

Information-theoretic Capacity of Clustered Random Networks

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Abstract—

We analyze the capacity scaling laws of clustered ad hoc networks in which nodes are distributed according to a doubly stochastic shot-noise Cox process. We identify five different operational regimes, and for each regime we devise a communication strategy that allows to achieve a throughput to within a poly-logarithmic factor (in the number of nodes) of the maximum theoretical capacity.

I. INTRODUCTION AND RELATED WORK

The capacity of ad hoc wireless networks has been traditionally studied considering single-user communication schemes over point-to-point links [1]. Only recently [2], [3], [4], information-theoretic scaling laws of ad hoc networks have been investigated, showing that multi-user cooperative schemes can achieve much better performance than traditional single-user schemes, especially in the low power attenuation regime.

In this paper, we follow the stream of work [2], [3], [4], analyzing the information-theoretic capacity of clustered random networks containing significant inhomogeneities in the node spatial distribution. In particular, we consider nodes distributed according to a doubly stochastic Shot-Noise Cox Process (SNCP) over a square region whose edge size can scale with the number of nodes.

We provide both information-theoretic upper-bounds to the achievable capacity and constructive lower-bounds, which are asymptotically tight to within a poly-log factor (in the number of nodes). Our study reveals the emergence of five operational regimes, in which different communication schemes combined with proper scheduling/routing strategies must be adopted to achieve the system capacity.

With respect to previous work, we provide several contributions. First, the analysis in [2], [3] is limited to networks in which nodes are uniformly distributed. In contrast, our complete characterization of the network capacity achievable under the SNCP model extends the analysis to a much broader class of network topologies (including the uniform distribution as a special case), which can take into account the clustering behavior usually found in real systems.

Second, the impact of inhomogeneities in the node spatial distribution has been first investigated in [4], where authors have found that for small path-loss exponents (i.e., $\alpha \in (2, 3]$) the capacity does not depend on how nodes are placed over the area. Instead, they show that capacity is significantly affected by the network topology for large path-loss exponents (i.e., $\alpha > 3$). However, their characterization of the capacity achievable for large path-loss exponents is limited to the case of adversarial node placement under a deterministic (given) degree of network regularity. Moreover, they impose a minimum separation constraint between the nodes which does not allow to introduce highly dense clusters over the area. At last, the analysis in [4] is limited to the case of extended networks (i.e., networks whose area grows linearly with the number of nodes¹).

Third, our constructive lower bounds require to employ novel scheduling/routing strategies in combination to existing cooperative

communication schemes. Such strategies represent an important contribution in themselves, as they could be adopted to cope with the nodes spatial inhomogeneity in more general topologies which cannot be described by the SNCP model considered here.

At last we emphasize that this work extends [5], [6], where we have analyzed the capacity of networks in which nodes are distributed according to a SNCP model, but considering single-user communication schemes only (i.e., traditional point-to-point links).

II. SYSTEM ASSUMPTIONS AND NOTATION

A. Network Topology

We consider a network composed of a random number N of nodes (being $E[N] = n$) distributed over a square region \mathcal{O} of edge length L , where L takes units of distance. The network physical extension L scales with the average number of nodes, since this is expected to occur in many growing systems. Throughout this work we will assume that $L = n^\gamma$, with $\gamma \geq 0$. To avoid border effects, we consider wrap-around conditions at the network edges (i.e., the network area is assumed to be the surface of a bi-dimensional Torus).

The clustering behavior of large scale systems is taken into account assuming that nodes are placed according to a shot-noise Cox process (SNCP). An SNCP [7] over an area \mathcal{O} can be conveniently described by the following construction. We first specify a homogeneous Poisson point process \mathcal{C} of cluster centres, whose positions are denoted by $\mathbf{C} = \{c_j\}_{j=1}^M$, where M is a random number with average $E[M] = m$. Each centre point c_j in turn independently generates a point process of nodes whose intensity at ξ is given by $qk(c_j, \xi)$, where $q \in (0, \infty)$ and $k(c_j, \cdot) = k(\|\xi - c_j\|)$ is a rotationally invariant dispersion density function, also called kernel, or shot; i.e., $k(c_j, \cdot)$ depends only on the euclidean distance $\|\xi - c_j\|$ of point ξ from the cluster centre c_j .

