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Traffic offloading in HetNet using power biasing considering different path loss exponent

THESIS

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DEDICATION

To

My professor for keeping the faith in me and constantly encouraging
me to put in my best towards the research

and

my parents and my brother for supporting me throughout
this journey

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LIST OF ABBREVIATIONS

HetNets	Heterogeneous networks
RSS	Received signal strength
QoS	Quality of service
3GPP	3rd Generation Partnership Project
SINR	Signal to interference plus noise ratio
PPP	Poisson point process
PLE	Path loss exponent
SBS	Small base stations
MBS	Macro base stations
FAP	Femto access point
BS	Base station
UE	User equipment
dB	Decibels
BC	Best connected
FS	Femto skipping
CoMP	Cooperative multipoint transmission

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ABSTRACT OF THE THESIS

Traffic offloading in HetNet using power biasing considering different path loss exponent

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With the advent of new cellular technology, the number of users is expected to grow at a drastic rate that comes with the cost of an increase in data traffic. Therefore, to provide enough capacity for all the users, node density must be increased. One way to achieve that is through cell splitting but that would lead to higher chances of intercell interference along with incurring higher costs of installing high power macro nodes. Another way to attain a higher network capacity is to overlay a network of small low power nodes over an existing network thereby creating a heterogeneous network, i.e., HetNet [1]. In HetNet, the user is made available with more than one type of base station differing in the transmit power level and physical size. But, even with multiple options at hand, the user terminal always tends to associate itself to the macro base station i.e., the station with the highest transmit power. The reason is, that associativity is based on the received signal strength values i.e., RSS values, therefore, irrespective of the distance between the user and the station, the user will always have a preference towards macro station over low tier stations. Because of the above-mentioned claim, the overall reason behind shifting towards low tier station nullifies, therefore, it is essential to offload the data traffic from the macro tier. Some of the techniques to offload data traffic are offloading via power control, offloading via femtocell deployment and offloading via biasing, out of which, the latter is of concern to the thesis [2]. The research so far focuses on the stationary user and its connectivity to a base station. With user velocity in the picture, comes the concept of handover and its associated delays. Handover delays in dense networks lower the effect of an overall increase in network capacity as it includes the transmission of control signals rather than effective data transmission thereby raising the overhead over the network. Few handover skipping schemes have been proposed to avoid frequent handovers whose underlying assumption is same path loss exponents for all the tiers and unbiased power levels [3]. In this thesis, the effect of different path loss exponents and biased power levels has been investigated and the effect on coverage probability has been studied. In the end, the simulation results obtained are compared with the work done by other researchers so far.

CHAPTER 1

Introduction

The rapid increase in population has posed a serious challenge on the existing cellular network to provide the users with higher data rates, improved coverage, and increased network capacity. Deployment of additional high-power macro nodes in the current system would solve the problem but requires a huge investment along with improved inter-cell interference techniques. Therefore, an overlay of another layer of small power nodes is considered to be a solution to satisfy the increasing data throughput needs [4]. Small cell nodes, i.e., femto and pico nodes have lower values of transmission power, smaller footprint, fewer number of users to be served, higher values of throughput and high quality of service i.e., QoS. A multitier network consisting of a network of small cells overlaid over existing macrocells is commonly known as heterogeneous networks or HetNets [5].

Densifying the network is equivalent to shrinkage of base station footprints which in turn lowers the value of sojourn time* and increases the handover rate* for users.

Sojourn time is defined as the average amount of time a mobile user is served by a base station. Handover rate is the expected number of handovers per unit time [6].

In the case of highly mobile scenarios, sojourn time for the users is very small, therefore, the dense networks are unable to support such users. As handover involves the transference of a set of control signals to and from the base station, therefore, it is as an additional overhead over the network reducing the overall throughput and data rate of the system. In order to avoid frequent handovers in a heterogeneous network, few handover skipping strategies were proposed showing the average throughput gain over different user velocities ranging from nomadic to high scales [3]. In a mobile situation, the user always keeps a track of the base station providing the highest value of signal strength to the user and reports it to the serving station accordingly to initiate the handover process. As per the adopted handover skipping strategy, the user might be asked to skip some of the base stations along its path to reduce the handover rate by compromising the highest signal to interference and noise ratio (SINR). Base station cooperation and interference cancellation techniques are employed alongside to eliminate the interfering signals from other base stations. Proposed handover skipping strategies as per [3] are as follows:

1. Best Connected Strategy: Received signal strength based association must always be satisfied whenever a handover request is initiated by the mobile station.
2. Femto Skipping Strategy: User may skip some of the femto base stations along its trajectory to avoid frequent handovers. During the femto blackout phase, base station cooperation is enabled that can be either intra or inter-tier in which the user is served by the second and third highest SINR providing stations.
3. Femto Disregard Strategy: This strategy is suited for high mobility profiles. In this, the user skips the entire femto tier enabling cooperation amongst the strongest macro stations only.
4. Macro Skipping Strategy: At extremely high velocities, average time within the coverage region of the macro station may become too small thereby allowing the user to skip some of the macro base stations along with skipping the femto tier. Therefore, the user alternates between macro best connectivity and macro blackout phase.

The proposed strategies aimed to derive the relationships for coverage probability and average throughput following certain assumptions, are listed below:

- Performance metrics for the proposed methodologies are quantified using stochastic geometry i.e., base stations and mobile nodes are assumed to have Poisson point process distribution (PPP).
- Base stations belonging to the same tier are assumed to have the same amount of transmit power.
- Channel gains are assumed to have Rayleigh distribution with unit power.
- Path loss exponent* is assumed to have the same value for all tiers in the network.
- User velocity is constant and stationary PPP analysis is performed.

> Path loss exponent marks its existence in Friis transmission equation whose value is 2 for free space model, otherwise varies from 2 to 4 where 4 is for relatively lossy environments. Path loss exponent indicates the rate of increase of path loss with respect to distance. Therefore, an environment with more clutter and higher spatial density has a higher value of path loss exponent [7].

The PPP assumption is widely accepted for modelling cellular networks and has been verified by several empirical studies in [3], [8], [9] and [10]. The second assumption stated above might alter the derived formulas depending upon the load attached to the station, the number of user terminals, channel state information acquired by the station, etc. Path loss exponent will also be different for different tiers in HetNet because of the differences in deployment and varied spatial density*.

Spatial density is defined as the number of base stations per square kilometre.

1.1 Thesis Overview

The remaining part of the thesis is organized as follows: Chapter 2 introduces the various traffic offloading techniques in heterogeneous networks and directs the thesis towards the power biasing method for traffic load balancing. Chapter 3 works on the amendments made in the derivations of coverage probability and distance distribution in the best-connected strategy [3] and presents the simulation results for the same. Chapter 4 discusses the effect of different path loss exponents and power biasing in femto skipping case. Finally, a conclusion of the overall research and future scope is presented.

CHAPTER 2

Traffic Load Balancing in HetNet

The deciding factor for handoff between different tiers of HetNet usually relies upon the received signal strength at the user terminal thereby making femto stations less preferable as compared to macro stations in a user's perspective. Moreover, the difference in power transmission levels of base stations belonging to different tiers leads to shrinkage of coverage regions of low power nodes leading to their underutilization [11]. Therefore, traffic offloading* techniques are required to balance the number of users in all the tiers.

> Traffic offloading to small base stations means to direct the users toward lower tier of HetNet to reduce the overhead on macro base stations i.e., MBS [2].

The metric used to quantify the user association with different tiers of HetNet is "tier association probability" which provides the percentage of users being served by individual tiers. In [2], the femto tier association probability in Nakagami m-fading environment has been investigated and formula for the same is listed below:

$$Pa = 1 - \int_0^\infty \left(\frac{\mu_a}{\mu_b}\right)^{m_a} \frac{B h^{m_a - 1}}{\beta(m_a, m_b)\left(1 + \frac{\mu_a}{\mu_b} h\right)^{m_a + m_b} \left(\left(\frac{P_a T}{P_b} h\right)^{\frac{2}{\eta}} A + B\right.} dh \tag{2.1}$$

Nakagami *m* fading environment is best suited for urban environments and is used to model frequent and fast fluctuations in the received signal power. Parameter *m* is generally known as the fading depth of the environment and if equal to 1, the overall distribution reduces to Rayleigh fading model [12]. According to the formula, the tier association probability depends upon three parameters i.e., relative transmission power of femto access points (FAP), the relative intensity of FAPs i.e., the number of femto nodes with respect to the macro nodes and a biasing factor included with the transmission power of the stations.

Biasing can be viewed as a virtual increase in the relative transmission power of FAPs. Biasing factor is introduced to push the users toward femto stations even though the strongest signal received is from the nearest MBS thereby offloading the users to femto tier and reducing the load on MBS. This, in turn, increases the users' minimum achievable rate but also increases the outage probability. Increasing the FAP intensity will lead to more number of femto nodes, therefore, there will be fewer number of users connected to each node which makes the selection of an optimum intensity a necessity [2].

There are some other techniques introduced in [1] to deal with the issue of load balancing in HetNet, namely cell range expansion using handover biasing and resource partitioning which is explained in brief below.

2.1 Traffic load balancing using cell range expansion

The biasing mechanism depends upon the bias value* which in turn decides the number of user terminals connected to the low power nodes. Cell range expansion using handover biasing makes use of a chosen bias value which decides the number of user terminals connected to the stations with an aim of pushing more users from macro stations towards the low power nodes, i.e., femto and pico nodes.

Bias value is defined as the threshold value that triggers handover between two cells [1].

Handover is initiated as soon as the difference in the signal strength received from different stations falls below a threshold value. A positive value of bias means that UE will be handed over from the macro to the low tier station, either pico or femto station when the signal strength drops below a bias value. Along with transferring data, control information is also shared among the stations providing information about the resources in use in MBS and the subframes free to use by FS. This strategy is adopted to avoid chances of interference by letting the low power station know about the interference pattern of the high power station eventually scheduling the user effectively in the cell extended region [1].

In [13], the concept of 'Range Expansion' using biasing has been discussed from a wider perspective. The above-stated approach is based on the received power on the user terminal. In this, a multiplicative SINR is assigned to each tier of BS depending upon the transmit power of BSs. This is achieved by sending pilot signals to the user and calculating the amount of biased received power and associating the user with the station that has the highest biased received power. The main problem with this is to develop an optimization algorithm to decide the best value of SINR bias in the sense of load balancing. An observation made in [13] is that the biasing factor is independent of the location of the base stations and users thereby making the biasing scheme easy to implement. The two ways to generate bias values as proposed in the paper are explained below.

A. SINR Bias

Users are associated with the BS that provides the highest biased SINR [13]. Biasing factor based association problem reduces to the conventional maximum signal strength based connectivity issue by making the bias value equal to 1 for all the tiers. Setting the bias value equal to 1 means that that the user terminal receives power based on the original transmit power of the base stations rather than the virtual power generated using biasing whereas setting it equal to $\frac{1}{P_j}$ associates the users based on the lowest path loss, where P_j is the power transmission level of the j^{th} tier.

B. Rate Bias

Under this biasing scheme, users are associated with the base station that serves the maximum biased rate. In rate bias, the biasing factor is in the exponential term of SINR i.e.,$(1 + SINR)^{B_j}$, where B_j is the biasing factor of the j^{th} tier, which is different from the SINR bias where the bias factor is directly multiplied to SINR.

2.2 Path Loss Exponent

Attenuation is defined as a reduction in the signal strength values which can occur due to several factors explained later in the text. Attenuation holds great importance in the wireless communication industry and is referred to as path loss* which is a function of distance travelled by the signal.

Path loss is defined as the ratio of transmitted to receive power. Measurement is done with respect to a reference distance,d_o and the value is usually expressed in decibels (dB).

$$PL(d) = PL(d_o) + 10nlog_{10}\left(\frac{d}{d_o}\right) \tag{2.2.1}$$

Where PL: Path loss.

d: Distance expressed in km,

n: Path loss exponent

Reference distance is assumed to be 1 km in most situations.

Reduction in signal strength is due to three basic physical phenomena i.e., reflection, diffraction, and scattering which in turn depend upon the properties of the propagation path and is characterized by its path loss exponent [7].

Path loss exponent represents the rate at which the received signal strength decreases with distance. Stronger is the level of attenuation, larger is the value of path loss exponent. Path loss exponent depends upon the propagation environment that can vary on the basis of density of the objects covering the region and foliage. It also depends upon the carrier frequency of the signal [14]. The value of *n* captures the effects of all the mechanisms that might affect the signal propagation leading to path loss [15].

The assumption considered so far of having the same path loss exponents in both the tiers in HetNet is valid only if the propagation environment is same. The femto tier is usually deployed in indoor areas whereas the macro tier is deployed for outdoor environments. Since the conditions of the indoor channel are different from the outdoor channel in terms of the type of obstruction, its composition material, area, size of the environment and distance between the obstructions, therefore, the path loss exponents should be different for different tiers. Values of path loss exponents for certain regions are provided in the table below.

Environment	Path Loss Exponent
Free Space	2
Urban Area	2.7 to 3.5
Suburban Area	3 to 5
In the building (Line of Sight)	1.6 to 1.8
In the building (Obstructed)	4 to 6
In factories (Obstructed)	2 to 3

Table 2. 1: Typical values of path loss exponent [16].

As seen from the table above, the value of path loss exponents varies depending upon the environment so different path loss exponents must be considered for different tiers of HetNet. Therefore, the second focus of this research is to investigate the effects of different PLEs for macro and femto tier on their individual coverage probabilities, distance distributions and their impact on the overall coverage probability of the system.

CHAPTER 3

Best Connected Strategy

'Best connected strategy' ensures the user association with the station based on the received signal strength. Received signal strength at the UE depends upon the transmission power of the stations and the relative distance between the user and the station. Station providing the maximum biased received power is connected to the UE irrespective of whether it belongs to the high or low power tier i.e., macro or femto stations respectively. Since the transmission power of the macro station is much higher as compared to the femto stations (considering 10 times in the research here depending upon the transmission power of the stations assumed in the simulations) therefore there is a higher tendency for the user to connect to the macro station as compared to the femto. To balance traffic between the two tiers, biasing factors are introduced. The effect of biasing on coverage probability and distance distributions are studied in this chapter. The second part of this chapter focuses on the effect of different path loss exponents on the coverage probability of individual tiers and the overall system.

3.1 Distance distribution and coverage probability analysis

Using [3] and [17], we derive the distance distribution* and coverage probability* of station belonging to both the tiers.

Distance distribution is the distribution of the distances between the user terminal and its serving base station either macro or femto in a two-tier HetNet.
Coverage probability is defined as the probability that the received SINR exceeds a given threshold.

Notations:

Subscript j is used to identify the tier whose value varies from 1 to K where K is the number of tiers considered in HetNet. Value of K can be greater than or equal to 2 in a HetNet based on the number of tiers overlaid over each other. K is taken as 2 in our analysis, namely macro and femto tier. Variable λ_j is the spatial density of the j^{th} tier. Base station in the j^{th} tier is modelled according to homogeneous PPP φ_j with intensity λ_j. Each tier has different values of path loss exponent also expressed as $\{\alpha_j\}$. UE is assumed to be located at the origin (by shifting the coordinates). $|Y_{ki}|$ is the distance between BS $i \epsilon \phi_k$ and the user, located at the origin.

Biased Received Power: $$P_{r,j} = P_j L_o \frac{R_j}{r_o}^{-\alpha_j} B_j \tag{3.1}$$

where, $\{R_j\}_{j=1 \rightarrow K}$: Distance of typical user from the nearest BS in the j^{th} tier.

