Online Probabilistic Activation Control of Base Stations Utilizing Temporal System Throughput and Activation States of Neighbor Cells for Heterogeneous Networks*

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SUMMARY In this paper, we propose an online probabilistic activation/deactivation control method for base stations (BSs) in heterogeneous networks based on the temporal system throughput and activation states of neighbor BSs (cells). The conventional method iteratively updates the activation/deactivation states in a probabilistic manner at each BS based on the change in the observed system throughput and activation/deactivation states of that BS between past multiple consecutive discrete times. Since BS activation control increases the system throughput by improving the tradeoff between the reduction in inter-cell interference and the traffic off-loading effect, the activation of a BS whose neighbor BSs are deactivated is likely to result in improved system performance and vice versa. The proposed method newly introduces a metric, which represents the effective ratio of the activated neighbor BSs considering their transmission power and distance to the BS of interest, to the update control of the activation probability. This improves both the convergence rate of the iterative algorithm and throughput performance after convergence. Computer simulation results, in which the mobility of the user terminals is taken into account, show the effectiveness of the proposed method.

key words: heterogeneous networks, probabilistic activation control, transmission power control

1. Introduction

In the 5th generation mobile communication system (5G) [1]–[3] and beyond [4], in order to actualize high capacity at low cost, dense heterogeneous networks [5]–[8] in which many small cells served by low-transmission-power pico-base stations (BSs) are overlaid onto the macro-cell coverage of a high-transmission-power macro-BS is considered as an essential technical component. However, the use of an excessively large number of BSs may cause severe inter-cell interference. Needless to say, the use of many ineffective BSs that do not yield an improvement in system performance will result in undesirable power consumption in a mobile network. Therefore, appropriate activation of each BS depending on the user or traffic load distribution within the system coverage is important if the deployment of a large number of BSs is to enhance fully the system performance.

There are extensive investigations into BS activation/deactivation control in heterogeneous dense networks, e.g., [9]–[16]. Probabilistic BS activation/deactivation control methods such as in [11] and [12] achieve optimal BS activation/deactivation taking into account the coupled problem among cells due to the activation/deactivation control of individual BSs. An interference-aware BS activation method is proposed in [13]. However, these methods require prior knowledge of probability distributions of user locations or the traffic load of the entire system coverage, which is in reality difficult to achieve. Application of machine learning to BS activation control has been considered, e.g., in [14]–[16]. Reference [14] investigates the reinforcement learning-based control of the number of activated BSs (in other words, the BS activation ratio over the system coverage). In this method, the number of states is limited because only the control of the number of activated BSs is considered; however, a detailed decision on which subset of BSs is activated is not achieved. Reference [15] investigates deep reinforcement learning-based joint control of all BS activation. This is an attractive approach, however, from [15] and references within survey paper [16], the application of the machine learning-based BS activation control method seems to be limited to relatively small networks (small number of BSs in network coverage) due to the limitation of the dimensions of activation states of BSs. To establish a realistic BS activation control method for 5G and beyond, it is essential to consider dynamic mobility, i.e., the change in traffic distribution over time, and the limited amount of inter-BS information exchanged in the system coverage where many macro-BSs and pico-BSs coexist. Members of our research group have reported a method for online probabilistic activation/deactivation control of BSs in heterogeneous networks [17]–[19]. The reported method does not rely on a priori knowledge of probability distributions of user locations or the traffic load of the entire system coverage. Therefore, complicated inter-BS cooperation and measurement at the user terminals are not necessary. This method also enables the online activation/deactivation control of BSs that track the changes in user/traffic distribution within the system coverage. The reported method requires only a single metric to be exchanged among BSs, which is the system throughput measure in each cell. The reported method adaptively controls the activation probability of each BS individually according to the time
variation in the system throughput and the temporal activation/deactivation states of each BS. Hereafter, the method in [18] is referred to as the conventional method.

The conventional method utilizes only the system throughput observed as information at neighbor BSs. Since the BS activation control increases the system throughput by improving the tradeoff between the reduction in inter-cell interference and the traffic off-loading effect, the activation of a BS whose neighbor BSs are deactivated is likely to result in improved system performance and vice versa. In short, we can expect that the use of information regarding activation states of neighbor BSs in addition to the shared system throughput information can further improve the performance of the BS activation control.

