Cooperative Spectrum Sensing for Cognitive Radios: Performance Analysis for Realistic System Setups and Channel Conditions

Marco Di Renzo[1], Laura Imbriglio[2], Fabio Graziosi[2], Fortunato Santucci[2], and Christos Verikoukis[1]

[1] Telecommunications Technological Center of Catalonia (CTTC)
08860 Castelldefels, Barcelona, Spain
{marco.di.renzo,cveri}@cttc.es
http://www.cttc.es

[2] University of L'Aquila, Dept. of Electrical and Information Engineering and Center of Excellence DEWS – 67100 L'Aquila, Italy
{laura.imbriglio,fabio.graziosi,fortunato.santucci}@univaq.it
http://www.dews.ing.univaq.it

Abstract. In this paper, we propose an analytical framework for analysis and design of cooperative spectrum sensing methods over correlated Log–Normal shadow–fading environments, when each cooperative user makes use of a simple Amplify and Forward (AF) relaying mechanism to send the detected signal to a sink node. We will show that the framework requires efficient and accurate methods for modeling the power–sum of correlated Log–Normal Random Variables (RVs), which well describe shadowing phenomena, and propose novel approximation methods to efficiently solve this problem. Numerical results will be shown to substantiate the proposed framework.

Keywords: Cognitive Radio, Spectrum Sensing, Cooperative Communications, Correlated Log–Normal Shadowing, Performance Analysis.

1 Introduction

Cognitive Radio (CR) is commonly considered a key enabling technology to provide high bandwidth to mobile users via heterogeneous wireless architectures and Dynamic Spectrum Access (DSA) capabilities (see, e.g., [1], [2]). Broadly speaking, a CR can be defined as "an intelligent wireless communication device that exploits side information about its environment to improve spectrum utilization" [3], and is likely to consist of several components, but mainly of a sensing, decision, and execution unit. Various definitions of CRs exist in the literature. However, a promising solution, which is based on the idea of opportunistic communications, is the so–called *interweave* paradigm, according to which a CR is defined as "an intelligent wireless communication system that periodically monitors the radio spectrum, intelligently detects occupancy in the different parts

F. Granelli et al. (Eds.): MOBILIGHT 2009, LNICST 13, pp. 125–134, 2009.

of the spectrum and then opportunistically communicates over spectrum holes with minimal (i.e., no harmful) interference to the active users" [3].

A fundamental element for the successful exploitation of interweave CRs is the design of robust spectrum sensing methods to detect licensee users transmitting over a given frequency band. Accordingly, several spectrum sensing methods have been proposed to enable CR functionalities, and studied via analytical frameworks and experimental activities, see, e.g., [4] and references therein for a survey, and [5]–[9] for analysis and design of specific spectrum sensing methods. Among the various proposals, cooperative spectrum sensing methods using energy–based detectors are often considered a good candidate to enable CR functionalities, as they provide a good trade–off for keeping the complexity of every cooperative node at a moderate level, as well as counteracting the limitations of energy–based detection in the low Signal–to–Noise Ratio (SNR) regime via distributed diversity [10]. Accordingly, several studies have been conducted to analyze the performance of such a kind of spectrum sensing methods over a variety of fading channels (see, e.g., [5], [7]). In these papers, the authors have recognized the importance of including the characteristics of wireless propagation for system analysis and design. In particular, they have pointed out the importance of accurately modeling correlated Log–Normal shadow–fading phenomena to properly analyze the impact of distributed cooperation. It has been shown that shadowing correlation can significantly reduce the performance of cooperation, which results in an optimal number of cooperative users yielding the highest cooperative gain and lowest traffic overhead due to cooperation. Moreover, asymptotic analyzes based on a different kind of detector have explicit shown the performance limits set by correlated shadowing [6].

In the light of the above results, there is a common understanding about the importance of developing accurate and simple frameworks for the analysis and design of cooperative spectrum sensing methods over correlated Log–Normal shadow–fading environments. Moreover, the importance of accurately modeling correlation has also been reinforced by some recent experiments, which have proposed specific statistical models to well describe Log–Normal shadow–fading correlation for cooperative networks [11]. However, despite there is a significant number of studies for the analysis of energy–based cooperative spectrum sensing methods (see, e.g., [4], [5], [7]), as far as correlated Log–Normal shadow–fading environments are considered, performance metrics are typically obtained via extensive numerical simulations, which do not yield, in general, a solid basis for a systematic system analysis and optimization.