B_j: Biasing value of the station belonging to the j^{th} tier. $B_j > 1$ extends the cell coverage range of the j^{th} tier BS,

P_j: Transmit power of station belonging to the j^{th} tier,

L_o: Path loss at the reference distance r_o

Transmit power ratio: $\widehat{P_j} = \dfrac{P_j}{P_k}$

Bias ratio: $\widehat{B_j} = \dfrac{B_j}{B_k}$

Path loss exponent ratio: $\widehat{\alpha_j} = \dfrac{\alpha_j}{\alpha_k}$

where subscript k denotes the serving BS and j denotes the interfering base station.

3.1.1 Per tier user association probability

In the Best Connected strategy, the user connects with the k^{th} tier station if the following condition is satisfied, i.e., $P_{r,k} > P_{r,j}\ for\ j \neq k$, where $P_{r,k}$ is the biased received power from the station. As in the analysis, we are considering the association of the user with the station belonging to the k^{th} tier so $n = k$, where n is the index of the tier with which the user is connected.

A_k: Tier association probability
$A_k \triangleq \boldsymbol{P}[n = k]$ i.e., probability of the user connecting with the k^{th} tier

Derivation:

If power from the k^{th} tier is greater than the maximum value of the powers received from the nearby stations, then the user will associate itself to the k^{th} tier. Mathematically, we can write it as follows:

$$\Rightarrow \quad E_{R_k}\left[\boldsymbol{P}\left[P_{r,k}(R_k) > max_{j,j\neq k} P_{r,j}\right]\right]$$

$$\Rightarrow \quad E_{R_k}\left[\prod_{j=1,j\neq k}^{K} \boldsymbol{P}\left[P_{r,k}(R_k) > P_{r,j}\right]\right]$$

$$\Rightarrow \quad P_k L_o \frac{R_k}{r_o}^{-\alpha_k} B_k > P_j L'_o \frac{R_j}{r_o}^{-\alpha_j} B_j$$

$$\Rightarrow \quad {R_j}^{\alpha_j} > \frac{P_j}{P_k}\frac{B_j}{B_k}\frac{L'_o}{L_o}{R_k}^{\alpha_k}{r_o}^{\alpha_j-\alpha_k}$$

$$\Rightarrow \quad E_{R_k}\left[\prod_{j=1,j\neq k}^{K} \boldsymbol{P}\left[R_j > \frac{P_j}{P_k}\frac{B_j}{B_k}^{\frac{1}{\alpha_j}} {R_k}^{\frac{\alpha_k}{\alpha_j}} \frac{L'_o}{L_o}{r_o}^{\alpha_j-\alpha_k^{\frac{1}{\alpha_k}}}\right]\right]$$

where, $\frac{L'_o}{L_o}{r_o}^{\alpha_j-\alpha_k}$ is the path loss at reference distance r_o.

As path loss exponents for both the tiers are not equal therefore the difference in exponential term cannot be equal to 0 thereby making the equation dependent on distance, r_o.

Further, integrating over the limit 0 to ∞

$$A_k = \int_0^{\infty} r * \boldsymbol{P}[\, R_j > (\widehat{P_j}\widehat{B_j})^{\frac{1}{\alpha_j}} r^{\widehat{-\alpha_j}}\, f_{R_k}(r)dr \tag{3.2}$$

In the above equation, $f_{R_k}(r)$ is the PDF of the distance R_k and is derived using the null probability of a 2D Poisson process with intensity λ in area A which is equal to exp(-λA).

$\boldsymbol{P}\left[\, R_j > (\widehat{P_j}\widehat{B_j})^{\frac{1}{\alpha_j}} r^{\widehat{-\alpha_j}}\right]$ is the probability of no station being closer to the user than the station belonging to the j[th] tier at a distance of $(\widehat{P_j}\widehat{B_j})^{\frac{1}{\alpha_j}} r^{\widehat{\alpha_j}}$ where j can range from 1 to K.

Comparing with the null probability distribution, we get

CDF: $\prod_{j=1,j\neq k}^{K} \exp\left(-\pi\lambda_j(\widehat{P_j}\widehat{B_j})^{\frac{2}{\alpha_j}} r^{\frac{2}{\widehat{\alpha_j}}}\right)$

Now,

$$f_{R_k}^{(r)} = 1 - \frac{d\boldsymbol{P}[R_k > r]}{dr}$$

After solving and further simplifying, we get

$$f_{R_k}^{(r)} = 2\pi\lambda_k r \exp(-\pi\lambda_k r^2) \tag{3.3}$$

Substituting (3.3) in (3.2),

$$A_k = \int_0^{\infty} r \prod_{j=1,j\neq k}^{K} \exp\left(-\pi\lambda_j(\widehat{P_j}\widehat{B_j})^{\frac{2}{\alpha_j}} r^{\frac{2}{\widehat{\alpha_j}}}\right) 2\pi\lambda_k r \exp(-\pi\lambda_k r^2)\ dr$$

As the product of exponentials is equal to the sum of their powers, therefore,

$$A_k = 2\pi\lambda_k \int_0^{\infty} r \exp\left(-\pi\lambda_k r^2 - \pi \sum_{j=1,j\neq k}^{K} \lambda_j(\widehat{P_j}\widehat{B_j})^{\frac{2}{\alpha_j}} r^{\frac{2}{\widehat{\alpha_j}}}\right) dr \tag{3.4}$$

in the case of $j = k$, $\widehat{P_j} = \widehat{B_j} = \widehat{\alpha_j} = 1$.

Simplifying the expression by combining the two terms in the expression, we get

$$A_k = 2\pi\lambda_k \int_0^\infty r \exp\left(-\pi\left(\sum_{j=1}^{K} \lambda_j (\widehat{P_j}\widehat{B_j})^{\frac{2}{\alpha_j}} r^{\frac{2}{\widehat{\alpha_j}}})\right)\right) dr$$

Lemma 1: Probability that a typical user is associated to the k^{th} tier

$$A_k = 2\pi\lambda_k \int_0^\infty r \exp\left(-\pi \sum_{j=1}^{K} \lambda_j (\widehat{P_j}\widehat{B_j})^{\frac{2}{\alpha_j}} r^{\frac{2}{\widehat{\alpha_j}}}\right) dr \tag{3.5}$$

Special case: When path loss exponents for both the tiers are equal

$\Rightarrow \widehat{\alpha_j} = 1,\ \widehat{B_j} = \widehat{P_j} = 1 \forall\ j\ \in 1 \rightarrow K.$

Therefore, the term in the round parenthesis in equation (3.5) becomes constant.

Further, solving the integration

$$A_k = \frac{\lambda_k}{\sum_{j=1}^{K} \lambda_j (\widehat{P_j}\widehat{B_j})^{\frac{2}{\alpha}}} = \frac{\lambda_k}{\sum_{j=1, j\neq k.}^{K} \lambda_j (\widehat{P_j}\widehat{B_j})^{\frac{2}{\alpha}} + \lambda_k} \tag{3.6}$$

Lemma 2: Cell load* of the k^{th} tier is

$$N_k = 2\pi\lambda^{(U)} \int_0^\infty r \exp\left(-\pi \sum_{j=1}^{K} \lambda_j (\widehat{P_j}\widehat{B_j})^{\frac{2}{\alpha_j}} r^{\frac{2}{\widehat{\alpha_j}}}\right) dr$$

Cell load is defined as the average number of users associated with a given station in the k^{th} tier.

3.1.2 Distance distribution to serving base station

User is located at the origin and is associated with the k^{th} tier. X_k is the distance between the user and its serving base station. Distribution of base stations is assumed to be PPP. Event $X_k > x$ is equivalent to $R_k > x$ given that user is associated with the k^{th} tier.

$$\boldsymbol{P}[X_k > x] = \boldsymbol{P}[R_k > x |\, n = k] = \frac{\boldsymbol{P}[R_k > x, n = k]}{P[n = k]}$$

where numerator is the joint probability distribution term.

From the derivation of Lemma 1, we can say that $\boldsymbol{P}[R_k > x, n = k] = \boldsymbol{P}\big[R_k > x, P_{r,k}(R_k) > max_{j, j\neq k} P_{r,j}\big]$. $A_k = \boldsymbol{P}[n = k]$, i.e., probability, that the user is associated with tier 'k'.

$$\boldsymbol{P}[X_k > x] = \frac{2\pi\lambda_k}{A_k} \int_0^\infty r \exp\left(-\pi \sum_{j=1}^{K} \lambda_j (\widehat{P_j}\widehat{B_j})^{\frac{2}{\alpha_j}} r^{\frac{2}{\widehat{\alpha_j}}}\right) dr$$

Outage probability averaged over cell coverage:

PDF: $f_{X_k} = \frac{dF_{X_k}(x)}{dx} = \frac{2\pi\lambda_k}{A_k} x exp\left\{-\pi \sum_{j=1}^{K} \lambda_j (\widehat{P_j}\widehat{B_j})^{\frac{2}{\alpha_j}} r^{\frac{2}{\widehat{\alpha_j}}}\right\}$

Macro base station association:

In [3], distance distribution between the user and its serving macro BS assuming same path loss exponent and without bias is as follows:

$$f_{R1}^{(BC)}(R) = \frac{2\pi\lambda_1 R}{A_m^{(BC)}} \exp\left(-\pi R^2 \left(\lambda_1 + \lambda_2 \frac{P_2^{\frac{2}{\eta}}}{P_1}\right)\right) \tag{3.7}$$

where R is the distance of the user from the macro BS.

Now, considering different PLEs and with biasing, the formula of distance distribution becomes

$$f_{R1}^{(BC)}(R) = \frac{2\pi\lambda_1 R}{A_m^{(BC)}} \exp\left\{-\pi \sum_{j=1}^{2} \lambda_j \left[\frac{(P_j B_j)}{(P_k B_k)}\right]^{\frac{2}{\alpha_j}} x^{\frac{2}{\widehat{\alpha_j}}}\right\} \tag{3.8}$$

If biasing factors are equal for both the tiers, then $\widehat{B_j} = 1$, so

$$f_{R1}^{(BC)}(R) = \frac{2\pi\lambda_1 R}{A_m^{(BC)}} \exp\left\{-\pi \left[\lambda_1 \left[\frac{(P_1 B_1)}{(P_1 B_1)}\right]^{\frac{2}{\alpha_1}} R^{\frac{\frac{2}{\alpha_1}}{\alpha_2}} + \lambda_2 \left[\frac{(P_2 B_2)}{(P_1 B_1)}\right]^{\frac{2}{\alpha_2}} R^{\frac{\frac{2}{\alpha_2}}{\alpha_2}}\right]\right\}$$

$$f_{R1}^{(BC)}(R) = \frac{2\pi\lambda_1 R}{A_m^{(BC)}} \exp\left\{-\pi \left[\lambda_1 R^2 + \lambda_2 \left[\frac{(P_2 B_2)}{(P_1 B_1)}\right]^{\frac{2}{\alpha_2}} R^{\frac{2\alpha_1}{\alpha_2}}\right]\right\}$$

where R shows the macro station association

Femto base station association:

User association with femto tier having a base station with intensity λ_2

$$f_{r1}^{(BC)}(r) = \frac{2\pi\lambda_2 r}{A_f^{(BC)}} \exp\left\{-\pi \left[\lambda_1 \left[\frac{(P_1 B_1)}{(P_2 B_2)}\right]^{\frac{2}{\alpha_1}} r^{\frac{\frac{2}{\alpha_1}}{\alpha_2}} + \lambda_2 \left[\frac{(P_2 B_2)}{(P_2 B_2)}\right]^{\frac{2}{\alpha_2}} r^{\frac{\frac{2}{\alpha_2}}{\alpha_2}}\right]\right\}$$

$$f_{r1}^{(BC)}(r) = \frac{2\pi\lambda_2 r}{A_f^{(BC)}} \exp\left\{-\pi \left[\lambda_1 \left[\frac{(P_1 B_1)}{(P_2 B_2)}\right]^{\frac{2}{\alpha_1}} r^{\frac{2\alpha_2}{\alpha_1}} + \lambda_2 r^2\right]\right\}$$

$A_k^{(BC)}$: Association probability when the user is connected to station belonging to k^{th} tier

$$A_k = 2\pi\lambda_k \int_0^\infty r \exp\left(-\pi \sum_{j=1}^{K} \lambda_j (\widehat{P_j}\widehat{B_j})^{\frac{2}{\alpha_j}} r^{\frac{2}{\widehat{\alpha_j}}}\right) dr$$

If the user is associated with the macro station, then k=1

$$A_m^{(BC)} = 2\pi\lambda_1 \int_0^\infty R \exp\left(-\pi[\lambda_1 \left(\frac{P_1 B_1}{P_1 B_1}\right)^{\frac{2}{\alpha_1}} R^{\frac{\frac{2}{\alpha_1}}{\alpha_1}} + \lambda_2 \left(\frac{P_2 B_2}{P_1 B_1}\right)^{\frac{2}{\alpha_2}} R^{\frac{\frac{2}{\alpha_2}}{\alpha_1}} \right) dR$$

$$= 2\pi\lambda_1 \int_0^\infty R \exp\left(-\pi[\lambda_1 R^2 + \lambda_2 (\widehat{P_2}\widehat{B_2})^{\frac{2}{\alpha_2}} R^{\frac{2\alpha_1}{\alpha_2}}] \right) dR$$

If the user is associated with femto base station i.e., k = 2

$$A_f^{(BC)} = 2\pi\lambda_2 \int_0^\infty r \exp\left(-\pi[\lambda_1 \left(\frac{P_1 B_1}{P_2 B_2}\right)^{\frac{2}{\alpha_1}} r^{\frac{\frac{2}{\alpha_1}}{\alpha_2}} + \lambda_2 \left(\frac{P_2 B_2}{P_2 B_2}\right)^{\frac{2}{\alpha_2}} r^{\frac{\frac{2}{\alpha_2}}{\alpha_2}}] \right) dr$$

$$= 2\pi\lambda_2 \int_0^\infty r \exp\left(-\pi[\lambda_1 \left(\frac{P_1 B_1}{P_2 B_2}\right)^{\frac{2}{\alpha_1}} r^{\frac{2\alpha_2}{\alpha_1}} + \lambda_2 r^2] \right) dr$$

3.1.3 Coverage Probability

Overall outage probability derived using Law of Total Probability is given by the expression

$$O = \sum_{k=1}^{K} O_k \, A_k$$

where, O_k: Outage probability of individual tier

A_k: User association probability with a given tier

Typical user $SINR_k(x)$, where x is the distance of the user from its associated BS is as follows

$$O_k \triangleq E_x[\boldsymbol{P}(SINR_k(x)) > T]$$

where T is the threshold or target SINR.

SINR of any user at a distance x from its associated base station in tier k is

$$SINR_k(x) = \frac{P_k g_{k,o} x^{-\alpha_k}}{\sum_{j=1}^{K} \sum_{i \in \varphi_{j \backslash B_{ko}}} P_j h_{ji} |Y_{ji}|^{-\alpha_j} + \frac{W}{L_o}}$$

where, $|Y_{ji}|$ is the distance from base station $i \in \varphi_j \backslash B_{ko}$ (except the serving base station B_{ko}) to origin because the user is located at the origin.

$g_{k,o}$: exponentially distributed channel power with unit mean from the serving base station.

h_{ji}: exponentially distributed channel power with unit mean from the i^{th} interfering base station in the j^{th} tier.

