Blind Handover Detection based on KLD: Channel Capacity and Outage Probability Estimations for Rice and Nakagami Models

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***Abstract*—The use of mobile cellular communication is growing all over the world, with the increasing popularity of mobile devices. Fifth Generation (5G) has recently emerged to satisfy the increasing demand for high data bit rates, to maintain network connectivity every time and everywhere, opening the possibility of connecting all the devices in the network. A key piece of this shift is the deployment of Small Cells over the Macrocells layer which introduces a new type of network called Heterogeneous Networks (HetNets), which involve more Handovers. In addition, the user has to select instantly and at inferior energy cost, the suitable base station in the midst of thousands. In this paper, to decide of the best Handover with reduced complexity of computation, we apply a Handover technique based on Distribution Analysis Detector combined with Compressive Sampling Techniques, after that, we propose to estimate the performance of networks in terms of Channel Capacity and Outage Probability based on Rice and Nakagami distribution models. We obtain Channel Capacity and Outage Probability by using concepts from Information Theory. Through numerical evaluations, we show that the Nakagami distribution model is more efficient than the Rice distribution model.**

***Index Terms*—5G Networks, Handovers, Channel Capacity, Outage Probability, Rice and Nakagami Models, Kullback Leibler Distance, Performance Estimation.**

I. INTRODUCTION

FROM 2010 to 2020, we can observe an evolution in the amount of traffic of mobile networks [3] and most of the devices work in a wireless manner, which relies on them with power battery and that can limit the amount of time they can operate, so, one of the biggest obstacles to this technology is the limited battery life.

To encounter this problem, Fifth Generation (5G) [2] [4] [5] [6] advises to consider the implementation of small cells [7], to decrease the transmit power and optimize energy consumption.

A wireless network designates a type of network which has the particularity of being wireless, capable of establishing a connection between several channels [8] sharing space and frequency band, and to provide continuous connectivity we need more handovers [9] [10] [11] between those channels. To establish a Handover there is lot of metrics: Received Signal Strength Indicator (RSSI), distance, load, battery, and Physical Cell Id (PCI) [12].

Today's world is data-driven. In many emerging applications such as medical imaging, video, data analysis, spectroscopy, etc., the amount of data generated is too high. The resulting Nyquist rate is so high that we end up with far many samples. This will pose a tremendous challenge, as it is extremely difficult to build such devices that are capable of acquiring samples at the necessary rate. We can overcome this computational challenge especially in dealing with high-dimensional data by "Compression" techniques.

For future wireless communication systems, the capacity is increasingly required to provide some new technologies at high data transmission rate throughput on limited bandwidth and power. The notion of channel capacity has been central to the development of wireless communication systems, with the advent of novel error correction coding mechanisms that have resulted in achieving performance very close to the limits promised by channel capacity.

The Handover between base stations and users affects the capacity of the network and there is a correlation between the cell quality and network performance. The Shannon capacity of a channel defines it's theoretical upper bound for the maximum rate of data transmission at an arbitrarily small bit error rate (BER), without any delay or complexity constraints. Therefore, the Shannon capacity represents an optimistic bound for practical communication schemes and also serves as a benchmark against which to compare the spectral efficiency of all practical adaptive transmission schemes.

The variability of channel capacity in a communication channel causes the change in the probability that a given information rate is not supported, called the outage probability, which is defined as the probability that the information rate is less than the required threshold information rate. It is the probability that an outage will occur within a specified time period.

In [13] the authors presented a new approach to perform efficient handover through the analysis of received signal Density Function (DF) based on some information theory tools, called, Kullback Leiber Distance (KLD), Akaike Information Criterion (AIC), and Akaike weights (AW).

The main objectives of this paper are to apply the Compressive Sampling on the proposed approach presented in [13] for Handover management on the Nakagami distribution model [19], to feed directly with the compressed measurements and determine blindly the best handover and the most convenable BS for each user and also estimate the

Manuscript received April 07, 2021; revised July 22, 2021.