One of the main reasons for the absence of sound analytical frameworks to analyze the above mentioned scenario is due to the inherent analytical complexity of handling correlated Log–Normal Random Variables (RVs) if compared to other fading distributions. However, in [12] we have recently proposed a general and simple framework for the analysis of cooperative CR systems over correlated Log–Normal shadowing and analyzed its accuracy for several system setups, as well as compared our proposed method with other techniques so far available in the literature and assessed its superiority. However, the system setup described in [12] heavily relies on the not very realistic assumption that the signals sensed by several cooperative users can be sent via an error–free reporting channel to a fusion center, which can then combine them to improve system performance. So, the main aim of this contribution is to propose an advanced system setup that can remove this unrealistic assumption, as well as propose a simple yet accurate framework for its performance analysis and design

More specifically, the following contributions and results are claimed in the present paper: i) we propose a two–step method for Log–Normal power–sum approximation, which is based on the Improved Schwartz–Yeh (I–SY) and Pearson type IV approximation frameworks, and allows to handle correlation among all links of the cooperative network, ii) differently from typical unrealistic assumptions where data sensed by every cooperative node are sent to a common central unit via an error–free feedback channel [5], we consider a more realistic Amplify and Forward (AF) relaying mechanism for data gathering, and iii) we quantify the impact of shadowing correlation on the performance of distributed and decentralized energy–based spectrum sensing methods.

The remainder of the manuscript is organized as follows. In Section 2, system model and cooperative spectrum sensing protocol will be introduced. In Section 3, the cooperative spectrum sensing problem will be formulated. In Section 4, the novel method for Log–Normal power–sum approximation will be presented for a generic cooperative network with AF relying. In Section 5, numerical and simulation results will be compared to assess the accuracy of the proposed approximation to compute Detection Probability in CR scenarios, and the impact of correlated shadowing on system performance will be investigated. Finally, Section 6 will conclude the paper.

2 System Model

Let us consider a typical CR network that performs spectrum sensing operations in a distributed and cooperative fashion (see, e.g., [9, pp. 20, Fig. 3]). In general, cooperative spectrum sensing is composed by four main and subsequent steps: 1) every CR performs spectrum sensing locally and independently from each other, 2) every measurement is sent to a common band manager via an error–free reporting channel, 3) based on the collected measurements, the band manager makes a decision about the status of the sensed frequency band, and 4) the band manager broadcasts back the final decision to the cognitive users, thus enabling or not the transmission of one CR over that frequency band.

In the above standard procedure, step 2) relies on the unrealistic assumption that a noise–free channel is available by every cooperative user to send data to a common central unit. With the aim to overcome this idealistic assumption, we consider a more realistic setup where the data sensed during step 1) are forwarded to the band manager via an AF relying mechanism [13]. By this way, the reporting channel (i.e., relay channel) is not assumed to be error–free, but the relay mechanism accounts for noise accumulation due to dual–hop transmissions, as well as the effect of wireless propagation. For the sake of simplicity, but without loss of generality, we assume that the AF protocol is implemented in a time–scheduled fashion such that collisions are avoided. Furthermore, similar to [5], we assume that the band manager is equipped with a simple energy–based detector for spectrum sensing, and that a Square–Law–Combining (SLC) mechanism is used to combine the signals forwarded by every cooperative (secondary) user.

3 Problem Statement

According to the system model described in Section 2, the cooperative spectrum sensing problem with AF relaying can be modeled as the well–known dual–hop parallel relay channel [14, pp. 1002, Fig. 1]. In particular in [14, pp. 1002, Fig. 1], i) S (i.e., source) represents the primary user to be detected, ii) D (i.e., destination) denotes the common band manager that wants to get access to the wireless medium and performs spectrum sensing, and iii) $\{R_l\}_{l=1}^{L}$ are the L active secondary users (i.e., relays), which help D to detect the active transmission of S via AF relaying.

