Capacity Bounds in Random Wireless Networks

Alireza Babaei, Prathima Agrawal, and Bijan Jabbari

Abstract: **We consider a receiving node, located at the origin, and a Poisson point process (PPP) that models the locations of the desired transmitter as well as the interferers. Interference is known to be non-Gaussian in this scenario. The capacity bounds for additive non-Gaussian channels depend not only on the power of interference (i.e., up to second order statistics) but also on its entropy power which is influenced by higher order statistics as well. Therefore, a complete statistical characterization of interference is required to obtain the capacity bounds. While the statistics of sum of signal and interference is known in closed form, the statistics of interference highly depends on the location of the desired transmitter. In this paper, we show that there is a tradeoff between entropy power of interference on the one hand and signal and interference power on the other hand which have conflicting effects on the channel capacity. We obtain closed form results for the cumulants of the interference, when the desired transmitter node is an arbitrary neighbor of the receiver. We show that to find the cumulants, joint statistics of distances in the PPP will be required which we obtain in closed form. Using the cumulants, we approximate the interference entropy power and obtain bounds on the capacity of the channel between an arbitrary transmitter and the receiver. Our results provide insight and shed light on the capacity of links in a Poisson network. In particular, we show that, in a Poisson network, the closest hop is not necessarily the highest capacity link.**

Index Terms: **Capacity, interference, Poisson point process (PPP).**

I. INTRODUCTION

The exact distribution of network self-interference, i.e., the interference originated from the set of nodes simultaneously transmitting with the desired transmitter, is not generally known in random networks. However, assuming that the receiver is subject to a Poisson field of interferers, characteristic function and cumulants of interference power have been found in [1]–[3].

For capacity analysis in a random Poisson network, two simplifying assumptions are usually made. First, interference is assumed to have a Gaussian distribution (e.g., [4], [5]). This assumption renders Shannon capacity result for additive white Gaussian noise (AWGN) channels applicable. The interference, however, is known to be non-Gaussian in a Poisson network [6]. Second, the Poisson point process (PPP) is assumed to model the interferers while the desired transmitter is assumed to be detached and its distance to the receiver to be deterministic [4]. This assumption simplifies the calculation of signal and interference statistics. In a more realistic scenario, the desired transmitter belongs to the PPP that models the locations of nodes in the wireless network. This leads to a more involved problem which is to obtain the statistics of interference when the receiver is subject to a Poisson field comprising of the desired transmitter as well as the interferers. Since the desired transmitter does not contribute to the interference, interference comes from a PPP with one point eliminated.

The Shannon capacity in Poisson wireless networks has been considered in [5]. The author makes the assumption that nodes transmit independent information flows and that every flow is impacted by other flows as if they were Gaussian noise. Based on this assumption, the author makes use of AWGN channel capacity. In their seminal work, Gupta and Kumar consider the transport capacity of wireless network by considering a protocol model and a physical model for successful reception over a hop [7]. Recently, the distribution of interference has been considered in capacity analysis. In [8], considering an ultra wideband (UWB) scenario, in which multiuser interference (MUI) is known to be non-Gaussian, it has been shown that by using higher order statistics of interference and designing receivers which are adapted to the non-Gaussian interference, capacity can improve dramatically. In [9], a generalized Gaussian model is used for interference originated from secondary network in a cognitive wireless network. Power control is used to shape the statistics of interference and to improve the capacity of a primary link. Shannon's capacity bound for the general additive channels can be used to explain the improvement in capacity when statistics of interference, higher than the second order, are considered. For a general additive channel, with the receiver output $y[n] = x[n] + z[n]$, where $z[n]$ is the additive noise/interference, we have

$$W \log_2 \left(1 + \frac{P_r}{N^*}\right) \leq C \leq W \log_2 \left(\frac{N}{N^*} + \frac{P_r}{N^*}\right) \quad (1)$$

where C is the channel capacity, W is the channel bandwidth, P_r is the signal power, N^* is the noise/interference entropy power, and N is the noise/interference power [9]. We consider an interference-limited case, where noise can be ignored compared to the interference. For a general distribution of interference, we have $N \leq N^*$. For fixed interference power, both of upper and lower bounds of capacity, therefore, decrease with the interference entropy power. For the Gaussian distributed interference, as a result of its maximum entropy property, capacity takes the minimum value and the bounds degenerate to equality[1]. We can see that, for a fixed interference power, Gaussian distributed interference is the worst case from capacity perspective whereas non-Gaussian interference can be advantageous to the link capacity.

The previous work for statistical characterization of interference focus on interference power (e.g., [1]–[3]). However, to obtain results for channel capacity, we need to characterize in-

Manuscript received November 26, 2010; approved for publication by Kai-Kit Wong, Division I Editor, August 22, 2011.

A. Babaei and P. Agrawal are with the Department of Electrical and Computer Engineering, Auburn University, Auburn, AL, USA, email: {ababaei, agrawpr}@auburn.edu.

B. Jabbari is with the Department of Electrical and Computer Engineering, George Mason University, Fairfax, VA, USA, email: bjabbari@gmu.edu.

[1] For the Gaussian case, we have $N = N^*$ and $C = W \log_2 (1 + P_r/N)$.

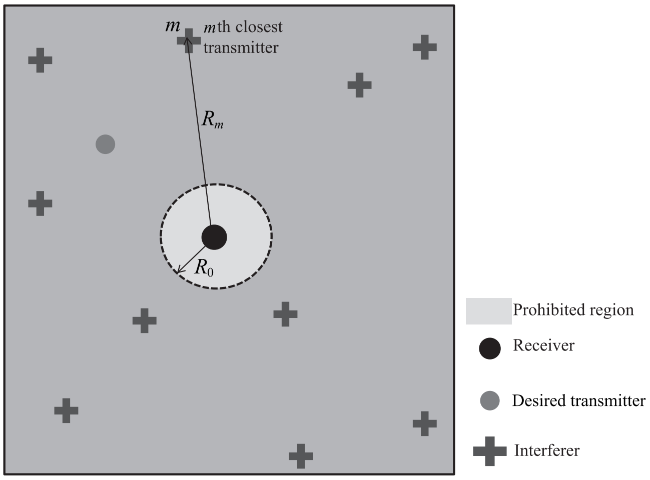

Fig. 1. System model (R_m is the distance between mth nearest transmitter and receiver and R_0 is the radius of the prohibited region).

terference amplitude. In this paper, we consider a Poisson field consisting of the desired transmitter and the interferers and obtain the cumulants of interference amplitude. We then show that the main reason for non-Gaussianity of interference is the interference originated from nodes which are in close proximity to the receiver[2]. We can therefore see that if the desired transmitter has a closer distance to the receiver,

- The received signal is stronger,
- The network self-interference power is smaller, and
- Intuitively, the network self-interference is closer to Gaussian.

This is because the considered node being the desired transmitter and not an interferer, excludes a major source of non-Gaussianity from the set of interferers.

These factors have conflicting effects on the channel capacity. While the first two results lead to higher channel capacity, interference closer to Gaussian means higher entropy power of interference which in turn has an inverse effect on channel capacity (see the upper and lower bounds in (1)). One consequence is that the closest hop may not be the highest capacity link. The aim of this paper is to verify this intuition using quantitative analysis and obtain analytical results on link capacities in Poisson random networks.