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performance of the network in terms of channel capacity and outage probability and compare between the two models of signal distribution Rice and Nakagami.

The remainder of the paper is structured as follows. The following presents some related work. A brief overview of Compressive Sampling (CS) in section 3. The Nakagami distribution model is described in section 4. In section 5, we represent KL Distance, the Maximum Likelihood Estimator, and the approach. After that, the Channel Capacity and the Outage probability for Rice and Nakagami distribution are estimated in section 6. Numerical evaluations are presented in Section 7 in order to compare our models. We end our paper by giving a conclusion.

II. Related Work

With the expeditious advancement in R&D of wireless technologies, the integration of various technologies offers multiple services anytime and anywhere. The major goal of this network is a seamless connection for the user. This process of change in the communication channel is called the handover, which is an important component in wireless network mobility management.

Diverse appropriate Handover management techniques are available in the literature. A crucial requirement is designed for the switch is based on one parameter measurement. Received Signal Strength Indicator (RSSI) protocol consider received signal strength as a criterion to select the appropriate channel for the user.

The proposed strategy in [14] considers hybrid RF small-cell networks, which create frequent unnecessary handover because the measurements are based only on RSSI. Furthermore, user mobility decreases the system throughput.

Otherwise, Chang et al. [15] evolved a handover decision method in two phases: RSSI prediction and Markov decision process. The strategy uses the traditional measure of RSSI and compares the RSSI values of the serving point of attachment. This approach increases the computation complexity and undesirable handovers.

In order to avoid the undesirable handovers, [16] proposed a new mathematical model, this strategy measures the RSSI available for the mobile user. The mobility of the mobile node in this scenario seems to be unnoticed.

In brief, for those strategies, the RSSI is the only criterion in the handover decision strategy. However, the signal fluctuations resulting from the fading effect cause the undesirable so-called ping pong effect, which raise the probability of call loss during the handover process.

There is also, computation handover decision in the literature, which fails to consider a network load, results in over-utilization of the network, so the network capacity becomes full, this causes call blocking and call dropping. The traditional strategies are the simplest ones because the handover relies on one parameter. Multiple parameters are adopted in [17] where the complexity still exists and the mobile terminal-based decision makes the handover policy unreliable in a heterogeneous environment.

There is a special feature, where the network node is allowed to start a handover process for a terminal without considering traditional measurements configuration is called the Blind Handover [18] like beacon pilot technique which have some drawbacks like the increase of the cost of the system infrastructure and the decrease on the network capacity because of the generation of interference on the target network.

III. Compressive Sampling

Compressive sensing [30] is an emerging research field that has applications in signal processing, error correction, medical imaging, seismology, and many other areas. It promises to efficiently recover a sparse signal vector via a much smaller number of linear measurements than its dimension.

Before we go into greater technical details, we will first give the general signal models discussed in this paper [1]. Let $x \in \mathbf{R}^N$ be a signal with expansion in an orthonormal basis Ψ as

$$x = \Psi s \tag{1}$$

where Ψ is a $N*N$ matrix and s is the sparse representation wavelet basis, in our conditions, in the Ψ basis if the coefficient sequence s is supported on a small set.

Hence, to recover all the N coefficients of x, vector s, from measurements y about x of the form

$$y = \Phi x = \Phi\Psi s = \Theta s \tag{2}$$

where Φ is $M*M$ matrix, called the Sensing Matrix. We are interested in the case that $M << N$, and the rows of Φ are incoherent with the columns of Ψ.

The aim of compressive sensing is to design the matrix Φ and a reconstruction algorithm so that for k-sparse signals we require only a "small" number of measurements, i.e. $m \approx k$.

In compressive sensing, random measurement matrices are generally used and l_1 minimization algorithms often use linear programming or other optimization methods to recover the sparse signal vectors. But explicitly constructible measurement matrices providing performance guarantees were elusive and l_1 minimization algorithms are often very demanding in computational complexity for applications involving very large problem dimensions.

The popular and powerful l_1 minimization algorithms generally give better sparsity recovery performances than known greedy decoding algorithms.