A. General case and main result: Derivation for network outage probability

Theorem 1: Outage probability of a typical user associated with the k[th] tier

$$O_k = 1 - \frac{2\pi\lambda_k}{A_k}\int_0^\infty x \exp\left\{-\frac{T}{SNR} - \pi\sum_{j=1}^{K} C_j x^{\frac{2}{\widehat{\alpha_J}}}\right\} dx$$

where,

$$SNR = \frac{P_k L_o x^{-\alpha_k}}{W}$$

$$C_j = \lambda_j \widehat{P_J}^{\frac{2}{\alpha_j}}\left[\widehat{B_J}^{\frac{2}{\alpha_j}} + \mathbb{Z}(T, \alpha_j, \widehat{B_J})\right]$$

$$\mathbb{Z}(T, \alpha_j, \widehat{B_J}) = \frac{2T\widehat{B_J}^{\overline{\frac{2}{\alpha_j - 1}}}}{\alpha_j - 2}\ {}_2F_1\left[1, 1 - \frac{2}{\alpha_j}; 2 - \frac{2}{\alpha_j}; \frac{-T}{\widehat{B_J}}\right]$$

where ${}_2F_1$: Gauss hypergeometric function

α_j: Path loss function for the j^{th} tier

T: Threshold

λ_j: Intensity of the j^{th} tier

P_k: Transmission power of the k^{th} tier

A_k: User association probability with the k^{th} tier

W: Thermal noise power

Hence, coverage probability of a typical user associated with the k^{th} tier

$$C_k = 1 - O_k = \frac{2\pi\lambda_k}{A_k}\int_0^\infty x \exp\left\{-\frac{T}{SNR} - \pi\sum_{j=1}^{K} C_j x^{\frac{2}{\widehat{\alpha_J}}}\right\} dx \qquad (3.9)$$

B. Simplified results of coverage probability in certain special cases:

In case of an interference limited network with no effect of thermal noise i.e., $W = 0$.

Corollary 1: No noise consideration and equal path loss exponent i.e., $\alpha_j = \alpha$

Coverage probability of a typical user associated with k^{th} tier

$$C_k = \frac{\sum_{j=1}^{K}\lambda_j (\widehat{P_J}\widehat{B_J})^{\frac{2}{\alpha}}}{\sum_{j=1}^{K}\lambda_j (\widehat{P_J})^{\frac{2}{\alpha}}\left[\widehat{B_J}^{\frac{2}{\alpha}} + \mathbb{Z}(T, \alpha_j, \widehat{B_J})\right]}$$

$\widehat{B_J}$ i.e., biasing factors are not the same for all the tiers

Coverage probability of a randomly chosen user:

$$C = \sum_{j=1}^{K} \left\{ \sum_{j=1}^{K} \frac{\lambda_j}{\lambda_k} \, (\widehat{P_j})^{\frac{2}{\alpha}} [\, \widehat{B_j} + \mathbb{Z}(T, \alpha_j, \widehat{B_j})] \, \right\}^{-1}$$

Coverage probability of a typical user:

$$C = \sum_{k=1}^{K} 2\pi\lambda_k \int_0^{\infty} x \exp\left\{ -\frac{T}{SNR} - \pi \sum_{j=1}^{K} C_j x^{\frac{2}{\widehat{\alpha_j}}} \right\} dx$$

From (3.9), we get

$$C_k = 1 - O_k = \frac{2\pi\lambda_k}{A_k} \int_0^{\infty} x \exp\left\{ -\frac{T}{SNR} - \pi \sum_{j=1}^{K} C_j x^{\frac{2}{\widehat{\alpha_j}}} \right\} dx$$

For macro tier, k=1, so the above equation becomes

$$C_m = \frac{2\pi\lambda_1}{A_1} \int_0^{\infty} R_1 \exp\left\{ -\frac{TW}{P_1 L_o R_1^{-\alpha_1}} - \pi \sum_{j=1}^{2} C_j R_1^{\frac{2}{\widehat{\alpha_j}}} \right\} dR1$$

$$C_m = \frac{2\pi\lambda_1}{A_1} \int_0^{\infty} R_1 \exp\left\{ -\frac{TW}{P_1 L_o R_1^{-\alpha_1}} - \pi \left(C_1 R_1^{\frac{2}{\widehat{\alpha_1}}} + C_2 R_1^{\frac{2}{\widehat{\alpha_2}}} \right) \right\} dR1$$

Where $C_j = \lambda_j \widehat{P_j}^{\frac{2}{\alpha_j}} \left[\widehat{B_j}^{\frac{2}{\alpha_j}} + \mathbb{Z}(T, \alpha_j, \widehat{B_j}) \right]$ from Theorem 1

$$C_1 = \lambda_1 \widehat{P_1}^{\frac{2}{\alpha_1}} \left[\widehat{B_1}^{\frac{2}{\alpha_1}} + \frac{2T\widehat{B_1}^{\frac{2}{\alpha_1 - 1}}}{\alpha_1 - 2} \;\; {}_2F_1 \left[1, 1 - \frac{2}{\alpha_1}; 2 - \frac{2}{\alpha_1}; \frac{-T}{\widehat{B_1}} \right] \right]$$

As the user is associated with the macro station so $\widehat{\alpha_1} = \frac{\alpha_1}{\alpha_1} = 1$, Similarly $\widehat{B_1} = 1$ and $\widehat{P_1} = 1$ therefore

$$C_1 = \lambda_1 \left[1 + \frac{2T}{\alpha_1 - 2} \;\; {}_2F_1 \left[1, 1 - \frac{2}{\alpha_1}; 2 - \frac{2}{\alpha_1}; -T \right] \right]$$

$$C_2 = \lambda_2 \widehat{P_2}^{\frac{2}{\alpha_2}} \left[\widehat{B_2}^{\frac{2}{\alpha_2}} + \frac{2T\widehat{B_2}^{\frac{2}{\alpha_2 - 1}}}{\alpha_2 - 2} \;\; {}_2F_1 \left[1, 1 - \frac{2}{\alpha_2}; 2 - \frac{2}{\alpha_2}; \frac{-T}{\widehat{B_2}} \right] \right]$$

$\widehat{P_2} = \frac{P_2}{P_1}$ and $\widehat{B_2} = \frac{B_2}{B_1}$ because the user is associated with the macro station (tier 1) therefore denominator has subscript 1.

$$C_2 = \lambda_2 \left(\frac{P_2}{P_1} \right)^{\frac{2}{\alpha_2}} \left[\left(\frac{B_2}{B_1} \right)^{\frac{2}{\alpha_2}} + \frac{2T \left(\frac{B_2}{B_1} \right)^{\frac{2}{(\alpha_2 - 1)}}}{\alpha_2 - 2} \;\; {}_2F_1 \left[1, 1 - \frac{2}{\alpha_2}; 2 - \frac{2}{\alpha_2}; \frac{-T}{\widehat{B_2}} \right] \right]$$

For femto tier, k=2

$$C_f = \frac{2\pi\lambda_2}{A_2}\int_0^\infty r\exp\left\{-\frac{TW}{P_2L_or^{-\alpha_2}} - \pi\left(C_1r^{\frac{2}{\widehat{\alpha_1}}} + C_2r^{\frac{2}{\widehat{\alpha_2}}}\right)\right\}dr$$

where, $A_1 = A_m^{(BC)}$ and $A_2 = A_f^{(BC)}$

For *k =2 and j = 1***:**

$\widehat{P_1}= \frac{P_1}{P_2}$; $\widehat{B_1}= \frac{B_1}{B_2}$; $\widehat{\alpha_1}= \frac{\alpha_1}{\alpha_2}$

$$C_1 = \lambda_1\widehat{P_1}^{\frac{2}{\alpha_1}}\left[\widehat{B_1}^{\frac{2}{\alpha_1}} + \mathbb{Z}(T,\alpha_1,\widehat{B_1})\right]$$

$$C_1 = \lambda_1\frac{P_1}{P_2}^{\frac{2}{\alpha_1}}\left[\frac{B_1}{B_2}^{\frac{2}{\alpha_1}} + \mathbb{Z}\left(T,\alpha_1,\frac{B_1}{B_2}\right)\right]$$

$$\mathbb{Z}(T,\alpha_1,\widehat{B_1}) = \frac{2T(\frac{B_1}{B_2})^{\frac{2}{\alpha_1-1}}}{\alpha_1-2}\ {}_2F_1\left[1,1-\frac{2}{\alpha_1};2-\frac{2}{\alpha_1};\frac{-T}{\widehat{B_1}}\right]$$

$$C_1 = \lambda_1\widehat{P_1}^{\frac{2}{\alpha_1}}\left[\widehat{B_1}^{\frac{2}{\alpha_1}} + \frac{2T(\frac{B_1}{B_2})^{\frac{2}{\alpha_1-1}}}{\alpha_1-2}\ {}_2F_1\left[1,1-\frac{2}{\alpha_1};2-\frac{2}{\alpha_1};\frac{-T}{\widehat{B_1}}\right]\right]$$

$$C_2 = \lambda_2\widehat{P_2}^{\frac{2}{\alpha_2}}\left[\widehat{B_2}^{\frac{2}{\alpha_2}} + \mathbb{Z}(T,\alpha_2,\widehat{B_2})\right]$$

Now, $\widehat{P_2} = 1$ and $\widehat{B_2} = 1$

$$C_2 = \lambda_2[1 + \mathbb{Z}(T,\alpha_2,\widehat{B_2})]$$

$$C_2 = \lambda_2\left[1 + \frac{2T(\widehat{B_2})^{\frac{2}{\alpha_2-1}}}{\alpha_2-2}\ {}_2F_1\left[1,1-\frac{2}{\alpha_2};2-\frac{2}{\alpha_2};\frac{-T}{\widehat{B_2}}\right]\right]$$

User association probability considering same path loss exponents:

$$A_m^{(BC)} = 2\pi\lambda_1\int_0^\infty R\exp\left(-\pi[\lambda_1R^2 + \lambda_2(\widehat{P_2}\widehat{B_2})^{\frac{2}{\alpha}}R^2]\right)dR$$

$$= 2\pi\lambda_1\int_0^\infty R\exp\left(-\pi R^2[\lambda_1 + \lambda_2(\widehat{P_2}\widehat{B_2})^{\frac{2}{\alpha}}]\right)dR$$

$$A_f^{(BC)} = 2\pi\lambda_2\int_0^\infty r\exp\left(-\pi[\lambda_1(\widehat{P_1}\widehat{B_1})^{\frac{2}{\alpha}}r^2 + \lambda_2r^2]\right)dr$$

$$= 2\pi\lambda_2 \int_0^\infty r \exp\left(-\pi r^2 [\lambda_1 (\widehat{P_1} \widehat{B_1})^{\frac{2}{\alpha}^2} + \lambda_2]\right) dr$$

And $A_f^{(BC)} = 1 - A_m^{(BC)}$

$$C_m^{(BC)} = \frac{2\pi\lambda_1}{A_m^{(BC)}} \int_0^\infty R_1 \exp\left\{-\frac{TW}{P_1 L_o {R_1}^{-\alpha}} - \pi R^2 (C_1 + C_2)\right\} dR1$$

$$C_m^{(BC)} = \frac{2\pi\lambda_1}{A_m^{(BC)}} \int_0^\infty R_1 \exp\left\{-\frac{TW}{P_1 L_o {R_1}^{-\alpha}} - \pi R^2 \{\lambda_1 A + \lambda_2 B\}\right\} dR1 \qquad (3.10)$$

$$A = \left(1 + \frac{2T}{\alpha - 2} \;\; {}_2F_1\left[1, 1 - \frac{2}{\alpha}; 2 - \frac{2}{\alpha}; -T\right]\right)$$

$$B = \left(\frac{P_2}{P_1}\right)^{\frac{2}{\alpha}} \left(\left(\frac{B_2}{B_1}\right)^{\frac{2}{\alpha}} + \frac{2T\left(\frac{B_2}{B_1}\right)^{\frac{2}{\alpha-1}}}{\alpha - 2} \;\; {}_2F_1\left[1, 1 - \frac{2}{\alpha}; 2 - \frac{2}{\alpha}; -\frac{T}{\frac{B_2}{B_1}}\right]\right)$$

Similarly

$$C_f^{(BC)} = \frac{2\pi\lambda_2}{A_f^{(BC)}} \int_0^\infty r \exp\left\{-\frac{TW}{P_2 L_o r^{-\alpha}} - \pi r^2 \{\lambda_1 C + \lambda_2 D\}\right\} dr \qquad (3.11)$$

$$C = \left(\frac{P_1}{P_2}\right)^{\frac{2}{\alpha}} \left((\frac{B_1}{B_2})^{\frac{2}{\alpha}} + \frac{2T(\frac{B_1}{B_2})^{\frac{2}{\alpha-1}}}{\alpha - 2} \;\; {}_2F_1\left[1, 1 - \frac{2}{\alpha}; 2 - \frac{2}{\alpha}; \frac{-T}{\frac{B_1}{B_2}}\right]\right)$$

$$D = \left(1 + \frac{2T}{\alpha - 2} \;\; {}_2F_1\left[1, 1 - \frac{2}{\alpha}; 2 - \frac{2}{\alpha}; -T\right]\right)$$

Overall coverage probability of the system is then given by

$$C^{(BC)} = A_m^{(BC)} C_m^{(BC)} + A_f^{(BC)} C_f^{(BC)} \qquad (3.12)$$

3.2 Simulation

Simulation of the above-derived formulas is performed in two different levels, one based on different biasing factors considering the same path loss exponents and the other based on different path loss exponents with no biasing.

I. Case of different biasing factors with same path loss exponents

$$A_m^{(BC)} = 2\pi\lambda_1 \int_0^\infty R \exp\left(-\pi R^2 [\lambda_1 + \lambda_2 (\widehat{P_2}\widehat{B_2})^{\frac{2}{\alpha}}]\right) dR$$

$$A_f^{(BC)} = 2\pi\lambda_2 \int_0^\infty r \exp\left(-\pi r^2 [\lambda_1 (\widehat{P_1}\widehat{B_1})^{\frac{2}{\alpha}^2} + \lambda_2]\right) dr$$

II. Case of different path loss exponents but same biasing factors

$$A_m^{(BC)} = 2\pi\lambda_1 \int_0^\infty R \exp\left(-\pi [\lambda_1 R^2 + \lambda_2 (\widehat{P_2})^{\frac{2}{\alpha_2}} R^{2\frac{\alpha_1}{\alpha_2}}]\right) dR$$

$$A_f^{(BC)} = 2\pi\lambda_2 \int_0^\infty r \exp\left(-\pi [\lambda_1 (\widehat{P_1})^{\frac{2}{\alpha_1}} r^{2\frac{\alpha_2}{\alpha_1}} + \lambda_2 r^2]\right) dr$$

3.2.1 Simulation results based on different biasing factors

The transmission powers of macro and femto stations are altered by introducing a biasing factor whose value ranges from 0 to 1 with an increment of 0.1. The threshold value is varied from -15 to 10 dB.

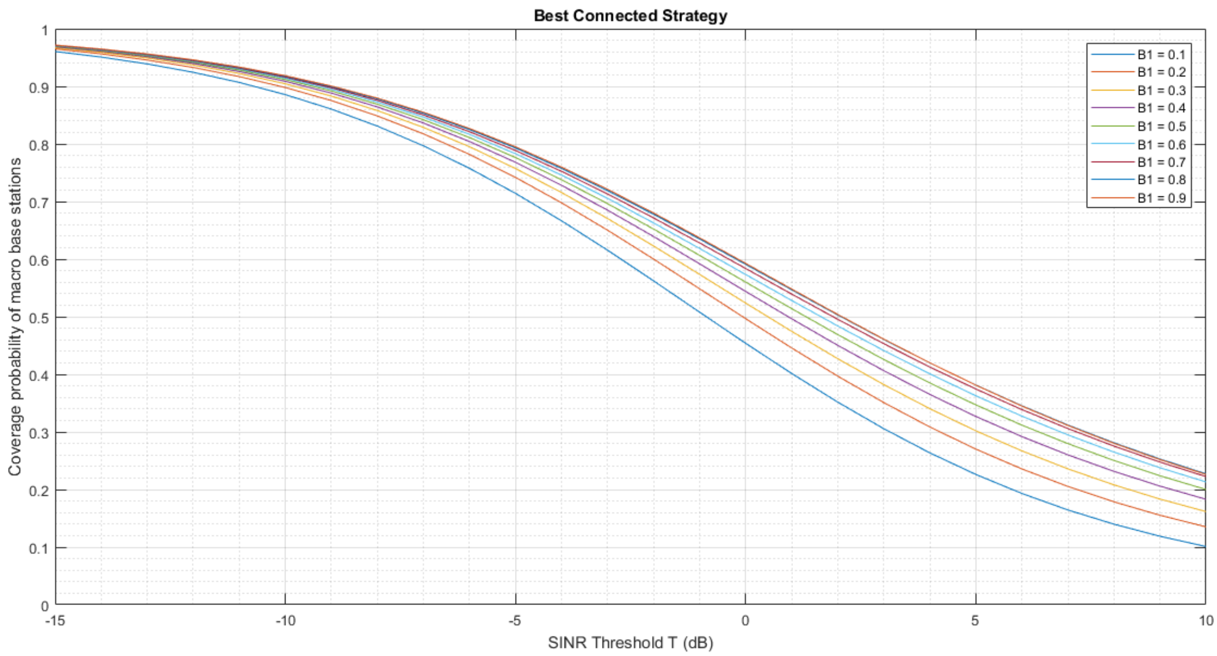

Figure 3. 1: Coverage probability of the macro base stations with respect to the varying threshold in dB for best-connected strategy.

