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***Abstract*—A common complication for routing in mobile sensor networks is how to efficiently control the forwarding behaviors of relay nodes so as to save their energy consumption and buffer usage while simultaneously satisfy the specified delivery performance requirement. Available works either assign each message with a lifetime, a maximum number of copies, or a sequence number, or flush special feedback information among the whole network after the message reception. In the former case, a relay node has no idea of the message reception status and will carry and forward the message until meeting the destination; while the latter could efficiently notify all relay nodes but demands extra communication resources. Different from previous studies, we consider in this paper an explicit probabilistic stopping mechanism for relay nodes. Under such mechanism, a relay node that is actively disseminating a message will stop spreading the message with a certain probability, after meeting another node having already received the message. We first develop a two-dimensional Markov chain framework to characterize the highly complicated dynamics until the end of message propagation, then conduct Markovian analysis to derive the associated important performance metrics, including the average time required for the completion of message propagation, the expectation and variance of the fraction of nodes finally receiving the message, and the probability that a given number of nodes end up with the message, etc. Finally, extensive numerical results are provided to analytically explore how the network parameter settings may affect these performance metrics.**

***Keywords*-mobile sensor networks; information propagation; routing; Markov chain;**

I. Introduction

Mobile sensor networks hold great promise for lots of applications, such as animal tracking, habitat monitoring, etc. In such networks, each node has only local knowledge, limited buffer space for storage, and constrained power energy for computation or message transceive [1]. Consequently, a node pair can communicate with each other only when they move into reciprocal communication range. As mobile nodes are usually sparsely distributed and move randomly in the network region, it is very difficult (if not impossible) to find or specify a routing path to deliver the traffic flow from the source to the destination. Note also that, establishing a routing path usually comes with lots of unavoidable communication overheads, such as routing request, routing respond, neighborhood update, etc., which necessarily impose a significant extra burden on the resource-limited sensor nodes. Furthermore, even after taking up lots of precious network resources, a newly established routing path may function effectively only for a short time period and become invalid soon due to the random node mobilities. Therefore, in light of the practical resource limitation at each node, the traditional route-based routing schemes function poorly and cannot be adopted in mobile sensor networks [2].

As a consequence, mobile sensor networks have switched to rely on node mobilities and their contact sequences to enable messages to be delivered from end to end. One common feature of such kind of routing schemes is that, multiple nodes are usually employed as relays to help the source to disseminate a message and thus improve its delivery performances (e.g., the end-to-end delivery probability, the delivery delay), so as to compensate the lack of communication opportunities. However, a common complication is how to efficiently control the forwarding behaviors of relay nodes so as to save their energy consumption and buffer usage while simultaneously satisfy the specified delivery performance requirement.

There has been several prior works in this line. In [2], a family of routing schemes were proposed for intermittently connected mobile networks, in which only a fixed number of copies will be distributed for each packet (or message). In [3], Liu *et al.* studied the impact of message lifetime on the message delivery performances, where a lifetime is assigned to each message copy, and a message will be dropped from the node buffers immediately after its expiration. Besides limiting the number of copies or message lifetime, sequence number based mechanism has also been proposed to help remove remnant copies of packets that have already been received by the destination node. In [4], each packet is labeled with a sequence number, and the destination node maintains a request number to indicate the sequence number of the packet that is currently under requesting. Relay nodes flush out all packets with sequence number less than the request number after obtaining it during the meeting with the destination. More recently, the mechanism in [4] has been further generalized to a group number based scheme [5]. It is also noticed that explicit notification based approach has also been proposed, under which a special anti-packet will be flooded among the whole network as soon as a packet is delivered from a relay node to the destination node [6]–[8].

Note that above works either assign each message with a lifetime [3], a maximum number of copies [2], or a sequence number [4], [5], or flush special feedback information among the whole network after the message reception [6]–[8]. In the former case, a relay node has no idea of the message reception status and will carry and forward the message until meeting the destination; while the latter could efficiently notify all relay nodes but demands extra communication resources.

Different from previous studies, we consider in this paper an explicit probabilistic stopping mechanism for relay nodes. Under such mechanism, a relay node that is actively disseminating a message will stop spreading the message with a certain probability, after meeting another node having already received the message. We first develop a two-dimensional Markov chain framework to characterize the highly complicated dynamics until the end of message propagation, then conduct Markovian analysis to derive the associated important performance metrics, including the average time required for the completion of message propagation, the expectation and variance of the fraction of nodes finally receiving the message, and the probability that a given number of nodes end up with the message, etc. Finally, extensive numerical results are provided to analytically explore how the network parameter settings may affect these performance metrics.

