

# Adaptive Base Station Switching Based on Feedback Control in Two-tier Femtocell Networks

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**Abstract**—Dynamic switching base station (BS) to improve the utilization is very important for reducing the energy consumption. Most of existing dynamic switching BS schemes require the switching threshold to be set in advance. The fixed switching threshold, however, fails to apply in practical two-tier femtocell networks, for it is difficult to precisely model that it may result in different switching operations and subsequent worse system performance. In this paper, we propose an adaptive BS switching scheme to regulate the threshold considering the time varying characteristic of the traffic profile in the two-tier femtocell networks. We apply feedback control methodology to formulate the adaptive BS switching as an adaptive real-time control problem. Performance evaluation reveals that the solution has excellent stability behavior and physical reliability. And simulation results also indicate that the adaptive switching scheme can achieve better performance than the fixed one.

**Index Terms**—dynamic base station switching, feedback control, green cellular networks, Two-Tier femtocell Networks

## I. INTRODUCTION

Financial and environmental considerations have motivated a trend in wireless communication network design and operation to minimize the amount of energy consumption. This trend is referred to as green radio communications. Reducing energy consumption has also economic impact on revenue, e.g., the wireless network operators are estimated to spend more than 10 billion dollars for electricity [1], a significant portion of their operational expenditure. Energy consumed by ICT (Information and Communication Technology) industry

is rising at 15-20 percent per year, doubling every five years [2][3]. Pushed by such needs of energy reduction, network operators are considering how to reduce the energy consumption in all components across base stations (BSs), mobile terminals (MTs), and backhaul networks.

The focus of this paper is on reducing the energy consumption in BSs, since BSs use a significant portion of energy used in cellular networks, reported to amount to about 60-80 percent [2]. The large number of BSs contributes a major portion of the energy consumption of cellular networks. When a BS is in its working mode, the energy consumption of processing circuits and air conditioner takes up about 60 percent of the total consumption. And so, control and optimization of energy consumption at BSs should be at the heart of any green communication scheme.

An important set of works on green communication has then been dedicated to the reduction of the transmitted power of the BSs; the idea is to find the minimal transmission power that ensures coverage and capacity [4][5]. This approach is essential for reducing the exposure of persons to electromagnetic radiations. However, alone, these schemes are not sufficient to reduce the energy consumption of wireless networks as a large part of energy consumption remains even for low output power. Therefore, by merely controlling the transmit power of radio equipment, the effect of energy saving is marginal.

In particular, LTE-Advanced (LTE-A) [6] introduces several significant improvements over previous LTE Release 9, notably the possibility of a Heterogeneous Network (HetNet) setting. The HetNet aspect we consider in this work is related to the deployment of femtocells, for the purpose of offloading a part of the traffic of the primary macro network [7][8].

Networks with overlapped coverage can cooperate to reduce their energy consumption by alternately switching on and off their resources according to the traffic load conditions. Almost all current cellular networks are facing issues arising from imperfect coverage, especially

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indoors. One cost-effective solution for mobile operators to improve coverage is the emerging femtocell network, where femtocell access points are overlaid on an existing macrocell and provide high-data-rate connections to users within a short range using the same radio-access technology as the macro underlay. Femtocells are expected to solve the problem of weak macro signals inside buildings, and help offload traffic from the macrocell network.

In dense urban areas, femtocells BSs are densely deployed, so coverage cells overlap with each other. Switching some BSs into sleep mode can reduce their energy consumption of the whole network[4]. This is the aim of the present work where we investigate a sleep/wake up mechanism for femtocells in a heterogeneous network, based on traffic load and user localization in the cell, which is known as dynamic planning.

A multitude of studies [9], [10], [11] have been recently studied the BS planning. The first work [9] made some simple simulations to show that BS planning was an efficient way to save energy. Marsan et al. [10] studied the BS switching strategy with several switching-off BS ratios. The research has also been extended to the two-tier femtocell network with the proposal of BS switching strategies [11]. Also, the BS switching strategy based on a snapshot approach not considering the traffic profile has been proposed. However, these prior works do not care about the BS switching condition which is the dominant factor for improving the system performance. This has driven us to this proposed scheme.

