

Article

Hop-by-Hop Worm Propagation with Carryover Epidemic Model in Mobile Sensor Networks

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Abstract: In the internet, a worm is usually propagated in a random multi-hop contact manner. However, the attacker will not likely select this random multi-hop propagation approach in a mobile sensor network. This is because multi-hop worm route paths to random vulnerable targets can be often breached due to node mobility, leading to failure of fast worm spread under this strategy. Therefore, an appropriate propagation strategy is needed for mobile sensor worms. To meet this need, we discuss a hop-by-hop worm propagation model in mobile sensor networks. In a hop-by-hop worm propagation model, benign nodes are infected by worm in neighbor-to-neighbor spread manner. Since worm infection occurs in hop-by-hop contact, it is not substantially affected by a route breach incurred by node mobility. We also propose the carryover epidemic model to deal with the worm infection quota deficiency that might occur when employing an epidemic model in a mobile sensor network. We analyze worm infection capability under the carryover epidemic model. Moreover, we simulate hop-by-hop worm propagation with carryover epidemic model by using an ns-2 simulator. The simulation results demonstrate that infection quota carryovers are seldom observed where a node's maximum speed is no less than 20 m/s.

Keywords: hop-by-hop worm propagation model; carryover epidemic model; mobile sensor network

1. Introduction

Worm attacks against sensor nodes are realistic in sensor networks, as demonstrated by [1,2] In particular, they show that a worm could be propagated by exploiting code injection vulnerabilities in

target sensor nodes. Wide-spread worm dissemination makes it possible for an attacker to rapidly gain control over the network.

To defend against a worm, it is very important to understand how a worm is propagated. In the sense that epidemic model [3] is good at modeling the spread of epidemic disease, researchers adapted it to worm propagation modeling in the internet and static sensor network [4–7]. However, these previous works do not consider node mobility which can greatly affect the worm infection capability and thus they are not appropriate for worm propagation in a mobile sensor network.

To mitigate this problem, we discuss a hop-by-hop worm propagation strategy in a mobile sensor network. In this strategy, worm infection is incurred only by neighbor-to-neighbor contact and thus node mobility will have little effect on worm propagation. Furthermore, we propose a carryover epidemic model in which the infection quota deficit in the current time slot is carried over to the next time slot. This model is adequate for the scenario where infection quota deficit occurs due to the frequent change of network topology and hence it is effective in the modeling of mobile sensor worm propagation. We analyze the cumulative number of infected nodes in the carryover epidemic model and derive Chernoff bounds on the number of time slots required for the whole network infection. Furthermore, we use an ns-2 simulator to evaluate the hop-by-hop worm propagation with carryover epidemic mode. The simulation results show that a worm infection quota deficit rarely occurs under the situation where a node's maximum speed is at least 20 m/s and thus worm infection is not delayed but completed in time. This indicates that node mobility makes it possible for a mobile node to have enough neighbors, leading to expedition of worm infection.

The rest of paper is organized as follows. In Section 2, we describe the related work. In Section 4, we describe hop-by-hop worm propagation strategy and the carryover epidemic model in a mobile sensor network. In Section 5, we analyze the hop-by-hop worm propagation with carryover epidemic model. In Section 6, we simulate hop-by-hop worm propagation with carryover epidemic model in mobile sensor network and present the simulation results. In Section 7, we conclude the paper.

2. Related Work

In this section, we first introduce the related work of sensor worm modeling and then bring up the worm modeling work in the literature of mobile networks.

In the context of sensor networks, several researchers [4–6,8] proposed worm propagation modeling in static sensor networks. More specifically, De *et al.* [4] modeled sensor worm propagation by using node deployment knowledge. De's work investigated how group deployment strategy affects the worm propagation in a sensor network. Khayam *et al.* [6] applied the signal processing technique to model sensor worm propagation. Khayam *et al.* explored the sensor worm propagation in terms of signal processing. Guo *et al.* [8] explored how to control worm propagation using the spatial correlation parameters. Feng *et al.* [5] examined the flux of worm dissemination using differential dynamical theory.

In the literature of mobile ad hoc networks, Mickens *et al.* [9,10] investigated queue-based propagation of malicious software under random waypoint model in mobile ad hoc networks. Valler *et al.* [11] compute a general epidemic threshold in the SIS (Susceptible-Infectious-Susceptible) model and demonstrate that the epidemic threshold is not influenced by mobile node's speed. Moreover,

there are related works that apply the concept of epidemic mobility to broadcasting or ad hoc routing. Specifically, Karlsson *et al.* [12] proposed broadcasting system that utilizes delay-tolerant data forwarding together with node mobility. In [13], the author proposed the combined version of AODV and DTN-based routing to take the benefits of both routing protocols.