The remainder of the paper is outlined as follows. In Section II, we introduce the considered system models and the performance metrics of interest. Section III presents the two-dimensional Markov chain framework and the related derivations. Section IV applies the developed theoretical framework to analytically explore the relationship between considered performance metrics and network parameters. Section V concludes the whole paper.

II. Preliminaries

A. System Models

Consider a mobile sensor network with n nodes moving randomly in the network region. Suppose the nodes are sparsely distributed that every time two nodes move within reciprocal transmission range, they can communicate with each other. Furthermore, we assume that only a limited number of packets can be transmitted during each node contact and we assume it to be W bits. Similar to previous studies [6], [7], we assume that for any two nodes, the occurrence of their contacts follows a Poisson distribution with inter-meeting intensity λ contacts/hour.

We consider a scenario where nodes need to disseminate their data to other nodes in the network. The data can be some events or measures sensed in a particular area, program packages to update embedded software, or system reconfigure commands, etc. Since our focus in this paper is to evaluate the impact of relay forwarding behaviors on network delivery performances, we assume that the data (or message) is of size no bigger than W bits and can be successfully transmitted during a single node contact. For the general case that the message is of size bigger than W bits and needs multiple contacts to be transmitted, please refer to [3] for details.

Without loss of generality, hereafter we focus on a specific message and study its propagation process in the network. In order to develop a general theoretical framework for characterizing the propagation process of the message and analyzing its delivery performances, we assume that there are m nodes, which are randomly and uniformly distributed in the network region, actively disseminating the message at the very beginning, $1 \leq m \leq n$. Note that as a node can obtain only limited knowledge when encountering other nodes, it makes individual decisions based on the acquired information so as to conserve its energy power and buffer space. Therefore, we consider in this paper an explicit probabilistic stopping mechanism for relay nodes, under which a relay node that is actively disseminating the message will stop spreading the message with a certain probability after meeting another node having already received the message.

Specifically, when a relay node R that is actively replicating copies for the message meets another node K, if K has not received the message yet, R replicates the message to K; if K is also actively disseminating the message, both R and K will stop spreading the message with probability $p/2$, since either of them has the same probability to become the transmitter, $0 \leq p \leq 1$; however, if K has already stopped disseminating the message, R will choose not to spread the message any more with probability p.

B. Performance Metrics

According to the probabilistic stopping mechanism adopted by each node, a node newly receiving the message will actively disseminate the message for a random time period, until it decides to stop spreading the message after meeting another node having already received the message. Therefore, one can see that, finally, there will be no nodes trying to disseminate the message in the network, i.e., the propagation process of the message will terminate in the end.

The first performance metric of our interest is the mean time required for the completion of the message propagation process. Given that there are m out of the n nodes actively disseminating the message at the very beginning, we denote by $t(m, n)$ the mean time it takes the message propagation process to terminate, i.e., the average lasting time of the propagation process. This metric can describe the statistical convergence speed of the dynamic stochastic process, i.e., how fast the probabilistic stopping behavior individually adopted by each node could drive the propagation process to end.

We are also interested with the fraction of mobile sensors that receive the message at the completion of the message propagation process. This performance metric is also called as the reach of a stochastic process, since it tells the degree (or percentile) for the message to finally make itself acquired by the n nodes. If we denote by $\mathbb{E}\{r(m,n)\}$ the mean value of the fraction of nodes finally receiving the message and denote by Var$\{r(m,n)\}$ its variance, one can see that $m/n \leq \mathbb{E}\{r(m,n)\} \leq 1$.

Another performance metric to be explored is the probability for a given number of nodes to end up with the message. We denote by $P(i)$ the probability that there are i nodes (including the initial m nodes) finally receiving the message, $m \leq i \leq n$. Actually, one can see that the probability mass function of discrete random variable $r(m,n)$ is closely related to $\{P(i)\}$. In particular,

$$\Pr\big(r(m,n) = j/n\big) = \begin{cases} 0 & \text{if } 0 \leq j < m; \\ P(j) & \text{if } m \leq j \leq n. \end{cases} \quad (1)$$

Furthermore, both $\mathbb{E}\{r(m,n)\}$ and Var$\{r(m,n)\}$ can be obtained by $P(i)$ as follows:

$$\mathbb{E}\{r(m,n)\} = \sum_{i=m}^{n} \frac{P(i)\cdot i}{n} \quad (2)$$

$$\text{Var}\{r(m,n)\} = \sum_{i=m}^{n} \frac{P(i)\cdot i^2}{n^2} - \Big(\sum_{i=m}^{n} \frac{P(i)\cdot i}{n}\Big)^2. \quad (3)$$