In this paper, we specifically propose a technique to adaptively adjust BS switching condition from the view of the system's primary performance metrics. It allows BSs with low utilization levels to be switched off, thereby increasing the energy efficiency of the radio access network, by migrating their traffic to the macro BS that can handle the overall traffic alone, without degrading the users Quality of Service (QoS). The original contributions of this paper are:

- We design the adaptive BS switching in two-tier femtocell networks based on feedback control techniques, and achieve better performance levels.
- We use system identification techniques to establish dynamic models for the two-tier network with unknown dynamics, which has been a major barrier for applying feedback control in adaptive BS management of such system.
- We design a dead-beat controller to determine the quantity of the switching threshold that needs to be regulated adaptively, not as some estimating way such as a stepwise adjusting way.

Note that the main advantage of applying control theory to our adaptive scheme is that control system is more reliable since a process failure affects only few control loops, and control calculations and reacting to process are completely independent.

The remainder of the paper is organized as follows. In Sec. II, we detail the system model. Sec. III describes an overview of the dynamic BS switching scheme. Sec. IV

derives the adaptive threshold strategy based on the feedback control that is the core of the algorithm. And the system identification analysis of the system model is developed in Sec. V. Numerical and simulation results are provided in Sec. VI. Sec. VII concludes this paper.

## II. SYSTEM MODELS

A two-tier femtocell network offsets the burden on the macrocell BS, provided the femtocells are judiciously placed in traffic hot spots. The traffic load in a wireless network can have spatial and temporal fluctuations due to user mobility and activities [12]. Observing the traffic profile in real cellular-based wireless access networks, it can be modeled as a periodic sinusoidal profile, as shown in Fig. 1. This is consistent also with the data presented in [12]. The traffic profile during the day time period (11 am - 9 pm) has higher value than that of the night time period (10 pm - 9 am). And, there is a difference in the traffic profile observed on a normal weekday and on a weekend/holiday period. Because BSs are planned to support the day time traffic, BSs with low utilization levels are allowed to be switched-off during the night time and the weekend period. This is why switching off redundant base-stations can save energy consumption. In this paper, we propose to dynamically switch BSs of the femtocells between active and sleep modes depending on the network traffic situation.

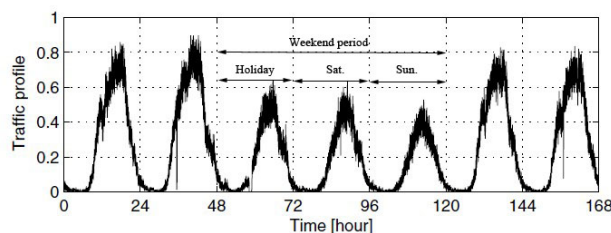


Figure 1. Normalized traffic profile during one week.

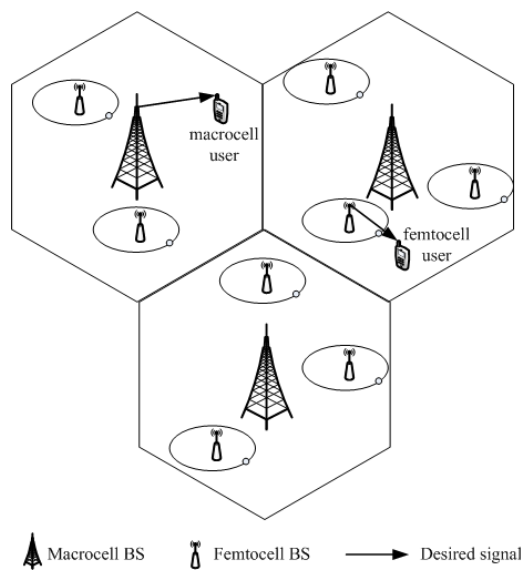


Figure 2. A two-tier femtocell network

First, we present the system model under consideration. Then we discuss the dynamic planning solutions in the

next section, which focus on switching off some femtocells to further improve the amount of energy saving.