Then it is shown that the recovered signal x^* is given by $x^* = \Psi s^*$, and s^* is the solution to the convex optimization program

$$\min_{\widetilde{s} \in \mathbf{R}^N} ||\widetilde{s}||_{l_1} subject\ to\ \Phi\Psi\widetilde{s} \ = \Theta\widetilde{s} \ = y \tag{3}$$

The compressive sampling (CS) theory affirms that there exists a counting factor $c > 1$ such that only $M := cS$ incoherent measurements y are needed to recover x with high probability.

In addition, we have to notice that except l_1-minimization solution other methods like greedy algorithms in [31] exist for recovering the sparse signal [32], [33], [31], [30].

Our intention is to apply the Handover detection using Distribution Analysis Detector (DAD) on the compressed measurements of the observed signal, so we have to maintain the linearity and properties of the original signal. For this consideration, we have to recognize the suitable sensing matrix conform to the detection technique.

To recognize the sensing matrix we start by examining the Fourier transform of the signal $x \in \mathbf{R}^N$ [34].

$$X_l = \sum_{n=0}^{N-1} x[n]exp(-wln),\ l = 0, 1, ..., N-1 \tag{4}$$

where $w = \frac{2\pi i}{n}$ and i is the imaginary unit. The Fourrier transform of the measured signal is

$$Y_k = \sum_{m=0}^{M-1} y[m]exp(-wkm),\ k = 0, 1, ...M-1 \tag{5}$$

And, to satisfy the detection algorithm directly by the compressed measurements we notice that,

$$Y_k(w) = aX_l(x),\ k \in 0, .., M-1,\ l \in 0, .., N-1 \tag{6}$$

where $a > 0$ is a constant, and $\hat{\Phi}_{n_k}$ is described as

$$\sum_{m=0}^{M-1} \phi_n[m]exp(-wkm) = \hat{\Phi}_{n_k},\ k = 0, .., M-1 \tag{7}$$

So finally, we achieve that

$$\hat{\Phi}_{n_k} = aexp(-wzn),\ z \in 0, .., N,\ k = 0, .., M-1 \tag{8}$$

And consequently from inverse Fourrier transform we have

$$\phi_n = a\delta(n-z),\ z \in 0, .., N \tag{9}$$

which means that any row vector of the sensing matrix is a Dirac Function, that is simply one column of each row is nonzero.

To make the sensing matrix we may begin by generating Φ^T matrix by randomly choosing M columns of an identity matrix N. The sensing matrix, Φ, is given by transpose of Φ^T , where the columns of the sensing matrix are unit-normed. So the sensing matrix Φ that we use has a form like this

$$\Phi \sim \begin{bmatrix} 0 & 1 & 0 & \dots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \dots & 1 & 0 & 0 \end{bmatrix}_{M*N} \tag{10}$$

This form of sensing matrix allow us to use the compressed measurements from each BS directly as input to the DAD algorithm and as a result avoiding the computation complexity of reconstructing the original signal.

IV. Nakagami distribution

In the early 1940s, the Nakagami distribution was introduced by Nakagami in [19]. The Nakagami distribution has gained a lot of attention lately, because of its capability to model a vast class of fading channel conditions and present a closer match to empirical data than the Rayleigh and Rice distributions.

The Nakagami distribution is based on the Normal, or Gaussian, distribution. The Nakagami DF is described by,

$$f(x) = \frac{2m^m}{\Gamma(m)\Omega^m} x^{2m-1} exp(-\frac{m}{\Omega}x^2)\ ,\ \ x \geq 0\ \ m \geq 1/2 \tag{11}$$

where m is a shape parameter, and Ω is the mean signal power, and the function Gamma is defined by, $\Gamma(m) = \int_0^\infty t^{m-1}exp(-t)dt$. For integer values of m, the distribution describes the summation of m orthogonal independent Rayleigh distributed random variable (r.v). That is, for N Rayleigh distributed r.v X_i, the DF of the r.v Y, defined as,

$$Y = \sqrt{\sum_{i=1}^{N} X_i^2} \tag{12}$$

is given by a Nakagami distribution with $m = N$.