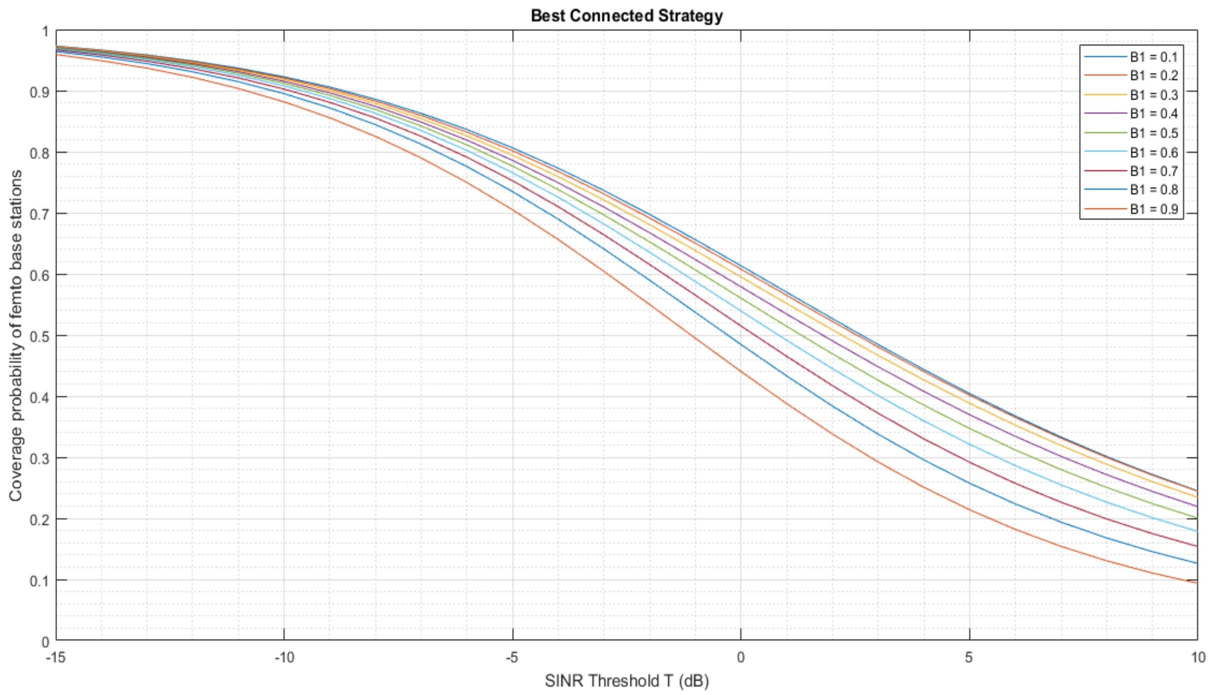

Figure 3. 2: Coverage probability of the femto base stations with respect to the varying threshold in dB for best-connected strategy.

Conclusion: In the graphs above, coverage probability of stations belonging to each tier is plotted against varying threshold values in dB. It can be seen from the graphs that with the increase in biasing values from 0 to 1, the coverage probability of macro base stations increases whereas for femto stations the value of coverage probability decreases. Overall, the coverage probability of both the stations decreases with an increase in the value of threshold which is concurrent to the observation made in the reference papers as well.

Coverage probability of the system in best-connected strategy:

Overall coverage probability in the best-connected case is given by the relation:

$$C^{(BC)} = A_m^{(BC)} C_m^{(BC)} + A_f^{(BC)} C_f^{(BC)}$$

Where $C_m^{(BC)}$is the coverage probability of the macro station and $C_f^{(BC)}$ is the coverage probability of the femto station. Since the weighted sum of individual coverage probability for each tier gives the overall coverage probability and the effect of biasing on both is opposite of each other therefore the overall coverage probability of the entire system remains the same which can also be verified by the plot shown below.

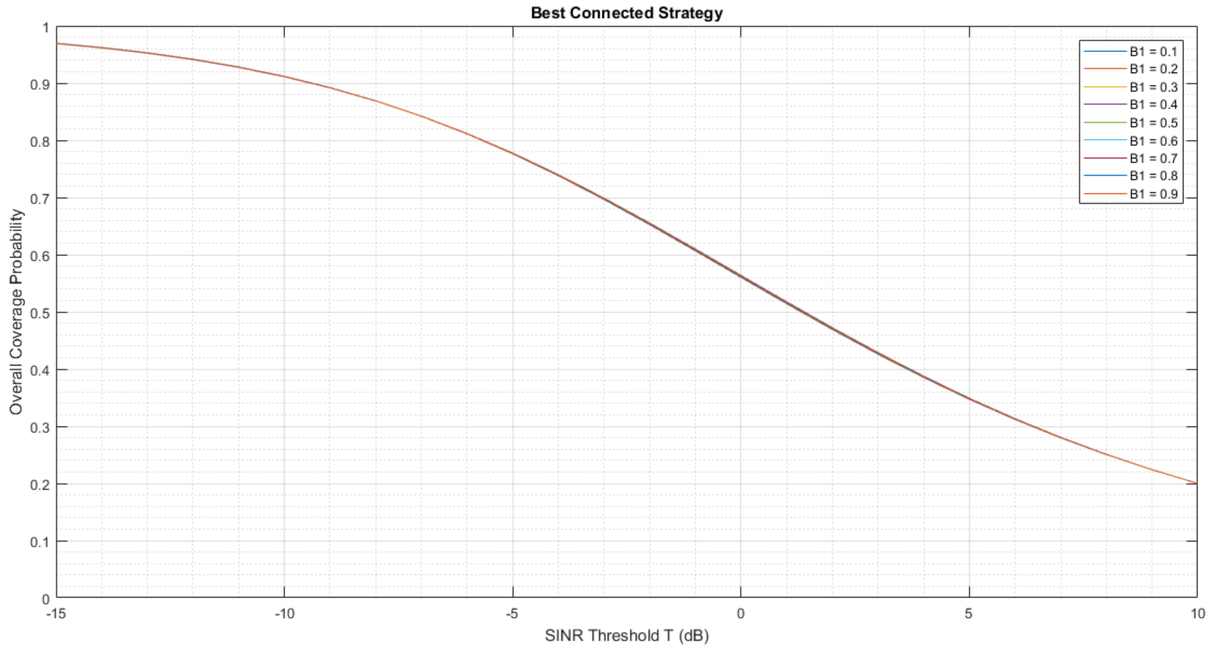

Figure 3. 3: Overall coverage probability of the system plotted against varying threshold values in dB for best-connected strategy.

:

3.2.2 Simulation results based on different path loss exponents

The coverage probability of different tier stations is plotted against varying threshold value with path loss exponent of the macro station be 4 and femto station being 3 and 5 respectively.

Case 1: Path loss exponent of the macro tier is 4 and for femto tier, PLE is 3

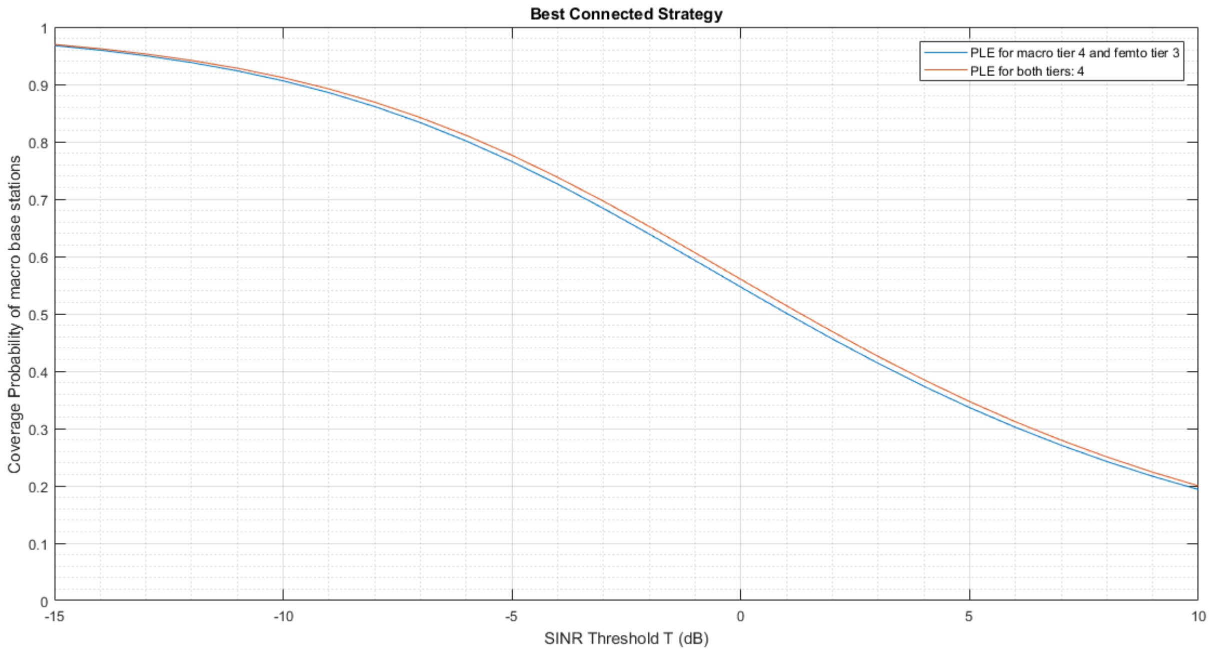

Figure 3. 4: Coverage probability of macro stations with PLE of femto tier as 3.

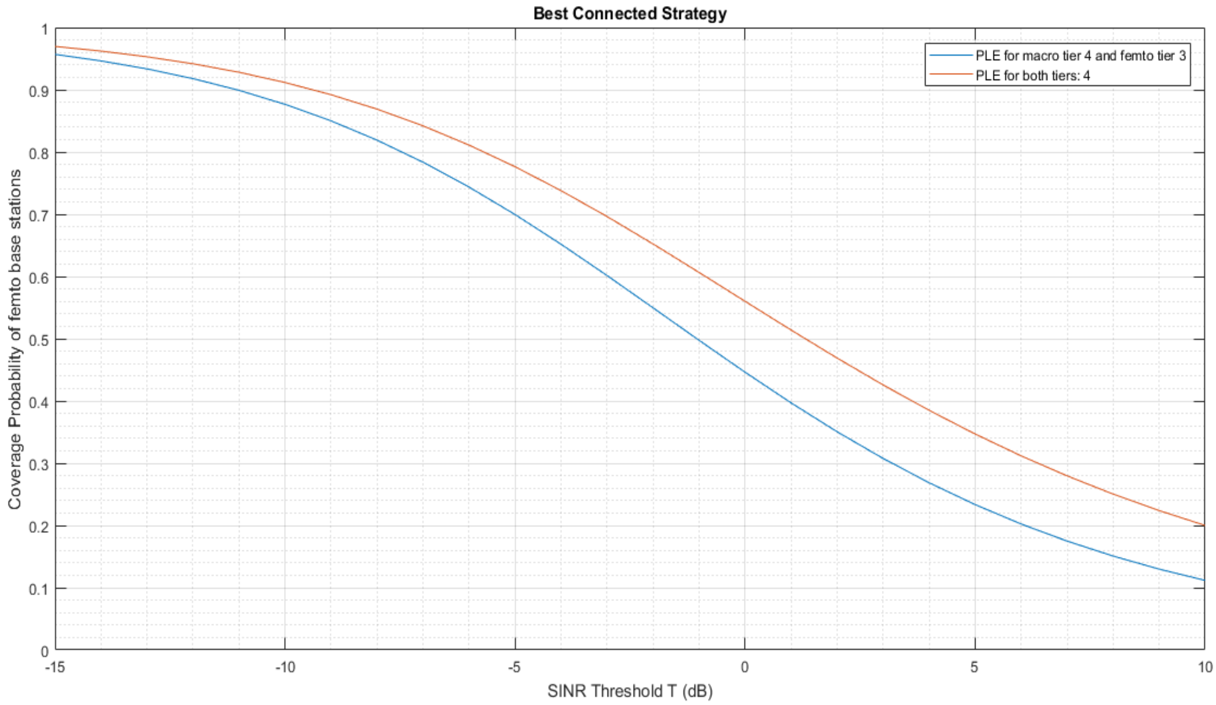

Figure 3. 5: Coverage probability of femto base stations with PLE of femto tier as 3.

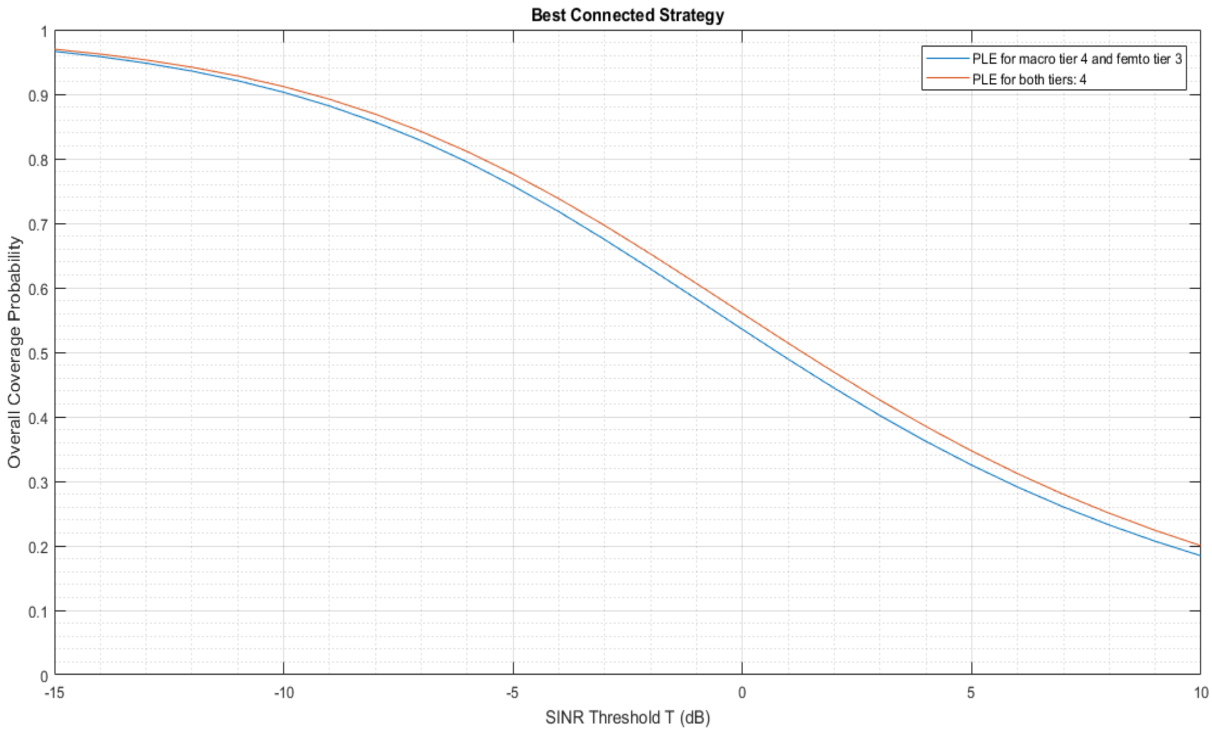

Figure 3. 6: Overall coverage probability with PLE of femto tier as 3.

