Optimal Capacity–Delay Tradeoff in MANETs With Correlation of Node Mobility

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***Abstract*—In this paper, we analyze the capacity and delay in mobile ad hoc networks (MANETs), considering the correlation of node mobility (correlated mobility). Previous studies on correlated mobility investigated the maximum capacity with the corresponding delay in several subcases; the problem of optimal capacity under various delay constraints (the optimal capacity–delay tradeoff) still remains open. To this end, we deeply explore the characteristics of correlated mobility and figure out the fundamental relationships between the network performance and the scheduling parameters. Based on that, we establish the overall upper bound of the capacity–delay tradeoff in all the subcases of correlated mobility. Then, we try to obtain the achievable lower bound by identifying the optimal scheduling parameters on certain constraints. Results demonstrate the whole picture of how the correlation of node mobility impacts the capacity, the delay, and the corresponding tradeoff between them.**

***Index Terms*—Capacity and delay tradeoff, correlated mobility, mobile ad hoc networks (MANETs).**

I. Introduction

SINCE the groundbreaking work by Gupta and Kumar [1], the study of capacity in large-scale wireless networks has gained great popularity within the research community. Gupta and Kumar showed that the per-node capacity is bounded by $O(1/\sqrt{n \log n})$ as the number of nodes n increases in a static network. Then, Franceschetti *et al.* [2] utilized the percolation theory to improve the per-node capacity up to $O(1/\sqrt{n})$, and the capacity still decays rapidly as n increases.

In their seminal work [3], Grossglauser and Tse verified that the network can achieve a constant per-node capacity of $O(1)$ when taking mobility into account, at the expense of unbounded delay. Therefore, researchers began to explore the relationship between the per-node capacity and the packet delay (capacity–delay tradeoff), for balancing the respective capacity and delay performance. It is well known that the independent and identically distributed (i.i.d.) mobility model plays an important role in the early investigations of how mobility influences the network performance for its mathematical tractability. Related studies in [4]–[6] provide some insights on the relationship between node mobility and the capacity–delay tradeoff.

For better and comprehensively understanding the impact of mobility on the capacity–delay tradeoff in wireless networks, literatures of the scaling performance under various mobility patterns were consecutively created by researchers. The related studies are Brownian motion mobility [7], random waypoint mobility [8], linear mobility [9], restricted mobility [10]–[12], and so on.

The aforementioned mobility models are either uniform or nonuniform over the network, basically covering the majority of the existing characteristics of node mobility, except the correlation of node mobility (correlated mobility). The mobility in real world exhibits certain degree of correlation [14]–[17], which stimulates us to investigate the impact of correlated mobility on the capacity–delay tradeoff in wireless networks.

Correlated mobility can be divided into three subcases based on different degrees of correlation of node mobility: 1) cluster sparse regime (node mobility shows strong correlation); 2) cluster dense regime (node mobility shows weak correlation); and 3) cluster critical regime (node mobility shows medium correlation). Ciullo *et al.* [13] first introduced correlated mobility into the scaling analysis of wireless networks. They obtained the maximum capacity with the corresponding packet delay in cluster sparse regime and the lower bound of capacity with the corresponding packet delay in cluster dense regime, respectively. However, the problem of optimal capacity performance under various delay constraints remains to be solved, which can provide significant insights for the better design of wireless networks requiring operating in various delay conditions. In this paper, we study the following open question:

- What is the optimal capacity–delay tradeoff with correlated mobility (in all subcases) in mobile ad hoc networks (MANETs)?

We first study the correlated mobility model and establish an upper bound on the optimal capacity–delay tradeoff in MANETs. Furthermore, we develop a scheduling policy to achieve the upper bound up to a logarithmic factor.

We summarize the main observations as follows.

1) The network generally performs worse in the cluster sparse regime (strong correlation of node mobility) than

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TABLE I
NOTATIONS

n	number of nodes
m	number of clusters
v	power law exponent of m: $m = \Theta(n^v), 0 < v \leq 1$
q	average number of nodes per-cluster, $q = n/m = \Theta(n^{1-v})$
R	radius of each cluster
β	power law exponent of R: $R = \Theta(n^\beta)$

in that of the i.i.d. mobility model because the strong correlation of node mobility has destroyed the network connectivity.

2) The optimal capacity–delay tradeoffs in cluster dense regime and in cluster critical regime both perform better than that in the i.i.d. mobility model, which is also better than the results in previous studies on correlated mobility.
3) The correlated mobility in cluster critical regime can achieve the best performance of the optimal capacity–delay tradeoff among the three subcases. It indicates that the medium correlation of node mobility can greatly benefit the network performance.

The main contribution of this paper is that we are the first to demonstrate a whole picture of how correlated mobility impacts the capacity–delay tradeoff in MANETs.

The rest of this paper is organized as follows. In Section II, we introduce our system model. In Section III, we briefly illustrate the optimal capacity–delay tradeoff in cluster sparse regime. In Section IV, we establish the upper bound of the optimal capacity–delay tradeoff in cluster dense regime; accordingly, the lower bound is derived in Section V. Section VI discusses the results, and Section VII concludes this paper.

II. SYSTEM MODEL

In the subsequent analysis throughout this paper, we apply the correlated mobility model to depict the motion of nodes. Specifically, we consider n nodes moving over an extended square of area n. All nodes are divided into $m = \Theta(n^v)$ groups, where $0 \leq v < 1$. Each group covers a circular area of radius $R = \Theta(n^\beta)$, where $0 \leq \beta \leq 1/2$. In particular, we call each group as a *cluster*. Note that each cluster on average contains $q = n/m$ nodes, and the result will not change, even if the value of q differs in clusters but that of $\Theta(n/m)$ remains unchanged. The related notations are shown in Table I.

Time Scale: Time is divided into slots of equal unit duration. Nodes move over slots following a correlated mobility fashion and remain static during each slot. In addition, we consider slow mobility time scale here, i.e., the speed of node movement is much slower than that of packet transmission. Thus, the multihop routing can be realized within one slot.

Correlated Mobility: Define a particular cluster center as j and one of its cluster members as i. Based on the features of correlated mobility, we describe the motion as follows.

- *The Motion of Cluster Center*: At the end of each slot, the network scheduler decides the position of each cluster center j in the next slot. In each slot, the position of cluster center j is randomly and uniformly chosen within the entire network area, independently from other cluster centers. After receiving the decision, all the cluster centers move to the scheduled positions in the next slot.
- *The Motion of Cluster Member*: Once the new position of cluster center j is selected, all nodes in this cluster move to the new region close to j, i.e., a circular area of $\Theta(R^2)$ that the cluster of j covers. Then, the position of cluster member i is randomly and uniformly chosen within the new region, independently from other nodes in this region.

We observe that reducing either the number of clusters or the area each cluster covers will achieve strong correlation of node mobility. Depending on the values of β and v, we can divide our analysis into three different regimes: 1) *Cluster sparse regime* $(v + 2\beta < 1)$: The total area mR^2 that all clusters cover is $o(n)$, which indicates strong correlation of node mobility; 2) *Cluster dense regime* $(v + 2\beta > 1)$: The total area mR^2 that all clusters cover is $\omega(n)$, which indicates weak correlation of node mobility; 3) *Cluster critical regime* $(v + 2\beta = 1)$: The total area mR^2 that all clusters cover is $\Theta(n)$, which indicates medium correlation of node mobility.[1]

Traffic Pattern: We assume that each node is a source node associated with one destination, which is randomly and independently chosen among all the other nodes in the network. We also assume that the destination is uniformly chosen among all the clusters, excluding the cluster of the source. Then, the source sends packets to the corresponding destination via a common wireless channel, and we utilize the protocol model [1] to reduce the interference.

Definitions of Asymptotic Throughput and Packet Delay: Let λ_i $(i = 1, \ldots, n)$ denote the sustainable rate of data flow for node i and D_b $(b = 1, \ldots, \lambda nT)$ represent the delay for packet b. Assume that $\lambda = \min\{\lambda_1, \lambda_2, \ldots, \lambda_{n-1}, \lambda_n\}$ and $\bar{D} = \sum_{b=1}^{\lambda nT} D_b/\lambda nT$. Then, $\lambda = \Theta(f(n))$ is defined as the asymptotic capacity if there exist two constants c and c', where $c > c' > 0$ that

$$\lim_{n\to\infty} \mathbf{Pr}\left(\lambda = cf(n) \text{ is achievable}\right) < 1$$

$$\lim_{n\to\infty} \mathbf{Pr}\left(\lambda = c'f(n) \text{ is achievable}\right) = 1.$$

Similarly, $\bar{D} = \Theta(g(n))$ is defined as the asymptotic delay.

III. CLUSTER SPARSE REGIME

The analysis of the capacity–delay tradeoff in cluster sparse regime $(v + 2\beta < 1)$ was addressed in our previous work [19]. Here, we show the main results for completeness.

A. Scheduling Policy

For a traffic stream $s \to d$, we denote s and d as the source and its destination, respectively. In addition, we denote C_s and C_d as two clusters containing s and d, respectively, where $C_s \neq C_d$. An opportunistic broadcasting scheme (nodes only broadcast messages when there exist a large number of nodes

[1]The degree of correlation of node mobility can be adjusted by changing the values of β and v.

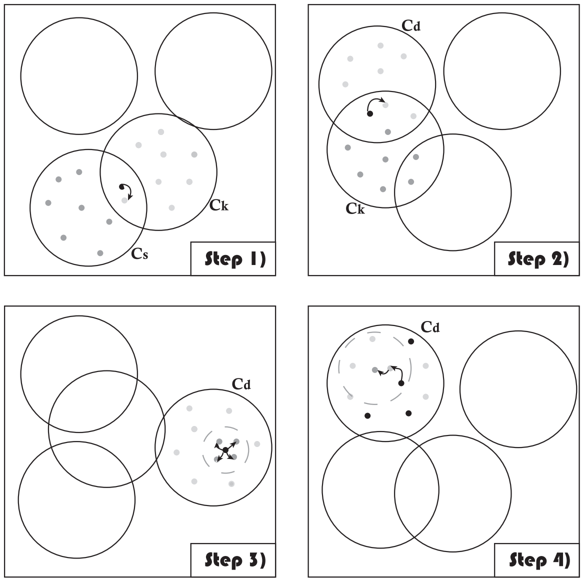

Fig. 1. Scheduling policy in cluster sparse regime.

around) is applied here to fully utilize the correlation of node mobility. We show the scheduling policy (see Fig. 1) as follows.