3.1 Notation

The following notation is used in what follows: i) G_l is the relay gain associated to relay R_l, ii) $\alpha_{l,SR}$ and $\alpha_{l,RD}$ are the fading amplitude of the source–to–relay and relay–to–destination hops in the l–th branch, respectively, iii) N_0 is the one–sided power spectral density of the Additive White Gaussian Noise (AWGN) at the input of $\{R_l\}_{l=1}^{L}$ and D, iv) $\gamma_{l,SR} = \alpha_{l,SR}^2 E_s \big/ N_0$ and $\gamma_{l,RD} = \alpha_{l,RD}^2 E_s \big/ N_0$ are the per–hop SNRs of the source–to–relay and relay–to–destination links in the l–th branch, respectively, and v) E_s is the average radiated energy in every transmission. In what follows, we will assume $\left\{\alpha_{l,SR}^2\ ,\ \alpha_{l,RD}^2\right\}_{l=1}^{L}$, i.e., the channel power gains, to be Log–Normal distributed and generically correlated RVs, as a consequence of shadow–fading propagation.

3.2 Analytical Formulation

According to [5], the decision statistic of a SLC distributed detector can be written as follows:

$$y_{\text{SLC}} = \sum_{l=1}^{L} y_l \tag{1}$$

where $\{y_l\}_{l=1}^{L}$ are the signals received by D from the L relays after square–and–integrate operation (i.e., energy detection).

Moreover, $\{y_l\}_{l=1}^{L}$ can be written as follows:

$$y_l = \frac{2}{\Psi_l} \int_0^T r_l^2(t)\, dt \tag{2}$$

where $r_l(\cdot)$ is the signal received by D from R_l, Ψ_l is one–sided power spectral density of the noise component of $r_l(\cdot)$, and T is the observation window.

By relying on the AF relay mechanism, $r_l(\cdot)$ can be written as follows [13]:

$$r_l(t) = (\alpha_{l,SR}\alpha_{l,RD}G_l)\,s(t) + (\alpha_{l,RD}G_l)\,n_{R_l}(t) + n_D(t) \tag{3}$$

where $s(\cdot)$ is the signal transmitted by terminal S, and $n_{R_l}(\cdot)$, $n_D(\cdot)$ are the AWGNs at the input of terminals R_l and D, respectively.

According to (3), Ψ_l in (2) can be readily computed as follows:

$$\Psi_l = \left(\alpha_{l,RD}^2 G_l^2 + 1\right) N_0 \tag{4}$$

In particular, we consider the well–known Channel State Information (CSI–) assisted relay mechanism, thus assuming that every relay R_l has full CSI about the S–to–R_l link. In such a case, the relay gain is $G_l = G_l^{CSI} = 1/\alpha_{l,SR}$ [13].

Following similar analytical steps as described in [5], it is possible to show that the performance of the cooperative and distributed spectrum sensing network can be characterized by two performance measures, i.e., False Alarm Probability ($\mathrm{P_{fa}}$) and Detection Probability ($\mathrm{P_d}$), which can be computed as follows, when conditioning upon the fading channel statistics:

$$\begin{cases} \mathrm{P_{fa}} = \dfrac{\Gamma\left(\frac{LN}{2}, \frac{\lambda}{2\sigma^2}\right)}{\Gamma\left(\frac{LN}{2}\right)} \\ \mathrm{P_d} = \int_0^{+\infty} Q_{\frac{LN}{2}}\left(\sqrt{\frac{a\xi}{\sigma^2}}, \sqrt{\frac{\lambda}{\sigma^2}}\right) f_{\gamma_t}(\xi)\, d\xi \end{cases} \tag{5}$$

