Ergodic Capacity Performance for Cognitive Radio under Lognormal Shadowing from Secondary User Perspective

Mohammed Abdel-Hafez[1], Nedaa Al Hussien[1], Khaled Shuaib[2], and Farag Sallabi[2]
[1]Department of Electrical Engineering, College of Engineering, United Arab Emirates University, P.O. Box 15551, Al-Ain, UAE
[2]College of Information Technology, United Arab Emirates University, P.O. Box 15551, Al-Ain, UAE
Email: {mhafez, nedaa_yousef, k.shuaib, f.sallabi}@uaeu.ac.ae

Abstract —In a cognitive radio network, spectrum sensing is the first and most vital function. It identifies spectrum opportunities that can be utilized by secondary users to enhance spectrum utilization and ergodic capacity. However, sensing performance is very tormented by channel fading and shadowing. This paper addresses the performance of ergodic capacity in cognitive radio networks under a Lognormal shadowing environment. We derived a new mathematical model for the secondary user network ergodic capacity when both accessing and sensing channels undergo Lognormal shadowing. Moreover, we developed exact analytical expressions for the capacity followed by numerical evaluation under different channel sensing and accessing conditions. Finally, the paper explored the effects of detection and accessing channels' parameters on the capacity.

Index Terms—Spectrum sensing; opportunistic access; cognitive radio; lognormal shadowing; ergodic capacity

I. Introduction

The evolution of wireless communications has introduced new services and applications that require high data rates and various Qualities of Services (QoS). This resulted in dramatically increasing demand on frequency spectrum to accommodate these new services or to enhance existing ones. However, the frequency spectrum is characterized by static frequency allocation schemes that assign the existing frequency bands only to licensed users. This is the case despite that measurements indicate underutilization of the spectrum by licensed users for significant periods of time [1]. This aggravates spectrum scarcity and makes it more difficult to accommodate the need for a higher range of the spectrum. Therefore, Cognitive Radio (CR) concept is a promising technology that has been planned to alleviate frequency spectrum scarceness and under-utilization by permitting unlicensed or Secondary Users (SU) to access the spectrum once licensed or Primary Users (PU) are inactive.

The two main characteristics of cognitive radio are cognitive capability and configurability [2]. The cognitive capability enables CR devices to interact with the surrounding radio environment in a real-time manner and be aware of signal parameters such as waveform, RF spectrum, communication network type/protocols, geographical information, user needs and security policies, etc. CR devices then adjust their radio operating parameters according to the information sensed to achieve optimal performance.

The authors in [3] investigated the effect of user collaboration in a Rayleigh fading channel. Their results showed that using more collaborative users would improve the spectrum utilization. In [4], the authors investigated and analyzed linear soft combination-based cooperative spectrum sensing schemes in Cognitive Radio networks. They focused on the allocation of optimal weights to individual cooperative SUs in AWGN channel. In [5], the authors used a different methodology where they studied sensing in Nakagami fading channel with integer fading parameter in non-collaborative situations. While in [6] the authors solved the spectrum-sensing problem in Nakagami fading with non-integer fading parameters in collaborative scenarios. Recently, the authors of [7] have produced a closed form and accurate solution to the spectrum-sensing problem in Lognormal shadowing channel.

The Complementary Receiver Operating Characteristics (CROC) curves are one way to evaluate the detection system performance. However, CROC does not show the percentage increase in spectrum utilization or ergodic capacity when using opportunistic spectrum access technique. Some researchers used capacity calculations to quantify the resulting increment in utilization. The authors in [8] studied the problem of designing sensing duration to maximize the achievable throughput (capacity) for the secondary network in AWGN channels. The authors formulated the sensing throughput trade-off problem mathematically and used an energy detection sensing scheme to prove that the formulated problem is indeed an optimal sensing time which yields the highest throughput for the secondary network. The authors of [9] investigated the capacity of fading channels subject to constraints on the power received at a third-party (primary) receiver when perfect channel information is available to both transmitter and receiver.

The contribution of [10] extended the work done in previous studies for the case of imperfect knowledge of

Manuscript received April 20, 2018; revised September 20, 2018.
Corresponding author email: mhafez@uaeu.ac.ae.
doi:10.12720/jcm.13.10.546-552

channel sensing and explored the impact on spectrum sharing systems, especially the channel capacity of secondary users. All previous studies are done either for AWGN channels or only individual cases of the fading channel types between a primary to primary receiver and the channel between a secondary and a primary receiver. The authors of [11] studied the capacity of cognitive radio from the interference temperature perspective. They ignored any cooperation between the primary and the secondary user. First, assuming that all four links associated with the primary/secondary transmitter/receiver will experience Rayleigh fading, the capacity is achieved via the water-filling power allocation strategy, subject to an average secondary to primary Interference-to-Signal ratio (ISR) constraint and a peak ISR constraint. Secondly, the results are extended to include path loss and channel fading to reflect the geometric relations between link pairs and network size. It is clear that most of the studies are from the primary receiver perspective. Therefore, all models were analyzed with power constraints to protect the primary user (PU) from high interference. Only in [8] the authors studied the capacity from the secondary receiver perspective in non-fading channels. The work of [12] presented the secondary users' network capacity in Rayleigh fading channels.