As special cases, Nakagami-m includes Rayleigh distribution when $m = 1$. For values of $m > 1$, the Nakagami distribution closely approximates the Ricean distribution and the parameters m and the Ricean factor K which determines the severity of the Ricean fading [19],

$$K = \frac{\sqrt{m^2 - m}}{m - \sqrt{m^2 - m}}\ \ ,\ \ m > 1 \tag{13}$$

$$m = \frac{(K+1)^2}{(2K+1)} \tag{14}$$

$$\Omega = \mu^2 + 2\sigma^2 \tag{15}$$

So,

$$\begin{cases} \mu^2 = & \frac{K\Omega}{K+1} \\ 2\sigma^2 = & \frac{\Omega}{K+1} \end{cases} \tag{16}$$

Nakagami distribution is more appropriate to use in analytical expression than Rice distribution because the Rice distribution equation consists of a Bessel function which is unreachable.

It is found in divers samples, that to describe the distribution of the measured fading of radio channels, the Nakagami distribution model is more convenient than Rice and Nakagami distributions models.

The Rayleigh distribution is described by the following DF,

$$p(x) = \frac{x}{\sigma^2} exp(-\frac{x^2}{2\sigma^2})\ \ ,\ \ \ x \geq 0 \tag{17}$$

where σ is the variance. And the signal amplitude distribution which has multi-path components with one dominant component emergent from a line of sight path between the transmitter and the receiver is described by the Rice distribution. It is described by the two-parameter DF,

$$p(x) = \frac{x}{\sigma^2} exp(-\frac{(x^2+\mu^2)}{2\sigma^2}) I_0(\frac{x\mu}{\sigma^2})\ \ ,\ \ \ x \geq 0 \tag{18}$$

where μ is the mean of the distribution, σ its variance, and $I_0(.)$ the modified Bessel function of the first kind, order zero.

One additional examination is that the Nakagami distribution models the majority of measured and simulated results more closely than a Ricean distribution and the Rayleigh distribution. This involves that the hypothesis used to derive a Rayleigh or Ricean distributed channel is not accurate for indoor communications.

V. KL Techniques for Nakagami distribution

The central objective of this section is to exploit the distribution analysis techniques based on KLD and AIC [13] [1] to calculate in blindly process the received signal DF modeled using Nakagami distribution for each BS and analyze Akaike weight in order to determine the appropriate handover.

Actually, the received signal for each BS is distributed according to an original DF f_k where $k \in \{1, 2, 3, 4, 5\}$ is the index of BS. Because we have just a finite number of observations, this function is usually unknown. To estimate the original DF, we use some observed data and an approximating model. We denote the approximating model as g_θ^k , where θ indicates the dimension of the parameter vector, which specifies the DF.

In information theory [20], to compute the distinction between the two DFs f_k and g_θ^k we use KLD, given by [21],

$$D(f_k \parallel g_\theta^k) = -h_i(x) - \int_X f_k(x) log(g_\theta^k(x))dx \quad (19)$$

where f_k and g_θ^k are DFs defined over a set X, and f_k is absolutely continuous with respect to g_θ^k and h(.) denotes differential entropy. This distance measure is not directly applicable, because the original DF f_k is unidentified. It is known, however, that the KLD is positive, this implies that,

$$-\int_X f_k(x) log(g_\theta^k(x))dx = h_i(x) + D(f_k \parallel g_\theta^k) \quad (20)$$

approaches the differential entropy of X from above for increasing quality of the model g_θ^k .

This expression (20) can be approximated by applying the weak law of large numbers [29] and averaging the log-likelihood values over N independent observations $x_1, x_2, ..., x_N$ according to,

$$-\int_X f_k(x) log(g_\theta^k(x))dx \approx -\frac{1}{N}\sum_{n=1}^{N} g_\theta^k(x_n) \quad (21)$$

The expected KLD is given by [24],

$$-E_\theta \left(\int_X f_k(x) log(g_\theta^k(x))dx \right) \quad (22)$$

This expression (22) can be estimated.

