Distributed versus Cluster-Based Cooperative Linear Networks: A Range Extension Study in Suzuki Fading Environments

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—**This paper studies two topologies for cooperative multi-hop linear networks; a distributed equi-distant node topology and a co-located group of nodes topology such that both topologies operate under composite shadowing-fading environment. The transmission from one hop to another in both topologies is modeled as a Markov process where the underlying channel model is drawn from a Suzuki distribution. The distribution of the sum of multiple Suzuki random variables (RVs) is obtained by a moment generating function (MGF)-based approximation technique. It is shown that the coverage of both topologies is different contingent upon the severity of shadowing and the transmit power of the radios. The optimal level of cooperation between nodes is shown to have a dependency on the path loss exponent such that a large number of cooperators is optimal for a small path loss exponent and vice versa for obtaining the maximum range of the network. Monte Carlo simulations are performed to validate the analytical model.**

I. Introduction

Cooperative transmission (CT) has attracted a lot of researchers in the past decade as an efficient tool to mitigate multi-path fading by achieving spatial diversity. It not only provides a way of reliable communication but also various other benefits of range extensions [1], energy efficiency [2], and increased capacity can be achieved at the expense of utilizing relay nodes. While a simple cooperative strategy employs a single relay node in addition to a source and a destination, a cooperative sensor network uses a multitude of sensors and provides longevity in range by employing multi-hop communications. In a multi-hop CT network, same message is propagated over a number of hops to a distant destination, where each hop contains a specified or arbitrary number of sensors. Opportunistic large array (OLA) is an example of such CT multi-hop networks in which a large number of sensor nodes deployed in an area propagates a message to a far away destination by using CT at each hop.

Range extension is one fundamental benefit that can be achieved by an OLA network if the nodes are deployed in an optimal fashion [3]. The deployment strategy becomes important when there is a fixed number of nodes and it is desired to service a certain area by having connectivity between them such that a message can be propagated to a destination with a certain reliability. Assume a hazardous situation where it is desirable to obtain a particular information with the use of mobile sensor robots as the environment is unsafe for humans (for instance, a poisonous chemical discharge in a factory). However, it is also desirable to deploy the sensor robots in such a way that the connectivity is maintained between the robots and the information can be exchanged over a specified distance. Following questions need answers, "what transmit power is required for the sensors to obtain a certain reliable communications, what level of cooperation is needed, what kind of topology is optimal, would an equi-distant topology be helpful or co-locating groups of nodes would work, what if environment is shadowed in addition to multi-path fading?" In this paper, we will study these situations by analyzing a cooperative multi-hop linear OLA network operating under composite shadowing-fading environment with an arbitrary path loss exponent.

Many contributions to OLA have appeared in literature. For instance, the concept was given in [4] with an assumption of infinite nodes in a area such that the power radiated from a fixed area remains constant. However, for practical finite-density networks, this approach might not be appropriate. Studies on finite density OLA networks include [5] and [6], where the upper bounds are derived on network coverage for a given transmit power. A Rayleigh fading channel model was assumed. However, practical channels are characterized by shadowing along with small-scale fading. As the received power in a cooperative network is the sum of transmitted powers from the cooperators of the previous level, a sum distribution of the received power, which becomes a Suzuki distribution, has been used in this paper. We use the approach of [7] to find the sum distribution of the Suzuki RV and formulate a Markov process that characterize the transmissions propagating from one level of nodes to the other under a composite shadow-fading environment.

In this paper, we study two topologies of linear network; a distributed *equi-distant* topology where the nodes are spaced equally apart from one another, and a *co-located* topology where the cooperating nodes are co-located in the form of a cluster and transmit as a multi-hop multiple-input multiple-output (MIMO), however the detection process is individual in each node as opposed to a conventional MIMO with joint detection. We will call the distributed node topology as the equi-distant one and the cluster-based topology as the co-located topology. It has been shown in this paper that the

