OPTIMAL TRADE-OFF BETWEEN POWER SAVING AND QOS PROVISIONING FOR MULTICELL COOPERATION NETWORKS

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The authors propose the semi-Markov decision process model-based stochastic optimization scheme for the optimal trade-off between power saving and QoS provisioning over multicell cooperation networks.

This work was supported in part by the U.S. National Science Foundation under Grant CNS-205726 and the U.S. National Science Foundation CAREER Award under Grant ECCS-0348694.

ABSTRACT

Multicell cooperation is emerging as a promising wireless communication technique to significantly improve the performance of cellular networks in terms of the coverage of high-data-rate services and the system throughput for the next generation wireless networks. On the other hand, multicell cooperation also imposes the new challenges associated with the two mutually conflicting constraints between the power/energy efficiency/saving and the QoS provisioning required by mobile users, which differ from the conventional cellular networks. To overcome the above problem, we propose the semi-Markov decision process model-based stochastic optimization scheme for the optimal trade-off between power saving and QoS provisioning over multicell cooperation networks. Our objective is to efficiently minimize the power consumption at base stations while guaranteeing diverse QoS provisioning for mobile users through multicell cooperation power scheduling. To achieve this goal, we apply finite-state Markov chains to model the mobile users' density, mobility, multicell cooperation power-profile scheduling, and QoS provisioning. Using these models, we formulate the SMDP-based stochastic optimization problem and develop an efficient iteration algorithm to implement our SMDP-based scheme. We evaluate our proposed schemes through numerical analyses, which show that our proposed schemes significantly outperform the other schemes in terms of minimizing power consumption while guaranteeing the required QoS provisioning.

INTRODUCTION

Recent years have witnessed the rapid emergence of a variety of multimedia wireless services over cellular networks, such as video conferences, mobile TV, music downloading, online gaming, and so on. Motivated by the concept of ubiquitous computing, these promising wireless services are designed to be available for people anytime and anywhere. Quality of service (QoS) provisioning plays a crucial role in supporting multimedia wireless services in cellular networks. Consequently, the research community has made significant efforts in the development of various advanced and efficient wireless cellular networking architectures to support the diverse QoS requirements. Among them, multicell cooperation networking is receiving significant research attention from both academia and the industry. This is because multicell cooperation enables significant performance improvement of cellular networks in terms of the coverage of high-data-rate services and system throughput. As a result, multicell cooperation is being adopted in various communication standards, including Third Generation Partnership Project (3GPP) [1] Long Term Evolution (LTE)-Advanced , or LTE-A [2], and IEEE 802.16m [3] for the next generation wireless networks.

However, multicell cooperation also imposes the new challenges associated with the two mutually conflicting constraints between the power/energy efficiency/saving and the QoS provisioning required by mobile users, which differ from conventional cellular network systems. On one hand, to ensure the demanded wireless transmission capacity for guaranteeing the stringent QoS provisioning over time-varying channels covering the sizable wireless cells, a large amount of power supply and consumption is desired/needed at the base stations to sustain the required wireless channel qualities [4, 5]. On the other hand, one of the main design goals/criterions of multicell cooperation networks is to minimize the power/energy consumption [1, 6] among all base stations through multicell cooperation and power scheduling, which, however, may significantly affect the QoS provisioning required by mobile users. Some standardization and research efforts have been made to address these problems. For instance, as a promising technique under the multicell cooperation framework in the LTE-A standard [2], the cooperative multipoint or coordinated multipoint (CoMP) [7] approach was proposed to improve the coverage of high data rates and increase the overall mulicell cooperation network throughput while efficiently mitigating intercell interference. While CoMP has the potential to improve QoS

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provisioning, it does not explicitly address any specific/concrete power scheduling schemes which take into account the trade-off between power saving and QoS provisioning over multi-cell cooperation networks. In [8] the authors studied a joint power and subcarrier allocation algorithm that aims at minimizing network power consumption with a lower-bounded data rate constraint. The authors of [9] developed a sleeping mode control scheme under the given performance requirements. In [10] the authors derived an optimal sleep mode policy to maximize a multiple-objective function of QoS and the power consumption. However, the above-mentioned research works only consider the simple power scheduling action of either totally switching off the base stations or keeping them in a fully operating state in a deterministic manner [11]. As a result, this type of deterministic switching-on/off mode control scheme is less effective for the important application scenarios where the mobile users' traffic loads are relatively heavy and their variations are highly random, especially when taking the users' mobility/location and dynamic traffic load density/distribution variations into account.