Finally, Chen *et al.* [14] explored the worm propagation model in mobile smartphone. In a bluetooth environment, Yan *et al.* [15] worked the impact of mobility models on epidemic dissemination of a SIS virus.

3. Assumptions

For worm propagation modeling, we assume mobile sensor networks in which sensor nodes wander throughout the network in a pre-determined or random manner. This assumption is essential to explore how a worm is propagated over mobile sensor networks. Furthermore, we assume that both worm infection strategy and number are considered for accurate worm propagation modeling. This assumption is reasonable in the sense that it is imperative to explore how many benign nodes are infected through what kind of worm propagation tactics. To meet this assumption, we introduce a hop-by-hop worm infection with carryover epidemic model strategy that is well-suited for mobile sensor networks in the next section.

4. Hop-By-Hop Worm Propagation in Mobile Sensor Networks

In this section, we describe a hop-by-hop worm propagation with carryover epidemic model in a mobile sensor network. Note that this model is also used as an assumption for worm detection in our previous work [16].

Many researchers have adopted an epidemic model [3] in order to model the infection quota, which is defined as the number of nodes that a worm infects per time slot in a network. This is because the epidemic model is useful at the quantification of infection quota in a series of time slots. The infection quota in the discrete time version of a simple epidemic model [3] is calculated in units of time slots by the following equation:

$$I_k = (1 + \theta N)I_{k-1} - \theta I_{k-1}^2 \quad (1)$$

where θ is a pairwise infection rate [3] and N is the total number of nodes in the mobile sensor network. I_0 indicates the number of worm originators. We define I_k as the cumulative infection quota from the 0th time slot to the k th time slot. As a consequence, the infection quota in the k th time slot is set to $I_k - I_{k-1}$.

Since the epidemic model only deals with the infection quota, there should be a model to describe how worm is spread through the mobile sensor network. To meet this need, we consider a a hop-by-hop worm dissemination strategy in mobile sensor network. Under this strategy, we assume that a sensor has *susceptible* or *infectious* state. All sensor nodes are initially set to the susceptible state except infectious worm originators. Each infectious node spreads worm to its one-hop neighboring susceptible nodes. Once a susceptible node is infected by a worm, it changes its state to infectious.

Although the epidemic model is good at modeling the infection quota, it may not be useful in the scenario in which infectious nodes in a time slot could have fewer neighboring susceptible nodes than the infection quota due to the network topology. To pacify this problem, we slightly change the discrete time version of simple epidemic model in such a way that we carry over the infection quota deficit in the current time slot to the next time slot, charging the total infection quota over the entire time period. More specifically, we denote q_k the infection quota deficit in the k th time slot. The infection quota in the first time slot is calculated as $I_1 - I_0$ and the infection quota in the k th time slot is accordingly computed as $I_k - I_{k-1} + q_{k-1}$ ($k \geq 2$). We call this modified version of epidemic model the *carryover epidemic model*. In the next section, we provide a quantitative analysis of the carryover epidemic model.

5. Analysis

In this section, we first present an analysis on the carryover epidemic model and then describe the analytical results on the number of time slots required for the entire network infection.

In the following Lemma, we first derive the cumulative number of infected nodes when the carryover epidemic model is used.

Lemma 1. *In carryover epidemic model, the cumulative number of infected nodes from the 0th time slot to the τ th time slot is $I_\tau - q_\tau$.*

Proof. Recall that $I_{t+1} - I_t + q_t$ is the infection quota in the $t + 1$ th time slot ($t \geq 1$) in carryover epidemic model, where $I_1 - I_0$ is the infection quota in the first time slot and q_t is the infection quota deficit in the t th time slot. The number of infected nodes in a time slot is the difference between the infection quota and the quota deficit in a time slot. Hence, the cumulative number of infected nodes from the 0th time slot to the τ th time slot is given by:

$$I_0 + I_1 - I_0 - q_1 + \sum_{t=1}^{\tau-1} I_{t+1} - I_t + q_t - q_{t+1} = I_\tau - q_\tau$$

□

If the entire network infection is completed in the τ th time slot, q_τ will be zero. Accordingly, by the Lemma 1, I_τ will be equal to the total number of nodes in the network.

