Coverage Probability Analysis for Uplink/Downlink Decoupled Access in Heterogeneous Cellular Networks

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Abstract. Cellular networks are evolving into wireless heterogeneous networks with various types of base stations (BSs) including macro base stations and femto base stations. Since the traditional coupled access method is not able to meet the communication needs of the current users, uplink (UL) and downlink (DL) decoupled access is proposed, which refers that the BS selected in UL is unnecessarily the same as in DL. We commence by deriving the association probabilities for UL and DL decoupled access. Subsequently, we derive explicit analytical expressions for the joint distance distribution. Leveraging the tools of stochastic geometry, we obtain precise formulas for the coverage probabilities. Furthermore, we investigate the influence of the path loss exponent on the network performance. To validate the efficacy of our proposed analytical framework, we conduct extensive Monte Carlo simulations.

Keywords: Heterogeneous cellular networks, downlink/uplink decoupled access, distance distributions, coverage probability.

1. Introduction

Current cellular networks are evolving into wireless heterogeneous networks with multiple types of base stations (BSs) including macro base stations (MBSs) and femto base stations (FBSs), as well as having different cell sizes [1], [2]. We are currently in the era of 5th Generation Mobile Communication Technology (5G), which is a new generation of broadband mobile communication technology with three major application scenarios, including enhanced mobile broadband (EMBB), ultra-high reliability low latency communication (URLLC) and massive machine class communication (MMTC). In the traditional association approach, the uplink (UL) and downlink (DL) of each user device (UD) are usually connected to a single fixed BS, which is also referred to as coupled access [3]. However, whether this correlation approach is optimal has received widespread academic attention, as coupled access has been discovered to be incapable of satisfying and securing user 5G communication requirements, particularly at the edge of the cell.

UL and DL decoupled access has been considered as an essential technical solution to solve the above problems. Decoupled access, as mentioned in [4], brings significant benefits in terms of network throughput, outage and power consumption, and at a lower cost. The authors in [5] indicate that to maximize the average received power, many UDs choose decoupled access, which refers to receiving from the MBS in DL and transmitting through the FBS in UL. In [6], a UL and DL decoupled access scheme is proposed with enhanced energy efficiency. The study conducted in [7] emphasize the potential improvements that can be achieved through UL and DL decoupled access, including enhanced UL performance, improved load balancing, and increased cell capacity. By UL and DL decoupled access, the authors in [8] highlight the opportunity for UDs to establish connections with various BSs and utilize distinct frequency bands for UL and DL transmissions.

The main objective of this paper is to analyze the coverage probability of heterogeneous cellular networks with UL and DL decoupled access. The main contributions of this paper are listed as follows.

An analytical framework is proposed to establish a new model for two-tier heterogeneous cellular networks including MBSs and FBSs.

The mathematical framework for analyzing the joint association probability in UL and DL decoupled access is established. Furthermore, specific analytical formulas are obtained to characterize the joint distance distribution. Additionally, the coverage probability is calculated by employing the tools of stochastic geometry.
Extensive Monte Carlo simulations are conducted to validate the significance of the analytical framework.

The remaining of this paper is structured as follows. Section II presents the system model. Section III derives the joint association probability, joint distance distributions, and coverage probability. Section IV presents the numerical results. Section V provides a conclusion to this paper.

2. System Model

We consider a model of a two-tier heterogeneous cellular network, as shown in Fig. 1, where the locations of the BSs follow an independent homogeneous Poisson point process (PPP) [9]. Each UD has the liberty to select the suitable UL and DL connections in relation to the BS, and there also exist UL and DL interferences between non-associated UD and the BS.

We denote by $\Phi_\nu$ with $\nu \in \{M, F, d\}$ the set of points with density $\lambda_\nu$ obtained from the PPP, which can be clearly expressed as:

$$\Phi_\nu = \{x_i \in \mathbb{R}^2, i \in \mathbb{N}_+\}, \quad (1)$$

where for MBSs $\nu = M$, for FBSs $\nu = F$, for UDs $\nu = d$.