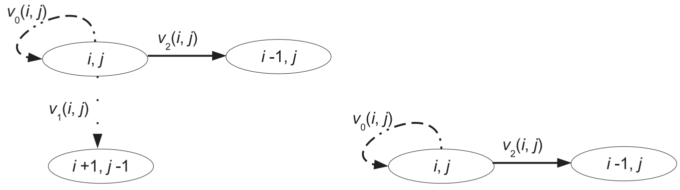
III. Two-Dimensional Markov Chain Framework and Derivations

In this section, we first develop a two-dimensional Markov chain framework to characterize the highly complicated dynamics until the end of message propagation process, then conduct Markovian analysis to derive the associated important performance metrics, including the average time $t(m,n)$ required for the completion of message propagation, the expectation and variance of the fraction of mobile sensors finally receiving the message, i.e., $\mathbb{E}\{r(m,n)\}$ and Var$\{r(m,n)\}$, and the probability $P(i)$ that i nodes end up with the message, etc.

A. Two-Dimensional Markov Chain Framework

We develop a two-dimensional Markov chain framework in three steps. First, we use a two-tuple to define a general network state which corresponds to a snapshot of the complicated message propagation process, and identify all transient states and absorbing states. Then, we define the transitions for each transient state and calculate the corresponding transition rates between neighboring states. Finally, after integrating the transitions among all network states, we obtain a full Markov chain framework to characterize the whole message propagation process.

Recall that each node makes individual decisions on whether or not to stop spreading the message. According to the node behaviors of disseminating the message, all the n nodes can be divided into three groups: the nodes that have not received the message yet, the nodes that are actively disseminating the message, and the nodes that have received the message but do not disseminate it. At the very beginning, we have m nodes actively disseminating the message, and $n-m$ nodes without receiving the message; while at the end of the message propagation process, there is no nodes actively disseminating the message.



(a) (b)

Figure 1. Transitions for a transient state (i,j), where $v_0(i,j)$, $v_1(i,j)$, and $v_2(i,j)$ correspond to the rates of self-loop transition, case 1 transition, and case 2 transition, respectively. (a) Case $1 \leq i \leq n$, $1 \leq j \leq n-m$. (b) Case $1 \leq i \leq n$, $j = 0$.

As motivated by the above divisions of nodes and also to capture all states that may appear within the message propagation process, we use a two-tuple (i,j) to represent a network state that there are i nodes actively disseminating the message and j nodes without receiving the message. Since the number of nodes is fixed in the considered network, the number of nodes that have stopped disseminating the message within the state (i,j) can be determined as $n-i-j$. Accordingly, the message propagation process starts from state $(m, n-m)$, and terminates at states $\{(0,k)|0 \leq k \leq n-m\}$. Obviously, the network state will never change if it evolves into $i=0$. Therefore, the states $\{(0,k)|0 \leq k \leq n-m\}$ are absorbing states, while the remaining states $\{(i,j)|1 \leq i \leq n, 0 \leq j \leq n-m\}$ are transient states.

Suppose the network is within a transient state (i,j) with $i \geq 1$, $j \geq 0$. Then, only one of the following three cases may happen:

- Case 1 Transition: a node replicates a copy of the message to another node and accordingly the network will transit to state $(i+1, j-1)$;
- Case 2 Transition: a node decides not to disseminate the message any more and accordingly the network will transit to state $(i-1, j)$;
- Self-loop Transition: neither of the above two cases happens and the network will stay in state (i,j).

Based on the above analysis for the possible transitions from a general transient state (i,j), if we denote by $v_0(i,j)$, $v_1(i,j)$, and $v_2(i,j)$, respectively, the transition rate to state (i,j), the transition rate to state $(i+1,j-1)$, and that to state $(i-1,j)$, the transitions for state (i,j) can be defined as Fig. 1. It is noticed from Fig. 1(b), there is only case 2 transition leaving state (i,j) when $j=0$.

After defining the transitions for each transient state (i,j), $i \geq 1$, $j \geq 0$, we now proceed to calculate the transition rates $v_0(i,j)$, $v_1(i,j)$, and $v_2(i,j)$. Note that the case 1 transition happens as long as one of the i nodes meets one of the j nodes. Since the inter-meeting time between any two nodes follows an exponential distribution with mean $1/\lambda$, the case 1 transition can be regarded as the minimum of $i \cdot j$ exponentially distributed variables. Therefore, the transition rate $v_1(i,j)$ can be given by

$$v_1(i,j) = i \cdot j \cdot \lambda \tag{4}$$

Similarly, we have

$$\begin{aligned} v_2(i,j) &= i \cdot (n-i-j) \cdot \lambda \cdot p + \binom{i}{2} \cdot \lambda \cdot \frac{p}{2} \cdot 2 \\ &= (n-j-\frac{i+1}{2}) \cdot i \cdot \lambda \cdot p \end{aligned} \tag{5}$$

and

$$\begin{aligned} v_0(i,j) &= -v_1(i,j) - v_2(i,j) \\ &= -\Big((1-p)j + (n-\frac{i+1}{2})p\Big) \cdot i \cdot \lambda \end{aligned} \tag{6}$$

If we integrate the transitions among all network states (including all transient states and absorbing states), we obtain a Markov chain framework as illustrated in Fig. 2, which is able to fully characterize the message propagation process. Given that there are m nodes actively disseminating the message at the very beginning, $1 \leq m \leq n$, as shown in Fig. 2, the two-dimensional Markov chain accordingly starts from the state $(m, n-m)$, and may become absorbed in an absorbing state $\{(0,k)|0 \leq k \leq n-m\}$.