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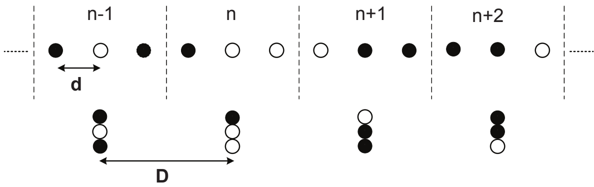


Fig. 1. Equi-distant and co-located network topologies.

equi-distant topology performs better under severe shadowing conditions. However, the choice of using the optimal topology depends on the transmit power of the radios. We also provide the optimal placement of nodes in a linear network that would guarantee a specific success probability for a given standard deviation of shadowing and the path loss exponent. It has been shown that a small-sized cluster provides maximum range for a high path loss exponent and vice versa. We quantify the maximum achievable distance for various values of path loss exponent and the optimal level of node cooperation.

The rest of the paper is organized as follows. Section II describes the equi-distant and co-located network topologies. In Section III, we model the network as a Markov chain, while in Section IV, we derive the transition probability matrix of the Markov chain. Section V discusses various simulation and analytical results, while Section VI concludes the paper.

II. System Description

Consider two linear topologies, an equi-distant and a co-located topology as shown in Fig. 1 In equi-distant topology, the nodes are at distance d away from each other and the network is divided into non-overlapping sets of nodes, such that each group or *level* comprises *M* nodes as shown in the top plot of Fig. 1. The M nodes in one level cooperate with each other to forward the same message signal to the M nodes of the next level. However, only those nodes take part in transmission that have decoded the data perfectly from the transmission of the previous level nodes. These nodes are called decode-and-forward (DF) nodes. The number of DF nodes in a level is unknown apriori, implying that the network is opportunistic. A node becomes a DF node when the signal-to-noise ratio (SNR) of the received signal, after post-detection combining, is greater than or equal to a modulation dependent threshold, τ. The DF nodes in Fig. 1 are shown by filled circles. We assume same transmit power, P_t, for all the nodes and label the set of indices of DF nodes at time instant or level *n* by $\mathbb{N}_n$. For example, from figure, $\mathbb{N}_{n+2} = \{1, 2\}$, and $\mathbb{N}_{n+1} = \{2, 3\}$. The received power at a *k*th node at time instant *n* is given by

$$P_{r,k}(n) = \frac{P_t}{d^\beta} \sum_{m \in \mathbb{N}_{n-1}} \frac{S_{mk}}{(M - m + k)^\beta}, \qquad (1)$$

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 composite channel coefficient, S_{mk}, from node *m* in level $(n-1)$ to node *k* in level *n* is modeled as a Suzuki random variable (RV), which is a combination of Rayleigh and log-normal RV.

For the co-located topology, the nodes are placed closed to each other (with at least half wavelength spacing so that independent fading assumption can be satisfied), such that the distance between adjacent group of nodes is D, where, $D \cong Md$. The node density and the hop distance of both topologies remain the same. Similarly, the received power in co-located case is, $P_{r,k}(n) = \frac{P_t}{D^\beta} \sum_{m \in \mathbb{N}_{n-1}} S_{mk}$. In this work, we assume that nodes in a level have perfect synchronization so that the DF nodes transmit the signal at the same time.

III. Modeling By Markov Chain

We represent the state of each node by a binary indicator RV, $\mathbb{I}$, such that $\mathbb{I}_k(n) = 1$ represents that the node k has decoded successfully at time n and $\mathbb{I}_k(n) = 0$ shows that it has not decoded the data correctly. In the same way, the state of each level can be represented as $\mathcal{X}(n) = [\mathbb{I}_1(n), \mathbb{I}_2(n), ..., \mathbb{I}_M(n)]$ where the outcome of $\mathcal{X}(n)$ is an M-bit binary word. Each outcome is a state, and there are 2^M total number of states, starting from 0 to $2^M - 1$ in decimal. If i_n represents the state at time instant n, then from Fig. 1, $i_{n-1} = \{101\}$ in binary, while $i_{n-1} = 5$ in decimal. It can be noticed that $\mathcal{X}$ constitutes a Markov process because the state at any time depends upon the transmissions from the previous level only. Further investigation reveals that the Markov chain can reach an absorbing state at any point in time with some nonzero probability, terminating the process of transmission. At that time, the state of the Markov chain will be 0 (decimal) and will happen only when all the nodes in a level fail to decode the message perfectly. Thus $\{0\} \cup T$ constitutes the state space of the Markov chain $\mathcal{X}$, where *T* is the finite transient irreducible state space; $T = \{1, 2, ..., 2^{M-1}\}$ and 0 being the absorbing state such that $\lim_{n\to\infty} \mathbb{P}\{\mathcal{X}(n) = 0\} \nearrow 1$ a.s. The Markov chain, $\mathcal{X}$, can be completely characterized by finding the transition probability matrix, $\mathbf{P}$, corresponding to $\mathcal{X}$. If we remove the transitions to and from the absorbing state, the resulting $\mathbf{P}$ is square, irreducible and right sub-stochastic with a dimension of $(2^M - 1) \times (2^M - 1)$.