1) When s meets a cluster C_k ($k = 1, \ldots, R_c^s$, where R_c^s is the maximum number of clusters that contain messages of s) that contains no messages of s, a relay will be created in C_k via one-hop unicast. We call this process *intercluster duplication*, and this process will not end until one of the relays meets C_d.
2) If one of the relays meets C_d, a new relay will be created in C_d via one-hop unicast. If not, the process goes back to step 1.
3) The newly created relay in C_d will create relays within C_d via broadcast (R_d^s denotes the total number of relays created in C_d). We call this process *intracluster duplication*.
4) If one of the relays in C_d is captured[2] by the destination within range l^s, the message of s will be transmitted to the destination via h^s-hop unicast transmission. If not, the process goes back to step 3.

B. Upper Bound of Capacity–Delay Tradeoff

Given the brief introduction of the scheduling scheme, we directly show the upper bound of the capacity–delay tradeoff in cluster sparse regime. See [19] for detailed proofs.

Theorem 1: In cluster sparse regime, let $\bar{D}^s = \Theta(n^{\tilde{d}})$ denote the mean delay averaged over all bits, and let λ^s be the capacity of each source–destination pair. The following upper bound holds:

$$\begin{cases} (\lambda^s)^3 \le O\left(\frac{m\bar{D}^s}{n}\log^3 n\right), & \tilde{d} \ge \frac{5}{2} - v - 6\beta \\ \lambda^s \le O\left(\frac{mR^4\bar{D}^s}{n^2}\log^3 n\right), & \tilde{d} < \frac{5}{2} - v - 6\beta \end{cases}$$

where $\lambda^s \le mR^2/n$, and $\bar{D}^s \ge n/(mR^2)$.

[2]We define an event that node A falls into a certain area that node B covers and the message of node A can be delivered to node B via multihop transmission in one slot. If the event happens, we say node A is captured by node B.

C. Achievable Lower Bound

We divide the unit slot into three subslots. The operation of each subslot is shown in the following.

1) Nodes (source and relays) create intercluster duplications and C_d receives messages from one of the intercluster duplications via one-hop unicast transmission. Each hop exploits the transmission range of r^s.
2) R_d^s intracluster duplications are created via broadcasting within C_d.
3) If one of the intracluster duplications is captured by the destination within range l^s, then the message of s will be delivered to the destination via h^s-hop unicast transmission. Each hop exploits the transmission range of r^s.

The detailed analysis of the capacity–delay tradeoff achieving scheme and the corresponding results were shown in our work [19], which are omitted here for simplicity.

IV. Cluster Dense Regime

In cluster dense regime ($v + 2\beta > 1$), where the node mobility shows weak correlation, we can observe that either the area each cluster covers or the number of clusters becomes larger compared with the situation in cluster sparse regime. Consequently, the clusters overlap each other with high probability (w.h.p.). The previous work in [20] identifies each point in the network being covered by $\Theta(mR^2/n) = \Theta(n^{v+2\beta-1})$ clusters w.h.p., which indicates that the nodes are almost distributed uniformly over the whole area of the network. We recall the scheduling scheme in cluster sparse regime that two mechanisms (intercluster and intracluster duplications) of duplicating messages are proposed to deliver the source packet to its destination as quickly as possible. Intuitively, we can still apply these two mechanisms to the performance analysis in cluster dense region. However, we have observed some special phenomenons during the analysis, which suggests adapting the message duplicating mechanism to the cluster dense regime. Thus, the deducing process of the case of cluster dense regime is very different from that of the case of cluster sparse regime, which is more complicated.

A. Topology Analysis and Some Observations

In cluster sparse regime, the correlation of node mobility is strong, where either the number of clusters or the area that each cluster covers is relatively small. Thus, all clusters are sparsely distributed over the network and rarely overlap each other. One cluster should move over slots to meet another cluster and duplicate messages of the source. However, in cluster dense regime, as the correlation degree of node mobility has been changed, the traditional scheduling scheme used in cluster sparse regime may be inefficient. In the following, we first take a look at some interesting observations.

We consider the case where a source cluster (or a cluster containing relays) meets another cluster that does not contain messages of the source. Intuitively, the larger the number of

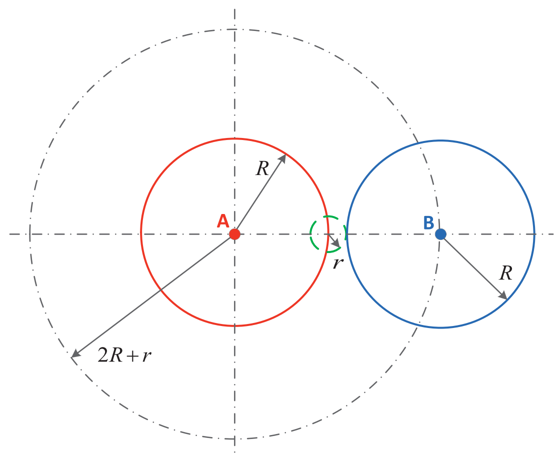

Fig. 2. Best case of intercluster duplication.

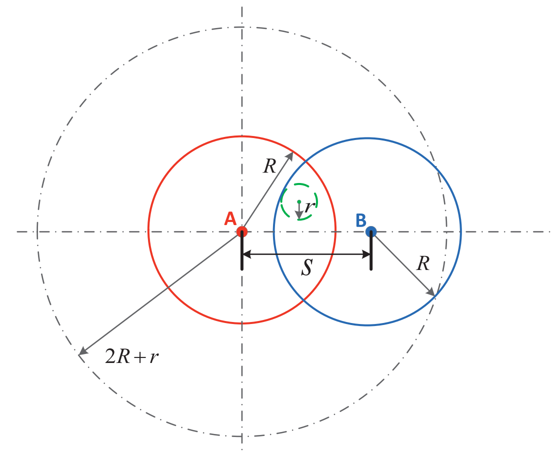

Fig. 3. Worst case of intercluster duplication.

message holders[3] in one cluster, the higher the probability we obtain to successfully hand over messages to another cluster that is not containing any message holder. However, the following lemma barely supports the preceding common view.

Lemma 1: For a particular source and its messages to be transmitted, define a cluster containing messages of the source as holder-cluster and a cluster containing no messages of the source as empty-cluster. Then, the probability of successful delivery of messages from holder-cluster to empty-cluster is independent of the number of relays that hold messages of the source in holder-cluster. We assume the transmission range as $r = o(R)$.

Proof: The logic of proof is outlined as follows: first, we demonstrate the best case where all nodes in holder-cluster contain messages of the source, after which we show the worst case where only one node in holder-cluster holds messages of the source. Then, we compare the probabilities of successful delivery of messages from holder-cluster to empty-cluster in the previous two cases and make a conclusion.

1) *Best Case*: Assume that all nodes in holder-cluster contain messages of the source. For messages being successfully delivered to the empty-cluster, we consider a critical situation where the center of holder-cluster A is $2R+r$ apart from the center of empty-cluster B (see Fig. 2). In this case, the delivery of messages can be operated on the borders of the two clusters (we assume that nodes are uniformly distributed in each cluster and that there exist nodes near the boundary w.h.p.). Thus, we conclude that the delivery of messages is successful w.h.p. if the distance between centers A and B is less than $2R + r$. Then, we derive the probability of successful message delivery from holder-cluster to empty-cluster as $((2R + r)^2/n) = \Theta(R^2/n)$.
2) *Worst Case*: Assume that only one node in holder-cluster contains messages of the source. As illustrated in Fig. 3, even when two clusters overlap with each other (the distance between A and B is s, where $s < 2R$), we cannot guarantee that the node conveying messages of the source exists in or near the overlapping region. Thus, we formulate the problem of successful message delivery as a conditional probability of $\Pr[Y|X]\Pr[X]$, where X denotes the event that center B falls into the circular area of radius $2R + r$ centered at A, and Y denotes the event that the only node carrying messages of the source falls into the overlapping area. Then, the probability of successful message delivery from holder-cluster to empty-cluster can be calculated as

$$
\begin{aligned}
\mathbf{P} &= \int \Pr\left[Y|X\right]\Pr[X]dX\\
&= \int_0^{2R} \frac{\pi R^2 \arccos\left(\frac{s}{2R}\right) - \frac{s}{2}\sqrt{R^2 - \frac{s^2}{4}}}{\pi R^2}\frac{\pi(2R+r)^2}{n}ds\\
&= \int_0^{2R} \frac{4}{n}\left[\pi R^2 \arccos\left(\frac{s}{2R}\right) - \frac{s}{2}\sqrt{R^2 - \frac{s^2}{4}}\right] ds\\
&= \int_0^{1} \frac{4}{n}\left[\pi R^2 \arccos\left(t\right) - R^2 t\sqrt{1-t^2}\right] dt\\
&= \left(\pi - \frac{1}{3}\right)\frac{4R^2}{n} = \Theta\left(\frac{R^2}{n}\right).
\end{aligned}
$$

Thus, the probability of successful message delivery from holder-cluster to empty-cluster is the same (in order sense) in the aforementioned two extreme cases. ■

Based on Lemma 1, we know that it is nonsense to add intracluster duplications for increasing the probability of successful message delivery from holder-cluster to empty-cluster. Next, the following two lemmas identify the disadvantages of creating intercluster duplications via traditional broadcast and one-hop unicast scheme.

Lemma 2: In cluster dense regime, an area of $\Theta(R^2)$ is covered by $\Theta(mR^2/n)$ clusters.