Considering a candidate model, the concept is to decide if the observed signal match with the candidate model. The AIC criterion is an unbiased approximation for (22), defined as,

$$AIC_k = -2\sum_{n=1}^{N} log(g_\theta^k(x_n)) + 2U \quad (23)$$

where U indicates the dimension of the parameter vector θ.

In our approach, we have to select the smallest AIC, from among the candidate models.

The parameter vector θ for each family needs an estimation using the minimum discrepancy estimator $\widehat{\theta}$, which minimizes the empirical discrepancy. This is the difference between the approximating model and the original model. The maximum likelihood estimator [22] is the minimum discrepancy estimator for the KLD [21].

It is recommend to compute the AIC differences,

$$\phi_k = AIC_k - AIC_{min} \quad (24)$$

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

AW can be computed using (23), with the intention of providing another measure of the strength of evidence for this model, where,

$$W_k = \frac{e^{-1/2\phi_k}}{\sum_{i=1}^{6} e^{-1/2\phi_i}} \ , where \ \ k \in \{1, 2, 3, 4, 5\} \quad (25)$$

In our problem, we model our signal between the BS and the users by a Nakagami distribution. So the DF for the received signal for each BS is given by the equation,

$$g(x) = \frac{2m^m}{\Gamma(m)\Omega^m} x^{2m-1} exp(-\frac{m}{\Omega}x^2) \ , \ \ x \geq 0 \ \ m \geq 1/2 \quad (26)$$

A. The Maximum Likelihood Estimator of the parameters

Consider a DF with unidentified parameter θ, associated with either a known DF, denoted as f_θ^k. As a function of θ with $x_1, x_2, ..., x_N$ fixed, the likelihood function is,

$$L_k(\theta) = f_\theta^k(x_1, x_2, ..., x_N) \quad (27)$$

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

$$\widehat{\theta} = \arg_\theta max \ L_k(\theta) \quad (28)$$

Generally, one assumes that the data drawn from a particular distribution are independent and identically distributed (iid) with unknown parameters. This considerably simplifies the problem because the likelihood can then be written as a product of N unvaried densities function, and since maxima are unaffected by monotone transformations, then we compute the logarithm of this expression to turn it into a sum,

$$L_k^*(\theta) = \sum_{n=1}^{N} log f_k(x_n|\theta) \quad (29)$$

So, the maximum likelihood is [23],

$$\widehat{\theta} = \arg_\theta max \frac{1}{N}\sum_{n=1}^{N} log(g_\theta^k(x_n)) \quad (30)$$

The maximum of this expression can be found numerically using optimization algorithms [24].

To compute the MLE, we will use a work already done about the estimation of the parameter of Nakagami distribution [25] [26].

B. The Approach

In this section, we present the approach to detect the best handover based on AIC in a Nakagami distribution signal.

The sequential diagram of the proposed algorithm is shown in Fig. 1 implemented in seven steps:

The initial signal can be modeled using Nakagami distribution.

Following the input of the values of the received signal for each BS (observations), in the first step we compute the Rice distribution parameters [13], then using the relations between Rice and Nakagami distribution to compute Rice Factor K and shape parameter m , then the DF for the received signal for each BS k. Once we get g_θ^k, we calculate AIC_k and W_k for each BS.

If the AW of Nakagami distribution of the BS_k is higher than the AW of other BSs, then there is no Handover, and if the AW of BS_k is lower than the Akaike weight of BS_i where $i \in \{1, 2, 3, 4, 5\}$ then there is Handover from BS_k to BS_i,

$$\lambda_{th}(x_n) = \begin{cases} W_k - W_i < \lambda_{threshold} & \text{Handover } (H_0) \\ W_k - W_i \geq \lambda_{threshold} & \text{No Handover } (H_1) \end{cases} \quad (31)$$