In Fig. 2, the system model is illustrated, where both the macrocell and femtocell networks, belonging to the same operator, are sharing the same licensed spectrum [4][13][14]. We assume that the macro BSs ensure complete coverage, as this is the case in dense urban areas where femtocells are likely to be deployed as hotspots of large capacity for the purpose of offloading traffic from the macro cells. They are likely to be connected to the macro BS via a (logical) interface. When femtocells are deployed, users that are within the range of a femtocell can detect the presence of two BSs: macro and femto, and are connected to the one offering them the best Signal to Interference plus Noise Ratio (SINR).

Assume a macrocell services a hexagonal region  $\mathcal{H}$  of radius  $R_c$ . Femtocells are randomly distributed in  $\mathcal{H}$  according to a homogeneous spatial Poisson point process (SPPP) with intensity  $\lambda_f$ . The spatial density works out the average number of femtocell BSs per macro cell, which is obtained as  $N_f = \lambda_f |\mathcal{H}|$ . The downlink interference scenario in the two-tier femtocell networks is considered here. And we focus the per-tier outage probability in the two-tier network [13] based on cochannel deployment of macrocell and femtocell users, and the effect of the density of randomly scattered femtocells. Based on the performance analysis, we propose the adaptive switching off the femtocells BSs scheme.

### III. SWITCHING SCHEME

In this article, we specifically propose to switch off femtocells when the cell is not heavily loaded and the macro BS can handle the overall traffic alone, without degrading the users Quality of Service (QoS) [15][16]. As traffic load increases in the cell, one or more femtocells will be switched ON. Observing the traffic profile in real cellular-based wireless access networks, it can be modeled as a periodic sinusoidal profile [15] [16]. The traffic profile during the day time period (11 am - 9 pm) has higher value than that of the night time period (10 pm - 9 am).

It is assumed that there is a central decision maker that controls the BS working mode. The following traffic assumptions are made [15] [16]:

- The call arrival of a BS  $b$  at time  $t$  is modeled as a Poisson Process with mean arrival rate  $\lambda_b(t)[call/sec]$ . And, each call is assumed to have a constant service time,  $h[sec/call]$ .
- The traffic profile of a BS  $b$ ,  $\rho_b(t) = \lambda_b(t) \cdot h$ , is a time varying function with  $D = 24h$  time period. Assuming that the overall system is homogeneous in statistical equilibrium, the subscript is ignored,  $\rho(t)$ .

- BSs only know the approximated sinusoidal traffic profile with mean  $M$  and variance  $V$ , i.e.

$$\bar{\rho}(t) = V \cdot \cos(2\pi(t + \phi)/D) + M.$$

- The traffic profile of the macrocell BS is similar with the femtocell BS.

Each femtocell BS only knows the number of neighboring BS,  $|N_b|$ . We assume the traffic profile is modeled as the sinusoidal with  $T$  period time, thus the femtocell BS switching off and on each occur only once during  $T$  period time. Hence, we partition the time into a set of periods,  $\mathcal{T} = \{1, 2, \dots, T\}$ , of constant duration  $\tau$  hours that can capture the large scale fluctuations in the traffic load along the day,  $T = D/\tau$ . Decisions on the BS working mode are made at the initial moment of each period  $T$ .

The BS switching idea is similar to [15]. Assumed active user equipments (UEs) served by a femtocell BS  $b$  are randomly distributed. If the BS  $b$  is switched off at time  $t_b^{off}$ , UEs are handed over to the neighboring macrocell BSs,  $N_b$ . And then the handover traffic is approximated as  $\bar{\rho}(t_b^{off})/N_b$ . Considering the handover traffic, the cell traffic of the neighboring macrocell BSs are calculated as [15]

$$\bar{\rho}_n(t_b^{off}) = \bar{\rho}(t_b^{off}) \cdot (1 + 1/|N_b|), \quad n \in N_b, \quad (1)$$

when the femtocell BS  $b$  is switched off at time  $t_b^{off}$ . Therefore, the femtocell BS  $b$  is switched off when it is satisfied

$$\bar{\rho}(t) \cdot (1 + 1/|N_b|) < \rho_{th}, \quad (2)$$

where  $\rho_{th}$  is the switching threshold.