II. SIGNAL AND INTERFERENCE STATISTICS

We consider a two-dimensional PPP with density λ that models the locations of the desired transmitter and the interferers and assume that the receiver is located at the origin (see Fig. 1). The desired transmitter and the interferers use the same power level P. Assuming that the desired transmitter is the mth nearest neighbor to receiver, the aggregate of signal and interference amplitudes is $Z = X_m + I_m$, where X_m is the received signal amplitude and I_m is the received interference amplitude. We denote the distance between the receiver and its mth nearest transmitter as R_m (see Fig. 1). The baseband model for the received signal from the mth nearest transmitter is $(\sqrt{P}a_m/R_m^{\alpha/2})\zeta_m e^{j\phi_m}$, where ζ_m is Rayleigh fading component with $E\{\zeta_m^2\} = 1$, $\alpha/2$ is the amplitude loss exponent[3], ϕ_m is a random phase shift uniformly distributed in $[0, 2\pi]$, and a_m is the complex-valued information symbol. Without loss of generality, we assume $P = 1$. Moreover, we can safely assume that ζ_m, R_m, and ϕ_m are independent. In order to characterize the signal and the interference, both in-phase and quadrature-phase components, need to be considered. In [11], the authors find the joint characteristic function of in-phase and quadrature-phase components of interference from finite-area as well as infinite-area Poisson field of interferers[4]. In this paper, we consider a binary phase shift keying (BPSK) modulation with real-valued equiprobable symbols $a_m \in \{-1, 1\}$ and therefore, only focus on the in-phase component. The analysis for a general constellation entails characterizing the quadrature-phase component as well which can be done using exactly the same approach[5]. With this assumption, and defining $U_m = \cos(\phi_m)$, we have $X_m = \zeta_m U_m a_m / R_m^{\alpha/2}$, $Z = \sum_i \zeta_i U_i a_i / R_i^{\alpha/2}$, and $I_m = \sum_{i \neq m} \zeta_i U_i a_i / R_i^{\alpha/2}$. Given that ϕ_m is uniformly distributed in $[0, 2\pi]$ and using transformation of random variables, the probability density function (pdf) of U_m [12] can be found as

$$f_{U_m}(u) = \frac{1}{\pi\sqrt{1-u^2}}, \quad -1 < u < 1. \tag{2}$$

In order to avoid the singularity in the path loss model for small distances, we consider a prohibited region around the receiver and assume that a node cannot transmit if its distance to the receiver is less than R_0 (see Fig. 1). In this section, we seek to obtain the statistics of Z, X_m, and I_m.

A. Cumulants of Sum of Signal and Interference

By using the Campbell's Theorem (see Appendix A), the nth cumulants of $Z = \sum_i \zeta_i U_i a_i / R_i^{\alpha/2}$ can be found as

$$\begin{aligned}\kappa_n(Z) &= 2\pi\lambda E\{a_i^n\} \\ &\quad \cdot \int_{-1}^{1}\int_{0}^{\infty}\int_{R_0}^{\infty}\left(\frac{\zeta u}{r^{\frac{\alpha}{2}}}\right)^n r\, dr f_\zeta(x)\, dx f_U(u)\, du \\ &= \begin{cases} \dfrac{2\pi\lambda\mu_n E\{\zeta^n\}}{\frac{n\alpha}{2} - 2} R_0^{2-\frac{n\alpha}{2}}, & \text{even } n \\ 0, & \text{odd } n\end{cases}\end{aligned}$$

which holds for $2 - n\alpha/2 < 0$[6] and is found using

$$E\{a_i^n\} = \begin{cases} 1, & \text{even } n \\ 0, & \text{odd } n.\end{cases}$$

Using (2), we have

$$\mu_n = E\{U_i^n\} = \int_{-1}^{1}\frac{u^n\, du}{\pi\sqrt{1-u^2}} = \frac{((-1)^n + 1)\,\Gamma(\frac{n+1}{2})}{\sqrt{\pi}n\Gamma\left(\frac{n}{2}\right)}$$

where $\Gamma(\cdot)$ denotes the gamma function[7].

[2] This has been shown to be the case for interference power in [3] and [10].

[3] α is the power loss exponent and its range of values is between 2 and 6 depending on the propagation conditions.

[4] In this paper, unlike [11], the PPP models the locations of both the desired transmitter and the interferers.

[5] Note that the capacity bounds in (1) can still be used with BPSK assumption as the bounds are concerned with the interference statistics and not the type of modulation that interferers use.

[6] Note that $\kappa_1(Z) = 0$ and the condition $2 - n\alpha/2 < 0$ holds for $n \geq 2$ and $\alpha > 2$.

[7] We have used Wolfram Alpha [13] to find this integral.

B. Cumulants of Signal

We assume that the desired transmitter is the mth nearest neighbor to receiver. In order to find the cumulants of signal amplitude (i.e., $X_m = \zeta_m R_m^{-\alpha/2} U_m a_m$), we first find its moments. Due to independence assumption of ζ_m, R_m, U_m, and a_m, we have

$$E\{X_m^n\} = E\{\zeta_m^n\} E\{R_m^{-n\frac{\alpha}{2}}\} E\{U_m^n\} E\{a_m^n\}.$$

For Rayleigh fading with $E\{\zeta_m^2\} = 1$, we have $E\{\zeta_m^n\} = \Gamma(1+\frac{n}{2})$, and $E\{U_m^n\}$ and $E\{a_m^n\}$ are found in the previous section. For a given n and α and depending on the value of n, closed-form and approximation results are found in [14] and [15] for $E\{R_m^{-n\alpha/2}\}$. Using these results, $E\{X_m^n\}$ can be found in closed-form. To obtain the cumulants of X_m, we note that the cumulants and the moments of a random variable can be uniquely determined from one another. In particular, we have $\kappa_1(X_m) = E\{X_m\}$ and for $n \geq 2$ [16],

$$\kappa_n(X_m) = E\{X_m^n\} - \sum_{k=1}^{n-1} \binom{n-1}{k-1} \kappa_{n-1}(X_m) E\{X_m^{n-k}\}.$$

C. Cumulants of Interference

In this section, we seek to find the cumulants of interference given that the transmitter is the mth nearest neighbor to the receiver, i.e., $\kappa_n(I_m)$ for $I_m = Z - X_m$. Since the distances, i.e., the random variables $\{R_i\}$, are not independent, $X_m = \zeta_m R_m^{-\alpha/2} U_m a_m$ and $I_m = \sum_{i\neq m} \zeta_i U_i a_i / R_i^{\alpha/2}$ also are not independent and $\kappa_n(I-m) \neq \kappa_n(Z) - \kappa_n(X_m)$.

