambda_u(t_{\text{update}})} \right| \geq \chi \quad (15)$$

where  $\lambda_u(t)$  is the current user density,  $\lambda_u(t_{\text{update}})$  is the last updated user density, and  $\chi$  is a designed parameter.

### C. Adaptive Power Control Process

In the following, we detail how the TPA scheme adjusts the proper transmission power of these  $K$  cells in the adaptive power control process. Cell  $q$  can find the minimum  $\text{RSRP}_{q,n}$  according to the measured RSRP of the served users. From (2) and (3), it follows that

$$\frac{P_{q,d}}{P_{q,r}} = \frac{\min_{n \in U_q} \text{RSS}_{q,n}}{\min_{n \in U_q} \text{RSRP}_{q,n}} \quad (16)$$

where  $P_{q,d}$  is the transmission power for transferring data and  $P_{q,r}$  is the transmission power of the reference signal (i.e., set to the maximum transmission power). Let  $\text{RSS}_{\text{th}} / \min_{n \in U_q} \text{RSRP}_{q,n} = \Gamma_q$  when  $\min_{n \in U_q} \text{RSS}_{q,n} = \text{RSS}_{\text{th}}$ , we can have

$$\begin{aligned} \frac{P_{q,d}}{P_{q,r}} &= \frac{\text{RSS}_{\text{th}}}{\min_{n \in U_q} \text{RSRP}_{q,n}} \\ \Rightarrow P_{q,d} &= \frac{\text{RSS}_{\text{th}}}{\min_{n \in U_q} \text{RSRP}_{q,n}} \cdot P_{q,r} = \Gamma_q \cdot P_{q,r}. \end{aligned} \quad (17)$$

If  $\min_{n \in U_q} \text{RSRP}_{q,n} \geq \text{RSS}_{\text{th}}$ , the adaptive power control based on (17) will be executed to determine  $P_{q,d}$  for interference reduction and energy saving.

## VI. SIMULATION RESULTS

We consider a three-sector macrocell with a radius (from center to vertex) of  $r_m = 400$  m, where each sector is hexagon shaped and has four clusters as shown in Fig. 2. Each cluster has ten small cells. The radius of a small cell cluster  $r_c$  is equal to 50 m. The users are distributed based on the PPP in a circular area. The center of the small cell cluster is the same, but with radius  $r_u = 70$  m. Path loss and shadowing are considered.

Small cells can operate in two transmission modes (i.e., active mode and sleeping mode). In the active mode, the basic circuit power  $P_0 = 6800$  mW and the slope of the load-dependent power consumption  $\Delta = 4$ . In the sleeping mode, the basic circuit power  $P_{\text{sleeping}} = 4300$  mW. In addition, we choose the reference signal transmission power  $P_{q,r} = 30$  dBm and the RSS of cell edge  $\text{RSS}_{\text{edge}} = -100$  dBm [40]. Other system parameters for small cells are summarized in Table II [41].

### A. Effect of RSS Threshold

We conduct an experiment to validate the impact of various  $\text{RSS}_{\text{th}}$ . Fig. 8 shows the total cell throughput versus the user density  $\lambda_u$  for various  $\text{RSS}_{\text{th}}$  in our proposed Bi-SON framework. For the coarse ON/OFF power control approach, the fixed transmission power of small cells is set to the maximum level (i.e., 30 dBm). From the figure, we have the following observations.

- 1) The performance for small cell systems with  $\text{RSS}_{\text{th}} = -60$  dBm approaches that of small cells with the coarse ON/OFF power control approach, because fewer small cells are operated in the active mode.

TABLE II  
UDSC PARAMETERS

Parameters	Value/Mode
System bandwidth	10 MHz
Total small cell number, $Q$	120
Density of small cell for a cluster, $\lambda_c$	1300 cells/km <sup>2</sup>
Path loss exponent, $\alpha$	3.67
Shadowing standard deviation, $\sigma_\xi$	4 dB
Load scaling parameter, $\zeta$	1

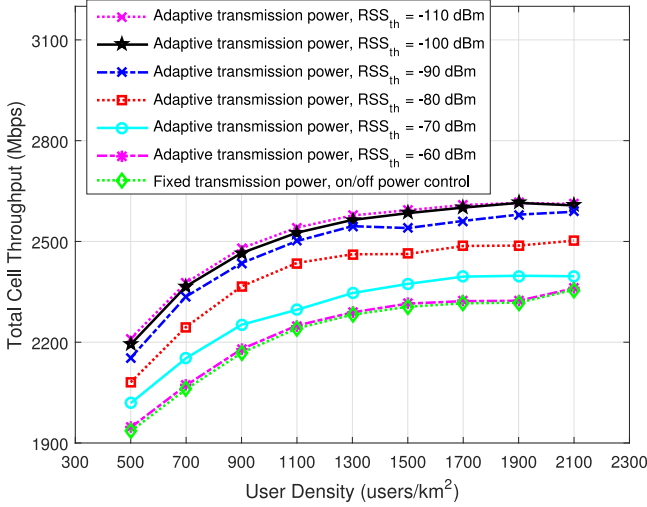


Fig. 8. Total cell throughput of different RSS threshold  $RSS_{th}$ .

