Coverage Aspects of Cooperative Multi-hop Line Networks in Correlated Shadowed Environment

Mudasar Bacha and Syed Ali Hassan
School of Electrical Engineering and Computer Science
National University of Sciences and Technology, H-12, Islamabad, 44000
Email: {mudasar.bacha, ali.hassan}@seecs.edu.pk

***Abstract*—We develop a stochastic model to characterize the effects of correlated shadow fading on a linear cooperative multi-hop wireless network. A one-dimensional network of equally-spaced nodes is considered, where a group of nodes transmits cooperatively to another group of nodes under large-scale fading effects. The transmission from one level to another is modeled as a Markov process and the transition probability matrix of the Markov chain is derived, which depends upon the underlying distribution of the received power. The received power is modeled as a log-normal random variable and its distribution is derived by using Fenton-Wilkinson's approach. The eigen-decomposition of the transition matrix provides insightful information about the network coverage and various other parameters. We quantify the values of signal-to-noise ratio margin required to get a desired coverage distance under a given quality of service and standard deviation of shadowing constraints. The accuracy of the model is validated by matching both the simulation and analytical results.**

I. Introduction

High data rate is becoming one of the main feature in next generation wireless systems owing to the ever increasing demands for multimedia services and web-related contents. However, channel fading and other transmission impairments severely limit the data rate capability of these networks. An efficient technique to combat channel fading is to exploit the spatial diversity by having many radios transmit the same message signal. This idea known as distributed multiple-input multiple-output (MIMO) was proposed as compared to the co-located MIMO, where the key difference is that multiple antennas at the front-end of the transmitters are distributed among widely separated radio nodes. In this way, multiple nodes form a virtual antenna array that achieves higher diversity gains [1]. This kind of cooperative transmission (CT) has attracted a large attention in the past few years in both cellular as well as sensor networks.

A simple and efficient physical layer CT scheme for large networks is Opportunistic Large Array (OLA) [2]. In an OLA transmission, a group of nodes, constituting a *level*, transmits the same message to another group of nodes under orthogonal fading channels. All nodes that have successfully decoded the message from the previous level nodes, relay the message together, without coordination with other relays and this process continues. OLAs have been shown to provide range extension as well as energy-efficiency in wireless networks. A considerable literature on OLA transmission has appeared. The authors in [3] studied the behavior of dense wireless cooperative networks. With *continuum* assumption, implying an infinite node density per unit area, they showed that if the decoding threshold is below a certain value, the message can be delivered to the destination regardless of how far it is. However, this assumption may not be appropriate for low density networks. In [4], the authors studied a finite density linear cooperative network and derived an analytical model for it. They provided upper bound on network coverage under a fading channel environment. However, they only considered small-scale fading and modeled the channel as independent Rayleigh fading with path loss having an arbitrary path loss exponent. Variants of linear OLA finite density networks with relay fading have been studied in [5].

In a practical wireless channel, large-scale fading, known as shadowing, also affects the performance of the network. A range extension study has been conducted in [6], where the authors study the impacts of independent shadowing and fading on linear OLA topologies. However, shadowing channel realizations are generally correlated and impact the system in a different manner. Therefore, in this paper, we study the impacts of shadowing on the performance of finite density multi-hop cooperative wireless networks. For simplicity, we assume shadowing correlation at the transmitter side, such that a node receives superimposed correlated copies of the same message from different transmitters. Shadowing is modeled as a log-normal random variable (RV) [7]. In cooperative networks, the received signal at a node is the sum of multiple transmitted signals each of which is affected by correlated shadowing. However, in literature, there is no closed-form expression for the probability density function (PDF) of the sum of multiple log-normal RVs [7]. There are different approximation techniques such as Schwartz and Yeh [8], Fenton-Wilkinson [9], and Farley [8], which estimate the sum of log-normal RVs as another log-normal RV. We use Fenton-Wilkinson method in this work. Our choice of using Fenton-Wilkinson method is supported by the accuracy and simplicity of this method proved in [10].