We use the following relationship for nth cumulant of $Z - X_m$ [16]:

$$\kappa_n(Z - X_m) = \sum_{j=0}^{n} \binom{n}{j} (-1)^{n-j} \kappa(\underbrace{Z, Z, \cdots}_{j}, \underbrace{X_m, X_m, \cdots}_{n-j})$$

where $\kappa(\underbrace{Z, Z, \cdots}_{j}, \underbrace{X_m, X_m, \cdots}_{n-j})$ indicates joint cumulants. We can therefore write

$$\begin{aligned}\kappa_n(I_m) &= \kappa_n(Z - X_m) \\ &= \kappa_n(Z) + (-1)^n \kappa_n(X_m) \\ &\quad + \sum_{j=1}^{n-1} \binom{n}{j} (-1)^{n-j} \kappa(\underbrace{Z, Z, \cdots}_{j}, \underbrace{X_m, X_m, \cdots}_{n-j}).\end{aligned} \tag{3}$$

For example, for $n = 2$, we have

$$\kappa_2(I_m) = \kappa_2(Z) + \kappa_2(X_m) - 2\kappa(Z, X_m)$$

and $\kappa(Z, X_m) = E\{ZX_m\} - E\{Z\}E\{X_m\}$. Therefore, to obtain the joint cumulants, we might need to have the joint statistics of Z and X_m. For the case of $\kappa_2(I_m)$, however, there is no need for joint statistics, as

$$\begin{aligned}E\{ZX_m\} &= E\left\{ X_m (X_m + \sum_{i\neq m} X_i) \right\} \\ &= E\{X_m^2\} + \sum_{i\neq m} E\{X_m X_i\} \\ &= E\{X_m^2\}.\end{aligned} \tag{4}$$

This result is found by noting that for $i \neq m$, we have

$$\begin{aligned}E\{X_m X_i\} &= E\{a_m\}E\{\zeta_m\}E\{U_m\}E\{a_i\}E\{\zeta_i\}E\{U_i\} \\ &\quad \cdot E\{R_m^{-\frac{\alpha}{2}} R_i^{-\frac{\alpha}{2}}\} \\ &= 0\end{aligned}$$

as $E\{U_i\} = 0$ and $E\{a_i\} = 0$. In the Appendix B, we find $\kappa_3(I_m) = 0$. To find higher order cumulants, however, joint statistics of distances will be required.

D. Joint Statistics of Distances in a Poisson Point Process

It is known that if nodes are distributed according to a two-dimensional PPP with density λ, the squared ordered distances from the receiver have the same distribution as the arrival times of a one-dimensional PPP with density $\lambda\pi$ [17], [18]. Consequently, for any set of indices $\{l_1, l_2, \cdots, l_n\}$ where $l_1 < l_2 < \cdots < l_n$, the joint pdf $f_{R_{l_1}^2, R_{l_2}^2, \cdots, R_{l_n}^2}(x_1, x_2, \cdots, x_n)$ can be found as follows:

$$\begin{aligned}&f_{R_{l_1}^2, R_{l_2}^2, \cdots, R_{l_n}^2}(x_1, x_2, \cdots, x_n) \\ &= f_{R_{l_1}^2, R_{l_2}^2 - R_{l_1}^2, \cdots, R_{l_n}^2 - R_{l_{n-1}}^2}(x_1, x_2 - x_1, \cdots, x_n - x_{n-1}) \\ &= \frac{(\lambda\pi)^{l_n}}{\Gamma(l_1)\Gamma(l_2 - l_1)\cdots\Gamma(l_n - l_{n-1})} \\ &\quad \cdot x_1^{l_1 - 1}(x_2 - x_1)^{l_2 - l_1 - 1} \cdots (x_n - x_{n-1})^{l_n - l_{n-1} - 1} e^{-\lambda\pi x_n}, \\ &\qquad 0 \leq x_1 \leq x_2 \leq \cdots \leq x_n\end{aligned}$$

which is found using the fact that $R_{l_1}^2$ and $R_{l_i}^2 - R_{l_{i-1}}^2$, $i > 2$ are independent Erlang random variables with rate parameter $\lambda\pi$ and shape parameters l_1 and $l_i - l_{i-1}$, respectively[8]. Using this joint pdf, we find $E\left\{ R_{l_1}^\beta R_{l_2}^\beta \cdots R_{l_n}^\beta \right\}$.

Proposition 1: We have

$$\begin{aligned}&E\left\{ R_{l_1}^\beta R_{l_2}^\beta \cdots R_{l_n}^\beta \right\} \\ &= \int_0^\infty \int_0^{x_n} \cdots \int_0^{x_2} x_1^{\frac{\beta}{2}} x_2^{\frac{\beta}{2}} \cdots x_n^{\frac{\beta}{2}} \\ &\quad \cdot f_{R_{l_1}^2, R_{l_2}^2, \cdots R_{l_n}^2}(x_1, x_2, \cdots, x_n)\, dx_1 \cdots dx_n \\ &= \frac{1}{(\lambda\pi)^{n\frac{\beta}{2}}} \prod_{k=1}^{n} \frac{\Gamma(l_k + k\frac{\beta}{2})}{\Gamma(l_k + (k-1)\frac{\beta}{2})}.\end{aligned} \tag{5}$$

Proof: See Appendix C. □

III. ENTROPY AND ENTROPY POWER OF INTERFERENCE

In this section, we seek to find $N^*(I_m)$, the entropy power of interference. The entropy power is related to the entropy, $h(I_m)$,

[8] In a one-dimensional Poisson process with density $\lambda\pi$, the inter-arrival times are independent and identically distributed (i.i.d.) exponential random variables with mean $1/\lambda\pi$ and sums of inter-arrival times are Erlang distributed. Particularly, $R_{l_1}^2$ is the sum of l_1 i.i.d. exponential random variables with mean $1/\lambda\pi$ and $R_{l_i}^2 - R_{i-1}^2$ is sum of $l_i - l_{i-1}$ i.i.d. exponential random variables with mean $1/\lambda\pi$ [15].

through [19]

$$N^*(I_m) = \frac{1}{2\pi e} \exp\left(2h(I_m)\right). \quad (6)$$

In the following, we use the Gram-Charlier expansion to approximate pdf of I_m. We then approximate its entropy. First, we introduce the normalized random variable $\tilde{I}_m$ with zero mean and unit variance as

$$\tilde{I}_m = \frac{I_m - \kappa_1(I_m)}{\sqrt{\kappa_2(I_m)}}. \quad (7)$$

From Gram-Charlier series expansion and by considering the first three terms, we have

$$f_{\tilde{I}_m}(x) \approx \phi(x)\left[1 + \kappa_3(\tilde{I}_m)\frac{H_3(x)}{3!} + \kappa_4(\tilde{I}_m)\frac{H_4(x)}{4!}\right]$$

where $H_i(x)$ is the ith order Chebyshev-Hermite polynomial, $\phi(x)$ is the pdf of standardized Gaussian distribution (i.e., with zero mean and unit variance), and using (7), we have

$$\kappa_n(\tilde{I}_m) = \frac{\kappa_n(I_m)}{\kappa_2^{n/2}(I_m)}, \quad n \geq 2.$$

The entropy of $\tilde{I}_m$ is by definition

$$h(\tilde{I}_m) = \int f_{\tilde{I}_m}(x)\log(f_{\tilde{I}_m}(x))\,dx.$$

Using the orthogonality of $\{H_i(x)\}$, and after some mathematical manipulation, we can show that

$$h(\tilde{I}_m) \approx 0.5\ln(2\pi e) - \frac{\kappa_3^2(\tilde{I}_m)}{2 \times 3!} - \frac{\kappa_4^2(\tilde{I}_m)}{2 \times 4!} \quad (8)$$

where $0.5\ln(2\pi e)$ is the entropy of standardized Gaussian distribution [20]. Also, from (7) and (8),

$$\begin{aligned} h(I_m) &= 0.5\ln(\kappa_2(I_m)) + h(\tilde{I}_m) \\ &= 0.5\ln(2\pi e\kappa_2(I_m)) - \frac{\kappa_3^2(I_m)}{12\kappa_2^3(I_m)} - \frac{\kappa_4^2(I_m)}{48\kappa_2^4(I_m)}. \quad (9) \end{aligned}$$

The entropy of interference, therefore, depends on its skewness (i.e., $\kappa_3(I_m)/\kappa_2^{3/2}(I_m)$) and kurtosis (i.e., $\kappa_4(I_m)/\kappa_2^2(I_m)$) as well as its variance (i.e., $\kappa_2(I_m)$). In the appendix, we show that $\kappa_3(I_m) = 0$ and therefore, the skewness of I_m is zero. Using (6) and (9), we have

$$N^*(I_m) = \frac{\kappa_2(I_m)}{\exp\left(\frac{\text{kurt}^2(I_m)}{24}\right)} \quad (10)$$

where kurt(I_m) indicates the kurtosis of I_m. As expected, for the case that I_m is Gaussian, we have kurt$(I_m) = 0$ and $N^*(I_m) = \kappa(I_m)$. This corresponds to the highest value that $N^*(I_m)$ can attain. On the other hand, the higher the kurt(I_m), the smaller $N^*(I_m)$ is. Note that by considering higher order cumulants in the Gram-Charlier approximation for pdf of I_m, $N^*(I_m)$ will depend on higher order cumulants as well. However, simulation results confirm that characterization of interference up to fourth order provides a good approximation for interference statistics.