To overcome the aforementioned problems, in this article we propose the semi-Markov decision process (SMDP) model-based stochastic optimization scheme to achieve the optimal trade-off between power saving and QoS provisioning over multicell cooperation networks with the dramatic variations in mobile users' traffic load density and mobility. The objective of our proposed stochastic optimization framework is to efficiently minimize the power consumption at the base stations while guaranteeing the diverse QoS provisioning for mobile users through multicell cooperation power scheduling. To achieve this goal, we apply finite-state Markov chain techniques to develop a set of analytic models to characterize mobile users' density, mobility, and multicell cooperation power-profile scheduling. Based on these models, we formulate the SMDP-based stochastic optimization problem to optimize the trade-off between power saving at base stations (BSs) and QoS provisioning to mobile users over multicell cooperation networks. We also develop an efficient iteration algorithm to implement our proposed SMDP-based optimization scheme. Then we conduct numerical analyses to evaluate our proposed schemes, which show that our proposed SMDP-based stochastic control process converges to the unique optimal solution and significantly outperforms the other schemes in terms of minimizing the power consumption at BSs while guaranteeing the required QoS provisioning to mobile users.

The rest of this article is organized as follows. First, we develop the system models for optimizing the trade-off between power saving and QoS provisioning over our multicell cooperation networks. Then, we formulate the SMDP-based stochastic optimization problem to derive the optimal power scheduling policy to optimize the trade-off between power saving and QoS provisioning through multicell cooperation. Finally, we conduct numerical analyses to evaluate our proposed schemes. The article then concludes.

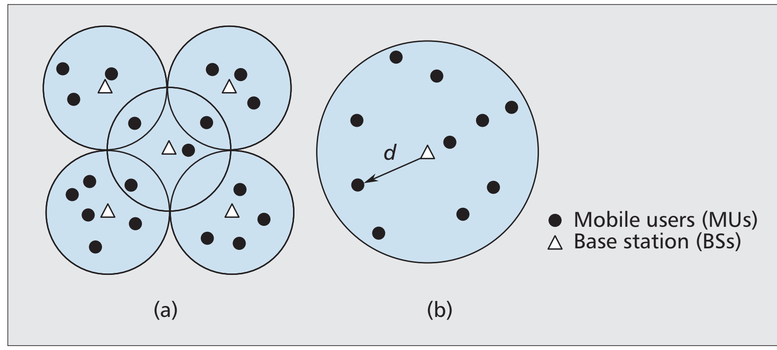

Figure 1. *Wireless cellular network model: a) muticell cooperation network model; b) single cell model with a base station at the center of the cell, where* d *denotes the radius distance from the base station of the cell to the mobile user.*

The System Models

Multicell Cooperation Network Model

We consider cellular networks where multicell cooperation is employed to minimize the power consumption at BSs while guaranteeing QoS provisioning to mobile users (MUs). Our cellular network model is illustrated by an example shown in Fig. 1. It is a cellular network with five cells. As shown in Fig. 1a, one central cell is surrounded by four neighboring cells. BSs are located at the respective center of the cells, illustrated by hollow triangles. As shown in Fig. 1b for each cell's internal architecture, a number of MUs, represented by solid dots, are randomly distributed in the cell with each MU located at the variable radius distance, denoted by d, between the BS and the MU. Clearly, the MUs' traffic load distributions among wireless cells are independent of each other. Within each cell, the BS can perceive or sense the users' information on mobility, dynamic behaviors, and traffic load spatial distributions, which all vary with time. The MUs' traffic load and distributions in each cell are characterized by the number of MUs, which varies with time. Thus, the power control of the BS in each cell needs to be dynamically scheduled and cooperated according to the traffic load variations in order to minimize the total power consumption while guaranteeing the QoS for mobile users.

Traffic Load Model for Mobile Users

For each wireless cell, our MUs' traffic load model consists of two components:
- Mobile users' density model
- Mobile users' mobility model

which are detailed as follows, respectively.

Mobile Users' Density Model — We use the finite-state Markov chain to model the MU density in each wireless cell. Assuming the maximal number of MUs that a cell can support is $(D - 1)$, our MU density Markov chain in each cell can have at most D state levels, with each level representing the number of MUs existing in the cell. Each cell's BS acquires/senses the current state of MU density through the sensing mechanism at the BS. Under the finite-state Markov chain model, the next state of user density in the cell is