Case 2: PLE for macro tier as 4 and for femto tier, PLE is 5

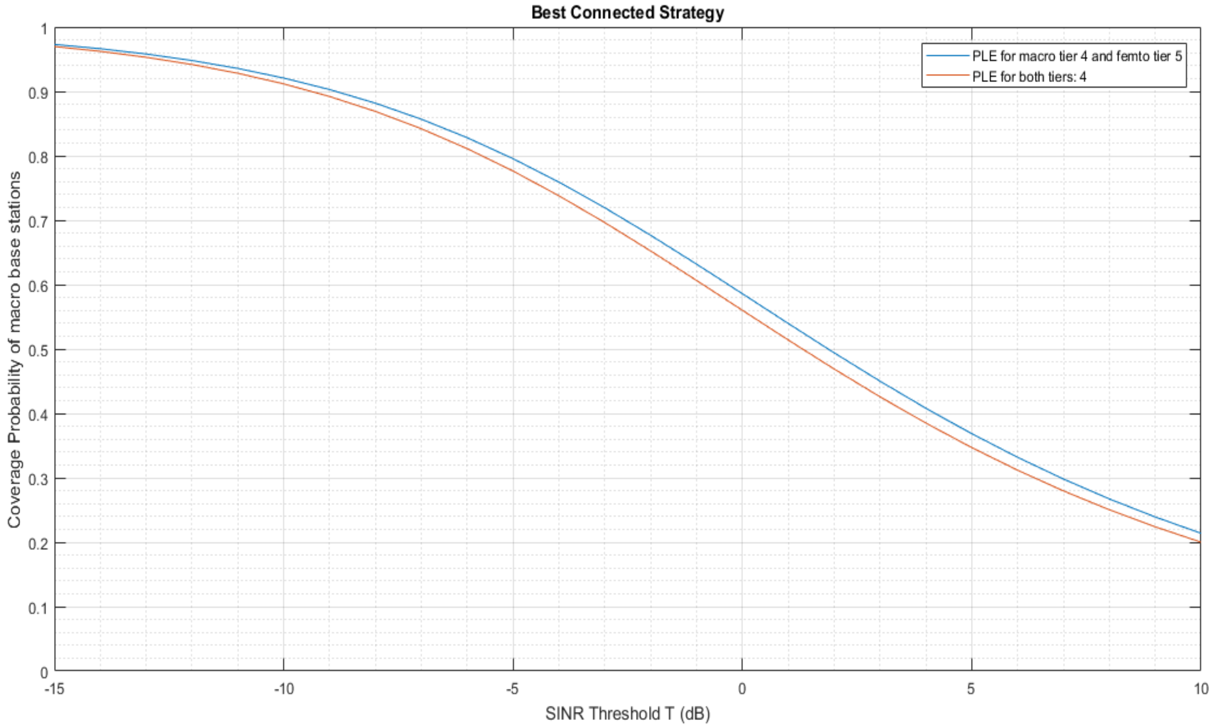

Figure 3. 7: Coverage probability of macro base stations with PLE of femto tier as 5.

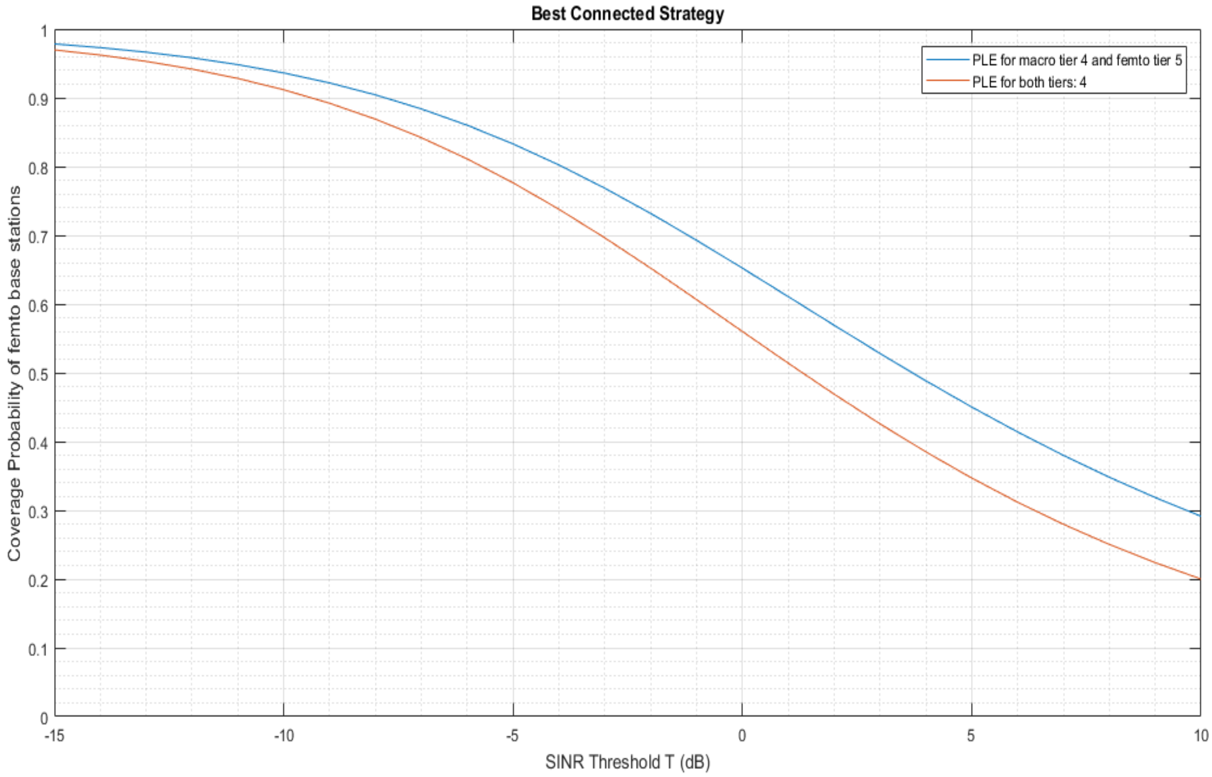

Figure 3. 8: Coverage probability of femto base stations with PLE of femto tier as 5.

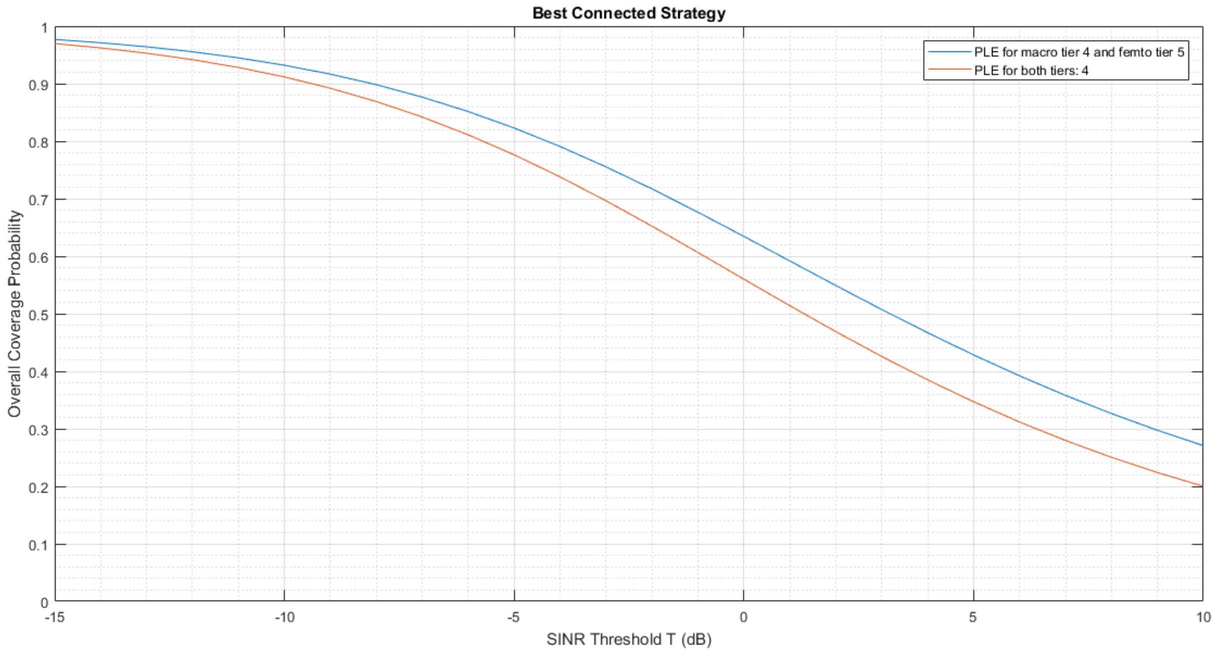

Figure 3. 9: Overall Coverage probability with PLE of femto tier as 5.

3.3 Conclusion

It can be seen from the above plots that coverage probability follows a consistent trend in all the cases of having a negative slope with an increase in the value of the threshold expressed in decibels. But variations in path loss exponent of the femto tier influences the probability value. Change in the value of PLE with femto tier having lower PLE as compared to macro tier produces a very slight change in the plot of coverage probability with the graph almost following the one with the case of same PLEs but with slightly smaller probability values. The difference in the values of coverage probabilities in the case of femto stations is more considerable and a higher dip in the plot can be noticed. Since the overall coverage probability is the combination of both macro and femto stations, therefore, the effect of a stronger dip in femto stations can still be noticed in the overall coverage probability plot with the one having same path loss exponents having higher values as compared to the one with different path loss exponents.

In contrast, if the macro tier has a lower value of path loss exponent than femto tier then the coverage probability values are smaller for the same path loss exponents case as compared to the different one. The difference in the values is still more noticeable in femto tier than macro tier and eventually in overall coverage probability.

Chapter 4

Femto Skipping Strategy

Femto skipping strategy ensures the user's connectivity with the station providing the maximum RSS, but with skipping a few femto stations along its path with an aim of reducing the overall handover rate. This introduces two different phases of association between the base station and the user equipment i.e., blackout and non-blackout phases. Non blackout is the situation where the association is entirely on the basis of RSS without an exception to any base station whereas blackout phase is the one in which the user skips a number of femto stations and is then served by the second and third strongest signal provider via non-coherent CoMP transmission where the cooperating stations may be any combination of femto and macro stations [3].

4.1 Distance distribution and coverage probability analysis

In the femto skipping scheme, UE switches between the blackout and non-blackout phases of association. The service distance distributions in the non-blackout phase are like the ones derived in the best-connected strategy whose formula is given below:

$$f_{R1}^{(FS)}(R) = f_{R1}^{(BC)}(R) = \frac{2\pi\lambda_1 R}{A_m^{(BC)}} \exp\left\{-\pi\left[\lambda_1 R^2 + \lambda_2 \left[\frac{(P_2B_2)}{(P_1B_1)}\right]^{\frac{2}{\alpha_2}} R^{\frac{2\alpha_1}{\alpha_2}}\right]\right\} \qquad 0 \le R < \infty$$

$$f_{r1}^{(FS)}(r) = f_{r1}^{(BC)}(r) = \frac{2\pi\lambda_2 r}{A_f^{(BC)}} \exp\left\{-\pi\left[\lambda_1 \left[\frac{(P_1B_1)}{(P_2B_2)}\right]^{\frac{2}{\alpha_1}} r^{\frac{2\alpha_2}{\alpha_1}} + \lambda_2 r^2\right]\right\} \qquad 0 \le r < \infty$$

Where,

$$A_m^{(FS)} = 2\pi\lambda_1 \int_0^\infty R \exp\left(-\pi[\lambda_1 R^2 + \lambda_2 (\widehat{P_2})^{\frac{2}{\alpha_2}} R^{2\frac{\alpha_1}{\alpha_2}}]\right) dR$$

$$A_f^{(FS)} = 2\pi\lambda_2 \int_0^\infty r \exp\left(-\pi[\lambda_1 (\widehat{P_1})^{\frac{2}{\alpha_1}} r^{2\frac{\alpha_2}{\alpha_1}} + \lambda_2 r^2]\right) dr$$

The derivation for service distance distribution in the blackout case is different from the non-blackout case as it involves the computation of the formulas mentioned above for each pair of cooperating base stations (i.e., macro and macro, femto and macro, femto and femto). The overall coverage probability of the system relies on the individual calculation which is a cumbersome task to do. In order to make the derivation less complicated, we make use of mapping theorem as described in [19] that makes an attempt to unify the analysis by mapping the two dimensional homogeneous PPPs into one equivalent non-homogeneous process.

Lemma 1: Two point processes as seen from the user's perspective can be mapped to a one-dimensional non-homogeneous PPP with intensity as derived below.

For macro station:

Intensity measure of the points inside a ball B of radius R: $\Lambda(B) = \pi\lambda_1 R^2$

Intensity function $: \lambda_1(x) = 2\pi\lambda_1 R^2$

Using mapping theorem, intensity measure on a line from 0 to y is as follows:

$$\Lambda([0, y]) = \pi\lambda_1 (P_1 y)^{\frac{2}{\eta_1}}$$

$$\lambda_1(y) = \frac{2}{\eta_1}\pi\lambda_1 P_1^{\frac{2}{\eta_1}} y^{\frac{2}{\eta_1}-1}$$

Similarly, for femto station:

$$\Lambda(B) = \pi\lambda_2 r^2$$

$$\lambda_2(x) = 2\pi\lambda_2 r^2$$

$$\Lambda([0, y]) = \pi\lambda_2 (P_2 y)^{\frac{2}{\eta_2}}$$

$$\lambda_2(y) = \frac{2}{\eta_2}\pi\lambda_2 P_2^{\frac{2}{\eta_2}} y^{\frac{2}{\eta_2}-1}$$

Using superposition theorem, the total intensity is:

$$\lambda(y) = 2\pi\frac{\lambda_1}{\eta_1} P_1^{\frac{2}{\eta_1}} y^{\frac{2}{\eta_1}-1} + 2\pi\frac{\lambda_2}{\eta_2} P_2^{\frac{2}{\eta_2}} y^{\frac{2}{\eta_2}-1}$$

$$\lambda(y) = 2\pi\left[\frac{\lambda_1}{\eta_1} P_1^{\frac{2}{\eta_1}} y^{\frac{2}{\eta_1}-1} + \frac{\lambda_2}{\eta_2} P_2^{\frac{2}{\eta_2}} y^{\frac{2}{\eta_2}-1}\right] \tag{4.1}$$

Where, λ_j : Intensity measure of the j^{th} tier

η_j: Path Loss Exponent of the j^{th} tier

P_j: Power of the base stations belonging to the j^{th} tier

The intensity measure defined above allows us to perform the unified analysis for the expression of coverage probability and distance distribution without taking different pair of cooperating base stations into account as demonstrated below:

Lemma 2: Derivation of conditional distance distribution of the skipped BS at a distance r_1 from the UE, conditioning on *x*, where *x* is the distance between the user and second strongest BS which can be either macro or femto is given below