In this paper, we propose an online probabilistic activation/deactivation control method for BSs based on the temporal system throughput and activation states of neighbor BSs. The information regarding the activation states of neighbor BSs is utilized in the adaptive step size of the activation probability of each BS. This contributes to a better convergence rate of the iterative algorithm and improved system performance after convergence. The effective ratio of the activated neighbor BSs is carefully defined considering the potential inter-cell interference calculated from the transmission power of neighbor BSs and the distance between BSs. The negative impact of the potential time variations in the activation/deactivation states of neighbor BSs is also considered in the definition of the effective ratio of the activated neighbor BSs. We note that since the activation/deactivation state is only 1-bit information per BS, the increase in the amount of inter-BS information exchanged via the backhaul in the proposed method is quite limited. We note that the contents of this paper are based on [20], but include enhanced evaluation and discussion.

The remainder of the paper is organized as follows. Section 2 describes the system model. Section 3 presents the proposed method. Section 4 shows numerical results and Sect. 5 concludes the paper.

2. System Model

Figure 1 shows the system model assumed in the paper. Many small cells served by low-transmission-power pico-BSs are overlaid onto the macro-cell coverage of a high-transmission-power macro-BS. The set of all BSs in the system is denoted as $\mathcal{N}_{\text{BS}}$. The set of macro-BSs in the system is denoted as $\mathcal{N}_{\text{macro}}$, while the set of pico-BSs in the system is denoted as $\mathcal{N}_{\text{pico}}$ ($\mathcal{N}_{\text{pico}} = \mathcal{N}_{\text{BS}} \setminus \mathcal{N}_{\text{macro}}$). We assume universal frequency reuse where the same frequency is used at both macro- and pico-BSs. The overall bandwidth per BS is denoted as $w_{\text{total}}$. The transmission power densities of the macro- and pico-BSs are denoted as $p_{\text{macro}}$ and $p_{\text{pico}}$, respectively. The transmission power density of BS $n$ is denoted as $p_{n}$. When $n \in \mathcal{N}_{\text{macro}}$, $p_{n} = p_{\text{macro}}$, while when $n \in \mathcal{N}_{\text{pico}}$, $p_{n} = p_{\text{pico}}$. The set of users in the system is denoted as $\mathcal{K}$.

Hereafter, the unit of discrete time, $t$, is set as the transmission activation/deactivation control cycle (update interval). The path gain between BS $n \in \mathcal{N}_{\text{BS}}$ and user $k \in \mathcal{K}$ at time $t$ is denoted as $g_{nk,t}$. The set of BSs that is activated at time $t$ is denoted as $\mathcal{N}_{\text{ON}}^{\text{BS}}[t]$, which is a subset of $\mathcal{N}_{\text{BS}}$. The user association is assumed to be updated at every $t$ based on the cell range expansion (CRE) method [21] depending on the activation states of all BSs. The set of users served by BS $n$ at time $t$ is denoted as $\mathcal{K}_{n}[t]$. The BS index to which user $k$ is connected at time $t$ is denoted as $n_{k}[t]$. The received signal-to-interference-plus-noise ratio (SINR) of user $k$ at time $t$ is denoted as $\gamma_{k,t}$, which is given as

$$\gamma_{k,t} = \frac{g_{n_{k}[t],k,t} p_{n_{k}[t]}}{\sum_{n \in \mathcal{N}_{\text{ON}}^{\text{BS}}[t]} g_{n,k,t} p_{n} + \sigma^{2}}, \quad (1)$$

where $\sigma^{2}$ is the receiver noise power density.