where i) $\Gamma(\cdot)$ and $\Gamma(\cdot,\cdot)$ denote the Gamma [16, pp. 255, Eq. (6.1.1)] and incomplete Gamma [16, pp. 260, Eq. (6.5.3)] functions, respectively, ii) $Q_m(\cdot,\cdot)$ is the generalized Marcum Q–function [7, pp. 73], iii) N is the number of degrees of freedom of the system [5], iv) λ is the detection/decision threshold used by D in the binary hypothesis testing problem to discriminate between presence and absence of a licensee user, and v) $\sigma^2 = 1$, $a = 2$. Moreover, $f_{\gamma_t}(\cdot)$ is the PDF of the end–to–end SNR, γ_t, in D. According to the AF/CSI relay mechanism, γ_t can be explicitly written as $\gamma_t = \sum_{l=1}^{L} \gamma_{l,t}$, where [13]:

$$\gamma_{l,t} = \frac{\gamma_{l,SR}\gamma_{l,RD}}{\gamma_{l,SR} + \gamma_{l,RD}} = \left(\frac{1}{\gamma_{l,SR}} + \frac{1}{\gamma_{l,RD}}\right)^{-1} \tag{6}$$

As $\mathrm{P_{fa}}$ in (5) is independent from channel statistics, in the present contribution we are mainly interested in developing a simple but effective framework to compute $\mathrm{P_d}$ in (5), which requires a closed–form expression for the PDF of γ_t. In Section 4 we will show that the computation of $f_{\gamma_t}(\cdot)$ boils down to have accurate and simple methods for approximating the power–sum of generically correlated Log–Normal RVs.

4 A Novel Method for Log–Normal Power–Sum Approximation

By carefully looking at $\gamma_{l,t}$ defined in Section 3.2, we can easily figure out that the inverse of end–to–end SNR in every dual–hop cooperative link is given by the summation of correlated Log–Normal RVs. So, modeling the distribution of the SNRs in Section 3.2 is equivalent to find the distribution of the inverse of a linear combination (i.e., power–sum) of generically correlated Log–Normal RVs.

The SNR $\gamma_{l,t}$ can be re–written as $\gamma_{l,t} = \left[\sum_{n=1}^{2} X_{l,n}\right]^{-1} = \left[\sum_{n=1}^{2} 10^{0.1 Y_{l,n}}\right]^{-1}$, where $\{Y_{l,n}\}_{n=1}^{2}$ is a vector of Normal RVs with mean vector ($\boldsymbol{\mu}_{Y_l}$) and covariance matrix ($\boldsymbol{\Sigma}_{Y_l}$) given as follows[1]:

$$\begin{cases} \boldsymbol{\mu}_{Y_l}(1) = -\mu_{l,SR} - 10\log_{10}(E_s/N_0) \\ \boldsymbol{\mu}_{Y_l}(2) = -\mu_{l,RD} - 10\log_{10}(E_s/N_0) \\ \boldsymbol{\Sigma}_{Y_l}(1,1) = \sigma_{l,SR}^2 \\ \boldsymbol{\Sigma}_{Y_l}(2,2) = \sigma_{l,RD}^2 \\ \boldsymbol{\Sigma}_{Y_l}(1,2) = \boldsymbol{\Sigma}_{Y_l}(2,1) = \rho_{l,\{SR,RD\}}\sigma_{l,SR}\sigma_{l,RD} \end{cases} \tag{7}$$

where i) $\mu_{l,SR}$ and $\mu_{l,RD}$ are the mean values, ii) $\sigma_{l,SR}^2$ and $\sigma_{l,RD}^2$ are the variances, and iii) $\rho_{l,\{SR,RD\}}$ is the correlation coefficient of RVs $\chi_{l,SR} = 10\log_{10}\left(\alpha_{l,SR}^2\right)$ and $\chi_{l,RD} = 10\log_{10}\left(\alpha_{l,RD}^2\right)$, i.e., the Normal RVs associated to the Log–Normal power gains $\alpha_{l,SR}^2$ and $\alpha_{l,RD}^2$, respectively.

According to the above analysis, the problem of computing $\mathrm{P_d}$ boils down to have general and flexible methods for managing the power–sum of correlated Log–Normal RVs. In particular, two main problems need to be addressed: i) first of all, the PDF of $\{\gamma_{l,t}\}_{l=1}^{L}$ needs to be estimated, which results in the need to have efficient tools for approximating the power sum of generically correlated Log–Normal RVs, and ii) secondly, the PDF of $\gamma_t = \sum_{l=1}^{L} \gamma_{l,t}$ needs to be computed, which, in general, results in dealing with the power–sum of correlated either Log–Normal or non–Log–Normal RVs depending on the assumptions done to compute the PDF of $\{\gamma_{l,t}\}_{l=1}^{L}$ [15].