Typical applications of this linear network include structural health monitoring of buildings and bridges where the nodes are aligned in a regular linear pattern, finding a route path from the source to the destination in mobile ad hoc networks (MANETS), and fault recognition in transmission lines for the future smart grid systems. This topology would also be consistent with a plastic communication cable, where sensor nodes

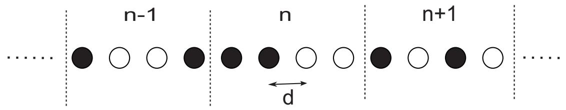

Fig. 1. System Model; $M = 4$.

are embedded in a plastic wire and cooperative transmission is performed to transmit the source message from one end of the wire to another. These wires find practical applications in air-industry having lighter weights as compared to general copper wires and reduce the unwanted high electric fields in the surroundings.

In this paper, we show that by utilizing a quasi-stationary Markov chain model for propagation of transmissions, and incorporating the shadowing effects in the underlying model, significant information about the coverage of the network can be quantified. It should be pointed out that the main contribution of this paper is the study of performance analysis of the network operating under correlated shadowing. However, as our our model is cooperative, there is a variation in the Fenton-Wilkinson's approach, which we will discuss in the next sections. The paper also describes the effects of various system parameters like shadow standard deviation, number of cooperating nodes, and transmit power constraints on the performance of the cooperative multi-hop network under consideration.

This paper is organized as follows. Section II describes our network parameters. In Section III, we model the network as discrete-time Markov chain, obtain the sum distribution of log-normal RVs by Fenton-Wilkinson's approximation, and find the transition probability matrix of the Markov chain. In Section IV, we validate our analytical model through numerical simulations, while Section V concludes this paper with certain recommendations of the future work.

II. System Description

Consider a linear network where the distance between the adjacent nodes is *d*, as shown in Fig. 1. The network is partitioned into non-overlapping groups of nodes, such that each group or *level* consists of M number of nodes. The nodes of a level cooperate with each other to send the same message signal to the next level. However, only those nodes take part in transmission that have decoded the data perfectly from the transmission of previous level nodes. These nodes are known as decode-and-forward (DF) nodes. Diversity in this network can be achieved by employing frequency diversity, where each radio is assigned an orthogonal frequency, or by using appropriate space-time code. Besides the partition constraint, this network is still opportunistic in the sense that it is unknown apriori how many nodes in a level can correctly decode the message. At any level, a node becomes DF, when the signal-to-noise ratio (SNR) of the received signal at that node, after post-detection combining, is greater than or equal to a modulation dependent threshold, τ. The filled circles in Fig. 1. show the DF nodes. We assume that the transmit power, P_t, is same for all nodes. We define $\mathbb{N}_n$ to be the set of indices of those nodes that decoded the message successfully at time instant or level *n*. For instance, from Fig. 1, $\mathbb{N}_{n-1} = \{1, 4\}$, $\mathbb{N}_n = \{1, 2\}$, and $\mathbb{N}_{n+1} = \{1, 3\}$. The received power at any time instant *n* on the *k*th node is given by

$$Pr_k(n) = \frac{P_t}{d^\beta} \sum_{m \in \mathbb{N}_{n-1}} \frac{\nu_{mk}}{(M - m + k)^\beta}, \tag{1}$$

where the summation is over the DF nodes in the previous level $(n-1)$ and β is the path loss exponent with a usual range of 2-4. The shadowing channel coefficient, ν_{mk}, from node *m* in level $(n-1)$ to node *k* in level *n* is log-normal RV; $\nu_{mk} = e^Y$, where $Y \sim \mathcal{N}\left(\bar{\mu}_Y, \bar{\sigma}_Y^2\right)$; $\bar{\mu}_Y = \lambda \mu_Y$ and $\bar{\sigma}_Y^2 = \lambda {\sigma_Y}^2$, where μ_Y (dB) is the mean of Y, σ_Y (dB) is the standard deviation of Y, and $\lambda = \ln 10/10$ [10]. The standard deviation, σ_Y, is called the dB spread and its typical value is between 6-12 dB for practical channels, depending upon the severity of the shadowing. We assume perfect synchronization between nodes of a level such that the DF nodes transmit the signal at the same time.