Next, we compute the average number of time slots required for the entire network infection. To do this, we employ discrete Poisson distribution to model the number of time slots required to infect the entire network. This is reasonable in the sense that discrete Poisson distribution is generally useful for random data counting and thus can be applied to randomly count the number of time slots required for the entire network infection. Specifically, we define a discrete Poisson random variable X with parameter μ . X indicates a time slot in which the entire network infection is finished. Putting it in differently, X times slots are needed to infect all nodes in the network.

We define $\Pr(X = j)$ as the probability that the entire network infection is completed in the j th time slot. Accordingly, $E[X]$ is the average number of time slots required for the entire network infection.

By the definition of discrete Poisson distribution, $\Pr(X = j)$ is given by:

$$\Pr(X = j) = \frac{e^{-\mu} \mu^j}{j!}$$

and $E[X] = \mu$.

Then the probability that the entire network infection is completed at most the τ th time slot is calculated as $\sum_{j=1}^{\tau} \Pr(X = j)$. Thus, $1 - \sum_{j=1}^{\tau} \Pr(X = j)$ is the probability that more than τ time slots are consumed to infect all nodes in the network.

Finally, we derive the Chernoff bounds on the number of time slots required for the entire network infection.

Lemma 2. *If $j > \tau$ and $\mu \leq j \left(\frac{\tau}{j-\tau}\right) \ln \frac{j}{\tau}$, then*

$$\Pr(X \geq j) \leq \frac{\tau^j}{j^j} e^{\mu \left(\frac{j}{\tau} - 1\right)}.$$

Proof. For any $y > 0$, the Markov's inequality is given by:

$$\begin{aligned} \Pr(X \geq j) &= \Pr(e^{yX} \geq e^{yj}) \\ &\leq \frac{E[e^{yX}]}{e^{yj}} \end{aligned}$$

Since $E[e^{yX}] = e^{\mu(e^y - 1)}$ is the moment generating function of the Poisson discrete random variable X , we have

$$\Pr(X \geq j) \leq e^{\mu(e^y - 1) - yj}$$

Given that $j > \tau$ and $\mu \leq j \left(\frac{\tau}{j-\tau}\right) \ln \frac{j}{\tau}$, by selecting $y = \ln\left(\frac{j}{\tau}\right) > 0$, we have

$$\Pr(X \geq j) \leq \frac{\tau^j}{j^j} e^{\mu \left(\frac{j}{\tau} - 1\right)} \leq 1$$

□

We investigate how j affects the Chernoff bound of $\Pr(X \geq j)$ when $\tau = 10$. As shown in Figure 1, the Chernoff bound of $\Pr(X \geq j)$ decreases as j increases. From this observation, as j is away from τ , it decays the Chernoff bound on the probability that the number of time slots required for the entire network infection is at least j . Given a fixed value of j , the Chernoff bound of $\Pr(X \geq j)$ increases as μ increases. This means that the Chernoff bound of $\Pr(X \geq j)$ rises as an average number of slots required for the entire network infection is close to τ .

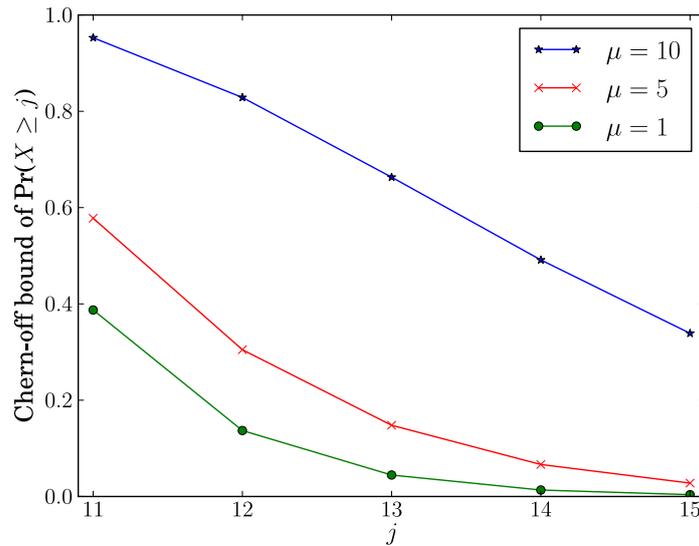


Figure 1. Chernoff bound of $\Pr(X \geq j)$ vs. j .