In this paper, we define the downlink system throughput based on proportional fairness [22] and its maximization is the purpose of the adaptive BS activation control, although the proposed method is applicable to any definition of the system throughput. Thus, the system throughput is defined by the geometric mean user throughput, which is equivalent to the log-sum of the user throughput. Proportional fairness is widely used in actual systems since it achieves a good tradeoff between the spectrum efficiency and fairness among users. The system throughput at the network level (over the entire system coverage) observed at time $t$, $\bar{R}[t]$, is represented as

$$\bar{R}[t] = \left( \prod_{k \in \mathcal{K}} r_{k}[t] \right)^{1/|\mathcal{K}|}. \quad (2)$$

In this paper, we assume orthogonal multiple access, since orthogonal frequency division multiple access (OFDMA) is used in 4G LTE, LTE-Advanced, and 5G NR. With proportional fairness, total system bandwidth $w_{\text{total}}$ of BS $n$ is equally divided and each divided bandwidth is allocated to each of the respective users in set $\mathcal{K}_{n}[t]$. Therefore, the throughput of user $k$ at $t$, $r_{k}[t]$, is represented as

$$r_{k}[t] = \frac{w_{\text{total}}}{|\mathcal{K}_{n_k}[t]|} \log_2 (1 + \gamma_{k}[t]). \quad (3)$$
3. Proposed Method

In the proposed method, the system throughput level, \( \overline{R}[t] \), is assumed to be shared by all BSs. To calculate \( \overline{R}[t] \), each BS \( n \) shares its local system throughput and \( |\mathcal{K}_n[t]| \) levels (simply two scalar numbers) with neighbor BSs at each time \( t \) using inter-BS information exchange through the backhaul.

At time \( t \), the activation probability of BS \( n \) is denoted as \( q_n[t] \), whose control is the purpose of the proposed method. To simplify the description of the proposed method, we denote the activated and deactivated states as ‘1’ and ‘0’, respectively. The activation/deactivation state of BS \( n \) at time \( t \) is represented by \( s_n[t] \in \{1, 0\} \). The proposed method updates \( q_n[t] \) at each time \( t \) as described below. After the update of \( q_n[t+1] \) is completed at each BS \( n \) individually, the activation or deactivation of the respective BSs is decided in a probabilistic manner using \( q_n[t+1] \). Since the activation/deactivation states of BSs may change from time \( t \) to \( t+1 \), the user association is re-performed among temporally activated BSs. The above process is repeated periodically over time for convergence and to track the change in the user/traffic load distribution.

In the following, the update procedure for \( q_n[t] \) is presented. Since the conventional and proposed methods update \( q_n[t] \) independently at each BS, we describe hereafter the control at a certain BS \( n \).

At each time \( t \), BS \( n \) first calculates \( \overline{R}_{n_{ON}}[t] \) and \( \overline{R}_{n_{OFF}}[t] \), which are the linear weighted moving average of the system throughput levels when BS \( n \) is activated or deactivated, respectively, during the past \( T_{avg} \) discrete times. Terms \( \overline{R}_{n_{ON}}[t] \) and \( \overline{R}_{n_{OFF}}[t] \) are respectively given as

\[
\begin{align*}
\overline{R}_{n_{ON}}[t] &= \frac{\sum_{i=t-T_{avg}+1}^{t} \left( T_{avg} - t + i \right) s_n[i]\overline{R}[i]}{\sum_{i=t-T_{avg}+1}^{t} \left( T_{avg} - t + i \right) s_n[i]} \\
\overline{R}_{n_{OFF}}[t] &= \frac{\sum_{i=t-T_{avg}+1}^{t} \left( T_{avg} - t + i \right) (1 - s_n[i])\overline{R}[i]}{\sum_{i=t-T_{avg}+1}^{t} \left( T_{avg} - t + i \right) (1 - s_n[i])}
\end{align*}
\]

(4)

The reason why we use the weighted moving average in (4) is to give more weight to the impact of more recent system states on the temporal activation control. Although we assume the linear weighted moving average in the paper, any other weighted averaging scheme such as the exponentially weighted moving average can be applied.