IV. CAPACITY BOUND

Given that the desired transmitter is the mth nearest neighbor to the receiver, the capacity bound in (1) can be written as

$$W\log_2\left(1 + \frac{X_m^2}{N^*(I_m)}\right) < C < W\log_2\left(\frac{\kappa_2(I_m) + X_m^2}{N^*(I_m)}\right)$$

where X_m^2 is the signal power. Let us denote the lower and upper bound of capacity as C_l and C_u, respectively. For the additive Gaussian channel, we have $N^*(I_m) = \kappa_2(I_m)$ and the bound degenerates to equality (i.e., $C = W\log_2\left(1 + X_m^2/\kappa_2(I_m)\right)$). Note that X_m is a random variable. To obtain meaningful deterministic values, one approach is to average the lower and upper bounds to find the ergodic capacity bounds (i.e., $\bar{C}_l = E\{C_l\}$ and $\bar{C}_u = E\{C_u\}$). This requires the pdf of X_m. In our approach, we consider an equivalent deterministic channel for the link between the desired transmitter and the receiver with the received power equal to $E\{X_m^2\}$ and define

$$\hat{C}_l = W\log_2\left(1 + \frac{E\{X_m^2\}}{N^*(I_m)}\right), \quad (11)$$

$$\begin{aligned} \hat{C}_u &= W\log_2\left(\frac{\kappa_2(I_m) + E\{X_m^2\}}{N^*(I_m)}\right) \\ &= W\log_2\left(\exp\left(\frac{\text{kurt}^2(I_m)}{24}\right) + \frac{E\{X_m^2\}}{N^*(I_m)}\right) \quad (12) \end{aligned}$$

where the second line in (12) is found using (10).

Note that to maximize the upper and lower bounds, using (10), (11), and (12), $\kappa_2(I_m)$ needs to be minimized whereas kurt(I_m) and signal power, i.e., $E\{X_m^2\}$, have to be maximized. In other words, the transmitter which leads to minimum interference power, maximum signal power and maximum kurtosis leads to the highest capacity link. To find the index of transmitter which maximizes the bounds, rigorous optimization of (11) and (12) is required which is an involved task. In the next section, we use simulation and an numerical results for this purpose.

V. SIMULATION AND ANALYTICAL RESULTS

We consider a two-dimensional PPP with density λ and assume that the receiver is located at the origin. The desired transmitter and interferers use the same power level, $P = 1$. The power loss exponent, α, is assumed to equal 3. Rayleigh fading with second moment equal to 1 is considered. The prohibited region (in which no node can transmit) is a circle with radius $R_0 = 1$ and with the center at the receiver. In subsection II.C, $\kappa_2(I_m)$ is obtained. Also, in the Appendix B, $\kappa_4(I_m)$ is found and we find $\kappa_1(I_m) = \kappa_3(I_m) = 0$. To find $\kappa_4(I_m)$, we need to have the value of $\sum_{i \neq m} E\{R_m^{-\alpha}R_i^{-\alpha}\}$ which requires the joint statistics of R_m and R_i, $i \neq m$. Proposition 1 is used to find this summation for two values of $\lambda = 0.01$ and $\lambda = 0.1$.

In Fig. 2, we show the analytical and simulation results for $E\{R_3^\beta R_6^\beta\}$ for different values of β and for $\lambda = 0.1$. We have verified the accuracy of result found in Proposition 1 for other combinations of distances and node densities and the analytical results match with simulation.

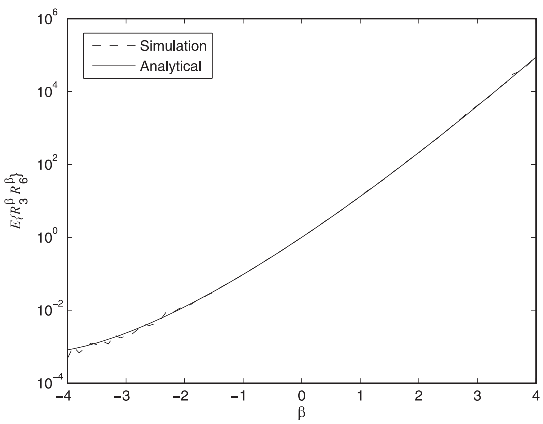

Fig. 2. Analytical and simulation results for $E\{R_3^\beta R_6^\beta\}$.

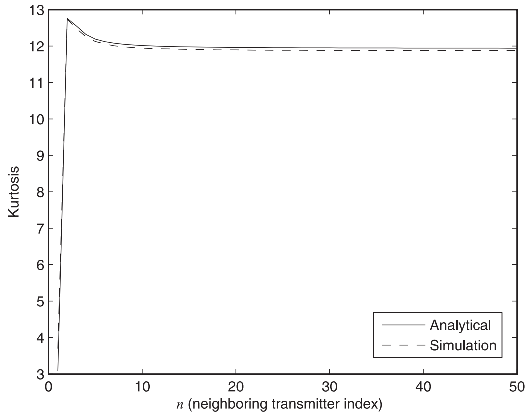

Fig. 3. Analytical and simulation results for kurtosis of interference vs. desired transmitter index ($\lambda = 0.01$).

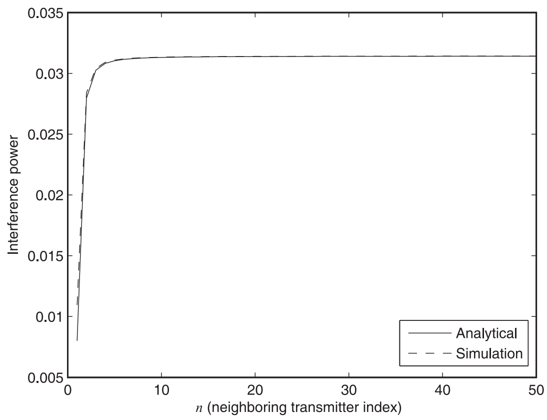

Fig. 4. Analytical and simulation results for interference power vs. desired transmitter index ($\lambda = 0.01$).

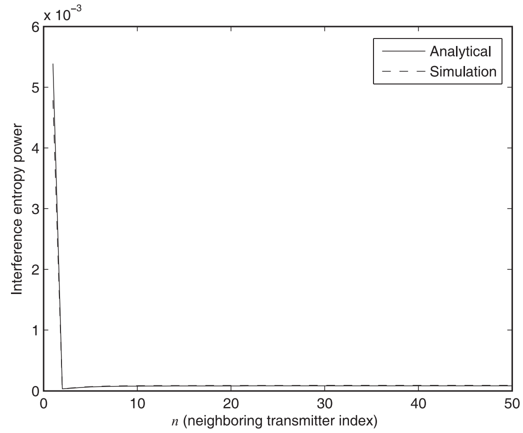

Fig. 5. Analytical and simulation results for entropy power of interference vs. desired transmitter index ($\lambda = 0.01$).