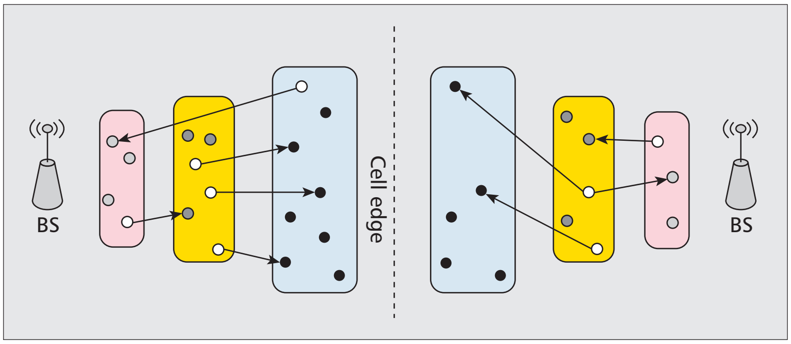

Figure 2. *Mobile user mobility model with different classes (categorized by the different radius distances from the BS to its corresponding MUs) denoted by the three different sizes of boxes.*

determined by the current state of user density and the Markov transition probability. Let $\mathcal{D} = \{0, 1, \ldots, (D - 1)\}$ represent the Markov-chain state space of user density in cell i, $N_i(t)$ denote the number of MUs in cell i with $N_i(t) \in \mathcal{D}$, and $\phi_{g_i h_i}(t)$ be the transition probability that the state of user density $N_i(t)$ changes from state g_i to state h_i, where g_i, $h_i \in \mathcal{D}$. Then the state transition probability matrix of user density is defined for cell i: $\Phi_i(t) = [\phi_{g_i h_i}(t)]$, where $\phi_{w_i z_i}(t) = \Pr\{N_i(t + 1) = h_i | N_i(t) = g_i\}$, $\forall\, g_i, h_i \in \mathcal{D}$.

Mobile Users' Mobility Model — We use the finite-state Markov chain to model the MU mobility in terms of MUs' spatial distributions in each wireless cell. According to users' different location distributions (e.g., an MU moves from the center location of the BS to the edge of the cell), we can shut down the BS or reduce its power for power/energy saving. To accurately model the impact of user mobility for cell power saving, we apply the k-means clustering algorithm [12, 13] to categorize the MUs into b classes according to the radius distances from the BS to the MUs. As shown in Fig. 2, for example, the MUs in each cell are classified into three classes ($b = 3$) illustrated by three different-sized boxes, respectively. The numbers of users in each class varies as MUs move around. Assuming that there are K ($\leq (D - 1)$) users in cell i, the spatial distribution state of k MUs' locations in cell i is denoted by $L_i(t) = (l_{i,1}, \ldots, l_{i,k})$, where $k = \{1, 2, \ldots, K\}$ and $l_{i,k}$ represents the current location (measured by the radius distance from the corresponding BS) of user k in cell i. Since there are b possible locations for each MU, there are totally b^k possible spatial location distributions for any k ($\leq K$) mobile users in cell i. The BS can acquire/sense the current state of MUs' spatial location distribution through a sensing mechanism, and the next state is determined by the current state and the user mobility Markov-chain transition probability. Let $\mathcal{L} = \{L_1, \ldots, L_{bK}\}$ stand for the user mobility Markov chain state space for K users' spatial distributions in a cell, and let $\varphi_{U_i V_i}(t)$ denote the probability that the state of users' location distribution in cell i moves from location state U_i to location state V_i at time t, where $\{U_i, V_i \in \mathcal{L}$. Then we have the $b^K \times b^K$ user mobility Markov chain state transition probability matrix of cell i, which is defined as $\Theta_i(t) = [\varphi_{U_i V_i}(t)]$, where $\varphi_{U_i V_i}(t) = \Pr\{L_i(t + 1) = V_i | L_i(t) = U_i\}$, $\forall\, U_i = (u_{i,1}, \ldots, u_{i,k}, \ldots, u_{i,K})$, $V_i = (v_{i,1}, \ldots, v_{i,k}, \ldots, v_{i,K}) \in \mathcal{L}$, where $u_{i,k}$, $v_{i,k}$ are the values that $l_{i,k}$ can take, respectively.