Moreover we assume that $k(\|\xi - c_j\|)$ is a non-negative, non-increasing, bounded and continuous function, whose integral $\int_{\mathcal{O}} k(c_j, \xi) d\xi$ over the entire network area is finite and equal to 1. In practice, the kernels considered in our work can be specified by first defining a non-negative, non-increasing continuous function $s(\rho)$ such that $\int_0^\infty \rho s(\rho) d\rho < \infty$ and then normalizing it over the network area \mathcal{O} :

$$k(c_j, \xi) = \frac{s(\|\xi - c_j\|)}{\int_{\mathcal{O}} s(\|\zeta - c_j\|) d\zeta}$$

Notice that, in order to have finite integral over increasing network areas, functions $s(\rho)$ must be $o(\rho^{-2})$, i.e., they must have a tail that decays with the distance faster than quadratically. In the following, we will be especially interested in functions $s(\rho)$ whose tail decays as a power-law:

$$s(\rho) = \min(1, \rho^{-\delta}) \quad \text{for } \delta > 2, \quad (1)$$

although our results apply to more general shapes as well.

At last, in our asymptotic analysis we can neglect the normalizing factor $\int_{\mathcal{O}} s(\|\zeta - c_j\|) d\zeta = \Theta(1)$.

Under the above assumptions on the kernel shape, quantity q equals the average number of nodes generated by each cluster centre (all

¹In [3] authors recognized the importance of letting the network area scale with the number of nodes in a general way, as this gives rise to a richer set of operational regimes.

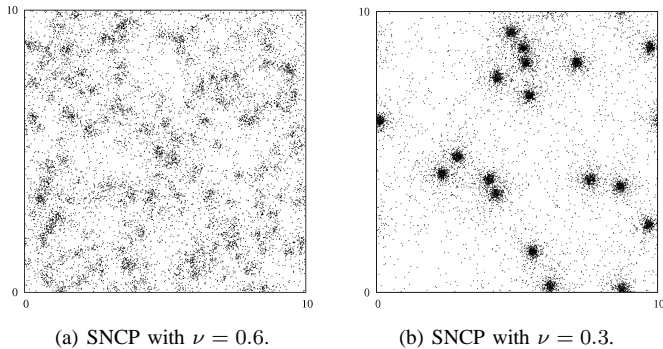


Fig. 1. Examples of topologies with $n = 10,000$ nodes distributed over the square 10×10 ($\gamma = 0.25$). In both cases $s(\rho) \sim \rho^{-2.5}$.

cluster centres generate on average the same number of nodes). In our work, we let q scale with n as well (clusters are expected to grow in size as the number of nodes increases). This is achieved assuming that the average number of cluster centres scales as $m = n^\nu$, with $\nu \in (0, 1)$. Consequently, the number of nodes per cluster scales as $q = n^{1-\nu}$.

The overall node process \mathcal{N} is then given by the superposition of the individual processes generated by the cluster centres. The local intensity at $\xi \in \mathcal{O}$ of the resulting SNCP is

$$\Phi(\xi) = \sum_{j=1}^M q k(\|\xi - c_j\|).$$

Notice that $\Phi(\xi)$ is a random field, in the sense that, conditionally over all (c_j) , the node process \mathcal{N} is an (inhomogeneous) Poisson point process with intensity function Φ . We denote by $\mathbf{X} = \{X_i\}_{i=1}^N$ the collection of nodes positions in a given realization of the SNCP.

Let $d_c = L/\sqrt{m} = n^{\gamma-\nu/2}$ be the typical distance between cluster centres. More precisely, d_c is the edge of the square where the expected number of cluster centres falling in it equals 1. We call

cluster-dense condition the case $\gamma < \nu/2$, in which d_c tends to zero as n increases;

cluster-sparse condition the case $\gamma > \nu/2$, in which d_c tends to infinity as n increases.

Figure 1 shows two examples of topologies generated by our SNCP, in the case of $n = 10,000$ and $\gamma = 0.25$. In both cases we have assumed $s(\rho) = \min(1, \rho^{-2.5})$. The topology in Figure 1(a) has been obtained with $\nu = 0.6$, hence it satisfies the *cluster-dense* condition ($\gamma < \nu/2$). The topology in Figure 1(b) corresponds to $\nu = 0.3$, and provides an example of the *cluster-sparse* condition ($\gamma > \nu/2$).

Recall that the local intensity of nodes at point ξ can be written as $\Phi(\xi) = \sum_j q k(c_j, \xi)$. We define the quantities: $\bar{\Phi} = \sup_{\xi \in \mathcal{O}} \Phi(\xi)$ and $\underline{\Phi} = \inf_{\xi \in \mathcal{O}} \Phi(\xi)$. The following lemma, proven in [5], characterizes the asymptotic behavior of $\bar{\Phi}$ and $\underline{\Phi}$:

Lemma 1: Consider nodes distributed according to the SNCP. Let $\eta(m) = d_c \sqrt{\log m}$. If $\eta(m) = o(1)$, it is possible to find two positive constants g_1, G_1 with $g_1 < G_1$ such that $\forall \xi \in \mathcal{O}$

$$g_1 \frac{n}{L^2} < \Phi(\xi) < G_1 \frac{n}{L^2} \quad \text{w.h.p.}^2 \quad (2)$$

When $\eta(m) = \Omega(1)$, it is possible to find two positive constants g_2, G_2 , such that, w.h.p., $\underline{\Phi} > g_2 q \log m s(d_c \sqrt{\log m})$ and $\bar{\Phi} < G_2 q \log m$.