![Fig. 1. UL and DL decoupled access model in heterogeneous cellular networks.](image)

We use $P_\nu$ to describe the transmitting power of UDs $\nu$ and assume that the transmitting powers for UL transmissions have the same numerical value. Moreover, since Slivnyak’s theorem [10] allows the distribution of point processes to be independent of the nodes at the origin, we will analyze the typical UD located at $x_0 = (0,0)$. The power received by a typical UD in DL from all MBSs or FBSs located at $x_\nu \in \Phi_\nu$, where $\nu \in \{M, F\}$ can be expressed as $S_{\nu,D}$. The power received by the BS in UL from all UDs can be expressed as $S_{\nu,U}$. These received powers are granted by:

$$S_{\nu,D} = P_\nu h_{x_\nu} X_{\nu}^{-\alpha}, \quad (2)$$

$$S_{\nu,U} = P_d h_{x_\nu} X_{\nu}^{-\alpha}, \quad (3)$$

where $X_{\nu}$, $\nu \in \{M, F\}$ are respectively the distances from points $x_\nu \in \Phi_\nu$ to the origin, $\alpha$ is the path loss exponent of the standard power loss propagation model ($\alpha > 2$), and $h_{x_\nu}$ represents the Rayleigh attenuation at point $x_\nu$, which follows an exponential distribution in the mean 1 and can be denoted as $h_{x_\nu} \sim \exp(1)$. $\sigma^2$ is the noise.

Therefore, we can construct SINR models for DL and UL. The DL SINR when UD is associated to vBS is:

$$\text{SINR}_{\nu,D} = \frac{S_{\nu,D}}{I_M + I_F + \sigma^2} \quad (4)$$
where the received power $S_{v,d}$ in the numerator is only related to the selected BSs, while the interference power in the denominator is related to the power of all other MBSs $I_M$ and FBSs $I_F$ and the constant noise power $\sigma^2$. Specifically, the interference power from other MBSs and FBSs can be expressed as:

$$ I_M = \sum_{x_i \in \Phi_M \setminus x_v} P_M h_{x_i} X_i^{-\alpha} $$

$$ I_F = \sum_{x_i \in \Phi_F \setminus x_v} P_F h_{x_i} X_i^{-\alpha} $$

Similarly, we can give UL SINR when UD is associated to vBS:

$$ \text{SINR}_v^U = \frac{s_{v,U}}{I_d + \sigma^2} $$

where, differently from DL, the received power in the numerator is not related to the selected BS but to the typical UD and the interference power from other BSs in the denominator becomes the interference power from other UDs besides the typical UD $I_d$, which can be expressed as:

$$ I_d = \sum_{x_i \in \Phi_d \setminus x_d} P_d h_{x_i} X_i^{-\alpha} $$

3. Analysis

3.1 Association Probability

In UL, UD association will always be the nearest BS at distance $X_v$, where $v \in \{M,F\}$, because the power output from UD is constant in UL. Therefore, in UL, if a MBS is selected it should satisfy, otherwise, the equipment will be associated with a FBS:

$$ P_M X_M^{-\alpha} > P_F X_F^{-\alpha} $$

In DL, since MBSs and FBSs have different transmitting powers, UD is associated with the BS from which it receives the highest average power, where the average power is obtained by averaging the received signals and is related to the fading. Therefore, in UL, if a MBS is selected it should satisfy, otherwise, the equipment will be associated with a FBS:

$$ P_d X_M^{-\alpha} > P_d X_F^{-\alpha} $$

The distribution of $X_v$ follows the null probability of 2D PPP, thus the probability density function (PDF) and cumulative distribution function (CDF) of $X_v$:

$$ f_{X_v}(x) = 2\pi \lambda_v x \exp(-\pi \lambda_v x^2), x \geq 0 $$

$$ F_{X_v}(x) = 1 - \exp(-\pi \lambda_v x^2), x \geq 0. $$

For two-layer heterogeneous networks, we give four possible combinations that can be used to select the BS type for DL and UL:

a) Case 1: UL BS = DL BS = MBS: The probability that UD will be associated with MBS in DL and UL is presented:

$$ \text{Pr}(X_M^{-\alpha} > P_F X_F^{-\alpha}, X_M^{-\alpha} > X_F^{-\alpha}). $$
Based on the facts that $P_F < P_M$, we obtain $P_F / P_M < 1$. We can find that $X_M^{-a} > X_F^{-a}$ is contained by $X_M^{-a} > X_F^{-a}$. Therefore, the association probability for Case 1 is figured as:

$$\Pr(\text{Case 1}) = \frac{\lambda_M}{\lambda_M + \lambda_F}$$

(14)