B. Derivations of Performance Metrics

Based on the absorbing continuous-time Markov chain shown in Fig. 2, we now proceed to derive the average time $t(m,n)$ required for the completion of message propagation, the expectation and variance of the fraction of mobile sensors finally receiving the message, i.e., $\mathbb{E}\{r(m,n)\}$ and $\mathrm{Var}\{r(m,n)\}$, and the probability $P(i)$ of i nodes receiving the message at the completion of message propagation, $m \leq i \leq n$. The basic methodology is as follows: first, we adopt the theory of absorbing Markov chain to derive the above performance metrics via matrix operations; then, we utilize the theory of blocking matrix to define the details for the related matrices.

It is easy to observe from Fig. 2 that, there are in total $n-m+1$ rows of network states, one absorbing state within each row. If we number these $n-m+1$ rows sequentially as $0,1,2,\ldots,n-m$ from top to down, then we can see that the total number of transient states in the k_{th} row can be determined as

$$L_k = k + m \qquad \text{if } 0 \leq k \leq n-m. \tag{7}$$

If we denote by β the total number of transient states in Fig. 2, then we have

$$\beta = \sum_{k=0}^{n-m} L_k = \frac{(n+m)(n-m+1)}{2}. \tag{8}$$

To facilitate the expressions, we number the β transient states sequentially as $1,2,3,\ldots,\beta$ in a left-to-right and top-to-down way, and number the $n-m+1$ absorbing states sequentially as $1,2,3,\ldots,n-m+1$ in a top-to-down way.

The continuous-time Markov chain in Fig. 2 defines all the incoming and outgoing transitions (or jumps) for all network states. Note that there exists an absorbing discrete-time Markov chain (DTMC) embedded just before the jumps of the Markov chain in Fig. 2, among which the transition from a transient state to another neighboring transient state may happen with certain probability closely related to the associated transition rates in Fig. 2. If we denote by $\mathbf{P} = (q_{ij})_{(\beta+n-m+1)\times(\beta+n-m+1)}$ the one-step transition matrix of the discrete-time Makrov chain embedded in Fig. 2, then we have

$$\mathbf{P} = \begin{pmatrix} \mathbf{Q} & \mathbf{R} \\ \mathbf{0} & \mathbf{I} \end{pmatrix}, \tag{9}$$

where $\mathbf{Q}$ is a $\beta \times \beta$ matrix defining the one-step transition probabilities among all β transient states in the embedded DTMC, $\mathbf{R}$ is of size $\beta \times (n-m+1)$ defining the one-step transition probabilities from β transient states to $n-m+1$ absorbing states, $\mathbf{0}$ is a $\beta \times \beta$ zero matrix, and $\mathbf{I}$ is the identity matrix of size $(n-m+1) \times (n-m+1)$. Note that (9) is also called as the canonical form of an absorbing Markov chain [9].

For the embedded DTMC, if we denote by $\mathbf{N}$ its fundamental matrix. Then according to the Markov chain theory [9], we have

$$\mathbf{N} = (\mathbf{I} - \mathbf{Q})^{-1}. \tag{10}$$

It is noticed that the tk-entry of the fundamental matrix $\mathbf{N}$, i.e., $\mathbf{N}(t,k)$, $t,k \in [1,\beta]$, actually represents the total number of visits to state k before the embedded DTMC becomes absorbed, given that the Markov chain initially starts from state t. It is further noticed from the transition rate (6), the sojourn time in each transient state is actually an exponentially distributed variable with mean $-1/v_0(i,j)$. Without incurring any ambiguity, hereafter, we use notations of $v_0(k)$, $v_1(k)$, and $v_2(k)$ interchangeably with $v_0(i,j)$, $v_1(i,j)$, and $v_2(i,j)$, respectively, to represent the transition rates for a transient state (i,j) with sequence id k.