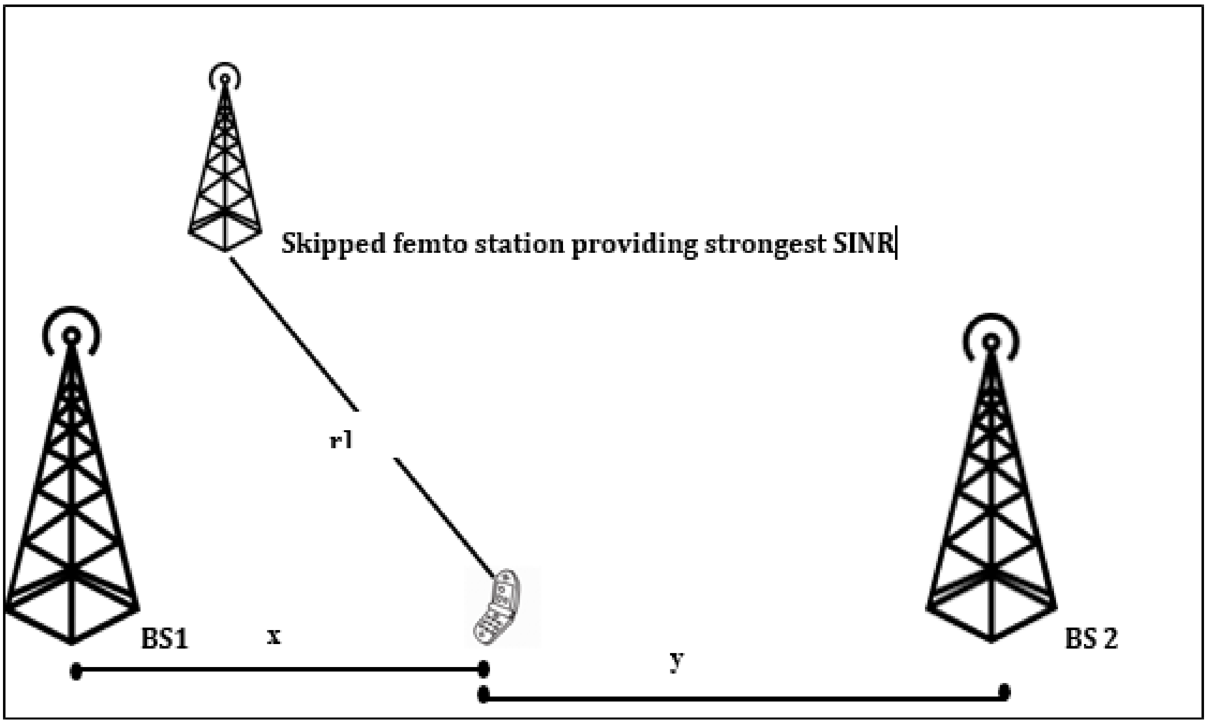

Figure 4. 1: Base station skipping scenario

$$f_{r_1(bk)}^{(FS)}\left(\frac{r_1}{x}\right) = \frac{\lambda(r_1)}{\int_0^x \lambda(z)dz} \qquad r_1 \leq x$$

$$\lambda(r_1) = \frac{2}{\eta_2}\pi\, \lambda P^{\frac{2}{\eta}} y^{\frac{2}{\eta}-1}$$

$$\int_0^x \lambda(z)dz = \frac{2}{\eta_2}\pi\, \lambda P^{\frac{2}{\eta_2}} \int_0^x z^{\frac{2}{\eta_2}-1} dz$$

$$\Rightarrow \pi\lambda P^{\frac{2}{\eta_2}} x^{\frac{2}{\eta_2}}$$

Therefore, the conditional distance distribution of $r_1$conditioned on the second strongest base station at a distance x is given by

$$f_{r_1(bk)}^{(FS)}\left(\frac{r_1}{x}\right) = \frac{2r_1^{\frac{2}{\eta_2}-1}}{\eta_2 x^{\frac{2}{\eta_2}}} \tag{4.2}$$

Calculating the service distance distribution in a single tier network using null probability analysis for any tier with path loss exponent η

$$f_Y(y) = \frac{d}{dy}\left(1 - e^{\Lambda(y)}\right)$$

$$f_Y(y) = \frac{d}{dy}\left(1 - e^{-\pi\lambda(Py)^{\frac{2}{\eta}}}\right)$$

$$\Rightarrow \frac{2}{\eta} e^{-\pi\lambda(Py)^{\frac{2}{\eta}}} \pi\lambda P^{\frac{2}{\eta}} y^{\frac{2}{\eta}-1}$$

where $f_Y(y)$ is the pdf of the service distance distribution in a single tier network.

PDF of r_1 i.e., the distance between the user and strongest femto BS in a two tier network with same path loss exponents for both the tiers is:

$$f_{r1}(r) = \frac{2\pi\lambda_2}{\eta A_f} P_2^{\frac{2}{\eta}} r^{\frac{2}{\eta}-1} e^{-\pi r^{\frac{2}{\eta}}\left(\lambda_1 P_1^{\frac{2}{\eta}} + \lambda_2 P_2^{\frac{2}{\eta}}\right)} \tag{4.3}$$

where A_f is the probability that $r_1 > R_1$ i.e., femto station provides the best signal to interference plus noise ratio.

For a two-tier network,

$$f_Y(y) = \frac{d}{dy}\left(1 - e^{-\Lambda(y)}\right)$$

Intensity measure for macro tier: $\Lambda_1(y) = \pi\lambda_1 (P_1 y)^{\frac{2}{\eta_1}}$

Intensity measure for femto tier: $\Lambda_2(y) = \pi\lambda_2 (P_2 y)^{\frac{2}{\eta_2}}$

Using superposition theorem,

$$\Lambda(y) = \pi\lambda_1 (P_1 y)^{\frac{2}{\eta_1}} + \pi\lambda_2 (P_2 y)^{\frac{2}{\eta_2}} = \pi\left(\lambda_1 (P_1 y)^{\frac{2}{\eta_1}} + \lambda_2 (P_2 y)^{\frac{2}{\eta_2}}\right)$$

$$f_Y(y) = \frac{d}{dy}\left(1 - e^{-\Lambda(y)}\right) = \frac{d}{dy}\left(1 - e^{-\pi\left(\lambda_1 (P_1 y)^{\frac{2}{\eta_1}} + \lambda_2 (P_2 y)^{\frac{2}{\eta_2}}\right)}\right)$$

$$f_Y(y) = \pi e^{-\pi\left(\lambda_1 (P_1 y)^{\frac{2}{\eta_1}} + \lambda_2 (P_2 y)^{\frac{2}{\eta_2}}\right)} \left\{\frac{2\lambda_1}{\eta_1} P_1^{\frac{2}{\eta_1}} y^{\frac{2}{\eta_1}-1} + \frac{2\lambda_2}{\eta_2} P_2^{\frac{2}{\eta_2}} y^{\frac{2}{\eta_2}-1}\right\}$$

Differentiating the above expression with respect to r and representing the pdf of the distance between the user and the femto station providing the strongest SINR by analogy with the single tier relation given in (3)

$$f_{r1}(r) = 2\pi\left(\frac{\lambda_1}{\eta_1}P_1^{\frac{2}{\eta_1}} + \frac{\lambda_2}{\eta_2}P_2^{\frac{2}{\eta_2}}\right) exp(-\pi(\lambda_1(P_1 r)^{\frac{2}{\eta_1}} + \lambda_2(P_2 r)^{\frac{2}{\eta_2}}))$$

Where,

$$\lambda_t = \frac{\lambda_1}{\eta_1}P_1^{\frac{2}{\eta_1}} + \frac{\lambda_2}{\eta_2}P_2^{\frac{2}{\eta_2}}$$

Now, deriving the conditional distance distribution of the third strongest BS conditioning on r_1.

$$P[x_2 < y|r_1] = 1 - \exp\left[-\int_{r_1}^{y} 2\pi\left(\frac{\lambda_1}{\eta_1}P_1^{\frac{2}{\eta_1}}r^{\frac{2}{\eta_1}-1} + \frac{\lambda_2}{\eta_2}P_2^{\frac{2}{\eta_2}}r^{\frac{2}{\eta_2}-1}\right)\mathrm{dr}\right] -$$
$$\left\{\exp\left[-\int_{r_1}^{y} 2\pi\left(\frac{\lambda_1}{\eta_1}P_1^{\frac{2}{\eta_1}}r^{\frac{2}{\eta_1}-1} + \frac{\lambda_2}{\eta_2}P_2^{\frac{2}{\eta_2}}r^{\frac{2}{\eta_2}-1}\right)\mathrm{dr}\right]\right\}\left\{\int_{r_1}^{y} 2\pi\left(\frac{\lambda_1}{\eta_1}P_1^{\frac{2}{\eta_1}}r^{\frac{2}{\eta_1}-1} + \frac{\lambda_2}{\eta_2}P_2^{\frac{2}{\eta_2}}r^{\frac{2}{\eta_2}-1}\right)\mathrm{dr}\right\}$$

Simplifying the terms:

$$\Rightarrow \int_{r_1}^{y} 2\pi\left(\frac{\lambda_1}{\eta_1}P_1^{\frac{2}{\eta_1}}r^{\frac{2}{\eta_1}-1} + \frac{\lambda_2}{\eta_2}P_2^{\frac{2}{\eta_2}}r^{\frac{2}{\eta_2}-1}\right)dr = \pi\left[\lambda_1 P_1^{\frac{2}{\eta_1}}\left(y^{\frac{2}{\eta_1}} - r_1^{\frac{2}{\eta_1}}\right) + \lambda_2 P_2^{\frac{2}{\eta_2}}\left(y^{\frac{2}{\eta_2}} - r_1^{\frac{2}{\eta_2}}\right)\right]$$

$$P[x_2 < y|r_1] = 1 - \exp\left\{-\pi\left[\lambda_1 P_1^{\frac{2}{\eta_1}}\left(y^{\frac{2}{\eta_1}} - r_1^{\frac{2}{\eta_1}}\right) + \lambda_2 P_2^{\frac{2}{\eta_2}}\left(y^{\frac{2}{\eta_2}} - r_1^{\frac{2}{\eta_2}}\right)\right]\right\} -$$
$$\exp\left\{-\pi\left[\lambda_1 P_1^{\frac{2}{\eta_1}}\left(y^{\frac{2}{\eta_1}} - r_1^{\frac{2}{\eta_1}}\right) + \lambda_2 P_2^{\frac{2}{\eta_2}}\left(y^{\frac{2}{\eta_2}} - r_1^{\frac{2}{\eta_2}}\right)\right]\right\}\left\{\pi\left[\lambda_1 P_1^{\frac{2}{\eta_1}}\left(y^{\frac{2}{\eta_1}} - r_1^{\frac{2}{\eta_1}}\right) + \lambda_2 P_2^{\frac{2}{\eta_2}}\left(y^{\frac{2}{\eta_2}} - r_1^{\frac{2}{\eta_2}}\right)\right]\right\}$$

Differentiating w.r.t y and after further simplification, we get

$$f\left(\frac{x_2}{r_1}\right) = \left(\pi^2\left[\lambda_1 P_1^{\frac{2}{\eta_1}}\left(y^{\frac{2}{\eta_1}} - r_1^{\frac{2}{\eta_1}}\right) + \lambda_2 P_2^{\frac{2}{\eta_2}}\left(y^{\frac{2}{\eta_2}} - r_1^{\frac{2}{\eta_2}}\right)\right]\right)\left(\frac{2}{\eta_1}\lambda_1 P_1^{\frac{2}{\eta_1}}y^{\frac{2}{\eta_1}-1} + \frac{2}{\eta_2}\lambda_2 P_2^{\frac{2}{\eta_2}}y^{\frac{2}{\eta_2}-1}\right)\left(\exp\left\{-\pi\left[\lambda_1 P_1^{\frac{2}{\eta_1}}\left(y^{\frac{2}{\eta_1}} - r_1^{\frac{2}{\eta_1}}\right) + \lambda_2 P_2^{\frac{2}{\eta_2}}\left(y^{\frac{2}{\eta_2}} - r_1^{\frac{2}{\eta_2}}\right)\right]\right\}\right) \tag{4.4}$$

Equation (4.4) can be compared with the one considering the same path loss exponent as derived in the paper which is written below [3]

$$f\left(\frac{x_2}{r_1}\right) = \frac{2}{\eta}\left(\pi\left(\lambda_1 P_1^{\frac{2}{\eta}} + \lambda_2 P_2^{\frac{2}{\eta}}\right)\right)^2 y^{\frac{2}{\eta}-1}\left(y^{\frac{2}{\eta}} - r_1^{\frac{2}{\eta}}\right)\exp\left(-\pi\left(\lambda_1 P_1^{\frac{2}{\eta}} + \lambda_2 P_2^{\frac{2}{\eta}}\right)\left(y^{\frac{2}{\eta}} - r_1^{\frac{2}{\eta}}\right)\right)$$

Overall intensity measure for same path loss exponents: $\left(\lambda_1 P_1^{\frac{2}{\eta}} + \lambda_2 P_2^{\frac{2}{\eta}}\right)$

Overall intensity measure for different path loss exponents: $\left(\frac{\lambda_1}{\eta_1} P_1^{\frac{2}{\eta_1}} + \frac{\lambda_2}{\eta_2} P_2^{\frac{2}{\eta_2}}\right)$

Where,

η_j: Path loss exponent of the j tier

P_j: Power of the j tier

λ_j: Intensity measure of j tier

In the case of the same path loss exponents for both the tiers, the value of η is assumed to be 4 as per [3]. The variation in path loss exponents across different tiers of HetNet has a significant impact on the overall intensity measure of the system thereby changing the overall coverage probability of the system which will be seen in a later stage.