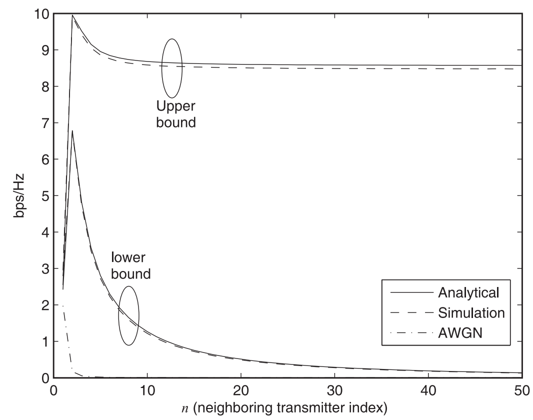

Fig. 6. Analytical and simulation results for upper and lower bounds of capacity and AWGN capacity vs. desired transmitter index ($\lambda = 0.01$).

In Figs. 3–6 for $\lambda = 0.01$ and in Figs. 7–10 for $\lambda = 0.1$, we have numerically evaluated the obtained analytical results for kurtosis of interference, interference power, entropy power of interference (from (10)), and upper and lower bounds of capacity (from (11) and (12)) when the desired transmitter node is any of the closest 50 neighbors of the receiver. Alongside, simulation results are shown which confirm the accuracy of the analytical values. Without loss of generality, we assume $W = 1$ which renders the capacity unit bps/Hz.

In Fig. 3, analytical and simulation results are shown for the kurtosis of interference when the desired transmitter node is any of the closest 50 neighbors. When the desired transmitter is the closest neighbor, the interference has the smallest kurtosis, which means the highest proximity to Gaussian distribution. This is expected and is a consequence of the closest neighbor, which is the major source of non-Gaussianity, being the desired transmitter rather than contributing to the aggregate interferer. As the distance of the desired transmitter to the receiver increases (i.e., as the index of transmitting node becomes larger), the kurtosis of interference will be almost fixed. This means that the more remote nodes have less influence on the kurtosis of interference. In Fig. 4, the interference power is shown when the desired transmitter node is any of the closest 50 neighbors (i.e., $\kappa_2(I_m)$, $1 \leq m \leq 50$). As expected, interference power will increase when the desired transmitter is a farther neighboring

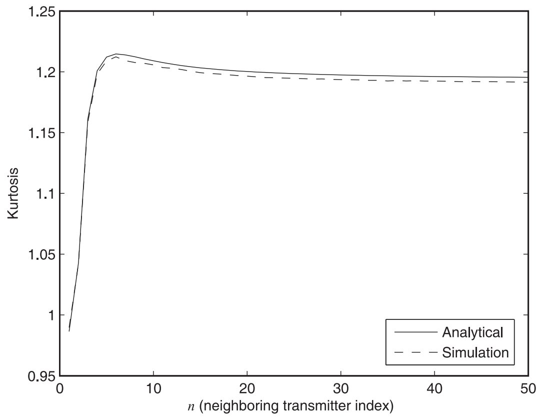

Fig. 7. Analytical and simulation results for kurtosis of interference vs. desired transmitter index ($\lambda = 0.1$).

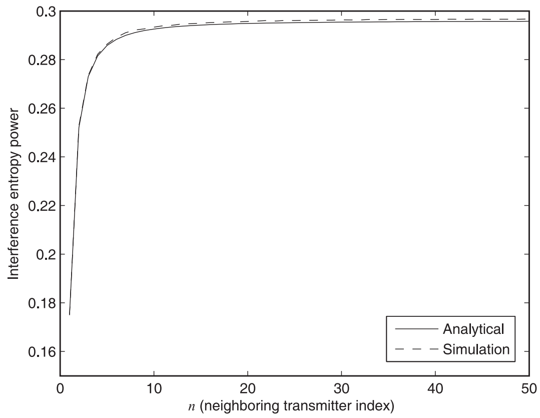

Fig. 9. Analytical and simulation results for entropy power of interference vs. desired transmitter index ($\lambda = 0.1$).

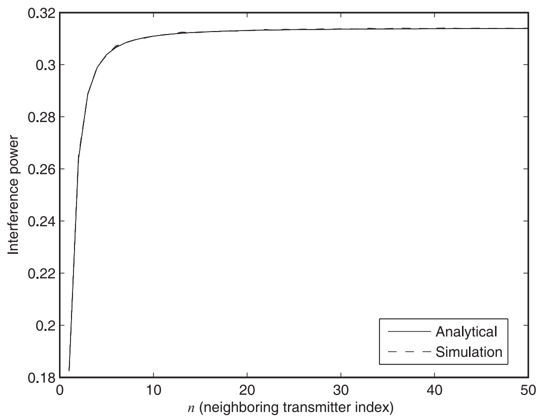

Fig. 8. Analytical and simulation results for interference power vs. desired transmitter index ($\lambda = 0.1$).

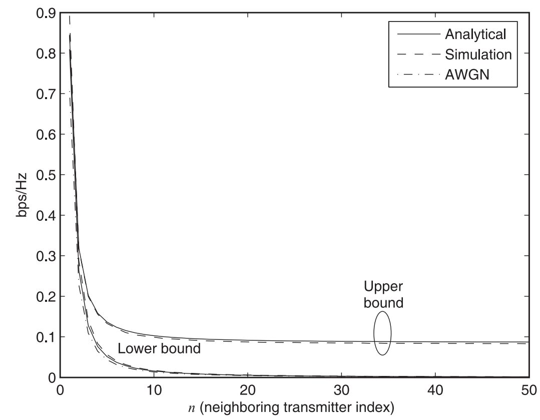

Fig. 10. Analytical and simulation results for upper and lower bounds of capacity and AWGN vs. desired transmitter index ($\lambda = 0.1$).

node. In Fig. 5, interference entropy power is shown versus the index of the desired transmitter. As seen from (10), both interference power and its kurtosis influence on the entropy power of interference. While the interference power monotonically increases with the transmitter index, the kurtosis does not show the same monotonic behavior. The behavior of interference entropy power, therefore, depends on which of these factors have the dominant effect. The results in Fig. 5 show that the kurtosis has the dominant effect and the entropy power has the minimum value when the desired transmitter is the second closest neighbor. Fig. 6 shows the analytical and simulation values for the upper and lower bounds of capacity versus the desired transmitter index. The results indicate that the lower and upper bounds of capacity have the maximum value when the desired transmitter is the second closest neighbor. Alongside, the AWGN capacity, which depends only on the power of interference, has been shown. As expected, AWGN capacity provides a pessimistic estimation of capacity by ignoring the higher order statistics of interference. Moreover, it is monotonically decreasing as it depends only on the interference power which monotonically increases as the index of desired transmitter increases.