Power Consumption Model for Base Stations

We use the finite-state Markov chain to model the transmit power scheduling in each cell. Assuming our transmit power the Markov chain in each cell has E power-state levels, with each level representing a transmit power level at the BS in a cell. Then we let $\mathcal{E} = \{0, 1, \ldots, (E - 1)\}$ represent the power scheduling Markov chain state space in cell i, $J_i(t)$ denote the implemented transmit power of cell i where $J_i(t) \in \mathcal{E}$ at time t, and $\psi_{w_i z_i}(t)$ be the Markov-chain state transition probability that the transmit power state of cell i moves from state w_i to state z_i at time t, where w_i, $z_i \in \mathcal{E}$. The BSs are assumed to be able to transmit at one of E discrete power levels, and each level corresponds to a state in the power scheduling Markov chain. At each decision time, all cells have the associated power profiles denoted $J(t) = [e_1, \ldots, e_i, \ldots, e_N]$, where N denotes the total number of cells in multicell networks, and e_i denotes the transmit power of cell i. Then the transmit power Markov-chain state transition probability matrix of cell i is defined as $\Psi_i(t) = [\psi_{w_i z_i}(t)]$, where $\Psi_{w_i z_i}(t) = \Pr\{E_i(t + 1) = z_i | E_i(t) = w_i\ \forall\ w_i\}$, $z_i \in \mathcal{E}$. For example, we set the BS transmit power to have $E = 4$ different power levels: 0, 5, 10, and 15 W, which are the values we will use in our numerical performance analyses, described later. Also, for the smoothness and convenience of power control, in this article our transmit-power control can only increase or decrease the transmit power across the neighboring transmit power levels. These imply that in this particular case, our power control Markov chain state space in cell i is represented by $\{0, 5, 10, 15\}$, and the Markov chain state transition can only take place across adjacent states.

The total operating power, denoted by $\mathcal{P}$, of a BS to cover a single cell usually includes two parts: a constant part $\mathcal{P}_{const}$, the power that is independent of the number of MUs and their distances, and the dynamic part, which varies proportionately with the traffic intensity denoted by ρ (which is equal to $(D - 1)$), supplying the power needed to transmit the signal from the BS to all the mobile users in a cell, and depends on ρ of the BSs. Therefore, the power consumption in cell i can be calculated by $\mathcal{P}_i = \mathcal{P}_{const} + \rho_i \mathcal{P}_{tran}(i)$ [14], where ρ_i is the traffic intensity of cell i, which varies over time, and $\mathcal{P}_{tran}(i)$ is the transmit power dynamically allocated to cell i.

Objective Functions and QoS Constraints for Mobile Users

The proposed optimal power scheduling for multicell cooperation scheme is based on the stochastic control theory. Due to the time-varying traffic distribution of wireless cells, we need to derive the optimal wireless-cell power scheduling policy to efficiently implement multicell cooperation, which aims at minimizing the total power consumption subject to the QoS-threshold constraint of signal-to-interference-plus-noise ratio (SINR). The SINR is calculated for each transmission power allocation and is used to determine the QoS achieved by an MU in the multicell cooperation network. Since the wireless channel quality is a time-varying function of multiple variables and parameters, we can derive its corresponding SINR implemented by MU k as follows:

$$\gamma_k(i) = \frac{\eta \mathcal{P}_{tran}(i)}{[d_k(i)]^{\xi}\left(N_0 + \sum_{j=1, j\neq i}^{N} \mathcal{P}_{tran}(j)\right)} \tag{1}$$

where $\gamma_k(i)$ represents the SINR for mobile user k in cell i, η is the propagation coefficient, ξ is the attenuation coefficient, typically ranging from 2 to 5, $\mathcal{P}_{tran}(i)$ represents the transmit power of cell i, $d_k(i)$ denotes the distance from mobile user k to the BS of cell i, and N_0 denotes the additive white Gaussian noise.