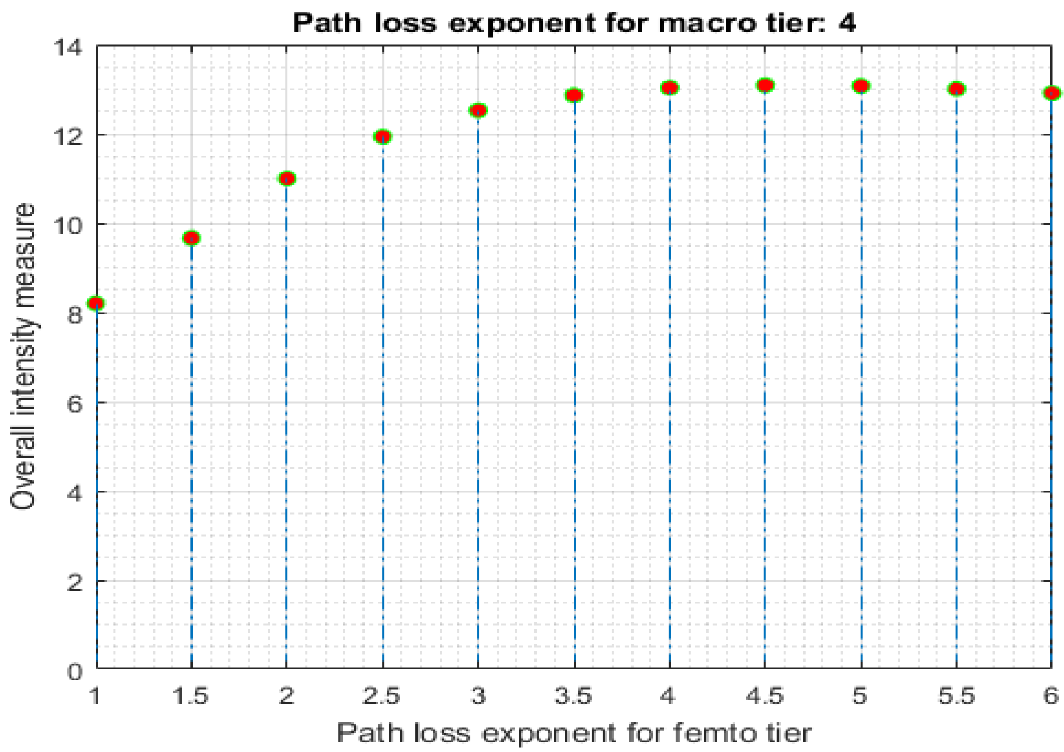

Figure 4. 2: Variation of overall intensity measure of the system with changes in femto tier's intensity

4.1.1 Derivation of joint conditional distribution

Assuming the second strongest BS to be a macro station,

$$f_{x_1}(x) = \frac{\lambda(x)}{\int_{r_1}^{y} \lambda(z)dz} \tag{4.5}$$

$$\lambda(x) = \frac{2}{\eta_1}\pi\lambda P^{\frac{2}{\eta_1}} x^{\frac{2}{\eta_1}-1}$$

$$\int_{r_1}^{y} \lambda(z)dz = \pi\lambda P^{\frac{2}{\eta_1}}(y^{\frac{2}{\eta_1}} - r_1^{\frac{2}{\eta_1}})$$

Substituting in (4.4), we get

$$f_{x_1}(x) = \frac{2x^{\frac{2}{\eta_1}-1}}{\eta_1(y^{\frac{2}{\eta_1}} - r_1^{\frac{2}{\eta_1}})}$$

Joint conditional distribution conditioned on r_1 is given by:

$$f_{x_1,x_2}\left(\frac{x,y}{r_1}\right) = f_{x_1}(x) f_{x_2}\left(\frac{y}{r_1}\right)$$

$$f_{x_1,x_2}\left(\frac{x,y}{r_1}\right) = \left(\frac{2x^{\frac{2}{\eta_1}-1}}{\eta_1(y^{\frac{2}{\eta_1}} - r_1^{\frac{2}{\eta_1}})}\right)\left(\pi^2\left[\lambda_1 P_1^{\frac{2}{\eta_1}}\left(y^{\frac{2}{\eta_1}} - r_1^{\frac{2}{\eta_1}}\right) + \lambda_2 P_2^{\frac{2}{\eta_2}}\left(y^{\frac{2}{\eta_2}} - r_1^{\frac{2}{\eta_2}}\right)\right]\right)\left(\frac{2}{\eta_1}\lambda_1 P_1^{\frac{2}{\eta_1}} y^{\frac{2}{\eta_1}-1} + \frac{2}{\eta_2}\lambda_2 P_2^{\frac{2}{\eta_2}} y^{\frac{2}{\eta_2}-1}\right)\left(\exp\left\{-\pi\left[\lambda_1 P_1^{\frac{2}{\eta_1}}\left(y^{\frac{2}{\eta_1}} - r_1^{\frac{2}{\eta_1}}\right) + \lambda_2 P_2^{\frac{2}{\eta_2}}\left(y^{\frac{2}{\eta_2}} - r_1^{\frac{2}{\eta_2}}\right)\right]\right\}\right)$$

Joint distribution $f_{x_1,x_2,r_1}(x,y,r_1)$ can then be written as

$$f_{x_1,x_2,r_1}(x,y,r_1) = f_{r_1}(r) f_{x_1,x_2}\left(\frac{x,y}{r_1}\right)$$

Further,

$$f_{x_1,x_2}(x,y) = \int_0^x f_{x_1,x_2,r_1}(x,y,r_1)dr_1$$

The derivation above can also be performed for the case when the second strongest BS is femto station. The only variation in the formula will be the replacement of η_1 with η_2 in $f_{x_1}(x)$.

4.1.2 Coverage Probability of femto skipping strategy

The overall coverage probability of femto skipping strategy includes the one offered during a blackout and non-blackout phases. Non blackout phase is like the best-connected case with the user association probability with the femto station being half of the one calculated during the best-connected case. By the law of total probability, the overall coverage probability for the femto skipping strategy can be written as [3]

$$C^{FS} = A_{m\overline{b_k}}^{FS} C_{m\overline{b_k}}^{FS} + A_{f\overline{b_k}}^{FS} C_{f\overline{b_k}}^{FS} + A_{bk}^{FS} C_{bk}^{FS}$$

where, $\overline{b_k}$ represents the non-blackout phase and b_k denotes the blackout phase

$C_{m\frac{FS}{b_k}}$: Coverage probability of the macro station in the femto skipping case in non-blackout phase, which is equal to C_m^{BC}

Similarly, $C_{f\frac{FS}{b_k}} = C_f^{BC}$

$A_{m\frac{FS}{b_k}}$: Macro association probability i.e., equal to A_m^{BC} in the best connected case.

In the blackout phase, the user skips the strongest femto BS and is served by the second and the third strongest stations via noncoherent CoMP [3]. In femto skipping case, the user shuffles between the non-blackout case and the blackout case where the former ensures the association with the BS with the strongest received signal strength at the user and the latter associates the user with the second and third strongest base stations. The user association probability can, therefore, be written as,

$$A_{f\frac{FS}{b_k}} = A_{bk}^{FS} = 0.5A_f^{BC}$$

Employing the mapping theorem defined before, the overall aggregate interference from both the tiers can be combined together and the formula of coverage probability in blackout phase can be derived in the same manner as derived in the paper [3].

$$L_{I_r}(s) = \int_0^x \frac{1}{1 + \frac{T{r_1}^{-1}}{x^{-1} + y^{-1}}} * f_{r_1(bk)}^{(FS)}\left(\frac{r_1}{x}\right) dr_1$$

$$f_{r_1(bk)}^{(FS)}\left(\frac{r_1}{x}\right) = \frac{2{r_1}^{\frac{2}{\eta_2}-1}}{\eta_2 x^{\frac{2}{\eta_2}}}$$

The conditional distance distribution of r_1 conditioned on the second strongest base station at a distance x derived earlier is $f_{r_1(bk)}^{(FS)}\left(\frac{r_1}{x}\right)$.

Similarly,

$$L_{I_{agg}}(s) = E\left\{e^{-s\sum_{i\in\varphi\backslash b_1}\frac{h_i}{u_i}}\right\}$$

Where, $L_{I_{agg}}(s)$ is the Laplace transform of the aggregate interference from both the tiers [3].

$$h_i \sim \exp(1)$$

$$L_{I_{agg}}(s) = exp - 2\pi\lambda_t\left(\int_y^\infty \frac{z^{\frac{2}{\eta_1}-1}}{1 + \frac{z(x^{-1} + y^{-1})}{T}} dz + \int_y^\infty \frac{z^{\frac{2}{\eta_2}-1}}{1 + \frac{z(x^{-1} + y^{-1})}{T}} dz\right)$$

where,

$$\lambda_t = \left(\frac{\lambda_1}{\eta_1} P_1^{\frac{2}{\eta_1}} + \frac{\lambda_2}{\eta_2} P_2^{\frac{2}{\eta_2}}\right)$$

4.2 Simulation Results

Simulations are performed in two phases, first one based on different biasing factors and the other one based on different path loss exponents of stations belonging to different tiers.

4.2.1 Simulation results based on different biasing factors

Different biasing factors include the case of having multiplicative terms with the transmission powers of the base stations. Therefore, the variation in the formula for overall coverage probability of the system as compared to the one in [3] is as mentioned below:

$$C_{(bk)}^{(FS)} = \int_0^{\infty}\int_x^{\infty} \frac{8}{\eta^3}\pi\lambda_t^3 x^{\frac{2}{\eta}-1} y^{\frac{2}{\eta}-1} \exp\left\{-\pi y^{\frac{2}{\eta}}\lambda_t - \frac{2\pi\lambda_t T y^{\frac{2}{\eta}-1}}{(\eta-2)(x^{-1}+y^{-1})}\ {}_2F^1\left(1,1-\frac{2}{\eta},2-\frac{2}{\eta},\frac{-T}{x^{-1}y+1}\right)\right\} \int_0^x \frac{r_1^{\frac{2}{\eta}-1}}{1+\frac{Tr_1^{-1}}{x^{-1}+y^{-1}}} dr_1\ dydx$$

$$\lambda_t = \lambda_1(B_1P_1)^{2/\eta} + \lambda_2(B_2P_2)^{2/\eta}$$

where, B_j is the biasing factor of the j^{th} tier.

In the simulation, the biasing factor of the macro tier is ranged from 0.1 to 1 with increments of 0.1 and for the femto tier, the biasing factor is $1-B_1$. The result of the simulation is shown below:

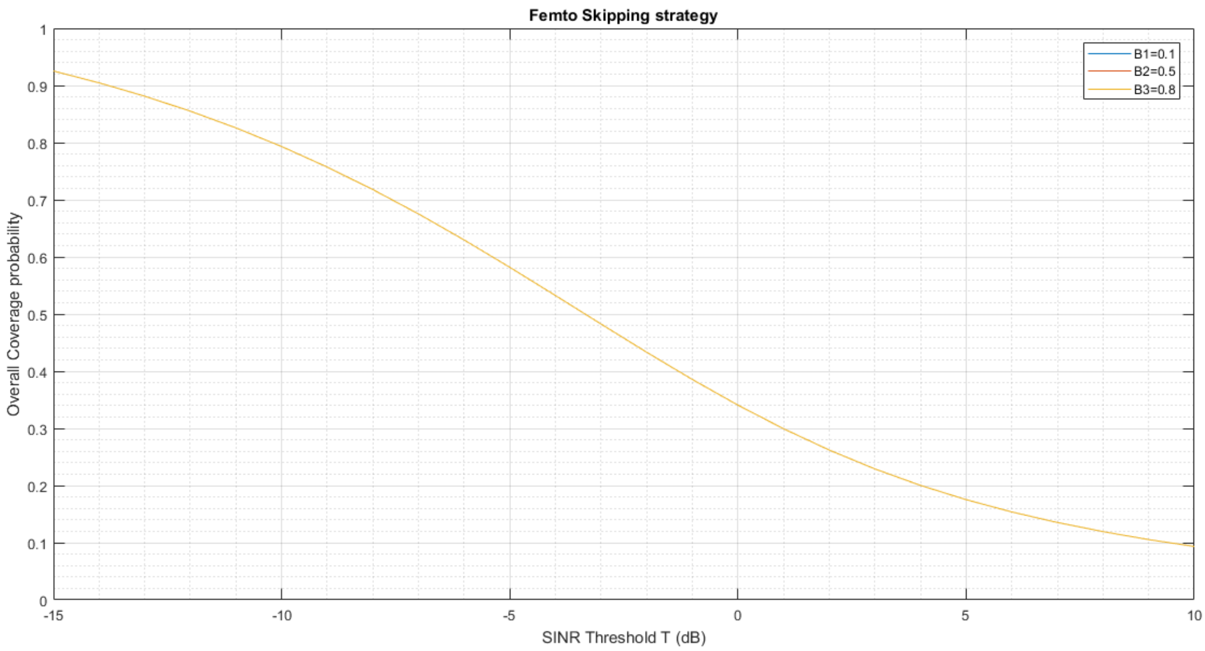

Figure 4. 3: Overall coverage probability of the femto skipping strategy.

Conclusion:

Biasing has no effect on the overall coverage probability in the femto skipping scheme.

4.2.2 Simulation results based on different path loss exponents

Coverage probability for macro and femto stations are plotted against varying threshold values in the non-blackout case with path loss exponent as 3 and 5 and the plots are compared with the graph obtained by using the same path loss exponent of 4 for both the tiers. Along with that, the overall coverage probability of the system considering both the blackout and non-blackout phases is also plotted with different PLEs for femto tier.

The overall coverage probability of the system is calculated by combining the effects of blackout and non-blackout phases as explained in Section 4.1.2. The formula for overall coverage probability is given below:

$$C^{FS} = A_{m\overline{b_k}}^{FS} C_{m\overline{b_k}}^{FS} + A_{f\overline{b_k}}^{FS} C_{f\overline{b_k}}^{FS} + A_{bk}^{FS} C_{bk}^{FS}$$

where $\overline{b_k}$ represents the non-blackout phase and b_k denotes the blackout phase.

Case 1: Path loss exponent of the macro tier is 4 and for femto tier, PLE is 3

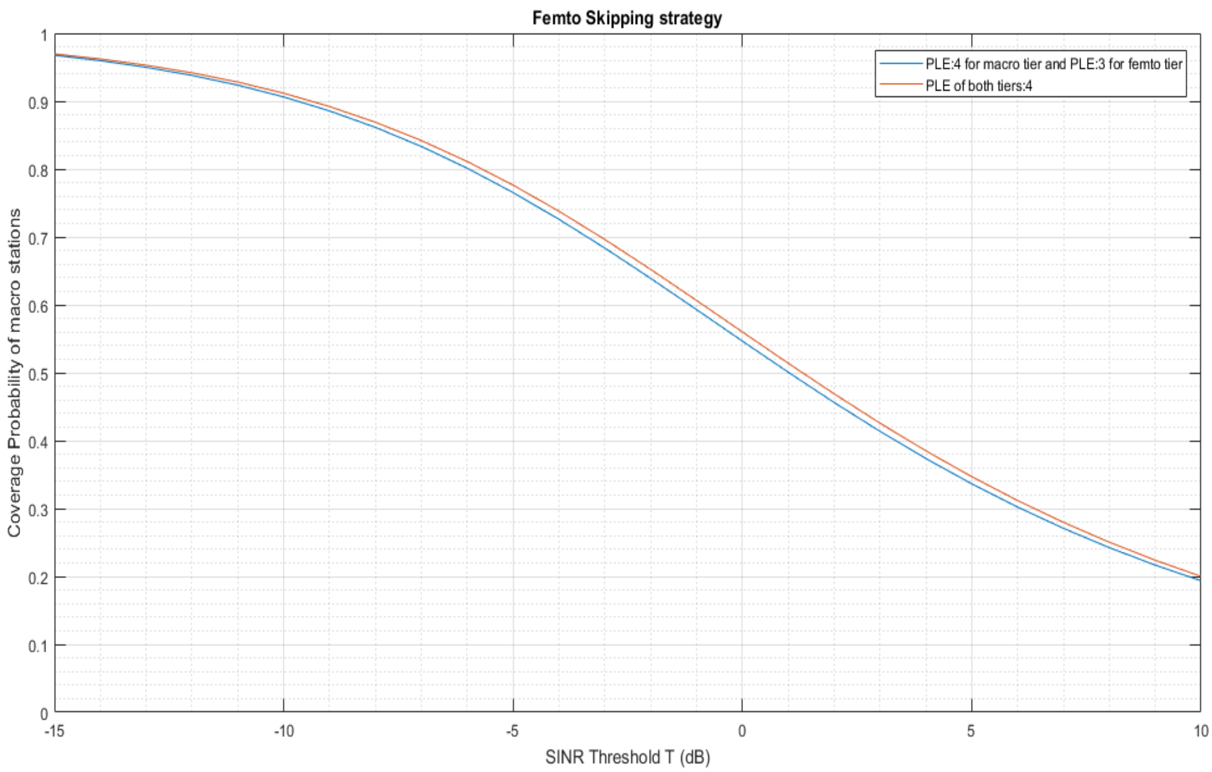

Figure 4. 4: Coverage probability of macro base stations with PLE of femto tier as 3.