In Fig. 7, the kurtosis of interference is shown versus the desired transmitter index for $\lambda = 0.1$. The interference is again closest to Gaussian (i.e., the kurtosis has the minimum value) when the desired transmitter is the closest node to the receiver. Fig. 8 shows that, as expected, the interference power monotonically increases with the desired transmitter index. It also has the dominant effect on the entropy power of interference (see (10)) and causes the entropy power to monotonically increase with the transmitter index as well (see Fig. 9). The lower and upper bounds of capacity are shown in Fig. 10 to monotonically decrease with the desired transmitter index for $\lambda = 0.1$. We can see from Figs. 8 and 9 that interference power and interference entropy power are almost equal. This is an indication that for $\lambda = 0.1$, the distribution of interference is close to Gaussian. This can also be seen from the kurtosis of interference in Fig. 7 which is relatively small. The AWGN capacity is also only slightly smaller than the lower bound of capacity.

Our results provide insight on the link capacities in Poisson wireless networks. As discussed, the capacity bounds depend on three factors: Signal power, interference power, and interference entropy power. The entropy power of interference is affected by the higher order statistics of interference. While, in a Gaussian interference scenario, the entropy power equals the variance (i.e., interference power) in a non-Gaussian case, it also depends on the higher order statistics like its kurtosis (see (10)). The interference power increases with the desired transmitter index. The kurtosis on the other hand, does not increase or decrease monotonically. As shown in Figs. 3 and 8, the kurtosis takes the minimum value when the closest neighbor is the desired transmitter. The kurtosis increases for the first few neighbors and then decreases and reaches a fixed value. The entropy power of interference, therefore, does not necessarily increase monotonically as we observed for the case of $\lambda = 0.01$. The signal and interference power on the other hand, increase and decrease monotonically with the desired transmitter index, respectively.

The above mentioned factors, i.e., signal power, interference power and entropy power of interference have conflicting effects on the channel capacity bounds. For $\lambda = 0.01$, the interference entropy power is minimum and as a consequence, upper and lower bounds of the channel capacity are maximum, not for the closest hop link, but for the link between the second nearest neighbor and the receiver. For $\lambda = 0.1$, however, the interference entropy power monotonically increases with the desired transmitter index. Consequently, the capacity bounds monotonically decrease with the desired transmitter index.

VI. CONCLUSIONS

In this paper, considering the higher order statistics of interference and by assuming a Poisson filed consisting of the desired transmitter as well as the interferers, we obtain bounds on the capacities of links in Poisson random networks. We use the Shannon's capacity bound for general additive channels for this purpose. We show that there is a tradeoff between entropy power of interference on the one hand and signal and interference power on the other hand which have conflicting effects on the channel capacity. We obtain closed form results for the cumulants of signal and interference amplitude and use them to obtain bounds for the links capacities. The links capacities are shown to be influenced by statistics of interference higher order than the variance. Therefore the uncorroborated Gaussian assumption of interference is rather naive and leads to pessimistic capacity results. Moreover, by showing that the capacity is not merely a function of interference power (i.e., second order statistics), but also depends on its higher order statistics (e.g., kurtosis), we show that the capacity is not necessarily a monotonically decreasing function of the hop distance between the receiver and the transmitter. Particularly, we have shown that the closest hop may not necessarily be the highest capacity link. For future work, the obtained bounds in (11) and (12) can be more exact by considering the pdf of signal power. Moreover, an optimization can be performed to find in closed-form, the neighboring transmitter that has the maximum capacity link to the receiver.

APPENDICES

A. Campbell's Theorem

Assume that Π is a PPP over a region S with density $\lambda(x),\ x \in S$ and assume that $f : S \to \mathbb{R}$ is a measurable function. Campbell's theorem [21] is a key result that gives the characteristic function of a sum of the form

$$F = \sum_{X \in \Pi} f(X).$$

The characteristic function is found as

$$\psi_F(\omega) = E\{e^{j\omega F}\} = \exp\left(\int_S (j\omega f(x) - 1)\lambda(x)dx\right).$$

Consequently, nth cumulant of F can be found as

$$\kappa_n = \frac{1}{j^n}\left[\frac{\partial^n \ln \psi_F(\omega)}{\partial \omega^n}\right]_{\omega=0} = \int_S f^n(x)\lambda(x)dx.$$

B. Cumulants of I_m

In subsection III.C, $\kappa_2(I_m)$ was found. Here, we obtain results for $\kappa_n(I_m),\ n = 1$, 3, and 4. For $n = 1$, using (3),

$$\kappa_1(I_m) = \kappa_1(Z - X_m) = \kappa_1(Z) - \kappa_1(X_m).$$

Since both $\kappa_1(Z)$ and $\kappa_1(X_m)$ equal 0, we have $\kappa_1(I_m) = 0$. For $n = 3$,

$$\begin{aligned}\kappa_3(I_m) &= \kappa_3(Z - X_m)\\ &= \kappa_3(Z) - \kappa_3(X_m) + 3\kappa(Z, X_m, X_m)\\ &\quad - 3\kappa(Z, Z, X_m)\end{aligned}$$

and we have

$$\begin{aligned}\kappa(Z, X_m, X_m) &= 2E^2\{Z\}E\{X_m\} - E\{Z^2\}E\{X_m\}\\ &\quad - 2E\{ZX_m\}E\{Z\} + E\{Z^2X_m\},\end{aligned}$$

$$\begin{aligned}\kappa(Z, Z, X_m) &= 2E\{Z\}E^2\{X_m\} - 2E\{ZX_m\}E\{X_m\}\\ &\quad - E\{Z\}E\{X_m^2\} + E\{ZX_m^2\}.\end{aligned}$$

To obtain $\kappa_3(I_m)$, $E\{ZX_m\}$, $E\{Z^2X_m\}$, and $E\{ZX_m^2\}$ need to be found. In (4), $E\{ZX_m\}$ is found to equal $E\{X_m^2\}$. Using the same approach,

$$\begin{aligned}E\{ZX_m^2\} &= E\{X_m^2(X_m + \sum_{i \neq m} X_i)\}\\ &= E\{X_m^3\} + \sum_{i \neq m} E\{X_m^2 X_i\} = E\{X_m^3\}\end{aligned}$$

which is found using $E\{U_i\} = 0$. Also,

$$\begin{aligned}E\{Z^2X_m\} &= E\{X_m(X_m + \sum_{i \neq m} X_i)^2\}\\ &= E\{X_m^3\} + 2\sum_{i \neq m} E\{X_m^2 X_i\} + \sum_{\substack{i \neq m\\ j \neq m}} E\{X_m X_i X_j\}\\ &= E\{X_m^3\}\end{aligned}$$

which is found using $E\{U_i\} = E\{U_m\} = 0$. Since the odd moments of Z and X_m equals 0 (see subsections II.A and II.B), we can see that $\kappa_3(I_m) = 0$. For $\kappa_4(I_m)$,

$$\kappa_4(I_m) = \kappa_4(Z - X_m)$$

$$= \kappa_4(Z) + \kappa_4(X_m) - 4\kappa(Z, X_m, X_m, X_m) + 6\kappa(Z, Z, X_m, X_m) - 4\kappa(Z, Z, Z, X_m)$$

and we have

$$\begin{aligned}\kappa(Z, X_m, X_m, X_m) = &-6E\{Z\}E^3\{X_m\} \\ &+ 6E\{ZX_m\}E^2\{X_m\} + 6E\{X_m^2\}E\{Z\}E\{X_m\} \\ &- 3E\{ZX_m^2\}E\{X_m\} - E\{Z\}E\{X_m^3\} \\ &- 3E\{ZX_m\}E\{X_m^2\} + E\{ZX_m^3\},\end{aligned}$$

$$\begin{aligned}\kappa(Z, Z, X_m, X_m) = &-6E^2\{Z\}E^2\{X_m\} \\ &+ 2E\{Z^2\}E^2\{X_m\} + 8E\{ZX_m\}E\{Z\}E\{X_m\} \\ &+ 2E\{X_m^2\}E^2\{Z\} - 2E\{Z^2X_m\}E\{X_m\} \\ &- 2E\{ZX_m^2\}E\{Z\} - E\{Z^2\}E\{X_m^2\} \\ &- 2E^2\{ZX_m\} + E\{Z^2X_m^2\},\end{aligned}$$

$$\begin{aligned}\kappa(Z, Z, Z, X_m) = &-6E^3\{Z\}E\{X_m\} \\ &+ 6E\{Z^2\}E\{Z\}E\{X_m\} + 6E\{ZX_m\}E^2\{Z\} \\ &- E\{Z^3\}E\{X_m\} - 3E\{Z^2X_m\}E\{Z\} \\ &- 3E\{Z^3\}E\{ZX_m\} + E\{Z^3X_m\}.\end{aligned}$$