4.1 A Two–Step Approximation for Computing $f_{\gamma_t}(\cdot)$

We propose a simple yet accurate two–step procedure for computing $f_{\gamma_t}(\cdot)$, and then use it for the estimation of $\mathrm{P_d}$ in (5).

Step 1: Improved Schwartz–Yeh (I–SY) Approximation for $\{\gamma_{l,t}\}_{l=1}^{L}$. The main idea of the Improved Schwartz–Yeh (I–SY) method [17] is to approximate the Log–Normal power–sum $\gamma_{l,t}$ with another Log–Normal RV, as follows:

$$f_{\gamma_{l,t}}(\xi) \cong \frac{10/\ln(10)}{\sqrt{2\pi\sigma_{l,I-SY}^2}\,\xi} \exp\left[-\frac{\left(10\log_{10}(\xi) - \mu_{l,I-SY}\right)^2}{2\sigma_{l,I-SY}^2}\right] \tag{8}$$

where $\mu_{l,I-SY}$ and $\sigma_{l,I-SY}$ are the parameters of the approximating PDF, which are obtained via moment matching in the logarithmic domain between $\gamma_{l,t}$ and the approximating Log–Normal RV, i.e.:

[1] We denote with $\mathbf{v}(i)$ the i–th element of vector $\mathbf{v}$, with $\mathbf{M}(i,j)$ the element in the i-th row and j–th column of matrix $\mathbf{M}$.

$$\begin{cases} \mu_{l,I-SY} = m^{(1)}_{\gamma_{l,t_{\mathrm{dB}}}} \\ \sigma_{l,I-SY} = \sqrt{m^{(2)}_{\gamma_{l,t_{\mathrm{dB}}}} - \left(m^{(1)}_{\gamma_{l,t_{\mathrm{dB}}}}\right)^2} \end{cases} \tag{9}$$

where $m^{(n)}_{l,t_{\mathrm{dB}}} = (-1)^n E\{[10\log_{10}(1/\gamma_{l,t})]^n\}$, and $E\{\cdot\}$ denotes statistical expectation.

$$m^{(n)}_{l,t_{\mathrm{dB}}} = (-1)^n \left(\frac{10}{\ln(10)}\right)^n \sum_{p_1=1}^{N_p} \sum_{p_2=1}^{N_p} \cdots \sum_{p_Q=1}^{N_p} \Pi_{\gamma_{l,t_{\mathrm{dB}}}}(\mathbf{p}) \left\{\ln\left[\Omega_{\gamma_{l,t_{\mathrm{dB}}}}(\mathbf{p})\right]\right\}^n \tag{10}$$

$$\begin{cases} \Pi_{\gamma_{l,t_{\mathrm{dB}}}}(\mathbf{p}) = \prod_{i=1}^{2} \frac{H_{p_i}}{\sqrt{\pi}} \\ \Omega_{\gamma_{l,t_{\mathrm{dB}}}}(\mathbf{p}) = \sum_{i=1}^{2} \exp\left[\frac{\ln(10)}{10}\left(\sqrt{2}\sum_{j=1}^{2} \boldsymbol{\Sigma}^{sq}_{Y_l}(i,j)\, x_{p_j} + \boldsymbol{\mu}_{Y_l}(i)\right)\right] \end{cases} \tag{11}$$

$$f_{\gamma_t}(\xi) \cong \frac{10}{\ln(10)} \frac{h}{\xi} \left[1 + \frac{(10\log_{10}(\xi) + u)^2}{d^2}\right]^{-m} \exp\left[-\nu \tan^{-1}\left(\frac{10\log_{10}(\xi) + u}{d}\right)\right] \tag{12}$$