Terms \( \overline{R}_{n_{ON}}[t] \) and \( \overline{R}_{n_{OFF}}[t] \) are indicators of how to update \( q_n[t] \) at the next time \( t+1 \). Thus, when \( \overline{R}_{n_{ON}}[t] \) is greater than \( \overline{R}_{n_{OFF}}[t] \), \( q_n[t+1] \) should be increased from \( q_n[t] \) so that BS \( n \) will be activated at \( t+1 \) with higher probability and vice versa. Actually, the conventional method in [18] updates \( q_n[t] \) based on \( \overline{R}_{n_{ON}}[t] \) and \( \overline{R}_{n_{OFF}}[t] \) using the following equation.

\[
q_n[t+1] = \begin{cases} 
\min \{q_n[t] + \varepsilon, 1 - \rho\}, & \overline{R}_{n_{ON}}[t] > \overline{R}_{n_{OFF}}[t] \\
\max \{q_n[t] - \varepsilon, 0 + \rho\}, & \overline{R}_{n_{ON}}[t] < \overline{R}_{n_{OFF}}[t]
\end{cases}
\]

(5)

Here, \( \varepsilon \) is a small positive constant that corresponds to the step size for the update of \( q_n[t] \). We note that the maximum and minimum values of \( q_n[t] \) are limited to \( 1 - \rho \) and \( \rho \), respectively, in order to avoid fixed activation/deactivation states when \( q_n[t+1] \) reaches 1 or 0. We can expect that as averaging interval \( T_{avg} \) increases, more stable control is possible. However, some level of randomness during the iterative algorithm may be beneficial for searching for better local optima (hopefully a globally optimal one). Therefore, an excessively long \( T_{avg} \) may result in poor system throughput after convergence for the sake of a faster convergence rate and stable operation.

Meanwhile, since the BS activation control increases the system throughput by improving the tradeoff between the reduction in inter-cell interference and the traffic off-loading effect, the activation of a BS whose neighbor BSs are deactivated is likely to result in improved system performance and vice versa. In short, using the information regarding activation states of neighbor BSs in addition to \( \overline{R}_{n_{ON}}[t] \) and \( \overline{R}_{n_{OFF}}[t] \) for the update of \( q_n[t] \) can improve the performance of the BS activation control, which is the aim of the proposed method.

The basic idea of the proposed method is as follows. First, if most of the BSs neighboring BS \( n \) are deactivated, the activation probability of BS \( n, q_n[t] \), is increased with a larger step size when \( q_n[t] \) is decided to be increased. This is because if most of the neighbor BSs are deactivated, the effect of increasing inter-cell interference on the neighbor cells by turning on the transmission of BS \( n \) is small, and the effect of traffic off-loading by geographical reuse of the frequency is large. Therefore, in this case, there is motivation to activate positively BS \( n \). On the contrary, if most of the BSs neighboring BS \( n \) are activated, the activation probability of BS \( n, q_n[t] \), is decreased with a larger step size when \( q_n[t] \) is decided to be decreased. This is because, in this case, turning on the transmission of BS \( n \) may cause severe inter-cell interference to neighbor cells and it is reasonable to deactivate positively the transmission of BS \( n \).

In the following, a detailed procedure for updating \( q_n[t] \) in the proposed method is described. The set of neighbor BSs to BS \( n \) is denoted as \( \mathcal{N}_n \). A subset of BS \( m \in \mathcal{N}_n \), which is activated at \( t \) (thus, \( s_m[t] = 1 \)) and increases the system throughput by its activation over the past \( T_{avg} \) times (thus, \( \overline{R}_m[t] > \overline{R}_m[t-1] \)), is denoted as \( \mathcal{N}_{m_{ON}} \). Similarly, a subset of BS \( m \in \mathcal{N}_n \), which is deactivated at \( t \) (thus, \( s_m[t] = 0 \)) and increases the system throughput by its deactivation over the past \( T_{avg} \) times (thus, \( \overline{R}_m[t] < \overline{R}_m[t-1] \)), is denoted as \( \mathcal{N}_{m_{OFF}} \). The distance between BS \( n \) and its neighbor BS
Specific features in the definition of \( f_n^{\text{ON}}[t] \) are as follows. First, the impact of mutual inter-cell interference between BSs \( n \) and \( m \) is taken into account based on the transmission power of BS \( m \), \( p_m \), and inter-BS distance \( l_{n,m} \). Term \( p_m/l_{n,m} \) in (6) represents a rough estimate of the relative level of inter-cell interference caused by BS \( m \) from which the users connected to BS \( n \) will suffer. Division of \( p_m \) by \( l_{n,m} \) is to consider the distance-dependent path loss. We note that since the actual inter-cell interference levels are dependent on the user positions, this is a rough estimate. For this reason, we do not consider the detailed decay factor of the distance-dependent path loss in (6) for simplicity.