- 2) The higher the  $RSS_{th}$ , the better the RSS. However, it causes more interference to the nonserved users. Hence, when we scale down  $RSS_{th}$ , the total cell throughput gradually rises due to the reduced interference.

Fig. 9 shows the energy efficiency versus the user density  $\lambda_u$  of small cells using the proposed Bi-SON framework for various values of  $RSS_{th}$ . We have the following observations.

- 1) The UDSC with a higher user density has smaller energy efficiency because of consuming more power.
- 2) Decreasing  $RSS_{th}$  can improve the energy efficiency of small cells due to less power consumption. The RSS at cell edge  $RSS_{edge}$  is  $-100$  dBm [40].

### B. Comparison of Energy-Saving Schemes

Fig. 10 compares the performance of the total cell throughput when using different energy-saving schemes: 1) baseline scheme where all the cells transmit with the maximum power, 2) ON/OFF power control, 3) interference-aware (IA) cell ranking and static performance model, 4) SIR cell ranking and static performance model, 5) IA cell ranking and D<sup>2</sup>PM, and 6) SIR cell ranking and D<sup>2</sup>PM. D<sup>2</sup>PM periodically collects the operation data of small cells to update its performance prediction model, but the static model does not correspond to the changes of user density. For simplicity, we assume that the polynomial curve of the static model is generated for 1300 users/km<sup>2</sup>. For

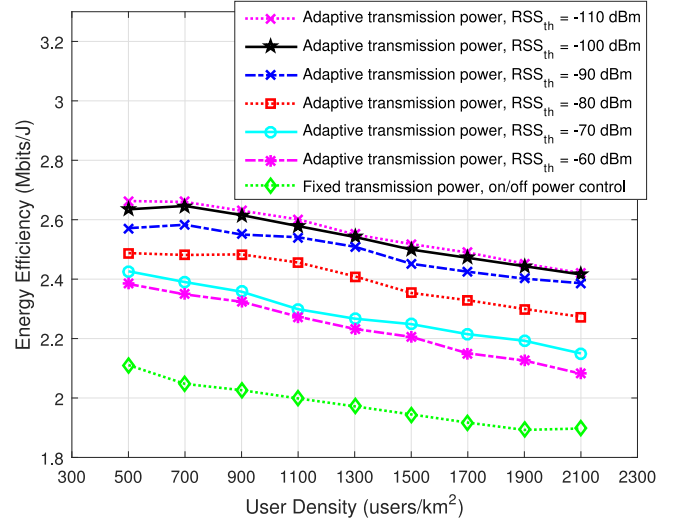


Fig. 9. Energy efficiency of different RSS threshold  $RSS_{th}$ .

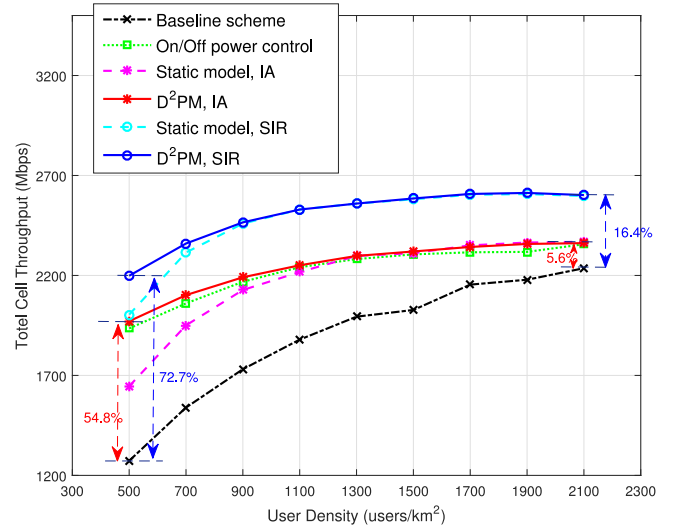


Fig. 10. Total cell throughput against the user density  $\lambda_u$  using different energy-saving methods.

comparison, the performance of UDSC with IA cell ranking in our previous work [42] was shown in the figure. From the figure, we have the following observations.

- 1) Generally, the total cell throughput increases with user density in all schemes, but at a logarithmic speed. In other words, adding more users may bring negligible throughput improvement for UDSC due to serious intercell interference. D<sup>2</sup>PM with SIR data outperforms the other schemes, improving 70% cell throughput over the baseline scheme when the user density is 500 users/km<sup>2</sup>. The static model with SIR data ranks second, which has poorer cell throughput than D<sup>2</sup>PM with SIR data when the user density is smaller than 1300 users/km<sup>2</sup>.
- 2) D<sup>2</sup>PM with IA data ranks third and delivers 55% improvement over the baseline scheme, but has only slight improvement compared to the coarse ON/OFF power control scheme.