Thus, the average time $t(m,n)$ required for the completion of message propagation in the considered network, can be given by

$$\begin{aligned} t(m,n) &= \sum_{k=1}^{\beta} \mathbf{N}(1,k) \cdot \Big(-\frac{1}{v_0(k)}\Big) \\ &= \mathbf{e} \cdot \mathbf{N} \cdot \mathbf{V_0}, \end{aligned} \tag{11}$$

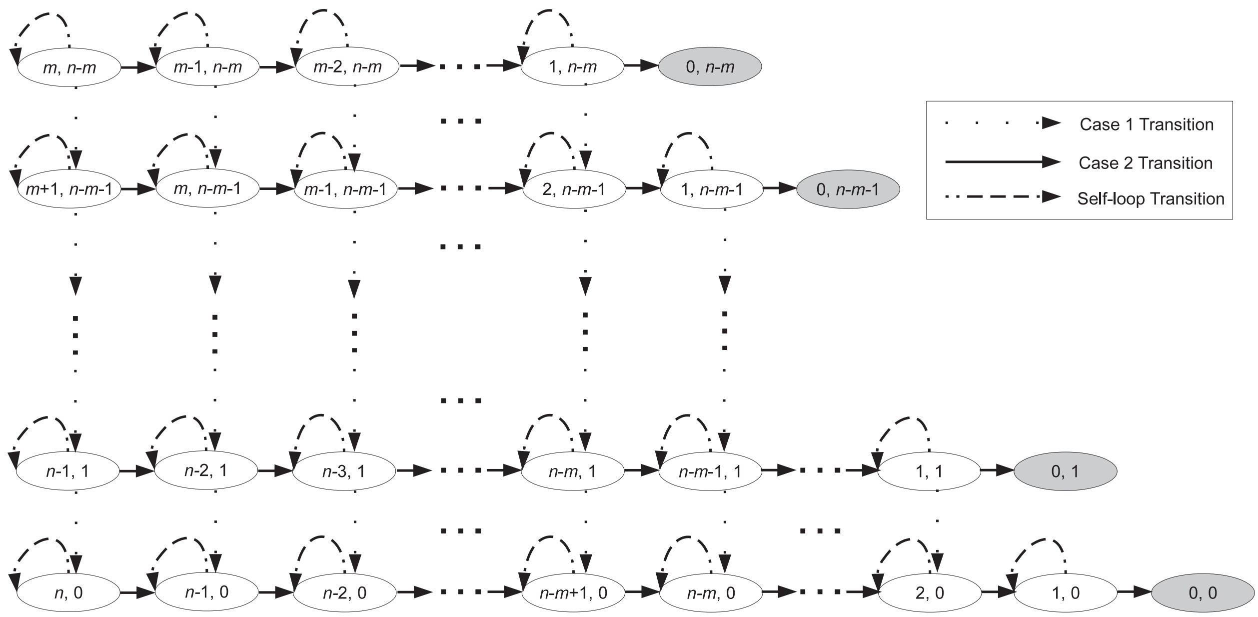


Figure 2. Transition diagram of the Markov chain for characterizing the message propagation process, $1 \leq m \leq n$. The shaded states are absorbing states.

where $\mathbf{e} = (1, 0, 0, \ldots, 0)$ is the initial row vector of size $1 \times \beta$, $\mathbf{V_0}$ is the $\beta \times 1$ average sojourn time vector defined as

$$\mathbf{V_0} = \Big(\frac{-1}{v_0(1)}, \frac{-1}{v_0(2)}, \frac{-1}{v_0(3)}, \ldots, \frac{-1}{v_0(\beta)}\Big)^T. \tag{12}$$

Now we proceed to derive the expectation and variance of the fraction of mobile sensors finally receiving the message, i.e., $\mathbb{E}\{r(m,n)\}$ and $\text{Var}\{r(m,n)\}$, and the probability $P(i)$ of i nodes receiving the message at the completion of message propagation. From (2) and (3), we can see that in order to derive $\mathbb{E}\{r(m,n)\}$ and $\text{Var}\{r(m,n)\}$, we need to first obtain $\{P(i)\}$, $m \leq i \leq n$. Recall that there are in total $n-m+1$ absorbing states, and the embedded Markov chain may enter each absorbing states with a certain probability. If we denote by b_k the probability that the Markov chain becomes absorbed in the absorbing state k, given the chain initially starts from transient state 1, therefore, we have

$$P(i) = b_{i-m+1} \qquad \text{if } m \leq i \leq n. \tag{13}$$

Equation (13) follows after the observation that if there are i nodes finally receiving the message, the Markov chain accordingly enters absorbing state $(0, n-i)$, which has a sequence id $i - m + 1$.