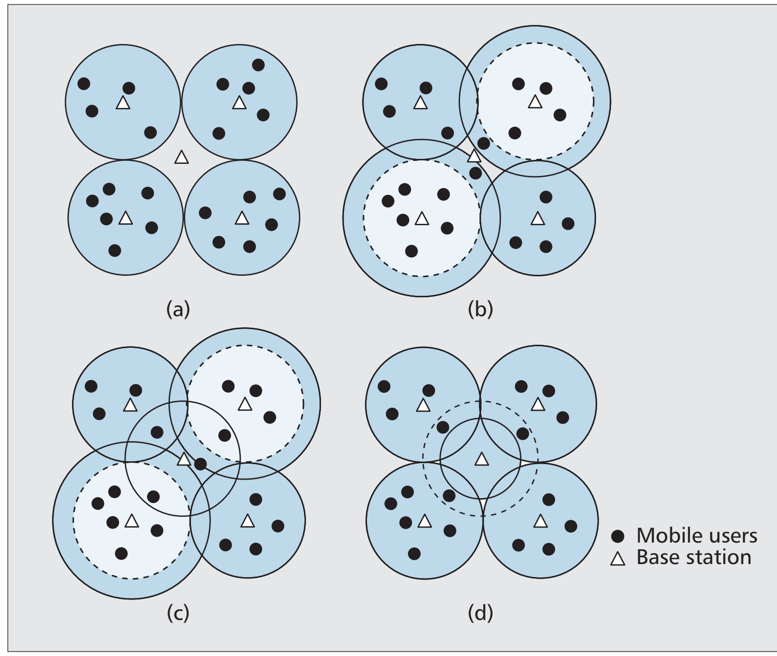

Figure 3. *Multicell cooperation power scheduling with time-varying mobile-users' traffic loads in multicell cooperation networks: a) the central cell is turned off while the transmit power of neighboring cells remain unchanged; b) the central cell is turned off while increasing the transmit power of two neighboring cells through multilevel power control to guarantee the QoS of MUs in the original central cell; c) the central cell remains unchanged while increasing the transmit power of two neighboring cells with multilevel power control to guarantee the QoS provisioning to mobile users in the central cell; d) the central cell decreases its transmit power through multilevel power control due to the reduced mobile users' traffic load while the neighboring cells remain unchanged.*

Stochastic Optimization for Optimal Trade-off between Power Saving and QoS Provisioning

Using the system models of MU density, mobility/spatial distribution, and power-profile scheduling described in "The System Models" section, for multicell cooperation power scheduling, we formulate the stochastic optimization problem by applying the semi-Markov decision process (SMDP) [15] model to achieve the optimal trade-off between power saving and QoS provisioning for multicell cooperation networks. Then we solve the stochastic optimization problem by deriving a set of optimal multilevel power scheduling policies and system reward functions that optimize the trade-off between power saving and QoS provisioning over multicell cooperation networks. Finally, we develop a concrete and efficient iteration algorithm to solve the SMDP-based stochastic optimization, which can yield the optimal decision/action functions to minimize the entire power consumption at BSs while guaranteeing the QoS provisioning required by MUs over multicell cooperation networks.

The SMDP Model and Its State and Action Functions

We observe that the optimization of trade-off between the power saving at BSs and QoS provisioning at MUs over multicell cooperation networks can be efficiently solved by formulating a stochastic optimization problem by using the SMDP model. In particular, we can develop the stochastic reward/utility and constraint functions to maximize the power saving subject to the constraints of QoS provisioning. To apply the SMDP model, we first need to define its state space and action functions. The SMDP state of each cell at time t is characterized by the state of user density, denoted by $N_i(t)$, the state of users' locations $L_i(t)$, and the state of transmit power of each cell, denoted by $E_i(t)$. Then the SMDP state of cell i can be expressed as $s_i(t) = \{N_i(t), L_i(t), E_i(t)\}$, and the state transition probability matrix of the SMDP model is defined as: $\mathbf{P}_i(t) = [\zeta_{s_i s'_i}(t)] = [\Phi_i(t), \Theta_i(t), \Psi_i(t)]$, where $\zeta_{s_i s'_i}(t) \triangleq \phi_{g_i h_i}(t)\varphi_{U_i V_i}(t)\psi_{w_i, z_i}(t)$, which is the SMDP state transition probability that the state of cell i changes from state s_i to state s'_i.

Let $\mathcal{S}$ be the state space of the SMDP model where $\mathcal{S} \triangleq \{\mathcal{D}, \mathcal{L}, \mathcal{E}\}$ and $\mathcal{A}$ are the SMDP model action space, denoted by $\mathcal{A} = \{a_1(t), a_2(t), a_3(t), a_4(t)\}$, respectively, where $a_1(t)$ denotes the action through which the central cell is turned off while the transmit power of neighboring cells remain unchanged; $a_2(t)$ denotes the action through which the central cell is turned off while increasing (within E levels) the transmit power of two neighboring cells through multilevel power control to guarantee the QoS of MUs in the original central cell; $a_3(t)$ denotes the action through which the central cell remains unchanged while the transmit power of two neighboring cells is increased with multilevel power control to guarantee the QoS provisioning to mobile users in the central cell; and $a_4(t)$ denotes the action through which the central cell decreases (within E levels) its transmit power through multilevel power control due to the reduced MUs' traffic load while the neighboring cells remain unchanged. Given the current SMDP state $s(t) \in \mathcal{S}$, and the selected action $a(t) \in \mathcal{A}$, the SMDP state transition probability function for the next state $s(t + 1)$ is denoted by $\Pr\{s(t + 1)|s(t), a(t)\}$. This function is Marko-