III. Modeling By Markov Chain

At a certain time *n*, the state of each node is represented by a binary indicator RV, $\mathbb{I}$, such that for *k*th node at time instant *n*, $\mathbb{I}_k(n) = 1$ represents that the node *k* has decoded and $\mathbb{I}_k(n) = 0$ represents that the node *k* has not decoded the data. The state of each level can be represented as $\mathcal{X}(n) = [\mathbb{I}_1(n), \mathbb{I}_2(n), ..., \mathbb{I}_M(n)]$. We notice that the outcome of $\mathcal{X}(n)$ is an M-bit binary word, each outcome comprises a state, and the total number of states are 2^M starting from 0 to $2^M - 1$ in decimal. For example $i_n = \{1100\}$ in binary, and $i_n = 12$ in decimal from Fig. 1. Since the state at any time depends upon the transmissions from previous level only, therefore $\mathcal{X}$ is a memoryless Markov process. It can be further noticed that the Markov chain, $\mathcal{X}$, can go into an absorbing state at any point in time with nonzero probability, thus terminating the transmissions. At that time the Markov chain will be in 0 state (decimal) and this state will occur when all the nodes in a hop fail to decode the message correctly. Thus the state space of Markov chain $\mathcal{X}$ is $\{0\} \cup S$, where 0 is the absorbing state and S is a finite transient irreducible state space; $S = \left\{1, 2, ..., 2^{M-1}\right\}$. If we remove the transitions to and from the absorbing state, the resulting transition matrix, $\mathbf{P}$, is square, irreducible, nonnegative and right sub-stochastic.

According to the theory of Markov chain, we know that a distribution $\mathbf{u} = (u_i, i \in S)$ is called ρ-invariant distribution if $\mathbf{u}$ is the left eigenvector of this particular transition matrix, $\mathbf{P}$, corresponding to the eigenvalue ρ, where ρ is the maximum eigenvalue of $\mathbf{P}$, i.e., $\mathbf{uP} = \rho \mathbf{u}$. Since $\forall n, \mathbb{P}\{\mathcal{X}(n) = 0\} > 0$, thus ultimate killing is certain. But we want to find the distribution of the transient states, before the killing state occurs. This type of limiting distribution is called the quasi-stationary distribution of the Markov chain [4], which is independent of the initial conditions of the process. This unique distribution is given by the ρ-invariant distribution for one-step transition probability matrix of the Markov chain on S. We can find the quasi-stationary distribution by first calculating the *maximum* eigenvector, $\hat{\mathbf{u}}$ of $\mathbf{P}$, then defining $\mathbf{u} = \hat{\mathbf{u}} / \sum_{i=1}^{2^M-1} \hat{\mathbf{u}}_i$, as a normalized version of $\hat{\mathbf{u}}$, that sums to one. Thus the unconditional probability of being in state j at time instant n is

$$\mathbb{P}\{\mathcal{X}(n) = j\} = \rho^n u_j, \; j \in S, n \geq 0. \tag{2}$$

We also let $T = \inf\{n \geq 0 : \mathcal{X}(n) = 0\}$ denotes the end of survival time, i.e., the time at which the killing occurs. It follows then $\mathbb{P}\{T > n + n_0 | T > n\} = \rho^{n_0}$, while the quasi-stationary distribution of Markov chain is, $\lim_{n\to\infty} \mathbb{P}\{\mathcal{X}(n) = j | T > n\} = u_j, \; j \in S$.