Proof: The association probability for Case 1 is specifically proven as follows:

$$\Pr(\text{Case 1}) = \Pr(X_M^{-a} > X_F^{-a})$$

$$= \int_0^{+\infty} (1 - F_{X_M}(x_M))f_{X_M}(x_M)dx_M$$

$$= \int_0^{+\infty} \exp(-\pi \lambda_F x_M^2)2\pi \lambda_M x_M \exp(-\pi \lambda_M x_M^2)dx_M$$

$$= \int_0^{+\infty} 2\pi \lambda_M x_M \exp(-\pi (\lambda_M + \lambda_F) x_M^2)dx_M$$

$$= \int_0^{+\infty} -\frac{\lambda_M}{\lambda_M + \lambda_F} e^{\lambda_F x_M^2} dt = \frac{\lambda_M}{\lambda_M + \lambda_F}$$

(15)

where (a) is to transform the integral variable to $t = -\pi (\lambda_M + \lambda_F)x_M^2$ in order to make the product function appear easier to compute.

Since the derivation process of the association probabilities is similar for the rest of the cases, for the other cases we will partially omit this process and only provide the final results.

b) Case 2: DL BS = MBS and UL BS = FBS: The probability that UD is associated with MBS and UL with FBS in DL is presented:

$$\Pr(X_M^{-a} > \frac{P_F}{P_M} X_F^{-a}; X_M^{-a} \leq X_F^{-a})$$

(16)

The domain that satisfies both of these events in Case 2 is $\frac{P_F}{P_M} X_F^{-a} < X_M^{-a} \leq X_F^{-a}$, thus the association probability of Case 2 is calculated as:

$$\Pr(\text{Case 2}) = \Pr(X_M^{-a} > \frac{P_F}{P_M} X_F^{-a}) - \Pr(X_M^{-a} \leq X_F^{-a})$$

$$= \frac{\lambda_F}{\lambda_F + \lambda_M} - \frac{\lambda_F}{\lambda_F + (\frac{P_F}{P_M})^{2a} \lambda_M}$$

(17)

Proof: The association probability of Case 2 can be split into two parts, where the proof of the former part can refer to the proof process of Case 1.

c) Case 3: DL BS = FBS and UL BS = MBS: The probability that UD is associated with FBS and UL with MBS in DL is presented:

$$\Pr(X_M^{-a} \leq \frac{P_F}{P_M} X_F^{-a}, X_M^{-a} > X_F^{-a})$$

(18)

Since the intersection of $X_M^{-a} \leq \frac{P_F}{P_M} X_F^{-a}$ and $X_M^{-a} > X_F^{-a}$ is the empty set, $\Pr(\text{Case 3}) = 0$.

d) Case 4: DL BS = UL BS = FBS: The probability that UD will be associated with FBS in DL and UL is presented:
\[
\Pr(X_M^\alpha \leq \frac{P_F}{P_M} X_F^\alpha, X_M^\alpha \leq X_F^\alpha). 
\] 

(19)

Since \(X_M^\alpha \leq X_F^\alpha\) is contained by \(X_M^\alpha \leq \frac{P_F}{P_M} X_F^\alpha\), the association probability for Case 4 is calculated as:

\[
\Pr(\text{Case 4}) = \Pr(X_M^\alpha \leq \frac{P_F}{P_M} X_F^\alpha) \\
= \frac{\lambda_F}{\lambda_F + (\frac{P_F}{P_M})^{2/\alpha} \lambda_M}. 
\] 

(20)

Proof: The proof of the association probability of Case 4 is similar to that of Case 1.

### 3.2 Distance Distributions

In this subsection, we derive the distance distribution from a typical UD to the BS it serves under three association conditions.

**a)** In the association Case 1, the PDF of distance distribution can be represented as:

\[
f_{X_M|\text{Case 1}} = \frac{(\exp(-\pi \lambda_F x_M^2))f_{X_M}}{\Pr(\text{Case 1})}. 
\] 

(21)

Proof: In Case 1 the distance between all UDs connected to the MBS satisfies \(X_M^{-\alpha} > X_F^{-\alpha}\). Thus the complementary cumulative distribution function (CCDF) of the distance from a typical UD to its associated BS can be expressed as:

\[
F_{X_M|\text{Case 1}}(x) = \Pr(X_M > x | X_F > X_M) \\
= \frac{\Pr(X_M > x, X_F > X_M)}{\Pr(\text{Case 1})} \\
= \int_x^\infty \frac{1}{(\pi \lambda_F X_M^2)}(\exp(-\pi \lambda_F x_M^2))f_{X_M} dx_M, 
\] 

(22)

where the CDF of the distance to the associated MBS is \(F_{X_M|\text{Case 1}} = 1 - F_{X_M|\text{Case 1}}\). After differentiating the CDF, we can obtain the PDF of the distance to the associated MBS.