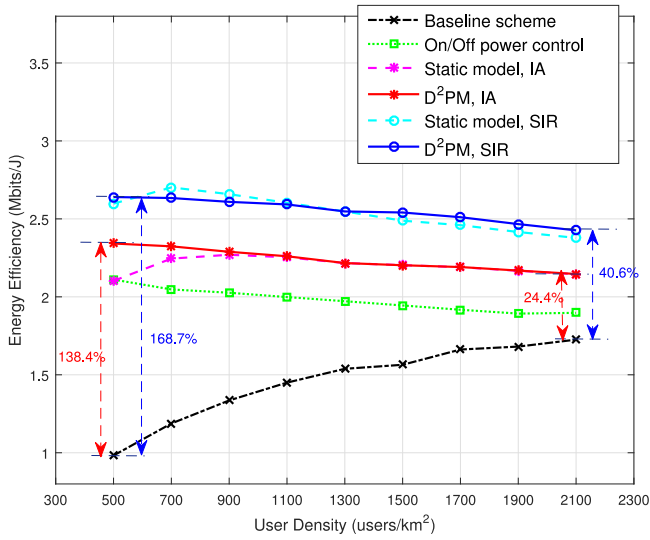


Fig. 11. Energy efficiency against the user density  $\lambda_u$  using different energy-saving methods.

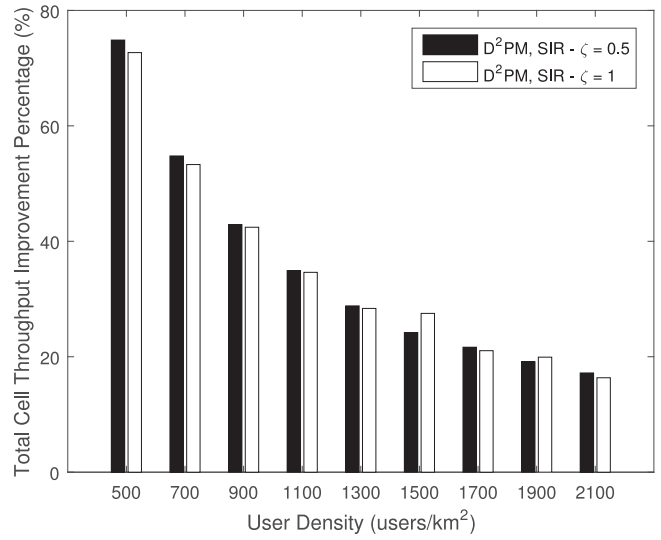


Fig. 12. Total cell throughput improvement percentage of UDSC with  $\zeta = 0.5$  and 1.

- 3) The static model with IA data performs worse than all the schemes except for the baseline scheme, when user density is smaller than the default value, but the performance gap vanishes when the user density grows large.
- 4) We note that both model update and observed data are crucial for power controlled UDSC.

Fig. 11 shows the energy efficiency against the user density  $\lambda_u$  of UDSC when various energy-saving methods are implemented. We observe that increasing user density may degrade the energy efficiency due to high interference except for the baseline scheme. Nevertheless, compared to the baseline scheme,  $D^2PM$  and the static model with SIR data can improve cell energy efficiency by 160% at user density equal to 500 users/km<sup>2</sup>. Even with only IA data, the static model and  $D^2PM$  can perform better than the ON/OFF power control scheme as the user density increases. Hence, the interference aware data are crucial for the energy efficiency performance of UDSC.

C. Impacts of Different Traffic Loads

We conduct an experiment to verify the effectiveness of our proposed Bi-SON (i.e., the  $D^2PM$  with SIR data) in the fully loaded and the nonfully loaded traffic conditions. In Fig. 12, compared to the baseline scheme, the improvement percentage of the total throughput with  $\zeta = 0.5$  in the nonfully loaded case is similar to that with  $\zeta = 1$  in the fully loaded case. Fig. 13 shows that the energy-saving percentage of energy consumption with  $\zeta = 0.5$  is smaller than that with  $\zeta = 1$ . Hence, the Bi-SON framework can improve the performance of UDSC in both fully loaded and nonfully loaded traffic conditions.