Proof: We assume that X_i^{oc} denotes the event that a particular cluster overlaps a certain area of $\Theta(R^2)$ within

[3]Message holders represent the relay nodes that contain the messages of the source.

the network. (If the event happens, then we have $X_i^{\mathrm{oc}} = 1$. Otherwise, $X_i^{\mathrm{oc}} = 0$.) From Fig. 2, we can obtain

$$\mathbf{P}\left[X_i^{\mathrm{oc}} = 1\right] = \frac{(2R+r)^2}{n} \leq \frac{9R^2}{n} = \frac{(2R+r)^2}{n} \geq \frac{4R^2}{n}.$$

We further denote X^{oc} as the total number of clusters that overlap a certain area of $\Theta(R^2)$, where $X^{\mathrm{oc}} = \sum_{i=1}^{m} X_i^{\mathrm{oc}}$. Using the multiplicative form of the Chernoff bound, we have

$$\mathbf{P}\left[X_{\min}^{\mathrm{oc}}\right] = \mathbf{P}\left[X^{\mathrm{oc}} > \frac{18mR^2}{n}\right] < \left(\frac{e}{4}\right)^{\frac{9mR^2}{n}} < O\left(\frac{1}{n}\right)$$

$$\mathbf{P}\left[X_{\max}^{\mathrm{oc}}\right] = \mathbf{P}\left[X^{\mathrm{oc}} < \frac{2mR^2}{n}\right] < e^{-\frac{mR^2}{2n}} < O\left(\frac{1}{n}\right).$$

Since $0 \leq X^{\mathrm{oc}} \leq m$, we have

$$\begin{aligned}\mathbb{E}[X^{\mathrm{oc}}] &= \mathbb{E}\left[X^{\mathrm{oc}}\mathbb{I}_{\{X_{\min}^{\bar{\mathrm{oc}}}\}}\right] + \mathbb{E}\left[X^{\mathrm{oc}}\mathbb{I}_{\{X_{\min}^{\mathrm{oc}}\}}\right] \\ &\leq \frac{18mR^2}{n} + m\frac{1}{n} \leq \frac{19mR^2}{n} \\ \mathbb{E}[X^{\mathrm{oc}}] &= \mathbb{E}\left[X^{\mathrm{oc}}\mathbb{I}_{\{X_{\max}^{\bar{\mathrm{oc}}}\}}\right] + \mathbb{E}\left[X^{\mathrm{oc}}\mathbb{I}_{\{X_{\max}^{\mathrm{oc}}\}}\right] \\ &\geq \frac{mR^2}{n} + 0\frac{1}{n} = \frac{mR^2}{n}.\end{aligned}$$

Then

$$\frac{mR^2}{n} \leq \mathbb{E}[X^{\mathrm{oc}}] \leq \frac{19mR^2}{n}.$$

Thus, an area of $\Theta(R^2)$ is covered by $\Theta(mR^2/n)$ clusters. ■

Lemma 3: If we have already created R_x intercluster duplications, where $R_x \leq \Theta(m)$, each point will still be covered by at least $\Theta(mR^2/n)$ empty-clusters.

Proof: We assume that X_i^{ec} denotes the event that a certain point within the network is covered by an empty-cluster (If the event happens, then we have $X_i^{\mathrm{ec}} = 1$. Otherwise, $X_i^{\mathrm{ec}} = 0$). Similarly, define X^{ec} as the total number of empty-clusters that cover a certain point within the network, where $X^{\mathrm{ec}} = \sum_{i=1}^{mR^2/n} X_i^{\mathrm{ec}}$. As there still exist $m - R_x = \Theta(m)$ empty-clusters, we have $\mathbf{P}[X_i^{\mathrm{ec}} = 1] = \Theta(1)$. According to the Chernoff bound, we have

$$\mathbf{P}\left[X_{\min}^{\mathrm{ec}}\right] = \mathbf{P}\left[X^{\mathrm{ec}} < \Theta\left(\frac{mR^2}{n}\right)\right] < e^{-\frac{mR^2}{8n}} < O\left(\frac{1}{n}\right).$$

Since $0 \leq X^{\mathrm{ec}} \leq m$, we have

$$\begin{aligned}\mathbb{E}[X^{\mathrm{ec}}] &= \mathbb{E}\left[X^{\mathrm{ec}}\mathbb{I}_{\{X_{\min}^{\bar{\mathrm{ec}}}\}}\right] + \mathbb{E}\left[X^{\mathrm{oc}}\mathbb{I}_{\{X_{\min}^{\mathrm{ec}}\}}\right] \\ &\geq \Theta\left(\frac{mR^2}{n}\right) + 0\frac{1}{n} = \Theta\left(\frac{mR^2}{n}\right).\end{aligned}$$

■

Lemma 2 tells us that clusters overlap with each other w.h.p. in cluster dense regime; thus, messages can be simultaneously transmitted to several empty-clusters via broadcasting, and it is much more efficient than the traditional one-hop unicast delivery when two clusters meet. Intuitively, we can still conduct the traditional broadcast scheme, which could be performed even better due to the highly overlapping feature of clusters in cluster dense regime. However, Lemma 3 proves that, when the number of intercluster duplications is less than $\Theta(m)$, each node will still be covered by at least $\Theta(mR^2/n)$ clusters that contain no duplications of the source message. This observation indicates that we should restrict the transmission power to some extents during each time of broadcast for making the $\Theta(mR^2/n)$ empty-clusters receive the duplications. Otherwise, the overly high transmission power not only does no good to the message dissemination but causes extra interference to other concurrent transmissions as well.

Thus, we apply u times broadcast scheme with a broadcast area of $A_d \in [1, \Theta(mR^2/n)]$. First, the source node will broadcast messages to the surrounding relay nodes. Then, in the second time of broadcast, the source node and the relay nodes that receive messages in the first time of broadcast simultaneously broadcast messages to other relay nodes. This process will carry on until the message is captured by the cluster of the targeting destination or each cluster holds the duplication of the source message.

Now, we introduce the general causal scheduling policy A in cluster dense regime, which is illustrated in Fig. 4. An opportunistic broadcast scheme is still applied here. For a particular message, the following proceed.

1) Nodes containing a certain message create relays via the kth broadcast with broadcast area A_d ($k = 1, \ldots, \Theta(u)$; R_c^d denotes the total number of intercluster duplications).[4]
2) If one of the relays is captured by a node in C_d within range l_1^d, the message will be transmitted to the node via h_1^d-hop unicast transmission. If not, we go back to step 1.
3) The captured relay in C_d creates new intracluster duplications via broadcast (R_d^d denotes the overall number of intracluster duplications within C_d).
4) If one of the intracluster duplications is captured by its destination within range l_2^d, the message will be transmitted to the destination via h_2^d-hop unicast transmission. If not, we go back to step 3.

This general causal scheduling policy A only performs well when the correlation of node mobility is relatively strong. When the correlation of node mobility becomes extremely strong, we shall redesign the scheduling policy to achieve the optimal network performance, which will be analyzed in Section IV-H. In the following analysis, we divide the general causal scheduling policy A into two parts based on the four steps in Fig. 4. One part is steps 1 and 2 (Part I), and the other is steps 3 and 4 (Part II).

Remark 1: Before studying the capacity–delay tradeoff, we briefly outline the logic sequence of the derivation of the tradeoff. First, we explore the fundamental relationship between the delay, the capacity, and the scheduling parameters, including the number of relays, the size of capture region, and the number of hops. These scheduling parameters correlate closely to the network performance. Then, we establish formulas to depict the quantitative relationship between them, which can be utilized to derive the upper bound of the capacity–delay tradeoff later. In addition, the deducing process is complex, with much mathematical tools being involved. We try hard to simplify it and emphasize key issues.

[4] d in variable R_c^d denotes the cluster dense regime of which the rule also holds for other variables used in cluster dense regime.

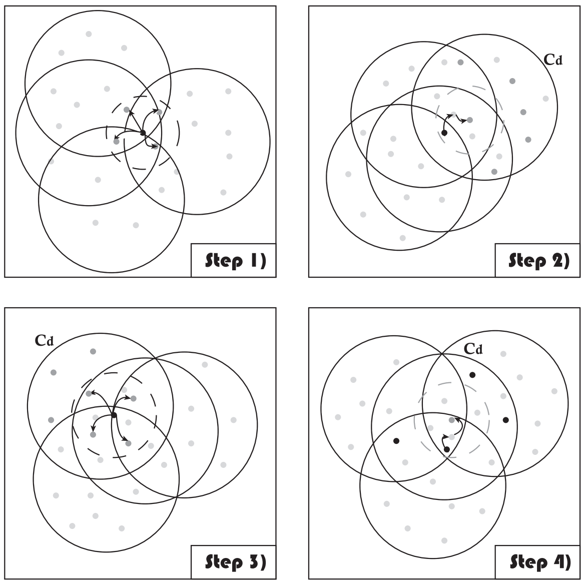

Fig. 4. Scheduling policy A in cluster dense regime.

B. Tradeoff for Delay of Part I

We denote $D_{\mathrm{I}1}^d$ as the delay of creating R_c^d intercluster duplications until one of the relay nodes is captured by a particular node in C_d. In addition, we denote $D_{\mathrm{II}1}^d$ as the delay of delivering the message from the captured relay node to the node in C_d.

Based on scheduling policy A, $D_{\mathrm{I}1}^d$ is equivalent to the time consumption of u times broadcast. Each time of broadcast, at least $\Theta(mR^2/n)$ empty-clusters will receive duplications of the source message from one relay node. Assume that $R_c^d = \omega(1) = n^{\hat{a}}$ and $A_d = n^{\alpha}$, where $\hat{a}$ and α are two constants greater than 0. We can easily obtain the equation of $(A_d)^u = R_c^d$; then, we have

$$u = \frac{\log n^{\hat{a}}}{\log n^{\alpha}} = \frac{\hat{a}}{\alpha} = \Theta(1).$$

Specifically, for the case of $R_c^d = \Theta(1)$ or the cluster critical regime, the delay $D_{\mathrm{I}1}^d$ can still be bounded by up to $\Theta(\log n)$, which is neglectable in order sense.

Next, we calculate the delay $D_{\mathrm{II}1}^d$ as follows:

$$\begin{aligned} D_{\mathrm{II}1}^d &= \frac{1}{\left(1 - \left(1 - \frac{R^2}{n}\right)^{R_c^d}\right) \frac{{l_1^d}^2 n/m}{R^2}} \\ &\geq \frac{m}{R_c^d {l_1^d}^2}. \end{aligned}$$

According to the analysis of $D_{\mathrm{I}1}^d$ and $D_{\mathrm{II}1}^d$, we show the whole delay of Part I through the following lemma.

Lemma 4: Under scheduling policy A in cluster dense regime, the delay for a particular bit b of Part I D_{1b}^d and the associated scheduling parameters comply with the following inequality:

$$c_1^d \log n \mathbb{E}\left[D_{1b}^d\right] \geq \frac{m}{\mathbb{E}\left[R_{cb}^d\right] \mathbb{E}\left[l_{1b}^d + \frac{1}{n}\right]^2} \tag{1}$$

where c_1^d is a positive constant. We use l_{1b}^d here to denote l_1^d of a particular bit b, which is convenient for the subsequent analysis. The similar rule holds for the other variables.

The proof of Lemma 4 is similar to the proof in [19, App. A], which is omitted here.

C. Tradeoff for Radio Resource, Half-Duplex, and Multihop of Part I

Based on Lemma 4, we can find that the delay can be reduced if we increase either the number of relays or the capture range because a larger number of relays results in a higher probability of the incidence that the packet is captured by the destination. This reason also holds for increasing the capture range.