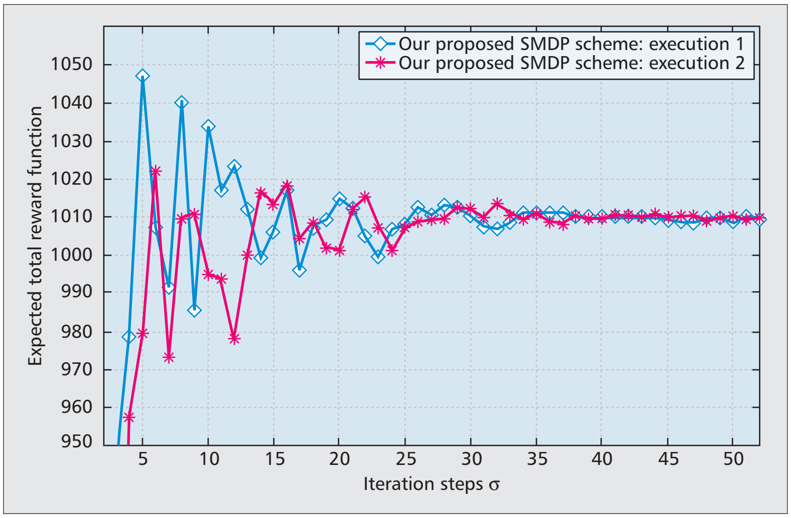

Figure 4. *The expected total reward function $\upsilon^{\pi}_{\sigma}(s)$ vs. the SMDP optimization iteration steps σ.*

vian because the state transition probability of the next state is independent of the previous states when given the current state.

In our SMDP model, at each decision epoch, the multicell cooperation power scheduling control has to decide how to allocate the transmit power to each cell according to the changes of cell state in terms of traffic load and power profiles. As indicated in Figs. 3a–d, the multicell cooperation with power scheduling is implemented by the selected action $a(t) \in \mathcal{A}$ at each SMDP model decision epoch.

The SMDP Reward and Policy Functions for Multicell Cooperation Power Scheduling

Since the objective of our proposed scheme is to minimize the total power consumption while guaranteeing QoS provisioning for MUs, we define the system reward function to be the function of power consumption for all cells with QoS provisioning constraints. Thus, we can define the system reward function as follows:

$$R(s(t),a(t)) = \frac{1}{\mathcal{P}(s(t),a(t))} \tag{2}$$

where $\mathcal{P}(s(t), a(t))$ is the total power at all BSs of the multicell cooperation networks as a function of the SMDP state and SMDP action for the optimal trade-off between power saving and QoS guarantee for multicell cooperation power scheduling under the current SMDP state and the action selected in our multicell cooperation networks. Given the current SMDP state and the selected SMDP action, we can derive the power consumption $\mathcal{P}(s(t), a(t))$ for our proposed multicell cooperation power scheduling scheme.

The SMDP decision rules specify a mapping function $\delta(t)$: $\mathcal{S} \to \mathcal{A}$, which selects an action function $a(t)$ for given cells' state at SMDP decision epoch t. Thus, our SMDP policy function, denoted by $\pi \triangleq (\delta(1), \delta(2), \ldots, \delta(t))$, is a sequence of decision rules that are used at all decision epochs $\{1, 2, \ldots, t\}$. Then we can define the expected total reward function of the SMDP model, which is defined as a utility function given in Eq. 3.

The Stochastic Power Saving Optimization and QoS Provisioning Constraints

We need to derive an optimal policy, denoted by π^*, for the optimal trade-off between power saving and QoS provisioning in multicell cooperation networks, which maximizes the expected total reward value under the given QoS-threshold SINR constraint on the kth mobile user's wireless channel SINR $\gamma_k(i)$ within cell i as follows:

$$\begin{cases} \upsilon^{\pi^*}(s(t)) = \max\limits_{a \in \mathcal{A}} \left\{ \begin{aligned} & R(s(t),a(t)) + \sum_{s(t+1)\in\mathcal{S}} \lambda \\ & \cdot \Pr\{s(t+1) | s(t),a(t)\} \upsilon^{\pi}(s(t+1)) \end{aligned} \right\} \\ \text{subject to}: \gamma_k(i) \geq \gamma_{th} \end{cases} \tag{3}$$

where $\upsilon^{\pi^*}(s(t))$ represents the maximum expected total reward value under the optimal policy π^* for the current state $s(t)$, λ is the discount factor, $\gamma_k(i)$ represents the SINR of user k in cell i (which is defined in Eq. 1), and γ_{th} denotes the targeted QoS-threshold SINR of MUs in a cell.

The Iteration Algorithm to Implement the Stochastic Power-Saving Optimization

We propose to use the iterative algorithm to solve the optimization problem specified by Eq. 3. In particular, we use the iterative algorithm [15] to derive a stationary optimal policy and the corresponding expected total reward function. The iterative algorithm is described as follows, where ε denotes an infinitesimal gap, $\sigma \in \{0, 1, 2, \ldots\}$ is the iteration steps index, and $\upsilon^{\pi}_{\sigma}(s(t))$ is defined in Eq. 3.