This paper reviews exact derived expressions for system performance regarding the probability of detection and probability of false alarm presented in [7], [12]. It addresses the ergodic capacity analyses from secondary user's network perspective. We evaluated the sensing scheme performance regarding the improvement in bandwidth utilization in different types of channel access methods. Moreover, we show the improvement due to using opportunistic spectrum access in generalized Lognormal shadowing channel. Finally, we obtained exact and numerical results under selected sensing and access channels' conditions.

The paper is organized as follows: Section II presents channel and systems model followed by spectrum sensing performance in Lognormal shadowing channel. Section IV presents the sensing and accessing models and the analysis of the ergodic capacity in the Lognormal channel. In section V, the numerical results for the secondary network capacity in the opportunistic spectrum access are presented. Finally, concluding remarks are highlighted in Section VI.

II. System and Channel Model

A. System Model

The detector model used in this paper is energy detection with the energy threshold λ, used in [7] and [12]. The output of the detector acts as a test statistics to test the two hypotheses H_0 and H_1, where H_0 and H_1 are the two hypotheses of the primary user's signal absence and presence, with corresponding probabilities $P(H_0)$ and $P(H_1)$, respectively.

In an AWGN channel, spectrum-sensing performance is evaluated using two probabilities: the probability of false alarm (P_f), and the probability of detection (P_d). High probability of detection guarantees protecting the PU from SU's interference. While the low probability of false alarm results in more spectrum opportunities for the SU, hence higher spectrum utilization.

B. Channel Model

In Lognormal shadowing, the PU's signal received by the SU fluctuates owing to the existence of associate obstacle between the transmitter and receiver. These fluctuations affect the local-mean power of the received signal. Empirical measurements indicate that the fluctuations within the local-mean power about the area-mean follow a Lognormal distribution, which suggests that it follows a standard distribution once expressed in a logarithmic scale (decibel units) [12,13, and 14].

$$f_\gamma(\gamma) = \frac{\xi}{\gamma\sigma_{dB}\sqrt{2\pi}} exp\left(\frac{-(\xi log_e\gamma - \mu_{dB})^2}{2\sigma^2{}_{dB}}\right), \gamma \geq 0 \quad (1)$$

where μ_{dB}, $\sigma^2{}_{dB}$ are the mean and variance of $(\xi log_e\gamma)$ respectively, and $\xi = \frac{10}{log_e(10)}$.

The lognormal distribution is usually characterized by dB-spread (σ_{dB}). The value of σ_{dB} depends on the type of the obstacle interfering with the signal traveling from the transmitter to the receiver. According to [14], the value of σ_{dB} lies between $3dB$ to $12dB$.

III. Spectrum Sensing Under Lognormal Shadowing

Under Lognormal shadowing, the input signal $r(t)$ is modeled as:

$$r(t) = \begin{cases} n(t) & H_0 \\ hs(t) + n(t) & H_1 \end{cases} \quad (1)$$

where $n(t)$ is the AWGN modeled as a zero-mean Gaussian random variable, and $s(t)$ is a PU transmitted signal, and h is the channel gain factor between the PU and the SU. Using energy detection for spectrum sensing, the decision on the PU's existence is made based on a binary hypothesis test, where H_1 denotes the PU's presence and H_0 denotes the PU's absence.

According to [7], the probability of detection under Lognormal shadowing, $P_{d,log}$, can be calculated by,

$$P_{d,log} = \frac{\xi}{\sigma\sqrt{2\pi}}\int_0^\infty Q_N\left(\sqrt{2\gamma}, \sqrt{\lambda}\right)\left(\frac{1}{\gamma}\right) exp\frac{-(\xi log_e\gamma - \mu_{dB})^2}{2\sigma^2{}_{dB}} d\gamma \quad (3)$$

The Generalized Marcum-Q function is defined by:

$$Q_N(a,b) = \int_b^\infty \frac{y^N}{a^{N-1}} e^{\left(-\frac{y^2+a^2}{2}\right)} I_{N-1}(ay)\, dy \quad (4)$$

where $I_{N-1}(ay)$ is the modified Bessel function of order (N-1), and y is a dummy variable. Assuming $x = \frac{\xi log_e\gamma - \mu}{\sqrt{2}\sigma}$, then $P_{d,log}$ can be written as:

$$P_{d,log} = \frac{1}{\sqrt{\pi}} \int_{-\infty}^{\infty} Q_N\left(\sqrt{2\, exp\left(\frac{x\sigma_{dB}\sqrt{2}+\mu_{dB}}{\xi}\right)}, \sqrt{\lambda}\right) e^{-x^2}\, dx \quad (5)$$