By the Perron-Frobenius theory of Markov chain, a distribution $\mathbf{u} = (u_i, i \in T)$ is called ρ-invariant distribution if $\mathbf{u}$ is the left eigenvector of this particular transition matrix, $\mathbf{P}$, which corresponds to ρ, where ρ is the maximum eigenvalue of $\mathbf{P}$, i.e., $\mathbf{uP} = \rho\mathbf{u}$. In the meantime $\forall n, \mathbb{P}\{\mathcal{X}(n) = 0\} > 0$, therefore ultimate killing is certain. However, we are interested in finding the distribution of the transient states, just before the absorbing state is reached. This limiting distribution is known as the quasi-stationary distribution of the Markov chain [5], and is independent of the initial conditions of the process. The ρ-invariant distribution for one-step transition probability matrix of the Markov chain on *T* gives us this unique distribution. To find the quasi-stationary distribution, we first calculate the *maximum* eigenvector, $\hat{\mathbf{u}}$, of $\mathbf{P}$. 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, gives the quasi-stationary distribution of $\mathcal{X}$. Hence the unconditional probability of being in state *j* at time instant *n* is given as

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

We also let $\Phi = \inf\{n \geq 0 : \mathcal{X}(n) = 0\}$ denotes the end of survival time, i.e., the time at which the killing occurs. It follows then

$$\mathbb{P}\{\Phi > n + n_0 | \Phi > n\} = \rho^{n_0}, \qquad (3)$$

while the quasi-stationary distribution of the Markov chain is given as $\lim_{n\to\infty} \mathbb{P}\{\mathcal{X}(n) = j|\Phi > n\} = u_j,\ j \in T$.

IV. Formulation of Transition Probability Matrix

In this section, we find the state transition probability matrix, $\mathbf{P}$, of the network, by considering the channel as composite fading channel. Let *i* and *j* represent two states of the system at time instant $(n-1)$ and n, respectively, such that $i, j \in T$. The received SNR at time instant n on the *k*th node is given as $\gamma_k(n) = P_{r,k}(n)/\sigma^2_{noise}$, where σ^2_{noise} is the noise variance at the *k*th receiver, and P_r is the received power as given in (1). For all the nodes in a level, we assume identical noise variance. Now for a node *k*, the conditional probability of being able to decode successfully at time *n* is given as

$$\mathbb{P}\{\mathbb{I}_k(n) = 1|\varphi\} = \mathbb{P}\{\gamma_k(n) > \tau|\varphi\}, \tag{4}$$

where the event φ is defined as $\varphi = \{\mathcal{X}(n-1) \in T\}$, indicating that the previous state is a transient state. Equation (4) can be written as

$$\mathbb{P}\{\gamma_k(n) \geq \tau|\varphi\} = \int_\tau^\infty p_{\gamma_{k|\varphi}}(y)dy, \tag{5}$$

where $p_{\gamma_{k|\varphi}}$ is the conditional PDF of the received SNR at the *k*th node conditioned on the state $\mathcal{X}(n-1)$. It can be observed that the received SNR at a certain node is the sum of the finite SNRs from the previous level nodes (assuming maximal ratio combining for coherent modulation scheme), each of which follows Suzuki distribution. However, the sum distribution of Suzuki RVs does not exist in closed-form. Therefore, to find the sum distribution of Suzuki RVs, we use the moment generating function (MGF)-based method as proposed in [7].