However, the more relays generated, the more radio resources consumed, which would decrease the network capacity. In addition, as the capture range increases, the number of concurrent transmissions within the area that the capture region covers is reduced, which poses a negative impact on the capacity performance. The following lemma verifies the aforementioned idea and presents us the fundamental relationship between the capacity and the related scheduling parameters.

Lemma 5: Under scheduling policy A in cluster dense regime, we have the following inequality hold to trade off the capacity and the associated scheduling parameters:

$$\sum_{b=1}^{\lambda_1^d nT} \frac{\Delta^2}{4} \frac{\mathbb{E}\left[R_{cb}^d\right] - 1}{n} + \mathbb{E}\left[\sum_{b=1}^{\lambda_1^d nT} \sum_{h=1}^{h_{1b}^d} \frac{\pi\Delta^2}{4} \frac{{r_b^h}^2}{n}\right] \leq c_2^d WT \log n \tag{2}$$

where c_2^d is a positive number, h_{1b}^d is the number of hops to reach C_d after being captured, and r_b^h is the transmission range of each hop.

Proof: The proof is similar to that in [19], which is omitted here for simplicity. ■

Based on the half-duplex transmission mechanism and the nature of multihop scheme, we have the following inequalities hold.

Lemma 6: The following inequality holds:

$$\sum_{b=1}^{\lambda_1^d nT} \sum_{h=1}^{h_{1b}^d} 1 \leq \frac{WT}{2} n. \tag{3}$$

Lemma 7: The following inequality holds:

$$\sum_{b=1}^{\lambda_1^d nT} \sum_{h=1}^{h_{1b}^d} r_b^h \geq l_{1b}^d. \tag{4}$$

D. Detailed Upper Bound on Capacity–Delay Tradeoff of Part I

Here, we mainly derive the capacity–delay tradeoff on the basis of fundamental tradeoffs established in Section IV-B and C. Then, we achieve the optimal values of scheduling parameters by making the upper bound tight.

From Lemma 4, we have

$$\begin{aligned}\sum_{b=1}^{\lambda_1^d nT} \mathbb{E}\left[R_{cb}^d\right] &\geq \frac{1}{c_1^d \log n} \sum_{b=1}^{\lambda_1^d nT} \frac{m}{\left(\mathbb{E}\left[l_{1b}^d\right]+\frac{1}{n}\right)^2 \mathbb{E}\left[D_{1b}^d\right]} \\ &\geq \frac{m}{c_1^d \log n} \frac{\sum_{b=1}^{\lambda_1^d nT} 1}{\sum_{b=1}^{\lambda_1^d nT} \mathbb{E}\left[D_{1b}^d\right]} \\ &\quad \times \frac{\left(\sum_{b=1}^{\lambda_1^d nT} 1\right)^3}{\left(\sum_{b=1}^{\lambda_1^d nT}\left(\mathbb{E}\left[l_{1b}^d\right]+\frac{1}{n}\right)\right)^2} \\ &= \frac{m}{c_1^d \log n} \frac{\left(\sum_{b=1}^{\lambda_1^d nT} 1\right)^3}{\bar{D}_1^d \left(\sum_{b=1}^{\lambda_1^d nT}\left(\mathbb{E}\left[l_{1b}^d\right]+\frac{1}{n}\right)\right)^2}.\end{aligned} \tag{5}$$

Inequality (5) is deduced by using Jensen's and Hölder's inequalities. From Lemma 5 and the Cauchy–Schwarz inequality, we obtain

$$\begin{aligned}&\sum_{b=1}^{\lambda_1^d nT} \frac{\Delta^2}{4} \frac{\mathbb{E}\left[R_{cb}^d\right]-1}{n} + \frac{\pi\Delta^2}{2WTn^2}\left(\sum_{b=1}^{\lambda_1^d nT} \mathbb{E}[l_{1b}^d]\right)^2 \\ &\leq c_2^d WT \log n \\ &\quad \times \frac{\Delta^2 m}{4c_1^d n \log n} \frac{\left(\sum_{b=1}^{\lambda_1^d nT} 1\right)^3}{\bar{D}_1^d \left(\sum_{b=1}^{\lambda_1^d nT}\left(\mathbb{E}\left[l_{1b}^d\right]+\frac{1}{n}\right)\right)^2} \\ &\quad + \frac{\pi\Delta^2}{2WTn^2}\left(\sum_{b=1}^{\lambda_1^d nT} \mathbb{E}\left[l_{1b}^d\right]\right)^2 - \frac{\Delta^2}{4}\lambda_1^d T \leq c_2^d WT \log n.\end{aligned}$$

If $\sum_{b=1}^{\lambda_1^d nT}[l_{1b}^d] < \lambda_1^d T$

$$\frac{\Delta^2 m}{4c_1^d n \log n} \frac{\left(\lambda_1^d nT\right)^3 n^2}{\bar{D}_1^d \left(\lambda_1^d T\right)^2} \leq c_2^d WT \log n$$

$$\lambda_1^d \leq \frac{4c_1^d c_2^d WT \bar{D}_1^d \log^2 n}{\Delta^2 n^5 mT}. \tag{6}$$

If $\sum_{b=1}^{\lambda_1^d nT}[l_{1b}^d] \geq \lambda_1^d T$

$$\begin{aligned}&\frac{\Delta^2 m}{4c_1^d n \log n} \frac{\left(\sum_{b=1}^{\lambda_1^d nT} 1\right)^3}{\bar{D}_1^d \sum_{b=1}^{\lambda_1^d nT}\left(\mathbb{E}\left[l_{1b}^d\right]\right)^2} \\ &\quad + \frac{\pi\Delta^2}{2WTn^2}\left(\sum_{b=1}^{\lambda_1^d nT} \mathbb{E}[l_{1b}^d]\right)^2 \leq c_2^d WT \log n \\ &\quad \times \sqrt{\frac{\pi\Delta^2 T^2}{8c_1^d W \log n} \frac{\left(\lambda_1^d\right)^3 m}{\bar{D}_1^d}} \leq c_2^d WT \log n\end{aligned} \tag{7}$$

$$\left(\lambda_1^d\right)^3 \leq \frac{8c_1^d c_2^{d2} W^3 \bar{D}_1^d \log^3 n}{\pi\Delta^2 m}. \tag{8}$$

TABLE II
OPTIMAL VALUES OF SCHEDULING PARAMETERS UNDER SCHEDULING POLICY A OF PART I ($\tilde{d} \geq (3-v-6\beta)/2$)

R_{cb}^d	$\Theta(n^{\frac{v-\tilde{d}}{3}}/\log n)$
l_{1b}^d	$\Theta(n^{\frac{v-\tilde{d}}{3}}/\log^{\frac{1}{2}} n)$
h_{1b}^d	$\Theta(n^{\frac{v-\tilde{d}}{3}}/\log n)$
r_b^h	$\Theta(\log^{\frac{1}{2}} n)$

TABLE III
OPTIMAL VALUES OF SCHEDULING PARAMETERS UNDER SCHEDULING POLICY A OF PART I ($\tilde{d} < (3-v-6\beta)/2$)

R_{cb}^d	$\Theta(n^{1-2\beta-\tilde{d}}/\log n)$
l_{1b}^d	$\Theta(n^{\frac{v+2\beta-1}{2}}/\log^{\frac{1}{2}} n)$
h_{1b}^d	$\Theta(n^{\frac{v+2\beta-1}{2}}/\log n)$
r_b^h	$\Theta(\log^{\frac{1}{2}} n)$

Comparing the two inequalities (6) and (8), we have

$$\left(\lambda_1^d\right)^3 \leq O\left(\frac{\bar{D}_1^d}{m}\log^3 n\right).$$

To obtain the tight upper bound of the capacity–delay tradeoff, the four inequalities (1), (3), (4), and (7) should hold. Denoting the delay of Part I by $\Theta(n^{\tilde{d}})$, then we can achieve the optimal values of scheduling parameters, which are shown in Table II.

Remark: According to scheduling policy A, the optimal scheduling parameters should meet the two constraints $1 \leq R_{cb}^d \leq m$ and $1 \leq l_{1b}^d \leq \sqrt{mR^2/n}$. Thus, we have $\tilde{d} \geq (3-v-6\beta)/2$, regardless of the logarithmic factor. If the case of $\tilde{d} < (3-v-6\beta)/2$ would be further investigated, which indicates the smaller delay, we should enlarge the capture range l_{1b}^d. Note that the aforementioned two constraints should still be satisfied; thus, we set the capture range as $l_{1b}^d = \sqrt{mR^2/n}$. Then, we recalculate the upper bound of the capacity–delay tradeoff on condition that $l_{1b}^d = \sqrt{mR^2/n}$, which follows the same deducing logic as in the case of $\tilde{d} \geq (3-v-6\beta)/2$, i.e.,

$$\lambda_1^d \leq O\left(\frac{R^2\bar{D}_1^d}{n}\log^3 n\right).$$

The corresponding optimal values of scheduling parameters are shown in Table III.

Theorem 2: Under scheduling policy A in cluster dense regime, let $\bar{D}_1^d$ denote the mean delay averaged over all bits, and let λ_1^d be the capacity of each source–destination pair. In Part I, the following upper bound holds:

$$\begin{cases}\left(\lambda_1^d\right)^3 \leq O\left(\frac{\bar{D}_1^d}{m}\log^3 n\right), & \tilde{d} \geq \frac{3-v-6\beta}{2} \\ \lambda_1^d \leq O\left(\frac{R^2\bar{D}_1^d}{n}\log^3 n\right), & \tilde{d} < \frac{3-v-6\beta}{2}.\end{cases}$$

E. Tradeoff for Delay of Part II

Denoting the delay of delivering the message from the captured node to the destination within C_d by $D_{\mathrm{II}2}^d$, we have

$$D_{\mathrm{II}2}^d = \frac{1}{\left(1-\left(1-\frac{{l_2^d}^2}{R^2}\right)^{R_d^d}\right)} \geq \frac{R^2}{R_d^d {l_2^d}^2}.$$

Similar to the analysis in Section IV-B, the delay of creating intracluster duplications can be bounded as a constant, which is omitted here.

Lemma 8: Under scheduling policy A in cluster dense regime, the delay for a particular bit b of Part II and the associated scheduling parameters comply with the following inequality:

$$c_3^d \log n \mathbb{E}\left[D_{2b}^d\right] \geq \frac{R^2}{\mathbb{E}\left[R_{db}^d\right]\mathbb{E}\left[l_{2b}^d+\frac{1}{n}\right]^2}. \quad (9)$$

The proof of Lemma 8 is similar to the proof in [19, App. A]; thus, we omit it for simplification.