The above result implies that $\underline{\Phi} = \Theta(\bar{\Phi})$ in the *cluster-dense* condition, i.e., when $\gamma < \nu/2$ (which implies $d_c = o(1/\sqrt{\log m})$),

²Throughout the paper, we adopt the terminology ‘with high probability’ (w.h.p.) to indicate events/properties that occur with a probability $p = 1 - O(\frac{1}{n})$, when $n \rightarrow \infty$.

TABLE I
SYSTEM PARAMETERS (n.a. = NOT APPLICABLE)

Symbol	Definition	scaling exponent
L	edge length of network area	$\gamma \geq 0$
m	average number of clusters	$0 < \nu < 1$
P	per-node power budget	0
α	path-loss exponent	n.a.
δ	decay exponent of $s(\rho)$	n.a.
d_c	typical distance between cluster centres	$\gamma - \nu/2$
q	average number of nodes per cluster	$1 - \nu$

whereas $\underline{\Phi} = o(\bar{\Phi})$ in the *cluster-sparse* condition, i.e., when $\gamma > \nu/2$ (which implies $d_c = \omega(1)$).

B. Communication Model

We use the same channel model as in [2], [3], [4]. Consider the generic time t , and let $V(t)$ be the set of nodes transmitting at time t . The signal received at time t by a node k is

$$y_k[t] = \sum_{i \in V(t) \setminus \{k\}} h_{i,k}[t] x_i[t] + z_k[t]$$

where $x_i[t]$ is the signal emitted by node i , and $\{z_k[t]\}_{k,t}$ are white circularly symmetric Gaussian noise, independently and identically distributed (i.i.d.) with distribution $\mathcal{N}_c(0, N_0)$ (with zero mean and variance N_0 per symbol). The complex baseband-equivalent channel gain $h_{i,k}[t]$ between i and k at time t is

$$h_{i,k}[t] = \sqrt{G} d_{ik}^{-\alpha/2} e^{j\theta_{ik}[t]}$$

where G is a constant gain, $\alpha > 2$ is the path-loss exponent, and $\{\theta_{ik}[t]\}_{i,k}$ are i.i.d. random phases with uniform distribution in $[0, 2\pi)$, which are assumed to vary in a stationary ergodic manner over time (fast fading). Moreover, $\{\theta_{ik}[t]\}_{i,k}$ and $\{d_{ik}\}_{i,k}$ are also assumed to be independent, $\forall i, k$. We should mention that a recent work [8] has put in discussion the validity of this assumption for very large n in the low path-loss regime $\alpha \in (2, 3)$. However, the strong impact of the assumptions on the location of scatterers suggests that channel modelling in the low path-loss regime for very large networks is somewhat delicate and requires further investigation.

We assume that each node is source and destination of a single flow, and that the resulting N flows (with $E[N] = n$) are established at random without any consideration of node locations. Let $\lambda(n)$ be the largest uniformly achievable rate of communications between sources and destinations. The aggregate system capacity is $C(n) = n\lambda(n)$. At last, we impose an average power constraint of P on the transmissions performed by each node, where P is a constant.

Table I summarizes the parameters of our model. For the quantities that are allowed to scale with n we have reported, in the third column, the restrictions on the scaling exponent in n , i.e., the assumptions on $\log_n(\langle \text{parameter} \rangle)$. Note that d_c and q are not native parameters, since they are derived from others, however we have included them in the table for convenience.

III. SUMMARY OF RESULTS

Similarly to previous work [2], [3], we express our results in terms of the scaling exponent e_C of the network capacity, defined as,

$$e_C = \lim_{n \rightarrow \infty} \frac{\log C(n)}{\log n}$$

The scaling exponent allows to ignore all poly-logarithmic factors, i.e., factors which are $O(\log n)^k$, for any finite k . Since our lower and upper bounds differ at most by a poly-logarithmic factor, the corresponding scaling exponents match, and we can claim that our characterization of the network capacity in terms of the scaling exponent is exact.