From (8), (9), it turns out that the I–SY method requires the computation of the log–moments $m^{(n)}_{l,t_{\mathrm{dB}}}$ of the power–sum $1/\gamma_{l,t}$. These log–moments have been recently computed in [12], and can be obtained (with $Q = 2$) as shown in (10) and (11) on top of this page, where $\mathbf{p}$ is a vector with elements $\{p_j\}_{j=1}^2$, and $\{x_p\}_{p=1}^{N_p}$, $\{H_p\}_{p=1}^{N_p}$ are zeros and weights of the N_p–order Hermite polynomial [16, Table 25.10, pp. 924], respectively. Moreover, $\boldsymbol{\Sigma}^{sq}_{Y_l} = \mathbf{U}\mathbf{V}^{1/2}$, and $\mathbf{U}$ and $\mathbf{V}$ are the matrices containing the eigenvectors and eigenvalues of $\boldsymbol{\Sigma}_{Y_l}$, respectively.

Step 2: Pearson Type IV Approximation for $\boldsymbol{\gamma_t}$. As a result of the I–SY approximation for $\{\gamma_{l,t}\}_{l=1}^L$ in Step 1, the computation of $f_{\gamma_t}(\cdot)$ boils down to the estimation of the PDF of the power–sum of generically correlated Log–Normal RVs. To get very accurate results, we propose to use a non–Log–Normal approximation method to estimate $f_{\gamma_t}(\cdot)$. Moving from the excellent matching accuracy at the PDF level shown by the Pearson type IV method introduced in [12], [15], we rely on this method for Step 2.

Accordingly, the PDF of γ_t, $f_{\gamma_t}(\cdot)$, is approximated as shown in (12) on top of this page, where h is a normalization factor, and u, m, d, ν are the parameters that define the Pearson type IV distribution [15]. These latter parameters can be computed from the non–central moments of RV $\gamma_{t_{\mathrm{dB}}} = 10\log_{10}(\gamma_t)$. Due to space constraints, we dot report in the present contribution the formulas that allow to obtain u, m, d, ν from the non–central moments, but they can be found in [15]. On the other hand, the most complicated task in this approximation is the computation of the non–central moments $m_{\gamma_{t_{\rm dB}}}^{(n)} = E\{[10\log_{10}(\gamma_t)]^n\}$, which cannot be directly derived from [15], as a consequence of the particular form taken by the end–to–end SNR $\{\gamma_{l,t}\}_{l=1}^{L}$ in (6) for each cooperative dual–hop link. As the main objective of the present paper is to analyze the accuracy of the proposed approximation, we will compute these moments from Monte Carlo simulations, while the development of a framework for their computation is left to a future contribution.

5 Numerical and Simulation Results

The aim of this section is to analyze the accuracy of the proposed approximations to compute $\mathrm{P_m} = 1 - \mathrm{P_d}$ (i.e., the Miss Detection Probability), as a function of the number of cooperative dual–hop links (L), and shadowing correlation among them. In particular, $\mathrm{P_m}$ will be obtained, via straightforward numerical integration techniques, from (5) by approximating the PDF of the SNR γ_t by using the two–step method described in Section 4.1. Analysis will be compared with Monte Carlo simulations to assess its accuracy.

The following system setup is considered for performance analysis: i) the detection/decision threshold λ is computed according to a Constant False Alarm (CFA) criterion [7] by using the formula for $\mathrm{P_{fa}}$ in (5) with $\mathrm{P_{fa}} = \{10^{-3}, 10^{-4}\}$; ii) without loss of generality, the Log–Normal RVs are assumed to be identically