The next step is to find the state transition probability matrix, $\mathbf{P}$, for our model, the eigenvector of which is quasi-stationary distribution. Let i and j denote a pair of states of the system at time instant $(n-1)$ and n, respectively, such that $i, j \in \{1, 2, ..., 2^M - 1\}$, where i and j are the decimal equivalent of the binary word formed by the set of indicator RVs. Let the received SNR at the kth node at time instant n be given as $\gamma_k(n) = Pr_k(n)/\sigma^2_{noise}$, where σ^2_{noise} is the variance of noise at kth receiver, and Pr is the received power as given in (1). Without the loss of generality, we assume identical noise variances for all the nodes at any time instant. Now for each node k, the conditional probability of being able to decode at time n is given as

$$\begin{aligned}&\mathbb{P}\{\text{node } k \text{ of level } n \text{ will decode } |\psi\} = \\ &\quad \mathbb{P}\{\mathbb{I}_k(n) = 1|\psi\} = \mathbb{P}\{\gamma_k(n) > \tau|\psi\},\end{aligned} \tag{3}$$

where the event ψ is defined as $\psi = \{\mathcal{X}(n-1) \in S\}$, implying that the previous state is a transient state. In the same way, the probability of outage or the probability of $\mathbb{I}_k(n) = 0$ is given as $1 - \mathbb{P}\{\gamma_k(n) > \tau|\psi\}$, where

$$\mathbb{P}\{\gamma_k(n) \geq \tau|\psi\} = \int_\tau^\infty p_{\gamma_{k|\psi}}(y)dy, \tag{4}$$

where $p_{\gamma_{k|\psi}}$ is the conditional PDF of the received SNR at the kth node conditioned on the state $\mathcal{X}(n-1)$. It can be noted that the received power at a certain node is the sum of the finite powers from the previous level nodes, each of which is log-normally distributed. However, the sum of log-normal RVs does not have a closed form expression [7]. Therefore, we use Fenton-Wilkinson's approximation method to find the sum distribution [9]. This method was originally developed for independent log-normal RVs, but it was extended for the approximation of correlated log-normal RVs in [10]. We want to find the complementary distribution function of the sum of N correlated log-normal RVs $(\gamma_1, \gamma_2, ..., \gamma_N)$, where $\max|N| \leq M$. Let $\gamma = \gamma_1 + \gamma_2 + ... + \gamma_N$. This method approximates the sum of log-normal RVs by an another log-normal RV. So γ becomes

$$\gamma = e^{Y_1} + e^{Y_2} + ... + e^{Y_N} \cong e^L, \tag{5}$$

where L is a Gaussian RV; $L = \sum_{m=1}^N Y_m$, and each Y_m is also Gaussian RV with mean μ_{Y_m} and variance $\sigma^2_{Y_m}$. To create a vector of N correlated Gaussian RVs $\mathbf{Y} = [Y_1, Y_2, ..., Y_N]^T$, where T denotes the transpose operation, first a vector of uncorrelated Gaussian RV, $\mathbf{X}$, is created. Then by using a linear transformation $\mathbf{Y} = \mathbf{CX}$, the desired correlated RVs are obtained. The matrix $\mathbf{C}$ is given as $\mathbf{\Gamma} = \mathbf{CC}^T$, and is found by using the Cholesky factorization [12], where $\mathbf{\Gamma}$ is the correlation matrix given by

$$\mathbf{\Gamma} = \begin{bmatrix} 1 & r_{12} & \cdots & r_{1N} \\ \vdots & \vdots & \ddots & \vdots \\ r_{N1} & r_{N2} & \cdots & 1 \end{bmatrix}. \tag{6}$$

$\mathbf{\Gamma}$ is symmetric and positive semi-definite, which is a necessary condition for correlation model [11]. It is important to mention that the size of $\mathbf{\Gamma}$ may change on every hop as the number of DF nodes may change from level to level. Remember that each X_m denotes the received SNR when mth node in the previous level transmits. We select identical variance σ^2 for each X_m, however, because of the path loss the mean of each X_m varies and is given as

$$\mu_{X_m} = \frac{P_t}{d^\beta (M - m + k)^\beta}, \tag{7}$$

where k is the position of the receiving node at time instant n, m is the position of the transmitting node at level $(n-1)$, and the rest of the variables have the usual meaning.