D. Impact of User Density Variation

Fig. 14 depicts a typical daily active user density  $\lambda_u$  in the weekdays and the weekend [43]–[45]. In the figure, we first note that the minimum user density is 500 users/km<sup>2</sup> at 4:00 and the

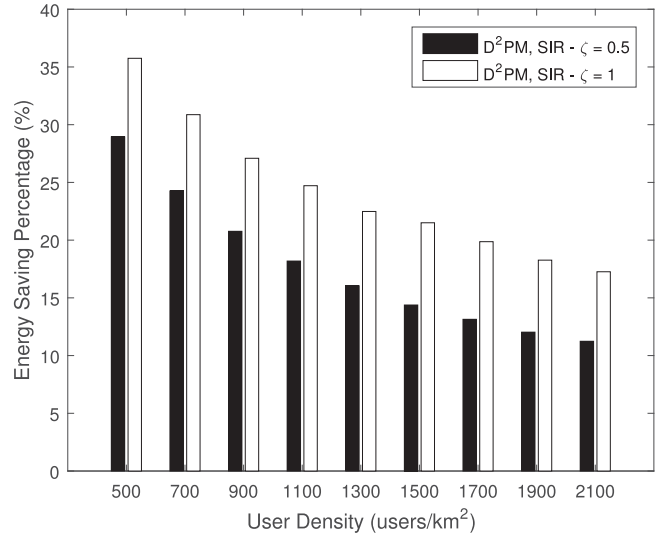


Fig. 13. Energy-saving percentage of UDSC with  $\zeta = 0.5$  and 1.

maximum user density is 2100 users/km<sup>2</sup> at 18:00 in the weekday. This observation suggests that the active user density may change very rapidly over time up to 1600 users/km<sup>2</sup>. Second, in the weekend, the minimal and the maximal user density are 500 users/km<sup>2</sup> at 6:00 and 1500 users/km<sup>2</sup> at 20:00, respectively. The user density variations in the weekend are smaller than that in the weekday when facing the variations of user density shown in Fig. 14.

From Figs. 10 and 11, we have shown that  $D^2PM$  has superior performance in comparison with other power control schemes.  $D^2PM$  has two adaptation functions: macroscopic model update for changing user density and the resultant interference scenario and microscopic power update at each small cell for achieving the predicted overall system performance.

Although model update improves the performance of UDSC by reducing the interference, how often a performance model

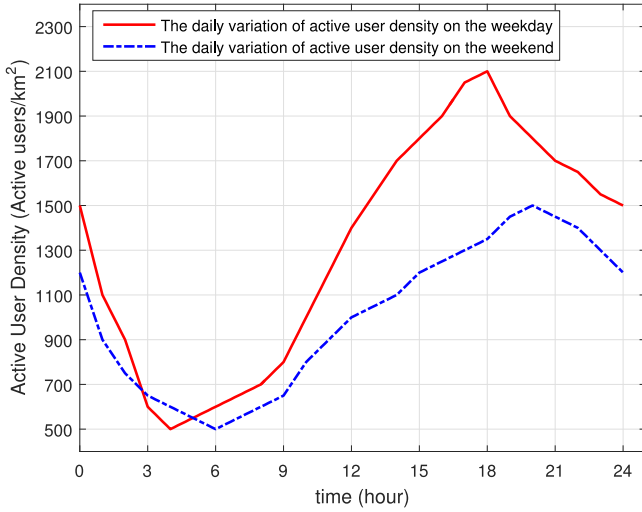


Fig. 14. Variation of active user densities in the weekday and the weekend.

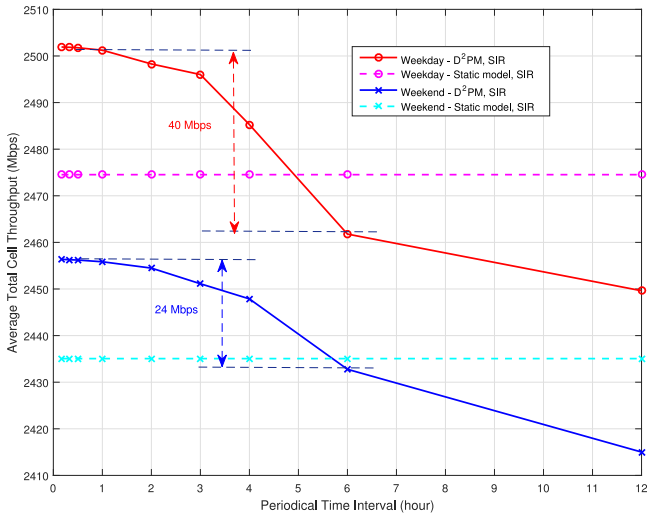


Fig. 15. Average total cell throughput performance of UDSC achieved by  $D^2PM$  with SIR data and the static model with SIR data.

in Bi-SON needs to be updated is an important design issue. Considering the daily traffic patterns as shown in Fig. 14, we study the effect of the update period on the cell throughput performance of  $D^2PM$ . The baseline is the static model for user density 1300 on the weekdays and 1000 users/ $km^2$  in the weekend, respectively. Fig. 15 shows the average total cell throughput performance of UDSC when  $D^2PM$  is switched to the fixed model update period equal to 10 min, 20 min, 30 min, 1 h, 2 h, 4 h, 6 h, and 12 h. We note that the performance of  $D^2PM$  with the update period of 1 h is similar to those of  $D^2PM$  with the update period of 10, 20, and 30 min. Clearly, considering the tradeoff between the performance and model update cost,  $D^2PM$  with 1 h model update is a better choice.