The MGF-based method approximate the sum of N Suzuki RVs $(S_1, S_2, ..., S_N)$ by a single log-normal RV $Y = 10^{0.1X}$, where X is a Gaussian RV with mean μ_X and standard deviation σ_X (in dBs). This method requires that both the MGFs of the Suzuki and the log-normal RV need to be in closed-form. However, the MGFs of both the Suzuki and log-normal RV do not exist in closed-form and can be numerically computed using the Gauss-Hermite quadrature integration [7]. Specifically, the MGF of *k*th Suzuki RV by Gauss-Hermite integration after discarding the remainder terms can be written as

$$\Psi_{S_k}(s; \mu_k, \sigma_k) = \sum_{c=1}^{C} \frac{w_c/\sqrt{\pi}}{1 + s\exp\left(\frac{\sqrt{2}\sigma_k a_c + \mu_k}{\xi}\right)}, \tag{6}$$

where C is the Hermite integration order and a large value of C corresponds to higher accuracy, w_c is the weight corresponding to the abscissas, a_c, and ξ is a constant; $\xi = 10/\ln 10$ [7]. The μ_k and σ_k are the mean and standard deviation of the *k*th Suzuki RV. Similarly, by using the Gauss-Hermite integration, the MGF of the log-normal RV $Y = 10^{0.1X}$ is given as

$$\Psi_Y(s; \mu_X, \sigma_X) = \sum_{c=1}^{C} \frac{w_c}{\sqrt{\pi}} \exp\left[-s\exp\left(\frac{\sqrt{2}\sigma_X a_c + \mu_X}{\xi}\right)\right], \tag{7}$$

where μ_X and σ_X are the mean and standard deviation of the Gaussian RV X. The task is to find the μ_X and σ_X of X as a function of the mean and standard deviation of the individual RVs $(S_1, S_2, ..., S_N)$. The μ_X and σ_X can be found by solving the following two equations

$$\Psi_Y(s_i; \mu_X, \sigma_X) = \prod_{k=1}^{N} \Psi_{S_k}(s_i; \mu_k, \sigma_k),\ \text{at } i = 1 \text{ and } 2. \tag{8}$$

By using (6) and (7), Equation (8) becomes

$$\sum_{c=1}^{C} \frac{w_c}{\sqrt{\pi}} \exp\left[-s_i\exp\left(\frac{\sqrt{2}\sigma_X a_c + \mu_X}{\xi}\right)\right] = \prod_{k=1}^{N} \left(\sum_{c=1}^{C} \frac{w_c/\sqrt{\pi}}{1 + s_i\exp\left(\frac{\sqrt{2}\sigma_k a_c + \mu_k}{\xi}\right)}\right),\ \text{at } i = 1 \text{ and } 2, \tag{9}$$

where, as already stated μ_X and σ_X are the unknown. The right hand side of (9) consists entirely of known quantities and is evaluated twice at s_1 and s_2. By evaluating at $s_1 = 0.2$, we can find μ_X, while using $s_2 = 1.0$ gives σ_X. The values of s_1 and s_2 have been found by solving an optimization problem as listed in [7]. It can be noted that (9) is a non-linear equation and can only be solved numerically. Once the values of μ_X and σ_X have been calculated, the description of the sum distribution can be completely specified, i.e., the sum of the Suzuki RVs has been approximated by a log-normal RV with calculated μ_X and σ_X. Hence the conditional probability that the received SNR ($Y^{(k)} = 10^{0.1X^{(k)}}$) at the kth node is greater than or equal to τ in (5) becomes

$$\mathbb{P}\left\{Y^{(k)} \geq \tau|\varphi\right\} = \mathbb{P}\left(10^{0.1X^{(k)}} \geq \tau\right) = \mathbb{P}\left(X^{(k)} \geq 10\log\tau\right) = Q\left(\frac{10\log\tau - \mu_X{}^{(k)}}{\sigma_X{}^{(k)}}\right), \tag{10}$$