Results are reported in Table II. The scaling exponent takes different expressions as functions of the four system parameters $\{\alpha, \gamma, \delta, \nu\}$, under the conditions specified in the third column of

TABLE II
SCALING EXPONENT OF NETWORK CAPACITY $\beta = 1 - \nu - \delta(\gamma - \nu/2)$.

e_C	regime	conditions
1	I	$\alpha\gamma \leq 1$
$2 - \alpha\gamma$	I	$\alpha\gamma > 1 \wedge \alpha \leq 3$
$\frac{\alpha-1-\alpha\gamma}{\alpha-2}$	II	$\alpha\gamma > 1 \wedge \alpha > 3 \wedge \gamma < \frac{1}{2} \wedge \frac{1-2\gamma}{\alpha-2} \geq \gamma - \frac{\nu}{2}$
$2 - \alpha\gamma + (\alpha - 3)\frac{\nu}{2}$	III	$\alpha\gamma > 1 \wedge \alpha > 3 \wedge [\gamma \geq \frac{1}{2} \vee (\gamma < \frac{1}{2} \wedge \frac{1-2\gamma}{\alpha-2} < \gamma - \frac{\nu}{2}) \vee (\gamma < \frac{\nu}{2} \wedge \beta > 0)]$
$\max[2 - \alpha\gamma + (\alpha - 3)\frac{\nu}{2}, \gamma + \beta\frac{\alpha-1}{\alpha-2}]$	III or IV	$\alpha\gamma > 1 \wedge \alpha > 3 \wedge \gamma \geq \frac{\nu}{2} \wedge \beta > 0$
$\max[2 - \alpha\gamma + (\alpha - 3)\frac{\nu}{2}, \gamma + \beta\frac{\alpha+1}{2}]$	III or V	$\alpha\gamma > 1 \wedge \alpha > 3 \wedge \beta \leq 0$

Table II. In particular, we can distinguish five operational regimes, denoted by latin numbers I,II,...,V, as reported in the second column of the table³. It can be verified that e_C varies with continuity in the four-dimensional space of parameters $\{\alpha, \gamma, \delta, \nu\}$. We observe that, under any regime, e_C is a non-increasing function of parameters $\{\alpha, \gamma, \delta\}$ and a non-decreasing function of ν . Figure 2 provides a graphical representation of the results in Table II for the particular case of $\nu = 0.3$ and $\delta = 2.5$.

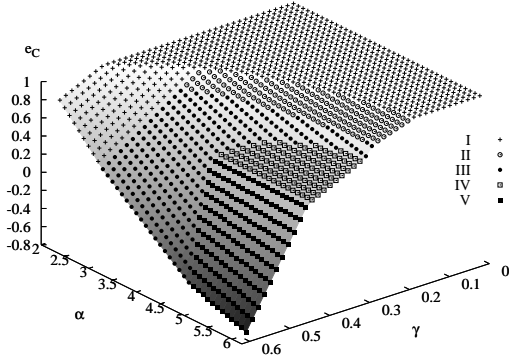


Fig. 2. Scaling exponent of network capacity as function of α and γ , for $\nu = 0.3$ and $\delta = 2.5$. Different marks are associated to the five possible regimes.

IV. UPPER BOUNDS

Upper-bounds are obtained extending the approach in [2], [3], [4], which is based on the computation of a bound to the information flow passing through a cut that divides the network in two parts.

First, by leveraging percolative arguments (see [5]), it is possible to find a strip of width Δ , with $\Delta = \Theta((qs(d_c) \log n)^{-1/2})$ in the *cluster-sparse* condition (i.e., for $\gamma > \nu/2$) and $\Delta = \Theta(L/\sqrt{n})$ in the *cluster-dense* condition (i.e., for $\gamma < \nu/2$), which divides the network area in two parts, and satisfies the following properties: i) the considered strip is empty of nodes; ii) every cluster centre lies at a distance greater than $g d_c$ from the strip, for a sufficiently small constant g .

Then, the information flow $\mathcal{C}(\mathcal{S}, \mathcal{D})$ from sources \mathcal{S} on the left to destinations \mathcal{D} on the right can be bounded by the power transfer $\mathcal{P}_{\mathcal{S}, \mathcal{D}}$ through the strip, as in [2], [3], [4]. Indeed, according to [4]:

$$\mathcal{C}(\mathcal{S}, \mathcal{D}) \leq b \mathcal{P}_{\mathcal{S}, \mathcal{D}} = b \sum_{i \in \mathcal{S}, k \in \mathcal{D}} P d_{ik}^{-\alpha} \quad (3)$$

for any

$$b > 4 \max \left(1, \max_{k \in \mathcal{D}} \sum_{i \in \mathcal{S}} \frac{|h_{ik}|^2}{\sum_{h \in \mathcal{D}} d_{ih}^{-\alpha}} \right)$$

³In the last two rows of the table, the actual regime depends on which term prevails in the $\max(\cdot)$ expression used in column one: we are in regime III if the first term is bigger than the second one.

being, for every k , $\sum_{i \in \mathcal{S}} \left(\frac{|h_{ik}|^2}{\sum_{h \in \mathcal{D}} d_{ih}^{-\alpha}} \right) = O(\log^5 n)$.