Second, the reason why only the neighbor BS sets \( f_n^{\text{ON}}[t] \) as subsets of \( N_n \), which are taken into account in the calculation of \( f_n^{\text{ON}}[t] \) is that since we use the measurement of \( f_n^{\text{ON}}[t] \) at time \( t \) to control the activation/deactivation state of BS \( n \) at time \( t+1 \), it is desirable to consider only those BSs in the \( f_n^{\text{ON}}[t] \) calculation whose activation/deactivation states are believed to be kept the same from time \( t \) to \( t+1 \) with high probability.

The proposed method updates \( q_n[t] \) based on \( f_n^{\text{ON}}[t] \) in addition to \( R_n^{\text{ON}}[t] \) and \( R_n^{\text{OFF}}[t] \) according to the following equation.

\[
q_n[t+1] = \begin{cases} 
\min\{q_n[t] + (1 - f_n^{\text{ON}}[t]) \cdot e, 1 - \rho\}, & R_n^{\text{ON}}[t] > R_n^{\text{OFF}}[t] \\
\max\{q_n[t] - f_n^{\text{ON}}[t] \cdot e, 0 + \rho\}, & R_n^{\text{OFF}}[t] > R_n^{\text{ON}}[t].
\end{cases}
\]

(7)

Here, a small positive constant, \( e \), can be recognized as the ‘unit’ step size for the update of \( q_n[t] \). When \( q_n[t+1] \) is controlled to be increased from \( q_n[t] \), its updating step size is set proportional to the effective ratio of the deactivated BSs nearby BS \( n \), (thus, \( 1 - f_n^{\text{ON}}[t] \)). When \( q_n[t+1] \) is controlled to be decreased from \( q_n[t] \), its updating step size is set proportional to the effective ratio of the activated BSs nearby BS \( n \), \( f_n^{\text{ON}}[t] \). This brings about faster adaptation of \( q_n[t] \) to the given environment (BS and user/traffic distributions). Since the activation/deactivation state information is represented using only 1 bit per BS, the increase in the amount of inter-BS information exchanged via the backhaul in the proposed method is quite limited.

4. Numerical Results

4.1 Simulation Parameters

The performance of the proposed method is evaluated by computer simulation. Table 1 gives the simulation parameters. The system bandwidth of all BSs is set to \( w_{\text{total}} = 9 \text{ MHz} \). The macro-BSs, pico-BSs, and user terminals are placed at random locations within a wrap-around 5 \( \times \) 5-square kilometer system coverage area based on the Poisson point process (PPP). The node densities of the macro-BSs, pico-BSs, and user terminals are set to 1, \( D_{\text{pico}} \), and 30 per square kilometer, respectively. Density \( D_{\text{pico}} \) is parameterized in the following evaluations. Figure 2 shows an example of the node locations where \( D_{\text{pico}} \) is set to 20. The transmission power levels of the macro- and pico-BSs are 46 dBm and 30 dBm, respectively. OFDMA is assumed as the multiple access scheme. As the propagation model, distance-dependent path loss and lognormally distributed random shadowing are assumed with the parameters given in Table 1. The receiver noise power density of user terminals is set to \(-165 \text{ dBm/Hz} \). The CRE method \[21\] is used for user association. The user throughput is calculated based on the Shannon formula. Note that the transmission power of the activated BS, which does not temporally serve any user terminal as a result of the user association process, is assumed to be lowered to the 10% level of its maximum

