

# Features detection based blind handover using kullback leibler distance for 5G HetNets systems

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## ABSTRACT

The Fifth Generation of Mobile Networks (5G) is changing the cellular network infrastructure paradigm, and small cells are a key piece of this shift. But the high number of small cells and their low coverage involve more Handovers to provide continuous connectivity, and the selection, quickly and at low energy cost, of the appropriate one in the vicinity of thousands is also a key problem. In this paper, we propose a new method, to have an efficient, blind and rapid handover just by analysing received signal probability density function instead of demodulating and analysing received signal itself as in classical handover. The proposed method exploits kullback leibler distance (KLD), akaike information criterion (AIC) and akaike weights, in order to decide blindly the best handover and the best base station (BS) for each user.

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## 1. INTRODUCTION

Mobile cellular communication [1] has become increasingly one of the most interesting research area over the past few years. The exponentially increasing demand for wireless data services [2] require a massive network densification that is neither economically nor ecologically viable with current cellular system architectures. Fifth Generation (5G) [3-4] have recently emerged to satisfy the increasing demand for high data bit rates. A crucial requirement for 5G networks is the deployment of Small Cells (SCs) [5] over Macrocells layer which introduces a new type of networks called Heterogeneous Networks (HetNets) [6]. A HetNet is simply the banding together of different sized cells to provide ultra dense coverage in defined geographic areas.

Small Cells (SCs) are low-powered cellular radio access nodes that operate in licensed and unlicensed spectrum that have a range of 10 meters to a few kilometers. They will be a crucial component of 5G networks, because they have the ability to significantly increase network capacity, density and coverage, especially indoors. They are a relatively low cost deployment option and, because they are low power devices [7], are relatively cheap and efficient to run to give a low total cost of ownership. Like every other technology, SCs have some drawbacks that give rise to some major concern on part of the end users.

In this paper, we are going to study the problem of the management of handovers. Handover is the practice of retaining a user's active connection when a mobile terminal changes its connection point to the access network (called "point of attachment") [8-9]. Because of the low coverage of SCs, it is essential to

support seamless handovers to provide continuous connectivity within any wide area network. In addition, due to the high number of SCs, handovers increase, and the selection, quickly and at low energy cost, of the appropriate one in the vicinity of thousands is also a key problem. Hence, we propose a new method to operate and manage a blind handover between a number of users and Base Stations of SCs.

Every handover process contains three phases logically [10]. The first step concerns the measurement or information gathering phase, where the UE measures the signal strength of every potential neighbor BS and the current serving station. The second phase is about the handover decision, where the current serving BS decides about initializing the handover based on the measured data from the first stage. And the last one, is the cell exchange, when the UE releases the serving evolved NodeB (eNB) and connects to the new one. For 5G Networks, Artificial Intelligence [11] can be broadly applied in the Blind Handover techniques. The usage of Artificial Intelligence techniques in the Handoff decision process will reduce the computation complexity which already exists in the conventional methods. The main idea is to operate efficient, blind and rapid handover just by analysing received signal probability density function(pdf) instead of demodulating and analysing received signal itself as in classical handover. The goal within our contribution is to exploit kullback leiber distance, akaike information criterion (AIC) and akaike weights [12-13] in order to decide blindly the best handover and the best BS for each user.

The remainder of the paper is organized as follows. We begin by introducing, a brief overview of related work in section 2. In section 3, we revisit KLD and present the formulation of our problem. In section 4 we give a brief review of model selection using AIC: the AIC is presented and the akaike weights are derived. The approach based on model selection is developed in Section 5. The evaluation of the result is in section 6. The last section will be devoted to the conclusion.