F. Tradeoff for Radio Resource, Half-Duplex, and Mutihop of Part II

Similar to Part I, we obtain the following three lemmas corresponding to three fundamental tradeoffs of radio resource, half-duplex, and multihop with respect to the scheduling parameters.

Lemma 9: Under scheduling policy A in cluster dense regime, we have the following inequality hold to trade off the capacity and the associated scheduling parameters:

$$\sum_{b=1}^{\lambda_2^d nT} \frac{\Delta^2}{4} \frac{\frac{mR^2}{n}\left(\mathbb{E}\left[R_{db}^d\right]-1\right)}{n} + \mathbb{E}\left[\sum_{b=1}^{\lambda_2^d nT}\sum_{h=1}^{h_{2b}^d} \frac{\pi\Delta^2}{4}\frac{{r_b^h}^2}{n}\right] \leq c_4^d WT \log n \quad (10)$$

where c_4^d is a positive number, h_{2b}^d is the number of hops to reach the destination after being captured, and r_b^h is the transmission range of each hop.

Lemma 10: The following inequality holds:

$$\sum_{b=1}^{\lambda_2^d nT}\sum_{h=1}^{h_{2b}^d} 1 \leq \frac{WT}{2}n. \quad (11)$$

Lemma 11: The following inequality holds:

$$\sum_{b=1}^{\lambda_2^d nT}\sum_{h=1}^{h_{2b}^d} r_b^h \geq l_{2b}^d. \quad (12)$$

G. Detailed Upper Bound on Capacity–Delay Tradeoff of Part II

Here, we derive the capacity–delay tradeoff within the cluster of destination. Following the same logical sequence for deriving the capacity–delay tradeoff of Part I, we also calculate the capacity–delay tradeoff of Part II on the basis of fundamental tradeoffs established in Section IV-E and F. Finally, we obtain the optimal values of scheduling parameters by making the upper bound tight.

From Lemma 8, we have

$$\sum_{b=1}^{\lambda_2^d nT}\mathbb{E}\left[R_{db}^d\right] \geq \frac{1}{c_3^d\log n}\sum_{b=1}^{\lambda_2^d nT}\frac{R^2}{\left(\mathbb{E}\left[l_{2b}^d\right]+\frac{1}{n}\right)^2\mathbb{E}\left[D_{2b}^d\right]} \geq \frac{R^2}{c_3^d \log n}\frac{\left(\sum_{b=1}^{\lambda_2^d nT} 1\right)^3}{\bar{D}_2^d\left(\sum_{b=1}^{\lambda_2^d nT}\left(\mathbb{E}\left[l_{2b}^d\right]+\frac{1}{n}\right)\right)^2}.$$

Based on Lemma 9 and the Cauchy–Schwarz inequality, we have

$$\sum_{b=1}^{\lambda_2^d nT}\frac{\Delta^2}{4}\frac{mR^2\mathbb{E}\left[R_{db}^d\right]}{n^2} + \frac{\pi\Delta^2}{2WTn^2}\left(\sum_{b=1}^{\lambda_2^d nT}\mathbb{E}\left[l_{2b}^d\right]\right)^2 \leq c_4^d WT\log n$$

$$\times\frac{\Delta^2 mR^4}{4c_3^d n^2\log n}\frac{\left(\sum_{b=1}^{\lambda_2^d nT} 1\right)^3}{\bar{D}_2^d\left(\sum_{b=1}^{\lambda_2^d nT}\left(\mathbb{E}\left[l_{2b}^d\right]+\frac{1}{n}\right)\right)^2} + \frac{\pi\Delta^2}{2WTn^2}\left(\sum_{b=1}^{\lambda_2^d nT}\mathbb{E}\left[l_{2b}^d\right]\right)^2 \leq c_4^d WT\log n.$$

If $\sum_{b=1}^{\lambda_2^d nT}[l_{2b}^d] < \lambda_2^d T$

$$\frac{\Delta^2 mR^4}{4c_3^d n^2\log n}\frac{(\lambda_2^d nT)^3 n^2}{\bar{D}_2^d(\lambda^d T)^2} \leq c_4^d WT\log n$$

$$\lambda_2^d \leq \frac{4c_3^d c_4^d WT\bar{D}_1^d\log^2 n}{\Delta^2 n^4 mR^2 T}. \quad (13)$$

If $\sum_{b=1}^{\lambda_2^d nT}[l_{2b}^d] \geq \lambda_2^d T$

$$\frac{\Delta^2 mR^4}{4c_1^d n^2\log n}\frac{\left(\sum_{b=1}^{\lambda_2^d nT} 1\right)^3}{\bar{D}_2^d\sum_{b=1}^{\lambda_2^d nT}\left(\mathbb{E}\left[l_{2b}^d\right]\right)^2} + \frac{\pi\Delta^2}{2WTn^2}\left(\sum_{b=1}^{\lambda_2^d nT}\mathbb{E}[l_{2b}^d]\right)^2 \leq c_4^d WT\log n$$

$$\sqrt{\frac{\pi\Delta^2 T^2}{8c_3^d W\log n}\frac{(\lambda_2^d)^3 mR^4}{n\bar{D}_2^d}} \leq c_4^d WT\log n \quad (14)$$

$$(\lambda_2^d)^3 \leq \frac{8c_3^d {c_4^d}^2 W^3 n\bar{D}_2^d\log^3 n}{\pi\Delta^2 mR^4}. \quad (15)$$

Comparing the two inequalities (13) and (15), we obtain the upper bound as follows:

$$\left(\lambda_2^d\right)^3 \leq O\left(\frac{n\bar{D}_2^d}{mR^4}\log^3 n\right).$$

To obtain the tight upper bound of the tradeoff, inequalities (9), (11), (12), and (14) should hold. Denoting the delay by

TABLE IV
OPTIMAL VALUES OF SCHEDULING PARAMETERS UNDER SCHEDULING POLICY A OF PART II ($\tilde{d} \leq 2 - 2v - 2\beta$)

R^d_{db}	$\Theta(n^{\frac{2-2v-2\beta-\tilde{d}}{3}}/\log n)$
l^d_{2b}	$\Theta(n^{\frac{v+4\beta-1-\tilde{d}}{3}}/\log^{\frac{1}{2}} n)$
h^d_{2b}	$\Theta(n^{\frac{v+4\beta-1-\tilde{d}}{3}}/\log n)$
r^h_b	$\Theta(\log^{\frac{1}{2}} n)$

TABLE V
OPTIMAL VALUES OF SCHEDULING PARAMETERS UNDER SCHEDULING POLICY A OF PART II ($\tilde{d} > 2 - 2v - 2\beta$)

R^d_{db}	$\Theta(1)$
l^d_{2b}	$\Theta(n^{\frac{2\beta-\tilde{d}}{2}}/\log^{\frac{1}{2}} n)$
h^d_{2b}	$\Theta(n^{\frac{2\beta-\tilde{d}}{2}}/\log n)$
r^h_b	$\Theta(\log^{\frac{1}{2}} n)$

$\Theta(n^{\tilde{d}})$, then we can achieve the optimal values of scheduling parameters shown in Table IV.

Remark: As the average number of nodes in each cluster is $\Theta(m/n)$, then the constraint $1 \leq R^d_{db} \leq n/m$ should be satisfied. In other words, the number of intracluster duplications should not exceed the number of total nodes in one cluster. Thus, we obtain $\tilde{d} \leq 2 - 2v - 2\beta$, regardless of the logarithmic factor. If we would like to increase the capacity at the expense of degrading the delay performance ($\tilde{d} > 2 - 2v - 2\beta$), we should reduce either the number of intracluster duplications or the capture range. Note that the aforementioned constraint should still be satisfied; thus, we set R^d_{db} as 1 and recalculate the upper bound following the same logic as in the case of $\tilde{d} \leq 2 - 2v - 2\beta$, i.e.,

$$\left(\lambda^d_2\right)^2 \leq O\left(\frac{\bar{D^d_2}}{R^2}\log^3 n\right).$$

The corresponding optimal values of scheduling parameters are shown in Table V.

Theorem 3: Under scheduling policy A in cluster dense regime, let $\bar{D^d_2}$ denote the mean delay averaged over all bits, and let λ^d_2 be the capacity of each source–destination pair. In Part II, the following upper bound holds:

$$\begin{cases} \left(\lambda^d_2\right)^2 \leq O\left(\frac{\bar{D^d_2}}{R^2}\log^3 n\right), & \tilde{d} > 2 - 2v - 2\beta \\ (\lambda^d_2)^3 \leq O\left(\frac{n\bar{D^d_2}}{mR^4}\log^3 n\right), & \tilde{d} \leq 2 - 2v - 2\beta. \end{cases}$$

Theorem 2 and Theorem 3 show us the tradeoffs of Part I and Part II of scheduling policy A, respectively. Then, the whole upper bound of the capacity–delay tradeoff of scheduling policy A can be derived easily.

Theorem 4: Under scheduling policy A in cluster dense regime, let $\bar{D^d_A}$ denote the mean delay averaged over all bits, and let λ^d_A be the capacity of each source–destination pair. Assume that $\bar{D^d_1} = \bar{D^d_2} = \bar{D^d_A}$. Then, we have

$$\lambda^d_A = \min\left\{\lambda^d_1, \lambda^d_2\right\}.$$

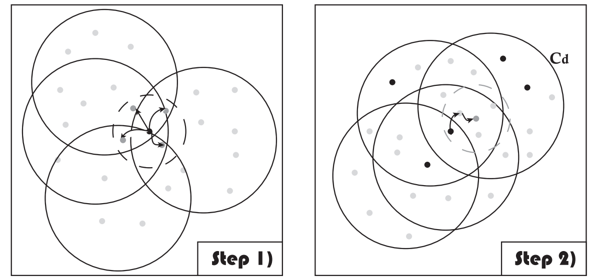

Fig. 5. Scheduling policy B in cluster dense regime.

H. Scheduling Policy B and Overall Upper Bound of Capacity–Delay Tradeoff

Previously, we derived the upper bound of the capacity–delay tradeoff in the case of relatively weak node correlation. Scheduling policy A was designed for better utilizing the characteristics of weak node correlation. However, as the node correlation is getting weaker (i.e., either the number of clusters or the area of each cluster tends to be even larger), scheduling policy A no longer performs well because the weaker node correlation results in the stronger overlapping among clusters. Thus, scheduling policy A fails to take advantage of the intracluster transmission (mainly refers to the transmission within C_d), which can save time and radio resources. Based on the new situation where nodes show extremely weak correlation, we have modified scheduling policy A and newly developed scheduling policy B, which is illustrated in Fig. 5, as follows.