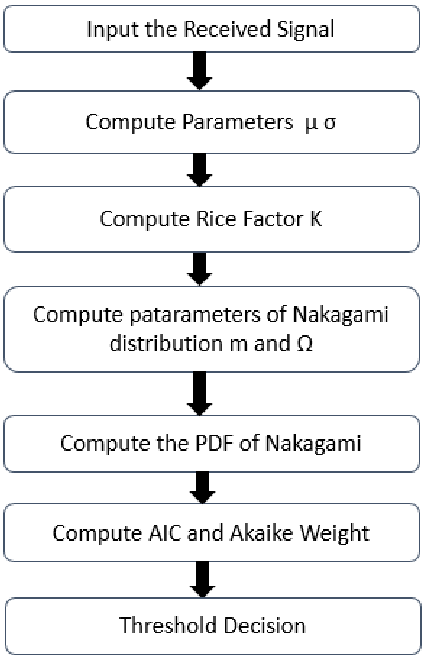

Fig. 1. Flowchart of our approach on Nakagami distribution signal

To compute the decision threshold we use the equation of the probability of false alarm P_{FA} [28], so, the threshold $\lambda_{threshold}$ for a given false alarm probability [28] is determined by solving the equation,

$$P_{FA} = P(\lambda_{th}(x) < \lambda_{threshold}|H_1) \quad (32)$$

VI. Channel Capacity and Outage Probability

The Handover between base stations and user affect the capacity of the network and there is a correlation between the cell-quality and network performance [27]. So, in this section, we will estimate the network performance in terms of channel capacity and outage probability for two signal distribution models, Rice and Nakagami.

A. Rice Distribution

First, let us give an entrance on channel capacity. In communication theory, the transmitted signals are ruined by some noise. To see how much information is possible to transmit over the channel, we maximize the mutual information between the transmitted variable X and the received variable Y, with the condition that the power is limited by P. Without the power constraint in the definition, we would be disposed to select as many signal alternatives as far apart as we like. Then we would be capable to transmit as much information as we like in single-channel use. With the power constraint, we obtain a more realistic system where we need to find other mechanisms that growing the power to get a greater information throughput over the channel.

So, the first definition of the "information" channel capacity is,

$$C = \max_{E(X^2)\leq P} I(X,Y) \quad (33)$$

The mutual information is given by,

$$I(X,Y) = H(Y) - H(Y|X) \quad (34)$$

where $H(Y)$ is the marginal entropy and $H(Y|X)$ is the conditional entropy.

The most common channel model, which is the so-called Gaussian channel, which can be presented as [8],

$$Y_i = X_i + Z_i, Z_i \sim \mathcal{N}(0, N) \quad (35)$$

This is a time-discrete channel with output Y_i at time i, where Y_i is the sum of the input X_i and the noise Z_i. The noise Z_i is drawn i.i.d. from a Gaussian distribution with variance N. The noise Z_i is assumed to be independent of the signal X_i.

So now, we can calculate the mutual information as follows,

$$\begin{aligned} I(X,Y) &= H(Y) - H(Y|X) && (36)\\ &= H(Y) - H(X+Z|X) && (37)\\ &= H(Y) - H(Z) && (38)\end{aligned}$$

since Z is independent of X, where h is the marginal entropy.

In statistics, for a given $X \sim \mathcal{N}(\sigma, \mu^2)$, the entropy is defined as,

$$\begin{aligned} H &= E(-log(p(x))) && (39)\\ &= \int_{-\infty}^{+\infty} p(x)(-log(p(x)))dx && (40)\\ H &= \frac{1}{2}log(2\pi\sigma^2 e) && (41)\end{aligned}$$

Applying this result to bound the mutual information, we obtain,

$$\begin{aligned} \max_{E(X^2)\leq P} I(X,Y) &= maxH(Y) - H(Z) && (42)\\ &= \frac{1}{2}log(2\pi e(P+N)) - \frac{1}{2}log(2\pi e(N)) && (43)\\ &= \frac{1}{2}log(1+\frac{P}{N}) && (44)\end{aligned}$$

Definition The channel capacity of a Gaussian channel with power constraint P, and noise variance N,

$$C = \frac{1}{2}log(1+\frac{P}{N}) \quad (45)$$

B. Nakagami Distribution

In this part, we want to estimate the performance of the Nakagami distribution signal in terms of channel capacity and outage probability, which are often based on concepts from information theory.