To further reduce unnecessary updates,  $D^2PM$  can change to the adaptive model update mode. The adaptive update scheme is to trigger the model update procedures only if the user density changes normalized to the previous user density exceeds the

TABLE III  
COMPARISON OF THE PERIODICAL UPDATED SCHEME AND THE ADAPTIVE UPDATED SCHEME

Periodical Updated Scheme					
Level		10 min	30 min	1 hour	2 hour
Weekday	Updating frequency	144	48	24	12
	Average total cell throughput (Mbps)	2501.92	2501.76	2501.24	2498.29
	Average energy efficiency (Mbits / J)	2.56	2.56	2.55	2.55
Weekend	Updating frequency	144	48	24	12
	Average total cell throughput (Mbps)	2456.37	2456.21	2455.84	2454.48
	Average energy efficiency (Mbits / J)	2.60	2.60	2.60	2.60

Adaptive Updated Scheme					
Level		$\chi = 0$	$\chi = 0.1$	$\chi = 0.2$	$\chi = 0.3$
Weekday	Updating frequency	144	23	11	6
	Average total cell throughput (Mbps)	2501.92	2501.66	2501.20	2499.71
	Average energy efficiency (Mbits / J)	2.56	2.55	2.55	2.56
Weekend	Updating frequency	144	19	8	6
	Average total cell throughput (Mbps)	2456.37	2455.90	2455.02	2453.40
	Average energy efficiency (Mbits / J)	2.60	2.60	2.59	2.60

predefined threshold  $\chi$ . In Table III, the performance of  $D^2PM$  in the adaptive model update mode  $\chi = 0, 0.1, 0.2,$  and  $0.3$  is compared with that of  $D^2PM$  in the periodical model update mode 10 min, 30 min, 1 h, and 2 h. One can observe that the adaptive model update mode with  $\chi = 0.2$  can achieve the similar performance as the periodical mode with 10 min, but reduce updates from 144 times to 8 times.

### E. Impacts of Different Cell Types

In 5G networks, small cells can be of multiple types, such as microcell, picocell, femtocell, etc. In [46], a potential network architecture for the ultra-dense heterogeneous networks (UDHN) was proposed, where macrocells, microcells, picocells, and femtocells are connected. The proposed UDHN can be viewed as an evolution of the current LTE heterogeneous networks and is compatible with the current LTE architecture. Here we investigate how various types of cells with different transmission power will affect the performance of Bi-SON. In Fig. 2, a cluster of ten picocells forms a group. Now we consider a cluster of one microcell, four picocells, and five femtocells forming a group. Table IV shows the power models of various types of cells [41]. Fig. 16 shows the energy efficiency improvement percentage versus user density  $\lambda_u$  of UDSC for the same type (i.e., picocell) and multiple types of small cells. We observe that the proposed Bi-SON (i.e., the  $D^2PM$  with SIR data) saves more energy in a scenario with various types of

TABLE IV  
POWER MODEL PARAMETERS FOR DIFFERENT SMALL CELL TYPES

	$P_{q,r}$ [W]	$P_0$ [mW]	$\Delta$	$P_{sleep}$ [mW]
Microcell	5	56000	2.6	39000
Picocell	1	6800	4.0	4300
Femtocell	0.1	4800	8.0	2900

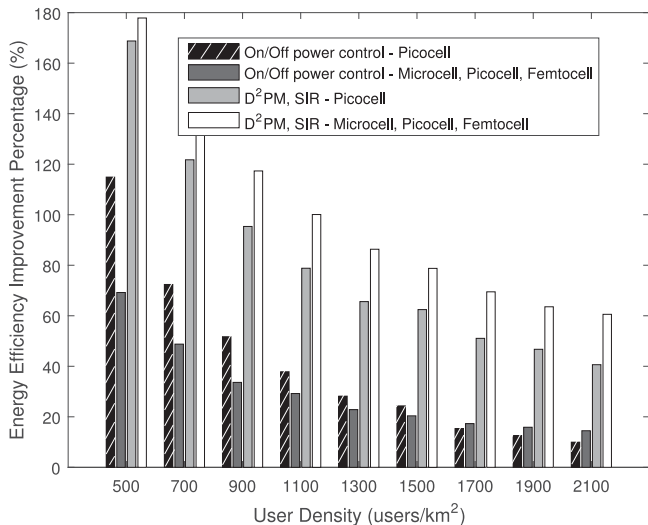


Fig. 16. Comparison of the energy efficiency improvement percentage versus user density  $\lambda_u$  of UDSC between the same type of small cells and the multiple types of small cells.

cells than that with the same type of cells. The  $D^2PM$  with SIR data for multiple types of small cells outperforms 178% energy efficiency over the baseline scheme when the user density is 500 users/km<sup>2</sup>. However, the switching ON/OFF power control in a scenario with various types of cells performs worse than in a scenario with the same type of cells. Therefore, we show that the proposed Bi-SON framework can also be applied to the multiple types of small cells for 5G heterogeneous networks.