During the switching-off period, the BS does not work at all in the networks. The femtocell BS is switched on when the traffic is only considering the approximated sinusoidal traffic profile

$$\bar{\rho}(t) > \rho_{th}. \quad (3)$$

If the switching threshold is set at a higher value, more energy is saved but the network outage probability is also increased, and vice versa. Considering the constraint, the switching threshold is so important that it may result in different switching operations and subsequent system performance. This is the main motivation of this paper.

Our work proposes to adaptively adjust the switching threshold from feedback control law, according to the two-tier femtocell network performance. In the literature, few works are concerned in this area. Especially, in the overlapped cellular network, the traffic load and user localization occur over time, the so it is even more difficult to precisely model because none of them is known a priori. These problems call for mechanisms that can control them effectively without depending on detailed insight into their internal structure or on precise models of their behavior. And that feedback control

strategy can be applied for behavior optimization in unpredictable or poorly modeled environments.

#### IV. THE PROPOSED ADAPTIVE SWITCHING SCHEME BASED ON FEEDBACK CONTROL

##### A. Our Feedback Control Framework

A key feature of the framework is its use of feedback control theory as a scientific underpinning. The framework enables system designers to systematically design adaptive BS switching systems with established analytical methods to achieve analytically provable performance guarantees in unpredictable environments. The major components of our feedback control architecture are a set of control related variables and a feedback control loop that maps a feedback control system structure to dynamic BS switching. Each feedback control loop is composed of a Monitor, a Controller, and an Actuator. It is the first step to determine an appropriate controlled variable, which can represent network performance well and truly.

In this study, we consider the per-tier outage probability in a two-tier network based on cochannel deployment of macrocell and femtocell users [13] as the system's primary performance metrics. The outage probability is the probability that the signal to interference ratio (SIR) at the reference receiver is below a specified threshold  $\gamma$ . Namely, a reception is assumed to be successful provided the SIR seen at the receiver exceeds a specified  $\gamma_c > 0$ , with an outage resulting if this condition is not satisfied.

In order to state the law which can be used for determining the controlled variable, it is necessary to introduce some definitions.

Define as the  $t$  th monitoring period the time interval  $[t-1, t]$ , where  $t = (t-1) + \Delta T$  and  $\Delta T$  is referred to as the local monitoring period duration.

Define  $Q_m(t)$  and  $Q_f(t)$  as the outage probabilities of the macrocell users and the femtocell users during the  $t$  th monitoring period. And define  $Q_m^{max}$ ,  $Q_f^{max}$  as the maximum tolerated outage probability of the macrocell and the femtocell, respectively. We define the normalized short-term probability  $\Pi_m(t)$ ,  $\Pi_f(t)$  during the  $t$  th monitoring period in the following way:

$$\Pi_m(t) = \frac{Q_m(t)}{Q_m^{max}}, \Pi_f(t) = \frac{Q_f(t)}{Q_f^{max}} \quad (4)$$

Defined as the short-term outage threshold trend [17] during each monitoring period, the parameter  $\Delta\delta(t)$  is given by the following expression:

$$\Delta\delta(t) = \Pi_m(t) - \Pi_f(t) \quad (5)$$

As mentioned in [17], if the optimum balancing among  $\Pi_m(t)$ ,  $\Pi_f(t)$  is achieved,  $\Delta\delta(t)$  is zero. It is the performance metric that characterize the system performance defined over a monitoring period.

So, the first step in designing the architecture is to decide the following key variables of the system in terms of control theory.