It is notable that for the DTMC embedded in the Markov chain of Fig. 2, only the last transient state in the $(k-1)_{th}$ row (i.e., the row with sequence id $k-1$), $1 \leq k \leq n-m+1$, has transition into the absorbing state k. Further note that the last transient state in the $(k-1)_{th}$ row corresponds to state $(1, n-m-k+1)$, which has a sequence id $\sum_{t=0}^{k-1} L_t = (2m+k-1)k/2$. Therefore, the probability that the Markov chain becomes absorbed in the absorbing state k can be determined as

$$b_k = \mathbf{N}\Big(1, \frac{(2m+k-1)k}{2}\Big) \cdot \frac{v_2(1, n-m-k+1)}{-v_0(1, n-m-k+1)}. \tag{14}$$

Combining (14) with (13), we have

$$P(i) = -\mathbf{N}\Big(1, \frac{(m+i)(i-m+1)}{2}\Big) \cdot \frac{v_2(1, n-i)}{v_0(1, n-i)}. \tag{15}$$

After obtaining $t(m,n)$, $\mathbb{E}\{r(m,n)\}$, $\text{Var}\{r(m,n)\}$, and $\{P(i)\}$ via matrix operations as derived in (11), (2), (3), and (15), we now proceed to utilize the theory of blocking matrix to derive the matrices $\mathbf{Q}$ and $\mathbf{N}$.

We first derive the matrix $\mathbf{Q}$. It is observed that for a transient state in Fig. 2, the Markov chain may either transit from it to a transient state in the same row or back to itself, or transit from it to another neighboring state in the next row. As motivated by such observation, we define the matrix $\mathbf{Q}$ as follows

$$\mathbf{Q} = \begin{pmatrix} \mathbf{Q}_0 & \mathbf{Q}_0^{'} & & & & & \\ & \mathbf{Q}_1 & \mathbf{Q}_1^{'} & & & & \\ & & \ddots & \ddots & & & \\ & & & \mathbf{Q}_k & \mathbf{Q}_k^{'} & & \\ & & & & \ddots & \ddots & \\ & & & & & \mathbf{Q}_{n-m-1} & \mathbf{Q}_{n-m-1}^{'} \\ & & & & & & \mathbf{Q}_{n-m} \end{pmatrix} \tag{16}$$

where each main diagonal entry $\mathbf{Q}_k$ is of size $L_k \times L_k$ and defines the one-step transition probabilities among transient states within row k of the DTMC embedded in Fig. 2, and each upper diagonal entry $\mathbf{Q}_k^{'}$ is of size $L_k \times L_{k+1}$ and defines the one-step transition probabilities from transient states of row k to that of row $k+1$ in the embedded DTMC.

We now proceed to derive submatrices $\{\mathbf{Q}_k\}$ and $\{\mathbf{Q}_k^{'}\}$. If we denote by $\mathbf{Q}_k(i,j)$ the ij-entry of $\mathbf{Q}_k$, $i,j \in [1, L_k]$, $k \in [0, n-m]$, then the non-zero entry of $\mathbf{Q}_k$ can be determined as

$$\mathbf{Q}_k(i,i+1) = \frac{v_2(k+m-i+1, n-m-k)}{-v_0(k+m-i+1, n-m-k)} \quad \text{if } 1 \leq i < L_k. \tag{17}$$

If we denote by $\mathbf{Q}_k^{'}(i,j)$ the ij-entry of $\mathbf{Q}_k^{'}$, $i \in [1, L_k]$, $j \in [1, L_{k+1}]$, $k \in [0, n-m-1]$, then the non-zero entry of $\mathbf{Q}_k^{'}$ can be determined as

$$\mathbf{Q}_k^{'}(i,i) = \frac{v_1(k+m-i+1, n-m-k)}{-v_0(k+m-i+1, n-m-k)} \text{ if } 1 \leq i \leq L_k. \tag{18}$$

Equations (17) and (18) follows after the fact that, the i_{th} transient state within the k_{th} row of Markov chain shown in Fig. 2 corresponds to state $(k+m-i+1, n-m-k)$.

From (10), one can see that we can obtain the fundamental matrix $\mathbf{N}$ based on $\mathbf{Q}$. Please refer to [10] for the details of derivation for matrix $\mathbf{N}$.