To obtain $\kappa_4(I_m)$, $E\{ZX_m^3\}$, $E\{Z^2X_m^2\}$, and $E\{Z^3X_m\}$ need to be found. We have

$$\begin{aligned}E\{ZX_m^3\} &= E\{X_m^3(X_m + \sum_{i\neq m} X_i)\} \\ &= E\{X_m^4\} + \sum_{i\neq m} E\{X_m^3X_i\} \\ &= E\{X_m^4\}\end{aligned}$$

which is found using $E\{U_i\} = 0$ and

$$\begin{aligned}E\{Z^2X_m^2\} &= E\{X_m^2(X_m + \sum_{i\neq m} X_i)^2\} \\ &= E\{X_m^4\} + 2\sum_{i\neq m} E\{X_m^3X_i\} + \sum_{\substack{i\neq m\\ j\neq m}} E\{X_m^2X_iX_j\}.\end{aligned}$$

We have $\sum_{i\neq m} E\{X_m^3\} = 0$ and

$$\sum_{\substack{i\neq m\\ j\neq m}} E\{X_m^2X_iX_j\} = \sum_{\substack{i\neq m\\ j\neq m\\ i\neq j}} E\{X_m^2X_iX_j\} + \sum_{\substack{i\neq m\\ j\neq m}} E\{X_m^2X_i^2\}.$$

We have $\sum_{\substack{i\neq m\\ j\neq m\\ i\neq j}} E\{X_m^2X_iX_j\} = 0$ and

$$\sum_{i\neq m} E\{E\{X_m^2X_i^2\}\} = E^2\{\zeta^2\}E^2\{U^2\}\sum_{i\neq m} E\{R_m^{-\alpha}R_i^{-\alpha}\}.$$

Also,

$$E\{Z^3X_m\} = E\{X_m(X_m + \sum_{i\neq m} X_i)^3\} = E\{X_m^4\} + 3\sum_{i\neq m} E\{X_m^3X_i\} + 3\sum_{\substack{i\neq m\\ j\neq m}} E\{X_m^2X_iX_j\}E\{X_m(\sum_{i\neq m} X_i)^3\}.$$

Using the same approach, we have $\sum_{i\neq m} E\{X_m^3X_i\} = 0$, $E\{X_m(\sum_{i\neq m} X_i)^3\} = 0$, and

$$\begin{aligned}E\{Z^3X_m\} &= E\{X_m^4\} + 3\sum_{\substack{i\neq m\\ j\neq m}} E\{X_m^2X_iX_j\} = E\{X_m^4\} \\ &+ 3E^2\{\zeta^2\}E^2\{U^2\}\sum_{i\neq m} E\{R_m^{-\alpha}R_i^{-\alpha}\}.\end{aligned}$$

To find $E\{Z^2X_m^2\}$ and $E\{Z^3X_m\}$, therefore, we need to have $\sum_{i\neq m} E\{R_m^{-\alpha}R_i^{-\alpha}\}$.

C. Proof of Proposition 1

Let $A = \frac{(\lambda\pi)^{l_n}}{\Gamma(l1)\Gamma(l_2-l_1)\cdots\Gamma(l_n-l_{n-1})}$. We then have

$$E\left\{R_{l_1}^{\beta}R_{l_2}^{\beta}\cdots R_{l_n}^{\beta}\right\} = A\int_0^{\infty}\int_0^{x_n}\cdots\int_0^{x_2} x_1^{\frac{\beta}{2}}x_1^{l_1-1}(x_2-x_1)^{l_2-l_1-1}\cdots x_{n-1}^{\frac{\beta}{2}}(x_n-x_{n-1})^{l_n-l_{n-1}-1}x_n^{\frac{\beta}{2}}e^{-\lambda\pi x_n}dx_1\cdots dx_{n-1}dx_n.$$

We first find

$$\int_0^{x_2} x_1^{\frac{\beta}{2}}x_1^{l_1-1}(x_2-x_1)^{l_2-l_1-1}dx_1 = x_2^{l_2+\frac{\beta}{2}-1}B\left(l_1+\frac{\beta}{2}, l_2-l_1\right)$$

where $B(.)$ is the beta function [22]. Using induction,

$$\begin{aligned}&\int_0^{x_n}\cdots\int_0^{x_2} x_1^{\frac{\beta}{2}}x_1^{l_1-1}(x_2-x_1)^{l_2-l_1-1}\cdots x_{n-1}^{\frac{\beta}{2}}(x_n-x_{n-1})^{l_n-l_{n-1}-1}dx_1\cdots dx_{n-1} \\ &= B\left(l_1+\frac{\beta}{2}, l_2-l_1\right)B(l_2+\beta, l_3-l_2)\cdots \\ &\cdot B\left(l_{n-1}+(n-1)\frac{\beta}{2}, l_n-l_{n-1}\right)x_n^{l_n+(n-1)\frac{\beta}{2}-1}\end{aligned}$$

and

$$\begin{aligned}E\left\{R_{l_1}^{\beta}R_{l_2}^{\beta}\cdots R_{l_n}^{\beta}\right\} &= AB\left(l_1+\frac{\beta}{2}, l_2-l_1\right) \\ &\cdot B(l_2+\beta, l_3-l_2)\cdots B\left(l_{n-1}+(n-1)\frac{\beta}{2}, l_n-l_{n-1}\right) \\ &\cdot\int_0^{\infty} x_n^{l_n+n\frac{\beta}{2}-1}e^{-\lambda\pi x_n}dx_n.\end{aligned}$$

Noting that

$$\int_0^{\infty} x_n^{l_n+n\frac{\beta}{2}-1}e^{-\lambda\pi x_n}dx_n = \frac{\Gamma\left(l_n+n\frac{\beta}{2}\right)}{(\lambda\pi)^{l_n+n\frac{\beta}{2}}}$$

and using the equality $B(x,y) = \Gamma(x)\Gamma(y)/\Gamma(x+y)$ [22], the result in (5) is found after simplification.

ACKNOWLEDGEMENTS

The authors would like to thank the reviewers for their valuable comments.

REFERENCES

[1] E. S. Sousa, "Performance of a spread spectrum packet radio network link in a Poisson field of interferers," *IEEE Trans. Inf. Theory*, vol. 38, no. 6, pp.1743–1754, Nov. 1992.

[2] M. Souryal, B. Vojcic, and R. Pickholtz, "Ad hoc, multihop CDMA networks with route diversity in a Rayleigh fading channel," in *Proc. IEEE MILCOM*, 2001, pp. 1003–1007.