The mean $\mu_L{}^{(k)}$ and standard deviation $\sigma_L{}^{(k)}$ of L at kth node in (5) in Fenton-Wilkinson's method is found by matching the first two moments of L with the first two moments of $(\gamma_1 + \gamma_2 + ... + \gamma_N)$. Let ϕ_1 and ϕ_2 represent the first and second moment of $(\gamma_1 + \gamma_2 + ... + \gamma_N)$, respectively, then matching the first moment gives

$$\mathbb{E}[\gamma] = e^{\mu_L{}^{(k)} + \sigma^2_L{}^{(k)}/2} = \sum_{m=1}^N e^{\mu_{Y_m} + \sigma^2_{Y_m}/2} = \phi_1. \tag{8}$$

In the same way, matching the second moment gives

$$\begin{aligned}\mathbb{E}\left[\gamma^2\right] = e^{2\mu_L{}^{(k)} + 2\sigma^2_L{}^{(k)}} = \sum_{m=1}^N e^{2\mu_{Y_m} + 2\sigma^2_{Y_m}} + 2 \sum_{m=1}^{N-1} \\ \sum_{l=m+1}^N \left\{ e^{\mu_{Y_m} + \mu_{Y_l}} e^{\frac{1}{2}\left(\sigma^2_{Y_m} + \sigma^2_{Y_l} + 2r_{ml}\sigma_{Y_m}\sigma_{Y_l}\right)} \right\} = \phi_2,\end{aligned} \tag{9}$$

where r_{ml} is the correlation coefficient between Y_m and Y_l. From (8) and (9) the $\mu_L{}^{(k)}$ and $\sigma^2_L{}^{(k)}$ can be obtained as

$$\mu_L{}^{(k)} = 2\ln\phi_1 - \frac{1}{2}\ln\phi_2, \tag{10}$$

$$\sigma^2_L{}^{(k)} = \ln\phi_2 - 2\ln\phi_1. \tag{11}$$

Hence the conditional probability of a single node, k, to decode correctly in (4) becomes

$$\begin{aligned}\mathbb{P}\left\{\gamma^{(k)} \geq \tau|\psi\right\} = \mathbb{P}\left(e^L \geq \tau\right) = \mathbb{P}\left(L \geq \ln\tau\right) = \\ Q\left(\frac{\ln\tau - \mu_L{}^{(k)}}{\sigma_L{}^{(k)}}\right),\end{aligned} \tag{12}$$

where $\gamma^{(k)}$ is the received SNR at kth node in the receiving level at time instant n, $\mu_L{}^{(k)}$ and $\sigma_L{}^{(k)}$ denote the mean and standard deviation of the SNR at node k, where $k = \{1, 2, ..., M\}$ and the respective SNR levels of other nodes change by (10) and (11), which are further dependent upon (7) and the number of transmitting nodes N. In (12), Q-function denotes the tail probability; $Q(x) = \frac{1}{2\pi}\int_x^\infty e^{-t^2/2}dt$. Equation (12) describes the success probability of one node. For M nodes in a level, let $\mathbb{N}_n^{(j)}$ and $\overline{\mathbb{N}}_n^{(j)}$ denotes the set of indices of those nodes, which are 1 and 0, respectively, at time instant n in state j, then the one-step transition probability for going from state i to j is given as

$$\mathbb{P}_{ij} = \prod_{k\in\mathbb{N}_n^{(j)}} \left\{Q\left(\frac{\ln\tau - {\mu_L}^{(k)}}{{\sigma_L}^{(k)}}\right)\right\} \times \prod_{k\in\overline{\mathbb{N}}_n^{(j)}} \left\{1 - Q\left(\frac{\ln\tau - {\mu_L}^{(k)}}{{\sigma_L}^{(k)}}\right)\right\}. \quad (13)$$