- Controlled Variable  $\Delta\delta(t)$ : the performance metric that characterizes the system performance defined over the  $t$  th monitoring period. It simultaneously pays attention to the short-term outage probability of each tier network.
- Performance reference/Set point: 0. It represents the desired system performance in terms of a controlled variable  $\Delta\delta(t)$ , i.e. the optimum balancing among  $\Pi_m(t)$  and  $\Pi_f(t)$  is achieved.
- Error  $E(t)$ :  $E(t) = 0 - \Delta\delta(t) = -\Delta\delta(t)$ . It shows the difference between the performance reference and the value of the corresponding controlled variable.
- Manipulated Variable  $\Delta\rho_{th}(t)$ : they are system attributes that can be dynamically changed by the scheduler to affect the values of the controlled variable, i.e. the network performance. If the switching threshold is changed to a higher value, more energy is saved but the network outage probability is also increased, and vice versa.

And a feedback loop of our architecture [18] is 1) the system periodically monitors and compares the controlled variable with the set point to determine the error; 2) the controller computes the required control with the control function of the system based on the error; 3) the actuators changes the value of the manipulated variable to control the system.

In the following, we will utilize feedback control theory and methodology [18] to design an adaptive BS switching scheme with proven performance guarantees. The corresponding design methodology includes

1. Using system identification to establish a dynamic model for the adaptive system;
2. Design a controller to compute the change to the switching threshold based on the dynamic model;
3. Tuning the control parameters to meet the performance specs requirements of our adaptive control system.

##### B. Modeling the System: A System Identification Approach

Modeling two-tier network with unknown dynamics has been a major barrier for applying feedback control in adaptive BS management of such system. As system identification methodology [18] provides a practical solution for solving such modeling problems. In this section, we use system identification techniques to establish dynamic models for the system.

In our system identification approach, the controlled system is approximated as a linear model described as a difference equation with unknown parameters, which describes the mathematical relationship between the input and the output of a system. Here, the input of the model is the change to BS switching threshold  $\Delta\rho_{th}(t)$ . The output of the model is the controlled variable  $\Delta\delta(t)$  that

characterizes the system performance. We observe that the output of a model depends on previous input and outputs of the model. Then, the dynamic BS switching scheme is formulated as a  $n$ th order difference equation with some unknown parameters,

$$\Delta\delta(t) = \sum_{i=1}^n a_i \Delta\delta(t-i) + \sum_{i=1}^n b_i \Delta\rho_{th}(t-i). \quad (6)$$

There are  $2n$  parameters  $\{a_i, b_i | 1 \leq i \leq n\}$  that need to be decided in an  $n$ th order model. Next, we can use a least squares estimator to estimate the model parameters.

Least-squares estimator [18] can estimate unknown parameters by recursion formula, if only a system is modeled to be the following standard structure,

$$y(m) = \Phi^T(m)\Theta(m) + e(m), \quad (7)$$

where  $\Phi^T(m)$  denotes the input-output observation vector,  $\Theta(m)$  denotes the unknown parameters vector,  $e(m)$  represents noise. White noise input has been commonly used for system identification [18]. The estimator is invoked periodically at every sampling instant. At the  $m$ th sampling instant, according to the above (7), we define the vectors  $\Phi(m)$  and  $\Theta(m)$ :

$$\begin{aligned} \Phi(m) &= (\Delta\delta(m-1) \cdots \Delta\delta(m-n) \\ &\quad \Delta\rho_{th}(m-1) \cdots \Delta\rho_{th}(m-n))^T, \\ \Theta(m) &= (a_1 \cdots a_n \ b_1 \cdots b_n)^T. \end{aligned} \quad (8)$$

Let  $\mathbf{R}(m)$  be a square matrix whose initial value is set to a diagonal matrix with the diagonal elements set to 10. The recursion formulas of the estimator's equations at sampling instant  $m$  are [18]:

$$\begin{aligned} \Gamma(m) &= [1 + \Phi^T(m)\mathbf{R}(m-1)\Phi(m)]^{-1} \\ \Theta(m) &= \Theta(m-1) + \Gamma(m)\mathbf{R}(m-1)\Phi(m) \\ &\quad [\Delta\delta(m) - \Phi^T(m)\Theta(m-1)] \\ \mathbf{R}(m) &= \mathbf{R}(m-1) - \Gamma(m)\mathbf{R}(m-1)\Phi(m) \\ &\quad \Phi^T(m)\mathbf{R}(m-1). \end{aligned} \quad (9)$$