**b)** In the association Case 2, since there are two cases of MBS and FBS as associated BSs, the PDF of distance distribution will be given for typical UDs associated with MBS or FBS:

\[
f_{X_M|\text{Case 2}} = \frac{(\exp(-\pi \lambda_F (\frac{P_F}{P_M})^2 X_M^2) - \exp(-\pi \lambda_F X_M^2))f_{X_M}}{\Pr(\text{Case 2})}. 
\] 

(23)

\[
f_{X_F|\text{Case 2}} = \frac{(\exp(-\pi \lambda_M X_F^2) - \exp(-\pi \lambda_M (\frac{P_M}{P_F})^2 X_F^2))f_{X_F}}{\Pr(\text{Case 2})}. 
\] 

(24)

Proof: The proof process for the PDF of distance distribution of Case 2 is similar to that of Case 1.

**c)** In the association Case 4, the PDF of typical equipment and distance from the FBS can be expressed as:

\[
f_{X_F|\text{Case 4}} = \frac{(\exp(-\pi \lambda_M (\frac{P_M}{P_F})^2 X_F^2))f_{X_F}}{\Pr(\text{Case 4})}. 
\] 

(25)

Proof: Likewise, the proof process for the PDF of distance distribution of Case 4 is similar to that of Case 1.
### 3.3 Coverage Probability

The probability that the SINR measured at the typical UD exceeds a predetermined threshold \( T \) at any time is defined as the coverage probability \([11]\), while the coverage probability happens to be also the CCDF of the SINR on the whole network, which can be written as:

\[
p_c(T, \lambda, \alpha) \triangleq \mathbb{P}(\text{SINR} > T)
\]  

We conclude that the association probability of Case 2 is much larger than the other cases, this subsection we focus on the coverage probability of Case 2.

a) In DL of Case 2, typical UDs are associated with MBSs, so the coverage probability of the DL can be calculated as:

\[
p_c(T, \lambda, \alpha) = \int_0^\infty f_{X_M|\text{Case 2}}(s) \mathbb{P}(s > T) dX_M.
\]  

Proof: The coverage probability of DL is specifically proven as follows:

\[
p_c(T, \lambda, \alpha) = \int_0^\infty f_{X_M|\text{Case 2}}(s) \mathbb{P}(s > T) dX_M
\]

\[
= \int_0^\infty f_{X_M|\text{Case 2}}(s) \mathbb{P}(h_{x_M} > \frac{x_M}{P_M} (I_M + I_S + \sigma^2)t) dX_M
\]

\[
= \int_0^\infty f_{X_M|\text{Case 2}}(s) \mathbb{P}(h_{x_M} > \frac{x_M}{P_M} (I_M + I_S + \sigma^2)t) dX_M
\]

\[
= \int_0^\infty f_{X_M|\text{Case 2}}(s) \mathbb{P}(h_{x_M} > \frac{x_M}{P_M} (I_M + I_S + \sigma^2)t) dX_M
\]

\[
= \int_0^\infty f_{X_M|\text{Case 2}}(s) \mathbb{P}(h_{x_M} > \frac{x_M}{P_M} (I_M + I_S + \sigma^2)t) dX_M
\]

where (b) multiplies \( h_{x_M} \) on both sides of the inequality so that only \( h_{x_M} \) remains on the left side of the inequality; (c) is because a positive random variable \( X \) satisfies \( E(X) = \int_{x>0} \mathbb{P}(X > t) dt \) and \( h_x \) obeys the e-exponential distribution \( h_x \sim \exp(1) \); (d) performs Laplace transform, in which \( L_1(j), \ v \in \{M, F\} \) is the Laplace transform of the random variable \( I_v \) at \( j = \frac{x_M}{P_M} t \), conditional on the distance from the nearest BS to the origin.