Equation (13) provides one entry of the matrix $\mathbf{P}$. Similar procedure is used to find all the entries of $\mathbf{P}$, which can then be used to find the quasi-stationary distribution of the Markov chain.

IV. Results

In this section, we present numerical results based on simulation and analysis. Various correlation models have been proposed in literature, however, we use an exponential model to characterize the correlation between the channel gains of various transmitters. More specifically, the correlation between transmitters decorrelates exponentially with distance [11]. The correlation coefficient between two transmitters x and y is given as $r_{xy} = \exp^{-|d_{xy}|/d_0}$, where d_{xy} is the distance between x and y and d_0 is a tunable parameter known as decorrelation distance. Without the loss of generality, we assume $d_0 = 1$ throughout our results.

For simulation purposes, we calculate the received power at each node based on the previous state (assuming an initial distribution for the first hop), which sets the indicator functions as either 0 or 1 depending upon the threshold criterion. These indicator functions form the current state and the process continues until an absorbing state is reached. We obtain the distribution of the chain by averaging over 1 million simulation trials. Fig. 2. shows the probability of state distribution of the Markov chain at different hops, for $M = 2$, $r_{xy} = 0.3$, and $\sigma = 4$dB. In this case, the total number of transient states is 3, namely $\{0, 1\}$, $\{1, 0\}$, and $\{1, 1\}$. The figure shows the probability of being in all three states at various hops by using both the network simulation results and the analytical model. It can be seen that analytical results are quite close to simulation results, which shows the validity of our analytical model. It can be noticed that as the hop count increases, the probability of being in transient state decreases, which shows that eventually the transmission will stop propagating. Similar results are obtained for other values of M, which are not shown here to avoid repetition. The rest of the figures, i.e., Figs. 3-5 are based on analytical expression (13).

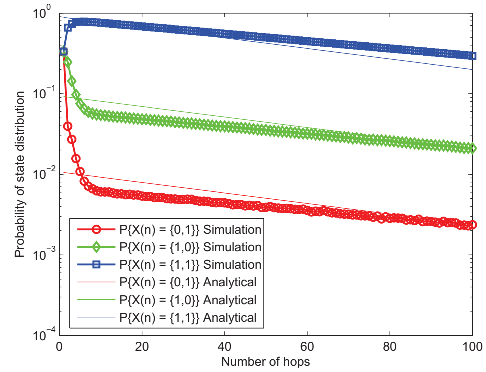

Fig. 2. Comparison of state distribution of analytical and simulation model; for $M = 2$.

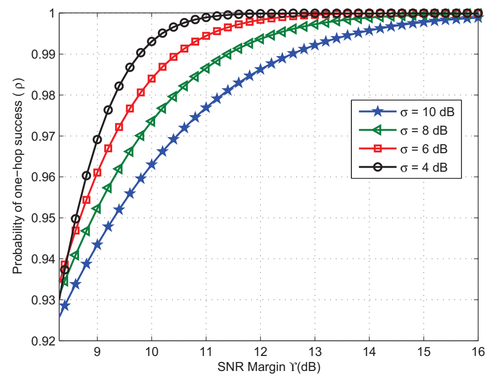

Fig. 3. Probability of one-hop success vs. SNR margin for $M = 3$.