where Q-function denotes the tail probability; $Q(x) = \frac{1}{2\pi}\int_x^\infty e^{-t^2/2}dt$. The success probability of a node depends upon the threshold τ, μ_X, and σ_X; while the μ_X and σ_X further depend on the number N of Suzuki RVs (the number of DF nodes) and the μ and σ of each Suzuki RV as given in (9). Equation (10) provides the success probability of a single node to decode. For M nodes in a level, consider $\mathbb{N}_n^{(j)}$ and $\overline{\mathbb{N}}_n^{(j)}$ as the sets of indices of those nodes, which are 1 and 0, respectively, at time instant n in state j, then the one-step transition probability of going from state i to j is given by

$$\mathbb{P}_{ij} = \prod_{k\in\mathbb{N}_n^{(j)}} \left\{Q\left(\frac{10\log\tau - \mu_X{}^{(k)}}{\sigma_X{}^{(k)}}\right)\right\} \times \prod_{k\in\overline{\mathbb{N}}_n^{(j)}} \left\{1 - Q\left(\frac{10\log\tau - \mu_X{}^{(k)}}{\sigma_X{}^{(k)}}\right)\right\}. \tag{11}$$

Equation (11) gives one entry of the matrix $\mathbf{P}$. Similarly, we can find all entries of $\mathbf{P}$ for every $i, j \in T$.

Finding the Maximum Achievable Distance from Transition Matrix

As mentioned, the transmission mechanism can be fully characterized by exploiting the Perron-Frobenius theorem of the Markov chain. The resulting Perron eigenvalue and the corresponding left eigenvector provides insightful information about the network coverage. The probability of one-hop success, which is the probability that at least one node in a level decodes, is given by the Perron-Frobenius eigenvalue, ρ, of $\mathbf{P}$. For a given probability of one-hop success, the probability of making n successful hops is given as ρ^n. If an end-to-end quality of service, η, is required to be maintained for n number of hops, then $\rho^n \geq \eta$. Conversely, given a desired quality of service (QoS), η, an upper bound on the number of hops is given as $n \leq \frac{\ln \eta}{\ln \rho}$. This implies that the number of successful hops is dependent upon ρ, which further depends on the number of nodes in a level, M. For instance, if the total number of nodes in a network is 24, an $M = 3$ implies 8 number of hops. Thus if $\eta = 95\%$ end-to-end probability of success is desired, then $\rho = \exp\left\{\frac{\ln \eta}{m}\right\}$, which turns out to be 0.9936. Hence, given M and n, the optimal deployment of nodes for range extension can be found by solving the following constraint optimization problem

$$\begin{aligned}&\text{Maximize } d \ \ (\text{or } \ D)\\ &\text{Subject to}\\ &\qquad \rho \geq \exp\left\{\frac{\ln \eta}{m}\right\},\end{aligned} \tag{12}$$

which can be easily solved by a simple search algorithm. Once the optimal value of d or D is computed, the coverage of the network can be achieved by taking a product of the hop distance with the number of hops.

V. Results and System Performance

In this section, we present our simulation and analytical results. In order to simulate the composite envelope, we generate the fading and shadowing processes separately and then multiply them together, while keeping unit mean for the fading envelope. For simulation purposes, we first assume an initial distribution of the first hop and then calculate the received power at a node in the next hop. The indicator function is set to 1 only if the received power is greater than the threshold, τ. Same procedure is repeated for all the nodes in the current hop, which forms the current state and the process continues until an absorbing (all-zero) state is encountered. Fig. 2 shows the probability of state distribution of the equi-distant topologies at different hops, for $\sigma = 10$ dB and $M = 2$. For $M = 2$, the total number of transient states is 3, namely $\{0, 1\}$, $\{1, 0\}$, and $\{1, 1\}$, and this figure shows the probability of being in these transient states at various hops by using both the simulation results and the analytical model. The simulation results are obtained by averaging over one million simulation experiments, whereas the analytical curves are obtained by using (2). It is clear from the figure that both the analytical and the simulation results are quite close to each other, which confirms the accuracy of the proposed analytical model.