Step 1: Set $\upsilon^{\pi}_{0}(s(t)) = 0$ for each state $s(t)$. Specify $\varepsilon > 0$ and initialize σ to be 0.

Step 2: For each state $s(t)$, compute $\upsilon^{\pi}_{\sigma+1}(s(t))$.

Step 3: If $|\upsilon^{\pi}_{\sigma+1}(s(t)) - \upsilon^{\pi}_{\sigma}(s(t))| < \varepsilon\{(1-\lambda)/(2\lambda)$, then go to **Step 4**;

Else, increase σ by 1, then go to **Step 2**.

Step 4: For each $s(t) \in \mathcal{S}$, compute the stationary optimal policy π^*.

The computational complexity of the iteration algorithm is $O(\|\mathcal{A}\| \|\mathcal{S}\|^2)$ [15], where $\|\cdot\|$ is the cardinality of a set. While the system state space can be large, in the real network implementation the computational and time complexity can be significantly reduced because the optimal transmit-power control policy searching through our proposed iteration algorithm is implemented by an offline approach. Once the optimal policy is obtained corresponding to a given space state through the offline approach, it is stored in an optimal-policy lookup table. Each entry of the lookup table specifies the optimal action policy for any given system state, consisting of the MU density state, MU location state, and BS transmit power state of each cell. For the online operation, at each decision epoch, the multicell cooperation power scheduling controller can quickly look up the table to obtain the optimal action policy corresponding to the current system state and then execute the optimal decision or the optimal action policy. The lookup table can readily be generated offline by using separate and independent high-speed computer systems with the super processing capability and power supply.

PERFORMANCE EVALUATIONS

We conduct numerical analyses to evaluate the performance of our proposed schemes based on the SMDP model for optimal trade-off between power saving at base stations and QoS provisioning to mobile users over multicell cooperation networks. The multicell cooperation in our numerical analyses follows the SMDP model-based stochastic power scheduling by using the action functions as described in Figs. 3a–d. Using the SMDP model-based power scheduling optimization and QoS provisioning constraints and solving for the stochastic optimization problem by the iteration algorithm described in "The Iteration Algorithm to Implement the stochastic Power-Saving Optimization" section, we obtain a set of numerical solution results detailed as follows. Our performance evaluation model consists of the following parameters: the constant transmit power of each cell is 500 W, the propagation coefficient η is –31.54 dB, the discount factor λ is 0.8, and the attenuation coefficient ξ is 3.

Figure 4 plots the convergence process of the two executions of the expected total reward function $\upsilon^{\pi}(s(t))$ specified in Eq. 3. We can obtain the following observations from Fig. 4. First, Fig. 4 shows that our SMDP-based stochastic control process for optimal multicell cooperation power scheduling is stable as it quickly converges to its equilibrium state from any initial state. Second, Fig. 4 confirms that there is always the optimal solution for our SMDP-based stochastic power scheduling. Finally, Fig. 4 shows that the multiple executions (we only plot two of them in Fig. 4 for lack of space) of the iteration algorithm for solving SMDP-based stochastic optimization converge to the unique optimal solution regardless of the initial states.[1] The above observations imply that our proposed SMDP-based stochastic optimization and its corresponding iteration algorithm are feasible and valid.

Figure 5 plots the power consumption functions against the MUs' traffic load under three different multicell cooperation power scheduling schemes, including our proposed SMDP scheme, the random scheme, and the static scheme, respectively. As shown in Fig. 5, although the average power consumption of these three schemes all increase as MUs' traffic load increases, our proposed SMDP scheme significantly outperforms the other two schemes, especially when the traffic load is heavy. This is because our proposed SMDP scheme consumes much less power than the other two schemes due to multicell cooperation power scheduling. In contrast, the static scheme statically allocates the maximum power specified by cell capacity, and the random scheme's average power allocation is also much larger than that of our proposed SMDP scheme as multicell cooperation is not employed.

Under the given power consumption dynamics and conditions obtained in Fig. 5, Fig. 6 plots the implemented average SINR functions against MUs' traffic load also for the same three power scheduling schemes. We observe that as the MUs' traffic load and power consumption increase, the average SINR implemented by our proposed SMDP-based scheme increases monotonically and is always much larger than the required QoS-threshold SINR, as shown in Fig. 6, which implies that our proposed SMDP scheme can guarantee much better QoS provisioning with the least power consumption, as shown in the corresponding Fig. 5 in multicell cooperation networks. Figure 6 also indicates that the implemented average SINR by our proposed SMDP scheme is much higher than that by the static scheme, and thus, our SMDP scheme can provide much better QoS provisioning than the static scheme. Figure 6 shows that the SINR implemented by our SMDP scheme and the static scheme can both guarantee the required QoS provisioning, because they are both larger than QoS threshold SINR as shown in Fig. 6, but the power consumed by the static scheme is much larger than that consumed by our proposed SMDP scheme, as shown in the corresponding Fig. 5. On the other hand, Fig. 6 also shows that the average SINR implemented by the random scheme cannot guarantee the QoS provisioning requirement because its implemented average SINR is often lower than the QoS-threshold SINR, as shown in Fig. 6.