1) Nodes containing a certain message create relays via the kth broadcast with area A_d ($k = 1, \ldots, \Theta(u)$; R^d_b denotes the overall number of relays).
2) If one relay is captured by the destination within range l^d_b, the message will be transmitted to the destination via h^d_b-hop unicast transmission. If not, we go back to step 1.

Remark: Basically, scheduling policy B is similar to the general scheduling policy [6] as the correlated mobility degenerates into the i.i.d. mobility when the node mobility shows extremely weak correlation. Here, we omit the fundamental tradeoffs of the radio resource, multihop, and half-duplex, which can be similarly derived as that in [6]. In the following, we only show the basic tradeoff of delay and directly give the upper bound of the capacity–delay tradeoff of scheduling policy B.

Lemma 12: Under scheduling policy B in cluster dense regime, the delay for a particular bit b and the associated scheduling parameters comply with the following inequality:

$$c^d_6 \log n \mathbb{E}\left[D^d_b\right] \geq \frac{n}{\mathbb{E}\left[R^d_b\right]\mathbb{E}\left[l^d_b + \frac{1}{n}\right]^2} \quad (16)$$

where c^d_6 is a positive constant.

Proof: Here, we only give the intuitive proof. The detailed proof is similar to the previous lemmas.

We assume that there are R^d_{bi} relays in the ith cluster, where $i = 1, 2, \ldots, \hat{m}$. Denoting X^{cap} as the event that at least one relay is captured by the destination, then, when $l_b^d \leq \Theta(R)$

$$\mathbf{P}[X^{\mathrm{cap}}] \leq 1 - \prod_{i=1}^{\hat{m}} \left(1 - \frac{\left(R - l_b^d\right)^2}{n} \frac{\left(l_b^d\right)^2}{R^2}\right)^{R_{bi}^d}$$

$$\leq 1 - \left(1 - \frac{c_6^d \left(l_b^d\right)^2}{n}\right)^{R_b^d} \leq \frac{c_6^d \left(l_b^d\right)^2 R_b^d}{n}$$

when $l_b^d > \Theta(R)$, we treat relays as $\Theta(R_b^d)$ intercluster duplications, because they are created by u times broadcast

$$\mathbf{P}[X^{\mathrm{cap}}] \leq 1 - \left(1 - \frac{c_6^d \left(l_b^d\right)^2}{n}\right)^{R_b^d} \leq \frac{c_6^d \left(l_b^d\right)^2 R_b^d}{n}.$$

Then, the average packet delay is

$$D_b^d = \frac{1}{\mathbf{P}[X^{\mathrm{cap}}]} \geq \frac{n}{c_6^d R_b^d \left(l_b^d\right)^2}.$$

By the Hölder's and Jensen's inequalities, we have

$$c_6^d \mathbb{E}\left[D_b^d\right] \geq \frac{n}{\mathbb{E}\left[R_b^d\right] \mathbb{E}\left[l_b^d\right]^2}.$$

If the number of needed relays is larger than the number of clusters m when $l_b^d > \Theta(R)$, this basic tradeoff [see inequality (16)] will no longer hold. Fortunately, we prove that it will not happen by contradiction. If $R_b^d > m$ when $l_b^d > R$, we have $(1-d)/3 > v$ and $2(1-d)/3 > 2\beta$. Combining the two equalities, we have $1 - d > v + 2\beta \geq 1$, which will make sense only if $d < 0$. Thus, the number of needed relays will not be larger than m when $l_b^d > \Theta(R)$. ■

Theorem 5: Under scheduling policy B in cluster dense regime, let $\bar{D}_B^d$ denote the mean delay averaged over all bits, and let λ_B^d be the capacity of each source–destination pair. The following upper bound holds:

$$\left(\lambda_B^d\right)^3 \leq O\left(\frac{\bar{D}_B^d}{n} \log^3 n\right).$$

So far, we have obtained both the upper bounds of the capacity–delay tradeoff of scheduling policy A and scheduling policy B in cluster dense regime, of which two results are presented in Theorems 4 and 5, respectively. Assuming $\bar{D}_A^d = \bar{D}_B^d = \bar{D}^d$, then the overall upper bound of the capacity–delay tradeoff in cluster dense regime can be derived easily.

Theorem 6: In cluster dense regime, let $\bar{D}^d$ denote the mean delay averaged over all bits, and let λ^d be the capacity of each source–destination pair. Assuming $\bar{D}_A^d = \bar{D}_B^d = \bar{D}^d$, then the following upper bound holds:

$$\lambda^d = \max\left\{\lambda_A^d, \lambda_B^d\right\}.$$

Note that scheduling policy A and scheduling policy B are both applicable to the cluster dense regime. Under what circumstance we should choose A or B to operate highly depends on the correlation degree of node mobility. Generally speaking, If $\lambda_A^d \geq \lambda_B^d$, we use scheduling policy A. Otherwise, we use scheduling policy B.

V. Lower Bound of the Cluster Dense Regime

We mainly investigate the achievable lower bound for the cluster dense regime here. Similar to the derivation of the upper bound, we calculate the lower bound under scheduling policy A and scheduling policy B, respectively. Given certain network conditions ($m = n^v$, $R = n^\beta$, and $\bar{D}^d = n^d$), we choose lower bound A if $\lambda_A^d \geq \lambda_B^d$. Otherwise, we choose lower bound B.

A. Lower Bound of Scheduling Policy A

Under scheduling policy A, we divide the unit time slot into four subslots. The basic operation of each subslot is shown in the following.

1) Nodes (source node and relays) create intercluster duplications via u times broadcast.
2) One of the intercluster duplications is captured by a node in C_d within range l_{1b}^d and is transmitted to the node via h_{1b}^d-hop unicast transmission. Each hop exploits the transmission range of r_b^h.
3) Nodes in C_d create R_{db}^d intracluster duplications via broadcast within C_d.
4) One of the intracluster duplications is captured by the destination within range l_{2b}^d and is transmitted to the destination via h_{2b}^d-hop unicast transmission. Each hop exploits the transmission range of r_b^h.

The value of scheduling parameters in the preceding scheme for achieving the lower bound are selected from Tables II–V on different delay-tolerant conditions and system parameters. Each cell owns a constant fraction $1/c_5^d$ of time to transmit by utilizing the time-division multiple-access (TDMA) mechanism. In the following, we describe in detail the lower bound achieving scheme.

1) In subslot 1, we divide the whole network into $\mathbb{T}_1^d = \lfloor n/(A_d \log n)\rfloor$ cells of equal area, where $A_d = \min\{mR^2/n, R_{cb}^d\}$ denotes the broadcast area. Nodes in each cell take turns to broadcast for at least $\lambda^d/(c_5^d \log n)$ fraction of one subslot, where $\lambda^d/(c_5^d \log n) \leq 1/(c_5^d A_d \log n)$. If any cell contains more than $c_5^d \log n/\lambda^d$ nodes, we call the operation $\mathrm{Error}_{\mathrm{IA}}^d$.
2) In subslot 2, we divide the whole network into $\mathbb{T}_2^d = \lfloor n/((l_{1b}^d)^2 \log n)\rfloor$ cells of equal area. If a certain message b is not captured within $\Theta(D^d)$ slots, we call it $\mathrm{Error}_{\mathrm{IIA}}^d$. Otherwise, we further divide each cell into $\mathbb{T}_3^d = (h_{1b}^d)^2$ mini cells of equal area. The captured message is transmitted to a node in C_d through mini cells via multihop transmission during subslot 2 (first along horizontal data path and then along vertical data path). If the network fails to transmit the captured message to a node in C_d within a certain subslot, we call the operation $\mathrm{Error}_{\mathrm{IIIA}}^d$.
3) In subslot 3, we divide the whole network into $\mathbb{T}_4^d = \lfloor n^2/(mR^2 R_{db}^d \log n)\rfloor$ cells of equal area. Nodes in each cell take turns to broadcast for at least $\lambda^d/(c_5^d \log n)$ fraction of one subslot, where $\lambda^d/(c_5^d \log n) \leq n/(c_5^d m R^2 R_{db}^d \log n)$. If any cell contains more than $c_5^d \log n/\lambda^d$ nodes, we call the operation $\mathrm{Error}_{\mathrm{IVA}}^d$.
4) In subslot 4, we divide the whole network into $\mathbb{T}_5^d = \lfloor n/((l_{2b}^d)^2 \log n)\rfloor$ cells of equal area. If a certain message

b is not captured within $\Theta(D^d)$ slots, we call it $\text{Error}^d_{\text{VA}}$. Otherwise, we further divide each cell into $\mathbb{T}^d_6 = (h^d_{2b})^2$ mini cells of equal area. The captured message is transmitted to its destination through mini cells via multihop transmission during subslot 4 (first along horizontal data path and then along vertical data path). If the network fails to transmit the captured message to its destination within a certain subslot, we call the operation $\text{Error}^d_{\text{VIA}}$.

Theorem 7: As $n \to \infty$, $\text{Error}^d_{\text{IA}} \to 0, \text{Error}^d_{\text{IIA}} \to 0, \ldots,$ $\text{Error}^d_{\text{VIA}} \to 0$. Thus, we can achieve the lower bound of the capacity–delay tradeoff of $\Theta(\lambda^d/\log n)$ per-node capacity with $\Theta(D^d \log n)$ delay.

Proof: The cases of $\text{Error}^d_{\text{IA}}$, $\text{Error}^d_{\text{IIA}}$, and $\text{Error}^d_{\text{IIIA}}$ are similar to that of $\text{Error}^d_{\text{IVA}}$, $\text{Error}^d_{\text{VA}}$ and $\text{Error}^d_{\text{VIA}}$; thus, we only prove the cases of $\text{Error}^d_{\text{IVA}} \to 0$, $\text{Error}^d_{\text{VA}} \to 0$, and $\text{Error}^d_{\text{VIA}} \to 0$, as follows.

1) $\text{Error}^d_{\text{IVA}}$: The problem can be modeled as an equivalent experiment, which is much easier to understand. We throw n balls into $\mathbb{T}^d_4$ urns, where the number of balls in each urn is denoted by X^d_{IV}. If $X^d_{\text{IV}} > c^d_5 \log n/\lambda^d$, $\text{Error}^d_{\text{IVA}}$ happens, i.e.,

$$\mathbb{E}\left[X^d_{\text{IV}}\right] = \frac{n}{\frac{n^2}{mR^2R^d_{db}\log n}} = \frac{\log n}{\lambda^d}.$$

Using the multiplicative form of the Chernoff bound

$$\mathbf{P}\left[X^d_{\text{IV}} > \frac{2\log n}{\lambda^d}\right] < \left(\frac{e}{4}\right)^{\frac{\log n}{\lambda^d}} < O\left(\frac{1}{n}\right).$$

As $n \to \infty$, $\mathbf{P}[X^d_{\text{IV}} > (2\log n/\lambda^d)] \to 0$, which indicates that $\mathbf{P}[\text{Error}^d_{\text{IVA}}] \to 0$ when $n \to \infty$.