Based on the Gauss-Hermite integration in [15], (5) can be written as:

$$P_{d,log} = \sum_{i=1}^{M} \frac{w_i}{\sqrt{\pi}} Q_N\left(\sqrt{2\, exp\left(\frac{a_i\sigma_{dB}\sqrt{2}+\mu_{dB}}{\xi}\right)}, \sqrt{\lambda}\right) \quad (6)$$

where M is the Hermite integration order with w_i and α_i are the weights and abscissas, respectively [15].

The probability of misdetection in Lognormal shadowing ($P_{m,log}$) is:

$$P_{m,log} = 1 - P_{d,log} \quad (7)$$

and

$$P_{m,log} = 1 - \sum_{i=1}^{M} \frac{w_i}{\sqrt{\pi}} Q_N\left(\sqrt{2\, exp\left(\frac{a_i\sigma_{dB}\sqrt{2}+\mu_{dB}}{\xi}\right)}, \sqrt{\lambda}\right) \quad (8)$$

The expression of (8) is a closed-form that can be evaluated easily. The accuracy of $P_{m,log}$ in (8) is investigated by calculating the probability of detection using three methods; Hermite approximation, Monte Carlo integration, and numerical integration.

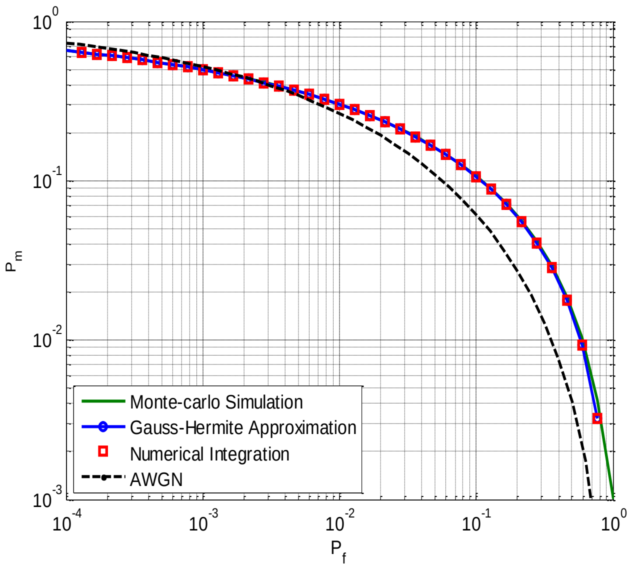

Fig. 1. CROC in the Lognormal channel for 1000 simulation runs where N=10 samples, average SNR= $10dB$, and $\sigma_{dB} = 2dB$.

The CROC curves in a Lognormal channel are shown in Fig. 1 using the three methods. The AWGN curve is provided as a reference, for an average $SNR = 10dB$ and $N = 10$ samples and $\sigma_{dB} = 2dB$. It is evident that the sensing performance is affected by shadowing. Also, comparing the three curves of $P_{m,log}$ proves that the Hermite approximation provides an accurate expression for the probability of misdetection in Lognormal shadowing.

IV. Ergodic Capacity of Cognitive Radio Under Lognormal Shadowing

Fig. 2 shows the proposed model for sensing and accessing scenarios in our opportunistic spectrum access system. Infrastructure sensors are distributed in the model to sense the primary user signal in a particular frequency band. The secondary user accesses the channel after it receives a permit from the band manager. The band manager then decides based on the information reported by the sensors. Therefore, there should be a separation between the detection and the access channels in this model.

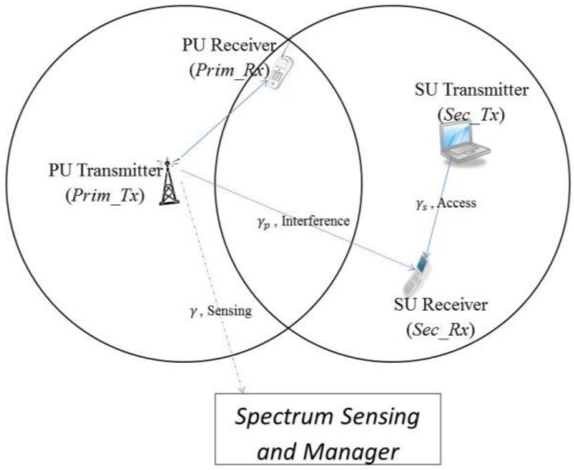

Fig. 2. Sensing-accessing system in Cognitive Network.