<table>
<thead>
<tr>
<th>System bandwidth, ( w_{\text{total}} )</th>
<th>9 MHz</th>
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<tbody>
<tr>
<td>Node density</td>
<td>Macro-BS</td>
</tr>
<tr>
<td></td>
<td>Pico-BS</td>
</tr>
<tr>
<td>User terminal</td>
<td></td>
</tr>
<tr>
<td>BS transmission power</td>
<td>Macro-BS</td>
</tr>
<tr>
<td></td>
<td>Pico-BS</td>
</tr>
<tr>
<td>Distance-dependent path loss</td>
<td>114.1 + 37.6 ( \log_{10}(r) ), ( r ) kilometers</td>
</tr>
<tr>
<td>Shadowing</td>
<td>Lognormal shadowing with standard deviation of 5 dB and inter-slope correlation of 0.5</td>
</tr>
<tr>
<td>Receiver noise power density</td>
<td>-165 dBm/Hz</td>
</tr>
<tr>
<td>User association</td>
<td>CRE method</td>
</tr>
</tbody>
</table>

Example of node locations.
transmission power since the data channel is not transmitted (10% is assumed to be consumed for transmitting reference signals, the broadcast channel, etc.). As the system throughput, we use the geometric mean user throughput.

The averaging interval of the system throughput levels for activation control, $T_{\text{avg}}$, is parameterized in the following evaluation. In addition to the proposed method, the conventional method [18] and the case where all the BSs are always activated are evaluated for comparison. We assume that the conventional method controls the activation of both the pico- and macro-BSs, which is the same as in the proposed method. The ε values in the conventional and proposed methods are set to 0.005 and 0.01, respectively. The ρ value of 0.01 is used in the conventional and proposed methods. We evaluate a static mobility environment in which the position of the user terminal does not change over time and a dynamic mobility environment in which users dynamically move. The random waypoint (RWP) model [23] is used to simulate user mobility. In the following evaluation, the initial setting of activation probability $q_n[0]$ of each BS $n$ at the 0-th iteration in a static mobility environment or at the initial time in a dynamic mobility environment is randomly selected to assess the worst case scenario in the activation control methods.

4.2 Simulation Results

First, we show the performance of the proposed method in the static mobility environment. Figure 3 shows the system throughput as a function of the number of iterations in the iterative algorithm of the activation/deactivation control. For comparison, we also show the performance of the conventional BS activation method and that where all BSs are always activated. Density $D_{\text{pico}}$ is set to 20. In the proposed and conventional activation control methods, $T_{\text{avg}}$ is set to 30. The proposed method improves the convergence rate of the iterative algorithm and the system throughput after convergence compared to the conventional method. This is because the proposed method takes into account the activation/deactivation state information of neighbor BSs, which makes it possible to obtain greater effects from traffic off-loading while suppressing the inter-cell interference.

In order to assess the difference in the distribution of the activated/deactivated BSs between the proposed and conventional methods, Fig. 4 shows the cumulative distribution of the minimum inter-BS distances between the activated BSs and that between the deactivated BSs. Density $D_{\text{pico}}$ is set to 20. In the proposed and conventional activation control methods, $T_{\text{avg}}$ is set to 30. The performance levels after a sufficient number of iterations, which is set to 15,000, are presented. The same holds for Figs. 5–8 and Table 2. The cumulative distributions of the minimum inter-activated BS distance are similar between the proposed and conventional methods, although that of the proposed method tends to be slightly shorter. On the other hand, the minimum inter-deactivated BS distance is considerably longer in the proposed method than in the conventional method.

Figure 5 shows the ratio of the activated surrounding BSs as a function of the maximum distance from the activated BS of interest to the surrounding BSs. In the figure, the vertical axis indicates the ratio of BSs in the active state in the set of BSs in the area that is defined by the maximum distance from the activated center BS, which is shown on the
horizontal axis. Figure 5 indicates that the proposed method has approximately the same BS activation ratio as the conventional method in the range where the distance from the activated BS of interest is sufficiently short. However, as the distance from the activated BS increases, the ratio of the activated surrounding BSs becomes roughly 10% higher than that for the conventional method.