Before discussing further result, let's define SNR margin, Υ, as the normalized received SNR at a node, i.e., $\Upsilon = P_t/\tau$. Let ρ_D and ρ_d represent the one-hop success probabilities for the co-located and the equi-distant network topologies, respectively. Fig. 3 shows the difference in success probabilities of the two topologies versus SNR margin for different values of σ, while keeping $M = 4$, and $\beta = 2$. It is important to mention that the hop distance is essentially the same for both the topologies of Fig. 3. It is clear from the figure that at

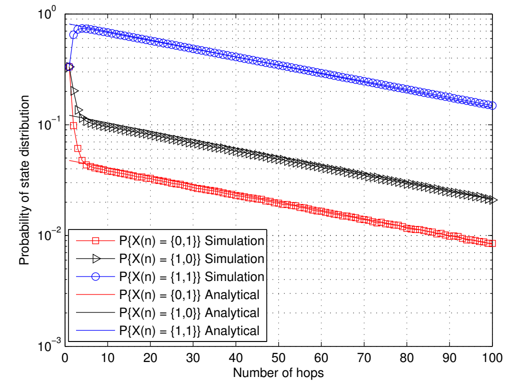


Fig. 2. Comparison of analytical and simulation model for $M = 2$.

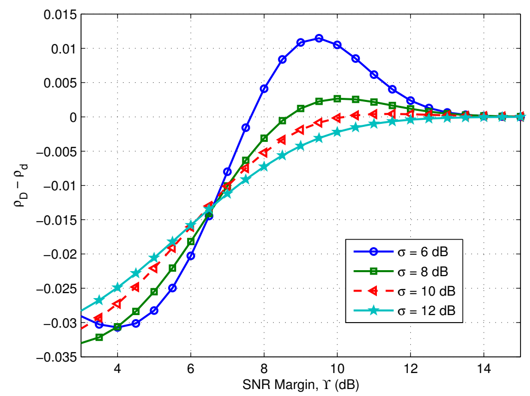
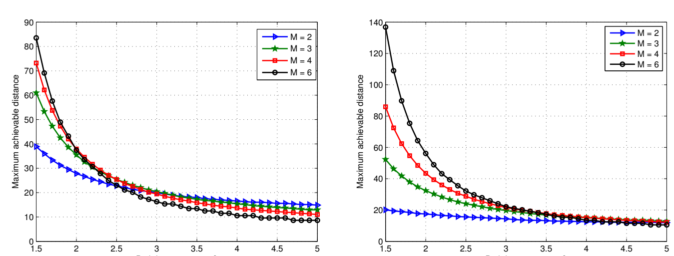


Fig. 3. Comparison of equi-distant and co-located topologies; $M = 4$ and $\beta = 2$.

lower values of Υ, the difference $(\rho_D - \rho_d)$ is negative, which indicates that the equi-distant topology performs better. In the equi-distant topology, the boundary nodes in a level are close to the next level boundary nodes and the transmissions from these boundary nodes can reach to the next level boundary nodes even at low Υ, providing a better performance at low Υ. At the median range of Υ, when σ is low, i.e., upto 8 dB, the co-located topology works better, but at higher σ, only the equi-distant topology provides the most reliable communication. At very higher SNR margin, the performance of both the topologies become equal, which indicates that a higher Υ has



(a) $\sigma = 6$dB (b) $\sigma = 12$dB

Fig. 4. Maximum achievable distance for fixed number of nodes versus path loss exponent.

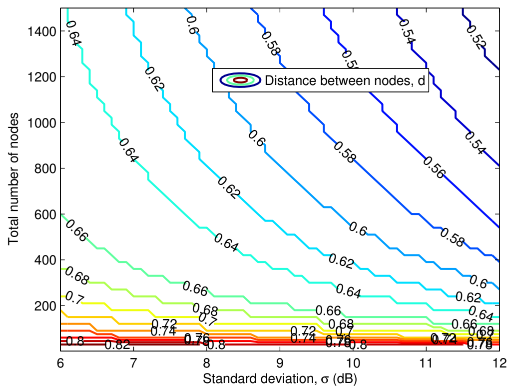


Fig. 5. Contours of of inter-nodal distance for $M = 3$ and $\Upsilon = 15$dB

overcome all the losses. Therefore, in order to get a reliable communication, a specific topology works optimal for given transmit power and σ.