Lemma 3. If $j < \tau + 1$ and $\mu \geq j \left(\frac{\tau+1}{j-\tau-1} \right) \ln \left(\frac{j}{\tau+1} \right)$, then

$$\Pr(X \leq j) \leq \frac{(\tau+1)^j}{j^j} e^{\mu \left(\frac{j}{\tau+1} - 1 \right)}.$$

Proof. For any $y < 0$, the Markov's inequality is given by:

$$\begin{aligned} \Pr(X \leq j) &= \Pr(e^{yX} \geq e^{yj}) \\ &\leq \frac{E[e^{yX}]}{e^{yj}} \end{aligned}$$

Since $E[e^{yX}] = e^{\mu(e^y-1)}$ is the moment generating function of the Poisson discrete random variable X , we have

$$\Pr(X \leq j) \leq e^{\mu(e^y-1)-yj}$$

Given that $j < \tau + 1$ and $\mu \geq j \left(\frac{\tau+1}{j-\tau-1} \right) \ln \left(\frac{j}{\tau+1} \right)$, by selecting $y = \ln \left(\frac{j}{\tau+1} \right) < 0$, we have

$$\Pr(X \leq j) \leq \frac{(\tau+1)^j}{j^j} e^{\mu \left(\frac{j}{\tau+1} - 1 \right)} \leq 1$$

□

We investigate how j affects the Chernoff bound of $\Pr(X \leq j)$ when $\tau = 10$. As shown in Figure 2, the Chernoff bound of $\Pr(X \leq j)$ increases as j increases. From this observation, as j is close to τ , it rises the Chernoff bound on the probability that the number of time slots required for the entire network infection is at most j . Given a fixed value of j , the Chernoff bound of $\Pr(X \leq j)$ increases as μ decreases. This means that the Chernoff bound of $\Pr(X \leq j)$ rises as an average number of slots required for the entire network infection is close to τ .

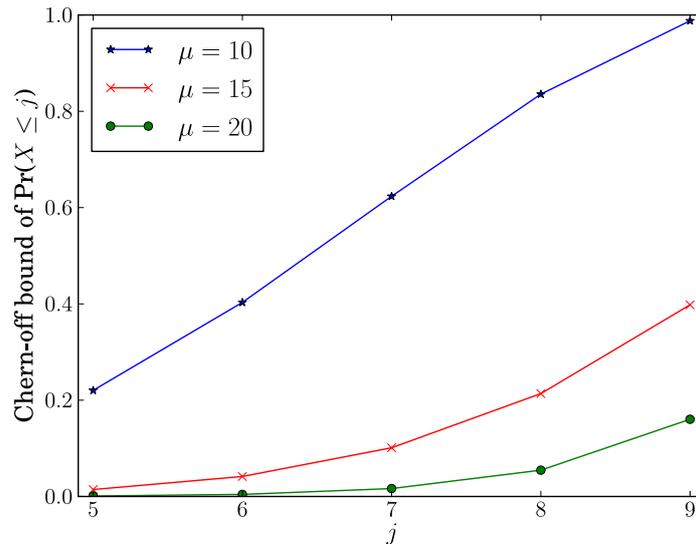


Figure 2. Chernoff bound of $\Pr(X \leq j)$ vs. j .

6. Simulation Study

In this section, we first describe the simulation setup and then present simulation results.

6.1. Simulation Configurations

We use the ns-2 network simulator to evaluate the hop-by-hop worm propagation strategy in a mobile sensor network. In our simulation, 100 mobile sensor nodes are placed within a square area of $500 \text{ m} \times 500 \text{ m}$. Furthermore, In order to configure node movement patterns, we use the Random Waypoint Mobility (RWM) model with the steady-state distribution provided by the Random Trip Mobility (RTM) model [17]. In particular, we generate a steady-state version of RWM model by using the program codes of [18].

We divide the entire time domain into 25 time slots and one time slot is 20 simulation seconds. Accordingly, all simulations are performed for 500 simulation seconds. We fix a pause time of 10 simulation seconds and a minimum moving speed of 1 m/s of each node. Each node uses IEEE 802.11 as the medium access control protocol in which the transmission range is 50 m. To investigate how node mobility affects hop-by-hop worm propagation strategy with the carryover epidemic model, we vary each node's maximum speed (V_{\max}) in the range of 20, 40, 80 m/s. In the discrete time version of carryover epidemic model, we configure the pairwise infection rate $\theta = 0.005, 0.01$.

Moreover, we assume that a susceptible node is infected by a single worm packet whose size is 46 bytes. This is reasonable because a single worm packet infection indicates the best case for the attacker and a data packet consists of 11 byte header, 28 byte data, and 7 byte meta information in Tiny OS 2.x.