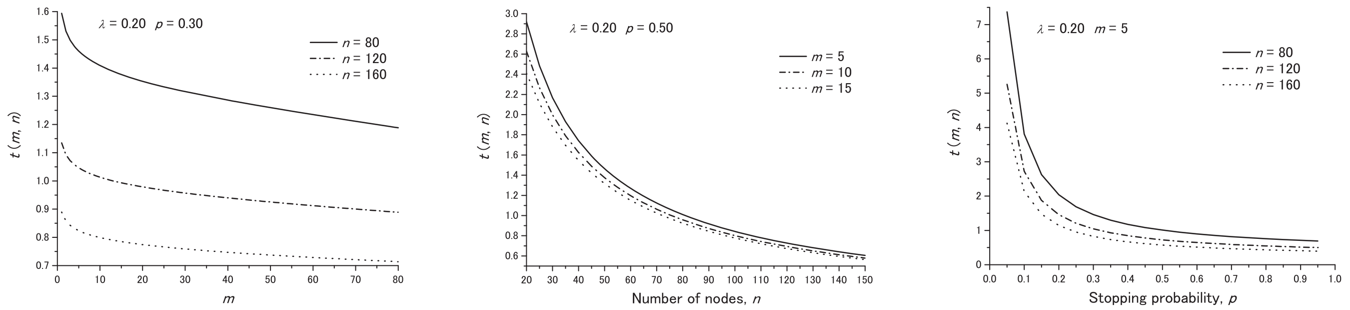
IV. Numerical Results

In this section, we proceed to apply the above theoretical framework to concrete network scenarios, so as to analytically evaluate the corresponding performance metrics, i.e., the average lasting time of the message propagation process $t(m,n)$, the mean value $\mathbb{E}\{r(m,n)\}$ of the fraction of nodes finally receiving the message and its variance $\text{Var}\{r(m,n)\}$, and the probability distributions of the number of nodes finally receiving the message $\{P(i)\}, i \in [m,n]$. Note that we present here only the numerical results under several network scenarios, the network performances under other network settings can also be obtained by our framework as well.

We summarize in Figs. 3(a), 3(b), and 3(c), respectively, how the average lasting time of message propagation process $t(m,n)$ varies with network parameters of m, n, and p. As shown in Fig. 3(a) that for each setting of n, the average lasting time $t(m,n)$ monotonically decreases as m increases, which means that increasing the number of nodes initially disseminating the message can improve the convergence speed of the message propagation process and thus shorten its propagation time. It is noticed that such monotonically decreasing behavior of $t(m,n)$ can be also observed from Figs. 3(b) and 3(c) as we increase the network size n and the stopping probability p. A further careful observation of Figs. 3(a), 3(b), and 3(c), indicates that there exists a common feature regarding the varying behaviors of $t(m,n)$ for all parameter settings in these three figures. Specifically, the $t(m,n)$ is extremely sensitive to the variations of m, n, and p when their values are relatively small. That is, $t(m,n)$ drops dramatically as parameters m, n, and p are within a small range, and becomes gradually insensitive to their variations as they increase up.

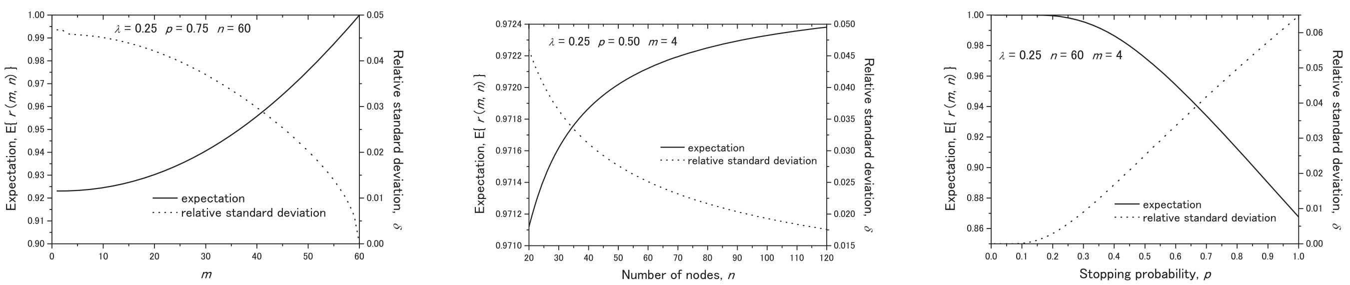
Recall that we consider for each node an explicit probabilistic stopping mechanism in the message propagation process. To further illustrate the impact of such mechanism on the message delivery performance, we show in Fig. 4 the relationship between network parameters (m,n,p) and the expected reach $\mathbb{E}\{r(m,n)\}$ and its relative standard deviation δ, where δ is defined as $\delta = \sqrt{\text{Var}\{r(m,n)\}}/\mathbb{E}\{r(m,n)\}$. One can observe from Fig. 4(a) (resp. Fig. 4(b)) that as m (resp. n) increases, the expected reach $\mathbb{E}\{r(m,n)\}$ monotonically increases, while the δ monotonically decreases. Such behaviors of $\mathbb{E}\{r(m,n)\}$ and δ mean that the explicit probabilistic stopping mechanism considered in this paper is very effective and has good scalability, since it can stably enable the message to be distributed to a majority of nodes (i.e., an increasing expected reach $\mathbb{E}\{r(m,n)\}$ and a decreasing relative standard deviation δ as the network scales up), while simultaneously conserving the transmit power and storage buffer for each node. However, both the behaviors of $\mathbb{E}\{r(m,n)\}$ and δ in Fig. 4(c) are totally different from that in Figs. 4(a) and 4(b). In particular, the $\mathbb{E}\{r(m,n)\}$ (resp. δ) monotonically decreases (resp. increases) as the stopping probability p increases. Actually, it can be explained as follows: as each node adopts a higher probability to stop disseminating the message after encountering a node having already received the message, the message has less chance to be transmitted in the network and thus the expected reach of the message becomes smaller.