In wireless communication, when a group of channels is active at the same time, the interference from the other channels is considered as noise, which means the presence of interference boundary.

To examine how much information is possible to transmit over the channel, we maximize the mutual information between X and Y, with the condition that the power is limited by P . The channel capacity formula is,

$$C = \sum_{0}^{\infty} log(1+\gamma)P(\gamma) \quad (46)$$

where γ is the SNR.

The protection for the channel between the user and desired BS must be guaranteed in a cellular network. This protection is guaranteed if the sum of all other BSs Transmitters' powers is not greater than the interference constraint P_T . Then, the desired BS verifies the outage probability constraint.

Since no data is sent when $C_k < T_k$ where T_k is the transmitted data rate, the optimal policy suffers a probability of outage P_{out}, which is well known as a performance metric in fading channels, equal to probability of not being able to successfully send a signal on a channel, given by,

$$P_{out} = P(C_k \leq T_k) \leq P_{outmax}, \forall k = 1, ..., L \qquad (47)$$

where P_{outmax} is the maximum outage probability.

VII. Numerical Application of Rice and Nakagami Distribution Models

For the numerical application of the approach presented above, we use the software package Matlab R2018a.

Each simulation setup is running several times in order to smooth up the results.

The complexity of Handover detection is an important concern in Handover management. Using the implementation steps in Fig. 1 , we will study the complexity required for two detectors (DAD and DAD with Compressive Sampling) to derive their Handover algorithm.

Table 1: Complexity Comparison of the two Handovers Detection Techniques

Handover Detection Technique	Complexity
Distribution Analysis Detector	2N
DAD + Compressive Sampling	2M

The complexity of the algorithm is measured through the number of complex multiplications that the algorithms have to perform for the calculation of the test statistics. We summarize the number of multiplications required for each technique in Table 1. Note that N refers to the number of samples of the received signal and M is the number of samples after compressive sampling. From these results, we find that compressive sampling decreases the complexity as compared to the simple Distribution Analysis Detector.

In terms to select the best BS for the user, we apply the approach in Fig.1, we compute the AW for the BSs with Nakagami distribution of the signal between the user and the BSs. Figure 2 illustrates the AW with Nakagami distribution of 10 BSs. From the figure we can see that the BS which has the maximum Akaike weight is the BS 10, so the best BS for the user is the BS 10.

Fig. 2 depicts also the comparison of two detector techniques (DAD and DAD with Compressive sampling) in term of Akaike Weight for 10 Base stations. From the numerical application results, we show that the two detectors give the same Akaike weight which means that the use of Compressive Sampling does not change the final result.

After that, we consider a cellular network with a user and $L = 10$ BSs, trying to communicate at the same time as a transmission, subject to mutual interference. For the numerical application, we take, $P_T = 50dBm$ (Power constraint).