To estimate $\mathcal{P}_{\mathcal{S}, \mathcal{D}}$, the left and right domains are partitioned, respectively, into squarelets $\{A_k\}_k$ and $\{B_h\}_h$, obtaining:

$$\mathcal{P}_{\mathcal{S}, \mathcal{D}} = P \sum_{i \in \mathcal{S}, k \in \mathcal{D}} d_{ik}^{-\alpha} \leq P \sum_h \sum_k \underline{d}_{hk} \overline{U}(A_k) \overline{U}(B_h)$$

where \underline{d}_{hk} is the minimum distance between points of A_k and points of B_h , while function $\overline{U}(A_k)$ ($\overline{U}(B_h)$) provides an upper bound to the number of nodes in A_k (B_h). To obtain tight upper bounds the size of A_k and B_h must be carefully chosen since, by increasing the size of A_k and B_h , on the one hand we obtain tighter bounds for $\overline{U}(A_k)$ and $\overline{U}(B_h)$; on the other, we obtain looser bounds \underline{d}_{hk} for the distance between nodes in A_k and nodes in B_h .

Furthermore, when $\Delta = o(1)$, a tighter bound can be obtained applying the Hadamard inequality (see [3]) to extract from the information flow the contribution of destinations receiving signals whose strength diverges. This contribution, associated to nodes in proximity of the cut, is in turn evaluated applying the Hadamard inequality iteratively, so as to split it into the contributions associated to individual destinations (which can be interpreted as MISO systems running in parallel). Each individual contribution is then bounded applying similar arguments as in [3].

The above mentioned five regimes derive from the fact that the dominant contribution to $\mathcal{C}(\mathcal{S}, \mathcal{D})$ changes while varying the system parameters. In regime I the dominant contribution is due to nodes lying at distance $\Theta(L)$ from the cut; in regime II the dominant contribution is provided by nodes which are jointly at distance $\omega(d_c \sqrt{\log n})$ and $o(L)$; in regime III it is due to nodes at distance $O(d_c \sqrt{\log n})$ and $\Omega(d_c)$; in regime IV it is due to nodes at distance $o(d_c)$ and $\omega(1/\sqrt{\Delta})$; at last, in regime V the dominant contribution is provided by nodes at distance $\Theta(1/\sqrt{\Delta})$. A detailed derivation of the upper-bounds can be found in [9].

V. LOWER BOUNDS

For each operational regime, it is possible to devise a communication scheme that approaches the corresponding upper bound to within a poly-log factor. All of our proposed schemes work as follows: first, a subset of nodes is identified, which forms the main infrastructure through which data is transferred across the network area. A finite fraction of time is then assigned to the rest of the nodes to exchange traffic with the nodes belonging to the main infrastructure (if needed). More precisely, time is divided into regular frames, each one comprising three phases of equal duration: i) an *access* phase, in which sources not belonging to the main infrastructure send data to the infrastructure; ii) a *transport* phase, in which data is transferred over the infrastructure; iii) a *delivery* phase, in which data is sent from the infrastructure to destinations not belonging to it. Since the *delivery* phase is analogous to the *access* phase (by exchanging the role of transmitters and receivers), we will focus on the *access* phase only, after presenting the *transport* phase.

Before proceeding, we report the lower bounds obtained in [3] for homogeneous networks. Given a Homogeneous Poisson Process (HPP) of intensity ψ over a square (or disc) of edge (radius) L , it is possible to achieve the aggregate capacity $C_n(L, \psi, \alpha)$:

$$C_n(L, \psi, \alpha) = \begin{cases} \omega(\bar{N}^{1-\epsilon}) & \bar{N} \geq L^\alpha \\ \omega(\bar{N}^{2-\epsilon} L^{-\alpha}) & \bar{N} < L^\alpha, \alpha < 3 \\ \omega(\bar{N}^{-\epsilon} L \psi^{\frac{\alpha-1}{\alpha-2}}) & \bar{N} < L^\alpha, \alpha \geq 3, \psi = \omega(1) \\ \omega(\bar{N}^{-\epsilon} L \psi^{\frac{\alpha+1}{2}}) & \alpha \geq 3, \psi = O(1) \end{cases} \quad (4)$$

w.h.p. for any $\epsilon > 0$. In the above expressions $\bar{N} = \psi L^2$ is the average number of nodes in the system.