Figure 6 shows the distribution of the allocated bandwidth to each user and the inter-cell interference power. The allocated bandwidth to each user and inter-cell interference power levels are averaged over 5,000 iterations (thus, from the 15,001-st iteration to the 20,000-th iteration). The inter-cell interference power is normalized by the receiver noise power. Figures 7 and 8 show the cumulative probabilities of the allocated bandwidth per user and inter-cell interference power, respectively, obtained from the data in Fig. 6. These figures show that the proposed method has roughly the same level of inter-cell interference power as the conventional method; however, the allocated bandwidth per user is clearly increased. Based on Figs. 6 and 7, the distribution of the allocated bandwidth per user appears discrete especially for the proposed method. We assume the downlink system throughput based on proportional fairness in the paper. With proportional fairness, the allocated bandwidth per user is equalized among all users connected to the same BS. Thus, the allocated bandwidth per user becomes 9 MHz, 4.5 MHz, 3 MHz, 2.25 MHz, and 1.8 MHz when the number of connected users to a BS is 1, 2, 3, 4, and 5, respectively, with a 9-MHz system bandwidth. This is the reason why the distribution of the allocated bandwidth per user appears discrete. Since we plot the allocated bandwidth per user averaged over 5,000 iterations, the averaged version of the allocated bandwidth per user can be different from the above discrete numbers when the user association changes due to the change in BS activation/deactivation states during the observed 5,000 iterations. A clearer discrete distribution of the allocated bandwidth per user averaged over 5,000 iterations in the proposed method compared to that for the conventional method indicates more stable activation control in the proposed method.

Table 2 summarizes the average ratio of activated BSs, average of the allocated bandwidth per user, and average of the normalized inter-cell interference power for the proposed and conventional methods. The proposed method more actively encourages BSs to be activated when the surrounding BSs are deactivated. As a result, the proposed method achieves more aggressive simultaneous activation of BSs that are sufficiently separated from each other from the viewpoint of mutual inter-cell interference compared to that for the conventional method. This is thanks to the consideration of the activation/deactivation states of the neighbor BSs in the proposed BS activation control. This brings about an increased efficiency in the geographical frequency reuse. Thus, as the number of activated BSs increases, the traffic off-loading effect is enhanced and the average number of connected users per activated BS decreases. This results in the increased bandwidth allocation per user. At the same time, a severe increase in inter-cell interference is avoided as given in Table 2. Furthermore, the proposed method suppresses the occurrence of coverage holes caused by the concentration of deactivated BSs. For these reasons, the proposed method is able to obtain a system throughput higher
than that attained by the conventional method.

Figure 9 shows the system throughput after convergence as a function of $T_{\text{avg}}$. Density $D_{\text{pico}}$ is set to 20. From the figure, we confirm that the dependence of the system throughput after convergence on $T_{\text{avg}}$ is not noticeable. A slight decrease in the system throughput as $T_{\text{avg}}$ increases is due to the reduced randomness during the iterative probabilistic algorithm which could be an obstacle to searching for better local activation/deactivation-state optima. Figure 10 shows the number of iterations required for convergence as a function of $T_{\text{avg}}$. The convergence condition is defined here as the number of iterations that first reaches the 120% value of the system throughput in the case where all the BSs are always activated. We see that a longer $T_{\text{avg}}$ is beneficial for a faster convergence rate as expected. However, we note that in a realistic dynamic user mobility environment where the user terminal moves over time, the use of an excessively long $T_{\text{avg}}$ may result in a reduction in system throughput due to the degraded tracking ability of the proposed activation control against the user mobility (change in the distribution of user terminals). In that sense, $T_{\text{avg}}$ of 30 seems to be an appropriate choice since further improvement in the convergence rate with $T_{\text{avg}}$ greater than 30 is limited.

Figure 11 shows the system throughput as a function of the pico-BS density, $D_{\text{pico}}$. In the proposed and conventional activation control methods, $T_{\text{avg}}$ is set to 30. This figure shows that the effect of the proposed method is increased as $D_{\text{pico}}$ is set high. As $D_{\text{pico}}$ increases, the traffic off-loading effect, in which the reduced number of connected users per BS increases the bandwidth allocated per user, is enhanced by using many pico-BSs in principle. On the other hand, the inter-cell interference caused by the pico-BS becomes a dominant degradation factor in the system throughput. The proposed method adaptively activates/deactivates each BS considering the activation/deactivation states of its neighbor BSs, which results in a more effective traffic off-loading effect thanks to the increased number of activated BSs while maintaining approximately the same level of inter-cell interference reduction compared to that for the conventional method.