At sampling instant  $m$ , we substitute the current estimates  $\Theta(m)$  (reckoned by (9)) into (6), the estimator “predicts” a value of the model output  $\Delta\hat{\delta}(m)$ . The estimate error is

$$\Delta\delta(m) - \Delta\hat{\delta}(m).$$

The objective of the least squares estimator is iteratively updating the parameter to estimate at each sampling instant so as to minimize

$$\sum_{0 \leq i \leq m} (\Delta\delta(m) - \Delta\hat{\delta}(m))^2.$$

Our experimental results (see Sec. V) achieve a third order difference equation to approximate the input-output relation of the dynamic open-loop model,

$$\Delta\delta(t) = \sum_{i=1}^3 a_i \Delta\delta(t-i) + \sum_{i=0}^1 b_i \Delta\rho_{th}(t-i) \quad (10)$$

with

$$(a_1, a_2, a_3, b_0, b_1) = (0.03355, 0.3851, 0.5073, -2.146, -5.48).$$

We convert the open-loop system model in (10) to a transfer function  $G(z)$  in  $z$ -domain:

$$G(z) = \frac{\Delta\delta(z)}{\Delta\rho_{th}(z)} = \frac{b_0 + b_1 z^{-1}}{1 - a_1 z^{-1} - a_2 z^{-2} - a_3 z^{-3}}. \quad (11)$$

### Controller design

In general, we can make use of the following simplified block diagram in Fig.2 to show the control system.  $W(z)$ ,  $E(z)$ ,  $U(z)$  and  $Y(z)$  are respectively, the set-point, the error, the controller output and the controlled output.  $D(z)$  represents the digital controller, while the block  $G(z)$  refers to the  $z$ -transform of the zero-order-hold device in series with the process being controlled.

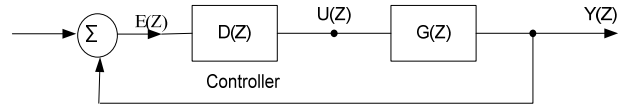


Figure 3. The system simplified block diagram

Firstly, we observe what the open-loop step response looks like according to (11)

$$\begin{aligned} Y(z) &= G(z)W(z) \\ &= -10.8023z^{-3} - 6.8323z^{-4} - 9.1316z^{-5} \\ &\quad - 28.9424z^{-6} - 5.9260z^{-7} - 26.6203z^{-8} \\ &\quad - 51.4846z^{-9} + \dots \end{aligned} \quad (12)$$

$W(z)$  represents the unit step input, i.e.

$$W(z) = 1 / (1 - z^{-1}).$$

So the sequences of the output  $y$  is

$$\{0, 0, 0, -10.8023, -6.8323, -9.1316, -28.9424, -5.9260, -26.6203, -51.4846, \dots\}.$$

It is emanative, and then the system is not stable. We must recur to some compensators to improve. Now, we are in a position to start designing digital controllers  $D(z)$  in Fig.2 to improve the performance.

The system (see Fig.2) has the closed loop transfer function:

$$\frac{Y(z)}{W(z)} = \frac{D(z)G(z)}{1 + D(z)G(z)} \quad (13)$$

Now suppose we wish the closed loop to respond in a certain manner, e.g.  $G_m(z)$ . In other words, it is desired that the closed loop has the dynamics of  $G_m(z)$

$$G_m(z) = \frac{Y(z)}{W(z)} \tag{14}$$

Then the controller that will give this closed loop response characteristic is that which satisfies the following equation:

$$D(z) = \left(\frac{1}{G(z)}\right)\left(\frac{G_m(z)}{1-G_m(z)}\right) \tag{15}$$

It is obtained by re-arranging the closed-loop transfer function and replacing by  $G_m(z)$ .

Thus, the required controller can be designed, for we have a model of the process with (11). Depending on  $G_m(z)$ , which is specified by the designer, different types of controllers will arise. The most common is dead-beat controller [19].