## 2. RELATED WORK

In mobile telecommunications systems, there are circumstances where it is desirable for a mobile terminal (such as a telephone, portable computer with communications capabilities, etc.), which is operating at a first frequency in a first network belonging to a first system to transfer to a second network operating at a second frequency (which may belong to a second system), that is, a system using a different type of technology and defined according to a different standard. Different types of handover may be envisaged:

If the primary network is a time division duplex (TDD) network [14] then, even while the mobile terminal is transmitting or receiving data/voice, there are time slots when it is inactive (that is, it is neither sending nor transmitting signals). These time slots can be used to perform measurements on channels operating at other frequencies, thus enabling the terminal to evaluate the performance of candidate target networks. However, if the primary network is a frequency division duplex (FDD) network [14], such as a Universal Mobile Telecommunication System (UMTS) FDD network then, when the terminal is active and currently transmitting or receiving data, there are no inactive periods available for performing measurements at other frequencies. So, in this case, the terminal cannot readily evaluate the performance of candidate target networks. Various techniques have been proposed to enable intra-system inter-frequency handovers, or inter-system handovers, to be performed by terminals operating in primary networks using FDD (such as UMTS FDD networks).

Many techniques have been proposed using measurements on the Target Network [15]: A first approach which enables measurements to be made on the target network is the “dual receiver” approach which means that mobile station has two receiver branches, one receiving branch measures the signal strength and quality on the other frequency while another receiving branch are keeping track on transmitting and receiving signals of the current frequency. This is especially suitable for antenna diversity in mobile station. This approach has a number of disadvantages. Firstly, power consumption of the terminal is increased. Secondly, if the terminal is adapted to operate both in UMTS FDD networks and in GSM 1800 networks then a problem can arise (due to the closeness of the frequencies of the UMTS FDD uplink band and the GSM 1800 downlink band) when the contemplated handover is from an UMTS FDD network to a GSM 1800 network. More specifically, if the frequencies corresponding to the UMTS FDD uplink band and the GSM 1800 downlink band are not perfectly isolated then the dual receiver terminal may not be able to demodulate them both. In such a case another technique would be required in order to enable the terminal to perform measurements on the target network. Finally, the mobile terminal comprises two receivers and, accordingly, requires extra circuitry compared to a standard terminal: which increases its size, cost and complexity.

A second approach which enables the terminal to make measurements on the target network consists in operating the terminal in ‘‘compressed mode’’ [16-18]. The compressed mode, often referred to as the slotted mode, is needed when making measurements from another frequency in a CDMA system without a full dual receiver terminal. The compressed mode means that transmission and reception are halted for a short time, in the order of a few milliseconds, in order to perform measurements on the other frequencies. The intention is not to lose data but to compress the data transmission in the time domain.

An existing feature in which the network node, e.g. an eNB in case of LTE, may initiate a handover procedure for a terminal without doing conventional measurement configuration and without considering measurement reports is Blind Handover. This feature may be beneficial when a fast handover is needed and candidate cell measurements are unavailable, or would impose an unwanted delay. Using the blind handover in such case removes the time and signaling needed to conduct handover measurements, hence giving the desired fast handover.

Blind Handover Techniques [15]: A beacon pilot blind handover technique has been proposed in which the target network, which normally operates at a frequency  $f_t$ , broadcasts a ‘‘beacon pilot’’ at the same frequency  $f_t$  as the frequency of the primary network. This beacon pilot consists of a pilot channel and a synchronisation channel and enables the mobile terminal to evaluate the propagation loss between itself and the target network. One disadvantage of the ‘‘beacon pilot approach is that it requires deployment of pilot antennas, increasing the cost of the system infrastructure. Another disadvantage arises in the case of an intra-system, inter-frequency handover between primary and target networks which are UMTS FDD networks operating at adjacent frequencies. In this case the pilot transmission can generate interference on the target network, making its capacity decrease.

Another known blind handover consists in a ‘‘direct blind handover in which a look-up table is held, for example, in the Radio Network Controller (RNC) of the primary network (assuming an UMTS FDD primary network). This look-up table (or ‘‘planning table’’) indicates, for each primary cell, which target cell should be used in a handover. If the handover is between systems having co-located cells then this blind handover method works reasonably well. However, in the case where the transfer is an inter-system transfer there is no guarantee that the boundaries of the cells of the two systems will be defined in the same locations. If the primary and target cells are not co-located then the quality of the connection available in the target cell will vary depending upon the geographic location of the mobile terminal within the primary cell. Thus, for mobile terminals at certain locations within the primary cell, the target cell specified in the planning table will not be the best one to use.