Fig. 3. shows the probability of one-hop success, ρ, which is the probability that at least one node in a level decoded successfully, versus SNR margin, Υ, for various values of shadowing standard deviation, σ, and keeping $M = 3$ fixed. One-hop success probability is given by the maximum eigenvalue of $\mathbf{P}$ and SNR margin, Υ, is defined by normalizing the received SNR at a node, which is a distance d away from its transmitter. Specifically, $\Upsilon = \frac{P_t}{d^\beta \tau}$. For the simulation results

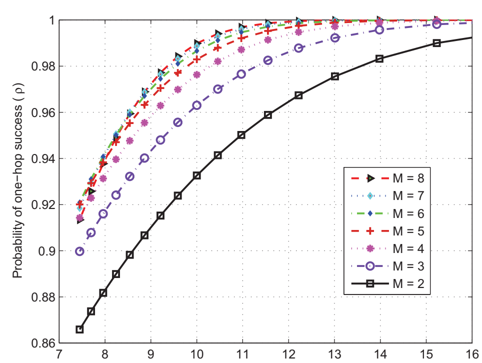

Fig. 4. Probability of one-hop success vs. SNR margin for σ = 10dB.

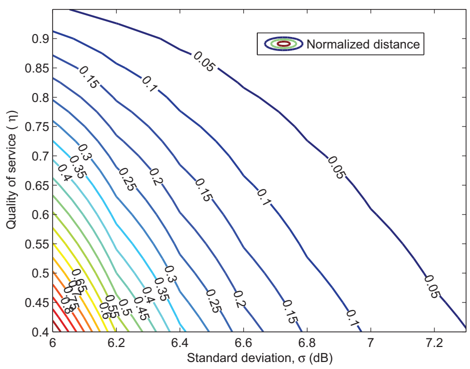

Fig. 5. Contours of normalized distance as a function of η and σ; $\Upsilon = 15$ dB and $M = 6$.

we keep unit P_t and unit d, while $\beta = 2$. It can be noticed that as the SNR margin is increased, the one-hop success probability also increases. However, by increasing the standard deviation, σ, of log-normal shadowing for a fixed value of Υ, the probability of success drops, which shows the effect of the severity of shadowing on the network performance. All curves for various σ converge at higher Υ, which shows that by increasing Υ we can overcome the loss incurred by shadowing.

In Fig. 4. by keeping the σ constant, we plot the probability of one-hop success, ρ, against Υ for various values of M. It can be seen that by increasing M, the probability of success also increases, which shows the effect of increased transmitter diversity on the system. For a fixed Υ, if we define the gain in success probability as, $\Delta\rho_{xy} = \rho|_{M=y} - \rho|_{M=x}$, then it can be seen that $\Delta\rho_{23}$ is larger as compared to $\Delta\rho_{34}$. For example at Υ of 8 dB, $\Delta\rho_{23} \approx 0.036$ while $\Delta\rho_{34} \approx 0.01$. Thus it shows that the diversity gain obtained while increasing M has a *diminishing* behavior and once reached to saturation, a further increase in M will not achieve any gain at a particular value of Υ.

From the deployment perspective of the network, it is some times required to optimize the values of certain parameters like transmit power of relays or distance between them. This optimization is done to obtain a certain quality of service (QoS), η. The QoS is the probability of delivering the message to a certain distance without being entered into the absorbing state, and the ideal value of η is 1. Thus the theory of quasi-stationary Markov chain [4] provides an upper bound on the number of hops, n_0, one can go with a given η, i.e., $\rho^{n_0} \geq \eta$, which gives $n_0 \leq \frac{\ln \eta}{\ln \rho}$. Multiplying the number of hops, n_0, by M provides the maximum distance that can be reached with a certain QoS, η. Fig. 5. shows the contours of normalized distance that can be reached as a function of η and σ, at a specific SNR margin of $\Upsilon = 15$ dB and $M = 6$. We normalize the distance by dividing it by the maximum distance, which for this particular case is $1.8167e8$. Normalization is only done for a better representation of the figure. It can be noticed that a particular coverage can be obtained having different combinations of η and σ. However, σ is environment dependent and by keeping all other parameters such as Υ and M fixed, the message can only reach larger distance with low QoS. Further, it can be noted from the figure that σ severely effects QoS. For example a normalized distance of 0.1 can be reached with $\eta \approx 0.9$ when $\sigma \approx 6$ dB, however, when $\sigma \approx 7$ dB, then the same normalized distance of 0.1 can be reached with $\eta \approx 0.4$, reflecting a loss in QoS. Hence it can be seen that the proposed model precisely quantifies the coverage area of a line network under various parameters. This could help a network deployer to efficiently decide various network parameters such as level of cooperation, SNR margin, and QoS for better system performance.