Based on the suggested model, one can notice three different channels. Sensing Channel: between the primary transmitter and the spectrum sensor with a specific signal-to-noise ratio γ. Interfering Channel: between the primary transmitter and the secondary receiver with signal-to-noise ratio γ_p. Accessing Channel: between the secondary transmitter and the secondary receiver with signal-to-noise ratio γ_s.

When the primary user utilizes a specific channel band, the spectrum sensor senses the primary channel occupancy via the sensing channel and reports it to the band manager. Subsequently, the secondary user uses this channel to communicate with the secondary receiver via the accessing channel. If a misdetected primary user uses the channel, it interferes with the secondary signal at the secondary receiver via the interfering channel. In this paper, we considered the ergodic capacity of the opportunistic spectrum access under the effect of all three channel parameters.

The secondary user's network operates in two scenarios at the primary user's licensed band:

- Perfect detection of an inactive primary user: In this case, C_0 denotes the capacity at the secondary link, which is the conditional capacity of the secondary network when it operates in the absence of primary users [16] measured in bits/second/Hz,

$$C_0 = log_2(1+\gamma_s) \quad (9)$$

where $\gamma_s = \frac{P_s}{N}$ is the signal-to-noise ratio of the channel between the secondary transmitter and the secondary receiver (*Sec_Tx-Sec_Rx*), P_s is the signal power of the secondary user, and N is the noise power at the secondary receiver.

- Misdetected active primary user: The secondary user uses the channel with a capacity of C_1, the conditional capacity of the secondary network when it operates in the presence of the primary user [16],

$$C_1 = log_2\left(1+\frac{\gamma_s}{1+\gamma_p}\right) \quad (10)$$

where $\gamma_p = \frac{P_p}{N}$ is the signal-to-noise ratio of the channel between the primary transmitter and the secondary receiver (*Prim_Tx-Sec_Rx*), and P_p is the primary user's signal power which represents the interference power.

Using the estimated values of $P(H_1)$ and $P(H_0)$ by observing a particular band for a period, provided by [1], the average capacity for the secondary network is written as,

$$C = C_0(1-P_f)\,P(H_0) + C_1 P_m\,P(H_1) \quad (11)$$

where C_0 and C_1 represent the conditional capacities under Lognormal shadowing in both sensing and accessing channels. P_m, P_f, and P_d are for both collaborative and non-collaborative sensing using soft and hard decision combining, provided earlier in this paper and in [7].

In the case of a Lognormal shadowing channel, the conditional capacity is the average capacity in AWGN over the Lognormal channel statistics. A Lognormal channel model is assumed for the sensing and accessing channels. The average capacity (9) over the pdf of γ_s is,

$$C_0 = \int_0^{\infty} log_2(1+\gamma_s) f_{\gamma_s}(\gamma_s)\, d\gamma_s \quad (12)$$

where, $f_{\gamma_s}(\gamma_s)$ is the pdf of the SNR, γ_s, of the accessing channel described by a Lognormal distribution, described by (1). Thus, the average conditional capacity is written as,

$$C_0 = \frac{\xi}{\sigma_{s(dB)}^2\sqrt{2\pi}}$$

$$\int_0^{\infty} log_2(1+\gamma_s)\,\frac{1}{\gamma_s}\,exp\left(\frac{-\left(\xi\, log_e\gamma_s - \mu_{s(dB)}\right)^2}{2\sigma_{s(dB)}^2}\right) \quad (13)$$

Similarly,

$$C_1 = \int_0^{\infty} log_2(1+\gamma_I) f_{\gamma_I}(\gamma_I)\, d\gamma_I \quad (14)$$

where $\gamma_I = \frac{\gamma_s}{1+\gamma_p}$ is the signal-to-interference plus noise ratio (SINR) in the interfering channel, γ_s and γ_p are the signal-to-noise ratio of accessing and interference links, respectively. It is known that γ_s and γ_p have a Lognormal distribution with distinct parameters σ_s and σ_p, respectively. Here γ_I is a new random variable where its *pdf*, $f_{\gamma_I}(\gamma_I)$, can be found by using [17] as follows,

$$f_{\gamma_I}(\gamma_I) = \int_1^{\infty} y f_{\gamma_s,\gamma_p}(y\gamma_I, y)\, dy \quad (15)$$

where $y = 1+\gamma_p$, $f_{\gamma_s,\gamma_p}(.,.)$ is the joint *pdf* and $\gamma_s = \gamma_I y$.