In addition, the Laplace transform \( L_1(j) \) and \( L_{I_F}(j) \) can be specifically calculated as:

\[
L_{I_F}(j) = \mathbb{E}(\prod_{x \in \Phi_F} \mathbb{E}_{h_{x_1}}(\exp(-jP_d h_{x_1} X_1^{-\alpha})))
\]

\[
= \mathbb{E}(\prod_{x \in \Phi_F} \frac{1}{1+jP_d X_1^{-\alpha}})
\]

\[
= \exp(-2\pi \lambda_d \int_0^\infty (1 - \frac{1}{1+jP_d X_1^{-\alpha}}) dX_1).
\]

where in (e) \( h_x \) obeys the e-exponential distribution \( h_x \sim \exp(1) \); (f) obeys the probability generating of the PPP, which states that \( \mathbb{E}(\prod_{x \in \Phi_F} f(x)) = \exp(-\lambda \int_{R^2} (1 - f(x)) dx) \).

\[
L_{I_F}(j) = \mathbb{E}(\prod_{x \in \Phi_F} \mathbb{E}_{h_{x_1}}(\exp(-jP_d h_{x_1} X_1^{-\alpha})))
\]

\[
= \mathbb{E}(\prod_{x \in \Phi_F} \frac{1}{1+jP_d X_1^{-\alpha}})
\]

\[
= \exp(-2\pi \lambda_d \int_0^\infty (1 - \frac{1}{1+jP_d X_1^{-\alpha}}) X_1 dX_1).
\]

The proof process of \( L_{I_F}(j) \) is similar to that of \( L_{I_M}(j) \).
b) In UL of Case 2, on the contrary, typical UDs are associated with FBSs, so the coverage probability of UL can be calculated as:

\[ p_c(T, \lambda, \alpha) = \int_0^\infty f_{x_F|\text{Case}2} \exp(-\sigma^2j) \mathbb{L}_d(j) \, dx_F. \quad (31) \]

Proof: The coverage probability of UL is specifically proven as follows:

\[
\begin{align*}
 p_c(T, \lambda, \alpha) &= \int_0^\infty f_{x_F|\text{Case}2} P(\text{SINR} > T) \, dx_F \\
 &= \int_0^\infty f_{x_F|\text{Case}2} P(\frac{\lambda h_{x_F}}{\lambda_d + \sigma^2} > t) \, dx_F \\
 &= \int_0^\infty f_{x_F|\text{Case}2} E(\exp(-\frac{\lambda h_{x_F}}{\lambda_d + \sigma^2} \cdot t)) \, dx_F \\
 &= \int_0^\infty f_{x_F|\text{Case}2} \exp(-\sigma^2j) \mathbb{L}_d(j) \, dx_F. \quad (32)
\end{align*}
\]

The proof process for UL is similar to that for DL, except that \( j = \frac{x_F^d}{P_d} t \), while the Laplace transform \( \mathbb{L}_d(j) \) can be specifically calculated as:

\[
\begin{align*}
\mathbb{L}_d(j) &= E(\prod_{x_F \in \mathbb{L}_d} \exp(-jP_d h_{x_F} X_{j_x})) \\
&= E(\prod_{x_F \in \mathbb{L}_d} \frac{1}{1+jP_d X_{j_x}}) \\
&= \exp(-2\pi j \int_{x_F}^\infty (1 - \frac{1}{1+jP_d X_{j_x}}) X_x \, dx_x). \quad (33)
\end{align*}
\]

The proof process of \( \mathbb{L}_d(j) \) is similar to that of \( \mathbb{L}_m(j) \).

4. Numerical Results

In the context of heterogeneous cellular network, the density of MBSs \( \lambda_M \) is set to 0.5, FBSs \( \lambda_F \) to 5, and UDs \( \lambda_d \) to 20 as the default values. During our simulation, the MBS operates with a transmit power \( P_M \) of 46 dBm, while the FBS \( P_F \) and UDs \( P_d \) have transmit powers of 20 dBm. The noise power \( \sigma^2 \) is set to \( 10^{-12} \) dBm. Additionally, the path loss exponent \( \alpha \) is predefined as 4 for the cellular mode. The specific values of the primary system simulation parameters are presented in TABLE I, where these parameters are referenced to [5] and [12].