2) $\text{Error}^d_{\text{VA}}$: Similar to the analysis of $\text{Error}^d_{\text{IVA}}$, we can also model the problem as an equivalent experiment. We throw $n\bar{D}^d \log n$ balls into $(R^2\mathbb{T}^d_4/n)(R^2\mathbb{T}^d_5/n)$ urns, where the number of balls in each urn is denoted by X^d_V. If $X^d_V = 0$, $\text{Error}^d_{\text{VA}}$ happens, i.e.,

$$\mathbb{E}\left[X^d_V\right] = \frac{n\bar{D}^d \log n}{\frac{R^2 n}{mR^2R^d_{db}\log n}\frac{R^2}{\left(l^d_{2b}\right)^2\log n}} = \log n.$$

Using the multiplicative form of the Chernoff bound

$$\mathbf{P}\left[X^d_V = 0\right] < \mathbf{P}\left[X^d_V < \frac{\log n}{2}\right] < \left(\sqrt{\frac{2}{e}}\right)^{\log n} = O\left(\frac{1}{n}\right).$$

As $n \to \infty$, $\mathbf{P}[X^d_V = 0] \to 0$, which indicates that $\mathbf{P}[\text{Error}^d_{\text{VA}}] \to 0$ when $n \to \infty$.

3) $\text{Error}^d_{\text{VIA}}$: To prevent the event of $\text{Error}^d_{\text{VIA}}$ from happening, three conditions should be satisfied.

   1) Each mini cell should contain at least one node.
   2) Each relay serves at most one certain source–destination pair.
   3) The number of horizontal or vertical data paths that pass though or originate from each mini cell should be bounded. Combining 1 and 2, we can estimate the total amount of messages that each mini cell should sustain, which is $\Theta(\log n/\lambda^d)$. In the following, we prove that each of the aforementioned three conditions will be satisfied by conducting four equivalent experiments, as follows.

   a) Experiment A: We throw n balls into $\mathbb{T}^d_5\mathbb{T}^d_6$ urns and denote the number of balls in each urn as $X^d_{\text{VI}_\text{a}}$. If $X^d_{\text{VI}_\text{a}} = 0$, $\text{Error}^d_{\text{VI}_\text{a}}$ happens (there exists at least one mini cell that does not contain a node), i.e.,

$$\mathbb{E}\left[X^d_{\text{VI}_\text{a}}\right] = \frac{n\bar{D}^d \log n}{\frac{n}{\left(l^d_{2b}\right)^2\log n}\left(h^d_{2b}\right)^2} = \log n.$$

   Using the multiplicative form of the Chernoff bound

$$\mathbf{P}\left[X^d_{\text{VI}_\text{a}} = 0\right] < \mathbf{P}\left[X^d_{\text{VI}_\text{a}} < \frac{\log n}{2}\right] < \left(\sqrt{\frac{2}{e}}\right)^{\log n} = O\left(\frac{1}{n}\right).$$

   As $n \to \infty$, $\mathbf{P}[X^d_{\text{VI}_\text{a}} 0] \to 0$, which indicates that $\mathbf{P}[\text{Error}^d_{\text{VI}_\text{a}}] \to 0$ when $n \to \infty$.

   b) Experiment B: We throw n balls into $\mathbb{T}^d_4\mathbb{T}^d_5$ urns.

   c) Experiment C: We throw $\mathbb{T}^d_4$ balls into $\sqrt{\mathbb{T}^d_6}$ urns.

   d) Experiment D: This is the combination of experiments B and C, which is created to calculate the total amount of messages that each mini cell should sustain. We throw n balls into $\mathbb{T}^d_5\sqrt{\mathbb{T}^d_6}$ urns and denote the number of balls in each urn by $X^d_{\text{VI}_\text{d}}$. If $X^d_{\text{VI}_\text{d}} > c^d_7 \log n/\lambda^d$, $\text{Error}^d_{\text{VI}_\text{d}}$ happens, i.e.,

$$\mathbb{E}\left[X^d_{\text{VI}_\text{d}}\right] = \frac{n}{\frac{n}{\left(l^d_{2b}\right)^2\log n}h^d_{2b}} = \frac{\log n}{\lambda^d}.$$

   Using the multiplicative form of the Chernoff bound

$$\mathbf{P}\left[X^d_{\text{VI}_\text{d}} > c^d_7\frac{\log n}{\lambda^d}\right] < \left(\frac{e}{4}\right)^{\log n} = O\left(\frac{1}{n}\right).$$

   With $n \to \infty$, $\mathbf{P}[X^d_{\text{VI}_\text{d}} > c^d_7 \log n/\lambda^d] \to 0$, which indicates that $\mathbf{P}[\text{Error}^d_{\text{VI}_\text{d}}] \to 0$, as $n \to \infty$, and $\mathbf{P}[\text{Error}^d_{\text{VIA}}] \to 0$, as $n \to \infty$.

■

B. Lower Bound of Scheduling Policy B

Under scheduling policy B, we divide the unit time slot into two subslots. The basic operation of each subslot is shown in the following.

1) Nodes (source node and relays) create R^d_b relays via u times broadcast.
2) One of the relays is captured by its destination within range l^d_b and is transmitted to the destination via h^d_b-hop unicast transmission. Each hop exploits the transmission range of r^h_b.

The values of scheduling parameters in the preceding scheme are selected from Table VI on different delay-tolerant

TABLE VI
OPTIMAL VALUES OF SCHEDULING PARAMETERS UNDER SCHEDULING POLICY B

R_b^d	$\Theta(n^{(1-\tilde{d})/3})$
l_b^d	$\Theta(n^{(1-\tilde{d})/3}/\log^{1/2} n)$
h_b^d	$\Theta(n^{(1-\tilde{d})/3}/\log n)$
r_b^h	$\Theta(\log^{\frac{1}{2}} n)$

conditions and system parameters. TDMA is applied as well, so each cell can have $1/c_5^d$ fraction of time to transmit. In the following, we describe our lower bound achieving scheme.

1) In subslot 1, we divide the whole network into $\mathbb{T}_1^d = \lfloor n/(A_d \log n)\rfloor$ cells of equal area. Nodes in each cell take turns to be active for at least $\lambda^d/(c_5^d \log n)$ fraction of one subslot to broadcast, where $\lambda^d/(c_5^d \log n) \le 1/(c_5^d A_d \log n)$. If any cell contains more than $c_5^d \log n/\lambda^d$ nodes, we call the operation $\text{Error}_{\text{IB}}^d$.
2) In subslot 2, we divide the whole network into $\mathbb{T}_2^d = \lfloor n/((l_b^d)^2 \log n)\rfloor$ cells of equal area. If a certain message b is not captured by the cell within $\Theta(D^d)$ slots, we call it $\text{Error}_{\text{IIB}}^d$. Then, we further divide each cell into $\mathbb{T}_3^d = (h_b^d)^2$ mini cells of equal areas. The message captured by the cell is transmitted to its destination through mini cells via multihop unicast transmissions during this subslot (first along horizontal data path and then along vertical data path). If the network fails to transmit the captured message to its destination within a certain subslot, we call the operation $\text{Error}_{\text{IIIB}}^d$.

Theorem 8: As $n \to \infty$, $\text{Error}_{\text{IB}}^d \to 0$, $\text{Error}_{\text{IIB}}^d \to 0$, $\text{Error}_{\text{IIIB}}^d \to 0$. Thus, we can achieve the lower bound of the capacity–delay tradeoff in cluster dense regime of $\Theta(\lambda^d/\log n)$ per-node capacity with $\Theta(D^d \log n)$ delay.

Proof: The proof is similar to that of Theorem 7, which we omit for simplification. ■

VI. DISCUSSION

The results of the upper and lower bounds of the capacity–delay tradeoff in cluster critical regime $(v + 2\beta = 1)$ can be obtained from the analysis of either the cluster sparse regime or the cluster dense regime. We will not repeat the deducing process of the cluster critical regime for simplification.

We have studied the capacity–delay tradeoff of correlated mobility for all subcases: the cluster sparse regime, the cluster dense regime, and the cluster critical regime. The impact of node correlation to the per-node capacity and packet delay will be discussed in the following.

In cluster sparse regime, the mobility of nodes performs strong correlation (i.e., the number of clusters is small, or nodes in each cluster move within a small region). Thus, clusters in the network suffer a certain degree of disconnectedness, which restricts the maximum per-node capacity (mR^2/n) and minimum packet delay $(n/(mR^2))$. The disconnectedness due to the strong correlation of node mobility greatly degrades the performance of the network, which we should try to avoid when we take into account the real application deployment.

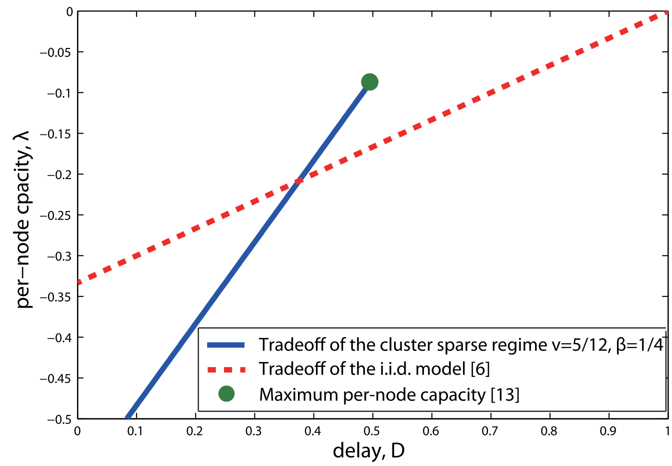

Fig. 6. Capacity–delay tradeoff: The cluster sparse regime ($v = 5/12$, $\beta = 1/4$) of correlated mobility versus the i.i.d. mobility. (The x- and y-axes represent the exponents of power law distribution, and this rule holds for the subsequent figures.)