Under the assumption that γ_s and γ_p are independent, (15) can then be written as,

$$f_{\gamma_I}(\gamma_I) = \int_1^{\infty} y f_s(y\gamma_I) f_y(y) dy \quad (16)$$

where $f_y(y) = f_{\gamma_p}(y-1)$. Hence,

$$f_{\gamma_s}(y\gamma_I) = \frac{\xi}{y\gamma_I\sigma_{s(dB)}\sqrt{2\pi}}\,exp\left(\frac{-\left(\xi\, log_e(y\gamma_I) - \mu_{s(dB)}\right)^2}{2\sigma_{s(dB)}^2}\right) \quad (17)$$

where $\bar{\gamma}_s$ is the average of the secondary user SNR, γ_s, and

$$f_y(y) = \frac{\xi}{(y-1)\sigma_{p(dB)}\sqrt{2\pi}}\,exp\left(\frac{-\left(\xi\, log_e(y-1) - \mu_{p(dB)}\right)^2}{2\sigma_{p(dB)}^2}\right) \quad (18)$$

where $\bar{\gamma}_p$ is the average of the primary user SNR, γ_p. The pdf of the SNIR, γ_I, described by (16) can be written as

$$f_{\gamma_I}(\gamma_I) = \int_1^{\infty} \frac{\xi^2}{\gamma_I(y-1)\sigma_{p(dB)}\sigma_{s(dB)}2\pi}\,exp\left(-\frac{\left(\xi\, log_e(y\gamma_I) - \mu_{s(dB)}\right)^2}{2\sigma_{s(dB)}^2} - \frac{\left(\xi\, log_e(y-1) - \mu_{p(dB)}\right)^2}{2\sigma_{p(dB)}^2}\right) dy \quad (19)$$

Numerical evaluation of C_0 and C_1 can be easily done using numerical methods by Matlab. In the next section, we present numerical examples for different sensing and accessing channel parameters that affect the average capacity.

V. Numerical Results

This section presents the Numerical results of ergodic capacity in Lognormal shadowing channel. It presents the effect of sensing and accessing channel conditions on the secondary network ergodic capacity. Under fixed sensing conditions, $\bar{\gamma}$ and σ, the effect of accessing channel parameters are discussed. Later, the effect of sensing conditions under fixed accessing channels conditions, i.e., $\bar{\gamma}_p$, σ_p, $\bar{\gamma}_s$ and σ_s, is studied for various detection parameters. Note that, SNR, SNR_p, and SNR_s represent the average SNR on every link, $\bar{\gamma}$, $\bar{\gamma}_p$ and $\bar{\gamma}_s$ respectively in all of the Figures.

The effect of accessing channel parameters are studied under various detection assumptions. Through the sensing channel, the average received SNR from the primary user is set to $\bar{\gamma} = 10dB$, the channel shadow spread parameter is assumed to be $\sigma = 6dB$ and probability of false alarm $P_f = 0.01$. Moreover, it is assumed that the average channel occupancy by the primary user is 60% of the time $(P(H_1) = 0.6)$ (based on averaging statistics in [1]).

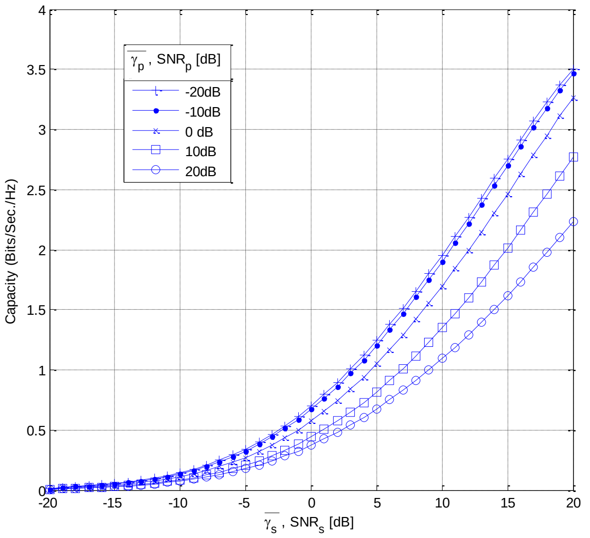

Fig. 3. Capacity versus $\bar{\gamma}_s$ for various values of $\bar{\gamma}_p$ with Lognormal Shadowing and $\sigma_s = \sigma_p = 6dB$.

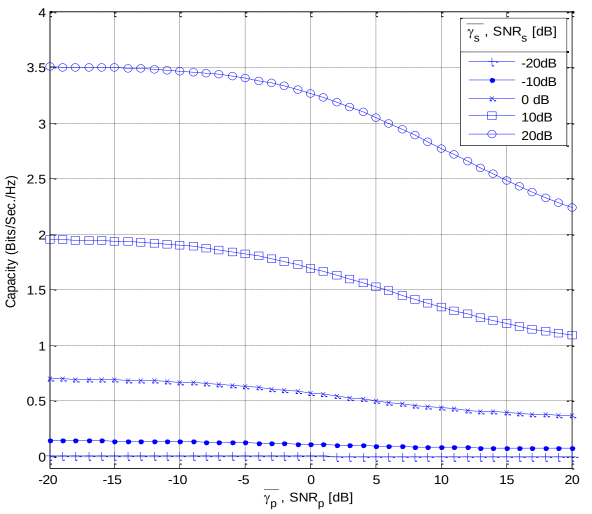

Fig. 4. Capacity versus $\bar{\gamma}_p$ and for various values of $\bar{\gamma}_s$, with Lognormal Shadowing.