## VII. CONCLUSION

Deploying dense small cells can improve communication link quality and thus provide high capacity to customers at the expense of increased intercell interference and higher energy consumption of the entire small cell network. The typical characteristics of UDSC, such as dynamic user density and severe interference, can be overcome by using their own cell operation data such as service users density and cell transmission power. In this paper, we have investigated the benefits of utilizing these data for establishing a performance prediction model aiming to adjust transmission power for throughput enhancement and energy saving. Specifically, we have developed an adaptive framework from both macroscopic and microscopic aspects in response to the variation of user density and interference scenario. From the macroscopic aspect, we have developed a ranking scheme for small cells based on their nonuniform traffic loads and the

resultant interference. We have further suggested a simple PR learning approach to determine how many small cells should lower the transmission power in order to achieve the best trade-off between system throughput and energy efficiency. From the microscope aspect, small cells will operate in three modes: 1) full transmission power, 2) idle mode, and 3) adaptive power mode. All these three operation modes are based on straightforward criteria, such as active user number and the required RSRP level. Thanks to the data-driven concept in Bi-SON, the abundant observed cell operation data can help these intuitive algorithms to achieve very good performance under an environment of dynamic channel condition and traffic variations.

Although the focus of this paper is on the power control for self-organizing UDSC, the proposed bi-adaptive framework can be naturally applied to characterize various kinds of radio resource management issues such as fast handoff and dynamic channel allocation. Data-driven radio resource management for heterogeneous wireless network, such as macrocells/small cells/device-to-device networks, and the data-driven application-aware radio resource management are the other two interesting future directions. Moreover, the availability of obtaining the cell operation data is the bottleneck for data-driven wireless network research. Hence, how to invent a mechanism to encourage the desirability of sharing cell operation data from cellular operators needs further studies as well.

## REFERENCES

- [1] E. Oh and B. Krishnamachari, "Energy savings through dynamic base station switching in cellular wireless access networks," in *Proc. IEEE Global Telecommun. Conf.*, Dec. 2010, pp. 1–5.
- [2] O. G. Aliu, A. Imran, M. A. Imran, and B. Evans, "A survey of self organisation in future cellular networks," *IEEE Commun. Surveys Tuts.*, vol. 15, no. 1, pp. 336–361, First Quarter 2013.
- [3] C. H. M. de Lima, M. Bennis, and M. Latva-aho, "Statistical analysis of self-organizing networks with biased cell association and interference avoidance," *IEEE Trans. Veh. Technol.*, vol. 62, no. 5, pp. 1950–1961, Jun. 2013.
- [4] A. Sanchez, J. Arauz, J. W. McClure, and Z. Miller, "Cooperative self-organized optimal power control for interference mitigation in femtocell networks," in *Proc. IEEE Colombian Conf. Commun. Comput.*, 2016, pp. 1–6.
- [5] Z. Zhou, M. Dong, K. Ota, and Z. Chang, "Energy-efficient context-aware matching for resource allocation in ultra-dense small cells," *IEEE Access*, vol. 3, no. 9, pp. 1849–1860, Sep. 2015.
- [6] Y. Jiang *et al.*, "Energy-efficient noncooperative power control in small-cell networks," *IEEE Trans. Veh. Technol.*, vol. 66, no. 8, pp. 7540–7547, Aug. 2017.
- [7] J. Zheng, Y. Wu, N. Zhang, H. Zhou, Y. Cai, and X. S. Shen, "Optimal power control in ultra-dense small cell networks: A game-theoretic approach," *IEEE Trans. Wireless Commun.*, vol. 16, no. 7, pp. 4139–4150, Dec. 2016.
- [8] L. C. Wang and C. W. Wang, "A near real-time signal to interference ratio measurement technique in a frequency-selective multipath fading channel for the wcdma system," in *Proc. Veh. Technol. Conf.*, Oct. 2001, pp. 752–756.
- [9] C. M. Bishop, *Pattern Recognition and Machine Learning*. New York, NY, USA: Springer, 2007.
- [10] J. Wu, J. Liu, and H. Zhao, "Dynamic small cell ON/OFF control for green ultra-dense networks," in *Proc. 8th Int. Conf. Wireless Commun. Signal Process.*, Nov. 2016, pp. 1–5.
- [11] C. T. Peng, L. C. Wang, and C. H. Liu, "Optimal base station deployment for small cell networks with energy-efficient power control," in *Proc. IEEE Int. Conf. Commun.*, Jun. 2015, pp. 1863–1868.
- [12] S. Samarakoon, M. Bennis, W. Saad, and M. Latva-aho, "Dynamic clustering and ON/OFF strategies for wireless small cell networks," *IEEE Trans. Wireless Commun.*, vol. 15, no. 3, pp. 2164–2178, Mar. 2016.