Finally, we evaluate the proposed method in a dynamic user mobility environment hereafter. In the RWP model, the velocity of user $k$ is randomly given based on a uniform distribution within the range of 0 to 4 km/h to simulate a pedestrian environment. User $k$ moves at the determined moving speed toward the destination, which is randomly selected within the system coverage for each user. After arriving at the destination, user $k$ takes a break with the thinking time of 10 s. After the break, user $k$ randomly determines a new destination and moving speed, and restarts movement.

Figure 12 shows the time variation of the system throughput in the RWP-based user mobility environment. Figure 13 shows the cumulative distribution of the system throughput in Fig. 12. Density $D_{\text{pico}}$ is set to 20. For comparison, the conventional method and the case where all the BSs are always activated are evaluated. In the proposed and

### Table 2
Comparison of proposed and conventional methods.

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<thead>
<tr>
<th></th>
<th>Proposed Method</th>
<th>Conventional Method</th>
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<tbody>
<tr>
<td>Average ratio of activated BSs</td>
<td>79.4%</td>
<td>70.5%</td>
</tr>
<tr>
<td>Average of allocated bandwidth per user</td>
<td>4.67 MHz</td>
<td>4.36 MHz</td>
</tr>
<tr>
<td>Average of normalized inter-cell interference power</td>
<td>47.1 dB</td>
<td>46.6 dB</td>
</tr>
</tbody>
</table>

Fig. 9 System throughput after convergence as a function of $T_{\text{avg}}$. Fig. 10 Number of iterations required for convergence as a function of $T_{\text{avg}}$. Fig. 11 System throughput as a function of pico-BS density, $D_{\text{pico}}$. Fig. 12 Time variation of the system throughput in the RWP-based user mobility environment. Fig. 13 Cumulative distribution of the system throughput in Fig. 12.
conventional methods, the update time interval of the activation control, $T_{\text{update}}$, is set to 100 ms and $T_{\text{avg}}$ is set to 30. The proposed method clearly achieves greater system throughput even in a dynamic user mobility environment compared to the conventional two methods. Thus, the BS activation control of the proposed method successfully tracks the dynamic changes in the user distribution due to mobility.

Figure 14 shows the time variation of the system throughput for the proposed method with $T_{\text{update}}$ as a parameter in the RWP-based user mobility environment. The performance with $T_{\text{update}}$ of 1000 ms is severely degraded compared to the cases with $T_{\text{update}}$ of 10 or 100 ms. This is because the activation control is not able to track the change in user distribution over time due to mobility. By using $T_{\text{update}} = 100$ ms, approximately the same performance as that for $T_{\text{update}} = 10$ ms is achieved after the initial adaptation of the activation states of the respective BSs to the temporal user distribution.

5. Conclusion

We proposed an online probabilistic activation/deactivation control implemented at BSs based on the temporal system throughput and activation states of neighbor BSs. The effective ratio of the activated BSs nearby the BS of interest ($f_{\text{ON}}^n[t]$) is carefully defined considering the potential inter-cell interference and time variation in activation/deactivation states of neighbor BSs. Adaptive update of the activation probability of BS $n$, $q_n[t]$, based on $f_{\text{ON}}^n[t]$ in addition to the temporal system throughput levels in the past allows for a faster convergence rate of the iterative algorithm in the given environment (BS and user/traffic distributions) and improved system performance after convergence. Since the activation/deactivation state information is represented using only 1 bit per BS, the increase in the amount of inter-BS information exchanged via the backhaul in the proposed method is quite limited. Detailed performance evaluation results showed that the proposed method considering the activation states of neighbor BSs achieves more aggressive simultaneous activation of BSs that are sufficiently separated from each other from the viewpoint of mutual inter-cell interference than the conventional method. This brings about increased efficiency in geographical frequency reuse, which results in the traffic off-loading effect and increased bandwidth allocation per user, while avoiding the increase in inter-cell interference. Furthermore, the proposed method suppresses the occurrence of coverage holes caused by the concentration of deactivated BSs. For these reasons, the proposed method achieves a higher system throughput than that for the conventional method both in static and dynamic mobility environments with a reasonable update time interval of the activation control.

References


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