The ergodic capacity of the secondary user for $\overline{\gamma_p} = [-20\ -10\ 0\ 10\ 20]\, dB$ is depicted in Fig. 3. Both *Prim_Tx-Sec_Rx* and *Sec_Tx-Sec_Rx* channels are Lognormal fading channels with $\sigma_p = \sigma_s = 6dB$. It is noticed that the secondary network ergodic capacity increases as the secondary user $SNR_s, \overline{\gamma_s},$ increases. It is also important to notice how the capacity decreases for high primary user $SNR_p, \overline{\gamma_p}$. It is evident that $\overline{\gamma_s}$ has the most effect on the capacity compared to $\overline{\gamma_p}$. The reason behind this is that most of the capacity gain is from utilizing the channel when the primary user is idle. The variation in the secondary user capacity for different values of $\overline{\gamma_p}$ is due to accessing the channel when the primary user is available but not detected by the sensor. Such minimal variation means that the probability of misdetecting the primary signal is small, and the primary user is well protected.

The capacity with respect to $\overline{\gamma_p}$, for different values of $\overline{\gamma_s}$, is presented in Fig. 4. It is clear that the capacity is highly affected by the secondary *SNR*. Besides, this Figure shows that $\overline{\gamma_s}$ has a significant effect compared to $\overline{\gamma_p}$ on the capacity. The effect of $\overline{\gamma_p}$ is evident for the high value of $\overline{\gamma_s}$. It is also clear that the gained capacity is negligible when $\overline{\gamma_s}$< 0 dB. So, a secondary user under good channel conditions is a plus for the opportunistic spectrum access system.

Fig. 5 shows how the capacity drops dramatically as the *SNR* of the primary user increases. For small values of primary $average\ SNR$ $(\bar{\gamma} < -5\ dB)$, the capacity saturates at a maximum value. Under low $\bar{\gamma}$, the secondary user assumes free accessible channel. On the other hand, when $\bar{\gamma}$ is above a certain threshold (>15 dB), the capacity of the secondary network saturates at a minimum value, which depends on the availability of the primary user.

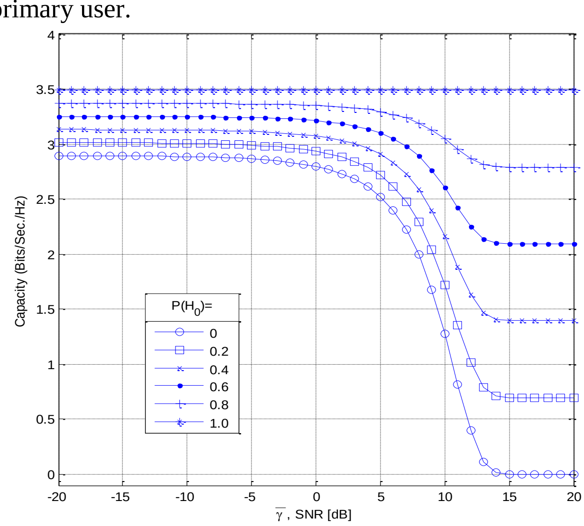

Fig. 5. Capacity versus $\bar{\gamma}$, for different percentages of primary user channel occupancy $P(H_0)$.

When the primary user is using the channel all the time $P(H_0)$ =0, the capacity of the secondary user drops to zero. Therefore, the minimum capacity allocated to the secondary user depends on the actual usage of the channel by the primary user. The capacity curve is high when the channel is free most of the time regardless of the primary channel conditions. On the other hand, the capacity is small when the channel is busy most of the time.

Examining this graph more closely conveys the primary user protection level since the secondary user is using the channel only when the received primary signal is either zero or very low. Such protection level determined by the system controller using the threshold λ or the value of desired probability of false alarm (λ is a function of the probability of false alarm).

The capacity with respect to $\bar{\gamma}$ for the different probability of false alarm values $P_f = [.001\ .01\ .05\ .1\ \ .2]$

is shown in Fig. 6. It is noticed that as the probability of false alarm increases, the maximum achievable capacity decreases. This is because when there is a high probability of false alarm the chance of using the un-occupied spectrum is missed, and as a result decreases the utilization. Therefore, the probability of a false alarm should be set small enough to maximize the channel utilization.