[3] A. Babaei and B. Jabbari, "Interference modeling and avoidance in spectrum underlay cognitive wireless networks," in *Proc. IEEE ICC*, Cape Town, South Africa, May 2010, pp. 1–5.

[4] J. Venkataraman and M. Haenggi, "Optimizing the throughput in random wireless ad hoc networks," in *Proc. 42nd Annual Allerton Conf. Commun. Control Comput.*, Oct. 2004.

[5] P. Jacquet, "Shannon capacity in Poisson wireless network model," *Problems of Inf. Theory*, vol. 45, no. 3, pp. 193–203, 2009.

[6] X. Yang and A. P. Petropulu, "Co-channel interference modelling and analysis in a Poisson field of interferers in wireless communications," *IEEE Trans. Signal Process.*, vol. 51, pp. 64–76, Jan. 2003.

[7] P. Gupta and P. R. Kumar, "The capacity of wireless networks," *IEEE Trans. Inf. Theory*, vol. 46, no. 2, pp.388–404, Mar. 2000.

[8] J. Fiorina and D. Domenicali, "The non validity of the Gaussian approximation for multi-user interference in ultra wide band impulse radio: From an inconvenience to an advantage," *IEEE Trans. Wireless Commun.*, vol. 8, no. 11, pp. 5483–5488, Nov. 2009.

[9] A. Babaei, P. Agrawal, and B. Jabbari, "Satistical shaping of interference to maximize capacity in cognitive random wireless networks," in *Proc. IEEE MILCOM*, San Jose, USA, 2010, pp. 123–127.

[10] A. Hasan and J. G. Andrews, "The Guard Zone in Wireless Ad hoc Networks," *IEEE Trans. Wireless Commun.*, vol. 6, no. 3, pp. 897–906, Mar. 2007.

[11] K. Gulati, B. L. Evans, J. G. Andrews, and K. R. Tinsely, "Statistics of co-channel interference in a field of Poisson and Poisson-Poisson clustered interferers," *IEEE Trans. Signal Process.*, vol. 58, no. 12, Dec. 2010.

[12] A. Papoulis and S. U. Pillai, *Probability, Random Variables, and Stochastic Processes*. 4th ed., McGraw-Hill, 2002.

[13] Wolfram alpha: Computational knowledge engine. [Online]. Available: http://www.wolframalpha.com

[14] A. Babaei and B. Jabbari, "Distance distribution of bivariate Poisson network nodes," *IEEE Commun. Lett.*, vol. 14, no. 9, pp. 848–850, Sept. 2010.

[15] M. Haengi, "On distances in uniformly random networks," *IEEE Trans. Inf. Theory*, vol. 51, no. 10, pp. 3584–3586, Oct. 2005.

[16] M. G. Kendall and A. Stuart, *The Advanced Theory of Statistics*. vol. 1, 3rd ed., Griffin, London, 1979.

[17] X. Liu and M. Haenggi, "Throughput analysis of fading sensor networks with regular and random topologies," *EURASIP J. Wireless Commun. Netw.*, pp. 554–564, Sept. 2005.

[18] R. Mathar and J. Mattfeldt, "On the distribution of cumulated interference power in Rayleigh fading channels," *Wireless Netw.*, vol. 1, no. 1, pp. 31–36, 1995.

[19] A. Dembo, T. Cover, and J. A. Thomas, "Information theoretic inequalities," *IEEE Tran. Inf. Theory*, vol. 37, no. 6, pp. 1501–1518, Nov. 1991.

[20] A. Hyvärinen, J. Karhunen, and E. Oja, *Independent Component Analysis*. John Wiley, 2001.

[21] J. F. C. Kingman, *Poisson Processes*. Oxford University Press, 1993.

[22] R. A. Askey and R. Roy, *Beta function.* NIST Handbook of Mathematical Functions, Cambridge University Press, 2010.

[23] S. Ihara, "On the capacity of channels with additive non-Gaussian noise," *Inf. Control*, vol. 37, pp. 34–39, 1978.

[24] M. Abramowitz and I. Stegun, *Handbook of Mathematical Functions*. Dover, 1972.

Alireza Babaei received his B.S. and M.S. degrees in Electrical Engineering from K. N. Toosi University of Technology and Iran University of Science and Technology, Tehran, Iran in 2003 and 2005, respectively, and his Ph.D. degree in Electrical and Computer Engineering from George Mason University (GMU), Fairfax, Virginia, USA in 2009. He is the recipient of an outstanding graduate student award from GMU and is currently a Postdoctoral Fellow at the Electrical and Computer Engineering Department of Auburn University. He has served as a Guest Editor for IEEE Wireless Communications magazine. His areas of active research are modeling and performance evaluation of random wireless networks, information theory, and cognitive radio networks.

Prathima Agrawal is the Samuel Ginn Distinguished Professor of Electrical and Computer Engineering and the Director of the Wireless Engineering Research and Education Center, Auburn University, Auburn, Alabama. She is also the Auburn Site Director of Wireless Internet for Advanced Technology (WICAT). WICAT is a National Science Foundation (NSF) Center under the Industry University Cooperative Research Center (IUCRC) program. Prior to her present positions, she was an Assistant Vice President of the Network Systems Research Laboratory and an Executive Director of the Mobile Networking Research Department, Telcordia Technologies (formerly Bellcore), Morristown, New Jersey, where she worked from 1998 to 2003. From 1978 to 1998, she worked in various capacities at AT&T/Lucent Bell Laboratories, including creating and serving as Head of the Networked Computing Research Department, Murray Hill, New Jersey. Her research interests include computer networks, mobile and wireless computing, and communication systems. She has published more than 200 papers in IEEE and other journals and conference proceedings in areas related to networks and VLSI. She holds 51 US patents. She received the Distinguished Alumnus Award from the Indian Institute of Science in 2006, the Telcordia CEO Award in 2000, and the Distinguished Member of the Technical Staff Award from AT&T Bell Laboratories in 1985. She is the recipient of the IEEE Computer Society's Distinguished Service Award in 1990 and the IEEE Third Millennium Medal in 2000. She is a Fellow of the IEEE and the Institution of Electronics and Telecommunications Engineers (IETE), India, and a Member of the ACM. She received the B.E. and M.E. degrees in Electrical Communication Engineering from the Indian Institute of Science, Bangalore, India, and the Ph.D. degree in Electrical Engineering from the University of Southern California in 1977.

Bijan Jabbari is a Professor of Electrical and Computer Engineering at George Mason University, Fairfax, VA, USA, and an Affiliated Faculty with ENST-Paris, France. He served as the Editor for Wireless Multiple Access for the IEEE Transactions on Communications, was the International Division Editor for Wireless Communications of the Journal of Communications and Networks, and was on the editorial board of Proceedings of the IEEE. He is a Coeditor of recent books on Multiaccess, Mobility and Teletraffic (Kluwer Publishing, Volume I and IV-VI). He is the past Chairman of the IEEE Communications Society Technical Committee on Communications Switching and Routing. He is a Fellow of IEEE and IEE, and is a recipient of the IEEE Millennium Medal in 2000 and the Washington DC Metropolitan Area Engineer of the Year Award, in 2003. He founded innovative laboratories for Internet and wireless communications research and is helping the industry adoption of new technologies. He continues research on multi-access communications and high performance networking. He received the Ph.D. degree in Electrical Engineering from Stanford University, Stanford, CA.