### 3. DESCRIPTION AND FORMULATION OF THE PROBLEM

The main idea in our contribution is to detect the best BS for each user (Best Handover) by exploiting model selection techniques and especially the AIC. It was shown in [19] that, when signal demodulation cannot be performed, the received wireless communication signal can be, roughly, modeled using Rayleigh and Rician distribution. Therefore, we propose to calculate in blindly process the Received Signal for each BS and Analyze AIC in order to determine the best handover. Figure 1 presents an illustrated model of Small Cells Network.

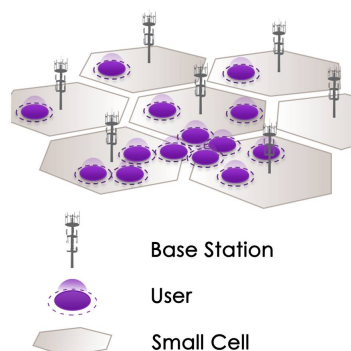


Figure 1. Model of small cells network

In this section, we will give a short review of the basic ideas. In fact, it is assumed that the samples of the Received Signal for each BS are distributed according to an original probability density function  $f_k$  where  $k \in \{1, 2, 3, 4, 5, 6\}$  is the index of BS, called the operating model. Since only a finite number of observations is available, the operating model is usually unknown. Therefore, approximating model (i.e candidate model) must be specified using the observed data, in order to estimate the operating model. The candidate model is denoted as  $g_\theta^k$ , where  $\theta$  indicates the U-dimensional parameter vector, which specifies the probability density function. In information theory [20], the Kullback-Leibler distance describes the discrepancy between the two probability density functions  $f_k$  and  $g_\theta^k$  and is given by [12]:

$$D(f_k \parallel g_\theta^k) = E(\log(f_k(x))) - E(\log(g_\theta^k(x)))$$

$$D(f_k \parallel g_\theta^k) = -h_i(x) - \int f_k(x) \log(g_\theta^k(x)) dx \quad (1)$$

where  $h(\cdot)$  denotes differential entropy. Since, the original probability density function  $f_k$  is not known, this distance measure is not directly applicable.

It is known, however, that the Kullback-Leibler distance is nonnegative, this implies that the Kullback-Leibler discrepancy,

$$-\int f_k(x) \log(g_\theta^k(x)) dx = h_i(x) + D(f_k \parallel g_\theta^k) \quad (2)$$

approaches the differential entropy of X from above for increasing quality of the model  $g_\theta^k$ .

Applying the weak law of large numbers [21], this expression (2) can be approximated by averaging the log-likelihood values given the model over N independent observations  $x_1, x_2, \dots, x_N$  according to:

$$-\int f_k(x) \log(g_\theta^k(x)) dx \approx -\frac{1}{N} \sum_{n=1}^N \log(g_\theta^k(x_n)) \quad (3)$$

The expected Kullback-Leibler discrepancy is given by [17]:

$$-E_\theta \left( \int f_k(x) \log(g_\theta^k(x)) dx \right) \quad (4)$$

This expression (4) cannot be computed, but estimated.

#### 4. MODEL SELECTION USING AKAIKE INFORMATION CRITERION

The information theoretic criteria was first introduced by Akaike in [8] for model selection. Assuming a candidate model, the idea is to decide if the distribution of the observed signal fits the candidate model. The AIC criterion is an approximately unbiased estimator for (4) and is given by:

$$AIC_k = -2 \sum_{n=1}^N \log(g_\theta^k(x_n)) + 2U \quad (5)$$

where U indicates the dimension of the parameter vector  $\theta$ .

One should select the model that yields the smallest value of AIC because this model is estimated to be the closest to the unknown reality that generated the data, from among the candidate models considered. The parameter vector  $\theta$  for each family should be estimated using the minimum discrepancy estimator  $\hat{\theta}$ , which minimizes the empirical discrepancy. This is the discrepancy between the approximating model and the model obtained by regarding the observations as the whole population. The maximum likelihood estimator [22] is the minimum discrepancy estimator for the Kullback-Leibler discrepancy [12].