From Fig. 5 and Fig. 6, the capacity saturates at a maximum value when $\bar{\gamma} < 0\ dB$ since the probability of misdetection reaches its maximum, $P_m = 1$. This is one of the drawbacks of the energy detection system which cannot perform well for low primary user's SNR.

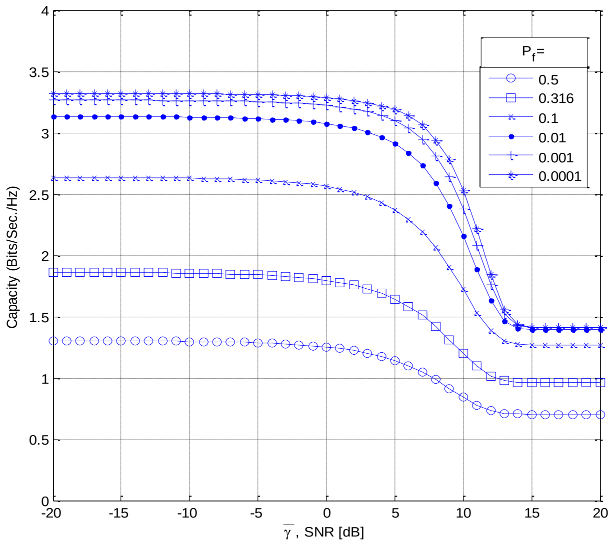

Fig. 6. Capacity versus $SNR, \bar{\gamma}$ for the probability of false alarm

VI. Conclusions

In this paper, the effect of Lognormal shadowing on the performance of the ergodic capacity of secondary user networks is investigated to quantify the improvement of implementing opportunistic spectrum access wireless networks. Closed-form expressions are derived from finding the ergodic capacity of the secondary network when the accessed channel undergoes Lognormal shadowing. Effects of sensing and accessing parameterson the capacity are studied. According to numerical results, one of three factors can increase the capacity; better secondary accessing channel, less primary interference or desired QoS of the primary user. Under the optimum design of an opportunistic spectrum access system, most of the capacity gained results from utilizing the channel when the primary user is idle rather than using the channel when the primary user is misdetected by the sensors. Therefore, the designer should be aware of choosing a good sensing system and then maximize the utilization using other factors to avoid degrading the service provided to the primary user.

References

[1] F. C. Commission, Spectrum Policy Task Force Report, FCC 02-155, ed: Nov. 2002.

[2] K. R. Liu and B. Wang, *Cognitive Radio Networking and Security, A Game-Theoretic View*, Cambridge University Press, 2011, 2011.

[3] A. Ghasemi and E. Sousa, "Opportunistic spectrum access in fading channels through collaborative sensing," *Journal of Communication*, vol. 2, no. 2, March 2007.

[4] B. Shen and K. S. Kwak, "Soft combination schemes for cooperative spectrum sensing in cognitive radio networks," *ETRI Journal*, vol. 31, no. 3, pp. 263-270, June 2009.

[5] F. F. Digham and M. Alouni, "On the energy detection of unknown signals over fading channels," *IEEE Transactions on Communication*, vol. 55, no. 1, January 2007.

[6] O. A. Bashir, M. Abdel-Hafez, and K. Shuaib, "Fading severity effects on collaborative sensing for opportunistic spectrum access," *Computer and Electrical Engineering Journal*, Elsevier, vol. 40, no. 2, pp. 577–586, February 2014.

[6] K. R. Liu and B. Wang, *Cognitive Radio Networking and Security, A Game-Theoretic View*, Cambridge University Press, 2011, 2011.

[7] N. A. Hussien, M. Abdel-Hafez, and K. Shuaib, "Collaborative sensing for cognitive radio under log-normal shadowing," in *Proc. 8th IEEE GCC Conference and Exhibition (GCC 2015)-Communication & Signal Processing*, Muscat, Oman, February 1-4, 2015.

[8] Y. Liang, Y. Zeng, E. Peh, and T. Hoang, "Sensing-throughput tradeoff for cognitive radio networks," *IEEE Trans on Wireless Communication*, vol. 7, no. 4, pp. 1326-1337, April 2008.

[9] A. A. El-Saleh, M. Ismail, M. A. M. Ali, and A. Alnuaimy, "Capacity optimization for local and cooperative spectrum sensing in cognitive radio networks," *World Academy of Science, Engineering and Technology*, vol. 38, pp. 69-75, Feb. 2009.

[10] J. Sun and H. Zhu, "Channel capacity analysis of spectrum-sharing with imperfect channel sensing," in *Proc. Fourth International Conference on Communications and Networking in China*, 2009, pp. 1-4.

[11] H. Cho and J. G. Andrews, "Upper bound on the capacity of cognitive radio without cooperation," *IEEE Transactions on Wireless Communications*, vol. 8, no. 9, pp. 4380-4385, September 2009.