Finally, we illustrate in Fig. 5 the probabilities of nodes finally receiving the message, $\{P(i)\}, i \in [m,n]$, i.e., the probability mass function of the number of nodes that have received the message at the completion of message propagation process. For the setting of $m = 5$, $n = 100$, Figs. 5(a) and 5(b) show the impacts of node inter-meeting intensity λ and stopping probability p, respectively. One can observe from Fig. 5(a) that the curves of all three λ settings there coincide with each other, which means that the number of nodes which have finally received the message is independent of the parameter λ. Actually, it can be mathematically proved via the DTMC embedded in Fig. 2. From the transition rates (4), (5), and (6) derived for each transient state, one can see that the transition probabilities among neighboring states in the embedded DTMC is independent of λ. Therefore, the absorbing state the embedded DTMC will finally enter and thus the number of nodes finally receiving the message are irrelevant to λ. As shown in Fig. 5(b) that, as stopping probability p increases, the curve of probability mass function becomes lower and wider, which corresponds to a larger varying range for the number of nodes finally receiving the message. Furthermore, a careful observation of Figs. 5(a) and 5(b) shows that there



(a) (b) (c)

Figure 3. An illustration of the relationship between the average lasting time $t(m,n)$ and network parameters (m,n,p). (a) $t(m,n)$ Vs. m. (b) $t(m,n)$ Vs. n. (c) $t(m,n)$ Vs. p.



(a) (b) (c)

Figure 4. An illustration of the expected reach $\mathbb{E}\{r(m,n)\}$ and its relative standard deviation δ, where $\delta = \sqrt{\mathrm{Var}\{r(m,n)\}}/\mathbb{E}\{r(m,n)\}$. (a) $\mathbb{E}\{r(m,n)\}$ and δ Vs. m. (b) $\mathbb{E}\{r(m,n)\}$ and δ Vs. n. (c) $\mathbb{E}\{r(m,n)\}$ and δ Vs. p.

exists a threshold value n_0, below which the corresponding probability is almost zero, i.e., $\{P(i) = 0 | m \leq i < n_0\}$. In other words, given parameters m, n, and p, at least n_0 nodes will finally receive the message.

V. Conclusion

In this paper we have considered an explicit probabilistic stopping mechanism for message propagation in mobile sensor networks, and investigated the impact of such mechanism on the message delivery performances. Specifically, a two-dimensional Markov chain framework was developed to characterize the complicated message propagation process. Based on the framework, closed-form expressions were further derived for the average lasting time of message propagation process $t(m,n)$, the expected reach $\mathbb{E}\{r(m,n)\}$ and the relative standard deviation δ, and the probability mass function of the number of nodes that have received the message at the completion of message propagation process. Finally, extensive numerical results were presented to illustrate how these performance metrics vary with network parameters (m,n,p,λ).

Our results show that the explicit probabilistic stopping mechanism considered in this paper is very effective and has good scalability, which can stably enable the message to be distributed to a majority of nodes while simultaneously conserving the transmit power and storage buffer for each node. One interesting finding is that $t(m,n)$ exhibits to be extremely sensitive to the variations of m, n, and p when their values are relatively small. Another finding is that given parameters m, n, and p there accordingly exists a threshold value n_0, and the explicit probabilistic stopping mechanism guarantees that at least n_0 nodes will finally receive the message.

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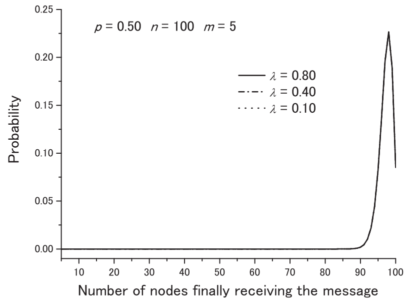
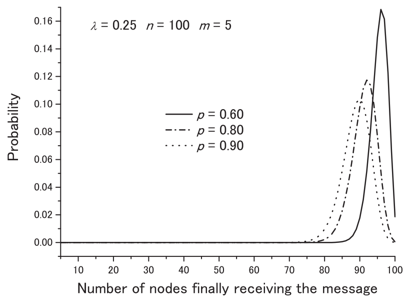


(a)



(b)

Figure 5. The probability distributions of nodes finally receiving the message, i.e., the probability mass functions of the number of nodes that have received the message at the completion of message propagation process.

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