1) *Dead-beat controller*

The basic idea in dead-beat control design is similar to that in the minimal prototype case: to achieve zero error at the sample points in a finite number of sampling periods for step references and step output disturbances (and with zero initial conditions). However, in this case we add the requirement that, for this sort of reference and disturbance, the controller output  $U(z)$  also reach its steady state value in the same number of intervals. If both of them are satisfied, the controlled system meets the stability.

According to (1) and  $U(z)G(z) = Y(z)$  (see Fig.2),  $U(z)$  is

$$U(z) = \frac{G_m(z)W(z)}{G(z)} \tag{16}$$

A digital control system is stable when the poles are within the unit circle. Consider the open-loop system  $G(z)$ . The zeros are

$$z = 0, 0, -2.5536.$$

The poles are

$$p = 0.9699, -0.4682 + 0.5512i, -0.4682 - 0.5512i.$$

$G(z)$  has the pure lag  $z^{-2}$ . And  $z = -2.5536$  is the zero just outside the unit circle, so the system is not stable.

To satisfy the performance specifications, we synthesize a minimum time dead-beat control [19]

$$G_m(z) = z^{-m} \prod_{i=1}^n (1 - k_i z^{-1}) (m_0 + m_1 z^{-1} + \dots + m_{q+p-1} z^{-q-p+1}),$$

$k_i$  are the zeros on or outside the unit circle respectively.  $q$  and  $p$  are the number of the zeros and poles on or outside the unit circle respectively.  $m$  is the transient lag. Then let the closed-loop transfer function be

$$G_m(z) = (1 + 2.5536z^{-1})m_0z^{-2}. \tag{17}$$

And  $G_m(1) = 1$ . Next we work out

$$m_0 = 0.2814.$$

The required dead-beat controller is therefore (for (11))

$$D(z) = \frac{0.2814(1 - 0.03355z^{-1} - 0.3851z^{-2} - 0.5073z^{-3})}{1 - 0.2814z^{-2} - 0.7186z^{-3}} \tag{18}$$

2) *Stability and Physical Reliability*

In dead-beat control design, the stability requires that the closed loop response  $Y(z)$  and the controller output  $U(z)$  both reach their steady state value. From (16), the controller output by series expansion is obtained

$$U(z) = 0.1428 + 0.2512z^{-1} + 0.2606z^{-2} - 0.0208z^{-3} - 0.0208z^{-4} - 0.0208z^{-5} - 0.0208z^{-6} - \dots$$

Then the dead-beat control series is obviously convergent.

Next we observe the closed loop response  $Y(z)$ .

$$Y(z) = G_m(z)W(z) = 0.2814z^{-2} + z^{-3} + z^{-4} + z^{-5} + \dots \tag{19}$$

The closed loop response is also stable.

From the above results we see that the instability problem has been solved by the dead-beat control law. The controller  $D(z)$  presented above has been derived for unstable plants with at most one zero or pole on/outside the unit circle. To do this we simply use zero or pole cancellation in the dead-beat controller design.

Besides, if the controller can be realized on the physical, current output of the controller can only be used only with the input of the current time, the previous input and the output. It has nothing to do with the future of the input. This requires digital controller transfer function cannot have  $z$  positive power series. In the controller transfer function  $D(z)$  (see (18)), the power series of the numerator is equal to that of the denominator. It indicates that it has not a  $z$  positive power series, so the controller is physical reliability.

In conclusion, the dead-beat controller satisfies the design requirements, i.e. stability and physical reliability. In the context of our scheme, the controller periodically monitors the short-term outage threshold trend difference between the macrocell users and the femtocell users, and then computes the manipulated variable  $\Delta\rho_{th}(t)$  according to

$$\Delta\rho_{th}(z) = D(z)E(z).$$

If  $\Delta\rho_{th}(t)$  is greater than 0, the switching threshold should be increased, otherwise, it should be decreased.