A. Transport phase

For what concerns the *transport* phase, our proposed schemes can be considered as special cases of a general class of scheduling-routing strategies, according to which the network area is partitioned into cells of edge size l . A cooperative multi-hop strategy is applied, in which MIMO communications are established between the nodes belonging to neighboring cells, and global multi-hopping at the cell level is employed to transfer data through the network. The proposed schemes essentially differ in: i) the subset of nodes which are used as the main infrastructure; ii) the chosen value of the cell edge size l . In particular, the value of l allows us to classify our schemes into five main communication strategies (for the *transport* phase) which can be associated by a one-to-one correspondence to the five operational regimes reported in Table II:

I: global MIMO, in which $l = \Theta(L)$, and nodes employ a MIMO communication scheme at global network scale, without the need of cell multi-hopping;

II: cooperative super-cluster hopping, in which nodes employ a cooperative multi-hop scheme, where $l = \omega(d_c \sqrt{\log n})$;

III: cooperative inter-cluster hopping, in which $l = \Theta(d_c \sqrt{\log n})$, i.e., the cell edge size is closely related to the typical distance d_c between cluster centres;

IV: cooperative sub-cluster hopping, in which $l = o(d_c)$ and $l = \omega(1/\Phi)$, i.e., the cell edge size is smaller (in order sense) than the typical distance between cluster centres, yet the cell is large enough to allow cooperation among an increasingly number of nodes falling in it;

V: traditional multi-hop scheme, in which $l = \Theta(1/\sqrt{\Phi})$, and nodes resort to the traditional point-to-point multi-hop scheme, since there is no advantage (in order sense) in employing cooperative techniques.

Notice that the above five strategies for the *transport* phase are applied to different infrastructures, which are selected depending on the combination of system parameters. The basic tool that we use to extract a subset of nodes forming the main infrastructure is a standard thinning technique, that can be applied to our class of point processes in the sense specified by the following lemma.

Lemma 2: Consider nodes $\mathbf{X} = \{X\}_1^N$ placed according to the considered SNCP. Then a subset of nodes $\mathbf{Z} \subseteq \mathbf{X}$ can be found w.h.p. such that \mathbf{Z} forms a homogeneous Poisson process with intensity Φ_0 , where $\Phi_0 = g_1 \frac{n}{L^2}$ in the *cluster-dense* condition and $\Phi_0 = g_2 q \log m s(d_c \sqrt{\log m})$ in the *cluster-sparse* condition. Here g_1 and g_2 are the constants defined in Lemma 1.

We identify the following three main infrastructures:

dense infrastructure, which is used in regimes I and II, but only for the *cluster-dense* condition ($\gamma < \nu/2$). In this case, we can apply Lemma 2 and extract a subset \mathbf{Z} of cardinality $\Theta(n)$, which can sustain the same capacity of a homogeneous system with n nodes;

clusters-core infrastructure, which is used in regimes I, II, III, for the *cluster-sparse* condition ($\gamma > \nu/2$). In this case, the set \mathbf{Z} is formed by all nodes falling within a finite distance from their cluster centre. The cardinality of this set is still $\Theta(n)$;

sparse infrastructure, which is used in regimes IV and V, for the *cluster-sparse* condition ($\gamma > \nu/2$). In this case, we can apply Lemma 2 and extract a subset \mathbf{Z} of points with density $\Phi_0 = \Theta(n^\beta)$, where $\beta = 1 - \nu - \delta(\gamma - \nu/2)$. The cardinality

of this set is $o(n)$.

Since both the dense infrastructure and the sparse infrastructure form a HPP, their capacity can be immediately obtained applying existing results for homogeneous system. The cluster-core infrastructure is not a HPP, however it can be regarded as being uniformly dense at resolution higher than d_c . Since in regime I,II,III the cell edge size is $\Omega(d_c \sqrt{\log n})$, MIMO communications between cells occur as if nodes in \mathbf{Z} were uniformly distributed (see [9] for more details). Moreover, it can be shown that the clusters-core infrastructure can sustain the load due to the cooperation overhead required within each cell, but we omit the details here.

B. Access phase

We recall that the *access* phase is used by sources to inject their traffic over the main infrastructure. Since the system capacity is ultimately determined by the main infrastructure, the goal is to design an *access* phase that does not constitute a system bottleneck, while at the same time inducing a uniform traffic matrix over the main infrastructure. These design principles led us to select the following three *access* strategies:

SISO access scheme. This is the simplest strategy, and it is used to access the dense infrastructure. In this case, it is sufficient to employ a single-hop point-to-point transmission between each source and one of the closest nodes belonging to \mathbf{Z} , thanks to the fact that the network is almost uniformly dense;

SIMO access scheme. This is used to access the nodes of the clusters-core infrastructure, employing a SIMO technique similar to the relaying scheme proposed in [4]⁴;

hierarchical access scheme. This is used to access the nodes of the sparse infrastructure, and required us to develop a novel scheduling-routing strategy specifically tailored to this case.