Consider a probability distribution parameterized by an unknown parameter  $\theta$ , associated with either a known probability density function or a known probability mass function, denoted as  $f_\theta^k$ . As a function of  $\theta$

with  $x_1, x_2, \dots, x_N$  fixed, the likelihood function is:

$$L_k(\theta) = f_{\theta}^k(x_1, x_2, \dots, x_N) \quad (6)$$

The method of maximum likelihood estimates  $\theta$  by finding the value of  $\theta$  that maximizes  $L_k(\theta)$ . The maximum likelihood estimator (MLE) [22] of  $\theta$  is given by:

$$\hat{\theta} = \underset{\theta}{\operatorname{argmax}} L_k(\theta) \quad (7)$$

Commonly, one assumes that the data drawn from a particular distribution are i.i.d. with unknown parameters. This considerably simplifies the problem because the likelihood can then be written as a product of N univariate probability densities:

$$L_k(\theta) = \prod_{n=1}^N f_k(x_n|\theta) \quad (8)$$

and since maxima are unaffected by monotone transformations, one can take the logarithm of this expression to turn it into a sum:

$$L_k^*(\theta) = \sum_{n=1}^N \log f_k(x_n|\theta) \quad (9)$$

Consequently, the expression of the maximum likelihood in our case is [19]:

$$\hat{\theta} = \underset{\theta}{\operatorname{argmax}} \frac{1}{N} \sum_{n=1}^N \log(g_{\theta}^k(x_n)) \quad (10)$$

The maximum of this expression can then be found numerically using various optimization algorithms [17]. This contrasts with seeking an unbiased estimator of  $\theta$ , which may not necessarily yield the MLE but which will yield a value that (on average) will neither tend to over-estimate nor under-estimate the true value of  $\theta$ . The maximum likelihood estimator may not be unique, or indeed may not even exist.

Because AIC contains various constants and is a function of sample size, we routinely recommend computing (and presenting in publications) the AIC differences (in addition to the actual AIC values):

$$\phi_k = AIC_k - AIC_{min} \quad (11)$$

where  $AIC_{min}$  denotes the minimum AIC value over all BSs.

Akaike weights can be computed using (5), in order to decide if the distribution of the Received Signal fits the candidate distribution or not. The Akaike weights can be interpreted as estimate for the probabilities that the corresponding candidate distribution show the best modeling fit. It provides another measure of the strength of evidence for this model, and is given by:

$$W_k = \frac{e^{-1/2\phi_k}}{\sum_{i=1}^6 e^{-1/2\phi_i}} \text{ where } k \in \{1, 2, 3, 4, 5, 6\} \quad (12)$$

The Akaike weights allow us not only to decide if the distribution of the Received Signal fits the Gaussian distribution, but also provide information about the relative approximation quality of this distribution.

The maximum Likelihood estimator is the minimum discrepancy estimator for the KL discrepancy [12]. In our problem, we want Line Of Sight (LOS) signal between the BS and the users. Consequently, we are going to use the Rice distribution [23]. So the probability density function for the Received Signal for each BS is given by:

$$g_{\theta}^k(x|\mu_k, \sigma_k) = \frac{x}{\sigma_k^2} \exp\left(-\frac{(x^2 + \mu_k^2)}{2\sigma_k^2}\right) I_0\left(\frac{x\mu_k}{\sigma_k^2}\right) \quad (13)$$

where  $I_0\left(\frac{x\mu_k}{\sigma_k^2}\right)$  is the modified Bessel function of the first kind with order zero,  $\mu_k$  is the mean or expectation

of the distribution (and also its median and mode) and  $\sigma_k$  is the standard deviation.

The approximated probability density function leads to the following log-likelihood function :

$$L_k^*(\mu_k, \sigma_k) = \log \left( \frac{\prod_{i=1}^N x_i}{\sigma_k^{2N}} \exp \left( \frac{-\sum_{i=1}^N (x_i^2 + \mu_k^2)}{2\sigma_k^2} \right) \prod_{i=1}^N I_0 \left( \frac{x_i \mu_k}{\sigma_k^2} \right) \right) \quad (14)$$