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Density of MBSs ( \lambda_M ) (nodes/km(^2))</td>
<td>0.5</td>
</tr>
<tr>
<td>Density of FBSs ( \lambda_F ) (nodes/km(^2))</td>
<td>5</td>
</tr>
<tr>
<td>Density of UDs ( \lambda_d ) (nodes/km(^2))</td>
<td>20</td>
</tr>
<tr>
<td>Transmit power of MBSs ( P_M ) (dBm)</td>
<td>46</td>
</tr>
<tr>
<td>Transmit power of FBSs ( P_F ) (dBm)</td>
<td>20</td>
</tr>
<tr>
<td>Transmit power of UDs ( P_d ) (dBm)</td>
<td>20</td>
</tr>
<tr>
<td>Noise power ( \sigma^2 ) (dBm)</td>
<td>( 10^{-12} )</td>
</tr>
<tr>
<td>Path loss exponent ( \alpha )</td>
<td>4</td>
</tr>
</tbody>
</table>
Fig. 2. Joint association probabilities for Cases 1 to 4 ($\alpha = 4$).

Fig. 3. Joint association probabilities for Cases 1 to 4 ($\alpha = 3$).

Fig. 2 shows the joint association probability for cases 1 to 4, which is the percentage of UDs selecting the number of each associated case at a particular density ratio $\lambda_F/\lambda_M$. As the density ratio $\lambda_F/\lambda_M$ increases, the UDs selected for Case 1 (UL BS = DL BS = MBS) decrease rapidly, while those selected for Case 2 (DL BS = MBS and UL BS = FBS) increase rapidly and then decrease slowly, and those selected for Case 4 (UL BS = DL BS = FBS) increase slowly. In UL, as the density ratio $\lambda_F/\lambda_M$ increases, the distance between FBSs and UDs decreases due to the higher density of FBSs. Consequently, the power received by FBSs in UL increases, which leads to a surge in the number of UDs selecting FBSs in UL while the number of UDs opting for MBSs decreases. On the other hand, in UL, MBSs initially enjoy an absolute advantage due to their significantly higher transmit power compared to FBSs. However, as the density of FBSs increases, the reduced distance between FBSs and UDs compensates for their lower transmit power. Consequently, there is an increase in the number of UDs choosing FBSs in DL, accompanied by a decline in the number of UDs selecting MBSs in DL. Thus, as the density ratio $\lambda_F/\lambda_M$ increases, the overall number of UDs selecting Case 1 decreases, while the overall number of UDs selecting Case 4 increases.
By observing Fig. 2 and Fig. 3, it is evident that the influence of path fading on the dominant case becomes more pronounced as the path loss exponent $\alpha$ increases. This heightened dominance of path fading results in an enhanced capability of FBSs to counterbalance the drawback of their lower transmit power through the advantage of their closer proximity to UDs. As a consequence, the joint association probability curves exhibit rapid changes across all scenarios.

Fig. 4 and Fig. 5 provide insights into the relationship between coverage probability and a predefined threshold $T$ in both DL and UL of Case 2, considering different path loss exponent $\alpha$. For a given path loss exponent $\alpha$, the coverage probability in both DL and UL experiences a continuous decline as the user’s requirement for SINR increases with the predefined threshold $T$. This decrease indicates a diminishing likelihood that the SINR measured on a typical UD will exceed the predefined threshold $T$. As the predefined threshold $T$ approaches infinity, the coverage probability tends to zero. Conversely, when the predefined threshold $T$ remains constant, the SINR in both DL and UL increases with the path loss exponent $\alpha$. This increase results in a higher probability of surpassing the predefined threshold $T$ for the SINR measured on a typical UD, consequently leading to an augmented coverage probability in both DL and UL. Comparing Fig. 4 and Fig. 5, it is evident that the coverage probability in UL connected to the FBSs is considerably lower than that in DL connected to the MBSs.

5. Conclusion

This letter has presented an analysis of the coverage probability for UL and DL decoupled access in heterogeneous cellular networks. In order to reach the ultimate objective, we have proposed an analytical framework that models a two-tier heterogeneous cellular network consisting of MBSs and FBSs. Our study has calculated the expressions for the association probability of UL and DL decoupled access and derived analytical expressions for the joint distance distributions. Furthermore, we have obtained the exact expressions for the coverage probability. To validate the effectiveness of
our proposed analytical architecture, we have conducted extensive Monte Carlo simulations. The simulation results have demonstrated that our analytical framework accurately captures the network behavior.

References