We now consider the problem of range extension for a certain topology. As the equi-distant case outperforms the co-located case at various values of SNR margin as shown in Fig. 3, the upcoming results will be presented for the equi-distant topology. For the range extension, we are given a fixed number, L, of nodes and we are looking for the maximum distance, d, between the nodes such that (12) is satisfied for a given η. Consider $L = 24$, and two different values of standard deviation of the shadowing, i.e., $\sigma = 6$dB and $\sigma = 12$dB, while keeping the QoS, $\eta = 0.9$. We find the coverage of the network by devising various levels of cooperation, i.e., $M \in \{2, 3, 4, 6\}$, such that a cooperation of two nodes, i.e., $M = 2$, requires 12 hops to cover the entire network, $M = 3$ requires 8 hops and so on. Fig. 4 shows the maximum achievable distance versus the path loss exponent for various levels of cooperation and two values of σ in plots (a) and (b), respectively. It is obvious from the figure that as the path loss exponent increases, the coverage of the network decreases. It can be noticed from both parts of the figure that at a lower value of β, choosing a larger M would provide the maximum coverage, however, at a larger β, a smaller M would provide the maximum range. This suggests that irrespective of the shadowing, a small cooperation is well-suited in high path loss environments and vice versa.

It is well known from the literature that the shadowing phenomenon models the fluctuation in the received power around a certain mean; the mean defines the path loss exponent. These fluctuations become large when the σ of shadowing is increased. To see the effect of increased σ, Fig. 4(b) represents the maximum achievable distance for $\sigma = 12$dB. It can be seen that at a lower β and larger M, the range of the network *increases* as the σ is increased to 12dB as compared to Fig 4(a) with $\sigma = 6$dB. This suggests that when the SNR margin is smaller, which corresponds to less average total power received from a cluster of 6 or 5 nodes, one can still get lucky and get a favorable shadowing outcome that allows the packet to stay alive, which eventually increases the ρ and correspondingly the coverage. As we add even more variation in the mean received SNR from any one node, we will see even milder slopes in these one-step probability of success curves, which then translates into distance using (12). Hence a larger number of cooperators will provide better coverage behavior for a large range of path loss exponents in high shadowed environments.

In Fig. 4, we kept the number of nodes in the network fixed and found the coverage of the network for different level of cooperation. However, it is important to see the effects of an increased L (i.e., larger number of hops) for the same level of cooperation, M. Fig. 5 shows the contours of optimal distance between the adjacent nodes as a function of number of nodes in the network and standard deviation of the shadowing, while keeping $M = 3$, $\eta = 0.9$, and $\Upsilon = 15$dB, for an equi-distant network topology. The optimal distance specifies the value such that maximum coverage of the network is achieved given that a certain QoS is satisfied. It can be noticed from Fig. 5 that as number of nodes in the network or σ increases, we need to place the nodes close to each other, such that the QoS is satisfied. For instance, fixing an L specifies that for the same network length, the distance between the adjacent nodes should become smaller if the σ is increased. Similarly, if σ is kept constant, a larger inter-nodal distance is optimal if the network length is decreased.

VI. Conclusion

In this paper, we studied the coverage of distributed equi-distant and co-located network topologies operating under composite shadowing-fading environment. We incorporated the composite channel model and the multi-hop transmission scenario into a Markov chain and then by employing the Perron-Frobenius theory of non-negative matrices, we found the maximum achievable coverage of the network under various system parameters and different levels of shadowing. We have shown that under severe shadowing, the equi-distant topology provides the maximum coverage. We also provided the optimal level of cooperation required to achieve the maximum coverage, for a fixed number of nodes, a range of path loss exponents, and standard deviation of shadowing. The optimal inter-node separation has been quantified for a given network length and standard deviation of shadowing.

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