[12] M. Abdel-Hafez, O. A. Bashir, and K. Shuaib, "Secondary users capacity in cognitive radio network over rayleigh fading channels," *Journal of Wireless Personal Communications*, vol. 78, no. 4, pp 1981-1994, October 2014.

[13] T. S. Rappaport, *Wireless Communications Principles and Practices*, Prentice-Hall, 2002.

[14] A. J. Goldsmith, L. J. Greenstein, and N. B. Mandayam, *Principles of Cognitive Radio*: Cambridge University Press, 2012.

[15] M. Abramowitz and I. A. Stegun, *Handbook of Mathematical Functions: with Formulas, Graphs, and Mathematical Tables*: Courier Dover Publications, 2012.
[16] C. Shannon, "A mathematical theory of communication." *Bell System Technology Journal*, 1948, pp. 623-656.
[17] A. Papoulis, *Probability, Random Variables, and Stochastic Processes*, Third Edition, McGraw-Hill, 1991.

Mohammed Abdel-Hafez is an associate professor in the Department of Electrical Engineering (Communications), United Arab Emirates University, UAE. He received his B.Sc, M.Sc, and Ph.D. degrees all in Electrical and Electronic Engineering from Eastern Mediterranean University, Northern Cyprus, and Turkey in 6/1992, 8/1994, and 11/1997, respectively. From 1992 to 1997 he was a Research Engineer at Department of Electrical and Electronic Engineering, EMU, Turkey. During the year 1995, he was an instructor at Jerusalem University, Department of Electrical Engineering. From 1997 to 1999 he was with Palestine Telecommunication Company (PALTEL) as data communication section manager. In August 1999, he joint Centre for Wireless Communications at the University of Oulu as senior research scientist and project manager. He is currently associate professor of Electrical Engineering at United Arab Emirates University in United Arab Emirates. He is a frequent visiting professor at Oulu University, Centre for Wireless Communications, Oulu, Finland. His research of interests includes performance analysis of mobile communication systems, future broadband wireless systems, Smart Grid, cooperative and Cognitive radio networks, 5G and mmwave systems, and UWB systems. Dr. Abdel-Hafez has published more than 75 conference or journal papers in the field of wireless communications and digital signal processing. Dr. Abdel-Hafez is listed in Marquis WhosWho in the word 2006 and Whoswho of Emerging Leaders 2007 and IEEE senior member.

Nedaa Al Hussien received her M.Sc. degree from the Department of Electrical Engineering, United Arab Emirates University, UAE, in 2015. Currently, she is a Ph.D. student in the Electrical and Computer Engineering Department at University of Victoria, British Columbia, Canada. Her research fields of interest are mainly in wireless communications, cognitive radio, smart grids and cooperative communications.

Khaled Shuaib Received his Ph.D. in Electrical Engineering from the Graduate Center of the City University of New York, 1999, his ME and BE in Electrical Engineering from the City College of New York, 1993 and 1991 respectively. Since September 2002, Khaled has been with the College of Information Technology (CIT), at the UAEU where he is currently a Professor and a Department Chair.. His research interests are in the area of network design and performance, communication networks, wireless sensor networks, IoT, network security and Smart Gri. Prior to joining the UAEU, Khaled had several years of industrial experience in the US working as a Senior Member of Technical staff at GTE Labs, Waltham, MA (Currently Verizon Technology Center) (1997-1999), and as a Principle Performance Engineer for Lucent Technologies, Westford, MA (1999-2002).

Farag Sallabi received the Ph.D. degree in electrical and computer engineering from the University of Ottawa, Canada in 2001, and the B.Sc. and M.Sc. Degrees in Electrical and Electronic Engineering from Benghazi University, Benghazi, Libya in 1987 and 1995 respectively. He is currently an Associate Professor at the Department of Computer and Network Engineering, College of Information Technology, United Arab Emirates University (UAEU). He served as the Principal Investigator (PI) or Co-PI on several research projects funded by the UAEU. He currently serves as a PI for a project funded by UAEU titled "Internet of Things Network Management for Smart Healthcare Systems". His research interests include quality of service provisioning in wired and wireless networks, routing in wireless sensor networks, performance evaluation of wireless sensor network, network management, smart buildings, Internet of Things and smart healthcare systems.

Dr. Sallabi has joined the UAEU in September 2002 to June 2012. From July 2012 to July 2015 he served as a Director General, Directorate General of Electronic Services, Ministry of Communications and Informatics in Libya where he was leading a project to develop and implement eGovernment program in Libya. He rejoined the UAEU on August 2015. He also worked at Sigpro Wireless in Canada, a company that develops and implements software and hardware for handheld devices from August 2001 to August 2002. He has served as a Technical Program Committee Member and a reviewer of many international conferences and journals.