V. SYSTEM IDENTIFICATION EXPERIMENTS

We use the identification method to establish a model for system control. By System Identification Toolbox of MATLAB, we run the system identification experiments. One ARX discrete model is identified by pseudo-random

binary sequence. We estimate a first order, a second order, a third order, and a fourth order respectively. Fig. 4 demonstrates that the estimated first and second order models have larger prediction error than the third order model. Although the accuracy of the prediction of the fourth order model has similar with the third one, it is more complex to realize. Hence the third order model is chosen as the best estimated model. The corresponding estimation parameters are

$$(a_1, a_2, a_3, b_0, b_1) = (0.03355, 0.3851, 0.5073, -2.146, -5.48).$$

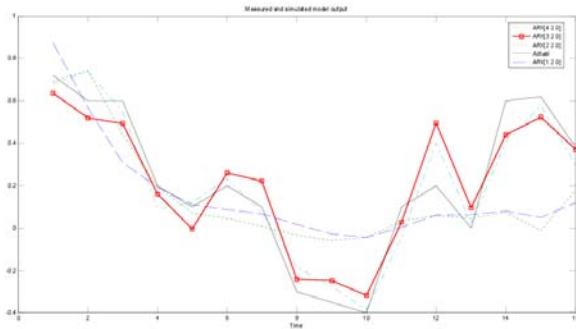


Figure 4. System identification results

VI. SIMULATION RESULTS

In this section, a series of simulations are conducted to compare our proposed adaptive BS switching scheme (AS) with a fixed BS switching scheme (FS) [15] in terms of traditional average performance measures. The system considers frequency division multiple access (FDMA) with 30 channels, a 10MHz bandwidth and a 2.3GHz radio frequency. The key simulation parameters are summarized in Table 1. We deploy the two-tier femtocell networks following the network model described in Sec. II. The setup consists of a hexagonal macrocell surrounded by two rings of interfering macrocells. In each macrocell region, cochannel femtocells are distributed with intensity  $\lambda_f$ . Three sectorized macrocells and omnidirectional femtocells are used [20].

TABLE I. SIMULATION PARAMETERS

	Macrocell	Femtocell
transmission power	43dB	23dB
radius	1000m	30m
penetration loss	-20dB	-5dB
path-loss exponent	$\alpha = 4$	
noise power	-120dB / Hz	
SINR threshold	4	
outage constraint	0.4	0.1

Fig. 5 shows the outage probability versus the number of simultaneously transmitting co-channel femtocells. By observing the figures, the shortcoming of the fixed scheme is immediately apparent. The outage probability is too low (below constraint) for smaller numbers of simultaneously transmitting co-channel femtocells. At higher numbers, the outage probability with a fixed switching threshold is still higher than our proposed scheme. When more numbers of femtocells transmits, the switching threshold need to be adjusted to a lower value that more femtocell BS is switched on. Thus the upper bound of the per-tier outage probability is maintained without degrading the users QoS, due to adaptive feedback control in our scheme.

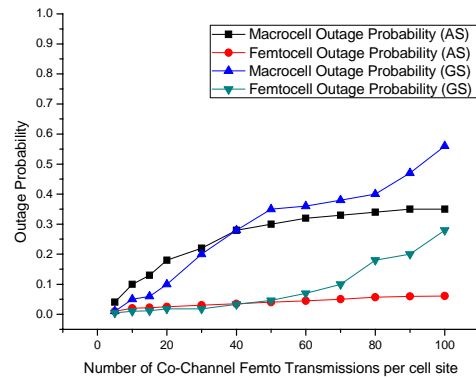


Figure 5. Outage Probability for AS and FS.

VII. CONCLUSION

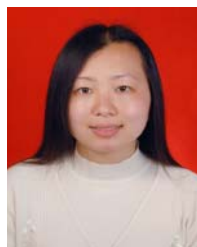
In this paper, we investigated the performance of a two-tier network with a cochannel femtocell deployment. The main contribution is that we have developed an novel adaptive BS switching algorithm based on feedback control theory to achieve the required QoS performance. The scheme is based both on a novel analytical model and employing standard feedback control design techniques. Our analysis have shown that the algorithm is stable and physical realizability. And our simulation results verify that the adaptive thresholds change can be beneficial to the ideal outage probability with the traffic load fluctuations.

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