Parameters  $\mu_k$  and  $\sigma_k$  are given by the solution of the following set of equations:

$$\begin{cases} \mu_k - \frac{1}{N} \sum_{i=1}^N x_i \frac{I_1(\frac{x_i \mu_k}{\sigma_k^2})}{I_0(\frac{x_i \mu_k}{\sigma_k^2})} = 0 \\ 2\sigma_k + \mu_k^2 - \frac{1}{N} \sum_{i=1}^N x_i^2 = 0 \end{cases} \quad (15)$$

where  $I_1(\frac{x_i \mu_k}{\sigma_k^2}) = -I_0(\frac{x_i \mu_k}{\sigma_k^2}) + \frac{\sigma_k^2}{2x_i \mu_k} I_0(\frac{x_i \mu_k}{\sigma_k^2})$  is the modified Bessel function [24] with order one. When  $\frac{x_i \mu_k}{\sigma_k^2} \gg 0.25$  and  $I_0(\frac{x_i \mu_k}{\sigma_k^2}) = \frac{\exp(\frac{x_i \mu_k}{\sigma_k^2})}{\sqrt{2\pi \frac{x_i \mu_k}{\sigma_k^2}}}$ , (15) can be expressed as:

$$\begin{cases} \mu_k^2 + \frac{1}{N} \sum_{i=1}^N x_i \mu_k - \frac{\sigma_k^2}{2} = 0 \\ \mu_k^2 - \frac{1}{N} \sum_{i=1}^N x_i^2 + 2\sigma_k^2 = 0 \end{cases} \quad (16)$$

Resolving (16), the MLE for the parameters  $\widehat{\mu}_k, \widehat{\sigma}_k$  can be expressed as:

$$\begin{cases} \widehat{\mu}_k = \frac{-2 \sum_{i=1}^N x_i + \sqrt{4(\sum_{i=1}^N x_i)^2 + 5N \sum_{i=1}^N x_i^2}}{5N} \\ \widehat{\sigma}_k^2 = \frac{1}{2} \widehat{\mu}_k^2 + \frac{1}{2N} \sum_{i=1}^N x_i^2 \end{cases} \quad (17)$$

And the parameter vector  $\theta = (\sigma_k, \mu_k)$

### 5. THE APPROACH

In this section, we present a new approach to detect the best handover based on exploiting model selection techniques and especially AIC introduced by Akaike in [12, 13]. We consider that the initial signal can be modeled using Gaussian distribution and its norm can be modeled using Rician distribution. After the input of the values of the Received Signal for each BS (observations), in the first step we compute the parameters  $\widehat{\mu}_k$  and  $\widehat{\sigma}_k$  (MLE parameters), then  $g_{\theta}^k$  the pdf for the Received Signal for each BS  $k$ . Once we get  $g_{\theta}^k$ , we calculate  $AIC_k$  and  $W_k$  for each BS. The Akaike weights allow us not only to decide if the distribution of the Received Signal fits the suitable distribution, but also provide information about the best signal (best BS) for each user. If the Akaike weight of Rician distribution of the  $BS_k$  is higher than the Akaike weights of other BSs, then there is no Handover, and if the Akaike weight of  $BS_k$  is lower than the Akaike weight of  $BS_i$  where  $i \in \{1, 2, 3, 4, 5, 6\}$  then there is Handover from  $BS_k$  to  $BS_i$ .

$$\lambda_{threshold}(x_n) = \begin{cases} W_k - W_i < \lambda_{threshold} & \text{Handover } (H_0) \\ W_k - W_i > \lambda_{threshold} & \text{No Handover } (H_1) \end{cases} \quad (18)$$

The decision threshold is determined by using the probability of false alarm  $P_{FA}$  [25]. The threshold  $\lambda_{threshold}$  for a given false alarm probability [25] is determined by solving the equation

$$P_{FA} = P(\lambda_{threshold}(x) < \lambda_{threshold} | H_1) \quad (19)$$

The flow chart of the proposed algorithm is shown in Figure 2, which can be implemented in four steps:

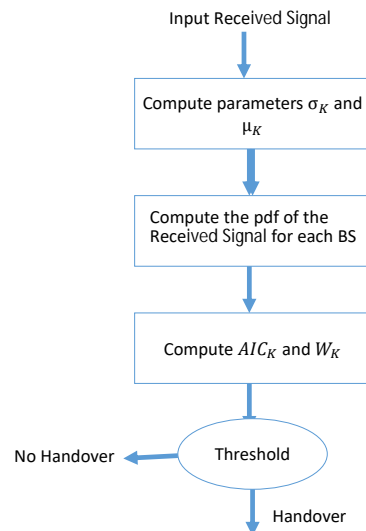


Figure 2. Flowchart of Algorithm of Blind Handover based on distribution analysis

## 6. RESULT AND ANALYSIS

The proposed Blind Detection approach is evaluated using the software package Matlab R2016a. The Figure 3, shows the values of Akaike Weights of the six BSs in a time  $t$ . We apply the approach in Figure 2 and we compute the Akaike Weights for the BSs in terms to choose the best BS for the user. Figure 3 depicts the Akaike Weights with Gaussian distribution obtained from the 6 BSs. It is clearly shown that the BS which has the Maximum Akaike weight is the first BS, so the best BS for the user is the  $BS_1$ .

In Figure 4 we can see the difference between Rice and Rayleigh Distribution of the Received Signal. When the Signal between the BS and the UE is suffering from shadowing by a high building over the sensing channel, it definitely can decrease the Received Signal due to the low received SNR. When the SNR is low, the noise distribution will dominate in the convolution and the resulting distribution will tend to become close to Gaussian even if the signal has an arbitrary non Gaussian distribution, and the envelope (norm) distribution of the signal is close to Rayleigh distribution.

Another important property is the contribution of the dominant propagation paths on the distribution of the Received Signal. The envelope distribution of the Received Signal tend to become close to Rician even if the input has a non Rician distribution. The Akaike weight of Rician distribution is higher than Akaike weight of Rayleigh distribution that mean that BS with Rician Distribution is the best for the UE.

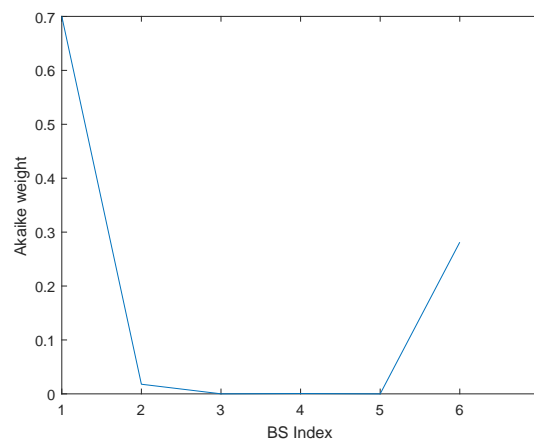


Figure 3. Akaike weights of the six BSs at time  $t$

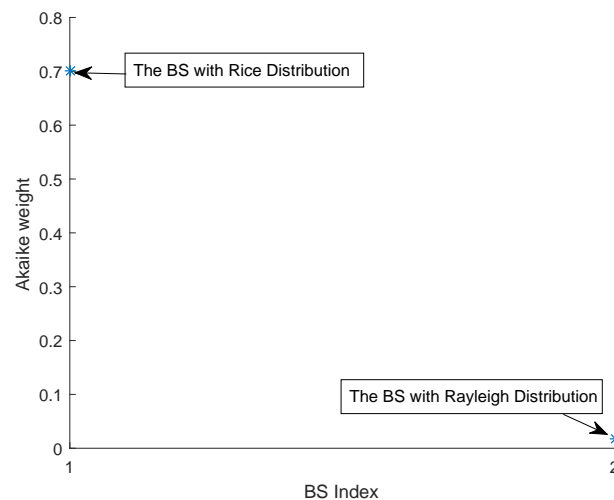


Figure 4. The comparison of akaike weight of two BSs with different distribution

## 7. CONCLUSION

In this work, we studied a new method to manage the handovers between a number of users and Base Stations of Small Cells. Our idea has been based on analysing the probability density function of the Received Signal for each BS, to provide an indication of the intensity of the Received Signal, and exploit KL Divergence, Akaike Information Criterion and Akaike Weight in order to decide the best handover and the best BS for each user. The proposed Blind Detection Approach is evaluated using the software package Matlab R2016a.

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## BIOGRAPHIES OF AUTHORS



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