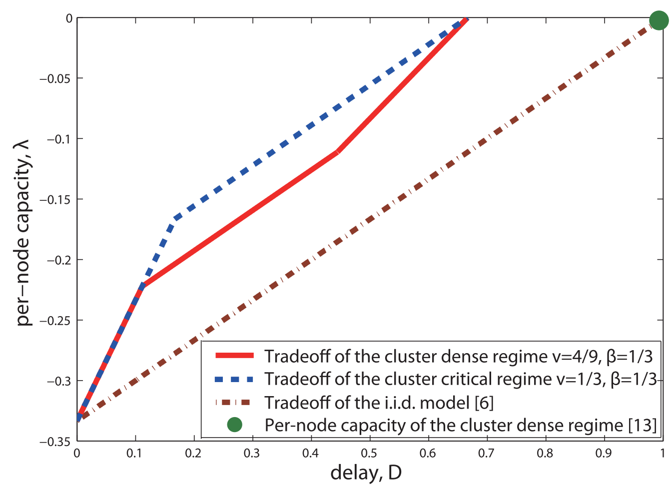

Fig. 7. Capacity–delay tradeoff in cluster dense regime ($v = 4/9$, $\beta = 1/3$), cluster critical regime ($v = 1/3$, $\beta = 1/3$), and i.i.d. mobility model.

Fig. 6 demonstrates the capacity–delay tradeoff in cluster sparse regime when $v = 5/12$ and $\beta = 1/4$. Although it generally performs worse than that of the i.i.d. mobility model, there still exists certain space we can explore to improve the tradeoff when high capacity becomes the major concern in real applications. Comparing the two curves in Fig. 6, we can easily find that the tradeoff in cluster sparse regime is better than the optimal tradeoff in i.i.d. slow mobility model [6] when considering the high-capacity region.

In cluster dense regime, the mobility of nodes shows weak correlation, and nodes of different clusters meet each other frequently. Obviously, the network will no longer suffer the disconnectedness and thus performs better than the i.i.d. mobility model. Fig. 7 illustrates the capacity–delay tradeoff in cluster dense regime ($v = 4/9$, $\beta = 1/3$), which is much better than that of the i.i.d. slow mobility model.

Fig. 7 also exhibits the capacity–delay tradeoff in cluster critical regime, which is better than that in cluster dense regime. The reason is that, when the node mobility shows weak correlation (even extremely weak correlation), the number of clusters is

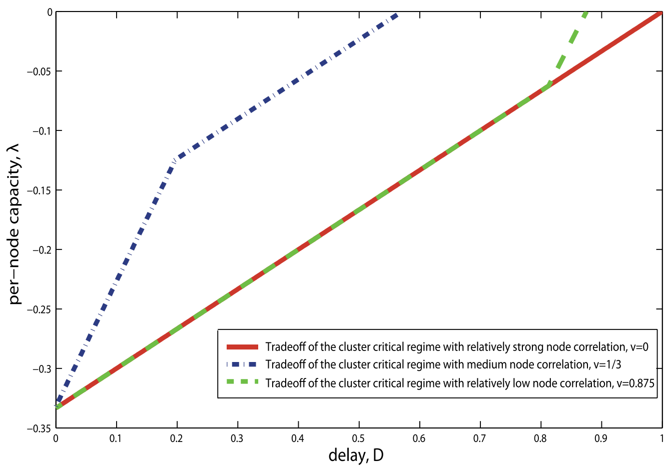

Fig. 8. Capacity–delay tradeoff in cluster critical regime with various values of v ($v + 2\beta = 1$).

large, and each cluster covers a large area of the network, which results in the severe competition of the limited radio resources and a longer delay within each cluster. On the contrary, in cluster critical regime, the node mobility shows medium correlation where the number of clusters or the area each cluster covers is neither too large nor too small. The medium correlation of node mobility benefits the network performance mainly in three aspects: 1) The connectivity is guaranteed (but not strongly connected); 2) clusters are loosely overlapped, which relieves the competition for radio resources among them compared with the case of cluster dense regime; and 3) each cluster covers a relatively small area, which reduces the transmission delay within the cluster. Thus, the node mobility in cluster critical regime can achieve better performance of capacity–delay tradeoff than that in cluster sparse regime and cluster dense regime.

Fig. 8 shows the capacity–delay tradeoff in cluster critical regime with various system parameters. We can easily find that, if either the value of v or β is too large, the network performance will be degraded. From numerous numerical experiments (not shown in this paper), we find that, when $v = 1/4$ ($\beta = 3/8$), the network can achieve the best per-node capacity of $\Theta(n^{-1/4})$ on condition that the packet delay remains to be $\Theta(1)$. When $v = 1/2$ ($\beta = 1/4$), the network can achieve the best packet delay of $\Theta(\sqrt{n})$ on condition that the per-node capacity remains to be $\Theta(1)$. Thus, in cluster critical regime, we believe that it is essential to balance the number of clusters (adjust parameter v) and the area that each cluster covers (adjust parameter β) on condition that $v + 2\beta = 1$ because these two system metrics greatly affect the network performance, which are also important for the system design in practice.

VII. Conclusion

This paper has mainly focused on the impact of correlation of node mobility on the capacity–delay tradeoff in MANETs. We have investigated the characteristics of correlated mobility and figured out the fundamental relationship between the capacity, the delay, and the associated system parameters, which afterward provides great help to derive the capacity–delay tradeoff. Results demonstrate a whole picture of how the correlated mobility affect the network performance in different degrees of correlation. We reveal that all the three kinds of different degrees of correlated mobility can enhance the performance of the capacity–delay tradeoff to some extents. In particular, the medium correlation of node mobility can better benefit the performance of the capacity–delay tradeoff compared with the strong or weak correlation of node mobility because it can effectively control the number of clusters and the area that each cluster covers, which further relieves the competition of limited radio resources and decrease the delay of the so-called "last mile" transmission.

References

[1] P. Gupta and P. R. Kumar, "The capacity of wireless networks," *IEEE Trans. Inf. Theory*, vol. 46, no. 2, pp. 388–404, Mar. 2000.
[2] M. Franceschetti, O. Dousse, D. N. C. Tse, and P. Thiran, "Closing the gap in the capacity of wireless networks via percolation theory," *IEEE Trans. Inf. Theory*, vol. 53, no. 3, pp. 1009–1018, Mar. 2007.
[3] M. Grossglauser and D. Tse, "Mobility increases the capacity of *ad hoc* wireless networks," *IEEE/ACM Trans. Netw.*, vol. 10, no. 4, pp. 477–486, Aug. 2002.
[4] M. Neely and E. Modiano, "Capacity and delay tradeoffs for *ad hoc* mobile networks," *IEEE Trans. Inf. Theory*, vol. 51, no. 6, pp. 1917–1937, Jun. 2005.
[5] S. Toumpis and A. J. Goldsmith, "Large wireless networks under fading, mobility, and delay constraints," in *Proc. IEEE INFOCOM*, Hong Kong, Mar. 2004, pp. 609–619.
[6] X. Lin and N. B. Shroff, "The fundamental capacity–delay tradeoff in large mobile *ad hoc* networks," in *Proc. IEEE MedHoc*, Bodrum, Turkey, Jun. 2004, pp. 1–13.
[7] A. E. Gamal, J. Mammen, B. Prabhakar, and D. Shah, "Throughput–delay trade-off in wireless network," in *Proc. IEEE INFOCOM*, Hong Kong, Mar. 2004, pp. 464–475.
[8] N. Bansal and Z. Liu, "Capacity, delay and mobility in wireless *ad hoc* networks," in *Proc. IEEE INFOCOM*, San Francisco, CA, USA, Apr. 2003, pp. 1553–1563.
[9] E. Perevalov and R. Blum, "Even one-dimensional mobility increases *ad hoc* wireless capacity," in *Proc. IEEE ISIT*, Lausanne, Switzerland, Jun. 2002, p. 352.
[10] M. Garetto, P. Giaccone, and E. Leonardi, "Capacity scaling in delay tolerant networks with heterogeneous mobile nodes," in *Proc. ACM MobiHoc*, Montreal, QC, Canada, Sep. 2007, pp. 41–50.
[11] J. Mammen and D. Shah, "Throughput and delay in random wireless networks with restricted mobility," *IEEE Trans. Inf. Theory*, vol. 53, no. 3, pp. 1108–1116, Mar. 2007.
[12] M. Garetto, P. Giaccone, and E. Leonardi, "Capacity scaling of sparse mobile *ad hoc* networks," in *Proc. IEEE INFOCOM*, Phoenix, AZ, USA, Apr. 2008, pp. 744–752.
[13] D. Ciullo, V. Martina, M. Garetto, and E. Leonardi, "Impact of correlated mobility on delay–throughput performance in mobile *ad hoc* networks," in *Proc. IEEE INFOCOM*, San Diego, CA, USA, Mar. 2010, pp. 1–9.
[14] J. Yoon, B. D. Noble, M. Liu, and M. Kim, "Building realistic mobility models from coarse-grained traces," in *Proc. ACM MobiSys*, Uppsala, Sweden, Jun. 2006, pp. 177–190.
[15] V. Naumov, R. Baumann, and T. Gross, "An evaluation of inter-vehicle *ad hoc* networks based on realistic vehicular traces," in *Proc. ACM MobiSys*, Uppsala, Sweden, Jun. 2006, pp. 108–119.
[16] M. Musolesi and C. Mascolo, "Designing mobility models based on social network theory," *Mobile Comput. Commun. Rev.*, vol. 11, no. 3, pp. 59–70, Jul. 2007.
[17] P. Hui and J. Crowcroft, "Human mobility models and opportunistic communications system design," *Philos. Trans. Roy. Soc. A*, vol. 366, no. 1872, pp. 2005–2016, Jun. 2008.
[18] X. Hong, M. Gerla, G. Pei, and C. Chiang, "A group mobility model for *ad hoc* wireless networks," in *Proc. ACM MSWIM*, Seattle, WA, USA, Aug. 1999, pp. 53–60.
[19] S. Yao, X. Wang, X. Tian, and Q. Zhang, "Delay–throughput tradeoff with correlated mobility of *ad hoc* networks," in *Proc. IEEE INFOCOM*, Toronto, ON, Canada, Apr. 2014, pp. 2589–2597.
[20] M. Penrose, *Random Geometric Graphs*. London, U.K.: Oxford Univ. Press, 2003.
[21] R. Durrett, *Theory and Examples*, 2nd ed. Belmont, CA, USA: Duxbury, 1996.

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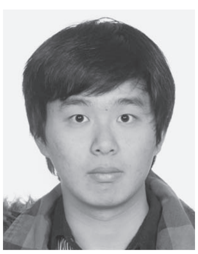

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