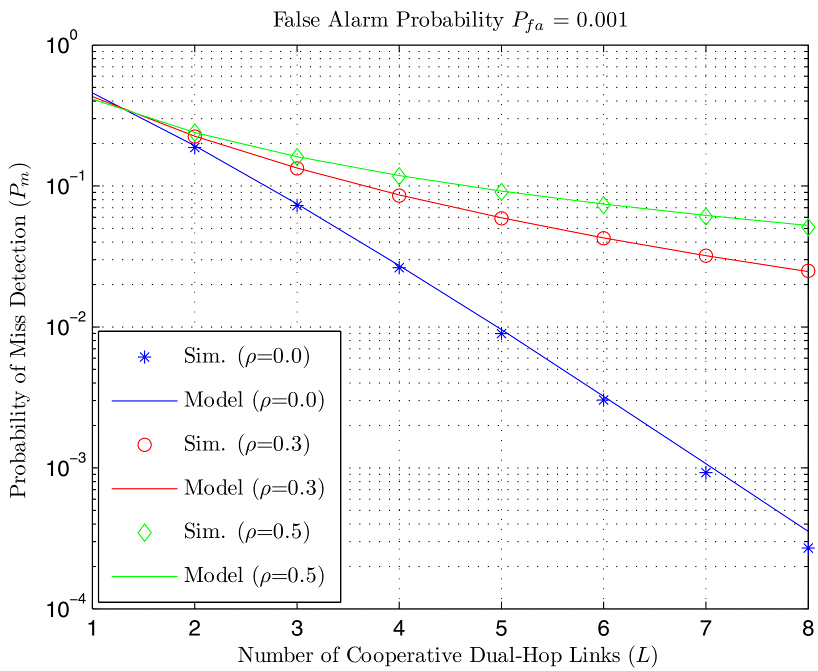

Fig. 1. $\mathrm{P_m}$ vs. number (L) of cooperative dual–hop links (CSI relays and $\mathrm{P_{fa}} = 10^{-3}$)

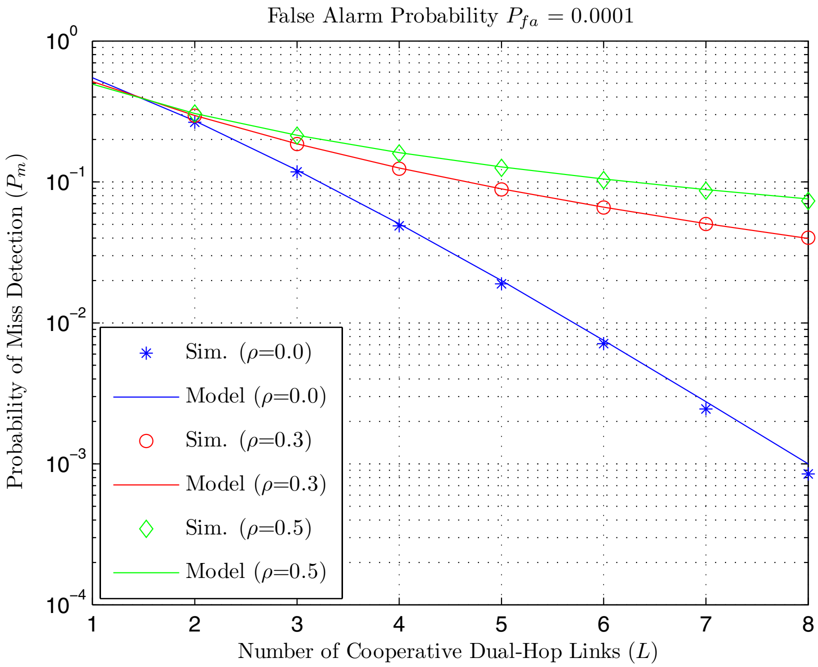

Fig. 2. $\mathrm{P_m}$ vs. number (L) of cooperative dual–hop links (CSI relays and $\mathrm{P_{fa}} = 10^{-4}$)

distributed with parameters $\mu = 15$ dB, $\sigma = 6$ dB, and with equal correlation coefficient $\rho = \{0.0, 0.3, 0.5\}$; iii) $N = 10$, iv) $N_p = 7$, and v) $E_s/N_0 = 0$ dB.

The results shown in Figure 1 and Figure 2 clearly illustrate that the proposed two–step approximation is pretty accurate for several system setups, and a limited number of GQR points (i.e., $N_p = 7$) is also required to get these good accuracies. We can observe that, in general, increasing the number of cooperative dual–hop links improves spectrum sensing capabilities (i.e., $\mathrm{P_m}$ decreases). However, the net gain obtained with cooperation gets significantly down when the cooperative links are subject to correlated shadowing.