V. Conclusion

A stochastic model for correlated shadowing for cooperative multi-hop linear network has been presented in this paper. The log-normal PDF of the received power is obtained using the Fenton-Wilkinson's method and is incorporated into the model. The coverage of this network is found by applying the Perron-Frobenius theory of nonnegative matrices. The effects of shadow standard deviation has been quantified on the performance of the network and it has been shown that an increase in the standard deviation of shadowing decreases the coverage of the network under a given transmit power constraint. As a future work, it is recommended to extend this model for two-dimensional network and study the joint effects of small-scale and large-scale fading on the performance of cooperative multi-hop networks.

References

[1] J. N. Laneman, D. N. C. Tse, and G. W. Wornell, "Cooperative diversity in wireless networks: Efficient protocols and outage behavior," *IEEE Trans. Inf. Theory*, vol. 50, pp. 3062-3080, Dec. 2004.

[2] A. Scaglione and Y. W. Hong, "Opportunistic large arrays: Cooperative transmission in wireless multi-hop ad hoc networks to reach far distances," *IEEE Trans. Signal Process.*, vol. 51, no. 8, pp. 2082-92, Aug. 2003.

[3] B. S. Mergen and A. Scaglione, "A continuum approach to dense wireless networks with cooperation," in *Proc. IEEE INFOCOM*, pp. 2755-2763, Mar. 2005.

[4] S. A. Hassan and M.A. Ingram, "A quasi-stationary Markov Chain model of a cooperative multi-hop linear network," *IEEE Trans. Wireless Commun.*, vol. 10, no. 7, pp. 2306-2315, July 2011.

[5] S. A. Hassan and M. A. Ingram, "The benefit of co-locating groups of nodes in cooperative line networks," *IEEE Commun. Lett.*, vol. 16, no. 2, Feb. 2012.

[6] M. Bacha and S. A. Hassan, "Distributed versus cluster-based cooperative linear networks: A range extension study in Suzuki fading environments," in *Proc. IEEE PIMRC*, London, Sep. 2013.

[7] G. L. Stuber, *Principles of Mobile Communications*. 3rd Ed., Springer Publisher, 2011.

[8] S. Schwartz and Y. Yeh, "On the distribution function and moments of power sums with lognormal components," *Bell Syst. Tech. J.*, vol. 61, pp. 1441-1462, 1982.

[9] L. F. Fenton, "The sum of lognormal probability distributions in scatter transmission systems," *IRE Trans. Commun. Syst.*, vol. CS-8, pp. 57-67, 1960.

[10] A. A. Abu-Dayya and N. C. Beaulieu, "Outage probabilities in the presence of correlated lognormal interferers," *IEEE Trans. Veh. Technol.*, vol. 43, pp. 164-173, 1994.

[11] S. S. Szyszkowicz, H. Yanik. and J. S. Thompson, "On the feasibility of wireless shadowing correlation models," *IEEE Trans. Veh. Technol.*, vol. 59, no. 9, pp. 4222-4236 Nov. 2010.

[12] T. Klingenbrunn and P. Mogensen, "Modeling cross-correlated shadowing in network simulations," in *Proc. IEEE VTC*, vol. 3, pp. 1407-1411, Sep. 1999.