Due to lack of space, we restrict ourselves to a brief description of the hierarchical access scheme, which is the most intriguing one⁵. In this case, traffic produced within highly dense regions of the network area (e.g., the clusters cores in Figure 1(b)) needs to be gradually spread out through a sequence of intermediate, local transport infrastructures nested one within the other. This construction is needed both to avoid the formation of local bottlenecks around the cluster centres, and to evenly balance the traffic towards the node of the main infrastructure. Intermediate transport infrastructures are obtained by applying the thinning technique of Lemma 2 within certain domains (specified later), surrounding the clusters' centres, nested one within the other. To simply and effectively balance the traffic data are delivered within each local infrastructure to randomly destination nodes.

The sequence $k = 0, 1, \dots, K_{\max}$ of nested domains is carefully chosen in such a way that: i) the first domain in the sequence coincides with the network area, hence the corresponding infrastructure is the main transport infrastructure of the network, of density Φ , which is shared by all data flows; ii) the infrastructure extracted in each domain $k > 0$ can pass to the infrastructure of domain $k - 1$ all traffic generated by nodes contained in it; iii) the total number of domains grows at most like $\log n$.

Conditions i) and ii) guarantee that the system capacity is throttled by the lowest infrastructure (the main transport infrastructure) and no bottleneck arises within any higher infrastructure. Condition iii) guarantees that, even if we devote to each layer- k infrastructure the same fraction of time, the total overhead due to the *access* phase causes at most a $\log n$ loss in the overall system capacity.

⁴In [4], authors present a technique that allows nodes located in low-density areas to relay their data over densely populated areas, by exploiting the diversity gain intrinsically available in high-density regions thanks to the presence of many nodes acting as an array of receiving antennas.

⁵The interested reader is referred to [9] for a detailed description and analysis of all *access* schemes.

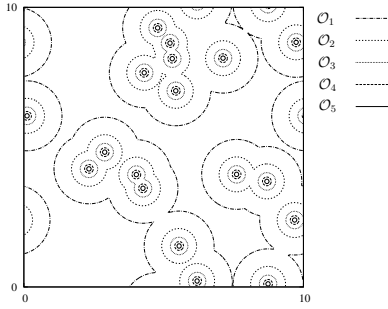


Fig. 3. Example of construction of nested domains \mathcal{O}_k for the topology depicted in Figure 1(b). Domain \mathcal{O}_1 is characterized by $d_1 = 0.5d_c$.

We now specify one possible way to jointly achieve the three conditions above. We build a sequence of nested domains \mathcal{O}_k , $k = 0, 1, 2, \dots, K_{\max}$, as follows. The first domain is $\mathcal{O}_0 = \mathcal{O}$, meeting condition i).

For the generic point $\xi \in \mathcal{O}$, let $d_{\min}(\xi) = \min_j \|\xi - c_j\|$ be the distance between ξ and the closest cluster centre. We define domains \mathcal{O}_k , for $k \geq 1$, as follows: $\mathcal{O}_k = \{\xi \in \mathcal{O} : d_{\min}(\xi) \leq d_k\}$, where d_k are a set of decreasing distances, i.e., $d_1 > d_2 > \dots > d_{K_{\max}}$. Domain \mathcal{O}_k is, in general, composed of a random number J_k of disjoint regions ($J_k \leq M$), corresponding to the connected components of the standard Gilbert's model of continuum percolation [10] with ball radius d_k . Figure 3 shows examples of domains \mathcal{O}_k having different values of d_k . Let $\{\mathcal{I}_k^j\}_j$ be the set of disjoint regions ($1 \leq j \leq J_k$) forming domain \mathcal{O}_k .

We set the largest d_k , namely d_1 , equal to $d_1 = \mu d_c$, where μ is a small constant. Choosing μ sufficiently small, in such a way that the associated Gilbert's model is below the percolation threshold (we need $\mu < \mu^*$, where $\mu^* \approx 0.6$), we have the property that the maximum number of clusters centres belonging to the same region \mathcal{I}_1^j is $O(\log n)$ w.h.p. [10]. Since by construction $\mathcal{O}_{k+1} \subset \mathcal{O}_k$, the same property holds for all $k > 1$. It follows that, in terms of physical extension, the area $|\mathcal{I}_k^j|$ of region \mathcal{I}_k^j lies w.h.p. in the interval $\pi d_k^2 \leq |\mathcal{I}_k^j| \leq \pi d_k^2 \log n$.