- [13] Y. B. Lin, L. C. Wang, and P. Lin, "SES: A novel yet simple energy saving scheme for small cells," *IEEE Trans. Veh. Technol.*, vol. 66, no. 9, pp. 8347–8356, Sep. 2017.
- [14] C. Liu, B. Natarajan, and H. Xia, "Small cell base station sleep strategies for energy efficiency," *IEEE Trans. Veh. Technol.*, vol. 65, no. 3, pp. 1652–1661, Mar. 2016.
- [15] B. O. Esmael, N. Agrawaland, R. Paulus, A. K. Jaiswal, and S. B. Salah, "Novel energy efficient & optimized downlink traffic scheduling schemes in LTE-A with dual connectivity enhancement," *Int. J. Appl. Eng. Res.*, vol. 12, no. 11, pp. 2916–2921, 2017.
- [16] A. Prasad and A. Maeder, "Energy saving enhancement for LTE-advanced heterogeneous networks with dual connectivity," in *Proc. IEEE 80th Veh. Technol. Conf. (Fall)*, Vancouver, BC, Canada, 2014, pp. 1–6.
- [17] E. Ternon, P. Agyapong, L. Hu, and A. Dekorsy, "Database-aided energy savings in next generation dual connectivity heterogeneous networks," in *Proc. IEEE Wireless Commun. Netw. Conf.*, Istanbul, Turkey, 2014, pp. 2811–2816.
- [18] C. Yang, H. Dai, J. Li, Y. Zhang, and Z. Han, "Distributed interference-aware power control in ultra-dense small cell networks: A robust mean field game," *IEEE Access*, vol. 5, no. 12, pp. 84–90, Dec. 2017.
- [19] C. Wang, T. S. Tsai, and H. J. Li, "QoS-aware interference control in OFDMA femtocell networks," in *Proc. Smart Grids, Green Commun. IT Energy-Aware Technol.*, Taipei, Taiwan, 2015, pp. 42–46.
- [20] S. Samarakoon, M. Bennis, W. Saad, M. Debbah, and M. Latva-aho, "Ultra dense small cell networks: Turning density into energy efficiency," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 5, pp. 1267–1280, May 2016.
- [21] I. Shgluof, M. Ismail, and R. Nordin, "Semi-clustering of victim-cells approach for interference management in ultra-dense femtocell networks," *IEEE Access*, vol. 5, pp. 9032–9043, Apr. 2017.
- [22] 3GPP, "Technical Specification Group Radio Access Network; Small cell enhancements for E-UTRA and E-UTRAN - Physical layer aspects (Release 12)," Sophia Antipolis Cedex, France, Tech. Rep. TR 36.872, Dec. 2013. [Online]. Available: <http://www.tech-invite.com/3m36/tinv-3gpp-36-872.html>
- [23] D. Lopez-Perez, I. Guvenc, G. D. L. Roche, M. Kountouris, T. Q. S. Quek, and J. Zhang, "Enhanced intercell interference coordination challenges in heterogeneous networks," *IEEE Wireless Commun.*, vol. 18, no. 3, pp. 128–147, Jun. 2011.
- [24] T. X. Brown, "Cellular performance bounds via shotgun cellular systems," *IEEE Sel. Areas Commun.*, vol. 18, no. 11, pp. 2443–2455, Nov. 2000.
- [25] A. Lars, Z. Jens, and B. S. Slimane, *Principle of wireless Communications*. Lund, Sweden: Studentlitteratur, 2006. [Online]. Available: <http://www.diva-portal.org/smash/record.jsf?pid=diva2%3A460175&dswid=-398>
- [26] S. Deb, P. Monogioudis, J. Miernik, and J. P. Seymour, "Algorithms for enhanced inter-cell interference coordination (eICIC) in LTE hetnets," *IEEE Trans. Netw.*, vol. 22, no. 1, pp. 137–150, Feb. 2014.
- [27] M. M. Ahamed and S. Faruque, "Path loss slope based cell selection and handover in heterogeneous networks," in *Proc. IEEE Electro/Inform. Technol.*, May 2015, pp. 499–504.
- [28] I. Ashraf, F. Boccardi, and L. Ho, "SLEEP mode techniques for small cell deployments," *IEEE Commun. Mag.*, vol. 49, no. 8, pp. 72–79, Aug. 2011.
- [29] A. Conte, A. Feki, L. Chiaraviglio, D. Ciullo, M. Meo, and M. A. Marsan, "Cell wilting and blossoming for energy efficiency," *IEEE Wireless Commun.*, vol. 18, no. 5, pp. 50–57, Oct. 2011.