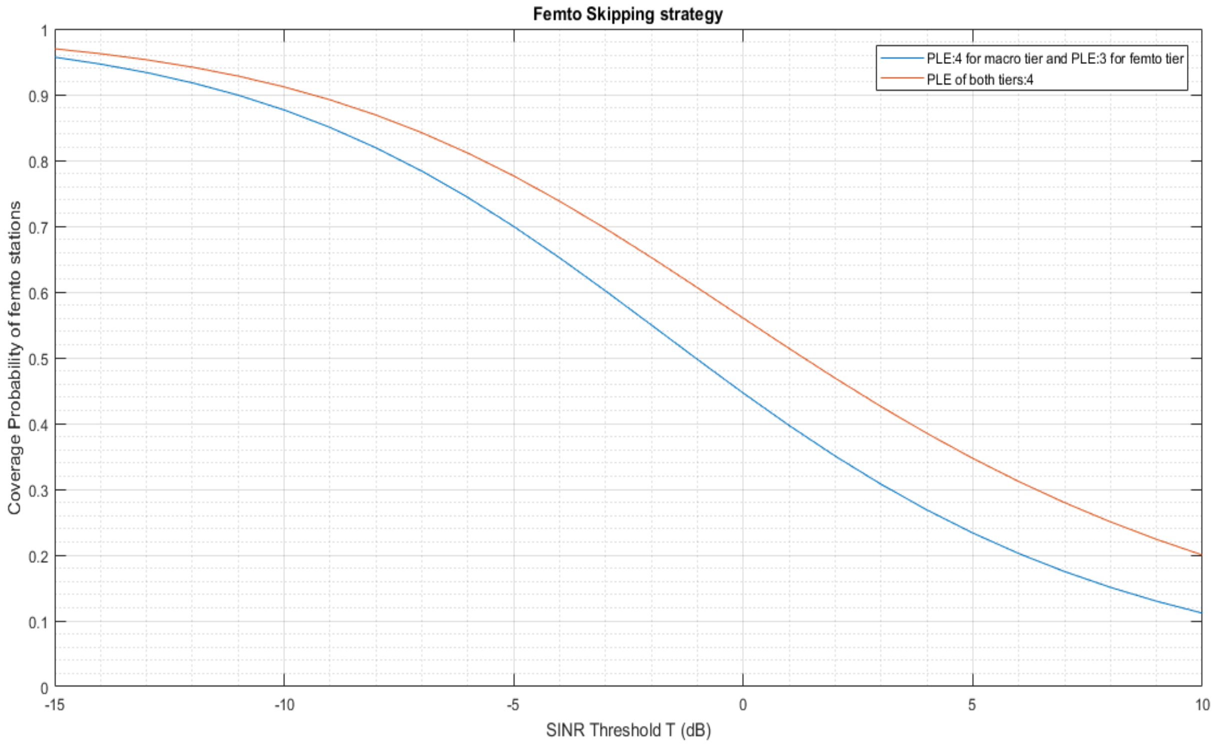

Figure 4. 5: Coverage probability of femto base stations with PLE of femto tier as 3.

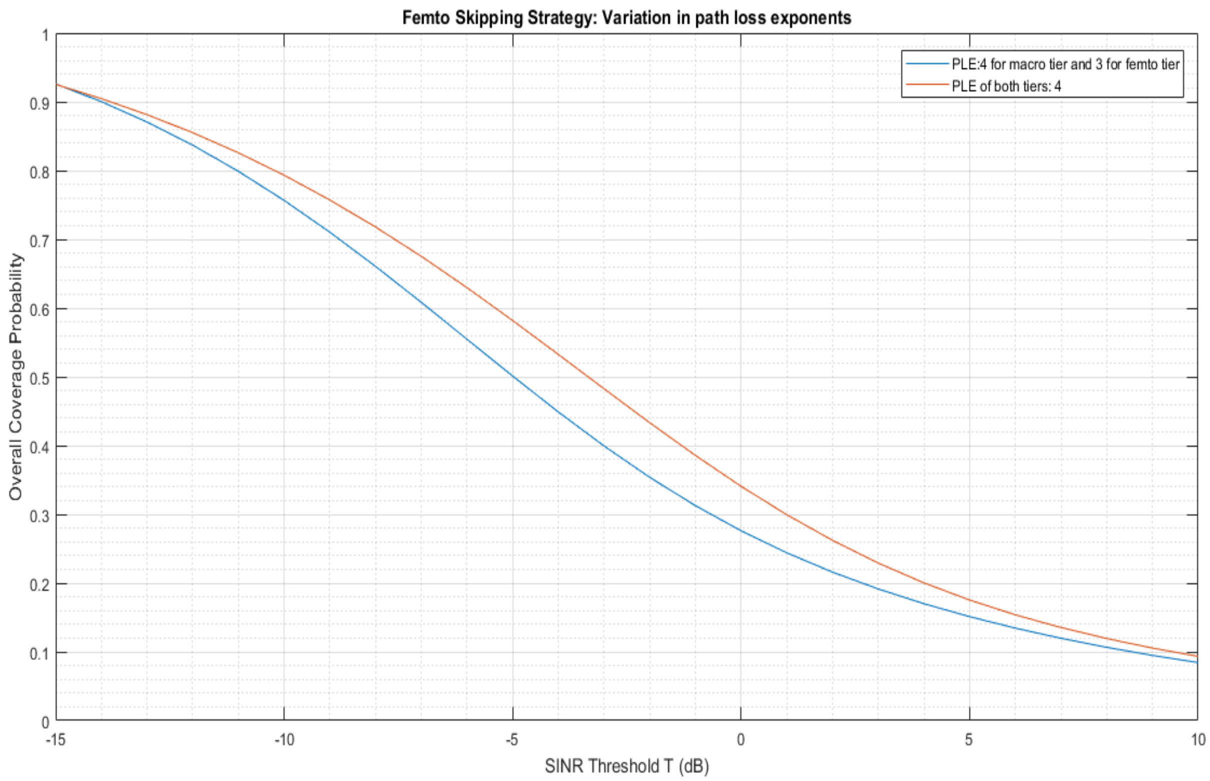

Figure 4. 6: Overall Coverage probability with PLE of femto tier as 3.

Case 2: Path loss exponent of the macro tier is 4 and for femto tier, PLE is 5

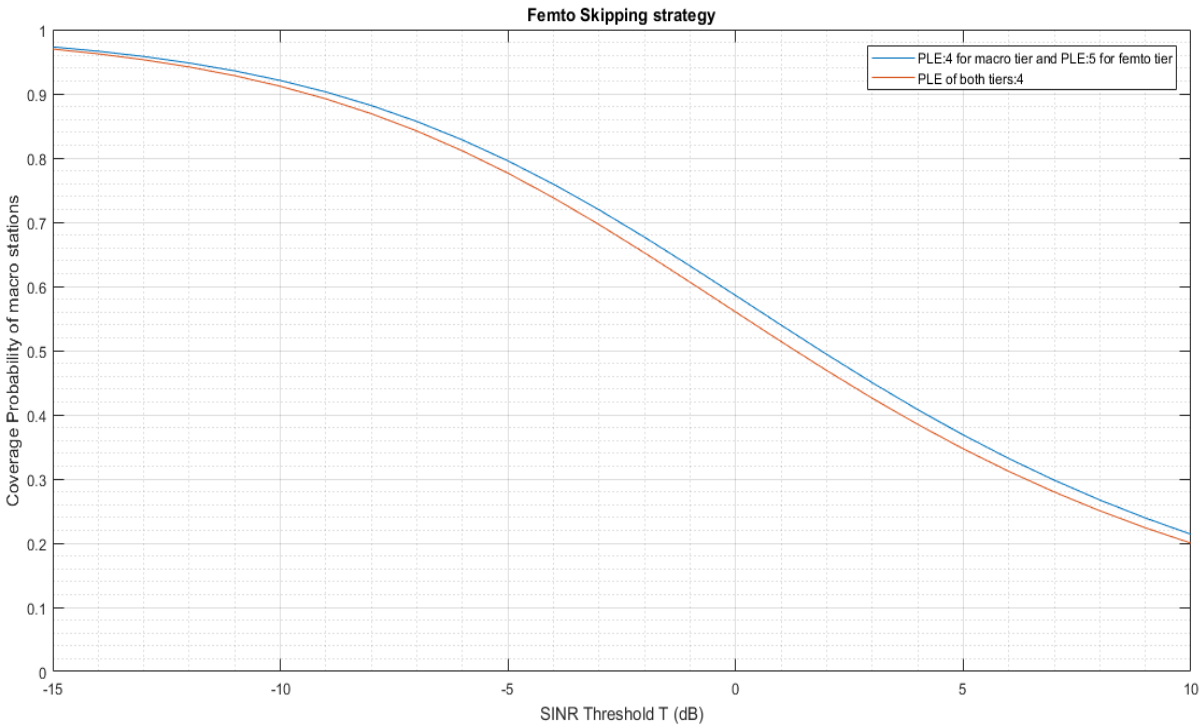

Figure 4. 7: Coverage probability of macro base stations with PLE of femto tier as 5.

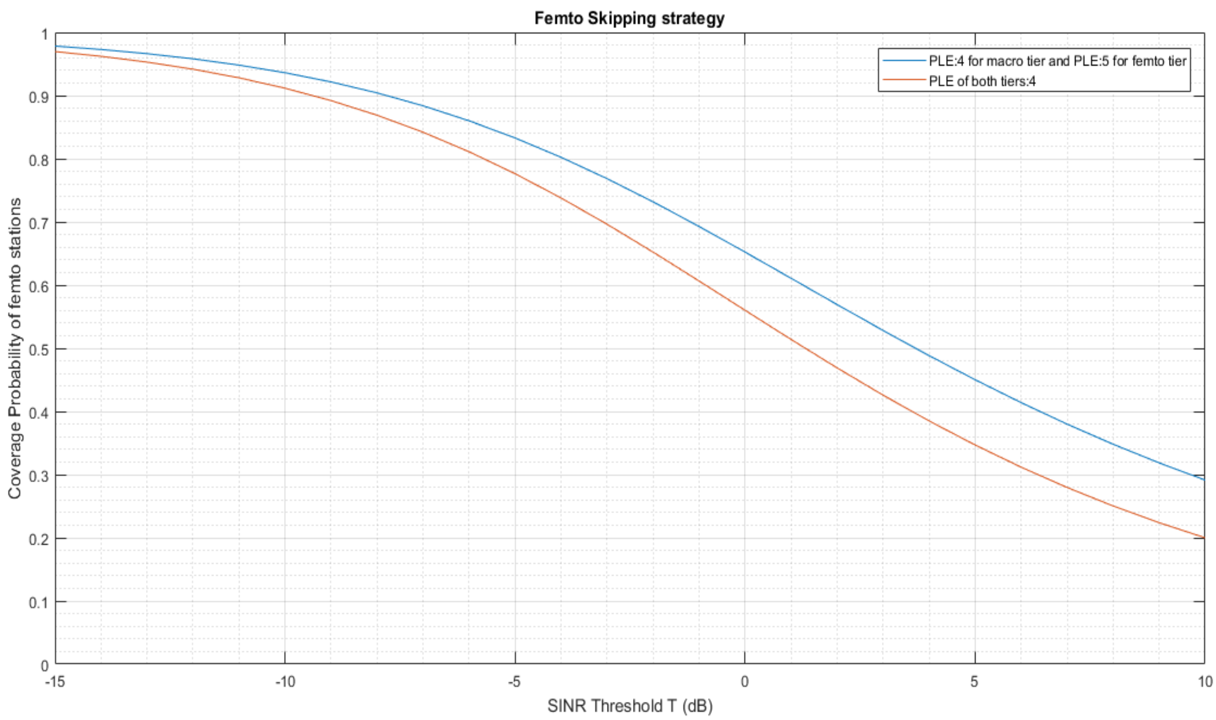

Figure 4. 8: Coverage probability of femto base stations with PLE of femto tier as 5.

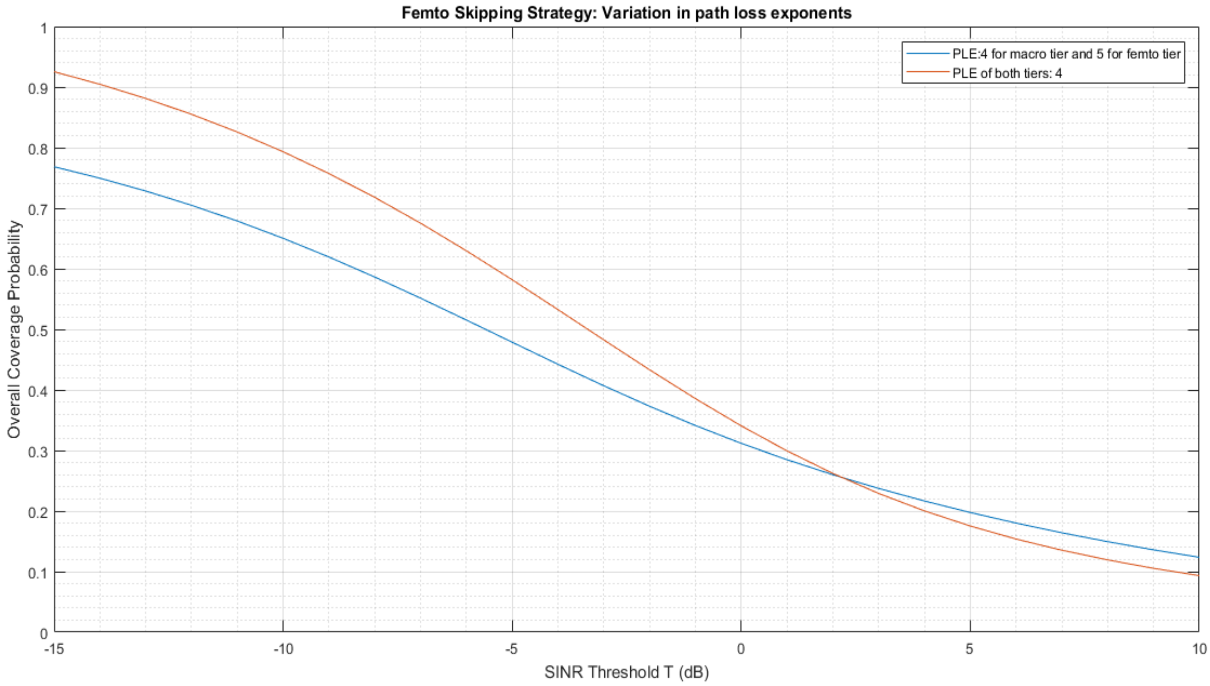

Figure 4. 9: Overall coverage probability with PLE of femto tier as 5.

Conclusion:

The overall trend of the variation of coverage probability with respect to increasing values of threshold remains consistent, i.e., with an increase in the threshold, coverage probability decreases in individual tier scenario or the case of the overall system. In terms of the macro tier, the variation in the values of coverage probability with respect to different path loss exponents is not so significant in comparison to the femto tier. The coverage probability of femto tier has higher values when the PLE for femto tier is taken to be higher than the macro tier but in the same way, the equation generates smaller values when PLE of the macro tier is higher than the femto tier. As the overall coverage probability is the cumulative effect of both the tiers, therefore, the curve for overall coverage probability with different PLEs intersects the plot considering same PLEs where the point of intersection depends upon the assumed PLE for femto tier.

Chapter 5

Conclusion

In this thesis, the effect of different path loss exponents and biasing was investigated over the coverage probability values in two schemes proposed in HetNets to avoid frequent handovers. Work in this research is different from the ones performed so far on the basis of several factors. Firstly, the analysis performed here is for a two-tier cellular network whereas the equations derived initially in the reference texts were for a single tier network. The derivations here are for any general cellular network and not just for finite cellular networks. In our analysis, certain parameters such as L and W, which are, the length and width of the network are considered as 1 for the sake of simplicity. Taking some other values can extend the analysis toward 'non-finite networks' also. But, that would require performing derivations again. Furthermore, the discussion here is not just focussed on homogeneous networks. Even, in the case of a femto skipping strategy, we have not even considered homogeneity in the network.

There are certain similarities also namely, consideration of stochastic geometry analysis. User association with the station is considered on the basis of maximum received signal strength. Coverage probability, in general, follows a constant trend of having a reduction in the values with the increase in the value of the threshold. Even, coverage probability improves when the path loss exponent has a larger value.

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