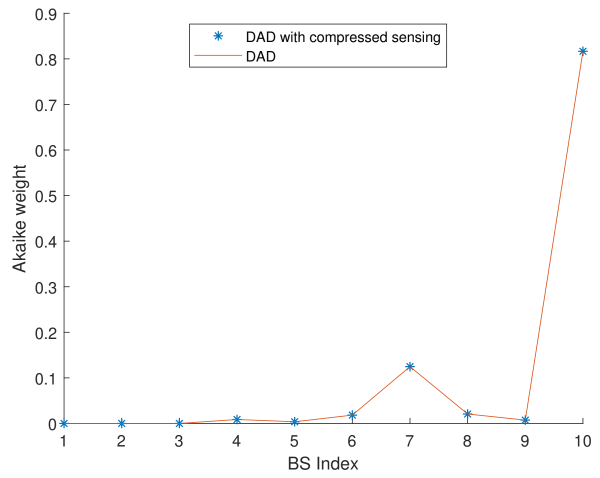

Fig. 2. Akaike Weight vs BS index

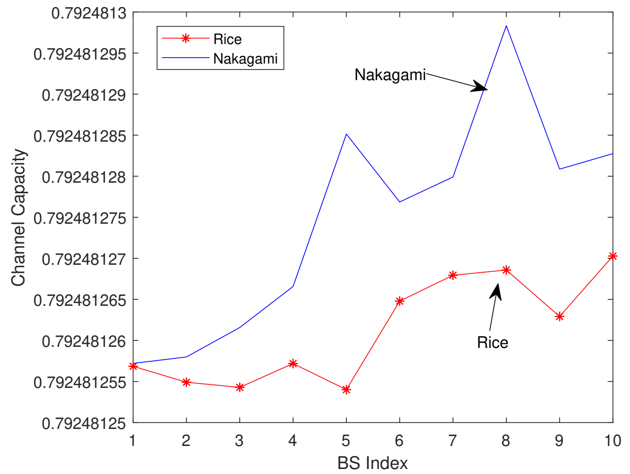

Fig. 3. Channel Capacity of Rice and Nakagami Distribution Channels (bits/s/Hz) vs BS index

To estimate the performance of the network, we compute the estimation of channel capacity and outage probability for Rice and Nakagami distribution signals between the user and BSs. The comparison of the performance of the two models, in term of channel capacity Fig.3, we can see that the channel capacity for Nakagami distribution model have greater values than Rice distribution model, which is normal because Nakagami channels can be seen as multiple Rice channels, and in term of outage probability Fig.4, we can see that the outage probability of Nakagami distribution model is lower than the Rice, so, we can conclude that the Nakagami channels are more efficient than Rice channels.

Figures 3 and 4 show the behavior of estimated values for 10 Channels, we can see that when the channel capacity increases, the Outage probability decreases, and vice versa, which confirms the correlation between the channel capacity and outage probability that we have mentioned in section 6.

VIII. Conclusion

In this paper, we applied a novel approach to manage handovers in a Nakagami distribution signal. This approach is based on analyzing the DF of the received signal between

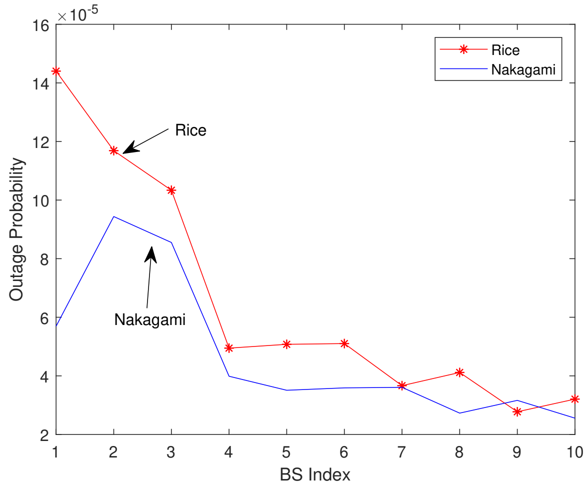

Fig. 4. Outage probability of Rice and Nakagami Distribution Channels vs BS index

the BS and the user using KLD, AIC, and Akaike Weight, to pick the suitable handover for each user. After that, we combine this approach with compressive sampling in order to make the detection possible with a fewer number of samples. The analysis of the complexity of the proposed technique shows that it can be reduced. The numerical comparison at different sampling rates shows that the newly designed scheme achieves the same performance as the DAD while preserving a low computational complexity.

We also presented a new approach to estimate the performance of the network channel, just by analyzing received signal DF and a comparison between Nakagami and Rice distribution models. In the first step, we computed the estimation of channel capacity and the outage probability for the Rice distribution model and the Nakagami distribution model. After that, we realized numerical applications of the proposed estimation of channel capacity and outage probability in order to show that Nakagami distribution model is better than the Rice distribution model.

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