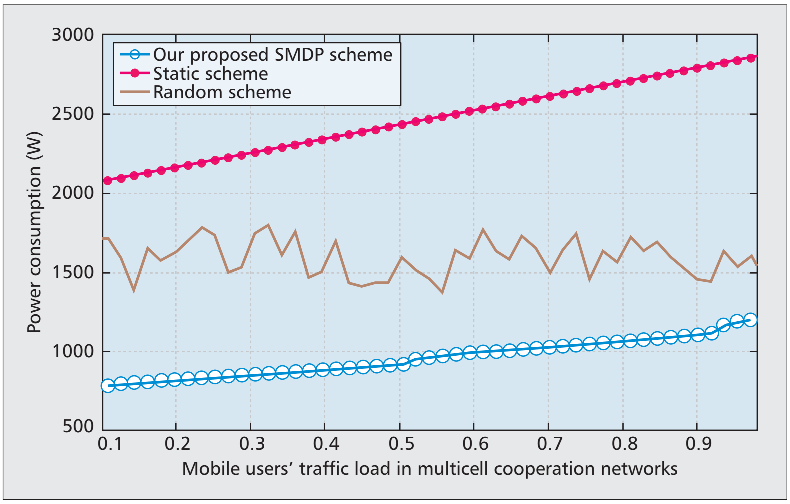

Figure 5. *Power consumption against mobile users' traffic load in multicell cooperation networks.*

CONCLUSIONS

We have proposed the semi-Markov decision process (SMDP) model-based stochastic optimization scheme for optimal trade-off between power saving and QoS provisioning over multicell cooperation networks. Our optimization objective is to minimize the power consumption at base stations while guaranteeing QoS provisioning to mobile users by using multicell cooperation power scheduling. Applying the finite-state Markov-chain techniques, we have developed a set of models to characterize mobile user density, mobility, multicell cooperation power-profile scheduling, and QoS provisioning.

[1] We only plot two executions in Fig. 4 for lack of space. In fact, we get the numerical results for more than two executions, which all converge to the same unique optimal solution regardless of the initial states.

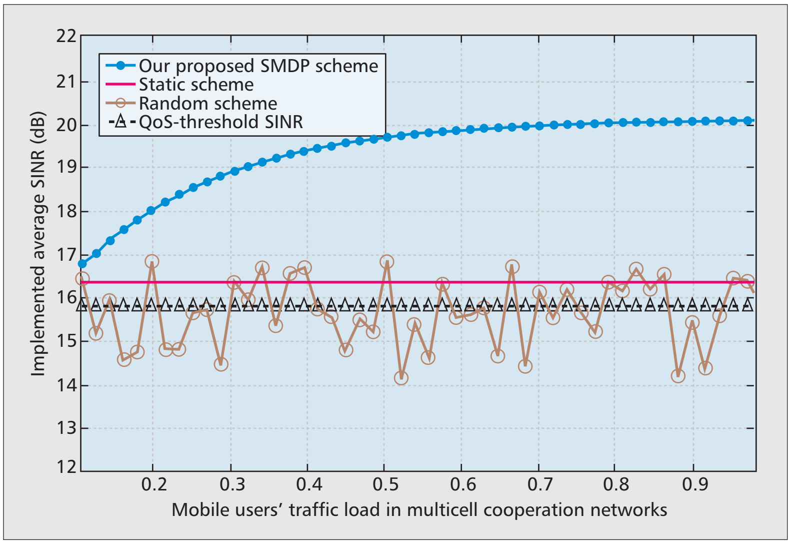

Figure 6. *The implemented average SINR of different schemes against the mobile-users' traffic load in the multicell cooperation networks.*

Based on these models, we have formulated the SMDP-based stochastic optimization problem to optimize the trade-off between the power saving at BSs and QoS provisioning to mobile users over multicell cooperation networks. We have also developed an efficient iteration algorithm to implement our proposed SMDP-based optimization scheme. Finally, we have conducted the numerical analyses to evaluate our proposed schemes, which show that our proposed SMDP-based stochastic control process converges to the unique optimal solution and significantly outperforms the other schemes in terms of minimizing the power consumption at BSs while guaranteeing the QoS provisioning to mobile users.

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