- [30] H. Holtkamp, G. Auer, V. Giannini, and H. Haas, "A parameterized base station power model," *IEEE Commun. Lett.*, vol. 17, no. 11, pp. 2033–2035, Nov. 2013.
- [31] 3GPP, "Technical Specification Group Radio Access Network; Evolved Universal Terrestrial Radio Access (E-UTRA); Further advancements for E-UTRA physical layer aspects (Release 9)," Sophia Antipolis Cedex, France, Tech. Rep. TR 36.814, 3GPP, Mar. 2010. [Online]. Available: <http://www.qtc.jp/3GPP/Specs/36814-900.pdf>
- [32] N. Sapountzis, S. Sarantidis, T. Spyropoulos, N. Nikaiein, and U. Salim, "Reducing the energy consumption of small cell networks subject to QoE constraints," in *Proc. IEEE Global Commun. Conf.*, Austin, TX, USA, 2014, pp. 2485–2491.
- [33] A. Imran, and A. Zohas, "Challenges in 5G: How to empower SON with big data for enabling 5G," *IEEE Netw.*, vol. 28, no. 6, pp. 27–33, Nov./Dec. 2014.
- [34] M. Rajabi, A. Mansourian, P. Pilesjo, F. Hedefalk, R. Groth, and B. Ahad, "Comparing knowledge-driven and data-driven modeling methods for susceptibility mapping in spatial epidemiology: A case study in visceral leishmaniasis," in *Proc. 17th AGILE Conf. Geographic Inform. Sci.*, Castellon, Spain, Jun. 2014, pp. 1–5.
- [35] H. Orouji, O. Bozorg, E. Fallah-Mehdipour, and M. A. Marino, "Modeling of water quality parameters using data-driven models," *Environ. Eng.*, vol. 139, no. 7, pp. 947–957, Jul. 2013.
- [36] D. P. Solomatine and A. Ostfeld, "Data-driven modelling: Some past experiences and new approaches," *J. Hydroinformatics*, vol. 10, no. 1, pp. 3–22, Jan. 2008.
- [37] E. Ternon, P. K. Agyapong, and A. Dekorsy, "Performance evaluation of macro-assisted small cell energy savings schemes," *EURASIP J. Wireless Commun. Netw.*, vol. 2015, no. 1, p. 209, 2015.
- [38] C. T. Peng, L. C. Wang, and C. H. Liu, "Optimal base station deployment for small cell networks with energy-efficient power control," in *Proc. IEEE Int. Conf. Commun.*, London, U.K., Feb. 2015, pp. 1863–1868.
- [39] C. H. Liu and L. C. Wang, "Optimal cell load and throughput in green small cell networks with generalized cell association," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 5, pp. 1058–1072, May 2016.
- [40] J. Parikh and A. Basu, "Effect of mobility on SINR in long term evolution systems," *Commun. Technol.*, vol. 7, no. 1, pp. 1239–1244, Mar. 2016.
- [41] G. Auer *et al.* "How much energy is needed to run a wireless network?," *IEEE Wireless Commun.*, vol. 6, pp. 12608–12619, 2018.
- [42] L. C. Wang, S. H. Cheng, and A. H. Tsai, "Bi-SON: Big-data self organizing network for energy efficient ultra-dense small cells," in *Proc. Veh. Technol. Conf. (Fall)*, Montreal, QC, Canada, Sep. 2016, pp. 1–5.
- [43] K. Hiltunen, "Utilizing eNodeB sleep mode to improve the energy-efficiency of dense LTE networks," in *Proc. IEEE Int. Symp. Pers. Indoor Mobile Radio Commun.*, London, UK, Sep. 2013, pp. 3249–3253.
- [44] E. Nan, X. Chu, W. Guo, and J. Zhang, "User data traffic analysis for 3G cellular networks," in *Proc. IEEE Commun. Netw. China*, Guilin, China, Aug. 2013, pp. 468–472.
- [45] M. Laner, P. Svoboda, S. Schwarz, and M. Rupp, "Users in cells: A data traffic analysis," in *Proc. IEEE Wireless Commun. Netw. Conf.*, Shanghai, China, Apr. 2012, pp. 3063–3068.
- [46] J. An, K. Yang, J. Wu, N. Ye, S. Guo, and Z. Liao, "Achieving sustainable ultra-dense heterogeneous networks for 5G," *IEEE Commun. Mag.*, vol. 55, no. 12, pp. 84–90, Dec. 2017.