6 Conclusions

In this paper, we have provided an analytical framework for the analysis of cooperative spectrum sensing techniques over correlated Log–Normal shadowing environments. Novel approximation methods have been introduced to handle correlated scenarios, and their accuracy has been validated via Monte Carlo simulations. Our empirical investigations show that the proposed two–step approach based on jointly using I–SY and Pearson type IV approximations offers a general, simple yet adequately accurate framework for performance analysis and design of efficient collaborative spectrum sensing methods over realistic propagation environments.

Acknowledgment

This paper is supported, in part, by the Torres Quevedo 2008 Program's aid (PTQ–08–01–06437), and the research projects PERSEO (TEC2006–10459/ TCM), LOOP (FIT–330215–2007–8), and m:VIA (TSI–020301–2008–3).

References

1. Mitola III, J., Maguire Jr., G.Q.: Cognitive radio: making software radios more personal. IEEE Personal Commun., 13–18 (August 1999)
2. Akyildiz, I.F., Lee, W.–Y., Vuran, M.C., Mohanty, S.: A survey on spectrum management in cognitive radio networks. IEEE Commun. Mag. 46, 40–48 (2008)
3. Goldsmith, A., Jafar, S.A., Maric, I., Srinivasa, S.: Breaking spectrum gridlock with cognitive radios: An information theoretic perspective. In: Proc. of the IEEE (to appear, 2009)
4. Letaief, K.B., Zhang, W.: Cooperative spectrum sensing. In: Cognitive Wireless Communication Networks, pp. 115–138. Springer, Heidelberg (2007)
5. Digham, F.F., Alouini, M.-S., Simon, M.K.: On the energy detection of unknown signals over fading channels. IEEE Trans. Commun. 55, 21–24 (2007)
6. Ghasemi, A., Sousa, E.S.: Asymptotic performance of collaborative spectrum sensing under correlated Log–Normal shadowing. IEEE Commun. Lett. 11, 34–36 (2007)
7. Ghasemi, A., Sousa, E.S.: Opportunistic spectrum access in fading channels through collaborative sensing. IEEE J. of Commun. 2, 71–82 (2007)
8. Ganesan, G., Li, Y.: Cooperative spectrum sensing in cognitive radio, Part I: Two user networks; Part II: Multiuser networks. IEEE Trans. Wireless Commun. 6, 2204–2222 (2007)
9. Unnikrishnan, J., Veeravalli, V.V.: Cooperative sensing for primary detection in cognitive radio. IEEE J. Sel. Topics Signal Process 2, 18–27 (2008)
10. Tandra, R., Sahai, A.: SNR walls for signal detection. IEEE J. Sel. Topics Signal Process 2, 4–17 (2008)
11. Agrawal, P., Patwari, N.: Correlated link shadow fading in multi–hop wireless networks. Tech. Report arXiv:0804.2708v2 (April 2008)
12. Di Renzo, M., Graziosi, F., Santucci, F.: Cooperative spectrum sensing in cognitive radio networks over correlated Log–Normal shadowing. In: IEEE Vehic. Technol. Conf., Barcelona, Spain (April 2009)
13. Hasna, M.O., Alouini, M.-S.: End–to–end performance of transmission systems with relays over Rayleigh–fading channels. IEEE Trans. Wireless Commun. 2, 1126–1131 (2003)
14. Di Renzo, M., Graziosi, F., Santucci, F.: On the performance of CSI–assisted cooperative communications over generalized fading channels. In: IEEE Int. Conf. Commun., vol. 1, pp. 1001–1007 (2008)
15. Di Renzo, M., Graziosi, F., Santucci, F.: A general formula for log–MGF computation: Application to the approximation of Log–Normal power sum via Pearson type IV distribution. In: IEEE Vehic. Technol. Conf., May 2008, vol. 1, pp. 999–1003 (2008)
16. Abramowitz, M., Stegun, I.A.: Handbook of mathematical functions with formulas, graphs, and mathematical tables, 9th edn., NY (1972)
17. Di Renzo, M., Graziosi, F., Santucci, F.: Performance of cooperative multi–hop wireless systems over Log–Normal fading channels. In: IEEE Global Commun. Conf., New Orleans, LA, USA (November 2008)