We further observe that the density of nodes at any point within \mathcal{O}_k ($k \geq 1$) can be lower bounded by $\lambda_k = q d_k^{-\delta}$, by considering the contribution of the closest cluster centre only. Hence, it is possible to extract from \mathcal{O}_k ($k \geq 1$) a set of points \mathbf{Z}_k forming a HPP with intensity λ_k . Note that in the domain \mathcal{O}_0 we have $\lambda_0 = \underline{\rho}$. Distances d_k , for $k \geq 2$, are then assigned in such a way that $\lambda_k = 2^{k-1} \lambda_1$, i.e., the intensities of the nested transport infrastructures form a geometric progression. This requires to set $d_k = d_1 2^{-\frac{k-1}{\delta}}$. Since the maximum node density in the network is $\bar{\Phi} < G_2 q \log m$ (see Lemma 1), we have $K_{\max} = 1 + \lfloor \log_2(q \log m / \lambda_1) \rfloor = O(\log n)$, hence the total number of domains satisfies condition iii).

It remains to show that each domain $k < K_{\max}$ can receive the traffic generated by domain $k+1$. To this purpose, we need to show that each region \mathcal{I}_k^j can handle the traffic produced by all components of domain $k+1$ nested in it. Let \mathcal{H}_{k+1}^j be the set of indexes h of regions \mathcal{I}_{k+1}^h falling in \mathcal{I}_k^j . Moreover, let M_k^j be the number of cluster centres falling within \mathcal{I}_k^j .

The area of \mathcal{I}_k^j can be expressed as $|\mathcal{I}_k^j| = M_k^j \pi d_k^2 \zeta_k$, where $\zeta_k < 1$ is a reduction factor that accounts for the overlapping among the discs of radius d_k forming region \mathcal{I}_k^j . The sum of the areas of all nested regions \mathcal{I}_{k+1}^h is instead given by $\sum_{h \in \mathcal{H}_{k+1}^j} |\mathcal{I}_{k+1}^h| = M_k^j \pi d_{k+1}^2 \zeta_{k+1}$, where $\zeta_{k+1} > \zeta_k$ because the degree of overlapping among the discs reduces for decreasing values of d_k . Since $(d_k/d_{k+1})^2 = 2^{2/\delta}$, we conclude that the ratio between $|\mathcal{I}_{k+1}^h|$ and

$\sum_{h \in \mathcal{H}_{k+1}^j} |\mathcal{I}_{k+1}^h|$ is bounded. This is important, as it allows to exploit to full capacity of the infrastructure extracted in \mathcal{I}_k^j to spread out the traffic coming from nested regions \mathcal{I}_{k+1}^h over the larger region \mathcal{I}_k^j .

Moreover, using the expressions (4) it can be shown that the aggregate capacity of nested regions \mathcal{I}_{k+1}^h is larger than the capacity of region \mathcal{I}_k^j . This allows to conclude that domain \mathcal{O}_0 (i.e., the main infrastructure) acts as the system bottleneck. Indeed, the number of points in \mathcal{I}_k^j is

$$M_k^j \pi \lambda_k d_k^2 \zeta_k = M_k^j \pi \lambda_1 d_1 2^{(k-1)(1-\frac{2}{\delta})} \zeta_k$$

The total number of points in regions \mathcal{I}_{k+1}^h has the same expression, substituting k with $k+1$. Since $\delta > 2$, and $\zeta_{k+1} > \zeta_k$, the total number of points in regions \mathcal{I}_{k+1}^h is larger. This guarantees that the aggregate capacities of the nested infrastructures is higher than the capacity of \mathcal{I}_k^j in the first regime of (4), in which $C_n = \omega(\bar{N}^{1-\epsilon})$.

In the third regime of (4), the capacity (either of region \mathcal{I}_k^j or the aggregate capacity of nested regions \mathcal{I}_{k+1}^h) would be proportional to $2^{k[\frac{\alpha-1}{\alpha-2} - \frac{1}{\delta} - \epsilon(1-\frac{2}{\delta})]} \zeta_k$. Since $\frac{\alpha-1}{\alpha-2} > 1 > \frac{1}{\delta}$, and ϵ is small, the capacity increases with k . At last, in the fourth regime of (4) the capacity would be proportional to $2^{k[\frac{\alpha+1}{2} - \frac{1}{\delta} - \epsilon(1-\frac{2}{\delta})]} \zeta_k$, which again increases with k . One can verify that capacities still form a non-decreasing sequence when we change regime passing from layer k to layer $k+1$.

We conclude that the chosen sequence of nested local infrastructures satisfies the conditions that allow to balance the traffic towards the nodes of the main infrastructure at most with a $\log n$ penalty factor to the system capacity.

VI. CONCLUSIONS

We have characterized the asymptotic capacity of networks whose nodes are distributed according to a doubly stochastic shot-noise Cox process. This point process provides an interesting, analytically tractable model of clustered random networks containing large inhomogeneities in the node density. Our study has revealed the existence of additional operational regimes with respect to those identified in previous work, and the need of novel scheduling and routing strategies, specifically tailored to each regime, to approach the maximum system capacity.

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