6.2. Simulation Results

We present the average of the results of 50 executions under the aforementioned simulation configurations. When $V_{\max} = 20 \text{ m/s}$, the cumulative number of infectious nodes up to the first time slot

(I_1) is 1.980 in both $\theta = 0.005$ and $\theta = 0.01$. Except the case of I_1 with $V_{\max} = 20$ m/s, the cumulative number of infectious nodes exactly matches with the cumulative infection quota of the discrete epidemic model under all other cases. This indicates that the infection quota carryover does rarely occur where a mobile node's maximum speed is at least 20 m/s. We infer from this observation that node mobility makes each node have sufficient neighbors, leading to infrequent incurrence of infection quota carryover. Moreover, as shown in Figures 3 and 4, the infection quota is fulfilled in the 17th and 9th time slot when $\theta = 0.005$ and $\theta = 0.01$, respectively. This means that the infection quota at the higher infection rate is achieved at the earlier time.

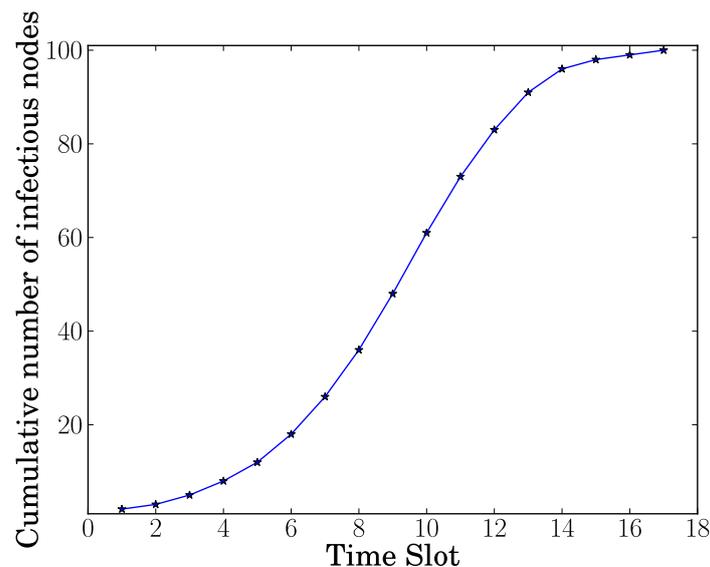


Figure 3. Cumulative number of infectious nodes when the pairwise infection rate θ is 0.005.

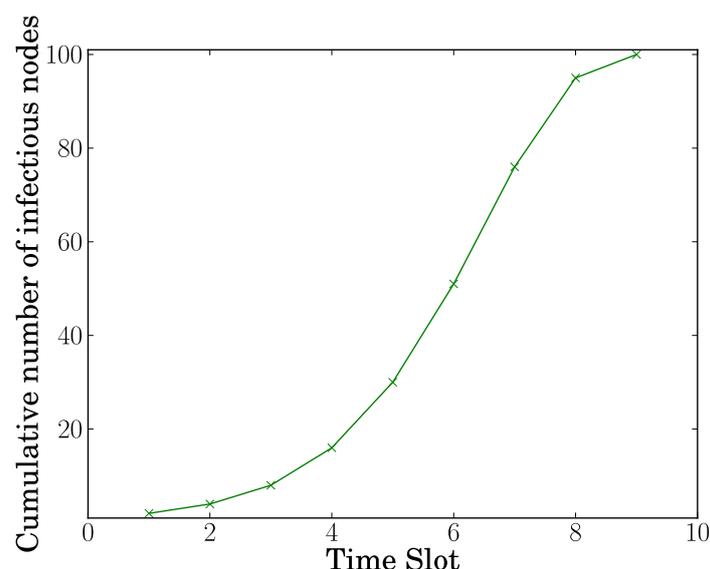


Figure 4. Cumulative number of infectious nodes when the pairwise infection rate θ is 0.01.

7. Conclusions

In this paper, we propose hop-by-hop worm propagation strategy with carryover epidemic model in mobile sensor networks and evaluate it by using an ns-2 simulator. In simulation, we rarely observe

infection quota carryover where a node's maximum speed is no less than 20 m/s. In addition, the infection quota is quickly achieved in the ninth time slot under high infection rate of 0.01. Furthermore, we derive the Chernoff bounds on the number of time slots for the entire network infection of the proposed model.

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Conflicts of Interest

The author declares no conflict of interest.

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